THE USE OF A GEOGRAPHIC INFORMATION SYSTEM (GIS) AND SATELLITE REMOTE SENSING FOR SMALL-AREA MORTALITY ANALYSIS

by

JAMES B. HOLT

(Under the Direction of C.P. LO)

ABSTRACT

A geographic information system (GIS) and satellite remote sensing were used to analyze all-cause mortality at the census tract level for Metropolitan Atlanta, Georgia, 1995-1999. The GIS was used to store, analyze, and display mortality data and sociodemographic and physical environmental variables, which were hypothesized to be causally-related to mortality. Satellite remote sensing was used to derive land-use/land-cover statistics for the study area and to facilitate dasymetric computation of population densities, which were used to areally-interpolate census data, to account for census geography changes, 1980-2000. Two hypotheses were tested: 1) the spatial distribution of selected area-level socio-demographic and physical environmental variables, in 1990, is significantly related to the spatial distribution of all-cause mortality, 1995-1999; and 2) the process of urbanization in Metropolitan Atlanta, 1980-2000, has resulted in a more dispersed spatial pattern of area-level variables significantly associated with all-cause mortality. Three variables were found, through multiple regression analysis, to be significantly related ($p < .01$) to the pattern of all-cause mortality in metropolitan Atlanta, 1995-1999: the percentage of blacks in the total population; the percentage of population over age 25 with high school diplomas or equivalent; and the percentage of total land area that was urbanized; with the expected number of deaths per tract as a control variable. Composite indices of these explanatory variables were mapped for 1980, 1990, and 2000. Areas with positive index values (predictive of higher mortality risk) were generally concentrated in the inner portions of the metropolitan area, corresponding to the traditional Central Business District (CBD) and its immediate surroundings. Areas with temporally increasing index values were initially in the CBD (1980-1990), but moved outward coincident with general patterns of suburban growth (1990-2000). Areas with decreasing index values (predictive of lower mortality risk) also expanded outward. Yet, in the 1990s there was a backfill of decreasing index values in many portions of the CBD. These results suggest a suburbanization/gentrification-induced spatio-temporal dispersion of factors significantly related to all-cause mortality in Atlanta.

INDEX WORDS: Geographic Information Systems, Satellite Remote Sensing, Mortality, Public Health, Medical Geography

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DEDICATION

This dissertation is dedicated to the memory of my father, Donald I. Holt.

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It is very difficult to adequately express my gratitude to my major professor, Dr. C.P. Lo. He has provided me with patient, expert advice over the past three years. He has a remarkable grasp of geographic issues relating to public health, and he is a world-renowned expert on GIS and remote sensing. I have always been amazed with the amount of time that he devotes to his work and to his students. I am extremely grateful to him for his support. I am most fortunate to have been his student, and I hope that my future career as a geographer reflects positively on him.

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I would also like to acknowledge my family for their support: first, my mother Jean Holt Pellon, who through her gift of a National Geographic Atlas for Christmas in 1975, started me on a lifelong appreciation of maps and geography. Her continued support has always meant the world to me. Next, I would like to acknowledge my son, Andrew, for providing me the indirect motivation to succeed: I want him to be as proud of me as I am of my father. And lastly, I want to thank my wonderful wife, Heidi, for all her support. When considering a return to school to pursue an advanced degree in Geography, little did she or I know at the time (2000) that I would be pursuing a doctorate (originally, my intentions were to pursue a masters degree), or that we would have the great fortune of raising a son (born in November, 2001), or that most weekends would be usurped by studying, or that many household maintenance chores would be put on the back burner for three years. I can’t thank her enough for her support; it has meant the world to me.

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CHAPTER 1

INTRODUCTION

Objectives

The main objective of this project is to use a geographic information system (GIS) together with remotely-sensed satellite imagery to facilitate the small-area spatial analysis of a public health issue. Recent advances in geospatial technologies and analytic methods have resulted in many new applications of GIS and remote sensing technology, particularly in forestry, agriculture, mining, water resource management, disaster response management, public safety, utilities, transportation, and business and real estate.

There has also been some application of GIS and remote sensing for public health research. However, most of these applications have been from the academic community and have not represented the widespread adoption of GIS and remote sensing by public health analysts. This is especially true for remote sensing, which while having demonstrable benefits for predicting and mapping areas susceptible for a variety of environmental and infectious diseases, is infrequently called upon to do so in practice. Remote sensing is even less-utilized for non-environmental and non-infectious disease applications, even though such data and technology can play an important role in surveillance and analysis of factors relating to chronic diseases.

GIS has been more widely adopted by the public health community. However, the majority of applications of GIS involve basic functionalities, particularly choroplethic mapping. While most current GIS software packages do not contain spatial statistical capabilities, which may have hampered the use of GIS for more sophisticated analyses in the past, GIS can be closely coupled with statistical software. A variety of statistical packages have the ability to import and export data from and to a GIS. Therefore, while much spatial analysis may be performed in a separate software package, the input to the spatial statistical program can come from a GIS and be displayed in a GIS after analysis.

Given this type of an interrelationship with statistical software, one of the more useful functions of a GIS is the manipulation of geospatial data for subsequent analysis. Often, data are not available for the specific administrative boundaries that are being used in a research study. The data may be available at a different spatial scale or available at the correct scale, but for boundaries that have changed over time (e.g., census tracts). Often a GIS can manipulate these data to conform to different scales and boundaries, a process generally known as areal interpolation. In some situations, ancillary data (often derived from remotely-sensed imagery) may be required in order to assist with areal interpolation. Therefore, in many situations spatial statistics, a GIS, and remote-sensing data can be linked together.

While GIS and remote-sensing represent the technical tools to facilitate the analysis of public health issues, spatial analysis techniques provide the conceptual and methodological tools. Standard statistical software packages that perform multivariate regression analysis can be used in addition to specialized statistical software packages that perform spatial analyses, such as cluster analysis and the assessment of spatial autocorrelation at global and local scales. Standard and spatial statistical packages can be used in conjunction to assess the spatial variation of regression parameters and residuals, and the results can be displayed graphically in a GIS in order to facilitate visualization and hypothesis generation.

For this dissertation, it was desired to conduct a public health research project that would take advantage of GIS and remote-sensing technology and spatial analysis methods. Given these overall objectives, the specific purpose of this research project is to use a GIS and remotely-sensed satellite imagery and census data to facilitate the analysis of mortality at the census tract level for a thirteen-county area in metropolitan Atlanta, Georgia, from 1995 to 1999. The spatial patterns of population growth and land use changes from 1980 to 2000 were examined, with emphasis on the effects of urban growth on the distribution of socioeconomic variables and selected physical environmental variables. These socioeconomic and physical environmental variables and relative changes in these variables resulting from the urban growth process from 1980 through 2000 were related to the pattern of all-cause mortality for Atlanta for 1995-1999, inclusive.

In particular, this research helped determine the existence of a significant relationship between patterns of socioeconomic and physical environmental variables resulting from rapid urban and suburban growth and the patterns of all-cause mortality for the metropolitan Atlanta region. It was hypothesized that the mortality rates are the result of not only individual-level health-related risk factors, but also the neighborhood context in which people live. This context is comprised of both the social environment and the physical environment. Therefore, this study placed primary importance on determining the influence of “place” on the health outcomes of the population. It was further hypothesized that similar spatial patterns would be found between socioeconomic and physical environmental variables and mortality rates.

The process of urbanization has resulted in changes in the social and physical environments, which may be manifested to some degree in the resulting all-cause mortality rates. It is possible that if mortality data (at the census tract level) were available historically to 1980, it would be possible to show a *change* in the pattern of mortality that would mirror the spatial changes in the social and physical environment over the same period. Likewise, if this study were to be completed prospectively it is possible that such a change analysis could be conducted. However, since census tract level mortality data prior to 1995 are not available, the current research was limited to a point-in-time analysis between the socioeconomic and physical environmental variables for 1990 and all-cause mortality, from 1995 through 1999.

This study is unique in that it represents an attempt to map and analyze mortality patterns at a finer spatial resolution than has been previously accomplished for this area. Most analyses of mortality patterns have been conducted at either the state or the county level, generally due to the lack of spatially-specific mortality data or to the scope of the mapping/analysis project. This project will complement recent work on mortality patterns, especially with respect to cancer, cardiovascular diseases, stroke, and all-cause mortality (U.S. Department of Health and Human Services, 1997; Devesa *et al*, 1999; Casper *et al*, 1999; Barnet *et al*, 2001; Casper *et al*, 2003); however, the scale of analysis is the census tract level rather than the state or county level. Furthermore, this analysis is limited to the Atlanta metropolitan area, rather than an entire state, region, or country.

The storage, analysis, and presentation of the data relied heavily upon the use of a GIS. In addition, the GIS enabled the derivation of key variables from existing data sources, especially census data and remotely sensed satellite imagery. This was particularly helpful in dealing with census tract geography changes over the period of this study (1980-2000).

The results of this study will be useful in informing public health policy decisions regarding resource allocations and interventions. Because this project is an ecological study, it should be considered as the first step toward a more comprehensive analysis of the interaction of individual and contextual influences on health; it is hoped that as individual-level data may become available in the future, a multilevel analysis can be built upon this initial work.

Research Hypothesis

The population growth of metropolitan Atlanta from 1980-2000, especially the process of suburbanization, has resulted in greater socioeconomic spatial variation, with increasing polarization from the downtown urban core to the suburban fringe. Along with this general socioeconomic polarization, there is a complex mixing of social class and socioeconomic position in the downtown urban core (as a result of gentrification) and in the outlying suburban fringe (as the result of the spatial diffusion of affluent households into previously rural agricultural areas). These changes in Atlanta's urban structure, due to the urbanization process, also have resulted in changes in the physical environment, such as land use, population density, and vegetative greenness, all of which are measures that can be derived from remotely sensed satellite data.

Previous public health research has demonstrated that linkages exist between health and measures of socioeconomic position, such as income, poverty, deprivation, wealth, and education (e.g., Osler *et al*, 2002; Sturm and Gresenz, 2002; Muller, 2002; Yen and Kaplan, 1999; Ben-Shlomo *et al*, 1996; Smith *et al*, 1996). Significant relationships also exist between health and urbanicity (Verheij, 1996; Vögele, 2000; Geronimus, 2000; Leviton, 2000; and McDade and Adair, 2001). Because these linkages hold at the individual, household, and neighborhood levels, variations in health outcomes should mirror spatial patterns of socioeconomic position and urbanicity. These spatial patterns are complex and are likely to be masked by aggregation of data at the county-level; only by examining these spatial patterns at a finer spatial resolution, such as census tracts, can the complexity of these patterns be discerned.

There are two hypotheses for this study: 1) the spatial distribution of selected area-level socio-demographic and physical environmental variables, in 1990, is significantly related to the spatial distribution of all-cause mortality, aggregated from 1995 through 1999; and 2) the process of urbanization in metropolitan Atlanta, Georgia, from 1980 through 2000 has resulted in more dispersed spatial pattern of those area-level variables that are significantly associated with poor health outcomes, specifically all-cause mortality.

To summarize: several forces have led to the changing urban structure of Atlanta, which is manifested in changes in the spatial patterns of the socioeconomic composition of neighborhoods and in the physical context of neighborhoods. The changing urban structure, operating through the changing spatial patterns of socioeconomic and physical environmental variables, is reflected in the overall pattern of population health in the region.

Study Area

The study area for this research project included thirteen counties in the metropolitan Atlanta area (Figure 1.1): Cherokee, Clayton, Cobb, Coweta, DeKalb, Douglas, Fayette, Forsyth, Fulton, Gwinnett, Henry, Paulding, and Rockdale. These counties correspond to the ten counties comprising the Atlanta Regional Commission

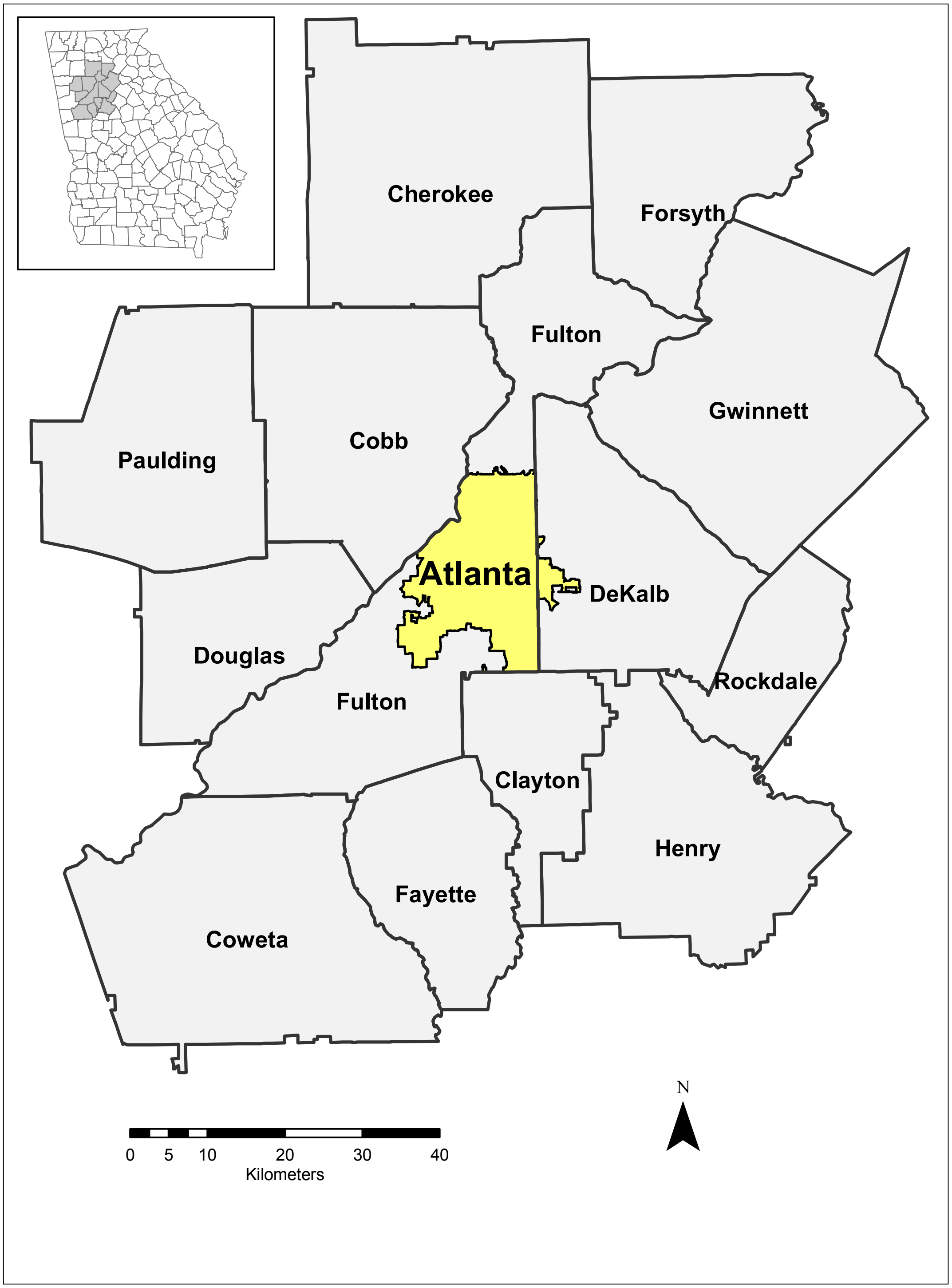

Figure 1.1. Thirteen-County Metropolitan Atlanta Study Area

with the addition of Coweta, Forsyth, and Paulding Counties. These counties represent the major Atlanta metropolitan area. Figure 1.2 depicts the principal cities, highways, railroads, and rivers of the study area.

The thirteen counties comprising this study area served to illustrate a range of census tracts across the metropolitan region: many are census tracts with previously urbanized populations; many are previously rural but have experienced significant suburbanization since 1980; many are still rural. Thus, a broad enough range of census tracts are available for analysis, which will contain a large variation in urbanization trends and in socioeconomic and demographic variables.

