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A SPATIAL ANALYSIS OF CRIME IN APPALACHIA

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CHAPTER ONE: THE SOCIAL ECOLOGY OF APPALACHIA

INTRODUCTION

The search for relationships between the ecological characteristics of places and levels of crime has a long and rich history in criminological research. Theoretical traditions rooted in social disorganization, economic strain, and spatial inequality have established a number of structural characteristics that vary systematically between locations and which are often highly correlated with rates of serious crime. The structural factors used to explain variations in crime often include measures of socioeconomic stratification (e.g., poverty, income inequality, residential segregation), racial composition (percent black, racial and ethnic diversity), and social disorganization (family disruption, residential mobility, unemployment).

One common denominator throughout much of this work on aggregate patterns of crime is the almost exclusive focus on urban and metropolitan locations. By comparison, there have been relatively few attempts to look at patterns of rural crime. As a result, one of the least understood topics in the field of criminology is that of rural and nonmetropolitan crime (Carter et al. 1982; Kowalski and Duffield 1990; Petee and Kowalski 1993; Weisheit, Falcone and Wells 1995; Weisheit and Wells 1996; Wilkinson 1984). The spatial dynamics of crime in rural locations can be understood as a product of social, economic and demographic factors which are often unique to those areas. Thus, there is a need for research on rural crime which takes location and geographic context seriously.

The focus of this study will be on the application of Geographic Information System (GIS) technologies and spatial analysis procedures to the study of aggregate crime patterns in Appalachia. The main advantage of using GIS and related technologies is that it enables the researcher to look more rigorously at the spatial patterns and ecological contexts of crime. Just as longitudinal study designs allow the researcher to take the dimension of time seriously, so does the use of GIS and spatial analytic procedures allow the researcher to take the dimension of space seriously. A common theme in the work of those who use GIS technologies is an appreciation for the fact that spatial and ecological analysis is not merely a poor substitute for individual-level analysis. Rather, the geographic context is seen as important in its own right as a distinct source of influences, outcomes, and structural effects.

Thus the most obvious advantage of using GIS throughout the data analysis process is that it gives the researcher an opportunity to examine the effects of location in a more systematic way. In addition, the analytical applications of GIS can be used in either an exploratory or confirmatory capacity. As an exploratory data analysis tool, GIS can be used to examine data visually, as a way of generating new hypotheses from the data or as a way of identifying unexpected spatial patterns. As a confirmatory data analysis tool, GIS has been given increased analytical power with the introduction and development of various spatial statistical packages.

BACKGROUND

Appalachia has historically been identified as a region plagued by poverty and related social problems. The region covers a 200,000 square-mile area that follows the spine of the Appalachian Mountains from southern New York to northern Mississippi. It includes all of West Virginia and parts of twelve other states: Alabama, Georgia, Kentucky, Maryland, Mississippi, New York, North Carolina, Ohio, Pennsylvania, South Carolina, Tennessee, and Virginia. According to the Appalachian Regional Commission, about 22 million people lived in the 399 counties of the Appalachian region as of 1998. Also, 42 percent of the region's population resides in rural areas compared with 20 percent of the national population.

While poverty and economic disadvantage have traditionally been linked to crime in the social ecology literature, the spatial pattern of this relationship is often complex. Furthermore, most of this literature has been limited to urban crime and it may be that the link between poverty and crime is different in urban and rural areas. In addition, population redistribution and industrial restructuring have had differential effects in urban and rural locations in recent years as well (Frey 1987; Fuguitt 1985; Johnson 1989, 1993; Kephart 1991; Long and DeAre 1988). One of the purposes of the present paper is to examine whether the theoretical links between poverty and crime vary between metropolitan and nonmetropolitan locations. In addition to measures of poverty, other structural measures will be employed as well, including demographic structure (age composition), racial composition (percent black), social capital (percent high school graduates), and family disruption (divorce).

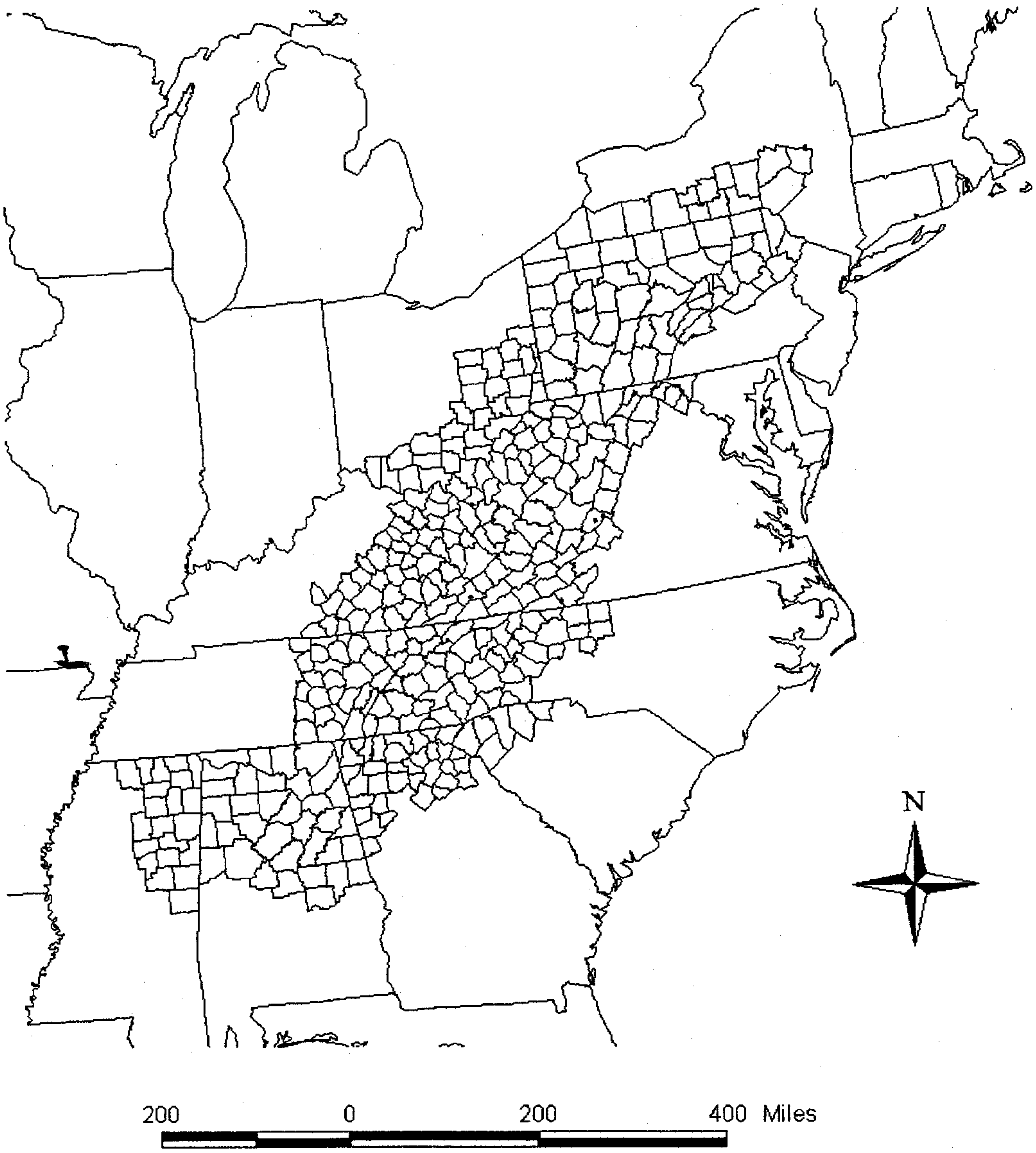
Appalachia poses the additional challenge of being a region characterized by a rich diversity of people and places. Economic depression in one location may be offset by economic growth in another. Some parts of the region have long been subject to cycles of growth and decline in the various timber, mining, and textile industries. Other parts of the region have benefited from the recent influx of newer service- and technology-based industries (Billings and Tickamyer 1993). Thus, as some locations are struggling to keep their declining communities alive, others are striving to slow down the rapid economic and population growth that technological innovation, better transportation systems, and spatial industrial restructuring have introduced. This rich diversity in topography, economic variability, and demographic change are what make Appalachia such a challenging region to characterize with regard to shifting patterns of crime.

AN OVERVIEW OF THE APPALACHIAN REGION

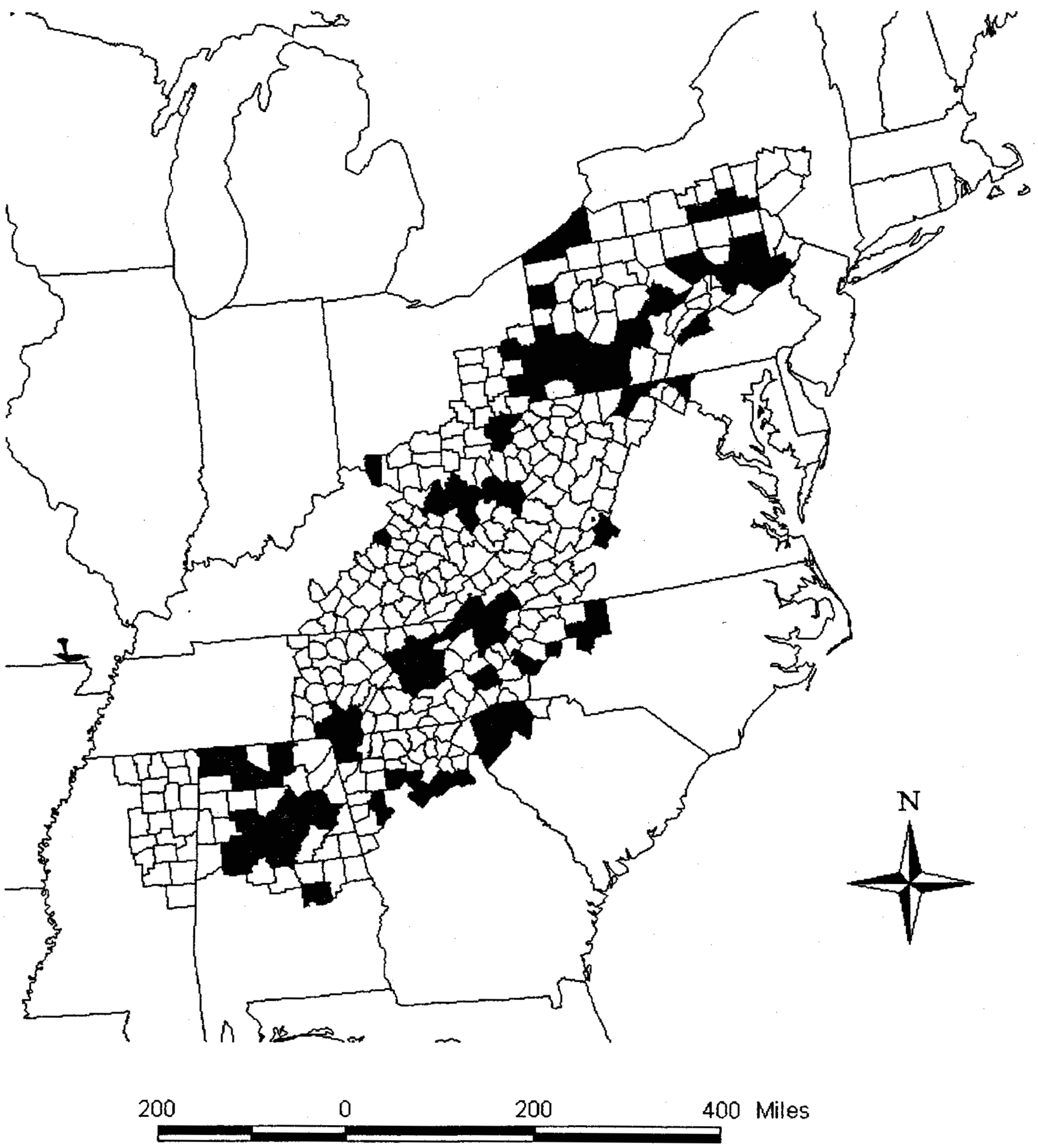
Prior to 1998, the Appalachian Region was defined by Congress to include 399 counties. In October of that year, seven new counties were added to this definition. Given the scope and time frame of the present study, the seven counties added to the Region in 1998 will not be included in the analyses. The 399 counties of the Appalachian Region extend across 1,200 miles from southeastern New York to northern Mississippi (see Map 1.1) and include about 22 million people in 13 different states.

The counties in Appalachia range from metropolitan counties comprising parts of Atlanta, Birmingham, Chattanooga, Cincinnati, Greensboro, Knoxville, Pittsburgh, and Roanoke to isolated rural counties in the mountains of Kentucky and West Virginia. The metropolitan counties in Appalachia are highlighted in Map 1.2. While 109 counties were classified in 1990 as metropolitan, the remaining 290 were classified as nonmetropolitan. In addition, of the 290 nonmetropolitan counties, 105 were categorized as completely rural (Map 1.3).

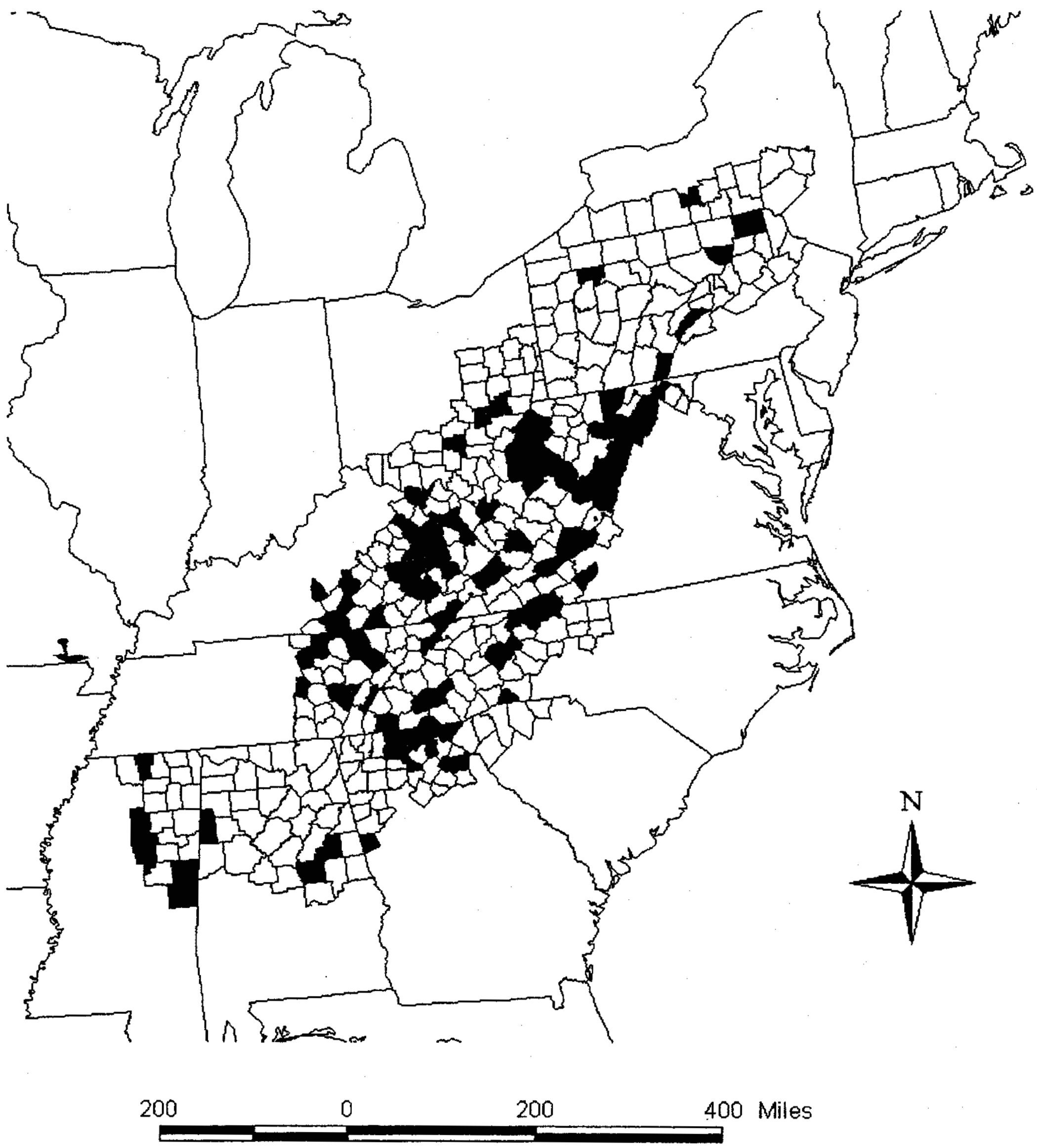
Map1.1
Appalachian Region Counties



Map1.2
Appalachian Region Metro Counties



Map1.3
Appalachian Region Rural Counties



SPATIAL INEQUALITY IN APPALACHIA

As indicated earlier, the Appalachian Region encompasses a rich demographic, economic, and spatial diversity. As a result, it is also a region, which defies easy or simple generalizations. While the metropolitan areas of Atlanta and those in the Carolinas have experienced rapid economic growth and demographic change, many rural areas in Kentucky, West Virginia and other core locations have labored under increasing poverty and declining populations. The outcome is a growing spatial inequality across different parts of the region characterized by tremendous economic, social, and demographic disparities among the counties that comprise Appalachia.

Douglas Massey argues that this geographic polarization is part of a larger national trend characterized by the spatial concentration of affluence and poverty (Massey 1996). Massey goes on to predict that "the advantages and disadvantages of one's class position will be compounded and reinforced through ecological mechanisms made possible by the geographic concentration of affluence and poverty, creating a deeply divided and increasingly violent social world" (1996:395). William Frey suggests that the social and economic differentiation of geographic space in the United States is reflected in a new type of "demographic balkanization" (Frey 1995). According to Frey, "industrial restructuring, immigration, and segmented redistribution patterns …have widened demographic disparities across broad regions and metropolitan areas" (1995:333), resulting in uneven spatial patterns of growth and decline.

Demographic shifts and structural changes in the national economy over the past couple decades have intensified chronic economic instability in many rural areas (Tickamyer and Duncan 1990). In Appalachia, less diverse local economies have long been at the mercy of boom and bust cycles for timber, coal, agriculture and manufacturing. Industrial restructuring has exacerbated local vulnerability to these cyclical trends and has led to the further entrenchment of poverty in these areas. While most empirical work in the restructuring literature focuses on urban areas, there are two points concerning rural restructuring that have direct relevance to the Appalachian experience. First, the decline of extractive, manufacturing and other high wage or "core" industries is often accompanied by growth of services in peripheral or low wage sectors. The rise of the service sector as the dominant industry in some locations has subsequently contributed to increased poverty in these areas (O'Hare 1988). Second, rural restructuring is often characterized by geographic unevenness. In addition to metro-nonmetro differences and differences based on relative proximity to metropolitan areas, regional shifts, such as the decline of the northern manufacturing belt relative to the sunbelt, have also contributed to spatial inequality (Kasarda 1995; Tolbert and Lyson 1992).

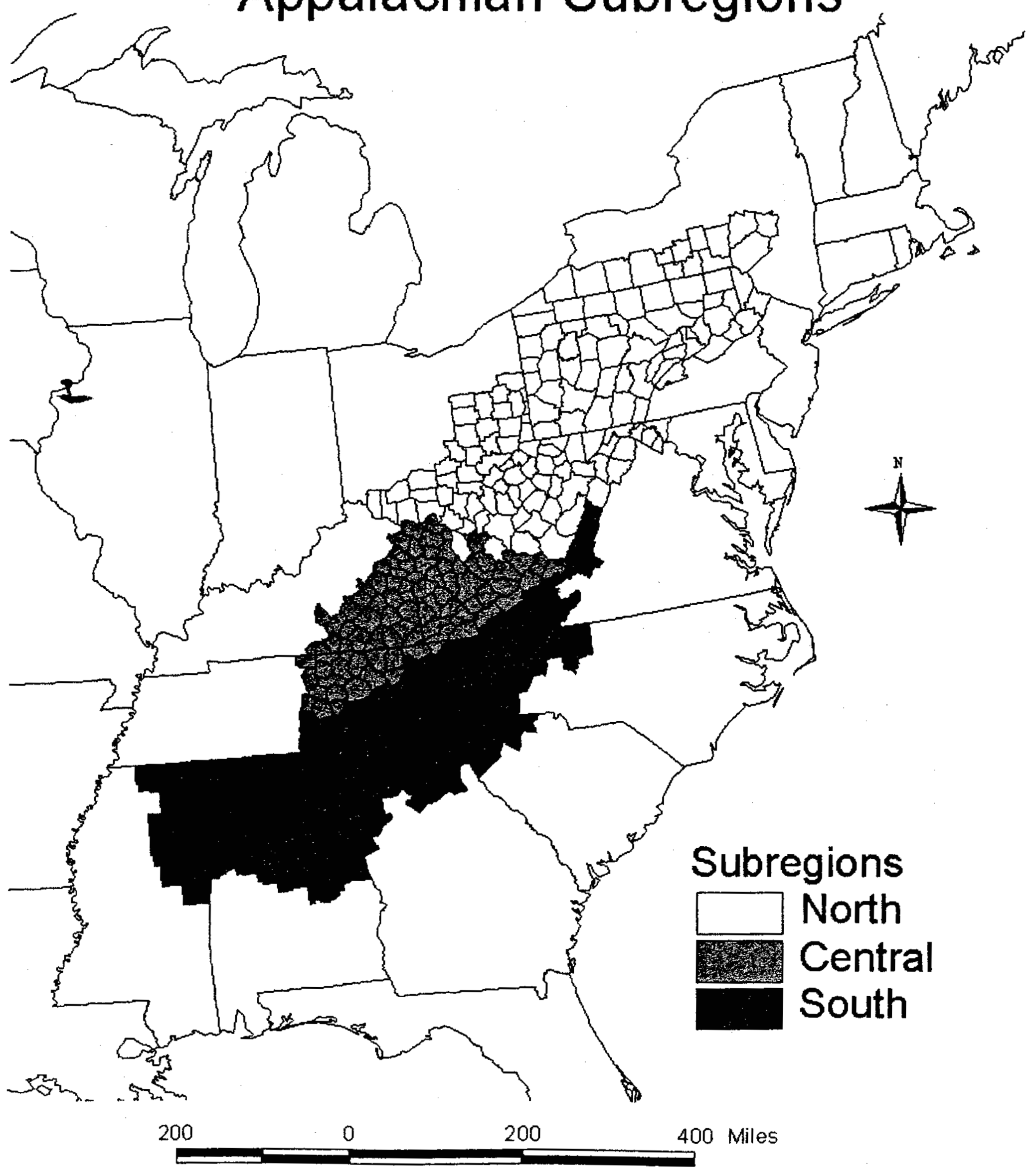
The demographic and structural changes affecting Appalachia are heterogeneous in their distribution across different geographic areas. They are also heterogeneous in their social consequences. As a result, the relationship between crime and various indicators of social disorganization will necessarily be more complex. This report will therefore focus on the spatial diversity of various social, economic, and demographic conditions and their relationship to crime in the Appalachian Region.

SCOPE OF THE STUDY

This study provides a descriptive and statistical profile of crime and related social, economic and demographic conditions in Appalachia. The analysis centers primarily on spatial diversity, with a special emphasis on nonmetropolitan and rural crime in particular. In order to portray the contextual diversity of crime in Appalachia, three different county classifications, each based on different criteria, are employed. The three classifications are: (1) the Appalachian Subregions, consisting of North, Central, and South Appalachia; (2) Beale County Codes which are based on metro-nonmetro designations, population size, and adjacency to metropolitan counties; and (3) Distressed County Codes which are based on measures of poverty, unemployment and per capita income.

The Appalachian Subregions are geographic regions specified by the Appalachian Regional Commission (see Map 1.4). The northern Appalachian subregion consists of 144 counties located in southern New York, about three-quarters of Pennsylvania, southeastern Ohio, several Maryland counties between Pennsylvania and West Virginia, and much of West Virginia. The central Appalachian subregion includes 85 counties located in the core of Appalachia. These are largely nonmetropolitan counties located in the mountains and coal country of eastern Kentucky, the southern part of West Virginia, southwestern Virginia, and parts of eastern Tennessee. The southern Appalachian subregion contains 170 counties extending from Virginia, through the Carolinas, to the edge of Atlanta, and across through northern Alabama and northeast Mississippi. Given the regional shifts in America's demographic and industrial geography from the older manufacturing regions of the "frostbelt" in the North to the more diversified economies of the "sunbelt" in the South (Kasarda 1995), and given the decline in extractive industries and subsequent restructuring in the core (Nord and Luloff 1993), these subregional distinctions will provide a useful template for comparing levels of crime across growing and declining locations.

Map 1.4
Appalachian Subregions

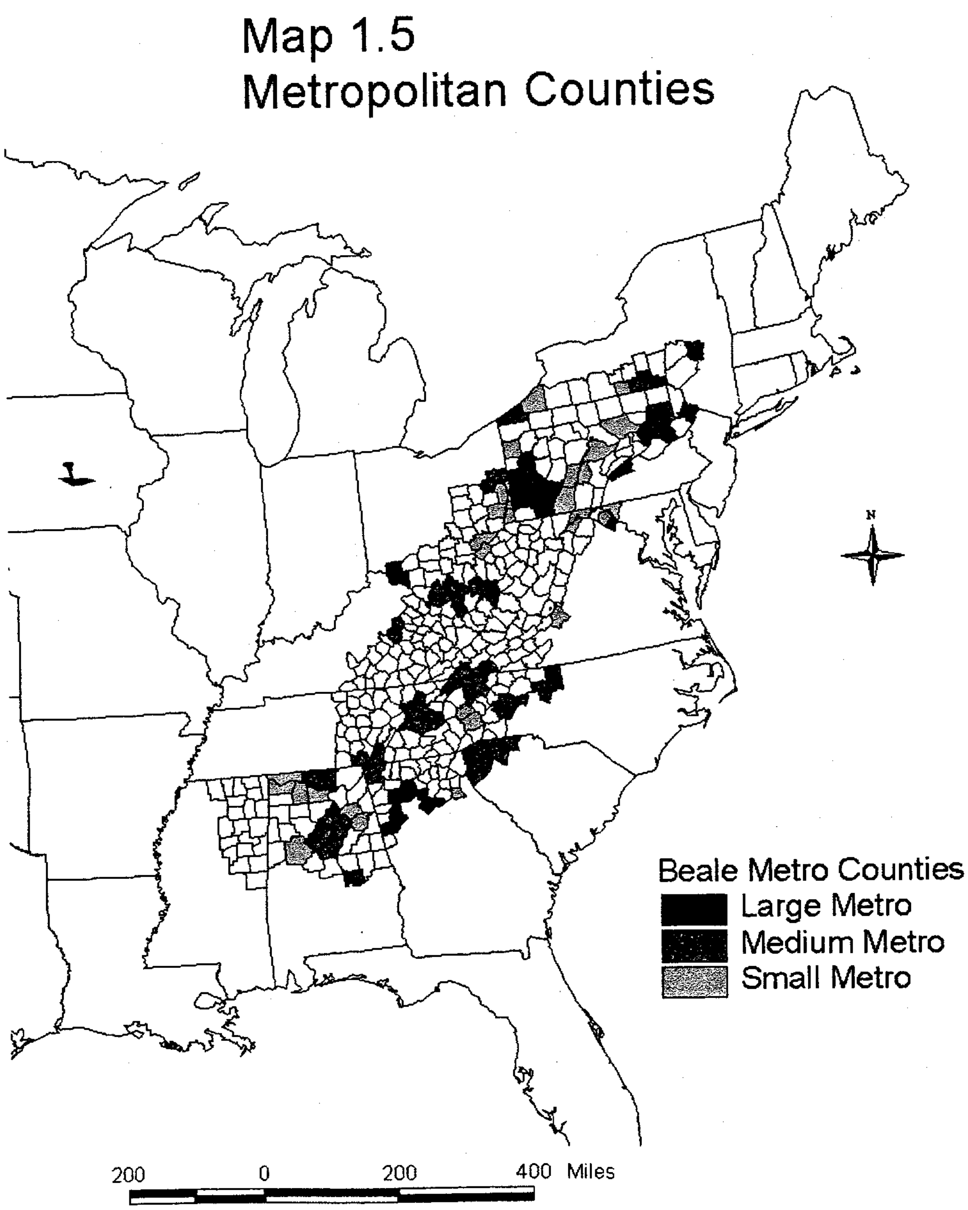


The second typology for comparing Appalachian counties is the Beale Code Classification of counties based on metro-nonmetro distinctions, population size, and adjacency to metropolitan areas. Calvin Beale, a geographic demographer with the Economic Research Service at the U.S. Department of Agriculture identified ten types of counties ranging from core metropolitan areas to isolated rural locations (see Table 1.1). The Beale codes were initially developed in 1983 using data from the 1980 U.S. Census of Population and Housing. In 1993, the codes were updated based on 1990 Decennial Census data. For the present study, 1993 Beale Codes will be used in order to reflect current county status.

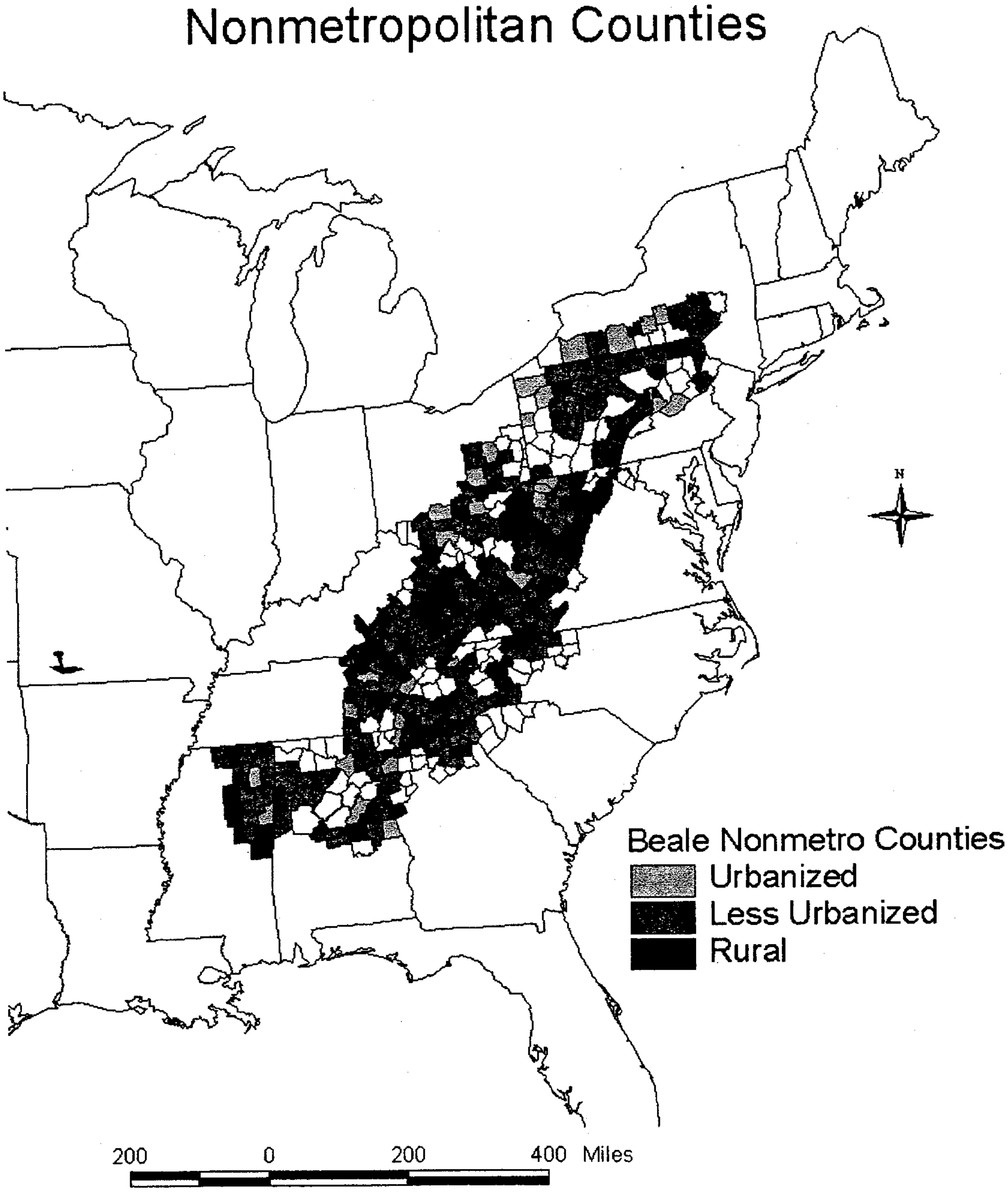
Table 1.1. Beale Code Classifications for Appalachian Counties, 1993.

Beale Code	Definition	Number of Counties
	Metropolitan Counties	
0	Central counties of metro areas of 1 million population or more	7
1	Fringe counties of metro areas of 1 million population or more	12
2	Counties in metro areas of 250,000-1,000,000 population	59
3	Counties in metro areas of less than 250,000 population	31
	Nonmetropolitan Counties	
4	Urban population of 20,000 or more, adjacent to metro area	19
5	Urban population of 20,000 or more, not adjacent to metro area	11
6	Urban population less than 20,000, adjacent to metro area	78
7	Urban population less than 20,000, not adjacent to metro area	77
8	Completely rural, adjacent to metro area	40
9	Completely rural, not adjacent to metro area	65

Beale code classifications provide a useful typology for comparing levels of crime across metropolitan and nonmetropolitan locations based on population size and metro-nonmetro proximity. Metropolitan counties (Beale Codes 0-3) are shown in Map 1.5, while nonmetropolitan counties (Beale Codes 4-9) are shown in Map1.6.



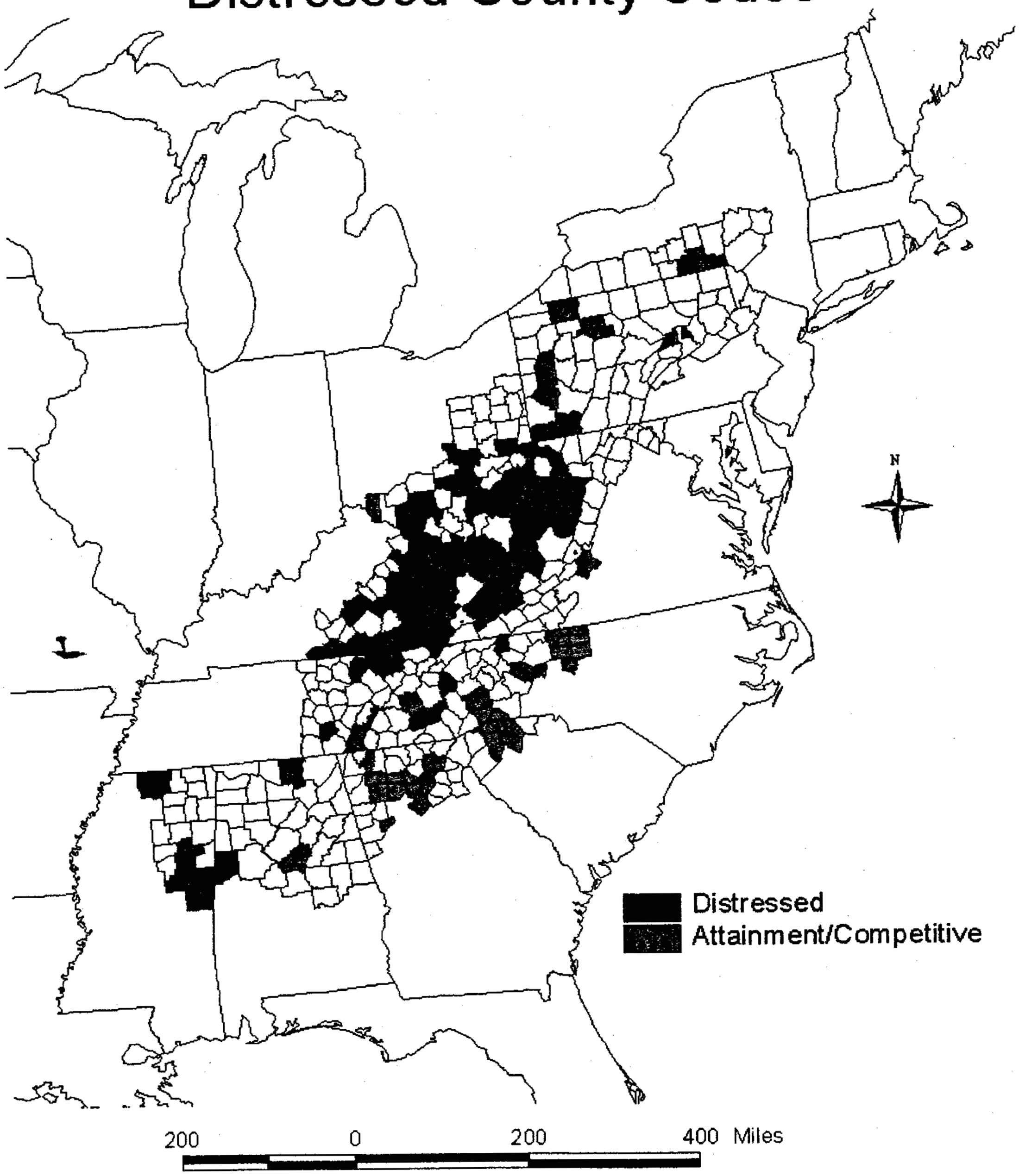
Map 1.6
Nonmetropolitan Counties



The third typology for comparing Appalachian counties is the 1996 Distressed County Codes. This classification is prepared annually by the Appalachian Regional Commission (ARC) and distinguishes between counties based on average unemployment rates, poverty rates, and per capita market income. Distressed County rankings range from 1 (worst) to 5 (best): (1) Distressed, (2) Transitional 1, (3) Transitional 2, (4) Competitive, and (5) Attainment counties. Counties with a distress ranking of 1 (Distressed) have at least 150% of the U.S. unemployment rate, 150% of the U.S. poverty rate, and less than 67% of the U.S. per capita market income. Counties with a distress ranking of 2 (Transitional 1) have two of these characteristics. Counties with a distress ranking of 3 (Transitional 2) have one of these characteristics. Counties with a distress ranking of 4 (Competitive) have levels of unemployment and poverty at or below the U.S. average, but less than 80% of the U.S. per capita market income. Counties with a distress ranking of 5 (Attainment) are compatible with U.S. levels on all three indicators. Of the 399 Appalachian counties, 97 are categorized as Distressed, 33 are ranked as Transitional (1), 233 as Transitional (2), 25 are Competitive, and 11 are categorized as Attainment counties according to the 1996 ARC rankings.

This typology is useful for comparing levels of crime across Appalachian counties according to relative levels of deprivation. The spatial distribution of distressed counties (Distress Code 1) and competitive/attainment counties (Distress Codes 4 and 5) is shown in Map 1.7. Note the clustering of distressed counties in the central coal-mining region of eastern Kentucky, West Virginia, southwestern Virginia, and eastern Tennessee.

Map 1.7
Distressed County Codes



DATA AND ANALYTICAL STRATEGIES

Rapid developments in GIS and related technologies have significantly improved the ability of researchers to look more rigorously at the spatial patterns and ecological contexts of crime. Although largely untapped, GIS has great potential to enhance criminological research in at least three ways: (1) data integration and visualization; (2) exploratory spatial analysis; and (3) confirmatory spatial analysis and statistical modeling.

To date, most GIS applications used in the study of crime have been limited to mapping and visualization. In part this is because the use of GIS and more sophisticated spatial analysis tools are still relatively new to most researchers and practitioners. It will be argued in this paper that the analytical applications of GIS can be used in either an exploratory or confirmatory capacity to expand the power of these technologies beyond their use as an automated mapping system. As an exploratory data analysis tool, GIS can be used to examine data visually, as a way of generating new hypotheses from the data or as a way of identifying unexpected spatial patterns. As a confirmatory data analysis tool, GIS has been given increased analytical power with the introduction and development of spatial statistical packages.

Data and Measures

For this project a unique data set has been compiled at the county level for all 399 counties in the Appalachian region. The data set is unique due to the diversity of sources used and due to the incorporation of this data into an integrated GIS database. In this way a number of independent and contextual variables identified as theoretically relevant in studies of crime and delinquency can be linked spatially within a GIS environment and thereby examined in ways previously not possible.

Dependent variables are the index crime rates derived from Uniform Crime Report (UCR) data for all index crimes at the county level in Appalachia. These offending rates are averaged across 3-years for two time periods, 1979-1981 and 1989-1991, in order to smooth out any year-to-year fluctuations. Separate analyses are done for property index crimes and violent index crimes

Independent and contextual variables have been selected based on theoretical grounds and previous research on the ecological contexts of crime. These include:

(1) Appalachian Subregional Codes consisting of North, Central, and South Appalachia;

(2) Beale Classification Codes based on a metro-nonmetro continuum;

(3) Distressed County Indicators based on measures of poverty, unemployment, and per capita income;

(4) Socioeconomic Indicators: poverty rate and unemployment rate;

(5) Demographic Distribution Indicators: population size and metro-nonmetro classifications;

(6) Demographic Composition Indicators: ages 15-29 (the high crime-prone years) and percent black;

(7) Demographic Change Indicators: residential mobility and population growth;

(8) Social Well-Being Indicators: female-headed households, percent divorced, and educational attainment.

The data set has been compiled from numerous secondary data sources including FBI Uniform Crime Reports as well as data from the U.S. Bureau of the Census, the U.S. Department of Agriculture, and the Appalachian Regional Commission. The temporal coverage for the independent and contextual variables depends on the data source, but is usually 1980 and 1990.

Data Integration and Visualization

A central purpose of this project is to demonstrate the contributions that geographic information systems and geographic information analysis can offer to the study of rural crime patterns. Perhaps the most familiar use of GIS technologies at the present time is the visualization of spatial data. Once the data has been compiled and integrated into a GIS database, the spatial patterning of crime and each of the independent variables can be represented and explored across the study area. Maps of variable distributions can provide insight into potential spatial clustering, heterogeneity, and spread. In addition, overlay functions enhance exploration of the relative association of crime with the socioeconomic and demographic characteristics of various locations.

Exploratory Spatial Analysis

More rigorous analyses of spatial patterns can be accomplished through the use of exploratory spatial data analysis (ESDA) procedures. A central feature of ESDA is the concept of spatial autocorrelation (Anselin and Bao 1997). In this study, both global and local indicators of spatial autocorrelation are employed to identify possible clusters or regional "hot spots" of crime. In using a global measure of spatial autocorrelation, the overall pattern of dependence or clustering in the data is summarized with a single indicator such as Moran's I (Cliff and Ord 1981). As a global measure of spatial autocorrelation, Moran's I is significant and positive when values of a variable for locations in spatial proximity tend to be more similar than what is normally expected, negative when they tend to be more dissimilar than what is normally expected, and approximately zero when the attribute values are randomly spread over space (Cliff and Ord 1981).

In order to calculate the Moran's I indicator of spatial autocorrelation, a contiguity spatial weights matrix will first be constructed from ArcView shape files using SpaceStat software (Anselin 1998). Spatial neighbors can be defined either by contiguity (where neighbors are defined according to boundary relationships) or by distance (where neighbors are defined according to critical distance bands around centroid locations). In the present study, first-order contiguity weights will be assigned to each location where neighbors are defined as sharing a common border.

With large data sets, the assessment of global spatial autocorrelation needs to be supplemented by local measures of spatial dependence as well. According to Anselin (1995a), local indicators of spatial autocorrelation achieve two objectives: (1) they can be used to identify significant patterns of spatial association around individual locations, such as hot spots or spatial outliers; and (2) they can be used to assess the extent to which the global pattern of spatial association is spread uniformly throughout the data or whether there are significant types of locations affecting the computation of Moran's I.

Measures of spatial autocorrelation can also be usefully visualized by means of Moran scatterplot maps in which patterns of local spatial association are decomposed into four categories, corresponding with four quadrants in a Moran scatterplot (Anselin 1996). These four quadrants identify four types of local spatial association between a specific location and its neighbors. Two of these categories imply *positive* spatial association: (Quadrant I) where a location with an above-average value is surrounded by neighbors whose values are also above average (high-high), or (Quadrant II) where a location with a below-average value is surrounded by neighbors whose values are also below average (low-low). The other two categories imply *negative* spatial association: (Quadrant III) where a location with an above-average value is surrounded by neighbors with below average values (high-low), or (Quadrant IV) where a location with a below-average value is surrounded by neighbors with above average values (low-high). The mapping of these quadrants on a Moran scatterplot map provides a visual representation of significant spatial clustering or spatial outliers, while a series of Moran scatterplot maps can also be used to represent spread or change over time.

Confirmatory Spatial Analysis and Statistical Modeling

In addition to exploratory spatial data analysis procedures, GIS offers opportunities for enhanced spatial modeling through the use of confirmatory spatial data analysis (CSDA) procedures as well. According to Anselin and Getis (1992), the standard tools of CSDA consist of four broad categories of methods: (1) diagnostics for the presence of spatial dependence and spatial heterogeneity in regression analysis; (2) methods to estimate regression models that explicitly take into account spatial effects; (3) methods to estimate models that are robust to the presence of spatial effects; and (4) spatial measures of model validity.

Utilizing these standard methods of CSDA, spatial regression models can be powerful tools for analyzing the relationships between spatially-referenced variables. Generally, the relationships between such variables are influenced by their relative spatial distributions. While classical regression methods assume that data are randomly sampled from a homogeneous data-generating process, spatial data often violate critical aspects of this assumption. First, spatially-referenced data are often spatially clustered, and therefore are not randomly scattered in space. Second, structural instability may occur when regression coefficients vary according to regional location or spatial scale.

Spatial effects in regression models thus primarily occur in two distinct forms: spatial dependence and spatial heterogeneity (Anselin and Griffith 1988). Spatial dependence exists whenever there is value similarity between observations in proximate locations. Spatial heterogeneity, on the other hand, exists whenever there are clusters of outliers, significant regional differences, or identifiable locational groupings based on spatial scale. Anselin (1995b) also distinguishes between spatial *nuisance* effects, which involve model residuals only, and *substantive* spatial effects, where values of y are systematically related to values of y in adjacent locations. Nuisance effects reduce model efficiency and can often be corrected by including a spatial error specification, while more serious substantive effects generate model bias and are corrected by including an explicit spatial lag term for y as an explanatory variable in the model.

Spatial regression modeling thus consists of several steps. First, a standard OLS regression model is estimated and forms the starting point for evaluating the presence of significant spatial effects. A spatial error model, which tests for spatial dependence as a nuisance effect, is then estimated and compared with the original OLS model. Finally, a spatial lag model, which explicitly tests for the significance of substantive spatial dependence is then estimated and compared with the other models for goodness-of-fit. Also, if spatial structural instability exists, then a spatial heterogeneity model can be used to distinguish between identifiable locational groupings based on regional location or spatial scale in the data.

