A CRIME-BASED TAXONOMY OF AMERICAN METROPOLITAN AREAS

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A CRIME-BASED TAXONOMY OF AMERICAN
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PREFACE

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CHAPTER I

INTRODUCTION

Statement of the Problem

Crime is a multifaceted topic which can be studied from a variety of perspectives. The tools of geographical analysis allow exploration of the spatial distribution of crime phenomenon, thereby facilitating further research into the causes of crime and at the same time providing a more scientific basis for decision making by officials in charge of crime fighting programs. If the geographical approach is able to identify certain regions of severe criminal activity, the resources of public institutions and the attention of academic researchers can be brought to bear upon these areas. Such findings will also provide administrators of cities and regions identified as having severe crime rates, a solid basis for lobbying efforts to obtain additional Federal or State funding for crime related programs. There is little doubt, therefore, that objective assessments of the severity of crime are vital if local officials are to deal realistically with the problem. Such assessments may have significant effects on the way in which government and private resources are allocated among SMSA's (Standard Metropolitan Statistical

Areas). Crime assessments, therefore, directly impact upon an SMSA's "image" and can thereby have tangible effects on trends in social and economic development.

Objectives

The purpose of this thesis is to classify SMSA's with respect to crime rates within population size-based classes. This classification will then allow for the discrimination of possible regions of high crime rates within these population size classes. This approach is strongly dependent upon acceptance of the hypothesis that crime rates increase with increasing population size. In addition, the classification produced should lend itself to an improved understanding of regional variations in crime.

CHAPTER II

LITERATURE REVIEW

Classification of Cities

Early studies dealing with the classification of cities relied mainly on economic characteristics and were restricted to fairly small data bases. Harris (1943) classified cities on the basis of percentages of the population involved in different occupational classes. Levels were subjectively set which determined class inclusion. For example, if 20 percent or more of the population was employed in wholesaling, the city was classed as a wholesaling center. A major weakness of the approach was the large number of cities which could only be classified as "diversified" (Johnson, 1967). Nelson (1955) took this approach one step further by using standard deviations as the basis for classification. This eliminated the use of subjectively determined classification criteria.

Moser and Scott (1961) classified 157 British towns having populations of 50,000 or more. Data were collected on a large number of socioeconomic variables for each town. Simple relationships between variables were explored by means of a correlation matrix. Principal component analysis revealed that most of the variation in the independent variables could be accounted for by only four components. Subjective evaluation of scatter diagrams of these four components was used to determine classes. More recent classification efforts have concentrated on the use of variables designed to measure the quality of life in different cities.

Jones and Flax (1970) used two approaches in classifying the 18 largest U.S. cities based on quality of life. The first simply involved converting data on 10 socioeconomic variables into z-scores (values adjusted so that the distribution has a mean =0.0 and standard deviation =1.0) and summing the result to provide a composite measure. The second method yielded very similar results and involved ranking the composite measures. Liu (1976) used three approaches to construct quality of life measures and then used the results to analyze population size-based classes of SMSA's (populations of 500,000; 200,000 to 500,000 and <200,000). Within these classes SMSA's having quality of life scores greater than the mean plus one standard deviation were classified as outstanding, and those having scores lower than the mean minus one standard deviation were classifed as substandard. Excellent, good and adequate classes fell in between and were separated by points based on the mean and a fraction of the standard deviation. Other quality of life studies have been performed subsequently, with wide variations in their methodological sophistication.

Classification of Cities Based on Their Crime Characteristics

The number of studies attempting to classify cities based on crime characteristics is comparatively limited, in comparison, to those which attempt to relate socioeconomic variables to urban crime rates. Although studies of this sort have a relationship to the crime-based classification of cities, it is only a tangential one. (See, for example, Schuessler and Slatin, 1964).

There are a number of ways in which areas may be evaluated based upon crime characteristics. The simplest approach is that taken by the FBI (Federal Bureau of Investigation, 1980-82) in its *Uniform Crime Report* (*UCR*) in which crimes are simply reported as the number of incidents per unit of population (usually 100,000 persons).

In the popular literature, Franke and Franke (1972, 1984) performed simple classifications of selected communities throughout the U.S. by choosing those which they considered to be "safe." Selection criteria included having below average crime rates, lack of disturbances during the 1960's and various subjective factors. Initially, it might be thought that selecting such anomalous areas would be a relatively simple matter, but the authors reported that it was not. As a general rule, communities were not selected unless their total crime rate, as reported in the UCR, was below 3,000 incidents per 100,000 population. Higher crime rates in the South and West forced an increase in the criterion to 4,000 incidents per 100,000 population. The authors were compelled to exclude some communities with low overall crime rates but high rates of violent crime, thereby revealing a bias probably shared by most people. Boyer and Savageau (1981) attempted to overcome this problem by assigning weights of 1.0 and 0.1 to violent and property crimes respectively. Two hundred and seventy seven SMSA's were ranked on the basis of property, violent and overall crime rates taken from the UCR. An alternative weighting scheme is presented in appendix A.

Normandeau and Schwartz (1971) classified 169 SMSA's on each of the seven UCR crime categories assigning a "+", "0", or "-" score to each. Cities having rates in the upper sextile of scores (the highest 16.7 percent of the distribution) received a "+", while those in the lowest received a "-". Although crude, this classification was the first attempt to quantify the crime rates of SMSA's using statistical methods. Its usefulness is mainly limited to identifying SMSA's with crime rates on the extremes of the distribution while not addressing the classification of the great majority of SMSA's.

Harries (1974) classified 134 SMSA's on the basis of UCR crime data using z-scores. The use of z-scores allows the reader to immediately recognize whether scores are above or below average and to compare the relative importance of each crime category in the overall crime rate. Harries (1976) classified 729 incorporated areas as part of a study that attempted to analyze social indicators regarded as correlates of crime. Thirty variables, including crime rates, were factor analyzed. Cities with crime rate z-scores greater than 0.75 or less than -0.75 were then selected, thereby isolating 128 high crime rate and 141 low crime rate communities. Each category was subjected to cluster analysis using seven socioeconomic factors. Four groups were identified among both high and low crime cities, and their socioeconimic characteristics were compared to a hypothetical 'ideal' low crime factor profile. The analysis suggested policy implications for law enforcement in distinctive types of cities.

General Concept and Methodology of Classification

Why Classify?

In any field of study, classification is an important first step that must be taken before hypotheses can be made which will determine the course of future investigation. To put it a simpler way, you cannot study a phenomenon until you are able to identify it as being distinctly different from other phenomena. Not only does classification facilitate inductive reasoning but it also makes possible the spread of knowledge by providing a common nomenclature. Although classification is 'primitive science,' it is a necessary first step in scientific investigations.

Social and economic classifications are widely used by administrators in the public and private sectors. Classifications of incorporated areas, based on economic factors, are heavily relied upon by decision makers in the business world (Hanson, 1984).

<u>How to Classify</u>?

There are two major forms of classification: subdivision and agglomeration (Abler et al, 1971). Both approaches require that all individuals fit into a category and that the categories do not overlap. The order in which individual objects are classified into intermediate categories, in both the subdivision and agglomerative approaches, is of great importance. For example, in the case of subdivision, there is a difference in the results of first dividing students by sex and then by hair length as opposed to dividing them first by hair length and then by sex. Regardless of the classification approach, a common problem faced is: how many classes are appropriate? It should be recalled that classifications have purposes, therefore the best number of classes is the number that optimizes the amount of useful information about the subject, given the problem at hand.

It is important to realize that classifications are usually made with specific goals in mind: no classification is unbiased. A classification designed for one purpose may be useless for another.

Cluster Analysis

Cluster Analysis involves the grouping of similar objects (Hartigan, 1975). Although the process seems intuitively obvious, the statistical methods used are not. Anderburg (1973) lists major steps in the process of clustering which are discussed below.

Initially, the data units to be clustered must be selected. If the results of the clustering are to be extrapolated to data units beyond those included in the sample, it is vital that the data units be selected for study in an random and independent manner.

The variables which are chosen must be descriptors of the data units, relative to the purpose at hand, they must strongly discriminate between data units. There is a choice of what is to be clustered beyond the data units themselves. In some cases it is useful to cluster the descriptors of the data units in order to determine if any inherent natural division exists independent of their association with the data units.

A common mistake in clustering is the failure to use homogeneous variables. If different relative units of measurement are associated with different variables (e.g. inches and miles), then these must first be corrected by the use of weighting factors before they can properly be combined into an index of similarity. A basis for for evaluating which data units are to be classed together must be chosen. The most common measure used is the Euclidean distance between units. A variety of more complicated measures are also available. Given such a measure, the investigator must still establish the criteria for what is a cluster and what is not. In some cases it may be immediately apparent that units separated by less than a certain distance should be clustered, but usually it is necessary to repeat the process of clustering several times in order to reveal various facets of the structure of the units.

The number of clusters obtained is usually not determined by the algorithm itself. In the hierarchical clustering approach, a series of outputs are generated with from one to N clusters. The investigator then chooses the best number of clusters based on his interpretation. In other approaches the number of clusters is specified by the user before the clustering algorithm is implemented.

Interpretation of results may be limited to no more than identifying natural divisions or may be taken one step further with results forming the basis of hypotheses which explain differences between clusters.

Relationship of Population Size to Urban Crime Rates

A widely held, and basically correct perception is that crime rates increase with greater population size. This phenomenon is closely related to the increased number of opportunities for crime resulting from more property, more social interaction and a higher density of people. Haynes (1973) proposed a model which combines population size and city area with the proportions of criminal to victim population to obtain a crime opportunity index. Regression analysis of burglary rates against population squared divided by area yielded an R-squared value of 0.76. The regression of burglary against population alone, however, yielded a much better result: R-squared =0.91.

Of course, other variables correlated with population size might also have a significant regression. Population size may well be a major factor in predicting urban crime rates, but it is reasonable to say that other factors which relate to the opportunity of committing a crime certainly play a significant role. For example, one might expect that two cities of equal population size and density, one of which relies on private vehicles for transportation and the other which uses only public transportation, might have significantly different robbery rates. However, the larger the population size, the more likely a city is to have factors such as mass transportation which provide more potential criminal-victim contact.

