NEW TOOLS OF ANALYSIS IN

QUANTITATIVE CRIMINOLOGY:

AN EXPLORATION

by

Arvind Verma

THESIS SUBMITTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

in the

SCHOOL OF CRIMINOLOGY

SIMON FRASER UNIVERSITY
JANUARY 1996

ISBN 0-612-17158-2

Title of Thesis/~~Project/Extended Essay~~

New Tools of Analysis in Quantitative Criminology:

An Exploration

Author: ______ ____________________
(signature)

Arvind Verma
(name)

29-01-96
(date)

APPROVAL

NAME: **Arvind Verma**

DEGREE: **Doctor of Philosophy (Criminology)**

TITLE OF THESIS: **New Tools of Analysis in Quantitative Criminology:** An Exploration

Examining Committee:

Chair Joan Brockman, LL. M.

Patricia L. Brantingham, Ph. D.
Senior Supervisor
Professor of Criminology

William G. Glackman, Ph. D.
Associate Professor of Criminology

Paul J. Brantingham, J.D., Dip. Crim.
Professor of Criminology

Raymond Corrado, Ph. D.
Internal External Examiner
Professor of Criminology

Michael D. Maltz, Ph. D.
External Examiner
Professor of Criminal Justice
University of Illinois at Chicago

Date Approved: Jan 29, 1996

ABSTRACT

This research is concerned with the exploration of new mathematical tools and their applications in criminology. At present, most of the quantitative methods being used in criminology are statistical in nature. Even the textbooks give the impression that quantitative techniques are synonymous with statistics and moreover, commonly associated with the positivistic perspective as well. However, despite the wide spread use of statistics, researchers rarely address their underlying assumptions about data, some of which may be serious enough to put in question the results obtained by their use.

This thesis argues against restricting quantitative methods within a narrow definition of statistical techniques. Instead, it stresses that criminological methodology ought to include a broader use of mathematics, particularly because of its rigor, clarity, the ability to structure and display inherent patterns. It also points out that mathematics has little to do with 'number crunching' and deals with mental constructs like sets, tesselations and fractals. Furthermore, mathematics also subsumes a constructionist perspective and could be useful for phenomenological studies as well. The thesis suggests that mathematics, of which statistics is but one part, has a wide range of techniques that could be useful for criminology. It also points out that new developments in criminology are looking for non-statistical mathematical techniques.

The thesis develops four different mathematical techniques and demonstrates their applications in police investigations, the ecological, spatial and the temporal analyses of crime. In particular, the thesis presents techniques from fuzzy logic, topology, Voronoi tesselations and range by standard deviation methodology developed by Mandelbrot. The thesis illustrates the availability of different mathematical tools and suggests expansion of research work in several new directions. It also seeks to raise the level of interest in mathematics amongst those endeavouring to study crime and apply the knowledge of this subject to the control of crime.

DEDICATION

This work is dedicated

to my parents and my grandmothers

who played such an important role

in molding my life

QUOTATION

गुरुर्ब्रह्मा गुरुर्विष्णु गुरुर्देवो महेश्वरः।

गुरुर्साक्षात् परब्रह्माः तस्मै श्री गुरवे नमः।।

GURU IS BRAHMA GURU IS VISHNU

GURU IS DEVA AND MAHESHWARA

GURU IS REALLY THE GOD

THAT IS THE GURU TO WHOM I BOW

ACKNOWLEDGMENTS

One of the pleasures in completing any work is the opportunity it provides to acknowledge the assistance given over the course of time by so many people.

Indeed, this dissertation would not have even been conceived without the encouragement and support by my senior supervisor Patricia Brantingham who made me appreciate mathematics once again. Her guidance and faith in the value of this work were crucial in keeping me on to the final goal. Paul Brantingham, who keeps a fatherly eye upon his students, remained sympathetic to my struggles and provided a constant source of practical tips to keep my work on the right track. Bill Glackman has remained the first friend that I made in Canada and never faltered in maintaining good humour with excellent judgment and support.

Ray Corrado, Margaret Jackson, Curt Griffiths, Ejjat Fattah and Noel Dyck have always provided encouragement, support and guidance and at times that were crucial. Aileen Sams and Donna first made me feel at home in the department and ever since have made me welcome in their offices.

Although, I was coming back to academics after twelve years in police, I was more apprehensive of settling my family in Canada than the challenge of passing examinations and writing term papers. Yet, my wife Chapla and children Juhi and Rishi never once complained about leaving a life of comfort in India and sharing the hardships and deprivations of a student life. There is no doubt that this dissertation would not have been possible without their quiet suffering and active assistance.

My friends from India, Ram Sewak Sharma, Ashok Singh and Suresh Lodha have always been supportive of my venture and have played important roles in my quest for knowledge. Bhaskar Bhattacharya and Arya Ray Chowdhary, the friends I made in Canada have not only helped in my work but also provided that typical Indian association which makes life bearable in difficult times.

My colleagues, Cheng Yang, Shihong Mu, Al Patentdo and Zack Fleming have been a source of encouragement and have gone out of their way to make our stay in Canada a memorable experience.

TABLE OF CONTENTS

APPROVAL	**II**
ABSTRACT	**III-IV**
DEDICATION	**V**
QUOTATION	**VI**
ACKNOWLEDGMENTS	**VII-VIII**
TABLE OF CONTENTS	**IX-XIII**
LIST OF TABLES	**XIV**
LIST OF FIGURES	**XV**
CHAPTER 1: INTRODUCTION	**1-6**
CHAPTER II: THE NATURE OF QUANTITATIVE RESEARCH METHODOLOGY	**7-40**
Quantitative & Qualitative Methodologies	7
Quantitative Methods & Statistics	13
Quantitative Research as a Special Paradigm	20
Nature of Qualitative Paradigm	22
Quantitative Methodology & Positivism	26
Positivism, Empiricism & Realism	27
Underneath the Paradigmatic Stance	31
CHAPTER III: STATISTICS	**41-79**
Ignoring Statistical Foundations	42
Statistics as a Subject distinct from Mathematics	43

Limitations of Statistics 58

CHAPTER IV : THE NATURE OF MATHEMATICS 80-107

Problems Associated with the Nature of Mathematics 81

Knowledge about Mathematics 82

Making sense of Mathematical Propositions 86

Computer Aided Mathematical Proofs 90

The Foundations of Mathematics 92

Mathematical Creativity 97

The Advantages of Using Mathematics 100

CHAPTER V: THE PATTERN THEORY OF CRIME 108-132

Theory and Method 108

The Pattern Theory of Crime 114

Backcloth, Nodes, Paths and Templates 117

The Cognition of Space 124

Modeling the Criminal Event 129

CHAPTER VI: CONSTRUCTION OF OFFENDER PROFILES USING FUZZY LOGIC 133-157

The Need for 'Imprecise' Logic 134

Applications of Fuzzy Logic based Techniques 137

Fuzzy Set Theory 139

Technique 141

Aggregation Techniques 144

Hypothetical Example 147

Summary 151

Implications: 153

CHAPTER VII: HOT SPOTS AND BURNING TIMES:

A TOPOLOGICAL ANALYSIS OF CRIME SPACE 158-194

Topological Properties 158

Basic Elements of Topology 161

Application of the Technique 166

Application 1: Topological Connectivity 174

Results 181

Application 2: Burning Times 184

Results 189

Implications 193

CHAPTER VIII: VORONOI DIAGRAMS:

ANALYSIS OF NODES AND PATHS 195-225

Application of Geometrical Techniques in Criminology 195

The Concept of Voronoi Diagrams 197

Mathematical Properties of Voronoi Diagrams 199

Pattern Analysis of Voronoi Point Generators 210

Nearest Neighbor Distance Technique for Voronoi Diagrams 214

NND Technique for Point Generators 215
NND Technique for Line Objects 218

Application of Delaunay Triangle based Technique 221

Implications 225

CHAPTER IX: THE FRACTAL DIMENSION OF POLICING 226-252

Time Series Analysis in Criminological Research 228

The Nature of Time Series Analysis 229

Emergency Calls for Police Services as Useful Crime Data 232

Utility of the CAD System 236

Analytical Tools and Data Sources: 243

Technique 244

Implications 248

Impact of Method upon Theory 251

CHAPTER X: CONCLUSION **253-256**

APPENDICES

APPENDIX 1: Classification of Quantitative Techniques 257-258

APPENDIX 2: Connectivity of Census Tracts 259-260

APPENDIX 3: 10% 'A' Cut by Ethnicity 261-262

APPENDIX 4: 10% 'A' Cut by Population Density 263-264

APPENDIX 5: 10% 'A' Cut by Rented Housing 265-266

APPENDIX 6: 10% 'A' Cut by Single Parent 267-268

APPENDIX 7: 25% 'A' Cut by Ethnicity 269-270

APPENDIX 8: 25% 'A' Cut by Population Density 271-272

APPENDIX 9: 25% 'A' Cut by Rented Housing 273-274

APPENDIX 10: 25% 'A' Cut by Single Parent 275-276

APPENDIX 11: 40% 'A' Cut by Ethnicity 277-278

APPENDIX 12: 40% 'A' Cut by Population Density 279-280

APPENDIX 13: 40% 'A' Cut by Rented Housing 281-282

APPENDIX 14: 40% 'A' Cut by Single Parent 283-284

APPENDIX 15: Temporal Distribution of Calls 285

APPENDIX 16: Program for Estimating the R/S Values 286

REFERENCES **299-323**

LIST OF TABLES

TABLE 2.1: Review of Quantitative Methods 20

TABLE 6.1: Fuzzy Offender Characteristics 149

TABLE 6.2: Summary of Witness Statements 150

TABLE 7.1: BNE Along Topologically Connected Census Tracts 182

TABLE 7.2: Distribution of Calls for Police Service in the Physical Plane 190

TABLE 7.3: Distribution of Calls for Police Service in the Temporal Plane 191

TABLE 8.3: Summary of Results from Delaunay Triangle Analysis 224

LIST OF FIGURES

FIGURE 1: Vancouver Census Tract Boundaries 287

FIGURE 2: Connectivity of Tracts by Ethnicity 288

FIGURE 3: Topologically Connected Census Tracts 289

FIGURE 4: Hot Spots by Enumeration Areas 290

FIGURE 5: Burning Times 291

FIGURE 6: Delaunay Triangle of Chevy Auto Thefts 292

FIGURE 7: R/S Values June '91 293

FIGURE 8: SR/S Values June '91 294

FIGURE 9: R/S Values Assaults 295

FIGURE 10: SR/S Values Assaults 296

FIGURE 11: R/S Values Theft from Cars 297

FIGURE 12: SR/S Values Theft from Cars 298

CHAPTER 1

INTRODUCTION

The reason people so often lie

is that they lack imagination:

They don't realize that the truth, too

is a matter of invention.

José Ortega y Gasset

This dissertation is primarily the outcome of my concern with the observation that almost all quantitative techniques in criminology are statistical in nature. The course contents of research methods, not only at the school of criminology, at the Simon Fraser University but also in the other universities, appear to treat quantitative methods as synonymous with statistics. Naturally, these statistics courses are not limited in nature or applications. Depending upon student interests, techniques ranging from regression to sophisticated factorial and time series analysis are being taught. Statistics is of course an extremely useful subject with wide utility in diverse fields.

However, limiting quantitative methods to the domain of statistics has resulted in restricting perspectives and appears to result in creating an impression in the minds of students of criminology that the only alternative to qualitative methods is some awesome number crunching through statistics. Even amongst my colleagues, the view is that to seek some alternate technique for their data analysis implies learning the popular computer programs specially designed for the statistical analyses in the social sciences and browsing through statistical books. A serious problem that has emerged from this limited view is that students have necessarily remained ignorant of differing perspectives and have failed to develop insights into other forms of data analysis. It is forgotten that mathematics is much broader subject than statistics and provides a wider spectrum of techniques catering to different perspectives. It is for these reasons that I have chosen a subject for my dissertation which is concerned with broadening research methodology.

My dissertation covers two major research issues. The first issue is the debate between quantitative and qualitative research methodologies. Many criminologists appear to confine quantitative methods to some form of numerical analysis, apparently on some deep rooted philosophical grounds. However, as my work will point out, quantitative methods are not as limited as many believe. There is power and abstraction afforded through the use of mathematics. Further, mathematics can also subsume many perspectives and, therefore, both the quantitative and qualitative practitioners can actually use mathematics as a research tool.

Secondly, my work will explore several different types of mathematics that have so far not been examined by criminologists in particular, and show the applicability of these new approaches in practical situations. Accordingly, my first chapter will deal with the debate between quantitative and qualitative methods and argue that there are parallel debates in mathematics too. The controversy between positivism and phenomenologism, for example, is also seen between constructive and formalist mathematics and, more significantly, both these schools have developed their particular methods of analysis. Thus, even for those who support the phenemonologist viewpoint, mathematical techniques from constructive mathematics are available for applications.

The second chapter will discuss the development of statistics and identify some limitations generally encountered in dealing with criminological data. The third chapter will describe the world of mathematics and explain the different viewpoints ranging from the formalist to the constructionist schools. It will also argue that mathematics is a creative subject and one that is capable of providing human beings with objective tools of analysis.

In the fourth chapter, the dissertation will argue that the recent developments in criminological theories have actually started demanding new kinds of mathematical tools. The chapter will outline Pattern theory and demonstrate that in applying this theory to the understanding and control of criminal behavior, modern and new mathematics not seen in criminological literature are essentially required.

The next section of the thesis will deal with the exploration and application of these mathematical tools. In particular, four techniques and their utility will be demonstrated. The first technique will be based upon fuzzy logic and it will be shown how this mathematics could be useful to criminological studies. It will be used to demonstrate its value in constructing offender profiles even in cases where information about the offender is limited. This technique will be useful in developing offender 'templates' as suggested by Pattern theory. Several additional possible applications of fuzzy logic in criminal justice studies will also be outlined.

The second technique based upon topology will form an important chapter of this thesis. It is an area of mathematics that has still not been used much in criminology despite its advantages. The chapter will describe various applications of topology in understanding criminal behavior and also show how it brings out the qualitative similarities between the physical and temporal dimensions of crime.

The third form of technique will be based upon geometrical figures of a particular kind. The properties of spatial tessellations known as Voronoi diagrams will be described and explored for possible applications in criminology. Their utilization in the spatial distribution of crime, in recognizing patterns and in point pattern analysis will be demonstrated.

The fourth technique, called range by standard deviation (R/S) will be explored with a specific viewpoint. It will be shown that mathematics is not only useful in the verification of some theory but also for developing one. The application of some mathematical technique in analyzing data could lead to new questions and insights that may demand a new explanation. It will be shown that calls for police service that are being used in many research studies as impartial official data may have, in fact, some built in memory. The R/S technique will be used here to demonstrate this memory effect. Through the use of this technique a fractal dimension of policing in Vancouver will also be explored.

The dissertation will also identify several other applications in criminology that could profitably be analyzed through the application of mathematics. Above all, the thesis seeks to raise the level of interest in mathematics amongst those endeavoring to study crime and apply the knowledge of this subject to its control.

---x---

CHAPTER II

THE NATURE OF QUANTITATIVE RESEARCH METHODOLOGY

The debate between quantitative and qualitative research methodologies is almost an endless one for "the disagreements are not over relative advantages or disadvantages but [are] a fundamental clash between methodological paradigms" (Cook and Reichardt 1979: 9). As Rist (1977: 43) has said, "Ultimately, the issue is not research strategies per se. Rather, the adherence to one paradigm as opposed to another that predisposes one to view the world and the events within it in profoundly differing ways".

This chapter will examine the debate and the underlying paradigms and also trace the historical developments that have led to the common notion of statistics as *the* quantitative research technique in criminology.

Quantitative & Qualitative Methodologies

Authors describing the nature of quantitative research methods frequently do so by contrasting them with the alternate techniques that are said to be qualitative in nature. The distinction between the two research methodologies is in fact entrenched in every discipline of the social sciences. For example, in psychology there is the debate between experimental and clinical methods while in sociology it is seen in the separation of observational fieldwork and statistical work based upon questionnaires. In criminology too, for example, analysis based on the official data is considered a quantitative technique while that of personal self reports content analysis based upon verbal descriptions falls into what is usually called qualitative analysis.

The common view of the division between quantitative and qualitative methodologies is that the former employs descriptions of objects, events and the relationships among them in numerical forms while the latter uses descriptions in words. This is generally an incorrect impression for every number, like *10* can be represented by word *ten* and every mathematical or logical association can also be stated in verbal terms. Naturally, most words cannot be equated with numerals, though techniques like semantic differential (Clifton 1975) or classical content analysis can translate aspects of verbal concepts numerically (Hunter 1985: 645).

The distinction chiefly seems to arise from the fact that qualitative techniques involve exploration of relationships between or among concepts whose constituent categories are unordered and comprise typologies, like 'users' or 'non-users' of cocaine. In contrast, the quantitative methods frequently involve propositions in which at least one concept is a set of ordered categories, like uses cocaine 'sometimes', 'often', 'frequently', etc. (Hunter 1985: 645).

A primary difference between the two methodologies appears to be related more with the number and nature of subject matters dealt by them respectively. Quantitative techniques tend to decontextualize the issue by refining the theory and looking for the minimum variables that can model the phenomenon. Qualitative techniques tend to look for more individual contexts behind the issue. For this reason too their differences are also apparent in the approach to operational definitions. The quantitative methods operate upon the contextualized variables by associating them with some kind of measurement whereas qualitative techniques attempt to provide a 'rich' description of the situation. According to Walker (1985) the techniques that are traditionally termed qualitative are those that are generally intended to determine what things 'exist' as opposed to quantitative methods that determine how *many* things there are in existence.

Lazarsfeld and Stauffer's assert their position firmly on the quantitative side since for them qualitative research is exploratory in function and is prefatory to quantitative research (*cited* in Filstead 1970).

For Babbie (1986: 85) "quantitative research essentially involves numerical analysis whereas qualitative does not". Further, "data collection methods such as surveys and experiments are primarily quantitative whereas others like field research is qualitative". Significantly, Babbie asserts that "quantitative researchers become enamoured of statistical artifacts" (1986: 94).

According to Bryman (1986: 1) quantitative research is typically taken to be exemplified by the social survey and by experimental investigations. On the other hand qualitative research is associated with participant observation and is unstructured in depth interviewing.

Beland and Blais (1989: 534) state, "By quantitative methods we mean the modalities of treating events rather than the properties of their measurement unit." In terms of the scheme of inquiry in the social sciences, this distinction is said to be apparent in the difference between hypothetico-deduction and analytic induction methods (Fielding and Fielding 1986: 10).

For Collins (1984) the distinction between quantitative and qualitative research is the difference between numerical or verbal measures. For McGraw and Watson (1976) the difference between the two types also comes from the level of measurement of the events studied since quantitative studies involve rational numbers and integers while qualitative studies involve events in ordered or unordered form.

Unfortunately, the two groups representing these divergent techniques exist as virtually separate subcultures, preferring to speak within their group and "betray not only a preference for one but also a distrust of the other", (Palys 1992: 3). The caricature of qualitative research is that it is 'soft' as compared to quantitative methods that are 'hard'; whereas qualitative researchers tease quantitative practitioners as 'number-crunchers', the riposte is that the former are 'navel-gazers' (Fielding and Fielding 1986: 10)!

Qualitative researchers complain that the operationalization of sociological concepts in quantitative indicators squeezes the meaning out of them while the other school argues that without such a process the general and universal character of the social world cannot be understood. Qualitative methods often involves an emphasis on process and a devotion to the study of local and small scale social situations in contrast to the emphasis on structure and the preference to the analysis at the societal levels by the quantitative methodologists (Hammersley 1989: 1-2).

Zelditch (1962: 567) states, "Quantitative data are often thought of as hard and qualitative data as real and deep; thus if you prefer hard data you are for quantification and if you prefer real and deep data, then you are for qualitative participant observation. What to do if you prefer data that are real, deep and hard is not immediately apparent".

Quantitative research is then for many a genre that is said to use a special language which appears to exhibit some similarities to the manner of the natural scientists, talking about variables, control, measurement and experiment.

Most research methods text books generally define quantitative research techniques as those associated with different approaches to data collection, such as survey design, experimental design and their analyses and other such methods all lying within the realm of statistics (*e.g.*, Adams and Schvaneveldt 1991; Babbie 1979; 1986; Blalock 1968; 1970; Bynner and Stribley 1979; Chadwick, Bahr and Albrecht 1984; Doby 1967; Foruse and Richer 1973; Goode and Halt 1952; Kidder, Judd and Smith 1986; McDaniel 1974; Maxfield and Babbie 1995; May 1993). "By quantitative methods researchers have come to mean the techniques of randomized experiments, quasi-experiments, paper and pencil 'objective' tests, multivariate statistical analyses, sample surveys, and the like" (Cook and Reichardt 1979: 7).

Quantitative Methods & Statistics

Whatever manner the definitions are given, it is clear that for most social science researchers, quantitative methods involve numerical measures and analysis within the framework of *statistics*. However, there are several stages in the research enterprise. Numerical treatment can occur in any one of them. For instance, the methodological procedures in social sciences research can be said to have three distinct dimensions. The first dimension deals with the framework of the research enterprise itself. This may be experimental, quasi-experimental or non-experimental depending upon whether the researcher manipulates the independent variable or whether s\he arbitrarily distributes the population among the variables of different categories (Beland and Blais 1989: 544). It may also be cross-sectional or temporal depending whether the analytical comparisons are made in space or time.

The second dimension is concerned with the origin of information. Thus, primary analyses could be distinguished from the secondary according to whether the researcher creates his\her data base or works on some available one. This dimension may also be identified by the distinction arising from the tool used for the data collection, namely, observation, questionnaire, official or other data sources or even content analysis. Finally, the third dimension involves the manipulation or analysis of the data in which the difference may arise according to the type of technique preferred, like statistics or content analysis.

It is probable that numerical measures may not be involved in all the three dimensions and may occur in only one or any two of the three dimensions. One is therefore at a loss to describe such a nature of research for it would appear to combine both the quantitative and qualitative techniques. Since, the distinguishing feature of the quantitative method is not only the involvement of numerical measures and statistical manipulations but also the use of numerical data, it is clear that numerical research in all three or any one or two dimensions will still be designated as a quantitative research methodology.

Thus, research in the first dimension may take the form of social survey which is the common method in sociology, generating quantifiable data for analysis and testing of theories (*e.g.,* Bryman 1986; Evans et al 1995; White 1992). Hirschi's (1969) research on delinquency too symbolizes such an approach falling in this dimension. A contrasting technique of the same genre is that of experimental design which appears to form the tradition in social psychology, an approach exemplified by such classic works as that of Skinner (1953); Milgram (1963) and even in criminology too (Coombes, Wong and Atkins 1994).

In the second dimension of the quantitative research work, data sources have been observations interview responses, questionnaires and official statistics (*e.g.*, Pretto 1991; Farnworth et al 1994; Lauritsen 1993; Singer, Levise and Jou 1993; Brantingham and Brantingham 1978; Light 1990; Stoddart 1991). In all these instances, even when the nature of data has been non-numerical, like the responses in questionnaire that are generally in spoken languages, the data has been converted into numerical measures through the use of some scales or dummy variables.

In the third dimension, the analysis of secondary data, official or collected from other sources, seen in the classical work of Durkheim (1951) and more recently in several studies (*e.g.*, Sherman, Gartin and Buerger 1989; Junger 1989; Bijleveld and Monkkonen 1991; Bachman 1991), has of course been restricted within the statistical framework, whether presented through frequency descriptives, cross-tabulations or examined through factorial methods or time-series analysis like ARIMA modeling..

The advent of computers has attracted even more adherents to these methods since most of the statistical computations have become easier. A greater application of such sophisticated techniques as factorial analysis, parametric and non-parametric path analysis, logit and probit methods, LISREL, all lying within the subject matter of the discipline of statistics is witnessed since the late sixties. Undoubtedly, the perception has grown and persists that quantitative research implies the use and application of statistics.

This is also apparent in any review of the quantitative techniques seen in the literature. For example, Beland and Blais (1989) examining the use of quantitative methods in sociological studies originating from Quebec report that ALL the methods were statistical in nature.

Another study by Poland (1983), though exclusively concerned with the quality and quantity of statistical methods in leading Criminal Justice journals, also included reference to mathematical methods. This study examined a total of 2390 articles in the following journals: *Journal of Criminal Law and Crime; Criminology; Crime and Delinquency; Journal of Police Science and Administration; Journal of Criminal Justice; Journal of Research on Crime and Delinquency; Police Chief* and *Forensic Science Journal*. In the period 1976 to 1980 Poland found 53% of these articles contained any quantitative material, indicating that qualitative procedures were equally preferred. He also identified 52 statistical techniques and reported that most common were frequency descriptives, rates and ratios appearing in more than 600 articles. Such descriptive parametric procedures were 4 times more than inferential parametric procedures such as T test, analysis of variance and the related F tests for differences in means.

Among non-parametric procedures, the most frequently used was the Chi-square, Spearman's rho, Goodman's gamma and Kendall's tau. Scaling procedures were used in only a handful of studies and the only mathematical procedures found in the literature were 42 articles using matrix algebra, 12 using calculus and 16 probability.

A comparative analysis of research methods in criminology and criminal justice journals was undertaken by Holmes and Taggart (1990). Examining 966 articles in the three journals viz.: *Criminology, Journal of Criminal Justice* and *Justice Quarterly* from 1976-1988, they too report that ALL quantitative methods were statistical in nature. Cohn and Farrington (1990) reviewing the state of British and north American journals go so far as to recommend that British researchers must use more quantitative methods (statistical) in order to gain recognition from their American counterparts!

As the first step in this dissertation and in an effort to assess the strength of emphasis on statistical techniques, the following journals were examined for the methodologies preferred by their authors: *Criminology, Journal of Criminal Justice, Canadian Journal of Criminology, Journal of Quantitative Criminology, British Journal of Criminology,* and *Australian and New Zealand Journal of Criminology*. The reason for choosing these journals was their popularity amongst criminology scholars, easy availability and the fact that these have been referred as the mainstream journals in the discipline by various authors (Parker and Goldfeder 1979; Fabianic 1980; Shichor, O'Brien and Decker 1981; Holmes and Taggart 1991; Cohn and Farrington 1990).

All the articles published in these journals for the period 1989-1993 were selected and examined for the type of methods used in the analysis or description of the subject matter. In the first instance, the articles were categorized into quantitative and qualitative techniques based upon the use and/ or non-use of numbers in the main argument. In this, even though some articles presented tabular data, these were still designated as qualitative since the *principal* theme did not really depend upon the data which appeared more for purpose of illustration.

The quantitative articles were primarily sub-divided into an 'advanced' level statistics generally comprising techniques like path analysis, log-linear analysis, logit, probit, LISREL, ARIMA. Additionally, those statistical techniques in which the authors discussed either the assumptions or the mathematical basis in the description of the analytical method were also designated as 'advanced'.

All the other articles using statistical techniques different from the above were sub-divided into three categories. Such subject matter as frequency descriptors, including tabular and graphical data were designated as 'Descriptive' while techniques pertaining to tests of significance, tests of hypothesis, Chi square tests, factor and discriminant analysis were defined as 'Analytic' techniques. The third category consisted of all 'Sampling' techniques used for the collection of data.

Articles using the statistical techniques but describing the underlying mathematical model (like the Poisson process), or those describing the use of any other type of mathematical techniques were categorized into 'Mathematics' which also included probability models, computer simulations and so on. A detailed list of the classification of all these methods is provided at appendix 1.

The results of this analysis are described below in table 1.1

TABLE 1.1

A REVIEW OF QUANTITATIVE METHODS

	Journals						
Stat. Methods	CJC	CJ	CRIM	JQC	BJC	ANZJ	TOTAL
Descriptive	16	28	17	8	29	17	115
Analytic	22	60	23	8	15	3	131
Sampling	2	1	0	1	4	0	8
Advanced	10	35	58	43	6	6	158
Qualitative	30	50	35	0	52	42	209
Mathematics	NIL	10	12	31	3	0	56
% statistical	62.5	67.4	67.6	65.9	49.5	38.2	
% mathematical	0	5.4	8.2	34.1	2.7	0	
% Qualitative	37.5	27.1	24.1	0	47.7	61.8	
Total	80	184	145	91	109	68	677

CJC: Canadian Journal of Criminology
BJC: British Journal of Criminology
CJ: Journal of Criminal Justice
JQC: Journal of Quantitative Criminology
ANZJ: Australian and New Zealand Journal of Criminology
CRIM: Criminology

Quantitative Research as a Special Paradigm

Quantitative Research is therefore not only seen to be a form of statistical analysis but is moreover portrayed to be following the natural sciences techniques. It is stated to be one which uses a special language exhibiting similarity to the ways in which the natural sciences function, a format using concepts of variables, control, measurement and experiment. This seems to imply that the logic and procedure of the natural sciences is taken to provide an epistemological yardstick against which the empirical research in criminology must be appraised before it can be treated as valid knowledge. Quantitative research is referred to mean more than the generation of quantitative information. "The epistemology upon which quantitative research is erected comprises a litany of preconditions for what is warrantable knowledge" (Bryman 1986). The assumptions and practice that are inherent in quantitative research are based upon the application of natural science's approach to the study of society (Cohen 1989).

"The phrases qualitative methods and quantitative methods mean far more than specific data- collecting techniques. They are more appropriately conceptualized as paradigms" (Filstead 1979: 34). According to such a view, quantitative methodology is associated with a separate and unique paradigmatic perspective, a predisposition to view the world and the events within it in a profoundly distinct way. Thus, "the quantitative paradigm is said to have a positivist, hypothetical-deductive, particularistic, objective, outcome oriented, and natural science world view" (Cook and Reichardt 1979: 9). Moreover, such paradigmatic labeling is further said to be based on two assumptions that bear a direct consequence to the use of this method. First, it is assumed that the method is irrevocably linked to the paradigm so that an allegiance to the techniques unquestionably implies that the world is seen and understood in a certain way. Secondly, the paradigm is also assumed to be fixed and rigid, almost cast in stone so that modifications, or other perspectives are not possible.

"At the heart of the distinction between the quantitative and qualitative paradigms lies the classic argument in philosophy between the schools of realism and idealism and their subsequent reformulations" (Filstead 1979: 34). This identification with empiricism or positivism has therefore implied a strong emphasis on the processes of measurement, counting, classification, procedures that are associated with 'number crunching' and the calculating face of statistics. The stress on empirical measurement appears thus to be responsible for linking quantitative research with this sub-discipline of mathematics. The association to this form of epistemological thinking has resulted in at least some use of the statistical techniques in quantitative research.

Nature of Qualitative Paradigm

The development of qualitative techniques is perhaps an outcome of the *revolt* against empiricism. "Turmoil and rapid social change in the institutions of the society during the eighteenth and nineteenth centuries caused the scholars to question the logic and method of science as it applied to the understanding of human beings" (Filstead 1979: 35). The German scholars were perhaps in the forefront of those advocating that mind is the source and creator of knowledge while acknowledging that physical reality does exist independently. Qualitative paradigm therefore adopted a humanistic stance to the understanding of the social reality, stressing one in which the social order evolves according to the view of the observer. "The qualitative paradigm perceives social life as the shared creativity of individuals" (Filstead 1979: 35).

Since the social world is dynamic and continuously changing, there will be multiple realities dependent upon the agents who are constructing and making sense of this transformation rather than responding mechanically in accordance with some social laws. For this reason the qualitative paradigm stresses the importance of ethnography as well as the understanding of the situation from the perspective of the participant.

The qualitative paradigm emphasizes that the basic technique must be 'grounded' in the data implying that the concepts and theories are derived from the data and illustrated by characteristics examples of the data (Glaser and Strauss

1967). Schultz (1967) calls them the first order concepts from which the second order concepts emerge that attempt to explain the phenomenon. Erickson vividly describes this analytical method by stating, "What qualitative research does best and most essentially is to describe key incidents in functionally relevant terms and place them in some relation to the wider social context, using the key incident as a concrete instance of the workings of abstract principles of social organization" (Erickson (1977: 61).

The qualitative researcher, while keeping the existing theoretical frameworks in mind, still prefers the 'theory' to emerge from the data itself, trying to understand how the subjects under study make sense of the social realities they encounter (Filstead 1979: 38). The data gathering techniques commonly used for such purposes are labeled as participant observation, in-depth interviewing, unstructured or semi-structured interviewing, content analysis and a combination of several of these methods in what is dubbed as the meta-analysis. These researchers are therefore inclined to capture their data in the actual language used by the subject for these are thought to be critical to the process of understanding the meaning being conveyed by the subject.

It is for this reason too that qualitative methods which are seen linked to another kind of paradigm, a phenomenological, inductive, holistic, subjective, process oriented and social anthropological world view (Palys 1992; Hammersley 1989), are frequently seen to be of a different nature and therefore not appropriate for being used *together* with quantitative techniques (Cook and Reichardt 1979: 10). Since, methods are associated with different paradigms that are mutually exclusive and even antagonistic, the understanding is that one must choose *between* the two techniques.

According to most authors the two techniques present contrasting and a wide variety of positions involving multiple issues. Hammersley (1989) identifies a number of them like realism versus phenomenalism, epistemology versus ontology or the belief that science is the single source of knowledge versus the one that it is one amongst many. Some other positions, like the belief that all the sciences possess the same methodology or that they differ in both assumptions and techniques, or even that the search for laws versus the identification of limited patterns is considered inherent in these methodologies. This debate raging for almost two hundred years has sometimes been unclear about where their proponents stand in relation to these issues and "...for these reasons no simple contrast is possible between the two positions" (Hammersley 1989: 6).

Quantitative Methodology & Positivism

The term methodology has an important epistemological meaning concerned with the role of theory in research efforts. In this role, methodology functions like theory in guiding the conduct of the inquiry, as Kaplan (1956) points out. All science begins in philosophy (Nagel 1961) and hence methodology has a philosophical base that is oriented towards techniques and ways of knowing. Methodology first becomes an approach towards research and then evolves into particular methods or techniques.

The philosophical base or the approach towards inquiry in quantitative methods is closely linked to the concept of positivism (Palys 1992). However, controversy over positivism begins immediately the term 'positivism' is used for there are so many different understandings about what the term implies and how it ought to be used (Miller R. 1987). At different historical times, the term has continually changed and developed the central ideas that are said to form the core of this philosophical basis.

In the social sciences, allegiance to or accusations of positivism are made in a number of different ways. Sometimes to be positivist means no more than to be scientific in some undisclosed manner although that fails to discriminate from other perspectives such as Marxism, functionalism, structuralism etc. Sometimes, "...to practice positivist sociology is to seek to establish causal explanations, or to search for fundamental laws or human behavior or historical change, or to insist upon objective empirical information systematically organized to generate or test hypotheses" (Halfpenny 1982: i).

Positivism is also considered a belief that only observable phenomena which is amenable to senses warrants to be considered as valid knowledge. In this form it is seen to be strongly associated with empiricism and 'objectivity'. The existence of these diverse understandings of 'positivism' among others reveal that the issue of what positivism is, and was, remains controversial. Since the nineteenth century there have been several uses of this term and various interpretations have emerged at different times.

Positivism, Empiricism and Realism

The name 'positivist philosophy' was originally coined by Parisian Auguste Comte to describe his systematic reconstruction of the history and development of scientific knowledge (Rhoads 1991). According to Comte, positive knowledge was the inevitable outcome of the development of individual mind and human knowledge. He propounded that positive philosophy has three components: firstly it is a theory of historical development in which knowledge improves and provides for social stability. Secondly, it is a theory of knowledge, the only kind that is trustworthy because it is grounded in observation. Lastly, it is a kind of unity of science thesis in which all branches can be integrated into a single natural system (Halfpenny 1982: 15).

His propositions therefore brought together a variety of themes that were current in nineteenth century thought and the reaction to it. It also emphasized a departure from the radical Kantian rationalists who insisted that knowledge can be deduced from 'self-evident ideas of pure reason' and that human thought alone can construct knowledge. For Comte, thought had to be guided by experience and reason had to be subjugated to reality. Positive philosophy was thus the empirical study that formulated laws like any other kind of positive science. According to this doctrine then, the division of phenomena into different divisions is an arbitrary convenience and there are no essential differences between various branches of knowledge.

John Stuart Mill too supported Comte's emphasis on empiricism but also stressed the methods of data analysis, especially the logic of induction as another important component (Halfpenny 1982: 16). Herbert Spencer reinforced the positivist spirit by emphasizing the role of social Darwinism. According to him, positivism is a theory of history in which the motor of progress that guarantees the superior forms of society is competition between increasingly differentiated individuals (Halfpenny 1982: 22).

Finally, Emile Durkheim adopted all of Comte's major themes- empiricism, sociologism, naturalism, scientism and social reformism. However, what is significance about Durkheim's connection with the understanding of positivism is that he added a new dimension to the abstract philosophical theme- that of statistics. Suicide (1951) symbolizes another conception of positivism in sociology of knowledge: a theory according to which the natural science of sociology consists of the collection and statistical analysis of *quantitative* data about society (Halfpenny 1982: 24). This variation is sometimes called Baynesianism (Miller R. 1987: 160) because of its reliance on Bayes' theorem.

Such a brief outline of nineteenth century positive systems does not indicate that there were no other versions and actors on the field. In philosophy a revolt against positivism took place in 1890s that led to the resurgence of idealism and romanticism, vehemently opposed to empiricism and naturalism. For scholars of this viewpoint, the human world is quite different from the natural world, being pervaded by meanings which must be studied in ways remote from those applicable in the sciences of nature (Outhwaite 1975). In America and Britain, sociology became involved in documenting practical social problems and applying anthropological techniques for studying societies. Throughout German speaking Europe, Marxism became a serious candidate for the natural science of society and was widely debated as an alternative to the French sociologistic and Anglo-American individualistic theories of progress (Bottomore 1979).

This is a sketch of the period but it indicates the various interpretations of the term positivism and its use in different contexts. Halfpenny's book (1982) in fact lists twelve different interpretations of the term positivism found in the literature. This itself should help in proclaiming that quantitative methods ought not to be restricted with one perspective. What is significant to note is that Comte's positivism was fused with statistics by Durkheim and the scientific study of society is now commonly considered to involve the production and test of social laws by the collection and manipulation of quantified social data.

However, the association with positivism for such a long period has implied that quantitative methodologies have been ascribed with several characteristics. Not only are these seen as involved with the use of numerical in the description of some phenomenon but are also said to ascribe to a logico-deductive inductive stance. The methodology is also seen as affirming the existence of the reality of that phenomenon, the objective nature of which is ultimately unfolded through careful observation, measurement, analysis and or inductive reasoning.

Accordingly, one who prefers to use statistical methodology is not only affirming the positivist stance but also asserting that empiricism is the correct epistemology. Moreover, the declaration is also that the objective world can only be understood by logically deducing hypotheses derived from theories built upon unbiased observations and modified if necessary through the inductive process before testing them with the greatest scrutiny. This process is circular and may start either with an observation or an explanation in accordance with the wheel of science as suggested by wallace (Palys 1991: 45).

Underneath the Paradigmatic Stance

Apart from the fact that this paradigm is not well stated nor necessarily associated with all the different types of quantitative methods in use, the application and conceptualization of these methods are itself variable in nature. Is the researcher who uses quantitative methods necessarily a logical positivist? This does not appear to be the case. Many social scientists who use quantitative techniques subscribe to a phenomenological stance. For instance, social psychological theories of attribution are phenomenological in nature since they are aimed at understanding behaviors and beliefs from the perspectives of the actors themselves (Becker 1958). Yet, most if not all, of attribution research is conducted in the laboratory with quantitative techniques (DeJoy 1994; Petty and Rosen 1991). Similarly, consider the case of introspection, a topic that is again clearly in the realm of phenomenologism. In review of research on introspection (Nisbet and Wilson 1977; Laplane 1992), the vast majority of studies used quantitative procedures such as randomized experiment and 'objective' behavioral measures.

Quantitative methods are also accused of being obtrusive (Palys 1992) Yet, some methods such as randomized experiments on occasion have been used in a completely unobtrusive manner (Lofland and Lejeune 1960). In fact, many field and laboratory experiments have been accused of being deceptive because the researcher and machination were said to be completely concealed (Davis 1961; Lofland 1961, Kelman 1972; Roth 1962; Kansas City 1977).

Similarly, quantitative methods cannot be said to be completely objective in nature. Scriven (1972 *cited* in Cook and Reichardt 1979: 12) states that the term subjective has two separate meanings. First, it means an influence of human judgment and second, a reference to the measurement of feelings and beliefs. According to the first interpretation all techniques are subjective and there is a general agreement that all facts are imbued with theory and so are at least partly subjective. The assignment of numbers, as is common in quantitative techniques, is clearly a subjective decision or interpretation. Thus, subjectivity is involved in the utilization of quantitative design and analysis (Boruch 1975). The second meaning implies that a measure is subjective because it taps human sentiments that are presumably not directly observable. Yet, victimization surveys, are routinely employed and considered standard measures for gauging public perceptions of crime and these are prime examples of quantitative measures that are subjective in nature.

It is commonly alleged that the researcher is insulated from the data in quantitative methods (Palys 1992). Feinberg (1977: 51) states, "[it] is astonishing that getting close to the data can be thought of as an attribute of only the qualitative approach". Most students of Brantinghams for example, walk the beat with the constables, pinpoint the location of pan handlers in the city, look for architectural designs by photographing buildings and yet do essentially quantitative research. In the similar vein, quantitative techniques cannot be accused of being "ungrounded, merely confirmatory and deductive" (Walker 1985). For Glaser and Strauss (1967: 17-18) too, "there is no fundamental clash between the purposes and capacities of qualitative and quantitative methods or data" and "that each form of data is useful for both verification and generation of theory".

Quantitative researchers are accused of assuming that reality is stable and unchanging (Filstead 1970). Though, some quantitative research designs are more 'rigid' than others, it does not seem appropriate to state that all such investigators conceive of a invariant reality. The time series quasi-experimental designs track temporal changes in some program against a background of natural transformations. "Taken to the extreme, no assessment strategy assumes a perfectly fixed reality, since the very purpose of the research is to detect change" (Cook and Reichardt 1979: 15).

The accusations that qualitative methods are valid but perhaps unreliable in contrast to quantitative techniques that are necessarily reliable but invalid (May 1993) also appears to be shortsighted. Reliability and validity are not inherent attributes of any measuring instrument, whether a ruler or the human eye (Cook and Reichardt 1979: 14). The accuracy depends on the nature, purpose and circumstances of usage, a quality true for both methodologies.

Finally, the split between those who advocate mathematical formulation of theories and those who contest that verbal statements are more appropriate for understanding of the nature of knowledge and the social world also seems outdated. As Collins (1984) points out, the language of computer simulation that has developed in recent times can be said to occupy a mediating position between the two forms.

For example, languages such as DYNAMO, JUSSIM, STELLAR are similar to the mathematical notations and equations in some respect. These specify relationships between particular variables, evaluate their quantitative levels and even offer graphic representations, though in discrete form. Simulation offers much of the power and precision of mathematical methods (Hannemas 1987). However, simulation is a good deal easier and user-friendly than formal mathematical language. Instead of learning about the meaning and relations between complex symbols, DYNAMO for instance, permits them to be entered in near verbal form. The actual calculations and computations are carried by the computer with the mathematical formulations remaining beneath the surface of the simulation language that operates as a higher order language. Simulation thus offers a middle path between mathematical language and weak statements of verbal theories.

Lanier and Carter (1993) used such a computer simulation to forecast homicide rates. As they display in their model, simulation can combine both qualitative and quantitative data for predicting, extrapolating and comparing the macro trends of the dynamic social systems. Computer simulation and system's related theory have been applied for at least two decades by demographers and economists and has been used in criminal justice arena too, *e.g.,* JUSSIM (Belkin et al 1972).

The above illustrates that the attributes of the paradigm is neither inherently nor ought to be linked to the quantitative methods, a remark true of the qualitative techniques too. This is not to say that paradigmatic stance is unimportant in choosing the method nor to deny that certain techniques are usually associated with specific perspectives. Researchers who use qualitative methods do subscribe to constructionist, phenomenological paradigm more often than to the realist, empiricist paradigm and there is an obvious correlation between the use of quantitative methods and a logico-positivist approach. Historically, quantitative methods were developed most directly for the verification or confirmation of the theories while qualitative techniques were preferred for getting closer to the data (Cook and Reichardt 1979: 17). But while the linkage that exists between paradigms and method can usefully guide one's choice of research strategy, the linkage should not determine that choice solely. The point here is that world views or paradigms are not the exclusive determinants of the choice of the techniques. The decision to use a particular research method should also depend upon the nature of data, preference for the form of communication and the demands of the study or inquiry at hand. That paradigm and method have been linked in the past does not mean that it is either necessary or wise to do so in the future. The objective of the research is not only to gain knowledge but also to present a fresh perspective.

Further, all of the attributes that are said to make up the paradigms are logically independent. Just as the quantitative techniques are not logically linked to any of the paradigmatic attributes, the attributes themselves are not logically linked to each other. "There is nothing to stop the researcher, except perhaps tradition, from mixing and matching the attributes from several paradigms to achieve the combination that is most appropriate for the research problem and setting at hand" (Cook and Reichardt 1979: 18).

The charge by the qualitative methodologists that their focus is on the social meanings that can only be understood through interaction of individuals hardly prevents the researcher from applying numerical techniques in this process. Even though Erickson's (1977: 61) decry that the qualitative methods use descriptive terms so as to relate them to the wider context still does not preclude the use of mathematics. It is only because of a belief of the qualitative methodologists that the actual words of the subject are critical to the process of conveying the meaning of their intentions that makes them prefer recording the data in the language of the subjects.

However, words may need to be interpreted or translated and finally communicated to a wider audience. Whatever may be the underlying paradigm the task of the researcher is primarily to convey the information obtained through some form of written notation system. Moreover, the qualitative practitioner also has the onerous task of devising an explanation of the phenomenon being studied consistent with its relationship with the world. The qualitative researcher has to make sense of the social realities of their subjects and build some theory, construct concepts and categories to provide an acceptable explanation.

Whereas the qualitative paradigm is "marked by a concern with the discovery of theory rather than the verification of theory" (Filstead 1979: 38) there is no escaping the fact that at the final stage the methodology has to put forth a set of variables, some causes or events that 'explain' the phenomenon and then perhaps generalize to other similar situations. There is nothing significant in this process or in this form of communication that could warrant a denial of the use of mathematical language. When there has to be a description, a proposition and its justification mathematical terminology could certainly be utilized. The demonstration by Nagel (1956) of the removal of ambiguity in language through the use of mathematical notation may also provide an argument for a greater use of mathematical symbols by the qualitative practitioner.

In any case, the above arguments certainly suggest that the *nature* of quantitative research and its methodology ought not to be confused nor confined to the techniques of numerical analyses. Rather, it should be understood that this form of research is one that is preferred by a large number of researchers because of their stress on the importance and use of *mathematics.*

The preference may be due to the observation that mathematics is a more appropriate means of communication, a special language, precise, concise and capable of revealing the deeply imbedded inherent patterns. It has the capability of not only developing the theories from its abstract generalizations but also linking it with several other structures hidden from the common perspectives. It is because of several such reasons that mathematics is preferable over ordinary language for communication, expression and modeling of the social behavior. Additionally, it could also be suggested that the difference in quantitative and qualitative methods is essentially the difference of preference between mathematics and the spoken languages.

The next chapter will point out that statistics is essentially based upon more general mathematical theories and the limited knowledge or lack of interest to its mathematical base has created a short sighted view of the subject matter. The chapter will also draw attention towards some of the limitations in the use of statistics and present illustrations of researchers going ahead with its use without addressing its appropriateness. Thereafter, the wide world of mathematics will be presented to suggest that it offers a range of excellent possible techniques that are available to social researchers, both for qualitative and quantitative perspectives.

---X---

CHAPTER III

STATISTICS

"When you can measure what you are speaking about and express it in numbers, you know something about it, but when you cannot measure it, when you cannot express it in numbers, your knowledge is of a meagre and unsatisfactory kind". Lord Kelvin

The social sciences, criminology in particular, have clearly split into two mutually antagonist camps of quantitative and qualitative methodologies. As has been argued in the previous chapter, the former is commonly associated almost exclusively with statistical techniques. The latter group of researchers consider such approaches a biased methodology. They frequently charge statistics with concentrating on irrelevant formalisms and by emphasizing numbers, causing distraction from the real theoretical questions that presumably can only be unearthed through verbal qualitative techniques. The charge appears to be partially true for, until recently, many statistical methodologist have displayed little concern for wider theoretical formations. The users of statistical techniques "have been the worst offenders in imposing a narrowly positivist orthodoxy on the field" (Collins 1984: 330).

Ignoring Statistical Foundations

Although statistical techniques are widely applied the problem arises primarily because most practitioners have shown little appreciation for its foundations and structures. For instance, many may not be aware or overlook the fact that statistics is only a particular branch of mathematics and its roots go deep into the logico-formalist school. It is also forgotten that statistics can be interpreted as a substantive theory of how chance factors operate in the world. There are underlying status assumptions and hidden theoretical formulations that need to be brought out into open. In this chapter an effort will be made to present the theoretical foundations and general manner of applying statistical techniques. Finally, several limitations that arise in ignoring their mathematical base will also be discussed.

Statistics are not neutral techniques. In 1957 Selvin initiated an acrimonious debate about the value and appropriateness of significance tests in sociology (Selvin 1957; McGinnis 1958; Morrison and Henkel 1969; Winch and Cambell 1969). He pointed towards the "conditions under which tests of significance may validly be used are almost impossible of fulfillment in sociological use" (1957: 50) and named 'problems of design' and 'problems of interpretation' that are peculiar to sociological research which makes these tests inapplicable'.

Although, the problem of randomization is difficult to establish in most research areas, the problem of interpretation stems largely from the fact that "those who apply tests of significance in data analysis do a very poor job of it by confusing statistical significance with substantive importance, by misinterpreting the random error components, or by engaging in data dredging exercises" (Namboodri, Carter and Blalock 1975: 5). There are compromises that have to be made to model the complexities of social life and this entails that we understand what we are doing by way of statistical analysis and the underlying nature of assumptions. This essentially implies a conception and awareness that behind the statistical techniques lies the world of mathematics, of algebra, matrices, equations, calculus and even geometry whose own assumptions need recognition.

Statistics as a Subject distinct from Mathematics

However, before we proceed any further, the differences if any between mathematics and statistics need to be described. Statistics as a distinct field has come to be recognized only in the 20th century (Stigler 1986: 1). Edgeworth in 1885 defined the subject from three different perspectives:

"as the arithmetical portion of the social sciences, as the science of means and as the science of those means which relate to social phenomenon" (*cited* in Stigler 1986: 363). Stigler himself defines it as "the quantitative technology for the empirical science" which provides the "logic and methodology for the measurement of uncertainty and for an examination of the consequences of that uncertainty in the planning and interpretation of experimentation and observation" (1986: 363).

The general usage of statistics such as the purely descriptive presentation of numerical data by way of frequency distributions or the application of arithmetical operations in transforming verbal responses have never been problematic even to the qualitative researchers. This is because statistics has widely been regarded as a method, a way to describe relationships and test theories, and not one to formulate them (Collins 1984). Apart from the ordinary use of determining the means, standard deviations and other descriptive forms and displaying relationships between different variables, the subject has largely been used for testing hypotheses.

A statistical test compares some given distribution, which one would like to interpret as resulting from some particular cause, against the range of distributions that could be regarded as produced by chance. Only if the null hypothesis is rejected (that the observed distribution is a result of chance) is the substantive theory supported. Naturally, statistics goes far beyond this basic test but usually in criminology, as seen in the examination of different journals, it does not.

However, in this procedure it is also held that for such a theory to be valid, the sample must be drawn without prejudice. The data must be obtained in a way as to avoid contamination by some systematic bias in drawing data, like the pre knowledge on part of the researcher. "Statisticians aim at the kind of untouched-by-human-hands mechanism by which theories can be 'neutrally' tested against an objective world" (Collins 1984: 331).

In this procedure the attention is focused towards the main theory, the one that is being tested, and makes it seem as if it were the only theory under consideration. But there is another theory also implicitly present- the theory that, in fact, certain distributions are produced by chance. The question to be probed is then the meaning of the term 'chance'. Ordinarily, chance is regarded as merely a negative classification, the absence of any degree of determination. When one cannot assign a reason that something happened, it is described as sheer accident, or chance.