In addition, previous urban geography research (Hartshorn, 1976; Hartshorn, 1986; Hartshorn and Muller, 1989; Fujü and Hartshorn, 1995; Hartshorn, 1998; Holloway and Wyly, 1999; Holloway and McNulty, 2000; and Holloway and Wyly, 2001) focused on the metropolitan Atlanta area; while others (Lo and Yang, 2000; Yang, 2000; Lo and Yang, 2002; Yang and Lo, 2002; Yang, 2002; and Yang and Lo, 2003) have conducted land-use/land-cover research on the same thirteen-county area of metropolitan Atlanta. By adhering to the same geographic boundaries in the current research project, it is hoped that comparisons could be made to previous research, where appropriate. All thirteen counties are readily available on one Landsat image, on which this research relies.

Growth of the Atlanta Metro Area

Atlanta represents one of the fastest-growing metropolitan areas in the United States, and is the economic and transportation center of the Southeast. Atlanta was founded as a transportation center in the mid-nineteenth century and its continued growth is tied to its excellent strategic location and transportation links. Today, Hartsfield

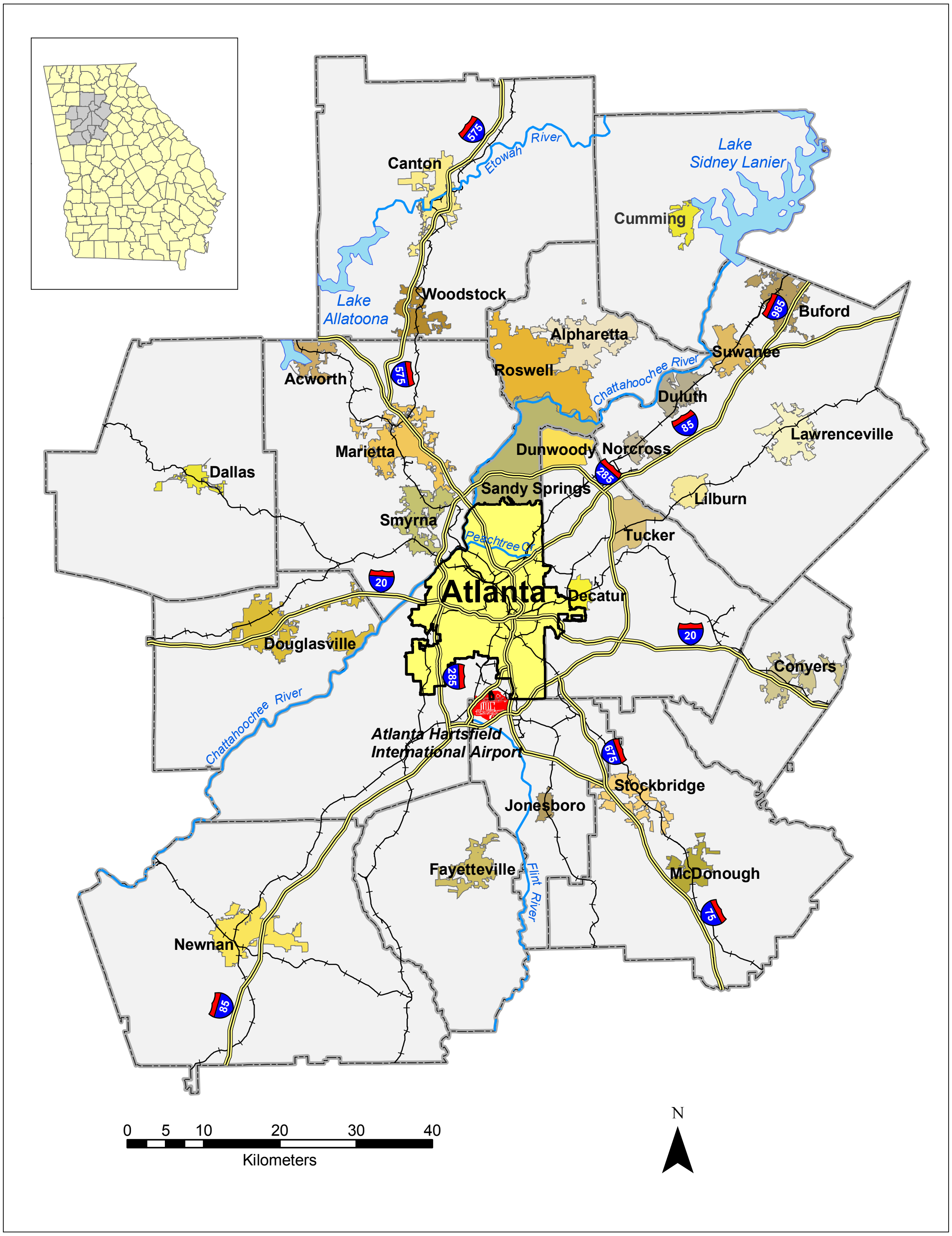

Figure 1.2. Principal cities, highways, railroads, and rivers, Metropolitan Atlanta, Georgia.

International Airport is the world’s busiest airport, and serves as a major international air hub. The highway network is highly developed and facilitates long-distance commuting and the growth of suburban bedroom communities. Much of the suburban development has occurred at convenient access points along the freeways that radiate outward from the central city. As a result, many new high-density commercial, office, and industrial centers are located in the outlying suburban areas near freeway exits and major intersections, particularly in the region’s northern sector (Atlanta Regional Commission, 2000a).

A diversified economic base is another reason for the dramatic growth of the Atlanta metropolitan area. Atlanta remains the predominant economic center in the Southeast (Atlanta Regional Commission, 2000a). The region’s economic growth reflects a diversified economy that is not dependent upon any single economic sector. Instead, the economic base of Atlanta is comprised of many sectors: service, wholesale and retail trade, government, manufacturing, consumer and health services, communications, utilities, and FIRE (finance, insurance, and real estate). During the period 1980 through 2000, more jobs were added in the services and trade sectors, while government and manufacturing jobs declined (Atlanta Regional Commission, 2000a).

This period also coincided with an expansion in international trade, a shift from an industrial economy to a service economy, and post-Fordism. In post-Fordism, traditional (Fordism) industrial locational criteria, such as proximity to industrial raw materials and an industrialized blue-collar labor force, were replaced with less stringent locational criteria, such as low building construction costs, an educated white-collar labor force, and access to sophisticated communications networks. In other words, industries were no longer confined to a narrow range of locational choices, but instead were free to select from a much wider range of areas in which to locate. Additionally, these choices included non-traditional locations such as suburban areas. These new locational considerations, when coupled with Atlanta's extensive transportation network and centralized location for the Southeast United States, led to dramatic growth in the area's services and trades sectors.

The recent growth and expansion of major American cities, such as Atlanta, may be explained by neoclassical economic theory as reflected in the multiple nuclei (Harris and Ullman, 1945) or urban realms (Vance, 1964) models of urban development. These theories argue that modern urban areas do not follow the development process suggested by the Chicago School model of concentric zones or rings (Burgess, 1925), nor the process suggested by the sectoral growth model (Hoyt, 1936-1937). Instead, modern cities follow a pattern of dispersed growth, centered around suburban business centers (Hartshorn and Muller, 1989) or edge cities (Garreau, 1991), which are spatially located well outside the traditional central area of the city and are generally located at the intersections of major transportation corridors.

The multiple nuclei model, first proposed by Harris and Ullman (1945), suggests that growth patterns tend to conform to a cellular structure in which multiple growth centers emerge. This type of growth structure was made possible by the widespread adoption of the automobile and facilitated by the construction of the urban freeway system.

Hartshorn and Muller (1989) built upon the work of Vance (1964), who studied the growth of San Francisco and proposed the urban realms model as a process of spatial change. The distinctive feature of the urban realms model was the development of diversified suburban business centers, which are an outgrowth of existing post-World War II suburban development. These mixed-use commercial centers (or suburban downtowns) provided specialized services and goods for their particular suburban areas. As a result of these changes, suburban residents no longer needed to obtain such goods and services from the traditional downtown area or Central Business District (CBD). This change represented the shift from a single-centered city to a polycentric city, comprised of self-sufficient outer suburban cities. Hartshorn and Muller (1989) suggested that this development of suburban downtowns followed a four-stage process, progressing from suburban bedroom communities, through suburban independence, through a period of catalytic suburban growth, and ending with a high-rise/high-technology stage in which suburban downtowns would surpass the traditional CBD in terms of retail sales volume and office activity.

Fujü and Hartshorn (1995) examined the growth of the metropolitan Atlanta area and compared this growth to the urban realms model, which suggests that the emergent suburban downtown areas should be self-contained and have little cross-connections to other downtowns in the metropolitan area. They sought to determine whether Atlanta followed this pattern or whether there were interconnections among the suburban downtowns and with the Atlanta CBD. Their analysis indicated that there were substantial cross-flows of people and goods throughout the region. They did not find that each suburban downtown was independent and self-sufficient. Instead, the Atlanta CBD, despite experiencing a severe decline in the volume of retail and white collar commercial office activity, remained very strong as a center of government functions; hotel, convention, entertainment, and sports activities; education; medical services; legal activity; advertising; and banking and accounting functions. Conversely, the suburban downtowns did not fully develop these functions, but instead relied upon their provision by the CBD. Retail sector jobs were found throughout the region, but tended to be most concentrated near major shopping malls and major highway intersections. Service sector jobs, especially those in the business services, were concentrated in the CBD, Buckhead (an affluent area north of the CBD), and the Georgia Highway 400 and northern I-285 perimeter highway corridors. Manufacturing jobs are mainly located outside of the I-285 perimeter, while many of the headquarters operations are located in the CBD (Fujü and Hartshorn, 1995; and Atlanta Regional Commission, 2000a).

Therefore, Atlanta had been transformed into an economically interdependent area, which was linked together by a complex transportation network centered around the automobile. Secondarily, Fujü and Hartshorn noted an imbalance of income and jobs between the northern half and the southern half of the metropolitan area (with the north being much more affluent), and a disproportionate concentration of poverty in the central city.

Most of the population and employment growth, from 1980 through 2000, has occurred to the north of the City of Atlanta, as growth has tended to radiate outward along the major arterial highways, such as I-75, I-85, and the Georgia Highway 400 expressway. Most of the top areas for population and employment increases are located well outside of the I-285 perimeter highway, which encircles the traditional Central Business District (CBD) and its surrounding inner suburbs. It is also notable that most of the areas of recent development were rural areas only ten-to-fifteen years ago (Atlanta

Regional Commission, 2000a). Such areas include Suwanee, Duluth, Cumming, Alpharetta, Woodstock, and Acworth.

Not all new population and employment gains were located in the northern suburbs, however. An interesting counterpoint to the outward radial development has been the recent post-1996 Olympics resurgence of the CBD and Midtown areas and the continued growth of the upscale Buckhead area. The CBD continues to be the metro area's most densely developed employment area and has the greatest diversity of economic activity. Midtown, which is located just north of the traditional CBD, is also developing at a rapid pace. Residential sections of Midtown (and portions of downtown Atlanta) have served as major areas of reinvestment, infill development, and gentrification efforts, as these areas have experienced a recent influx of affluent residents (Atlanta Regional Commission, 2000a).

Table 1.1 illustrates the rapid increase in population for the thirteen-county metro area (U.S. Census Bureau, www.census.gov, accessed May 17, 2002). Several counties grew at a rate exceeding the metro average of 85.9% for the twenty-year period 1980-2000. These counties represent areas on the suburban fringe of the metro area. The counties containing the city of Atlanta (Fulton and DeKalb) experienced the lowest rate of population increase over the same period.

The counties with the highest overall population rate increase for the entire period were (in decreasing order of growth) Gwinnett, Forsyth, Henry, Fayette, Paulding, Cherokee, Coweta, and Cobb, all of which more than doubled in population. The counties with the lowest growth rates were (in increasing order of growth) DeKalb, Fulton, Clayton, and Douglas, all of which grew at a rate less than the overall rate for the

Table 1.1. Population Growth, 1980-2000, Metropolitan Atlanta (Source: U.S. Census Bureau, 2002).

County	1980	1990	2000	% change 1980-1990	% change 1990-2000	% change 1980-2000
Cherokee	51699	90204	141903	74.5	57.3	174.5
Clayton	150357	182052	236517	21.1	29.9	57.3
Cobb	297718	447745	607751	50.4	35.7	104.1
Coweta	39268	53853	89215	37.1	65.7	127.2
DeKalb	483024	545837	665865	13.0	22.0	37.9
Douglas	54573	71120	92174	30.3	29.6	68.9
Fayette	29043	62415	91263	114.9	46.2	214.2
Forsyth	27958	44083	98407	57.7	123.2	252.0
Fulton	589904	648951	816006	10.0	25.7	38.3
Gwinnett	166903	352910	588448	111.4	66.7	252.6
Henry	36309	58741	119341	61.8	103.2	228.7
Paulding	26110	41611	81678	59.4	96.3	212.8
Rockdale	36747	54091	70111	47.2	29.6	90.8
13-County Total	1989613	2653613	3698679	33.4	39.4	85.9

thirteen-county region. Clayton County's growth is somewhat constrained by the presence of Atlanta's Hartsfield International Airport, the major center of employment within the county.

It is interesting to note that the very modest overall population growth in Fulton and DeKalb Counties took place despite the rapid increase in population in selected portions of those counties (north Fulton and south DeKalb); this indicates that the traditional core areas of these counties, which contain the City of Atlanta (the traditional Downtown or Central Business District), grew at a much slower rate (or lost population) than the county averages would indicate. Data from the U.S. Census Bureau for 1990 and 2000 and the Atlanta Regional Commission (ARC) for 1970 and 1980 indicate that the City of Atlanta lost population from 1980 to 2000, with an even more precipitous decline since 1970 (Table 1.2). The Census Bureau data were used for 1990 and 2000 as the Atlanta Regional Commission's data for 1990 were adjusted to account for a supposed undercount by the Census Bureau.

Table 1.2. Population Change, 1970-2000, City of Atlanta (Source: U.S. Census Bureau, 2002; and Atlanta Regional Commission, 2002).*

1970	1980	1990	2000	% change 1970-1980	% change 1980-1990	% change 1990-2000	% change 1970-2000	% change 1980-2000
495039	424922	394017	416474	-14.2	-7.3	+5.7	-15.9	-2.0

The significance of these changes is the apparent shift in economic importance from the traditional downtown central business district (CBD) to the outlying urban fringe areas. This pattern is consistent with the urban geography literature which suggests such changes for major urban areas for the same period. It is important to note that the trend in the decline in the City of Atlanta's population from 1970 to 2000 may be changing: the city's population actually grew by 5.7% from 1990 to 2000 but it is still well below the metro average of 39.4%. As a result, for the period of analysis for this dissertation, 1980-2000, the net population change for the City of Atlanta was a loss of 2.0%. This suggests that the city may have been somewhat successful in its recent efforts to lure back old residents and attract new residents to new multi-unit apartment complexes and loft conversions. These efforts at post-Olympics gentrification are described in the monograph commissioned by Research Atlanta, Inc. (Hartshorn, 1998).

According to data from the ARC (Atlanta Regional Commission, 2000b), over seventy percent of the growth in the 1980s was spread over the northern arc of the region. This trend continued into the 1990s. However, growth had rapidly accelerated in the

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* Although the period of interest for this study was 1980 through 2000, population data for Atlanta from 1970 is included to highlight the trend of the dramatic population decrease through the year 2000.

southern arc of counties (all south of Interstate 20). In the 1980s, the northwest sector in particular (Cobb County) accounted for the majority of new growth. As Cobb County began to be built out, and with the addition of Georgia Highway 400 (a major limited access highway into the north Fulton County area), growth began to shift to the north and northeast sectors (north Fulton County and Gwinnett County).

In addition to sources previously mentioned that have examined the factors influencing the patterns of urban growth in the Atlanta area and sought to explain them in theoretical terms, additional research has been conducted to quantify the spatial growth of the Atlanta area, with particular emphasis on changes within specific land use categories. Lo and Yang (2000 and 2002), Yang (2000), and Yang and Lo (2002) conducted an analysis of Landsat Multispectral Scanner (MSS) and Thematic Mapper (TM) satellite images of the Atlanta area. By analyzing MSS images from 1973, 1979, 1983, 1987, 1988, 1992, and TM images from 1987, 1997, and 1998, Lo and Yang were able to quantify the changes in land use for the thirteen counties in the metro Atlanta area. By performing an unsupervised ISODATA (Iterative Self-Organizing Data Analysis) classification, they obtained very high accuracies for each of six land use/cover categories (high-density urban use, low-density urban use, cultivated/exposed land, cropland or grassland, forest, and water), in most cases exceeding 80%. The overall classification accuracy is 90%, and the kappa index of agreement (a measure of the improvement in accuracy over a random assignment of pixels to land use classes) of 0.878. Details on the ISODATA classification methodology are provided in Lo and Yang (2000), Yang (2000), Yang and Lo (2002), and Yang (2002).