Regional Variations in Crime

A region can be defined as an area having one or more dominant features. The selection of features which will define a region is critical. Only those features which actually relate to real characteristics of an area should be considered. In the context of crime rates, a crime 'region' is a large area in which crime rates are roughly homogeneous.

Schuessler (1961-1962) identified socio-economic variables which predicted variations in crime rates, using principle component analysis. Crimes of murder and aggravated assault were closely tied to family, education and household expense variables. Property crimes were closely linked with minority factors. These two associations suggest economic factors as a primary determinant of crime variations. An additional factor was the level of migration into an area. Areas receiving large numbers of immigrants are more apt to experience increased crime rates. This is probably due to a combination of the social and economic dislocation often experienced by immigrants coupled with the loss of their traditional moral institutions.

Harries (1971) discussed regional patterns of crime in the United States based on population-specific crime rates. States in the north central region showed much lower crime rates in all categories than did other regions. In the murder category, the southern states stood out because of their higher rate.

The Southern violence phenomenon (Harries, 1974, 1985) is a good example of how culture can affect peoples' attitudes toward specific crimes. Inhabitants of the southern United States are, by upbringing, more apt to own a gun and to use it when a dispute occurs. This may be due to a traditionally low standard of living inherent in the plantation system, which may produce a lower regard for the value of life and an increased level of pent-up frustrations.

Summary

A variety of approaches have been used in classifying cities, some of which relate to their crime environments, either directly or indirectly. Taken collectively, these past studies form the basis for this thesis by contributing appropriate techniques as well as a sense of the overall direction of the research effort within which it exists. Building upon this foundation, the following section will outline the methodology which this study will follow.

CHAPTER III

RESEARCH DESIGN

Measurement of Crime

The Uniform Crime Report (UCR) is a yearly compilation of crime data in the U.S. by the Federal Bureau of Investigation, a branch of the U.S. Department of Justice. Each month, local law enforcement agencies report the number of offenses which fall into eight different categories: murder, rape, robbery, aggravated assault, burglary, larceny-theft, motor vehicle theft and arson. It is the most comprehensive source of geographically-based crime data for the United States.

Hindelang (1974) assessed the shortcomings of the UCR by comparing it against two other sources of data: homicide statistics collected by the National Center for Health Statistics (NCHS) and the 1967 National Opinion Research Center (NORC) victimization survey. The close agreement of the two data bases with the UCR served to call into question the previously advanced criticisms of it. Criticisms were that the statistics were being manipulated by the police to serve their own ends, that the population base used in calculating rates was incorrect and so significantly distorted the results, and that the FBI tabulating procedures were faulty. Comparison of NORC and UCR data revealed differences in the proportions of crimes falling into each UCR category but showed that the ranking of the frequencies of the categories remained essentially intact.

A widespread criticism of the UCR is that the different crime categories are weighted equally. Rankings of the crime severity in areas based on UCR overall crime rates and on UCR data modified by several weighting schemes, were quite similar. This somewhat surprising result was attributed to the high proportion of property crimes in the overall crime rate (five out of six offenses known). In the case of multiple crime incidents only one crime is reported -- the most serious. The undereporting of crime occurences, together with the lack of any measure of seriousness within categories, are major problems with the UCR data (Sellin and Wolfgang, 1964).

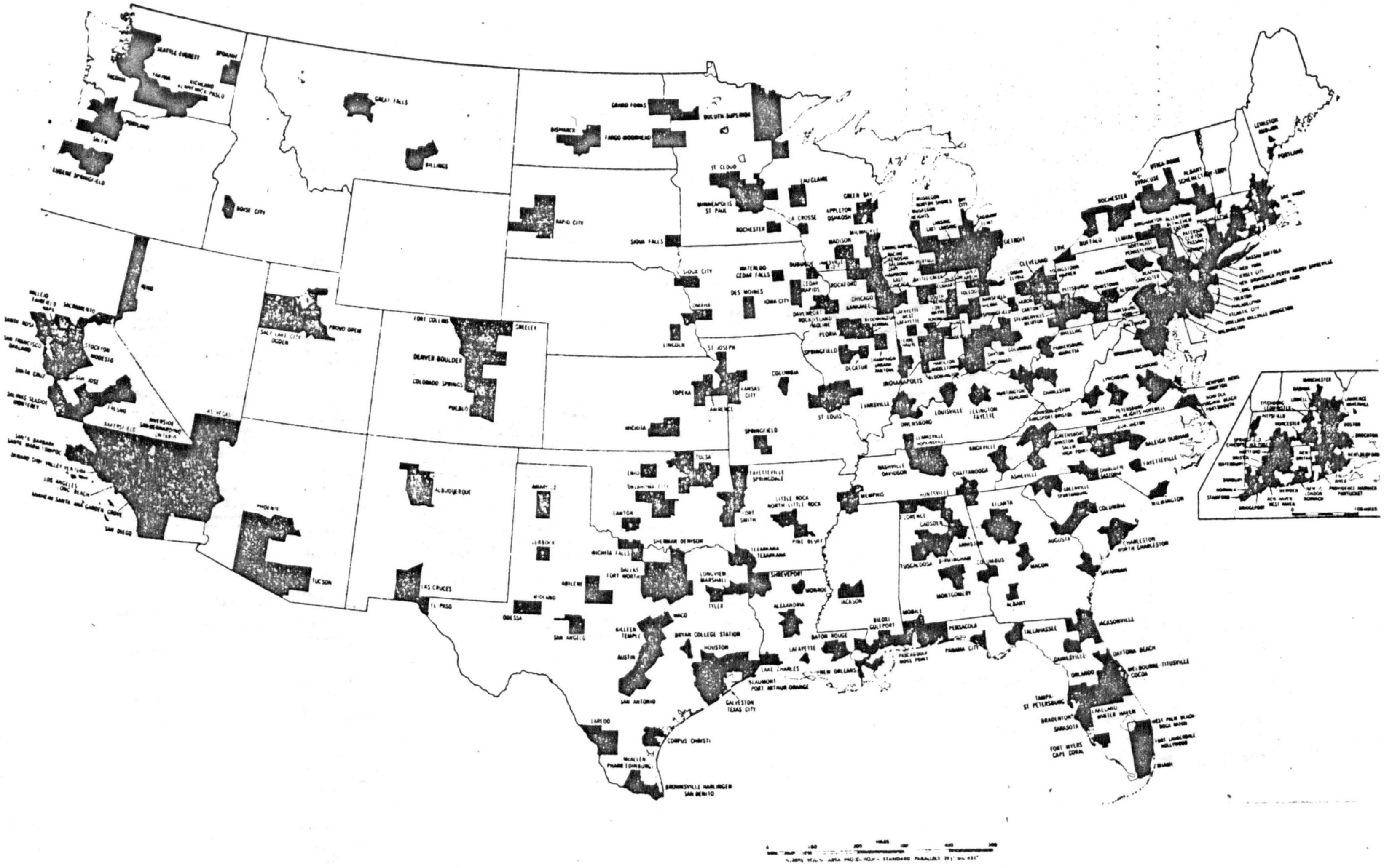
Gottfredson et al. (1980) also criticized this method, pointing out that the assumption of additivity in multiple crime incidents is not correct. Incidents in which one person is the victim of multiple crimes should be perceived as more serious than the total seriousness of an equivalent number of incidents in which the same crimes are distributed one per victim.

Choice of Areal Units for Analysis

SMSA's are areas designated by the Office of Management and Budget of the United States government for the purpose of standardizing statistics relating to metropolitan areas (Figure 1). In general, an area is considered an SMSA if it includes a city of 50,000 population or more, or contains a city with 25,000 population and contiguous places having a population density of at least 1000 persons per square mile with a total of an additional 50,000 people. Usually, SMSA's are composed of one or more counties, but special criteria apply to New England where smaller areal units are used.

Two major choices of areal units exist in the study of inter-metropolitan crime: incorporated areas and SMSA's. Urbanized areas are not a viable option owing to the lack of a coherent base of crime data. Data for the cities and SMSA's, however, is readily available in the UCR. Harries (1976) pointed out that incorporated areas usually leave out suburbs and rural rings, thereby overemphasizing inner cities with high crime rates. Normandeau and Schwartz (1971) advanced four arguments in favor of the use of SMSA's as units of analysis: 1) a high proportion of the nation's population is in SMSA's; 2) SMSA's contribute a disproportionately large percentage of total crime; 3) the city/suburb complexes they represent are becoming increasingly more important functional units in crime control; and 4) large numbers of SMSA's exist.

On the other hand, SMSA's in some instances tend to overrepresent low density, contiguous rural areas in situations where counties are of relatively large area, such as the nation's extreme case: San Bernardino county.



(Source: U.S. Government Printing Office, Washington D.C., 1980.)

Figure 1. Standard Metropolitan Statistical Areas

California.