In the case of the spatial error model, a spatial weights matrix is modeled as part of the error term. The spatial error model, then, tests for the consequences of ignoring spatial error dependence in the initial OLS regression model. Model comparisons are based on various diagnostics for model fit, heteroskedasticity, and spatial autocorrelation. If the spatial error model proves to be a better fit, spatial error dependence may be interpreted as a nuisance effect due primarily to spatial autocorrelation in the error terms. According to Anselin and Rey (1991), while spatial error autocorrelation does not cause OLS regression estimates to be biased, it does affect their efficiency (variance).

A more substantive form of spatial dependence occurs when the dependent variable of interest at one location is jointly determined by its values at other locations. In this case, the correct model should include an explicitly specified spatial autoregressive term as one of the explanatory variables. This spatial autoregressive parameter is represented by a spatial lag term for the dependent variable which is calculated as a weighted average of the values in locations neighboring each observation.

The spatial autoregressive coefficient can be interpreted in two ways. First, the spatial lag term is included with other explanatory variables as a way to assess the degree of spatial dependence in the data while controlling for the effect of the other variables in the model. Second, the inclusion of the spatial lag parameter provides a way to assess the significance of the other (non-spatial) explanatory variables while controlling for spatial dependence. Either way, if the specified spatial lag model is the correct one, then no significant spatial dependence should remain in the residuals.

In spatial regression analysis, two methodological concerns are central to the specification of appropriate models: (1) testing for the presence of spatial autocorrelation by means of appropriate diagnostics for spatial error models and spatial lag models, and (2) implementing alternative estimation techniques when structural instability and spatial heterogeneity are evidenced in the data. Structural instability occurs when regression coefficients vary according to regional location or spatial scale. The stability of regression coefficients in the presence of spatial heterogeneity can be assessed by means of a Chow test within a seemingly unrelated regression (SUR) framework (Anselin 1990).

In the present study, models for spatial heterogeneity will be implemented by jointly estimating the coefficients for metropolitan and nonmetropolitan locations as well as for each of the three Subregional locations. In addition, a test for the stability of regression coefficients (the Chow statistic) will be implemented as a test on the null hypothesis that the coefficients are the same across locations.

Summary

Throughout this study the unit of analysis is the county. The demographic and socioeconomic profile of the Appalachian Region in Chapter 2 and the descriptive overview of crime in Chapter 3 are both arranged according to geographical classifications and county typologies. First, a descriptive summary focuses on aggregate data for the Appalachian Region as a whole, followed by Subregional breakdowns based on North, Central, and South designations. This is followed by further analyses using the 1993 Beale Codes and the 1996 Distressed County Code typologies. In Chapter 4, Exploratory Spatial Data Analysis (ESDA) procedures are utilized to examine global and local patterns of spatial autocorrelation. Chapter 5 presents more formal bivariate and multivariate spatial modeling of crime using Confirmatory Spatial Data Analysis (CSDA) procedures.

CHAPTER TWO: DEMOGRAPHIC AND SOCIOECONOMIC PROFILE

INTRODUCTION

To better understand the dynamics of crime in Appalachia, it is first necessary to establish the demographic and socioeconomic context of the Region. This chapter provides a descriptive portrait of the changing social, economic, and demographic conditions in the Appalachian Region with the primary focus placed particularly on the large and often growing differences in aggregate characteristics and indicators of well-being between counties and subregions. The analysis centers on spatial inequality along several key dimensions: socioeconomic characteristics, indicators of social well-being, and demographic distribution, composition, and change.

In order to portray the multifaceted nature of spatial diversity in Appalachia, three county classification typologies are utilized in the following analyses, each based on different criteria. The three typologies are (1) Appalachian Subregions (useful for comparisons across growing and declining locations); (2) Beale County Codes (useful for comparisons across metro and nonmetro locations based on population size and metro-nonmetro proximity); and (3) the Appalachian Regional Commission's Distressed County Codes (useful for comparisons between counties based on relative levels of deprivation).

Each section begins by documenting characteristics across Appalachia and by Subregion, followed by further breakdowns according to Beale Code and Distressed County Code categories. The first section provides a description of the spatial distribution and dynamics of Appalachia's population, focusing on population size, change, and residential mobility. The second section contains an overview of trends in population composition, including age structure and racial diversity. The third section focuses on the relative social well-being of Appalachian counties, particularly as reflected in educational attainment, family stability, and changing household structures. The fourth section contains a socioeconomic profile of Appalachia, with particular attention paid to poverty, unemployment, and changing industrial composition.

POPULATION DISTRIBUTION AND CHANGE

To give a sense of the variation in Appalachia's population over time, this section focuses on population distribution and population dynamics for the years 1980, 1990, and 1996. Population distribution and change patterns within the Appalachian Region are first compared with the U.S. overall, followed by comparisons across Subregion, Beale Code, and Distressed County Code categories. Total population counts for 1980, 1990, and 1996 form the basis for the comparisons.

The Appalachian Region covers 195,608 square miles, compared with the total U.S. land area of 3,536,278 square miles. Although covering only 5.5 percent of the United States land area, the Appalachian Region contains nearly 10 percent of the U.S. population (see Table 2.1). Nevertheless, while the total population of the Region increased from 20,366,372 in 1980 to 21,783,778 in 1990, this actually represented a relative decrease from 8.9 to 8.2 percent of the U.S. population during the same period.

Within the Appalachian Region, half of the population resided in the Northern Subregion in 1980. By 1996, however, there is an obvious shift of the population toward the Southern Subregion. Given this trend, there is a strong possibility that Southern

Appalachia will become the most populated Subregion within the next decade. This also corresponds with the national trend of population movement from the North to the South over the past twenty years (Frey 1995).

Table 2.1. Total Population and Percentage of U.S. Population in Appalachia by Region and Subregion: 1980, 1990, 1996

Subregion	Population	% of Region	% of U.S.
1980			
North	10,236,294	50.3	4.5
Central	2,115,118	10.4	0.9
South	8,014,960	39.3	3.5
Total	20,366,372	100.0	8.9
1990			
North	9,917,942	47.9	4.0
Central	2,015,406	9.7	0.8
South	8,768,533	42.4	3.5
Total	20,701,881	100.0	8.3
1996			
North	10,075,104	46.3	3.8
Central	2,097,899	9.6	0.8
South	9,610,775	44.1	3.6
Total	21,783,778	100.0	8.2

Comparisons across Beale Code categories show that about 40 percent of Appalachian residents lived in nonmetropolitan counties as of 1990, compared with 20 percent of the U.S. population. Between 1980 and 1996 the metropolitan population in Appalachia increased only slightly from 57.6 percent to 58.5 percent of the population (see Table 2.2). While there is some evidence of suburbanization among the larger metropolitan areas in Appalachia (fringe county population in metro areas of 1 million or more increased from 3.1 percent of Appalachian residents in 1980 to 4.1 percent in 1996), there is little evidence of trends toward metropolitanization among the population of Appalachia from 1980 to 1996. Also, while 2.4 percent of the U.S. population resided in rural counties in 1990, over 6 percent of Appalachian residents lived in the 105 completely rural counties of Appalachia during the same time period. Thus, while there has been a national trend toward a new urban revival in the United States in recent years (Frey 1993), Appalachia has remained relatively unchanged, with a larger percentage of the population residing in completely rural locations than the nation as a whole.

Table 2.2. Appalachian Population and Percentage of Population by Beale Code: 1980, 1990, 1996

	1980		1990		1996	
Beale Code*	Population	Percent	Population	Percent	Population	Percent
Metro						
0	2,613,853	12.8	2,671,664	12.9	2,798,185	12.8
1	623,701	3.1	743,606	3.6	886,108	4.1
2	5,886,237	28.9	6,087,955	29.4	6,415,393	29.5
3	2,614,008	12.8	2,572,755	12.4	2,631,599	12.1
Total Metro	11,737,799	57.6	12,075,980	58.3	12,731,285	58.5
Nonmetro						
4	1,530,119	7.5	1,518,392	7.3	1,564,620	7.2
5	681,286	3.4	677,002	3.3	709,400	3.3
6	2,761,791	13.6	2,834,343	13.7	3,012,602	13.8
7	2,350,873	11.5	2,301,557	11.1	2,400,384	11.0
8	513,293	2.5	531,092	2.6	573,544	2.6
9	791,211	3.9	763,515	3.7	791,943	3.6
Total Nonmet	8,628,573	42.4	8,625,901	41.7	9,052,493	41.5
Total	20,366,372	100.0	20,701,881	100.0	21,783,778	100.0

*Beale Code Definitions:
0 = Central counties of metro areas with 1 million population or more
1 = Fringe counties of metro areas with 1 million population or more
2 = Counties in metro areas of 250,000 – 1,000,000 population
3 = Counties in metro areas of less than 250,000 population
4 = Urban population of 20,000 or more, adjacent to a metro area
5 = Urban population of 20,000 or more, not adjacent to a metro area
6 = Urban population of 2,500 – 19,999, adjacent to a metro area
7 = Urban population of 2,500 – 19,999, not adjacent to a metro area
8 = Completely rural (no places with a population of 2,500 or more), adjacent to a metro area
9 = Completely rural (no places with a population of 2,500 or more), not adjacent to a metro area

Over 75 percent of Appalachia's population live in counties designated as having a distress ranking characterized by one or more of the following characteristics (Distress

Codes 1-3): (1) at least 150 percent of the U.S. unemployment rate, (2) at least 150 percent of the U.S. poverty rate, or (3) less than 67 percent of the U.S. per capita market income. At either end of the Distressed County Code continuum, 10.7 percent of Appalachia's population lived in the 97 counties designated as Distressed counties in 1996 (counties with distress rankings on all three indicators), while 4.8 percent lived in the 11 counties designated as Attainment counties (counties compatible with U.S. levels on all three indicators). This represents a slight decline in the percentage of the population living in Distressed counties (from 11.9 percent in 1980 to 10.7 percent in 1996) and an increase of the percentage living in Attainment counties (from 2.5 percent in 1980 to 4.8 percent in 1996). Thus, there appears to be some shifting of the population towards more economically prosperous locations accompanied by population losses for counties with the most distressed economic conditions.

Table 2.3. Appalachian Population and Percentage of Population by 1996 Distress Codes: 1980, 1990, 1996

	1980		1990		1996	
Distress Code*	Population	Percent	Population	Percent	Population	Percent
1 Distressed	2,430,636	11.9	2,275,285	11.0	2,334,678	10.7
2 Transitional-1	703,699	3.5	679,965	3.3	704,415	3.3
3 Transitional-2	12,685,481	62.3	12,766,307	61.7	13,330,793	61.2
4 Competitive	4,043,512	19.8	4,172,880	20.1	4,366,060	20.0
5 Attainment	503,044	2.5	807,444	3.9	1,047,832	4.8
Total	20,366,372	100.0	20,701,881	100.0	21,783,778	100.0

*Distress codes are based on measures of unemployment, poverty, and per capita income and are assigned by the Appalachian Regional Commission.

Residential mobility data is derived from the Decennial Census for 1980 and 1990 and refers to county-level in-migration patterns based on place of residence five years before the census. While there was a slight increase in the residential mobility rate from

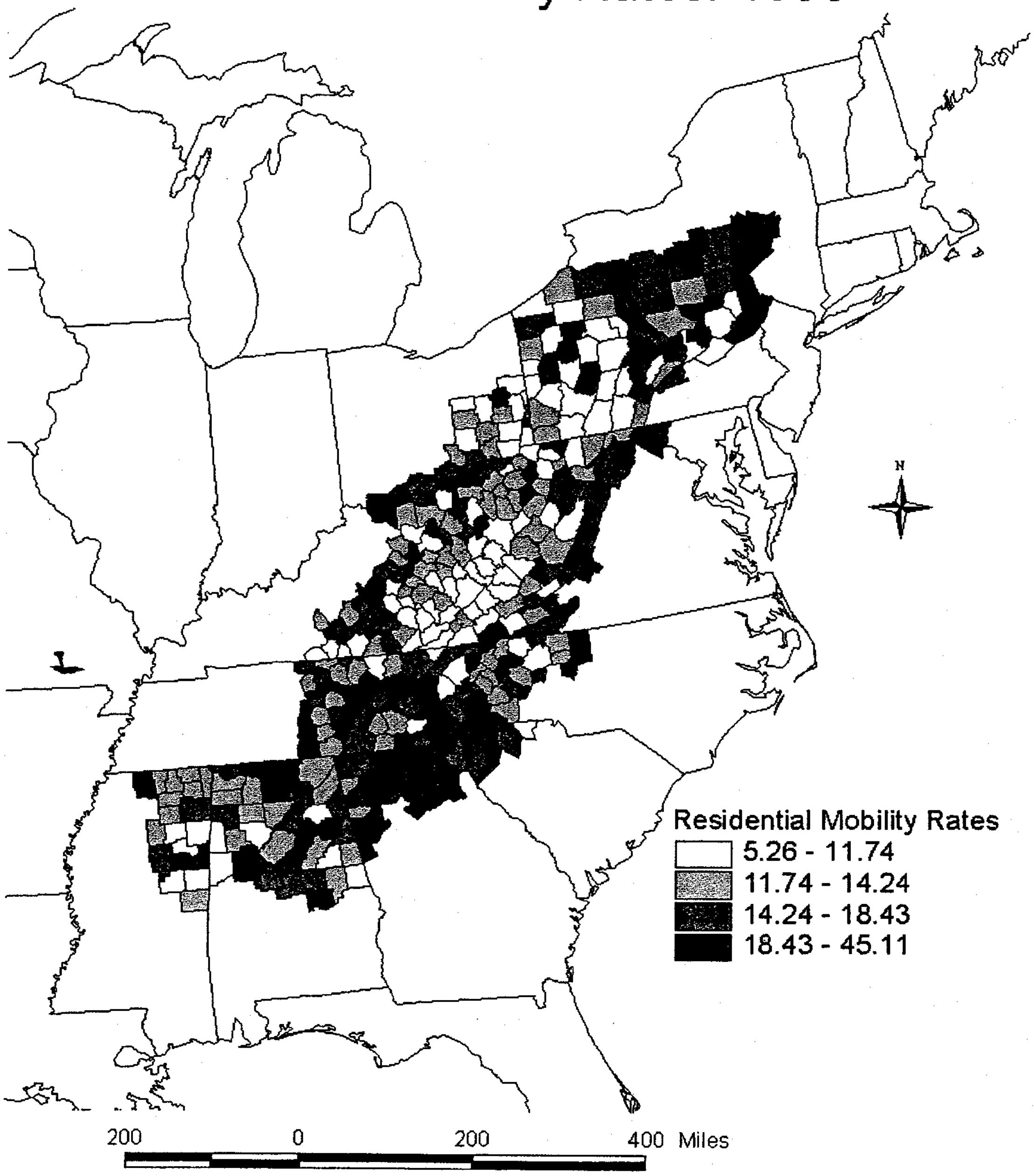
15.6 (per 100 persons) in 1980 to 16.2 in 1990, migration into Appalachian counties remained substantially lower than the national rate of 21.3 (see Table 2.4).

Subregional differences reflect substantial variation in migration patterns across the Appalachian Region (Table 2.4). While in-migration has decreased in Central Appalachia, the Northern Subregion has experienced a modest increase and the Southern Subregion a more substantial increase in the volume of new residents. In fact, in-migration rates for Southern Appalachia are rapidly approaching those for the nation as a whole. Most of this activity appears to be centered in or near metropolitan centers in northern Georgia, Tennessee, and the western part of the Carolinas (see Map 2.1).

Table 2.4. Residential Mobility Rates for Appalachia by Region and Subregion: 1980-1990

Region	1980 Mobility Rate	1990 Mobility Rate	Percent Change
North Appalachia	13.74	14.08	+0.34
Central Appalachia	15.59	13.29	-2.30
South Appalachia	17.90	19.23	+1.33
Total Appalachia	15.57	16.18	+0.61
United States	21.33	21.25	-0.08

Map 2.1
Residential Mobility Rates: 1990



Comparisons across Beale code categories (Table 2.5) also show migration increases for metro areas in general, especially for larger metro areas (Beale code 0) and their fringe counties (Beale code 1). Both the map of residential mobility (Map 2.1) and the table of comparisons across Beale code categories (Table 2.5) indicate that Regional migration streams tend to converge in and near the larger metropolitan centers, especially in the Southern Subregion. Furthermore, a substantial proportion of this activity appears to be taking place around the Atlanta metropolitan area.

Table 2.5. Residential Mobility Rates for Appalachia by Beale Code: 1980-1990

Beale Code*	1980 Mobility Rate	1990 Mobility Rate	Percent Change
Metro			
0	13.38	15.73	+2.35
1	18.20	23.05	+4.85
2	15.90	16.66	+0.76
3	14.93	15.77	+0.84
Total Metro	15.24	16.65	+1.41
Nonmetro			
4	14.02	14.77	+0.75
5	21.38	21.02	-0.36
6	16.22	16.01	-0.21
7	15.84	14.36	-1.48
8	16.83	16.59	-0.14
9	14.58	13.18	-1.40
Total Nonmet	16.02	15.53	-0.49

*Beale Code Definitions:
0 = Central counties of metro areas with 1 million population or more
1 = Fringe counties of metro areas with 1 million population or more
2 = Counties in metro areas of 250,000 – 1,000,000 population
3 = Counties in metro areas of less than 250,000 population
4 = Urban population of 20,000 or more, adjacent to a metro area
5 = Urban population of 20,000 or more, not adjacent to a metro area
6 = Urban population of 2,500 – 19,999, adjacent to a metro area
7 = Urban population of 2,500 – 19,999, not adjacent to a metro area
8 = Completely rural (no places with a population of 2,500 or more), adjacent to a metro area
9 = Completely rural (no places with a population of 2,500 or more), not adjacent to a metro area

Comparisons across Distress code categories (Table 2.6) show that residential mobility is highly correlated with economic well-being. While Distressed Counties are experiencing a decline in the volume of new residents, both Competitive and Attainment Counties are registering substantial increases. In fact, residential mobility rates for Attainment Counties in 1990 were nearly 70 percent higher than for the United States as a whole. This corresponds with research showing a strong correlation between employment growth, economic well-being, and larger in-migration streams (Massey 1990).

Table 2.6. Residential Mobility Rates for Appalachia by Distress Code: 1980-1990

Distress Code*	1980 Mobility Rate	1990 Mobility Rate	Percent Change
1 Distressed	14.70	12.55	-2.15
2 Transitional-1	14.62	13.23	-1.39
3 Transitional-2	15.45	15.81	+0.36
4 Competitive	14.56	16.12	+1.56
5 Attainment	32.42	35.52	+3.10

*Distress codes are based on measures of unemployment, poverty, and per capita income and are assigned by the Appalachian Regional Commission.

Overall, there is substantial variation in the patterns of growth, decline and mobility of the population across the Appalachian Region. While the population of Appalachia grew between 1980 and 1996, the overall growth rate did not keep pace with growth nationwide. As a result, Appalachia's share of the U.S. population fell from 8.9 percent in 1980 to 8.2 percent in 1996. Nevertheless, while population declined in the Northern and Central Subregions, population growth in Southern Appalachia actually exceeded that for the U.S. as a whole between 1980 and 1996.

Population distribution patterns within Appalachia also reveal the relatively nonmetropolitan character of the Region. Just over 40 percent of Appalachia's population resides in nonmetropolitan counties, compared with 20 percent nationwide. Furthermore, over 6 percent of Appalachian residents live in completely rural counties, compared with 2.4 percent of the U.S. population. Unlike the rest of the nation, there is little evidence of metropolitanization taking place in Appalachia between 1980 and 1996.

While there has been a slight decline in the percentage of the population living in counties characterized as highly distressed based on measures of unemployment, poverty, and per capita income (Distress Code 1), over 75 percent still live in counties characterized as disadvantaged according to at least one of these indicators (Distress Codes 1-3). The remaining 25 percent live in Competitive and Attainment Counties, a slight increase from 22 percent in 1980. Thus, while there has been some shifting of the population towards economic prosperity, a significant majority is still living in substantial poverty and economic hardship.

POPULATION COMPOSITION

This section focuses on both the age structure and the racial composition of Appalachia for the years 1980 and 1996. Changes in the age structure reflect the extent to which a region is aging and the extent to which the dependent population is growing or declining in relation to the working-age population. Changes in the racial and ethnic composition of an area reflect the extent to which the population is becoming more diverse or more homogeneous over time.

The line chart in Figure 2.1 represents the percentage age distribution for Appalachia in 1980 and 1996. There is an apparent aging of the population with those in the younger age groups comprising a smaller proportion of the population between 1980 and 1996. For all age groups under 30, the percentage contribution to the total population in 1996 is below that for 1980, reaching a two percent drop for those in their mid-teen and young adult years (ages 15-24). Further evidence for the aging of Appalachia's population is found in the oldest age groups where the 1996 line crosses above the 1980 line at ages 65 to 69 and remains higher through ages 75 and over. Thus, the number of people in the younger age groups is diminishing over time, while the number in the older age groups is increasing (Table 2.7).

Figure 2.1. Percentage Age Distribution of Appalachian Population: 1980 and 1996

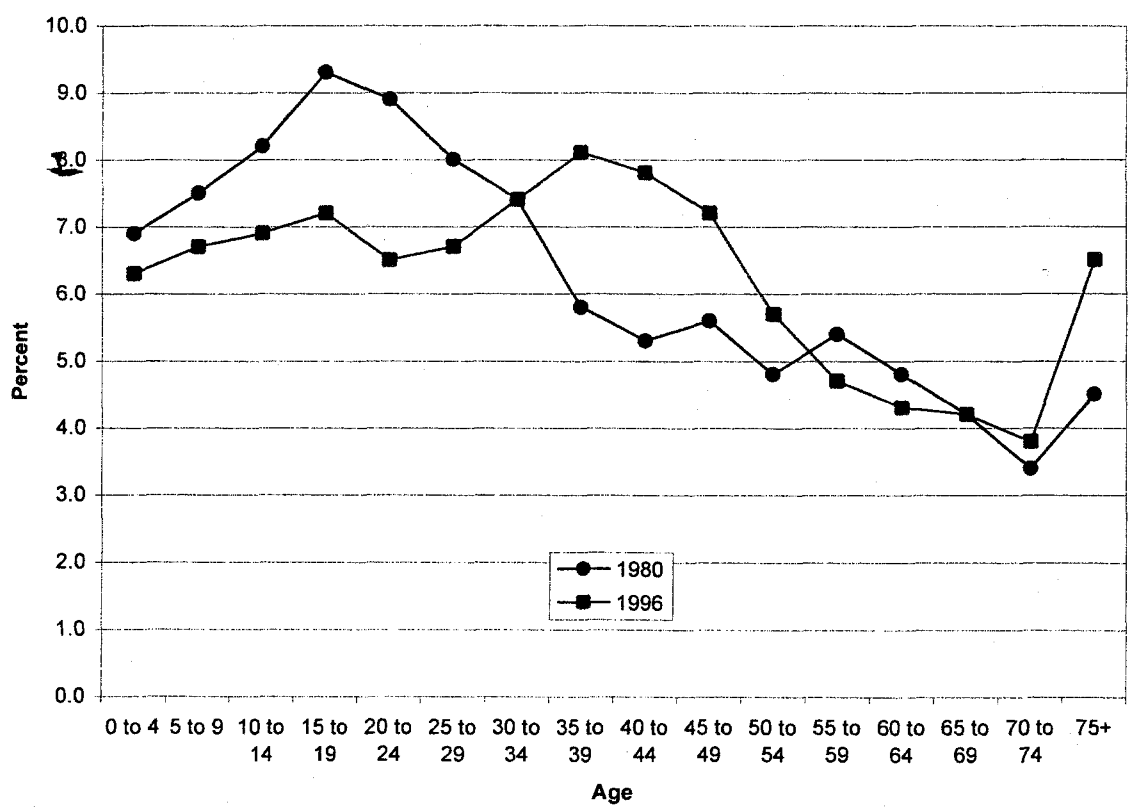
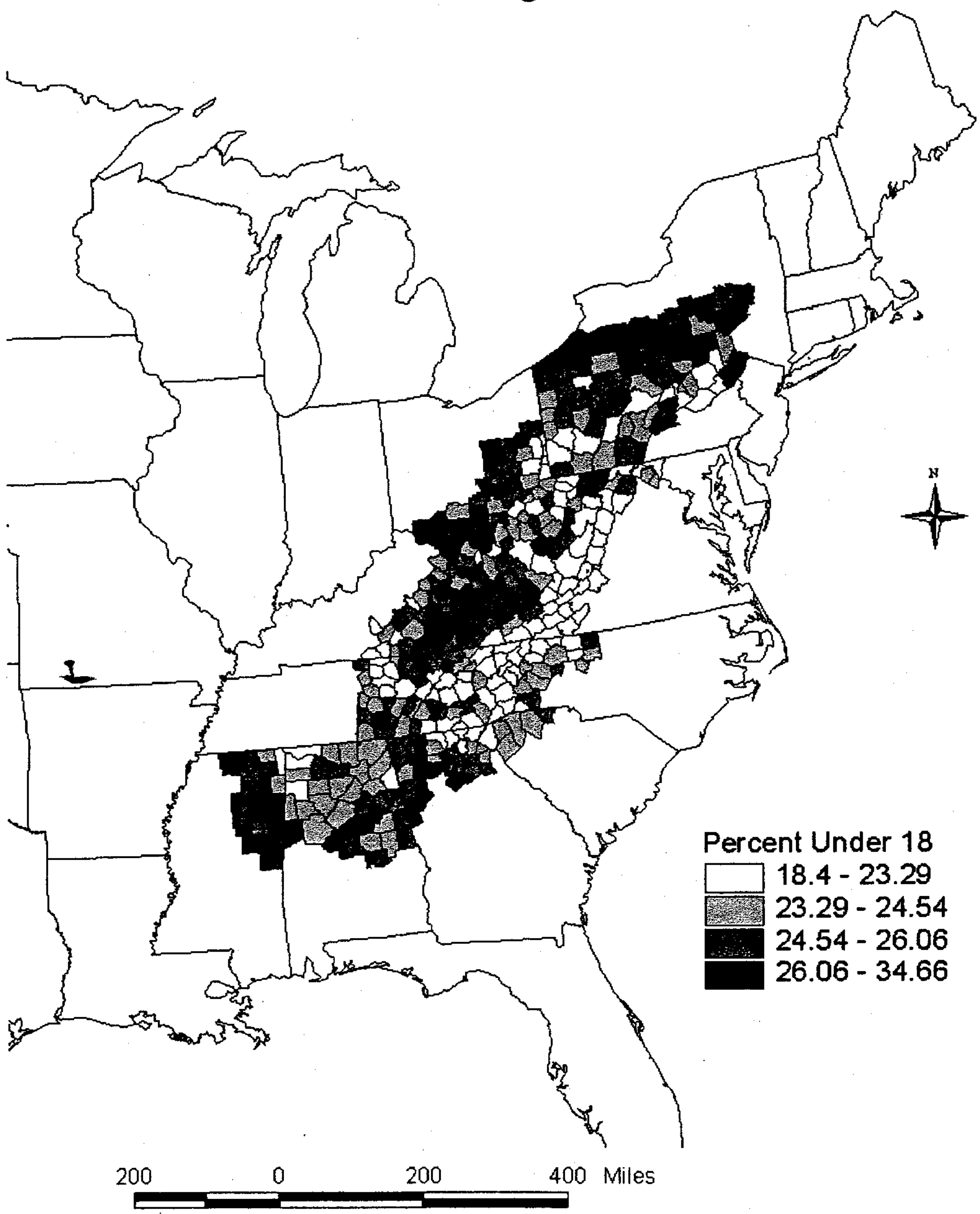


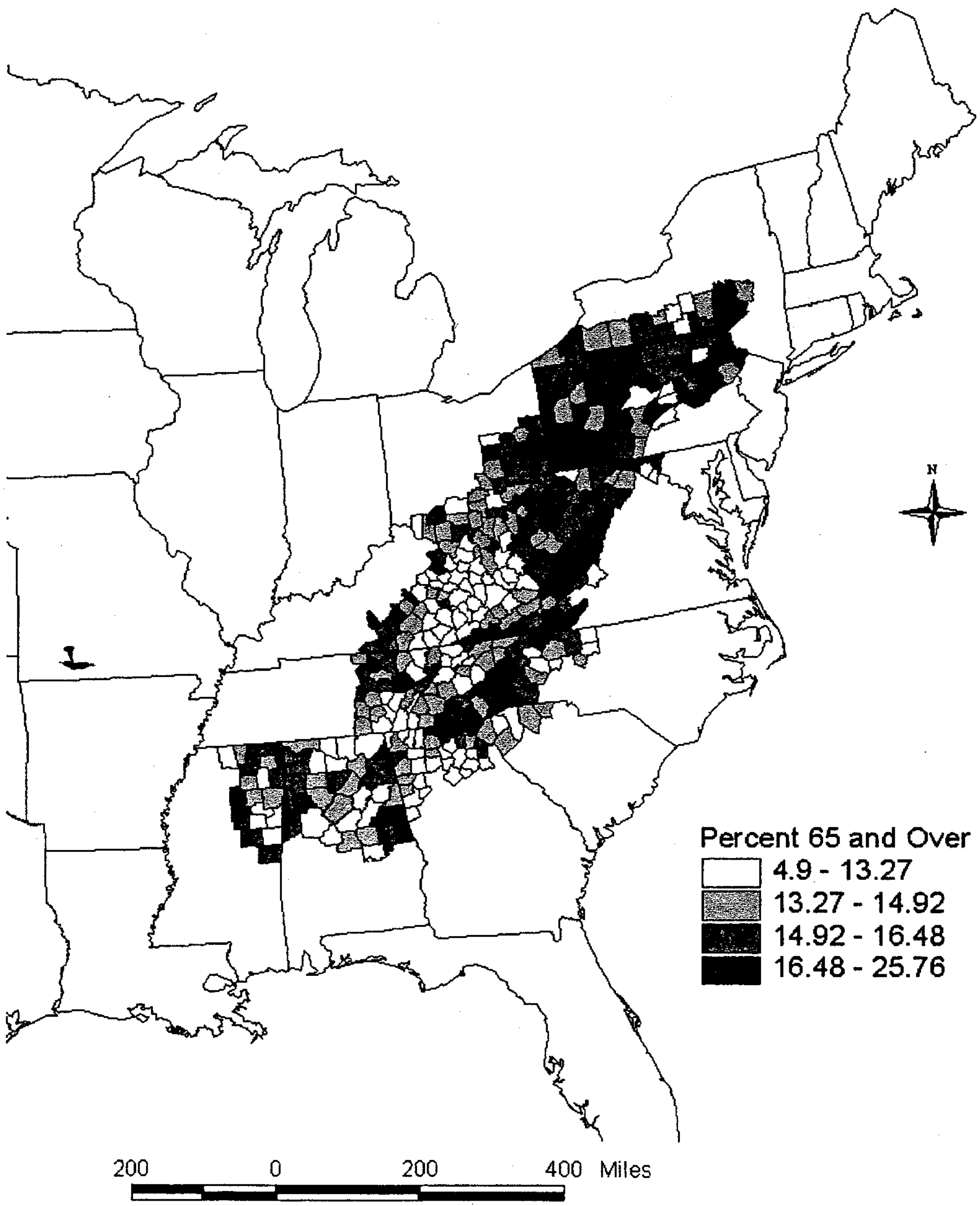
Table 2.7. Age Distribution in Appalachia: 1980-1996					
	1980		1996		
Age Groups	Number	Percent	Number	Percent	% Change
0 to 4	1,409,196	6.9	1,376,401	6.3	-0.6
5 to 9	1,527,812	7.5	1,456,975	6.7	-0.8
10 to 14	1,669,037	8.2	1,507,109	6.9	-1.3
15 to 19	1,894,282	9.3	1,563,782	7.2	-2.1
20 to 24	1,807,588	8.9	1,413,596	6.5	-2.4
25 to 29	1,618,883	8.0	1,452,450	6.7	-1.3
30 to 34	1,507,319	7.4	1,612,395	7.4	0.0
35 to 39	1,181,675	5.8	1,771,059	8.1	+2.3
40 to 44	1,086,411	5.3	1,692,787	7.8	+2.5
45 to 49	1,133,213	5.6	1,572,107	7.2	+1.6
50 to 54	979,803	4.8	1,229,011	5.7	+0.9
55 to 59	1,104,469	5.4	1,028,206	4.7	-0.7
60 to 64	987,535	4.8	932,554	4.3	-0.5
65 to 69	851,638	4.2	925,465	4.2	0.0
70 to 74	684,229	3.4	830,908	3.8	+0.4
75 and over	923,282	4.5	1,418,973	6.5	+2.0
Total	20,366,372	100.0	21,783,778	100.0	

The ratio of the number of working age persons compared with those under the age of 18 and over age 65 is called the dependency ratio. This ratio shows the proportion of the population that is typically able to support those who are not able to participate in the labor force. The spatial distribution of the population under 18 is shown in Map 2.2 and the distribution of those 65 and over is shown in Map 2.3. Counties with the highest percentage of persons under the age of 18 are located along the borders of southern New York and southern Ohio in Northern Appalachia, along the western section of Kentucky in the Central Subregion, and in the counties surrounding Birmingham and Atlanta in Southern Appalachia. Aging counties with high percentages of persons 65 and over are predominately found in Pennsylvania and down along the borders of West Virginia, Virginia, and North Carolina.

Map 2.2
Percent Under Age 18: 1996



Map 2.3
Percent Age 65 and Over: 1996



The dependency ratios for Appalachia and for the three Subregions for 1996 are shown in Table 2.8. The dependency ratios for both the U.S. and Appalachia are equal to 0.634. However, for Appalachia, the percentage share of elderly dependents is larger and the percentage share of younger dependents is smaller than for the United States as a whole. Again, this represents an aging trend among the Appalachian population. Among the Subregions, Northern Appalachia has the highest percentage of persons age 65 and over (16 percent) as well as the largest dependency ratio (0.672). The smallest dependency ratio occurs in Southern Appalachia, where a larger percentage of the working age population suggests an increased capacity to support dependents in the Subregion. Interestingly, the largest percentage of younger dependents is found in the Central Subregion where 25 percent of the population is under the age of 18. Again, these Subregional variations in age structure reveal the substantial diversity of the Region as a whole.

Table 2.8. Dependency Ratios for Appalachia by Subregion: 1996

Area	Percent less than 18	Percent 18-64	Percent 65 and over	Dependency Ratio[1]
North Appalachia	24.0	59.7	16.2	0.672
Central Appalachia	25.1	61.4	13.5	0.631
South Appalachia	24.3	62.7	13.1	0.597
Total Appalachia	24.2	61.2	14.6	0.634
United States	26.0	61.2	12.8	0.634

[1] Dependency Ratio = Persons under 18 and over 65 divided by persons between 18 and 64.

Dependency ratios for metro and nonmetro locations according to Beale code categories are shown in Table 2.9. Overall, the dependency ratio for nonmetro counties is higher at 0.661 than for metro locations (0.647). The largest percentage of younger dependents is found in the fringe counties of large metro areas (Beale Code 1) while the largest percentage of older dependents are located in the smaller metro counties (Beale Code 3) as well as adjacent nonmetro (Beale Codes 4, 6, and 8) and rural counties (Beale Codes 8 and 9).

Table 2.9. Dependency Ratios for Appalachia by Beale Code: 1996

Beale Code*	Percent less than 18	Percent 18-64	Percent 65 and over	Dependency Ratio
Metro				
0	23.5	61.7	14.8	0.621
1	26.0	61.7	12.3	0.619
2	23.7	62.3	14.0	0.606
3	23.8	60.7	15.5	0.647
Nonmetro				
4	24.9	59.9	15.2	0.671
5	24.2	62.4	13.4	0.602
6	24.7	60.2	15.1	0.662
7	25.1	60.5	14.4	0.653
8	24.9	60.1	15.0	0.664
9	24.6	60.2	15.2	0.661

* Beale Code Definitions:
0 = Central counties of metro areas with 1 million population or more
1 = Fringe counties of metro areas with 1 million population or more
2 = Counties in metro areas of 250,000 – 1,000,000 population
3 = Counties in metro areas of less than 250,000 population
4 = Urban population of 20,000 or more, adjacent to a metro area
5 = Urban population of 20,000 or more, not adjacent to a metro area
6 = Urban population of 2,500 – 19,999, adjacent to a metro area
7 = Urban population of 2,500 – 19,999, not adjacent to a metro area
8 = Completely rural (no places with a population of 2,500 or more), adjacent to a metro area
9 = Completely rural (no places with a population of 2,500 or more), not adjacent to a metro area

Based on Distress Code criteria (Table 2.10), the lowest dependency ratio occurs among Attainment counties, where the ratio is 0.517. The most distressed counties have the highest dependency ratios at 0.656 (Distress Code 1) and 0.659 (Distress Code 2). In general, there is a clear decline in the ratio of dependents to the working age population as counties become more economically advantaged.

Table 2.10. Dependency Ratios for Appalachia by Distress Codes: 1996

Distress Code*	Percent less than 18	Percent 18-64	Percent 65 and over	Dependency Ratio
1 Distressed	25.5	60.4	14.1	0.656
2 Transitional-1	24.8	60.3	14.9	0.659
3 Transitional-2	24.0	60.8	15.2	0.646
4 Competitive	23.5	62.0	14.5	0.614
5 Attainment	26.6	65.9	7.5	0.517

*Distress codes are based on measures of unemployment, poverty, and per capita income and are assigned by the Appalachian Regional Commission.

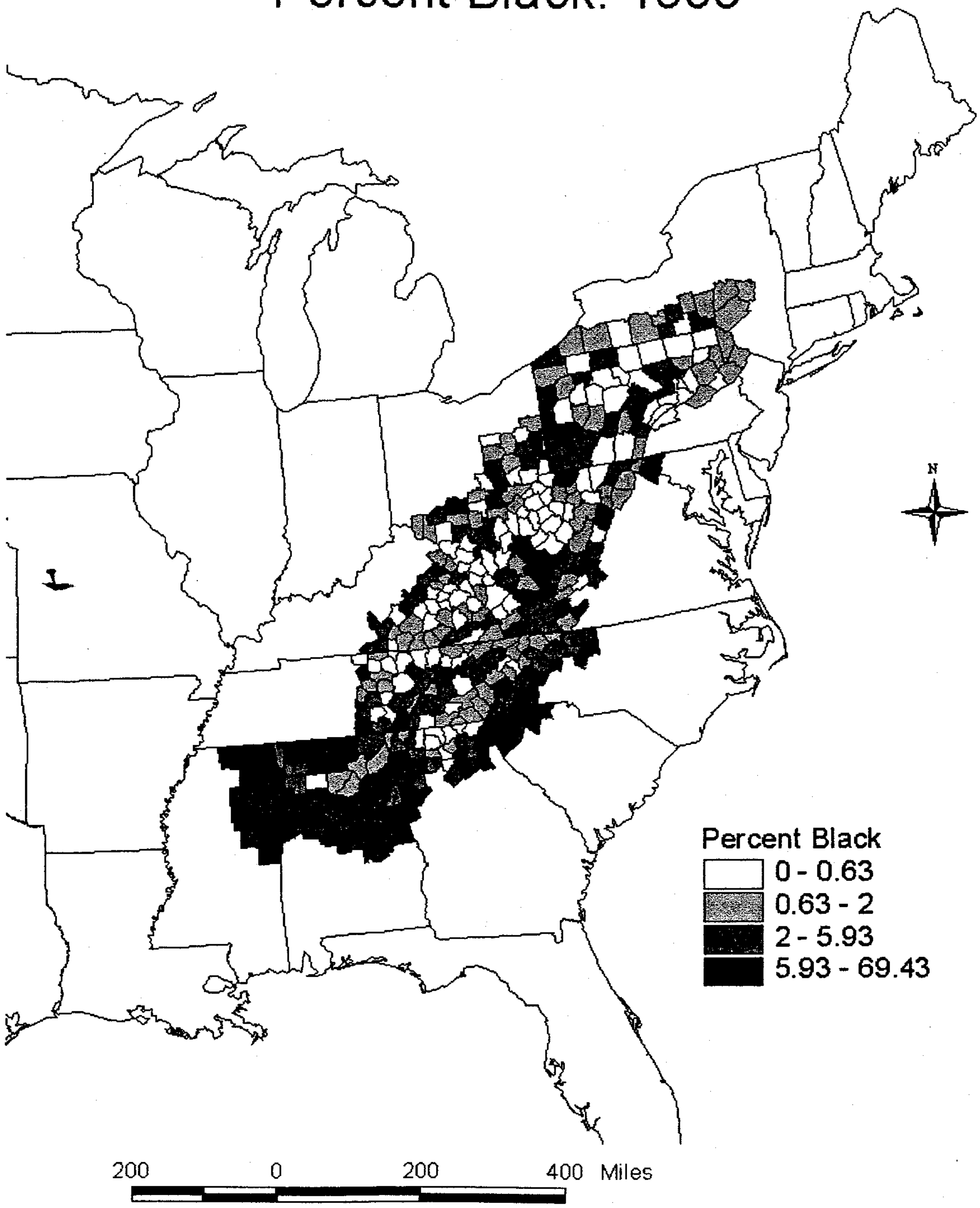
The racial and ethnic composition of Appalachia is much less diverse than that of the United States as a whole (Table 2.11). Between 1980 and 1996, the percentage of non-Hispanic Whites in Appalachia had dropped slightly from 92 percent to just above 90 percent. Nationwide, the percentage of non-Hispanic Whites went from just under 80 percent in 1980 to 73 percent by 1996, a drop of nearly 7 percent. Blacks increased from 7 percent of the Appalachian population in 1980 to 7.7 percent by 1996, while the percentage of Hispanics in the population increased only slightly from 0.6 percent in 1980 to 0.9 percent in 1996. During the same period, the percentage of Blacks in the U.S. increased from 11.5 to 12.0, while the U.S. Hispanic population increased dramatically from 6.5 percent in 1980 to 10.7 by 1996.

Overall, the Appalachian Region is much less diverse racially and ethnically than the United States, but, as with the age structure, the racial composition of the population varies substantially by Subregion (Table 2.11). Racial diversity is highest in Southern Appalachia, with over 13 percent classified as Black (see Map 2.4) and 84.5 classified as White in 1996. The Central Subregion is the most homogeneous, with almost 97 percent of the population White, 2 percent Black and 0.5 percent Hispanic. Over time, there has been little change in racial composition within each Subregion between 1980 and 1996.

Table 2.11. Racial Composition of Appalachia by Region and Subregion: 1980-1996

	1980		1996		
Region	Population	Percent	Population	Percent	% Change
North Appalachia					
White	9,819,332	95.9	9,541,761	94.7	-1.2
Black	311,436	3.1	361,490	3.6	+0.5
Hispanic	53,763	0.5	81,683	0.8	+0.3
Central Appalachia					
White	2,042,734	96.6	2,031,128	96.8	+0.2
Black	51,843	2.5	46,620	2.2	-0.3
Hispanic	14,875	0.7	10,662	0.5	-0.2
South Appalachia					
White	6,869,055	85.7	8,124,291	84.5	-1.2
Black	1,052,803	13.1	1,267,880	13.2	+0.1
Hispanic	53,378	0.7	112,811	1.2	+0.5
Total Appalachia					
White	18,730,121	92.0	19,697,180	90.4	-1.6
Black	1,416,082	7.0	1,675,990	7.7	+0.7
Hispanic	122,016	0.6	205,156	0.9	+0.3
United States					
White	180,906,000	79.9	193,978,000	73.1	-6.8
Black	26,142,000	11.5	31,912,000	12.0	+0.5
Hispanic	14,609,000	6.5	28,269,000	10.7	+4.2

Map 2.4
Percent Black: 1996



The distribution of Whites and Blacks across Beale Code categories (Table 2.12) shows a much higher concentration of Blacks in metro counties, while Whites are more equally divided between metro and nonmetro locations. The smaller nonmetropolitan counties which are nonadjacent to metro areas (Beale Codes 7 and 9) experienced the largest declines in the percentage share of the Black population between 1980 and 1996, while the largest increases took place in and around large metro counties (Beale Codes 0 and 1). Interestingly, the largest increases in the percentage non-Hispanic Whites took place in the fringe counties of large metro areas (Beale Code 1), accompanied by declines in the central counties (Beale Code 0). This seems to correspond with the general notion of "White flight" from central cities to the suburbs in recent years (Frey 1995).

Table 2.12. Percentage Racial Composition of Appalachia by Beale Code: 1980-1996						
Beale Code	1980		1996		White % change	Black % change
	Percent of White Population	Percent of Black Population	Percent of White Population	Percent of Black Population		
Metro						
0	12.8	12.9	12.6	13.4	-0.2	+0.5
1	3.1	2.1	4.2	2.5	+1.1	+0.4
2	27.7	45.1	28.1	45.3	+0.4	+0.2
3	13.0	11.2	12.2	11.1	-0.8	-0.1
Total Metro	56.6	71.3	57.1	72.3	+0.5	+1.0
Nonmetro						
4	7.8	4.1	7.4	4.3	-0.4	+0.2
5	3.2	4.5	3.1	4.4	-0.1	-0.1
6	14.0	8.2	14.4	8.1	+0.4	-0.1
7	11.8	8.5	11.4	7.8	-0.4	-0.7
8	2.6	1.1	2.8	1.0	+0.2	-0.1
9	4.0	2.3	3.8	2.1	-0.2	-0.2
Total Nonmetro	43.4	28.7	42.9	27.7	-0.5	-1.0

*Beale Code Definitions:
0 = Central counties of metro areas with 1 million population or more
1 = Fringe counties of metro areas with 1 million population or more
2 = Counties in metro areas of 250,000 – 1,000,000 population
3 = Counties in metro areas of less than 250,000 population
4 = Urban population of 20,000 or more, adjacent to a metro area
5 = Urban population of 20,000 or more, not adjacent to a metro area
6 = Urban population of 2,500 – 19,999, adjacent to a metro area
7 = Urban population of 2,500 – 19,999, not adjacent to a metro area
8 = Completely rural (no places with a population of 2,500 or more), adjacent to a metro area
9 = Completely rural (no places with a population of 2,500 or more), not adjacent to a metro area

Comparisons across Distress Code categories (Table 2.13) show increases in the percentage of both Whites and Blacks living in Attainment Counties, accompanied by decreases for both groups in Distressed Counties. Although Whites are more likely than Blacks to reside in Distressed Counties, they are also more likely to reside in Attainment Counties. Blacks, on the other hand, are more highly concentrated than Whites in Competitive Counties. Overall, Blacks are more likely to reside in counties that are economically better off, with 35 percent of the Black population residing in Competitive and Attainment Counties (Distress County Codes 4 and 5) in 1996 compared with 24 percent of the non-Hispanic White population.

Table 2.13. Percentage Racial Composition of Appalachia by Distress Code: 1980-1996						
	1980		1996			
Distress Code	Percent of White Population	Percent of Black Population	Percent of White Population	Percent of Black Population	White % change	Black % change
Distressed	12.2	8.5	11.1	7.2	-1.1	-1.3
Transitional-1	3.4	3.7	3.2	3.4	-0.2	-0.3
Transitional-2	62.9	54.9	62.0	54.3	-0.9	-0.6
Competitive	19.0	31.2	18.9	31.6	-0.1	+0.4
Attainment	2.5	1.7	4.8	3.5	+2.3	+1.8

* Distress codes are based on measures of unemployment, poverty, and per capita income and are assigned by the Appalachian Regional Commission.