Thus, a shopper caught in the midst of an attempted robbery and hit by a bullet ricocheting from the wall is said to be an accidental victim. Yet, the path that bullet took from the gun chamber to the wall and then bouncing on to the victim's head can be described quite precisely by the law of the acceleration of gravity, the thrust provided by the internal chemical explosion, the momentum given by the spring action, the hardness of the wall etc. Where it hit was due to the direction and velocity with which it left the chamber, the position of the offender and that of the victim, the way the wind was blowing and so forth. The hit by the bullet on the head was thus not at all uncaused. It was an accident only in that one did not know the *initial* conditions in which it took place.

Exactly the same can be said about social processes that appear as random matters of chance. For example, an offender mobility study (Capone and Nicols 1976) that concentrated on the series of variables leading up through the completion of the offence say, explained only about 40 percent of the variance in offender target selection. Does that mean the other 60 percent is purely a matter of chance? Only if we mean by this that, knowing as much as the official data tells us about what has happened from the commission of such crimes, we can predict target selection in several places no more closely than within a certain range, the argument seems agreeable. But the other variation is not necessarily mysterious; it is likely determined by other facts: awareness spaces of the offender, lack of guardianship, target attractiveness, structural changes in the economy, (Collins 1975, Cohen and Felson 1979; Brantingham and Brantingham 1993a) that are simply not entered into the individual level behavior theory.

Chance, then, does not mean the absence of causality. It may mean the absence of causality that we know about, from the point of view of what we are looking at. Stated more precisely, it means that causality has different orders that are essentially unconnected. The fact that the victim was standing by the counter when the offender walked and fired the gun is also a series of causes: the intention to go to the shopping place, to buy something that is further influenced by the social class culture, which made the victim and the offender go to that shop at that particular time when the events took place. There need not be anything uncaused about any aspect of the situation, either in the social motivation that made possible the target selection of the shop, the decision of the victim to shop at that place or the physics that made the bullet hit the unfortunate head.

However, these causal orders are unconnected for there is no relation between the victim going to shop at the time when the offender in the commission of the crime fired the gun and the bullet hit as it did. It is this *unconnectedness* of different causal orders in the universe that gives rise to the phenomena of chance.

In scientific experiments too, it is common knowledge that even careful and precise measurements never yield the same results in successive observations. These irregularities or 'errors' are regarded as unavoidable due to insignificant and perhaps undetectable causes. In accounting for such irregularities, "mathematicians like Gauss and Laplace [have] lumped together all these 'disturbances' or unconnected events under the name of chance and laid the foundation for the theory of errors of observation, a mathematical achievement of first order" (Newman 1956: 1457). Chance, in this important sense, is not just the matter of luck. It has its own assumptions and mathematical laws, which are precisely what the discipline of statistics has been founded upon.

These are the laws describing how various distributions arise from the combination of events that are causally independent. It is not surprising that the mathematical theory of statistics arose from the works of Pascal, Bernoulli and others on gambling and the other games of chance where the outcomes are deliberately made independent of each other. The flipping of the coins, the drawing of black or red balls from a container, the combination of playing cards in some sequence are all mechanical situations in which independent results are produced in the form of long series. It is the counting of distributions under these circumstances that gives rise to empirical generalizations to which other mathematical models are fitted.

Later, these models were extended to physical situations, like the study of heated particles by Poisson, observational errors of astronomers by Gauss, human demographic patterns by Quetélet, characteristics of biological populations by Fischer and Pearson and so on (Stigler 1986). These applications gave the distributions against which the observed hypotheses are tested now in order to reject the null hypothesis of causation as merely the result of chance.

The interpretation of these statistical distributions has been a matter of debate for quite some time (Collins 1984: 334). The traditional 'frequency theory of probability' by Bernoulli and others regarded distributions as empirical facts. Statistics has also been viewed as the work of a logical system since it can be derived mathematically by making assumptions about the independence of the elements and based upon axioms of additive, associative and other rules. Further, the assumptions about independence of *elements* can be exchanged with that of independent *observations* since these also give rise to the same form of distributions (Collins 1984: 334). The adoption of statistical theory to social variables by Quetélet and Durkheim became more acceptable by supportive work from Lexix, Galton, Edgeworth, Pearson and others (Stigler 1986). The treatment of observations of social characteristics as independent events and as statistical deviations from a 'true' average value then became a logical conclusion (Maltz 1994a).

According to Keynes (1921) too there are several orders of causality and each one of them implies a certain level of interrelations from which a theory can be formulated. The theory of statistical test therefore usually implies the existence of two different causal forms. The first produces random distributions wherever certain aspects of the world consists of independent orders of causality and the other is the explicit theory under observational test (Hacking 1975; Fine 1973; Gillies 1973; Savage 1954).

Collins (1984) draws two conclusions from the inference that statistics implies a subjective interpretation. First that statistics testing is not so important as a methodological criterion of theoretical validity. It is more a matter of faith than an ultimate criterion of truth and there are certainly other ways of validating a theory than exclusive reliance on the test against an empty null hypothesis. "The fact that it is done is more a matter of social relationships and understanding within the community of researchers than any sign of scientific progress" (Collins 1984: 335).

The other judgment is that the value of statistics lies more as a theory than as a method. Carrying out of statistical tests of significance of any given pattern of relations is actually a comparison of one theory with another: the theory being tested and the theory of some sort of structure produced by observations occurring by chance. However, as Collins further states (1984: 335) this does not imply that when the null hypothesis is not rejected the phenomenon is unexplained. Generally it means that one has extended the range of application of a statistical model of the universe and therefore the understanding of the world is based more upon logical grounds than proved by statistical tests.

There is no way to test a statistical model statistically: the demonstration simply compares the structure of data with a given pattern. There is no logical way to test the legitimacy of a theory of statistical distributions by comparing it against another statistical distribution. As Keynes (1921) pointed out, the theory of probability is not based upon any probability and in its use for methodological purpose it is accepted as a given structure, not something to be tested in itself.

For several such reasons, statistical tests are not so meaningful for the advancement of knowledge as commonly assumed to be. A considerable number of assumptions, as described below are required before one can decide that the statistical test fits the matter at hand. The statistical tests above all require 'judgment of relevance' to the matter before application ought to be attempted. To calculate a probability distribution requires a set of exclusive and exhaustive alternatives of equal probability.

However, most cases cannot be judged to be valid strictly against this background. For instance, in a case of research that has the experimental, control and actual data types all available to the researcher, one cannot say which one produces the most probable generalization. The answer cannot be stated quantitatively for there are no grounds for comparison.

On the other hand, in the development of theories in the natural sciences, the evidence is weighed quite differently (Collins 1984: 336). In physics for example, data sources as mentioned above will be evaluated and integrated according to how well their principles fit together logically. Those implications that tie up with other principles that have already been established as basic components of other theories will be given special consideration. Thus, the existence of black holes pointed by the mathematical solutions to theory of relativity are accepted because these fit with the other implications of the same theory like the collapse of the stars. In fact, mathematics plays the crucial role in establishing that the new principles are in tune with those established as the basic components of the theory. The criterion is that of the judgment of relevance rather than some meeting or failure of an arbitrary level of statistical significance (Collins 1984: 337).

How much evidence it takes to disprove a theory varies with the logical relations of that theory to the other knowledge (Keynes 1921: 225). Choosing 0.05 or 0.001 or any other level for the test of any hypothesis is purely arbitrary. The common practice of reporting the results as significant or not without the actual probability level can at best reduce the range of information. Even then with all the theoretical and empirical evidence available to the researcher it is still possible be decide whether the result is useful or not. The concept of proof is a matter of social customs and the ability of the researcher to satisfy everyone that he or she is not cheating or deluding through the explanation. It appears that in criminology and other social sciences significant statistical criterion are imposed not because these are logically necessary or required but because there is the need to guard against the intellectual dishonesty of the researcher. "The community of theorists are less concerned with whether a given finding is true than with whether it can pass the hurdle of a very high level of ritual distrust imposed upon it" (Collins 1984: 339). This belies the fact that in statistical tests the procedure is to test the opposite hypothesis and accept the result only if there is less than a mere 5% or less probability that this result is due to chance, a procedure commonly misunderstood by many researchers.

Another problem with the methodology followed by many in the social sciences is that generalizations are produced by comparison with other cases that are held to be similar in a statistically significant manner. Yet, in this methodology, the emphasis is for a large sample simply because one cannot compare without an adequate number of cases. But, history for example, presents us with only a certain number of instances of social upheavals and there is nothing one can do about it. A police chief may have only one major breakdown of law and order situation to plan for deployment tactics and preventive detentions. Therefore, if the arguments propounded by practitioners of statistics are true, then historical, social, anthropological and linguist analysis and others with limited data such as administrative decisions are doomed. These subject matters have little data for comparison purposes and this means that statistical tests cannot be used and no generalizations of their theory is possible.

It may be pointed out that the desire to have samples in order to make inferences about the population essentially arises in cases where the population is large and difficult to examine individually. In some cases a general inference about the population may be all that is required and in this special case a small sample result may satisfactorily serve the purpose.

Obviously then the statistical assumption that generalizations cannot be made without a large sample of cases is wrong or of limited utility. This presumption may even lead to an amusing situation. For instance, if one had 100 cases and all were examined then no generalization is possible because that amounts to a tautological explanation. However, if the same generalization is made by examining 50 cases and then checking if the other 50 fit the model, the generalization becomes acceptable. Yet, it is the same generalization and the same amount of total evidence, only in one case it is rejected according to the conventional method and accepted in the other instance.

The methodological theory in question is therefore improper. The statistical formalities do not operate to increase the knowledge but only to express suspicions against theorists who might cheat or cannot examine their own presuppositions. This is a social criterion and not a logical one (Collins 1984: 339).

Yet, research designed to test a theory based upon a small number of cases can be acknowledged by checking if its implications fall within the range that have become acceptable. It is here that mathematics can in fact make an important contribution to establish the validity of the theory by displaying the coherence of its explanatory principles with other well grounded theories. Thus, the principles of some theory under consideration could be stated in abstract terms of mathematical symbols. Mathematical analysis could then be used to reduce the statement to fewer terms or show its consistency with principles and evidence found elsewhere. A theory about the naxalite revolution (Mukherjee and Yadav 1982) could perhaps be shown to be formally related to theories and evidence about peasant revolts (Das 1983) and about other revolutions (Dasgupta 1975) through the use of mathematical symbols. Further, mathematical analysis may suggest that these theories are consistent with the principles induced from the study of geopolitics of the Indian nation (Kohli 1990).

Clearly, mathematical formulation has important potential for demonstrating theoretical coherence. Theories that can be formulated in axiomatic and deductive form can be shown to produce results consistent with a wide range of empirical applications and therefore lay strong claim of validity. The future of mathematics in social sciences is more significant on the theoretical side than in the methodological form of statistical test (Collins 1984: 344).

Limitations of Statistics

In ignoring the underlying principles of statistics researchers also end up overlooking the limitations of these methods in handling various kinds of data. The aspiration that statistics would provide a powerful methodology for criminology and the social sciences has not been successful because the subject can be challenged from a variety of standpoints that range from technical disputes to epistemological quarrels. For example, the descriptive power of statistics can be said to be inadequate due to the measurement errors in official data (Wolfgang 1963; Cicourel 1964; Phillips and Ruth 1993). This inadequacy may also be seen as posing technical issues in estimating validity and reliability (Zeller and Carmines 1980; Nanton 1992) or official bias in recording procedures (Lowman and Palys 1991).

The appropriateness of multivariate statistics has even been questioned in the past, because for a period of time, measures of covariation had been developed only for interval-level data (and Chi-square for nominal data)

(Halfpenny 1982: 41). Most social science data is generally of the ordinal type to which parametric statistical methods are broadly inappropriate. The developments both in scaling ordinal data through Likert or Thurstone scales (Upshaw 1968; Gehrlein 1990) and in devising a family of ordinal level covariation measures (Siegel 1956; Barnhart and Sampson 1994) appear to have overcome some of the early technical difficulties but problems persist. Many researchers have argued that fundamental issues about the nature of causal relations in the social sciences have been untouched in the application of statistical methods (Levison 1974; Davidson 1980 both *cited* in Halfpenny 1982), despite the introduction of path analytical models (Blalock 1968; Boudon 1971) or even such modern techniques as LISREL (Hoelter 1983; Crank, Payn and Jackson 1993).

Frequently, the application of probability in tests of significance as a means of generalizing sample data can be controversial too like the early arguments concerning the meaning of probability statements. Fischer (1930) had proposed that on the basis of observations on a random sample and a known sampling distribution, a permissible range for the population parameter can be calculated. Neyman (1937) differed stating that whether or not the parameter is in the given interval is not a case of probability, for either it is in (probability 1) or it is not (probability 0). He suggested that the probability be associated with the confidence interval- the probability that the interval derived form the sample contains the population parameter, an idea that seems to have become acceptable. It is interesting to note that with the development of fuzzy logic, Fischer's proposition can again be examined, with the grade of membership defining the permissible range for the population parameters.

However, confidence interval estimation has now been discarded in favor of hypothesis testing where the null hypothesis is explicitly tested on the assumption that only chance generated the sample findings (however see Broadhurst and Loh 1995). In opposition is the alternate hypothesis that the sample findings can be generalized to the population (Sinchich 1990). The standard procedure is to derive a distribution of some feature of all the samples of a chosen size by making some assumptions about the sampled data. These presumptions are that the data is randomly drawn, that its properties of interest are distributed normally and that the null hypothesis is true for it. The appropriate feature of the test statistics is then compared with the sampling distribution to see how rare the sample is. If the probability of such a sample being drawn is say less than α in a 100 chance (where α is typically 5, 1 or 0.1) then the null hypothesis is rejected provided the other assumptions hold true. The finding asserted by the alternate hypothesis is said to be statistically significant at α% level.

In other words this implies that on the evidence of the sample findings about the substantive hypothesis and provided the assumptions about the nature of data are true, there is less than α% chance that the null hypothesis is rejected when in fact it is true. The significance level α is the probability of taking the sample findings to indicate or signify that the substantive research hypothesis is true of the population when it is in fact peculiar to the sample only. This is called the Type I error. The chance of failing to reject the null hypothesis when it is false is designated as the Type II error. The balance would depend upon whether it is preferable to risk rejecting what ought to be accepted or to risk accepting what ought to be rejected.

The common mistakes that are made in the use of such significance tests arise in confusing the statistical significance with substantive one (Namboodri, Carter and Blalock 1975: 9). An exception may be the case where one knows the population or when minor differences are significant when 'n' is large but of little practical importance. That is, the probability that the correct decision has been made in generalizing the sample findings to the population is confused with the theoretical or practical consequences. As Maltz (1994a: 440) suggests, inferences about the population from any kind of sample may be drawn on the basis of other kinds of arguments than merely on the basis of the sampling distribution.

Several other kinds of confusion arise too: assuming the level of significance with the strength of relationship; distorting the results by stressing only the significant results; failing to take account of the power of statistical tests which is the probability of accepting the alternate hypothesis when it is true; discarding the fact that there are sources of errors other than sampling; and, employing statistical tests when the data are about the whole population and not about the sample (*e.g.*, Atkins and Jarrett 1979; Maltz 1994a; Morrison and Hankel 1969; Simon 1954; Sincich 1990; and Sterling 1959).

There also seems to be a tendency amongst some social scientists to acknowledge that the assumptions are violated and yet talk of "robustness" and "can still produce useful results" (*cited* in Maltz 1994a: 444). For instance, Tittle and Welch (1983: 665) acknowledge that "...This approach requires a number of assumptions", and that "...it creates problems in interpreting tests of significance for the various contexts are not independent, violating one of the assumptions for the statistical inference". Nevertheless, they justify going ahead with the statistical analysis for "...theoretical and logical reasons"; "...to test in an exploratory way" and to "...stimulate others"! Sentences like "...there is always the possibility that unmeasured and uncontrolled variables may account for the negative relations" (Logan 1972: 73) are also not uncommon in criminological literature.

In a similar vein, statistical data analyses especially regression analysis that has been an important tool in the study of criminal behavior have been contested too. These are based upon some underlying assumptions about the nature of data which many contend is not always true (Maltz 1994a). For example, any parametric statistical analysis must establish two essential properties of the data, that of linearity and normality. That is, the data can be described using only the first power and that the bell curve is an appropriate fit for it. Failure to pass these two tests rule out a broad range of statistical methods whose applications assume these properties. This range includes classical ordinary least square (OLS) regression analysis as well as two and three stage least square analysis. Similarly, both single and multiple variable models of crime phenomenon are called into question if the methods used to identify and estimate them require normality and linearity. Thus researchers need always test for these properties before choosing a modeling method. Before testing one does not know whether parametric techniques (requiring normality) or non-parametric techniques (not requiring normality) are suitable (Neuburger and Stokes 1991).

Similarly, linear modeling methods such as OLS or 2-stage least-square-analysis require that the value of the error term (that is the variability not explained by the model) be normally distributed. Failure to meet this requirement would mean that the usual tests applied in model building (the T-test) cannot be used. The general population is hardly ever distributed like the classical bell shape curve, more often it displays leptokurtosis or 'fat tail' due to the skewed distribution of age groups in a growing or aging population.

In this case, one would have a mirage rather than a model, although the difference might not be readily apparent. Before using these methods one also needs to know that the underlying pattern (or process) one is modeling is really linear or close to it. However, rather than test for linearity, model builders assume it which may again lead to a costly error if the series is not of such nature. Linear models, like OLS may be able to approximate non-linear behavior over extended periods, but when the behavior moves outside a narrow range, the approximation breaks down.

It is not as if these shortcomings have gone undetected by the practitioners. The use of statistics in the social sciences has gone through a number of phases in the attempt to cover the lapses and build models in accordance with the nature of data. The early applications of quantitative methods in social science were the elementary statistical techniques to observational data mainly concerned with the description and inference concerning frequency distributions. The transformation came with Bernoulli and Laplace laying the foundation for the application of probability to the measurement of uncertainty in the social sciences (Stigler 1986: 163).

However, it was really the efforts of Quetélet that marked the first tangible step towards applying statistical techniques to the social sciences. His early work *Research on population, births, deaths, prisons, poor houses etc. in the Kingdom of the Low countries* (1827) pleaded for a new census through the adoption of Laplace's method (Stigler 1986: 163). He also made two important contributions towards the application of statistics to social data: the concept of the average man (l'homme moyen) and the fitting of the probability distributions to empirical observations. Another modification in the application of statistics to social sciences came through Poisson's work on probability theory. He used it to analyze the formation of juries' verdict and French conviction rates.

Naturally, this did not go unchallenged and no less than Comte himself criticized "...the vain pretension of a large number of geometers that social studies can be made positive by fanciful subordination to an illusory mathematical theory of chance" (*cited* in Stigler 1986: 194). John Stuart Mill too is stated to have referred to these works as "the real opprobrium of mathematics" (Stigler 1986: 195).

Despite opposition of this kind, statistical concepts were modified and increasingly applied to the social data by pioneering efforts of outstanding mathematicians as Galton, Edgeworth, Yule, Pearson and Fischer. "After the introduction of least squares for the analysis of social data a new discipline slowly came in existence, one that is the product of many minds working on many problems in many fields" (Stigler 1986: 361). From Pearson's method of fitting frequency curves to the general theory of parametric inference developed by Fischer, to Yule's contribution to correlational and regressional techniques that opened the world of multivariate analysis, statistics has undergone transformations that few subjects could boast. "From the doctrine of chances to the calculus of probabilities, from least squares to regression analysis, the triumphs of nineteenth century statistics are as influential as those associated with the name of Newton and Darwin" (Stigler 1986: 361).

The developments have continued even more vigorously in the twentieth century. For instance, dissatisfaction with the quality of data from official sources, one on which Quetélet and other pioneers had built their work has led to several important developments in the design and collection of sample data. The preference for victim and other kinds of surveys over official data sources is an illustration of this shift. "During the 1940s and the 1950s, it had become common to construct scales based on questionnaires to measure attitudes or socio-economic status" (Collins 1984: 341).

A related phenomenon was that instead of searching for uni-dimensional structure the large number of variables were subjected to factor analysis that produced multi-dimensional structures (Schmid 1960a and 1960b). A whole new approach categorized as factorial ecology came into existence, soon to be displaced by multivariate analyses in which the emphasis was on establishing causal conditions and testing them for independence from each other. This involved the construction of various measures of association and significance for interval, ordinal and nominal variables. In the 1960s the path diagrams appear to have become popular used for measuring series of causes occurring in different time periods. This has been followed by log-linear analysis to examine particular influence within the context of numerous others.

Sociological data has always been multivariate but until recently the analysis of such data could not proceed beyond the summary measures for each variable and simple cross tabulations of pairs of variables. The availability of cheap and powerful computers including the developments of user friendly software specially designed for the social scientists have at last made possible a large scale effort to probe the structure of data. Increasing technical developments in computer based analytical procedures have not surprisingly, greatly promoted the recent popularity of ARIMA modeling, LISREL, probit, logit and other techniques. It is not unusual at present to find articles in social science journals utilizing sophisticated techniques ranging from path analysis (Prentky 1989); log-linear models (Bunn, Caudill and Gropper 1992); cluster analysis (McShane and Noonan 1993); discriminant analysis (Land, McCall and Cohen 1991); canonical factor analysis (Regoli, Crank and Culbertson 1991); factor analysis (Palmer, Guimond, Baker and Bégin 1989); latent variable models (Keane 1993); and the whole class of stochastic models (Copas and Tarling 1988) that display a kind of mathematical maturity earlier seen only in natural science journals.

The present period appears to be the stage where mathematical modeling is increasingly being used along within statistical methods to explore the social phenomena. Respected periodicals such as *The Journal of Quantitative Criminology, Justice Quarterly, Crime and Delinquency* and even *Criminology* have articles that one would commonly associate more with mathematical or natural science journals. Although, these techniques are still considered part of statistical literature in form and context, one would argue that these should rightly be regarded as part of traditional mathematics. These techniques basically involve matrix algebra, analysis, calculus and geometry, concepts that are part of traditional mathematics. In the development of these descriptive, multivariate, stochastic, structural and hierarchical models, it is not wrong to state that the statistician is inevitably coming back home, to mathematics!

The replacement of one technique by the other is usually seen as a methodological advance. "Each solves some problem previous method has been unable to tackle but this advancement is by no means absolute. The advancement of some techniques in favor of others constitutes a theoretical loss" (Collins 1984: 345). For instance, multivariate techniques at one period appeared most appropriate for research associated with developing or testing a theory about individual attitudes and behaviors.

However, this form of cross-sectional analysis was not appropriate to deal with relations in time and therefore to deal with these problems, path models were developed. These have been used successfully in their special area of application: understanding how such factors as parental income, peer-group aspirations affect later period chronic delinquency. But this 'advancement' actually involves another kind of theoretical loss. Path diagrams, for instance, rule out studies of the macro dimension and the entire macro-historical dimension is simply ruled out of consideration by this method (Horan 1978). Similarly, methods that aggregate characteristics across individuals destroy all structural information about social networks, "...like running them through a centrifuge" (Wellman 1983: 165-66, 169).

Every method has its strengths and weaknesses, its theoretical resonance and ideological biases. However, instead of elevating one specific method to a high status, one should regard the various techniques as a tool box, to be used when appropriate for different problems. In particular, a special method ought to be chosen for its appropriateness, the insight it provides and the linkage it generates with other parts of the theory. Due to a narrow focus, plus the effect of dealing in purely methodological issues, most statistical techniques in criminology and the social sciences seem unaware of the theoretical assumptions involved in choosing those methods or are willing to use the techniques to suggest a theory even when the assumptions are knowingly violated.

Statistical techniques have also been affected by the fact that when non-linear dynamics are involved, a deterministic system can generate random looking results that nevertheless exhibit persistent trends, cycles (both periodic and non-periodic) and long term correlation (Mandelbrot 1986: 45). Compounding the problem is also the difficulty and lack of criterion in deciding which statistical or mathematical technique can be appropriately applied to a particular data set. The rules for choosing parametric over non-parametric methods, for example, have not really been established. Thus, for the same data set, different methods may lead to quite different interpretations and conclusions. Further, developments in Chaos theory are pushing statistical work in new directions, (*e.g.,* Barnsley 1988; Batty 1991; DeCola 1991; Neuburger and Stokes 1991) and their applications are not yet sought in criminology.

The technical resources needed to apply many of these newer techniques are so daunting that not surprisingly, few criminologist have ventured into its applications. The lack of a mathematical or strong quantitative background amongst most criminologists may also be an inhibiting factor.

Additionally, new data sources are becoming available to researchers that have been little utilized in criminological work. The emergency calls for police service is a recent trend (Sherman, Gartin and Buerger 1989) but "data from schools and juvenile justice agencies, from police and fire departments, from welfare and health agencies, from planning and building departments", are also potential sources, as suggested by Maltz (1994c: 5-6). Moreover, as he points out, "...not all can be used using standard statistical techniques", (1994c: 1).

Some of these problems can still be overcome by more informed use of statistical tests like the use of confidence interval when appropriate instead of the reliance over discrete probability. "But the fundamental problem remains, of establishing that the underlying assumptions about the nature of data, the sampling method and the population are valid and these cannot be met easily in social research" (Halfpenny 1982: 44). Some researchers have maintained that such 'technical' issues have been 'solved' by the development of statistical tests that do not rely on specifying the exact form of population- the so called distribution free or non-parametric statistics (Siegel 1956), or by advances in sampling theory (Lazerwitz 1968) or by the invention of test statistics for non-random samples like matched pairs.

However, it is debatable whether the problem of justifying statements about the population on the basis of empirical information from a sample are at present well established. The difficulties in this generalization are indicators of major epistemological problems with empiricism, causality and induction in the social sciences, problems that statistical techniques cannot solve by themselves. The statistical techniques popular amongst criminological literature "...engender a predisposition to ignore mulitple modes of behaviour, to treat all situations as having common origins, to embrace a single cognitive model of reality, and to overlook any treatments that do not apply to the whole population" (Maltz 1994a: 450).

It seems fit to reiterate that though statistics as a technique has its limitations, the underlying world of mathematics of which statistics is but one of several hundred branches, appears a more appropriate methods bank to be used in criminological researches. Although the complexities of criminal behavior is overwhelming, the problems that are set in theorization and research are generally narrow and relatively simple. The theories of crime such as differential association, labeling, social control or rational choice propose a limited perspective about the complex human behavior that is considered criminal by convention. For their expression, the rich and precise language of mathematics becomes a powerful and useful tool. The precision of its notation, the simplicity of its exposition and the potential for expansion into complexity gives mathematics an edge as a language for communicating and comparing these theories of crime.

As suggested earlier, one of the areas where mathematics can immediately play an important role is with regard to the transformation of verbal theories into mathematical ones (Blalock 1968; 1981). The most common mathematical formulation could involve reducing the propositions into mathematical terms and establishing functional relations between them. Mathematics provides a concise and simple way of presenting issues and since elegance and simplicity are considered significant criteria for the acceptance of a theory in the scientific literature, mathematical formalization should be a desired endeavor. Coleman's (1990) efforts in this regard are noteworthy though such efforts naturally will have their limitations.

Further, the kind of issues that have been treated by statistical analysis are the areas that could benefit most by concentrating on the underlying mathematical model that is rarely explained or acknowledged. In fact, mathematical models play an important theoretical role and ought to be seen as substantive theory instead of being relegated to the quantitative research methods textbooks. Thus, human behavior and social processes can not only be described through the use of mathematical functions (Greenberg 1979; Coleman 1964; Leik and Barbara 1975) but may also be modeled by its structures (Brantingham and Brantingham 1993b).

This area seems to have been seriously neglected in the social sciences although in the physical sciences, for example, a mathematical model is not simply a basis against which to test some other theory but one for providing the model itself. Poisson's theory for the propagation of heat as a process involving the independent interaction of numerous small particles evolved from the mathematical treatment of their movements and the mathematics itself provided the model. The black hole theory is not tested against some other types of theory and its mathematics creates and describes the 'physical' entity entirely. Surprisingly, it is only in the social sciences that mathematics is considered purely a procedure and not a substantive model in itself.

In the realm of theory construction, mathematics is capable of playing at least an equally important and crucial role as any other subject. As a logically consistent system of transformations, mathematics has the convincing property of being capable of paralleling the general concepts of what the theory is all about and therefore can be a powerful language capable of building and representing theories in criminology.

An additional advantage of applying mathematics is that beginning with some basic concepts larger, complex structures can be erected that may be useful in describing criminal and social behavior. Thus, the concept of set is almost naive but it contains properties upon which intricate structures can be constructed from such a basic building block. Mathematics has numerous other kinds of blocks and structures of which statistics is but a prominent one. Thus, different geometries like Euclidean, Reimannian or Lobachevskian, concepts like fractals, groups, spaces, or filters and relations like isomorphism, mapping, commutativity and others constitute a basic building language for representing the characteristics of a particular kind of world. Topology, graph theory, combinatorial mathematics, calculus, differential equations, spatial tesselations, fuzzy logic and many others are branches of mathematics that could be usefully applied in the social sciences (*e.g.*, Coleman 1964; Fararo 1973; Leik and Barbara 1975; Greenberg 1979; Smithson 1987; Brantingham, Brantingham and Verma 1992).

Mathematics with its symbols and functional relationships can even serve as a proxy for theoretical and experimental manipulations in criminological explanations. The behavior of an actual offender, or an offence or its control process may be predictable by the behavior of these symbols alone, if one knows their initial conditions and appropriate isomorphic relationships. At the least, mathematical notations can assist in reducing complex theoretical explanations into simpler, easily understandable relationships.

Before examples from the world of mathematics can be cited for applications in criminology it appears fruitful to examine the varied nature of mathematics. It is the contention of this dissertation that mathematics, apart from being the genesis of quantitative methodology, also provides the link between qualitative and quantitative techniques.

Within the qualitative methodology if there is any attempt to describe or 'explain' some phenomenon in terms of some other factors, the rich language of mathematics could be most useful. This is possible irrespective about the philosophical position of the researcher for mathematics subsumes both the perspectives. "On a deeper level the ideas within the mathematical models and structures are not dissimilar to the deep format of arguments in the structuralist and phenomenological stance" (Collins 1984: 330), a matter that will be explored in the next chapter on mathematics.

---X---

CHAPTER IV

THE NATURE OF MATHEMATICS

μηδεις αγεωμετρητοζ εισιτω

(entrance forbidden to non-mathematicians)

inscription over the gate of Platonic academy

As it is impossible to give a simple description of art or power or humour, so with the nature of mathematics for there is hardly any unanimity about the subject matter amongst the scholars. Most definitions given in the texts or propounded by mathematician themselves are illuminating and provide some aspect about the subject but all this is not sufficiently enlightening. Felix Klein describes it as the science of self evident things; Benjamin Peirce as the science that draws necessary conclusions; and for Aristotle it is the study of quantity. Whitehead considers its nature as the development of all types of formal, necessary and deductive reasoning, while for Descartes it is the science of order and measure. Russel considers the subject identical with logic but for Hilbert it is a meaningless formal game. The list can be extended with statements from other scholars but it is clear that mathematics appear to have different meanings to different people.

Problems Associated with the Nature of Mathematics

Amongst philosophers, the nature of mathematics has always been one of the great sources of problems. For the Greeks, mathematics meant geometry and the problem stemmed from Euclid's first definition: a point is one that has no dimension, but there was clearly no way to describe this in practice. Anything without parts seem impossible to imagine and moreover, the world cannot be built by points for even infinitely many points would have no extension. Since Euclidean geometry was considered to be representative of the physical world the problem was of assigning meaning to these geometrical terms and whether its principles were true. Later on, the creation of non-Euclidean geometries introduced more problems for if those contained laws that were incompatible with the laws of Euclidean geometry than the notion of mathematical truth became a vague entity. One law cannot be incompatible with another and yet both seem to exist simultaneously.

Number theory posed even more intangible problems dealing with the meaning of the terms used, the possibility of attaining truth and whether truth was indeed the concern of mathematicians. The geometries developed by the Greeks proposed only hypothetical principles and did not assert the existence of anything but number theory introduced the concept of mathematical existence. It clearly states that there exists a number 'y' such that x times y equals x, whatever x (except 0) may be (Here y is 1). It is not apparent what sort of existence is being talked about and consequently what type of mathematical reality is being asserted by such statements.

Another fundamental question about mathematics is whether this knowledge is *a priori* or empirical in nature. This distinction is important since it effects clarification of basic concepts and raises fundamental problems of knowledge and its acquisition. Thus, physics, chemistry, archeology all are primarily concerned with matters of empirical knowledge and therefore must rely upon observations to establish their conclusions. On the other hand, logic (and for some mathematics itself) is concerned only with a priori knowledge seeking rules governing the validity of arguments. It is therefore unconcerned about any observations in reaching its conclusions. The nature of mathematics is blurred in this respect, for it is like physics or like logic or partly like both in some proportion. The problem is compounded further since how a priori knowledge is attained and exchanged between mathematicians of different backgrounds is an equally contentious issue.

Knowledge about Mathematics

The traditional view of mathematics going back even to Plato has been that it is purely a rational study of immaterial forms. That the subject is concerned exclusively with numbers, shapes, patterns and functions that do not occur in the physical world, although there may be some imperfect examples in the universe. The geometer studying straight lines and circles still draws lines that are not straight, nor perfect are the circles. Also, since the objects of study are not physical there is no way to have any empirical knowledge about them. Therefore, mathematics is an a priori discipline, independent of experience. Plato is said to have remarked that mathematicians study ideals which can be seen only by the mind. Heinrich Hertz, the discoverer of wireless waves also states, "one cannot escape the feeling that these mathematical formulas have an independent existence" (*cited* in White 1956: 2355).

However, such a realist interpretation of mathematics runs into considerable difficulty in explaining for instance, the case of natural numbers. The problem of attempting a literal interpretation to these numbers is analogous to the problem of explaining the nature of 'universals', the properties such as virtue, redness or squareness. Mathematics, like these universals appear to have abstract entities, located neither in space nor time. Yet, despite their intangible, immaterial nature there is still knowledge about it that clearly asserts its existence. Realism propounds the claim that mathematics, like universals consists of real abstract entities, just like concrete objects and that the mind has the power to discover and comprehend them by means of rational insights. The position of Realists regarding the existence of numbers is thus the assertion that numbers are abstract entities existing independently of our thinking. Hardy (1967: 123) states unequivocally that "mathematical reality lies outside us, that our (mathematician's) function is to discover or observe it, and that the theorems which we prove, and which we describe grandiloquently as our 'creations' are simply notes of our observations". Edward Everett, the first American to win a doctorate at Gottingen, reflectively commented, "In the pure mathematics we contemplate absolute truths which existed in the divine mind before the morning stars sang together, and which will continue to exist there when the last of their radiant host shall have fallen from heaven" (*cited* in Bell 1931: 20).

The question as to how one gains knowledge of these abstract objects is one that has been bitterly debated from the period of Kant to present day philosophers and to which no consensual solution has emerged. The attempt has also been to propose the opposite view like that of physicist Bridgman who asserts equally strongly that mathematics is a human invention. Kasner and Newman (1940: 359) too comment that mathematical truths have no existence independent and apart from our own minds and moreover, non-Euclidean geometry is the proof that mathematics is man's own handiwork, subject only to the limitations imposed by the laws of thought.

White (1956: 2351) borrowing from anthropological terminology, mentions that mathematics in its entirety, its truths and its realities is a part of human culture and like languages, institutions, tools, the arts, it too is the cumulative product of ages of endeavor of human species. Henri Poincaré (*cited* in Kasner and Newman 1940: 16) similarly supports that the axioms of geometry are mere conventions, customs that are neither synthetic a priori judgments nor experimental facts.

According to the sociology of mathematics then, it is the formation of cultural tradition that facilitates progress. The communication of concepts from person to person places ideas in the mind which, through interaction, form new syntheses that are passed on in turn to others. The locus of mathematical reality is thus in cultural tradition, the continuum of symbolic behavior. However, this view appears to ignore the fact that despite cultural differences, vast time periods and stages of societal development, scholars have conceived the same kind of mathematics whether in Greece, Arabia, India or China in the past when communications systems were undeveloped. Since cultural differences and long distances do account for the variations in language, dress, traditions and norms of behavior it seems amazing that everywhere the same nature of mathematics was developed and pursued.

Another view is that of the nominalist who hold that there are no abstract entities that could be identified as numbers. For them numbers and mathematics are simply ideas that comes into being at certain time and therefore may be located in time if not in space. This viewpoint has been challenged by Frege who argued that "if right angles exist only in the mind then one should speak about my Pythagorean theorem of my right angles and your Pythagorean theorem of your right angles" (*cited* in Goodman 1991: 119). Since there is indisputable communication about mathematical constructs unlike some mental phenomenon as emotions or feelings, this appears to suggest that mathematical objects are probably not mental in nature.

Making Sense of Mathematical Propositions

For John Stuart Mill mathematics was an empirical science differing from other empirical sciences like astronomy, physics etc. because of a more general subject matter and because its propositions have been tested and confirmed to a greater extent. According to such a viewpoint mathematical theorems have been so clearly established that these are regarded as certain while the propositions of other empirical subjects are still thought of as 'probable' or very highly accepted. However, an empirical hypothesis is open to refutation and, theoretically, is at least disconfirmable (Popper 1975). Mathematical propositions like

2*3= 6 cannot be refuted on empirical grounds for the numbers are *defined* in a manner that the relationship is tacitly understood to hold true without any observations.

It is because of this reason that arguments have been made to suggest that mathematics is true by virtue of the meanings of its words. Proponents of this viewpoint suggest that mathematicians deduce their theorems by logical inference from self evident axioms. "Mathematics is said to be true by convention, true by definition or logically true" (Goodman 1991: 120). This school believes that the truths of mathematics, in contra-distinction to the hypotheses of empirical sciences, require neither factual evidence nor any other justification because they are 'self-evident'. However, many mathematical theorems are so difficult to prove that even to the specialist they appear as anything but self evident. It is further well known that some of the most interesting results in fields such as set theory and topology are contrary to the deeply ingrained intuitions and the customary feeling of self evidence.

There are also certain conjectures in mathematics, propositions like that of Fermat's last theorem [1] or Goldbach's theorem [2], that show not all mathematical truths can be self evident. These propositions, though elementary

---

[1] It states $x^n + y^n = z^n$ is impossible for integer n>2.

[2] that every even number is the sum of two prime numbers.

in concept are yet undecided till the present time and therefore impossible to state as 'self evident' in any sense. Finally, even if one were to argue that self evidence is attributable only to the basic postulates of mathematics from which all other propositions follow, then one has to conclude that 'self evidence' is a subjective criterion and "...cannot constitute an adequate basis for decisions as to the objective validity of mathematical propositions" (Hempel 1956: 1620).

In another sense, mathematical theorems are said to be analytic because these are all tautological in nature. Such an analytical nature of mathematics follows the tradition that can be traced back to Kant for whom analytic sentences are true by virtue of the meaning of the term involved and differ from the synthetic type that are true by virtue of the fact of the matter. The validity of mathematics is said to have been derived from the stipulations which determine the meaning of its concepts and therefore the propositions are considered 'true by definition'. Almost all the theorems of arithmetic, algebra and analysis for instance, can be deduced from Peano's axioms and the definition of mathematical terms that are not 'primitives' in his system. The deduction requires only the principles of logic and in some cases the axiom of choice.

Such a thesis of logicism about the nature of mathematics therefore asserts that the propositions of mathematics are devoid of all factual content and convey no information whatever on any empirical subject. This form of description lead to the conclusion that the traditional conception of the subject as the 'science of quantity' is both inadequate and misleading. Mathematics can draw conclusions from any set of axioms and that the validity of the inferences does not depend upon any particular interpretation assigned to the axioms. The sole question before the mathematician is not whether the axioms are true but whether the conclusions are necessary logical consequences of the initial assumptions. This followed Russell's statement, "Pure mathematics is the subject in which we do not know what we are talking about, nor whether what we are saying is true" (*cited* in Newman 1956: 1670).

W.V. Quine has argued against this position suggesting that there is no way in which the concepts can be said to be sufficiently clear to provide a precise sense in which say, Zermelo Fraenkel set theory is analytic. Thus, set theory is not logically true and not in any standard logical sense true by definition. "The feeling of many mathematicians that the axioms of set theory somehow follow from what we mean by 'set' is no more profound than the common feeling that Newton's second law is a consequence of what we mean by 'force' and 'mass'" (Goodman 1991: 122). Nobody would say for instance that classical dynamics is true a priori implying thereby that the same criterion ought to be applied to mathematics also.

Computer Aided Mathematical Proofs

The final confusion about the nature of mathematics arises from the recent trend amongst mathematicians for relying extensively upon computers. Appel Haken's 'solution' to the four colour problem is a computer programme running for more than 1200 hours of computer time (Appel, Haken and Koch 1977). The reliance is becoming so complete that computer produced facts are now seen as part of mathematics and also because no other solution is available nor often possible. However, it is difficult to imagine that a result that can be established only by hours of computer time is true by virtue of the meaning of the symbols used in its formulations! The computer usage is thus clearly undermining the a priori position of mathematics since an "analytic truth ought to be recognizable as such merely by thinking" (Goodman 1991: 122).

Tymoczko (1979) has further argued that computer useage in mathematics has called into question the distinction between the a priori position of mathematics and posteriori nature of the natural sciences. Pointing to the 'proof' of 4 colour problem he states (1979: 76) that it is unlike any other traditional proof in the subject. Mathematical theorems are considered proved if these are convincing to other mathematicians, are surveyable or are formalizable (that is proveable by logic). However, the proof of the 4 colour problem is not surveyable and there is no known formal proof. The proof propounded and accepted by the mathematical community required a computer run to fill the gap and this run is not surveyable. It is more in the nature of experimentation in mathematics for the machine was directed to 'search' for certain configurations, test its implications and report yes or no to the basic querry. The truth depended upon the reliability of the machine, which is an engineering matter and that of programming about which little can be said of its validity (Goodman 1981).

At the present stage it is difficult to state whether a computer programme does what it is instructed to dc. It is a task for the computer sciences and there does not exist any general established criterion for achieving it. Programmes are written in special languages, are quite complex and may contain bugs or flaws that go unnoticed for a long time. For all these reasons a mathematical proof obtained through computer is of entirely different nature that raises several new questions about the nature of mathematics.

But for most mathematicians, there is an obvious advantage in the abstract nature of mathematics since it provides the freedom in developing a great variety of propositions in which the meanings of the terms can become more general, less explicit and thus their use much broader, the inferences less confined. Nevertheless, mathematical propositions flow from non-defintional set of axioms or postulates that are not proved within the theory. Thus, in Peano's axioms about the number system the meanings of '0', 'natural number' and 'successor' etc. have to be clearly explained. This implies that it cannot be determined whether a given set of axioms underlying some system is internally consistent and that no mutually contradictory proposition can be derived from it.

So long as the axioms are about a definite domain of objects, like the familiar space, the axioms can be ascertained as true by comparison, as done for Euclidean geometry. But with the invention of non-Euclidean geometries this is no longer possible for they are not evidently true of the ordinary space of our experience. The attempt by Hilbert of converting geometric propositions into algebraic representations still left the problem unsolved for now the need was to demonstrate the internal consistency of the algebraic system. The attempt by Russell and Whitehead who advocated reducing all mathematics to the set of formal logic merely transformed the question to whether the fundamental postulates of logic are consistent.

It was the genius of Gödel that finally led to rest such attempts to make mathematics a consistent formal system. In the first place he showed that no proof is possible for the formal consistency of the system that is comprehensive enough to contain the whole of arithmetic. That is, any proof of inference must itself employ axioms that need further proof for their own consistency. Further, he even concluded that any other system in which say, arithmetic can be developed, is essentially incomplete. For given any consistent set of postulates there will be true statements that are not derivable from this set. Thus, in the number system, even if some additional axioms are added to take care of theorems like that of Fermat or Goldbach to make them derivable, there will be further arithmetic truths that cannot be established by the augmented set of axioms. "The import of Gödel's conclusions suggest that an axiomatic approach to say number theory cannot exhaust the domain of arithmetic truths and that mathematical proof does not coincide with the exploitation of a formalized axiomatic method" (Nagel and Newman 1956: 1694).

Even Kant's view that numbers like Euclidean geometry are both a priori and synthetic defies the rature of mathematics. According to him the synthetic a priori knowledge of Euclidean geometry rests upon the awareness of space as a 'form of intuition' and upon the mind's awareness of its own capacity to construct spatial figures in pure imagination. But this form of reasoning commits one to the doctrine of *potential* infinite or of *indefinite* totalities as opposed to the doctrine of *actual* infinite. According to this principle there cannot be any largest number since one can count beyond any number up to which one has counted. Yet, to have infinite numbers would require the mind to imagine that many numbers presupposing an infinite length of time to do so which is impossible.

However, for the school of intuitionist mathematicians who subscribe to a very different nature of mathematics, there is no contradiction in this form of reasoning since for them the pure intuition of temporal counting serves as the point of departure for the mathematics of numbers. For this group of mathematicians headed by the Dutch Brouwer, Cantor's argument that there are more real numbers than natural numbers is unacceptable since it is 'non-constructive' in practice. Intuitionism holds that the source of mathematics is the insight which we intuitively comprehend from experience of the external world.

Intuitionism is akin to 'constructionism' in the sense that it asserts the truth of any mathematical object only after a demonstration that it is possible to do so in practice. The reality of mathematical knowledge is true only to the extent that has been successfully constructed by the mathematician. This branch of mathematics then is diametrically opposed to the positivist notion of asserting the existence of the reality being deciphered by the mathematician. It is more in the nature of phenomenonalism that one can know only by actual action of the process. However, Brouwer noticed that in dealing with the subject of say, infinite sequence of numbers, the assertions that there is a number and there is no such number, the relation of contradictory opposites no longer exists. Thus, in certain mathematical problems dealing with infinite sets the elementary rule of the excluded middle is not admissible without an additional arbitrary assumption.

The intuitionist method therefore rejected all those previous mathematical results in whose derivation the tertium exclusuum was used, including in particular all those theorems which rests upon the so-called indirect proofs. Accordingly, if for an unknown quantity x it can be proved that the assumption that there is no such x leads to a contradiction, then for intuitionists, the existence of x is unproved. The students of Brouwer demand a 'constructive' proof, a method by which the quantity x can be calculated.

From the point of view of Intuitionism, one must possess a constructive proof of any mathematical statement before it can be said that the statement is true. In this sense the intuitionist believe with Kant that whatever the mind creates it must in principle be able to know through and through (Barker 1989: 74). Intuitionism therefore takes a more puritanical standard of logical rigour than traditionally taken by mathematicians of the genre of Cantor, Hilbert and others of different schools. It leads to the rejection not only of Cantor's theory of transfinite but also many others like the theorem in analysis that every bounded set of real numbers has a least upper bound, or even the rejection of Zermelo's axiom of choice.

Such a conceptualist philosophy of mathematics works considerable havoc upon classical mathematics by rejecting its important methods of reasoning and some of its axioms. Critics have strongly objected to this doctrine arguing that its concepts that numbers and sets are brought into existence by pure intuition of the process of counting is exceedingly woolly and objectionable if taken literally. There is no proof that mind can only count at finite speed in pure intuition and that it cannot construct transfinite numbers.

Moreover, associating this mathematics with Kantian philosophy has also implied that its foundations have been shaken by the course that science has since taken and the doubts cast upon Kant's *'Critique of Pure Reason'*. Thus, Kants ideas about the place of space and time in physics correspond with Newtonian physics that have been overtaken by Einstein's theory of relativity. According to Kant, space and time have nothing to do with each other for they stem from quite different sources- that space is the intuitional form of our outer sense and time of our inner sense (Hahn 1956: 1957). The theory of relativity, as we all commonly know propounds that there is no absolute space nor time, only its combination, the 'universe' that has absolute physical meaning. Similarly, Kant's thesis that arithmetic, the study of numbers also rests upon pure intuition has been opposed by Russell who set out to prove that in complete contradiction, arithmetic belongs exclusively to the domains of intellect and logic.

Mathematical Creativity

The nature of mathematics clearly defies any representation, yet in most respects it is like other scientific theories. It is *created* to solve some particular problem and then goes on to develop a life of its own. It is difficult to support the view that these are simply deductive structures based on axioms. These are more of "structures of reasoning based on conjecture and bold extrapolation" (Goodman 1991: 123). Georg Cantor struggled with the problems in analysis in the theory of Fourier series. In order to solve these problems he was led to innovate and develop daring conjectures that were required to solve the growing needs of his theory. Mandelbrot attempting to measure the coastline of Britain was forced to analyze the relation between the scale of measurement and the dimension of the object that forced him to introduce the concept of fractal and the 'fractional dimension'. Every mathematical object is thus a similar construction and outcome of the attempts to get around a problem of synthesis and analysis.

It is precisely this activity that introduces a type of creativity found in the fine arts. The mathematicians who first formulated the non-Euclidean geometry displayed the same form of creativity found in the works of Rembrant, Chopin, Chaplin or Tagore. "A mathematician , like a painter or a poet, is a maker of patterns that are more permanent than theirs because they are made with ideas" (Hardy 1967: 84). Mathematical imagination equals if not surpasses that required by the fine arts since the mathematician is not confined by the material forms available to the other creators. Moreover, mathematical patterns like the painter's or poet's, are also beautiful for these ideas, like the colours or the words fit together in a harmonious way (Hardy 1967). "Mathematics provides a world of pure abstraction, a life in the 'wildness of logic' and where reason is the only handmaiden" (Berlinghoff 1967: 2). No doubt mathematical theories rise in response to the needs of natural and even behavioral sciences, but the creative mathematician often generalizes the original solution and from it builds a logical edifice, investigating questions of abstract structure without further regard to the world around.

"The mathematician is entirely free, within the limits of his imagination, to construct the worlds he pleases" (Sullivan 1956: 2020). "In their prosaic plodding mathematics shows that the world of pure reason is stranger than the world of pure fancy" (Kasner and Newman 1940: 362). Since mathematics is a free activity, unconditioned by the external world, it ought to be described as an art than a science. It is as independent as music or art and is an activity governed by the same rules imposed upon the symphonies of Ravi Shankar, the paintings of Ajanta and the poetry of Omar Khayyam. It is no wonder that most mathematicians describe the same feelings and experiences as other artists, one of beauty and harmony in creating structures, forms and elegant relations that provides them with the same form of esthetic emotions. As Hardy (1967) suggests, a mathematician is less interested in the results than in the beauty of the methods.

Unlike the fine arts mathematics can also be used to illuminate natural phenomenon although it remains subjective and the product of the free creative imagination. As an art mathematics creates new worlds and as a science it explores them.

"It is a common unifying force present in all human intellectual endeavor, forever broadening the horizons of the mind, exploring virgin territories and organizing new information into weapons for another assault on the unknown. It is a language, a tool, and a game, a method of describing things conveniently and efficiently, a shorthand adapted at playing the game of common sense. It demands a novelists imagination, a poets perception of analogy, an artists appreciation of beauty and a politicians flexibility of thought- it is indeed integral and indispensable for human existence" (Berlinghoff 1967: 2).

Further, like arts, mathematics is not for amusement or merely to satisfy an esthetic emotion but also to reveal some aspect of reality. Almost a millenium before, the Indian sage Shankar pronounced, ऐको ब्रह्म द्धितीय नास्ति, our consciousness and the external world are not two independent entities. "The external world is largely our own creation and we understand much of what we have created with which we must create" (Sullivan 1956: 2021). Just as the real function of art is to increase our self consciousness, to make us more aware of what we are and therefore of what the universe in which we live really is, so does mathematics also performs this function.

The Advantages of Using Mathematics

Although, the ordinary spoken languages are capable of providing rich descriptions and possess beauty of expression that could stir the dullest imagination, still there exist several limitations to their usage. The ordinary words are created for use in everyday life where their meanings are familiar in limited circumstances. These could also be extended to wider spheres without bothering if they still have a foothold in reality. "The disastrous effects of such [application] in the political sphere where all words have a much vaguer meaning and human passion that often drowns the voice of reason..." (Weyl 1956: 1836) is apparent to everyone of us! Ernest Nagel (1956) in an ingenious way translated into symbolism passages from Alice in Wonderland and showed how the transformation of words and sentences into symbols illustrates vividly the confusion and ambiguities of ordinary languages.

On the other hand by its symbolic construction mathematics has unfettered itself from the vagueness of the languages and has built a more efficient system of communication than the modern languages. Through its system of abstraction in symbols, a mathematician is free to forget what the symbols stand for and concentrate, like the librarian, only on the catalogue alone. The details are unimportant and what matters is that once the initial symbolic scheme S_0 is given, further work can be carried along by an absolutely rigid construction that leads from S_0 to S_1 to S_2 and so on. The idea of iteration, familiarly encountered with natural numbers can be extended in a purely symbolic manner, the construction of not only 1 or 2 but 3, 4, 5, ... and even to manifold dimensions. Its characteristics of being completely precise is the tool that makes long chains of reasoning possible and exciting.