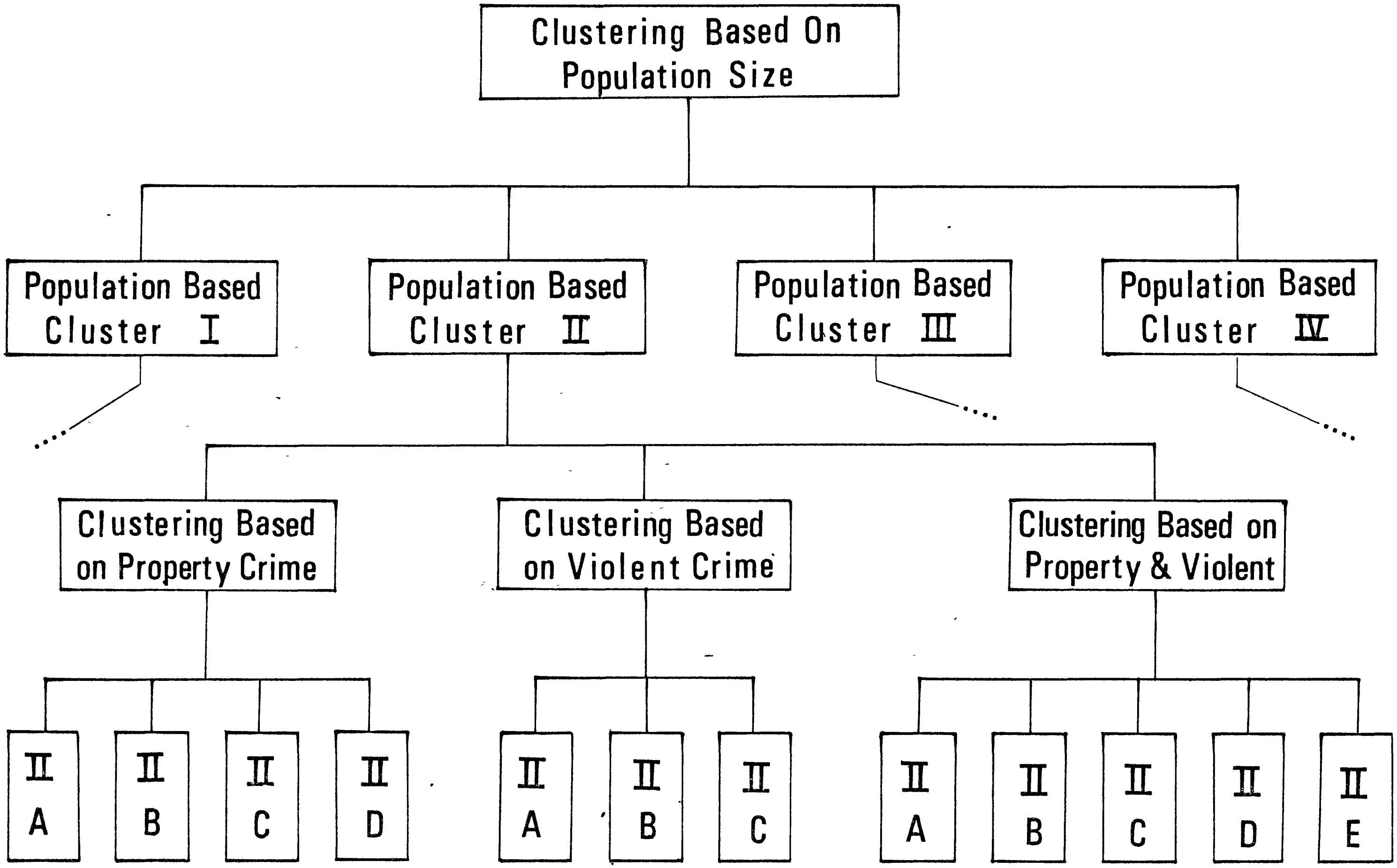
Operational Design

Clustering Analysis

A total of 293 SMSA's formed the data base for this study, all of which appear at least once in the UCR for 1980, 1981 or 1982. An average of the values for these years for population size, violent crime rate and property crime rate was used for all analyses. The violent crime rate was the sum of murder, rape, robbery and aggravated assault rates while the property crime rate was the sum of larceny, burglary and motor vehicle theft. The three largest SMSA's (New York, Chicago and Los Angeles) were removed from the data base because they exerted an unduly large effect on the clustering process.

Clustering procedures were used at two different stages in data analysis (Figure 2). All SMSA's were initially subjected to cluster analysis on the basis of population size alone in order to develop "natural," rather than arbitrary population size classes (such arbitrary size classes are used in the UCR). The algorithm used was the Ward method, which was part of the Statistical Analysis System cluster procedure.

clusters were chosen as the appropriate number based on the arbitrary criterion of including an additional cluster only when R-squared values increased by 5 percent or more. At this point, the three largest SMSA's (which



(Due to limited space, the complete sequence is only shown for population-based cluster II.)

Figure 2. Flow Chart Illustrating Sequence of Clustering Analysis Used in this Study

had been excluded thus far from clustering) were placed in the cluster having the largest mean population size. One-way analysis of variance (ANOVA), was used to test for significant differences between clusters at the 0.05 significance level. This test was used to verify that mean crime rates differed significantly between clusters.

In the next step, each population-based cluster was subjected to cluster analysis three times: once on the basis of violent crime rates, once on property crime rates and once on both types together to produce a two dimensional analysis. Once again, an additional cluster was included only when it increased R-squared values by 5 percent or more. Significant differences between clusters were tested for in the previous manner.

Discrimination of Crime Regions

Maps were produced which showed the spatial distribution of SMSA's having the highest crime rates within each population-based cluster. The SMSA's mapped were from those crime-based clusters having the highest particular crime rate within each population-based cluster. If a cluster contained 10 or more SMSA's, it was mapped separately, otherwise it was mapped together with all other clusters having less than 10 SMSA's. In addition, a composite map showing all clusters for each particular crime classification was produced.

The composite maps produced were subjectively evaluated to discern the presence of regional patterns.

If 40% or more of the total SMSA's in a given area were high crime rate SMSA's, it was considered to be a valid region.

Summary

Two hundred and ninety three SMSA's were divided into population based groups through cluster analysis. Each of the resulting clusters were then subdivided on the basis of crime rates: property, violent, and the sum of both. The final product takes the form of maps showing the spatial distributions of the crime-based clusters.

CHAPTER IV

RESULTS OF ANALYSIS

Population-based Clustering

Cluster analysis yielded four clusters of ascending mean population size (Table I). Clusters I and IV had much higher coefficients of variation than did clusters II and III. In the case of cluster I, the large number of SMSAs was probably responsible. Cluster IV artificially included the three largest SMSA's, the smallest of which had a population size of 7,097,813. This is much larger than the next smallest SMSA, Houston. Analysis of Variance revealed that clusters were significantly different (Table II).

Crime Rate-based Clustering

Several trends are apparent in the classifications which are based upon property crime rate, violent crime rate and a combination of the two. In the case of property crime rate-based clusters (Table III), the proportion of SMSA's included in those clusters within the highest mean property crime rates (ID, IIC, IIIC, and IVA) increases as the mean population size increases.

In the violent crime-based classification (Table IV),

TABLE I

SIMPLE DESCRIPTIVE STATISTICS FOR SMSA CLUSTERS DETERMINED ON THE BASIS OF AVERAGE POPULATION SIZE

Cluster	N	Mean	SD*	CV*	Min.	Max.
I	195	187,637	84,025	45	67,702	394,755
II	60	624,718	169,065	27	404,624	974,360
III	28	1,630,838	440,490	27	1,037,018	2,603,817
IV	10	5,162,115	2,072,500	42	3,004,402	9,124,285

* SD represents Standard Deviation
* CV stands for Coefficient of Variation
(Source: Calculations by the author)

TABLE II

SELECTED DATA FROM ANOVA RESULTS TESTING FOR SIGNIFICANT DIFFERENCES BETWEEN CLUSTERS DETERMINED ON THE BASIS OF AVERAGE POPULATION SIZE

Mean	498,256
F-value (F)	1,031
Degrees of freedom (df)	3
Significance Level (P)	0.0001

(Source: Calculations by the author)

TABLE III

SIMPLE DESCRIPTIVE STATISTICS FOR SMSA CLUSTERS DETERMINED ON THE BASIS OF AVERAGE PROPERTY CRIME RATE*

Cluster	N	%	Mean	SD	Min.	Max.	SE
I A	65	33	5,911	280	5,435	6,552	34
I B	70	36	4,536	463	3,719	5,334	55
I C	34	17	3,077	483	1,734	3,584	83
I D	26	13	7,303**	916	6,656	11,000	180
		100					
II A	28	47	6,173	397	5,545	6,801	75
II B	17	28	5,442	243	4,585	5,377	59
II C	7	12	7,960**	579	7,200	8,938	219
II D	8	13	3,550	609	2,578	4,269	215
		100					
III A	9	32	6,842	269	6,592	7,265	90
III B	7	25	5,837	237	5,539	6,064	90
III C	5	18	8,164**	593	7,607	9,130	265
III D	6	21	4,971	217	4,641	5,190	89
III E	1	4	2,963	.	2,963	2,963	.
		100					
IV A	5	50	7,174**	187	6,993	7,438	81
IV B	2	20	5,397	227	5,236	5,558	161
IV C	2	20	6,218	421	5,920	6,516	298
IV D	1	10	4,569	.	4,569	4,569	.
		100					

* Roman numerals represent population-based clusters. Letters represent crime rate-based clusters within each population cluster.

** SMSA's contained in these clusters are mapped in figures 3 to 5.

(Source: Calculations by the author)

however, this trend is not apparent. In fact, the two smaller mean population size clusters (I & II) have a much higher proportion of their SMSA's included in those clusters having the highest mean violent crime rate (IC & IIB). When both crime rates are combined for a two-dimensional analysis (Tables V & VI), it is apparent that a much larger proportion of SMSA's contained in the cluster of highest mean crime rate are in the largest population size clusters (IVA for property crime dimension and IVD for violent crime dimension). Note that in both dimensions, the highest crime rates are for the Miami SMSA (IIIE for both dimensions). A complete list of all SMSA's contained in clusters having the highest mean crime rates is given in Appendixes B, C and D. The statistical significance of differences between the crime rate-based clusters is given in Tables VII, VIII and IX.

Crime Regions

The spatial distributions of those SMSA's which are included in clusters having the highest mean crime rates are shown in figures 3 to 11. In the case of all high property cirme rate SMSA's (Figure 5), there are concentrations in the southwest, Florida and along a line from Michigan to Texas. In the case of all high violent crime rate SMSA's (Figure 8), there are concentrations along the Gulf Coast and Florida, along a line stretching from northern Texas to North and South Carolina and in the Great Lakes Region. When the two dimension case is

TABLE IV

SIMPLE DESCRIPTIVE STATISTICS FOR SMSA CLUSTERS DETERMINED ON THE BASIS OF AVERAGE VIOLENT CRIME RATE*

Cluster	N	%	Mean	SD	Min.	Max.	SE
I A	89	46	220	80	57	346	8
I B	67	34	453	62	362	578	8
I C	39	20	715**	103	595	985	16

		100					
II A	16	27	568	60	497	654	15
II B	17	28	860**	112	722	113	27
II C	27	45	358	88	45	478	17

		100					
III A	10	36	551	59	493	639	19
III B	9	32	784	79	683	916	26
III C	3	11	1,068	99	1,007	1,182	57
III D	5	18	351	80	239	445	36
III E	1	4	1,767**	.	1,767	1,767	.