In summary, the age structure for the Region as a whole has been steadily shifting from the younger age groups to the older age groups over time. Thus, compared with the rest of the nation, there is a significant aging effect taking place in Appalachia. This is especially true of the Northern Subregion. Dependency ratios are higher in Northern Appalachia, in nonmetropolitan counties, and in more distressed counties.

Compared with the U.S., the Appalachian Region is not very diverse, racially or ethnically. The highest concentrations of Blacks are found in metropolitan counties primarily located in the Southern Subregion. Hispanics represent a very small segment of the Appalachian population, a trend that does not vary much over time or across Subregions.

SOCIAL WELL-BEING

Social well-being can be defined in terms of both human capital and social capital. Chronic problems of unemployment and poverty in Appalachia are often rooted in low levels of educational attainment and limited job skills, a reflection of persistent deficits in individual human capital. Deficits in human capital are often further exacerbated by deficits in social capital as well, which are reflected in the gradual erosion of family and community ties. This section describes recent trends in the human and social capital of Appalachia as measured by changing levels of education, family stability, and household structure for 1980 and 1990.

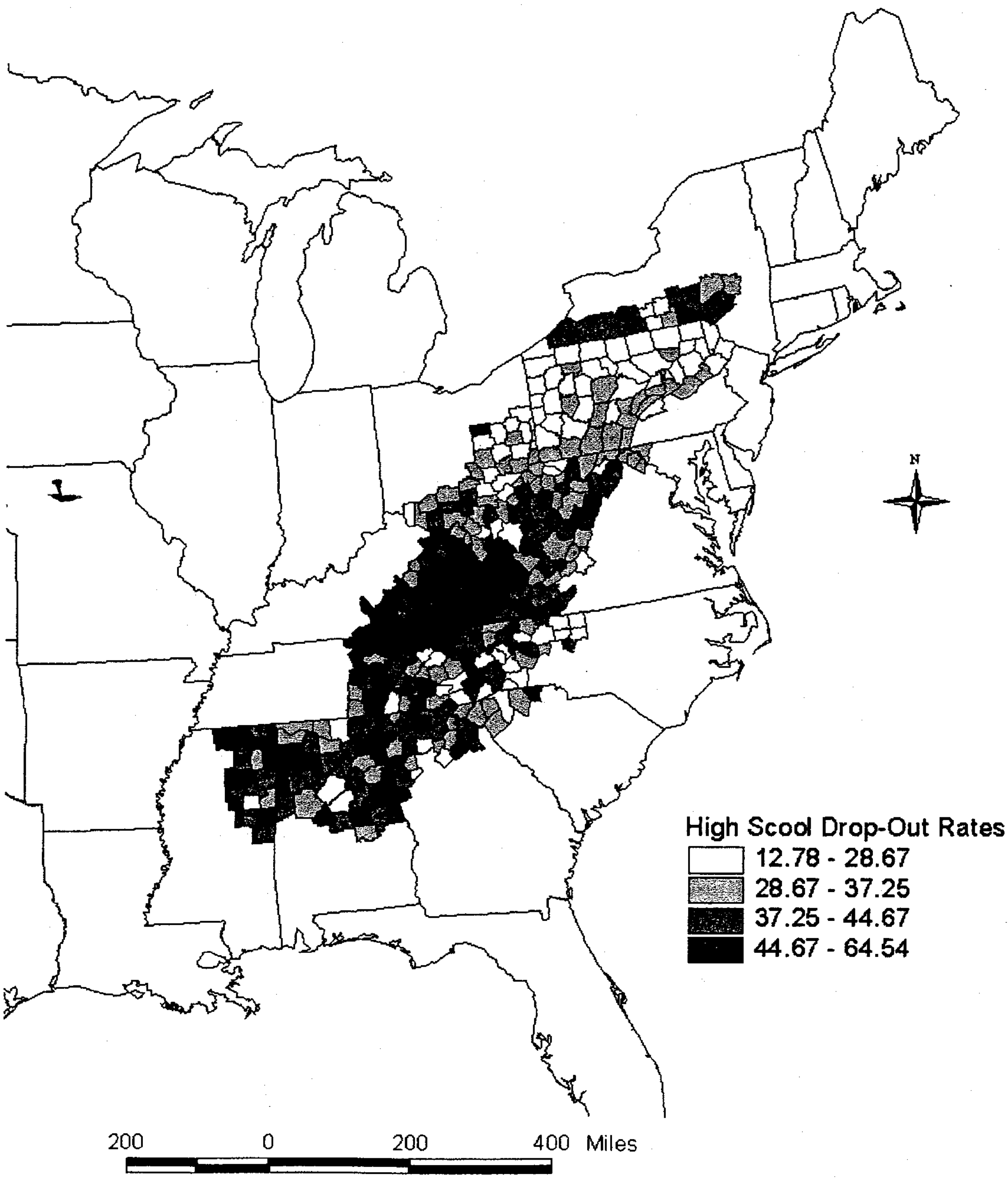
Between 1980 and 1990, the educational attainment level of the population in Appalachia increased substantially (Table 2.14). The percent of the population aged 25 or older with at least some college education increased from 22 percent in 1980 to about 33 percent by 1990. At the same time, the percentage of high school dropouts decreased from 42.6 percent in 1980 to 31.6 percent in 1990. In fact, increases in educational attainment levels between 1980 and 1990 were larger in Appalachia than for the U.S. as a whole. Nevertheless, the Region still lags behind the rest of the nation in terms of the smaller percentage of the population that has completed a college degree and also in terms of the larger percentage that has not graduated from high school.

Table 2.14. Educational Attainment in Appalachia by Region and Subregion: 1980-1990			
Region	1980	1990	Percent Change
North Appalachia			
Less than High School	36.5	26.7	-9.8
High School Graduate	41.5	40.6	-0.9
Some College	10.6	18.3	+7.7
College Graduate	11.5	14.4	+2.9
Central Appalachia			
Less than High School	57.7	46.7	-11.0
High School Graduate	26.9	30.4	+3.5
Some College	7.7	14.1	+6.4
College Graduate	7.6	8.8	+1.2
South Appalachia			
Less than High School	46.8	33.9	-12.9
High School Graduate	29.6	29.7	+0.1
Some College	12.0	21.1	+9.1
College Graduate	11.6	15.3	+3.7
Total Appalachia			
Less than High School	42.6	31.6	-11.0
High School Graduate	35.4	35.0	-0.4
Some College	10.8	19.1	+8.3
College Graduate	11.2	14.3	+3.1
United States			
Less than High School	31.4	22.4	-9.0
High School Graduate	36.8	38.4	+1.6
Some College	14.9	17.9	+3.0
College Graduate	17.0	21.3	+4.3

Persons age 25 years and over.

The largest declines in the percentage of the population without a high school education were observed in Southern Appalachia, where there was a decline of almost 13 percent (Table 2.14). Northern Appalachia nevertheless continues to have the lowest high school dropout rates at 27 percent, while the highest rates are found in the Central Subregion at nearly 47 percent (see Map 2.5). With regard to the percentage of the population with at least some college education, the Southern Subregion has surpassed both Northern and Central Appalachia in terms of higher educational attainment levels with 36.4 percent for the South compared with 32.7 for the North and about 23 percent for the Central Subregion, but still lags behind U.S. levels (at 39.2 percent).

Map 2.5
High School Drop-Out Rates: 1990



Educational levels for metro and nonmetro locations according to Beale code categories are shown in Table 2.15. There are strong links between nonmetro location and lower educational attainment. The percentage of the population with less than a high school diploma were largest for the four most rural categories (Beale Codes 6-9) and lowest for counties in large metro areas (Beale Code 0). There are also strong links between metro location and higher educational attainment. The percentage of the population with a college education was almost 22 percent for large metro counties (Beale Code 0). For the most rural counties (Beale Code 9), however, only about 8 percent of the population had a college degree. Overall, the data point to substantial geographic variations in educational attainment across the rural-urban continuum.

Table 2.15. Educational Attainment in Appalachia by Beale Code: 1990

Beale Code*	Less than High School (%)	High School Graduate (%)	Some College (%)	College Graduate (%)
Metro				
0	21.5	36.4	21.8	20.3
1	30.8	38.1	18.5	12.6
2	29.4	32.4	21.3	16.8
3	28.2	37.9	20.0	13.9
Total Metro	27.4	34.8	21.0	16.8
Nonmetro				
4	31.1	39.4	18.1	11.4
5	30.7	31.1	19.8	18.5
6	36.1	36.9	16.6	10.4
7	41.8	33.0	15.4	9.8
8	40.7	37.2	14.0	8.1
9	48.0	30.8	13.5	7.8
Total Nonmetro	37.7	35.3	16.3	10.7

*Beale Code Definitions:
0 = Central counties of metro areas with 1 million population or more
1 = Fringe counties of metro areas with 1 million population or more
2 = Counties in metro areas of 250,000 – 1,000,000 population
3 = Counties in metro areas of less than 250,000 population
4 = Urban population of 20,000 or more, adjacent to a metro area
5 = Urban population of 20,000 or more, not adjacent to a metro area
6 = Urban population of 2,500 – 19,999, adjacent to a metro area
7 = Urban population of 2,500 – 19,999, not adjacent to a metro area
8 = Completely rural (no places with a population of 2,500 or more), adjacent to a metro area
9 = Completely rural (no places with a population of 2,500 or more), not adjacent to a metro area

Educational attainment levels in Appalachia are also clearly tied to levels of economic distress (Table 2.16). Among the most distressed counties (Distress Code 1), almost 44 percent of the population had less than a high school education, compared with about 22 percent in the Attainment Counties. Conversely, while only about 9 percent of the population had completed a college education in Distressed Counties, nearly 23 percent were college graduates in the Attainment Counties.

Table 2.16. Educational Attainment in Appalachia by Distress Code: 1990

Distress Code*	Less than High School (%)	High School Graduate (%)	Some College (%)	College Graduate (%)
1 Distressed	43.8	33.7	13.8	8.7
2 Transitional-1	39.4	35.5	15.9	9.2
3 Transitional-2	31.7	36.5	18.7	13.1
4 Competitive	25.8	32.4	22.1	19.7
5 Attainment	21.7	29.5	26.1	22.7

* Distress Codes are based on measures of unemployment, poverty, and per capita income and are assigned by the Appalachian Regional Commission.

Social capital is often defined in terms of family and community social networks representing resources that can enhance social well-being and provide a margin of protection or security in times of economic distress. The percentage distribution of marital status and stability in Appalachia by Subregion and compared with the U.S. is shown in Table 2.17. Interestingly, the divorce rate in 1990 was lower for Appalachia (at 7.5 percent) than for the nation as a whole (at 8.3 percent). Also, nearly 61 percent of the Appalachian population was married in 1990, compared with about 58 percent of the U.S. population.

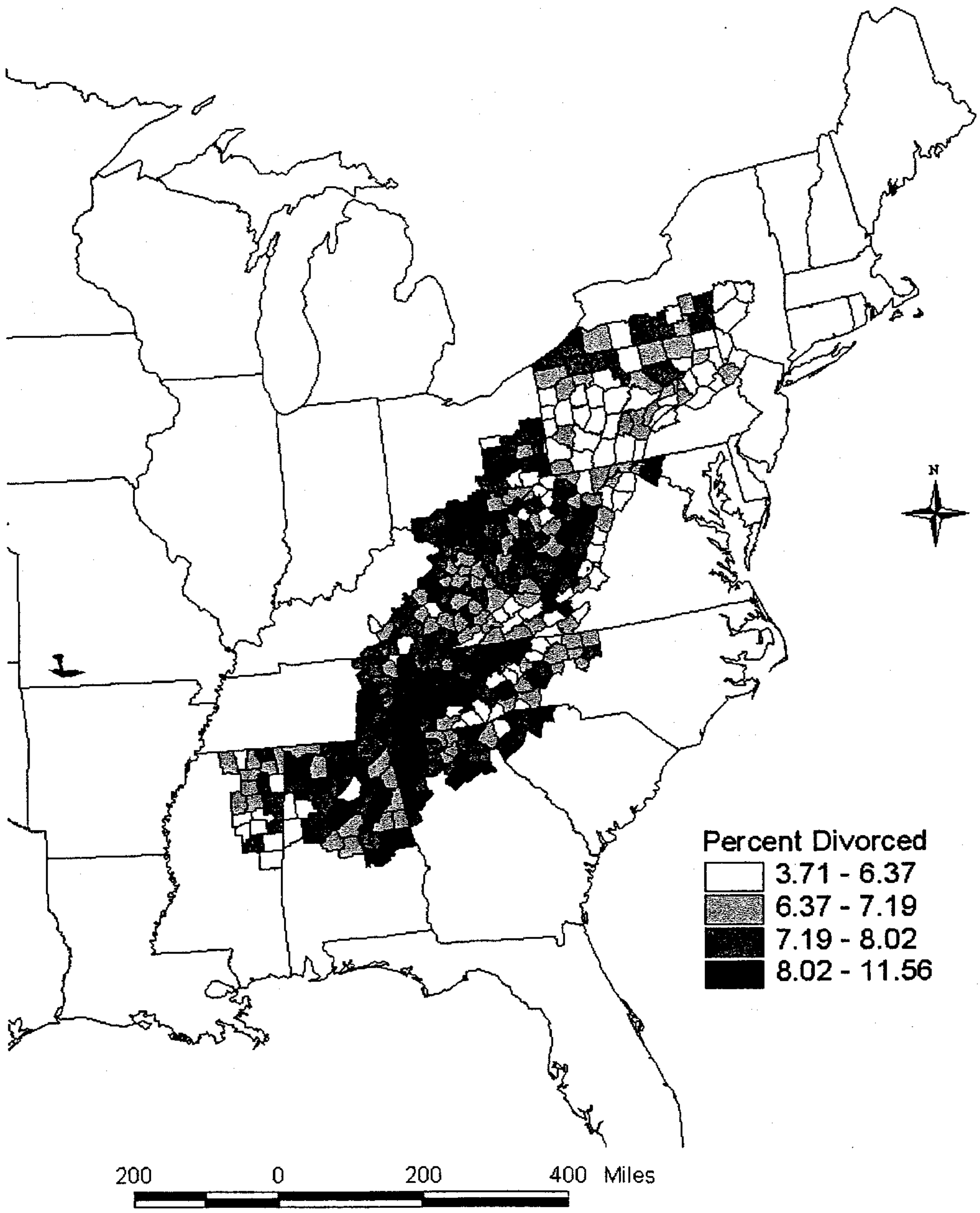
Subregional variations show higher divorce rates in Southern Appalachia at 8.2 percent than either the Northern or Central Subregions (at 6.9 percent and 7.5 percent respectively). The spatial distribution of percent divorced is shown in Map 2.6. The highest concentrations of marital disruption are located in southern Ohio in the Northern Subregion, and throughout eastern Tennessee and northern Georgia in the Southern Subregion. These concentrations tend to be located near the metropolitan areas of Cincinnati and Columbus in the North and near the metro areas of Knoxville, Chattanooga, and Atlanta in the South.

Table 2.17. Marital Status of the Population in Appalachia by Region and Subregion:1980-1990

Region	1980	1990	Percent Change
North Appalachia			
Never Married	25.0	24.6	-0.4
Married	61.3	59.2	-2.1
Widowed	9.0	9.3	+0.3
Divorced	4.7	6.9	+2.2
Central Appalachia			
Never Married	20.3	20.2	-0.1
Married	66.4	63.5	-2.9
Widowed	8.4	8.8	+0.4
Divorced	4.9	7.5	+2.6
South Appalachia			
Never Married	21.6	21.7	+0.1
Married	64.5	62.0	-2.5
Widowed	8.2	8.1	-0.1
Divorced	5.7	8.2	+2.5
Total Appalachia			
Never Married	23.2	23.0	-0.2
Married	63.1	60.8	-2.3
Widowed	8.6	8.7	+0.1
Divorced	5.1	7.5	+2.4
United States			
Never Married	26.1	26.5	+0.4
Married	60.1	57.8	-2.3
Widowed	7.6	7.4	-0.2
Divorced	6.2	8.3	+2.1

Persons age 15 years and over

Map 2.6
Percent Divorced: 1990



This pattern can also be observed in Table 2.18, which provides comparisons across metro and nonmetro locations based on Beale Code categories. Overall, metropolitan divorce rates (at 7.7 percent) are higher than nonmetropolitan divorce rates (at 7.3 percent), with the highest rates of divorce taking place in medium sized metro counties at 8.2 percent (Beale Code 2) and the lowest rates taking place in rural counties nonadjacent to metro areas at 6.7 percent (Beale Code 9).

Table 2.18. Marital Status of the Population in Appalachia by Beale Code: 1990

Beale Code*	Never Married	Married	Widowed	Divorced
Metro				
0	25.2	58.9	8.9	7.0
1	21.5	63.7	7.6	7.2
2	23.5	59.8	8.5	8.2
3	24.1	59.7	8.9	7.3
Total Metro	23.9	59.8	8.6	7.7
Nonmetro				
4	22.9	60.3	9.0	7.8
5	26.7	57.4	8.3	7.6
6	20.9	63.2	8.7	7.2
7	21.6	62.2	9.0	7.2
8	19.5	64.7	8.7	7.1
9	19.7	64.3	9.3	6.7
Total Nonmetro	21.7	62.1	8.9	7.3

*Beale Code Definitions:
0 = Central counties of metro areas with 1 million population or more
1 = Fringe counties of metro areas with 1 million population or more
2 = Counties in metro areas of 250,000 – 1,000,000 population
3 = Counties in metro areas of less than 250,000 population
4 = Urban population of 20,000 or more, adjacent to a metro area
5 = Urban population of 20,000 or more, not adjacent to a metro area
6 = Urban population of 2,500 – 19,999, adjacent to a metro area
7 = Urban population of 2,500 – 19,999, not adjacent to a metro area
8 = Completely rural (no places with a population of 2,500 or more), adjacent to a metro area
9 = Completely rural (no places with a population of 2,500 or more), not adjacent to a metro area

Although divorce rates vary unsystematically across Distress Code categories (Table 2.19), the percentage of the population divorced is 7.3 percent in Distressed Counties compared with 8 percent in the Attainment Counties. Thus, there is some increase in marital instability accompanying corresponding increases in economic well-being.

Table 2.19. Marital Status of the Population in Appalachia by Distress Code: 1990				
Distress Code*	Never Married	Married	Widowed	Divorced
1 Distressed	22.1	61.3	9.3	7.3
2 Transitional-1	20.5	62.5	9.2	7.8
3 Transitional-2	22.9	60.8	8.9	7.4
4 Competitive	24.6	59.1	8.6	7.7
5 Attainment	20.8	66.4	4.8	8.0

*Distress codes are based on measures of unemployment, poverty, and per capita income and are assigned by the Appalachian Regional Commission.

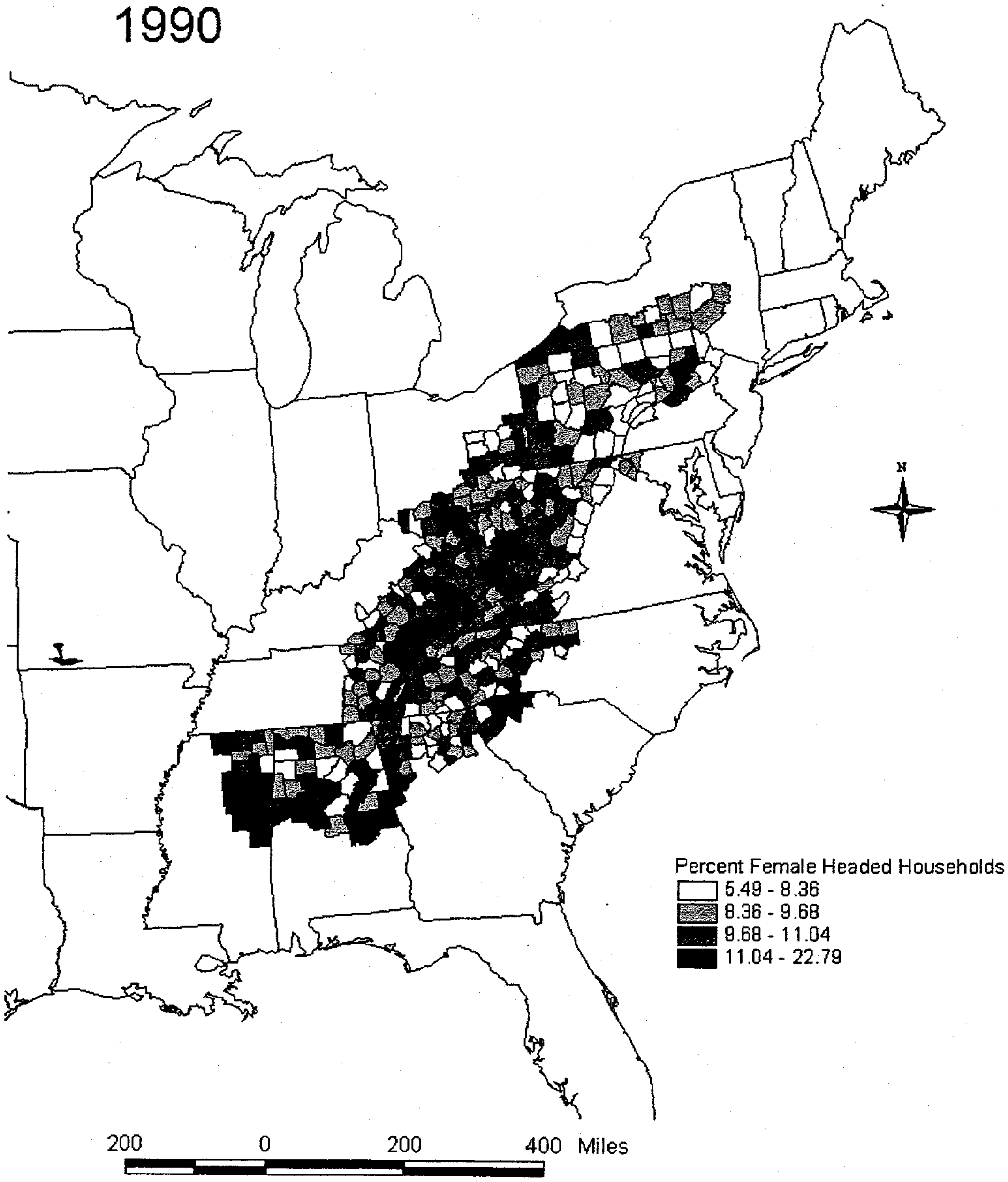
The percentage of household and family types in Appalachia for 1980 and 1990 is shown in Table 2.20. These data reveal several interesting patterns. First, married couple households have declined as a percentage of all households over time. Second, single-headed households have increased for both male-headed households and female-headed households. However, female-headed households have increased at a faster rate and also include a higher percentage of all households (at 10.4 percent) than male-headed households (at 2.7 percent). Third, non-family households constituted over one-fourth of all households in 1990, an increase of over 4 percent since 1980. Although non-family households are increasing at a faster rate in Appalachia, these patterns clearly reflect trends observed for the United States as a whole (Table 2.20).

Subregional patterns show remarkable similarity in the distribution of household and family types for North, Central, and South Appalachia (Table 2.20). Each Subregion experienced declines in married-couple family households, with substantial increases in nonfamily households and moderate increases in female-headed households. The spatial distribution of percent female-headed households is shown in Map 2.7. Although comparatively scattered geographically, higher concentrations of female-headed households can be found in West Virginia, Kentucky, Mississippi, and Alabama.

Table 2.20. Household and Family Type by Region and Subregion: 1980-1990

Region	1980	1990	Percent Change
North Appalachia			
Married Couple	64.3	58.7	-5.6
Female Headed	9.0	10.0	+1.0
Male Headed	2.4	2.8	+0.4
Non-Family	24.3	28.5	+4.2
Central Appalachia			
Married Couple	70.2	64.0	-6.2
Female Headed	9.3	10.6	+1.3
Male Headed	2.3	2.8	+0.5
Non-Family	18.2	22.6	+4.4
South Appalachia			
Married Couple	66.7	61.0	-5.7
Female Headed	10.0	10.8	+0.8
Male Headed	2.2	2.7	+0.5
Non-Family	21.1	25.5	+4.4
Total Appalachia			
Married Couple	65.9	60.2	-5.7
Female Headed	9.4	10.4	+1.0
Male Headed	2.3	2.8	+0.5
Non-Family	22.4	26.6	+4.2
United States			
Married Couple	60.9	56.2	-4.7
Female Headed	10.2	11.3	+1.1
Male Headed	2.5	3.2	+0.7
Non-Family	26.4	29.3	+2.9

Map 2.7
Percent Female-Headed Households: 1990



Household and family type comparisons between metropolitan and nonmetropolitan locations accross Beale Code categories is shown in Table 2.21. Metro counties had a lower percentage of married couple households (at 58.8 percent) than nonmetro counties (at 62.1 percent). Conversely, metro counties had higher percentages of female-headed households (at 10.8 percent) and nonfamily households (at 27.7 percent) than nonmetro counties (at 9.9 percent and 25.1 percent, respectively). The highest percentage of married couple families and the lowest percentage of female-headed and nonfamily households were found in fringe counties of large metro areas (Beale Code 1) and in completely rural areas (Beale Codes 8 and 9). Nevertheless, while rural-urban differences are evident in the data, the overall picture is one of relative homogeneity rather than diversity.

Table 2.21. Household and Family Type by Beale Code: 1990

Beale Code*	Married Couple	Female Headed	Male Headed	Non-Family
Metro				
0	57.3	10.8	2.7	29.2
1	64.9	9.2	3.0	22.9
2	58.6	11.2	2.7	27.5
3	59.3	10.1	2.7	27.9
Total Metro	58.8	10.8	2.7	27.7
Nonmetro				
4	59.9	10.2	2.9	27.0
5	57.0	10.6	2.6	29.8
6	63.2	9.4	2.9	24.5
7	62.5	10.5	2.8	24.2
8	64.8	8.9	3.1	23.2
9	64.0	10.0	3.1	23.9
Total Nonmetro	62.1	9.9	2.9	25.1

*Beale Code Definitions: 0 = Central counties of metro areas with 1 million population or more
1 = Fringe counties of metro areas with 1 million population or more
2 = Counties in metro areas of 250,000 – 1,000,000 population
3 = Counties in metro areas of less than 250,000 population
4 = Urban population of 20,000 or more, adjacent to a metro area
5 = Urban population of 20,000 or more, not adjacent to a metro area
6 = Urban population of 2,500 – 19,999, adjacent to a metro area
7 = Urban population of 2,500 – 19,999, not adjacent to a metro area
8 = Completely rural (no places with a population of 2,500 or more), adjacent to a metro area
9 = Completely rural (no places with a population of 2,500 or more), not adjacent to a metro area

The distribution of household and family types across Distress Code categories is depicted in Table 2.22. Although some differences can be observed between Distressed counties and Attainment Counties, among the intermediate categories there tends to be more similarities than differences. Perhaps the most significant difference, however, is that a larger share of female-headed households are found in the most Distressed Counties (at 11.5 percent) compared with the Attainment counties (at 7.9 percent).

Table 2.22. Household and Family Type by Distress Code: 1990

Distress Code*	Married Couple	Female Headed	Male Headed	Non-Family
1 Distressed	61.5	11.5	3.0	24.0
2 Transitional-1	62.1	10.7	2.8	24.4
3 Transitional-2	60.4	10.2	2.8	26.6
4 Competitive	56.9	11.1	2.8	29.2
5 Attainment	67.5	7.9	2.5	22.1

* Distress codes are based on measures of unemployment, poverty, and per capita income and are assigned by the Appalachian Regional Commission.

In summary, while there have been some improvements in human capital, Appalachia still lags behind the rest of the nation in terms of educational attainment levels. This comparative lack of education and job skills remains problematic for many parts of Appalachia and continues to undermine efforts to improve employment growth and economic conditions. Persistent problems of low human capital are further compounded by declines in family stability and corresponding reductions in community social capital. The rise in female-headed families is often associated with low family income and high rates of economic distress. Relative disadvantage in terms of both individual human capital and community-level social capital have thus contributed to persistent problems of poverty and distress in the Region and do not appear to be improving significantly over time.

SOCIOECONOMIC PROFILE

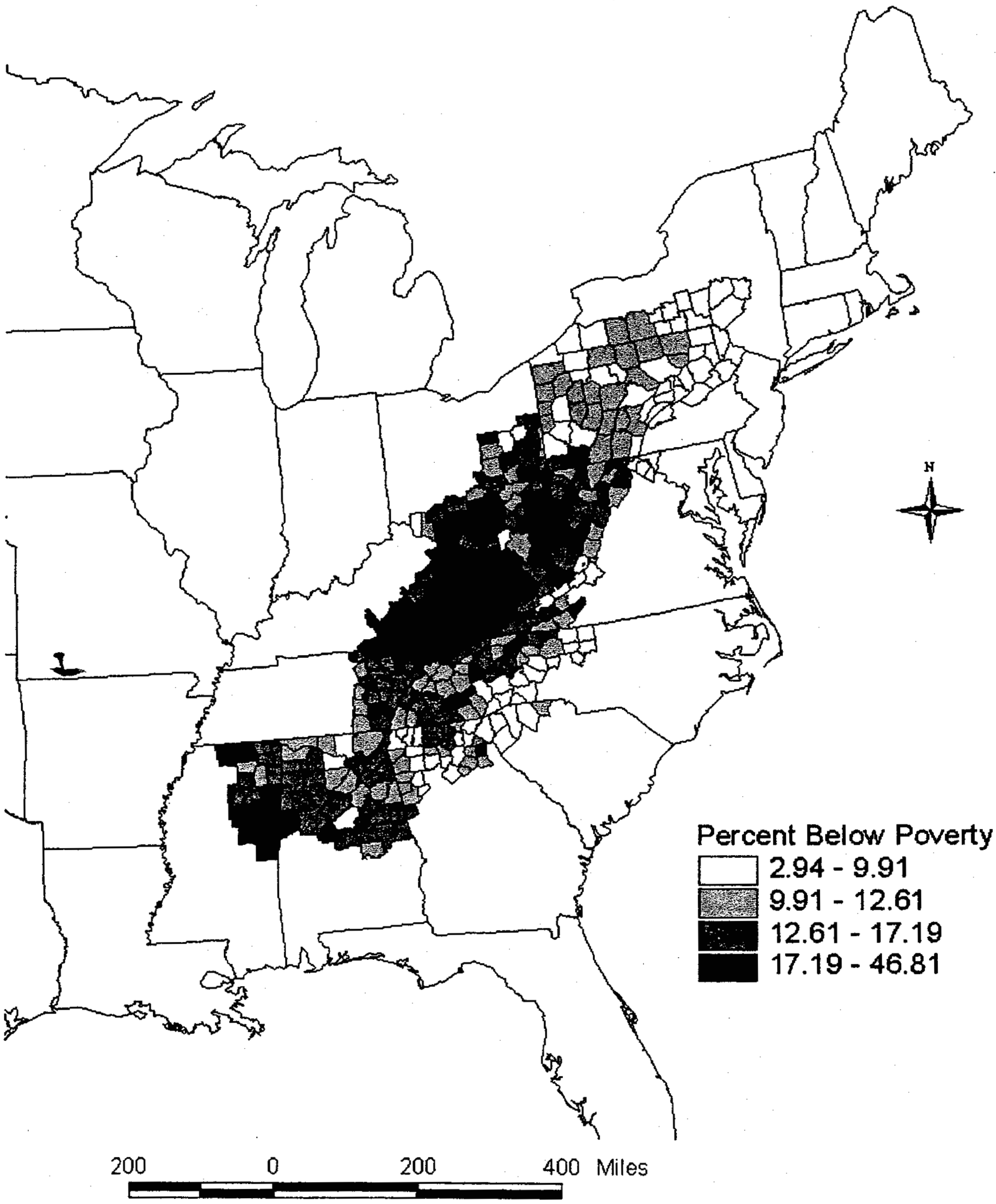
While poverty and unemployment are often linked to educational attainment levels and changing household structures, patterns of shifting industrial structure also determine the types and quality of jobs that are available and the degree to which the local or regional economy is vulnerable to larger market forces and changes in the national economy. This section focuses on family poverty rates, unemployment rates, and changing industrial composition in order to develop a profile of economic well-being in the Appalachian Region.

Between 1980 and 1990, the family poverty rate in Appalachia rose from 11 percent to 11.9 percent (see Table 2.23). During this same period, the U.S. poverty rate for families increased from 9.6 percent to 10 percent. Subregional comparisons reveal significantly higher rates of poverty in Central Appalachia than in North and South Appalachia (see Map 2.8). The family poverty rate in the Central Subregion rose from 19.2 percent in 1980 to 22.2 percent in 1990, compared with an increase from 8.4 percent to 10.7 percent in the North and a decline from 12 percent to 10.9 percent in the South.

Table 2.23. Percent of Families Below Poverty Level in Appalachia by Region and Subregion: 1980-1990

Region	1980 Percent Below Poverty Level	1990 Percent Below Poverty Level	Percent Change
North Appalachia	8.4	10.7	+2.3
Central Appalachia	19.2	22.2	+3.0
South Appalachia	12.0	10.9	-1.1
Total Appalachia	11.0	11.9	+0.9
United States	9.6	10.0	+0.4

Map 2.8
Families Below Poverty Level: 1990



Family poverty rates also vary significantly across the rural-urban continuum (Table 2.24). While family poverty has increased between 1980 and 1990 for both metro and nonmetro locations, overall increases for nonmetro counties have been higher than those for metro counties. Levels of poverty were highest in nonadjacent and rural counties (Beale Codes 5, 7, 8 and 9), and lowest in the largest metropolitan areas and their suburban fringe counties (Beale Codes 0 and 1).

Table 2.24. Percent of Families Below Poverty Level in Appalachia by Beale Code: 1980-1990

Beale Code	1980 Percent Below Poverty Level	1990 Percent Below Poverty Level	Percent Change
Metro			
0	6.3	8.0	+1.7
1	9.8	9.4	-0.4
2	9.9	10.2	+0.3
3	9.5	10.6	+1.1
Total Metro	9.0	9.8	+0.8
Nonmetro			
4	9.8	11.6	+1.8
5	11.3	13.4	+2.1
6	12.1	12.7	+0.6
7	15.4	17.9	+2.5
8	16.2	16.0	+0.2
9	21.2	21.7	+0.5
Total Nonmet	13.6	15.0	+1.4

*Beale Code Definitions: 0 = Central counties of metro areas with 1 million population or more
1 = Fringe counties of metro areas with 1 million population or more
2 = Counties in metro areas of 250,000 – 1,000,000 population
3 = Counties in metro areas of less than 250,000 population
4 = Urban population of 20,000 or more, adjacent to a metro area
5 = Urban population of 20,000 or more, not adjacent to a metro area
6 = Urban population of 2,500 – 19,999, adjacent to a metro area
7 = Urban population of 2,500 – 19,999, not adjacent to a metro area
8 = Completely rural (no places with a population of 2,500 or more), adjacent to a metro area
9 = Completely rural (no places with a population of 2,500 or more), not adjacent to a metro area

As expected, poverty rates are highly correlated with levels of economic distress (Table 2.25). Less expected was the degree to which the gap between Attainment

Counties and Distressed Counties has widened between 1980 and 1990. Families residing in Distressed Counties experienced a 5.1 percent increase in poverty between 1980 and 1990, compared with a 2.6 percent decline in Attainment Counties. While 1980 poverty rates in Distressed Counties were about two and a half times as high as those in Attainment Counties, by 1990 poverty rates were roughly five times as high in Distressed Counties as in Attainment Counties.

Table 2.25. Percent of Families Below Poverty Level in Appalachia by Distress Code: 1980-1990

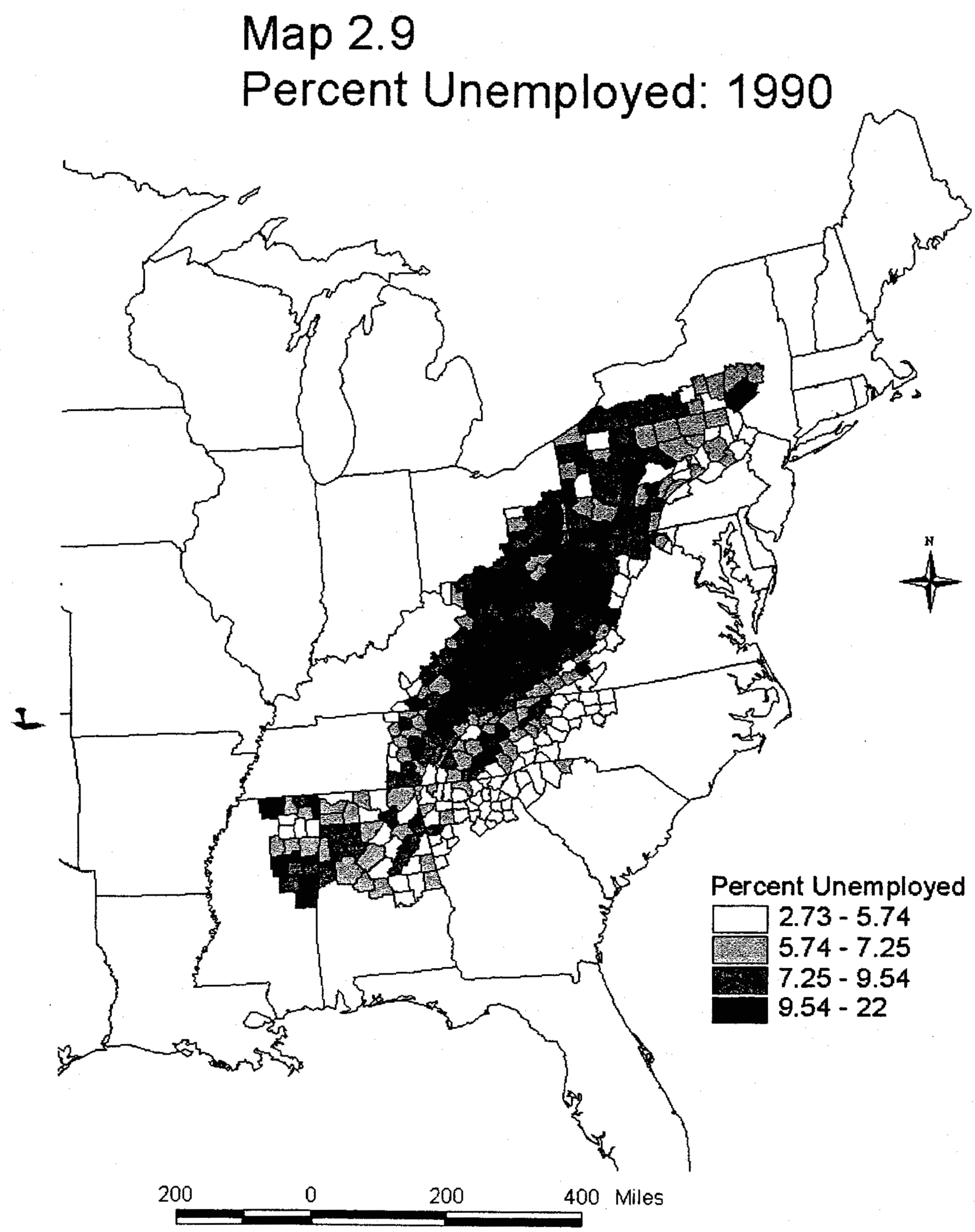
Distress Code	1980 Percent Below Poverty Level	1990 Percent Below Poverty Level	Percent Change
1 Distressed	18.4	23.5	+5.1
2 Transitional-1	14.7	16.5	+1.8
3 Transitional-2	10.4	11.3	+0.9
4 Competitive	8.2	8.3	+0.1
5 Attainment	7.2	4.6	-2.6

* Distress codes are based on measures of unemployment, poverty, and per capita income and are assigned by the Appalachian Regional Commission.

Unemployment is measured by the number of people in the labor force who are unemployed divided by the total number of people in the labor force ages 16 and over. In Table 2.26, unemployment rates for all persons and for men and women are shown as percentages for the United States, Appalachia, and the three Subregions of Appalachia. While the percentage decline in total unemployment between 1980 and 1990 was larger for Appalachia than for the U.S., Appalachia's unemployment rate in 1990 (at 6.8 percent) still exceeded that of the nation (at 6.3 percent).

Comparing Subregions, Central Appalachia had the highest unemployment rate in 1990 and was also the only Subregion to experience a percentage increase in total unemployment between 1980 and 1990. The highest unemployment rates also tend to be spatially clustered in the center of Appalachia (Map 2.9). Men had higher rates of unemployment in both the Central and Northern Subregions, while women had higher rates of unemployment in the South.

Table 2.26. Unemployment in Appalachia by Region and Subregion: 1980-1990					
	1980		1990		
Region	Number	Percent	Number	Percent	% Change
North Appalachia					
Men	229,174	8.7	199,132	7.9	-0.8
Women	130,548	7.5	131,941	6.6	-0.9
Total	359,722	8.2	331,073	7.3	-0.9
Central Appalachia					
Men	52,109	10.8	49,342	10.7	-0.1
Women	24,413	8.8	32,408	9.6	+1.2
Total	76,522	10.1	81,750	10.2	+0.1
South Appalachia					
Men	128,935	6.2	121,498	5.1	-1.1
Women	110,655	7.2	126,033	6.3	-0.9
Total	239,590	6.6	247,531	5.7	-0.9
Total Appalachia					
Men	410,218	7.9	369,972	6.9	-1.0
Women	265,616	7.5	290,382	6.7	-0.8
Total	675,834	7.7	660,354	6.8	-0.9
United States					
Men	3,921,798	6.5	4,281,622	6.4	-0.1
Women	2,888,664	6.5	3,510,626	6.2	-0.3
Total	6,810,462	6.5	7,792,248	6.3	-0.2


Map 2.9
Percent Unemployed: 1990
Percent Unemployed
2.73 - 5.74
5.74 - 7.25
7.25 - 9.54
9.54 - 22
N
200
0
200
400 Miles

Trends in unemployment are inversely related to population size and adjacency to metro locations (Table 2.27). Overall, unemployment rates are lowest for metropolitan counties. Among nonmetropolitan locations, counties adjacent to metro areas have lower unemployment than nonadjacent counties in each population size category. The lowest unemployment in 1990 occurred in large and medium-sized metropolitan counties (Beale Codes 0 and 2). The highest unemployment rate was 9.4 percent in completely rural counties not adjacent to metro areas (Beale Code 9).

Table 2.27. Unemployment in Appalachia by Beale Code: 1980-1990

Beale Code	1980 Unemployment (%)	1990 Unemployment (%)	Percent Change
Metro			
0	7.1	6.0	-1.1
1	7.3	6.4	-0.9
2	6.9	6.0	-0.9
3	8.2	6.7	-1.5
Total Metro	7.2	6.1	-1.1
Nonmetro			
4	8.4	7.4	-1.0
5	7.0	7.1	+0.1
6	8.3	7.3	-1.0
7	8.7	8.6	-0.1
8	9.3	8.1	-1.2
9	9.5	9.4	-0.1
Total Nonmet	8.5	7.9	-0.6

*Beale Code Definitions: 0 = Central counties of metro areas with 1 million population or more
1 = Fringe counties of metro areas with 1 million population or more
2 = Counties in metro areas of 250,000 – 1,000,000 population
3 = Counties in metro areas of less than 250,000 population
4 = Urban population of 20,000 or more, adjacent to a metro area
5 = Urban population of 20,000 or more, not adjacent to a metro area
6 = Urban population of 2,500 – 19,999, adjacent to a metro area
7 = Urban population of 2,500 – 19,999, not adjacent to a metro area
8 = Completely rural (no places with a population of 2,500 or more), adjacent to a metro area
9 = Completely rural (no places with a population of 2,500 or more), not adjacent to a metro area

As expected, unemployment increases with increasing levels of economic distress (Table 2.28). Distressed Counties had the highest unemployment rates, at 12.1 percent, and were the only counties to experience rising unemployment between 1980 and 1990. Unemployment rates for Competitive Counties and Attainment Counties, at 5.4 and 3.6 percent, were both lower than the national rate of 6.3 in 1990. Since both poverty rates and unemployment rates are components of the criteria used to classify counties as distressed, it is not surprising to see direct relationships between poverty and economic distress and unemployment levels and economic distress. Nevertheless, the divergence between Distressed and Attainment Counties and the degree to which this gap has been widening over time is an unforeseen trend.

Table 2.28. Unemployment in Appalachia by Distress Code: 1980-1990

Distress Code*	1980 Unemployment (%)	1990 Unemployment (%)	Percent Change
1 Distressed	11.0	12.1	+1.1
2 Transitional-1	8.9	8.8	-0.1
3 Transitional-2	7.8	6.7	-1.1
4 Competitive	6.3	5.4	-0.9
5 Attainment	4.1	3.6	-0.5

* Distress codes are based on measures of unemployment, poverty, and per capita income and are assigned by the Appalachian Regional Commission.

Information on the industrial structure for 1980, 1990, and 1996 is derived from Regional Economic Information System (REIS) data. National patterns of changing industrial structure over the past century have been characterized by shifts in the economy from farming and extractive industries to manufacturing and then towards service industries (Kasarda 1995). These shifts are particularly disruptive for local economies that rely heavily on one or two major industries, especially when the economic base of a community is seriously undermined or lost entirely. This is especially true for those parts of Appalachia that have suffered the loss of mining and extractive industry jobs without concurrent growth in either manufacturing or services to replace those jobs.

Overall trends in the changing industrial structure of Appalachia are shown in Table 2.29. Especially notable are fairly rapid declines in manufacturing from about 25 percent of all jobs in 1980 to less than 18 percent in 1996. Modest declines in farming, mining, and government employment were offset by increases in retail trade and service industry employment. This transition from manufacturing and mining to services and retail trade can have serious consequences if accompanied by corresponding declines in job quality and family income.

Table 2.29. Employment by Industry for the Appalachian Region: 1980, 1990, 1996

Industry	1980		1990		1996	
	Number	Percent	Number	Percent	Number	Percent
Farm	397,460	4.5	339,725	3.3	302,010	2.7
Ag., Forest, Fishing	36,033	0.4	70,680	0.7	78,737	0.7
Mining	229,494	2.6	148,807	1.5	96,860	0.9
Construction	438,926	5.0	574,147	5.6	650,923	5.8
Manufacturing	2,173,603	24.7	1,997,414	19.6	1,969,046	17.6
Transportation, Communication, Utilities	424,081	4.8	457,325	4.5	494,763	4.4
Wholesale Trade	339,755	3.9	409,659	4.0	448,772	4.0
Retail Trade	1,338,091	15.2	1,729,557	17.0	2,008,256	17.9
Finance, Insurance, Real Estate	465,327	5.3	525,299	5.2	600,202	5.4
Service	1,604,581	18.2	2,434,225	23.9	2,914,681	26.0
Government	1,333,825	15.2	1,422,650	14.0	1,498,989	13.4
Military	107,769	1.2	126,167	1.2	104,007	0.9
State, Local	1,047,426	11.9	1,128,551	11.1	1,238,959	11.1
Total Employment	8,803,864		10,176,753		11,198,488	

Employment by industry for the United States is shown in Table 2.30. Compared with employment patterns for the nation as a whole, employment in Appalachia is more heavily concentrated in manufacturing, mining, farming, construction, and retail trade. While the share of employment in manufacturing is still larger in Appalachia, the percentage decline in manufacturing employment between 1980 and 1996 was greater for the Appalachian Region (a 7.1 percent decline, from 24.7 percent to 17.6 percent) than for the United States (a 5.6 percent decline, from 18.2 percent to 12.6 percent). Employment in the service sector accounted for 30.5 percent of the nation's workforce in 1996, compared with 26 percent of Appalachia's workforce. In addition, the percentage of jobs in services increased by 8.6 percent between 1980 and 1996 (from 21.9 percent to 30.5 percent) for the U.S., compared with an increase of 7.8 percent (from 18.2 percent to 26 percent) for Appalachia. These industrial restructuring trends indicate that Appalachia may be lagging behind the rest of the nation in making the transition from a goods-producing to a service-based economy.