Thus, in the analysis of physical nature, the phenomenon is reduced to simple elements each of which varies over a certain range of possibilities that can be surveyed *a priori* because these can be constructed *a priori* in a purely combinatorial manner from symbolic material. For instance, light can be polarized into monochromatic light beams with few variable characteristics like wave length that varies over the symbolically constructed continuum of real numbers.

It is because of this *a priori* construction that one can speak of quantitative analysis of nature and the word quantitative ought to be interpreted in this wider sense of the term (Weyl 1956: 1844). It is in fact erroneous to think that mathematics is the science of quantity or that of number and space, of the countable and the measureable for all these are too narrow. These definitions are founded on the misconception that the activity of the mathematician consists in calculating, computing or number crunching. "Extensive areas of mathematics have nothing to do with numbers and even when the mathematician is occupied with numbers, it is generally not in a computational manner" (Saaty and Weyl 1969: 12).

As described before, the prime number problems associated with Fermats, or Goldbach's theorems are examples of investigations that are unconcerned with computation and arithmetic in the usual sense but rather with the task of uncovering structural relations in the order of numbers. It is well known for instance, that even Euclid was aware that a large branch of geometry had nothing to do with measurement.

Finally, the connection between a given continuum and its symbolic scheme is established by the notion of isomorphism, a topological mapping by a continuous one-to-one transformation. Mathematics is therefore indispensable as an instrument for the validation of such knowledge. The theories of empirical sciences cannot be applied universally without the help of mathematics and these have to use the symbols, their functional relationships for expression. Even in the development and test of these theories and establishment of their predictions, there is the requirement of deduction from the general to the particular or an induction from the particular to the general (Palys 1991: 45), a process difficult without the techniques of mathematics.

It is for this reason that a quantitative methodology for criminology ought to be associated with mathematics in general rather than statistics in particular for then not only can the researcher tap the techniques available from a larger bank but also break the shackles of positivist philosophy that has surrounded it. If the model demands a realist interpretation then mathematics of Hardy, Hertz and others is available with its immense power and variability. On the other hand if the researcher is a believer in phenonmenalism and skeptical of the official statistics, then too Brouwer's 'intuitionist' mathematics can be depended upon which too asserts that nothing can be believed unless 'constructively' proved.

Finally, the world of mathematics is full of creation and 'wild' imagination that can be useful in constructing models befitting the situation or representing an argument through its symbolism to provide greater rigour and logical consistency. For criminological purposes then, mathematics can provide useful tools, appropriate models and a strict procedure of verification that any researcher may demand.

Clearly then, there is a need to extend the nature of quantitative methods by incorporating new tools from mathematics that can be applied in criminology. Viewing them as part of the general subject matter of mathematics, quantitative techniques can then be either the familiar number crunching type or those borrowing the structures, relations, abstractness or the logical format of mathematics. Moreover, quantitative methods can also call upon the creative powers of mathematics to explore offender cognition, target selection and preventive measures to develop new arrangements and tools which may provide even deeper insights into the subject matter of crime and its control. Just as calculus, game theory and fractals were developed to deal with particular physical problems there is the possibility that exploration of criminal behavior may lead to the creation of some newer form of mathematics.

Even if a working model that accurately describes or predicts criminal behavior may not be immediately possible, the important aspect is to remember that the fundamentals could be captured and the work can be started. Variables can be added, relations modified and results interpreted in other contexts. "The way to understanding is through doing and the way to truth is through error" (Saaty and Weyl 1969: 276). Mathematics even makes possible the estimation of errors made in understanding some relationship and could suggest ways to correct them. Mathematics is the only language that is without any bias derived from content and, being contentless and independent of specific experience, it is the only cosmopolitan language possessed by human beings. It makes possible the linking of theories widely different in content but with similar logical structure. Therefore, descriptions of criminal behavior, although embedded in context and differing in content could still be compared if there is a common pattern underlying them. Additionally, different explanations of such behaviors could also be compared through the use of mathematical symbols to judge if there is anything common amongst them. Mathematics could serve as the communicating language for criminology.

The concepts in pure mathematics with its study of abstract structures can provide techniques and concepts which possess exciting possibilities for applications in criminology. Pure mathematics deal entirely with mental constructs as fields, space, numbers, fractals and different forms of relations between them. These non worldly abstract studies, concerned with proving theorems with exactness and certitude yield powerful methods These constructs and relations like mapping, exclusion, continuity, commutativeness can turn out to be extremely useful in explaining criminal behavior in social settings if these could be given empirical content with some segment of the social phenomenon. Simple reasoning and conceptual relationships can help create a structure of an abstract world that nonetheless could have practical utility in deriving knowleoge about the empirical world.

The central concern of my research work is this face of quantitative methodology, the construction of abstract structures and their relationships which seem to hold equal promise for the social sciences as they have done for the natural sciences. The following chapters will outline a few concepts and structures from mathematics that can provide new tools of analyses in the study and control of criminal behavior.

However, before describing some such new tools it is pertinent to point out that recent developments in criminology have also started *demanding* the applications of a different nature of quantitative techniques. In the next chapter a brief description of this so called Pattern theory will be provided to assert that the need to extend the definition of quantitative methods has been made and that new developments in criminology are ripe for a new mathematical perspective.

---X---

CHAPTER V

THE PATTERN THEORY OF CRIME

This chapter will argue that the emergence of different theories of crime create the demand for the development of various tools of analysis. We will argue that the developments in methodology are influenced by the parallel growth in theories and moreover, the two also reciprocate each other. We will then describe the exposition of Pattern theory of crime and argue that these new developments in the etiology of crime are paving the way for new tools of analysis in criminology, methods that are looking for a different form of mathematics than hitherto practiced so far.

Theory and Method

This debate between theory, method and observations is pertinent to this thesis since it seeks to develop new tools of analysis and therefore needs to justify the importance of these tools. The justification is based upon the argument over the primacy of subject matter or of the method, that is whether theory determines method or vice versa in 'explaining' or dealing with the observed facts.

One argument holds that the topics of research are set by theoretical developments within the subject and that these in turn make their own unique selection or development of research techniques that have to be adapted to the particular requirement of the topic (Rose 1954: 245). Proponents of the primacy of the method hold that there is but one scientific method and that only the topics researchable in terms of this method lead to valid knowledge.

The claim is often made that the methodology of the social sciences are radically different from the natural sciences. It is for instance commonly stated that the complexities and ever changing dynamics of the social processes cannot be controlled , manipulated or even isolated like the physical objects. However, as Rudner (1966: 4-5) points out, these kind of arguments confuse the methodology with techniques. For just as we do not 'manipulate' the galaxies to study about the universe we do not need to control the social processes to understand the underlying causes.

The differences of techniques in any particular discipline are to be expected depending upon the variety of phenomena being investigated. Thus, physics employs techniques ranging from the measurement of physical objects to acceleration of atomic particles in the cyclotron. The use of the pendulum is undoubtedly radically different from the application of an electric circuit.

However, to say that this implies a different methodology becomes a rather startling claim for underlying the use of any instrument or technique, the physicist remains aware of the basic scientific method that forms the basis of his or her logic of justification. It is this common method of science that forms the rationale for the rejection of any hypothesis amongst the scientific community.

Therefore, to state that the social sciences have a different method would imply that they have altogether a different manner of justifying their claims or supporting their theories. Further, "..to hold such a view is to deny that all of the science is characterised by a common logic of justification in its rejection of the hypotheses or theories" (Rudner 1966: 5).

The view that the social sciences are methodologically distinct also confuses the notions of discovery and validation. It is improper to talk about a logic of discovery, meaning that there is some fixed manner in which something is accepted as being known for the first time.

However, a logic of explanation is the manner that is asserted when we speak about the scientific method. The context of discovery may be dependent upon the prevailing social, psychological, political or economic conditions that play an important role in thinking up new hypotheses. On the other hand, the claim that a certain hypotheses has been disapproved by the evidence *is* a matter belonging to the subject of validation.

This distinction needs to be kept in mind when the primacy of the method over the theory is being talked about. Undoubtedly, in studying criminal behavior we are restricted in the use of certain techniques, like controlled experimentation or manipulation of social variables. The collection of data is also largely dependent upon a few limited methods like survey techniques. Yet, one can get over these limitations possibly through other non-obtrusive techniques.

However, in the application of different techniques the logic of justification remains essentially the same, the attempt to explain some phenomenon in terms of some other situational factors. In these attempts sometimes there is a satisfactory explanation that may develop into a theoretical proposition and at other periods, the technique itself may lead to different insights into the genesis of the phenomenon. It is impossible to hold otherwise that the debate between theory and method is irresolvable and is akin to the chicken and egg debate. Many-a-times it is the theory that is formulated first and which leads to the development of a method to test the theory. The story of Newton's theory of gravity is one such classic example- he formulated the idea of gravitational force but then had to develop calculus to prove his theory and its theoretical implications (Cambell 1956: 1826).

However, the reverse is true too, a technique may also lead to the growth of theoretical conceptualizations. The example of differential equations based upon Ampère's and Faraday's laws to represent electrical and magnetic forces were well known for sometime. In working out the solutions to these equations Maxwell experimented with the idea of interchanging the symbols amongst themselves. This suggested to him that so long as the symbols X, Y, Z, t were related in some way, there might be electric current in circumstances in which it had been believed till then that electricity could not flow. Maxwell's feeling for symbolism gave him the idea that there might be such a current and that a perturbation in one place could be reproduced at another far off place by 'waves' travelling even through empty space. This was the genesis of radio waves as is well known now (Cambell 1956: 1827-28). Subsequently, experiments confirmed his theory and radio waves were 'discovered' by Hertz in 1888 while Marconi commercialized them.

The theory of relativity was also the consequence of solutions of mathematical equations providing Einstein the concept of relativity of space and time. The present developments in theoretical physics, the concept of black hole, 'curvature' of the universe, big bang theory and many others is only the exposition of what mathematical solutions appear to be implying. The theories of physicists are only the concretization of what the mathematicians suggest.

In some ways this dissertation presents a similar situation. The exploration of new techniques is partly influenced by the desire to go beyond statistics but is also inspired by the presentation of Pattern theory of crimes by Brantingham and Brantingham (1993a) that actually suggests the use of new mathematical tools. Therefore, before proceeding with the actual developments of new tools of analysis, the main propositions of the Pattern theory will be presented. It will be shown how these new developments in criminology encourage looking for methods that are conceptually non-statistical in nature and based upon non-numerical mathematical structures.

This we believe will aptly justify the efforts of this thesis in developing new tools of analyses in criminology. For these tools can serve both as a means for testing the Pattern theory of crime and additionally prepare the groundwork for new theoretical developments in criminology. As Einstein and Infeld (1942: 95) point out, "To raise new questions, new possibilities, to regard old problems from a new angle, requires creative imagination and a mark of real advance in science", a task that this thesis sees before itself.

The Pattern Theory of Crime

That the environment, especially the physical supports and restricts criminal activities is an age old observation. Ashok Priyadarshi, the Magadh emperor of India in 250 BC had sanctioned installation of torchlights in his capital Patliputra to keep the streets safe (Upadhyaya 1978: 45). Research in the etiology of crime ever since the time of Quetélet (1968) has demonstrated the complex relationship between the environment and criminal behavior at different levels of spatial and temporal resolutions. Criminal activity patterns are shaped by environmental opportunity structures (Butcher 1991; Rengert 1991; Clarke 1992; Felson

1993). Not only are criminal events influenced by the environment but economic and physical factors affect the concentration of delinquents in the urban population or even make some offenses obsolete (*e.g.,* Shaw and McKay 1942; Baldwin and Bottoms 1976; Walsh 1994). The residential layouts developed even from a social objective eventually leads to a skewed distribution of the offending population while the environmental patterns even determine the victims amongst the people (*e.g.,* Wikstrom 1991; Fattah 1991).

The earlier attempts of explaining criminal behavior have focused upon unicausal models: *e.g.,* Sutherland's differential socialization (1947), Cloward and Ohlin's blocked opportunity (1960) or even Taylor, Walton and Young's capitalist societal structure (1973). As Brantingham and Brantingham (1993a: 260) point out, the primary weakness in these attempts have been to equate crime with criminality, which is but one of the factors influencing the crime occurrence. An alternate theoretical movement since the 1970s under the name of 'Environmental Criminology' has attempted to develop a different frame for criminal events by incorporating an inter-disciplinary approach in which "...crimes are viewed as etiologically complex" [patterns of behavior] (Brantingham and Brantingham 1993a: 264).

This approach argues that the appearance of a criminal event is not spontaneous but begins with someone who is in a state of readiness, who either has a motivation or is able to spot some opportunity. Any of these desires in turn are formed over a long period of time based on the goals or objectives set out by the individual. Further, these goals are dependent upon the psychological, social, cultural and economic background of the person. Naturally, this also implies that opportunities and the state of readiness will be non-uniformly distributed in the society since these will vary with the characteristics of the offender and the target or victim.

Finally, the 'backcloth' (Brantingham and Brantingham 1993b: 6) of environment composed of such factors as social, legal, economical, political, physical and even atmospherical factors forms the settings in which some specific behavior takes place and gets the label 'crime'. Such a new approach to crime pays particular attention to understand how an individual perceives and gains knowledge of his or her environment that shapes the motivation and which additionally, is facilitated by the presence of criminal opportunities (*e.g.*, Carter and Hill 1979; Felson 1987; Cornish and Clarke 1986).

Despite the fact that such a view of crime is complex and complicated, this theory still suggests the existence of discernible patterns in the phenomena of crime. The pattern recognition is based upon the study of "...specific criminal events, the site, the situation, the activity backcloth, the probable crime templates, the triggering events and the general factors influencing the readiness or willingness of the individuals to commit crimes" (Brantingham and Brantingham 1993a: 284-285). These patterns are "recognizable inter-connectiveness of objects, processes and ideas" (Brantingham and Brantingham 1993a: 264) observed through the cognitive process of seeing similarities in actions and locations, and viewing the decision process in conjunction with the surrounding environments. This broad outlook, described as the Pattern theory points towards the recognition and understanding of both individual and aggregate patterns of behavior at many levels of resolution, levels which depend upon "...the backcloth, the site, the situation, an individual's readiness, the routine activities and the distribution of targets" (Brantingham and Brantingham 1993a: 266).

Backcloth, Nodes, Paths and Templates

The theory asserts that the difficulties in identifying discernible patterns can be overcome by placing the criminal event over varying layers of resolution on a backcloth and to consider changes in this backcloth itself as the various levels of resolution are examined. Thus, for example, Pattern theory describes the environmental backcloth of the physical dimension through the concept of nodes, paths and templates at different levels.

Nodes have been described as the points of concentration of crime in any region. These concentrations appear to occur for all types of criminal behavior ranging from robberies, thefts, homicides and even family troubles. These 'hot spots' of crimes as they have popularly been labeled, are almost universal phenomenon and have been reported in such diverse places as Chicago, Vancouver, Sweden and even Madras in India that these are now well known in criminological literature (*e.g.,* Sherman, Gartin and Buerger 1989; Brantingham, Mu and Verma 1994; Wikstrom 1991; Sivamurty 1982).

There is something peculiar about these points for irrespective of time periods, changing social and economic conditions and despite cultural variances, almost every urban centre appear to be plagued by such hot spots of crime. It is clear that these are the outcome of some specific structural arrangement that leads to the creation of major opportunities and victimization in these places. As

Brantingham and Brantingham (1984; 1991) have clarified, these nodes appear to be the intersecting points of movements to and from home to work to entertainment places and are also observed on the pathways falling enroute. Every offender develops knowledge about his or her area based upon these daily routine activities and therefore tends to commit crimes in familiar surroundings, where targets are recognized and get away routes are learned.

It is no wonder that "most property crime targets generally fall near the nodal points of offenders' routine daily activity patterns along their normal travel paths" (Rengert and Wasilchick 1985) while personal crimes tend to concentrate in homes or places of drinking and socializing (*e.g.,* Roneck and Pravatiner 1989; Fattah 1991; Wikstrom 1991). Undoubtedly, crime is largely concentrated around major attractors like shopping places, sport arenas, offices, schools and arterial roads. As Cohen and Felson (1979) and Felson (1993) have pointed out, crime is highly patterned by routine activities of everyday life.

Pattern theory explains this by drawing a network of nodes and paths of routine activities of individual offenders. This is of course true for any individual who generally moves in limited regions and through familiar routes for most of the times. These areas are then known by daily transactions and provide opportunities or reveal targets for persons looking for them or noticing them over and over again. The familiar 'distance decay' model also explains the same phenomenon pointing out that most property offenders tend to commit crimes near their homes. Research by Porteous (1977), Rengert and Wasilchick (1985), Feeny (1986), Gabor et al (1987) and Cromwell, Olson and Avary (1991) all have reported similar patterns, that crime occurs near known places and travel routes of individual offenders.

Even crime sites of multiple offenders tend to concentrate around high activity nodes sometimes described in the literature as 'crime generators' or 'hot spots'. As Brantingham and Brantingham (1993a) argue, these clusters are the result of general development of cognitive images, environmental perception, distance and direction recognition that leads towards target selections. Further, these 'awareness spaces' (1993a: 270), whether based on places where someone eats or drinks, or where someone works, or so on, influence what that person knows about the environment. Once such knowledge is acquired and forms part of a person's general awareness space, it begins to influence other types of behavior, such as choosing a place to burglarize, or places to buy (or steal) cigarettes, or corners to hang out on.

The routes between these nodes are also the sites for high criminal offences although the concentration is naturally at the end points of these paths. Major road arteries with high volume of traffic are areas that fall within the awareness space of large number of people and thus may show trends of higher rates of crimes than other areas (Alston 1994; Beavon, Brantingham and Brantingham 1994; Brantingham and Brantingham 1984; Duffala 1976). Pattern theory suggests that the structure of road networks influences how far crimes spread from the major pathways. Complex inter-connectivity of side roads pose long term learning problems for those passing near by and therefore would show lesser rates of crimes than simple grid structured road networks around important road layouts.

Pattern theory also points towards the research about how people learn about pathways, about cognitive maps and representations (Garling, Book and Lindberg 1984; Garling 1989; Garling and Golledge 1989). The work by Letkemann (1973), Gabor et al (1987), Rengert and Wasilchick (1985) also supports these assertions that usual travel paths leads to identification of attractive targets for most offenders.

However, not all places become attractive targets for these are not seen as 'suitable' for reasons of expected booty or for the difficulty in penetrating the place or because the offender is after something else. It is seen that targets that are seen as attractive for robbery are not so for burglary or theft and so on. Pattern theory therefore also talks about the 'distinctiveness' of the target that varies by the offender, by site, by situation and with the variations in the environmental backcloth (1993a: 266).

Since the choice of a particular target is guided by decisions based upon different factors, the theory also develops concepts like 'crime templates' to explain how these decisions are made. Brantingham and Brantingham (1993a: 269-270) suggest that the environment provides cues about the immediate characteristics and backcloth that is reinforced by experience into an overall template, a sort of mental map or model that assists in identifying objects, places or situations. These templates are "...more [of] a holistic image with complex interaction of pasts and relationships seen from varying perspectives" (1993b: 12) depending upon the cone of resolution.

The distinctiveness of targets or images are influenced by the edges bounding the areas, its homogeneity, the pathways and landmarks within the areas. Garling and Golledge (1989) and Garling (1989) also suggest that images or perceptions are shaped by sharp breaks or variations in visual landscapes, although the interests and learning differences may give rise to differential images. The importance of the edge effect has been well established by Brantingham and Brantingham (1975; 1978) by using sophisticated topological technique in their study of Tallahassee, Florida. This has also been borne out in studies of Shaw and McKay (1942), Herbert and Hyde (1985) and Walsh (1986) in which the gradual or sharp transitions between housing forms and densities influence concentration of crimes in these 'transitional' areas. Newman's 'defensible space' (1972) is another similar concept emphasizing the distinctiveness of residential architecture in the study of crime patterns.

Pattern theory also suggests that crime and criminal events are better understood as processes, like "mathematically functional relationships" [which would reveal] "the variations in the links between different elements and how they interact" (Brantingham and Brantingham 1993a: 277). The patterns then become understandable when the decision process, the activities of both the offenders and victims, seen against the backcloth of environmental processes which encourage, restrict or support them and the triggering events are all analyzed as different streams but flowing together or towards each other.

"[These] patterns are understandable because they contain some similarity or commonality when viewed from the perspective of the processes in activities and criminal decision making: the use of goals for actions; the construction and use of templates in search behavior; the development of a state of readiness awaiting a triggering event; the process of the triggering event itself".

(Brantingham and Brantingham 1993a: 286)

The Cognition of Space

However, our understanding of spatial representation and its relationship with behavior is encumbered by the difficulty of defining and describing space. There is no unanimity in even its basic conceptualization. Plato and Clark believed space to be absolute while Leibnitz and Kant argued that 'empty space' has no relevance and that space can only be expressed as an expression of a set of relationships among objects (Lieben 1981: 4). Despite this conceptual pluralism much of the work in psychology and criminology on spatial concepts still seem to assume implicitly that the mature concept of space is only a 3-dimensional Euclidean model. In contrast physics and other natural and physical sciences, like bio-chemistry, astronomy have adopted non-Euclidean models in their theoretical formulations, thereby enhancing the strengths of their models, a process which needs to be followed in criminology too[2].

Further, the manner in which humans perceive their space and develop their 'cognitive map' (Downs 1981: 160) is a significant and important question in pattern theory, but there is still, only a rudimentary understanding of its process. There are several types of problems in building any typology of this process chiefly because the key building terms 'space', 'environment' are still quite fuzzy concepts. For example, space with respect to a person has been variously described as not only a simple location but as an expression of feeling, a conceptual abstraction, a tool for memory and problem solving (Lieben 1981: 8).

Moreover, the many and diverse differences across physical environments, make it difficult for categorizing their relevant variables. The fact that there are relatively few standardized measures of the physical environment is not unexpected given the incredible diversity in the environments and variables of potential interest. Many a times it may not be possible to use such standardized

---

[2] Alston (1994) and Rossmo (1995) have made a beginning by using manhattan distances

measures if the definition of the units imply differing scales. Thus, the earlier concept of hot spot (Sherman, Gartin and Buerger 1989) differs from that of Weisburd for whom it means a corner, a block or even a number of blocks depending upon the kind of drug dealing activities. There are also both 'built' and 'natural' environments and each is divisible into major and minor settings depending upon the context of interest. Without a generally-accepted taxonomy of important environmental variables, it is indeed difficult to document how these variables affect spatial behavior and its perception.

Some attempts to distinguish the environment can be made on the extent to which they are differentiated. For example, the number and types of units in a given area may vary: thus, neighborhoods may become discernible by the highly individualized or highly similar residential units. Neighbourhoods might be distinguished by uniformity or irregularity of spacing of dwelling units. Similarly, land marks are an important variable for spatial representation. Apart from the number and diversity of elements within environments there could also be variations in the manner and extent to which these elements are organized.

Two regions may contain an equal number of roads but one may be organized into a neat grid while the other may not have any regular arrangement at all. The former may then be more conducive to learning the layout of the area, to a better environmental cognition (Hart 1981: 206) and may enhance the use of cartesian coordinates in conceptualizing spatial abstraction. The former is likely to be represented topologically with concepts of similarity and connectedness, the way children conceive their school layouts (Siegel 1981: 171).

Environments can be differentiated in other, more qualitative ways as well, as in the distinction between 'carpentered' and 'uncarpentered' environments (Lieben 1981: 24). Westerners are typically exposed to angular shapes but other traditional cultures as those of Zulus in Africa and Santhal tribals in India, emphasize roundness. These distinctions may be related to the natural conception of spatial distances rather than through the cartesian, polar or some other 'artificial' coordinate systems.

Not only spatial concepts are enhanced by environment's differentiation, but the opposite holds true too. Berry (1971), reported that Canadian Inuits are more field independent than the Temme of West Africa which occurs as result of differences in ecologies. Apparently, Inuits learn to pick out seemingly minor variations from a generally monotonous barren land while Temme need not do so because of being surrounded by a highly differentiated jungle. The differences in perspectives are really the outcome of both the external environment as well as the socio-cultural traditions.

Finally, the characteristics of the individuals are important too in the construction of their cognitive maps. Thus, a city may present a highly differentiated and diverse space, but this is functionally true only for the individuals who have the capacity and motivation to explore that environment. An older person is less likely to venture far from his or her home than a younger, energetic individual. The cultural values too affect the social and environmental experiences.

For example, different cultures vary with respect to the freedom children are permitted to explore areas away from home. Restrictions for movements outside the home environment are placed even upon women in many cultures. The discouragement to explore space and have less opportunity to acquire spatial knowledge and skills may in turn reduce ability to assimilate spatial information in the future due to the lack of developing prerequisite knowledge (Lieben 1981: 28).

Modeling the Criminal Event

Although this discussion of influences on spatial representation and behavior is sparse, it does illustrate the large complexity and reciprocity of influences. It points to the importance of attending not only to individuals, but to their broader biological, social and historical contexts in which these are embedded.

Crime is not only a matter of individual behavior but ought to be seen as a complex event. It not only involves the actions of offenders, victims, and /or guardians but situational and environmental factors too. However, despite the differences in spatial and behavioral representations, there do exist similarities that can be understood and modelled. Pattern theory argues that these similarities are to be found in ways people 'see' their environment, the manner in which cognition is sharpened to select suitable targets and develop appropriate crime templates. Such cognitive behavior is suggested to be modelled through the concept of nodes, edges and templates; concepts that are difficult to deal through the present statistical techniques and which therefore require a different framework for describing and analyzing them.

Representation of a backcloth, edges or templates requires imagination and methodological innovation since traditional techniques are limited to Euclidean measures and finite number of variables. Brantingham and Brantingham (1993b: 8-9) therefore rightly argue for mathematical models that use non-statistical mathematical techniques such as topology, fractal geometry so that "...patterns, designs, edges 'stand out' in attempts at representation of the uncountable complexity of the never static backcloth".

The theme that emerges most consistently from the above discussion is the need to recognize and respect multiple definitions of space and spatial representations, and correlatively, a need to use diverse tools for studying these factors. Maltz (1994c: 19) for instance, has argued for a new way of analyzing crime related data, through the application of computer graphical techniques to let the "data speak for themselves, not mediated through a statistical model".

Brantingham and Brantingham (1993a: 286) too have asserted,

"...future advancements in this field of [criminal] research may require more reliance on alternative analytic tools such as point-set or algebraic topology, or non-linear models and fractal constructs as well as a continual expansion into alternative

methodologies to gain a better understanding of crime occurrence within a cognitive as well as a more objectively defined environment",

a position we cannot but agree wholeheartedly and which forms the *raison d'être* of this dissertation. As pointed out by Maltz (1994a: 456), there is a growing trend towards the applications of new methods borrowed from ecology, epidemiology, event history, survival analysis, sociolinguistics, life course analysis, geography, computer mapping and simulations, one that is attempting to move away from statistical methodology. All this appears to strengthen the belief that criminologists are becoming dissatisfied with the common statistical techniques and are searching for alternative ways to explore and analyze the crime data. The demand for 'new tools of analysis in criminology' is therefore undisputed and growing.

The next phase of this dissertation is to develop some such new tools and demonstrate their applications in different spheres. In the next chapter we will explore a kind of mathematics that appear to promise excellent techniques in constructing the templates of the offender. As explained by pattern theory, "people [tend to] use a template as a mental short cut in appraising places and situations" (Brantingham and Brantingham 1993b: 12). Since every offender tends to develop a particular kind of a template, one way to model it is through the identification of what the detectives tend to describe as their 'modus operandi'. In practice this becomes a difficult task for the variables used in matching the factors that constitute any modus operandi are generally fuzzy in nature. For this reason we will explore in the next chapter a technique based upon fuzzy logic and see how this kind of mathematics can be useful in profiling the crime template for a specific offence.

---X---

CHAPTER VI

CONSTRUCTION OF OFFENDER PROFILES USING FUZZY LOGIC

In the previous chapter a brief outline of the pattern theory of crime was presented in which it was suggested that offenders develop a kind of 'mental' template in searching for suitable targets. At present, there is no established technique that could profile any such a template since it is so individualistic and involves a large number of factors.

However, we know and the theory also asserts that despite such individual differences there are set patterns that are understandable. In fact, police detective work is dependent on deciphering such patterns that are determined by habitual actions of offenders. In the commission of crime, most habitual offenders adopt a fixed mode of behaviour, in terms of chosen time period, target preference, region of operation and even the manner of committing the crime. In common police terminology such behavioural pattern is described as the 'modus operandi' of the offender and a good detective attempts to established this by looking for recognizable style in the commission of the crime.

Thus, in burglary cases, the pattern sought is the time, place, mode of entry into the premises and the items stolen or left behind that usually forms such a modus operandi. In serial killings, apart from the place, time and mode of killing, the characteristics of the victim, the nodes of the residence, work place and acquaintances of the offender may form the set pattern or the modus operandi (Alston 1994).

Although, context makes clear some of the factors involved in the commission of the crime, like the name of an associate, still some variables remain roughly estimated and pose problems for the police in establishing the modus operandi. Since these factors are imprecise in nature it is difficult to use or develop any of the standard mathematical techniques to profile the offender. In this chapter we will explore a new kind of mathematics based upon fuzzy logic that could be useful in understanding the templates of the offenders.

The Need for 'Imprecise' Logic

In everyday conversation we generally use imprecise and implied terms like 'it's a **hot** day', or that 'it's an **early** morning meeting', and 'there is only a **short** time allotted to each speaker'. Ordinarily, we understand intuitively the implied meanings of these terms even though each is individual specific. For some people, early morning implies a time period before 9:30 AM while for others it may be 6.00 AM. Yet, we can communicate easily in such fuzzy terms that the best computer is unable to replicate. There are several reasons for this difference but a significant characteristic is the capability of human beings to communicate in fuzzy terms. "The difference between human brain and the computers lies in the ability of the former to think and reason in imprecise, non-quantitative terms" (Zadeh *cited* in Kaufmann 1975).

It is this proficiency that makes it possible for humans to decipher different scripts, handwriting, comprehend a variety of sounds, interpret multiple meaning responses and focus on information that is relevant in order to make the decision. Also, unlike the computer, human brain has not only the powers of similar reasoning and thinking logically but of taking things globally, peripherally and holistically. Cognition comes even though the term may be imprecise or having several shades of meanings.

Again, unlike the computer that deals with dichotomous categorizations, human beings can still communicate in nuances that may have multiple interpretations. Thus, a human being can perceive and treat a piece of information that is fuzzy in nature and respond to it in an unambiguous, clear manner by taking a range of possible interpretations.

At present, our analytical procedures generally follow the Boolean logic system in which the law of the excluded middle is deeply entrenched. For this reason at present we can deal with data that can have only two possible interpretations- either it is true or false, either it means yes or no and so on. This system precludes any possibility of a situation falling in between, like something not being true but not false also. The Boolean logician would place this into an 'impossible' category and thus reject its validity. Yet, from experience we know that despite best efforts there are situations in which it is not possible to take either of the extreme possibilities. Perhaps, realizing the need to deal with such cases, Zadeh (1965) developed a new form of logic system that he called fuzzy logic in which he stipulated that an element can be a member of a given set in an uncertain manner.

Unlike the classical mathematical set theory in which an element can be only in two situations, a member of the set or not its member, fuzzy logic generalizes the possibilities and introduces the concept of shades of membership patterns. It therefore incorporates the condition that an element is either a member or not a member of some set but also *extends* the condition by introducing the possibility of membership falling in mixed modes.

Apart from the natural generalization to the concept of belongingness, another clear advantage of using such a theory of logic is that it allows the structuring of all that is separated by imprecise terminology. Uncertain situations, language, thoughts, expressions, feelings and even perceptions can now be modeled by mathematical techniques based upon this system of logic. The system is essentially based upon the axiom that there exists "Fuzzy sets or classes with unsharp boundaries in which the transition from membership to non-membership is gradual rather than abrupt" (Kauffman 1975 XIII).

Applications of Fuzzy Logic based Techniques

The techniques based upon fuzzy logic can find several applications in criminal justice fields. For instance, it has been shown to be useful in dealing with the vast amount of data on criminal profiles (McDowell 1990; Wu and Desai 1994). This kind of data available with the investigative departments has grown into unmanageable proportions due to the development of criminal information systems. The Violent Crime Location Analysis System (VICLAS) that maintains information about violent crime and serial offenders developed by the Royal Canadian Mounted Police (RCMP) for example, uses more than 500 variables as input. Although, the VICLAS system has been developed to maintain records of violent predators, especially sex offenders and serial killers, even with a modest number of cases, the information stored in the system becomes unwieldy and difficult to process. Similarly, the police computer aided dispatch systems that keep records of every emergency call are also growing extremely large for investigators and managers to handle comfortably.

Even other specialized systems like for instance, the computer archive with the Chicago police department has reportedly more than 18000 records on homicide cases alone; the Criminal Investigation Departments of police in India are obligated to maintain records of ALL the serious cognizable (indictable) offences till the period of final disposal of the case by the court. This has implied maintaining records for about fifteen years- due to the pendency of cases in the courts. All these record systems have grown so large in volume that it is difficult to keep track of information contained within these archives (National Crime Record Bureau 1992).

This is now the situation with most of the North American and other large police forces that are collecting and recording vast amounts of information. Investigations that depend upon the need to analyze the information contained in these systems are becoming almost impossible to carry out. Similarly, efforts to construct the templates of serial or multiple offenders is generally running into even greater difficulties due to the lack of tools dealing with the fine gradations of the information variables.

This section deals with one such application in police investigation where clues pointing towards the likely offender are generally imprecise and admit a range of possibilities. We will outline a model based upon fuzzy logic that can help the investigators in constructing a comparative template which may point towards the likely offender(s). The model is actually the *Modus Operandi* technique which is used by most police officers in narrowing down the list of likely suspects. Since the modus operandi method attempts to match likely suspects against the approximate profiles built from the scarce evidence the technique of fuzzy logic appears appropriate and could be profitably used in such investigations.

As a practical example we will use the case of Motor Vehicle theft in which multiple offences by a single individual are more probable. The technique could be applied in any type of an offence.

Fuzzy Set Theory

A set S is said to be fuzzy when an element can belong partially to it, rather than having to belong completely or not at all. Fuzzy set theory therefore begins with an assignment of grade of membership values which are not restricted to 0 (non-membership) or 1 (full membership).

In classical set theory, membership is binary, since there are only two possible states, membership and non-membership. Conventionally, these are assigned the values 1 and 0 respectively. These two values comprise what can be called the valuation set, which is the set of possible membership values. However, a set is said to be fuzzy if the valuation set contains values between 0 and 1. In most versions of fuzzy set theory, the valuation set is the interval [0,1]. The higher the membership value, the more an element belongs to the concerned set S (Zadeh 1965; Zimmerman 1985).

Note that the valuation set need not contain numerical values. Verbal membership values have also been utilized by Kempton (1978) in his anthropological studies of fuzzy linguist categories such as 'absolutely not a'; 'in some ways a'; 'sort of a'; 'primarily a', 'best example of a' etc. These membership values are merely an ordered set of verbal hedges, but they successfully elicit fuzzy judgments from respondents (Nowakowska 1977). Given the concept of degree of membership in the set S, the corresponding degree of membership in 'not-S' ($\neg S$) called the negation of S is denoted as mS(x) = 1- mS(x) where mS(x) is membership value in S (Smithson 1982).

Technique

Let Ω be the set of auto suspects. An auto thief (suspect) p Ω, can be categorized by assigning to it the values of a finite set of fuzzy parameters relevant to him/her. Examples of such parameters may include *places* or *times* of operation, preferred vehicle *type*, *busy* or *isolated* road conditions of theft sites, *value* of the vehicle or the goods inside, *mode* of getting into the car, *purpose* of theft and so on, where the highlighted parameters are fuzzy in concept (Zadeh 1965). Each parameter is specific to some feature of the offender p in question.

Thus, p can be associated with a mathematical object F_k = [$m_1(p)$, $m_2(p)$, $m_3(p)$,...$m_r(p)$] where $m_i(p)$ is the measurement procedure of parameter i and $m_i(p)$ is that particular value. For example, we may have $m_j(p)$= time period i.e. day, evening or night; or $m_k(p)$= place which refers to the boundary limits of some particular neighborhood; $m_l(p)$= value in terms of costly or low priced car and so on.

Here F_k will be called the pattern class and many such pattern classes $F_{k\in I}$ of mathematical objects could be associated with p. This will depend upon the various combinatorial values of $m_i(p)$ where I = 1....r. The set F of all such mathematical objects will be called the pattern space. The objective is then to assign a given object to a class of objects similar to it, having the same structure. According to Zadeh (1965), such a class is often a fuzzy set F_y. A recognition algorithm when applied to it yields the grade of membership $M_F(p)$ of p in the class F. In case the parameter is exactly known, such as the time of theft (someone may have noticed the car being driven away), then the grade of membership in time parameter will be 1 in accordance with the definition of fuzzy set.

We will first define a fuzzy pattern class F based upon the measures of parameters in question. The easiest way of doing this is to assign this class a 'deformable' prototype (Dubois & Prade 1980: 317) constructed through the information available from convicted and old suspects. The assignment can be done by giving an interval of measures to each of the selected variables. Thus, *young* may mean 15-19 years of age, *costly* may imply a dollar value of around 5,000 dollars etc. Other features like ethnicity (Chinese *looking*), *casually* dressed, *tall*, *local* could also be added based upon the information made available from statements of victims or knowledge of detectives about the active suspects. The measurement of these variables could be carried out through some form of smaller or larger scale developed for this purpose.

A prototype may then be something like- {young, Asian, smart looking, Robson/Granville street areas, evening, (prefers)

Japanese cars, medium valued, lighted locations, (uses) duplicate keys... and so on}. As can be seen, all these are fuzzy variables with a range of membership values. However, with larger data sets of suspects and over the years, more and more information gets built into the system which would help in reducing some of the fuzzy measurements or in building more representative prototypes.

Finally, a new auto theft offence will be analyzed about its attributes and for its membership values in each parameter. Some definite information will always be available, such as the make of the car and place of theft. Based upon these values and the information provided by the complainant or witness, the investigating officer can then assign the values of 1 or 0 or decide upon the grade of membership into other parameters.

Mathematically, let $F_{k \in I}$ be a fuzzy prototype pattern class defined by the fuzzy features $f_1 \ldots f_r$, where f_i is the fuzzy values of feature i. Symbolically, $F_k = \{f_1 \ldots f_r\}$ where f_1 is (*tall*), f_2 is (Chinese *looking*), f_3 is (...*around* Robson street) f_4 is (*busy* street...), f_5 is (*shabby* clothes) and so on. Each f_i will be having an interval of values. For example, *busy* may imply the situation when 15-25 cars pass a street crossing per minute. An information about some suspect hanging *around* Robson street could mean the area is within four blocks on either side of Robson street and so on.

F_k will have a minimum value n obtained by aggregating all the minimum values of f_i and similarly a maximum value m. An object p, that is a suspect of this theft will be characterized with respect to the class F_k by the r membership values- $f_k m_i(p)$, i=1..r. The value of p, denoted by $M_{F_k}(p)$ will be constructed by *aggregating* the $m_i(p)$s in some manner. This $M_{F_k}(p)$ can then be compared to the maximum and minimum values of different prototype pattern classes $F_{k \in I}$ which provides a numerical measure of the likelihood of a suspect belonging to a specific pattern class F_k (a group of suspects or a particular gang).

Aggregation Techniques

Several aggregating schemes have been developed (Zadeh et al 1975; Smithson 1987) but literature review suggests that the choice of aggregation is very context dependent (Dubois & Prade 1980: 319). We will outline two different aggregation techniques which are based upon Zadeh's (1965) original paper.

Given an object p with membership values $F_{k \in I}$ $m_i(p)$ where i = 1....r and each F_k is a feature class, we can extend the classical union and intersection of ordinary set theory concepts to these fuzzy sets also by the following procedure:

$$\cap\ (mA, mB) = \min\ (mA, mB) \text{ and}$$

$$\cup\ (mA, mB) = \max(mA, mB) \text{ where}$$

$\cap$ is the logical 'and' and $\cup$ is the 'or' operator on the fuzzy sets A, B.

These operators have the following properties:

1. min(0,A)= 0 for any A $\neq$ 0.
2. max(1, A)= 1 for any A $\neq$ 1.
3. min(A, A)= max(A, A) = A (idempotency)
4. min(A, B)= min(B, A) &

   max(A, B)= max(B, A) (Commutativity)
5. min (min(A, B), C)= min(A, (min(B, C))

   & max (max(A, B), C)= max (A, (max(B, C))

   (Associativity)

6 min (A, max(B, C))= max (min(A, B),min(A, C))

and

max (A, min(B, C))= min (max(A, B), max(A, C))

(Distributivity).

Another technique suggested is to use the product operators:

$$\cap\ (mA, mB) = mA*mB \text{ and}$$

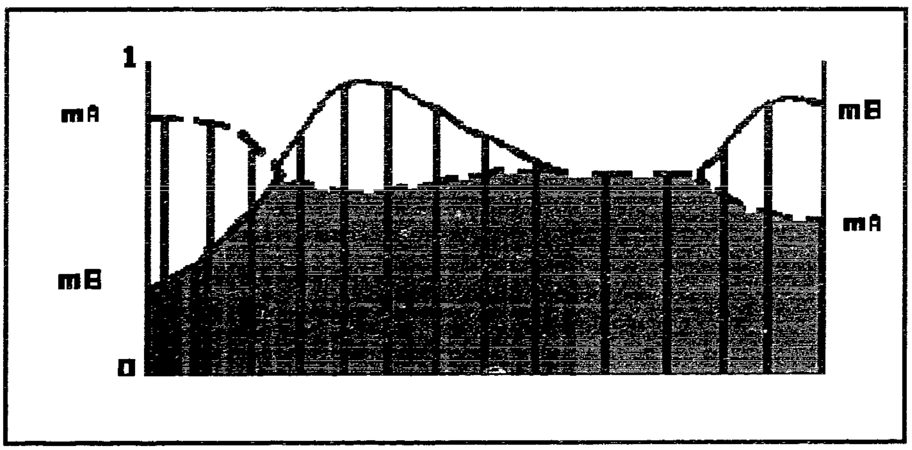
$$\cup\ (mA, mB) = mA + mB - mA*mB.$$

The product operators have all the properties listed above except idempotency and distributivity. However, we can replace idempotency by an inequality since we know that for any positive numbers x and y, such that $x < 1$ and $y < 1$,

$$x*y \leq \min(x,y).$$

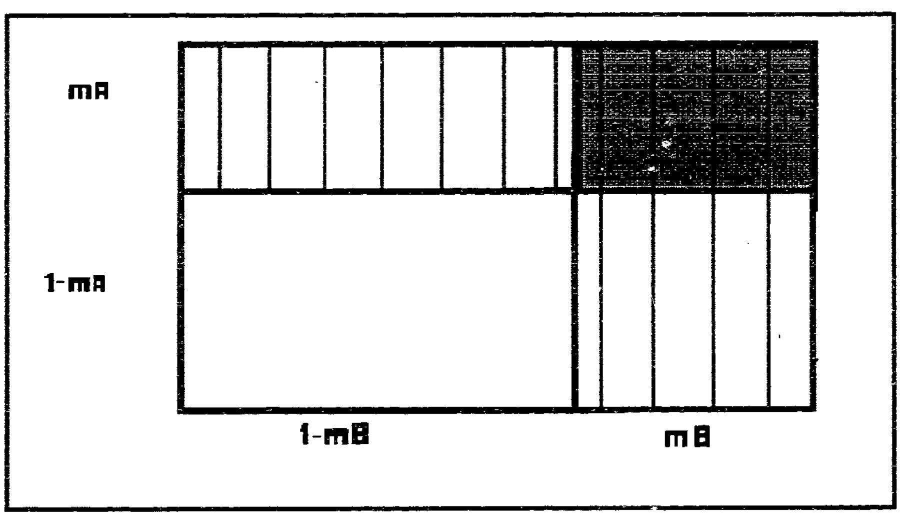
Both the min-max and product operators have graphical interpretations along the lines of useful Venn diagrams. See figures 6.1 and 6.2 below:

Fig. 6.1

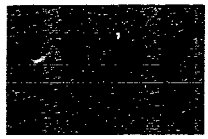


Min-Max Operator

Fig. 6.2



Product Operator



$\cap$ (mA,MB)

$\cup$ (mA,mB)

Finally, after selecting an assigning procedure (say the min-max one) the value $MF_k(p)$ can be calculated by aggregating all the values $m_i(p)$ for $i = 1.....r$.

Usually there are several fuzzy pattern classes $F_1...F_s$ and the problem could be to assign a given object to a definite class. When the membership values $M_{Fi}(p)$ are available, p can be assigned to the class F_k such that

$$MF_k(p) = max_j\ M_{Fj}(p),\quad j = 1....s,$$

otherwise a new pattern class F_{s+1} may be created for p.

Hypothetical Example

Consider the situation in which an investigator obtains some fuzzy information about the suspect from the descriptions provided by few 'eye' witnesses. In such a hypothetical situation the fuzzy terms could be analyzed following the technique as mentioned above. For instance, suppose the witnesses mentioned that the offender was *tall*, with *brown* colour hair, wearing *dirty* clothes and was a *young* person. As indicated, these are fuzzy terms that mean different characteristics to different witnesses. To determine the overlapping range of these characteristics, the investigator could hold an in depth examination of their perceptions to fix a range within which they could be describing these characteristics.

Consider the fuzzy characteristic *tallness*, it is fuzzy because for one witness 166 cms. and above is the height that makes a person tall. For witness 2, only a height of 172 cms. and above is tall while for the third a person is tall if he /she is over 170 cms. How about 168 cms. or 166 cms.? Is this height 'tall' for witness 1? A detailed examination of this witness' perception may suggest that for him/her, any person of height 165 cms. or below is definitely not tall (membership value is 0) while 166-167 is tall perhaps with 0.15 membership value. It is possibly 0.7 for 169-170 and 1 for over 173 cms. Thus for each witness, there is a minimum range of height of membership value <0.1 and a maximum range of value >0.9 for describing this fuzzy characteristics of tallness. As suggested above, the police investigator could obtain this information and possible ranges with membership values by a detailed examination of perceptions of each of the witnesses. This may be done by displaying a measuring scale and letting the witness point out the range over which he/she considers someone as 'tall'.

Such membership values could then be obtained for the other characteristics too by developing a suitable scale of references. Thus, shades of brown on a scale of ten could be shown to the witnesses to determine the minimum and maximum placement of membership values for the fuzzy description of 'brownness' of hair. Thus, for witness 1 the brownness may begin with the shade marked 4 with membership value of 0.1 and may end with value 0.9 for the shade marked 8 on this scale. Continuing further, for each witness a range of shades could similarly be determined for what they perceive and describe as brown. Finally, each of the fuzzy characteristics that the witnesses provided about the suspected offender could thus be reduced to a range of numbers on a suitable scale. The hypothetical information, in terms of minimum and maximum values of a 'young' suspect being 'tall', with 'brown' hair, wearing 'dirty' clothes obtained from four witnesses is suggested in table 6.1 below.:

TABLE 6.1

	Fuzzy Offender Characteristics			
	Tall	***Brown***	***Dirty***	***Young***
		Hair	Clothes	
measuring units	cms	scale 1-10	scale 1-12	years
Witness I	167-172	6-8	7-9	22-28

Witness II	166-170	7-8	7-9	20-24
Witness III	169-173	6-9	8-10	21-25
Witness IV	168-171	7-9	8-9	20-27

Here, the given values are the minimum and maximum values provided by the subjective judgment of each of the witnesses. Using the min-max operators, the descriptions from the three witnesses of the likely suspect may then be summarized as shown in table 6.2:

TABLE 6.2

Summary of Witness Statements

	Tall	*Brown*	*Dirty*	*Young*
		Hair	Clothes	
measuring units	cms	scale 1-10	scale 1-10	years
Min range	166-69	6-7	7-8	20-22
Max range	170-73	8-9	9-10	24-28

The suspect is then likely to have the following features: an average height of 169.5 cms, brown hair shade of 7.5 on a uniform scale, dirtiness of the clothes being 8.5 on some other scale and age around 23.5 years. Here, the average of the min-max values have been taken though other combinations, like min-min and max-max could also be experimented. The investigator could determine this by judging how well this information matches with other evidence available to him/her.

Summary

To sum up, the above technique suggests the following procedure:

1. Determine all the variables (features) which relate a crime type to the suspected offender/s. For example, their physical characteristics, socio-economic background, crime type, modus-operandi used, time/place preferred, present activity, friends or associates etc. This kind of information is usually maintained by all police departments for property offences. Indian police, for instance, maintains a register called Crime Directory Part II which contains the above mentioned details about the offenders suspected, arrested or convicted for crimes of dacoities, burglaries, house thefts, theft from vehicles etc.

2. Develop a set of prototypes (profiles) of likely suspects based upon variables determined above. This may be done by first clustering all suspects into different groups based upon their past activities and involvement in different crimes. For example, all offenders associated with the crime of burglary during night time in a particular area of city

may be grouped together. They may further be classified on the basis of descriptions or scores on the above selected variables, like economic condition, preference for stolen goods and so on. Finally, a profile of prototype for each suspect falling in this sub-classification could be developed based upon the available information. Some variable may have a definite value, like date of birth, mole on cheek, present address and for others a range of min-max values could be considered in these prototypes. Thus, Hari Singh, previous suspect in burglary may have this possible profile: Height- 168 cms.; age- 22 years, 4 months; colour of hair- 6-8 *black* on some scale of 10; operates *near* mall road area- 2-3 blocks around mall road; keeps *few* associates- 1-2 friends; etc.

3. For any new crime, collect information about the offence, modus operandi and suspected offenders. Some of this information may be definite, physical in nature while the other fuzzy depending upon the statements given by the witnesses.

4. There is no problem in handling the definite or clear evidence about the suspect. The fuzzy descriptors could then be manipulated by assigning membership values to their features and aggregating their values using some operating scheme taking in account their grades of memberships.

5. Determine the prototypes to which these aggregated values belong and choose that prototype whose maximum value is close to this aggregated value.

6. If no prototype can be assigned, create another and add to the set of original ones.

Implications:

Fuzzy logic can provide a powerful method for applications in the criminal justice fields. Since a large category of data such as citizen responses, attitudes, opinions and even official data involving hundreds of variables is generally fuzzy in nature, the possibilities for the utilization of this form of mathematics is extensive. The following suggests a few such cases:

The nature of evidence accepted in the court for final determination of guilt or innocence is as fuzzy in character as one collected by the police investigating agencies. The characteristics of physical and oral evidence is generally described in terms that involve shades of meaning and interpretations, one so skillfully maneuvered by the legal professionals. Furthermore, legal terminology usually gets embroiled in differences that are based more on historical, jurisdictional and societal norms rather than on language. An act reprehensible to the established 'morality' of the society (Shourie 1980), is the kind of statement that confronts most legal practitioners and in which there are multiple layers of understanding involved. Such fuzziness or the shades of meanings that are introduced during testimonies or cross examination by the defense lawyers could create difficulties for the prosecution to successfully prove 'beyond any reasonable doubt' the guilt of offenders charged by the police.

A possible field of application is that of comparative studies in law. It is generally acknowledged that international comparative legal studies are difficult since the meaning of offences differ considerably (Kuner 1991; Booysen 1993; Peletz 1993; Brugger 1994; Yang 1994). For instance, 'Law' in Chinese language may mean 'fa: a set of rules' or 'shizhaifa: a living law'. Similarly, 'legality' could mean 'fazhi: rule of the law or rule by law' in translation. It is interesting to note that Chinese scholars define another kind of legality, 'socialist legality' a fuzzy concept in itself!

Legal terms like 'good faith' of section 52 Indian Penal Code (IPC) or 'lurking' house trespass of section 443 of IPC (Government Of India 1966), 'goondaism (Government Of India 1975), 'hooliganism' (liu-mang: in Chinese law) have different shades of meanings even within these respective countries. Further, legal terminology that is commonly used in almost all the written codes, like 'human rights', 'official responsibilities', 'social morality', 'duties of the citizen', 'due process', 'fundamental rights', 'autonomy', 'reasonable person', and 'due diligence' that are commonly used but mean differently to different people. These are even more fuzzy in nature and could admit a large number of different interpretations (Tamanaha 1989).

The use of fuzzy logic technique in determining the grade of meanings of such legal terms is therefore likely to narrow down and pin-point the different range of interpretations. This obviously calls for a new form of research work but the possibility is immense and exciting.