As a result of their classification, Lo and Yang determined that from 1973 through 1997, high-density urban use almost doubled, from 4.35% of total land area to 8.24%. Low-density urban use increased from 11.63% of total area in 1973 to 25.49% in 1997. These increases were offset by dramatic decreases in the percent of land area covered by forest (62.60% in 1973 to 49.51% in 1997) and cropland/grassland (18.97% in 1973 to 12.66% in 1997).

Lo and Yang also assessed the spatial patterns of growth by the use of a geographic information system (GIS) overlay function. They noted that high-density urban use spread outward from a small concentration in the inner part of the city, linearly along major transportation arteries, until about 1983. From 1983 through 1992, high-density urban use growth concentrated in three separate areas: Gwinnett County (northeast of Atlanta), Cobb County (northwest of Atlanta), and Clayton and Henry Counties (southeast of Atlanta). This helped to confirm the existence of a multi-centered urban growth pattern, consistent with characterizations such as multiple-nuclei urban models and edge cities (summarized by Knox and Pinch, 2000) and urban realms or suburban downtowns (Fujü and Hartshorn, 1995). The concentration of high-density urban use increased even further from 1992 through 1997, as build-up was quite pronounced around these extended urban centers. Changes in low-density urban use, which are associated mainly with residential development, were especially noted in the counties on the urban fringe: Gwinnett, north Fulton, Forsyth, Fayette, and Henry counties (Lo and Yang, 2000; Lo and Yang, 2002).

Data Sources

The following data were obtained or derived from existing data sources for the current research. All-cause mortality data were obtained from the Georgia Division of Public Health. These data are available for individual decedents with their last known residential addresses, for 13 metropolitan Atlanta counties from 1995 through 1999, inclusive. These data are geocoded to the latitude and longitude of the decedents' residential addresses, if available. The individual point location data corresponding to the decedents' residential addresses were utilized for one portion of this research project. In addition, these data are spatially aggregated to the census tract level for further analysis and presentation.

Individual mortality data prior to 1995 were not available for this study. The Georgia Division of Public Health is geocoding data from 1990-1994, but there is no estimated date of completion for this effort – it is likely to take at least two years (personal communication with Robert Attaway, Data Manager and Data Resources Unit Director, Office of Health Information and Policy, Georgia Division of Public Health, January 24, 2002). Also not available (at the individual level) are health risk behavior data, such as from the Behavioral Risk Factor Surveillance System (BRFSS) or the National Health Interview Survey.

Socioeconomic and demographic data were obtained from Geolytics, Inc., a retail provider of value-added U.S. decennial census data. Specifically, U.S. Census Long Form (SF-3) data were obtained for 1980, 1990, and 2000. This research project utilized selected original variables from the SF-3 as well as user-derived variables from the SF-3 data.

Satellite imagery were obtained from the U.S. Geological Survey, EROS Data Center, for 1982 (Scene ID: LT4019036037082350, Landsat 4, Thematic Mapper, Path 019, Rows 036-037 (50% offset), acquired December 16, 1982); for 1984 (LT5019036037084172, Landsat 5, Thematic Mapper, Path 019, Rows 036-037 (50% offset), acquired June 20, 1984); for 1990 (Scene ID: LT5019036037090268, Landsat 5, Thematic Mapper, Path 019, Rows 036-037 (50% offset), acquired September 25, 1990); and for 2000 (Scene ID: L71019036-03620000928, Path 019, Row 036, acquired September 28, 2000; and Scene ID: L71019037-03720000928, Path 019, Row 037, acquired September 28, 2000).

Landsat satellites are a series of earth-observing satellites that have provided continuous data since 1972. Landsat 5 and Landsat 7 were launched in 1984 and 1999, respectively. They each have a sun-synchronous orbit at an altitude of 705 kilometers, which results in a sensor ground swath width of 185 kilometers. This altitude and an orbital inclination of 98.2 degrees ensure that each satellite will pass over the same point on Earth every 16 days. Because of the sun-synchronous orbit, the satellites pass over the equator at the same crossing time each path, thus ensuring temporal comparability of images taken on different days. The primary sensor on Landsat 5 is the Thematic Mapper (TM), which covers seven bands in the electromagnetic spectrum (blue-green; green; red; near-infrared; mid-infrared (2 bands); and thermal infrared). The nominal ground resolution of each band is 30 meters (except thermal infrared – 120 meters). The primary sensor on Landsat 7 is the Enhanced Thematic Mapper Plus (ETM+), which is similar in band coverage to the Landsat 5 TM. The major enhancement in ETM+ is the addition of a 15 meter resolution panchromatic band, and an increased resolution of 60 meters in the thermal infrared band. Together, these Landsat satellites provide multispectral data that are useful in mapping land-cover and assessing land-use at a variety of scales, including metropolitan areas such as Atlanta, Georgia.

Land use/cover classification maps and data for 13 metro Atlanta counties (1973, 1979, 1983, 1987, 1992, 1998-99) were provided by Dr. C.P. Lo, University of Georgia, through the support of a NASA EOS Interdisciplinary Science (IDS) research grant (NAS8-97081). These land use/cover maps and data were used as comparisons to land use/cover data derived by the author specifically for this research project.

Color infrared (CIR) digital orthophoto quadrangles (DOQs) of metropolitan Atlanta (February 1999) were used for ground truthing of the satellite-derived land use/cover map for 2000. These 55 DOQs were obtained by purchase from the Georgia GIS Clearinghouse. Black-and-white and color aerial photographs of portions of the metropolitan Atlanta area (particularly Gwinnett County, 1988 and 1989) were obtained from the University of Georgia Map Room, and were used for ground truthing of satellite-derived land use/cover data for 1990.

Road network data were obtained from the National Transportation Atlas Database: 2002, published by the U.S. Department of Transportation, Bureau of Transportation Statistics, and from ESRI (Environmental Systems Research Institute, Redlands, CA). These data were used to assist in classification of land use/cover.

County boundary files were obtained from the Digital Environmental Atlas of Georgia, Version 2, published jointly by the Georgia Geologic Survey and the U.S. Geological Survey. Census tract boundary files were obtained from the U.S. Census Bureau for 1990 and 2000. For 1980, census tract boundaries were obtained from

Geolytics, Inc., which created the census tract boundaries based upon Census TIGER/Line Files, which are no longer downloadable from the Census Bureau. The 1980 Geolytics census tract boundaries were manually "cleaned" in order to remove hundreds of small polygons corresponding to small-to-large bodies of water, as the 1990 and 2000 census tract boundary files did not include such objects. Boundaries for the city of Atlanta were obtained from the Atlanta Region Information System, Volume 1b, published by the Atlanta Regional Commission (ARC).

Organizational Framework

The remainder of this dissertation is organized as manuscripts of research papers. Chapter 2 is a review of the literature on public health research using GIS and remote sensing technology. The following four chapters are substantive and relate to the various research hypotheses and methodologies as described in the "Objectives" section, above. The final chapter is an overall summary and conclusion of the research project. Each substantive chapter contains a separate background discussion, a separate research methodology, and separate conclusions, specific to that particular part of the overall research project. The conclusion chapter is intended to summarize and integrate the results of each preceding section, as well as to point out the limitations of the research findings and to suggest avenues for additional research. A comprehensive bibliography of cited literature is included after the final chapter. The following six chapters are:

- *Chapter 2: Literature Review on Public Health Research Using Geographic Information Systems (GIS) and Remote Sensing Technology*
- *Chapter 3: Extraction of Census Tract Level Land-use and Land-Cover Change Data of the Atlanta Metropolitan Area, Georgia, from Landsat Imagery*

- *Chapter 4: Dasymetric Mapping of Population Densities and Adjustments to Census Tract Geography, Metropolitan Atlanta, 1980-2000*
- *Chapter 5: A spatial analysis of mortality, Metropolitan Atlanta, 1995-1999*
- *Chapter 6: Small-area Analysis of the Association Between Sociodemographic Composition and Urban Context and Mortality, Metropolitan Atlanta, Georgia*
- *Chapter 7: Summary and Overall Conclusions*

CHAPTER 2

PUBLIC HEALTH RESEARCH USING GIS AND REMOTE SENSING[*]

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[*] Holt, J.B. and C.P. Lo. To be submitted to *International Journal of Geographic Information Science*

Introduction

Three general bodies of literature were consulted for this dissertation, which focused on the use of geographic information systems (GIS) and remote-sensing technology for use in public health research. Each literature type will be discussed in turn: 1) medical geography; 2) applications of geographic information systems (GIS) to public health issues; and 3) application of remote sensing technology to public health issues.

The medical geography literature was consulted in order to place this research project into a disciplinary context and to examine how this current research may be an extension of previous research in the medical geography tradition. The literature on applications of GIS and remote sensing technology were consulted in order to assess the current state-of-the-art in the use of these technologies for public health research. A second purpose for reviewing the GIS and remote sensing literature was to determine areas for new applications, and to assess how this dissertation could serve as an extension of presently-adopted techniques.

Medical Geography

The subdiscipline of medical geography examines the importance of place (context) on health (Eyles and Woods, 1983; Howe and Phillips, 1983; Jones and Moon, 1987; Kearns and Gesler (Eds.), 1997; Lochner *et al*, 1999; McGlashan and Blunder (Eds.), 1983; Meade (Ed.), 1980, Meade and Earickson, 2000; and Pyle, 1983). Medical geography also may be described as the application of geography to the study of health, disease, and health care. It draws upon the concepts and techniques of many disciplines, such as epidemiology, anthropology, sociology, and economics, and it adds spatial and ecological perspectives. As such, medical geography, as with geography in the general sense, is an interdisciplinary field, which bridges the gap between the social, the physical, and the biological sciences (Meade and Earickson, 2000).

Medical geography focuses on the human ecology of disease: the interrelationships between a population, their habitat, and their behaviors, in order to investigate how and why human disease and health vary geographically. Population refers to the collection of individuals as potential hosts for disease. An individual's resistance and susceptibility to disease are determined by several factors, such as physiological status, immunological status, nutritional status, age, gender, and genetics. Habitat includes not only the physical environment but also the built environment and the social environment. Behavior is the observable part of culture that is shaped by social norms, economic constraints, and an individual's psychology (Meade and Earickson, 2000).

The closely-related field of social epidemiology also addresses the critical importance of place (i.e., habitat) as an influence on health. Social epidemiology is the study of the social distribution and determinants of health states (focusing on exposures rather than on outcomes). Health behaviors are seen as the product of both personal factors as well as the individual's social condition. Social epidemiology also draws upon notions of social capital and collective efficacy to help define the social environment. The primary difference between medical geography and social epidemiology is that the former has a more inclusive view of habitat, in which the social environment is but one of three separate aspects of habitat that are examined for their impact on health, through their interactions with behavior and population characteristics. The other aspects of habitat are the natural environment and the built environment (Meade and Earickson, 2000). Social epidemiology, on the other hand, tends to focus exclusively on the social environment.

The history of medical geography *as a subdiscipline of geography* has been traced back to the middle of the twentieth century by Meade and Earickson (2000). Others, including Meade and Earickson, have suggested (or examined claims) that the *roots* of medical geography go back much further (Gilbert, 1958; Barrett, 1993; Barrett, 1996; Barrett, 2000; McLeod, 2000; Brody *et al*, 2000; and Monmonier, 2002), even to the time of Hippocrates, who understood the potential for a connection between air, water, and place-related factors on health. Gilbert (1958) and Barrett (1993, 1996, and 2000) describe many early uses of the concepts of medical geography, whether known at the time as medical cartography, medical climatology, medical topography, or medical geography. They cite many examples from the late 1700s and early 1800s in Great Britain, France, Spain, and Germany. The first application of mapping to diseases, however, did not occur until at least 1832, precipitated by the introduction of cholera to Great Britain.[*]

In this latter regard, the most famous recounting of disease-mapping and effective epidemiologic intervention is attributed to Dr. John Snow, who is claimed by multiple disciplines as a founding member of their discipline (epidemiology and medical geography). According to oft-repeated fact (or legend), Snow, who had in 1849 developed a theory on the transmission of cholera[**], investigated an outbreak of cholera

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[*] Gilbert (1958) estimates that approximately 118,600 people died from cholera in the United Kingdom from four separate epidemics (1831-32, 1848-49, 1853-54, and 1866).

[**] Snow's theory was that cholera was spread by contaminated water; this was in opposition to the prevailing theory that the transmission mode was by miasmata (or "bad air").

in the Soho district of London in 1854. During his investigation, Snow, an anesthesiologist by training, produced a dot map of cholera deaths. By also noting the locations of public water pumps in the Soho district, Snow was able to determine, through spatial reasoning, that the majority of cholera cases were spatially located closer to the water pump at Broad Street than to any other water pump (representing perhaps an early version of a voronoi diagram). He then convinced the Board of Guardians of the Parish of St. James to remove the pump handle (or removed it himself, depending upon which version of the story one believes). Following removal of the pump handle, the number of cholera deaths dropped precipitously (which may have been attributed to the fact that the cholera epidemic had run its course; again, depending upon which account ones believes).

Recent scholars (McLeod, 2000; Brody *et al*, 2000; and Monmonier, 2002) all claim that the Snow account is a myth; that there is no *proof* that he actually constructed a dot map prior to the publication of his subsequent report on the cholera outbreak. They suggest that the map was produced after the outbreak for his published report, and that he was merely relying upon basic “shoe-leather epidemiology” techniques in order to determine that the cases were clustered around the Broad Street pump. To the contrary, there is no conclusive proof that he did not produce the map at the time of the outbreak, as the documentary evidence concerning the map itself is indeed vague. However, such arguments miss the more important point: Snow was using spatial analysis, whether facilitated by a paper map or a mental map. As McLeod (2000) points out (p. 928), “He proceeded to the corner of Cambridge and Broad Streets where the Broad Street pump was situated. Standing there, he *realized* [emphasis added] that all but 10 of the [83] deaths were located closer to that pump than any other public water pump." If Snow could conduct such a spatial analysis of 83 cholera deaths and 11 water pumps without the aid of a map, then one must certainly marvel over his mental capacities. And if the map was not important or necessary for Snow to determine the location of the offending pump, then what was his purpose in producing such a map for his published account of the outbreak investigation? Most likely, it was to aid the readers in their interpretation of the outbreak and its causal factors. If true, that would tend to confirm the usefulness of a disease map for spatial analysis. Whether the account of Snow's map is true or not, the example of his cholera map for the spatial analysis of disease is still valid. It highlights the usefulness of visualization in the exploration and confirmation of hypotheses.

Returning to the history of medical geography as a subdiscipline of geography, Meade and Earickson (2000) credit Jacques May as the "father of medical geography in the United States" (Meade and Earickson, 2000, p. 7) with the publication of his seminal paper "Medical Geography: Its Methods and Objectives" (May, 1950). May called for the investigation of diseases to include the interrelationship between pathological factors (e.g., causative agents, vectors, intermediate hosts, reservoirs, and man) and geographical factors or "geogens", such as the physical environment, human or social factors, and biological factors. His initial focus, in line with the general focus of public health in that era, was on infectious diseases. As May's experience base was that of a physician in Indochina, Africa, and the Caribbean, he gave particular emphasis to diseases commonly found in the tropics, such as cholera, malaria, dengue, Filariasis, and yellow fever.

Similarly, Meade and Earickson (2000) identify Andrew Learmonth as a pioneer in medical geography in the United Kingdom. Learmonth's particular area of interest was the Indian Subcontinent, and like May, he focused on tropical diseases. He was instrumental in defining medical geography for the international geography community with his 1st Report of the Commission on Medical Geography (Ecology) of Health and Disease to the International Geographical Union, in 1952.