Table 2.30. Employment by Industry for the United States: 1980, 1990, 1996

Industry	1980		1990		1996	
	Number	Percent	Number	Percent	Number	Percent
Farm	3,798,000	3.3	3,147,000	2.3	2,945,000	1.9
Ag., Forest, Fishing	909,000	0.8	1,452,400	1.0	1,889,600	1.2
Mining	1,277,600	1.1	1,042,900	0.7	823,900	0.5
Construction	5,654,200	4.9	7,264,000	5.2	8,036,000	5.3
Manufacturing	20,781,100	18.2	19,634,600	14.1	19,198,900	12.6
Transportation, Communication, Utilities	5,672,100		6,560,600	4.7	7,304,400	4.8
Wholesale Trade	5,741,700	5.0	6,651,900	4.8	7,009,100	4.6
Retail Trade	17,883,900	15.7	22,840,700	16.4	25,858,600	16.9
Finance, Insurance, Real Estate	8,756,000	7.7	10,695,600	7.7	11,353,800	7.4
Service	24,999,600	21.9	38,662,900	27.8	46,583,700	30.5
Government	18,758,000	16.4	21,232,000	15.3	21,654,000	14.2
Military	2,501,000	2.2	2,750,000	2.0	2,218,000	1.5
State, Local	13,263,000	11.6	15,245,000	11.0	16,563,000	10.8
Total Employment	114,231,200		139,184,600		152,657,000	

Subregional variations in employment by industry are shown in Table 2.31 (Northern Appalachia), Table 2.32 (Central Appalachia), and Table 2.33 (Southern Appalachia). In the Northern Subregion, the largest employers are manufacturing, retail trade, service industries, and government. The percentage share of employment in manufacturing declined by 8.4 percent (from 22.9 percent to 14.5 percent) between 1980 and 1996, while the percentage share of employment in retail trade increased slightly from 16.2 percent to 18.6 percent (a 2.4 percent increase) and more dramatically in the service sector from 20.5 percent to 29 percent (an 8.5 percent increase).

Table 2.31. Employment by Industry for the Northern Appalachian Subregion: 1980, 1990, 1996

Industry	1980		1990		1996	
	Number	Percent	Number	Percent	Number	Percent
Farm	138,625	3.2	118,232	2.5	104,609	2.1
Ag., Forest, Fishing	16,552	0.4	30,040	0.6	35,425	0.7
Mining	117,439	2.7	75,481	1.6	47,231	0.9
Construction	207,154	4.8	246,320	5.2	257,523	5.2
Manufacturing	1,000,038	22.9	769,091	16.3	724,732	14.5
Transportation, Communication, Utilities	235,251	5.4	231,796	4.9	238,261	4.8
Wholesale Trade	170,239	3.9	182,245	3.9	183,663	3.7
Retail Trade	707,716	16.2	843,906	17.9	930,418	18.6
Finance, Insurance, Real Estate	239,060	5.5	260,228	5.5	294,712	5.9
Service	892,501	20.5	1,288,892	27.4	1,445,876	29.0
Government	629,526	14.4	642,428	13.6	672,041	13.5
Military	38,777	0.9	47,127	1.0	38,123	0.8
State, Local	524276	12.0	527,517	11.2	564,950	11.3
Total Employment	4,359,657		4,710,220		4,990,422	

The top employers in the Central Subregion in 1980 were farming, mining, manufacturing, retail trade, services, and government. By 1996, the percentage share of employment in farming had declined by almost 3 percent (from 10 percent to 7.1 percent) and by almost 8 percent in mining (from 12.1 percent to 4 percent). Manufacturing employment has remained relatively steady in Central Appalachia, while employment in retail trade has increased by 2.6 percent (from 14.5 percent to 17.1 percent) and by 5.4 percent in services (from 15.7 percent to 21.1 percent).

Table 2.32. Employment by Industry for the Central Appalachian Subregion: 1980, 1990, 1996

Industry	1980		1990		1996	
	Number	Percent	Number	Percent	Number	Percent
Farm	74,665	10.0	70,752	8.6	63,396	7.1
Ag., Forest, Fishing	3,183	0.4	5,873	0.7	6,006	0.7
Mining	90,573	12.1	54,410	6.6	35,742	4.0
Construction	35,117	4.7	40,391	4.9	49,600	5.5
Manufacturing	111,007	14.9	128,430	15.6	130,102	14.6
Transportation, Communication, Utilities	40,253	5.4	41,295	5.0	45,134	5.1
Wholesale Trade	24,759	3.3	25,094	3.0	26,413	3.0
Retail Trade	108,181	14.5	128,282	15.6	152,880	17.1
Finance, Insurance, Real Estate	28,529	3.8	30,589	3.7	32,679	3.7
Service	117,410	15.7	154,105	18.7	188,743	21.1
Government	109,446	14.7	124,017	15.1	136,800	15.3
Military	8,249	1.1	10,677	1.3	8,788	1.0
State, Local	89,448	12.0	102,418	12.4	117,331	13.1
Total Employment	745,791		823,141		893,798	

Like the Northern Subregion, the largest employers in Southern Appalachia are manufacturing, retail trade, service industries, and government. Between 1980 and 1996, manufacturing employment declined by 7.7 percent (from 28.7 percent to 21 percent), while employment in retail trade increased by 3.3 percent (from 14.1 percent to 17.4 percent) and by 8 percent in services (from 16.1 percent to 24.1 percent).

Table 2.33. Employment by Industry for the Southern Appalachian Subregion: 1980, 1990, 1996						
Industry	1980		1990		1996	
	Number	Percent	Number	Percent	Number	Percent
Farm	184,170	5.0	150,741	3.2	134,005	2.5
Ag., Forest, Fishing	16,298	0.4	34,767	0.7	37,306	0.7
Mining	21,482	0.6	18,916	0.4	13,887	0.3
Construction	196,655	5.3	287,436	6.2	343,800	6.5
Manufacturing	1,062,558	28.7	1,099,893	23.7	1,114,212	21.0
Transportation, Communication, Utilities	148,577	4.0	184,234	4.0	211,368	4.0
Wholesale Trade	144,757	3.9	202,320	4.4	238,696	4.5
Retail Trade	522,194	14.1	757,369	16.3	924,958	17.4
Finance, Insurance, Real Estate	197,738	5.3	234,482	5.1	272,811	5.1
Service	594,670	16.1	991,228	21.3	1,280,062	24.1
Government	594,853	16.1	656,205	14.1	690,148	13.0
Military	60,743	1.6	68,363	1.5	57,096	1.1
State, Local	433,702	11.7	498,616	10.7	556,678	10.5
Total Employment	3,698,416		4,643,392		5,314,268	

Overall, job growth occurred primarily in services and retail trade for all three Subregions. Northern Appalachia was hit hardest by job losses in manufacturing while Central Appalachia was particularly affected by job losses in mining. Numerical growth in employment characterized every industry sector in Southern Appalachia except farming and mining, with the largest gains taking place in the service sector. Total employment in the South increased from 3,698,416 in 1980 to 5,314,268 by 1996, an increase of 43.7 percent, compared with a 14.5 percent increase in the North and a 19.8 percent increase in the Central Subregion.

Employment by industry for metropolitan and nonmetropolitan locations is shown in Table 2.34 (metropolitan counties) and Table 2.35 (nonmetropolitan counties). Metropolitan counties are more reliant on manufacturing and services for employment than nonmetropolitan counties. Nonmetropolitan counties, on the other hand, are more reliant than metropolitan counties on farming, mining, and government employment. Metropolitan counties experienced a larger percentage drop in manufacturing employment (an 8.9 percent drop from 24.4 percent in 1980 to 15.5 percent in 1996) compared with nonmetropolitan counties (which experienced a 4.1 percent drop from 25.1 percent in 1980 to 21 percent in 1996). Declines in manufacturing, however, were offset by gains in the service sector with an increase of 8.7 percent (from 19.7 percent in 1980 to 28.4 percent in 1996) for metropolitan counties and an increase of 6.3 percent (from 15.9 percent in 1980 to 22.2 percent in 1996) for nonmetropolitan counties.

Table 2.34. Employment by Industry for Metropolitan Counties (Beale Codes 0-3): 1980, 1990, 1996

Industry	1980		1990		1996	
	Number	Percent	Number	Percent	Number	Percent
Farm	133,686	2.5	110,509	1.8	96,550	1.4
Ag., Forest, Fishing	19,939	0.4	40,915	0.7	48,792	0.7
Mining	57,324	1.1	37,443	0.6	26,716	0.4
Construction	284,472	5.3	376,802	6.0	420,636	6.1
Manufacturing	1,308,298	24.4	1,113,506	17.8	1,073,213	15.5
Transportation, Communication, Utilities	275,366	5.1	296,221	4.7	316,987	4.6
Wholesale Trade	243,915	4.6	302,001	4.8	329,362	4.8
Retail Trade	853,099	15.9	1,105,427	17.6	1,275,297	18.4
Finance, Insurance, Real Estate	316,883	5.9	371,166	5.9	422,723	6.1
Service	1,058,091	19.7	1,639,651	26.1	1,968,388	28.4
Government	801,599	15.0	854,203	13.6	889,007	12.8
Military	67,820	1.3	78,153	1.2	63,650	0.9
State, Local	611,509	11.4	655,995	10.5	714,780	10.3
Total Employment	5,358,588		6,270,312		6,930,980	

*Beale Code Definitions:
0 = Central counties of metro areas with 1 million population or more
1 = Fringe counties of metro areas with 1 million population or more
2 = Counties in metro areas of 250,000 – 1,000,000 population
3 = Counties in metro areas of less than 250,000 population

Table 2.35. Employment by Industry for Nonmetropolitan Counties (Beale Codes 4-9): 1980, 1990, 1996

Industry	1980		1990		1996	
	Number	Percent	Number	Percent	Number	Percent
Farm	263,774	7.7	229,216	5.9	205,460	4.8
Ag., Forest, Fishing	16,094	0.5	29,765	0.8	29,945	0.7
Mining	172,170	5.0	111,364	2.9	70,144	1.6
Construction	154,454	4.5	197,345	5.1	230,287	5.4
Manufacturing	865,305	25.1	883,908	22.6	895,833	21.0
Transportation, Communication, Utilities	148,715	4.3	161,104	4.1	177,776	4.2
Wholesale Trade	95,840	2.8	107,658	2.8	119,410	2.8
Retail Trade	484,992	14.1	624,130	16.0	732,959	17.2
Finance, Insurance, Real Estate	148,444	4.3	154,133	3.9	177,479	4.2
Service	546,490	15.9	794,574	20.3	946,293	22.2
Government	532,226	15.4	568,447	14.6	609,982	14.3
Military	39,949	1.2	48,014	1.2	40,357	0.9
State, Local	435,917	12.7	472,556	12.1	524,179	12.3
Total Employment	3,445,276		3,906,441		4,267,508	

*Beale Code Definitions:
4 = Urban population of 20,000 or more, adjacent to a metro area
5 = Urban population of 20,000 or more, not adjacent to a metro area
6 = Urban population of 2,500 – 19,999, adjacent to a metro area
7 = Urban population of 2,500 – 19,999, not adjacent to a metro area
8 = Completely rural (no places with a population of 2,500 or more), adjacent to a metro area
9 = Completely rural (no places with a population of 2,500 or more), not adjacent to a metro area

Employment by industry according to Distressed County categories is given in Table 2.36 (Distress Code 1: Distressed Counties), Table 2.37 (Distress Code 2: Transitional-1 Counties), Table 2.38 (Distress Code 3: Transitional-2 Counties), Table 2.39 (Distress Code 4: Competitive Counties), and Table 2.40 (Distress Code 5: Attainment Counties). Mining employment is inversely related to levels of economic distress, with mining comprising a larger share of jobs in Distressed Counties than in other counties. Declines in mining employment (an 8.7 percent drop from 13.5 percent in 1980 to 4.8 percent in 1996) were almost offset by gains in service sector employment (an increase of 7 percent from 15.6 percent in 1980 to 22.6 percent in 1996). Overall, employment growth in Distressed Counties was only 10.9 percent between 1980 and 1996, compared with Appalachia's employment growth rate of 27.2 percent.

Table 2.36. Employment by Industry for Distressed Counties (Distress Code 1): 1980, 1990, 1996

Industry	1980		1990		1996	
	Number	Percent	Number	Percent	Number	Percent
Farm	63,900	8.2	57,828	7.2	52,418	6.0
Ag., Forest, Fishing	2,593	0.3	5,007	0.6	5,487	0.6
Mining	105,535	13.5	64,820	8.1	41,561	4.8
Construction	38,201	4.9	37,369	4.6	47,128	5.4
Manufacturing	104,635	13.3	99,398	12.4	105,388	12.1
Transportation, Communication, Utilities	43,113	5.5	41,600	5.2	43,444	5.0
Wholesale Trade	21,254	2.7	20,878	2.6	21,031	2.4
Retail Trade	115,947	14.8	133,742	16.6	156,813	18.0
Finance, Insurance, Real Estate	28,748	3.7	29,021	3.6	31,044	3.6
Service	122,459	15.6	162,372	20.2	196,672	22.6
Government	135,613	17.3	144,748	18.0	156,812	18.0
Military	9,383	1.2	11,967	1.5	10,222	1.2
State, Local	115,170	14.7	122,080	15.2	135,754	15.6
Total Employment	783,880		804,421		869,270	

Transitional Counties (Distress Codes 2 and 3) were more reliant on manufacturing than either Competitive or Attainment Counties by 1996. Growth in service sector employment was also more moderate in Transitional Counties. These trends indicate that Distressed and Transitional Counties are lagging behind Competitive and Attainment Counties in making the shift from a goods-producing to a service-based economy.

Table 2.37. Employment by Industry for Transitional-1 Counties (Distress Code 2): 1980, 1990, 1996						
Industry	1980		1990		1996	
	Number	Percent	Number	Percent	Number	Percent
Farm	18,956	7.1	16,825	5.8	14,936	4.9
Ag., Forest, Fishing	1,227	0.5	1,902	0.7	2,132	0.7
Mining	15,014	5.6	9,880	3.4	7,241	2.4
Construction	12,171	4.6	15,587	5.4	16,949	5.5
Manufacturing	57,422	21.6	54,864	19.0	52,681	17.2
Transportation, Communication, Utilities	14,924	5.6	13,747	4.8	12,994	4.2
Wholesale Trade	6,883	2.6	8,146	2.8	6,476	2.1
Retail Trade	39,342	14.8	48,533	16.8	56,417	18.4
Finance, Insurance, Real Estate	10,258	3.9	10,952	3.8	12,994	3.8
Service	44,094	16.6	58,999	20.4	6,476	24.1
Government	45,290	17.0	48,905	16.9	56,417	15.4
Military	3,139	1.2	3,997	1.4	11,725	1.1
State, Local	35,057	13.2	38,589	13.4	73,873	12.9
Total Employment	266,298		288,684		307,097	

Table 2.38. Employment by Industry for Transitional-2 Counties (Distress Code 3): 1980, 1990, 1996						
Industry	1980		1990		1996	
	Number	Percent	Number	Percent	Number	Percent
Farm	270,227	4.9	231,228	3.7	205,540	3.0
Ag., Forest, Fishing	23,842	0.4	44,899	0.7	49,287	0.7
Mining	101,049	1.8	65,362	1.1	41,865	0.6
Construction	261,875	4.8	343,122	5.5	391,517	5.8
Manufacturing	1,418,361	25.9	1,302,980	21.0	1,272,523	18.8
Transportation, Communication, Utilities	258,208	4.7	275,487	4.4	297,022	4.4
Wholesale Trade	203,602	3.7	231,070	3.7	248,717	3.7
Retail Trade	830,273	15.1	1,054,319	17.0	1,219,862	18.0
Finance, Insurance, Real Estate	280,829	5.1	301,948	4.9	342,466	5.0
Service	970,938	17.7	1,420,434	22.8	1,675,376	24.7
Government	847,550	15.5	889,502	14.3	941,019	13.9
Military	71,150	1.3	80,390	1.3	65,552	1.0
State, Local	668,964	12.2	714,388	11.5	788,220	11.6
Total Employment	5,484,921		6,219,291		6,783,096	

Declines in manufacturing employment between 1980 and 1996 were highest for Competitive Counties (9.2 percent decline) and Attainment Counties (9 percent decline). These declines in manufacturing were offset by rapid growth in services, with a 9.6 percent increase for both Competitive and Attainment Counties. Overall, Attainment Counties have an industrial structure that is very similar to the U.S. as a whole. Employment growth has also more than doubled in Attainment counties between 1980 and 1996, which is well above employment growth nationwide.

Table 2.39. Employment by Industry for Competitive Counties (Distress Code 4): 1980, 1990, 1996

Industry	1980		1990		1996	
	Number	Percent	Number	Percent	Number	Percent
Farm	34,583	1.6	26,404	1.1	22,684	0.8
Ag., Forest, Fishing	7,125	0.3	14,120	0.6	17,293	0.6
Mining	7,214	0.3	7,709	0.3	5,390	0.2
Construction	113,226	5.4	146,508	5.8	149,296	5.5
Manufacturing	556,711	26.4	483,509	19.3	469,460	17.2
Transportation, Communication, Utilities	101,177	4.8	114,809	4.6	124,958	4.6
Wholesale Trade	99,683	4.7	117,176	4.7	123,965	4.5
Retail Trade	329,925	15.7	431,128	17.2	480,406	17.6
Finance, Insurance, Real Estate	135,148	6.4	161,635	6.4	182,131	6.7
Service	438,547	20.8	707,926	28.2	829,390	30.4
Government	281,408	13.4	299,122	11.9	306,122	11.2
Military	21,852	1.0	25,732	1.0	20,459	0.8
State, Local	207,560	9.9	219,922	8.8	236,442	8.7
Total Employment	2,105,720		2,510,054		2,725,568	

Table 2.40. Employment by Industry for Attainment Counties (Distress Code 5): 1980, 1990, 1996						
Industry	1980		1990		1996	
	Number	Percent	Number	Percent	Number	Percent
Farm	9,794	6.0	7,440	2.1	6,432	1.3
Ag., Forest, Fishing	1,246	0.8	4,752	1.3	4,538	0.9
Mining	682	0.4	1,036	0.3	803	0.2
Construction	13,453	8.3	31,561	8.9	46,033	9.0
Manufacturing	36,474	22.4	56,663	16.0	68,994	13.4
Transportation, Communication, Utilities	6,659	4.1	11,682	3.3	16,345	3.2
Wholesale Trade	8,333	5.1	32,389	9.1	48,583	9.5
Retail Trade	22,604	13.9	61,835	17.5	94,758	18.5
Finance, Insurance, Real Estate	10,344	6.3	21,743	6.1	32,836	6.4
Service	28,543	17.5	84,494	23.8	139,370	27.1
Government	23,964	14.7	40,373	11.4	47,687	9.3
Military	2,245	1.4	4,081	1.2	4,438	0.9
State, Local	20,675	12.7	33,572	9.5	38,858	7.6
Total Employment	163,045		354,303		513,457	

In summary, Southern Appalachia has experienced the strongest economic growth between 1980 and 1996. Family poverty levels have declined, unemployment has dropped below the national average, and the industrial structure of Southern Appalachia has shifted rapidly away from goods production to a service-based economy. The Central Subregion has been most reliant on extractive industries and, with the loss of jobs in mining, family poverty and unemployment have risen accordingly. The Northern Subregion, which has traditionally been reliant on manufacturing, has been less successful in retaining manufacturing employment than the South. This is consistent with the movement of manufacturing from the North to the South during the 1970s and 1980s.

Differences in industrial structure across Subregions, across metro-nonmetro locations, and across Distress Code categories have profound affects on poverty rates and unemployment in the Region. Problems of economic decline related to industrial restructuring in one area may often be matched by rapid growth and a healthy economy in another area. While Appalachia is often characterized as lagging behind the rest of the United States in economic growth and well-being, these findings again point to the great diversity of the Region.

SUMMARY

Each of the sections in this chapter has examined different aspects of the demographic, social, and economic profile of Appalachia. A key theme throughout is that Appalachia's character varies widely by subregion. This is evidenced by substantial variations in population growth, population composition (although the racial and ethnic composition of Appalachia is much more homogeneous than the rest of the nation), social well-being, and economic conditions. Nevertheless, certain patterns can also be discerned.

Areas experiencing population decline are often characterized by declines in social and economic well-being as well. Residents in these areas have low levels of educational attainment, high unemployment, and high rates of poverty. Industrial restructuring is often characterized by the loss of key industries, usually in mining or manufacturing, without corresponding shifts to comparable jobs in other sectors. Counties experiencing demographic, social, and economic decline are:

- more likely to be found in Central Appalachia,
- more likely to be rural and not adjacent to metropolitan areas,
- more likely to be reliant on mining and extractive industries, and

- more likely to be defined by the Appalachian Regional Commission as Distressed Counties.

Approximately 10 percent of the population in Appalachia resides in these counties.

Other parts of the Region, on the other hand, have experienced rapid demographic, social, and economic growth. These areas are often characterized by high levels of educational attainment, low unemployment and low rates of poverty. Industrial restructuring is characterized by relatively smooth transitions from goods producing to services producing economies. Counties experiencing rapid growth are:

- more likely to be found in Southern Appalachia, especially near the larger metropolitan areas, and
- more likely to be defined by the Appalachian Regional Commission as Competitive and Attainment Counties.

About 25 percent of the population in Appalachia resides in these counties.

While parts of the Region are experiencing growing spatial inequalities characterized by tremendous economic, social, and demographic disparities, at least 65 percent of the population live in counties lying somewhere between these extremes. Yet, it is also true that a majority of Appalachia's population continue to reside in counties designated as having a distress ranking characterized by one or more of the following characteristics: at least 150 percent of the U.S. unemployment rate, at least 150 percent of the U.S. poverty rate, or less than 67 percent of the U.S. per capita market income. While there does appear to be some shifting of the population towards economically prosperous locations, a majority still live in substantial poverty and economic hardship compared with the rest of the nation.

CHAPTER THREE: CRIME IN APPALACHIA: A DESCRIPTIVE OVERVIEW

INTRODUCTION

Beginning with the work of Shaw and McKay (1942), poverty and economic disadvantage have traditionally been linked to crime in the social ecology literature. The social and economic distress experienced by much of Appalachia would thus seem to make the Region particularly vulnerable to increasing rates of crime and violence. This chapter provides a descriptive overview of crime patterns in the Appalachian Region compared with the U.S. as a whole, as well as variations across the Region based on Subregion, Beale Code, and Distressed County Code classifications. Using the Federal Bureau of Investigation's *Uniform Crime Reports* (UCR), data on index crimes are averaged across three years for two time periods, 1978-1982 and 1994-1996, in order to smooth out any year-to-year fluctuations. For these two time periods, the crime data are also converted to rates (per 100,000 population). Descriptive profiles are presented for property index crimes and violent index crimes, as well as for individual crime categories within these two indices.

CHANGES IN APPALCHIAN CRIME RATES

Contrary to what would be expected based on the theoretical links between economic disadvantage and crime, regional crime rates in Appalachia are lower than those for the nation as a whole (Table 3.1). Overall, crime in the Region is about 50 to 65 percent of the national levels (Table 3.2). Nevertheless, between 1980 and 1995, crime has been increasing at a faster rate in Appalachia than for the U.S. as a whole, going from

47 percent to 53 percent of the national average for violent crime and from 58 percent to 65 percent of the national average for property crime.

Table 3.1. Crime Rates in Appalachia (U.S.): 1979-1981, 1989-1991 and 1994-1996

	1979-1981	1989-1991	1994-1996
All Index Crimes	3284.6 (5786.4)	3458.5 (6230.2)	3421.0 (5385.6)
Violent Crimes	261.1 (561.3)	356.1 (739.4)	376.6 (710.8)
Murder	6.7 (10.1)	5.8 (9.6)	5.2 (8.6)
Rape	17.2 (36.0)	26.4 (39.4)	26.3 (37.5)
Robbery	75.7 (226.9)	80.5 (266.1)	83.6 (236.8)
Assault	161.6 (288.3)	243.3 (424.4)	261.5 (427.8)
Property Crimes	3023.5 (5225.1)	3102.4 (5490.8)	3044.4 (4674.8)
Burglary	968.4 (1621.7)	853.1 (1276.8)	712.4 (1016.3)
Larceny	1785.5 (3123.9)	1957.3 (3399.1)	2080.6 (3068.5)
Auto Theft	269.7 (479.4)	292.0 (814.9)	251.3 (590.0)

Table 3.2. Crime Rates in Appalachia as Percentage of U.S. Rates: 1979-1981, 1989-1991 and 1994-1996

	1979-1981	1989-1991	1994-1996
All Index Crimes	57	56	64
Violent Crimes	47	48	53
Murder	66	60	60
Rape	48	67	70
Robbery	33	30	35
Assault	56	57	61
Property Crimes	58	57	65
Burglary	60	67	70
Larceny	57	58	68
Auto Theft	56	36	43

The percent change in index crimes between 1979-1981 and 1994-1996 for Appalachia as a whole are presented in Table 3.3. The general trend is a large percentage increase for violent index crime (+ 44 percent) and relatively no change for property index crime (+ 0.7 percent). The highest increases reported were for rape (+ 53 percent) and assault (+ 62 percent), while murder rates dropped by 22 percent and burglary rates by 26 percent.

Table 3.3. Crime Rates in Appalachia and Percent Change in Crime Rates: 1979-1981 and 1994-1996			
	1979-1981	1994-1996	Percent Change
All Index Crimes	3284.6	3421.0	+ 4.2
Violent Crimes	261.1	376.6	+ 44.2
Murder	6.7	5.2	- 22.4
Rape	17.2	26.3	+ 52.9
Robbery	75.7	83.6	+ 10.4
Assault	161.6	261.5	+ 61.8
Property Crimes	3023.5	3044.4	+ 0.7
Burglary	968.4	712.4	- 26.4
Larceny	1785.5	2080.6	+ 16.5
Auto Theft	269.7	251.3	- 6.8

SUBREGIONAL VARIATION

Although crime in Appalachia is relatively low compared with the U.S. as a whole, there are substantial variations within the Region and between different types of crime. This section focuses on changes in the various index crimes over time for the three Appalachian Subregions, with particular attention to the two time periods 1979-1981 and 1994-1996. The mean index crime rates for 1979-1981 are shown in Table 3.4 and the mean index crime rates for 1994-1996 are presented in Table 3.5. Overall crime rates for both time periods were highest in the South. For violent index crimes, the Central Subregion had the lowest rates in 1979-1981 while the Northern Subregion had the lowest rates in 1994-1996. In fact, the Central Subregion experienced the largest percentage increases in both violent crime (+ 83 percent) and property crime (+ 12 percent) between 1979-1981 and 1994-1996 (Table 3.6).

Table 3.4. Crime Rates in Appalachia by Subregion: 1979-1981			
	North	Central	South
All Index Crimes	3008.3	1800.8	4054.7
Violent Crimes	216.8	160.5	347.2
Murder	3.8	10.2	9.5
Rape	15.1	11.5	21.5
Robbery	79.0	27.2	84.4
Assault	118.9	111.6	231.8
Property Crimes	2791.5	1640.3	3707.5
Burglary	857.0	616.6	1211.9
Larceny	1676.1	840.9	2187.3
Auto Theft	258.4	182.7	308.3

Table 3.5. Crime Rates in Appalachia by Subregion: 1994-1996			
	North	Central	South
All Index Crimes	2613.2	2135.0	4510.0
Violent Crimes	234.9	294.4	543.0
Murder	2.9	6.7	7.5
Rape	23.1	24.4	30.1
Robbery	61.6	21.9	117.8
Assault	147.4	241.4	387.7
Property Crimes	2378.3	1840.6	3967.0
Burglary	519.7	512.2	954.1
Larceny	1668.8	1169.4	2679.7
Auto Theft	189.8	159.1	333.2

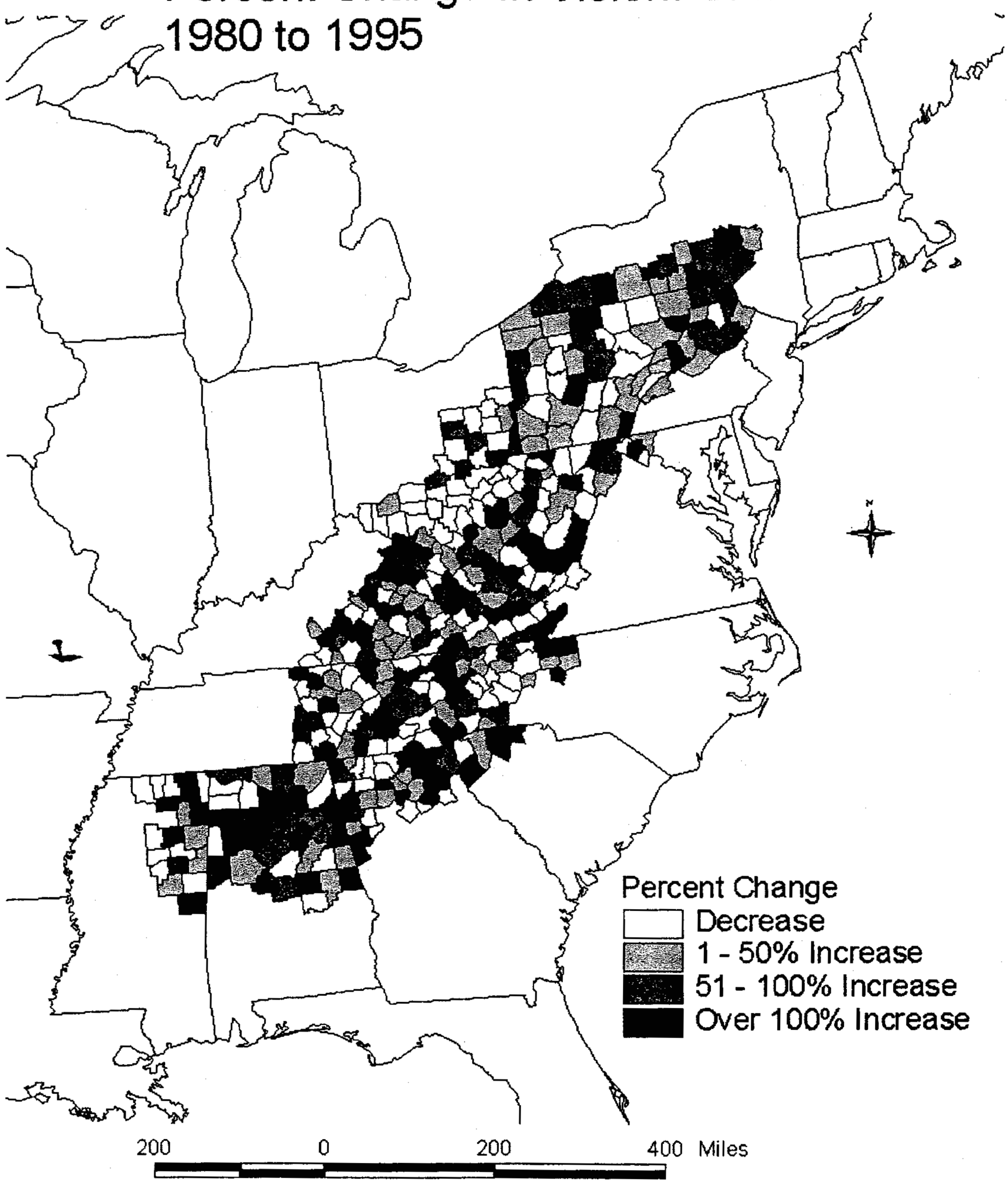
Table 3.6. Percent Change in Appalachian Crime Rates by Subregion: 1979-1981 vs. 1994-1996			
	North	Central	South
All Index Crimes	-13.1	+18.6	+11.2
Violent Crimes	+8.3	+83.4	+56.4
Murder	-23.7	-34.3	-21.1
Rape	+53.0	+112.2	+40.0
Robbery	-22.0	-19.5	+39.6
Assault	+24.0	+116.3	+67.3
Property Crimes	-14.8	+12.2	+7.0
Burglary	-39.4	-16.9	-21.3
Larceny	-0.4	+39.1	+22.5
Auto Theft	-26.5	-12.9	+8.1

By 1994-1996, overall index crime rates had increased for Central and Southern Appalachia, but not for the Northern Subregion (Table 3.6). Although the South continued to have the highest crime rates, the Central Subregion experienced the most dramatic percentage increases in crime. Further, while all three Subregions experienced considerable percentage increases in rape, substantial declines were reported for both murder and burglary (Table 3.6). Robbery declined in both Northern and Central Appalachia but increased substantially in the South.

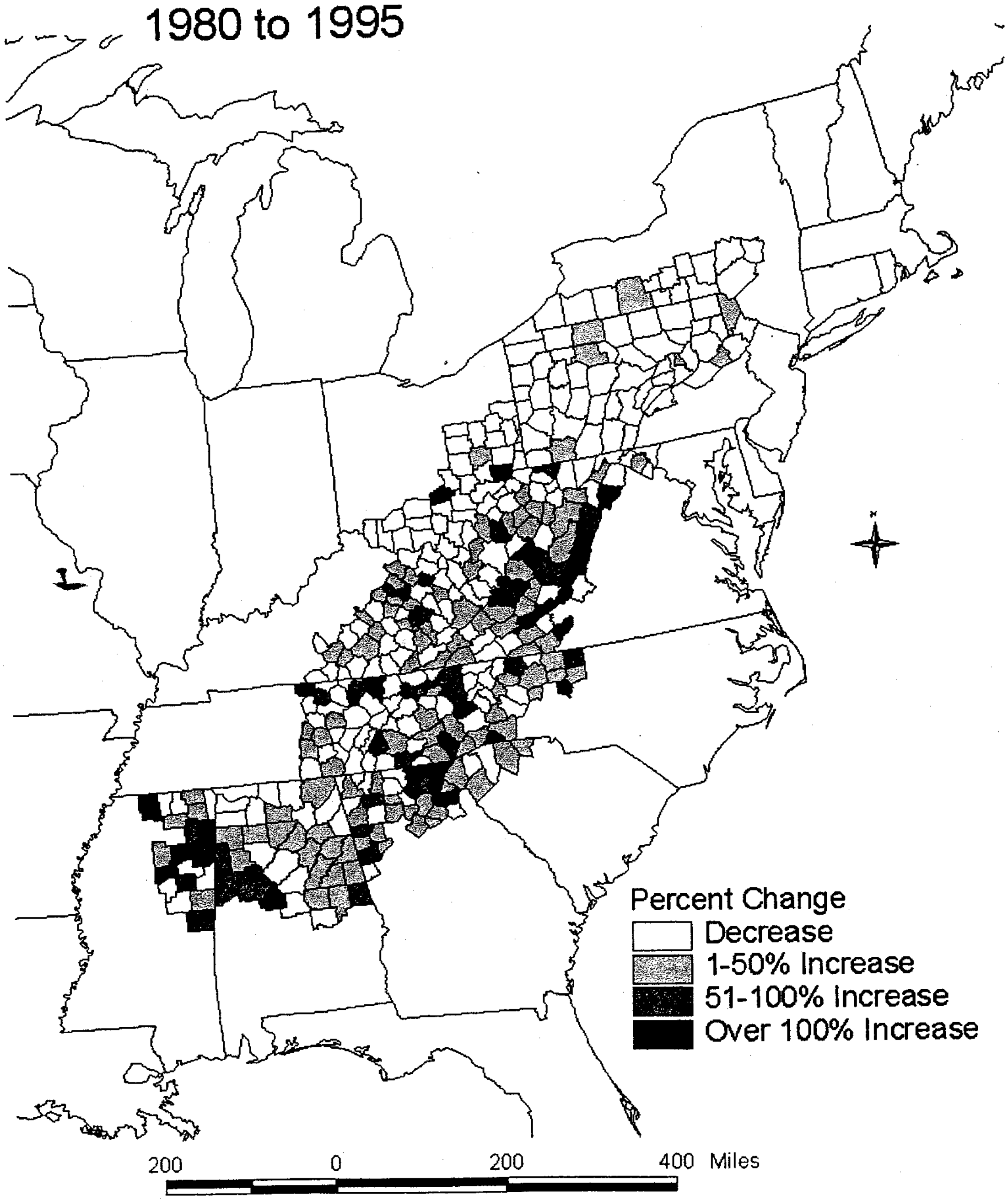
The Central Subregion reported the largest percentage increase in violent index crime (+ 83 percent), at nearly twice the rate for Appalachia as a whole (+ 44 percent). The spatial distribution of the percentage change in violent crime rates is shown in Map 3.1. Counties with the largest percentage increase in violent crime are scattered throughout the Region, but tend to be more concentrated in the Central and Southern Subregions. Further analyses indicated that most of the increase in violent crime in the South occurred in or near metropolitan counties, while most of the increase in violent crime in the Central Subregion occurred in nonmetropolitan (especially rural) counties.

While changes in property index crimes were considerably less dramatic, the Central Subregion also reported the largest increase in property crime between 1979-1981 and 1994-1996 (+ 12 percent). The spatial distribution of the percentage change in property crime rates is shown in Map 3.2. Counties with increases in property crime are almost nonexistent in the North. As with violent crime, most of the counties with substantial increases in property crime are also located in the Central and Southern Subregions. Unlike the spatial distribution of violent crime, however, counties experiencing the largest percentage increases in property crime appear to be primarily nonmetropolitan (especially rural) counties located along the eastern and southern periphery of the Region.

Map3.1.
Percent Change in Violent Crime Rates:
1980 to 1995



Map3.2.
Percent Change in Property Crime Rates: 1980 to 1995



METROPOLITAN – NONMETROPOLITAN VARIATION

This section describes changes in the various index crimes across metropolitan and nonmetropolitan county categories (Beale Code categories). The mean index crime rates for 1979-1981 are presented in Table 3.7 and the mean index crime rates for 1994-1996 are shown in Table 3.8. Overall crime rates in 1979-1981 were highest in medium-sized metro (Beale Code 2) and large metro (Beale Code 0) counties. By 1994-1996, overall crime rates were highest in urbanized nonmetropolitan counties not adjacent to metropolitan areas (Beale Code 5) and medium-sized metro counties (Beale Code 2). Also, the largest percentage change in index crime rates (Table 3.9) took place in all three categories of nonmetropolitan counties not adjacent to metropolitan areas (Beale Codes 5, 7, and 9) and in the fringe counties of large metro areas (Beale Code 1), with the largest increases taking place in nonadjacent rural counties (Beale Code 9).

Violent crime rates nearly doubled in rural counties adjacent to metropolitan areas (Beale Code 8). Medium-sized metro counties (Beale Code 2) also experienced dramatic increases in violent crime with an increase of 63 percent between 1979-1981 and 1994-1996. Meanwhile, violent crime declined by 12 percent in large metro counties (Beale Code 0). Thus, while violent crime has steadily decreased in large metropolitan areas, large percentage increases in violent crime have been taking place in smaller metro areas and nonmetro counties adjacent to metro locations. In fact, a reversal of the crime gradient across nonmetropolitan counties adjacent to metro areas seems to be taking place, with the largest increases taking place in rural counties (Beale Code 8), followed by less urbanized counties (Beale Code 6), and then by more urbanized nonmetro locations (Beale Code 4). This may indicate that a spatial diffusion process is driving violent crime from central cities to the suburbs and to more remote areas.

Property crime rates declined in all metro county categories (Beale Codes 0, 2, and 3) and in nonmetropolitan counties adjacent to metro areas, both urbanized (Beale Code 4) and rural (Beale Code 8) between 1979-1981 and 1994-1996. Overall, the largest percentage increases in property crime occurred in large metro fringe counties (Beale Code 0) and in nonmetropolitan counties not adjacent to metro areas (Beale Codes 5, 7, and 9). A closer examination shows that much of this change is being fueled by fairly large increases in larceny. Thus, while burglary rates have declined across most locations, larceny rates have been on the rise. In fact, in the more remote rural locations (Beale Code 9), the larceny rate has nearly doubled.

Table 3.7. Crime Rates in Appalachia by Beale Codes: 1979-1981

	Metro				Nonmetro					
	0	1	2	3	4	5	6	7	8	9
All Index	3517	2818	4486	3474	3293	3275	2284	1975	1660	1028
Violent	380	166	377	241	188	169	142	153	104	131
Murder	5	7	8	5	5	6	5	9	6	9
Rape	24	11	25	15	12	15	9	10	10	9
Robbery	190	42	106	53	42	40	24	23	13	11
Assault	161	106	238	168	129	108	104	112	75	102
Property	3137	2652	4109	3233	3105	3106	2142	1822	1556	897
Burglary	982	907	1281	947	955	897	769	655	711	439
Larceny	1659	1474	2487	2082	1944	1995	1221	998	725	362
Auto Theft	496	271	342	204	206	215	152	169	120	96

Beale Code Definitions:
0 = Central counties of metro areas with 1 million population or more
1 = Fringe counties of metro areas with 1 million population or more
2 = Counties in metro areas of 250,000 – 1,000,000 population
3 = Counties in metro areas of less than 250,000 population
4 = Urban population of 20,000 or more, adjacent to a metro area
5 = Urban population of 20,000 or more, not adjacent to a metro area
6 = Urban population of 2,500 – 19,999, adjacent to a metro area
7 = Urban population of 2,500 – 19,999, not adjacent to a metro area
8 = Completely rural (no places with a population of 2,500 or more), adjacent to a metro area
9 = Completely rural (no places with a population of 2,500 or more), not adjacent to a metro area

Table 3.8. Crime Rates in Appalachia by Beale Codes: 1994-1996										
	Metro				Nonmetro					
	0	1	2	3	4	5	6	7	8	9
All Index	3215	3187	4679	3503	3017	3830	2509	2236	1729	1407
Violent	334	240	616	336	265	316	221	225	195	170
Murder	4	3	8	4	3	4	4	5	5	6
Rape	27	20	35	24	23	24	19	20	20	22
Robbery	128	40	149	66	39	58	24	20	13	11
Assault	175	177	424	243	200	229	175	181	157	131
Property	2881	2947	4063	3167	2752	3514	2288	2011	1534	1237
Burglary	526	697	954	675	629	737	632	564	556	471
Larceny	1962	1988	2756	2325	1971	2551	1504	1307	858	671
Auto Theft	393	263	354	166	152	225	152	140	121	94

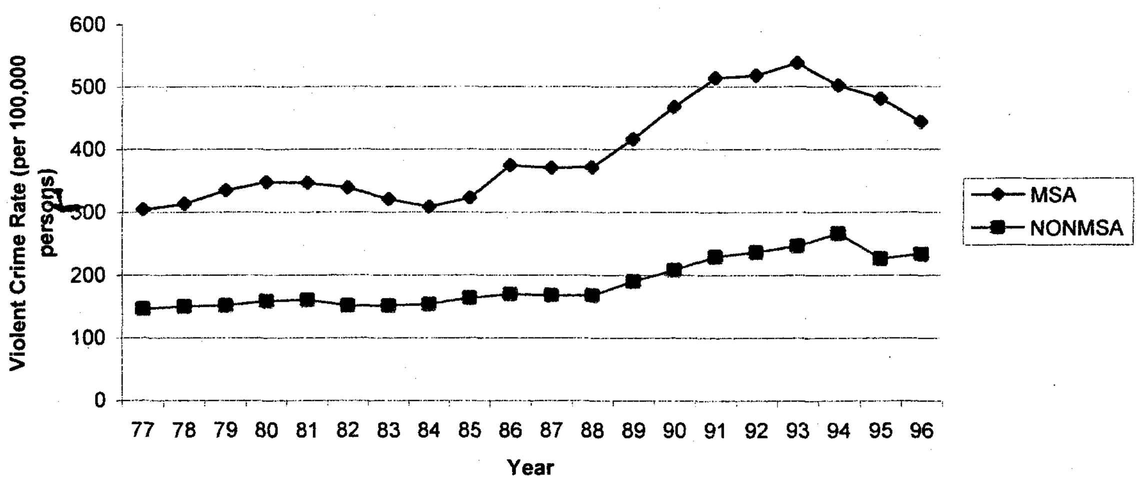
*Beale Code Definitions:
0 = Central counties of metro areas with 1 million population or more
1 = Fringe counties of metro areas with 1 million population or more
2 = Counties in metro areas of 250,000 – 1,000,000 population
3 = Counties in metro areas of less than 250,000 population
4 = Urban population of 20,000 or more, adjacent to a metro area
5 = Urban population of 20,000 or more, not adjacent to a metro area
6 = Urban population of 2,500 – 19,999, adjacent to a metro area
7 = Urban population of 2,500 – 19,999, not adjacent to a metro area
8 = Completely rural (no places with a population of 2,500 or more), adjacent to a metro area
9 = Completely rural (no places with a population of 2,500 or more), not adjacent to a metro area

Table 3.9. Percent Change in Appalachian Crime Rates by Beale Codes: 1979-1981 vs. 1994-1996										
	Metro				Nonmetro					
	0	1	2	3	4	5	6	7	8	9
All Index	-9	+13	+4	+1	-8	+17	+10	+13	+4	+37
Violent	-12	+45	+63	+39	+41	+87	+56	+47	+88	+30
Murder	-20	-57	0	-20	-40	-33	-20	-44	-17	-33
Rape	+11	+82	+40	+60	+92	+60	+111	+100	+100	+144
Robbery	-33	-5	+41	+25	-7	+45	0	-13	0	0
Assault	+8	+67	+78	+45	+55	+112	+68	+62	+109	+28
Property	-8	+11	-1	-2	-11	+13	+7	+10	-1	+38
Burglary	-46	-23	-26	-29	-34	-18	-18	-14	-22	+7
Larceny	+18	+35	+11	+12	+1	+28	+23	+31	+18	+85
Auto Theft	-21	-3	+4	-19	-26	+5	0	-17	+1	-2

*Beale Code Definitions:
0 = Central counties of metro areas with 1 million population or more
1 = Fringe counties of metro areas with 1 million population or more
2 = Counties in metro areas of 250,000 – 1,000,000 population
3 = Counties in metro areas of less than 250,000 population
4 = Urban population of 20,000 or more, adjacent to a metro area
5 = Urban population of 20,000 or more, not adjacent to a metro area
6 = Urban population of 2,500 – 19,999, adjacent to a metro area
7 = Urban population of 2,500 – 19,999, not adjacent to a metro area
8 = Completely rural (no places with a population of 2,500 or more), adjacent to a metro area
9 = Completely rural (no places with a population of 2,500 or more), not adjacent to a metro area

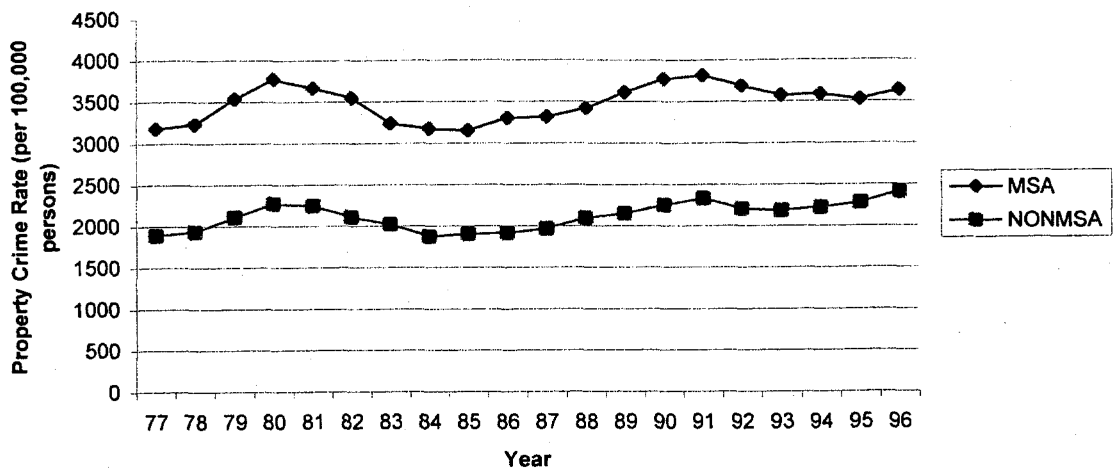
Regional crime rate trends in Appalachia for metropolitan and nonmetropolitan counties between 1977 and 1996 are shown for violent crime in Figure 3.1 and for property crime in Figure 3.2. In general, the trend line for metropolitan violent crime suggests three temporal periods: (1) a period of relative stability from 1977 to 1984; (2) a period of increasing violent crime rates from 1984 to 1993; and (3) a period of declining violent crime rates from 1993 to 1996. The trend line for nonmetropolitan violent crime, while less pronounced and lagged by one or two years, follows a similar pattern.