Similarly, as indicated earlier (chapter II-III), fuzzy logic techniques are likely to be useful for qualitative analysts too. The qualitative researchers collect data through various techniques that attempt to interpret the subjectivity of some phenomenon. They always face the problem of matching their records with one another and even with their own subsequent research work. In fact validity of their technique is generally considered doubtful due to the differences that arise from the nature of their data recording procedures (Maxfield and Babbie 1995). These problems are said to arise when they attempt to give meaning to their recorded data for the terminology is left open to interpretation.

Similarly, in data collection through observational method that involves more than one observer, it is always problematic to reconcile the records of all the researchers since there are bound to be individual differences in the significance of the observed events. The same action may be interpreted differently- a possibility that the practitioners acknowledge openly and which in fact is stated to be the reason of preference for this method. It here that fuzzy logic could assist by quantifying their differences and thus reducing the range of possible interpretations. Since fuzzy logic can deal with such shades of meanings, it is reasonable to expect that it could begin to reconcile these individual differences. Ironically, fuzzy logic based mathematics could turn out to be bridge that is crossed by both the qualitative and quantitative practitioners!

Fuzzy logic techniques can also be useful to the police managers for not only building offender profiles but also for analyzing other kinds of data that is non-dicotonomous and fuzzy in nature. Thus, for example, fuzzy logic could be useful in weighing the contribution made by an officer for promotional purposes since some of it may be 'good' and some 'weak', concepts that are clearly fuzzy in nature. Similarly, the hot spots analysis involves imprecise boundaries in which the area under consideration may vary upon the meaning of the term 'high' rates of crime. By extending the notion of fuzzy boundaries, it is possible to determine the seriousness of the actual threat in these small areas that may be useful to the officers in man-power deployments. A regionalization procedure that involves such fuzzy boundaries will be introduced in the next chapter.

Clearly, fuzzy logic can provide a vast range and varieties of applications in the criminal justice fields since most of the data is fuzzy in nature. Undoubtedly, there are limitations to the fuzzy logic based techniques since this kind of mathematics has a formal structure that depends upon the interpretation given by the mathematician and the user to the fuzzy words. There are several constraints to the capability of reducing words or nuances to a numerical measure. Above all, a strong mathematical technique that can handle imprecise and fuzzy data is undoubtedly going to strengthen the analytical capabilities of the social researchers.

-----x-----

CHAPTER VII

HOT SPOTS AND BURNING TIMES

A TOPOLOGICAL ANALYSIS OF CRIME SPACE

Brantingham and Brantingham (1993a) have introduced the concept of Nodes, Edges and Templates in their exposition of Pattern theory. They have suggested that the 'Environmental Backcloth' creates neighborhood edges, general movements and awareness patterns which gets focused on certain 'activity nodes' and the 'travel paths' between and to these nodes. These nodes and edges partition areas into low or high criminal activities. Further, the awareness of these areas and boundaries assists in the development of crime 'templates' by the motivated offenders who can thus identify 'suitable targets'. The model thus proposes several levels of analysis to explain criminal behaviors: activity nodes and the travel paths, regional edges and the crime templates developed by the offenders. We will propose some mathematical techniques to identify and study these levels.

Topological Properties

We will begin by exploring the use of Point-Set Topology which we believe provides better tools of analysis and can trigger new ideas and understandings of criminal behavior.

Topology is qualitative mathematics (Mansfield 1963: 1), one without numbers. It is concerned with the intrinsic qualitative properties of spatial configuration that are independent of size, location or shape. Thus, for example, a rubber band even after stretching or bending retains its property of a close circuit which is an intrinsic property of the rubber band.

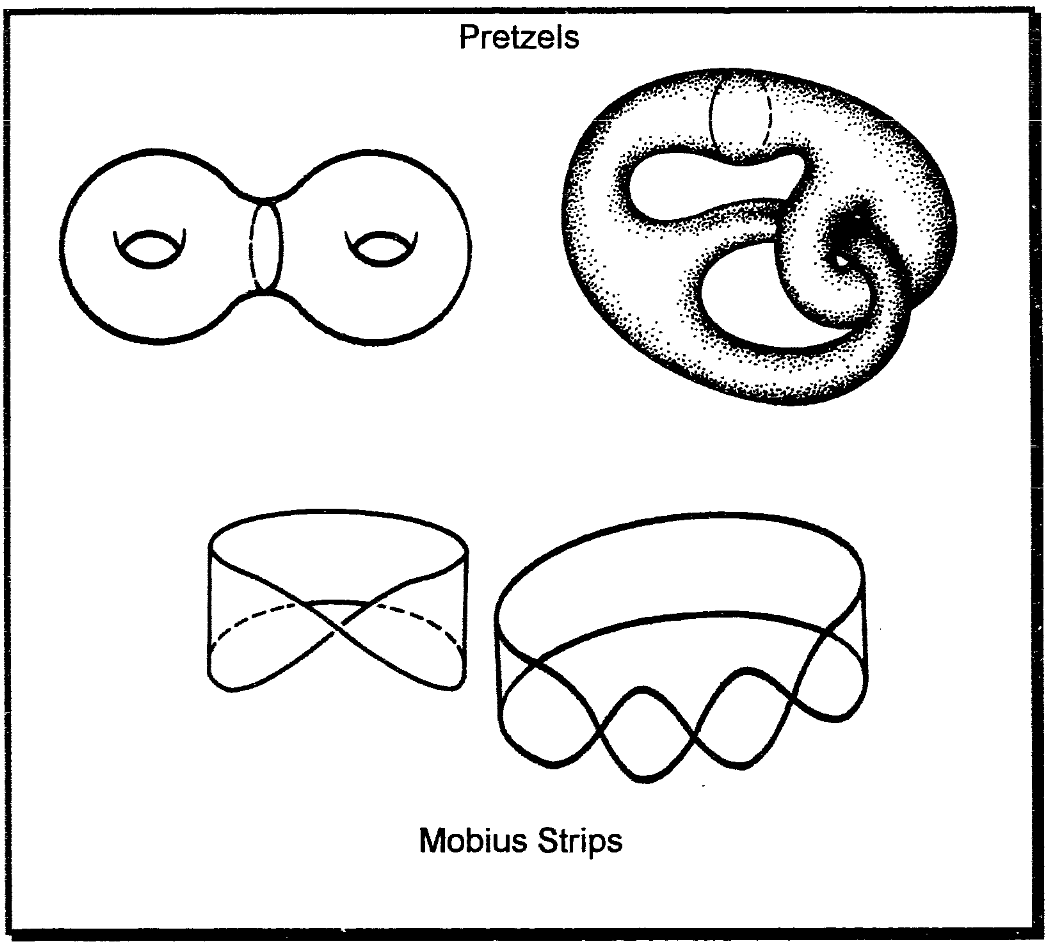


Figure 7.1

In figure 7.1 above a double pretzel on the upper left is topologically homeomorphic to the linked arm pretzel on the upper right. The next two figures display a broad rubber band that can be converted into a single and multiple mobius strips, all being similar topologically. Indeed, a topologist has been described as one who does not know the difference between a doughnut and a coffee cup since both these objects have the same topological property! The objects whose intrinsic properties can be studied by topology can be virtually anything: a geometric figure, the physical surface of some landscape, a collection of functions or processes and even some 'abstract space'.

These areas of mathematics can also focus on the spatial relations where the concept of 'space' may be modified according to the need. The definition need not be limited to geographical space but could be extended to social relations, conceptual interactions and temporal connections. There is no restriction in extending the technique to concepts being looked into by the researcher for the property common to all objects of topological study is that they are sets. The elements of the set may be anything, a crime site, a criminal event, a police function, a time period or group of police officers.

The definitions of composing sets can thus be extended to criminal events, locations, modus operandi, gang members, police operations, criminal justice policies and naturally targets of offenders. The rules for union and intersection of these sets could be adopted to suit the convenience and then topological techniques could be applied to construct models of continuity, interior or exterior regions, neighborhoods to look for intrinsic qualitative properties that remain invariant for the comparison of different sets.

A literature review reveals that although Lewin (1936) pointed towards the applicability of topological spaces in Psychology, the only application in criminology so far has been in the classical paper by Brantingham and Brantingham (1975) where the concept was used to construct connected spaces amongst residential blocks. The topological spaces so generated clearly revealed the 'edge effect' between block neighborhood boundaries; crime was significantly greater near boundary areas than in interior regions. This paper suggested a process of 'Regionalization' using topological techniques. We will outline this technique based on Point Set Topology and apply it in a preliminary manner to show its applicability for the Pattern theory of crime.

Basic Elements of Topology

The set is used in mathematics to denote a collection of objects and we will use the term 'point' to denote an element or member belonging to the set. If A is a set and p is a point of A we write $p \in A$. If p is not a point then we write $p \notin A$. Two sets A and B are said to be equal if for all $p \in A$ implies $p \in B$ and vice versa. B is subset of A means that every p $\in$ B also $\in$ A. From elementary set theory we learn that for these sets the operation of union, intersection can be defined and that these operations have the properties of being commutative, associative, idempotative and distributive. Further, index sets can be used that helps in proving the theorems of De Morgan:

Let $\{ A_\alpha : \alpha \in \lambda \}$ be an indexed collection of subsets of a set X where λ is any set.

Then

a) $X \sim \cup \{ A_\alpha : \alpha \in \lambda \} = \cap \{ X \sim A_\alpha : \alpha \in \lambda \}$ and

b) $X \sim \cap \{ A_\alpha : \alpha \in \lambda \} = \cup \{ X \sim A_\alpha : \alpha \in \lambda \}$

We will also be using the following definitions:

i) An open interval is any set of the form $\{ p \in R: a< p <b\}$ where R is the set of all real numbers and a, b are real numbers such that $a < b$.

ii) A set $\Omega \subset R$ is said to be open if (a) $\Omega = \emptyset$ or (b) $\Omega \neq \emptyset$ and for each $p \in \Omega$ there is an open interval Ψ such that $p \in \Psi$ and $\Psi \subset \Omega$.

iii) Let f be a function whose domain and range are subsets of R, and let Ω be a subset of R. The inverse image under f of Ω denoted by $f^{-1}[\Omega]$ is the set $\{ p \in R | f(p) \in \Omega\}$.

iv) Let f a be a function whose domain is all of R. The function f is defined to be continuous if the inverse image under f of every ω-open set is a ω-open set.

v) Let X be a non-empty set and Γ be a collection of subsets of X. The collection Γ is said to be a topology for X if Γ satisfies each of the following three conditions:

a) $X \in \Gamma$ and $\varnothing \in \Gamma$.

b) If $A_\alpha \in \Gamma$ for all $\alpha \in \lambda$, then

$$[\cup \{ A_\alpha \mid \alpha \in \lambda \}] \in \Gamma.$$

c) If A_α where $\alpha = 1, 2, 3, 4, \ldots n$ are members of Γ then

$$[\cap \{ A_\alpha \mid \alpha = 1, 2, 3, 4, \ldots n\}] \in \Gamma.$$

If Γ is a topology for the set X, the members of Γ are called Γ-open sets of the topology, and the pair (X, Γ) is called a topological space.

vi) Let X be a set and let Γ and Π be two topologies for X. If $\Pi \subset \Gamma$, that is if every Π-open set is Γ-open set, then we say that Π is coarser than Γ or that Γ is finer than Π. If $\Pi \not\subset \Gamma$ and $\Gamma \not\subset \Pi$, then Π and Γ are not comparable.

vii) Let (X, Γ) be a topological space. A subset F of X is said to be Γ-closed if $(X\sim F) \in \Gamma$. That is F is Γ-closed if and only if $X\sim F$ is Γ-open.

viii) Let (X, Γ) be a topological space and $p \in X$. A subset N of X is called a Γ-neighbourhood of p if and only if there is a Γ-open set G such that $p \in G \subset N$.

ix) Let Φ be a family of subsets of a set X. Then the family of all sets, each of which is the union of a subfamily of Φ, is called the family generated by Φ and is denoted by Φ^*. We also say that Φ generates Φ^*. Then, for a topological space (X, Γ) Φ is called a base for the topology Γ iff $\Phi^* = \Gamma$.

x) Two subsets A and B of a space X are said to be separated iff $A \neq \varnothing$, $B \neq \varnothing$, and $A \cap B^- = A^- \cap B$, where A^- and B^- are the complements of A and B respectively.

xi) A subset ϑ of a topological space (X, Γ) is said to be connected iff ϑ is not the union of two separated sets.

xii) Let (X, Γ) be a topological space and let ϑ be a subset of X. The point $p \in X$ is said to be a cluster point of ϑ if every Γ-neighbourhood of p contains at least one point of ϑ other than p. That is, p is a cluster point of ϑ iff N, a Γ-neighbourhood of p implies that

$$\{ N \sim (p) \} \cap \vartheta \neq \varnothing.$$

xiii) Let (X, Γ) be a topological space and let ϑ be a subset of X. A point p is a Γ-interior point of ϑ if ϑ is a Γ-neighbourhood of p.

xiv) All points belonging to the complement of ϑ are said to be exterior points.

xv) Let A and B be two non empty sets. The Cartesian product of A and B, denoted as A x B is the set of all ordered pairs (a,b) such that $a \in A$ and $b \in B$. That is $A \times B = \{(a,b) \mid a \in A, \text{ and } b \in B\}$.

xvi) Let A and B be two non empty sets. A function f from A to B is any non empty subset of A x B with the property that no two distinct members of f have the same first coordinate. Thus $(a,b) \in f$ and $(a,c) \in f$ implies $b = c$. The function f is said to be a mapping of A into B if the domain of f is A and the range of f is some subset of B. This is described as f: A-->B. The function f is said to be a mapping of A onto B if the domain of f is A and the range is B.
This may be described as $f: A \xrightarrow{onto} B$.

xvii) The function f is said to be 1-1 (one to one) if distinct points of A have distinct images under f in B. That is, f is 1-1 iff (a_1, b) f and (a_2, b) f implies $a_1 = a_2$.

xviii) Let (A, Γ) and (B, Π) be two topological spaces and let f be a mapping from (A, Γ) into (B, Π). The mapping f is said to be continuous (or more precisely Γ-Π continuous) if $f^{-1}(G)$ is Γ-open whenever G is Π-open. That is, the mapping is continuous iff the inverse image under f of every Π-open set is a Γ-open set. If f(H) is Π-open set whenever H is a Γ-open set, then f is called bicontinuous.

Finally, the function f is called a Γ-Π homeomorphism of A onto B if f is 1-1 and bicontinuous mapping of A onto B. The spaces (A, Γ) and (B, Π) are said to be homeomorphic.

Two topological spaces are said to be topologically equivalent iff they are homeomorphic. A property when possessed by a topological space is also possessed by every space homeomorphic to the given space and this is called a topological invariant or an intrinsic qualitative property of the space.

Application of the Technique

We will show how the above mentioned mathematical concepts can be adopted to construct Topological spaces of sets of variables representing different characteristics of the urban milieu by using the concept of Basis. These variables could be Social Housing (H); Young males (M); Unemployment levels (E); Single parent Family (F); Housing classifications (C); Types of tenure (T) Social economic status (SE) Family size (Z) and so on. Depending upon the availability of data, other such variables can also be added- like rates of Alcohol consumption, school drop out, numbers of shops/ malls/ offices/ restaurants, the flow pattern of commuters etc. The criterion is the particular *theoretical* model one is using for causal explanation. Thus U, a set of urban areas can be identified as the set of vectors consisting of factors (H,M,E,F,C,T,SE,Z...). For instance, an enumeration area[1] (Ea_i) $\in$ U may be characterized by h_i- percentage of social housing in the area; m_i- percentage of young males in the population; e_i- percentage unemployed; and so on. Thus $Ea_i = \{h_i, m_i, e_i ......\}$.

These factors may exist at different spatial or temporal levels like census tracts, enumeration areas, police beats etc. but any level can be broken down into the basic, smaller units which forms their building blocks and then combined into a higher level of regionalization. Brantingham and Brantingham (1975) have shown how these building blocks can be conceived as open sets of a basis that can then be used to construct a topological space.

[1] **Enumeration area is the smallest geographical unit in Canada census for population enumeration purposes.**

According to their proposition, each variable of interest may be used to create a separate topology and in each such space, the basis could be constructed by clustering the smallest unit of analysis- blocks, police beats, enumeration areas or census tracts. Naturally, smaller the unit, the more sharper will be the topological structure, but constraints of data availability may inhibit such analysis. The technique then suggests to cluster these units by maintaining internal unit to unit similarity or what is defined as their homogeneity. For example, all units having population densities within an acceptable range will be combined to form larger regions.

Thus, the basis set is the set of all contiguous units such that inter unit variation of the variable under scrutiny is less than some predetermined percentage. By changing the percentage, the inter unit variation is changed and new basis sets are constructed, which provides a large number of varieties of sets. These building sets can thus be used to partition the urban space into homogeneous and non-homogeneous regions with respect to that characteristic. For instance, by considering the percentage to be 20% which will imply that two adjacent units have population density within 20% difference of each other, all such contiguous units will be clustered into a larger 'homogeneous' region. Based on these concepts Brantingham and Brantingham (1978) suggested the following mathematical technique to construct the basis sets:

Let B_i be a basis set and e_j be a unit (perhaps a block, enumeration area or the census tract) Let $f(b_j)$ be a functional value associated with the unit, say unemployment rate, percent non-English speaking families, proportion of young males, etc. Then a basis set is

$$B_i = \{ b_i \mid f(b_i) - f(b_h) \mid \leq \max \{ af(b_j), af(b_h) \} \}$$

where $b_i \cap b_h \neq 0$ and $b_j \quad B_i$.

(The units have a street of vacant lot in common)

$0 < a < 1 \quad b_i \neq b_h$ and $I = 1, 2, 3 \ldots n; h = 1, 2 \ldots\ldots m$

For example, if the mean proportion of young males in a household is being considered, then $f(b_i)$ is the mean proportion of young males for the unit area. If the variation from unit to unit is fixed at say 5% then a = 0.05 and the basis sets are all contiguous units where the inter unit variation is less than 5%. Each group of units which cluster together for a fixed inter unit variation form a set and the family of sets which are generated as variation ranges from zero to sufficiently large N, forms the basis of the urban area. As the inter unit variation is changed, new basis sets are constructed and the boundaries of the contiguous regions change accordingly.

Moreover, for $a_{i-1} < a_i < a_{i+1}$, all real and less than 1 there will exist the relation:

$$\ldots B_j(a_{i-1}) \subseteq B_j(a_i) \subseteq B_j(a_{i+1}) \ldots$$

As seen above, many chains and nests of basis sets and boundary regions are created as the inter unit variation is increased or decreased.

Based upon this fascinating technique, Brantingham and Brantingham (1975) could demonstrate the importance of topological boundaries, showing that these so called edges partition regions into 'natural' or commonly understood neighbourhoods. From these topological partitions they could deduce that the burglary rates for the boundary blocks are higher than the corresponding rates for the interior blocks.

We will extend this concept by introducing the notion of fuzzy edges and permeability of borders. Once the above technique has been used to construct contours of homogeneous and heterogeneous regions for each variable of interest, we can then look for the regions which are heterogeneous for most of the variables. These will be the ones whose boundaries *change* with different characteristics. Here we are making the similar assumptions as made by Brantingham and Brantingham (1975) that a homogeneous region is one where concept of 'my' area or 'my' neighborhood, commonality and similarity exist on grounds that people with similar socio-economic, social values and cultural background would be living together. Therefore, an outsider would stand exposed as a stranger, thus minimizing the possibility of crimes by outsiders.

On the other hand, heterogeneous region will have no common characteristic and thus likely to be the play field of persons from other regions. By identifying the composing blocks (smallest units) of these regions, we can then use Venn diagram method to identify those regions which are most heterogeneous. Such regions are likely to have high activity nodes as proposed by Pattern theory because these are the regions where strangers are unlikely to be detected and thus it will be a place for greater criminal opportunities.

The urban area set U will thus be partitioned into several regions, with high level of homogeneity in one part and heterogeneity in another. If we stipulate that interunit variation may be graded, that is the value of 'a' is an interval rather than discrete, or that 'a' values change at small intervals then one may consider some units to be slowly blending into another. We will describe regions or such units as being fuzzy homogeneous if their borders 'slowly' blend into neighboring units and others as being strongly homogeneous with sharp borders.

Next, we will consider another characteristics, say unemployment rate (u) and construct a new topology for U in a similar manner. This will partition U again in homogeneous (same unemployment rate) and fuzzy homogeneous (varying unemployment rate) contours. This partitioning may put units in different contiguous relations than the earlier partitioning. Therefore, examining the units which remain homogeneous or fuzzy homogeneous in both the cases, will give us overlapping contours over two characteristics.

Thus, suppose units B_n, B_o, B_p are homogeneous for the variable young males and B_n, B_r, B_p are homogeneous for the variable unemployment, then clearly units B_n and B_p are homogeneous over both. On the other hand, B_o and B_r change their boundaries over these characteristics and will thus be considered to have fuzzy boundaries. Even for the same characteristic if boundaries of some units are changed with a 'small' modification in the value of 'a', we will still call these units as being fuzzy homogeneous. {'Small' will naturally be dependent upon our own definition}.

This exercise will be carried for all the other variables under consideration and for some values of 'a'. We will then identify the regions which remain homogeneous or fuzzy homogeneous over *all* the variables. Clearly, these areas have very distinct characteristics. Homogeneous areas are those which have 'impermeable' boundaries, where all members are more or less the same and therefore likely to have very similar behavior patterns. 'Fuzzy' homogeneous regions will have permeable boundaries with gradations of pcrousity and will show mixed characteristics. Their members behaviors will also be varied and these areas will likely be having the high activity crime nodes.

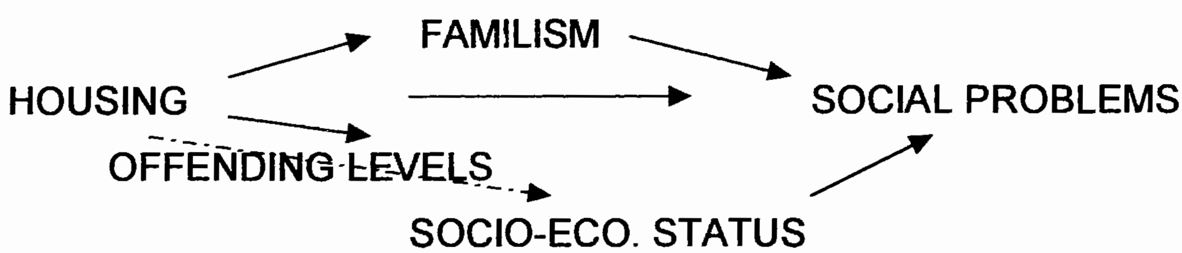
As Brantingham and Brantingham (1975) have further suggested, the process may be simplified if all these topologies are considered simultaneously, as a product topology over U. Thus $\bigcap_{i \in I} X_i$ may be defined as the product space formed by the Cartesian product of all single topological spaces. The basis for this product space is the collection of all sets of the form $\bigcap_{i \in I} B_i$, where B_i is open in X_i and I is the finite index set. Obviously, an area which has the same basis set for all the composing topologies and even for different variations will be distinct and with sharp boundaries. On the other hand, complex patterned nests and chains of fuzzy borders are created if the bordering units are different for composing variables in their topologies. Our interest lies in those units which remain distinct, that is these are the ones which are strongly homogeneous or constantly fuzzy homogeneous and are thus going to have low or high activity nodes respectively. The nodes are likely to be the 'hot' spots of crime if the units are fuzzy homogeneous or will be low crime neighborhoods if the units are strongly homogeneous.

Application 1: Topological Connectivity

We will now outline an application of topology in identifying concentrations of offender activities in an urban area. In particular, we will consider a theoretical model similar to one proposed by Wikstrom (1991) in which units of Stockholm were categorized into varying degrees of criminal activities by using factorial ecological techniques for certain census variables. We will suggest a fuzzy topological technique with the added notion of 'fuzzy' edges determining the 'porosity' of borders for such a model of urban space.

Wikstrom argued that the for any city, its population size, density, heterogeneity, social background are all important in determining the characteristics of the inhabitants and that social control will be weaker in large urban centers. In particular, the regional differences in types of housing like single dwelling or multi-storeyed, rented or owned types generally influences the composition of the population. This is usually true since preference for houses depends upon family strength and economic capabilities. This further implies that more crime prone social groups, those which are economically and socially weak, are segregated to certain regions and this in turn influences the social control over the younger people. Thus, the area variations in type of housing strongly influence population composition which in turn influences the area offender rate (1991: 178-180).

By looking into the distribution of variables constructed from housing, (tenure, residence type etc.) familism (composition of population, family size, dependents etc.) and social-economic status (family income, type of job), the distribution of 'social problems areas' (identified by offender residences), of Stockholm could be explained. Wikstrom (1991: 182) used the following relationship for explanation:



We will analyze a similar theoretical model using fuzzy topology (Zadeh et al 1975). Instead of constructing artificial variables like housing, familism used in the statistical technique, we will construct topological spaces, formed by the concept of basis sets from different variables and look for their intersecting regions. The different levels of intersections may be construed as the 'loadings' on constituent variables, though naturally the attempt is not to explain their variance. Thus, the housing space can be built by considering the basis sets formed by the variables like proportion of residents in 'detached houses', in 'social housing projects', in 'privately rented flats' in 'multi storied buildings' and in 'multi family units' etc.. Units with mean proportion of houses having similar characteristics as these could be joined in different combinations to form the basis set where the combinations will vary as the value of 'a' is increased from 0 to infinity.

Moreover, by analyzing the level of contiguity (the value of 'a' as above), we can identify the units or their composite contours as being strong or fuzzy homogeneous. That is if for large 'a' the units remain distinct then these are to be called strongly homogeneous, if these could be combined for smaller values of 'a' then we will call them fuzzy homogeneous and heterogeneous for very small value of 'a'. Thus, the basis sets of this topology will partition the urban area into contours of homogeneous and fuzzy homogeneous units that may consist of enumeration or census areas (or wards as used by Wikstrom 1991).

In a similar fashion, other explanatory factors like familism and socio-economic status could also be considered by building their own topological spaces. The basis sets for these could be the average size of household, proportions of family income, ethnicity, educational levels of parents, nature of employment, recipients of public assistance, and such variables as also used by Wikstrom (1991).

By 'superimposing' the partitions of the urban space, through different variables, on one another, we can then check their combined state of homogeneity. Thus, it may be possible that some regions show strong homogeneity for most of the variables while others may change their status. In our topological notation, the former is an area having the same basis sets for all the component topologies and for many levels of variation. If the model looks for the congregation of the social problems in terms of say low rent housing, family composition through single or working parent families, and social status in terms of family income, nature of occupation and ethnicity, (as tested by Wikstrom 1991) then the above procedure will identify these areas as being composed of regions or units intersecting on all the variables.

Once the urban area has been partitioned into different contours of homogeneity, we can then use Venn diagram method to identify the regions which intersect for most of the above variables. The result will be the identification of those enumeration areas, census tracts or basic units which have a higher proportion of social problems as defined by the composing variables. We may not expect similar identification as obtained by Wikstrom since the objective is not to explain variance but to present the combination of factors in a more visible manner. The overlapping contours in the Venn diagram would show the process being followed and the graphical representation will be more meaningful than the 'cold' numbers of the Gini index and Factorial values of Wikstrom's method.

This model was tested on the census tracts of Vancouver in the following fashion: At first, the census tracts of Vancouver were examined to determine which ones are geographically adjacent to each other. Figure I gives the census boundaries of Vancouver city and the tract numbers from which adjoining tracts were observed. From the above map a matrix of census tracts connected physically was first constructed. The matrix of this connectivity is shown on appendix 2.

As the next step, a theoretical model which suggests concentration of criminal behavior in regions where ethnicity, single parent families, low income housing and population density are in greater proportion than neighbouring regions was considered. These variable elsewhere have been shown to correlate highly with crime variables (Brantingham and Brantingham 1978; 1984 and Wikstrom 1991). It was hypothesized that places where most of the topological spaces formed from these variables would intersect will show higher rates of burglary than places where the intersection level is smaller. The argument here is the same as presented by Brantingham and Brantingham

(1975) where they had hypothesized strangers committing such crimes around the neighbourhood edges. The literature supporting this kind of hypothesis is extensive in criminological studies (Aitken and Prosser 1990; Baldwin and Bottoms 1976; Bennett 1989; Brantingham and Brantingham 1984; Brower, Dockett and Taylor 1983; Brown and Altman 1991; Butcher 1991; Cromwell, Olson and Avary 1991).

To develop a test for such a hypothesis, the values of census variables of population density, ethnicity, rented housing and single family were obtained from Statistics Canada (1992). Based upon the technique described above, for each of these variables, the connectivity of geographically adjoining tracts was estimated at the 'a' level cuts of 10, 25 and 40 percent. The three values of a were chosen with the expectation that the absolute differences between the various census tracts will stand out and show clear distinction between the homogeneous and heterogeneous regions.

The procedure was as follows: first for each of the census tracts, the percentages of the four variables mentioned above was determined from the census. These values were then compared for each of the census tracts with the values of the tracts that were contiguous to it (from appendix ii) and if the absolute difference was less than the corresponding 'a' than the two tracts were declared connected. Such comparisons were made for all the census tracts, for all the four variables and for the three values of the 'a' cuts. The matrices of connectivity for each of these variables was thereafter constructed for each of the three 'a' cuts. These can be seen on appendix 3-14.

The figure II for example gives the connectivity of census tracts at 25% 'a' cut by ethnic population, calculated on the basis of mother tongue. The matrix upon which the above picture was constructed is given on appendix 8.

The connectivity of each census tract was examined for the selected four census variables. This involved four possibilities: two contiguous tracts, were connected for one census variable, or two or three or for all the four variables. Further, for each variable, the level of connectivity could also vary for the three values of 'a' giving in total 12 levels of connectivity and 3 levels of complete non-connectivity.

According to our criteria we would expect differences in the permeability of census edges based upon the level of connectivity. We would say that 12 level connectivity indicates a complete porous edge while smaller levels indicate fuzzy permeability. Thus, '0' level would indicate a strong or an impermeable edge.

Finally, all connected census tracts were classified into topologically similar or homogeneous regions at the level of twelve, eleven, ten and smaller levels of connectivity, for all the variables and at the three different percentage levels. For instance, 10 level would mean the tracts are connected for all the four variables but for 'a' cut of only 40% for one of the variables.

From this larger set two subsets were selected. The first set of tracts was the one whose edges had connectivity at 12 level, that is: these were the basis sets for which the 'a' cut was 10% and the connectivity criteria held for *all* the four census variables. The second set consisted of all those tracts whose edges remained disconnected even when the 'a' cut was 40% for all the four variables.

Results

The following results were obtained:

There were a total of nine edges that were 'impermeable' even at 40% cuts for all the four variables. In contrast, there were eleven edges that were 'porous' for all the four variables at the smallest 10% level cut. These edges are shown in figure III.

According to our criteria the latter set would be expected to be troubled by outsiders while there appears smaller possibility of strangers victimizing around the former set of edges. The burglary offences around these two sets of edges for the year 1993 were estimated two blocks along both sides of these boundaries. The rates of crimes were estimated by using the *length* of the corresponding edges as the denominator since the permeability was considered dependent upon the tract length that provided the corridor of movement. These crime totals, length of edges and the calculated rates are shown in table 7.1 below:

Table 7.1

BNEs along Topologically Connected Census Tracts

40%CONNECTIVITY			10%CONNECTIVITY		
BNETOT	EDGE-LENGTH	BNERATE	BNETOT	EDGE-LENGTH	BNERATE
24	1.78	13.48315	23	1.18	19.49153
1	0.97	1.030928	7	0.6	11.66667
3	1.04	2.884615	9	0.84	10.71429
3	0.92	3.26087	2	0.9	2.222222
1	0.93	1.075269	28	1.17	23.93162
3	0.87	3.448276	11	1.24	8.870968
3	0.98	3.061224	13	1.32	9.848485
5	0.95	5.263158	37	0.94	39.3617
28	0.92	30.43478	24	1.73	13.87283
			15	0.94	15.95745
			39	0.76	51.31579

Here, the BNETOT refers to the total incidents of burglary that were located around that edge, while BNERATE was obtained by considering the edge length as the denominator without any standardization. For the two rates that were obtained, a T-Test was done to determine if there were any significant differences between them.

The t-statistics had a value of -2.17093126 while the $P(T \leq t)$ one tail was found to be 0.02219313. The T test result shows that crime rate was significantly lower for the set that had 0 level of connectivity when compared to the set that had 12 level of topological connectivity.

Although, this study is still in a preliminary stage and makes assumptions about criminal behaviours that may be unwarranted, the topological regionalization technique does appear to assist in identifying between regions of high and low crime rates. To strengthen the fuzzy demarcation of these edges we need to employ more variables and 'a' cuts of smaller differences. Naturally, the technique of combining tracts into larger regions through Venn diagram method becomes complicated as the variables and 'a' values are increased.

Although, the above mentioned procedure has limitations but clearly, it does demonstrate that the areal distribution of crime may be analyzed using such an alternate technique. The advantage of this simple technique is that it looks at regions connected topologically, to the way in which cognition of a place might take place; a task that appears difficult through statistical techniques.

Application 2: Burning Times

The concept of nodes and edges have been developed from the research done on the criminality of place. It has been argued for example that criminal behavior is facilitated by certain opportunities seen in a particular place by the motivated offender. A strong component of this argument is the theory of routine activities that points to the coming together of the offender and the victim at a place in the absence of the guardian (see Cohen and Felson 1979 for the original work).

However, in this situation it is not only the layout of the place that is crucial but also the *time period.* The coming together of the offender and the victim is determined not only by the location but equally by the timing of their movement. The day or evening period they may go to work or for recreation is significant in determining when the criminal event can take place at the location of their interaction. Obviously, the criminality of some place is not in the building or its location but in the nature of routine activities that take creates the possibility of the criminal event there. Since, these activities come into operation only at a specific time period, the criminality of that place can be alleged for only those specific periods. At other time periods these places are as 'normal' or crime free as any other. We may sum this by saying that such criminogenic spots are 'hot' only during definite times. In other words, if there are hot spots than there will be 'burning' times!

We will establish this relationship between the concept of the criminality of place with its time period by the simple technique of topological homeomorphism. We have already seen the usefulness of topology in determining the 'edges' as described by Pattern theory and how it can help in identifying high, medium or low regions of crimes as influenced by different social characteristics. Recalling that topology is the study of qualitative characteristics, the mathematics suggests that these qualitative properties of nodes, fuzzy edges, interior exterior regions ought to be retained even after any transformation of the topological space.

For instance, if topology assists in determining the nodes, edges and boundaries on the *physical* plane, it also points towards the possibility of a similar situation in the *temporal* dimension. Thus, if we can show that the physical and the time dimensions of a crime space are homeomorphic then topology states that two homeomorphic spaces are topologically invariant and share the same qualitative intrinsic properties. We will demonstrate this concept now and point towards some of its implications.

Let (X, Γ) be a topological space where X is the set of all crime locations of a region, city, police district under consideration. A member of X designated as c is then some crime site which has distinct x and y coordinates on the map. Here x and y may be the longitudes and latitudes, the Universal Transverse Mercator (UTM) coordinates or any such other in some different projection of the map of the city.

Then $X = \{c \mid$ c is a crime site with some specific geographical parameters $(a,b)\}$.

Let Γ is a subset of X defined as follows:

$\Gamma = \{c \in X \mid$ c is a set of all crime sites lying on a segment of street between any two intersections$\}$.

The intersection of any two subsets of Γ is the segment of street common to any two different streets and thus $\in \Gamma$. Similarly, the union of two sets of Γ is the combined street segment which also $\in \Gamma$. The null set $\in \Gamma$ and since any crime site lies on some street segment, $X \in \Gamma$ also. Clearly this defines a topology with the usual union and intersection operations on c.

Similarly, let Y be the set of specific time of crimes occurring at the above mentioned crime sites. Since every crime record has a time period associated with it, this set actually exists and is non empty. Thus, $Y = \{t \mid t$ is the specific time of occurrence of the crime in that region$\}$. Here t may be measured in date or time coordinates, for example (930126, 225604) where 930126 is a specific date and 225604 is the usual hour, minute, second time unit.

Let Ψ be the set of all time segments of Y. That is

$$\Psi = \{t \in \Psi \mid t \text{ is any specific time} > 0\}.$$

The intersection of any two subsets of Ψ is the time period common to two different periods and thus $\in \Psi$. Similarly, the union of two sets of Ψ is the combined period of time which also $\in \Psi$. The null set $\in \Psi$ and since any crime occurs at some specific time, $X \in \Psi$ also. Clearly, Ψ too defines a topology since the usual union and intersection operations on its elements result in some time segments that are also members of Ψ. Thus (Y, Ψ) defines a topological space in the common mathematical sense.

Let f be a mapping of X into Y by the following rule:

$$f(c) = t.$$

That is the function f maps every crime site into the time dimension, the specific time of occurrence of that crime. Since every crime incident is distinct, therefore f is 1-1. (It is extremely unlikely that two crime incidents occur at the same site and at the same small unit of time. In such cases these are treated as the same incident if it involves different violations of the criminal code and more than one victims or offenders).

The same situation would work for the geographical components. When a common address of two incidents is a building then the two would still be distinct if located through a smaller unit of measurement, say down to a meter, elevation etc. Therefore, in the case when different crimes may be registered from the same address one could still argue that the actual incident would have taken place at a distinct location. Thus, even if the official record shows the same geographical coordinates pertaining to the same address, one could distinguish between them by considering smaller coordinate scales of the x and y values, say in minutes. This procedure would make f 'onto' for every distinct time period in Y will be associated with a specific crime site and by definition the domain of f is X and the range is Y.

Finally, f is also a continuous mapping of X onto Y since the inverse image of any set of time periods in Y are associated with a set of crime sites that lie in some street segment. That is $f^{-1}[\Omega]$ is the set $\{c \in X \mid f(c) \in \Omega\}$ and where Ω is some time segment of Y. Since Ω by definition is an open set in Ψ and $f^{-1}[\Omega] \in \Gamma$ then $f^{-1}[\Omega]$ is Γ-open. On the other hand, the image of any set $G \in \Gamma$, f(G) is the set of time segments associated with those crime sites that lie in the street segment G. This makes f(g) an open set in Ω. We can thus say that the mapping $f : X \longrightarrow Y$ represents a 1-1, onto, continuous and bicontinuous mapping of the topological spaces (X, Γ) and (Y, Ω). But this makes these two topological spaces homeomorphic and thus similar in every way.

The implications of this mathematical relationship are interesting. As there are connected regions in the physical dimension so too are there connected time periods for the phenomenon of crime. If there are sharp boundaries on the physical plane then there are also sharp boundaries in the time dimension. If there are 'hot spots' of crime sites on the city map then there are 'burning times' on the time map. We will illustrate this by exploring the physical and temporal distribution of the crime phenomenon for the period of 31 days of January 1993 from the records of Vancouver police 911 call data. In order to compare these two spaces we examined the frequency distributions of calls for these two dimensions- the geographical and the temporal planes.

Results

In the physical plane all calls for service for the month of January 1995 were first geocoded for illustrative purposes. These were then grouped by street names and aggregated for each distinct street.

The results are shown below in table 7.2:

Table 7.2

Distribution of Calls for Police Service in the Physical Plane

# of streets	Total calls for service	% of total calls	Cumulative % of total calls
6	4412	16.4	16.4
8	2595	9.8	26.2
20	3939	14.7	40.9
14	1866	8.01	48.9
26	2619	10.0	58.9
39	2735	10.1	69.0
71	2786	10.1	79.1
99	2308	9.1	88.2
989	3072	11.8	100

Considering that there are a total of 1281 distinct streets in Vancouver and in January the calls for service recorded by the police total 26822, it is clear that a mere 3.75% of streets account for almost 48% of all the calls.

Similarly, the same calls were identified by their time of call to the police and aggregated at hourly intervals. The results for this situation in the temporal plane is shown below in table 7.3:

Table 7.3

Distribution of Calls for Police Service in the Temporal Plane

# of Hourly segments	Total # of calls for service	% of total calls	Cumulative % of total calls
32	2631	9.81	9.81
43	2705	10.09	19.90
51	2701	10.08	29.98
55	2652	9.90	39.88
62	2702	10.08	49.96
66	2667	9.95	59.91
73	2707	10.10	70.01
80	2678	9.97	79.98
97	2687	10.02	90.0
184	2692	10.0	100

Thus, 32.6% of hourly time segments account for 49.97% of all the calls. Analogously, there are few 'burning times' that contain a large percentage of crime 'periods' in the temporal plane. If the calls are aggregated at smaller time intervals, like minutes or less, the results may be even more dramatic.

The relationship could be illustrated graphically too as follows: The calls could be aggregated for a comparable unit for both the dimensions and then plotted on similar scales. Thus, for the month of January, in the temporal dimension if calls are aggregated hourly it involves 31*24 = 744 points in the temporal plane. These could be compared to the aggregation of crime sites falling within the 770 enumeration areas that involve virtually similar number of units on the geographical plane.

The matrix of the 744 temporal points for the month of January is given on appendix 16. The three dimensional figures, one for the physical plane and the other for the temporal plane are given on figures IV and V which illustrate their topological surfaces. As may be seen on the two figures, both the three dimensional plots show peaks and valleys and concentration of crime 'points' in their temporal or spatial distributions. The sharp and gradual edges as seen in the figure suggest a comparative fuzziness of boundaries on the temporal plane too. Just like the physical dimension, there are homogeneous time intervals with permeable 'borders', both for high and low crimes.

Implications

The implications flowing from such a topological analysis are far reaching. Not only does there exist a clear one to one correspondence between the physical and temporal topological spaces but the same homeomorphism can be shown to exist between other indices of the criminal event too as pointed by the Pattern theory. The 'topological spaces' of offenders, victims, and legal codes that can be formed through some criteria of open sets have obvious relationship with the physical and temporal spaces. By defining a similar one-to-one and onto function that maps say the offender 'space' to the corresponding physical, temporal or victim 'space' would suggest that these have the same qualitative properties.

Thus, amongst the set of all offenders, there are a few who are involved in most of the crimes, the 'serious' repeat offenders. Amongst the group of victims there are some who are victimized repeatedly or more frequently than others and it should be no surprise if these kind of victims and offenders share a large number of common characteristics- like income, social status, living space, family background and naturally activity spaces.

The concept of homeomorphism suggests that a similar characterization is likely to be seen in the case of legal 'space' too. Not surprisingly, amongst all the legal provisions only a few are violated more frequently. Cheats, forgerers and white collar criminals are involved only in violating legal contracts, regulations and breaches of trust cases. On the other hand, 'serious' offenders transcend property and body offence codes. Thus, likewise we can say there exists 'hot' codes in the law that are infringed repeatedly.

The proper relationship amongst all these concepts can only be worked out by a greater amount of knowledge than available at present but the mathematics behind it appears reasonably straight forward. Topology provides a powerful approach for analyzing the relationships between these different aspects of the crime phenomenon that can inject new perspectives into the way we view and deal with criminal behavior.

---X---

CHAPTER VIII

VORONOI DIAGRAMS: ANALYSIS OF NODES AND PATHS

The attempt to distinguish between various shapes and sizes may perhaps have been the motivation for the Greeks to develop the geometrical concepts of point, line and angle, but from the earliest Euclidean geometry to the Reinmann and Fractal geometry, this branch of mathematics has come a long way. The underlying concept behind geometry is the partitioning of space into a set of regions based upon some criteria and proportionality. The line, arc, radius, circumference, angle, area, projection, distance between points are some of the building blocks that have found wide spread applications in civil engineering, organic chemistry, nuclear physics, archaeology and even in the efforts to determine the shape of the universe.

Application of Geometrical Techniques in Criminology

In criminology too, the spatial distribution of criminal events, offender residences, police sting operations, location of courts have been studied through geometrical techniques(for *e.g.*, Coburn 1988; Harries 1990; Wikstrom 1991; Langworthy and Lebeau 1990; Lamber and Luskin 1991). In this section we will describe a particular kind of mathematics based upon such geometrical properties. After a brief exposition about the mathematical technique of spatial tessellation, its usefulness in analyzing the properties of nodes and even the backcloth as called for by the Pattern theory will be outlined.

A branch of algebraic topology, graph theory is a well developed mathematical tool to analyze nodes and the paths and of modeling a variety of relationships amongst a large set of point like objects. It is capable of revealing the connectivity amongst the nodes, examine routes, paths and cycles and has already found wide application in geography (Tinkler 1972; Good 1975) and even in sociometry. However, for analytical purposes, graph theory reduces the node to a point and does not take into account the neighboring space around the node. Thus, for a crime site or an activity node, the interest is not only in the exact location but in the immediate surrounding space as well. For these and other reasons we will look into the applicability of a geometrical technique that suggest methods to construct and consider the sphere of influence around the point like and other shaped objects.

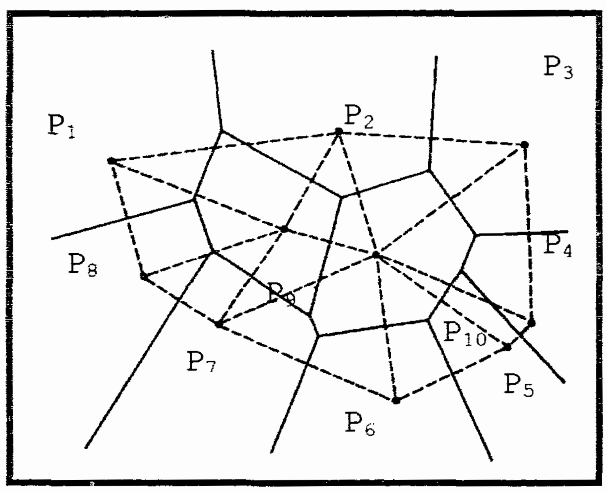
The Concept of Voronoi Diagrams

The mathematics of the Voronoi diagram and spatial tessellation, variously known as Thiessen polygons or Dirichlet domains (Okabe, Boots and Sugihara 1992) is based upon a simple concept. These tesselations are formed by associating with each point in the pattern all locations in the study area that are closer to it than to any other point in the pattern space. Thus, if there are two points the perpendicular bisector of the line joining the two points divides the space between them. For three points the picture becomes more complicated because it now involves the division through the bisectors of three lines and the process goes for greater number of points in a similar fashion. Those locations in the study area that are equidistant from two points will lie on the boundary of two adjacent polygons.

Similarly, any locations that are equidistant from three or more points in the pattern will form the vertices of adjacent polygons. The result is the creation of a tessellation of contiguous space exhaustive polygons or Voronoi diagrams. These contiguous spaces represent the partitioning of the area into the neighborhoods of the points.

In these polygons three edges are incident at each vertex. The occurrence of more than three edges at a vertex is very rare since for this to form four neighboring points in the pattern must lie on the circumference of a circle whose interior contains no other points. In this partitioning of space a second diagram called a Delaunay tessellation, can be constructed by joining those points that share a common Voronoi edge.

The following figure 8.1 illustrates the concept:



---- Delaunay Triangles

—— Voronoi Diagrams

Fig. 8.1

These two partitioning of space have found wide spread usage in such diverse fields such as anthropology, archaeology, astronomy, biology, crystallography, geography, metrology, operations research, physics, physiology and urban planning

(Okabe, Boots and Sugihara 1992: 2). Applications in these fields have used the concept of Voronoi space along with different mathematical techniques based upon matrices, set theory, calculus, graph theory and even stochastic point processes. We will briefly outline the definitions, descriptions and mathematical properties associated with Voronoi diagrams and then describe some techniques for analyzing different kinds of crime patterns.

Mathematical Properties of Voronoi Diagrams

Consider a finite number of n distinct points in the Euclidean plane labeled as p_1, $p_2 \ldots p_n$, each having the location vectors x_1, $x_2 \ldots x_n$. These points are distinct and $x_i \cap x_j$ $i \neq j$, i, j I_n. Let p be some point with the location vector x. Then the distance between p and another point p_i is given by

$$d(p, p_i) = ||x - x_i|| = \text{sqrt}[(x_1 - x_{i1})^2 + (x_2 - x_{i2})^2].$$

If p_i is the nearest point to p then we have the relation

$$||x - x_i|| \leq ||x - x_j|| \text{ for } j \neq i, i, j \quad I_n.$$

Finally, if $P = \{p_1, p_2 \ldots p_n\}$ is the set of points and

$x_i \neq x_j$ for $i \neq j$, i, j I_n, the region

$V(p_i) = [\ x |\ ||x - x_i|| \leq ||x - x_j|| \text{ for } i \neq j, i, j \quad I_n]$

is called the Voronoi polygon associated with the point p and the set $V = \{V(p_1), V(p_2), \ldots V(p_n)\}$ is called the

Voronoi diagram generated by the set of points P. For this reason, the set P is called as the generator set for the Voronoi diagram.

Since the relation between nearest points is defined in terms of $\leq$ and not strictly $<$, the Voronoi polygons form a closed set where the set of its boundaries which consists of line segments or infinite lines are known as Voronoi edges. Clearly, $V(p_i) \cap V(p_j) \neq \emptyset$ and the set $V(p_i) \cap V(p_j)$ gives a Voronoi edge.

This definition can easily be extended to any m dimensional plane as follows:- If $P = \{p_1, p_2, \ldots p_n\} \subset R^m$, where as before $2 \leq n < \infty$ and $x_i \neq x_j$ for $i \neq j$, i, j I_n.

The region given by:

$$V(pi) = [\, x \mid \|x - x_i\| \leq \|x - x_j\| \text{ for } i \neq j,\ i,\ j \quad I_n]$$

is the m dimensional Voronoi polyhedron associated with p_i and the set $V = \{V(p_1), V(p_2), \ldots V(p_n)\}$ is the m dimensional Voronoi diagram generated by P.

Since any polygon could be defined in terms of its half planes, the Voronoi diagram could also be expressed in alternate terms. Let the bisector line between the points p_i

and p_j be $b(p_i, p_j)$. Clearly, any point on this bisector is equidistant from the two points p_i and p_j and so

$b(p_i, p_j) = \{x| \ ||x-x_i|| \leq ||x-x_j||\} \ i \neq j.$

The bisector divides the plane into two half planes given by: $H(p_i, p_j) = \{x| \ ||x-x_i|| \leq ||x-x_j||\} \ i \neq j.$

In such a case the region $V(p_i) = \bigcap_{j \in In \setminus \{i\}} H(p_i, p_j)$ associated with the generator pi and where $x_i \neq x_j$ for $i \neq j$, i, j $\in I_n$ is called the Voronoi polygon for p_i while $V(P) = \{V(p_1), \ldots V(p_2)\}$ is the planar Voronoi diagram generated by the set $P = \{ p_1, .. p_n\}$. This alternate definition is useful in computing the vertices of the Voronoi diagrams and it could similarly be extended to the m-dimensional plane.

Just as any planar graph has its dual graph, the Voronoi diagram has its dual tessellation called Delaunay tessellation that is formed when the set of points p_1, p_2, ... p_n are not on the same line, since otherwise a triangulation cannot be obtained. Thus, for the Voronoi diagram V(P), generated by the set of non- collinear points

$P = (p_1, p_2, \ldots p_n)$ where $3 \leq n < \infty$,

Let $Q = \{q_1, q_2, \ldots q_n\}$ be the set of Voronoi vertices in V(P) and $x_{i1}, \ldots x_{ik_i}$ be the location vectors of those Voronoi polygons that share the vertex q_i. Then the set

$D = [T_1, T_2, \ldots T_n]$ where T_i is defined as

$$T_i = \{ x \mid x = \sum_{j=1}^{ki} \lambda_j x_{ij}, \text{ where } \sum_{j=1}^{ki} \lambda_j = 1, \lambda_j \geq 0, j \in I_{k_i} \}$$

is called the Delaunay triangulation of P.

The Delaunay triangle is similarly a closed set and it contains the line segments of its boundaries. Although, a triangle is defined for a two dimensional space, the definition of Delaunay tessellation can be similarly extended to multiple dimensions.