		100					
IV A	5	50	676	83	550	741	37
IV B	3	30	876	56	826	937	32
IV C	1	10	1,303	.	1,303	1,303	.
IV D	1	10	1,709**	.	1,709	1,709	.

		100					

* Roman numerals represent population-based clusters. Letters represent crime rate-based clusters within each population cluster.
** SMSA's contained in these clusters are mapped in figures 6 to 8.
(Source: Calculations by the author)

TABLE V

PROPERTY DIMENSION VALUES: SIMPLE DESCRIPTIVE STATISTICS FOR SMSA CLUSTERS BASED ON A TWO-DIMENSIONAL ANALYSIS OF AVERAGE PROPERTY AND VIOLENT CRIME RATE*

Cluster	N	%	Mean	SD	Min.	Max.	SE
I A	51	26	5,774	544	4,899	7,810	76
I B	53	27	3,502	713	1,734	5,088	78
I C	39	20	4,480	425	3,450	5,128	68
I D	37	20	6,276	597	5,435	8,380	98
I E	15	8	7,295**	1,237	5,764	11,000	319
		100					
II A	23	38	5,506	569	4,650	6,699	119
II B	11	18	5,986	541	5,158	6,742	163
II C	10	17	3,768	707	2,578	4,691	223
II D	13	22	6,712	735	5,686	7,976	204
II E	3	5	8,420**	511	7,917	8,938	295
		100					
III A	8	29	4,792	787	2,963	5,541	278
III B	6	21	6,379	483	5,539	6,793	197
III C	7	25	6,309	507	5,707	7,087	192
III D	6	21	7,692	419	7,199	8,295	171
III E	1	4	9,130**	.	9,130	9,130	.
		100					
IV A	3	30	7,254**	206	7,031	7,438	119
IV B	3	30	5,998	484	5,558	6,516	279
IV C	2	20	4,902	472	4,569	5,236	334
IV D	2	20	7,056	88	6,993	7,118	63
		100					

* Roman numerals represent population-based clusters. Letters represent crime rate-based clusters within each population cluster.

** SMSA's contained in these clusters are mapped in figures 9 to 11.

(Source: Calculations by the author)

TABLE VI

VIOLENT DIMENSION VALUES: SIMPLE DESCRIPTIVE STATISTICS FOR SMSA CLUSTERS BASED ON A TWO-DIMENSIONAL ANALYSIS OF AVERAGE PROPERTY AND VIOLENT CRIME RATE*

Cluster	N	%	Mean	SD	Min.	Max.	SE
I A	51	26	338	91	114	476	13
I B	53	27	182	74	57	341	10
I C	39	20	456	129	281	710	21
I D	37	20	565	88	407	741	15
I E	15	8	814**	88	702	985	23
		100					
II A	23	38	433	64	283	525	13
II B	11	18	620	71	502	728	21
II C	10	17	280	87	145	420	28
II D	13	22	816	66	632	916	18
II E	3	5	1,067**	71	990	1,130	41
		100					
III A	8	29	492	183	239	768	65
III B	6	21	949	146	787	1,182	60
III C	7	25	508	86	364	609	33
III D	6	21	722	110	621	916	45
III E	1	4	1,767**	.	1,767	1,767	.
		100					
IV A	3	30	845	104	733	937	60
IV B	3	30	764	54	725	826	31
IV C	2	20	591	58	550	632	41
IV D	2	20	1,506**	287	1,303	1,709	203
		100					

* Roman numerals represent population-based clusters. Letters represent crime rate-based clusters within each population cluster.

** SMSA's contained in these clusters are mapped in figures 9 to 11.

(Source: Calculations by the author)

TABLE VII

PROPERTY CRIME: RESULTS OF ANOVA PROCEDURE TESTING THE SIGNIFICANCE OF DIFFERENCES BETWEEN CRIME RATE BASED CLUSTERS WITHIN EACH POPULATION-BASED CLUSTER

Cluster	Mean	F	P	df
I	5,109	434	0.0001	3
II	5,711	165	0.0001	3
III	6,288	97	0.0001	3
IV	6,367	46	0.0002	3

(Source: Calculations by the author)

TABLE VIII

VIOLENT CRIME: RESULTS OF ANOVA PROCEDURE TESTING THE SIGNIFICANCE OF DIFFERENCES BETWEEN CRIME RATE BASED CLUSTERS WITHIN EACH POPULATION-BASED CLUSTER

Cluster	Mean	F	P	df
I	399	551	0.0001	2
II	557	164	0.0001	2
III	689	111	0.0001	4
IV	902	63	0.0001	3

(Source: Calculations by the author)

TABLE IX

PROPERTY AND VIOLENT CRIME: RESULTS OF ANOVA PROCEDURE TESTING THE SIGNIFICANCE OF DIFFERENCES BETWEEN CRIME RATE BASED CLUSTERS WITHIN EACH POPULATION-BASED CLUSTER

Cluster	Mean	F	P	df
I				
Property	5,109	171	0.0001	4
Violent	399	177	0.0001	4
II				
Property	5,711	48	0.0001	4
Violent	557	143	0.0001	4
III				
Property	6,288	28	0.0001	4
Violent	689	27	0.0001	4
IV				
Property	6,367	20	0.0015	3
Violent	902	18	0.0023	3

(Source: Calculations by the author)

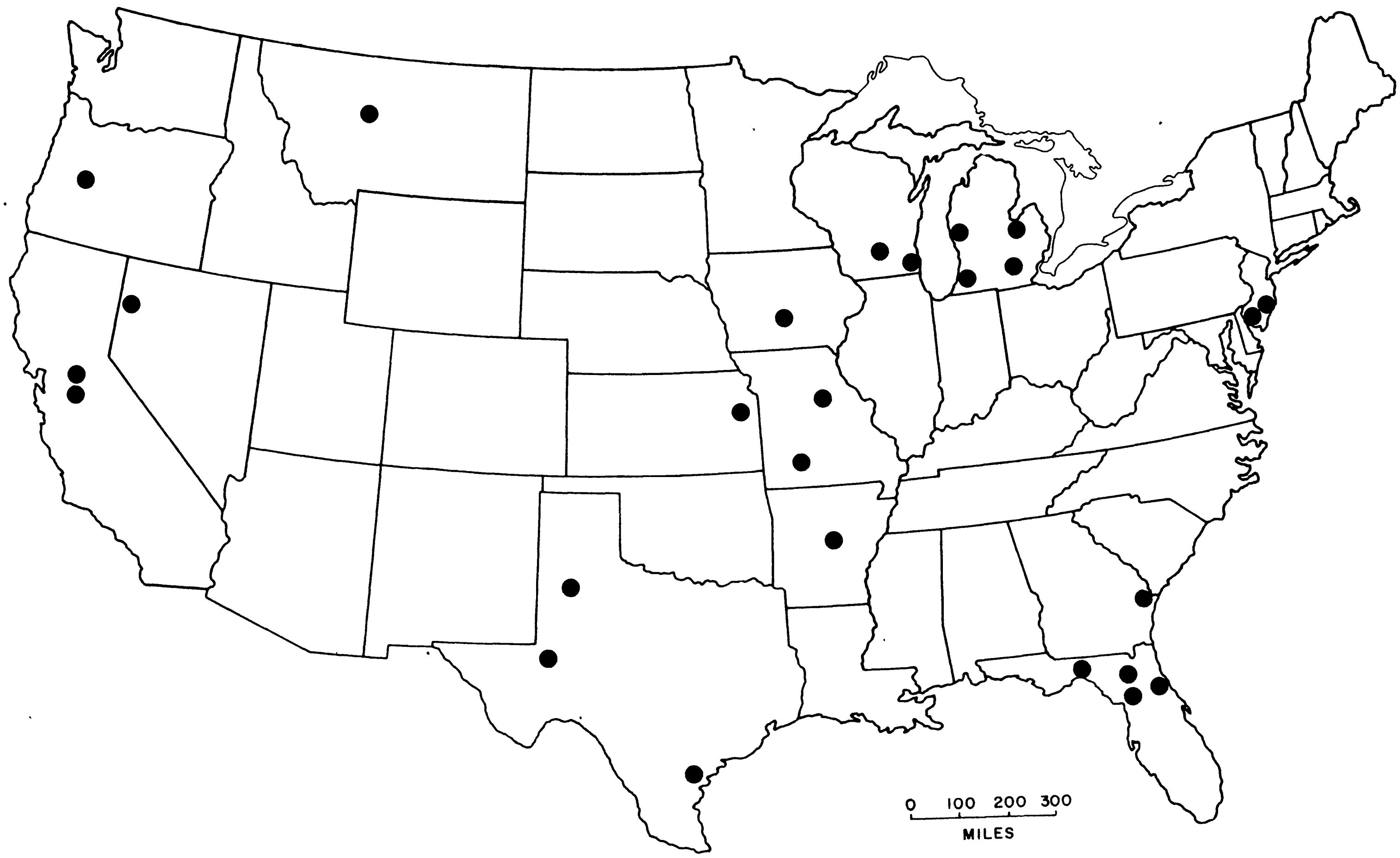


Figure 3. Distribution of SMSA's Having Highest Property Crime
Rates Within Population-based Cluster I D
Population Size Range: 67,702 - 394,755

Figure 4. Distribution of SMSA's Having Highest Property Crime Rates Within Population-based Cluster II - IV Population Size Ranges:

Cluster II C (●): 404,624 - 974,360
Cluster III C (★): 1,037,018 - 2,603,817
Cluster IV A (⊛): 3,004,402 - 9,124,285