Figure 3.1. Appalachian Region Violent Crime Rate Trends for Metropolitan and Nonmetropolitan Counties: 1977-1996



The trend lines for both metropolitan and nonmetropolitan property crime exhibit similar "wavelike" patterns characterized by slight peaks in 1980 and 1991 which are followed by periods of decline. While both metro and nonmetro crime rates have generally followed similar patterns over time, metropolitan rates for both violent and property index crimes have remained consistently above nonmetropolitan crime rates throughout this twenty-year period.

Figure 3.2. Appalachian Region Property Crime Rate Trends for Metropolitan and Nonmetropolitan Counties: 1977-1996



VARIATION BY ECONOMIC DISTRESS

Variation in crime rates across ARC Distressed County Code categories for the 1979-1981 period are reported in Table 3.10 and for the 1994-1996 period in Table 3.11. Competitive Counties consistently have the highest crime rates in both time periods for overall index crime as well as for violent crime and property crime. Overall, the distress county gradient is not clear for any crime category. In fact, the most distressed counties are often characterized by the lowest crime rates. Violent crime rates are consistently higher in Transitional-2 and Competitive Counties where economic and employment growth are in transition. By contrast, property crime rates are higher in Competitive and Attainment Counties where economic and employment growth are becoming more established.

Table 3.10. Crime Rates in Appalachia by Distress Codes: 1979-1981					
	Distressed	Transitional1	Transitional2	Competitive	Attainment
All Index	1829	1960	3240	4468	3247
Violent	161	152	228	441	207
Murder	9	7	6	7	7
Rape	12	9	15	27	17
Robbery	29	22	60	163	46
Assault	111	113	147	244	138
Property	1668	1808	3012	4027	3040
Burglary	590	631	968	1226	1081
Larceny	889	1051	1808	2358	1704
Auto Theft	188	126	236	443	255

* Distress codes are based on measures of unemployment, poverty, and per capita income and are assigned by the Appalachian Regional Commission.

Table 3.11. Crime Rates in Appalachia by Distress Codes: 1994-1996					
	Distressed	Transitional1	Transitional2	Competitive	Attainment
All Index	2003	2175	3267	4584	3610
Violent	234	234	347	576	224
Murder	5	5	5	7	3
Rape	23	16	25	35	20
Robbery	25	23	71	159	54
Assault	181	190	246	376	146
Property	1769	1941	2920	4008	3386
Burglary	492	526	697	891	639
Larceny	1115	1306	2009	2726	2380
Auto Theft	162	110	214	390	367

* Distress codes are based on measures of unemployment, poverty, and per capita income and are assigned by the Appalachian Regional Commission.

While the most distressed counties (Distressed and Transitional-1) do have the lowest crime rates, they are nevertheless also experiencing the largest percentage increases in overall index crime along with Attainment Counties (Table 3.12). Violent crime has been increasing at a faster rate in the more distressed counties than in more prosperous locations. Property crime, on the other hand, has been increasing at a faster rate in the most prosperous Attainment Counties. While burglary has declined significantly, larceny and auto theft have risen substantially in Attainment Counties. In

Distressed and Transitional Counties, the rise in violent crime has been driven primarily by substantial increases in reported rape and assault.

Table 3.12. Percent Change in Appalachian Crime Rates by Distress Codes: 1979-1981 vs. 1994-1996					
	Distressed	Transitional1	Transitional2	Competitive	Attainment
All Index	+10	+11	+1	+3	+11
Violent	+45	+54	+52	+31	+8
Murder	-44	-29	-17	0	-57
Rape	+92	+78	+67	+30	+18
Robbery	-14	+5	+18	-25	+17
Assault	+63	+68	+67	+54	+6
Property	+6	+7	-3	-1	+11
Burglary	-17	-17	-28	-27	-41
Larceny	+25	+24	+11	+16	+40
Auto Theft	-14	-13	-9	-12	+44

SUMMARY

While crime in Appalachia is low compared to national averages, part of this is due to the predominately nonmetropolitan character of the Region. Crime levels in nonmetropolitan areas in every part of the country are almost always well below those of metropolitan locations. Nevertheless, crime rate patterns over time also suggest that crime has been increasing at a faster rate in Appalachia than for the nation as a whole. Furthermore, between 1980 and 1995, violent crime has exhibited a substantially larger increase than property crime throughout the Region.

When broken down by Subregion, these Regional trends exhibit some interesting variations. Overall index crime rates have consistently been higher in the South. This may partially be attributed to the relatively large number of metropolitan counties located in the South compared with the rest of the Region (although the Northern Subregion has nearly as many metropolitan counties as the South). It may also be related to the patterns of rapid population growth and increased population mobility which are coming to characterize many metropolitan and nonmetropolitan counties in Southern Appalachia. Nevertheless, the largest percentage increases in crime, especially violent crime, are taking place in Central Appalachia.

As noted in the demographic and socioeconomic profile summary of Appalachia in Chapter 2, counties experiencing demographic, social, and economic decline are more likely to be found in Central Appalachia and are also more likely to be rural and not adjacent to metropolitan areas. These same counties are also experiencing the largest percentage increases in both violent and property crime. Thus, there does appear to be a strong link between social and economic decline and growing crime rates, especially for violent crime.

CHAPTER FOUR: EXPLORATORY SPATIAL DATA ANALYSIS: THE SPATIAL PATTERNS OF CRIME IN APPALACHIA

INTRODUCTION

Geographic Information Systems (GIS) and spatial analysis applications have significantly improved the ability of researchers and crime analysts to look more closely at the spatial patterns and locational contexts of crime. As a visualization tool, GIS can be used to integrate data from diverse sources into a single georeferenced database containing observations from neighboring locations. Spatial patterns can then be represented and visualized across locations, providing insight into potential spatial clustering, heterogeneity, and spread over time. As an exploratory data analysis tool, GIS and spatial analysis applications can be used to examine data more rigorously as a way of generating new hypotheses from the data or as a way of identifying unexpected spatial patterns.

A central purpose of this chapter is to show the value of applying GIS and exploratory spatial analysis procedures to the study of aggregate crime patterns. Moving beyond the manual pin-mapping approaches of a decade ago, desktop GIS technologies have introduced crime analysts to new ways of visualizing and mapping crime. Applications for dynamic visualization and mapping in a GIS environment now make it possible to inductively describe and visualize spatial distributions, identify unusual observations or spatial outliers, and discover patterns of spatial association.

While visualization and mapping applications are perhaps the most familiar use of GIS, more rigorous analyses of spatial patterns can be accomplished through exploratory spatial data analysis (ESDA) procedures. A central feature of ESDA is the use of formal statistical tests to assess the degree of spatial randomness observed in the data. Most of the available ESDA tools provide different ways of determining whether the underlying pattern is uniform over space or whether there is statistical evidence of spatial patterning, including clusters, heterogeneity, or spread. These include nearest neighbor analysis tests for point pattern data and spatial autocorrelation tests for aggregated data or point data that have intensity values applied to them.

VISUALIZATION AND MAPPING APPLICATIONS

This section deals primarily with the application of ArcView choropleth mapping and the SpaceStat (Anselin 1998) dynamic ESDA extension (DynESDA) for visualizing and mapping the relative density and distribution of crime in Appalachia. Choropleth mapping is a common technique for representing data summarized by statistical or administrative areas and is particularly useful for obtaining a general picture of the overall spatial distribution of crime. Most of the time, choropleth maps are used in crime mapping applications to show the relative density or amount of crime taking place in different areas. This is done by assigning graduated colors or varying shades across the range of value categories, going from lowest to highest.

As a first step, the general statistical distribution of the data is represented by the histograms for violent crime in Figure 4.1 and for property crime in Figure 4.2.

Figure 4.1

Statistical Distribution of Violent Crime, 1994-1996

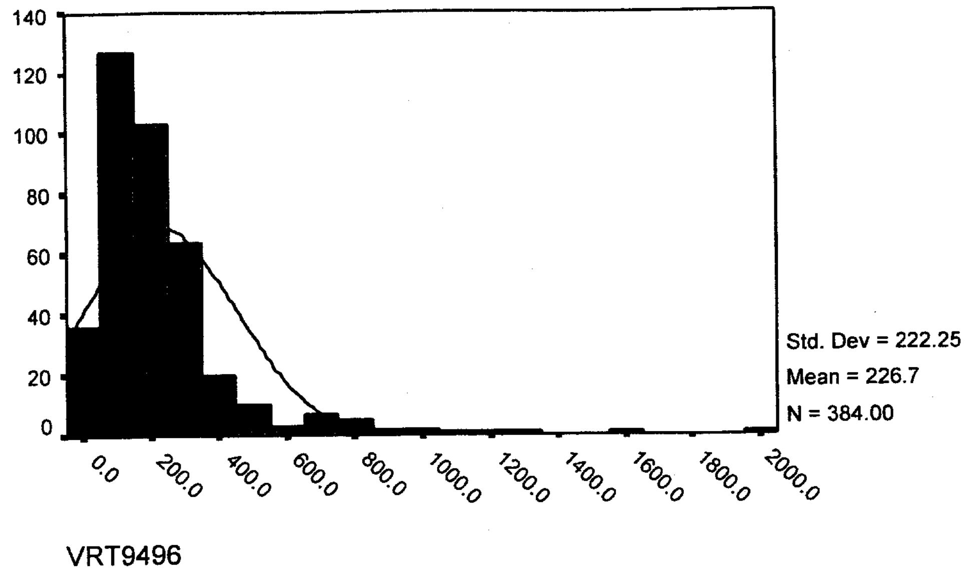
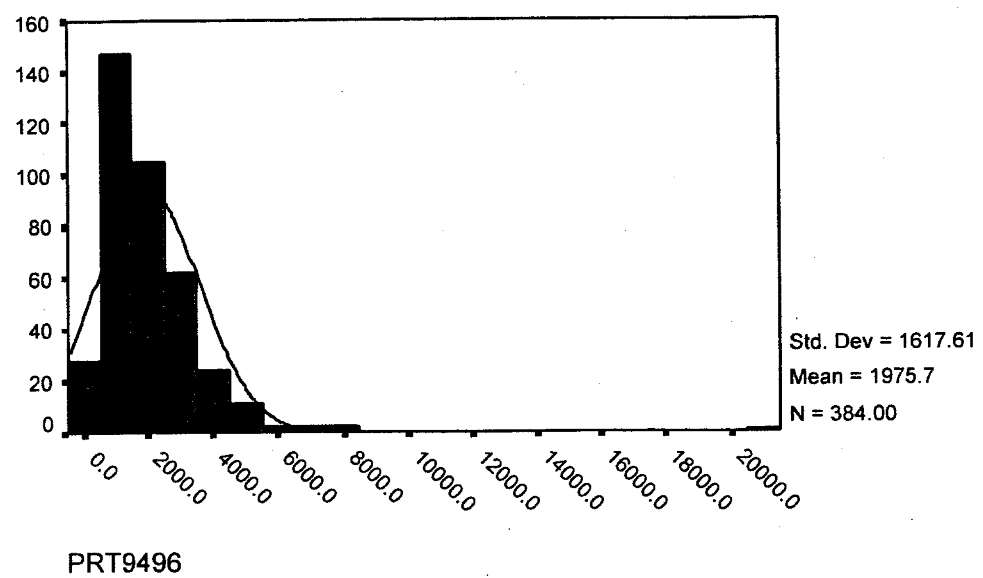


Figure 4.2

Statistical Distribution of Property Crime, 1994-1996



As with most crime data, the distributions for both violent and property crime are positively skewed. Knowing the statistical distribution of the data provides necessary guidance for deciding which mapping classification sheme to use for creating class groupings with similar values. Ideally, the classification scheme employed should minimize the inner class variance as much as possible and maximize the variance between classes as much as possible. In other words, the range of values within each class should be more similar to one another, while the difference in values between classes should be as far apart as possible.

The five most common classification methods are natural breaks, quantile, equal area, equal interval, and standard deviation. The default classification option in ArcView is natural breaks. Using this approach, class categories are identified based on natural groupings in the data. Arcview uses a statistical procedure to identify optimal groupings so that values within a class are more similar and values between classes further apart. Usually, class breaks are set to correspond with relatively large jumps in the distribution of values. The quantile classification method assigns an equal number of areas to each class. Thus, given the 399 counties comprising the Appalachian Region and four class categories, this would yield about 100 counties in each class grouping, with the lowest 100 in the first group and the highest 100 in the last group. The equal area method creates classes in which the sum of the areas in each class are approximately equal. The equal interval approach divides the distribution of values so that the range of values within each class is identical. In other words, the difference between the highest and lowest value is the same for each class grouping. With the standard deviation approach, class breaks are defined by standard deviational distances from the mean.

Using natural breaks to classify data tends to be useful when mapping data values that are not evenly distributed, since it places value clusters in the same class. The disadvantage of using this approach is that it is often difficult to make comparisons between maps since the classification scheme utilized is unique to each dataset.

The quantile classification method arranges all observations from low to high and assigns equal numbers of observations to each classification category. This approach is useful when the data values are fairly evenly distributed or when there is a need to highlight a proportion of the observations. For example, if the objective is to show which counties are in the top 20 percent for violent crime, the quantile method of classification would be selected using five class categories. The disadvantage in using this approach, especially with positively skewed data, is that differences between classes may be exaggerated since a few widely ranging adjacent values may be grouped together in one class while an equal number of relatively homogeneous values may be grouped together in another class.

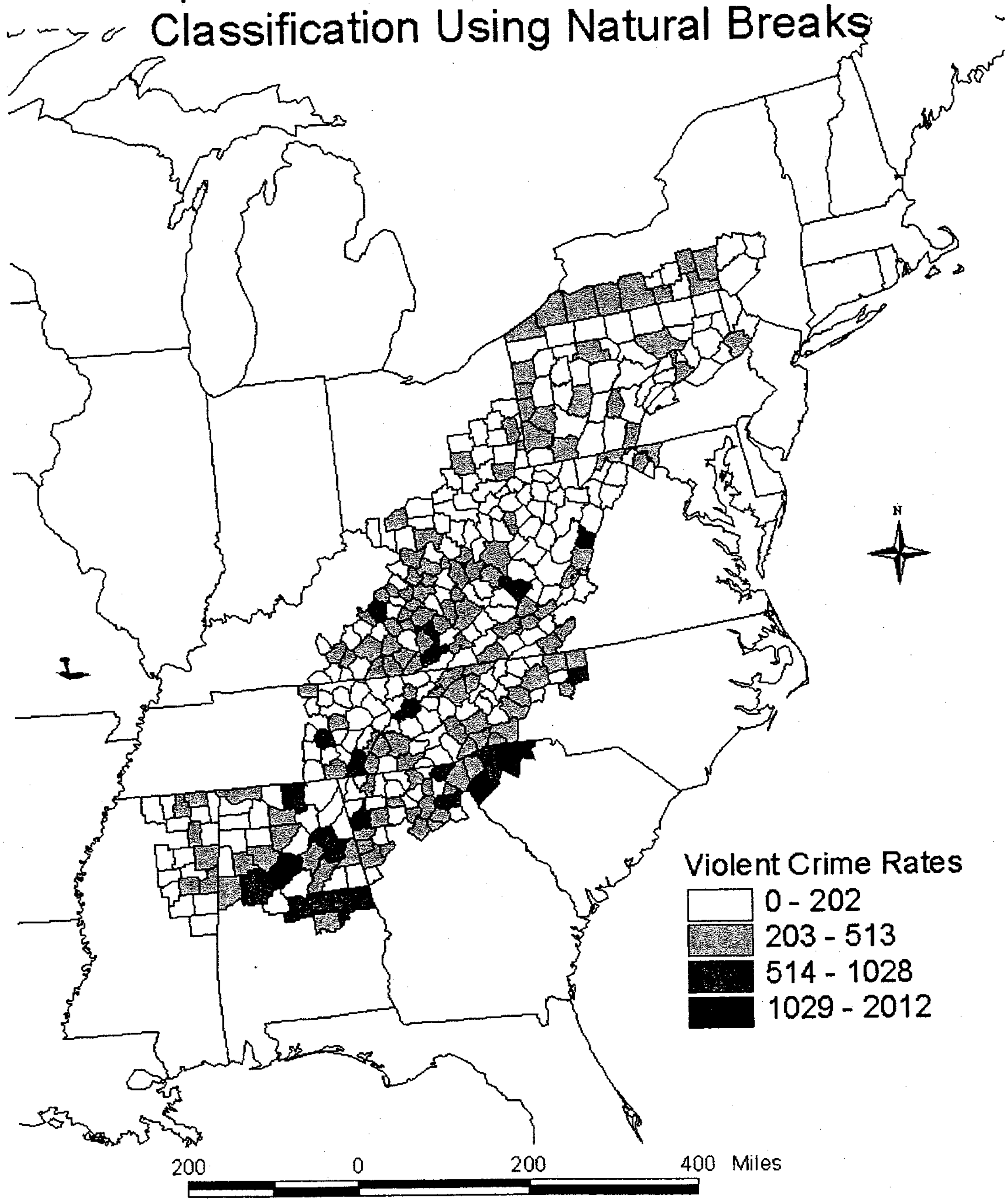
Equal area classification is similar to the quantile classification method except that each county is given a weight in the classification equal to its area rather than equal to 1. As a result, counties with larger land areas are given more weight in the classification scheme. This approach is useful when the units of analysis are all approximately the same size. The disadvantage in using this method is that it tends to hide the variation in crime between smaller counties.

In using the equal interval classification method, the range of values is the same for each class. This approach is useful when the data is normally distributed and one is interested in emphasizing observations around the mean. The disadvantage in using this method with positively skewed data is that most of the observations will be assigned to the lower value categories while only a few observations will be assigned to the higher value categories. However, when the objective is to emphasize outlying counties with high crime rates or high crime clusters, this could be a useful approach to classifying and mapping the data.

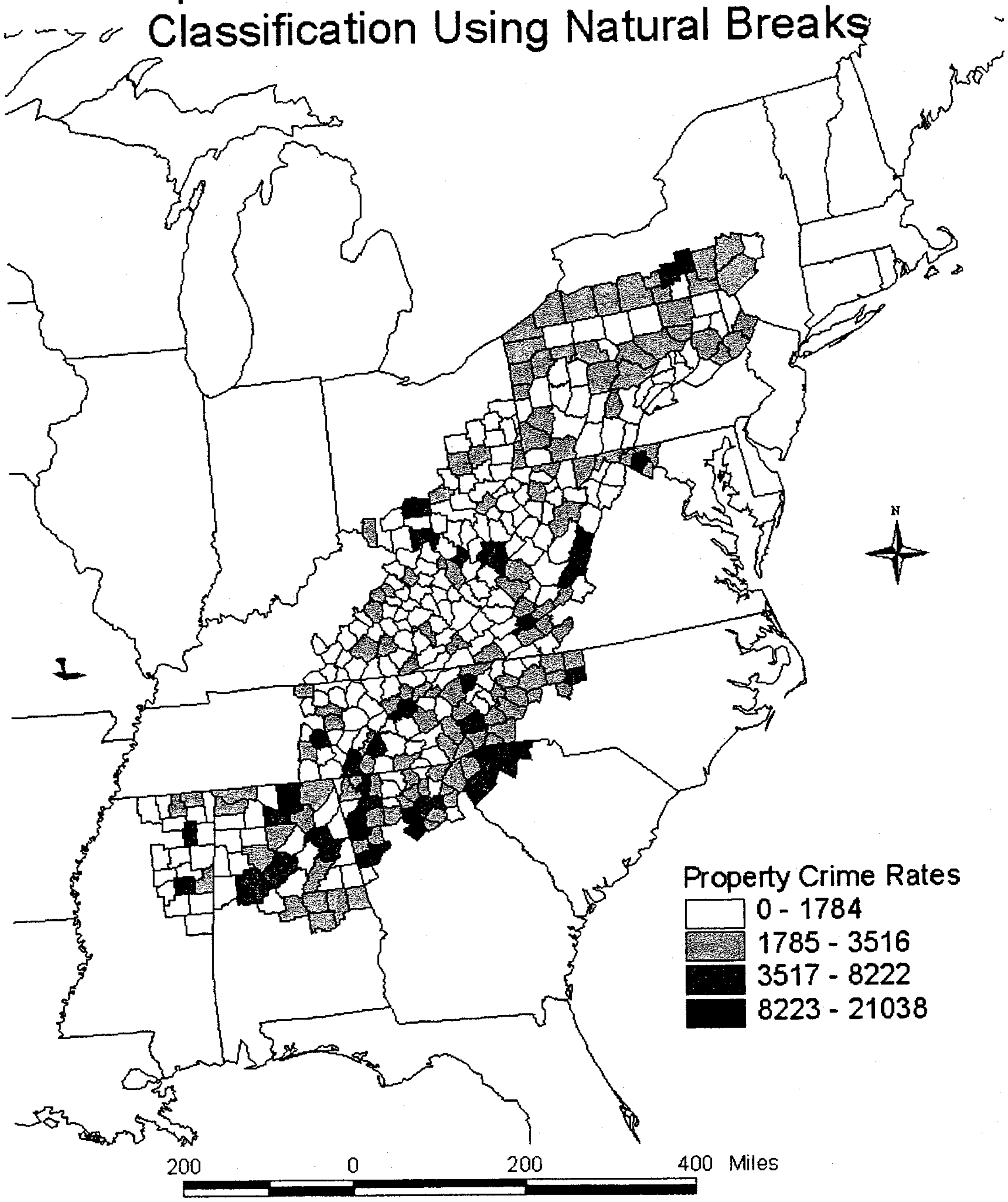
With the standard deviation classification method, each class is defined by its standard deviational distance from the mean. Again, with positively skewed distributions, outliers and hot spot county clusters can be easily isolated and identified. The disadvantage in using this approach is that the map does not show the actual values in each class, only how far each class category is from the mean.

Map 4.1 shows the distribution of violent crime averaged across three years for 1994-1996 based on a natural breaks classification scheme, while Map 4.2 shows the distribution of property crime for 1994-1996 using natural breaks. Using natural breaks places outliers in a category of their own and emphasizes the differences between counties with the highest rates and those with the lowest rates of crime. The map for violent crime (Map 4.1) shows a clustering of outliers with high rates of violent crime along the South Carolina border and down into Alabama. The map for property crime, on the other hand (Map 4.2), shows clustering in the South and also in the Central Subregion.

Map 4.1
Spatial Distribution of Violent Crime:
Classification Using Natural Breaks

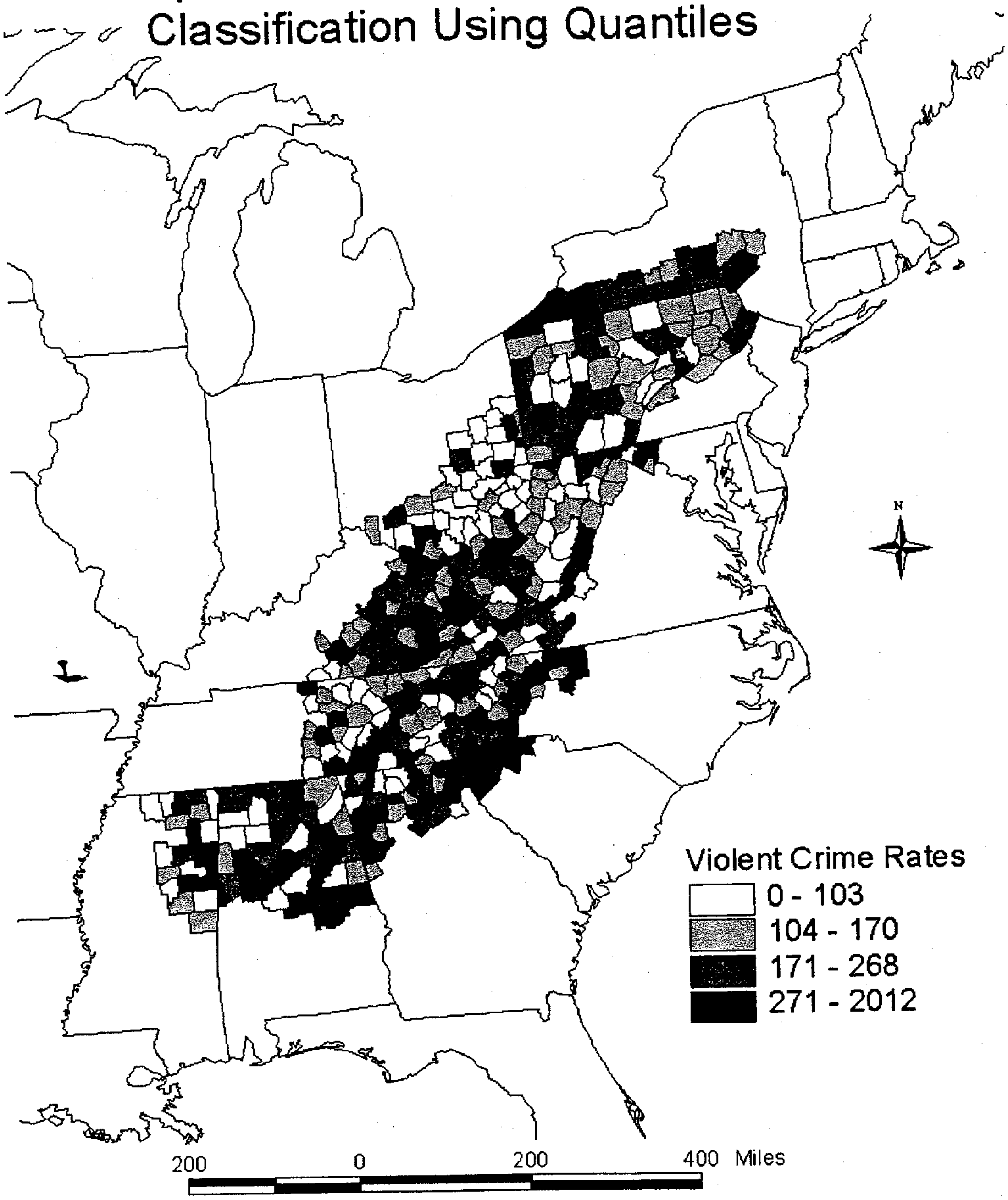


Map 4.2
Spatial Distribution of Property Crime: Classification Using Natural Breaks

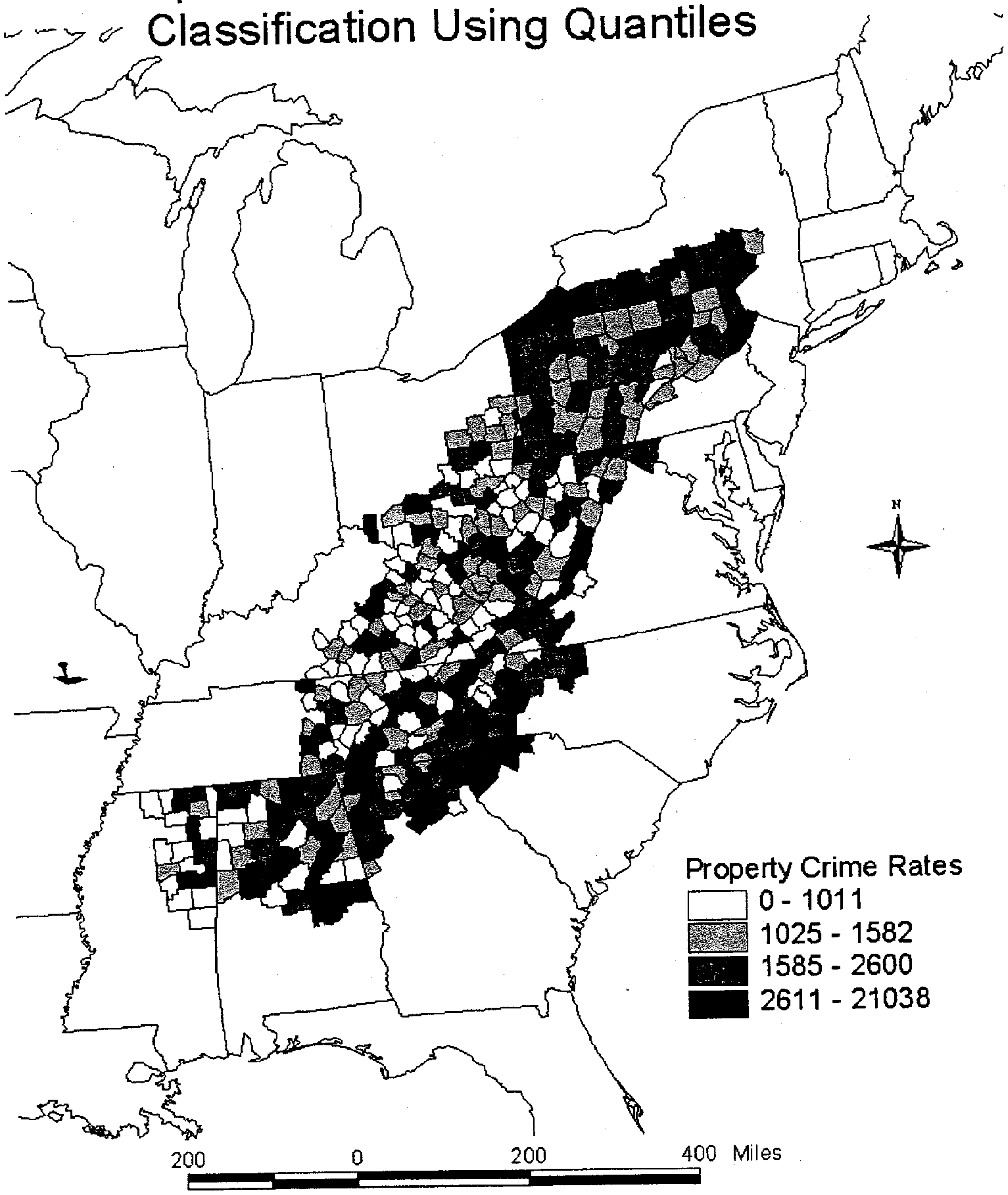


Map 4.3 shows the distribution of violent crime averaged across three years for 1994-1996 based on quantile classifications, while Map 4.4 shows the distribution of property crime for 1994-1996 using quantiles. In this case, using quantiles with four categories makes it possible to identify those counties which are in the top 25 percent and bottom 25 perccent for both violent and property crime rates. For violent crime (Map 4.3), counties with the highest crime rates are clustered along the more urbanized counties of the eastern and southern border in the South and among the more rural counties of Kentucky in the Central Subregion. For property crime (Map 4.4), counties with the highest rates are also clustered in generally the same areas of the South, but more so in the Northern Subregion than violent crime.

Map 4.3
Spatial Distribution of Violent Crime:
Classification Using Quantiles



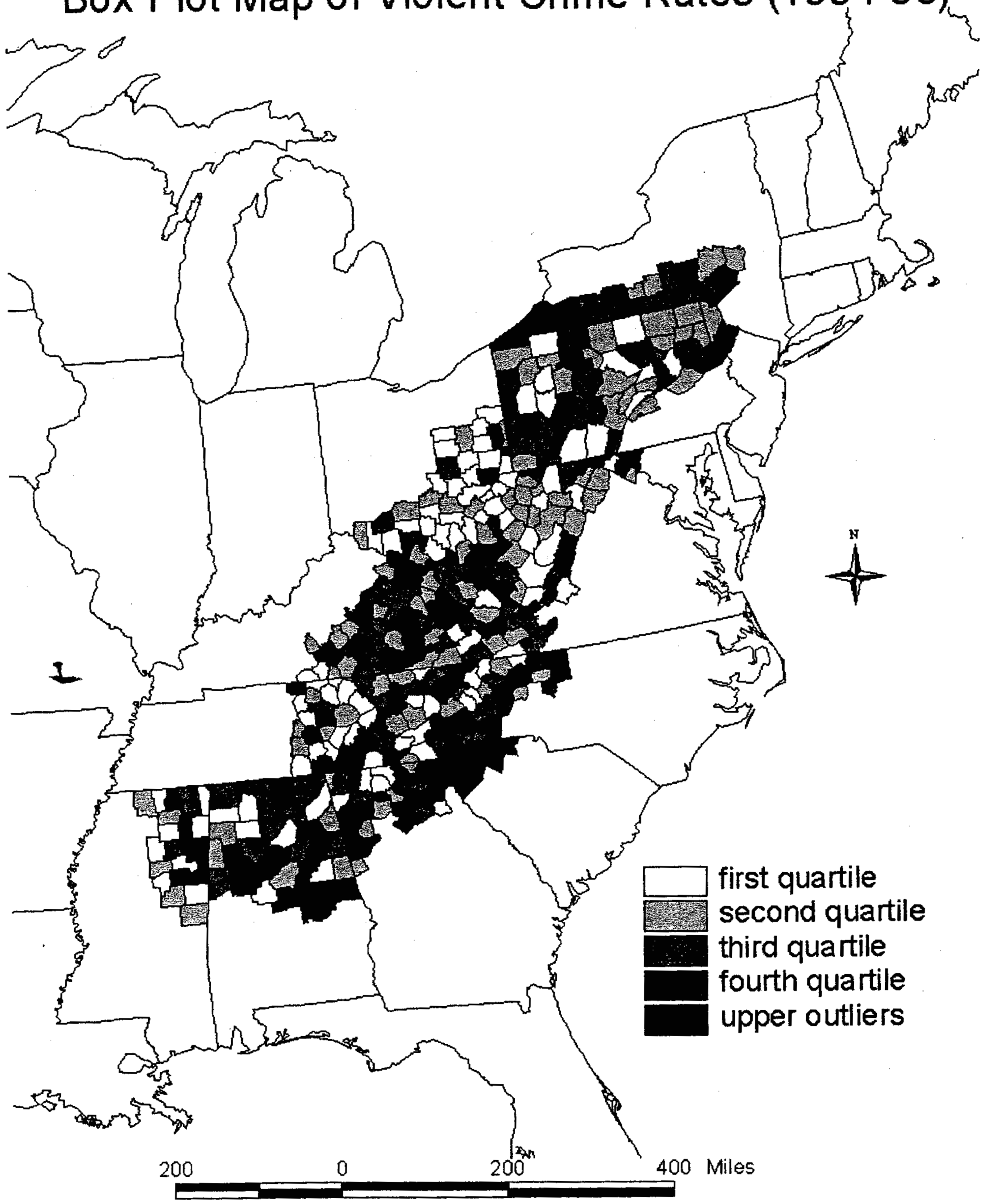
Map 4.4
Spatial Distribution of Property Crime: Classification Using Quantiles



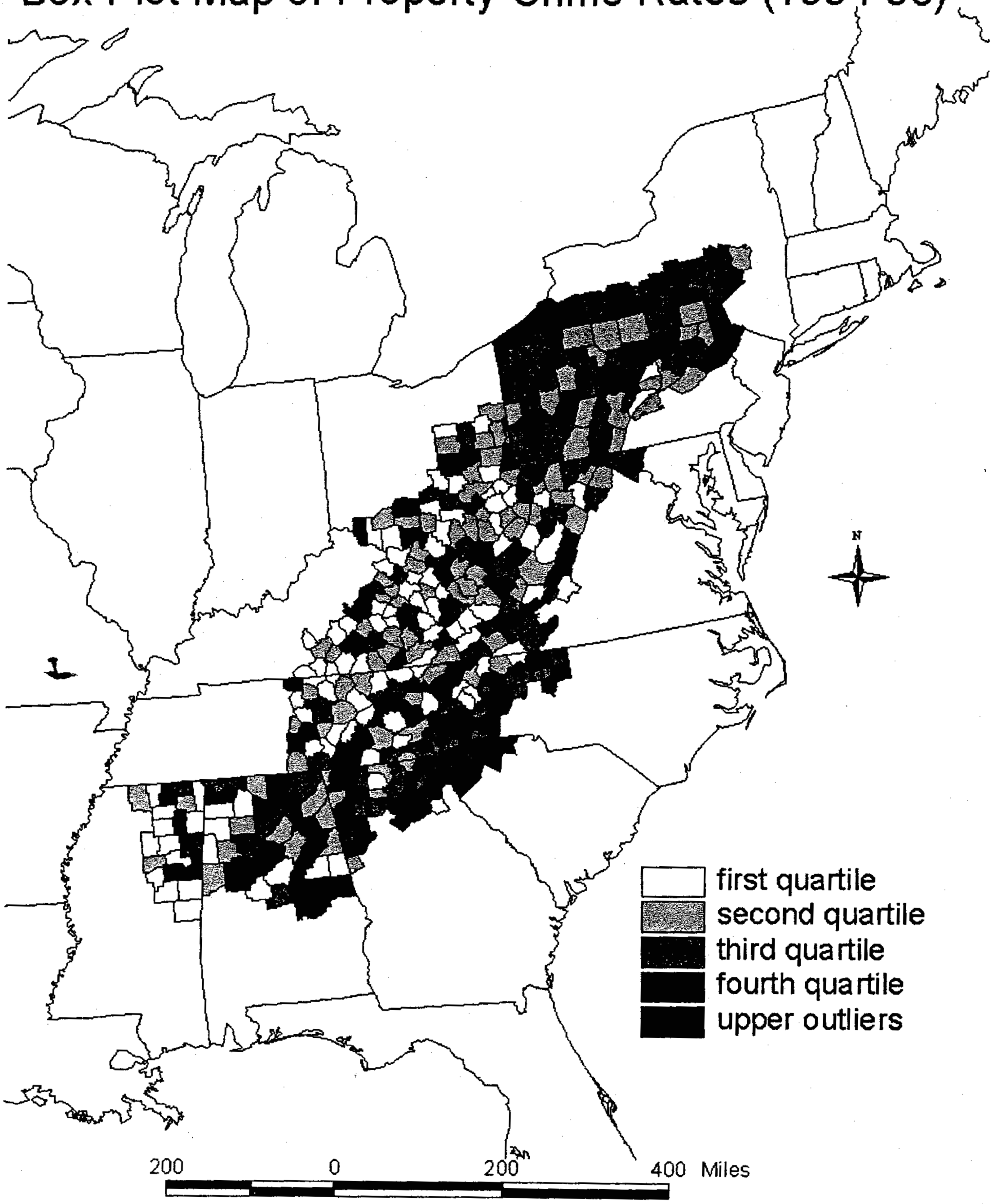
To further extend these visualization and mapping applications using choropleth maps, the SpaceStat DynESDA extension for ArcView was also utilized to produce dynamically linked histograms, boxplots, scatterplots, and Moran scatterplots. With this ArcView extension, maps and associated graphs are dynamically linked in the sense that when observations are highlighted in one view, the corresponding observations in the other views are highlighted as well. The DynESDA ArcView extension thus provides a powerful tool for interactive exploratory analyses using various types of maps and graphing capabilities in a dynamically-linked environment.

For initial exploratory purposes, box plot maps maps are generated to further describe the overall distribution of both violent and property crime and to identify outliers. A box plot map is essentially a quartile map in which outliers are highlighted. In order to be considered an outlier, the county's crime rate must fall above the upper boundary of the interquartile range by an amount that is at least one and one-half times the value of the interquartile range. Map 4.5 shows a box plot map for violent crime averaged across three years for 1994-1996, while Map 4.6 depicts a box plot map for property crime averaged across the years 1994-1996. Both the descriptive statistics generated by SpaceStat and the box plot maps identify 26 counties as upper outliers for violent crime (Map 4.5) and 11 counties as upper outliers for property crime (Map 4.6). The pattern confirms what was revealed by the choropleth maps, with clustering of high violent crime rates in the South and Central Subregions and clustering of high property crime rates in the South and North Subregions.

Map 4.5
Box Plot Map of Violent Crime Rates (1994-96)



Map 4.6
Box Plot Map of Property Crime Rates (1994-96)



ESDA USING MEASURES OF SPATIAL AUTOCORRELATION

For more rigorous analyses of spatial patterns, SpaceStat provides tools for constructing spatial weights and tests for the presence of global and local spatial autocorrelation. In using a global measure of spatial autocorrelation, the overall pattern of spatial dependence or clustering in the data is summarized with a single indicator such as Moran's I. As a global measure of spatial autocorrelation, Moran's I is positive when values for locations in spatial proximity tend to be more similar than what is normally expected based on randomness, negative when they tend to be more dissimilar than what is normally expected, and approximately zero when the attribute values are randomly spread over space.

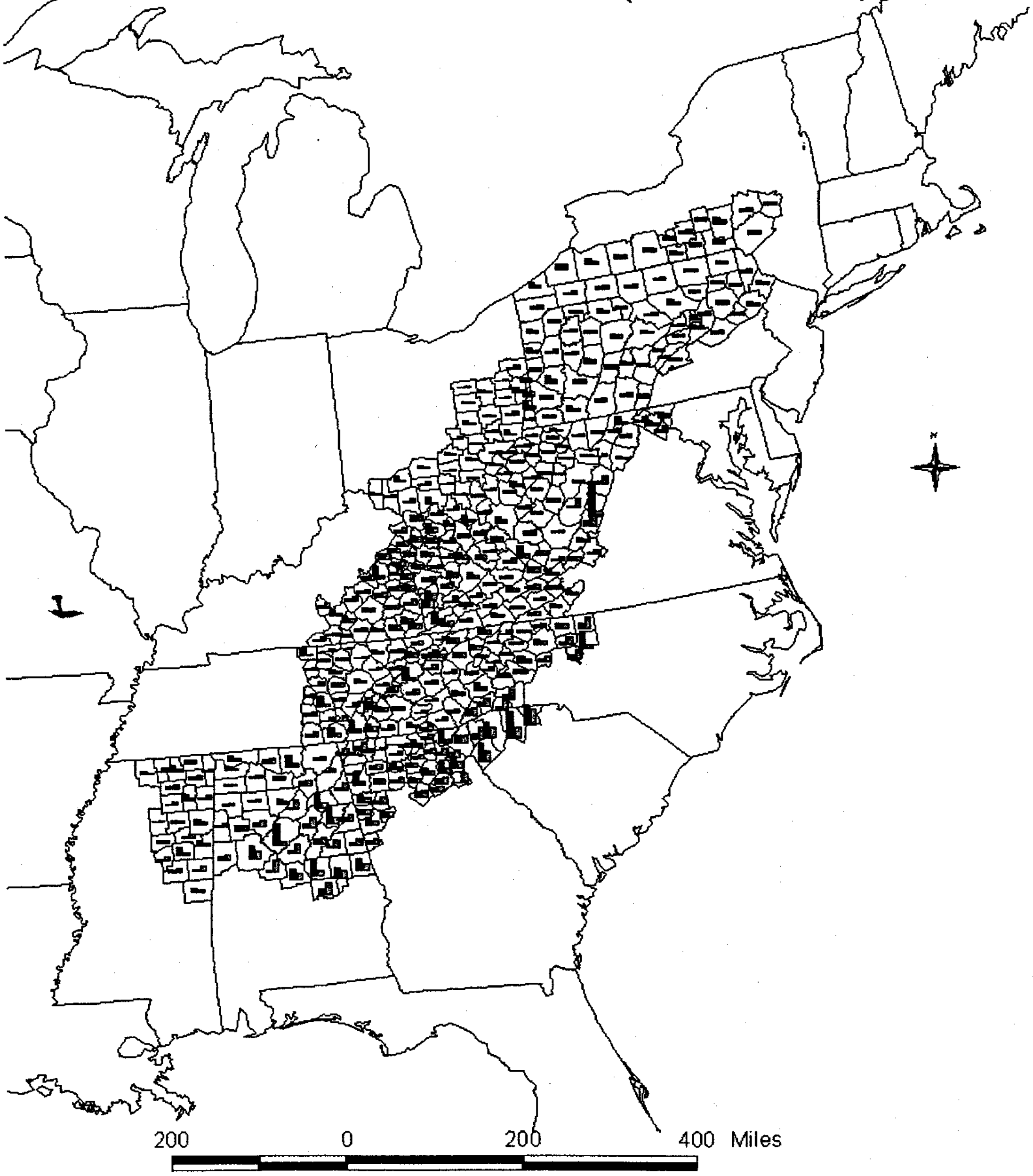
In order to calculate the Moran's I indicator of spatial autocorrelation, a spatial weights matrix must first be constructed. Spatial weights can be defined either by contiguity (where neighbors are identified according to boundary relationships, in which 1 = adjacent and 0 = nonadjacent) or by distance (where neighbors are identified according to a distance-based metric around centroid locations which decreases with distance between locations). In the analyses presented here, spatial weights are calculated based on contiguity, in which neighbors are defined as sharing a common border.