Voronoi diagrams have several interesting properties; for instance a Voronoi polygon is a non- empty convex set and the union of all Voronoi polygons cover the space. Specifically, $\cup V(p_i) = R^2$ while

$$[V(p_i) \setminus \partial V(p_i)] \cap [V(p_j) \setminus \partial V(p_j)] = \varnothing \text{ for } i \neq j,\ i,\ j \quad I_n$$

where $\partial V(p_i)$ represents the edge of the polygon. The Voronoi diagram V(P) is thus a unique tessellation for P and it has several topological properties with respect to the number of Voronoi vertices, edges and polygons. To examine the topological properties, the planar graph induced from the Voronoi diagram first needs to be constructed. Let $N = \{n_1, \ldots n_{nv}\}$ be the vertices and $M = \{ m_1, \ldots m_{ne} \}$ be the edges of V(P). Since a geometric graph does not have infinite edges, the infinite edges of the Voronoi diagram needs to be modified. This can be done by placing a dummy point n_0 far away from the diagram, cutting every infinite Voronoi edge at some point and joining its end points to n_0. Let $\{m_{h1}, \ldots m_{hn_c}\}$ be the edges induced from $\{m_1, \ldots m_{nc}\}$ with modifications and let $M_h = [M \backslash \{m_1, \ldots m_{nc}\}] \cup \{m_{h1}, \ldots m_{hn_c}\}$. Then $N_{+1} = N \cup (n_0)$ and M_h will form a planar graph $G(N_{+1}, M_h)$.

For such a Voronoi graph, the Euler formula applicable to any planar graph will hold true and so we have the relation $(n_v + 1) - n_e + n = 2$. This implies that for any Voronoi diagram in R^2, $n_v - n_e + n = 1$
where the three represent the number of vertices, edges and generators points respectively. Since every vertex in the Voronoi graph has at least three edges, the number of edges in it is not less than $3(n_v + 1)/2$. This implies that for $3 \leq n < \infty$, $n_e < 3n - 6$ and $n_v < 2n - 5$.

The Delaunay triangle is also a unique tessellation and its vertices, edges have close relations with that of the Voronoi diagrams. The number of Delaunay vertices equal the number of generating points P while its circumcentres equal the number of Voronoi vertices. In general, the number of edges of the Delaunay triangle is greater than or equal to that of the corresponding Voronoi diagram. The Delaunay triangulation of the points P may also be regarded as a connected graph consisting of nodes given by the points of P and the paths formed by the edges of its triangle.

There are several other properties of the Delaunay graph that have special names like Gabriel subgraph, relative neighbourhood graph and the nearest neighbour graph (Okabe, Boots and Sugihara 1992: 115). An important property is that of the size of the angles of these triangles which we will demonstrate as another kind of geometrical technique for analyzing the distribution of some criminal events.

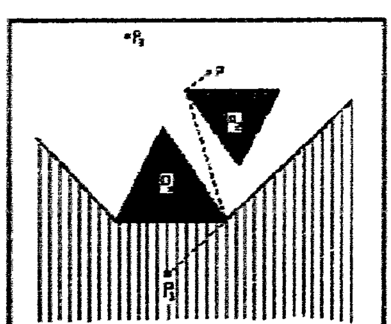
The beauty of mathematics lies in its ability to generalize starting from simple concepts. This has been done in the case of Voronoi tesselations too by introducing different structures and processes in the generation of these figures. Thus, in case the set of points P is generated by a homogeneous Poisson process the resulting tessellation are known as Poisson Voronoi diagrams and Poisson Delaunay triangles respectively. The manner of their generation and properties of their sides, angles, edge lengths, area perimeter have been widely explored in several kinds of applications. For instance, Poisson Voronoi diagrams have been utilized in investigating the quantum field theory, conductivity of granular composites and in modeling the growth of clusters formed by metal vapour (*cited* in Okabe, Boots and Sugihara 1992: 278-9). Their most significant use lies as a normative model against which other 'normal' tesselations can be compared.

Similarly, the concept of straight line distance can be generalized by considering 'obstacles' between the set of points. These may arise from such natural obstructions as rivers, roads or buildings. Due to their presence one cannot take the direct shortest distance line and has to 'go around' them. Voronoi tesselations can take these into account by developing the 'shortest' path or the visible shortest path diagrams.

For instance, let B be the set of obstacles,

$B = (O_1, O_2 \ldots O_m)$ and $O_i \cap O_j = \emptyset$ for $i \neq j$. Then in the region $S = R^2 \backslash O$ the distance between a point p and another p_i can be defined as the length of all the shortest paths amongst continuous paths connecting p and p_i that do not intersect obstacles $O_i \backslash \partial O_j$, i, j I_n.

Fig. 8.2



The figure 8.2 above demonstrates the method. Further generalization is possible by considering objects that are not point like. Thus, instead of the generator set of points P, one may consider the set of line like objects

$$L = \{ L_1, L_2, \ldots L_n \} \quad \text{where}$$

$L_i \cap L_j = \emptyset$ for $i \neq j$ $i, j \quad I_n$ and the distance from a point p to L_i is given by

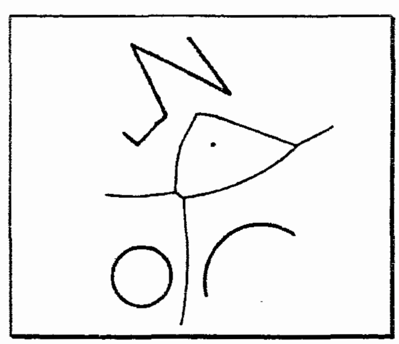
$$D_s(p, L_i) = \min_{x_i} \{ \; || x - x_i || \; | \; x_i \quad L_i \}.$$

The Voronoi diagram for such line objects is then the set

$$V(L_i) = [p \mid D_s(p, L_i) \leq D_s(p, L_j),), \; i \neq j \; i, j \quad I_n.$$

Note that the line here may be a straight segment or a curved arc. The concept is illustrated in the figure 8.3 with a line, an arc and a point as the generators shown below.

Fig. 8.3



In an almost identical fashion, the concept can then be extended from the line to an area.

Let $A = \{ A_1, A_2, \ldots A_n \}$

where $A_i \cap A_j = \emptyset$ for $i \neq j$ $i, j \quad I_n$.

Since the area may not be convex, it could have 'holes' in which other areas may reside. The shortest distance from a point to any area A_i can similarly be defined as :

$$D_s(p, A_i) = \min x_i \{ ||x-x_i|| \mid x_i \quad A_i \}.$$

Correspondingly, the area Voronoi diagrams are given by the set:

$$V(A_i) = [p \mid D_s(p, A_i) \leq D_s(p, A_j), i \neq j \quad i, j \quad I_n].$$

The figure 8.4 below illustrates an area Voronoi diagram.

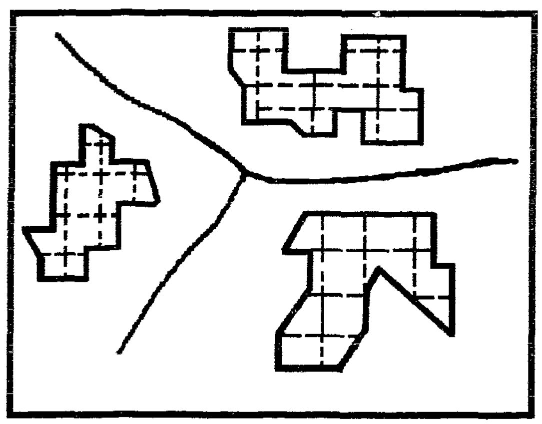


Fig. 8.4

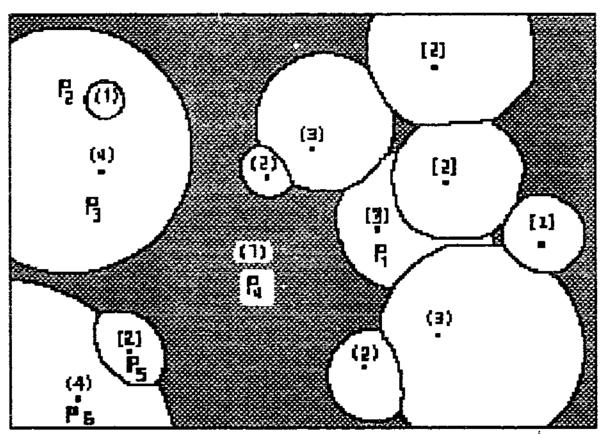
Until now no distinction has been made between the objects themselves except for their locations. Sometimes it may be necessary to assign weights to the generator objects, like a homicide site being more important than burglary for police response purposes. Voronoi tesselations can be modified to reflect the different weights of each of the generators by considering a weighted distance between the respective objects.

For instance, a set of points $P = \{ p_1, p_2, \ldots p_n\}$ may have some weights w_i attached with each of them. If $W = \{w_1, w_2, \ldots w_n\}$ are the corresponding weights then the weighted distance may be given by the following definition:

$$D_w = 1/w_i \{ ||x-x_i|| \} \text{ where } w_i > 0.$$

Clearly, weights may be defined in a variety of ways depending upon the model being proposed. The gravity model where $D_w = 1/w^2$ is one such famous model that has its roots in Voronoi diagrams. The Voronoi diagram in figure 8.5 below reflects the weights of generator points:

Fig. 8.5



Finally, Voronoi tesselations can be drawn on surfaces other than the two dimensional Euclidean plane, like spheres, cylinders, cones or polyhedrals. Further generalization is possible by combining some or all of these different possibilities like considering an area object, weighted by its size and drawn on a curved surface with lakes and buildings as natural impediments.

Pattern Analysis of Voronoi Point Generators

We will demonstrate different applications of the Voronoi tesselations in analyzing the distribution of criminal events by examining the angles of Delaunay triangles and the effect of point and line generators. The technique seems appropriate since a distribution of crime sites may be represented as a set of n distinct points, $S=\{s_1, s_2, \ldots s_n\}$, in a bounded region B in either R^2 or R^3.

We call them empirical point patterns even though individual crime sites or the objects affecting their distribution may not be points themselves, like burgled houses, railway lines, or even districts with law and order breakdowns. However, it is possible to consider them as points because the physical sizes of these locations will be very small relative to both the distances between them and the extent of region in which they occur. (Troublesome districts would be analyzed relative to the other districts in the province or even the country and therefore could still be considered as a point element).

The examination of these empirical point patterns may be useful in learning more about the phenomena represented and the processes responsible for creating it as suggested by Pattern theory. For one, their analysis may lead us to develop an explanatory model that could throw light upon the locational behavior of the phenomenon. For example, even when the knowledge is rudimentary, information obtained from the analysis of such patterns may enable us to acquire some initial insight into the process. The realization that objects are placed differently towards the margins of the boundary than they are at the centre may lead us to investigate the possibility of different forces operating at those locations or the same forces but operating with different intensities.

In instances where the focus is upon the location of the individual points of S with respect to other points of S or on their distribution over the bounded region B, then polygons constructed through the Voronoi diagrams can be utilized. At other times we may be interested in how the members of S are located with respect to other objects that are not members of S but are still located in B. These objects may be point, line or area type and for which the technique of nearest neighbourhood analysis is particularly suitable.

In the case when the focus is only on the members of S it is useful to consider a theoretical point pattern with respect to which other patterns can be compared. Such a theoretical point pattern can be obtained from the operation of a Poisson point process as mentioned before. The Poisson Voronoi diagram is such an illustration. This could be considered as one that is created randomly in a completely undifferentiated manner and used as an idealized standard. Even if little is known about the process we can test it by hypothesizing that it has been created by chance. The tests can then be done based upon some selected characteristics of the Voronoi tessellation, like the length of the edges, the angles of triangles, the distance between objects and so on.

Several classes of point patterns can be recognized using complete spatial randomness (CSR) as a benchmark. Clustered point patterns are those in which the points are significantly more grouped in the bounded region B than they are in CSR whereas regular patterns or dispersed point patterns are those in which the points are more spread out over B than they would be in CSR. Environmental inhomogeneity is said to be the case in which some subareas of B are less likely to receive a point than other subareas. The establishment of neighbourhood watch system, or intensive patrolling may be one reason for such a situation. In these circumstances, we would expect to find more points in the subareas of B favoured by offenders than elsewhere, thereby producing a clustered pattern.

Another situation is when points may either attract or repulse one another. Drug dealing locations for instance may act as an attractor for consumers while sites for gang hangouts may act as repellent for ordinary citizen since these places may appear dangerous. The former is likely to produce a clustered pattern whereas the latter will likely produce a spread out pattern. The hypothesis of CSR or any other concerning the spatial nature of the empirical point pattern can then be tested by comparing measures of selected characteristics of the empirical point pattern with those of the hypothesized pattern.

There are two possible types of measures: arrangement measures that describe the location of points relative to other points; and dispersion measures that take into account the locations in relation to the area included within the bounded region. In other words, arrangement measures are concerned with those characteristics of the pattern that remain invariant under translation, rotation and reflexion and under change of scale, while dispersion measures may change under such conditions. In the following sections we will first outline two techniques under the dispersion measure system and then apply a triangle based test using the Delaunay tessellation concept.

Nearest Neighborhood Distance Technique for Voronoi Diagrams

We have already seen that algebraic topology, especially graph theory can provide a good arrangement measure for point pattern analysis. A variation of the Voronoi diagram based pattern analysis is the nearest neighbour method (NND) that involves a form of dispersion measure. There is a common NND method too which is a statistical technique examining the distribution of point like objects over a region that has other physical objects. The technique involves estimating the nearest neighbour distances and then comparing them with those expected under CSR using a variety of tests. However, this technique "does not directly deal with the physical objects *affecting* the distribution of these point like objects" (Okabe, Boots and Sugihara 1992: 422).

The NND method as an application of Voronoi diagram can be utilized for examining the effects of various kinds of Voronoi generators upon the distribution of certain elements over the same region. Here we will describe the procedure of this particular NND method by considering how point like objects, for instance bars or line like objects such as truck routes affect specific crimes around their vicinity.

NND Analysis for Point Generators

Consider a region S in which m physical point objects (the bars for instance) are located in the region and n point like objects (the crime sites) are distributed over the region excluding the area occupied by the objects. A set of m objects in the region R^2 can be represented by a set of points denoted by

$$O= (O_1, O_2, \ldots O_m) \quad (1 \leq m < \infty)$$

where $O_i \cap O_j = \varnothing,\ i \neq j,\ i, j \quad I_n.$

A set of the n point like elements can be represented by a set of points distributed over the remaining space

$$S_0 = S \setminus \bigcup_{i=1}^{n} O_i$$

and as before can be denoted by

$$P = \{p_1, p_2, \ldots, p_n\}, \quad (1 \leq n < \infty)$$

with location vectors $\{x_1, x_2, \ldots, x_n\}$.

Given O and P, we can define the distance from a point p_i in R^2 to an object in O_j by

$$d(p_i, O_j) = \min_{u_i}\{|x_i - u_j| \ x_j \quad O_j\}$$

where $|x_i - u_j|$ is the Euclidean distance $\{d(p_i, O)\}$ between $x_i \quad S_o$ and $u_j \quad O_j$. With $d(p_i, O_j)$, we next define the distance from a point pi to the nearest object O_j in O by

$$d(p_i, O) = \min_{ui}\{ d(p_i, O_j),\ j \quad I_n \}$$

We will call this distance the nearest neighbor distance, or briefly the NN distance, from p_i to O. These $d(p_i, O)$ can be efficiently computed using the Voronoi diagram for the objects O. We first observe in which Voronoi polygon V the point pi is located. Once p_i $V(O_j)$ is known, $d(p_i,O)$ is readily given by $d(p_i,O_j)$.

Third, we define D as follows:

$$D= 1/n \sum_{i=1}^{n} d(p_i, O)$$

We will call D the average nearest neighbor distance, or the average NN distance. Now, consider the contention that points P are independently and randomly distributed according to the uniform distribution over S_o. This premise implies that objects O do not affect the distribution of points P. Under this presumption the NN distance $D_i = d(p_i,O)$ is a random variable; consequently D is also a random variable. Let E(D) be its expected value and D be an observed value of D. If the pattern is as expected the observed value D is close to E(D). Using this property, we can define an index by R= D/E(D).

If this were so we may expect that R be close to unity. If we observe R < 1 this represents a pattern where the points P are more closely distributed around objects O than they would be in the random distribution. If we observe $R > 1$ then the points P are more sparsely distributed around objects O than they would be in the random distribution.

Since D is the average of independent random variables D_i having the same distribution with a finite mean, the central limit theorem then guarantees that the distribution of D asymptotically approaches the normal distribution with mean $E(D)= E(D_i)$ and variance $Var(D)= Var(D_i)/n$, where $D_i = d(p_i,O)$ is the NN distance from a point p_i to O. It follows from this property that the random variable $R= D/E(D)$ asymptotically follows the normal distribution with $E(R)=1$ and $Var(R)= Var(D_i)/\{nE(D_i)^2\}$ as n increases. This variable then could be used as a test statistics to determine whether the points P are independently and randomly distributed according to the uniform distribution over S_o. The test could help us find out for example, if the distribution of crime sites (points P) is affected by the location of bars (objects O).

The NND technique could also be used to examine the impact of line like objects, such as the effect of truck routes upon the distribution of robbery sites. It is known that robberies are frequently committed by using some get away vehicles for avoiding detection (Capone and Nichols 1976; Langworthy and Labeau 1990; Canter 1993). Moreover, "[a]reas along major travel paths are known by many persons and, consequently, by more potential offenders" (Beavon, Brantingham and Brantingham 1994: 119). It is therefore probable that arterial roads that serve as major truck routes and high speed highways are likely to influence the location of such robberies for these will provide quick get away routes known to the motivated robbers.

NND Technique for Line Objects

When the area occupied by an object O_i is very narrow and long relative to the whole region S_o, we may regard the object as a line segment and O as a set of line segments. To calculate $d(p_i,O)$ one can assume that set of line like objects O is represented by set of chains of straight line segments. A curved line could also be approximated by the chain of connected small straight line segments. With this modification, the procedure is the same as that of the NND method for point like objects described above. First the construction of Voronoi diagrams $V = \{V(O_1),...,V(O_n)\}$ generated by the decomposed set of the line generator set O is undertaken. Next, find in which Voronoi region a point p_i is placed. Once p_i $V(O_j)$ is known, the NN distance $d(p_i,O)$ is immediately given by $d(p_i,O_j)$. The rest of the technique closely follows the one described above.

This technique could also be extended for area like objects. Since in the real world there will be more than one type of objects the index R could be generalized into a multivariate index like $r = (d_1/E(d_1); \ldots d_n/E(d_n))$ where each d_i is the average NN distance defined for the objects o_i, $i \in I_n$. This technique could be useful in analyzing the spatial distribution of crimes around the 'awareness space' of some offender since that consists of home, work place, travel paths and entertainment areas (Brantingham and Brantingham 1984) which are point, line or area like objects respectively.

In the application of this Voronoi diagram based NND method, a number of additional assumptions may have to be made regarding the nature of data. For instance, it is taken for granted that the crime sites are *point* like when in some cases these may be *line* like (Hit and run) or *area* like (B&E) depending upon the type of case. If this is considered significant then $d(p_i, o)$ may have to be modified accordingly. Secondly, the objects themselves, like the bars or the truck routes will not be the only objects influencing the crime sites, other commercial establishments or such objects will be present too. Their impact may have to be discarded or reduced by choosing suitable time period or region for examination.

Thirdly, and more importantly, it is assumed that the points are randomly distributed in a two dimensional plane. However, the distribution of crime sites is generally not independent and constrained by objects all around. The use of multi NND method may have to be considered. Lastly, the shortest Euclidean distance measure (distance along the straight line joining the two points) may need to be modified by taking the Manhattan distance.

In estimating the index R one will require to compute the mean of D to carry out the statistical test. This requires a knowledge about the probability distribution function F(D), of D that is generally difficult to obtain. This function will depend upon the size and shape of the area under consideration that will vary from case to case. However, by using the Voronoi diagram concept Okabe, Boots and Sugihara (1992: 425-431) have suggested partitioning the Voronoi polygons into smaller triangles and then using the area functions to estimate the function F(D). Since this type of computation increases exponentially with the number of generators, the estimation of E(D), the mean of the average nearest neighbor distance is quite complicated and beyond the scope of this exploratory study. Voronoi diagram based NND studies are rather difficult to carry out in practice and would require elaborate computer programming for various kinds of computations but these techniques appear promising for criminology.

Application of Delaunay Triangle based Technique

As before let P be a set of points generated by some Poisson process and D(P) be its Delaunay triangles. In R^2 the probability density function f(x) of x, a random angle of any randomly selected triangle has been derived as

$$f(x) = 4[(\pi - x)\cos x + \sin x]\sin x/3\pi \quad \{0 < x < \pi\}$$

(Okabe, Boots and Sugihara 1992: 417).

The probability $F(\varphi \leq x)$ for $\varphi \leq x$ can therefore be determined by integrating f(x) as: $F(\varphi \leq x) = \int_0^x f(\varphi)\, d\varphi$ and therefore

$$F(\varphi \leq x) = (1/3)\ 2\sin^2\varphi + \{\varphi\cos 2\varphi - (3\sin 2\varphi)/2 + 2\varphi\}\pi^{-1}\Big]_0^x$$

However, in this procedure one is required to take a random sample of triangles from the set of Delaunay triangles and then examine and compare their angular values with some theoretical distribution. Instead, Mardia, Edwards and Puri (1977) have suggested to use the information available from the value of the angles themselves. Miles (1970) derived the probability density function of a pair of angles χ, δ selected at random from an arbitrary triangle of the Poisson Delaunay triangle D_P as

$$f(\chi,\delta)= \{(8/3)\pi\}[\sin\chi \sin\delta \ \sin(\chi+\delta)] \quad (\chi > 0, \delta > 0, (\chi+\delta) < \pi.$$

By integrating over all the values of angle δ we can obtain

$$f(\chi)= 4[(\pi - \chi)\cos\chi + \sin\chi]\sin\chi/(3\pi) \quad (0 <\chi< \pi)$$

as the pdf of a randomly selected angle of an arbitrary triangle of D_p.

Mardia, Edwards and Puri (1977) have then derived the minimum angle of an arbitrary Delaunay triangle as

$$f(\chi_{min})= (2/\pi)[\ \pi- 3\chi_{min})\sin2\chi_{min} + \cos2\chi_{min} - \cos4\chi_{min}\ ] \quad (0 < \chi_{min} < \pi/3).$$

Assuming that the values of χ_{min} are independent for the triangles of the Delaunay triangles the marginal density function of the minimum angle χ_{min} of all the triangles in D(S) can then be used as a possible comparative parameter.

In such a case the marginal density function for probability of $\chi_{min} \leq x$ will be given by:

$$F(\chi_{min}\leq x)= \{1+1/(2\pi) \ \ \{6\chi_{min} -2\pi\}\cos2\chi_{min} -\sin2\chi_{min} -\sin4\chi_{min}\} \Big|_0^x \quad \{0< x \leq \pi/3\}$$

Values of P(z) for angles between 1 and 60 degrees have been derived from this equation (Boots & Getis 1988: 75-76). The proposed procedure is then to identify and estimate the minimum angle χ_{min}. These observed frequencies are then cumulated to give F(z) as the proportion of χ_{min} in some specific interval. The edge effect is discounted here by not considering the triangle whose circumcentre does not lie in the bounded region B.

The values of F(z) so obtained could then be compared with the corresponding values P(z) produced by some complete spatial random set of triangles using a one-sample Kolmogorov-Smirnov test (Yeates 1974; Massey 1951). This test involves taking the absolute difference between the values of F(z) and P(z) for corresponding values of z and the largest of the values determines the test statistics D_{max}, which is compared with the appropriate value from statistical tables of critical values (Okabe, Boots and Sugihara 1992: 417-422).

The principle behind the test is that if the points were arranged perfectly regularly, all the Voronoi diagrams would be regular hexagons and all the triangles will be equilateral. If the points were located so that they approximate a square grid, the resulting diagram will all be four sided and the triangles close to right angled with minimum angles being 45 degrees or so. Thus, a significant excess of angles close to 60 degrees or 45 degrees indicate a pattern close to hexagon or square grid respectively.

Finally, in a pattern that has clusters of points some Delaunay triangles will have edges that represent links between points on the periphery of different clusters. Such triangles will be obtuse so that their minimum angles will be small. The distributions of such points will be indicative of a clustered arrangement of points, again pointing towards a behavior pattern. If the points are weighted then instead of taking the perpendicular bisector, a proportional bisection may be considered.

As a way of an explanatory example we will demonstrate this mathematical technique by examining the spatial distribution of certain kind of auto theft locations between February 1991 and December 1992. This period was chosen for illustrative purposes only. We will examine those crimes in which 'Chevy' auto was involved assuming that the selection of a particular type of vehicle may be suggestive of a specific behavior pattern. This illustration is limited for descriptive purposes and simplicity of tables, though the technique naturally can be applied for a larger set of points in n-dimension space too.

The chart on figure VI shows the locations, the tessellation spaces and Delaunay triangles for a set of 10 auto thefts involving Chevy cars in Burnaby. These 10 were chosen for illustrative purposes because these were located in one area and therefore could be the crimes committed by the same set of offender(s) (Fleming 1994). The following values of the minimum angles (in degrees) were obtained from the chart: 12, 13, 17, 21, 22, 23, 24, 25, 27, 40 . The table 8.1 below gives the cumulative totals, probability and differences:

Table 8.1

Summary of Results from Delaunay Triangle Analysis

Degrees	Frq	Cum.Frq	Cum.Prop. F(z)	Cum.Ex Prop.P(z)
0-5	0	0	0.0	0.0152
6-10	0	0	0.0	0.0602
11-15	2	2	0.2	0.1331
16-20	1	3	0.3	0.2302
21-25	5	8	0.8	0.3464
26-30	1	9	0.9	0.4743
31-35	0	9	0.9	0.6056
36-40	1	10	1.0	0.7309
41-45	0	10	1.0	0.8408
46-50	0	10	1.0	0.9266
51-55	0	10	1.0	0.9812
56-60	0	10	1.0	1.0000

Finally, the absolute differences of F(z)-P(z) are calculated and the maximum D_{max} is then obtained. From the table we get the maximum value to be 0.4536. The critical value from the tables for $\alpha = 0.10$ is 0.368 for n = 10 (Massey 1951). The result is not found to be significant for any smaller values of α. The conclusion that these auto theft sites form a cluster is not so strongly supported, though the result appears to hold for with a type I error of 10%. It may therefore be worthwhile for the investigator to examine these *nodes* together, for these may be part of the same operation or modus operandi.

Implications

The technique of Voronoi diagrams can easily be extended to any n-dimensional space where points become objects with vector values. Furthermore, the spatial analysis of crime sites, offender residences, the territorial boundaries of gangs, areas of operation of serial offenders and police patrol coverage, can all be analyzed by Voronoi diagram based techniques. It brings into play powerful geometrical concepts, along with sharp analytical techniques of calculus, analysis, algebra and trigonometry to offer exciting possibilities for the researcher. It also demonstrates how beginning with simple concepts, mathematical techniques can gradually be built upon into complex structures that could be applied in a variety of fields with some fruitful results.

---x---

CHAPTER IX

THE FRACTAL DIMENSION OF POLICING

In the previous chapters we have seen how mathematical techniques lead to the development of new and different perspectives in the study of criminal behaviour. We have presented the mathematics of fuzzy logic that can provide a powerful tool and model to explore the holistic and fuzzy nature of human thinking and communicating abilities. Based upon it a technique was developed that could be applied in profiling offender templates and differences that are fuzzy in nature.

Topology on the other hand provides a useful bag of techniques that appear better able to model the natural surroundings through the conceptualization of interior, exterior regions, edges and boundaries in our habitat. Topology was also seen to provide a link between the spatial and temporal dimensions of the criminal events. Similarly, voronoi diagrams provide another set of powerful techniques that are useful in exploring the geometrical properties of the nodes, edges, physical situation factors and awareness spaces.

However, moving beyond templates, activity spaces and beyond the subject matter of criminal behaviors, many different kinds of mathematical technique can also be examined to explore the criminal justice system dynamics. The manner of handling citizen problems, responding to calls for service, or managing the resources to meet new challenges has been handled through a variety of ways. One of the most useful and indeed widely utilized methodology is that of operations research (OR).

As (Maltz 1994 b: 201-202) points out, "The criminal justice system is an information-intensive public bureaucracy", that "...is overflowing with data, providing excellent opportunities for studies aimed at detecting patterns in the data". Not surprisingly, efforts to find patterns in this vast body of data has led to the development of several kinds of mathematical modeling techniques that have found applications in such diverse fields as simulation techniques of the system, studying criminal careers, recidivism, the deterrent effect of death penalty, in projecting prison populations, or in estimating the size of criminal populations (*e.g.*, Belkin et al 1972; Blumstein et al 1988; Ehlrich 1975; Greenberg 1978; Lattimore and Baker 1992; Maltz 1984; Rossmo and Routledge 1990; Stull 1994). Another major area of application of these techniques have been in police studies ranging from resource management to patrol allocation models (*e.g.*, Larson 1975; Chaiken and Dormont 1978b; Bodily 1978; Chelst 1978; Green and Kolesar 1984; Colville 1989).

Time Series Analysis in Criminological Research

Similarly, examining the system on a longitudinal basis to see how it behaves over a period of time and to look for inherent patterns has also been a common methodology. Such time series analysis is an indispensable tool for the studies in criminology and large contribution to the literature has been made on these techniques (Bennett 1991; Hale and Sabbagh 1991; Lin, MacKenzie and Gulledge 1986; Macmillan 1995; Powers, Hanssens and Hser 1993).

However, time series analysis have commonly imposed artificial restrictions to study patterns within the data. In some ways restrictions themselves have created artificial patterns that may even have hidden the basic nature of the stochastic process. In this chapter we will briefly outline the limitations in the common statistical analysis of time series data and explore another method that attempts to provide a different insight into the phenomenon. As an example we will use the police calls for service data, spread over a limited time period and analyze it through this technique. We will demonstrate that such police data has a fractal dimension and that it calls into question various kinds of assumptions made upon this data as well as the system dynamics that is considered neutral in its data entry practices.

The Nature of Time Series Analysis:
One of the purposes of a time series analysis is the need to forecast events based upon the information from past events. The basic procedure is to analyze the past time data, identify a pattern and then extend this pattern into the future to prepare the forecast (Bowerman and O'Connell 1979: 5).

Naturally, the underlying expectation is that the identified pattern will continue in the future. However, the time series data X_T (T= 1,2,...,n) with interval between X_T and X_{T+1} being fixed and constant is different from other kinds of data because the order of the values is equally important. Time series has four major components: trend, cycle, seasonal variations and irregular fluctuations, that commonly occur in any combination or may occur all together. It is for this reason that no single best forecasting technique exists and all time series models include some degree of errors.

In general, error terms are included to take care of unknown factors that may affect dependent variable, or to account for measurement problems and thirdly to account for the unpredictable element of randomness in human responses (Ostrom 1978: 12). Due to the probabilistic nature of the equations in temporal series, some assumptions about the error terms have to be made. In particular, the following kinds of assumptions are made:

I. Error terms have expected mean of value 0.

II. Errors have constant variance over all the observations.

III. Terms corresponding to different points in time are not correlated.

Additionally, a major problem is that of the aggregation of data over some fixed interval. Some variables have a continuous existence, like process of aging, movement of people, temperature and so on. Some are aggregated and then presented, like official statistics, census variables and offenders incarcerated in state prisons. In some cases there is little control over the time frame and in others usually there is some choice but not an unlimited one. In all such cases there is the need to give attention to the selection of the time interval over which values are being aggregated. Clearly then, in time series analysis there will not be uncontested and universal rules for analyzing the data: a great deal will depend upon the objective of the study (Kendall 1973: 6).

In this section we will examine a particular kind of time series analysis that attempts to avoid making some of the above mentioned assumptions and shifts the focus from crime, event, time to system response. Such a change in perspective also calls for an alternative approach, a process that involves a different nature of analytical methodology. The technique that we will outline here leads to an unexpected result about the temporal distribution of the data points and demands a new look at the way system is functioning and recording the events. It also presents the case where a technique raises new questions and throws new light upon the situational factors. We will demonstrate this technique with reference to the calls for police service that are recorded by the computer aided dispatch (CAD) system of Vancouver police department. The nature of these calls range from complaints about the commission of some crime to need for police assistance in handling disputes, public annoyance, officer assistance call and so on. These calls form the emergency response basis for the Vancouver police patrolling units and the registration system for public complaints about crime.

Emergency Calls for Police Services as Useful Crime Data

The number of calls for service received by the police department have great significance and several utilities, both for organizational planning and for its daily operations. Calls for service have been used as measures of crime; as arrest patterns on developing robbery trends and for analyzing informal social control in residential urban environments (Bursik, Grasmick and Chamlin 1990; Warner and Pierce 1988; Taylor, Gottfredson and Brower 1981). Sherman, Gartin and Buerger (1989) have discussed its strengths and weaknesses and found it to be a suitable source of information on crime and police functions.

Although, there exists a large literature regarding the problems of using police data (*e.g.*, Wolfgang 1963; Kituse and Cicourel 1963; Biderman and Reiss 1967; Wheeler 1967; Black 1970; Hindelang 1974; Skogan 1975; Hindelang, Hirschi and Weis 1981; Bottomley and Pease 1986; Lowman and Palys 1991) the data obtained from the CAD system is said to overcome some of the earlier criticisms of the official sources. The CAD system in use with most large police departments is primarily meant for the efficient dispatch of police officers in response to calls for service. As an incidental result of performing its primary functions, the CAD system also provides a number of benefits as collection and output of crime related information. In this system, the 911 calls are centrally processed at one location where the computer system automatically stamps the time of receipt of the call. The system adds the day, month and year and the time in hours, minutes and seconds for every call being recorded.

The category and nature of the call is identified by a police handler who directs a patrolling car, if required, to visit the place of call origin. The nature of call by code is also simultaneously entered into the system by the handler. Thus, within a short period, the call for service is coded and registered into the system as a permanent record.

Primarily, it is the largest data collection procedure that is moreover unscreened (Sherman, Gartin and Buerger 1989). The citizen action of dialing 911 immediately results in automatic recording of the location and time of the call. Of course we have already shown how the temporal dimension of criminal events are homeomorphic to their spatial space, are non-uniformly distributed and have peaks and valleys. These clearly reflect patterns of criminal events that apparently are guided by activities of everyday life. However, the police records upon which the temporal space was constructed is itself the result of different kinds of processes. These are the decisions of victims and offenders that leads to the commission of the criminal event, the individual decisions that result in a call to the police as well as the decision made by the dispatcher in recording this information into a set category. The third process too is equally significant though it has been maintained by scholars to be free of human discretion (Sherman, Gartin and Buerger 1989: 35).

The CAD recording system is meant to keep a stable and consistent definition of incidents over time. On receiving the information, the complaint is promptly coded into a specific nature of the incident that is modified only later by actual description by the visiting officers. The data is also easily accessible to researchers and machine readable for analytical purposes. The system is therefore said to increases uniformity and reduce errors in the recording.

Apart from the above mentioned facilities, the CAD system includes Standard Automated Management Reports, which assist analyses related to Response Time, Incident Queuing, Dispatch Activity, Workload, Units Fielded, Officer Activity and even personnel services (MU and Brantingham 1992). Undoubtedly, CAD is beginning to be seen as a vital and practical source of information both for crime incidents and policing purposes.

A major problem with this data is that the time stamped by the computer is about the origin of the call and not the time of offense itself. Frequently, the time of the offense is never learnt, as in auto theft cases in which only the time of discovery are known to the police. However, police response is typically based upon the time complaint is received and the actual time of the offence is frequently estimated only by the visit of investigating officers to the scene of crime. Moreover, as the previous analysis of 'burning times' suggests, the emergency calls for service do correspond to the seriousness of the offences. Thus, even with the time period of the receipt of the call, this data set is a useful source of information. However, the limitation of this data set is that the spatial coordinates are of the place from where the call was made rather than where the event took place. Since in general the call for service is usually made from within a block or so of the place where the event took place the data does approximate the place of event.

Although the "under reporting is not the outcome of decision making practices of the department or the patrol officers"

(Bursik, Grasmick and Mitchell 1990: 437), the discretion of recording the calls "generally lies with the operators who dispatch the cars" (Antunes and Scott 1981: 168). Despite some limitations the system is designed to ensure minimal human intervention and discretion thereby creating a system of increased accuracy in recording of the crime data.

As Biderman and Reiss (1967) suggest, there is no 'true' count of criminal events, only different socially organized ways of classifying them, each with different flavors and biases. With this understanding calls to police provide the most faithful and extensive account of what the public tells the police about crime or order maintenance (Sherman, Gartin & Buerger 1989). Considering that Vancouver police receive around 30000 calls for service in a month, information of this nature is valuable and at present, impossible to obtain from survey techniques or other sources.

Utility of the CAD System

For the police this automated computer aided dispatch system has become an indispensable data bank for manpower deployment, emergency planning, resource allotment and policy matters. In Vancouver, this data bank is also being used in operations and in information exchange with the city government. The number of calls per some unit time period determine how police resources and manpower reserves are deployed. Thus, evening hours that usually have much larger number of calls for service require greater number of police officers and patrol cars to be sent to the streets than early afternoon hour periods when calls are less.

Supervisors and police administrators frequently struggle with work shift policies such as rotating vs. fixed days off, the 5 to 8 versus 4 to 10 plan or the 1 to 2 officer per car schedules due to the uncertain nature and number of calls. "Such issues lie at the heart of proper allocation of police resources and changes in deployment policies can have a major impact on the productivity and efficiency of a department" (Police Chief 1989).

However, all such decisions are dependent upon the expected number and nature of calls. A proper estimate of the number of calls for service at some period of time is thus crucial for any police manager to plan the optimum and efficient use of his her resources. An ideal department always strives to have extra officers and material resources to respond quickly to any citizen call for service, the response time being as short as possible. Indeed, OR based linear programming techniques are useful in this form of modeling and have been applied in police studies (*e.g.,* Caulkins 1993; Green 1984; Kern 1989; Police Chief 1989).

Since the number of calls varies from a low around midnight hours to an unmanageable high during evening shifts, with wide fluctuations in between, it is always a problem to anticipate the number of calls and keep in reserve, surplus officers to respond promptly. Ideally, if the number of calls are low, the department would wish to deploy fewer officers, and during 'rush' periods would like to have more officers. The perfect match is to have one and only officer ready as soon as the call is received. A large number of these problems have been studied through operation research techniques (Kern 1989; Caulkins 1993; Maltz 1994b)

"The police patrol administrator is always faced with the difficult task of using scarce resources to serve an uncertain demand" (Kern 1989). In practice, the response time varies considerably, being chiefly dependent upon the availability of officers. This may lead to a dangerous situation when no officer is available at the receipt of a high priority call. On the other hand, it is uneconomic to have officers waiting with no call in sight. The problem therefore is to adopt a policy so as to match the number of calls received with the available number of officers without creating undue delays.

In analyzing the frequency distribution of calls the standard method has been to determine their mean and variance and estimate a range which has a high degree of confidence level. Police administrators have sought to improve the performance of patrol deployment by making in general two highly inter-related decision types: patrol sector design, in which the officers are assigned a sector and allowed to patrol in their own manner. In the second type, patrols are assigned on a geographical basis such that all together the area is covered by the shortest response time period (Kern 1989). Numerous management scientists have also attempted to develop patrol allocation models and algorithms for minimizing the response time in view of the uncertain or random nature of calls for service (*e.g.*, Larson 1975; Kansas City 1977 vol. I & II; Beltrani 1977; Bodily 1978; Chaiken and Dormont 1978a & b; Chelst 1978; Green 1984; Kesslu 1985; Birge and Pollock 1989).

Now, almost all police departments follow either the sectoral or the geographical coverage systems for patrolling purposes and sometimes innovate for specific tasks. Generally, such plans for personnel or vehicle deployments are based upon the standard form of statistical analysis, estimating for means and standard deviations to obtain the confidence interval. However, as any police manager knows, the methodology is not perfect and there are periods where the confidence level is seriously breached. The fault naturally does not lie in the mathematical ability of the concerned manager but in the common use of statistical techniques for the situation where the underlying assumptions of the model used may not be valid (Maltz 1994a).

In fact, in the use of statistical methods, little thought if ever is given to the nature of data. Although, statistical methods of this type clearly require the data to be randomly generated and to come from a uniformly distributed population, this requirement is never verified and rarely given any serious consideration. The methodology of determining the confidence interval for such calls for police service is thus, essentially based upon the assumption that these calls are a random selection from a uniformly distributed population. Hence, if these assumptions are violated then the whole class of statistical methods whose application assumes these properties ought to be ruled out. Consequently, building confidence intervals to estimate the fluctuations of police call data may be totally inappropriate (and therefore faulty) if the nature of data is different for the underlying assumptions of the model.

Additionally, the range of fluctuations of calls around its average is dependent upon the time interval over which the range is examined. This range would naturally change according to the length of time used for measurement. If the series of calls is random in nature, then the range will increase with the square root of the interval length in accordance with the $T^{1/2}$ rule. But for any non-random time series, such as the police call data, the statistical analysis would be dependent upon the time period chosen. The average number of calls and its variance will vary if the interval is a day or a week or a month. The police patrol administrator will determine different range of minimum and maximum calls depending upon the chosen interval of time. This is naturally quite artificial for different interpretations have to be given for different time periods of considerations. Thus, any statistical modeling for police data is at best a crude artificial exercise capable of providing any form of result as desired.

Instead of treating the recording of police data as an outcome of random external processes, these fluctuations should really be seen as being in part dependent upon the police system: number and type of dispatchers, recording procedures, citizens faith and reliance upon police services, workload and shift duty system where there is a constant change in personnel (Larson 1975; Kern 1989).

The nature of calls to police is also dependent upon disputes, actions continuing from before- the police call being the last straw, the flash point of dispute or the discovery of criminal behaviour after it has taken place. Police officers also learn to recognize nature of calls from previous experiences and thus learn to record, categorize in manner from old habits. Thus, any time series of calls (as also perhaps spatial) is likely to have a memory effect, a dependency upon previous conditions. It is pertinent to point out that the two bear a strong topological relationship, as described in chapter VII.

What we propose to show is that the police call data and thus all criminal events, are not random in their distribution and have a longitudinal memory. The assertion is that past events influence the present, and that the data of 911 calls for service are not records of random events happening at the recorded time but data of events continuing from before. We will also show that this data has a fractal dimension, a constant number that provides an estimate of its memory time period. The results would suggest that common statistical techniques are inappropriate for analyzing police data for deployment as the underlying assumptions about the data are being violated. The implications are clear: police managers must adopt other kinds of methods, perhaps from Chaos theory or other branches of mathematics for analyzing their data.

Since, common statistical analysis can be done only if the call data is randomly distributed some other more complex statistical techniques have been developed for the time series but which make other kinds of assumptions. Therefore, what we propose here is the R/S analytical technique that makes no such assumptions. This methodology has been developed by Mandelbrot (1972) and which is based upon the Hurst exponent (1951). In this method, range of fluctuations around an average are calculated for different time periods and the measure is standardized by division of its variance (thus also called as the Rescaled Range analysis). The examination of the variation of this rescaled range with the different time periods provides an estimate of the inherent trend in the observations recorded.

Analytical Tools and Data Sources:

This analysis will be based upon the data obtained from the 911 calls for service of Vancouver police through their CAD system. The CAD data has been made available under controlled access to the Simon Fraser University Research

Data library by Vancouver police and the data is available in machine readable format. A computer program routine has been built in that facilitates retrieval by time period, nature or place of call, or many other variables as required. The data used in this analysis was obtained from the period 1990-1993 for different months and for different crime types. The strengths and weaknesses of this data source has already been discussed above and therefore we will directly proceed to the development of the technique.

TECHNIQUE

Based upon the procedure developed by Hurst in his study of fluctuations of Nile river in Aswan Dam, we define an existing time series as follows:

$$X(t,N) = \sum_{z=1}^{t} (i_z - A_N) \qquad \text{(i)}$$

where

$X(t,N)$ = cumulative deviations over N periods

i_z = number of calls in hour z

A_N = Average number of calls over N periods.

The range then becomes the difference between the maximum and minimum levels attained in (i) above.

Thus $R = \text{Max}[X(t,N)] - \text{Min}[X(t,N)]$

where R = range of X; Max(X) = maximum value of X

and Min(X) = minimum value of X.

Based upon the above definitions, we examined an hourly frequency distribution of police service calls and calculated its range of fluctuations for different time periods. To explore this technique we picked a month's data, the hourly frequencies of emergency calls for the month of June 1991. This provided 720 data points (24 x 30) from which the values of R were calculated for time periods starting from 5 to 360. Thus, the 720 data points were first divided into 145 non-overlapping intervals of five hourly time periods (720/5) and range of each of these periods was calculated. Standard deviation of the calls around the means of each intervals for each time period was also calculated. This provided 145 values of R and a similar number of values of standard deviations. From these 145 values of R/S were calculated and their mean value taken for that interval. This procedure was repeated for N = 5, 6,7...360[1].

The frequency distribution of the calls and the estimated R/S values for different time periods were then calculated by this program and plotted as on a log-log graph shown on figure VII.

---

[1] The complete program written for this purpose is attached as appendix 16.

According to Hurst, $R/S = (a*n)^H$ (Hurst 1951) where H is the hurst exponent. In order to estimate the value of H we can take logs of both sides and plot log (R/S) vs. log(N). The slope of the graph will indicate an estimate of H. This procedure makes no assumption about the shape of the underlying distribution and thus makes no demand upon the nature of data.

The impact of the present on the future can be expressed as a correlation $C = 2^{(2H-1)} - 1$ (Peters 1991: 64). Here C is the correlation measure and H is the Hurst exponent. For the case when $H = 0.5$, $C = 0$, that is the series is random and there is no correlation between the past and the present. For values of $0 < H < 0.5$, the series is ergodic: if the past values are large then the present will be small and vice versa. When $0.5 < H < 1$ it is a trend reinforcing series; high values of past are likely to push the present values even higher. Such persistent series are defined as 'Fractional Brownian motion' and are more common in nature (Mandelbrot 1986: 8). It is known that $H = 0.5$ for series which is a random walk and its cumulative deviations increase with the square root of the time period.

Our calculation of the police call data from the log-log plot gives the value $H = 0.621$. This indicates that many of the calls are associated with events that are not independent. In other words, the recording of the calls for service at the present time is being determined by past events.

In order to test whether the calls for service records were being influenced by past events or some additional factor that has time dependency or 'effective memory', the data was scrambled, that is randomly distributed. This was done by entering random numbers from a table along-side the distribution of calls and then sorting the two distributions by the column of random numbers. This procedure scrambles the calls in a random fashion. The 'new' series of calls was again analyzed for its R/S values by the same procedure. The time series of (i) was used again but with the scrambled 'new' frequency distribution of calls and through the same program routine. The 'new' SR/S values were similarly plotted on log-log graph against the varying time interval from 5 to 360 (see figure VIII).

Interestingly, when the call data (720 points) were scrambled (arranged randomly) the same analysis gives the value of H to be 0.49, a value close to 0.5. A similar treatment of random numbers also led to the same result, H = 0.50, despite any type of scrambling of these random numbers. The implications are clear: scrambling destroys the 'memory' effect and makes the time series random in nature. But in other words, the police call data does reflect a 'memory' and bears influence of the past values. This demonstrates that it is not randomly distributed over time and application of any statistical technique that assumes independence over it is likely to be misleading.

Implications

Mandelbrot (1972) has shown that the inverse of the Hurst exponent, 1/H is the fractal dimension of the distribution. Accordingly, the fractal dimension of police call data is 1/0.62 which is 1.61. For H = 0.5, a random series the fractal dimension is 2 and for all other values this dimension lies between 1 and 2. Peters (1991: 101) has suggested that the value at which the slope of the graph in R/S vs. N log/log plot starts dropping provides an estimate of the average cycle of the original data series. In our case the slope drops approximately at log(N) = 3.4, that is N = 30.

In order to judge the stability of this result, a similar analysis was done for some other months and for some specific crime types. In particular, frequency distributions of calls for service for the period June 1992, to compare the results for another year and January 1993 to explore another different time period was undertaken.

Similar analysis of specific crime types like 'thefts from autos' and 'assaults' was also done about their underlying patterns and periodic cycles. These particular crime types were chosen because these have a much greater 'density' of distribution than the others that have a large number of 'gaps' with zero values. All these time series data was analyzed using the same computer program and from the resultant graphs, an estimate was made about their slopes. The results constituting the period and type of crime analysis, the slope of the R/S series, the Hurst component values and the ensuing fractal dimensions are summarized below:

Crime Type	**H**	**Fractal Dimension**
Assaults		
R/S values	0.59531	1.68
SR/S values	.488934	2.04
Theft from Auto		
R/S values	0.57163	1.75
SR/S values	.548452	1.82
calls-Jan'93		
R/S values	0.62214	1.61
SR/S values	0.49312	2.02
calls-June'92		

R/S values	0.622076	1.61
SR/S values	0.475337	2.05

The log-log graphs of the R/S values and the scrambled SR/S values for the crime of assaults and theft from motor vehicles are displayed as figure IX - XII.

The greater value of the fractal dimension for a series implies it fluctuates more widely (Peters 1992). Thus, the higher fractal dimension for the crimes of assaults and thefts from autos indicates that their periodicity is greater than for the total calls for service. The fractal dimension therefore provides a unit of analysis for the fluctuations of different types of calls and a different method of examining the time series data. Moreover, R/S offers a method to analyze such fluctuations of specific crime series without demanding anything about their underlying nature.

This is only a tentative examination of the technique and its application to the police call data. Further, examination of data for different months and for longer time needs to be done before a more precise value for the fractal dimension can be estimated. Since this is a new technique that is being applied to the police call data it is difficult to conjecture the reasons for such a fractal dimension to this time series. This requires research beyond the scope of such an exploratory analysis.

Impact of Method upon Theory

Clearly then, R/S technique appears to initiate a stage where the method will influence the theory. In the application of statistical techniques, by making some assumptions about the nature of the data, useful results could be obtained to explain the reason for the trends in the time series. On the other hand, a different nature of mathematical analysis which avoids making the same kind of assumptions ends up creating a radically different perspective that now demands a new theoretical explanation.

By eliminating any assumptions about the nature of the data, the technique does assist in displaying some inherent trends but these in turn naturally raise several questions. Why do different crime types display periodicity if the argument is that the police handlers are somehow influencing the recording procedure? What is the periodicity of the series telling us? These are questions that remain unanswered at present and call for greater in depth analysis of the data as well as an examination of the procedures involved in recording of the data.

Moreover, as this thesis has been arguing, criminologists need to pay greater attention to the other kinds of mathematical techniques and structures. Fractals have been used in the description of the shape of the universe (Martinez 1990; Perdang 1990; Iuo and Schramm 1992), in ecological studies (Meltzer and Hastings 1992), in the exploration of geographical data (The Geographical Magazine 1992), in studying organizations (Wheatley 1993), in examining the structure of materials (Fahmy, Russ and Koch 1991), in medical sciences (Majumdar, Weinstein and Prasad 1993) and in many other kinds of subject matters. This kind of mathematics that reveals patterns within patterns appears to be the kind most appropriate and useful in explaining the crime phenomenon. The patterns at the micro level have similar characteristics at the macro level and this is a clear indication of the state that has a fractal dimension. Above all, this kind of mathematics provides a useful concept to develop a different nature of criminological inquiry, one that sees events from the individual stage but transcending to the group level.

---X---

CHAPTER X

CONCLUSION

This dissertation has argued for placing a greater emphasis upon mathematics in criminology and to assert that quantitative methods ought to be associated with mathematics rather than just statistical techniques. The dissertation also pointed out that at the philosophical level mathematics bridges the gap between quantitative and qualitative methodologies and therefore mathematics should not be a pariah to the latter group of researchers. The essential difference between the two kinds of approaches lies generally in a preference by the researcher for mathematics over language as a tool of communication.

Furthermore, the major effort of this dissertation has been in the exploration and description of some mathematical techniques, little or never applied so far in criminology and displaying their usefulness for this subject. The treatment of these techniques in such an exploratory study had to be necessarily limited to the analysis of some small data sets with the wish to demonstrate their potentiality. Much work remains ahead to probe deeper into these and other mathematical techniques and to explore their applications in a wide variety of crime data. However, the dissertation hopefully contributes to the growth of criminological literature by raising awareness amongst its practitioners of new possibilities and approach to the study of crime. The consequence of this work may widen the debate about the utility of quantitative methods and different kinds of mathematical techniques in exploring the crime phenomena.

In each of the sections that describe the techniques, possibilities for several new fields that could be investigated through them have also been pointed out. Nevertheless, it needs to be stated that these are not the only appropriate techniques that could be used. Mathematics, as has been stated again and again, is rich in terms of techniques and there are several other branches that could profitably be used by the criminologist. The subject matter of mathematics in this respect has immense possibilities chiefly because of the creativity it affords to the researcher. Mathematics provides a powerful impetus to mental imagery, intuition and the freedom to move across a multidimensional field of data that may be unconnected or connected inappropriately. The interplay between mathematics and creative imagination and the application of its powerful techniques to criminal justice system data is likely to provide strength in understanding the fascinating world of criminal behaviour. As Miller A. (1987: 312) points out, "...mental imagery is a key ingredient in creative scientific thinking", and there is no better tool than mathematics to unleash creative imagination in criminological research.