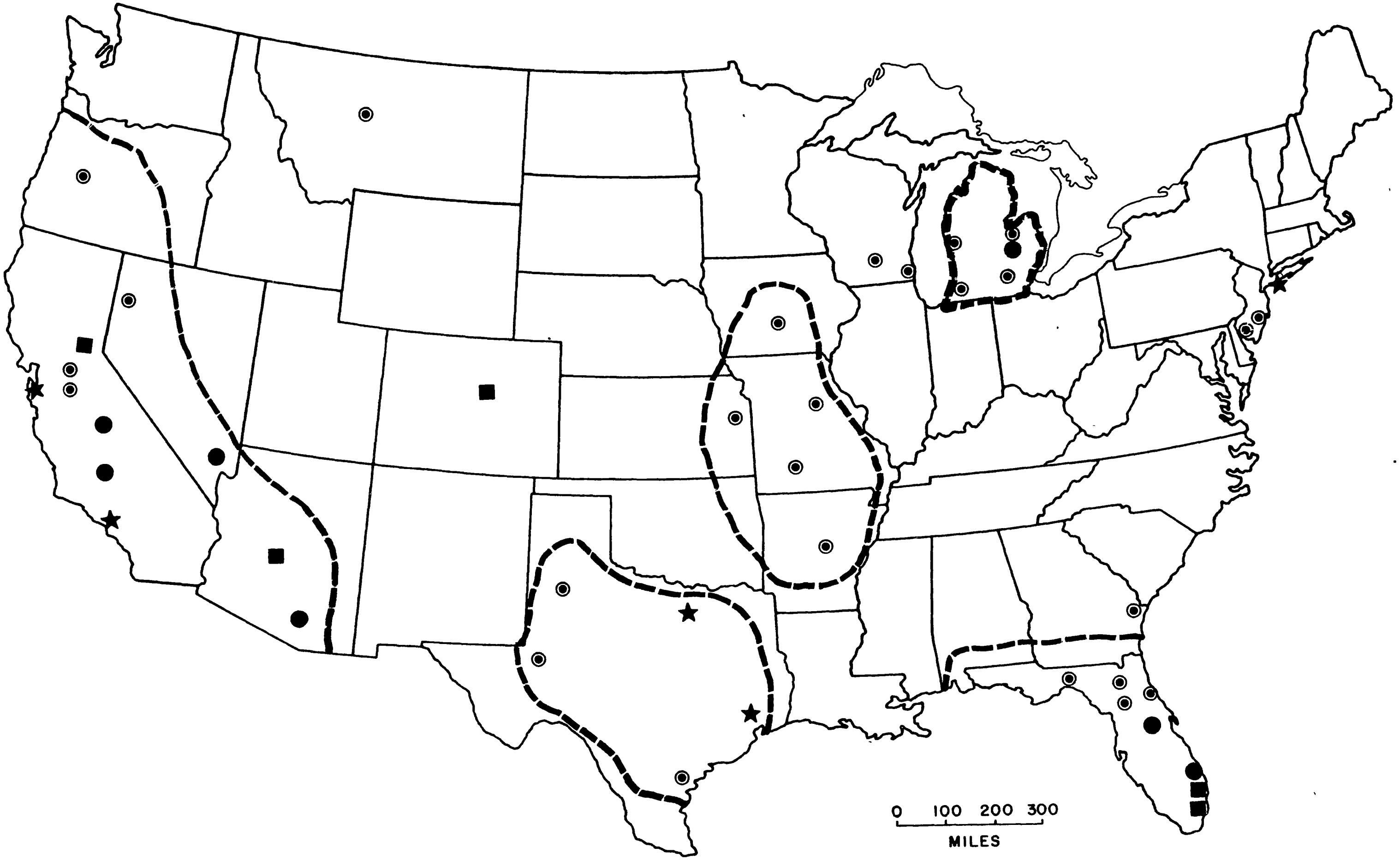


Figure 5. Composite Map Showing Distribution of SMSA's Having Highest Property Crime Rates; Population Size Ranges:
Cluster I D (◉): 67,702 - 394,755
Cluster II C (●): 404,624 - 974,360
Cluster III C (■): 1,037,018 - 2,603,817
Cluster IV A (★): 3,004,402 - 9,124,285

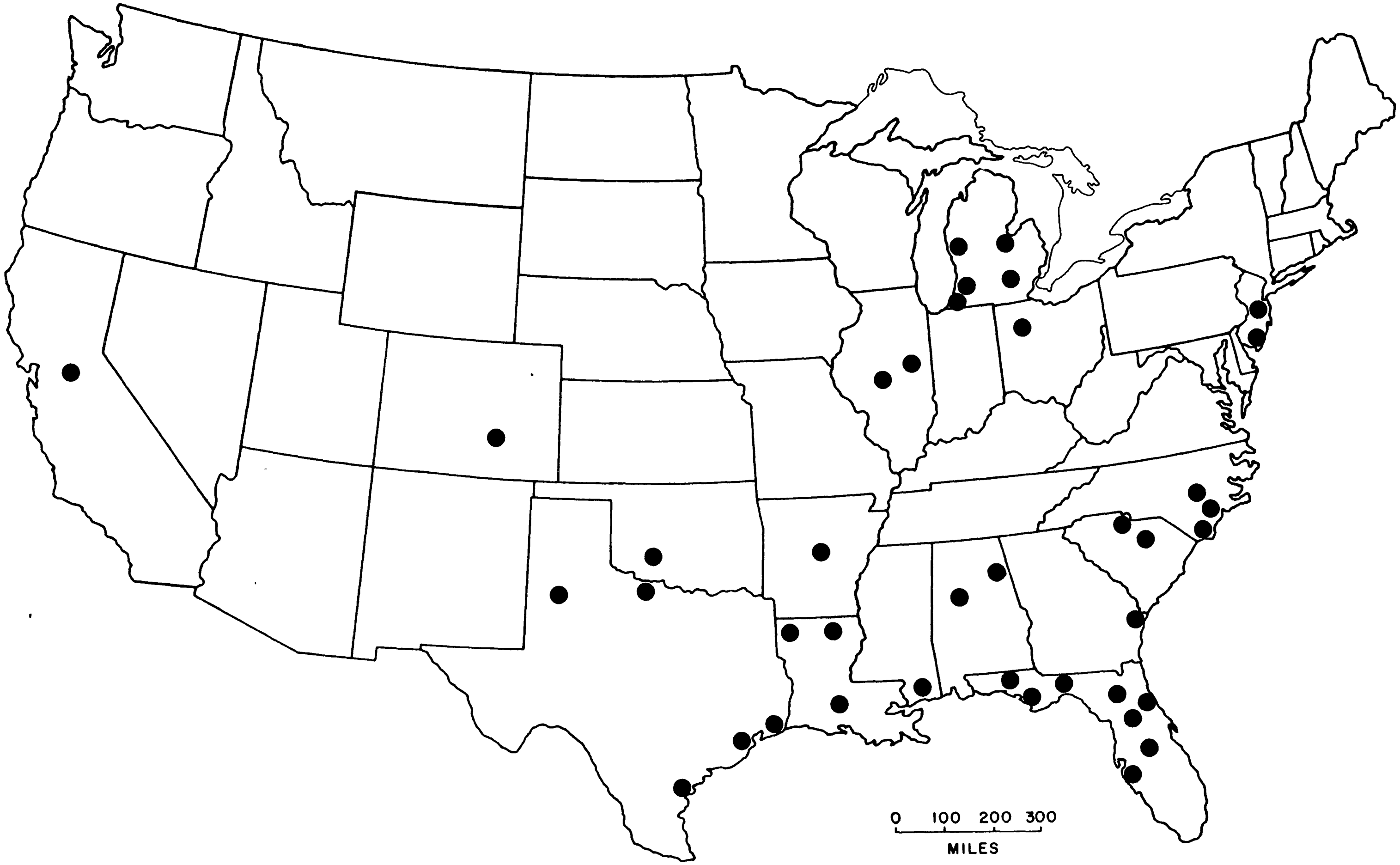


Figure 6. Distribution of SMSA's Having Highest Violent Crime Rates Within Population-based Cluster I C Population Size Range: 67,702 -394,755

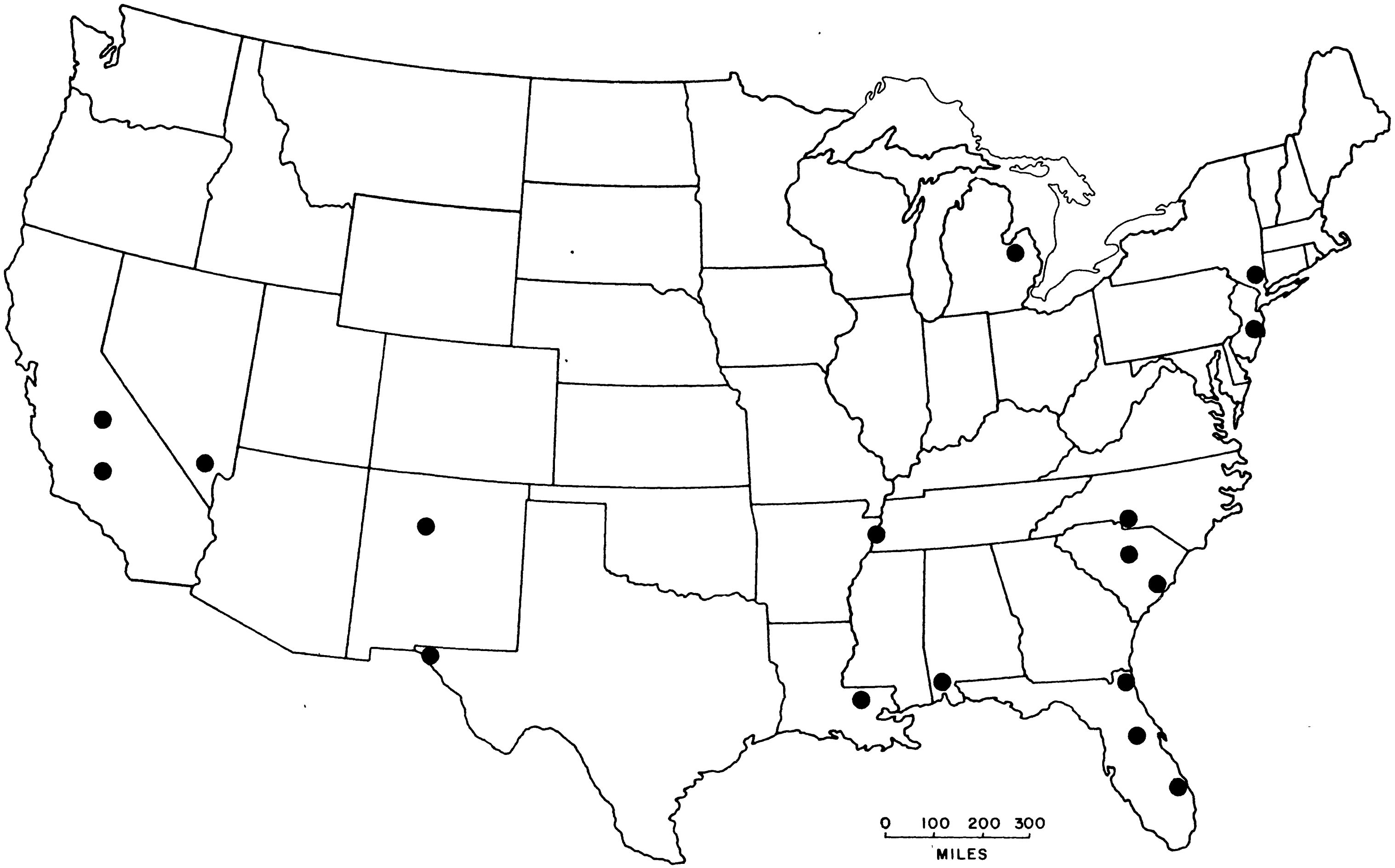


Figure 7. Distribution of SMSA's Having Highest Violent Crime Rates Within Population-based Cluster II B Population Size Range: 404,624 - 974,360