The study of the interrelationship between geography and disease received much attention in the 1950s and 1960s, particularly in the United Kingdom. A. Leslie Banks, in a series of lectures delivered to the Royal Geographical Society, and published in the *Geographical Journal* (Banks, 1956; and Banks, 1959), acknowledged the emergence of two vastly different types of diseases that warranted the attention of medical geographers: those endemic to developing countries (typically infectious diseases) and those more prevalent in western countries (especially chronic diseases).[*] Mapping of diseases for the purpose of showing spatial patterns of variations in disease mortality, on a national scale, commenced with the publication of the National Atlas of Disease Mortality in the United Kingdom (Howe, 1963). Dudley Stamp was also instrumental in advancing the use of mapping to examine morbidity and mortality patterns (Stamp, 1964).

American academic interest in medical geography as a subdiscipline has been more recent. John Hunter, at Michigan State University, has been credited by Earickson and Meade as the first American academic medical geographer, who was responsible for training many medical geographers from the 1960s through the 1990s. Meade, was the first to receive a doctorate in medical geography, from the University of Hawaii in 1974.

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[*] This coincided with the epidemiologic transition in western countries: as a result of earlier successful public health interventions to reduce disease and death resulting from infectious and environmentally-related diseases, populations in those countries experienced longer life expectancies, and consequently, higher morbidity and mortality from chronic diseases.

Other geographers, such as Andrew Cliff, Peter Haggett, and Matthew Smallman-Raynor, investigated the geographic structure of epidemics and were responsible for developing Hägerstrand's theory of spatial diffusion into the modern theories of epidemic diffusion: contagious diffusion, hierarchical diffusion, and transfer (or relocation) diffusion (Cliff and Ord, 1981; Cliff and Haggett, 1989; Haggett, 2000; and Smallman-Raynor and Cliff, 2001).

Meade and Earickson (2000) have described medical geography as traditionally encompassing two broad areas of research: the ecology of disease, and the analysis of health service delivery.[*] Recently, however, some have attempted to "reform" medical geography into the geography of health (Kearns, 1994a; Kearns, 1994b; Dorn, 1994; Moon, 1995; and Kearns and Gesler, 1997). These geographers argued that while the traditional focus on place was still useful (regarding differences between locations, and differences relating to spatial distances, mobility and diffusion processes), it was imperative to include an understanding of "structuring of meaning and understanding in the places where people live, experience sickness and use health services" (Moon, 1995, p. 1). What was needed, according to Kearns and Dorn, was an inclusion and focus on social theory. Mayer and Meade (1994) countered Kearns, specifically, by saying that the traditional focus on the ecology of disease included numerous factors: social, economic, behavioral, cultural, environmental, and biological. Therefore, what was being argued was not necessarily the scope of analysis, but rather the method of analysis. This debate was essentially echoing the conflict of epistemological approaches in geography in general during the 1970s, 1980s, and 1990s: quantitative/spatial analysis (positivism) versus qualitative analysis (humanism, structuralism, and postmodernism).

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[*] It is the former area, the ecology of disease, to which the research discussed in this dissertation is related.

There did not appear to be a consensus on the call to reform medical geography into the geography of health, and today there are examples of both traditions of research (quantitative and qualitative) in the medical geography/geography of health literature*.

A recent work by Gustafsson (1997) summarizes the approach used in this dissertation to study the importance of place on the health of the population. He stated that interactions between the physical environment, the built environment, and the people have considerable relevance for health. He suggested that rather than focusing our public health efforts toward achieving national target goals for the overall population (e.g., *Healthy People 2010*, U.S. Department of Health and Human Services, 2000), more research focus is needed on the relative improvements between places on the significance of geographic variations in improvements. The bottom line is: "place" should be incorporated with other complex influences on health (Gustafsson, 1997).

The importance of mapping, and by extension, spatial reasoning and analysis, as applied to this dissertation, is perhaps best described by Dudley Stamp in his response to an address by Banks to the Royal Geographical Society in 1959:

> "…the mathematician thinks in symbols; the geographer thinks in maps. Therein should lie our first and great contribution. The making of a map must not be regarded as something final but simply as one of a series of experiments. Outline maps ought to be treated as scrap paper. Whatever data may be available, plot them on maps. Try showing them in different maps; the rough maps may just show the inadequacy of the factual material; perhaps one will show some curious pattern, some unexplained anomaly, some irregularity in distribution. It is then that the enquiring scientific mind will say 'But why?' – and the investigation is on its way." (Stamp, quoted in Gilbert *et al*, 1959, p. 214).

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* Mayer and Meade suggested (p. 105) that "for decades many medical geographers have considered that the field should more appropriately be called '*public health geography*' (emphasis added), except that the wording sounds too clumsy."

Applications of Geographic Information Systems (GIS) to Public Health Issues

Geographic information systems (GIS) have been used in many countries for the description and analysis of health issues ranging from infectious diseases, such as malaria, to environmentally-caused diseases, such as lead poisoning, and most recently to chronic diseases, such as cardiovascular disease and cancer. Public health GIS is still in its infancy: most applications of GIS to this field are relatively recent, dating from the late 1980's and early 1990's. Despite some well-documented successes, public health GIS experts are endeavoring to establish GIS as an accepted discipline in a setting traditionally dominated by epidemiologists, physicians, biostatisticians, and behavioral scientists. This situation is complicated by the fact that GIS software is still evolving, public health GIS practitioners and academicians are continually developing new techniques and applications for GIS, and suitable data for analysis are often unavailable. Despite these concerns, GIS has a large number of enthusiasts in public health. With the development of enabling technology, methodology, training, and appropriate data, GIS is likely to become an indispensable component of public health practice.

For the present review, a selection of approximately sixty recent texts and peer-reviewed articles on GIS and public health were consulted. While not a completely exhaustive listing of public health GIS literature, this sample highlights the most relevant issues relating to the uses of GIS in public health. Mirroring the maturation of GIS in general, the articles can be arranged on a chronological continuum: the earliest articles focused on the potential uses of GIS in public health; at about the same time, other articles urged caution in the application of untested methodology to this field; later articles documented early experiments at applying GIS to public health; and the most recent articles reflect an assessment (and in most cases an affirmation) of earlier applications and discuss new applications for future development. The applications-related articles can be grouped into two categories: articles describing specific case studies, and review articles, which described several specific examples.

A typology of GIS articles, as they relate to public health, can be proposed: 1) overview articles of a general nature, especially relating to summarizing past and future directions for GIS in public health; 2) applications articles, relating to specific case examples; 3) methodological articles, relating to both GIS operations and spatial statistics; and 4) roles and infrastructure articles, with particular emphasis on the need for interdisciplinary collaboration and enabling hardware, software, and systems.

A second typology, relating to the purpose of each public health GIS study, also can be proposed. In this instance, four relatively distinct applications are discernable: 1) descriptive epidemiological studies; 2) exploratory spatial data analyses, especially concerned with hypothesis generation; 3) planning public health interventions; and 4) evaluating public health interventions.

Several examples from each category of the second typology will be discussed. Following that discussion, several enabling methodologies and technologies will be discussed, as well as other factors related to the conduct of those studies. That section will be followed by a detailed discussion of limiting factors and methodological concerns for current studies with suggestions on how they may be overcome in the future. Lastly, possible future directions for GIS in public health will be presented.

Descriptive Epidemiological Studies

Descriptive epidemiological studies have three basics purposes. The first purpose is to describe or call attention to the extent of a public health problem. For example, by mapping the spatial extent and variation of heart disease rates, attention is drawn to the higher burden of this disease across several states in the Southeastern United States. A second purpose is to help prompt questions about the existence of apparent spatial patterns, disparities, or clusters. This second purpose is directly related to the third: preparing for exploratory spatial data analysis (ESDA), during which potentially related variables are considered.

Of the articles reviewed, almost one-half are descriptive epidemiological studies. Of the remaining articles, descriptive epidemiological techniques were often used as a precursor to follow-on activities (such as ESDA) or public health intervention planning, which were the foci of those particular studies. It is difficult to conceive of any public health activities that did not originally involve descriptive epidemiology in some form. It is important to note that descriptive epidemiology does not require the use of GIS, nor does it need involve the use of graphic devices such as maps. However, GIS enables automated data management, analysis, and display, and therefore is a very efficient method of performing descriptive epidemiological studies. Furthermore, the visualization enabled by GIS adds a very effective dimension to the ability of epidemiologists and other public health experts to analyze a public health issue.

One example (Gilbert, 1958) of how descriptive epidemiological studies predate computerized GIS is the use of maps in England in the 1850’s to map diseases, especially cholera. Gilbert calls this era the “Golden age of geographic cartography” leading to the development of “Medical Topography”, which later became “Medical Geography” (Gilbert, p. 172). Several cholera outbreaks impacted England in the nineteenth century (1831-32, 1848-49, 1853-54, 1866, 1873, and 1893), which prompted questions relating to their causal factors. Mapping disease outbreaks allowed for the testing of alternate hypotheses, epitomized by the well-know work of John Snow in 1854. Hypothesizing that cholera was a water-borne disease, Snow overlaid maps of the locations of city water pumps with the location of people infected by cholera. Snow determined that the local outbreaks of cholera in the Soho district of London were clustered around the Broad Street water pump. Snow convinced local authorities to remove the handle of the Broad Street water pump, which resulted in the end of the cholera outbreak.

The articles relating to descriptive epidemiology can be grouped under the following headings (Table 2.1): 1) infectious diseases; 2) environmentally caused diseases; 3) chronic diseases; 4) injuries; 5) health services provision; and 6) general mortality (all causes). Perhaps the most extensive use of GIS for descriptive epidemiological studies has been in the realm of infectious diseases. Carrat and Valleron (1992) describe the use of kriging to portray the spatial and temporal extent of an influenza-like illness in France. Utilizing point data, Carrat’s and Valleron’s method produced a series of time-specific isopleth maps showing the extent of this disease. The temporal nature of their map series enables the viewer to visualize the spread of the disease from the northern port cities across the heart of France to the Mediterranean coast.

Table 2.1. Selected GIS Applications to Public Health Issues.

Infectious Diseases	**Environmental Diseases**	**Chronic Diseases**
Influenza (Carrat and Valleron, 1992) Anthrax (Cherkasskiy, 1999) Water-borne (Clarke *et al*, 1996) Vector-borne (Clarke *et al*, 1996; Vecchioli, 1996) Lyme Disease (Clarke *et al*, 1996) Malaria (Kazmi and Usery, 2001) Rift Valley Fever (Kazmi and Usery, 2001) Schistosomiasis (Kazmi and Usery, 2001) Guinea Worm (Kazmi and Usery, 2001) Lymphatic Filariasis (Lindsay and Thomas, 2000) Cholera (Gilbert, 1958)	General (Bartels and van Beurden, 1998; Pine and Diaz, 2000) Lead (Clarke *et al*, 1996) Electromagnetic Fields (Clarke *et al*, 1996) Airborne Toxins (Moore, 1995) Ecological Health (Zandbergen, 1998)	Infant Mortality (Andes and Davis, 1995) Famine (Guha-Sapir, 1995) Heart Disease (Barnett *et al*, 2001; Casper *et al*, 1999) Cancer (Devesa *et al*, 1999; Webster *et al*, 1994)
Injuries	**Health Care**	**Mortality Patterns**
Traffic Accidents (Raybould and Walsh, 1995) General (Clarke *et al*, 1996)	Health Provision (Gordon and Womersley, 1997) Access to Care (Philips *et al*, 2000)	(Murray *et al*, 1998) (Pickle *et al*, 1999) (Walter and Birnie, 1991)

Cherkasskiy (1999) describes the plans for development of an anthrax registry in Russia. The mapping of natural features, such as soil types, along with the prevalence and distribution of anthrax might enable a better understanding of the disease. The registry is intended to track anthrax distribution through space and time.

Clarke *et al* (1996) describe several areas in which descriptive mapping techniques are helpful to understanding diseases. They emphasize stimulating the visual half of the brain. Their examples include applications in lead poisoning prevention, water-borne diseases, injuries, exposure to electromagnetic fields, vector-borne diseases, and Lyme disease. Vecchioli (1996) demonstrates that the use of visualization is not new, but rather extends well back into the nineteenth century. Vecchioli describes early examples of how maps were used to convey spatial information about the patterns of vector-borne diseases in Washington, DC. Early epidemiologists were attempting to determine interrelationships among diseases, their contagious aspect and potential causes. So useful were these maps from the 1890s that they served as a catalyst for Congress to mandate that various infectious diseases be reported to public health authorities.

Kazmi and Usery (2001) report on the vast potential for the use of a GIS together with remote sensing data for the control of several infectious diseases, such as malaria, Rift Valley Fever, Schistosomiasis, and Guinea Worm Disease. By using remotely-sensed satellite data, scientists can identify habitats suitable for the distribution of infectious disease hosts and vectors. GIS can then be used to determine which of these areas contain human populations vulnerable to these diseases. Remote sensing is much more cost- and time-effective for monitoring than existing public health techniques, such as field surveys.

In a somewhat similar vein, Lindsay and Thomas (2000) utilized a GIS to produce a climatic data map of areas favorable for the distribution of Filariasis. Their resulting risk map will be useful for areas in which no field data exists. Their work will also help stratify areas for countrywide and regional surveys to better estimate high-risk populations. By identifying the climate regions that favor disease distribution, Lindsay and Thomas hoped to be able to identify, by proxy, those areas in which Filariasis would be most prevalent. After producing their interpolated climate map, they validated their model by multivariate logistic regression. They found that their climate model correctly predicted 81 percent of the infected sites, and 86 percent of the uninfected sites, for an overall prediction accuracy of just over 84 percent.

Bartels and van Beurden (1998) describe the value of mapping environmental health risks to human health. In The Netherlands, GIS modeling of environmental hazards is used in order to provide scientific data to political decision makers. In this way, policymakers can make better-informed decisions about health resource allocations as well as decisions that could potentially affect the health of the environment. The public also benefits from having the data presented in a visual format, as they are better able to understand and support government policy decisions.

Zandbergen (1998) describes the value of using GIS to model ecological risk in an urban watershed in British Columbia. The resulting watershed profile indicates the potential for adverse impacts on not only fish habitat and recreation, but also on public health. This is an example of how GIS can have a role in public health issues without mapping or analyzing demographics or health-outcomes data. In this case, environmental risks to the watershed would have a direct adverse impact on the water resource, and potentially a secondary adverse impact on the health of the people who use the water. The health of the watershed is thus used as a marker for potential adverse health effects for the human population.

In response to the California Air Toxics “Hot Spots” Information and Assessment Act of 1987, California has used a GIS to help create a database for a multipathway air toxics health risk assessment (Moore, 1995). Specifically, analysts map point sources of harmful emissions, and then use a Gaussian plume model to determine the footprint of the area at most risk of the toxic hazards. GIS is used for data analysis and management as well as for risk communication to state officials and to the public.

Pine and Diaz (2000) describe the use of GIS to create a community environmental health profile. Analysts map population data, economic characteristics, environmental data, and public health data in order to compose an overall profile of a community’s environmental health. This profile is useful for highlighting potential associations between environmental and health outcomes, and could point the way to further prospective, retrospective, and cross-sectional studies of these types of relationships. Pine and Diaz caution against drawing inappropriate or misleading conclusions from such a profile; rather, the profile should serve only as a first step in alerting health officials to potential problems.

GIS has also been used (to a lesser extent than for infectious or environmental diseases) in descriptive epidemiological studies of non-infectious diseases and health outcomes. Andes and Davis (1995) describe an early use of GIS for mapping infant mortality rates, in Alaska. In this case, a surface model of mortality rates was constructed using Inverse Squared Distance interpolation; this model was then used to prompt questions about social and institutional environments that explain differential infant mortality rates. The next step in the procedure (not yet conducted at the time of the article's publication) was to be a statistical analysis with respect to infant mortality as a function of economic and subsistence conditions, educational levels, distances to health care facilities, and other socioeconomic variables of interest.

Data on cancer mortality (Devesa *et al*, 1999) and for mortality due to all causes (U.S. Department of Health and Human Services, 1997) have been mapped in the United States for several decades. As an example of the usefulness of this type of approach, Devesa *et al* (1999) summarize the changes in mortality patterns from lung cancer between 1950 and 1994. Walter and Birnie (1991) describe international efforts to map mortality data, and Murray *et al* (1998) and Pickle *et al* (1999) discuss two recent national atlases of mortality in the United States.