Some indication about the potential of mathematics has been given by Greenberg's book 'Mathematical Criminology' (1979) where the author demonstrates the application of such diverse techniques as calculus, linear algebra, matrix algebra, probability theory and certain kinds of stochastic processes. Coleman (1964), Fararo (1973), Leik and Meeker (1975) too have outlined different techniques that may be applied in criminological studies. Maltz (1994b) has further opened the field by outlining the utility of operation research techniques in the study of criminal justice system.

Several other authors have demonstrated application of Network analysis (Sarnecki 1990), different kinds of econometric modeling techniques (Reilly and Witt 1992; Alkan, Demange and Gale 1991) and computer simulations (Stull 1994; Kern 1989) that appear to be initiating a new era of quantitative methods to the discipline of criminology. Further possibilities could lie in the mathematics of group theory, fourier series analysis, differential equations, vector algebra and fractal geometry.

The movement towards a search for new techniques going beyond statistics has already emerged in criminology literature and the number of methodologists searching for alternative ways to analyze crime data is growing steadily. Therefore, if this dissertation succeeds in generating interest amongst the criminology fraternity for a greater and creative usage of mathematics and an approach different from the standard statistical techniques then this effort would be considered to be well rewarded.

---x---

APPENDIX 1

CLASSIFICATION OF QUANTITATIVE TECHNIQUES

The articles were classified on the basis of the *dominant* technique used for the analysis and justification of the subject matter. In the instance where the author himself /herself indicated the technique, as in the 'Keyword', that was accepted, otherwise amongst all the techniques used, the one that was most 'advanced' in nature was determined as the dominant one. In general, the following chart provides the types of techniques and their classification scheme followed consistently:

Descriptive: Summary statistics, including table frequencies and graphs, charts.

Analytical: Correlations, Testing of hypotheses through T-tests, Chi-square tests, Regression, ANOVA, Factorial Analysis, Discriminant Analysis, Principal Component Analysis.

Sampling: Any quantitative techniques discussing or illustrating sampling of population.

Advanced: Multivariate Analysis, Canonical Correlation, Non-Parametric Statistics, Cluster Analysis, MANOVA, OLS, Logit, Probit, Tobit, Path Analysis, ARIMA, LISREL, Time Series analysis, Stochastic processes, Survival Function Analysis, Causal Modeling.

Mathematics: Poisson process models, Probability models, Markov chain models, Growth-Decay models, Econometric models, Network analysis, computer simulation techniques. Those advanced statistical methods that discussed the assumptions, built the mathematical model through equations, relationship amongst variables etc. have also been included under this classification.

Qualitative: Apart from the common techniques under this head, the articles where the numbers were at best used for illustration rather than for any analysis or justification of the argument have also been included.

---x---

APPENDIX 2

CONTIGUITY OF CENSUS TRACTS

TRACTS				Adjacent tracts						
	A:B	A:C	A:D	A:E	A:F	A:G	A:H	A:I	A:J	A:K
1	2	15.01	15.02							
2	1	15.02	15.01	14	3	13.02				
3	2	13.02	11	4						
4	3	13.02	11	6	5					
5	4	6	7							
6	5	4	11	10.02	7					
7	5	6	10.02	10.01	9	8				
8	7	9	22	23	24					
9	8	7	22	21	23	20	10.01	10.02		
10.01	9	10.02	7	21	20	19	12	11		
10.02	7	6	11	12	10.01	9				
11	4	3	13.02	13.01	12	10.01	10.02	6		
12	11	13.02	13.01	18.02	19	20	10.01	10.02		
13.01	13.02	14	18.01	18.02	19	12	11			
13.02	3	2	14	13.01	12	11	4			
14	2	15.02	17.01	18.01	13.01	13.02				
15.01	1	2	15.02	16.01						
15.02	2	1	15.01	16.01	17.01	14				
16.01	15.01	16.02	17.02	17.01	15.02					
16.02	16.01	17.01	17.02	35	36.01	36.02				
17.01	15.02	16.01	16.02	17.02	34.01	18.01	14	34.02		
17.02	17.01	16.01	16.02	35	34.02	34.01				
18.01	14	17.01	34.01	33	18.02	13.01				
18.02	13.01	18.01	34.01	33	30	19	12			
19	12	18.02	33	30	29	20	10.01	13.01		
20	10.01	12	19	29	28	21	9			
21	9	10.01	20	28	40	41	27	22		
22	9	21	27	23	8					
23	8	22	27	26	25	24				
24	8	23	26	25						
25	24	23	26	42	43					
26	23	27	41	42	25	24				
27	22	21	41	42	26	23				
28	20	29	39	40	41	21				
29	20	19	30	31.01	39	40	28			
30	19	18.02	33	32	31.02	31.01	29			
31.01	30	31.02	38	39	29					
31.02	30	33	32	37	38	39	31.01			
32	33	34.01	34.02	37	38	31.02	30			
33	18.02	18.01	34.01	34.02	32	31.02	30	19		
34.01	18.01	17.01	17.02	34.02	32	33	18.02			
34.02	34.01	17.02	17.01	35	37	32	33			

TRACTS				Adjacent tracts						
35	17.02	16.02	36.01	52.01	51	50.02	37	34.02		
36.01	16.02	36.02	52.01	51	35					
36.02	16.02	36.01	52.01							
37	32	34.02	35	51	50.02	50.01	38	31.02		
38	31.02	32	37	50.01	49.01	39	31.01			
39	29	31.01	31.02	38	50.01	49.01	40	28		
40	28	29	39	49.01	48	41	21			
41	27	21	28	40	49.01	48	46	45.02	42	26
42	25	26	41	46	45.02	44	43			
43	25	42	45.02	44						
44	43	42	45.02	45.01						
45.01	44	45.02	46	47						
45.02	42	41	46	47	45.01	44	43			
46	41	48	47	45.01	45.02	42				
47	46	48	45.01	45.02						
48	41	40	49.01	49.02	47	46				
49.01	40	39	38	50.01	57..0	59.01	49.02	48	41	
49.02	49.01	48								
50.01	38	37	50.02	56	57	59.01	49.01	39		
50.02	37	35	51	54	56	57	50.01			
51	35	36.01	52.01	52.02	54	56	50.02	37		
52.01	36.01	36.02	35	51	54	52.02				
52.02	52.01	51	54	53						
53	52.02	54	55.01	55.02						
54	51	52.01	52.02	53	55.01	56	50.02			
55.01	54	53	55.02	56						
55.02	55.01	53	56							
56	50.02	51	54	55.01	55.02	58	57	50.01		
57	49.01	50.01	50.02	56	58	59.01				
58	56	57	59.01							
59.01	49.01	50.01	57	58	59.02	64	65	66		
59.02	59.01	60	64	65						
60	59.02	61	63	64						
61	60	62	63	64						
62	61	63	67	68						
63	60	61	62	64	65	67				
64	60	61	63	67	65	59.02	59.01			
65	64	59.02	59.01	66	67	63				
66	65	59.01	67							
67	68	62	63	64	65	66				
68	62	63	67							

APPENDIX 3

CONNECTIVITY BY ETHNICITY 10% CUT

TRACTS	Adjacent tracts									
	A:B	A:C	A:D	A:E	A:F	A:G	A:H	A:I	A:J	A:K
1.00	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2.00	0	1	0	0	0	0	#N/A	#N/A	#N/A	#N/A
3.00	0	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
4.00	0	1	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
5.00	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
6.00	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
7.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
8.00	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
9.00	0	0	0	1	1	0	0	0	#N/A	#N/A
10.01	0	0	0	0	1	1	0	0	#N/A	#N/A
10.02	0	1	0	1	0	0	#N/A	#N/A	#N/A	#N/A
11.00	1	0	0	1	1	0	0	0	#N/A	#N/A
12.00	1	0	0	1	0	0	0	1	#N/A	#N/A
13.01	1	1	1	1	0	0	1	#N/A	#N/A	#N/A
13.02	1	0	1	1	0	1	1	#N/A	#N/A	#N/A
14.00	0	0	1	1	1	1	#N/A	#N/A	#N/A	#N/A
15.01	0	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
15.02	1	0	1	1	0	0	#N/A	#N/A	#N/A	#N/A
16.01	1	1	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A
16.02	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
17.01	0	0	1	1	1	1	1	1	#N/A	#N/A
17.02	1	0	1	1	1	1	#N/A	#N/A	#N/A	#N/A
18.01	1	1	1	0	1	1	#N/A	#N/A	#N/A	#N/A
18.02	1	0	1	1	0	0	1	#N/A	#N/A	#N/A
19.00	0	0	0	1	0	0	1	0	#N/A	#N/A
20.00	1	0	0	0	0	0	0	#N/A	#N/A	#N/A
21.00	1	0	0	0	0	0	0	0	#N/A	#N/A
22.00	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
23.00	0	0	0	0	1	1	#N/A	#N/A	#N/A	#N/A
24.00	0	1	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
25.00	1	1	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
26.00	0	1	0	0	0	0	#N/A	#N/A	#N/A	#N/A
27.00	0	0	0	0	1	0	#N/A	#N/A	#N/A	#N/A
28.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
29.00	0	0	0	0	0	0	0	#N/A	#N/A	#N/A
30.00	1	0	1	1	1	0	0	#N/A	#N/A	#N/A
31.01	0	0	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A
31.02	1	1	1	0	0	0	0	#N/A	#N/A	#N/A
32.00	1	1	1	0	0	1	1	#N/A	#N/A	#N/A
33.00	1	0	1	1	1	1	1	0	#N/A	#N/A
34.01	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
34.02	1	1	1	1	0	1	1	#N/A	#N/A	#N/A

TRACTS			Adjacent tracts							
35.00	1	1	1	1	1	0	0	1	#N/A	#N/A
36.01	1	0	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
36.02	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
37.00	0	0	0	0	0	1	0	0	#N/A	#N/A
38.00	0	0	0	0	0	0	0	#N/A	#N/A	#N/A
39.00	0	0	0	0	0	0	0	0	#N/A	#N/A
40.00	0	0	0	0	0	1	0	#N/A	#N/A	#N/A
41.00	0	0	0	1	0	0	1	1	0	0
42.00	0	0	0	0	1	0	1	#N/A	#N/A	#N/A
43.00	0	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
44.00	1	0	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
45.01	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
45.02	1	1	1	0	0	1	1	#N/A	#N/A	#N/A
46.00	1	0	0	0	1	0	#N/A	#N/A	#N/A	#N/A
47.00	0	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
48.00	0	0	0	0	1	0	#N/A	#N/A	#N/A	#N/A
49.01	0	0	0	0	#N/A	0	0	0	0	#N/A
49.02	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
50.01	0	1	0	0	0	0	0	0	#N/A	#N/A
50.02	0	0	0	0	0	0	0	#N/A	#N/A	#N/A
51.00	1	1	1	1	1	0	0	1	#N/A	#N/A
52.01	1	0	1	1	1	1	#N/A	#N/A	#N/A	#N/A
52.02	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
53.00	1	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
54.00	1	1	1	1	0	0	0	#N/A	#N/A	#N/A
55.01	0	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
55.02	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
56.00	0	0	0	0	1	0	0	0	#N/A	#N/A
57.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
58.00	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
59.01	0	0	0	0	0	0	1	1	#N/A	#N/A
59.02	0	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
60.00	1	1	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
61.00	1	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
62.00	0	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
63.00	1	0	0	1	1	0	#N/A	#N/A	#N/A	#N/A
64.00	1	1	0	0	0	1	0	#N/A	#N/A	#N/A
65.00	0	0	1	1	0	1	#N/A	#N/A	#N/A	#N/A
66.00	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
67.00	0	0	0	0	0	1	#N/A	#N/A	#N/A	#N/A
68.00	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A

APPENDIX 4

CONNECTIVITY BY POPULATION DENSITY 10% CUT

TRACTS			Adjacent tracts							
density	A:B	A:C	A:D	A:E	A:F	A:G	A:H	A:I	A:J	A:K
1.00	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
3.00	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
4.00	0	0	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
5.00	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
6.00	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
7.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
8.00	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
9.00	0	0	0	0	1	0	0	0	#N/A	#N/A
10.01	0	1	0	0	0	1	0	0	#N/A	#N/A
10.02	0	0	0	0	1	0	#N/A	#N/A	#N/A	#N/A
11.00	1	0	0	0	0	0	0	0	#N/A	#N/A
12.00	0	0	0	0	0	0	0	0	#N/A	#N/A
13.01	1	0	0	0	0	0	0	#N/A	#N/A	#N/A
13.02	0	0	1	1	0	0	0	#N/A	#N/A	#N/A
14.00	0	0	0	0	1	1	#N/A	#N/A	#N/A	#N/A
15.01	0	0	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
15.02	0	0	1	0	0	0	#N/A	#N/A	#N/A	#N/A
16.01	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
16.02	0	1	0	0	0	0	#N/A	#N/A	#N/A	#N/A
17.01	0	0	1	0	0	0	0	1	#N/A	#N/A
17.02	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
18.01	0	0	1	0	0	0	#N/A	#N/A	#N/A	#N/A
18.02	0	0	0	1	0	0	0	#N/A	#N/A	#N/A
19.00	0	0	0	0	0	0	1	0	#N/A	#N/A
20.00	0	0	0	0	0	1	0	#N/A	#N/A	#N/A
21.00	0	0	1	0	0	0	0	0	#N/A	#N/A
22.00	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
23.00	0	0	0	1	1	0	#N/A	#N/A	#N/A	#N/A
24.00	0	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
25.00	1	1	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
26.00	1	0	0	0	1	1	#N/A	#N/A	#N/A	#N/A
27.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
28.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
29.00	0	0	0	0	0	0	0	#N/A	#N/A	#N/A
30.00	0	0	0	0	0	0	0	#N/A	#N/A	#N/A
31.01	0	1	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A
31.02	0	0	0	0	1	1	1	#N/A	#N/A	#N/A
32.00	0	0	0	0	0	0	0	#N/A	#N/A	#N/A
33.00	1	0	0	0	0	0	0	0	#N/A	#N/A
34.01	1	0	0	0	0	0	0	#N/A	#N/A	#N/A
34.02	0	0	1	0	0	0	0	#N/A	#N/A	#N/A

TRACTS			Adjacent tracts							
35.00	0	0	1	1	0	0	0	0	#N/A	#N/A
36.01	0	1	1	0	1	#N/A	#N/A	#N/A	#N/A	#N/A
36.02	0	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
37.00	0	0	0	0	0	0	0	0	#N/A	#N/A
38.00	1	0	0	0	0	1	1	#N/A	#N/A	#N/A
39.00	0	1	1	1	0	0	0	0	#N/A	#N/A
40.00	0	0	0	0	0	0	0	#N/A	#N/A	#N/A
41.00	0	0	0	0	0	0	0	0	0	0
42.00	0	0	0	0	0	0	0	#N/A	#N/A	#N/A
43.00	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
44.00	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
45.01	0	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
45.02	0	0	0	0	1	0	0	#N/A	#N/A	#N/A
46.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
47.00	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
48.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
49.01	0	0	0	0	#N/A	1	0	0	0	#N/A
49.02	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
50.01	0	0	0	1	1	0	0	0	#N/A	#N/A
50.02	0	0	0	0	0	0	0	#N/A	#N/A	#N/A
51.00	0	0	0	0	1	1	0	0	#N/A	#N/A
52.01	1	0	1	0	0	1	#N/A	#N/A	#N/A	#N/A
52.02	1	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
53.00	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
54.00	1	0	0	0	1	1	0	#N/A	#N/A	#N/A
55.01	1	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
55.02	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
56.00	0	1	1	1	0	0	0	1	#N/A	#N/A
57.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
58.00	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
59.01	1	0	0	0	0	0	0	0	#N/A	#N/A
59.02	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
60.00	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
61.00	0	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
62.00	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
63.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
64.00	0	1	0	0	0	0	0	#N/A	#N/A	#N/A
65.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
66.00	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
67.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
68.00	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A

APPENDIX 5

CONNECTIVITY BY RENTED HOUSING 10% CUT

TRACTS	Adjacent tracts								
	A:B	A:C	A:D	A:E	A:F	A:G	A:H	A:I	A:J	A:K
1.00	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2.00	0	1	0	0	0	0	#N/A	#N/A	#N/A	#N/A
3.00	0	0	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
4.00	1	0	0	1	0	#N/A	#N/A	#N/A	#N/A	#N/A
5.00	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
6.00	0	1	0	1	0	#N/A	#N/A	#N/A	#N/A	#N/A
7.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
8.00	0	0	0	1	0	#N/A	#N/A	#N/A	#N/A	#N/A
9.00	0	0	0	0	1	0	0	0	#N/A	#N/A
10.01	0	1	0	0	0	1	1	0	#N/A	#N/A
10.02	0	1	0	0	0	0	#N/A	#N/A	#N/A	#N/A
11.00	0	1	0	1	1	0	0	0	#N/A	#N/A
12.00	1	0	0	0	0	0	1	0	#N/A	#N/A
13.01	0	0	1	1	0	0	1	#N/A	#N/A	#N/A
13.02	0	0	0	0	1	0	0	#N/A	#N/A	#N/A
14.00	0	1	0	0	1	0	#N/A	#N/A	#N/A	#N/A
15.01	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
15.02	1	0	0	0	0	1	#N/A	#N/A	#N/A	#N/A
16.01	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
16.02	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
17.01	0	0	0	0	1	0	0	0	#N/A	#N/A
17.02	0	0	0	1	0	1	#N/A	#N/A	#N/A	#N/A
18.01	0	0	1	1	0	1	#N/A	#N/A	#N/A	#N/A
18.02	1	1	0	1	1	0	0	#N/A	#N/A	#N/A
19.00	1	0	0	0	0	0	1	0	#N/A	#N/A
20.00	0	0	0	0	0	1	0	#N/A	#N/A	#N/A
21.00	0	0	1	0	0	0	0	0	#N/A	#N/A
22.00	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
23.00	1	0	0	0	0	1	#N/A	#N/A	#N/A	#N/A
24.00	1	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
25.00	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
26.00	0	1	0	0	0	0	#N/A	#N/A	#N/A	#N/A
27.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
28.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
29.00	0	1	0	1	0	0	0	#N/A	#N/A	#N/A
30.00	0	1	1	0	0	0	0	#N/A	#N/A	#N/A
31.01	0	1	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
31.02	0	0	0	0	0	0	1	#N/A	#N/A	#N/A
32.00	0	0	1	0	0	0	0	#N/A	#N/A	#N/A
33.00	1	1	1	0	0	0	1	0	#N/A	#N/A
34.01	0	0	1	1	0	1	1	#N/A	#N/A	#N/A
34.02	1	0	0	1	0	1	0	#N/A	#N/A	#N/A

TRACTS			Adjacent tracts							
35.00	1	0	0	0	1	0	0	1	#N/A	#N/A
36.01	0	1	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
36.02	0	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
37.00	0	0	0	0	0	0	0	0	#N/A	#N/A
38.00	0	0	0	1	0	1	0	#N/A	#N/A	#N/A
39.00	0	0	0	1	0	0	1	0	#N/A	#N/A
40.00	0	0	1	0	0	0	0	#N/A	#N/A	#N/A
41.00	0	0	0	0	0	1	0	1	0	0
42.00	0	0	0	0	0	1	0	#N/A	#N/A	#N/A
43.00	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
44.00	0	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
45.01	0	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
45.02	0	1	0	0	0	0	0	#N/A	#N/A	#N/A
46.00	0	1	1	0	1	0	#N/A	#N/A	#N/A	#N/A
47.00	1	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
48.00	1	0	0	1	1	1	#N/A	#N/A	#N/A	#N/A
49.01	0	0	0	0	#N/A	0	0	0	0	#N/A
49.02	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
50.01	1	0	1	1	1	0	0	1	#N/A	#N/A
50.02	0	0	0	0	0	1	1	#N/A	#N/A	#N/A
51.00	1	0	0	1	1	0	0	0	#N/A	#N/A
52.01	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
52.02	0	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
53.00	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
54.00	0	0	0	0	0	0	0	#N/A	#N/A	#N/A
55.01	0	0	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
55.02	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
56.00	1	0	0	0	0	0	1	1	#N/A	#N/A
57.00	0	1	1	1	0	0	#N/A	#N/A	#N/A	#N/A
58.00	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
59.01	0	0	0	1	0	1	1	0	#N/A	#N/A
59.02	0	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
60.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
61.00	1	0	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
62.00	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
63.00	1	1	0	0	1	1	#N/A	#N/A	#N/A	#N/A
64.00	1	1	0	1	1	1	1	#N/A	#N/A	#N/A
65.00	1	1	1	1	1	0	#N/A	#N/A	#N/A	#N/A
66.00	1	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
67.00	1	0	1	1	1	1	#N/A	#N/A	#N/A	#N/A
68.00	0	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A

APPENDIX 6

CONNECTIVITY BY SINGLE PARENT 10% CUT

TRACTS	Adjacent tracts								
	A:B	A:C	A:D	A:E	A:F	A:G	A:H	A:I	A:J	A:K
1.00	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2.00	0	0	0	0	1	1	#N/A	#N/A	#N/A	#N/A
3.00	1	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
4.00	0	0	0	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
5.00	0	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
6.00	1	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
7.00	0	0	0	0	1	0	#N/A	#N/A	#N/A	#N/A
8.00	0	0	0	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
9.00	0	1	1	0	1	0	0	0	#N/A	#N/A
10.01	0	0	0	0	0	0	0	0	#N/A	#N/A
10.02	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
11.00	0	1	1	0	0	0	0	0	#N/A	#N/A
12.00	0	0	1	1	0	0	0	0	#N/A	#N/A
13.01	0	1	0	1	0	1	0	#N/A	#N/A	#N/A
13.02	1	1	0	0	0	1	0	#N/A	#N/A	#N/A
14.00	0	0	0	0	1	0	#N/A	#N/A	#N/A	#N/A
15.01	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
15.02	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
16.01	0	1	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
16.02	0	0	1	1	0	0	#N/A	#N/A	#N/A	#N/A
17.01	0	0	0	0	0	0	0	0	#N/A	#N/A
17.02	0	0	1	1	0	0	#N/A	#N/A	#N/A	#N/A
18.01	0	0	1	1	1	0	#N/A	#N/A	#N/A	#N/A
18.02	1	1	1	1	1	0	1	#N/A	#N/A	#N/A
19.00	0	0	0	0	0	0	0	0	#N/A	#N/A
20.00	0	0	0	0	0	1	0	#N/A	#N/A	#N/A
21.00	0	0	1	0	0	0	0	0	#N/A	#N/A
22.00	1	0	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A
23.00	1	1	1	1	0	1	#N/A	#N/A	#N/A	#N/A
24.00	1	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
25.00	1	1	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A
26.00	1	1	0	0	0	1	#N/A	#N/A	#N/A	#N/A
27.00	1	0	0	0	1	1	#N/A	#N/A	#N/A	#N/A
28.00	0	0	0	1	0	0	#N/A	#N/A	#N/A	#N/A
29.00	0	0	1	0	0	0	0	#N/A	#N/A	#N/A
30.00	0	1	1	0	1	0	1	#N/A	#N/A	#N/A
31.01	0	1	0	1	0	#N/A	#N/A	#N/A	#N/A	#N/A
31.02	1	0	1	0	0	1	1	#N/A	#N/A	#N/A
32.00	0	1	1	0	0	1	1	#N/A	#N/A	#N/A
33.00	1	1	0	0	0	0	1	0	#N/A	#N/A
34.01	0	0	0	0	1	1	1	#N/A	#N/A	#N/A
34.02	0	0	0	0	0	1	0	#N/A	#N/A	#N/A

TRACTS			Adjacent tracts							
35.00	1	1	0	0	0	0	0	0	#N/A	#N/A
36.01	0	1	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
36.02	0	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
37.00	0	0	0	0	0	1	1	0	#N/A	#N/A
38.00	0	0	1	1	0	0	0	#N/A	#N/A	#N/A
39.00	0	1	1	0	0	0	0	0	#N/A	#N/A
40.00	1	0	0	0	0	0	0	#N/A	#N/A	#N/A
41.00	0	0	0	0	1	0	0	0	1	0
42.00	0	0	1	0	0	0	0	#N/A	#N/A	#N/A
43.00	1	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
44.00	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
45.01	0	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
45.02	0	0	1	0	1	0	0	#N/A	#N/A	#N/A
46.00	0	1	0	1	1	0	#N/A	#N/A	#N/A	#N/A
47.00	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
48.00	0	0	0	0	0	1	#N/A	#N/A	#N/A	#N/A
49.01	0	0	0	0	#N/A	0	0	0	1	#N/A
49.02	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
50.01	1	1	0	0	1	0	0	0	#N/A	#N/A
50.02	0	0	0	0	1	0	0	#N/A	#N/A	#N/A
51.00	0	0	0	0	1	0	0	0	#N/A	#N/A
52.01	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
52.02	0	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
53.00	1	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
54.00	1	0	0	0	0	0	0	#N/A	#N/A	#N/A
55.01	0	0	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
55.02	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
56.00	1	0	0	0	0	0	0	0	#N/A	#N/A
57.00	0	1	0	0	0	0	#N/A	#N/A	#N/A	#N/A
58.00	0	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
59.01	0	0	0	0	0	0	0	1	#N/A	#N/A
59.02	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
60.00	0	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
61.00	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
62.00	0	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
63.00	0	0	0	0	0	1	#N/A	#N/A	#N/A	#N/A
64.00	1	0	0	0	1	0	0	#N/A	#N/A	#N/A
65.00	1	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
66.00	0	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
67.00	0	0	1	1	1	0	#N/A	#N/A	#N/A	#N/A
68.00	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A

APPENDIX 7

CONNECTIVITY BY ETHNICITY 25% CUT

TRACTS	ADJACENT TRACTS									
	A:B	A:C	A:D	A:E	A:F	A:G	A:H	A:I	A:J	A:K
1.00	1	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
3.00	0	0	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
4.00	0	0	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A
5.00	0	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
6.00	1	1	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A
7.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
8.00	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
9.00	0	0	0	0	1	0	1	1	#N/A	#N/A
10.01	0	1	0	0	0	1	0	1	#N/A	#N/A
10.02	0	0	1	0	1	0	#N/A	#N/A	#N/A	#N/A
11.00	1	1	0	0	0	1	1	1	#N/A	#N/A
12.00	0	1	1	0	0	0	0	0	#N/A	#N/A
13.01	1	1	0	1	0	1	0	#N/A	#N/A	#N/A
13.02	0	0	1	1	1	0	0	#N/A	#N/A	#N/A
14.00	0	0	1	1	1	1	#N/A	#N/A	#N/A	#N/A
15.01	1	0	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
15.02	0	1	1	0	1	0	#N/A	#N/A	#N/A	#N/A
16.01	0	1	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
16.02	0	1	1	1	1	0	#N/A	#N/A	#N/A	#N/A
17.01	1	0	1	1	0	0	1	1	#N/A	#N/A
17.02	1	1	1	0	1	1	#N/A	#N/A	#N/A	#N/A
18.01	1	0	1	1	1	1	#N/A	#N/A	#N/A	#N/A
18.02	1	1	1	1	0	0	1	#N/A	#N/A	#N/A
19.00	0	0	0	0	1	0	1	0	#N/A	#N/A
20.00	0	0	0	0	0	1	0	#N/A	#N/A	#N/A
21.00	0	0	1	1	0	0	0	0	#N/A	#N/A
22.00	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
23.00	0	0	0	1	1	1	1	#N/A	#N/A	#N/A
24.00	0	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
25.00	1	1	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A
26.00	1	1	0	1	1	1	#N/A	#N/A	#N/A	#N/A
27.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
28.00	1	0	0	0	0	1	#N/A	#N/A	#N/A	#N/A
29.00	0	1	1	0	0	0	0	#N/A	#N/A	#N/A
30.00	0	0	0	1	0	0	1	#N/A	#N/A	#N/A
31.01	0	1	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A
31.02	0	1	1	0	1	1	1	#N/A	#N/A	#N/A
32.00	1	0	1	0	0	0	1	#N/A	#N/A	#N/A
33.00	1	1	1	1	1	1	0	0	#N/A	#N/A
34.01	1	0	1	0	1	1	1	#N/A	#N/A	#N/A
34.02	0	0	1	1	0	1	0	#N/A	#N/A	#N/A

TRACTS			ADJACENT TRACTS							
35.00	0	0	1	1	0	0	0	1	#N/A	#N/A
36.01	0	1	1	0	1	#N/A	#N/A	#N/A	#N/A	#N/A
36.02	0	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
37.00	0	0	0	0	1	0	1	1	#N/A	#N/A
38.00	1	1	0	0	0	1	1	#N/A	#N/A	#N/A
39.00	0	1	1	1	0	0	0	0	#N/A	#N/A
40.00	0	0	0	0	0	0	0	#N/A	#N/A	#N/A
41.00	0	0	0	0	0	1	0	1	1	0
42.00	1	1	0	0	0	0	1	#N/A	#N/A	#N/A
43.00	1	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
44.00	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
45.01	0	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
45.02	0	1	0	0	1	0	0	#N/A	#N/A	#N/A
46.00	0	0	0	1	0	0	#N/A	#N/A	#N/A	#N/A
47.00	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
48.00	1	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
49.01	0	0	0	0	#N/A	1	0	0	0	#N/A
49.02	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
50.01	0	0	0	1	1	0	0	0	#N/A	#N/A
50.02	1	0	0	0	0	0	0	#N/A	#N/A	#N/A
51.00	0	1	1	1	1	1	0	0	#N/A	#N/A
52.01	1	1	1	0	0	1	#N/A	#N/A	#N/A	#N/A
52.02	1	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
53.00	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
54.00	1	1	1	0	1	1	0	#N/A	#N/A	#N/A
55.01	1	0	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
55.02	1	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
56.00	0	1	1	1	1	0	1	1	#N/A	#N/A
57.00	0	1	0	1	1	0	#N/A	#N/A	#N/A	#N/A
58.00	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
59.01	1	0	0	1	0	0	0	0	#N/A	#N/A
59.02	1	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
60.00	0	1	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
61.00	1	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
62.00	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
63.00	1	0	0	0	1	0	#N/A	#N/A	#N/A	#N/A
64.00	0	1	0	0	0	0	0	#N/A	#N/A	#N/A
65.00	0	0	0	0	0	1	#N/A	#N/A	#N/A	#N/A
66.00	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
67.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
68.00	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A

APPENDIX 8

CONNECTIVITY BY POPULATION DENSITY 25% CUT

TRACTS	ADJACENT TRACTS								
	A:B	A:C	A:D	A:E	A:F	A:G	A:H	A:I	A:J	A:K
1.00	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2.00	0	1	1	0	0	0	#N/A	#N/A	#N/A	#N/A
3.00	0	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
4.00	1	1	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A
5.00	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
6.00	0	0	0	1	0	#N/A	#N/A	#N/A	#N/A	#N/A
7.00	0	0	0	0	1	0	#N/A	#N/A	#N/A	#N/A
8.00	0	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
9.00	1	0	0	1	1	0	0	0	#N/A	#N/A
10.01	0	1	0	0	1	1	1	0	#N/A	#N/A
10.02	0	1	1	1	1	0	#N/A	#N/A	#N/A	#N/A
11.00	1	1	1	1	1	0	1	1	#N/A	#N/A
12.00	1	1	1	1	1	0	1	1	#N/A	#N/A
13.01	1	1	1	1	0	1	1	#N/A	#N/A	#N/A
13.02	1	0	1	1	1	1	1	#N/A	#N/A	#N/A
14.00	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
15.01	0	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
15.02	1	0	1	1	1	1	#N/A	#N/A	#N/A	#N/A
16.01	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
16.02	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
17.01	1	1	1	1	1	1	1	1	#N/A	#N/A
17.02	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
18.01	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
18.02	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
19.00	1	1	1	1	0	1	1	0	#N/A	#N/A
20.00	1	0	1	0	1	0	0	#N/A	#N/A	#N/A
21.00	1	0	0	0	0	0	0	0	#N/A	#N/A
22.00	0	0	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A
23.00	1	0	0	0	1	1	1	#N/A	#N/A	#N/A
24.00	1	1	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
25.00	1	1	0	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
26.00	1	1	0	0	1	1	#N/A	#N/A	#N/A	#N/A
27.00	0	1	0	0	1	1	#N/A	#N/A	#N/A	#N/A
28.00	1	1	1	0	0	0	#N/A	#N/A	#N/A	#N/A
29.00	0	0	0	1	1	0	1	#N/A	#N/A	#N/A
30.00	1	1	1	1	1	0	0	#N/A	#N/A	#N/A
31.01	0	0	0	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
31.02	1	1	1	1	0	0	0	#N/A	#N/A	#N/A
32.00	1	1	1	1	0	1	1	#N/A	#N/A	#N/A
33.00	1	1	1	1	1	1	1	1	#N/A	#N/A
34.01	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
34.02	1	1	1	1	1	1	1	#N/A	#N/A	#N/A

TRACTS			ADJACENT TRACTS							
35.00	1	1	1	1	1	0	1	1	#N/A	#N/A
36.01	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
36.02	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
37.00	1	1	1	1	1	1	1	1	#N/A	#N/A
38.00	0	0	1	0	0	0	1	#N/A	#N/A	#N/A
39.00	1	0	0	0	0	1	0	0	#N/A	#N/A
40.00	0	0	0	0	1	1	0	#N/A	#N/A	#N/A
41.00	0	0	0	1	1	1	1	1	1	0
42.00	1	0	1	1	1	1	1	#N/A	#N/A	#N/A
43.00	0	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
44.00	1	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
45.01	0	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
45.02	1	1	1	1	0	1	1	#N/A	#N/A	#N/A
46.00	1	1	1	0	1	1	#N/A	#N/A	#N/A	#N/A
47.00	1	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
48.00	1	1	0	1	1	1	#N/A	#N/A	#N/A	#N/A
49.01	1	1	0	0	#N/A	0	1	0	1	#N/A
49.02	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
50.01	1	1	1	0	0	0	0	0	#N/A	#N/A
50.02	1	0	0	0	1	0	0	#N/A	#N/A	#N/A
51.00	1	1	1	1	1	0	0	1	#N/A	#N/A
52.01	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
52.02	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
53.00	1	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
54.00	1	1	1	1	1	0	1	#N/A	#N/A	#N/A
55.01	1	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
55.02	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
56.00	1	0	0	0	1	1	0	0	#N/A	#N/A
57.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
58.00	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
59.01	1	0	0	0	1	1	1	1	#N/A	#N/A
59.02	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
60.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
61.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
62.00	1	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
63.00	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
64.00	1	1	1	0	1	1	1	#N/A	#N/A	#N/A
65.00	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
66.00	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
67.00	0	0	1	0	1	1	#N/A	#N/A	#N/A	#N/A
68.00	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A

APPENDIX 9

CONNECTIVITY BY RENTED HOUSING 25% CUT

TRACTS	ADJACENT TRACTS									
	A:B	A:C	A:D	A:E	A:F	A:G	A:H	A:I	A:J	A:K
1.00	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2.00	0	1	0	0	1	1	#N/A	#N/A	#N/A	#N/A
3.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
4.00	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
5.00	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
6.00	1	1	1	0	1	#N/A	#N/A	#N/A	#N/A	#N/A
7.00	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
8.00	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
9.00	1	1	1	0	1	0	1	1	#N/A	#N/A
10.01	1	1	1	1	1	0	0	0	#N/A	#N/A
10.02	0	0	0	0	1	0	#N/A	#N/A	#N/A	#N/A
11.00	1	1	1	0	1	1	0	1	#N/A	#N/A
12.00	1	1	1	1	0	0	0	0	#N/A	#N/A
13.01	0	1	1	1	1	1	1	#N/A	#N/A	#N/A
13.02	1	1	0	0	0	1	0	#N/A	#N/A	#N/A
14.00	1	0	0	1	1	0	#N/A	#N/A	#N/A	#N/A
15.01	0	0	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
15.02	1	0	1	0	1	0	#N/A	#N/A	#N/A	#N/A
16.01	0	1	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
16.02	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
17.01	1	0	1	1	0	1	0	0	#N/A	#N/A
17.02	1	1	1	1	0	1	#N/A	#N/A	#N/A	#N/A
18.01	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
18.02	1	1	1	1	1	0	1	#N/A	#N/A	#N/A
19.00	1	1	0	1	1	0	0	1	#N/A	#N/A
20.00	1	0	0	0	1	1	0	#N/A	#N/A	#N/A
21.00	0	0	1	0	0	0	0	0	#N/A	#N/A
22.00	1	0	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
23.00	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
24.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
25.00	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
26.00	1	1	0	0	1	1	#N/A	#N/A	#N/A	#N/A
27.00	1	0	0	0	1	1	#N/A	#N/A	#N/A	#N/A
28.00	1	0	0	1	0	1	#N/A	#N/A	#N/A	#N/A
29.00	0	1	1	1	1	0	0	#N/A	#N/A	#N/A
30.00	0	1	1	1	1	1	1	#N/A	#N/A	#N/A
31.01	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
31.02	1	1	1	0	0	1	1	#N/A	#N/A	#N/A
32.00	1	1	1	0	0	1	1	#N/A	#N/A	#N/A
33.00	1	1	1	0	1	1	1	0	#N/A	#N/A
34.01	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
34.02	1	1	0	1	1	1	1	#N/A	#N/A	#N/A

TRACTS			ADJACENT TRACTS							
35.00	1	1	1	0	1	0	0	1	#N/A	#N/A
36.01	1	1	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A
36.02	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
37.00	1	1	0	0	1	1	1	0	#N/A	#N/A
38.00	0	1	1	1	0	1	1	#N/A	#N/A	#N/A
39.00	1	1	1	0	0	1	0	0	#N/A	#N/A
40.00	1	0	0	0	0	0	1	#N/A	#N/A	#N/A
41.00	0	0	0	0	1	1	1	1	1	0
42.00	1	0	1	1	1	1	1	#N/A	#N/A	#N/A
43.00	1	1	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
44.00	1	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
45.01	0	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
45.02	1	1	1	0	1	0	0	#N/A	#N/A	#N/A
46.00	1	1	0	1	1	1	#N/A	#N/A	#N/A	#N/A
47.00	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
48.00	1	0	1	0	0	1	#N/A	#N/A	#N/A	#N/A
49.01	0	1	0	0	#N/A	0	0	1	1	#N/A
49.02	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
50.01	1	1	1	0	1	0	0	1	#N/A	#N/A
50.02	1	0	0	0	1	1	1	#N/A	#N/A	#N/A
51.00	1	0	1	1	1	0	0	0	#N/A	#N/A
52.01	0	0	0	1	1	0	#N/A	#N/A	#N/A	#N/A
52.02	0	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
53.00	1	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
54.00	1	0	1	1	0	0	0	#N/A	#N/A	#N/A
55.01	0	0	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
55.02	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
56.00	1	0	0	1	1	1	0	1	#N/A	#N/A
57.00	0	1	0	0	1	0	#N/A	#N/A	#N/A	#N/A
58.00	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
59.01	0	0	0	0	1	0	0	1	#N/A	#N/A
59.02	1	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
60.00	0	0	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
61.00	0	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
62.00	1	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
63.00	1	0	0	1	1	1	#N/A	#N/A	#N/A	#N/A
64.00	1	0	1	1	1	0	0	#N/A	#N/A	#N/A
65.00	1	0	0	0	1	1	#N/A	#N/A	#N/A	#N/A
66.00	0	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
67.00	0	0	1	1	1	0	#N/A	#N/A	#N/A	#N/A
68.00	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A

APPENDIX 10

CONNECTIVITY BY SINGLE PARENT 25% CUT

TRACTS	ADJACENT TRACTS									
	A:B	A:C	A:D	A:E	A:F	A:G	A:H	A:I	A:J	A:K
1.00	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2.00	0	1	0	1	1	1	#N/A	#N/A	#N/A	#N/A
3.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
4.00	1	1	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A
5.00	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
6.00	0	1	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A
7.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
8.00	0	0	0	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
9.00	0	0	0	0	0	0	1	1	#N/A	#N/A
10.01	1	1	0	0	0	1	1	1	#N/A	#N/A
10.02	0	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
11.00	1	1	1	1	1	1	0	1	#N/A	#N/A
12.00	1	1	1	1	1	0	1	1	#N/A	#N/A
13.01	1	1	1	1	0	1	1	#N/A	#N/A	#N/A
13.02	0	1	0	1	0	1	0	#N/A	#N/A	#N/A
14.00	1	1	0	1	1	0	#N/A	#N/A	#N/A	#N/A
15.01	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
15.02	1	0	0	0	0	1	#N/A	#N/A	#N/A	#N/A
16.01	0	1	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A
16.02	1	0	1	1	0	0	#N/A	#N/A	#N/A	#N/A
17.01	0	0	0	0	0	1	0	0	#N/A	#N/A
17.02	1	0	1	1	1	1	#N/A	#N/A	#N/A	#N/A
18.01	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
18.02	1	1	1	1	1	0	1	#N/A	#N/A	#N/A
19.00	1	1	1	1	1	0	1	1	#N/A	#N/A
20.00	0	0	0	0	0	1	0	#N/A	#N/A	#N/A
21.00	0	0	1	0	0	0	0	0	#N/A	#N/A
22.00	1	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
23.00	1	0	0	0	0	1	#N/A	#N/A	#N/A	#N/A
24.00	1	1	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
25.00	1	1	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
26.00	0	1	0	0	1	0	#N/A	#N/A	#N/A	#N/A
27.00	0	0	0	0	1	0	#N/A	#N/A	#N/A	#N/A
28.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
29.00	0	1	0	1	0	0	1	#N/A	#N/A	#N/A
30.00	1	1	1	1	0	0	0	#N/A	#N/A	#N/A
31.01	0	1	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A
31.02	0	0	1	0	0	0	1	#N/A	#N/A	#N/A
32.00	1	1	1	0	0	1	1	#N/A	#N/A	#N/A
33.00	1	1	1	1	1	0	1	1	#N/A	#N/A
34.01	1	0	1	1	1	1	1	#N/A	#N/A	#N/A
34.02	1	1	0	1	0	1	1	#N/A	#N/A	#N/A

TRACTS	ADJACENT TRACTS								
35.00	1	1	1	1	1	0	0	1	#N/A	#N/A
36.01	0	1	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
36.02	0	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
37.00	0	0	0	0	1	1	1	0	#N/A	#N/A
38.00	0	0	1	1	0	1	0	#N/A	#N/A	#N/A
39.00	0	0	0	1	1	0	1	0	#N/A	#N/A
40.00	0	0	1	0	1	1	0	#N/A	#N/A	#N/A
41.00	0	0	0	0	1	1	1	1	0	0
42.00	0	0	0	0	0	1	1	#N/A	#N/A	#N/A
43.00	0	1	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
44.00	1	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
45.01	0	1	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
45.02	0	1	0	1	1	0	0	#N/A	#N/A	#N/A
46.00	1	1	1	1	1	0	#N/A	#N/A	#N/A	#N/A
47.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
48.00	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
49.01	0	0	0	0	#N/A	0	1	0	1	#N/A
49.02	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
50.01	1	1	1	1	1	1	0	1	#N/A	#N/A
50.02	1	0	0	0	1	1	1	#N/A	#N/A	#N/A
51.00	1	1	1	1	1	0	0	0	#N/A	#N/A
52.01	0	0	1	1	1	1	#N/A	#N/A	#N/A	#N/A
52.02	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
53.00	1	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
54.00	1	0	1	1	0	0	0	#N/A	#N/A	#N/A
55.01	0	0	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
55.02	1	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
56.00	1	0	0	1	1	1	1	1	#N/A	#N/A
57.00	0	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
58.00	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
59.01	0	1	1	1	1	1	1	1	#N/A	#N/A
59.02	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
60.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
61.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
62.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
63.00	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
64.00	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
65.00	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
66.00	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
67.00	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
68.00	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A

APPENDIX 11

CONNECTIVITY BY ETHNICITY 40% CUT

TRACTS	ADJACENT TRACTS								
	A:B	A:C	A:D	A:E	A:F	A:G	A:H	A:I	A:J	A:K
1.00	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2.00	1	1	1	1	0	1	#N/A	#N/A	#N/A	#N/A
3.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
4.00	1	1	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A
5.00	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
6.00	0	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
7.00	1	0	0	0	1	1	#N/A	#N/A	#N/A	#N/A
8.00	0	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
9.00	1	1	1	1	1	0	0	0	#N/A	#N/A
10.01	0	1	1	0	1	1	1	1	#N/A	#N/A
10.02	1	1	1	1	1	0	#N/A	#N/A	#N/A	#N/A
11.00	1	1	1	1	1	1	1	1	#N/A	#N/A
12.00	1	1	1	1	1	1	1	1	#N/A	#N/A
13.01	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
13.02	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
14.00	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
15.01	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
15.02	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
16.01	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
16.02	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
17.01	1	1	1	1	1	1	1	1	#N/A	#N/A
17.02	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
18.01	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
18.02	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
19.00	1	1	1	1	1	1	1	1	#N/A	#N/A
20.00	1	1	1	1	1	0	0	#N/A	#N/A	#N/A
21.00	1	0	0	1	1	1	1	1	#N/A	#N/A
22.00	0	0	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A
23.00	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
24.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
25.00	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
26.00	1	1	0	1	1	1	#N/A	#N/A	#N/A	#N/A
27.00	0	1	0	1	1	1	#N/A	#N/A	#N/A	#N/A
28.00	1	1	1	0	0	1	#N/A	#N/A	#N/A	#N/A
29.00	1	0	0	1	1	0	1	#N/A	#N/A	#N/A
30.00	1	1	1	1	1	1	0	#N/A	#N/A	#N/A
31.01	0	0	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
31.02	1	1	1	1	1	0	0	#N/A	#N/A	#N/A
32.00	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
33.00	1	1	1	1	1	1	1	1	#N/A	#N/A
34.01	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
34.02	1	1	1	1	1	1	1	#N/A	#N/A	#N/A

TRACTS			ADJACENT TRACTS							
35.00	1	1	1	1	1	1	1	1	#N/A	#N/A
36.01	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
36.02	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
37.00	1	1	1	1	1	1	1	1	#N/A	#N/A
38.00	1	1	1	1	0	0	1	#N/A	#N/A	#N/A
39.00	1	1	0	0	0	1	1	1	#N/A	#N/A
40.00	0	0	0	1	1	1	0	#N/A	#N/A	#N/A
41.00	0	0	0	1	1	1	1	1	1	0
42.00	1	0	1	1	1	1	1	#N/A	#N/A	#N/A
43.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
44.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
45.01	0	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
45.02	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
46.00	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
47.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
48.00	1	1	0	1	1	1	#N/A	#N/A	#N/A	#N/A
49.01	1	1	0	0	#N/A	1	1	1	1	#N/A
49.02	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
50.01	1	1	1	1	0	0	0	0	#N/A	#N/A
50.02	1	1	1	1	1	0	1	#N/A	#N/A	#N/A
51.00	1	1	1	1	1	1	1	1	#N/A	#N/A
52.01	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
52.02	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
53.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
54.00	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
55.01	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
55.02	1	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
56.00	1	0	0	1	1	1	0	0	#N/A	#N/A
57.00	0	1	0	0	0	0	#N/A	#N/A	#N/A	#N/A
58.00	1	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
59.01	1	0	0	0	1	1	1	1	#N/A	#N/A
59.02	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
60.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
61.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
62.00	1	1	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
63.00	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
64.00	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
65.00	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
66.00	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
67.00	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
68.00	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A

APPENDIX 12

CONNECTIVITY BY POPULATION DENSITY 40% CUT

TRACTS	ADJACENT TRACTS								
	A:B	A:C	A:D	A:E	A:F	A:G	A:H	A:I	A:J	A:K
1.00	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2.00	1	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
3.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
4.00	1	0	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A
5.00	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
6.00	1	1	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A
7.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
8.00	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
9.00	0	0	0	0	1	0	1	1	#N/A	#N/A
10.01	1	1	1	1	0	1	0	1	#N/A	#N/A
10.02	1	1	1	0	1	1	#N/A	#N/A	#N/A	#N/A
11.00	1	1	0	0	1	1	1	1	#N/A	#N/A
12.00	1	1	1	1	1	0	1	1	#N/A	#N/A
13.01	1	1	1	1	0	1	1	#N/A	#N/A	#N/A
13.02	1	0	1	1	1	1	0	#N/A	#N/A	#N/A
14.00	0	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
15.01	1	0	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
15.02	1	1	1	0	1	1	#N/A	#N/A	#N/A	#N/A
16.01	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
16.02	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
17.01	1	1	1	1	0	1	1	1	#N/A	#N/A
17.02	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
18.01	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
18.02	1	1	1	1	1	0	1	#N/A	#N/A	#N/A
19.00	0	0	0	0	1	1	1	0	#N/A	#N/A
20.00	0	0	0	0	1	1	0	#N/A	#N/A	#N/A
21.00	0	0	1	1	0	0	0	0	#N/A	#N/A
22.00	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
23.00	0	0	1	1	1	1	1	#N/A	#N/A	#N/A
24.00	0	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
25.00	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
26.00	1	1	0	1	1	1	#N/A	#N/A	#N/A	#N/A
27.00	0	1	0	0	1	1	#N/A	#N/A	#N/A	#N/A
28.00	1	0	0	0	0	1	#N/A	#N/A	#N/A	#N/A
29.00	0	1	1	0	0	0	1	#N/A	#N/A	#N/A
30.00	1	1	1	1	0	0	1	#N/A	#N/A	#N/A
31.01	1	1	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A
31.02	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
32.00	1	1	1	0	1	1	1	#N/A	#N/A	#N/A
33.00	1	1	1	1	1	1	1	0	#N/A	#N/A
34.01	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
34.02	0	1	1	1	0	1	1	#N/A	#N/A	#N/A

TRACTS	ADJACENT TRACTS								
35.00	0	1	1	1	1	0	0	1	#N/A	#N/A
36.01	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
36.02	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
37.00	1	0	0	1	1	0	1	1	#N/A	#N/A
38.00	1	1	1	1	0	1	1	#N/A	#N/A	#N/A
39.00	0	1	1	1	1	0	0	0	#N/A	#N/A
40.00	0	0	0	0	0	0	0	#N/A	#N/A	#N/A
41.00	0	0	0	0	0	1	0	1	1	1
42.00	1	1	1	0	0	0	1	#N/A	#N/A	#N/A
43.00	1	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
44.00	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
45.01	0	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
45.02	1	1	1	0	1	0	1	#N/A	#N/A	#N/A
46.00	1	0	1	1	1	0	#N/A	#N/A	#N/A	#N/A
47.00	1	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
48.00	1	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
49.01	0	0	0	0	#N/A	1	0	0	0	#N/A
49.02	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
50.01	1	0	0	1	1	0	0	1	#N/A	#N/A
50.02	1	0	0	0	0	0	0	#N/A	#N/A	#N/A
51.00	1	1	1	1	1	1	0	0	#N/A	#N/A
52.01	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
52.02	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
53.00	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
54.00	1	1	1	0	1	1	0	#N/A	#N/A	#N/A
55.01	1	0	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
55.02	1	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
56.00	0	1	1	1	1	1	1	1	#N/A	#N/A
57.00	1	1	0	1	1	1	#N/A	#N/A	#N/A	#N/A
58.00	0	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
59.01	1	0	0	1	1	0	0	0	#N/A	#N/A
59.02	1	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
60.00	0	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
61.00	1	1	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
62.00	1	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
63.00	1	1	0	0	1	0	#N/A	#N/A	#N/A	#N/A
64.00	1	1	0	0	0	0	0	#N/A	#N/A	#N/A
65.00	1	0	0	0	0	1	#N/A	#N/A	#N/A	#N/A
66.00	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
67.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
68.00	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A