Once the spatial weights matrix has been created, a spatial lag bar chart map can be used to visually assess the presence of spatial outliers and spatial clusters. This is accomplished by first constructing a spatial lag measure for each county consisting of the spatially weighted average of the crime rates for all immediately surrounding counties. The results can then be imported into ArcView using the SpaceStat extension. Map 4.7

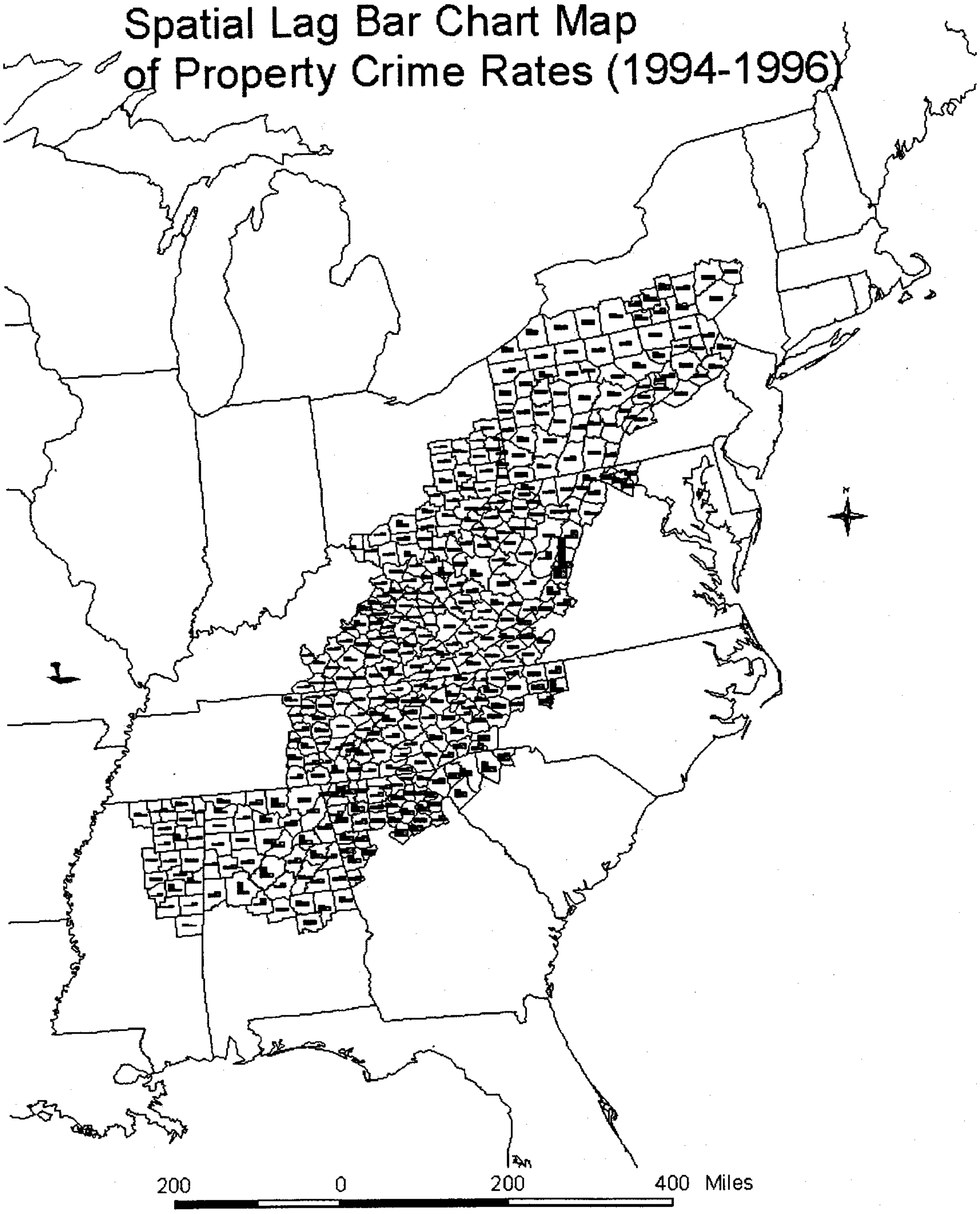
shows a spatial lag bar chart map for violent crime averaged across three years for 1994-1996, while Map 4.8 depicts a spatial lag bar chart map for property crime averaged across the three year period 1994-1996. The crime rates for each county are represented by the bar with darker shading while the corresponding spatial lag for each county is represented by the bar with lighter shading. Similar heights for the bars indicate positive spatial autocorrelation, or clustering of like values (either low or high). Contrasting heights for the bars indicate negative spatial autocorrelation, or the presence of spatial outliers. Locations of negative spatial association may indicate areas of high crime (darker shaded bars) surrounded by low crime neighbors (lighter shaded bars), or low crime surrounded by high crime neighbors.

The spatial lag bar chart map for violent crime (Map 4.7) shows several outliers with high violent crime rates surrounded by counties with lower rates along the eastern and southern border of the Region. By contrast, the spatial lag bar chart map for property crime (Map 4.8) shows very few outliers. Both maps indicate a high degree of positive spatial autocorrelation for both violent crime and property crime, with noticeable clustering of similar levels of crime in counties and their surrounding neighbors.

Map 4.7
Spatial Lag Bar Chart Map of Violent Crime Rates (1994-1996)



Map 4.8
Spatial Lag Bar Chart Map
of Property Crime Rates (1994-1996)

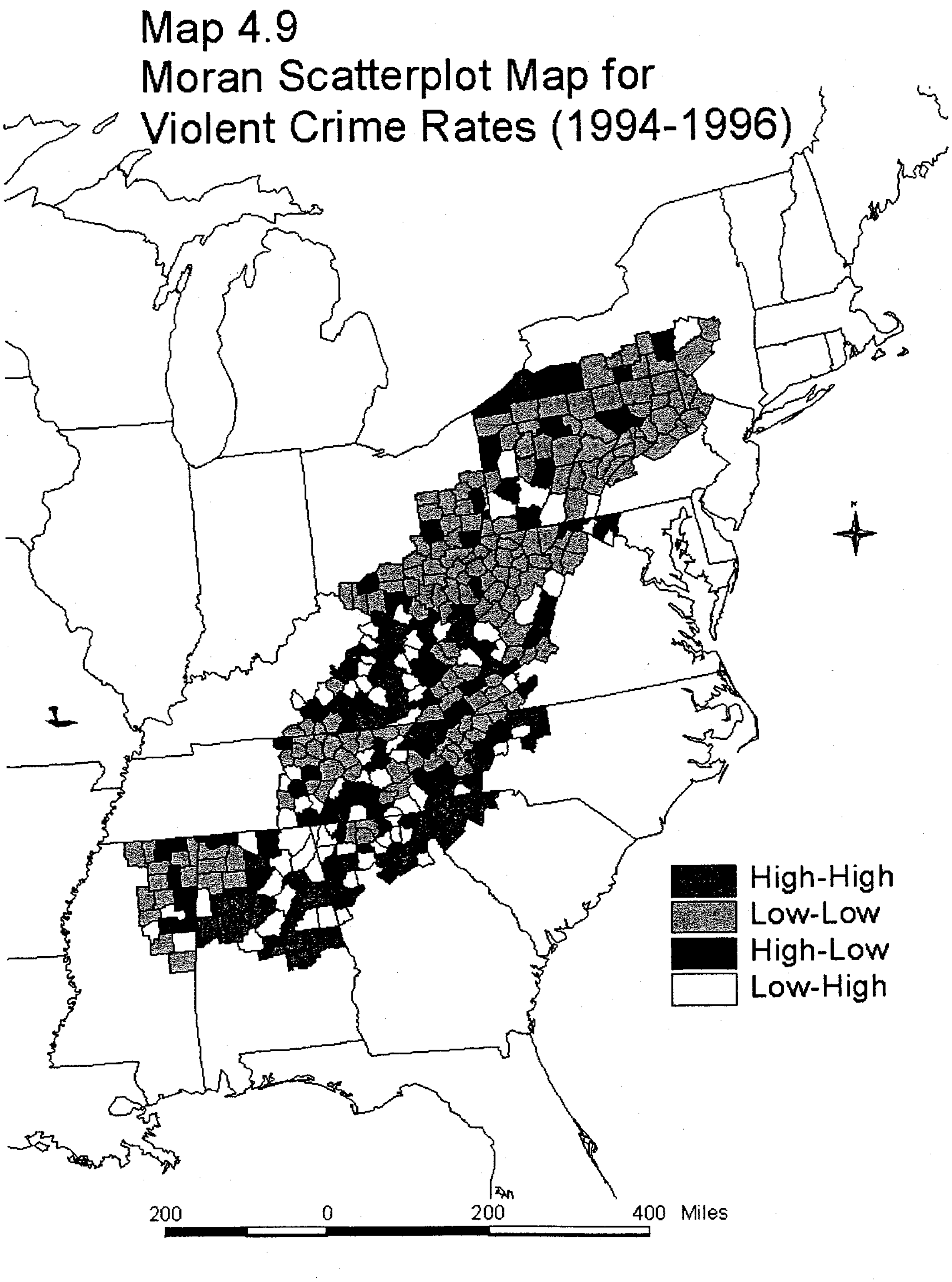


Global indicators of spatial autocorrelation and spatial correlograms are next used to assess the presence and range of spatial association. The global Moran's I for violent crime rates averaged across a three year period for the years 1994-1996 is 0.18 and is highly significant (z-value = 5.92, prob < 0.001), indicating positive spatial autocorrelation across counties. Similarly, the global Moran's I for property crime rates averaged for the three year period of 1994-1996 is 0.16 and is highly significant as well (z-value = 5.52, prob < 0.001).

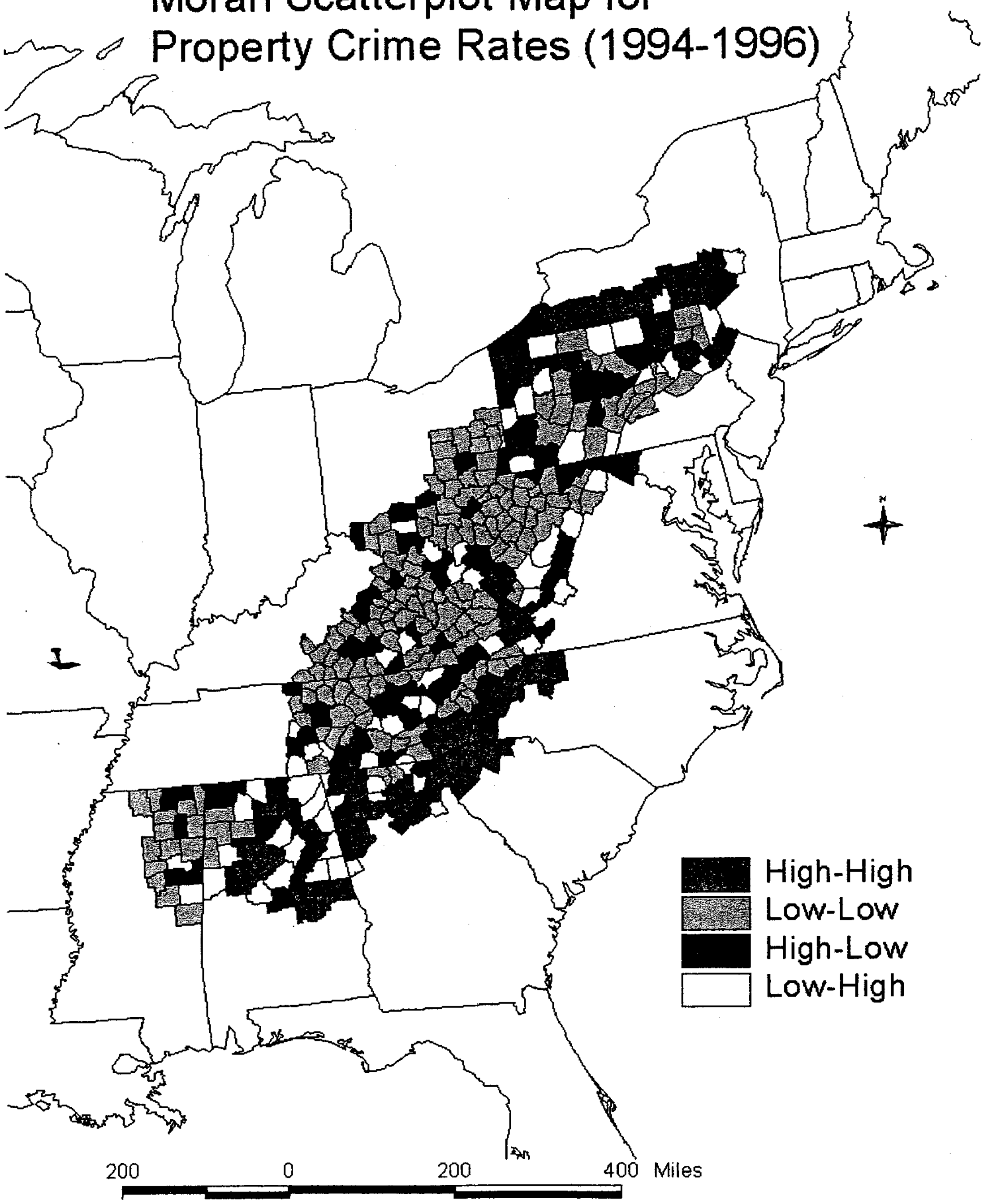
Global measures of spatial autocorrelation can also be decomposed and visualized using the SpaceStat extension with ArcView by means of a Moran Scatterplot map, in which the global Moran's I is decomposed into four categories, corresponding with four quadrants in a Moran scatterplot. These four quadrants identify four types of spatial association between a location and its neighbors. Two of these categories imply positive spatial association: (Quadrant I) where a location with an above-average value is surrounded by neighbors whose values are also above average (high-high), or (Quadrant II) where a location with a below-average value is surrounded by neighbors whose values are also below average (low-low). The other two categories imply negative spatial association: (Quadrant III) where a location with an above-average value is surrounded by neighbors with below average values (high-low), or (Quadrant IV) where a location with a below-average value is surrounded by neighbors with above average values (low-high). The mapping of these quadrants on a Moran scatterplot map thus provides a visual representation of significant spatial clustering and the location of influential spatial outliers.

Map 4.9 is a Moran scatterplot map for violent crime averaged over three years for the period 1994-1996, while Map 4.10 is a Moran scatterplot map for property crime averaged for the three years 1994-1996. High values of violent crime are primarily clustered along the southeastern border and throughout the interior of the Central and Southern Subregions. High values of property crime tend to be clustered primarily along the southeastern and northern boundaries of the Region, with several outlying counties with high rates of property crime scattered along the interior. Both maps indicate a high degree of spatial autocorrelation for both high and low values of violent and property crime.

Spatial correlograms are also used to model the spatial-temporal patterns of crime across different levels of contiguity. Moran's I coefficients (standardized as z-values) are graphed at increasing levels of contiguity to reveal the extent to which spatial autocorrelation varies and changes according to distance. Moran's I are positive when neighboring locations are similar in levels of crime, negative when they are dissimilar, and approximately zero when crime rates fluctuate randomly and independently across locations. Correlograms are analyzed by looking at their shape and the relative change in significant autocorrealtion coeficients across levels of contiguity. Significant patterns can be identified by looking for departures from a normal linear gradient, often represented by peaks or valleys in the graph. When correlograms are plotted over time, the appearance of peaks represent significant clusters of values which may be spreading across various levels of distance or contiguity. By plotting correlograms separately for each Subregion, it also becomes possible to identify whether there is evidence of spatial heterogeneity in the data.


Map 4.9
Moran Scatterplot Map for
Violent Crime Rates (1994-1996)
High-High
Low-Low
High-Low
Low-High
200
0
200
400 Miles

Map 4.10
Moran Scatterplot Map for
Property Crime Rates (1994-1996)



The spatial correlograms in Figures 4.2 through 4.7 model spatial autocorrelation patterns up to six levels of contiguity for violent crime and property crime in each of the three Appalachian Subregions. The correlograms vary substantially across Subregions indicating the presence of spatial heterogeneity and variations in the spatial-temporal processes of clustering and spread operating in each of the three Subregions.

In the Northern Subregion, there is a steady decline in the spatial autocorrelation of violent crime over time, with autocorrelation patterns approaching nonsignificance for all levels of contiguity by 1995 (Figure 4.3). While property crime continues to exhibit significant positive spatial autocorrelation up to the third level of contiguity, there is a visible decline in the strength of this relationship over time (Figure 4.4).

In the Central Subregion, the spatial autocorrelation measures for violent crime increase across the first three levels of contiguity between 1980 and 1990, peaking at the third level of contiguity (Figure 4.5). This may point to a diffusion process operating between 1980 and 1990. Between 1990 and 1995, however, the spatial autocorrelation of violent crime in Central Appalachia slips into nonsignificance. Property crime in the Central Subregion, on the other hand, exhibits no significant spatial autorrelation patterns for any of the three time periods (Figure 4.6).

In the Southern Subregion, the spatial autocorrelation of violent crime increases slightly between the first two levels of contiguity over time (Figure 4.7). The spatial autocorrelation of property crime, while stronger than that of violent crime, exhibits a similar pattern of increase between the first two levels of contiguity over time as well (Figure 4.8).

Figure 4.3. Spatial Correlograms of Violent Crime for the Northern Subregion

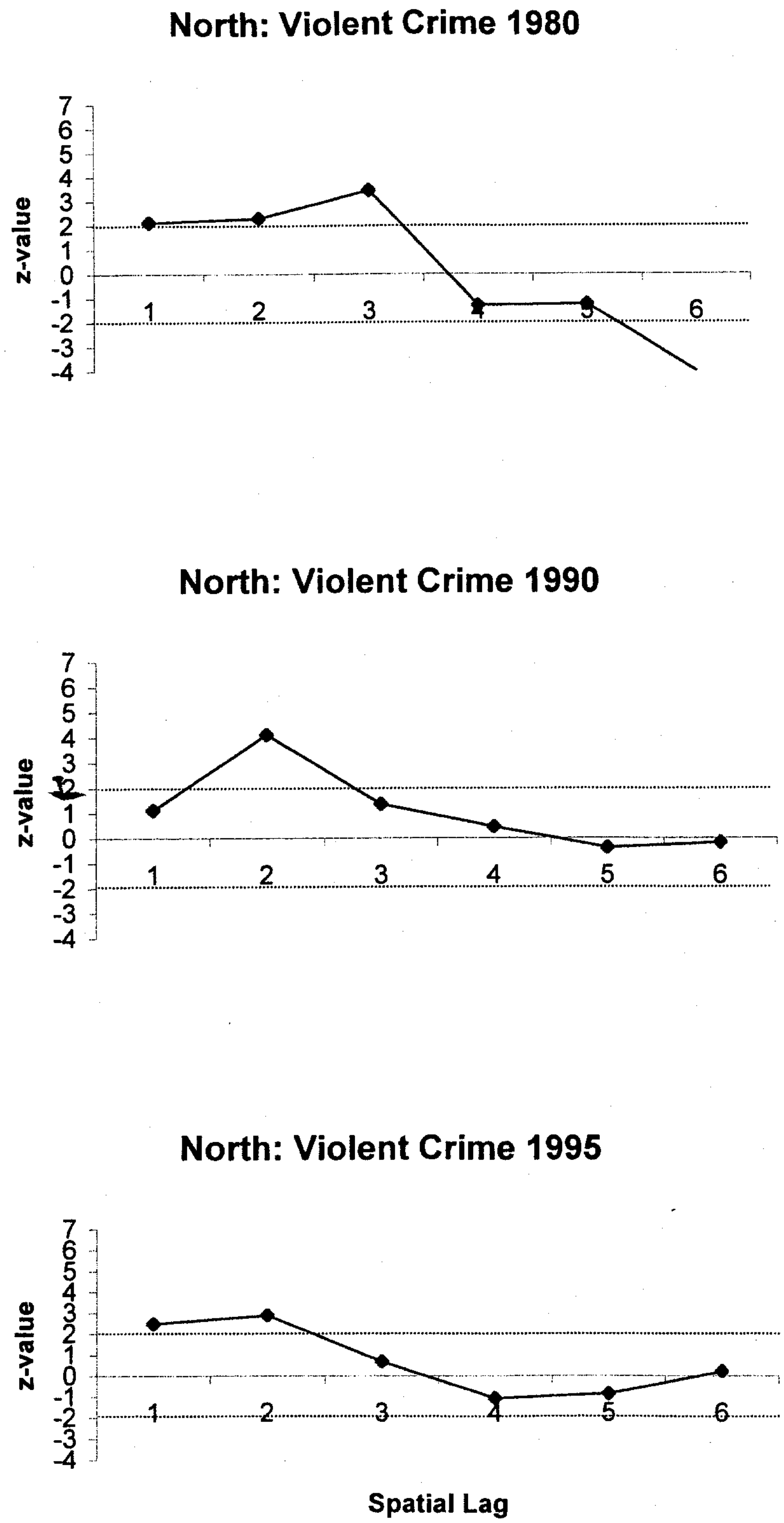
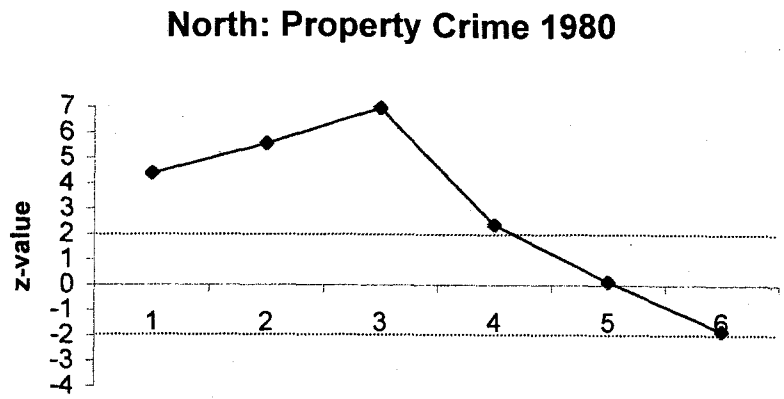
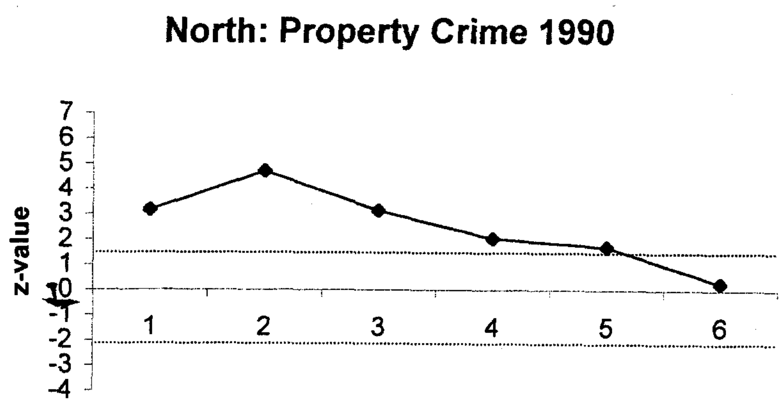


Figure 4.4. Spatial Correlograms of Property Crime for the Northern Subregion





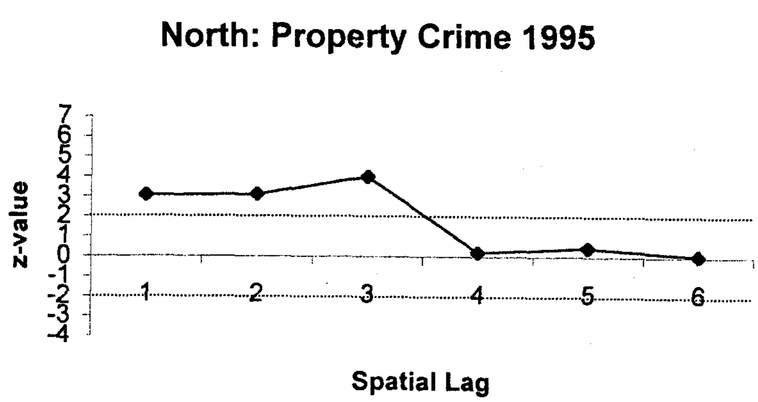


Figure 4.5. Spatial Correlograms of Violent Crime for the Central Subregion

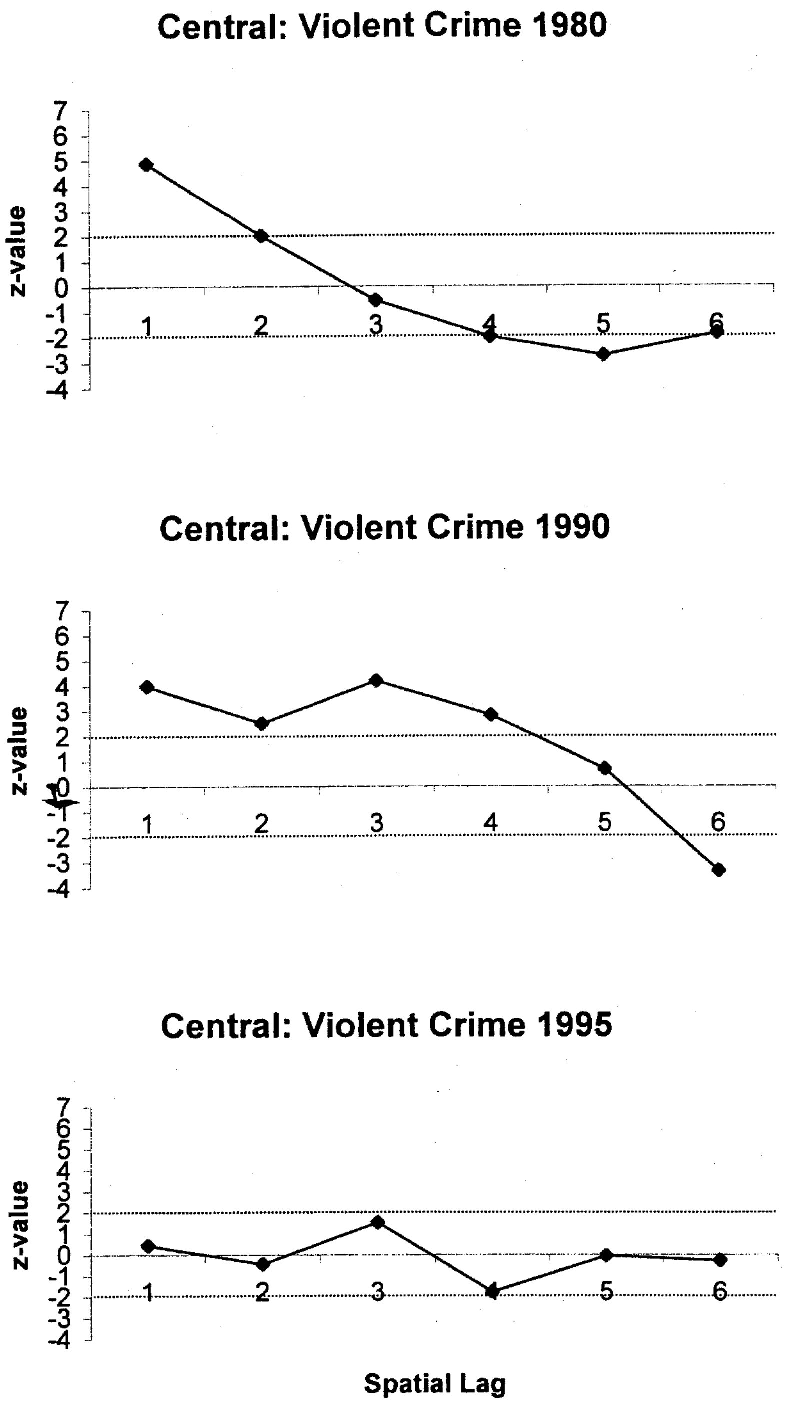


Figure 4.6. Spatial Correlograms of Property Crime for the Central Subregion

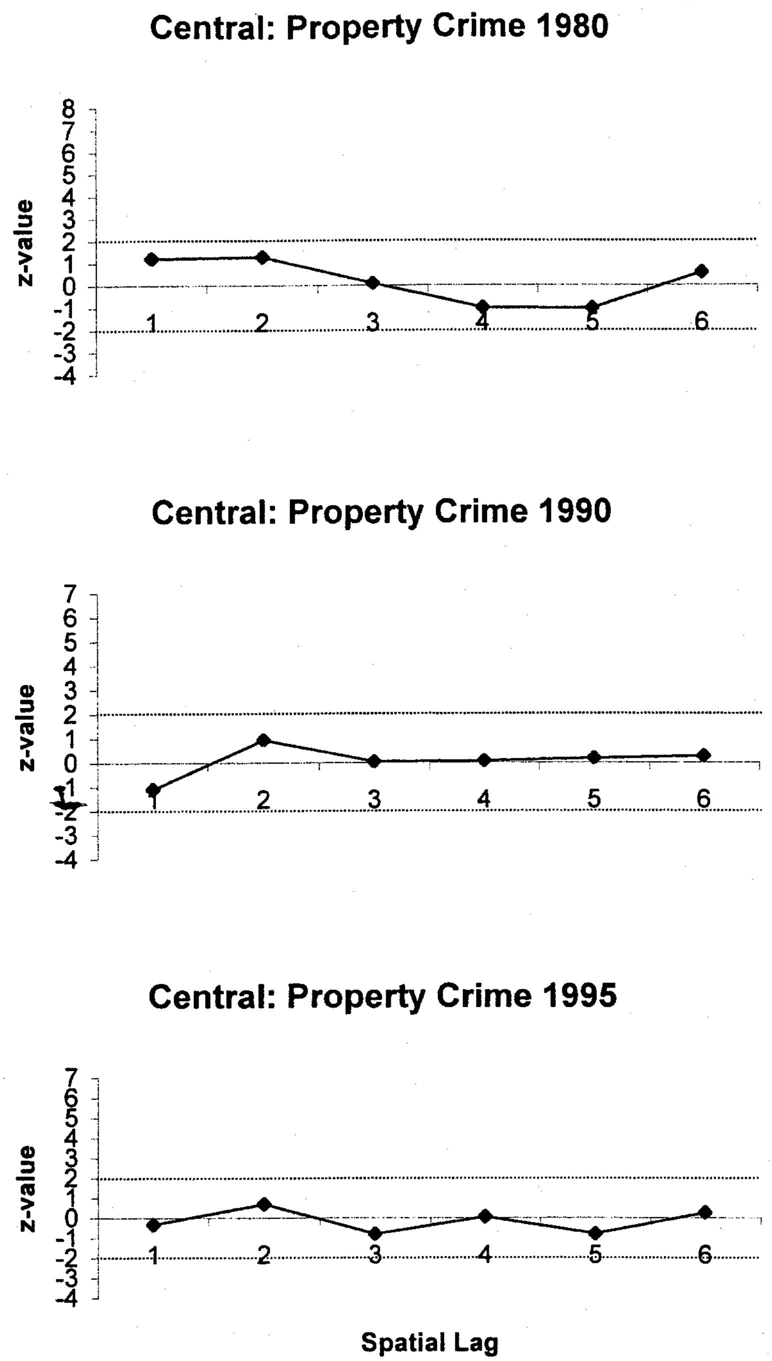
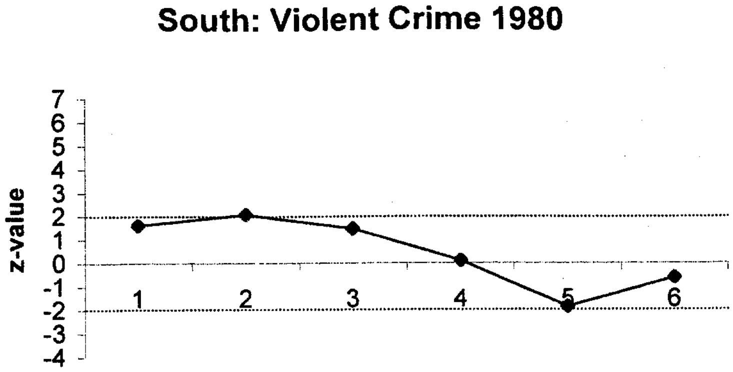
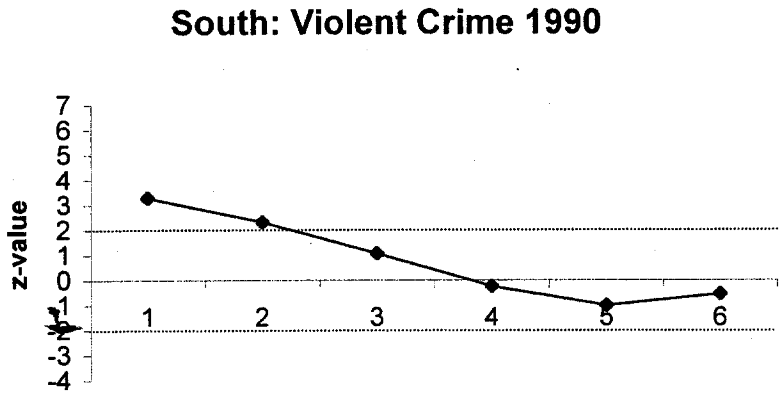


Figure 4.7. Spatial Correlograms of Violent Crime for the Southern Subregion





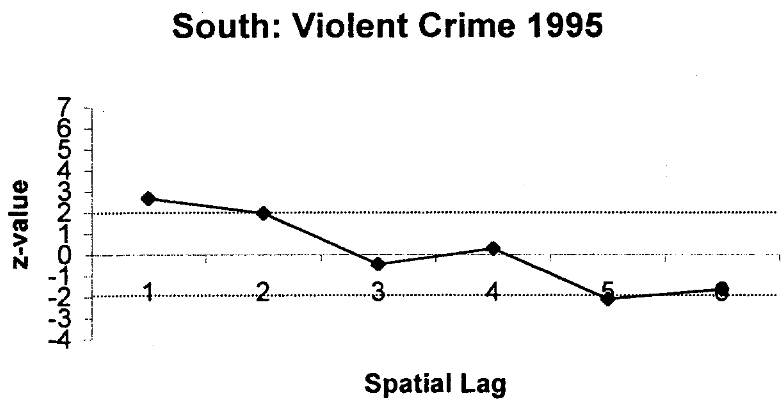
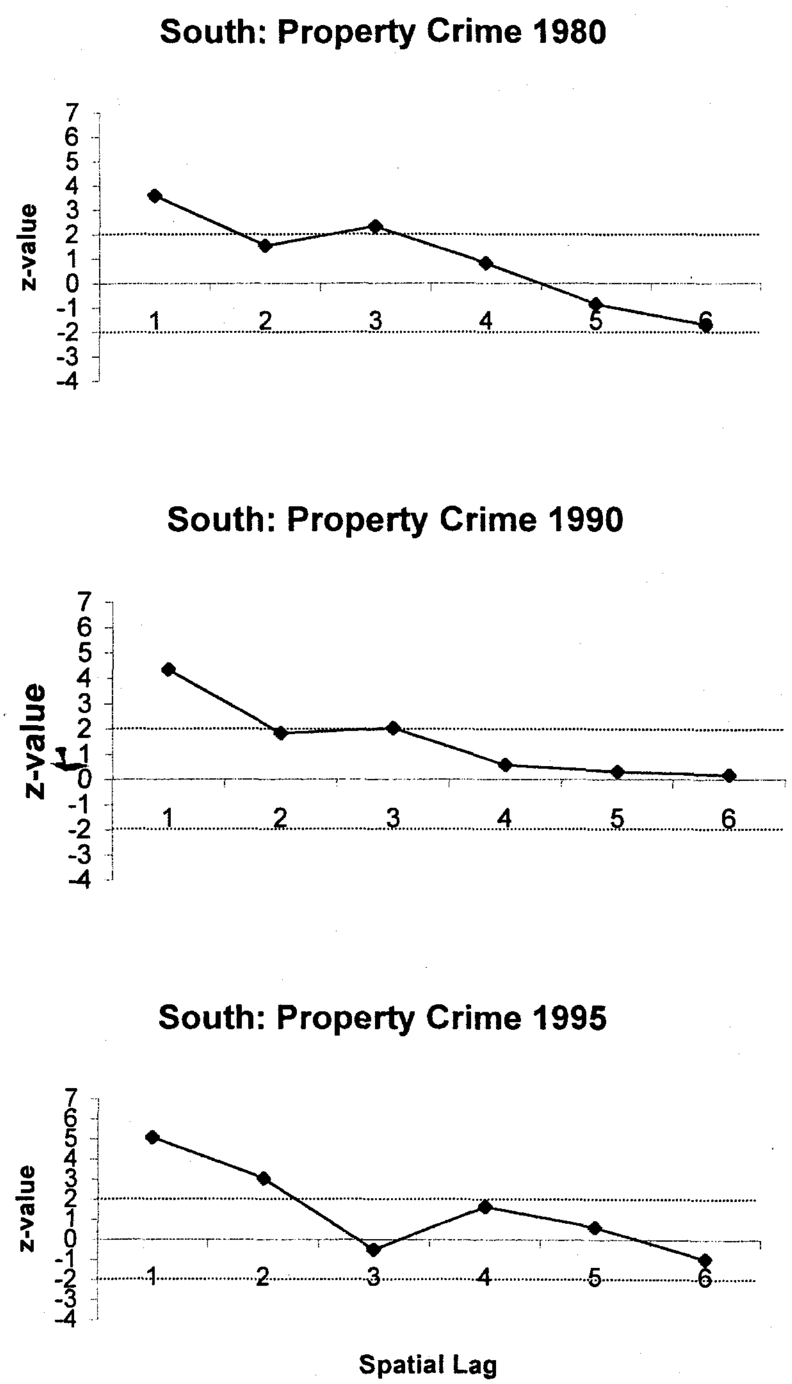


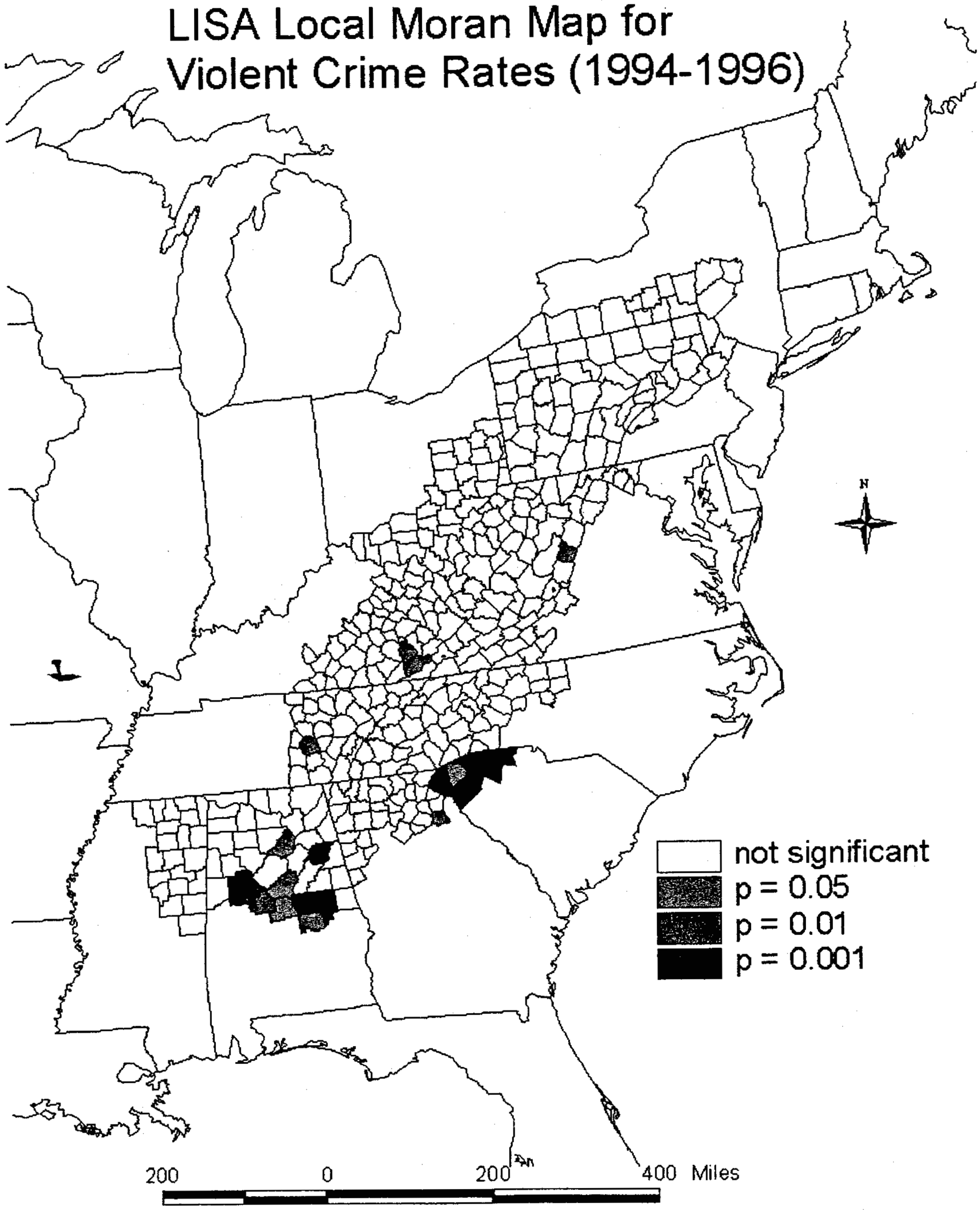
Figure 4.8. Spatial Correlograms of Property Crime for the Southern Subregion



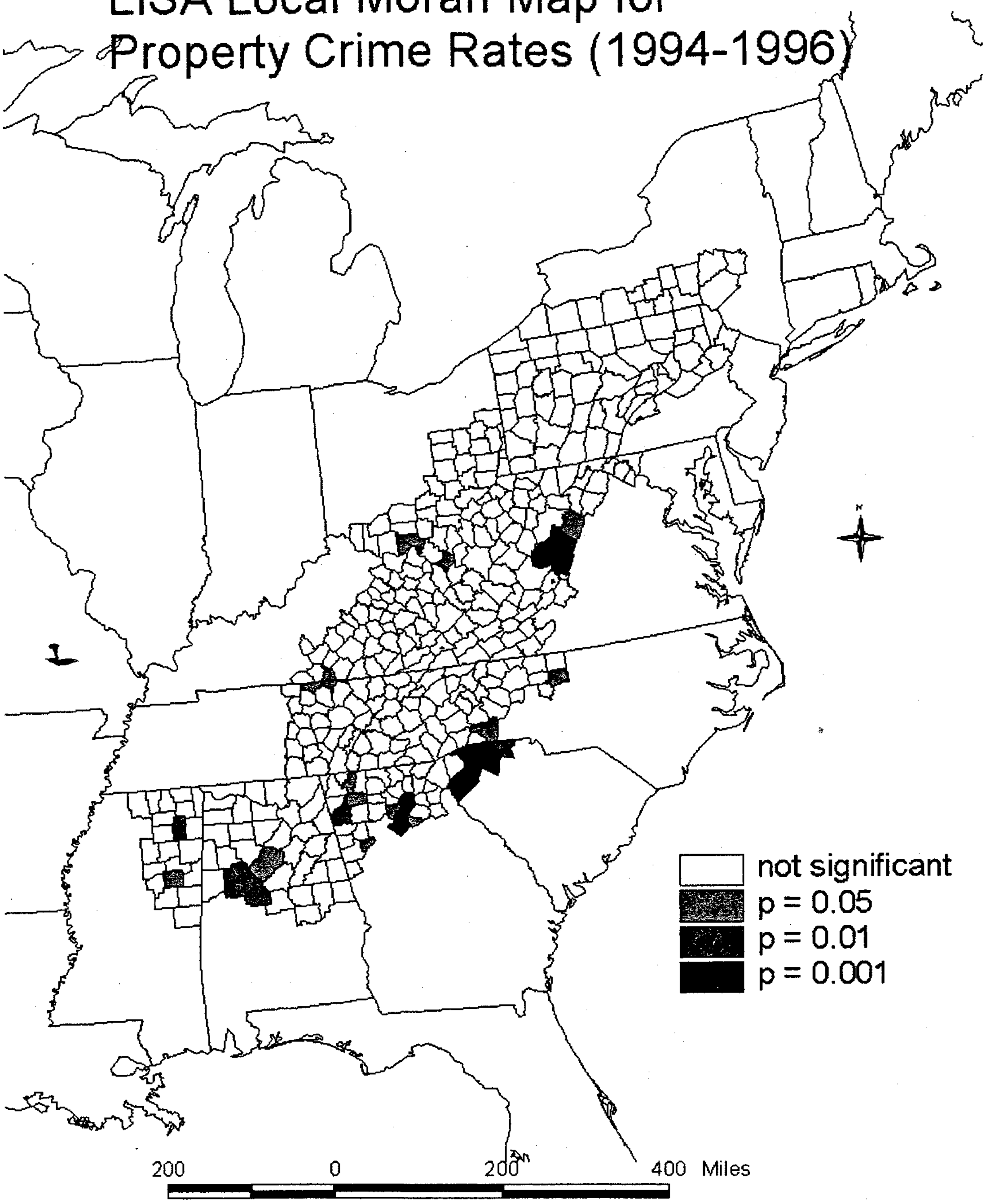
With larger data sets, the assessment of global spatial autocorrelation needs to be supplemented by local measures of spatial dependence as well. According to Anselin (1995a), local indicators of spatial autocorrelation achieve two objectives: (1) They can be used to identify significant patterns of spatial association around individual locations, such as hot spots or spatial outliers; and (2) they can be used to assess the extent to which the global pattern of spatial association is spread uniformly throughout the data or whether there are significant types of locations affecting the computation of Moran's I.

Measures of local spatial autocorrelation can be visualized by means of LISA local Moran maps. Map 4.11 is a Local Moran map for violent crime averaged across three years for the period 1994-1996, while Map 4.12 is a Local Moran map for property crime averaged for the three years 1994-1996. The local Moran map for violent crime (Map 4.11) shows that a significant clustering pattern is present in two locations, both located in the South. The LISA local Moran map can also be dynamically linked with a Local Moran scatterplot using the SpaceStat DynESDA extension in ArcView. In this case, all the counties highlighted on the map with significant LISA statistics are located in the first quadrant of the scatterplot where locations with above-average values are surrounded by neighboring counties whose values are also above average (high-high). The local Moran map for property crime (Map 4.12) echoes the patterns found on the local Moran map for violent crime with the addition of a third cluster further north near the Virginia-West Virginia border. As was the case with the LISA statistics for violent crime, these local clusters of property crime are located in the first quadrant of the Moran scatterplot where locations with above-average values are surrounded by neighbors whose property crime rates are also above average.

Map 4.11
LISA Local Moran Map for Violent Crime Rates (1994-1996)



Map 4.12
LISA Local Moran Map for
Property Crime Rates (1994-1996)



SUMMARY

At least two summary findings emerge from this application of ESDA to county-level rates of violent and property crime in Appalachia. First, the strong spatial autocorrelation patterns of both violent and property crime indicate clearly that these spatial patterns are not random. In some locations, the spatial autocorrelation of crime remains significant even across several levels of contiguity. Spatially significant clusters of both violent and property crime are also observed in many of the mapping applications. This robust and significant relationship across several "high crime" clusters thus provides empirical support for the hypothesis that the spatial patterns of violent and property crime are positively related to the unique characteristics and spatial proximity of particular locations.

Second, while significant spatial autocorrelation trends are evident in several "high profile" locations throughout the Region, substantial Subregional variations in the spatial-temporal patterns of violent and property crime exist as well. This indicates that perhaps different spatial processes may be operating in different Subregional locations. Thus, the data also provide empirical support for the hypothesis that spatial and temporal patterns of violent and property crime vary by Subregional location.

In the next chapter, these hypotheses will be explored further by applying Confirmatory Spatial Data Analysis (CSDA) procedures to test for the presence of spatial heterogeneity and spatial autocorrelation through formal modeling in a spatial regression framework. Specifically, both bivariate and multivariate spatial regression modeling procedures will be utilized to evaluate the effects of each of the following demographic and socioeconomic covariates on the rate of violent crime and property crime in

Appalachia for 1980 and 1990: residential mobility, percent Black, percent of the population ages 15 to 29, High School drop out rates, percent divorced, percent of households that are female headed, percent unemployed, and percent of families below poverty. For each bivariate and multivariate model, comparisons will also be made across Subregions and between metropolitan and nonmetropolitan locations.