Casper *et al* (1999) and Barnett *et al* (2001), in a collaboration between the U.S. Centers for Disease Control and Prevention (CDC) and the West Virginia University's Office for Social Environment and Health Research, produced two national atlases of heart disease mortality. These atlases, one for women's mortality rates and the other for men's, illustrate potential disparities in heart disease deaths for various racial and ethnic groups. These data prompt further explorations regarding the existence of statistically significant disparities. As the "social environment provides the context within which individuals are exposed to structural risk factors (e.g. lack of economic opportunity, poverty, and social isolation) that contribute to the adoption of disadvantageous behaviors (e.g. cigarette smoking, physical inactivity, poor diet)…identifying the places that bear the greatest burden of heart disease mortality is a necessary first step to targeting appropriate resources to improving the local social environment and health outcomes in those communities (Casper *et al*, 1999, p.16)." In both atlases, county-level data were aggregated for a five-year period (1991-95). Due to the potential instability of rates for counties with low populations, the mortality rates were smoothed using a Nearest Neighbor averaging procedure. The resulting rates were then age-adjusted to the 1970 United States population.

The previous examples utilized national data sets. Webster *et al* (1994) describe an example of a similar study on a much smaller scale. Webster and colleagues mapped data on cancer in children in the West Midlands area of Great Britain from 1980 to 1984. As this is a relatively rare condition in children, and one that is strongly autocorrelated at the regional scale, they used kriging in order to produce a map of the underlying risk for cancer. They suggest that this could have been the first use of geostatistics in that public health.

GIS has also been used to a limited degree to map injuries. Clarke *et al* (1996) allude to injury mapping as one of several GIS applications. Raybould and Walsh (1995) performed a basic descriptive study of road traffic accidents in Tyne and Wear and in Northumberland, England. GIS was used to locate accident sites within their respective census wards. They then computed two accident rates using different numerators: one was based upon the location of the accident, and the other was based upon the location of the victim's residence. They were able to produce visualizations of the accident rates, and they were also able to demonstrate how the rates varied based upon the numerator used for each rate. A potential value of such a comparison might be to explore whether there is a statistically valid difference between the two computed rates (which would indicate that many accidents are occurring outside of the victims' area of residence, as measured by census ward), and if so, what areas and commuting patterns might account for high accident rates.

One last area for which GIS has been used for descriptive studies is issues of access to medical care. In Great Britain, Gordon and Womersley (1997) used GIS to describe the relationship between population and the provision of health services. They defined catchments and practice populations, and related health service provision (or uptake) to measures of deprivation, thus prompting further questions about the potential disparities of health service provision with respect to socioeconomic factors.

Philips *et al* (2000) used a GIS to map addresses of patients from a Community Health Center (CHC) in Boone County, Missouri, to determine if the original service area intended for the CHC matched the actual area of residences of its patients (it didn't). This type of study can illuminate mismatches between demand for health care services and the availability of services, and can lead to better resource allocation decisions and planning of new facilities.

Exploratory Spatial Data Analyses

The purpose of exploratory spatial data analysis (ESDA) is to explore potential "spatially determined aspects of disease etiology or even to help in defining hypotheses to be tested in comprehensive epidemiological research (Douven and Scholten, 1995, p. 117)." ESDA involves examinations of spatial distributions of disease, tests for potential disease patterns and clusters, and searches for covariation with disease-causing factors. Douven and Scholten draw a clear distinction between ESDA and confirmatory data analysis. The former is a data-driven approach, where no pre-determined hypothesis is tested. Instead, the data is analyzed with the aim of gaining new insights from the data and formulating new hypotheses about relationships between the data. Contrary to ESDA, confirmatory data analysis is a model-driven approach, where a pre-conceived hypothesis is tested for confirmation or rejection. It is common for both techniques to be applied sequentially to the same data set.

At the time of Douven's and Scholten's writing (1995), most GIS packages did not incorporate sophisticated statistical tools that could perform either ESDA or confirmatory statistical analyses. This is a recurring theme in the literature from the past several years: although a GIS can provide cues to potential spatial relationships among data, it is most often necessary to test these relationships in separate statistical packages, such as SAS or SPSS (Bailey, 1998; Vine *et al*, 1998). A notable exception has been the availability of the S-Plus, which contains a set of spatial statistical tools and functions as an extension to ArcView GIS (Environmental Systems Research Institute (ESRI), Redlands, California).

ESRI also has introduced a new "Geostatistical Analyst" extension to its suite of desktop GIS products, "ArcGIS 8.x". While potentially quite useful this extension is solely a statistical surface generation package that provides the ability to create continuous statistical surfaces from a set of sampled point data. Although the extension contains sophisticated autocorrelation assessment tools, it does not contain operators for testing significance of relationships between statistical data sets, nor does it have the ability to perform any type of data smoothing operations, nor cluster detection and significance testing.

ESRI's Spatial Analyst extension to ArcGIS provides the ability to conduct cell, neighborhood, and zonal analyses on raster format data, which can be useful for performing analytical operations or transformations to raster data. However, these functions do not permit the statistical testing of hypothesized relationships among variables.

Recent releases of spatial statistical packages represent examples of loose coupling with GIS (Goodchild, 1991, quoted in Bailey, 1998), in that the output of these software packages can be exported in shapefile or database format for direct incorporation into a standard GIS. Conversely, GIS data can be imported directly into these packages for spatial analysis. However, the interfaces are separate for each software package. Examples of such packages include CrimeStat II (Levine, 2002), SaTScan version 3.1(Kulldorff and Information Management Services, Inc., 2003), and DMAP (Rushton and Armstrong, 1997). All three software packages are available free-of-charge, and provide a variety of data analysis functionality, primarily for point data.[*] Examples of data analyses that can be performed are spatial autocorrelation assessment, cluster detection, nearest-neighbor analyses, and Monte Carlo simulations.

Even with limitations on the integration between statistical analysis and GIS data storage manipulation and display, GIS can be an essential tool for ESDA. The following are examples of the many applications of ESDA with GIS in public health, summarized in Table 2.2.

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[*] There are spatial autocorrelation programs available for raster data. RookCase, a program developed by Sawada at the University of Ottawa (Sawada, 1999) is an add-on module to Microsoft Excel. Similarly, the Idrisi raster data GIS (Clarke Labs, 2002) can perform spatial analysis and spatial autocorrelation on raster cell data; both functions can be conducted within the main Idrisi program.

Some examples will highlight the application of GIS ESDA to infectious diseases. Clarke *et al* (1996) provide a general overview of several applications, of which water-borne diseases, vector-borne diseases, and Lyme Disease are just a few.

Table 2.2. Selected Studies Using Exploratory Spatial Data Analysis for Public Health Issues.

Infectious Diseases	**Environmental Diseases**
Clarke *et al* (1996) Glass *et al* (1995) Kistemann *et al* (2002) Kitron *et al* (1997) Openshaw (1996)	Aylin *et al* (1999) Clarke (1996) Lloyd (1995) Vine (1998)
Chronic Diseases	**Injuries**
Gatrell and Dunn (1995) Gatrell and Bailey (1996) Rushton *et al* (1996) Lovett *et al* (1986) Roche *et al* (2002) Troped *et al* (2001)	Clarke *et al* (1996) Wallace and Wallace (1998)

Glass *et al* (1995) describe how fifty-three environmental variables at the residences of Lyme Disease patients in Baltimore County, Maryland, were mapped. A risk model was then developed, using logistic regression analysis. The model was validated with case data from the distribution of cases in the following year, 1991. The purpose of the study was to demonstrate that GIS could be a useful tool for rapidly identifying risk factors of zoonotic disease over large areas.

Kitron *et a*l (1997) mapped incidence data for Lacrosse Encephalitis with population data, in Illinois, in order to derive incidence rates. They then performed global and local spatial statistics (e.g. Getis-Ord local statistic) as a quantitative analysis of aggregation and degree of clustering, vector distribution and their determinants. They found that there was a significant clustering of cases around Peoria, Illinois.

Openshaw (1996) argues that GIS can be quite useful for modeling spatial processes and for tracking diffusion of diseases, especially as applied to tropical medicine. As with Douven and Scholten (1995), Openshaw agrees that GIS is very good at performing various functions, but that it is limited by the fact that GIS packages themselves did not include sophisticated data analysis capabilities; he considered GIS in this respect to be inadequate.

Aylin *et al* (1999) provide an overview of how the United Kingdom's Small Area Health Statistics Unit (SAHSU) was developed. Its purpose is to serve as a special, rapid response (three-day response time) unit to produce estimates of relative risk for a health condition for defined populations around an environmental point source. The goal, using GIS and statistical software, is to assess whether disease clusters exist, and to alert the Health Authority to their existence. The SAHSU also produces maps for annual health reports; these maps include smoothed, small area, ward-level maps to show variations in disease distribution.

Lloyd (1995) describes a specific environmental example of ESDA using GIS. Lloyd assessed the impact of environmental pollutants from steel foundries on the lung cancer rates for three small towns in Scotland. He mapped the addresses of lung cancer decedents, evaluated airborne pollutant dispersal by local wind and topographical analyses. He was thus able to define zones of differing levels of metals pollution. Next, he computed Standardized Mortality Rates (SMRs) for these zones. He assessed the statistical significance of elevated cancer incidence for each of the zones based upon the degree of metals pollution. Lloyd found that there were statistically high rates of lung cancer in the three towns (Armadale, Bathgate, and Kirkintilloch) directly in the downstream pollution footprint of the steel foundries. Lloyd's study shows the value in conducting small area analyses of disease distributions, as possible environmental causes may be ill-defined or masked in small-scale (i.e., cartographic scale) geographic patterns of disease, which are typically mapped in most atlases of morbidity and mortality (Lloyd, 1995).

Gatrell and Dunn (1995) and Gatrell and Bailey (1996) describe several methods of ESDA made possible through GIS: linked plots, data brushing, and the coupling of analytical tools, which allows for fluent movement between the methods. They discuss the need for a GIS to be able to analyze spatial autocorrelation, which is especially useful in cluster detection. These authors lists several illustrations of ESDA, including spatial point pattern analyses (studies of leukemia in Lancashire and Burkitt's Lymphoma in Uganda) and small area analyses (studies of childhood mortality in Auckland, New Zealand and childhood leukemia in Britain). In all these cases, the importance of data visualization is stressed; this is one key advantage of using GIS for these types of studies.

In one specific example, Gatrell and Dunn (1995) performed a cluster analysis on the incidence of cancer of the larynx in the Lancashire and Greater Manchester area. They examined the possible links to environmental exposures, after which they analyzed the spatial relationships between laryngeal cancer and proximity to hospital and industrial waste incinerators. They used a combination of area-based and point-based approaches to cluster detection and analysis. Gatrell and Dunn found that there was not a significant elevation in laryngeal cancer risk associated with living in proximity to a hospital incinerator.

Kistemann *et al* (2002) describes the use of GIS to support the ecological patterns of tuberculosis incidence in Cologne, Germany. GIS was used to georeference, store, analyze, and display data for that project. Multiple regression analysis was accomplished in S-Plus through a linkage with ArcView GIS (ESRI, Redlands, California).

Roche *et al* (2002) describe the use of the spatial scan statistic in SaTScan 3.0 (Kulldorff, 2002) in conjunction with a GIS in order to assess potential health event clusters. They applied their techniques to the investigation of areas with high incidence of breast cancer in New Jersey. They were able to identify two areas in which incidence of late-stage breast cancer was significantly elevated in comparison to the remainder of the state. They analyzed several demographic factors that may have been causally linked to underutilization of appropriate screening procedures (e.g., mammograms) for the early detection of breast cancer. They concluded that the two areas with elevated incidence had very high percentages of black or Hispanic women as well as high percentages of non-English speaking households. They also were able to identify additional potentially-related factors for further study: lack of health insurance, lack of routine health care, prejudicial treatment in health care delivery, and lack of knowledge about breast cancer screening. Interestingly, through GIS overlay analysis, they found that there was a much higher percentage of women with late-stage breast cancer who lived within a two mile radius of a certified mammography facility; this suggested that location of mammography services does not appear to be causally-related to stage of breast cancer diagnosis in the study area.

Planning Public Health Interventions

The ultimate purpose in establishing a statistical relationship between causal factors and disease outcomes is to implement effective public health control measures or interventions. Several studies have demonstrated how this has been facilitated through the use of GIS (Table 2.3).

Several authors point out that intervention planning could have proceeded without the use of GIS; however, GIS is used advantageously to reduce costs and time associated with collection and analysis of data, and perhaps more importantly, it facilitates the analysis of spatial aspects of disease and related factors. As Glass *et al* (1995) argue, using GIS enables public health officials to rapidly identify risk factors for a disease (in this case, Lyme Disease), which is prevalent over large, multi-state, areas.

Traditional public health data sources can also be used within the context of a GIS to help establish intervention priorities. Reissman *et al* (2001) used a GIS to map locations in Jefferson County, Kentucky, of children living in houses constructed prior to 1950 (older houses are more likely to contain lead-based paint). They overlaid data on children's' blood lead screening levels (a more traditional public health data source than either remote sensing data or climate data) to determine associations between the age of housing and elevated blood lead levels; this enabled them to highlight areas where screening efforts need to be improved. As a result, lead paint remediation efforts can be better targeted and child lead screening efforts improved.

Taylor and Chavez (2002) describe the use of GIS for the planning of teen pregnancy prevention interventions in California. They used a GIS to store, analyze, and map the areas in which teen births were statistically elevated. They conducted their analysis at the census tract level in order to more precisely target their interventions.

Table 2.3. Selected Studies of GIS Use for Planning Public Health Interventions.

Study	**Disease Application**
Cherkasskiy (1999)	Anthrax
Glass *et al* (1995)	Lyme Disease
Kitron *et al* (1994)	Malaria
Miranda *et al* (2002)	Lead Poisoning
Mostashari *et al* (2003)	West Nile Virus
Omumbo *et al* (1998)	Malaria
Philips *et al* (2000)	Provision of Community Health Care Service
Popovich and Tatham (1997)	Immunizations, especially for Pertussis
Reissman *et al* (2001)	Lead Poisoning
Taylor and Chavez (2002)	Teenage Pregnancy
Yilma and Malone (1998)	Fasciolosis
Yoon (1995)	Schistosomiasis

Mostashari *et al* (2003) used the spatial scan statistic as implemented in SaTScan 2.1[*] (Kulldorff, 2002) to analyze the clustering of dead birds as a method for predicting areas of human West Nile Virus activity. By comparing the spatial locations of dead bird reports against an historical baseline in New York City, epidemiologists were able to identify areas with significantly elevated numbers of avian deaths. Using this information, New York City public health officials were able to initiate early larval control activities and prioritize scarce mosquito-collection and laboratory testing

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[*] SaTScan 2.1 was an earlier version of the current release, version 3.1 (Kulldorff, 2003).

resources. Mostashari *et al* conclude that preemptive measures to reduce mosquito breeding were implemented four weeks prior to the laboratory confirmation of West Nile Virus activity in vertebrate hosts and arthropod vectors.

Evaluating Public Health Interventions

The potential for using GIS to evaluate public health interventions is perhaps the most underutilized. Most of the literature that was reviewed concentrated on the formative stages of a public health analysis: determining whether public health action is warranted, and if so, whether any particular areas or populations require special attention. As GIS can be used to determine the presence of significantly high occurrences of a disease, and help illuminate potential causal factors of disease, GIS can also be used to determine if public health interventions have had any ameliorating effect upon targeted diseases. The same GIS operations and statistical tests applied to ascertain the presence of unusually high spatially correlated disease rates can be used to determine whether these disease rates have been positively impacted by public health action. GIS can be especially well suited for longitudinal studies, assessing first the baseline health conditions of an area or population and then the post-intervention conditions of the same area at a point in the future.

An example of an evaluation study, using GIS, is the study by Philips *et al* (2000), previously cited. Philips and colleagues compared the actual health service area for a Boone County, Missouri, Community Health Center (CHC) with the area that was originally anticipated to represent the future service area for the CHC. In fact, the CHC was specifically located in its current location in anticipation that it would serve the needs of a defined population. Because the CHC draws many of its patients from outside the anticipated service area, the assumptions and logic used to determine the CHC location can be called into question. Furthermore, using the methods and results of studies such as this may help health service planners to make better resource allocation decisions in the future.