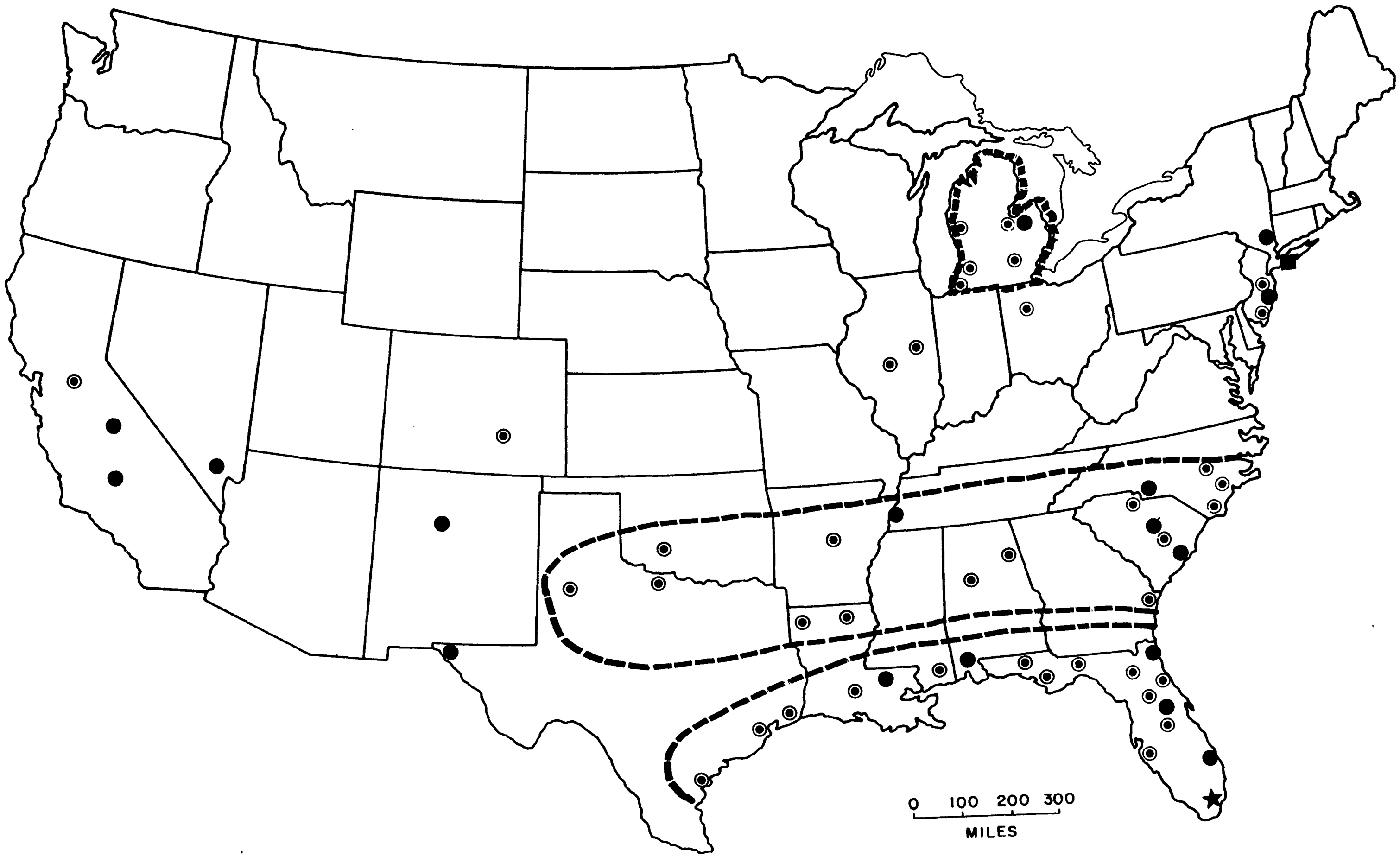


Figure 8. Composite Map Showing Distribution of SMSA's Having Highest Violent Crime Rates; Population Size Ranges:

Cluster I C (◉):	67,702 -	394,755
Cluster II B (●):	404,624 -	974,360
Cluster III E (★):	1,037,018 -	2,603,817
Cluster IV D (■):	3,004,402 -	9,124,285

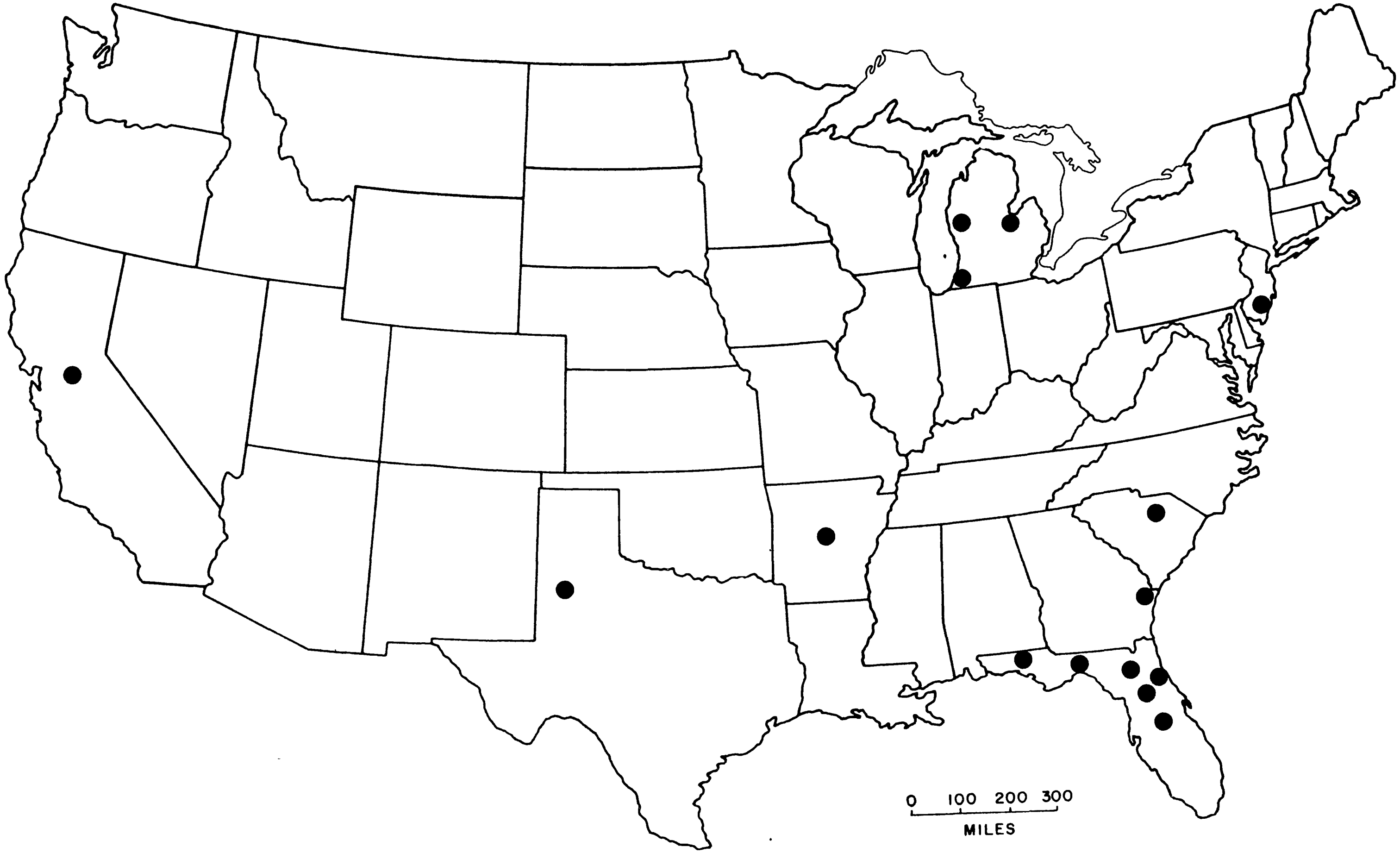


Figure 9. Distribution of SMSA's Having Highest
Property and Violent Crime Rates Within
Population-based Cluster I E
Population Size Ranges: 67,702 - 394,755

Figure 10. Distribution of SMSA's Having Highest Property and Violent Crime Rates Within Population-based Clusters II to IV.
Population Size Ranges:
Cluster II E (■): 404,624 - 974,360
Cluster III E (☆): 1,037,018 - 2,603,817
Cluster IV A (★): 3,004,402 - 9,124,285