APPENDIX 13

CONNECTIVITY BY RENTED HOUSING 40% CUT

TRACTS	ADJACENT TRACTS									
	A:B	A:C	A:D	A:E	A:F	A:G	A:H	A:I	A:J	A:K
1.00	1	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2.00	1	1	0	1	1	1	#N/A	#N/A	#N/A	#N/A
3.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
4.00	1	1	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A
5.00	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
6.00	0	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
7.00	0	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A
8.00	0	0	0	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
9.00	0	0	1	0	0	0	1	1	#N/A	#N/A
10.01	1	1	1	0	0	1	1	1	#N/A	#N/A
10.02	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
11.00	1	1	1	1	1	1	1	1	#N/A	#N/A
12.00	1	1	1	1	1	0	1	1	#N/A	#N/A
13.01	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
13.02	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
14.00	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
15.01	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
15.02	1	1	0	1	1	1	#N/A	#N/A	#N/A	#N/A
16.01	0	1	1	0	1	#N/A	#N/A	#N/A	#N/A	#N/A
16.02	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
17.01	1	0	0	1	1	1	0	0	#N/A	#N/A
17.02	1	0	1	1	1	1	#N/A	#N/A	#N/A	#N/A
18.01	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
18.02	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
19.00	1	1	1	1	1	0	1	1	#N/A	#N/A
20.00	0	0	0	0	0	1	0	#N/A	#N/A	#N/A
21.00	0	0	1	0	0	0	0	0	#N/A	#N/A
22.00	1	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
23.00	1	0	0	0	1	1	#N/A	#N/A	#N/A	#N/A
24.00	1	1	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
25.00	1	1	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
26.00	0	1	0	0	1	1	#N/A	#N/A	#N/A	#N/A
27.00	0	0	0	0	1	0	#N/A	#N/A	#N/A	#N/A
28.00	0	1	0	0	0	0	#N/A	#N/A	#N/A	#N/A
29.00	0	1	1	1	0	0	1	#N/A	#N/A	#N/A
30.00	1	1	1	1	1	0	1	#N/A	#N/A	#N/A
31.01	1	1	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A
31.02	1	1	1	1	0	0	1	#N/A	#N/A	#N/A
32.00	1	1	1	0	0	1	1	#N/A	#N/A	#N/A
33.00	1	1	1	1	1	1	1	1	#N/A	#N/A
34.01	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
34.02	1	1	1	1	0	1	1	#N/A	#N/A	#N/A

TRACTS			ADJACENT TRACTS							
35.00	1	1	1	1	1	0	0	1	#N/A	#N/A
36.01	0	1	0	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
36.02	0	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
37.00	1	1	0	0	1	1	1	1	#N/A	#N/A
38.00	1	0	1	1	1	1	1	#N/A	#N/A	#N/A
39.00	1	1	1	1	1	1	1	0	#N/A	#N/A
40.00	0	0	1	1	1	1	0	#N/A	#N/A	#N/A
41.00	0	0	0	1	1	1	1	1	1	0
42.00	0	1	0	0	1	1	1	#N/A	#N/A	#N/A
43.00	0	1	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
44.00	1	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
45.01	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
45.02	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
46.00	1	1	1	1	1	0	#N/A	#N/A	#N/A	#N/A
47.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
48.00	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
49.01	0	0	0	1	#N/A	0	1	1	1	#N/A
49.02	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
50.01	1	1	1	1	1	1	1	1	#N/A	#N/A
50.02	1	0	0	0	1	1	1	#N/A	#N/A	#N/A
51.00	1	1	1	1	1	0	0	0	#N/A	#N/A
52.01	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
52.02	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
53.00	1	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
54.00	1	1	1	1	0	0	0	#N/A	#N/A	#N/A
55.01	0	0	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
55.02	1	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
56.00	1	0	0	1	1	1	1	1	#N/A	#N/A
57.00	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
58.00	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
59.01	0	1	1	1	1	1	1	1	#N/A	#N/A
59.02	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
60.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
61.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
62.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
63.00	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
64.00	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
65.00	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
66.00	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
67.00	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
68.00	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A

APPENDIX 14

CONNECTIVITY BY SINGLE PARENT 40% CUT

TRACTS	ADJACENT TRACTS								
	A:B	A:C	A:D	A:E	A:F	A:G	A:H	A:I	A:J	A:K
1.00	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2.00	0	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
3.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
4.00	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
5.00	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
6.00	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
7.00	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
8.00	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
9.00	1	1	1	1	1	1	1	1	#N/A	#N/A
10.01	1	1	1	1	1	0	0	1	#N/A	#N/A
10.02	1	0	0	0	1	1	#N/A	#N/A	#N/A	#N/A
11.00	1	1	1	1	1	1	1	1	#N/A	#N/A
12.00	1	1	1	1	1	0	1	0	#N/A	#N/A
13.01	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
13.02	1	1	0	1	1	1	1	#N/A	#N/A	#N/A
14.00	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
15.01	0	0	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
15.02	1	0	1	0	1	0	#N/A	#N/A	#N/A	#N/A
16.01	0	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
16.02	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
17.01	1	1	1	1	1	1	1	0	#N/A	#N/A
17.02	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
18.01	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
18.02	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
19.00	1	1	1	1	1	0	0	1	#N/A	#N/A
20.00	1	0	0	0	1	1	1	#N/A	#N/A	#N/A
21.00	0	1	1	1	1	0	1	1	#N/A	#N/A
22.00	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
23.00	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
24.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
25.00	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
26.00	1	1	0	0	1	1	#N/A	#N/A	#N/A	#N/A
27.00	1	1	0	1	1	1	#N/A	#N/A	#N/A	#N/A
28.00	1	0	0	1	0	1	#N/A	#N/A	#N/A	#N/A
29.00	0	1	1	1	1	1	1	#N/A	#N/A	#N/A
30.00	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
31.01	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
31.02	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
32.00	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
33.00	1	1	1	1	1	1	1	1	#N/A	#N/A
34.01	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
34.02	1	1	1	1	1	1	1	#N/A	#N/A	#N/A

TRACTS	ADJACENT TRACTS									
35.00	1	1	1	1	1	0	0	1	#N/A	#N/A
36.01	1	1	0	1	1	#N/A	#N/A	#N/A	#N/A	#N/A
36.02	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
37.00	1	1	1	1	1	1	1	1	#N/A	#N/A
38.00	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
39.00	1	1	1	1	1	1	0	0	#N/A	#N/A
40.00	1	0	0	0	0	0	1	#N/A	#N/A	#N/A
41.00	1	0	1	1	1	1	1	1	1	1
42.00	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
43.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
44.00	1	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
45.01	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
45.02	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
46.00	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
47.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
48.00	1	0	1	1	1	1	#N/A	#N/A	#N/A	#N/A
49.01	1	1	0	0	#N/A	1	0	1	1	#N/A
49.02	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
50.01	1	1	1	1	1	0	1	1	#N/A	#N/A
50.02	1	0	1	0	1	1	1	#N/A	#N/A	#N/A
51.00	1	1	1	1	1	0	0	1	#N/A	#N/A
52.01	0	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
52.02	0	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
53.00	1	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
54.00	1	1	1	1	0	0	0	#N/A	#N/A	#N/A
55.01	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
55.02	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
56.00	1	0	0	1	1	1	1	1	#N/A	#N/A
57.00	1	1	1	1	1	0	#N/A	#N/A	#N/A	#N/A
58.00	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
59.01	0	0	0	0	1	1	1	1	#N/A	#N/A
59.02	1	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
60.00	1	1	1	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
61.00	0	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
62.00	1	0	0	1	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
63.00	1	0	0	1	1	1	#N/A	#N/A	#N/A	#N/A
64.00	1	1	1	1	1	1	1	#N/A	#N/A	#N/A
65.00	1	1	1	1	1	1	#N/A	#N/A	#N/A	#N/A
66.00	1	1	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
67.00	0	0	1	1	1	1	#N/A	#N/A	#N/A	#N/A
68.00	1	0	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A

APPENDIX 15

TEMPORAL DISTRIBUTION OF TOTAL CALLS

DATE	DAILYFRQ	% CALLS	CUM %	HOURS	HRLYFRQ	% CALLS	CUM %
930101	849	3.17	3.17	0	1130	4.21	4.21
930102	706	2.63	5.80	1	1010	3.77	7.98
930103	590	2.20	8.00	2	876	3.27	11.24
930104	718	2.68	10.68	3	687	2.56	13.80
930105	789	2.94	13.62	4	495	1.85	15.65
930106	837	3.12	16.74	5	358	1.33	16.98
930107	799	2.98	19.72	6	325	1.21	18.19
930108	825	3.08	22.80	7	541	2.02	20.21
930109	837	3.12	25.92	8	1071	3.99	24.20
930110	745	2.78	28.69	9	1492	5.56	29.77
930111	842	3.14	31.83	10	1339	4.99	34.76
930112	889	3.31	35.15	11	1444	5.38	40.14
930113	817	3.05	38.19	12	1320	4.92	45.06
930114	842	3.14	41.33	13	1471	5.48	50.55
930115	911	3.40	44.73	14	1536	5.73	56.28
930116	906	3.38	48.11	15	1692	6.31	62.58
930117	748	2.79	50.90	16	1270	4.73	67.32
930118	992	3.70	54.59	17	1348	5.03	72.34
930119	784	2.92	57.52	18	1284	4.79	77.13
930120	1034	3.86	61.37	19	1433	5.34	82.47
930121	963	3.59	64.96	20	1131	4.22	86.69
930122	904	3.37	68.33	21	1221	4.55	91.24
930123	1016	3.79	72.12	22	1158	4.32	95.56
930124	748	2.79	74.91	23	1190	4.44	100.00
930125	911	3.40	78.31				
930126	945	3.52	81.83				
930127	922	3.44	85.27				
930128	1043	3.89	89.16				
930129	925	3.45	92.60				
930130	1129	4.21	96.81				
930131	856	3.19	100.00				

APPENDIX 16

PROGRAM FOR ESTIMATING THE R/S VALUES

```
real xtn(140,360), mn(140), sdv(140), rxtn(140), rbys(140)
      real c1(720), maxxtn(140), minxtn(140), rbysm
      integer ng
      write (*,*) "enter number of calls"
      read (*,*) n
      open (unit=1, file='sj93tcar.inp')
      open (unit=2, file='srs93car.out')
      do 100 i=1,n
100   read (1,*) c1(i)
      write (*,*) "enter min & max numbers in each group"
      write(*,*)"the numbers should be +ve integers between 5 and 360"
        read (*,*) ng_min, ng_max
      do 2000 ng=ng_min, ng_max
      rbysm=0
      ing=n/ng
      do 1000 i=1,ing
         mn(i)=0
         do 200 j=(i-1)*ng+1, i*ng
200          mn(i)=mn(i)+c1(j)
         mn(i)=mn(i)/ng
         sdv(i)=0
         do 300 j= (i-1)*ng+1, i*ng
300        sdv(i)=sdv(i)+(c1(j)-mn(i))*(c1(j)-mn(i))
         sdv(i)=sqrt(sdv(i)/(ng-1))
         do 400 j=1,ng
400          xtn(i,j)=0
         maxxtn(i)=-1000
         minxtn(i)=1000
         do 600 j=1,ng
             do 500 k=(i-1)*ng+1,(i-1)*ng+j
500              xtn(i,j)=xtn(i,j)+(c1(k)-mn(i))
             if(xtn(i,j) .gt. maxxtn(i)) maxxtn(i)=xtn(i,j)
600          if(xtn(i,j) .lt. minxtn(i)) minxtn(i)=xtn(i,j)
         rxtn(i)=maxxtn(i)-minxtn(i)
         rbys(i)=rxtn(i)/sdv(i)
         rbysm= rbysm+rbys(i)
1000     continue
         rbysm=rbysm/ing
2000     write(2,*)ng,rbysm
         stop
         end
```

FIGURE I

VANCOUVER
CENSUS TRACT BOUNDARIES

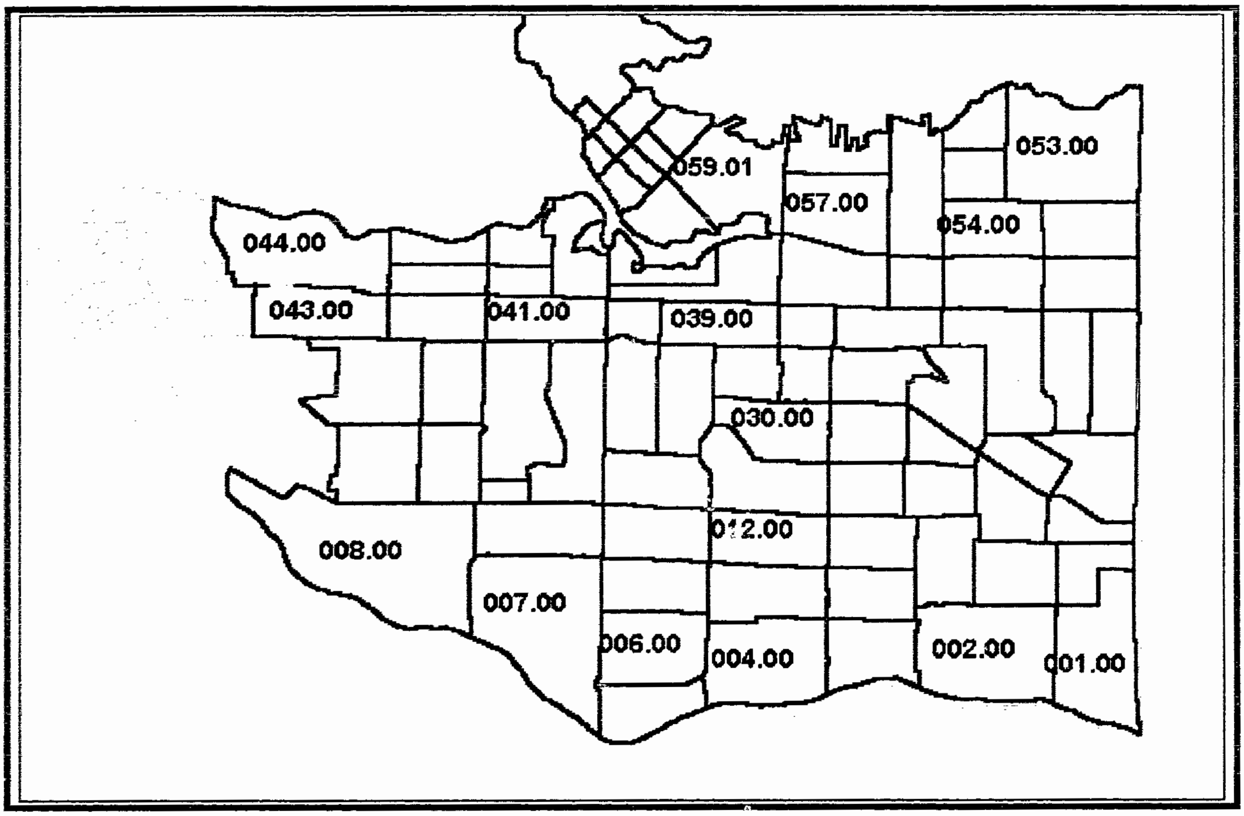
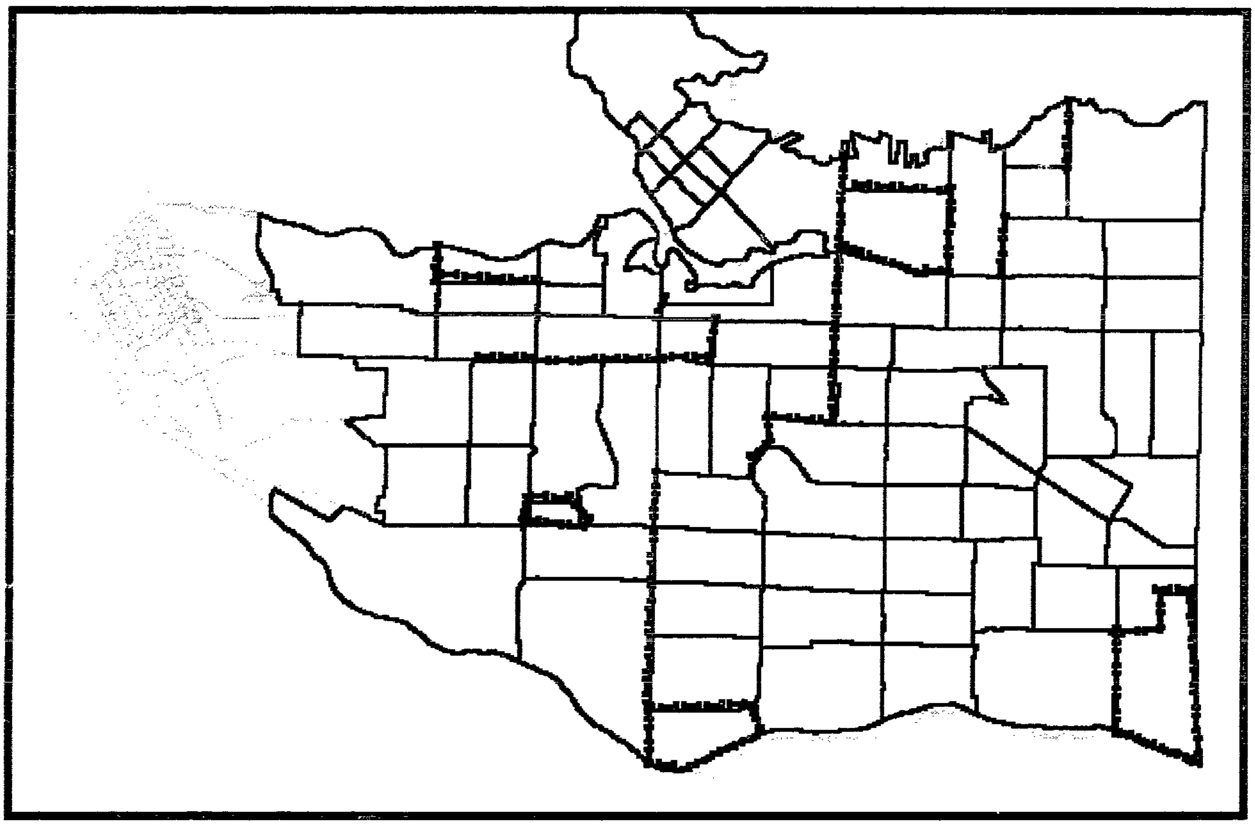


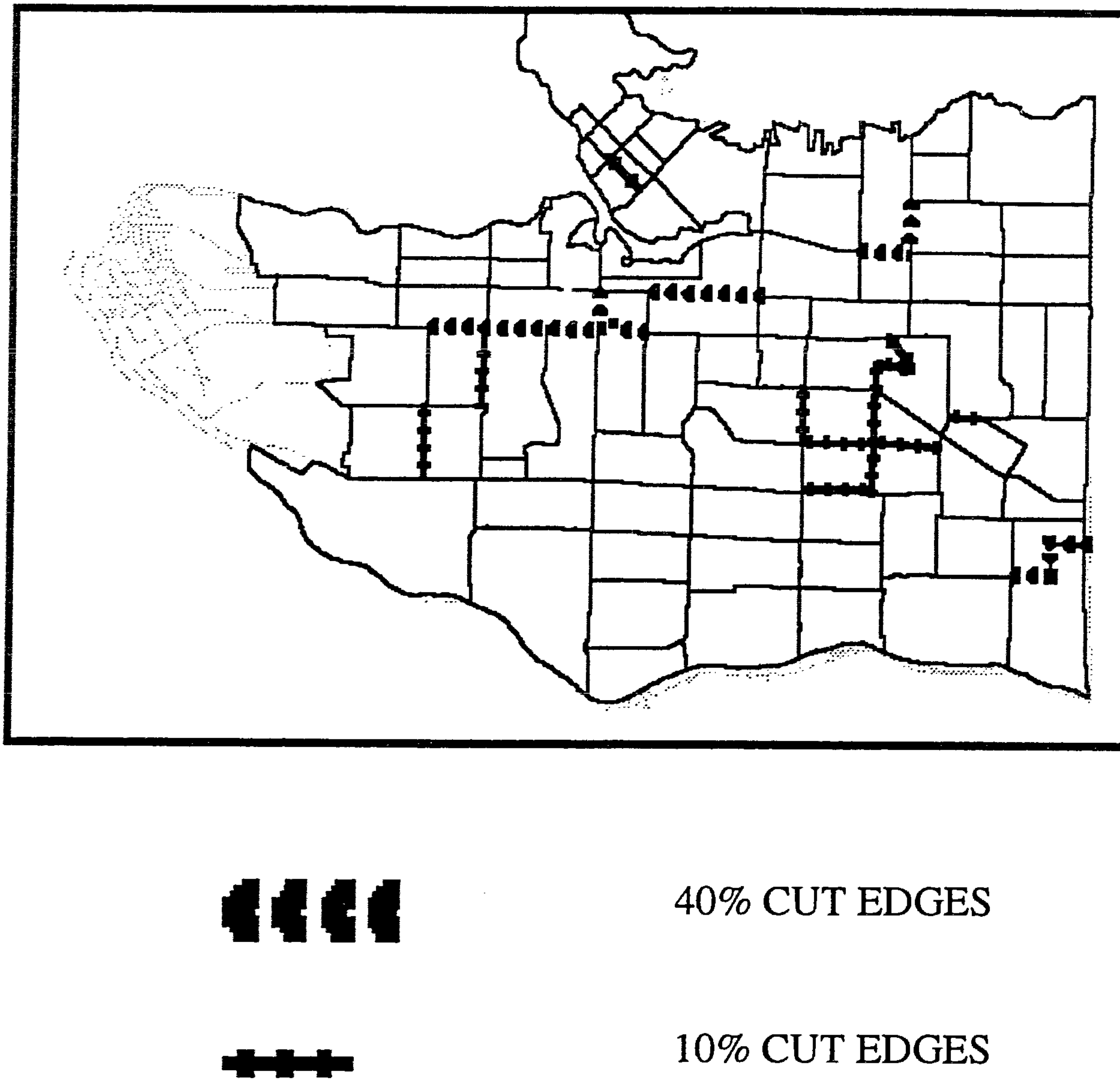
FIGURE II

TOPOLOGICAL CONNECTIVITY BY ETHNIC POPULATION



Connected Edges

TOPOLOGICAL CONNECTIVITY VANCOUVER CENSUS TRACTS



<u>FIGURE IV</u>

HOT SPOTS BY ENUMERATION AREAS

VANCOUVER- JAN '95

CALLS FOR POLICE SERVICE

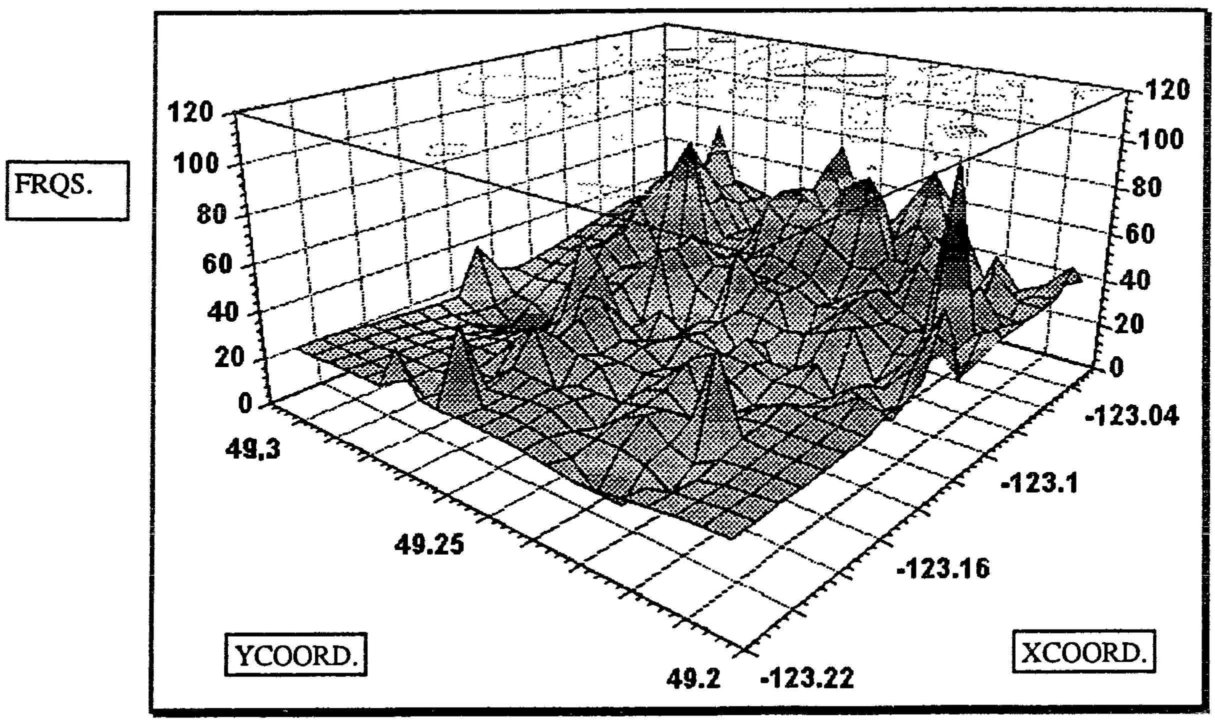
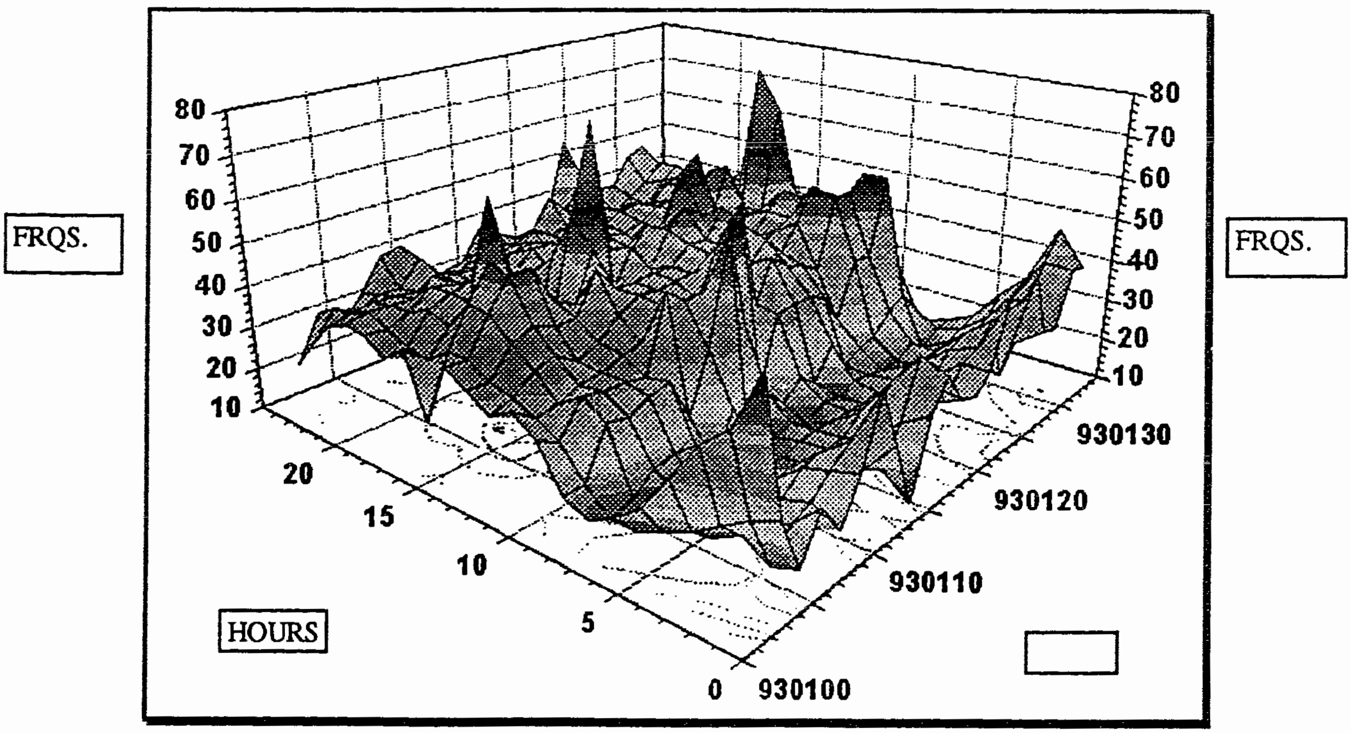


FIGURE V

BURNING TIMES

VANCOUVER- JAN '95

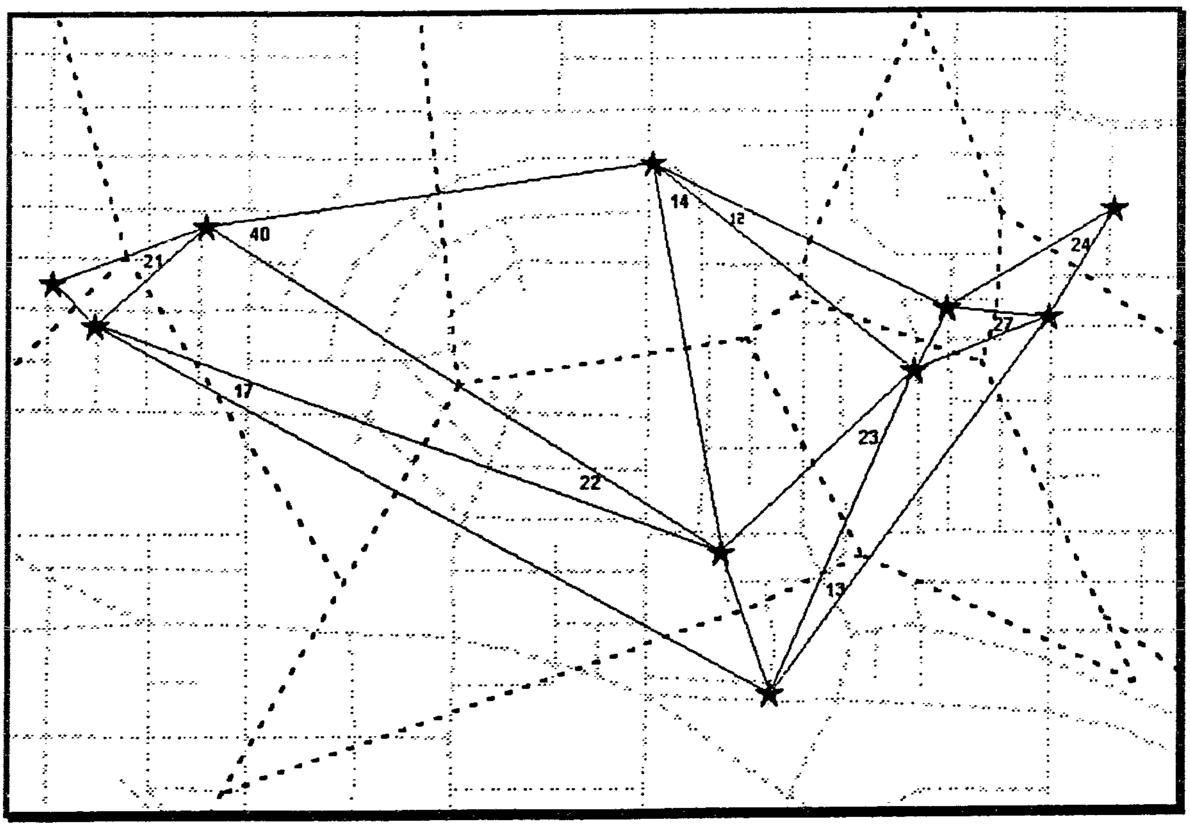
CALLS FOR SERVICE



<u>**FIGURE VI**</u>

VORONOI DIAGRAM & DELAUANY TRIANGLES

CHEVY AUTO THEFT ANALYSIS



Numbers represent Angles in the Triangles

FIGURE VII

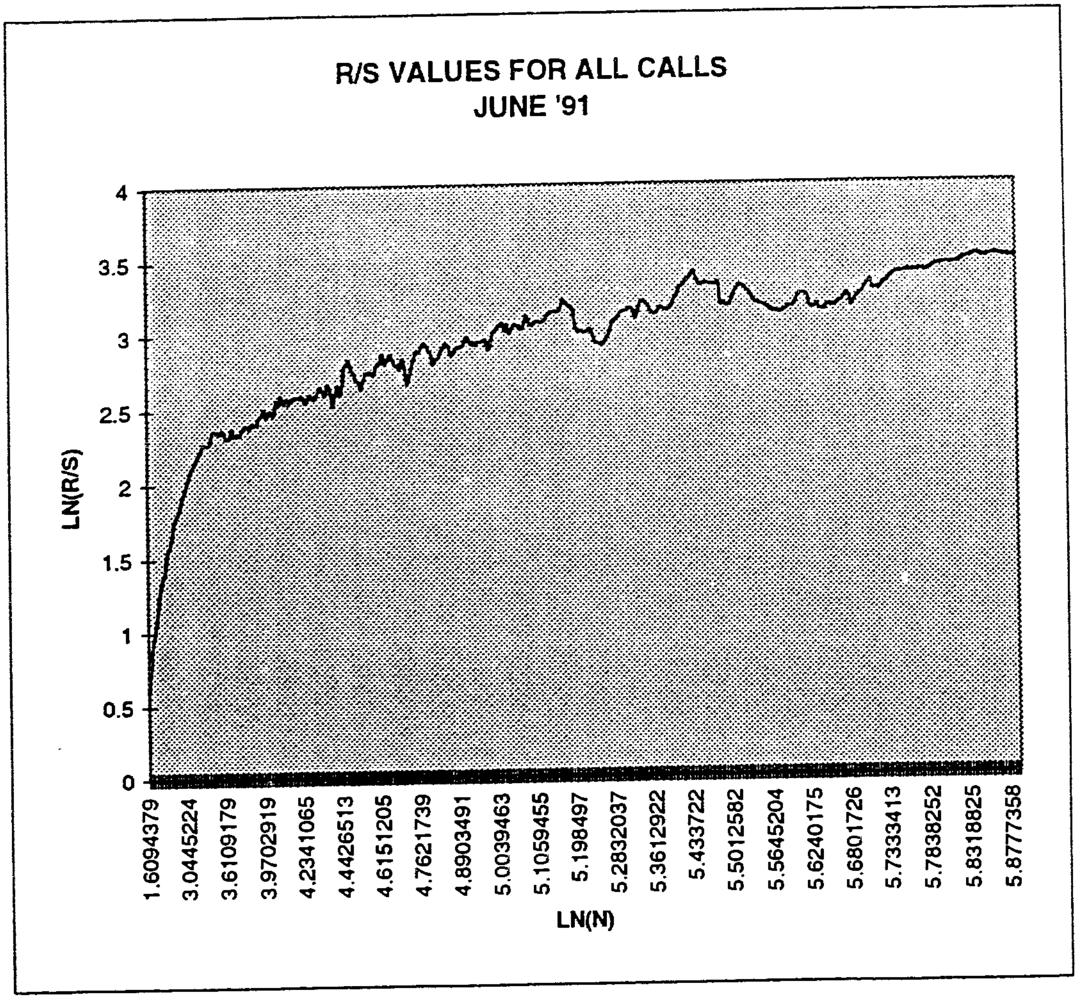
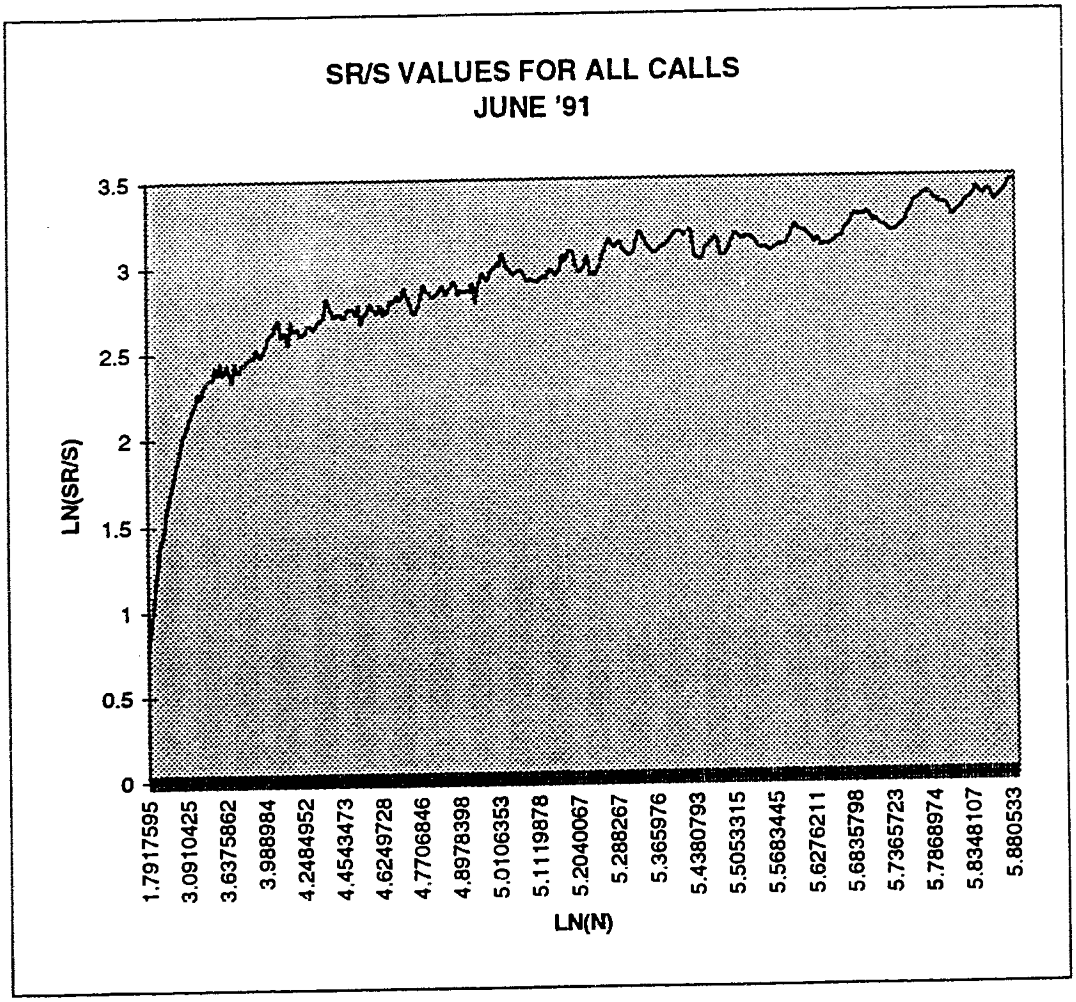
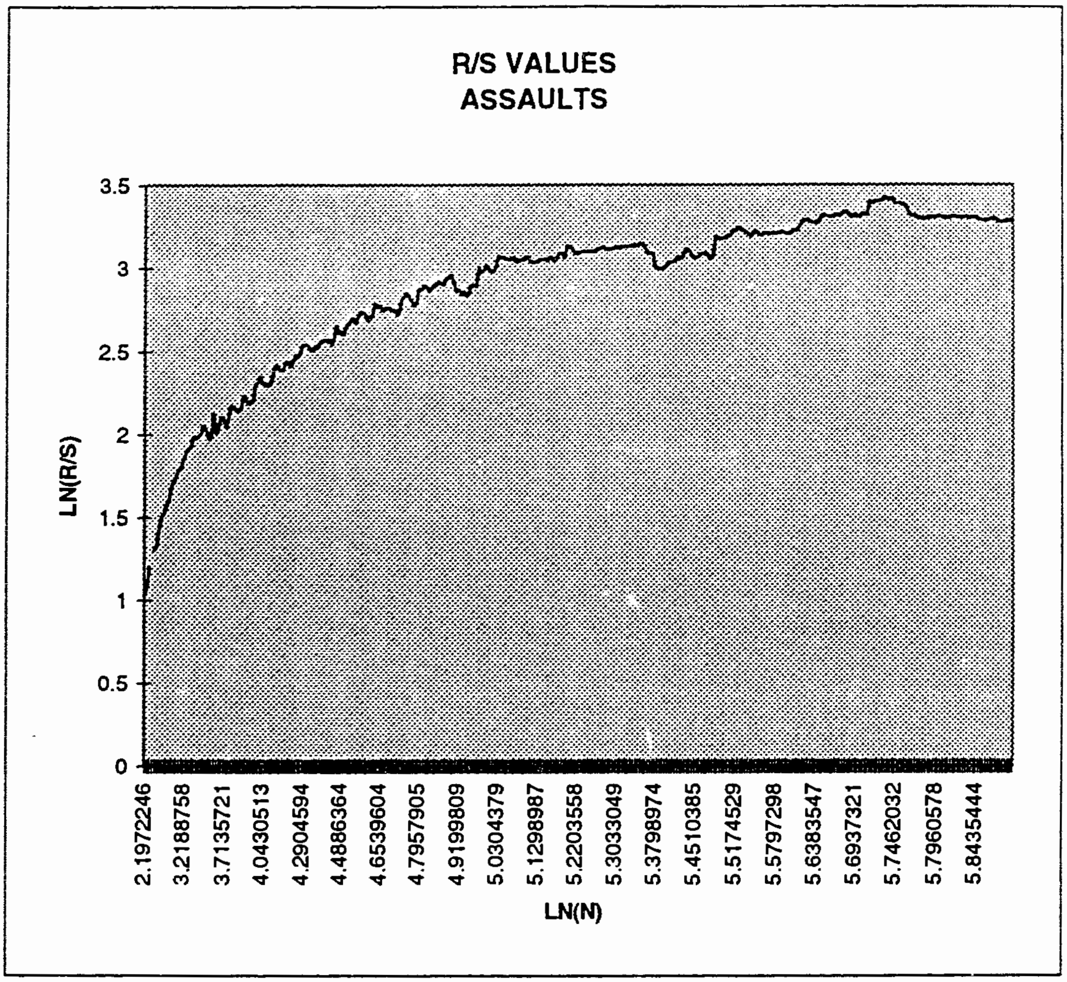

R/S VALUES FOR ALL CALLS
JUNE '91
LN(R/S)
4
3.5
3
2.5
2
1.5
1
0.5
0
1.6094379
3.0445224
3.6109179
3.9702919
4.2341065
4.4426513
4.6151205
4.7621739
4.8903491
5.0039463
5.1059455
5.198497
5.2832037
5.3612922
5.433722
5.5012582
5.5645204
5.6240175
5.6801726
5.7333413
5.7838252
5.8318825
5.8777358
LN(N)

FIGURE VIII



SR/S VALUES FOR ALL CALLS
JUNE '91
LN(SR/S)
3.5
3
2.5
2
1.5
1
0.5
0
1.7917595
3.0910425
3.6375862
3.988984
4.2484952
4.4543473
4.6249728
4.7706846
4.8978398
5.0106353
5.1119878
5.2040067
5.288267
5.365976
5.4380793
5.5053315
5.5683445
5.6276211
5.6835798
5.7365723
5.7868974
5.8348107
5.880533
LN(N)

FIGURE IX



R/S VALUES
ASSAULTS
LN(R/S)
3.5
3
2.5
2
1.5
1
0.5
0
2.1972246
3.2188758
3.7135721
4.0430513
4.2904594
4.4886364
4.6539604
4.7957905
4.9199809
5.0304379
5.1298987
5.2203558
5.3033049
5.3798974
5.4510385
5.5174529
5.5797298
5.6383547
5.6937321
5.7462032
5.7960578
5.8435444
LN(N)

FIGURE X

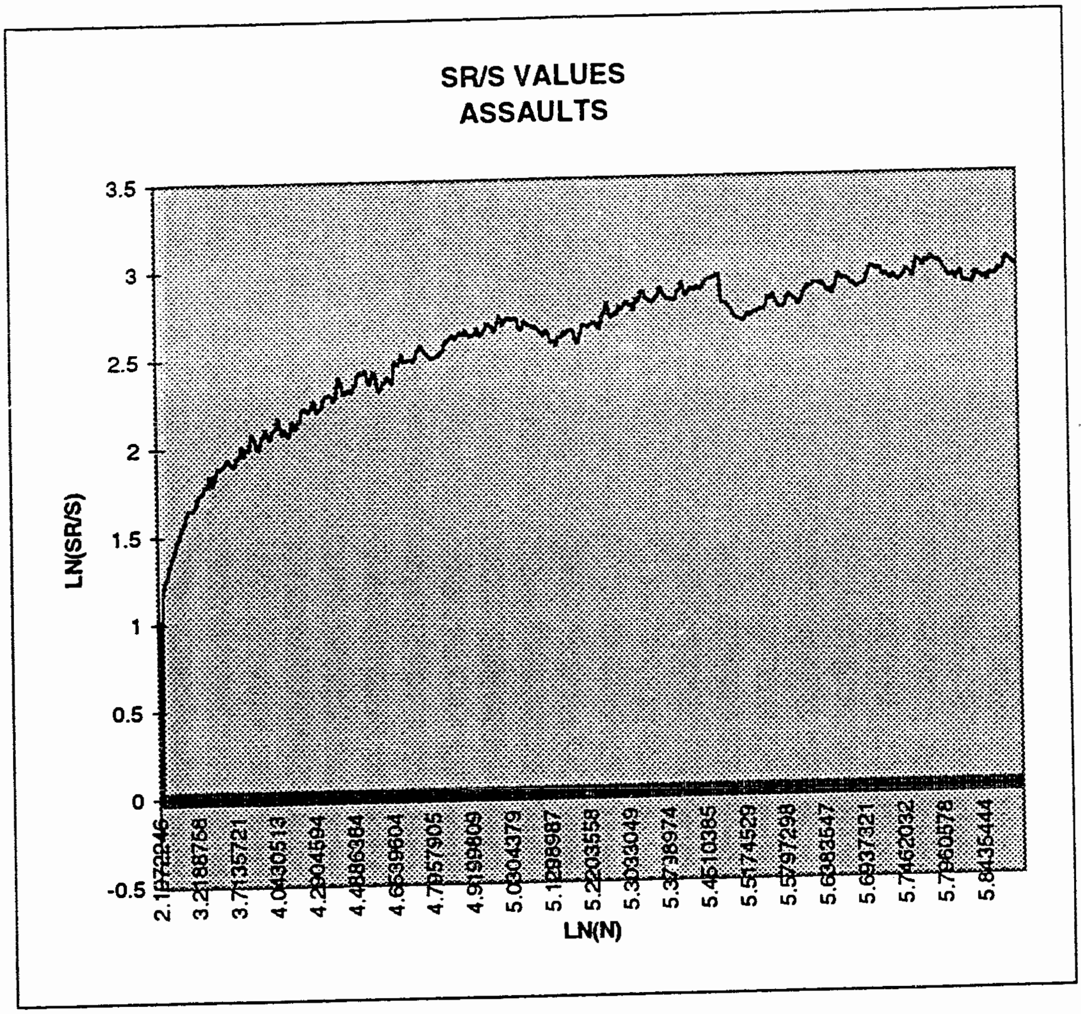
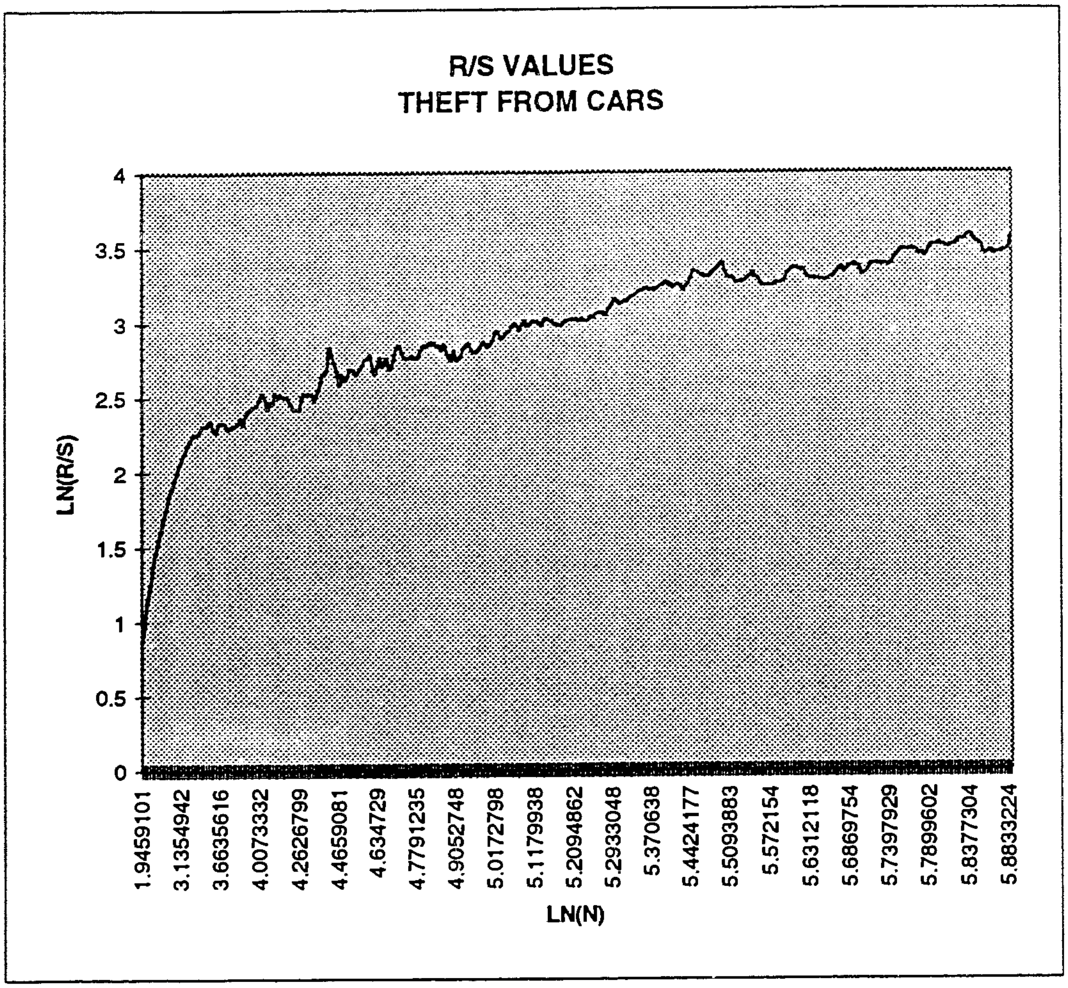
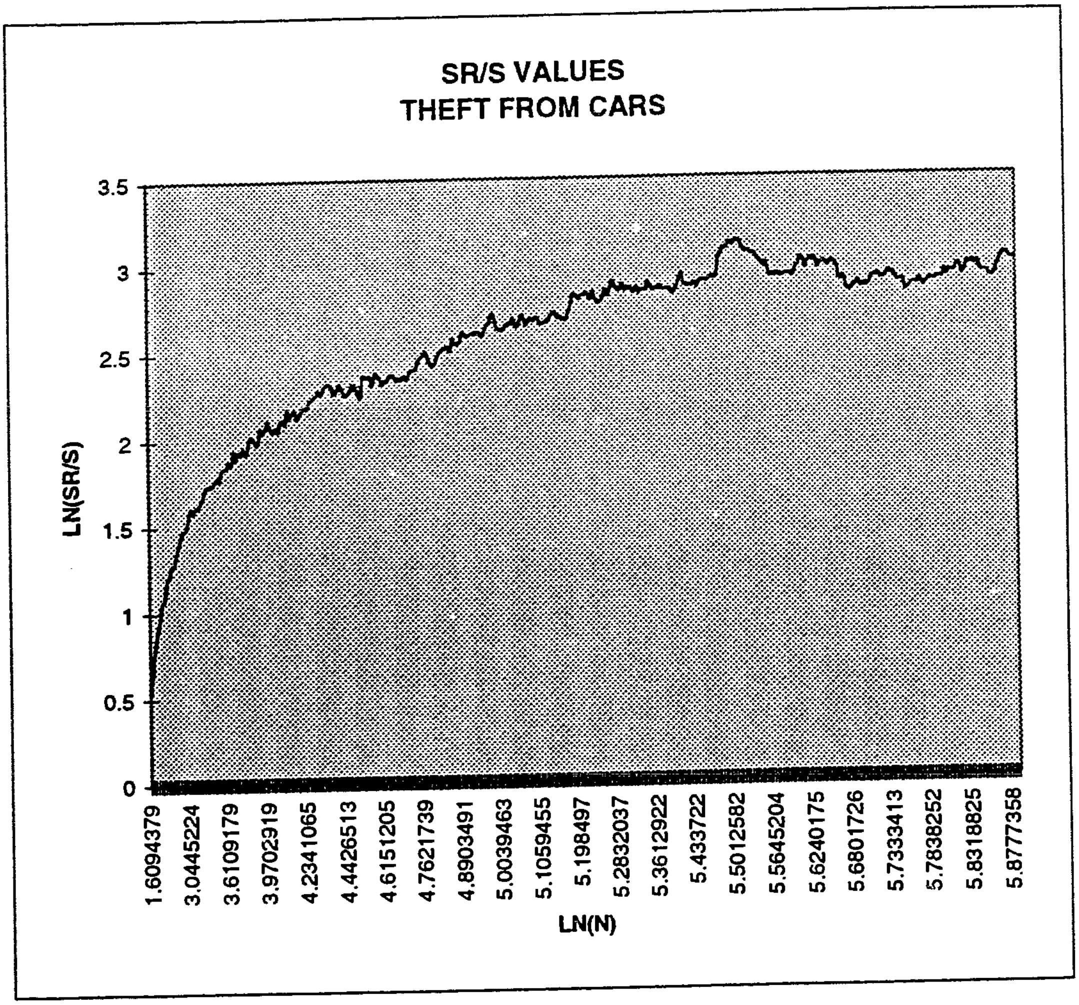


FIGURE XI



R/S VALUES
THEFT FROM CARS
LN(R/S)
4
3.5
3
2.5
2
1.5
1
0.5
0
1.9459101
3.1354942
3.6635616
4.0073332
4.2626799
4.4659081
4.634729
4.7791235
4.9052748
5.0172798
5.1179938
5.2094862
5.2933048
5.370638
5.4424177
5.5093883
5.572154
5.6312118
5.6869754
5.7397929
5.7899602
5.8377304
5.8833224
LN(N)

FIGURE XII



SR/S VALUES
THEFT FROM CARS
LN(SR/S)
3.5
3
2.5
2
1.5
1
0.5
0
1.6094379
3.0445224
3.6109179
3.9702919
4.2341065
4.4426513
4.6151205
4.7621739
4.8903491
5.0039463
5.1059455
5.198497
5.2832037
5.3612922
5.433722
5.5012582
5.5645204
5.6240175
5.6801726
5.7333413
5.7838252
5.8318825
5.8777358
LN(N)

REFERENCES

Adams, Gerald R. and Schvaneveldt, Jay D. (1991). *Understanding Research Methods.* New York: Longman.