Lovett *et al* (2002) conducted a similar study in East Anglia, in the United Kingdom. They analyzed the spatio-temporal proximity between patient residences and the locations of general practitioner locations in order to assess the provision of equitable health services by the United Kingdom's National Health Service (NHS). They used a GIS to calculate measures of accessibility by incorporating data on general practitioner locations, bus routes and other forms of community transportation, and road network characteristics. They found that 13% of the population could not reach the location of a general practitioner by bus; 5% of the population had a drive of longer than 10 minutes and had no suitable transportation alternatives; and the lowest levels of personal mobility and the highest health needs coincided in areas in which there was no bus service nor alternative forms of community transportation.

Limiting Factors and Methodological Concerns

Despite these several enabling factors, many lingering limitations and concerns remain. These factors can be considered as technical, methodological, and human/infrastructure. To begin with, the technical concerns center on data quality and availability. As an example, although TIGER line files are quite useful for geocoding purposes, many users have noted inaccuracies or gaps in the data. This has been partially addressed by commercial vendors, such as Tele Atlas (formerly Etak) and Geographic

Data Technology (GDT), both of which perform field verification and updates of street data from TIGER line files.

Additionally, public health analysts often lack access to vital statistics records that are geocoded to the residence level. In many cases, this locational data is not collected (e.g., county of residence may be collected, but residential street addresses are not); in other cases, when it has been collected, it is either masked or stripped from the dataset in order to protect the confidentiality of individuals. While it is possible to obtain such information in many instances, it involves a lengthy approval process, and in all cases, the reporting of the analytical results must in done in a manner such that the identification of individuals is not possible.

Often, geocoded information, if it's available at all, is only specific to the county or state level. This shortfall has been addressed by the U.S. Department of Health and Human Services, through the establishment of a Healthy People 2010 objective for improving health. Specifically, Healthy People 2010 Objective 23.3 states: "Increase the proportion of all major national, State, and local health data systems that use geocoding to promote nationwide use of geographic information systems (GIS) at all levels. (U.S. Department of Health and Human Services, 2000, p. 23-10)" This document further states that of the 22 major health data systems in the United States, only 10 contain geocoded data (U.S. Department of Health and Human Services, 2000).

Much of the professional GIS literature, and especially the public health related GIS literature, mentions several methodological concerns. These issues are very important to consider when beginning an analysis of public health data.

The most commonly mentioned methodological concern is the “ecological fallacy”. Essentially, variance in the data will change with spatial scale. In other words, patterns of association may vary based on the scale of analysis. Any inferences made about an association at a scale other than that scale in which the association was originally measured may be fallacious (Meade and Earickson, 2000). Therefore, if one were using county-level data, it would be incorrect to make an inference about the population of a census block based upon the data from the county in which the census block is contained. Likewise, it would be incorrect to make an inference about the county based upon data from one of its constituent census blocks. This latter case is an instance of the atomistic fallacy (which is mentioned *much* less than the converse: the ecological fallacy). This issue is very closely related the Modifiable Area Unit Problem (MAUP). As the data are aggregated to different scales, associations among the data will change. At higher levels of aggregation, the data is subject to central tendency leveling (Meade and Earickson, 2000). For example, one would expect to observe a higher degree of variation in the data at the individual county level than one would observe if all county data were aggregated to the state level.

A second methodological issue that must be considered is spatial autocorrelation, the degree to which objects or feature attributes at some location are similar to other objects or feature attributes at nearby locations. Additionally, spatial autocorrelation is scale dependent. The same phenomenon, measured at different spatial scales, can exhibit different amounts of spatial correlation at each scale (Goodchild, 1986). Because many statistical procedures rely upon the assumption of independent observations, spatially autocorrelated data can be problematic in that the standard errors of statistical models, such as regression, can be underestimated. This could lead to invalid tests of significance, for example, leading an analyst to conclude that a statistically significant relationship between or among variables exists when in fact it may not. Techniques exist for determining spatial autocorrelation, such as Moran's I and Geary's C indices, and for removing or adjusting for the autocorrelation, such as adding an independent variable that accounts for interactions among locations, changing the function form of the association to non-linear, or including an autoregressive error term (Goodchild, 1986).

A third problematic issue stems from limits due to the theoretical constructs of space (e.g. artificial administrative boundaries). Most public health disease rates are referenced to either states or counties. Yet, in reality disease distribution does not respect artificially determined administrative boundaries. When mapping disease rates, the impression is often presented of disease rates that change dramatically at the boundaries between counties. One potential solution to this issue might be to consider the disease rates (an areal measure) as conceptual point data, then mapping the data to the centroid of the administrative unit (e.g. county), then creating a statistical surface from the data. The result would be an isopleth map, which would tend to smooth the distribution of the disease rates. Care must be used in selecting interpolation methods, and one must realize that this technique is subject to limitations as well.

Applications of Remote Sensing Technology to Public Health Issues

The National Research Council (NRC) monograph *People and Pixels: Linking Remote Sensing and Social Science* (Liverman *et al*, 1998) highlights a growing trend in the application of remote sensing technology to social problems. In that volume, numerous members of the Committee on the Human Dimensions of Global Change describe the rationale for using remote sensing data for social science. They acknowledge that the social sciences and the remote sensing community had not previously had a close working relationship, perhaps mainly because of the technical training and physical science backgrounds of most of those in the remote sensing community, and the equally myopic training of those in the social sciences. However, with the prevalence of remote sensing data from NASA satellites as well as (at that time) anticipated availability of commercial satellite data, the National Academy of Science's NRC called for new, innovative uses of remotely sensed data in the social sciences.

One particular area that received some mention in the NRC publication is the application of remote sensing to health-related studies. Paul R. Epstein (1998) gives five brief examples in his chapter: 1) monitoring coastal algal blooms and toxic phytoplankton in order to provide early warning of conditions favorable for shellfish poisoning and cholera; 2) monitoring habitats of potential disease vectors (mosquitoes and rodents); 3) creating climate models that can be useful in predicting conditions favorable to disease outbreaks; 4) predicting changes in disease distributions through the use of climate-change models; and 5) analyzing high-altitude (tropospheric) temperatures in order to understand the potential spread of diseases at high altitudes.

In addition to the examples from Epstein, and the examples previously given under the subsection "*GIS applications to public health issues*", many other applications of remotely sensed data for the control of diseases have been described in the literature. It is interesting to note that in the overwhelming majority of cases, the applications to human health focused on infectious diseases. In particular, infectious diseases are those diseases which result from the invasion of a human body by living creatures, generally microorganisms (Meade and Earickson, 2000). They are often, but not always contagious among humans (although they can be contagious between animals or between animals and humans, but not necessarily human-to-human). Infectious diseases normally require a host (or reservoir), such as a bird or rodent, and a vector (for transmission of the disease), such as an insect.

Infectious diseases used to be much more prevalent in the United States, but in the last century, due mostly to the successes of public health interventions, infectious diseases have declined dramatically. Chronic diseases (diseases of the heart, malignant neoplasms, cerebrovascular diseases, and chronic lower respiratory diseases) are now the leading causes of death in the United States in 2000, the most recent year for which statistics have been published (U.S. Department of Health and Human Services, 2002). This is not true, however, in many developing nations. Many, if not most, of these developing nations lack the resources to conduct in-depth field surveys of conditions that may be favorable for disease outbreaks. In other words, they cannot conduct detailed studies of potential vector habitats or changes in local or regional climatic and vegetative conditions, which may be precursors to the incidence and spread of infectious diseases.

Epstein (1998) did not stress the very valuable contribution that remote sensing can make with respect to the limited resources of developing nations. While his overview did describe the technical advantages and applications of remotely sensed data, he missed a main point of using such data: it replaces other data that is much more time- and labor-intensive to collect. In fact, in many situations, these data cannot be collected at all, due to economic, physical, and political constraints. This may represent the major advantage of using remotely sensed data for the control of infectious diseases. Public health officials, charged with disease control efforts, can target their interventions to the determination of habitats suitable to for host and vector populations, through the use of remotely-sensed data, with *limited or no physical presence* necessary in the suspected areas.

The use of remote sensing for infectious disease control typically involves the assessment of either climate conditions or vegetation conditions. The goal is to identify the particular climatic and vegetative envelopes that are associated with specific hosts and vectors. Huh and Malone (2001) highlighted several important aspects of remotely-sensed satellite data that can be of great benefit to public health scientists in predicting and controlling diseases. The first major benefit of using satellite data is that it provides, for the first time, a synoptic view of the world to medical scientists, who until now have been limited to fragmented and partial views of conditions on the earth's surface. These fragmented views were obtained only at the expense of costly fieldwork. Huh and Malone delineate several detectable environmental factors, which have utility in disease control efforts:

- Diurnal temperature maximum/minimum/difference
- Sea/water/land surface temperatures
- Water/soil moisture/standing water/atmospheric water vapor
- Condition of vegetative canopy
- Structure and dynamics of low atmosphere/dimensions of airborne aerosols
- Topography and mineralogy

Huh and Malone (2001) identify several specific satellites and sensors that have current and projected future utility for public health disease monitoring. These include but are not limited to:

- NOAA AVHRR (visible, near-infrared, and thermal infrared bands)
- Landsat MSS (especially red and near-infrared bands)
- Hyperspectral radiometers such as AVIRIS, MODIS, and MOMS
- Synthetic Aperture Radar (SAR), such as Radarsat
- New satellites such as NEMO, IRS-P5, Orbview-3 and –4, and EROS-A2 and –B1

The following are several brief examples that highlight the utility of remotely sensed data for control of infectious diseases. Pope *et al* (1992) described the operational testing and evaluation of Landsat Thematic Mapper (TM) data as well as airborne synthetic aperture radar for identifying dambos (intermittently flooded areas) that are potential mosquito breeding habitats in Kenya. Previous studies had shown that the use of an NDVI (Normalized Difference Vegetation Index) computed from NOAA's AVHRR (Advanced Very High Resolution Radiometer) data could predict regionalized areas that have sufficient vegetative cover for mosquito breeding. However, these data were limited by coarse spatial resolution, and could not serve to pinpoint areas in which mosquito breeding is most likely to occur. Pope and colleagues found that dry season TM images were useful for identifying sedge and short grass most closely associated with mosquito breeding sites along the Kamiti and Kiu Rivers in northern Kenya. They also employed a synthetic aperture radar (SAR), which enabled detection of dambos despite the presence of clouds, as would be typical during periods in which flooding is expected to occur. By using these two methods, in conjunction with AVHRR NDVI indices, it is possible to obtain early warning of impending Rift Valley Fever outbreaks and to accurately locate potential breeding sites and to assess their capacity to sustain mosquito breeding habitats.

Hay *et al* (1998) derived a novel approach to produce seasonal risk maps for malaria in Kenya. In contrast to previous efforts to map mosquito habitats and thus predict mosquito numbers and specific areas of malaria risk, this study focused on determining seasonal variations in climate conditions favorable for mosquito breeding. They utilized the Advanced Very High Resolution Radiometer (AVHRR) data from the National Oceanic and Atmospheric Administrations (NOAA) polar-orbiting meteorological satellites and the High Resolution Radiometer (HRR) data on the European Organization for the Exploitation of Meteorological Satellites' (EUMETSAT) geostationary Meteosat satellites. Hay and colleagues observed a high and consistent correlation between temporal changes in the Normalized Difference Vegetation Index (NDVI) and temporal changes in malaria cases across Kenya.

Thomson *et al* (1999) described the creation of a kala azar (also known as visceral leishmaniasis) risk map for Sudan. Kala azar, transmitted by the vector *Phlebotomus orientalis* (sand fly), recently killed over 100,000 people in eastern Sudan. The sand fly has fairly specific habitat and climate requirements, which can be mapped with appropriate data. However, climatic and habitat conditions have changed in Sudan over the past century, highlighting the need for current data. Due to political instability and the vast expanse of territory, it is difficult to obtain data via ground survey. Therefore, environmental proxies obtained from weather monitoring satellites can greatly offset these difficulties. The distribution of *Phlebotomus orientalis* is limited to a "climate space" with specific rainfall (400-1200 mm) and temperature parameters (34-38°C), and with specific soil types and the occurrence of *Acacia-Balanites* woodland. Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) were used to identify soil types and temperatures that were determined by logistic regression to be predictors for the distribution of *Phlebotomus orientalis.* Soil data, mean annual daily maximum temperatures and rainfall amounts were overlaid in Idrisi GIS software in order to produce an initial risk map for kala azar. The final step in preparation of the risk map was to overlay the spatial distribution of *Acacia-Balanites* woodland. The resulting risk map for kala azar may greatly facilitate disease monitoring and control efforts in Sudan.

Malone *et al* (2001) described a global collaborative network that will be established in order to provide worldwide surveillance and control for snail-borne diseases. Snail-borne diseases, such as schistosomiasis, are prevalent in parts of Central and South America, Africa, and Asia, and cause thousands of deaths annually. A World Health Organization coalition will establish an integrated control program that will use GIS, global climate model data, soils, landuse and topographic maps, data from earth observing satellites, disease prevalence data, information on the distribution and abundance of snail hosts, and digital maps of key environmental factors that reflect conditions necessary for the propagation of snail-borne disease host agents. In particular, this "minimum medical database" will contain landuse basemaps prepared with Landsat MSS/TM/ETM+ data, global 1-kilometer Normalized Difference Vegetation Index (NDVI) decadal time series data for 1992 and 1995, global 1-kilometer Tmax decadal time series data for 1992 and 1995, and the Digital Chart of the World (DCW) basemap.

Guptill (2001) described a current United States Geological Survey (USGS) and Centers for Disease Control and Prevention (CDC) effort to use remote sensing and GIS to monitor and predict the outbreak of infectious diseases in the Gulf Coast region of Alabama. Many of the casualties from natural disasters occur as the result of the exposure of displaced persons to infectious disease vectors, and to exposure to unsanitary conditions conducive to illnesses such as cholera, dysentery, and typhoid fever. Guptill (2001) suggests the use of high-resolution remote sensing imagery taken after a natural disaster to direct response personnel and medical supplies to the highest priority areas, and a test study currently is being conducted in Mobile, Alabama.

Several other examples have been published relating to cholera (Ali *et al*, 2002), mosquito and malaria control (Welch *et al*, 1989; Wood *et al*, 1992; and Kleinschmidt *et al*, 2001), Filariasis prevalence (Crombie *et al*, 1999), and schistosomiasis (Abdel-Rahman *et al*, 2001). Additional examples are summarized in *Spatial Analysis, GIS, and Remote Sensing Application in the Health Sciences* (Albert *et al*, 2000). Likewise, the entire February 2002 issue of *Photogrammetric Engineering and Remote Sensing* (*PE&RS*) is devoted to Remote Sensing and Human Health. In the *PE&RS* special issue, however, the foci were exclusively infectious diseases: West Nile Virus (Rogers *et al*, 2002); Rift Valley fever (Anyamba *et al*, 2002); ebola (Tucker *et al*, 2002); *Mycobacterium bovis* infection (McKenzie *et al*, 2002); malaria (Omumbo *et al*, 2002); schistosomiasis (Seto *et al*, 2002); and human helminth distributions (Brooker *et al*, 2002). The overriding constant in all these cases is the use of remotely-sensed satellite imagery to assess variables associated with the *physical* environment, which has direct application in the control and prevention of vector-borne diseases.

What has *not* been discussed in the public health literature has been the potential application of remotely sensed data to chronic disease control and prevention. This is an overlooked area that has untapped potential. This type of application is also very consistent with the spirit of *People and Pixels* (Liverman *et al*, 1998): the discovery of the context in which social phenomena occur.

There are many social and environmental indicators that predispose individuals to certain health risk behaviors that can lead to the development of chronic diseases. Such indicators or their proxies can be distinguished through the innovative uses of remotely-sensed satellite imagery or aerial photographs. For example, indices of poverty or quality-of-life can be computed by using air photos and satellite images (Green, 1957; Davies *et al*, 1973; and Jensen and Cowen, 1999.). The poverty indices can then be correlated to other disease risk factors in order to help explain or to predict the prevalence of certain chronic diseases. Likewise, remotely-sensed imagery can be used to compute vegetative (or "greenness") indices and to determine apparent surface temperatures, which can serve as markers for neighborhood-level environmental quality-of-life (Weber and Hirsch, 1992; and Lo and Faber, 1997). Satellite monitoring can also be used to determine measures of air quality that may have various impacts on human health.