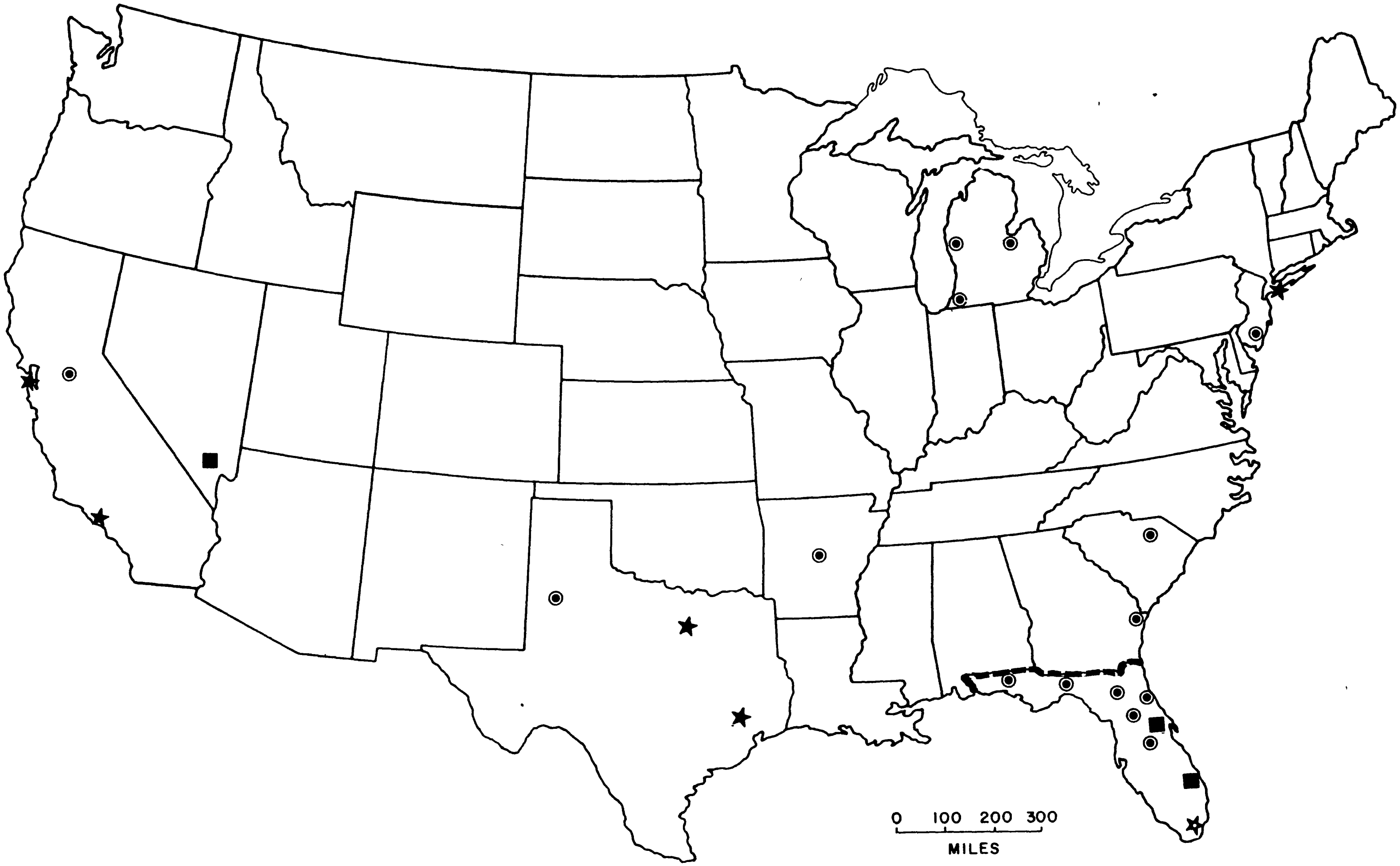


Figure 11. Composite Map Showing Distribution Having Highest Property and Violent Crime Rates; Population Size Ranges:

Cluster I E (◉): 67,702 - 394,755
Cluster II E (■): 404,624 - 974,360
Cluster III E (✫): 1,037,018 - 2,603,817
Cluster IV A or D (★): 3,004,402 - 9,124,285

considered (Figure 11) concentrations appear in Florida and to a lesser extent Michigan.

Five possible regions were discriminated based on the distribution of high property crime rate SMSA's (Figure 5). A western region stretching from Eugene, Oregon to Tucson, Arizona and including Reno and Las Vegas, Nevada is composed of 57% high property crime rate SMSA's. The state of Florida is composed of 47% high property crime rate SMSA's. An interesting series of possible regions appears to stretch from Michigan to Texas. Taken as a whole the percentage of high property crime rate SMSA's in the region is low, but when subregions in Michigan, part of the plains states and central Texas are isolated, a stairstep pattern emerges. The percentages of high property crime rate SMSA's in these areas are 50%, 45% and 28%, respectively. No regions were discriminated in the north-eastern parts of the country.

Three regions were discriminated on the basis of violent crime rates (Figure 8). The areas strectching along the Gulf Coast from Corpus Christi, Texas up to and including the entire state of Florida is composed of 70% high violent crime rate SMSA's, the highest proportion of any region discriminated, regardlesss of the crime rate considered. A Sunbelt region from Lubbock, Texas to the eastern coast is composed of 45% high violent crime rate SMSA's. It could be argued that these two regions should be combined, since few SMSA's are located between them. Michigan is the third region with 60% of its SMSA's in high violent crime rate clusters. Once again, no regions were detected in the north-east.

When the two dimensional case involving both property and violent crime rates is considered, only Florida stands out as a region with 41% of its SMSA's in the high crime rate cluster (figure 11).

CHAPTER V

DISCUSSION AND CONCLUSION

The approach taken in this study is an alternative way of looking at the nature and distribution of high crime rate urban areas within the United States. By heavily relying upon clustering procedures, a more representative picture of crime is possible as compared to the standard practice of using arbitrarily chosen threshold values to classify SMSA's on the basis of crime rate. In applying the results of this study, the inherent problems of using SMSA's as units of analysis should be taken into account (see Chapter IV). The fact that different criteria are used for defining SMSA's in the New England region may have biased results for that area.

The crime regions discriminated form the basis for further research into the possible causes of their formation. Factors associated with social instability are likely to be strongly correlated with these regions. Factory closings in the automobile industry may have been responsible for Michigan's high crime rates. The migration of workers out of Michigan and towards Texas may have been responsible for the stairstep pattern observed. In Florida, the effects of the Mariel boat-lift, coupled with an already volatile mixture of poor minority groups who are defenders and victims, are likely explanations for the severity of crime. The existence of the Southern violence phenomenon is once again borne out by the Sunbelt and Gulf Coast Regions. The western property crime region is difficult to explain, but may be associated with high mobility in this area.

The lack of any regions in the North East is probably as significant as the presence of any other regions. Social stability coupled with low mobility may be possible explanations.

If we accept the hypothesis that population size and crime rate have a strong positive correlation, then the severe crime rate SMSA's and regions identified by this study are entities worthy of a disproportionately large share of resources allocated to combating crime and its causes as well as more attention from academic researchers. The New England region is not an appropriate region to allocate high per capita levels of anti-crime resources, if the results of this study are correct.

It should be emphasized that the results do not provide an accurate picture of the most dangerous SMSA's, instead they show those SMSA's which, within the constraints of their "natural" population size classes, have the highest crime rates. The distinction is an important one, since the results of this study could easily be misinterpreted.

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APPENDIXES

APPENDIX A

PROCEDURE USED IN DETERMINATION OF WEIGHTS

A) Review of Survey Data

Seriousness scores for each of the UCR crime categories were derived from Bureau of Justice Statistics Bulletin (January, 1984) by selecting crime situations which both fit the UCR crime category definition and were comparable with the typical crime pattern discussed under the heading "nature" of crime in the UCR (FBI, 1980- 1982) and then calculating the average of the scores.

Murder and Nonnegligent Manslaughter

Definition:

Willful (nonnegligent) killing of one human being by another. Not included in the count for this offense classification are deaths caused by negligence, suicide or accident; justifiable homicides, and attempts to murder or assaults to murder which are scored as aggravated assaults.

The Typical Homicide:

Victim-male, white

Offender-male

Method-firearms

Crime Situations:

35.6--A person intentionally injures a victim. As a result, the victim dies.

Weight=35.6

Forcible Rape

Definition:

The carnal knowledge of a female forcibly and against her will. Assaults or attempts to commit rape by force or threat of force are also included. However, statutory rape (without force) and other sex offenses are not included.

The Typical Rape:

Method-by force: attempted not included

Crime Situations:

30.0--A man forcibly rapes a woman. Her physical injuries require hospitalization.

25.8--A man forcibly rapes a woman. No other physical injury occurs.

20.1--A man forcibly rapes a woman. Her physical injuries require treatment by a doctor but not hospitalization.

Weight=25.3

Robbery

Definition:

The taking or attempting to take anything of value from the care, custory, or control of a person or persons by force or threat of force or violence and/or by putting the victim in fear.

The Typical Robbery:

Average-$800

Location-street or highway

Method-firearms

Crime Situations:

16.5--A person robs a victim of $1,000 at gunpoint. The victim is wounded and requires treatment by a doctor but not hospitalization.

9.7--A person robs a victim of $1,000 at gunpoint. No physical harm occurs.

Weight=13.1

Aggravated Assault

Definition:

An unlawful attack by one person upon another for the purpose of inflicting severe or aggravated bodily injury. 1) this type of assault is usually accompanied by the case of a weapon or by means likely to produce death or great bodily harm. 2) attempts are included since it is not necessary that an injury result when a gun, knife or other weapon is used which could and probably would result in serious personal injury if the crime were successfully completed.

The Typical Aggravated Assault:

Method-guns, knives,bodily force

Victim-unspecified

Crime Situations:

24.8--A person intentionally shoots a victim with a gun. The victim requires hospitalization.

19.0--A person intentionally shoots a victim with a gun. The victim requires treatment by a doctor but not hospitalization.

18.0--A person stabs a victim with a knife. The victim requires hospitalization.

17.8--A person intentionally shoots a victim with a gun. The victim is wounded slightly and does not require medical treatment.

17.1--A person stabs a victim with a knife. The victim requires treatment by a doctor but not hospitalization.