Aitken, S. and Prosser, R. (1990). Resident's Spatial Knowledge of Neighbourhood Continuity and Form. *Geographical Analysis.* 22:303-325.

Alkan, Ahmet; Demange, Gabrielle and Gale, David. (1991). Fair Allocation of Indivisible Goods and Criteria of Justice. *Econometrica: Journal of the Econometric Society.* 59(4). 1023-1040.

Alston, Jonathan. (1994). *The Serial Rapists' Spatial Pattern of Target Selection.* Unpublished MA thesis. Burnaby: Simon Fraser University.

Antunes, George and Scott, Eric J. (1981). Calling the cops: Police Telephone Operators and Citizen Calls for Service. Journal of Criminal Justice. 9(2): 165-180.

Appel, K.; Haken, W. And Koch, J. (1977). Every Planar Map is Four Colourable. *Illinois Journal of Mathematics.* 21: 429-567.

Atkins, L. and Jarrett, D. (1979). The Significance of 'Significance Test'. In J. Irvine and I. Miles. (Eds.); *Demystifying Social Statistics.* London: Pluto Press.

Babbie, Earl R. (1979). *The Practice of Social Research.* Belmont, Ca: Wadsworth Publishing Company.

Babbie, Earl R. (1986). *Observing Ourselves: Essays in Social Research.* Belmont, Ca: Wadsworth Publishing Company.

Bachman, Ronet. (1991). An Analysis of American Indian Homicide: A Test of Social Disorganization and Economic Deprivation at the Reservation County Level. *The Journal of Research in Crime and Delinquency.* 28(4): 456-70.

Baldwin, J. and Bottoms, A. E. (1976). *The Urban Criminal.* London: Tavistock.

Barker, Stephen F. (1989). *Philosophy of Mathematics.* Englewoods Cliffs, NJ: Prentice Hall.

Barnhart, H. X. and Sampson, A. R. (1994). Overview of Multinomial Models for Ordinal Data. *Communications in Statistics: Theory and Method* 23(12): 339-340.

Barnsley, M. (1988). *Fractals Everywhere*. Boston, MA: Academic Press.

Batty, M. (1991). *Generating Urban Forms from Diffusive Growth*. Environment and Planning. 23: 511-544.

Beavon, Daniel J. K.; Brantingham, P. L. and Brantingham, P. J. (1994). The Influence of Street Networks on the Patterning of Property Offences. In Ronald V. Clarke (Ed.); *Crime Prevention Series. Volume II*. Monsey, New York: Criminal Justice Press. pp. 115-148.

Becker, H. S. (1958). Problems of Inference and Proof in Participant Observation. *American Sociological Review*. 169: 652-60.

Beland, Francois and Andre Blais. (1989). Quantitative Methods and Contemporary Sociology in Francophone Quebec. *Canadian Review of Sociology and Anthropology*. 26 (3): 533-56.

Belkin, J.; Blumstein, A.; Glass, W. and Lettre, M. (1972). JUSSIM, An Interactive Computer Program and its uses in Criminal Justice Planning. *Proc. International Symposium on Criminal Justice Information and Statistics Systems*, Project SEARCH, Sacramento, CA.

Bell, E.T. (1931). *Men of Mathematics*. London: Cambridge University Press.

Beltrani, E. (1977). *Models for Public System Analysis*. New York: Academic Press.

Bennet, Richard R. (1991). Development and Crime: A Cross-National, Time-Series Analysis of Competing Models. *The Sociological Quarterly*. 32(3): 343-363.

Bennett, T. (1989). Burglar's Choice of Targets. In D. Evans and D. Herbert, (Eds.); *The Geography of Crime*. London: Routledge.

Berlinghoff, William P. (1968). *Mathematics: The Art of Reason*. Boston: D.C. Heath and Company.

Berry, J. W. (1971). Temme and Eskimo Perceptual Skills. *cited* in Lynn S. Lieben, Arthur H. Patterson & Nora Newcombe (Eds.); *Spatial Representation and Behavior across the Life Span: Theory and Application*. (1981). NY Academic Press. pp. 24.

Biderman, A. D., and Reiss, Jr., A. J. (1967). On Exploring the 'Dark Figure' of Crime. *The Annals of the American Academy of Political and Social Science*. 374: 1-15.

Bijleveld, Catrien C. J. H. and Monkkonen, Eric H. (1991). The Dynamics of Police Behavior: A Data Re-Analysis. *Historical Methods*. 24(1): 16-24.

Birge, J. R. and Pollock, S. M. (1989). Modelling Rural Police Patrol. *OR: The Journal of the Operational Research Society*. 40(1): 41-54.

Black, D. J. (1970). The Production of Crime Rates. *American Sociological Review*. 35: 733-747.

Blalock, Herbert M. Jr. (1968). The Measurement Problem: A Gap between the Languages of Theory and Research. In Herbert M. Jr. Blalock, and A. B. Blalock (Eds.); *Methodology in Social Research*. N.Y.: McGraw Hill.

Blalock, Herbert M. Jr. (1970). *An Introduction to Social Research*. Englewood Cliffs, N.J.: Prentice Hall.

Blalock, Herbert M. Jr. (1981). *Conceptualization and Measurement in the Social Sciences*. Beverely Hill: Sage.

Blumstein, A.; Cohen, J.; Das, S.; and Moitra, S. D. (1988). Specialization and Seriousness during Adult Criminal Careers. *Journal of Quantitative Criminology*. 4(4): 303-345.

Bodily, Samuel E. (1978). Police Sector Design: Incorporating Preferences of Interest Groups for Equality and Efficiency. *Management Science*. 24(12): 1301-1313.

Boots, Barry N. and Getis, Arthur. (1988). *Point Pattern Analysis.* Beverly Hills, Ca.: Sage.

Booysen, Hercules. (1993). The Wide Meaning, the Narrow Meaning and an International Law Meaning of Article VIII(2)(b) of the International Monetary Fund Agreement. *The Comparative and International Law Journal*. 26(3): 352-363.

Boruch, R. F. (1975). On Common contentions about Randomized Experiments for Evaluating Social Programs. In R. F. Boruch and H. W. Riecken (Eds.); *Experimental Testing of Public Policy.* Boulder: Westview.

Bottomley, A. K. and Pease, K. (1986). *Crime and Punishment: Interpreting the Data*. Milton Keynes, UK: Open University Press.

Bottomore, T. (1979). Marxism and Sociology. In T. Bottomore and R. A. Nisbet (Eds.); *A History of Sociological Analysis.* London: Heinmann. pp. 118-148.

Boudon, R. (1971). *The Logic of Sociological Explanation.* Harmondsworth: Penguin.

Bowerman, Bruce L. and O'Connell, Richard T. (1979). *Time Series and Forecasting.* North Scituate, Mass.: Duxbury Press.

Brantingham, P. J. and Brantingham, P. L. (1975). Residential Burglary and Urban Forms. *Urban Studies.* 12: 273-284.

Brantingham, P. J. and Brantingham, P. L. (1978). A Topological Technique for Regionalization. *Environment and Behavior.* 10: 335-353.

Brantingham, P. J. and Brantingham, P. L. (1984). *Patterns in Crime.* New York: Macmillan Publishing Company.

Brantingham, P. J. and Brantingham, P. L. (1991). *Environmental Criminology.* Prospect Heights, IL: Waveland Press.

Brantingham, P. J. and Brantingham, P. L. (1993a). Environment, Routine and Situation: Toward a Pattern Theory of Crime. In Ronald V. Clarke and Marcus Felson (Eds.); *Routine Activity and Rational Choice: Advances in Criminological Theory. Vol. V.* New Brunswick, NJ: Transaction Publishers.

Brantingham, P. J. and Brantingham, P. L. (1993b). Nodes, Paths and Edges: Considerations on the Complexity of Crime and the Physical Environment. *Journal of Environmental Psychology.* 13: 3-28.

Brantingham, P. J., Brantingham, P. L. & A. Verma. (1992). *Crime Pattern Analysis Using Point Set and Algebraic Topology.* Paper presented at the American Society of Criminology, New Orleans.

Brantingham, P. J., Mu, Shihong. and A. Verma. (1994). *The Ecological Rhythms and Routines of Crime in Vancouver.* Paper presented at the American Society of Criminology, Miami.

Broadhurst, R. G. & Loh, N. S. (1995). Rearrest Probabilities for the 1984-1993 Apprehended Western Australian Population: A Survival Analysis. *Journal of Quantitative Criminology.* 11(3).

Brower, S.; Dockett, K. and Taylor, R. B. (1983). Resident's Perception of Territorial Features and Perceived Local Threat. *Environment and Behavior.* 15: 419-437.

Brown, B. and Altman, I. (1991). Territoriality and Residential Crime: A Conceptual Framework. In P. L. Brantingham and P. J. Brantingham (Eds.); *Environmental Criminology.* Prospect Heights, IL: Waveland Press. pp. 55-76.

Brugger, Winfried. (1994). Legal Interpretation, Schools of Jurisprudence, and Anthropology: Some Remarks from a German Point of View. *The American Journal of Comparative Law.* 42(2): 395-422.

Bryman, Alan. (1986). *Quantity and Quality in Social Research.* London: Unwin Hyman.

Bunn, Douglas N.; Caudill, Steven B.; and Gropper, Daniel M. (1992). Crime in the Classroom: An Economic Analysis of Undergraduate Student Cheating Behaviour. *The Journal of Economic Education.* 23 (3): 197-218.

Bursik, Robert J. (Jr).; Grasmick, Harold G.; Chamlin, Mitchell B. (1990). The Effect of Longitudinal Arrest Patterns on the Development of Robbery Trends at the Neighborhood Level. *Criminology.* 28(3): 431-450.

Butcher, D. (1991). *Crime in the Third Dimension: A Study of Burglary Patterns in a High Density Residential Area.* Unpublished MA Thesis. Burnaby, B.C.: Simon Fraser University.

Bynner, John and Stribley, Keith M. (1979). *Social Research: Principles and Procedures.* Suffolk: Longman.

Cambell, D. T. (1979). *Qualitative and Quantitative Methods in Evaluation Research.* Beverely Hills, California: Sage.

Cambell, Norman. (1956). Numerical Laws and the use of Mathematics in Science. James R. Newman (1956). *The World of Mathematics Vol. III.* New York: Simon and Schuster. pp. 1814-1829.

Canter, Philip. (1993). State of the Statistical Art: Point Pattern Analysis. In Carolyn Rebecca Block and Margaret Dabdoub (Eds.) *Workshop on Crime Analysis through Computer Mapping.* Proceedings 1993: Illinois Criminal Justice Information Authority. pp. 199-210.

Capone, D. and Nicohols, W. (1976). Urban Structure and Criminal Mobility. *American Behavioral Scientist*. 20: 199-201.

Carter, R. and Hill, K. Q. (1979). *The Criminal's Image of the City*. New York, NY: Pergamon.

Caulkins, Jonathan P. (1993). Local Drugs Markets Response to Focused Police Enforcement. *Operations Research*. 41(5): 848-863.

Chadwick, Bruce A; Bahr, Howard M. and Albrecht, Stan L. (1984). *Social Science Research Methods*. Englewood Cliffs, NJ: Prentice Hall.

Chaiken, Jan. M. and Dormant, P. (1978a). Patrol Car Allocation Model: Background. *Management Science*: 24(12): 1280-1290.

Chaiken, Jan. M. and Dormant, P. (1978b). Patrol Car Allocation Model: Capabilities and Algorithms. *Management Science*: 24(12): 1291-1300.

Chelst, Kenneth. (1978). An Algorithm for Deploying a Crime Directed (Tactical) Patrol Force. *Management Science*: 24(12): 1314-1327.

Cicourel, A.V. (1964). *Method and Measurement in Sociology*. New York: Free Press.

Clarke, Ronald V. (Ed.). (1992). *Situational Crime Prevention: Successful Case Studies*. Albany, NY: Harrow and Heston.

Clifton, Rodney A. (1975). Self-concepts and Attitudes: A Comparison of Canadian Indian and non-Indian Students. *Canadian Review of Sociology and Anthropology*. 12: 577-584.

Cloward, Richard A. and Ohlin, Lloyd E. (1960). *Delinquency and Opportunity: A Theory of Delinquent Gangs*. New York: The Free Press.

Coburn G. (1988). *Patterns of Homicide in Vancouver, 1980-1986*. Unpublished MA Thesis. Burnaby, B.C.: Simon Fraser University.

Cohen, Bernard P. (1989). *Developing Sociological Knowledge: Theory and Method*. Chicago: Nelson Hall.

Cohen, L. E. and Felson, M. (1979). Social Change and Crime Rate Trends: A Routine Activity Approach. *American Sociological Review*. 44: 588-608.

Cohn, Ellen G. and Farrington, David P. (1990). Differences between British and American Criminology: An Analysis of Citations. *British Journal of Criminology*. 30(4): 467- 482.

Coleman, James S. (1964). *Introduction to Mathematical Sociology*. London: Collier-Macmillan Ltd.

Coleman, James S. (1990). *Foundations of Social Theory*. Camb. Mass. Harvard University Press.

Collins, Randall. (1975). *Conflict Sociology*. New York: Academic Press.

Collins, Randall. (1984). Statistics versus Words. In Collins, Randall (Ed.); *Sociological Theory 1984*. San Francisco: Jossey Bass.

Colville, Ian. (1989). Scenes from a Budget: Helping the Police with Accounting Enquiries. *Financial Accountability and Management in Government*. 5(2): 89-106.

Cook, Thomas D. and Reichardt, Charles S. (Eds.). (1979). *Qualitative and Quantitative Methods in Evaluative Research*. Beverely Hills, London: Sage Publications.

Coombes, M; Wong, C and Atkins, D. (1994). Crime Risk in Urban and Rural Neighborhoods: An Experimental Analysis of Insurance Data. *Environment, Planning and Design*. 21(4): 489-512.

Copas, John B. and Tarling, Roger. (1988). Stochastic models for Analyzing Criminal Careers. *Journal of Quantitative Criminology*. 4(2): 173-86.

Cornish, D. and Clarke, R.V. (1986). *The Reasoning Criminal*. New York, NY: Springer-Verlag.

Crank, John P.; Payn, Betsy and Jackson, Stanley. (1993). The Relationship between Police Belief Systems and Attitudes toward Police Practices. *Criminal Justice and Behaviour*. 20(2): 199-221.

Cromwell, P. F.; Olson, J. N. and Avary, D. W. (1991). *Breaking and Entering: An Ethnographic Analysis of Burglary*. Newbury Park, CA: Sage.

Das, Arvind N. (1983). *Agrarian Unrest and Socio-economic Change in Bihar 1900-1980*. New Delhi: Manohar Press.

Dasgupta, Biplab. (1975). *The Naxalite Movement*. Bombay: Allied Publishers.

Davis, F. (1961). Comment on 'Initial Interaction of New Comers in Alcoholics Anonymous'. *Social Problems* 8: 364-365.

Decola, L. (1991). Fractal Analysis of Multiple Spatial Autocorrelation among Point Data. *Environment and Planning*. 23: 545-556.

DeJoy, D. M. (1994). Managing Safety in the Workplace: An Attribution Theory, Analysis and Model. *Journal of Safety Research*. 25(1): 3-18.

Diggle, P. J. (1983). *Statistical Analysis of Spatial Point Patterns*. New York: Academic Press.

Doby, John T. (1967). *An Introduction to Social Research*. New York: Appleton Century Crafts.

Downs, R. M. (1981). Maps and Metaphors for Spatial Representation. In Lynn, S Lieben.; Arthur H. Patterson and Nora Newcombe. (Eds.); *Spatial Representation and Behavior across the Life Span: Theory and Application.* NY Academic Press. pp. 143-166.

Dubois, Didier and Prade, Henri. (1980). *Fuzzy Sets and Systems: Theory and Applications.* NY: Academic Press.

Duffala, D. C. (1976). Convenience Stores: Armed Robbery and Physical Environmental Features. *American Behavioral Scientist*. 20: 227-246.

Ehlrich, I. (1975). The deterrent Effect of Capital Punishment: A Question of Life and Death. *American Economic Review*. 65: 397-417.

Einstein, Albert and Infeld, Leopold. (1942). *The Evolution of Physics*. New York: Simon and Schuster.

Erickson, F. (1977). Some Approaches to Injury in School-Community Ethnography. *Anthropology and Education Quarterly* 8: 58-69.

Evans, David T.; Cullen, Francis T.; Dunaway, Gregory and Burton, Velmer S. Jr. (1995). Religion and Crime Re-examined: The Impact of Religion, Secular Controls and Social Ecology on Adult Criminality. *Criminology*. 33(2): 195-224.

Fabianic, D. (1980). Perceived Scholarship and Readership of Criminal Justice Journals. *Journal of Police Science and Administration*. 8: 15-20.

Fahmy, Y.; Russ, J.C. and Koch, C.C. (1991). Application of fractal geometry measurements to the evaluation of fracture toughness of brittle intermetallics. *Journal of materials research*. 6(9): 1856-61.

Fararo, Thomas J. (1973). *Mathematical Sociology: An Introduction to Fundamentals*. New York: Wiley.

Farnworth, Margaret; Thornberry, Terrence P.; Krohn, Marvin D. and Lizotte, Alan J. (1994). Measurement in the Study of Class and Delinquency: Integrating Theory and Research. *Journal of Research in Crime and Delinquency*. 31(1): 312-61.

Fattah, E.A. (1991). *Understanding Criminal Victimization: An Introduction to Theoretical Victimology*. Scarborough, Ontario: Prentice Hall.

Feeney, F. (1986). Robbers as decision makers. In D. Cornish & R. Clarke, (Eds.); *The Reasoning Criminal*. NY, Springer-Verlag, pp. 53-71.

Felson, Marcus. (1987). Routine Activities and Crime Prevention in the Developing Metropolis. *Criminology*. 25: 911-932.

Felson, Marcus. (1993). *Crime and Everyday Life: Insight and Implications for Society*. Pine Forge Press.

Fielding, Nigel G. and Fielding, Jane L. (1986). *Linking Data*. London: Sage.

Fienberg, S. E. (1977). The Collection and Analysis of Ethnographic Data in Education Research. *Anthropology and Education Quarterly*. 8: 58-69.

Filstead, W. J. (Ed.). (1970). *Qualitative Methodology*. Chicago: Markham.

Filstead, W. J. (1979). Qualitative Methods: A Needed Perspective in Evaluation Research. In Thomas D. Cook and Charles S. Reichardt, (Eds.); *Qualitative and Quantitative Methods in Evaluative Research*. Beverely Hills, London: Sage Publications.

Fine, Terrence L. (1973). *Theories of Probability: An Examination of Foundations*. New York: Academic Press.

Fischer, R. A. (1930). Inverse Probability. *Proceedings of the Cambridge Phiolosohical Society*. 26: 528-35.

Fleming, Zackery Tyler. (1994). *Exploring Auto theft Patterns in British Columbia: A Case Study of "top-end" Problem-Oriented Policing*. Unpublished MATHEMATICS Thesis, Burnaby, B.C.: Simon Fraser University.

Foruse, Dennis P. and Richer, Stephen. (1973). *Social Research Methods.* Englewood Cliffs, N.J.: Prentice Hall.

Gabor, T.; Baril, M.; Cusson, M.; Elie, D.; LeBlanc, M. and Normandeau, A. (1987). *Armed Robbery: Cops, Robbers and Victims.* Springfield, IL: Charles C. Thomas.

Garling, T. (1989). The Role of Cognitive Maps in Spatial Decisions. *Journal of Environmental Psychology.* 9: 269-278.

Garling, T. and Golledge, R. G. (1989). Environmental Perception and Condition. In E. H. Zube and G. T. Moore (Eds.); *Advances in Environmental Behaviour and Design Vol. II.* New York, NY: Plenum Press, pp. 203-236.

Garling, T.; Book, A. and Lindberg, E. (1984). Cognitive Mapping of Large-Scale Environments: The Interrelationships of Action Plans, Acquisition and Oreintation. *Environment and Behavior.* 16: 3-34.

Gehrlein, W. V. (1990). Inducing Relations on Incomplete Ordinal Data. *Quality and Quantity.* 24(1): 17-36.

Geographical Magazine. (1992). *Fractals: Their Practical Application to Geography.* 64(5): 32-36.

Gillies, D. A. (1973). *An Objective Theory of Probability.* London: Methuen.

Glaser, B. and Strauss, A. L. (1967). *The Discovery of Grounded Theory.* Chicago: Aldine.

Good, C.M. (1975). Periodic markets and travelling traders in Uganda. *Geographical Review.* 65(1): 45-72.

Goode, William J. and Halt, Paul K. (1952). *Methods in Social Relations.* New York: McGraw Hill.

Goodman, N. D. (1981). The Experimental Foundations of Mathematical Knowledge. *History and Philosophy of Logic.* 2: 55-65.

Goodman, N. D. (1991). Modernizing the Philosophy of Mathematics. *Synthese.* 88(2): 119-126.

Government of India. (1966). *Indian Penal Code.* Nasik: Government of India Press.

Government of India (1975). *Maintenance of Internal Security Act-1975.* Faridabad: Government of India Press.

Green, L. (1984). Multiple Dispatch Queueing Model of Police Patrol Operations. *Management Science.* 30(6): 653-664.

Green, L. and Kolesar, Peter. (1984). A Comparison of the Multiple Dispatch and M/M/c Priority Queueing Models of Police Patrol. *Management Science.* 30(6): 665-670.

Greenberg, D. F. (1978). Recidivism as Radioactive Decay. *Journal of Research in Crime and Delinquency.* 24:124-125.

Greenberg, D. F. (1979). *Mathematical Criminology.* New Brunswick, NJ: Rutgers University Press.

Hacking, !an. (1975). *The Emergence of Probability.* Cambridge: Cambridge University Press.

Hahn, Hans. (1956). The Crisis in Intuition. In James R. Newman, (Ed.): *The World of Mathematics Vol. III.* (1956). New York: Simon and Schuster. pp. 1956-1976.

Hale, Chris and Sabbagh, Dima. (1991). Testing the Relationship between Unemployment and Crime: A Methodological Comment and Empirical Analysis using Time Series Data from England and Wales. In *The Journal of Research in Crime and Delinquency.* 28(4): 400-417.

Halfpenny, Peter. (1982). *Positivism and Sociology: Explaining Social Life.* London: George Allen and Unwin (Publishers). Ltd.

Hammersley, M. (1989). *The Dilemma of Qualitative Method: Herbert Blumer and the Chicago Tradition.* London: Routledge.

Hannemas, Robert A. (1987). *Computer Assisted Theory Building: Modeling Dynamic Social Systems.* Beverely Hills, Ca. Sage.

Hardy, G. H. (1967). *A Mathematician's Apology.* Cambridge (Eng.): The University Press.

Harries, K. D. (1990). *Serious Violence.* Springfield, IL: Charles C. Thomas.

Hart, Roger A. (1981). Children's Spatial Representation of the Landscape: Lessons and Questions from a Field Study. In Lynn, S. Lieben, Arthur H. Patterson and Nora Newcombe. (Eds.): *Spatial Representation and*

Behavior across the Life Span: Theory and Application. NY Academic Press pp. 195-232

Hempel, Carl G. 1956. On the Nature of Mathematical Truths. In James R. Newman (Ed.); *The World of Mathematics Volume III.* (1956). New York: Simon and Schuster. pp. 1619-1634.

Herbert, D. T. and Hyde, S. W. (1985). Environmental Criminology: Testing some Area Hypotheses. *Transactions: Institute of British Geographers.* 10: 259-274.

Hindelang, Michael J. (1974). The Uniform Crime Reports Revisited. *Journal of Criminal Justice.* 2: 1-17.

Hindelang, Michael J.; Hirschi, Travis and Weis, Joseph G. (1981). *Measuring Delinquency.* Beverely Hills, London: Sage.

Hirschi, Travis. (1969). *Causes of Delinquency.* Berkeley: University of California Press.

Hoelter, Jon W. (1983). Factorial Invariance and Self-Esteem: Reassessing Race and Sex Differences. *Social Forces.* 61(1): 834-846.

Holmes, Malcolm D. and Taggart, William A. (1990). A Comparative Analysis of Research Methods in Criminology and Criminal Justice Journals. *Justice Quarterly* 7: 421-37.

Holmes, Malcolm D. and Taggart, William A. (1991). Institutional Productivity in Criminal Justice and Criminology: An Examination of Author Affiliation in Selected Journals. *Journal of Criminal Justice* 19 (6): 549-61.

Horan, Patrick. (1978). Is Status Attainment Research Atheoretical? *American Sociological Review.* 43: 334-41.

Hunter, A. A. (1985). Doing it with Numbers. *Canadian Review of Sociology and Anthropology.* 22: 645-72.

Hurst, H. E. (1951). Long term storage of Reservoirs. *cited* in Peters, Edgar E. (1991). *Chaos and Order in the Capital Market.* New York: John. pp. 64.

luo, X. and Schramm, D.N. (1992). Fractals and Cosmological Large-Scale Structure. *Science.* 256 (5056): 513-515.

Junger, Marianne. (1989). Discrepancies Between Police and Self-Report Data for Dutch Racial Minorities. *The British Journal of Criminology.* 29(3): 273-284.

Kansas City, Missouri Board of Public Commission. (1977). *Response Time Analysis Study. Vol. I (Methodology) & Vol. II (Analysis).* Kansas City Mo. Board of Police Commissioner.

Kaplan, Abraham. (1956). Sociology knows the Language of Mathematics. In James R. Newman (Ed.); *The World of Mathematics. Vol. II.* New York: Simon and Schuster. pp. 1294-1313.

Kasner, Edward and Newman, James R. (1940). *Mathematics and the Imagination.* New York: Simon and Schuster.

Kaufmann, A. (1975). *Introduction to the Theory of Fuzzy Subsets. Vol. I.* New York: Academic Press.

Keane, Carl. (1993). The Impact of Financial Performance on Frequency of Corporate Crime: A Latent Variable Test of Strain Theory. *Canadian Journal of Criminology.* 35(3): 293-308.

Kelman, H. C. (1972). The Rights of the Subject in Social Research: An Analysis in terms of Relative Power and Legitimacy. *American Psychologist.* 27: 989-1016.

Kempton, W. (1978). Category Grading and Taxonomic Relations: A Mug is a sort of Cup. *cited* in M. Smithson. (1987). *Fuzzy Set Analysis for Behavioral and Social Sciences.* NY: Springer-Verlag.

Kendall, M. G. (1973). *Time Series.* London: Griffin.

Kern, Gary M. (1989). A Computer Simulation Model for the Study of Police Patrol Deployment. *Simulation.* 52(6): 226- 232.

Kesslu, David A. (1985). One-or two-officer cars? A Perspective from Kansas City. *Journal of Criminal Justice.* 13 (1): 49-64.

Keynes, J. M. (1921). *A Treatise on Probability.* London: Macmillan.

Kidder, Louise H. ; Judd, Charles M. and Smith, Eliot R. (1986). *Research Methods in Social Relations.* New York: Holt, Reinchart and Winston.

Kituse, J. I., and Cicourel, A.V. (1963). A Note on the Use of Official Statistics. *Social Problems.* 11: 131-139.

Kohli, Atul. (1990). *Democracy and Discontent: India's Growing Crisis of Governability.* New York: Cambridge University Press.

Kuner, Christopher B. (1991). The Interpretation of Multilingual Treaties: Comparison of Texts versus the Presumption of Similar Meaning. *The International and Comparative Law Quarterly.* 40(4): 953-964.

Lamber, Julia and Luskin, Mary Lee. (1991). City and Town Courts: Mapping their Dimensions. *Indiana Law Journal.* 67(1): 59-84.

Land, Kenneth C.; McCall, Patricia L.; and Cohen, Lawrence E. (1991). Characteristics of U.S. Cities with Extreme High or Low Crime Rates: Results of Discriminant Analysis of 1960, 1970 and 1980 Data. *Social Indicators Research.* 24 (3): 209-232.

Langworthy, Robert H. and LeBeau, James L. (1990). Temporal Evolution of a Sting Clientele. *American Journal of Police: An Interdisciplinary Approach.* 9(2): 101-114.

Lanier, Mark and Carter, David L. (1993). Applying Computer Simulation to Forecast Homicide Trends. *Journal of Criminal Justice.* 21(5): 467-479.

Laplane, D. (1992). Reviews: Use of introspection in Scientific Psychological Research. *Behavioural Neurology.* 5(4): 99-204.

Larson, R. (1975). *Urban Police Patrol Analysis.* Cambridge MA: MIT Press.

Lattimore, P. K. and Baker, J. R. (1992). The Impact of Recidivism and Capacity on Prison Populations: A Projection Model. *Journal of Quantitative Criminology.* 8: 155-173.

Lauritsen, Janet L. (1993). Sibling Resemblance in Juvenile Delinquency: Findings from the National Youth Survey. *Criminology.* 31(3): 387-410.

Lazerwitz, B. (1968). Sampling Theory and Procedures. In H. M. Blalock, and B. A. Blalock (Eds.); *Methodology in Social Sciences.* New York: McGraw-Hill.

Leik, Robert K. and Meeker, Barbara F. (1975). *Mathematical Sociology.* Englewood Cliff, N.J. Prentice Hall.

Letkemann, P. (1973). *Crime as Work.* Englewood Cliffs, NJ: Prentice Hall.

Lewin, K. (1936). *Principles of Topological Psychology.* New York: McGraw-Hill.

Lieben, Lynn, S.; Patterson, Arthur H. and Newcombe, Nora. (Eds.). (1981). *Spatial Representation and Behavior Across the Life Span: Theory and Application.* NY: Academic Press

Light, Stephen C. (1990). Measurement Error in Official Statistics: Prison Rule and Infraction Data. *Federal Probation.* 54(4): 63-68.

Lin, Bin-Shan; MacKenzie, Doris Layton and Gulledge, Thomas R. Jr. (1986). Using ARIMA Models to Predict Prison Populations. *Journal of Quantitative Criminology.* 2(3): 251-264.

Lofland, J. (1961). Reply to Davis' comment on 'Initial Interaction'. *Social Problems.* 8: 365-367

Lofland, J. and Lejeune, R. A. (1960). Initial Interaction of New Comers in Alcoholics Anonymous: A Field Experiment in Class Symbols and Socialization. *Social Problems.* 8:102-111.

Logan, Charles H. (1972). General Deterrent Effects of Imprisonment. *Social Forces.* 51(1): 64-73.

Lowman, J., and Palys, T. (1991). Interpreting Criminal Justice System Records of Crime. In *Canadian Criminology.* M. Jackson and C. Griffiths. (Eds.); (1991). Burnaby: Simon Fraser University.

McDaniel, Clyde O. Jr. (1974). *Research Methodology: Some Issues in Social Science Research.* Dubuque, Iowa: Kendall Publishing Co.

McDowell, Charles P. (1990). "False Alligators" and Fuzzy Data: A New look at Crime Analysis. *The Police Chief.* 57 (3): 44-45.

McGinnis, R. (1958). Randomization and Inference in Sociological Research. *American Sociological Review.* 23: 408-414.

McGraw, D. and Watson, G. (1976). *Political and Social Inquiry.* New York: Wiley.

McShane, Frank J. and Noonan, Barrie A. (1993). Classification of Shoplifters by Cluster Analysis. *International Journal of Offender Therapy and Comparative Criminology.* 37(1): 29-40.

Macmillan, Ross. (1995). Changes in the Structural Life Courses and the Decline of Social Capital in Canadian Society: A Time Series Analysis of Property Crime Rates. *Canadian Journal of Sociology.* 20(1): 51-80.

Majumdar, Sharmila; Weinstein, Robert S. and Prasad, Rahul R. (1993). Application of Fractal Geometry Techniques to the Study of Trabecular Bone. *Medical Physics*. 20(6): 1611-20.

Maltz, Michael D. (1984). *Recidivism*. Orlando, FL: Academic Press.

Maltz, Michael D. (1994a). Deviating from the Mean: The Decline of the Significance of Significance. *Journal of Research on Crime and Delinquency*. 31(4): 434-463.

Maltz, Michael D. (1994b). Operations Research in Studying Crime and Justice: Its History and Accomplishments. S. M. Pollock (Eds.); *Handbooks in OR and MS*, Vol. 6. Chapter 7. Elsevier Science B. V.

Maltz, Michael D. (1994c). Space, Time and Crime: Life Course Analysis and the Micro-Ecology of Crime. In John Eck and David Weisburd (Eds.); *Crime and Place*. Criminal Justice Press. (in print).

Mandelbrot, B. (1972). Statistical Methodology for non-periodic Cycles: From the Covariance to R/S Analysis. *Annals of Economic and Social Measurement*. 1(3): 259-290.

Mandelbrot, B. (1986). *The Fractal Geometry of Nature*. New York, Freeman.

Mansfield, M. J. (1963). *An Introduction to Topology*. Princeton: Van Nostrand

Mardia, K. V., Edwards, R., and Puri, M. L. (1977). Analysis of Central Place Theory. *cited* in B. N. Boots, & Arthur Getis. (1988). *Point Pattern Analysis*. New Delhi: Sage.

Martinez, V. J. (1990). Fractals and Multifractals in the Description of the Cosmic Structure. *Vistas in Astronomy*. 33 (3/4): 337-356.

Massey, F. J. Jr. (1951). The Kolmogrov - Smirnov Test for Goodness of Fit. *American Statistical Association Journal*. 46: 70.

Maxfield, Michael G. and Babbie, Earl. (1995). *Research Methods for Criminal Justice and Criminology*. Belmont, Cal.: Wadsworth Publishing Company.

May, Tim. (1993). *Social Research: Issues, Methods and Processes*. Buckingham, Philadelphia: Open University Press.

Meltzer, M. I. and Hastings, H. M. (1992). The Use of Fractals to assess the Ecological Impact of Increased Cattle Population: Case Study from the

Runde Communal Land, Zimbabwe. *The Journal of Applied Ecology*. 29(3): 635-646.

Milgram, Stanley. (1963). Behavioral Study of Obedience. *Journal of Abnormal and Social Psychology*. 67: 371-378.

Miles, R. E. (1970). On the Homogeneous Planar Poisson Point Process. *cited* in A. Okabe; B. Boots and K. Sugihara. *Spatial Tesselations: Concepts and Applications of Voronoi Diagrams*. (1991). West Sussex, England: Wiley. pp. 325.

Miller, Arthur I. (1987). *Imagery in Scientific Thought*. Cambridge, England: MIT Press.

Miller, Richard W. (1987). *Fact and Method: Explanation, Confirmation and Reality in the Natural and Social Sciences*. Princeton, NJ: Princeton University Press.

Morrison, D. E. and Henkel, R. E. (1969). *The Significance Test Controversy: A Reader*. London: Butterworth.

Mu, Shihong and Brantingham, P. J. (1992). *The Vancouver CAD Program: A Consideration of the joint Project on the Use of Computer Aided Dispatch Data being Conducted by Vancouver Police Department and the School of Criminology*. Unpublished report to Statistics Canada. Burnaby, B.C.: Simon Fraser University.

Mukherjee, Kalyan and Yadav, R. S. (1982). For Reasons of State: Oppression and Resistance, a Study of Bhojpur Peasantry. In *Agrarian Movements in India*. Das, Arvind N. (Ed.). London: Frank Cass. pp. 119-47.

Nagel, Ernest. (1961). *The Structure of Science*. New York: Harcourt, Brace & World.

Nagel, Ernest and Newman, James R. (1956). Godel's Proof. In James R. Newman, (Ed.); *The World of Mathematics Vol. III*. (1956). New York: Simon and Schuster. pp. 1668-1695.

Nagel, Ernest. (1956). Symbolic Notation, Haddocks' Eyes and the Dog-walking Ordinance. In James R. Newman (Ed.); (1956). *The World of Mathematics Vol. III*. New York: Simon and Schuster. pp. 1878-1900.

Namboodiri, N. Krishnan; Carter, Lewis F. and Blalock, Hubert M. (1975). *Applied Multivariate Analysis and Experimental Designs*. New York: McGraw Hill.

Nanton, Philip. (1992). Official Statistics and Problems of Inappropriate Ethnic Categorisation. *Policy and Politics*. 20(4): 277-286.

National Crime Records Bureau. (1992). *Crime in India 1991*. Faridabad: Government of India Press.

Neuburger, Hugh and Stokes, Houston H. (1991). Testing the Appropriateness of Statistical Methods. *Financial Analysts Journal*. 47(4): 83-88.

Newman, James R. (1956). *The World of Mathematics Volumes I-IV*. New York: Simon and Schuster.

Newman, O. (1972). *Defensible Space: Crime Prevention through Urban Design*. New York, NY: Macmillan.

Neyman, J. (1937). Outline of a Theory of Statistical Estimation based on the Classical Theory of Probability. *Royal society of London Philosophical transactions*. 236: 333-80.

Nisbet, R. E. and Wilson, T. D. (1977). Telling more than we can Know: Verbal Reports of Mental Processes. *Psychological Review*. 84: 231-59.

Nowakowska, M. (1977). Methodological Problems of Measurement of Fuzzy Concepts in the Social Sciences. *Behavioral Science*. 22: 107-115.

Okabe, A.; Boots, B. and Sugihara, K. (1992). *Spatial Tesselations: Concepts and Applications of Voronoi Diagrams*. West Sussex, England: Wiley.

Ostrom, Charles W. (1978). *Time Series Analysis: Regression Techniques*. Beverely Hills, London: Sage.

Outhwaite, W. (1975). *Understanding Social Life: The Method called Verstehen*. London: Allen & Unwin.

Palmer, Douglas L.; Guimond, Serge; Baker, Michael W. and Bégin, Guy (1989). A Factor-Analytic Study of English and French forms of a Measure of Attitudes towards Convicts and Ex-Convicts. *Canadian Journal of Criminology*. 31(4): 155-167.

Palys, T. S. (1992). *Research Decisions: Quantitative and Qualitative Perspectives*. Toronto: Harcourt Brace Jovanovich.

Parker, L.C. and Goldfeder, E. (1979). Productivity Ratings of Graduate Programmes in Criminal Justice based on Publication in Ten Critical Journals. *Criminal Justice.* 7: 125-33.

Peletz, Michael G. (1993). Sacred Texts and Dangerous Words: The Politics of Law and Cultural Rationalization in Malaysia. *Comparative Studies in Society and History.* 35(1): 66-109.

Perdang, J. (1990). Astrophysical Fractals: An Overview and Prospects. *Vistas in Astronomy.* 33 (3/4): 249-294.

Peters, Edgar E. (1991). *Chaos and Order in the Capital Market.* New York: John.

Peters, E. (1992). R/S Analysis using Logrithmic Returns. *Financial Analyst Journal.* 48(6): 81-82.

Petty, Linda C. and Rosen, Ellen F. (1991). Using HyperCard to Teach Person Perception and Attribution Concepts. *Behavior Research Methods, Instruments, & Computers.* 23(2): 247-319.

Phillips, David P. and Ruth, Todd E. (1993). Adequacy of Official Suicide Statistics for Scientific Research and Public Policy. *Suicide and Life-Threatening Behavior.* 23(4): 307-319.

Poland, James M. (1983). Statistical Characteristics of Criminal Justice Data. *Journal of Police Science and Administration.* 11(3): 282-89.

Police Chief 1989. *Policies in Action, Strategic Issues in Patrol Deployment: A Computer Analysis.* 56(2): 59.

Popper, K. R. (1975). *The Logic of Scientific Discovery.* London: Huthcinson.

Porteous, J. D. (1977). *Environment and Behavior: Planning and Everyday Life.* Reading, MA: Addison-Wesley.

Powers, K. I.; Hanssens, D. M. and Hser, Y. I. (1993). Long Term Time Series Forecasting of Social Interventions for Narcotics Use and Property Crime. *Mathematical and Computer modelling.* 17(2): 89-108.

Prentky, Robert A. (1989). A Path Analytic Approach to the Validation of a Taxonomic System for Classifying Child Molesters. *Journal of Quantitative Criminology.* 5 (3): 231-258.

Pretto, R. (1991). *Opportunity and Occupational Crime: A Case Study of Employee Property Crime in the Work Place*. Unpublished MA Thesis. Burnaby, B.C.: Simon Fraser University.

Quetélet, L. A. J. (1968). *A Treatise on Man and the Development of his Faculties.*. New York: B. Franklin. Reprint of the 1842 ed.

Regoli, Bob; Crank, John P.; and Culbertson, Robert G. (1991). Using Composite Measures in Police Cynicism Research: An Application of Canonical Factor Regression. *Journal of Quantitative Criminology*. 7 (1): 41-59.

Reilly, Barry and Witt, Robert. (1992). Crime and Unemployment in Scotland: An Econometric Analysis Using Regional Data. *Scottish Journal of Political Economy*. 39(2): 213-228.

Rengert, G. (1991). Crime in Philadelphia: A Critique of An Opportunity Structure Model: An Empirical Study. In P. J. Brantingham and P. L. Brantingham (Eds.); *Environmental Criminology*. Prospect Heights, IL: Waveland Press. pp. 189-201.

Rengert, G. and Wasilchick, J. (1985). *Suburban Crime: A Time and Place for Everything*. Springfield, IL: Charles C. Thomas.

Rhoads, John K. (1991). *Critical Issues in Social Theory*. University Park, Pennsylvania: Pennsylvania State University Press.

Rist, R. C. (1977). On the Relations among Education Research Paradigms: from Disdain to Détente. *Anthropology and Education Quarterly*. 8: 42-49.

Roncek, D. and Pravatiner, M. A. (1989). Additional Evidence that Taverns Enhance nearby Crime. *Sociology and Social Research*. 73: 185-188.

Rose, Arnold M. (1954). *Theory and Method in the Social Sciences*. Minneapolis: The University of Minnesota Press.

Rossmo, D. K. and Rutledge, R. (1990). Estimating the Size of Criminal Populations. *Journal of Quantitative Criminology*. 6 (3): 293-314.

Rossmo, Darcy Kim. (1995). Geographic Profiling : Target Patterns of Serial Murderers. Simon Fraser University. Theses (School of Criminology).

Roth, J. A. (1962). Comments on 'Secret Observation'. *Social Problems* 9: 283-284.

Rudner, Richard S. (1966). *Philosophy of Social Science*. Englewood Cliffs: Prentice Hall.

Sarnecki, Jerzy. (1990). Delinquent Networks in Sweden. *Journal of Quantitative Criminology*. 6(1): 31-50.

Saaty, Thomas L. and Weyl, Joachim F. (1969). *The Spirit and the Uses of the Mathematical Sciences*. New York: McGraw Hill.

Savage, Leonard J. (1954). *The Foundations of Statistics*. New York: Wiley.

Schmid, Calvin F. (1960a). Urban Crime Areas, Part I. *American Sociological Review*. 25(4): 527-542.

Schmid, Calvin F. (1960b). Urban Crime Areas, Part II. *American Sociological Review*. 25(5): 655-678.

Schultz, A. (1967). *The Phenomenology of the Social World*. Evanston: Northwestern University Press.

Selvin, H. C. (1957). A Critique of Tests of Significance in Survey Research. *American Sociological Review*. 22: 519-527.

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

Sherman, L. W; Gartin, P. R. and Buerger, M. E. (1989). Hot Spots of Predatory Crime: Routine Activities and the Criminology of Place. *Criminology*. 27: 27-55.

Shichor, D; O'Brien, R; and Decker, D. (1981). Prestige of Journals in Criminology and Criminal Justice. *Criminology*. 19: 461-69.

Shourie, Arun. (1980). *Institutions in the Janata Phase*. New Delhi: Popular Prakashan.

Siegel, S. (1956). *Non-parametric Statistics for the Behavioral Sciences*. New York: McGraw-Hill.

Siegel, Alexander W. (1981). The Externalization of Cognitive Maps by Children and Adults: In Search of Ways to Ask better Questions. In Lynn S. Lieben, Arthur H. Patterson and Nora Newcombe (Eds.); *Spatial Representation and Behavior across the Life Span: Theory and Application*. NY: Academic Press. pp. 167-194.

Simon, H. A. (1954). Spurious Correlation: A Causal Interpretation. *Journal of The American Statistical Association*. 49: 467-79.

Singer, Simon I.; Levise, Murray and Jou, Susyan. (1993). Heavy Metal Preference, Delinquent Friends, Social Control and Delinquency. *Journal of Research in Crime and Delinquency*. 30(3): 317-329.

Sincich, Terry. (1990). *Statistics by Examples*. San Francisco: Dellen Publishing.

Sivamurty, A. 1982. The Spatio-Temporal Variation in the Incidence of Theft in Madras City. *Indian Journal of Criminology*. 10(2): 108-115.

Skinner, B. F. (1953). *Science and Human Behavior*. New York: Macmillan.

Skogan, W. G. (1975). Measurement Problems in Official and Survey Crime Rates. *Journal of Criminal Justice*. 3:17-32.

Smithson, M. (1982). Applications of Fuzzy Set Concepts to Behavioral Sciences. *Journal of Mathematical Social Sciences*. 2: 257- 274.

Smithson, M. (1987). *Fuzzy Set Analysis for Behavioral and Social Sciences*. London: Springer-Verlag.

Statistics Canada. (1992). *1991 Census of Canada: Population and Dwelling Counts*. Ottawa: Statistics Canada.

Sterling, T. D. (1959). Publication Decisions and their Possible Effects on Inferences Drawn from Tests of Significance- or Vice Versa. *Journal of the American Statistical Association*. 54: 30- 4.

Stigler, S. M. (1986). *The History of Statistics: The Measurement of Uncertainty before 1900*. Cambridge, MA: Harvard University Press.

Stoddart, Kenneth. (1991). It's Easier for the Bulls Now: Official Statistics and Social Change in a Canadian Heroin-Using Community. *Journal of Drug Issues*. 21(1): 83-104.

Stull, Judith C. (1994). Convict: A Computer Simulation of the Criminal Justice System. *Computers in Human Services*. 11(3 / 4): 261-268.

Sullivan, John William Navin. (1956). Mathematics as an Art. In James R. Newman (Ed.); *The World of Mathematics Vol. III.* (1956). New York: Simon and Schuster. pp. 2015-2021.

Sutherland, E. H. (1947). *Principles of Criminology.* (4th ed.). Philadelphia: Lippincott.

Tamanaha, Brian Z. (1989). Post-1997 Hong Kong: A Comparative Study of the Meaning of "High Degree Of Autonomy". *California Western International Law Journal.* 20(1): 41-66.

Taylor, I; P. Walton and J. Young. (1973). *The New Criminology*. London, Routledge and Kegan Paul.

Taylor, Ralph B.; Gottfredson, Steven D. and Brower, S. (1981). Informal Social Control in the Residential Urban Environment. *cited* in Sherman, L. W; Gartin, P. R. & Buerger, M. E. (1989). Hot Spots of Predatory Crime: Routine Activities and the Criminology of Place. *Criminology*. 27: 55.

Tinkler, K. J. (1973). The Topology of rural periodic market systems. *Geographical Analysis.* 55: 121-133.

Tittle, Charles R. and Welch, Michael R. (1983). Religiosity and Deviance: Toward a Contingency Theory of Constraining Effects. Social Forces. 61(3): 653-682.

Tymoczko, T. (1979). The Four Color Problem and its Philosophical Significance. *Journal of Philosophy*. 76: 57-83.

Upadhyaya, Vasudeva. (1978). *A Study of Hindu Criminology*. Delhi: Chaukhambha Orientalia.

Upshaw, H. S. (1968). Attitude Measurement. In H. M. Blalock and B. A. Blalock (Eds.); *Methodology in Social Research*. New York: McGraw-Hill. pp. 60-111.

Walker, Robert. (1985). An Introduction to Applied Qualitative Research. In Walker, R. (Ed.); *Applied Qualitative Research*. Ants, England: Gower.

Walsh, Dermot P. (1986). Victim Selection Procedures among Economic Criminals: The Rational Choice Perspective. In D. Cornish and R. V. Clarke (Eds.). *The Reasoning Criminal.* New York, NY: Springer-Verlag. pp. 38-56.

Walsh, Dermot P. (1994). The Obsolescence of Crime Forms. In Ronald V. Clarke (Ed.); *Crime Prevention Series. Vol. II.* Monsey, New York: Criminal Justice Press. pp. 149-163.

Warner, Barbara D. and Pierce, Glenn L. (1988). Re-Examining Social Disorganization Theory Using Calls to the Police as a Measure of Crime. *Criminology.* 31(4): 493-518.

Wellman, Barry. (1983). Network Analysis: Some Basic Principles. In Randall Collins (Ed.); *Sociological Theory 1983.* New York: Academic Press.

Weyl, Hermann. (1956). The Mathematical Way of Thinking. In James R. Newman (Ed.); *The World of Mathematics Vol. III.* (1956). New York: Simon and Schuster. pp. 1832-1849.

Wheatly, Margaret J. (1993). The `New Science' of Leadership. *Industry Week.* 242(2): 16-22.

Wheeler, S. (1967). Criminal Statistics: A reformulation of the problem. *Journal of Criminal Law and Criminology.* 58: 317-324.

White, Helene Raskin. (1992). Early Problem Behavior and later Drug Problems. *Journal of Research in Crime and Delinquency.* 29(4): 412-429.

White, Leslie A. (1956). The locus of Mathematical Reality: An Anthropological Note. In James R. Newman, (Ed.): *The World of Mathematics Vol. IV.* (1956). New York: Simon and Schuster. pp. 2348-2364.

Wikstrom, P.-O. H. (1991). *Urban Crime, Criminals, and Victims: The Swedish Experience in an Anglo-American Comparative Perspective.* New York: Springer-Verlag.

Willmer, M. A. P. and Gaston, Kevin. (1990). A Computer Simulation as Training Aid and Research Tool for Use by the Police. *Leadership and Organization Development Journal.* 11(4): 10-16.

Winch, R. F. and Cambell, D. T. (1969). Proof: No. Evidence? Yes. The Significance of Tests of Significance. *American Sociologist.* 4: 140-143.

Wolfgang, M. E. (1963). Uniform Crime Reports: A Critical Appraisal. *University of Pennsylvania Law Review.* 111: 708-738.

Wu, Jian Kang and Desai, Narasimhalu. (1994). Identifying Faces using Multiple Retrievals. *Ieee Multimedia.* 1(2): 27-38.

Yang, Chang. (1994). Public Security Offences and their Impact on Crime Rates in China. *British Journal of Criminology.* 34(1): 54-68.

Yeates, M. (1974). *An Introduction to Quantitative Analysis in Human Geography.* New York, McGraw-Hill.

Zadeh, L. A (1965). Fuzzy Sets: *Information and Control.* 8: 338-353.

Zadeh, L. A.; Fu, K. S.; Tanaka, K and Shimura, M. (Eds.). (1975). *Fuzzy Sets and Their Applications to Cognitive and Decision Process.* New York: Academic Press.

Zelditch, Jr. M. (1962). Some Methodological Problems of Field Research. *American Journal of sociology.* 67: 566-576.

Zeller, R. A. and Carmines, E. G. (1980). *Measurement in the Social Sciences: The Link between Theory and Data.* London: Cambridge University Press.

Zimmerman, H. J. (1985). *Fuzzy Set Theory and its Applications.* Leiden: Klerwer.

---x---