The application of remote sensing to the control of infectious diseases is important and will likely remain so. However, because chronic diseases are by far the major causes of mortality in the United States and other developed nations, the use of remote sensing for prevention and control of chronic diseases offers great promise and needs to be explored more fully.

Remote sensing can also assist in the assessment and prevention of chronic diseases in a somewhat indirect way. Because census-derived data are often used for analysis of chronic diseases and their risk factors, changes in census geography (e.g., tracts, block groups, Metropolitan Areas, etc.) cause difficulties in any analysis that involves temporal aspects. For example, in this research project, changes in census-derived variables were analyzed over the period 1980-2000. During that period, many new census tracts were created and some census tract boundaries were shifted. This made the assessment of change in the census-derived data challenging for those effected tracts. By using satellite imagery to create land use/cover maps, it is possible to determine areas of residential extent, which in turn, permitted the determination of the extent of change (in terms of residential population) resulting from census tract boundary shifts or tract splits. The extent of changes is then used to weight the data from two censuses (1980 and 2000) to conform to the boundaries of the 1990 census. In this manner, it is possible to estimate the changes in variables of interest, from 1980 through 2000, in terms of the 1990 census tract boundaries. Additional specifics of this procedure will be detailed in later sections.

In summary, while remotely-sensed satellite imagery has traditionally been used to study and control infectious diseases, there are two additional applications that can facilitate the analysis of chronic diseases: 1) the derivation of indicators of the physical and social environment that are related to, or affect, health risk behaviors for chronic diseases; and 2) the use of remotely-sensed satellite imagery to adjust census-derived data in order to compensate for temporal changes in census geography. Both applications are used in this dissertation.

The research in this dissertation represents an ecological study in the positivist tradition of medical geography. It includes the consideration of the effects of place on health, through the quantitative analysis of potential causal factors. It also utilizes spatial epidemiologic techniques to assess the degree of concentration or spatial autocorrelation in mortality events.

This study represents an extension of the previous applications of GIS in public health research, by using a GIS to conduct the analysis of all-cause mortality at the census tract level in the United States. The use of remote sensing technology is unique, in that it facilitates the derivation of land-use/land-cover data (which are some of the independent variables under consideration) as well as enabling the areal interpolation of census variables from incompatible census tract boundaries. It is also unique in that it represents the use of remote sensing technology for a non-infectious disease public health research project.

CHAPTER 3

ISODATA CLASSIFICATION OF LANDSAT IMAGERY TO DETECT CENSUS TRACT LEVEL LAND-USE AND LAND-COVER CHANGES IN METROPOLITAN ATLANTA, GEORGIA, 1984-2000[*]

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[*] Holt, J.B. and C.P. Lo. To be submitted to *Remote Sensing of Environment*

Introduction

The primary purpose of this research project is to quantify census tract level land-use and land-cover changes for the thirteen-county Metropolitan area of Atlanta, Georgia, from 1984 to 2000. The land-use and land-cover statistics were to be used as independent variables in a larger ecological study, assessing the relationship between urbanization-driven changes in the spatial distribution of socioeconomic and physical environmental variables and the patterns of all-cause mortality for the thirteen-county Metropolitan Atlanta area. A secondary purpose of this study is to derive specific delineations of residential areas for use as ancillary data for dasymetric mapping of population density for the study period. Additionally, these ancillary data would enable areally interpolated adjustments of selected census-derived variables in order to compensate for changes in census tract geography from 1980 to 2000.

Study Area

The study area for this research project included thirteen counties in the metropolitan Atlanta area (Figure 3.1): Cherokee, Clayton, Cobb, Coweta, DeKalb, Douglas, Fayette, Forsyth, Fulton, Gwinnett, Henry, Paulding, and Rockdale. These counties correspond to the ten counties comprising the Atlanta Regional Commission with the addition of Coweta, Forsyth, and Paulding Counties. These counties represent the major Atlanta metropolitan area. Figure 3.2 depicts the principal cities, highways, railroads, and rivers of the study area. The thirteen counties comprising this study area served to illustrate a range of census tracts across the metropolitan region: many are census tracts with previously urbanized populations; many are previously rural but have experienced significant suburbanization since 1980; many are still rural.

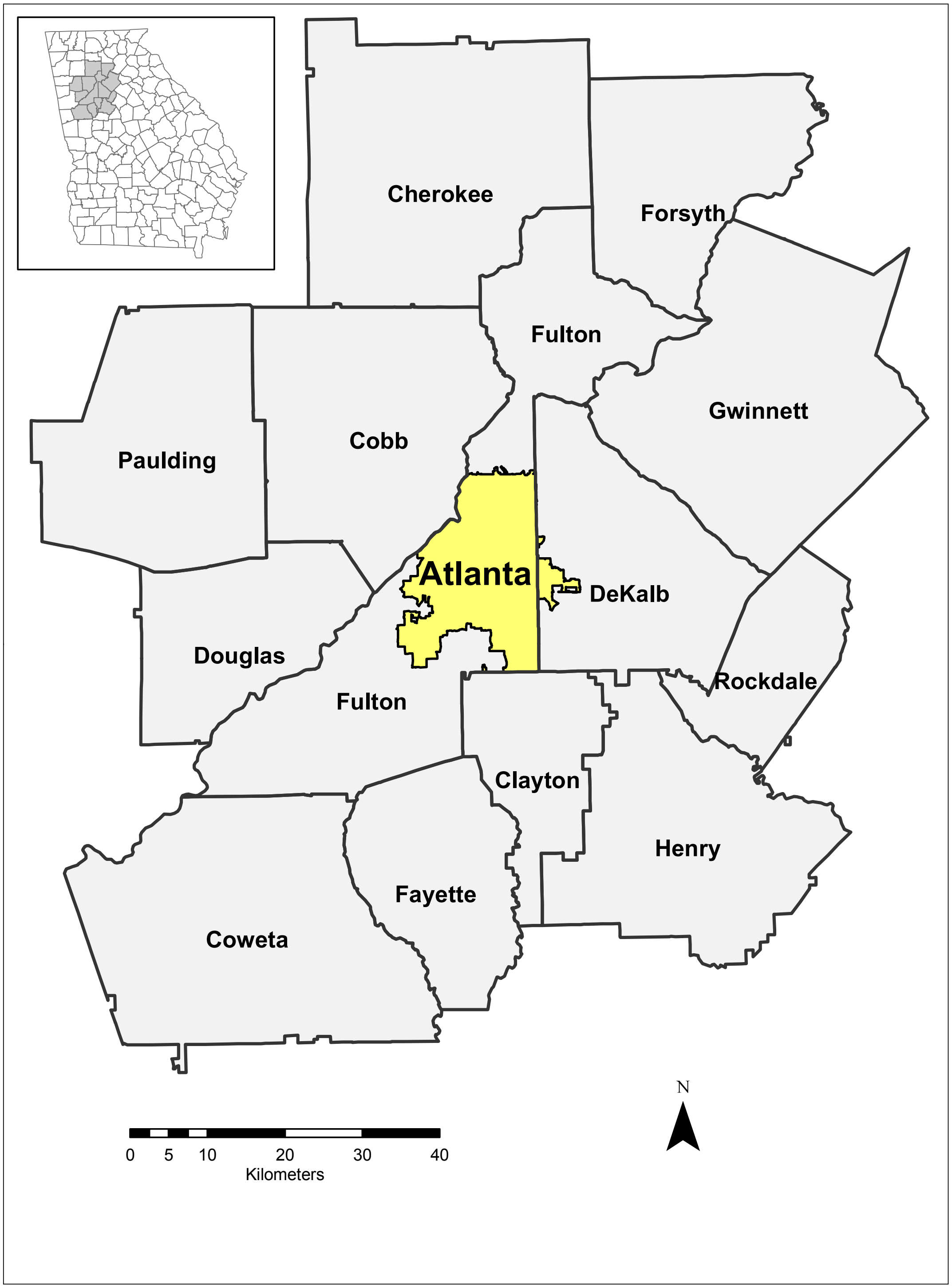

Figure 3.1. Thirteen-County Metropolitan Atlanta Study Area.

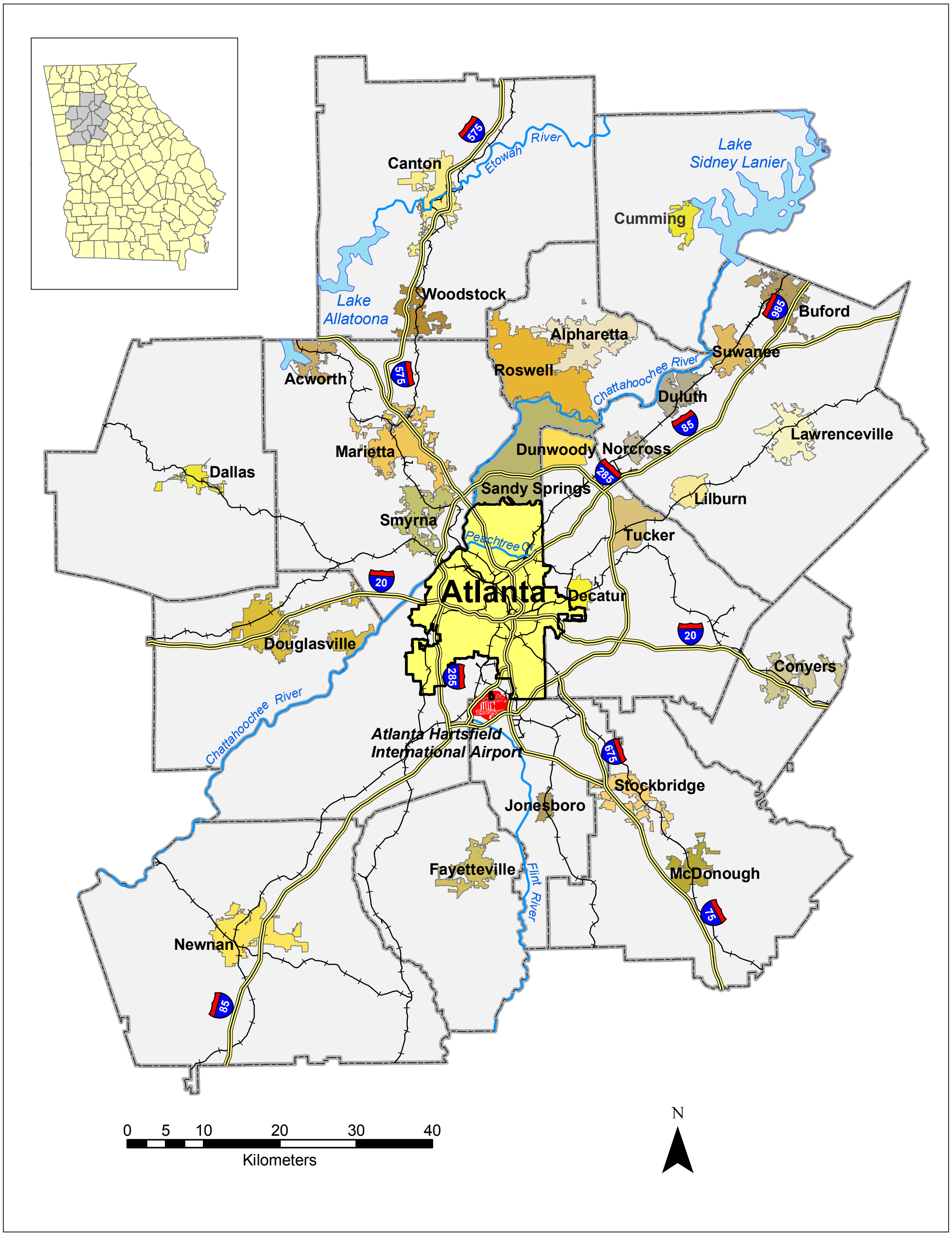

Figure 3.2. Principal cities, highways, railroads, and rivers, Metropolitan Atlanta, Georgia.

Previous Research

This thirteen-county area, comprising Metropolitan Atlanta, has been the subject of previous research on the quantification of urban spatial growth (Yang 2000; Lo and Yang 2000; Yang, 2002; and Yang and Lo, 2002), and the determination of drivers of land-use and land-cover change (Lo and Yang; 2002). In that research, Lo and Yang employed an unsupervised ISODATA classification to a time-series of Landsat Multispectral Scanner (MSS), Landsat Thematic Mapper (TM), and Landsat Thematic Mapper Plus (ETM+) imagery. Land-use and land-cover statistics were extracted at the census tract level and the county level, although only the statistics for the overall study area were reported in the literature. They demonstrated that the Metropolitan Atlanta area experienced substantial changes in land-use and land-cover from 1973 through 1999. The predominant change was the expansion of urbanized land-uses at the expense of losses to forested land-cover and agricultural land-use. Specifically, they found that high-density urban land-use increased by 82.6 percent and low-density urban land-use increased by 131.2 percent, while cropland and grassland decreased by 26.1 percent and forested land decreased by 11.6 percent, from 1973 to 1987. From 1987 to 1999, high-density urban land-use increased by 61.2 percent and low-density land-use increased by 59.1 percent, while cropland and grassland decreased by 14.1 percent and forested land decreased by 17.9 percent (Lo and Yang, 2002).

Lo and Yang utilized satellite data for the following years: 1973 (MSS), 1979 (MSS), 1987 (TM), 1993 (TM), and 1999 (ETM+). Data for the current study were obtained for the following years: 1982 (TM), 1984 (TM), 1990 (TM), and 2000 (ETM+).

Growth of the Atlanta Metro Area

Table 3.1 illustrates the rapid increase in population for the thirteen-county metro area (U.S. Census Bureau, www.census.gov, accessed May 17, 2003). Several counties grew at a rate exceeding the metro average of 85.9% for the twenty-year period 1980-2000. These counties represent areas on the suburban fringe of the metro area. The counties containing the city of Atlanta (Fulton and DeKalb) experienced the lowest rate of population increase over the same period.

The counties with the highest overall population rate increase for the entire period were (in decreasing order of growth) Gwinnett, Forsyth, Henry, Fayette, Paulding, Cherokee, Coweta, and Cobb, all of which more than doubled in population. The counties with the lowest growth rates were (in increasing order of growth) DeKalb, Fulton, Clayton, and Douglas, all of which grew at a rate less than the overall rate for the thirteen-county region. Clayton County's growth is somewhat constrained by the presence of Atlanta's Hartsfield International Airport, the major center of employment within the county.

It is interesting to note that the very modest overall population growth in Fulton and DeKalb Counties took place despite the rapid increase in population in selected portions of those counties (north Fulton and south DeKalb); this indicates that the traditional core areas of these counties, which contain the city of Atlanta, grew at a much slower rate (or lost population) than the county averages would indicate. Data from the U.S. Census Bureau for 1990 and 2000 and the Atlanta Regional Commission (ARC) for 1970 and 1980 indicate that the City of Atlanta lost population from 1980 to 2000, with an even more precipitous decline since 1970 (Table 3.2). The Census Bureau data were used for 1990 and 2000 as the ARC data for 1990 were adjusted to account for a supposed undercount by the Census Bureau.

Table 3.1. Population growth, 1970-2000, Metropolitan Atlanta (Source: U.S. Census Bureau).

County	1980	1990	2000	% chg 80-90	% chg 90-00	% chg 80-00
Cherokee	51699	90204	141903	74.5	57.3	174.5
Clayton	150357	182052	236517	21.1	29.9	57.3
Cobb	297718	447745	607751	50.4	35.7	104.1
Coweta	39268	53853	89215	37.1	65.7	127.2
DeKalb	483024	545837	665865	13.0	22.0	37.9
Douglas	54573	71120	92174	30.3	29.6	68.9
Fayette	29043	62415	91263	114.9	46.2	214.2
Forsyth	27958	44083	98407	57.7	123.2	252.0
Fulton	589904	648951	816006	10.0	25.7	38.3
Gwinnett	166903	352910	588448	111.4	66.7	252.6
Henry	36309	58741	119341	61.8	103.2	228.7
Paulding	26110	41611	81678	59.4	96.3	212.8
Rockdale	36747	54091	70111	47.2	29.6	90.8
13-County Total	1989613	2653613	3698679	33.4	39.4	85.9

Table 3.2. Population change, 1970-2000, City of Atlanta (Source: U.S. Census Bureau, 2000; and Atlanta Regional Commission, 2002).