11.9--A person intentionally injures a victim. The victim is treated by a doctor and hospitalized.

11.8--A person stabs a victim with a knife. No medical treatment is required.

8.5--A person intentionally injures a victim. The victim is treated by a doctor but is not hospitalized.

7.3--A person beats a victim with his fists. The victim is hurt but does not require medical treatment.

6.9--A person beats a victim with his fists. The victim requires hospitalization.

6.2--A person beats a victim with his fists. The victim requires treatment by a doctor but not hospitalization.

Weight=13.6

Burglary

Definition:

The unlawful entry of a structure to commit a felony or theft. The use of force to gain entry is not required to classify an offense as burglary. Burglary in this program is categorized into three subclassifications: forcible entry, unlawful entry where no force is used, and attempted forcible entry.

The Typical Burglary:

Location-residential

Method-forcible entry

Average-$880

Crime Situations:

9.6--A person breaks into a home and steals $1,000.

Weight=9.6

Larceny-Theft

Definition:

The unlawful taking, carrying, leading, or riding away of property from the possession or constructive possession of another. It includes crimes such as shoplifting, pocket-picking, purse-snatching, thefts from motor vehicles, thefts of motor vehicle parts and accessories, bicycle theft, etc, in which no use of force, violence or fraud occurs. Does not include embezzlement "con" games, forgery, and worthless checks.

The Typical Larceny-Theft:

Average-$300

Type-motor vehicle associated or from buildings

Crime Situations:

3.6--A person steals property worth $100 from outside a building.

Weight=3.6

Motor Vehicle Theft

Definition:

The theft or attempted theft of a motor vehicle. Excludes the taking of a motor vehicle for temporary use by those persons having lawful access.

The Typical Motor Vehicle Theft:

Average-$3,500

Item-automobile

Crime Situations:

10.8--A person steals a locked car and sells it.

8.0--A person steals an unlocked car and sells it.

4.4--A person steals an unlocked car and later abandons it undamaged.

Weight=7.7

B) Specification of Weights

The following list (see p64) summarizes the weights obtained in section A together with other possible weighting values. The actual values to be used in the clustering procedure are shown in parentheses and were derived by means of a linear scale transformation putting the weights on a scale from 1 (larceny theft) to 100 (homicide) (Smith, 1975). For the purpose of comparison, other possible weighting values are also listed.

Several points can be advanced in defense of the crime seriousness weights proposed. First it should be noted the survey data upon which they are based is the most comprehensive information available on the national opinion of the seriousness of crime. Secondly, these weights were adapted by the Bureau of Justice Statistics Bulletin survey in such as so as to match UCR crime categories well, thereby making possible the analysis of UCR crime data (the most complete data base in existence for the U.S.). Lastly, the linear scale transformation of the weights makes them more comprehensible while retaining an interval scale of measurement.

CRIME SERIOUSNESS WEIGHTS

Crime Categories	Proposed Weights	President's Commission on Law Enforcement and Adm. of Justice (1967)	Sellin-Wolfgang	National Median Served in Month (NCCD, 1969)	Average Sentence Imposed on Offenders (SSPI, 1979)
Murder/Manslaughter	35.6 (100.00)	400,000,000	26.0	50.87	NA
Forcible Rape	25.3 (68.14)	10,000,000	18.0	52.71	124.2
Robbery	13.1 (30.39)	10,000	5.0	33.33	109.2
Aggravated Assault	13.6 (31.94)	20,000	5.4	15.37	NA
Burglary	9.6 (19.56)	200	2.4	11.87	51.6
Larceny-Theft	3.6 (1.00)	100	2.2	14.19	NA
Motor Vehicle Theft	7.7 (13.68)	900	2.9	14.58	NA

APPENDIX B

SMSA'S COMPOSING CRIME RATE-BASED CLUSTERS
HAVING THE HIGHEST MEAN PROPERTY CRIME
RATES WITHIN POPULATION-BASED
CLUSTERS

Cluster	SMSA	Property Crime Rate
I D 1	Madison, Wis	6,656
I D 2	Benton Harbor, MI	6,675
I D 3	Kenosha, Wis	6,689
I D 4	Ocala, FL	6,739
I D 5	Vineland-Millville-Bridgeton, NJ	6,769
I D 6	Ann Arbor. MI	6,779
I D 7	Corpus Christi, TX	6,783
I D 8	Muskegon-Norton Shores-Muskegon, MI	6,831
I D 9	Little Rock-North Little Rock, Ark	6,970
I D10	Columbia, MO	6,844
I D11	Eugene-Springfield, OR	6,846
I D12	Lawrence, KS	6,858
I D13	Springfield, MO	6,869
I D14	Reno, Nev	6,925
I D15	Modesto, CA	6,981
I D16	Saginaw, MI	7,091
I D17	Lubbock, TX	7,106
I D18	Tallahassee, FL	7,229
I D19	DesMoines, Iowa	7,548
I D20	Daytona Beach, FL	7,570
I D21	Savannah, GA	7,575
I D22	Stockton, CA	7,776
I D23	Great Falls, Mont	7,810
I D24	Odessa, TX	8,380
I D25	Gainsville, FL	8,580
I D26	Atlantic City, NJ	11,000
II C 1	Flint, MI	7,200
II C 2	Fresno, CA	7,454
II C 3	Bakersfield, CA	7,828
II C 4	Orlando, FL	7,917
II C 5	Tucson, AZ	7,976
II C 6	West Palm Beach-Boca Raton, FL	8,406
II C 7	Las Vegas, Nev	8,938
III C 1	Denver-Boulder, CO	7,607
III C 2	Phoenix, AZ	7,889
III C 3	Fort Mayers-Cape Coral	7,897
III C 4	Sacramento, CA	8,294
III C 5	Miami, FL	9,130
IV A 1	Los Angeles, CA	6,993
IV A 2	Houston, TX	7,031
IV A 3	New York, NY-NJ	7,118
IV A 4	San Francisco, CA	7,293
IV A 5	Dallas-Fort Worth, TX	7,438

APPENDIX C

SMSAs COMPOSING CRIME RATE-BASED CLUSTERS HAVING THE HIGHEST MEAN VIOLENT CRIME RATES WITHIN POPULATION BASED CLUSTERS

Cluster	SMSA	Violent Crime Rate
I C 1	Panama City, FL	595
I C 2	Champaign-Urbana-Rantoul, IL	596
I C 3	Jacksonville, NC	597
I C 4	Corpus Christi, TX	603
I C 5	Tuscaloosa, AL	604
I C 6	Bradenton, FL	606
I C 7	Springfield, IL	607
I C 8	Lawton, OK	616
I C 9	Trenton, NJ	620
I C10	Shreveport, LA	622
I C11	Kalamazoo-Portage, MI	629
I C12	Wichita Falls, TX	644
I C13	Fayetteville, NC	658
I C14	Anniston, AL	663
I C15	Jackson, MI	666
I C16	Biloxi-Gulf Port, MS	667
I C17	Wilmington, NC	688
I C18	Monroe, LA	691
I C19	Pueblo, CO	696
I C20	Lafayette, LA	697
I C21	Stockton, CA	702
I C22	Ocala, FL	704
I C23	Mansfield, OH	710
I C24	Florence, SC	710
I C25	Benton Harbor, MI	723
I C26	Galveston-TX City, TX	735
I C27	Beaumont-Port Anthur-Orange, TX	741
I C28	Daytona Beach, FL	745
I C29	Lubbock, TX	751
I C30	Tallahassee, FL	753
I C31	Muskegon-Norton Shores, MI	786
I C32	Pensacola, FL	817
I C33	Saginaw, MI	830
I C34	Little Rock, Ark	834
I C35	Lakeland-Winter Haven, FL	856
I C36	Savannah, GA	873
I C37	Rock Hill, SC	899
I C38	Atlantic City, NJ	957
II B 1	El Paso, TX	722
II B 2	Charlotte-Gastonia, NC	728
II B 3	Albuquerque, NM	773
II B 4	Paterson-Clifton, Passaic, NJ	791
II B 5	Bakersfield, CA	799
II B 6	Jersey City, NJ	820
II B 7	Baton Rouge, LA	823
II B 8	Jacksonville, FL	824
II B 9	Fresno, CA	830
II B10	Mobile, AL	834
II B11	Charleston-N. Charleston, SC	840

II B12	Flint, MI	855
II B13	Memphis Tenn-Ark-Miss	868
II B14	Columbia, SC	916
II B15	Orlando, FL	990
II B16	West Palm Beach-Boca Raton, FL	1082
II B17	Las Vegas, Nev	1130
III E 1	Miami, FL	1767
IV D 1	New York, NY-NJ	1709

APPENDIX D

SMSAs COMPOSING CRIME RATE-BASED CLUSTERS HAVING THE HIGHEST MEAN PROPERTY CRIME RATES WITHIN POPULATION-BASED CLUSTERS

Cluster	SMSA	Crime Rates Property	Violent
I E 1	Muskegon, MI	5764	899
I E 2	Benton Harbor, MI	6065	856
I E 3	Rock Hill, SC	6458	817
I E 4	Tallahasse, FL	6675	724
I E 5	Lakeland-Winter Haven, FL	6739	704
I E 6	Stockton, CA	6831	786
I E 7	Ocala, FL	6970	834
I E 8	Pensacola, FL	7091	830
I E 9	Daytona Beach, FL	7106	751
I E10	Gainsville, FL	7229	753
I E11	Little Rock, Ark	7570	745
I E12	Savannah, GA	7576	873
I E13	Atlantic City, NJ	7776	702
I E14	Saginaw, MI	8581	985
I E15	Lubbock, TX	11000	957
II E 1	Orlando, FL	7917	990
II E 2	West Palm Beach-Boca Raton, FL	8406	1082
II E 3	Las Vegas, Nev	8938	1130
III E 1	Miami, FL	9130	1767
Property			
IV A 1	Houston, TX	7031	866
IV A 2	San Francisco, CA	7293	937
IV A 3	Dallas-Fort Worth, TX	7438	733
Violent			
IV D 1	Los Angeles, CA	6993	1303
IV D 2	New York, NY-NJ	7118	1709

VITA 2

Mei-Lin Beem

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