CHAPTER FIVE: CONFIRMATORY SPATIAL DATA ANALYSIS: SPATIAL REGRESSION MODELS OF CRIME

INTRODUCTION

Spatial regression models are powerful tools for analyzing the relationships between spatially-referenced variables. Generally, the relationships between such variables are influenced by their relative spatial distributions. While classical regression methods assume that data are randomly sampled from a homogeneous data-generating process, spatial data often violate critical aspects of this assumption. First, spatially-referenced data are often spatially clustered, and therefore are not randomly scattered in space. Second, structural instability may occur when regression coefficients vary according to regional location or spatial scale.

Thus, with aggregate data, spatial effects are characterized by two components: *spatial dependence* and *spatial heterogeneity.* The first type of spatial effect, spatial dependence, exists whenever there is value similarity between observations in proximate locations. Anselin (1988) distinguishes between spatial dependence as a *substantive* effect and spatial dependence as a *nuisance* effect. In the case of substantive spatial dependence, values of the variable of interest are systematically related to values in adjacent locations and therefore contribute substantial spatial effects to the model. Nuisance effects, on the other hand, result from spatial dependence between ignored variables in the model and are reflected in the error terms. Nuisance effects reduce model efficiency and can be corrected by including a spatial error specification, while more serious substantive effects generate model bias and are corrected by including a spatial lag term as an explanatory variable in the model. The second type of spatial effect, spatial heterogeneity, exists whenever there are significant regional differences or identifiable groupings based on spatial scale. Spatial heterogeneity thus represents a more general problem of structural instability and can therefore produce significantly different outcomes in the form of different response functions or systematically varying parameters.

In spatial regression analysis, two methodological concerns are central to the specification of appropriate models: (1) testing for spatial dependence by means of appropriate diagnostics for spatial lag and spatial error effects, and (2) implementing alternative estimation techniques when structural instability and spatial heterogeneity occur in the data. In the present study, a method of spatial modeling will be employed whereby spatial effects can be systematically included and compared across models (cf. Florax and Folmer 1992). A standard OLS regression model is first estimated and forms the starting point for evaluating the presence of significant spatial effects. If regression diagnostics for the basic OLS model indicate that spatial effects are indeed significant, spatial parameters are then estimated based on diagnostic outcomes.

At least three modeling possibilities exist for addressing significant spatial dependence: lag, error, and spatial predictor models. If substantive spatial dependence is identified as a significant problem, a spatial lag model can be estimated which includes a lagged dependent variable as an additional explanatory term in the model. If spatial dependence is primarily limited to the error term, a spatial error model can be estimated which includes a coefficient for the autoregressive error term. If the omission of spatially lagged independent variables is an important cause for spatially correlated residuals, a spatial predictor model can then be estimated which includes spatial lag terms for the explanatory variables. In the present study, models for spatial heterogeneity will be implemented by jointly estimating coefficients for metropolitan and nonmetropolitan locations and for each of the three Subregional locations: North, Central, and South Appalachia. The stability of regression coefficients across metro-nonmetro and Subregional locations will then be assessed using Chow tests within a seemingly unrelated regression framework.

MODEL VALIDATION PROCEDURES

The point of departure for the specification of a spatial model for crime is the standard linear regression model:

$$y = X\beta + \varepsilon \tag{5.1}$$

where y is a vector of observations on the dependent variable, X is a matrix of observations on the explanatory variable(s), and ε is an error term.

Spatial effects, in the form of spatial dependence and spatial heterogeneity, as well as combinations of the two, can be incorporated based on diagnostic tests and goodness-of-fit criteria. The formal expressions for the models used in the present study are outlined in Table 5.1.

Table 5.1. Formal Expressions of Spatial Dependence and Spatial Heterogeneity	
Spatial Dependence	
Spatial Lag Model: $y = \rho Wy + X\beta + \varepsilon$	(5.2)
Spatial Error Model: $y = X\beta + \varepsilon$, where: $\varepsilon = \lambda W\varepsilon + \mu$	(5.3)
Spatial Predictor Model: $y = X\beta + WX\beta + \varepsilon$	(5.4)
Spatial Heterogeneity	
Spatial Structural Instability: $y_i = X_i\beta_i + \varepsilon_i$, for which $z_i = 1$ $y_j = X_j\beta_j + \varepsilon_j$, for which $z_j = 2$	(5.5)

Notation: W, spatial weight matrix; ρ, λ, spatial autoregressive coefficients; ε, μ, error terms; z_i, z_j regional location and/or spatial scale

Three forms of spatial dependence are considered , which are listed as (5.2)-(5.4) in Table 5.1: (1) a spatial lag model (5.2), which includes a spatially lagged dependent variable; (2) a spatial error model (5.3), which includes a spatial autoregressive error term; and (3) a spatial predictor model (5.4), which includes spatially lagged explanatory variables. In addition, a model for spatial structural instability (5.5) is considered as well, in which the model coefficients can differ according to regional location or spatial scale.

With the exception of model 5.4, standard Ordinary Least Squares (OLS) estimation is inappropriate and techniques based on the maximum likelihood principle have therefore been applied (cf. Cliff and Ord 1981; Anselin 1988). In a standard regression context, tests for spatial dependence are typically based on the application of a Moran statistic to the residuals (cf. Cliff and Ord 1981). Alternatively, in the context of maximum likelihood estimation, asymptotic Wald, Likelihood Ratio (LR) or Lagrange Multiplier (LM) tests can be applied for diagnostics on various combinations of spatial effects (cf. Anselin 1988).

In order to implement this method of spatial modeling, the alternative hypothesis of spatial dependence needs to be expressed in the form of an omitted variable problem. Thus, for a test against the presence of a spatially lagged dependent variable, this general framework consists of testing the null hypothesis $\rho = 0$ in the following setup:

H_0: $y = X\beta + \varepsilon$
H_1: $y = \rho Wy + X\beta + \varepsilon$

where ρ is the spatial autoregressive coefficient for the dependent variable. To test this hypothesis, an asymptotic t-test on the spatial autocorrelation coefficient ρ will be applied, in addition to a Lagrange Multiplier test on remaining spatial error autocorrelation.

The test for spatial error autocorrelation consists of testing for spatial dependence in the error term λ, with the null hypothesis $\lambda = 0$. This can be specified as:

H_0: $y = X\beta + \varepsilon$
H_1: $y = X\beta + \varepsilon$, where: $\varepsilon = \lambda W\varepsilon + \mu$

and where λ is the spatial autoregressive function in the error term. Similar to the approach taken for the spatial lag model, an asymptotic t-test will be used to test for the significance of the spatial error autoregressive coefficient. In addition, the validity of spatial lag versus spatial error autocorrelation is assessed in a more rigorous fashion by means of a Wald test for the Common Factor hypothesis (Anselin 1988).

Finally, a spatial Chow test for structural instability in the presence of spatial autocorrelation will be used to test for spatial heterogeneity (Anselin 1990). In this case, the stability of regression coefficients across metropolitan-nonmetropolitan and Subregional locations will be tested to determine whether there is structural instability based on regional location and spatial scale. This amounts to a test for spatial heterogeneity of the form:

For metro-nonmetro locations:

$y_i = X_i\beta_i + \varepsilon_i$, for which $z_i = 1$ (metropolitan location)
$y_j = X_j\beta_j + \varepsilon_j$, for which $z_j = 0$ (nonmetropolitan location)

and where:

H_0: $\beta_i = \beta_j$
H_1: $\beta_i \neq \beta_j$

For Subregional locations:

$y_i = X_i\beta_i + \varepsilon_i$, for which $z_i = 1$ (Northern Subregion)
$y_j = X_j\beta_j + \varepsilon_j$, for which $z_j = 2$ (Central Subregion)
$y_k = X_k\beta_k + \varepsilon_k$, for which $z_k = 3$ (Southern Subregion)

and where:

H_0: $\beta_i = \beta_j = \beta_k$
H_1: $\beta_i \neq \beta_j \neq \beta_k$

Thus, this is a test on the null hypothesis that the coefficients are the same for metropolitan and nonmetropolitan locations and for each of the three Subregional locations.

METRO-NONMETRO BIVARIATE MODEL RESULTS FOR VIOLENT CRIME

GIS offers opportunities for enhanced spatial modeling through the use of confirmatory spatial data analysis (CSDA) procedures. According to Anselin and Getis (1992), the standard tools of CSDA consist of four broad categories of methods: (1) diagnostics for the presence of spatial dependence and spatial heterogeneity in regression analysis; (2) methods to estimate regression models that explicitly take into account spatial effects; (3) methods to estimate models that are robust to the presence of spatial effects; and (4) spatial measures of model validity.

Utilizing these standard methods of CSDA, this section presents metro-nonmetro bivariate models of violent crime which evaluate the effects of each of the following demographic and socioeconomic dimensions on the rate of violent crime at the county level in Appalachia for 1980 and 1990: residential mobility, percent Black, percent of the population ages 15 to 29, High School drop out rates, percent divorced, percent of households that are female headed, percent unemployed, and percent of families below poverty. For each bivariate model, four model combinations are generated and compared: (1) an ordinary least squares (OLS) regression model with no spatial effects; (2) a maximum likelihood model containing a spatial lag term for the dependent variable; (3) a maximum likelihood model containing a spatial autoregressive error term; and (4) an OLS regression model containing a spatial lag term for the independent variable. To test for spatial heterogeneity and structural instability, separate coefficients for metropolitan and nonmetropolitan locations are jointly estimated for each of the four models for 1980 and for 1990.

SpaceStat software (Anselin 1998) in an ArcView GIS environment was used to run the regression models. Tables 5.2 through 5.9 present results for the series of models regressing violent crime rates on residential mobility (Table 5.2), percent Black (Table 5.3), percent of the population ages 15 to 29 (Table 5.4), High School drop out rates (Table 5.5), percent divorced (Table 5.6), percent female headed households (Table 5.7), percent unemployed (Table 5.8), and percent of families below poverty (Table 5.9). The nonspatial OLS results indicate that percent Black, percent divorced, and percent female headed households are positively related to violent crime in both 1980 and 1990. These are all significant predictors of violent crime in both metropolitan and nonmetropolitan locations. Residential mobility and percent of families below poverty, on the other hand, are not significant predictors of violent crime in either metro or nonmetro locations. Percent of the population ages 15 to 29 becomes less significant as a predictor of violent crime in metropolitan areas between 1980 and 1990 but substantially increases as a predictor of violent crime in nonmetropolitan locations between1980 and 1990. High School drop out rates and percent unemployed are negatively related to violent crime in metropolitan locations only.

The Lagrange Multiplier (LM) tests for the presence of spatial autocorrelation are significant for the presence of both spatial lag and spatial error autocorrelation in every case. When tests for both spatial lag and spatial error dependence have high values, the one with the highest value will tend to indicate the correct alternative. For four of the models (percent black, High School drop out rates, percent divorced, and percent female headed households) the spatial error model is specified as the correct model, while for the other four models (residential mobility, percent ages 15 to 29, percent unemployed, and percent of families below poverty) the spatial lag model is the more appropriate alternative. When the LM tests provide stronger evidence for the spatial lag model, spatial autocorrelation takes on more substantive meaning and must be modeled with a lag specification for the dependent variable.

In accordance with these diagnostic specifications, the introduction of a spatial lag term is highly significant for the four models indicated. Nevertheless, even after estimating spatial lag models, significant levels of spatial error autocorrelation still remain in the models for residential mobility, percent unemployed, and percent of families below poverty. This indicates the presence of other spatial effects which may need to be modeled as well. The OLS spatial predictor model for residential mobility indicates that the spatial lag for this predictor of violent crime is significant for metropolitan locations in both 1980 and 1990. The spatial predictor model for percent unemployed indicates that the spatial lag for this independent variable is significant for metro locations in 1990, while that for percent of families below poverty is significant for nonmetro locations in 1980. The need for a mixed model is also substantiated by the Tests for the Common Factor hypothesis (TCF) in these models. In combination with other diagnostics, the rejection of the Common Factor hypothesis provides further evidence that an omitted spatial lag may be the main spatial effect rather than spatial dependence in the error term.

In summary, different mechanisms seem to be operating with regard to levels of violent crime in metropolitan and nonmetropolitan locations. While percent Black, percent divorced, and percent female headed households are significant positive predictors of violent crime in both metro and nonmetro locations, High School drop out rates and percent unemployed are significant predictors of violent crime in metropolitan areas only. Residential mobility and percent families below poverty are not significant predictors of violent crime in either metropolitan or nonmetropolitan counties.

Table 5.2. Metro-Nonmetro Model Estimates for the Regression of Violent Crime on Residential Mobility: 1980 and 1990

	1980				1990			
	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.19**				0.32**		
λ			0.19*				0.33**	
MSA								
Intercept	197**	170**	217**	62.0	278**	231**	356**	136*
Res Mob	0.7	0.2	-0.1	-1.2	0.3	-1.5	-3.2	-4.1
W-Mob				10.3**				13.4**
NONMSA								
Intercept	155**	127**	150**	173**	137**	83**	130**	120**
Res Mob	-1.3	-1.2	-1.2	-1.2	1.7	1.4	1.4	1.2
W-Mob				-1.2				1.6
R^2	0.08	0.09	0.10	0.10	0.09	0.13	0.14	0.12
-2 Log-Lik	-2421	-2418	-2418	-2418	-2497	-2485	-2485	-2491
LM-err	6.8**	7.9**		8.0**	27.7**	8.1**		26.5**
LM-lag	9.0**		2.9+	9.8**	31.6**		7.6**	28.2**
TCF			8.0*				7.4*	
Chow:Mob	0.9	0.5	0.2	0.0	0.2	1.1	2.3	2.6
Chow:W-mob				6.2*				5.6*

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.3. Metro-Nonmetro Model Estimates for the Regression of Violent Crime on Percent Black: 1980 and 1990

	1980				1990			
	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.11				0.19**		
λ			0.33**				0.35**	
MSA								
Intercept	107**	89**	89**	132**	105**	63**	83**	127**
Black	17.9**	17.6**	22.1**	24.5**	31.7**	30.4**	36.5**	36.6**
W-Blk				-12.2**				-10.1**
NONMSA								
Intercept	128**	113**	121**	132**	152**	118**	139**	158**
Black	1.2*	1.1+	1.5*	3.6**	2.5**	2.0*	2.7*	6.9**
W-Blk				-3.1*				-5.5*
R^2	0.34	0.35	0.51	0.39	0.47	0.48	0.62	0.49
-2 Log-Lik	-2355	-2353	-2343	-2340	-2394	-2387	-2375	-2386
LM-err	11.6**	8.3**		20.2**	27.6**	5.0*		35.6**
LM-lag	3.4+		27.3**	17.6**	15.8**		5.2*	39.8**
TCF			20.2**				10.5**	
Chow:Blk	115**	112**	133**	82.4**	190**	186**	202**	87.4**
Chow:W-blk				10.7**				1.4

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.4. Metro-Nonmetro Model Estimates for the Regression of Violent Crime on Percent Ages 15 to 29: 1980 and 1990								
	1980				1990			
	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.21**				0.29**		
λ			0.20**				0.29**	
MSA								
Intercept	-356**	-406**	-361**	-421	-62	-70	17	-231
Age	21.9**	22.3**	22.2**	21.8**	15.6*	12.7*	12.5*	14.6*
W-Age				2.6				8.8
NONMSA								
Intercept	110*	83	109*	114	-47	-84	-31	-236
Age	0.9	0.8	0.9	1.0	9.5**	8.8**	8.4**	8.7**
W-Age				-0.2				9.4
R^2	0.13	0.15	0.15	0.13	0.12	0.16	0.14	0.14
-2 Log-Lik	-2409	-2405	-2405	-2409	-2489	-2479	-2480	-2487
LM-err	9.9**	3.4+		9.9	20.6**	14.3**		18.6**
LM-lag	11.6**		0.3	11.6	28.5**		1.2	23.7**
TCF			0.4				3.5	
Chow:Age	19.4**	21.3**	20.9**	19.0**	0.8	0.4	0.4	0.7
Chow:W-age				0.1				0.0

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.5. Metro-Nonmetro Model Estimates for the Regression of Violent Crime on High School Drop-Out Rates: 1980 and 1990

	1980				1990			
	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.26**				0.32**		
λ			0.37**				0.34**	
MSA								
Intercept	397**	394**	581**	147*	388**	343**	491**	221*
<HS	-4.4**	-5.4**	-8.7**	-9.6**	-3.3	-4.4*	-6.2**	-6.1**
W-<HS				10.2**				7.6**
NONMSA								
Intercept	105**	76*	137**	67+	112**	77+	148**	51
<HS	0.6	0.4	-0.2	-2.2+	1.3	0.7	0.1	-1.7
W-<HS				3.6**				4.5*
R^2	0.11	0.13	0.21	0.19	0.10	0.13	0.14	0.13
-2 Log-Lik	-2415	-2408	-2402	-2397	-2495	-2483	-2482	-2489
LM-err	19.3**	0.5		16.3**	27.8**	8.1**		27.3**
LM-lag	16.0**		19.2**	19.9**	33.1**		5.6*	33.7**
TCF			26.5**				10.3**	
Chow:<HS	13.3**	19.4**	29.1**	15.2**	3.7+	5.0*	6.2*	2.5
Chow:W-<HS				8.6**				0.9

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.6. Metro-Nonmetro Model Estimates for the Regression of Violent Crime on Percent Divorced: 1980 and 1990								
	1980				1990			
	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.22**				0.31**		
λ			0.44**				0.39**	
MSA								
Intercept	-183**	-233**	-368**	140+	-247**	-309**	-442**	-141
Div	75.4**	77.4**	111**	115**	70.0**	67.8**	95.9**	79.0**
W-Div				-106**				-24.1
NONMSA								
Intercept	10	-16	-19	58**	70	20	37	116
Div	26.4**	25.2**	31.1**	31.4**	13.0+	12.0	15.7+	17.2+
W-Div				-14.9				-10.5
R^2	0.23	0.24	0.39	0.30	0.15	0.19	0.23	0.16
-2 Log-Lik	-2386	-2381	-2367	-2367	-2483	-2471	-2465	-2482
LM-err	32.4**	21.2**		42.6**	36.8**	0.1		38.4**
LM-lag	13.6**		31.5**	39.2**	33.3**		18.3**	40.9**
TCF			31.6**				1.4	
Chow:Div	17.9*	21.2**	42.3**	39.8**	12.9**	13.7**	21.9**	11.9**
Chow:W-div				20.8**				0.4

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.7. Metro-Nonmetro Model Estimates for the Regression of Violent Crime on Percent Female Headed Households: 1980 and 1990								
	1980				1990			
	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.21**				0.35**		
λ			0.27**				0.36**	
MSA								
Intercept	-474**	-520**	-483**	-379**	-707**	-814**	-704**	-864**
FHH	76.7**	77.4**	78.4**	76.7**	100**	102**	101**	100**
W-FHH				-10.9				16.9
NONMSA								
Intercept	-11	-33	-15	-21	21	-19.3	-8	84
FHH	16.6**	15.6**	16.6**	16.1**	14.4**	11.9**	16.2**	20.6**
W-FHH				1.6				-12.4
R^2	0.36	0.37	0.39	0.36	0.33	0.37	0.37	0.34
-2 Log-Lik	-2351	-2345	-2343	-2351	-2439	-2420	-2421	-2437
LM-err	18.8**	0.6		21.5**	56.9**	0.1		54.6**
LM-lag	15.1**		1.8	19.8**	49.9**		0.1	52.2**
TCF			0.6				1.5	
Chow:FHH	69.8**	77.5**	77.5**	66.9**	75.4**	95.4**	79.7**	56.1**
Chow:W-Fhh				0.8				4.8*

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.8. Metro-Nonmetro Model Estimates for the Regression of Violent Crime on Percent Unemployed: 1980 and 1990

	1980				1990			
	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.16*				0.30**		
λ			0.17*				0.29**	
MSA								
Intercept	327**	283**	329**	323**	422**	302**	355**	470**
Unemp	-15**	-14**	-16**	-17*	-21*	-14	-10	-4
W-Unem				1.3				-23*
NONMSA								
Intercept	124**	102**	123**	120**	182**	118**	168**	185**
Unemp	1.0	0.9	1.0	0.6	-2.1	-1.2	-1.6	-1.5
W-Unem				0.9				-0.9
R^2	0.10	0.11	0.11	0.10	0.10	0.13	0.12	0.11
-2 Log-Lik	-2417	-2415	-2415	-2417	-2494	-2484	-2485	-2492
LM-err	4.0*	12.1**		4.0*	20.1**	15.5**		17.8**
LM-lag	6.7**		2.1	6.8**	27.4**		1.5	25.3**
TCF			0.1				4.7+	
Chow:Unem	8.8**	7.0**	7.1**	4.1*	3.9*	2.0	0.5	0.0
Chow:W-ue				0.0				3.1+

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.9. Metro-Nonmetro Model Estimates for the Regression of Violent Crime on Percent of Families Below Poverty: 1980 and 1990								
	1980				1990			
	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.20**				0.31**		
λ			0.21**				0.31**	
MSA								
Intercept	245**	218**	277**	204**	334**	242**	322**	349**
Pov	-3.6	-4.4	-6.2+	-9.4*	-4.8	-3.3	-2.6	-1.2
W-Pov				8.7+				-4.4
NONMSA								
Intercept	127**	101**	130**	110**	158**	101**	154**	145**
Pov	0.4	0.3	0.0	-2.9	0.4	0.3	-0.1	-2.4
W-Pov				4.5*				3.6
R^2	0.08	0.09	0.10	0.10	0.09	0.13	0.12	0.09
-2 Log-Lik	-2421	-2417	-2417	-2418	-2497	-2485	-2486	-2496
LM-err	8.5**	5.8*		7.8**	26.2**	13.8**		25.9**
LM-lag	10.1**		5.5*	11.0**	31.7**		4.2*	32.4**
TCF			7.4*				2.7	
Chow:Pov	1.4	2.0	2.6	1.7	1.1	0.6	0.2	0.0
Chow:W-pov				0.6				1.3

Significance Levels: +p<.10, * p<0.05; ** p<0.01

METRO-NONMETRO BIVARIATE MODEL RESULTS FOR PROPERTY CRIME

Tables 5.10 through 5.17 present results for the series of models regressing property crime rates on residential mobility (Table 5.10), percent Black (Table 5.11), percent of the population ages 15 to 29 (Table 5.12), High School drop out rates (Table 5.13), percent divorced (Table 5.14), percent female headed households (Table 5.15), percent unemployed (Table 5.16), and percent of families below poverty (Table 5.17). Again, the nonspatial OLS regression models indicate slightly different outcomes for metropolitan and nonmetropolitan locations. While percent Black and percent female headed households are positively related to property crime in metropolitan areas, residential mobility (in 1980) is positively related to property crime in nonmetropolitan locations. These findings are further substantiated by the significant Chow test results for the stability of the individual coefficients across metro-nonmetro locations in these models.

The LM tests for the presence of spatial autocorrelation are significant for the presence of both spatial lag and spatial error autocorrelation for all models. For each of these models, the spatial lag model is also specified as the more appropriate alternative. Nevertheless, substantial spatial error effects remain for five of the eight models (residential mobility, percent ages 15 to 29, High School drop out rates in 1980, percent divorced in 1980, and percent unemployed), even in the presence of significant spatial lag terms. For all but one of these (percent ages 15 to 29), the residual spatial error effects can partially be accounted for by significant lagged predictors in the OLS spatial predictor models. For these models with significant spatially lagged predictor variables, the need for a mixed model is also substantiated by significant results on the tests for the Common Factor Hypothesis.

The spatial lag models indicate that property crime is significantly and positively related to property crime in neighboring locations, even after controlling for the effects of the predictor variable of interest in each of the bivariate models where a spatial lag model is designated. The significance of the spatially lagged predictor variables, especially for those with residual spatial error effects, provide evidence for significant spatial effects operating through both the dependent and independent variables. Interestingly, the "local" effects of percent Black, percent divorced, and percent female headed households on property crime is positive, while the "neighborhood effects" of the surrounding counties is negative. On the other hand, the "local" effects of High School drop out rates and percent of families below poverty on property crime is negative, while the "neighborhood effects" of the surrounding counties is positive. This type of reversal in spatial effects may indicate a type of buffering effect in the case where the relationship goes from positive to negative. In the case where spatial effects go from negative in the "local" context to positive in the "neighborhood" context, this may point to a type of diffusion process operating across county boundaries. In either case, significant spatial lag terms for the explanatory variables provide evidence for substantial "spillover" effects with regard to the relationship between dependent and independent variables and the degree to which they may covary spatially.

Table 5.10. Metro-Nonmetro Model Estimates for the Regression of Property Crime on Residential Mobility: 1980 and 1990								
	1980				1990			
	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.32**				0.26**		
λ			0.32**				0.25**	
MSA								
Intercept	2306**	1677**	2739**	625	1734**	1373**	2120**	1015**
Res Mob	24.1	16.0	8.6	0.4	55.5**	42.0**	39.4*	33.1+
W-Mob				128.5**				68.1*
NONMSA								
Intercept	684**	205	714**	353	459*	156	513**	86.0
Res Mob	59.4**	52.8**	53.2**	56.4**	74.0**	64.0**	67.0**	62.3**
W-Mob				23.0				35.2+
R^2	0.19	0.23	0.25	0.22	0.26	0.28	0.28	0.28
-2 Log-Lik	-3354	-3340	-3341	-3348	-3208	-3200	-3201	-3203
LM-err	20.12**	16.4**		22.3**	9.5**	7.4**		8.8**
LM-lag	33.4**		2.4	32.0**	19.7**		0.1	12.3**
TCF			12.5**				7.8*	
Chow:Mob	2.9+	3.4+	4.6*	6.5*	1.0	1.5	2.0	1.9
Chow:Wmob				5.6*				1.0

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.11. Metro-Nonmetro Model Estimates for the Regression of Property Crime on Percent Black: 1980 and 1990								
	1980				1990			
	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.35**				0.34**		
λ			0.48**				0.45**	
MSA								
Intercept	2057**	1229**	1963**	2299**	1923**	1150**	1908**	2093**
Black	119**	117**	177**	182**	141**	135**	181**	179**
W-Blk				-117**				-77**
NONMSA								
Intercept	1698**	1037**	1500**	1759**	1615**	994**	1432**	1674**
Black	-8.0	-4.0	2.9	30.2*	-0.6	0.3	7.9	40.5*
W-Blk				-49**				-51**
R^2	0.25	0.29	0.49	0.30	0.29	0.33	0.49	0.32
-2 Log-Lik	-3339	-3322	-3310	-3325	-3201	-3184	-3174	-3194
LM-err	45.7**	0.7		53.1**	51.0**	1.5		56.2**
LM-lag	41.2**		8.7**	59.9**	43.5**		4.7*	61.7**
TCF			16.9**				11.2**	
Chow:Blk	54.0**	54.1**	74.0**	35.0**	64.9**	65.1**	74.4**	27.3**
Chow:W-blk				4.7*				0.6

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.12. Metro-Nonmetro Model Estimates for the Regression of Property Crime on Percent Ages 15 to 29: 1980 and 1990								
	1980				1990			
	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.36**				0.34**		
λ			0.36**				0.35**	
MSA								
Intercept	-2909**	-3746**	-2735**	-3213	-965	-1206	-120	-1488
Age	218**	218**	217**	218**	166**	141**	136**	163**
W-Age				12.3				27.3
NONMSA								
Intercept	-377	-943*	-401	-807	-436	-1005*	-549	-213
Age	80.2**	77.0**	77.9**	78.9**	92.9**	91.1**	93.9**	93.9**
W-Age				18.1				-11.1
R^2	0.23	0.27	0.29	0.23	0.22	0.26	0.29	0.22
-2 Log-Lik	-3345	-3328	-3328	-3345	-3219	-3203	-3203	-3219
LM-err	30.7**	8.7**		30.9**	28.6**	7.5**		27.3**
LM-lag	43.4**		0.7	44.1**	40.0**		1.9	41.1**
TCF			0.3				0.4	
Chow:Age	8.7**	10.2**	10.0**	8.7**	2.5	1.3	0.9	2.2
Chow:W-age				0.0				0.4

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.13. Metro-Nonmetro Model Estimates for the Regression of Property Crime on High School Drop-Out Rates: 1980 and 1990								
	1980				1990			
	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.24**				0.32**		
λ			0.43**				0.38**	
MSA								
Intercept	5588**	5983**	7243**	3498**	4063**	3426**	4810**	3249**
<HS	-66**	-67**	-104**	-111**	-42**	-46**	-61**	-56**
W-<HS				87.5**				37.3*
NONMSA								
Intercept	4186**	3317**	4496**	3963**	3067**	2186**	3042**	2999**
<HS	-48**	-40**	-55**	-65**	-36**	-28**	-38**	-39**
W-<HS				21.3+				5.0
R^2	0.33	0.35	0.49	0.38	0.22	0.25	0.31	0.23
-2 Log-Lik	-3316	-3309	-3296	-3302	-3219	-3205	-3201	-3217
LM-err	38.2**	17.2**		31.0**	40.6**	0.7		37.9**
LM-lag	17.3**		17.5**	39.3**	33.8**		6.3*	37.8**
TCF			18.9**				1.4	
Chow:<HS	2.1	5.5*	11.5**	7.5**	0.1	1.3	1.9	0.8
Chow:W-<HS				10.3**				2.1

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.14. Metro-Nonmetro Model Estimates for the Regression of Property Crime on Percent Divorced: 1980 and 1990

	1980				1990			
	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.36**				0.35**		
λ			0.58**				0.47**	
MSA								
Intercept	-560	-1639**	-2851**	2588**	-1431*	-2117**	-3092**	-204
Div	630**	672**	1095**	1032**	546**	528**	784**	653**
W-Div				-1052**				-279**
NONMSA								
Intercept	-210	-674*	-548+	-31	270	-287	-195	762
Div	397**	355**	437**	416**	187**	176**	232**	231**
W-Div				-56				-111
R^2	0.29	0.34	0.55	0.36	0.24	0.28	0.41	0.25
-2 Log-Lik	-3327	-3308	-3286	-3308	-3214	-3197	-3186	-3210
LM-err	69.5**	13.8**		76.2**	52.5**	1.0		54.6**
LM-lag	45.6**		16.1**	88.1**	44.5**		14.7**	65.0**
TCF			28.2**				3.8	
Chow:Div	4.2*	8.7**	31.8**	21.8**	11.2**	12.1**	22.9**	12.2**
Chow:W-div				25.1**				1.3

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.15. Metro-Nonmetro Model Estimates for the Regression of Property Crime on Percent Female Headed Households: 1980 and 1990								
	1980				1990			
	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.40**				0.40**		
λ			0.46**				0.44**	
MSA								
Intercept	-1718**	-2948**	-2041**	1275	-1126	-2451**	-1417*	-403
FHH	498**	529**	562**	502**	390**	429**	442**	392**
W-FHH				-343*				-77.7
NONMSA								
Intercept	1817**	721*	927**	3451**	1807**	854**	1083**	2978**
FHH	-18.1	23.9	68.9+	64.7	-19.7	4.4	39.9	95.6*
W-FHH				-266**				-231**
R^2	0.23	0.28	0.38	0.28	0.21	0.26	0.34	0.24
-2 Log-Lik	-3344	-3322	-3316	-3332	-3222	-3200	-3197	-3213
LM-err	51.6**	0.1		43.1**	55.1**	0.0		49.7**
LM-lag	51.7**		4.7*	53.5**	53.4**		2.2	55.5**
TCF			13.5**				11.4**	
Chow:FHH	39.9**	44.5**	43.6**	28.5**	28.1**	35.4**	30.8	13.4**
Chow:W-Fhh				0.3				2.2

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.16. Metro-Nonmetro Model Estimates for the Regression of Property Crime on Percent Unemployed: 1980 and 1990								
	1980				1990			
	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.32**				0.26**		
λ			0.35**				0.28**	
MSA								
Intercept	4031**	3065**	4462**	3540**	4524**	3587**	4496**	4617**
Unemp	-173**	-147**	-214**	-272**	-277**	-228**	-262**	-245**
W-Unem				154+				-43
NONMSA								
Intercept	2131**	1437**	1983**	2313**	2404**	1761**	2280**	2519**
Unemp	-52.5*	-40.7*	-45.0+	-33.0	-92**	-72**	-85**	-66*
W-Unem				-40.4				-40
R^2	0.18	0.21	0.25	0.19	0.24	0.26	0.26	0.24
-2 Log-Lik	-3357	-3344	-3343	-3355	-3214	-3206	-3206	-3214
LM-err	24.6**	7.8**		25.8**	12.7**	4.2*		11.8**
LM-lag	33.0**		4.6*	35.5**	20.5**		0.0	18.5**
TCF			3.0				1.6	
Chow:Unem	4.7*	4.0*	6.6*	8.3**	8.4**	6.4*	5.6*	4.2*
Chow:W-ue				3.8+				0.0

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.17. Metro-Nonmetro Model Estimates for the Regression of Property Crime on Percent of Families Below Poverty: 1980 and 1990

	1980				1990			
	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.22**				0.22**		
λ			0.29**				0.26**	
MSA								
Intercept	3828**	3280**	4315**	3295**	4160**	3453**	4329**	4025**
Pov	-106**	-103**	-148**	-195**	-135**	-117**	-147**	-168**
W-Pov				122**				40.2
NONMSA								
Intercept	2783**	2208**	2730**	2761**	2591**	2031**	2536**	2584**
Pov	-71**	-60**	-71**	-75**	-59**	-49**	-59**	-60**
W-Pov				5.5				1.9
R^2	0.28	0.29	0.33	0.29	0.28	0.29	0.31	0.28
-2 Log-Lik	-3331	-3325	-3322	-3327	-3205	-3199	-3197	-3204
LM-err	16.1**	0.6		16.0**	12.9**	0.0		12.9**
LM-lag	13.0**		3.6+	19.6**	13.6**		0.7	15.9**
TCF			6.1*				0.3	
Chow:Pov	1.3	2.1	4.6*	6.6*	5.7	4.8	5.4*	4.9*
Chow:W-pov				5.7*				0.7

Significance Levels: +p<.10, * p<0.05; ** p<0.01

SUBREGIONAL BIVARIATE MODEL RESULTS FOR VIOLENT CRIME

Tables 5.18 through 5.25 present results for the series of models regressing violent crime rates on residential mobility (Table 5.18), percent Black (Table 5.19), percent of the population ages 15 to 29 (Table 5.20), High School drop out rates (Table 5.21), percent divorced (Table 5.22), percent female headed households (Table 5.23), percent unemployed (Table 5.24), and percent of families below poverty (Table 5.25). In general, the results of the nonspatial OLS models indicate that percent Black, percent divorced, and percent female headed households are significant positive predictors of Subregional rates of violent crime in both the North and South, while High School drop out rates, percent ages 15 to 29, percent unemployed, and percent families below poverty are significant predictors of violent crime in Southern Appalachia only. For Central Appalachia, only percent ages 15 to 29 (1990) and percent female headed households (1980) are significant predictors of violent crime. Residential mobility, on the other hand, is not a significant predictor of violent crime in any Subregional location.

The LM tests for the presence of spatial autocorrelation are significant for the presence of both spatial lag and spatial error autocorrelation for all models. For four of these models (residential mobility, percent ages 15 to 29, percent unemployed, and percent families below poverty in 1990), the spatial lag model is specified as the more appropriate alternative. Nevertheless, substantial spatial error effects remain for each of these models, even with the addition of significant spatial lag terms. For all but one of these (percent ages 15 to 29), the remaining spatial error effects can partially be accounted for by significant lagged predictors in the OLS spatial predictor models. In the case of these models with significant spatially lagged predictor variables, the need for a mixed model is also substantiated by significant results on the tests for the Common Factor Hypothesis.

In summary, as with the metro-nonmetro models for violent crime, different mechanisms seem to be operating with regard to levels of violent crime across Subregional locations. While percent Black, percent divorced, and percent female headed households are significant positive predictors of violent crime in general, High School drop out rates, percent ages 15 to 29, percent unemployed, and percent families below poverty are significant predictors of violent crime in Southern Appalachia. Over time, Central Appalachia has only a limited number of significant predictors of violent crime (percent ages 15 to 29 in 1990 and percent female headed households in 1980), while residential mobility is not a significant predictor of violent crime in any Subregional location.

Table 5.18. Subregional Model Estimates for the Regression of Violent Crime on Residential Mobility: 1980 and 1990								
	1980				1990			
Variable	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.21**				0.29**		
λ			0.22**				0.30	
NORTH								
Intercept	157**	129**	158**	152**	152**	111**	155**	143*
Res Mob	-1.5	-1.5	-1.6	-1.6	-0.6	-0.7	-0.8	-0.7
W-Mob				0.3				0.8
CENTRAL								
Intercept	134**	95*	116*	274**	170**	105*	143*	258**
Res Mob	0.8	1.3	2.0	3.0	1.0	1.7	2.8	3.4
W-Mob				-11.1*				-8.9
SOUTH								
Intercept	175**	142**	183**	112*	203**	150**	231**	112+
Res Mob	-0.1	-0.4	-0.6	-0.5	2.3	1.1	0.5	0.0
W-Mob				4.1				7.3*
R^2	0.03	0.04	0.03	0.04	0.07	0.09	0.06	0.08
-2 Log-Lik	-2432	-2428	-2427	-2429	-2501	-2492	-2492	-2498
LM-err	11.0**	7.4**		10.0**	22.2**	6.1*		21.6**
LM-lag	11.2**		13.6**	10.5**	23.0**		7.5**	21.6**
TCF			5.0				4.9	
Chow:Mob	0.3	0.8	1.1	0.9	0.4	0.5	0.7	0.4
Chow:W-mob				2.9+				2.6+

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.19. Subregional Model Estimates for the Regression of Violent Crime on Percent Black: 1980 and 1990

Variable	1980 OLS	1980 LAG	1980 ERR	1980 OLS (Spatial)	1990 OLS	1990 LAG	1990 ERR	1990 OLS (Spatial)
W-Y		0.20**				0.28**		
λ			0.32**				0.47**	
NORTH								
Intercept	93**	69**	92**	111**	102**	63**	94**	124**
Black	27.8**	26.8**	30.0**	32.2**	27.7**	27.1**	31.8**	31.4**
W-Blk				-16.7+				-17.9
CENTRAL								
Intercept	143**	112**	138**	156**	175**	121**	160**	208**
Black	2.2	2.8	4.0	4.4	4.5	5.1	8.3	9.8
W-Blk				-9.2				-24.6
SOUTH								
Intercept	142**	107**	122**	170**	189**	122**	133**	235**
Black	3.1**	3.1**	4.8**	9.6**	5.8**	5.4**	10.6**	17.6**
W-Blk				-9.4**				-16.6**
R^2	0.13	0.14	0.20	0.21	0.16	0.18	0.31	0.27
-2 Log-Lik	-2410	-2406	-2401	-2391	-2482	-2473	-2462	-2456
LM-err	18.8**	11.1**		17.9**	41.0**	20.9**		43.9**
LM-lag	10.2**		47.3**	21.0**	23.0**		63.7**	47.8**
TCF			31.7**				40.8**	
Chow:Blk	11.0**	21.0**	21.3**	8.2**	4.1*	8.6*	7.9*	2.0
Chow:W-blk				0.3				0.1

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.20. Subregional Model Estimates for the Regression of Violent Crime on Percent Ages 15 to 29: 1980 and 1990								
	1980				1990			
Variable	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.20**				0.27**		
λ			0.20**				0.27**	
NORTH								
Intercept	103	75	98	196	152+	106	138	198
Age	1.1	1.2	1.3	1.2	-0.4	-0.1	0.2	-0.3
W-Age				-3.7				-2.2
CENTRAL								
Intercept	10	-9	25	-105	-266+	-286+	-217	-570
Age	5.4	4.9	4.7	4.9	19.9**	18.5**	17.6**	18.8**
W-Age				4.9				14.4
SOUTH								
Intercept	-118	-143+	-110	-171	-151	-185+	-123	-265
Age	11.5**	11.1**	11.2**	11.4**	17.7**	16.1**	16.3**	17.1**
W-Age				2.3				5.7
R^2	0.06	0.07	0.06	0.06	0.12	0.14	0.11	0.12
-2 Log-Lik	-2425	-2421	-2421	-2425	-2490	-2482	-2483	-2489
LM-err	9.5**	4.4*			19.2**	3.9*		19.1**
LM-lag	10.1**		2.6		20.9**		0.6	19.4**
TCF			0.7				1.9	
Chow:Age	3.1*	6.0*	5.8+	2.9+	5.7**	10.1**	9.3**	5.1**
Chow:W-age				0.4				0.9

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.21. Subregional Model Estimates for the Regression of Violent Crime on High School Drop-Out Rates: 1980 and 1990

	1980				1990			
Variable	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.19**				0.28**		
λ			0.24**				0.30**	
NORTH								
Intercept	204**	177**	226**	145*	261**	202**	253**	262**
<HS	-1.8	-1.7	-2.3+	-4.1*	-3.7+	-3.1	-3.5	-3.6
W-<HS				3.8+				-0.1
CENTRAL								
Intercept	192*	163+	213+	34	139	125	238+	-195
<HS	-0.7	-0.7	-1.1	-2.2	0.9	0.1	-1.2	-3.0
W-<HS				4.1				10.8*
SOUTH								
Intercept	659**	615**	671**	568**	497**	416**	506**	482**
<HS	-9.2**	-9.0**	-9.5**	-9.5**	-6.6**	-6.4**	-7.0**	-6.7**
W-<HS				2.1				0.5
R^2	0.17	0.18	0.18	0.19	0.11	0.14	0.11	0.13
-2 Log-Lik	-2400	-2396	-2394	-2397	-2492	-2483	-2482	-2489
LM-err	12.7**	0.8		12.3**	23.0**	1.0		21.4**
LM-lag	9.7**		6.6*	13.1**	23.0**		4.5*	22.5**
TCF			5.2				5.3	
Chow:<HS	14.5**	28.8**	25.3**	6.9**	3.2*	5.3+	3.9	0.8
Chow:W-<HS				0.2				2.4+

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.22. Subregional Model Estimates for the Regression of Violent Crime on Percent Divorced: 1980 and 1990								
	1980				1990			
Variable	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.21**				0.28**		
λ			0.39**				0.36**	
NORTH								
Intercept	-51	-67	-63	-8	117	59	58	202+
Div	38.5**	36.1**	41.4**	43.6**	3.8	6.3	11.9	9.7
W-Div				-14.1				-18.2
CENTRAL								
Intercept	65	33	38	163+	285*	207+	226+	528*
Div	17.1	17.2	22.3+	24.8+	-13.7	-10.5	-6.7	0.1
W-Div				-27.8				-46.2
SOUTH								
Intercept	-109**	-147**	-204**	132*	-210**	-260**	-323**	117
Div	57.0**	57.2**	75.9**	82.9**	60.4**	57.5**	74.7**	89.4**
W-Div				-74.1**				-72.2**
R^2	0.19	0.20	0.29	0.25	0.15	0.17	0.19	0.19
-2 Log-Lik	-2397	-2392	-2382	-2381	-2485	-2476	-2471	-2476
LM-err	31.0**	27.9**		33.2**	33.2**	6.6*		32.9**
LM-lag	11.9**		36.6**	31.8**	22.6**		22.1**	33.1**
TCF			26.5**				14.9**	
Chow:Div	4.3*	9.4**	16.2**	8.3**	10.4**	18.4**	22.5**	13.0**
Chow:W-Div				4.4*				2.5+

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.23. Subregional Model Estimates for the Regression of Violent Crime on Percent Female Headed Households: 1980 and 1990								
	1980				1990			
Variable	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.23**				0.30**		
λ			0.31**				0.44**	
NORTH								
Intercept	-96	-127*	-115+	37	-21	-78	-92	87
FHH	28.1**	28.1**	30.5**	30.6**	17.9*	19.3*	25.2**	20.9*
W-FHH				-18.8				-14.8
CENTRAL								
Intercept	-49	-67	-19	-254+	14	-14	46	-136
FHH	21.4**	19.5**	17.9*	15.9+	16.0	13.2	12.3	9.9
W-FHH				27.7+				20.3
SOUTH								
Intercept	-116**	-163**	-160**	69	-58	-129*	-215**	218**
FHH	31.5**	32.1**	36.2**	35.9**	30.0**	29.4**	45.0**	54.2**
W-FHH				-24.3**				-51.1**
R^2	0.18	0.20	0.22	0.21	0.16	0.18	0.26	0.23
-2 Log-Lik	-2398	-2392	-2387	-2390	-2482	-2472	-2462	-2465
LM-err	25.6**	6.5*		18.9**	46.5**	18.3**		40.8**
LM-lag	14.5**		12.4**	20.8**	26.0**		38.0**	43.3**
TCF			10.9*				24.8**	
Chow:FHH	0.7	2.2	4.3	2.3	1.1	2.6	8.6*	7.6**
Chow:W-Fhh				4.9**				6.2**

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.24. Subregional Model Estimates for the Regression of Violent Crime on Percent Unemployed: 1980 and 1990								
	1980				1990			
Variable	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.19*				0.27**		
λ			0.18*				0.26**	
NORTH								
Intercept	127**	107*	135**	66	195**	144**	185**	208**
Unemp	0.5	0.0	-0.4	-2.1	-6.0	-4.6	-5.0	-3.5
W-Unem				9.4				-4.0
CENTRAL								
Intercept	116**	95*	127**	29	115+	86	145*	-11
Unemp	2.9	2.2	1.7	-1.2	6.1	4.1	3.1	-5.3
W-Unem				12.1+				23.2*
SOUTH								
Intercept	254**	210**	245**	296**	351**	259**	316**	466**
Unemp	-11.3**	-9.7*	-10.2*	-6.7	-17.3*	-13.4*	-12.4+	-2.2
W-Unem				-10.3				-33.3**
R^2	0.05	0.06	0.04	0.06	0.09	0.11	0.07	0.12
-2 Log-Lik	-2428	-2425	-2425	-2426	-2497	-2490	-2491	-2490
LM-err	6.9**	9.1**		5.4*	14.8**	9.9**		9.5**
LM-lag	8.1**		0.8	6.2*	18.6**		0.0	11.8**
TCF			4.8				10.4*	
Chow:Unem	3.7*	5.3+	4.6+	0.3	4.0*	4.7+	2.9	0.0
Chow:W-ue				2.3+				6.7**

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.25. Subregional Model Estimates for the Regression of Violent Crime on Percent of Families Below Poverty: 1980 and 1990								
	1980				1990			
Variable	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.16*				0.23**		
λ			0.17*				0.23**	
NORTH								
Intercept	152**	131**	155**	149**	203**	159**	199**	206**
Pov	-1.9	-1.9	-2.2	-3.9	-4.7+	-3.9	-4.4	-4.2
W-Pov				3.1				-0.7
CENTRAL								
Intercept	131**	111**	139**	83	83	64	111	-32
Pov	0.7	0.6	0.3	-1.6	4.1+	3.1	2.8	-2.6
W-Pov				4.6				11.7*
SOUTH								
Intercept	321**	283**	322**	301**	412**	328**	403**	442**
Pov	-10.7**	-9.9**	-10.8**	-11.9**	-13.4**	-11.4**	-12.9**	-10.1*
W-Pov				2.7				-5.6
R^2	0.09	0.10	0.09	0.10	0.12	0.14	0.11	0.14
-2 Log-Lik	-2418	-2416	-2415	-2417	-2489	-2484	-2484	-2486
LM-err	6.5*	0.0		6.3*	11.7**	3.4+		9.5**
LM-lag	5.9*		2.9+	6.8**	14.0**		0.0	11.2**
TCF			2.7				5.6	
Chow:Pov	9.5**	16.3**	16.1**	4.1*	10.6**	14.8**	13.7**	0.8
Chow:W-pov				0.1				2.8+

Significance Levels: +p<.10, * p<0.05; ** p<0.01

SUBREGIONAL BIVARIATE MODEL RESULTS FOR PROPERTY CRIME

Tables 5.26 through 5.33 present results for the series of Subregional models regressing property crime rates on residential mobility (Table 5.26), percent Black (Table 5.27), percent of the population ages 15 to 29 (Table 5.28), High School drop out rates (Table 5.29), percent divorced (Table 5.30), percent female headed households (Table 5.31), percent unemployed (Table 5.32), and percent of families below poverty (Table 5.33). As with the bivariate models for violent crime, the nonspatial OLS regression models for property crime indicate slightly different outcomes across Subregional locations. While percent Black is positively related to property crime primarily in Northern Appalachia, percent female headed households is positively related to property crime only in Southern Appalachia. For the percent Black bivariate model of property crime, as well as the models for percent divorced and percent of families below poverty, these findings of significant Subregional variation are further substantiated by the significant Chow test results for the stability of the individual coefficients across Subregions.

The LM tests for the presence of spatial autocorrelation are significant for the presence of both spatial lag and spatial error autocorrelation for all models. For five of the models (percent black, High School drop out rates, percent divorced, percent female headed households, and percent of families below poverty) the spatial error model is specified as the correct model, while for the other three models (residential mobility, percent ages 15 to 29, and percent unemployed) the spatial lag model is the more appropriate alternative. Again, the inclusion of a spatial lag operator in the model indicates the presence of significant spatial autocorrelation effects in the dependent variable so that property crime rates in one location are significantly and positively related to property crime rates in neighboring locations, even after controlling for the effects of the other predictor(s) in the model.

While residential mobility, percent black, percent ages 15 to 29, percent divorced, and percent female headed households are positively related to property crime, High School drop out rates, percent unemployed, and percent of families below poverty are negatively related to property crime. Surprisingly, these proxies for relative resource deprivation (education, relative affluence, and employment) are all negatively related to levels of crime in Appalachia. In this context, it may be that levels of family and community stability are more directly related to levels of crime, while relative levels of resource deprivation are operating indirectly through family and community stability. It may also be that counties with high levels of poverty provide fewer opportunities for property crime, while counties with higher percentages of broken families increase the propensity to commit property crimes.

Table 5.26. Subregional Model Estimates for the Regression of Property Crime on Residential Mobility: 1980 and 1990

Variable	1980 OLS	1980 LAG	1980 ERR	1980 OLS (Spatial)	1990 OLS	1990 LAG	1990 ERR	1990 OLS (Spatial)
W-Y		0.34**				0.26**		
λ			0.34**				0.26**	
NORTH								
Intercept	1584**	907**	1639**	1461**	1012**	614*	1093**	783+
Res Mob	37.5*	33.8*	34.3*	36.3*	58.4**	52.3**	53.0**	54.0**
W-Mob				8.9				19.8
CENTRAL								
Intercept	-90	-448	-115	7	630+	291	486	1072*
Res Mob	89.0**	81.6**	87.7**	90.5**	40.4	40.7+	48.4+	52.9+
W-Mob				-7.6				-44.6
SOUTH								
Intercept	1174**	662*	1407**	54	803**	469	1037**	56
Res Mob	47.7**	37.5*	33.2*	40.1*	78.9**	64.9**	65.1**	60.1**
W-Mob				72.9*				60.7*
R^2	0.13	0.17	0.13	0.14	0.21	0.22	0.18	0.22
-2 Log-Lik	-3368	-3355	-3355	-3365	-3222	-3215	-3216	-3218
LM-err	31.7**	4.1*		33.5**	14.2**	1.5		15.1**
LM-lag	33.4**		1.5	32.0**	17.4**		0.2	14.0**
TCF			5.2				7.1+	
Chow:Mob	1.3	2.6	3.2	1.3	1.1	0.9	0.5	0.0
Chow:W-mob				1.3				2.5+

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.27. Subregional Model Estimates for the Regression of Property Crime on Percent Black: 1980 and 1990								
	1980				1990			
Variable	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.39**				0.36**		
λ			0.49**				0.49**	
NORTH								
Intercept	1902**	1063**	1841**	2182**	1588**	923**	1573**	1778**
Black	212**	210**	269**	283**	218**	211**	248**	250**
W-Blk				-270**				-157
CENTRAL								
Intercept	1167**	623**	1016**	1310**	973**	522**	826**	1064**
Black	68.1	70.5	92.3+	94.7	110+	104+	122*	125*
W-Blk				-109				-67
SOUTH								
Intercept	1959**	1108**	1622**	2258**	2203**	1329**	1817**	2520**
Black	5.5	11.5	35.9**	73.0**	4.6	11.0	41.5**	88.2**
W-Blk				-98.0**				-116**
R^2	0.12	0.16	0.21	0.20	0.14	0.18	0.24	0.25
-2 Log-Lik	-3372	-3354	-3347	-3351	-3236	-3222	-3214	-3212
LM-err	49.6**	0.6		46.4**	42.2**	2.8+		38.5**
LM-lag	43.1**		35.6**	53.8**	35.4**		34.3**	45.8**
TCF			30.4**				37.1**	
Chow:Blk	7.5**	15.6**	18.1**	6.0**	8.6**	16.7**	15.6**	4.0*
Chow:W-blk				1.3				0.2

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.28. Subregional Model Estimates for the Regression of Property Crime on Percent Ages 15 to 29: 1980 and 1990								
	1980				1990			
Variable	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.36**				0.32**		
λ			0.37**				0.33**	
NORTH								
Intercept	-249	-856	15	-2091	192	-295	393	230
Age	94.9**	87.9**	84.8**	93.1**	80.1**	74.4**	71.0**	80.2**
W-Age				73.5				-1.8
CENTRAL								
Intercept	-1116	-1839	-1664	743	-844	-1424	-1174	-112
Age	93.7*	102*	113**	102*	88.7+	96.0*	100.8*	91.3+
W-Age				-80				-34.6
SOUTH								
Intercept	-1749*	-2270**	-1565*	-2399	-1619*	-2017**	-1320*	-2592+
Age	149**	141**	141**	147**	173**	158**	159**	168**
W-Age				28				49
R^2	0.16	0.20	0.17	0.17	0.19	0.23	0.19	0.19
-2 Log-Lik	-3361	-3345	-3345	-3359	3225	-3213	-3212	-3225
LM-err	39.7**	1.8		39.1**	30.5**	0.4		31.7**
LM-lag	40.2**		2.5	39.8**	30.7**		0.9	31.9**
TCF			1.6				0.7	
Chow:Age	1.0	1.9	2.1	0.9	2.7+	4.5+	4.8+	2.3
Chow:W-age				1.1				0.4

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.29. Subregional Model Estimates for the Regression of Property Crime on High School Drop-Out Rates: 1980 and 1990								
	1980				1990			
Variable	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.26**				0.30**		
λ			0.35**				0.35**	
NORTH								
Intercept	5467**	4406**	5547**	5293**	3399**	2632**	3428**	3503**
<HS	-80.6**	-68.2**	-82.3**	-87.5**	-46.7**	-40.6**	-47.4**	-43.6*
W-<HS				11.2				-6.5
CENTRAL								
Intercept	5216**	4560**	5593**	3490**	3616**	3111**	4090**	2229*
<HS	-64.2**	-59.4**	-71.1**	-80.2**	-49.5**	-47.2**	-60.0**	-65.7**
W-<HS				44.6+				44.9
SOUTH								
Intercept	7418**	6732**	7608**	6171**	4648**	3769**	4602**	4802**
<HS	-102**	-99.2**	-106**	-107**	-62.6**	-57.6**	-62.0**	-61.3**
W-<HS				28.5				-5.3
R^2	0.36	0.38	0.39	0.37	0.21	0.24	0.23	0.22
-2 Log-Lik	-3307	-3298	-3292	-3304	-3220	-3209	-3206	-3219
LM-err	34.5**	6.0*		33.6**	33.7**	2.0		33.8**
LM-lag	21.0**		6.0*	36.7**	27.0**		4.2*	30.5**
TCF			4.0				3.2	
Chow:<HS	2.6+	7.3*	4.6	1.1	0.5	1.1	0.6	0.5
Chow:W-<HS				0.5				1.2

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.30. Subregional Model Estimates for the Regression of Property Crime on Percent Divorced: 1980 and 1990								
	1980				1990			
Variable	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.31**				0.29**		
λ			0.47**				0.41**	
NORTH								
Intercept	780+	4	-53	2394**	979+	285	331	2151+
Div	298**	321**	476**	488**	134+	154*	229**	215**
W-Div				-529**				-250*
CENTRAL								
Intercept	-764	-1010+	-842	-1015	783	368	433	1445
Div	429**	391**	431**	409**	50.3	55.1	84.8	87.5
W-Div				72				-125
SOUTH								
Intercept	-1585**	-1927**	-2056**	-582	-2257**	-2550**	-2854**	-750
Div	728**	670**	822**	841**	598**	548**	676**	732**
W-Div				-314*				-332**
R^2	0.31	0.34	0.40	0.34	0.26	0.29	0.33	0.28
-2 Log-Lik	-3323	-3310	-3298	-3315	-3209	-3198	-3190	-3202
LM-err	52.6**	15.9**		54.1**	41.0**	10.3**		40.0**
LM-lag	30.3**		15.4**	56.6**	25.9**		13.4**	44.3**
TCF			12.4**				10.9*	
Chow:Div	7.6**	11.6**	12.4**	5.3**	14.1**	22.9**	26.2**	13.1**
Chow:W-Div				2.5+				0.3

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.31. Subregional Model Estimates for the Regression of Property Crime on Percent Female Headed Households: 1980 and 1990								
	1980				1990			
Variable	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.41**				0.37**		
λ			0.46**				0.47**	
NORTH								
Intercept	1798**	454	909	5587**	1667**	730	1117+	3090**
FHH	48.8	104	160*	120	26.8	51.9	88.7	67.0
W-FHH				-534**				-195*
CENTRAL								
Intercept	319	-376	-89	890	566	79	344	412
FHH	105	119	140+	120	56.1	56.7	66.0	49.9
W-FHH				-77				20.8
SOUTH								
Intercept	259	-791+	-452	2596**	1508**	398	196	3691**
FHH	191**	214**	268**	247**	73.2+	99.2**	202**	265**
W-FHH				-308**				-404**
R^2	0.12	0.17	0.18	0.17	0.11	0.15	0.20	0.20
-2 Log-Lik	-3371	-3351	-3345	-3359	-3243	-3228	-3221	-3223
LM-err	60.7**	1.6		42.3**	46.1**	4.1*		34.8**
LM-lag	48.5**		17.5**	50.2**	37.9**		26.6**	42.1**
TCF			13.5**				30.2**	
Chow:FHH	1.3	2.2	2.7	1.4	0.2	0.6	3.5	4.2*
Chow:W-Fhh				2.0				4.1*

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.32. Subregional Model Estimates for the Regression of Property Crime on Percent Unemployed: 1980 and 1990								
	1980				1990			
Variable	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.35**				0.27**		
λ			0.36**				0.28**	
NORTH								
Intercept	3033**	2178**	3019**	3219**	2905**	2259**	2920**	2954**
Unemp	-93.8*	-83.1+	-91.7+	-85.7	-116**	-99.3**	-118**	-107*
W-Unem				-28.6				-14.8
CENTRAL								
Intercept	1735**	1260**	1861**	1057	1414**	1111**	1600**	612
Unemp	-40.6	-41.7	-57.2	-72.1+	-23.1	-26.9	-44.4	-95.2*
W-Unem				94.3				147*
SOUTH								
Intercept	2900**	2010**	2814**	2987**	3697**	2816**	3412**	4531**
Unemp	-123**	-99*	-114*	-114*	-236**	-192**	-193**	-126*
W-Unem				-21.3				-242**
R^2	0.11	0.15	0.12	0.11	0.19	0.21	0.18	0.22
-2 Log-Lik	-3373	-3359	-3358	-3372	-3227	-3219	-3219	-3220
LM-err	36.4**	1.1		35.8**	15.5**	0.3		12.4**
LM-lag	35.2**		4.1*	36.0**	18.3**		0.1	12.1**
TCF			1.6				11.6**	
Chow:Unem	1.2	1.3	1.0	0.2	6.9**	8.8*	5.7+	0.1
Chow:W-ue				0.8				6.9**

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.33. Subregional Model Estimates for the Regression of Property Crime on Percent of Families Below Poverty: 1980 and 1990								
	1980				1990			
Variable	OLS	LAG	ERR	OLS (Spatial)	OLS	LAG	ERR	OLS (Spatial)
W-Y		0.21**				0.15*		
λ			0.25**				0.19*	
NORTH								
Intercept	3410**	2779**	3376**	3467**	2898**	2533**	2925**	2861**
Pov	-117**	-100**	-113**	-108**	-77**	-70**	-79**	-83**
W-Pov				-14.5				9.4
CENTRAL								
Intercept	2284**	1933**	2419**	1569**	1642**	1431**	1712**	1091*
Pov	-45**	-43**	-53**	-74**	-20	-19	-24	-52*
W-Pov				62.4*				56+
SOUTH								
Intercept	4214**	3566**	4198**	4180**	4463**	3930**	4430**	4572**
Pov	-157**	-142**	-158**	-159**	-177**	-161**	-176**	-165**
W-Pov				4.5				-21
R^2	0.27	0.29	0.28	0.28	0.30	0.30	0.30	0.30
-2 Log-Lik	-3332	-3327	-3326	-3330	-3199	-3196	-3195	-3197
LM-err	15.5**	1.2		14.4**	6.9**	1.3		6.3*
LM-lag	11.9**		1.1	15.1**	5.2*		0.2	5.7*
TCF			4.0				3.3	
Chow:Pov	11.0**	17.3**	16.0**	3.3*	20.3**	32.2**	31.5**	4.3*
Chow:W-pov				1.3				1.2

Significance Levels: +p<.10, * p<0.05; ** p<0.01

MULTIVARIATE MODEL RESULTS FOR VIOLENT CRIME

The previous sections of this chapter have examined various bivariate relationships between a number of demographic and socioeconomic variables and violent and property crime rates in Appalachia for 1980 and 1990. Many of these relationships were found to be highly significant. Insights gained from the exploratory phase of the analysis in Chapter 4, together with specification tests for spatial autocorrelation constructed from the least squares residuals of the bivariate models, also provide clear evidence of strong positive spatial autocorrelation effects for both violent crime and property crime at the county level.

This section, and the section to follow, present multivariate regression models of violent crime and property crime for metropolitan and nonmetropolitan locations and across Subregions for 1980 and 1990 in Appalachia. In developing these models, two concerns were addressed. First, the high degree of multicollinearity between several variables necessitated using a reduced number of predictors. Due to the relative racial homogeneity of the nonmetropolitan parts of the Region, as well as multicollinearity issues, percent Black was dropped from the multivariate models. The high degree of multicollinearity between unemployment and poverty, and the theoretical interest in the role of poverty on crime in Appalachia, resulted in the unemployment rate being omitted from the multivariate models also. Finally, population size was included instead of residential mobility in order to capture differences within, as well as between, metropolitan and nonmetropolitan categories.

Second, evidence of positive spatial autocorrelation in the previous analyses necessitated the use of spatial diagnostics in order to investigate the extent to which this spatial clustering may be explained by the various structural covariates in the multiple regression models. As with the bivariate regression models, this is accomplished by testing for the presence of residual spatial autocorrelation and evaluating whether this indicates the presence of spatial error or spatial lag effects.

Table 5.34 contains the results for the OLS and spatial multivariate models regressing violent crime rates on population size, percent of the population ages 15 to 29, High School drop out rates, percent female headed households, divorce rates, and poverty rates for 1980 and 1990 across metropolitan and nonmetropolitan locations. The OLS models for 1980 and 1990 show consistent positive effects for population size and percent female headed households in both metropolitan and nonmetropolitan locations. In metropolitan locations, the High School drop out rate goes from nonsignificance in 1980 to positive significance in 1990, while the divorce rate goes from positive significance in 1980 to nonsignificance in 1990. In nonmetropolitan locations, both the percent of the population ages 15 to 29 and the High School drop out rate go from nonsignificance in 1980 to positive significance in 1990, while the divorce rate goes from positive significance in 1980 to nonsignificance in 1990. The negative coefficients for the percent of families below poverty is counterintuitive but may suggest that higher poverty rates are correlated with reduced opportunities for violent crime once other indicators of social and economic deprivation are controlled for.

The spatial Chow tests for the stability of individual coefficients across metropolitan-nonmetropolitan locations show significant differences between metropolitan and nonmetropolitan counties for the effects of percent of the population ages 15 to 29 and percent female headed households on violent crime in 1980 and for the effects of population size, percent of the population ages 15 to 29, percent female headed households, and percent of families below poverty on violent crime in 1990. These diagnostics substantiate significant model outcome differences between metropolitan and nonmetropolitan locations and thus point to the need to adequately model variation across metro-nonmetro categories.

The Lagrange Multiplier (LM) tests for the presence of spatial autocorrelation indicate the need for a spatial error specification in 1980 but a spatial lag model in 1990. The change from a spatial error specification in 1980 to a spatial lag specification in 1990 suggests that a process of diffusion may be operating with regard to violent crime. Specifically, the evidence from the spatial diagnostics and the estimates of the spatial models reveal a high degree of spatial autocorrelation in the data, even after controlling for the effects of various demographic and socioeconomic predictors of violent crime. Furthermore, this process appears to be increasing over time, indicating a pattern of increased clustering and outward spread.

Table 5.34. Metro-Nonmetro Multivariate Regression Model Estimates of Violent Crime: 1980 and 1990				
	1980		1990	
Variable	OLS	Spatial	OLS	Spatial
W-Y		NI		0.30**
λ		0.39**		NI
MSA				
Intercept	-883**	-754**	-1362**	-1331**
Population	0.0002**	0.0002**	0.0002*	0.0002*
Ages 15 to 29	16.9**	14.8**	22.6**	20.1**
HS Drop Out	0.6	-2.6	4.1*	2.3
Fem HH	55.0**	49.7**	113.7**	111.4**
Divorce	34.9**	40.6**	17.2	15.9
Poverty	-6.3+	0.9	-25.1**	-21.2**
NONMSA				
Intercept	-147*	-87	-235**	-238**
Population	0.0006*	0.0008**	0.0011**	0.0011**
Ages 15 to 29	0.8	0.1	7.1**	6.5**
HS Drop Out	1.3	0.7	2.7*	1.7+
Fem HH	12.8**	10.4**	13.3**	10.7**
Divorce	17.4**	17.6**	2.3	3.5
Poverty	-1.3	-1.0	-3.0+	-1.9
R^2	0.47	0.47	0.47	0.50
-2 Log-Lik	-2311	-2297	-2392	-2378
LM-err	33.3**		33.3**	
LM-lag	25.8**		38.6**	
Coefficient Stability:				
Pop	2.4	5.0*	5.2*	5.4*
Age	16.1**	15.0**	7.8**	6.9**
Educ	0.2	2.5	0.4	0.1
Fem HH	24.9**	22.1**	66.0**	76.0**
Divorce	2.5	3.3+	1.1	0.9
Poverty	1.5	0.1	17.0**	14.8**

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.35 presents the results for the OLS and spatial multivariate models regressing violent crime rates on population size, percent of the population ages 15 to 29, High School drop out rates, percent female headed households, divorce rates, and poverty rates for 1980 and 1990 across Subregional locations. The OLS models show substantial Subregional variations. In Northern Appalachia, only population size remains a significant predictor of violent crime between 1980 and 1990. Divorce rates go from highly significant in 1980 to nonsignificance by 1990, while both percent female headed households and percent of families below poverty go from nonsignificance in 1980 to significant positive (percent female headed households) and significant negative (percent of families below poverty) predictors of violent crime in 1990. In Central Appalachia, only percent female headed households is a significant predictor of violent crime in 1980, while in 1990 percent ages 15 to 29 and percent of families below poverty are significant positive predictors. In Southern Appalachia, population size and percent female headed households remain significant positive predictors of violent crime between 1980 and 1990, while percent of families below poverty remains a significant negative predictor. Additionally, the High School drop out rate and percent ages 15 to 29 go from nonsignificance in 1980 to positive significance in 1990.

As with the metro-nonmetro model diagnostics, the Lagrange Multiplier (LM) tests for the presence of spatial autocorrelation indicate the need for a spatial error specification in 1980 and a spatial lag specification in 1990. The shift from a spatial error specification in 1980 to a spatial lag model in 1990, as well as significant differences in Subregional model coefficients, suggest that processes of spatial diffusion as well as Subregional differentiation in spatial effects may be operating and increasing over time with regard to violent crime in Appalachia.

Table 5.35. Subregional Multivariate Regression Model Estimates of Violent Crime: 1980 and 1990				
	1980		1990	
Variable	OLS	Spatial	OLS	Spatial
W-Y		NI		0.15**
λ		0.21**		NI
NORTH				
Intercept	-125	-135	20.2	-19.9
Population	0.0003**	0.0003**	0.0002*	0.0002*
Ages 15 to 29	1.1	1.5	-0.02	0.3
HS Drop Out	-1.7	-1.9	-0.6	-0.6
Fem HH	10.5	11.8+	29.2**	28.9**
Divorce	36.5**	34.4**	-7.5	-6.5
Poverty	1.9	2.6	-6.8*	-6.3*
CENTRAL				
Intercept	-12.6	-1.6	-134	-178
Population	0.00004	-0.0001	0.0009	0.0010
Ages 15 to 29	2.7	2.6	15.8**	15.6**
HS Drop Out	-1.8	-1.6	-3.0	-2.5
Fem HH	21.8*	18.5*	3.8	3.8
Divorce	-3.5	1.2	-9.8	-8.1
Poverty	0.8	0.4	5.0+	4.1
SOUTH				
Intercept	24.7	31.3	-173+	-201*
Population	0.0011**	0.0010**	0.0018**	0.0018**
Ages 15 to 29	1.1	0.8	5.6+	5.0
HS Drop Out	-0.8	-1.1	2.7*	2.4+
Fem HH	24.2**	23.9**	34.8**	32.4**
Divorce	0.7	3.5	-3.7	-2.5
Poverty	-8.3**	-7.4**	-18.3**	-15.8**
R^2	0.52	0.52	0.57	0.58
-2 Log-Lik	-2292	-2288	-2354	-2350
LM-err	8.1**		7.4**	
LM-lag	7.0**		8.9**	
Coefficient Stability:				
Pop	15.7**	31.8**	34.8**	75.9**
Age	0.1	0.2	3.5*	7.0*
Educ	0.1	0.1	1.7	2.8
Fem HH	1.5	2.4	3.5*	6.5*
Divorce	6.9**	9.4**	0.1	0.2
Poverty	6.2**	9.4**	13.4**	20.7**

Significance Levels: +p<.10, * p<0.05; ** p<0.01

MULTIVARIATE MODEL RESULTS FOR PROPERTY CRIME

Table 5.36 contains the results for the OLS and spatial multivariate models regressing property crime rates on population size, percent of the population ages 15 to 29, High School drop out rates, percent female headed households, divorce rates, and poverty rates for 1980 and 1990 across metropolitan and nonmetropolitan locations. The OLS models for 1980 and 1990 show consistent positive effects for percent ages 15 to 29 and the divorce rate and consistent negative effects for the poverty rate in both metropolitan and nonmetropolitan locations. In metropolitan locations, there are also consistent positive effects for percent female headed households. In nonmetropolitan locations, there are also consistent positive effects for population size, while the High School drop out rate goes from negative significance in 1980 to nonsignificance in 1990.

The spatial Chow tests for the stability of individual coefficients across metropolitan-nonmetropolitan locations show significant differences between metropolitan and nonmetropolitan counties for the effects of population size, percent of the population ages 15 to 29, and percent female headed households on property crime in 1980 and for the effects of population size, percent of the population ages 15 to 29, percent female headed households, the divorce rate, and percent of families below poverty on property crime in 1990. Again, as with the metro-nonmetro model outcomes for violent crime, these diagnostics substantiate significant model outcome differences between metropolitan and nonmetropolitan locations and thus point to the need to adequately model variation across metro-nonmetro categories.

The Lagrange Multiplier (LM) tests for the presence of spatial autocorrelation indicate the need for a spatial error specification in both 1980 and 1990. The evidence from the spatial diagnostics thus suggest that a lag, or diffusion process, better describes violent crime patterns than property crime patterns in Appalachia for the periods under study. While there is evidence of substantial spatial autocorrelation for violent crime rates in the sense that levels of violent crime in neighboring locations affect one another, the spatial autocorrelation for property crime is primarily limited to the error term. This suggests that the appearance of spatial clustering for property crime results primarily from a spatial similarity in the ignored variables represented by the error term.

Table 5.36. Metro-Nonmetro Multivariate Regression Model Estimates of Property Crime: 1980 and 1990

	1980		1990	
Variable	OLS	Spatial	OLS	Spatial
W-Y		NI		NI
λ		0.43**		0.41**
MSA				
Intercept	-4876**	-4573**	-6854**	-7606**
Population	0.0004	0.0005	0.0012+	0.0009
Ages 15 to 29	150**	138**	175**	181**
HS Drop Out	-21.6	-34.8*	10.5	19.1
Fem HH	350**	313**	447**	485**
Divorce	456**	547**	404**	451**
Poverty	-82.6*	-43.9	-212**	-264**
NONMSA				
Intercept	-188	288	-1258**	-852
Population	0.0089**	0.0106**	0.0118**	0.0147**
Ages 15 to 29	53.9**	45.5**	89.1**	74.8**
HS Drop Out	-16.6*	-21.8*	-5.8	-10.2
Fem HH	-1.5	8.5	22.9	31.6
Divorce	347**	316**	191**	181**
Poverty	-34.0**	-30.6*	-50.4**	-48.1**
R^2	0.59	0.61	0.60	0.62
-2 Log-Lik	-3183	-3162	-3093	-3075
LM-err	41.6**		19.6**	
LM-lag	22.3**		12.0**	
Coefficient Stability:				
Pop	12.3**	17.9**	18.9**	31.0**
Age	6.9**	7.4**	6.0*	10.2**
Educ	0.1	0.5	1.2	3.5+
Fem HH	20.8**	16.3**	29.8**	31.9**
Divorce	1.1	4.0*	5.9*	7.3**
Poverty	1.7	0.1	23.2**	23.8**

Significance Levels: +p<.10, * p<0.05; ** p<0.01

Table 5.37 presents the results for the OLS and spatial multivariate models regressing property crime rates on population size, percent of the population ages 15 to 29, High School drop out rates, percent female headed households, divorce rates, and poverty rates for 1980 and 1990 across Subregional locations. As with the models for violent crime, the OLS models show substantial Subregional variations. In Northern Appalachia, only percent ages 15 to 29 and the divorce rate remain significant predictors of property crime between 1980 and 1990. High School drop out rates go from negative significance in 1980 to nonsignificance by 1990, while percent of families below poverty go from nonsignificance in 1980 to negative significance in 1990. In Central Appalachia, only the divorce rate is a significant predictor of property crime in 1980, while in 1990 population size and percent ages 15 to 29 are significant positive predictors. In Southern Appalachia, population size, percent ages 15 to 29, percent female headed households, and the divorce rate all remain significant positive predictors of property crime between 1980 and 1990, while percent of families below poverty remains a significant negative predictor.

As with the metro-nonmetro model diagnostics for property crime, the Lagrange Multiplier (LM) tests for the presence of spatial autocorrelation indicate the need for a spatial error specification in both 1980 and 1990 for the Subregional models as well. Again, this indicates that spatial dependence is primarily limited to the error term and is thus less of a substantive concern than it is for violent crime patterns.

Table 5.37. Subregional Multivariate Regression Model Estimates of Property Crime: 1980 and 1990				
	1980		1990	
Variable	OLS	Spatial	OLS	Spatial
W-Y		NI		NI
λ		0.30**		0.19*
NORTH				
Intercept	2099*	1220	-1154	-1294+
Population	0.0006	0.0007	0.0011+	0.0011+
Ages 15 to 29	42.6*	51.7*	82.4**	83.2**
HS Drop Out	-78.5**	-70.7**	-1.8	-0.7
Fem HH	41.5	58.0	78.2	80.7
Divorce	370**	405**	253**	265**
Poverty	4.8	7.6	-94.0**	-95.8**
CENTRAL				
Intercept	149	71.3	-20.6	-149
Population	0.0103	0.0129*	0.0173*	0.0194*
Ages 15 to 29	59.4+	60.73*	83.6*	78.7*
HS Drop Out	-36.1+	-37.3+	-35.6	-33.8
Fem HH	-16.9	18.0	39.5	41.1
Divorce	318**	280*	6.3	19.3
Poverty	9.6	4.8	7.0	6.1
SOUTH				
Intercept	-267	96.1	-1587*	-1717*
Population	0.0073**	0.0074**	0.0077**	0.0076**
Ages 15 to 29	60.2**	49.7*	103**	101**
HS Drop Out	-11.9	-16.4	-1.9	-2.8
Fem HH	98.0**	100*	155**	160**
Divorce	316**	309**	233**	242**
Poverty	-100**	-88.6**	-170**	-164**
R^2	0.62	0.62	0.65	0.65
-2 Log-Lik	-3166	-3158	-3065	-3062
LM-err	13.3**		4.8*	
LM-lag	9.6**		2.7	
Coefficient Stability:				
Pop	14.3**	31.2**	16.6**	34.4**
Age	0.2	0.1	0.3	0.5
Educ	5.5**	6.7*	0.9	1.6
Fem HH	1.0	1.0	1.4	3.1
Divorce	0.2	1.2	2.6+	5.1+
Poverty	9.6**	12.5**	18.7**	32.6**

Significance Levels: +p<.10, * p<0.05; ** p<0.01

SUMMARY

The application of confirmatory spatial data analysis (CSDA) procedures to county-level rates of violent and property crime in Appalachia yield several summary findings. First, neither violent crime nor property crime is randomly distributed geographically. For both 1980 and 1990, county-level crime rates exhibit significant positive spatial autocorrelation patterns. Both the spatial regression modeling results, as well as the exploratory spatial data analysis (ESDA) applications in the previous chapter, reveal a distinct pattern of spatial clustering and spread in the data. Although the spatial autocorrelation patterns for violent crime are more substantial than those for property crime, both types of crime exhibit significant spatial groupings characterized by regional hot spots and shifting concentrations of crime density.

Second, these patterns of spatial autocorrelation persist even after controlling for a number of theoretically relevant demographic and socioeconomic predictors of crime. This suggests that crime rates are influenced by more than just the internal characteristics of any given location. Instead, levels of crime are strongly affected by conditions in neighboring locations as well. This means that modeling efforts must explicitly include spatial parameters in the form of either spatial error or spatial lag specifications in order to adequately capture these spatial autocorrelation effects.

Third, after controlling for the effects of these demographic and socioeconomic predictors of crime, various diagnostic tests for spatial dependence indicate that the spatial effects for property crime are primarily residual in nature while those for violent crime are more substantial. This indicates that while a spatial error model may be sufficient for addressing the residual spatial autocorrelation patterns of property crime, a spatial lag model is needed to capture the more substantial spatial autocorrelation patterns of violent crime. These findings further suggest that processes of diffusion may be operating with regard to violent crime in the Region.

Fourth, there are significant outcome differences for metropolitan and nonmetropolitan locations. One implication of this finding is that different theoretical constructs of crime may need to be applied in metropolitan and nonmetropolitan locations. This further suggests that global theories of crime may need to be modified to accommodate geographic heterogeneity and variations based on spatial scale.

Finally, there are significant regional differences in model outcomes for structural effects as well as spatial effects. In addition to Subregional differences in the effects of various demographic and socioeconomic predictors of crime, there are also significant Subregional differences in the clustering and spread of crime. Overall, these findings lend support to prior studies that have found higher rates of violent crime in the South. Spatial concentrations of both violent crime and property crime tend to be more pronounced in the South as well.

In summary, the bivariate and multivariate spatial regression model results demonstrate the existence of meaningful spatial patterns of violent and property crime at the county level in Appalachia. These spatial effects include patterns of both spatial dependence and spatial heterogeneity. Patterns of spatial dependence point to the existence of clustering and possible diffusion processes, especially in the case of violent crime. Patterns of spatial heterogeneity point to the existence of significant differences in levels of crime based on regional location or spatial scale.

CHAPTER SIX: SUMMARY AND CONCLUSIONS

SUMMARY OF FINDINGS

Both exploratory and confirmatory spatial data analysis procedures in a GIS environment were used to examine the social ecology and spatial patterns of violent and property crime in Appalachia at the county level for 1980 and1990. Several major findings have emerged from this research. *First, Appalachia is a Region which is marked by a substantial amount of demographic and socioeconomic diversity.* This study documents the large and often growing differences in aggregate characteristics and indicators of well-being between counties and subregions. While the Region as a whole is often characterized as lagging behind the rest of the nation in terms of economic growth and social capital, these summary observations often mask the spatial inequality and growing diversity that exists within the Appalachian Region. In order to portray the multifaceted nature of spatial diversity in Appalachia, three county classification typologies were utilized: (1) the three geographic Subregions of Appalachia, (2) counties classified by the 1996 ARC Distressed County Codes, and (3) counties categorized by the 1993 Beale Codes across a rural-urban continuum. These county classification typologies were then used to make comparisons across the dimensions of population distribution and change, population composition, social well-being, and socioeconomic conditions.

Overall, it was found that areas experiencing population decline are often characterized by declines in social and economic well-being as well. Residents in these areas have low levels of educational attainment, high unemployment, and high rates of poverty. Industrial restructuring is often characterized by the loss of key industries, usually in mining or manufacturing, without corresponding shifts to comparable jobs in other sectors. Counties experiencing demographic, social, and economic decline are:

- more likely to be found in Central Appalachia,
- more likely to be rural and not adjacent to metropolitan areas,
- more likely to be reliant on mining and extractive industries, and
- more likely to be defined as Distressed Counties.

Other parts of the Region, on the other hand, have experienced rapid demographic, social, and economic growth. These areas are often characterized by high levels of educational attainment, low unemployment and low rates of poverty. Industrial restructuring is characterized by relatively smooth transitions from goods producing to services producing economies. Counties experiencing rapid growth are:

- more likely to be found in Southern Appalachia, especially near the larger metropolitan areas, and
- more likely to be defined by the as Competitive and Attainment Counties.

In spite of this diversity, it is also true that a majority of Appalachia's population continue to reside in counties designated as having a distress ranking characterized by one or more of the following characteristics: at least 150 percent of the U.S. unemployment rate, at least 150 percent of the U.S. poverty rate, or less than 67 percent of the U.S. per capita market income. While there does appear to be some shifting of the population towards economically prosperous locations, a majority still live in substantial poverty and economic hardship compared with the rest of the nation.

Second, regional crime rates in Appalachia are lower than those for the nation as a whole. While the social and economic distress experienced by much of Appalachia would seem to make the Region particularly vulnerable to increasing rates of crime and violence, crime in Appalachia is only about 50 to 65 percent of the national levels. Nevertheless, between 1980 and 1995, crime has been increasing at a faster rate in Appalachia than for the nation as a whole. While crime in Appalachia is low compared to U.S. averages, part of this is due to the predominately nonmetropolitan character of the Region. Crime levels in nonmetropolitan areas in every part of the country are almost always well below those of metropolitan locations.

When broken down by Subregion, these Regional trends exhibit some interesting variations. Index crime rates have consistently been higher in the South. This may partially be attributed to the relatively large number of metropolitan counties located in the South compared with the rest of the Region. It may also be related to the patterns of rapid population growth and increased population mobility which are coming to characterize many metropolitan and nonmetropolitan counties in Southern Appalachia. Nevertheless, the largest percentage increases in crime, especially violent crime, are taking place in Central Appalachia where many counties are experiencing rapid demographic, social, and economic declines.

Third, the spatial autocorrelation patterns of both violent crime and property crime indicate that these spatial patterns are not random. In some locations, the spatial autocorrelation of crime remains significant even across several levels of contiguity. This robust and significant relationship across several "high crime" clusters indicates that the spatial patterns of violent crime and property crime are positively related to the unique characteristics and spatial proximity of particular locations.

The application of exploratory spatial data analyis (ESDA) and confirmatory spatial data analysis (CSDA) procedures to county-level rates of violent crime and property crime in Appalachia further confirms that crime is not randomly distributed in space. Moreover, these patterns of spatial autocorrelation persist even after controlling for a number of theoretically relevant demographic and socioeconomic predictors of crime. This suggests that crime rates are influenced by more than just the internal characteristics of any given location. Instead, levels of crime are strongly affected by conditions in neighboring locations as well.

Fourth, the spatial autocorrelation patterns for violent crime are indicative of a spatial diffusion process. Evidence from various diagnostics tests and spatial regression model estimates suggest that a spatial lag model better captures the spatial autocorrelation patterns of violent crime in the Region. In the case of a spatial lag specification, levels of violent crime are significantly related to levels of violent crime in neighboring locations. This provides evidence for the existence of contagion or diffusion processes. Furthermore, the change from a spatial error specification in 1980 to a spatial lag specification in 1990 further confirms that a process of diffusion may be operating with regard to violent crime.

Fifth, there are significant outcome differences for metropolitan and nonmetropolitan locations. Significant coefficient differences between metropolitan and nonmetropolitan locations in the bivariate and multivariate spatial regression models provide evidence of substantial spatial heterogeneity based on spatial scale. These model outcome differences suggest that different mechanisms may be operating with regard to levels of violent crime and property crime in metropolitan and nonmetropolitan locations.

One implication of this finding is that different theoretical constructs of crime may need to be applied in metropolitan and nonmetropolitan locations. This further suggests that global theories of crime may need to be modified to accommodate spatial heterogeneity and variations based on spatial scale.

Sixth, there are significant regional differences in model outcomes for structural effects as well as spatial effects. In addition to Subregional differences in the effects of various demographic and socioeconomic predictors of crime, there are also significant Subregional differences in the clustering and spread of crime. While significant spatial autocorrelation trends are evident in several "high profile" locations throughout the Region, substantial Subregional variations in the spatial-temporal patterns of violent and property crime exist as well. This indicates that perhaps different spatial processes may be operating in different Subregional locations. Thus, the data provide empirical evidence of substantial spatial heterogeneity based on regional location as well.

IMPLICATIONS

The findings contained in this study demonstrate the importance of incorporating spatial effects into empirical models of crime. A related implication is that global theories of crime may need to be further modified or expanded in order to take spatial patterns and spatial dynamics more explicitly into account. Given recent developments in GIS technology and spatial analysis applications, there is now available a rich array of tools that can be applied to the study of crime in its spatial context. This opens the door for new ways to explore, visualize, and understand hot spots and clusters of crime, spatial diffusion processes, and differences based on spatial scale or location.

The results of this study thus have both theoretical and methodological implications and point to several directions for future research. First, the results indicate that different processes may be operating in metropolitan and nonmetropolitan locations. While a number of factors have traditionally been linked to crime in the social ecology literature, the spatial pattern of these relationships is often complex. Furthermore, most of this literature has been limited to urban crime and it may be that the link between various ecological characteristics and crime are different in urban and rural locations. In fact, it could be said that one of the least understood topics in the field of criminology is that of rural and nonmetropolitan crime. Thus, there is a need for further research on rural crime which takes location and geographic context seriously. Future studies may therefore need to address the spatial dynamics of crime in rural locations as a product of social, economic, and demographic factors which are often unique to those areas.

Second, these findings also point to the need for spatially-informed theory construction in the field of criminology. Recent studies on the social ecology of crime have tended to operationalize the relationship between communities and crime from either a stratification perspective (e.g. Blau and Blau 1982) or else from a social control perspective (e.g. Kornhauser 1978). Those who have taken a stratification perspective have emphasized structural factors such as income inequality and residential segregation to explain variations in the rate of crime. Those who have taken a social control perspective have emphasized the relative capacity of communities and various social institutions to produce normative conformity and social integration.

Ecological studies in the stratification tradition have searched for links between structural socioeconomic conditions and variations in aggregate crime rates. Krivo and

Peterson (1996) found that extremely disadvantaged neighborhoods have higher levels of crime and that these patterns are consistent for both whites and blacks. On the other hand, Blau and Blau (1982) argue that high rates of violent crime result from relative income inequality rather than absolute disadvantage, especially relative inequality between racial groups.

Other studies in the stratification tradition have examined the links between crime and spatial stratification, especially the extreme residential segregation of blacks. Peterson and Krivo (1993), using race-specific crime rates, have found that racial segregation is associated with higher rates of black urban homicide. Logan and Messner (1987) found that racial residential segregation is associated with violent crime in suburban neighborhoods as well. Shihadeh and Flynn (1996) have further contended that the multidimensional nature of segregation needs to be taken into account in order to disentangle the links between hypersegregation and crime. Thus, in addition to the Index of Dissimilarity, which measures the degree of unevenness in the spatial distribution of blacks versus whites, Massey and Denton (1988) have identified several other dimensions of racial segregation as well, including exposure, clustering, concentration, and centralization. According to Shihadeh and Flynn (1996), these each need to be examined in order to see how spatial and economic stratification has taken on a multidimensional character in the black community and how this process of hypersegregation has contributed to the overall increase in rates of black urban violence.

Ecological studies in the social control tradition have searched for links between aggregate crime rates and measures of social-disorganization such as formal and informal community-level social controls, family disruption, and residential mobility. Some studies in the social control tradition have looked at the dynamics of community change and population mobility and the implications these processes have had for the spatial distribution of high crime areas (Bursik and Webb 1982; Schuerman and Kobrin 1986). Others have examined the effect of family disruption on crime and delinquency rates at the community level. Sampson (1987) found that the effect of black male unemployment on black violent crime is primarily mediated by its effect on family disruption. Shihadeh and Steffensmeier (1994) also found that the effect of economic inequality on black urban violence is primarily mediated by family disruption.

These two ecological approaches to the study of crime may provide fruitful theoretical directions for studying the spatial dynamics of crime. Testing the relative merits of the stratification and social control perspectives from a more spatially informed model-building approach should therefore prove to be a promising direction for future research as well. Based on the implications of the present study, it may well be that a spatially-informed stratification model of crime would be more appropriately applied to the metropolitan and urban context, while a spatially-informed social control perspective might be more applicable to the nonmetropolitan and rural context.

Finally, the present research shows the value of applying Geographic Information System (GIS) technologies and spatial analytic procedures to the study of aggregate crime patterns. The main advantage of using GIS and related technologies is that it enables the researcher to look more rigorously at the spatial patterns and ecological contexts of crime. Furthermore, the analytical applications of GIS can be used in either an exploratory or confirmatory capacity. As an exploratory data analysis tool, GIS can be used to examine data visually as a way of generating new hypotheses from the data or as a way of identifying unexpected spatial patterns. As a confirmatory data analysis tool, GIS has been given increased analytical power with the introduction and development of spatial statistical packages such as SpaceStat (Anselin 1998) and CrimeStat (Levine 1999). Thus, future studies could benefit substantially by systematically investigating the factors associated with crime from a spatial perspective utilizing the contributions that GIS and geographic information analysis can provide. By employing spatial analytic procedures within a GIS environment, contextual and ecological factors identified as theoretically relevant in studies of crime and delinquency can be linked spatially and thereby examined in ways previously not possible.

Overall, the findings of the present study show how important spatial and contextual analysis can be in the study of violent and property crime across various levels of geography. By combining graphical, analytic and statistical tools in a GIS environment, researchers can explore spatial patterns which may warrent further empirical investigation as well as formally test spatially-informed theoretical models for their applicability at different spatial scales and locations.

APPENDIX: Responses to Reviewers' Comments

In response to reviewers' comments, the following issues were addressed:

1. The study is not grounded in the theoretical/criminological literature.

   While it is true that I am not testing specific hypotheses derived from traditional criminological theory, I have attempted to locate this study within the long tradition of criminological research that has focused primarily on the social ecology and locational contexts of crime. In addition, I have derived my choice of explanatory variables based on theoretical traditions rooted in social disorganization, economic strain, and spatial inequality, theoretical traditions which have established a number of structural characteristics that vary systematically between locations and which are often highly correlated with rates of serious crime (a point I make in the first chapter of the report and reiterate throughout). It should also be noted that the primary purpose of the study is not to test existing theoretical constructs but rather to explore new methodological and theoretical applications which may have broader implications for future developments in criminological theory and research. This is especially true in the case of rural crime, an area that has received relatively little attention in the literature. The results of this study indicate that different processes may be operating in urban and rural contexts and therefore highlight the need for further research on rural crime that takes location and geographic context seriously. In the final chapter of the report (Chapter 6), I briefly explore these theoretical implications by looking specifically at recent studies on the social ecology of crime that have been done from either a stratification perspective or from a social control perspective and how a more spatially-informed approach to theory construction could be used to test the relative merits of these two perspectives.

2. There are numerous "implied" findings that beg for interpretation or further explanation.

   Again, the primary purpose of the present study is to explore new methodological and theoretical applications that may have broader implications for future developments in criminological theory and research. Given the exploratory nature of this study, a number of findings emerged which could be explored more thoroughly from any number of theoretical perspectives. The primary purpose of this study, however, is to establish the need for more spatially-informed theoretical perspectives and to demonstrate the value of using GIS technologies and spatial-analysis applications. Also, future research could explore these findings from different levels of aggregation. Given the regional focus of this study, it was not feasible to focus on specific localities except as these affected larger regional trends.

3. “Percent Black” was dropped from the analysis due to collinearity problems, yet it figures prominently in a discussion in the implications section in Chapter 6. It seems that the importance of this variable would require that other variables be dropped instead .

   The reference made by the reviewer to the importance of “percent Black” is found in a section of the report that discusses previous research on the social ecology of crime from both stratification and social control perspectives. Most of this research has been done in urban locations and, in this context, “percent Black” has often been found to be an important predictor of crime. In the present study, however, the context is predominately rural. As noted in the report, most of the Appalachian region is racially homogeneous, with over 90% White and about 8% Black (compared with 73% White and 12% Black for the U.S. as a whole). Given the relative racial homogeneity of the region and given the high degree of collinearity with other, more contextually meaningful predictors (such as female-headed households), it was decided that “percent Black” should be dropped from the final model (this is discussed in Chapter 5, “Confirmatory Spatial Data Analysis: Spatial Regression Models of Crime”).

4. Suggestion of a diffusion process deserves more substantial commentary.

   Given the limitations of the present study, it was not feasible to explore possible diffusion processes in further depth. This topic is substantial enough to serve as the primary focus for a future research project. Also, there is very little research on the diffusion of crime in general (let alone in predominately rural areas) to provide theoretical guidance as to the dynamics and causative factors which may be driving these processes.

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