1970	1980	1990	2000	% change 70-80	% change 80-90	% change 90-00	% change 70-00	% change 80-00
495039	424922	394017	416474	-14.2	-7.3	+5.7	-15.9	-2.0

The significance of these changes is the apparent shift in economic importance from the traditional downtown central business district (CBD) to the outlying urban fringe areas. This pattern is consistent with the urban geography literature which suggests such changes for major urban areas for the same period. It is important to note that the trend in the decline in the City of Atlanta's population from 1970 to 2000 may be changing: the city's population actually grew by 5.7% from 1990 to 2000 (yet still well below the metro average of 39.4%). As a result, for the period of analysis for this dissertation, 1980-2000, the net population change for the City of Atlanta was a loss of 2.0%. This suggests that the city may have been somewhat successful in its recent efforts to lure back old residents and attract new residents to new multi-unit apartment complexes and loft conversions. These efforts at post-Olympics gentrification are described in the monograph commissioned by Research Atlanta, Inc. (Hartshorn, 1998).

According to data from the ARC (Atlanta Regional Commission, 2000), over seventy percent of the growth in the 1980s was spread over the northern arc of the region. This trend continued into the 1990s, however, growth had rapidly accelerated in the southern arc of counties (all south of Interstate 20). In the 1980s, the northwest sector in particular (Cobb County) accounted for the majority of new growth. As Cobb County began to be built out, and with the addition of Georgia Highway 400 (a major limited access highway into the north Fulton County area), growth began to shift to the north and northeast sectors (north Fulton County and Gwinnett County).

Lo and Yang (2002) also assessed the spatial patterns of growth by the use of a geographic information system (GIS) overlay function. They noted that high-density urban land-use spread outward from a small concentration in the inner part of the city, linearly along major transportation arteries, until about 1983. From 1983 through 1992, high-density urban land-use growth concentrated in three separate areas: Gwinnett County (northeast of Atlanta), Cobb County (northwest of Atlanta), and Clayton and Henry Counties (southeast of Atlanta). This helped to confirm the existence of a multi-centered urban growth pattern, consistent with characterizations such as multiple-nuclei urban models and edge cities (Knox and Pinch, 2000) and urban realms or suburban downtowns (Hartshorn and Muller, 1989; and Fujü and Hartshorn, 1995). The concentration of high-density urban use increased even further from 1992 through 1997, as build-up was quite pronounced around these extended urban centers. Changes in low-density urban land-use, which are associated mainly with residential development, were especially noted in the counties on the urban fringe: Gwinnett, north Fulton, Forsyth, Fayette, and Henry counties (Lo and Yang, 2000; Lo and Yang, 2002).

Research Methodology

Data Acquisition

Satellite Images

For this study, four Landsat scenes were obtained: 1982 (TM), 1984 (TM), 1990 (TM), and 2000 (ETM+). Medium-resolution data, such as Landsat TM and Landsat ETM+, were desirable due to the areal extent of the study area, the match between spatial resolution and residential land parcel size, and the relative low cost of obtaining Landsat data. Higher resolution commercial satellite data, while providing greater spatial and radiometric resolution (e.g., 11-bit quantization for IKONOS versus 8-bit for Landsat), has the following disadvantages for this type of study: 1) much higher cost; 2) much smaller areal coverage per scene (approximately 13 km x 13 km nominal scene coverage for IKONOS versus 185 km x 185 km scene coverage for Landsat), thus requiring multiple scenes for this particular study area, further compounding the cost issues; 3) much higher computer processing times required due to the larger number of pixels; and 4) the additional difficulty of performing parcel-sized land-use and land-cover classifications, due to the greater spectral heterogeneity within a given land parcel area

(Toll, 1985; Irons *et al*, 1985; and Cushnie, 1987). A specific difficulty with ultra-high spatial resolution data, such as IKONOS, is that pixel-based classifications are not appropriate because each pixel is associated to components of an object or area and not related to the character of an object or area as a whole (Ehlers *et al*, 2003, p. 316). Finally, IKONOS has only a short history; data prior to 1999 are not available.

Table 3.3 contains details on the acquisition dates, Landsat satellite numbers, nominal spatial resolutions, scene locational data, geometric rectification accuracy, and radiometric normalization for the imagery used in this classification. It is desired to have all imagery from the same season of the year, to facilitate scene-to-scene comparisons. Leaf-on images, taken in late-spring or early-summer would have been especially desirable, as vegetation would have been in its stage of most vigorous growth, thus facilitating the differentiation and classification of forested lands and croplands/ grasslands. However, the desirability of cloud-free images precluded the acquisition of images from late-spring, a season of greater cloudiness than mid-to-late summer. As a compromise, mid-to-late summer cloud-free images were obtained. The only exception is the 1982 Landsat 4 TM image. Landsat 4, the first of the second generation Landsat satellites was the first to deploy with the Thematic Mapper array. Previous Landsats (1-3) contained the Multispectral Scanner (MSS) sensor, with a nominal Instantaneous Field of View (IFOV) of 79 meters. Thematic Mapper, with an IFOV of 30 meters, provides greater spatial resolution and is a better match for this type of study.

The earliest cloud-free TM imagery that could be obtained for the Atlanta study area is a scene from December, 1982. Because the beginning date of the larger study, of which this particular project is a component, is 1980, the selection of a 1982 image is a

Table 3.3. Characteristics of Landsat imagery used for land-use and land-cover classification in the Atlanta metropolitan area.

Date	**Type of Imagery**	**Landsat Number**	**Nominal Spatial Resolution (meters)**	**Scene Location**	**Path #**	**Row #**	**Rectification RMSE (meters)**	**Rectification Control Points Used**	**Radiometric Normalization**
20 June 1984	TM	5	30	Center-shifted[*]	019	036-037	10.0	14	Yes
25 Sept 1990	TM	5	30	Center-shifted[*]	019	036-037	5.5	13	No
28 Sept 2000	ETM+	7	30[**]	North Atlanta[***]	019	036	18.25	16	No
28 Sept 2000	ETM+	7	30	South Atlanta	019	037	18.25	16	No

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[*] These scenes were ordered with a specification for a 50% southward shift in the scene nadir for Path 019, Row 036, to ensure that the study area of Metropolitan Atlanta would be in the center of the resulting scene.

[**] Resolution is for the visible, near-infrared, and mid-infrared bands. Nominal spatial resolution for the thermal infrared band is 60 meters; and nominal spatial resolution for the panchromatic band is 15 meters.

[***] ETM+ scenes cannot be center-shifted, therefore two scenes were obtained in order to cover the study area.

compromise. To have obtained 1980 satellite data would have required the use of Landsat MSS, which would have introduced a different spatial resolution into the classification process. It was decided that the better option in this case is to remain consistent with respect to spatial resolution, and to recognize that land-use and land-cover changes over the period 1980-2000 would be somewhat underestimated in extent by the use of satellite imagery dating from 1982 (or subsequent).

The 1982 Landsat TM scene was obtained and briefly analyzed. It was determined not to use this scene because the time-of-year of acquisition did not coincide with the other three images (1984, 1990, and 2000), and because there is a distinct lack of spectral contrast in the image. Rather than radiometrically correct the 1982 image to compensate for the lack of contrast, it was decided to proceed with the classification of the 1984 Landsat 5 TM image as the beginning image of the sequence. This involved the further compromise of temporal data, as the first image is now four years removed from the starting point of the study. This limitation must be recognized in the final analysis of the land-use and land-cover statistics.

The Atlanta Metropolitan study area spans two rows (036 and 037) in Path 019 of the Landsat Worldwide Reference System (WRS). The scenes for 1982, 1984, and 1990 were ordered with a request for a 50% southward shift in the image nadir for the row 036 images. The resulting scenes were therefore centered over the Atlanta area. This is not possible for the Landsat 7 ETM+ scene for 2000; therefore two ETM+ scenes were required. The two 2000 scenes were mosaicked together and clipped to include the Atlanta area in one scene.

Reference Data

In order to assist with the land-use and land-cover classification for the Landsat images, using the unsupervised ISODATA approach, it is necessary to obtain reference data. These reference data also served to assist in the classification accuracy assessments of the 1990 and 2000 images[*]. Reference data consisted of primarily three sources: 1) Color Infrared (CIR) Digital Orthophoto Quarter Quadrangles (DOQQs) ; 2) true color and black-and-white (B/W) aerial photographic prints; and 3) Digital Raster Graphics (DRGs).

DOQQs are digital images that have the properties of orthographic projections. They are derived from digitized perspective photographs (in this case, 1999 aerial photograph stereo pairs of the Atlanta area) through differential rectification in order to remove image displacements that are caused by terrain relief and camera tilt. As a result, DOQQs combine the image characteristics of a photograph with the geometric qualities of a map. The DOQQs used for this study were 3.75 x 3.75 minute quarter-quadrangles with a 1 meter ground resolution (e.g., pixel size). The DOQQs were georeferenced to the Universal Transverse Mercator (UTM) coordinate system on the North American Datum of 1983 (NAD 83). DOQQs must meet horizontal National Map Accuracy Standards (NMAS) at 1:12,000 scale. The NMAS require 90 percent of well-defined sampled points to fall within 33.3 feet horizontal accuracy (at 1:12,000 scale, this translates to 1/30 inch). The vertical accuracy must exceed that of a level 1 Digital Elevation Model (DEM) with a root-mean-squared-error (RMSE) of 7 meters or less (U.S. Department of the Interior, 1996).

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[*] Adequate reference information did not exist for the 1984 scene. This issue will be further addressed in the section on accuracy assessment.

The DOQQs were produced and distributed in GeoTiff format by the U.S. Geological Survey. Table 3.4 lists the fifty-four DOQQs that were obtained as reference data for this study.

The 9 x 9 inch B/W photographs were acquired in 1988 by the U.S. Geological Survey as part of the National Aerial Photography Program (NAPP) and have a nominal scale of 1:40,000. Additionally, true color and B/W photos were commercially produced in 1989 (1:39,400 nominal scale), and served as additional reference data to supplement the USGS NAPP aerial photographs. Tables 3.5 and 3.6 provide details on the USGS NAPP B/W photos and the commercial color and B/W photos, respectively.

Digital Raster Graphics (DRGs) were used for the selection of ground control points (GCPs) for geometric rectification of the Landsat images. DRGs were downloaded from the Georgia GIS Clearinghouse (www.gis.state.ga.us) for the same USGS 7.5” quadrangles as the CIR DOQs, although not all DRGs were eventually used for the selection of GCPs. DRGs are georeferenced, rectified images of scanned

U.S. Geological Survey (USGS) topographic maps. DRGs are produced with output resolutions of at least 250 dots per inch (dpi) and can be as high as 500 dpi[*]. DRGs are normally georeferenced to the datum of the source topographic map and they are projected to the UTM projection. DRGs will preserve the original horizontal accuracy of the source map. DRGs are georeferenced by assigning computed UTM values to every latitude and longitude tick on the source map, as well as the corners of the maps’ neatlines. In the case of the 7.5 x 7.5 minute quadrangles used in this study, the tick spacings were 2.5 minutes, resulting in a total number of 16 referenced ticks (U.S.

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[*] A revised standard for the production of DRGs, issued in 2001, provides the option of increased output resolution up to 1000 dpi, although this is not required (U.S. Department of the Interior, 2001).

Table 3.4. Digital Orthophoto Quadrangles (DOQQs) used as reference data (USGS 7.5" Quadrangles). (Source: State of Georgia, Center for Geographic Information Systems, Georgia Institute of Technology.)

USGS 7.5" Quadrangle	**USGS 7.5" Quadrangle**
Acworth	Lawrenceville
Atlanta NE	Loganville
Atlanta NW	Lost Mountain
Atlanta SE	Luxomni
Atlanta SW	Mableton
Auburn	Madras
Austell	Marietta
Ben Hill	McDonough
Birmingham	Mountain Park
Bold Springs	Newnan North
Buford Dam	Newnan South
Burnt Hickory Ridge	Norcross
Campbellton	Palmetto
Canton	Redan
Chamblee	Rico
Chestatee	Riverdale
Conyers	Roswell
Cumming	Sandy Springs
Dallas	Senoia
Duluth	Sharpsburg
Fairburn	Snellville
Fayetteville	South Canton
Hampton	Stockbridge
Hog Mountain	Stone Mountain
Jonesboro	Suwanee
Kelleytown	Taylorsville
Kennesaw	Tyrone

Table 3.5. USGS NAPP photos used as reference data. (Source: University of Georgia Map Library).

Date	**Format**	**Flight Line**	**Photograph Number**
January 29, 1988	Black and White	52	314
January 29, 1988	Black and White	52	316
January 29, 1988	Black and White	52	318
January 29, 1988	Black and White	52	320
January 29, 1988	Black and White	52	322
January 29, 1988	Black and White	52	324
January 29, 1988	Black and White	52	326
January 29, 1988	Black and White	53	314
January 29, 1988	Black and White	53	316
January 29, 1988	Black and White	53	318
January 29, 1988	Black and White	53	320
January 29, 1988	Black and White	53	322
January 29, 1988	Black and White	53	324
January 29, 1988	Black and White	53	326
January 28, 1988	Black and White	54	316
January 28, 1988	Black and White	54	318
January 28, 1988	Black and White	54	320
January 28, 1988	Black and White	54	322
January 28, 1988	Black and White	54	324
January 28, 1988	Black and White	54	326
January 26, 1988	Black and White	55	318
January 26, 1988	Black and White	55	320
February 9, 1988	Black and White	55	322
February 9, 1988	Black and White	55	324
February 9, 1988	Black and White	55	326

Table 3.6. Commercial aerial photographs used as reference data. (Source: University of Georgia Map Library).

Date	**Format**	**Flight Line**	**Photograph Number**
May 11, 1988	Color	E	18
May 11, 1988	Color	E	19
May 11, 1988	Color	E	22
May 11, 1988	Color	F	18
May 11, 1988	Color	F	19
May 11, 1988	Color	F	20
May 11, 1988	Color	F	21
May 11, 1988	Color	F	22
February 10, 1989	Black and White	D	18
February 10, 1989	Black and White	D	19
February 10, 1989	Black and White	D	20
February 10, 1989	Black and White	D	21
February 10, 1989	Black and White	D	22
February 10, 1989	Black and White	E	18
February 10, 1989	Black and White	E	19
February 10, 1989	Black and White	E	20
February 10, 1989	Black and White	E	21
February 10, 1989	Black and White	E	22
February 10, 1989	Black and White	F	18
February 10, 1989	Black and White	F	19
February 10, 1989	Black and White	F	20
February 10, 1989	Black and White	F	21
February 10, 1989	Black and White	F	22
February 10, 1989	Black and White	G	18
February 10, 1989	Black and White	G	19
February 10, 1989	Black and White	G	20
February 10, 1989	Black and White	G	21
February 10, 1989	Black and White	G	22
February 10, 1989	Black and White	H	18
February 10, 1989	Black and White	H	19
February 10, 1989	Black and White	H	20
February 10, 1989	Black and White	H	21
February 10, 1989	Black and White	H	22

Department of the Interior, 2001). The scale of the DRGs, based on the source topographic maps, is 1:24,000.

Field Survey

A limited amount of field survey was performed in order to assist in the classification and accuracy assessment of the 2000 Landsat scene, and to a lesser degree for the 1990 Landsat scene. This field survey was performed in an as-needed basis in Gwinnett County, primarily in order to provide reference data for difficult-to-classify ISODATA clusters. The ground survey was greatly facilitated by the fact that the author has lived in west-central Gwinnett County for over eight years, experiencing much of the land-use and land-cover change first-hand during the period 1995-2003.

Digital Image Processing

Image Preprocessing

The first step in image preprocessing is the creation of a single mosaicked image for the 2000 Landsat ETM+ scene. This is necessary because the scene is not center-shifted as is the case with the 1982, 1984, and 1990 scenes. Therefore, to ensure that the Atlanta study was completely covered by satellite imagery, two Landsat ETM+ scenes were necessary. The image mosaic was performed using ERDAS Imagine 8.6 software (Leica Geosystems, Atlanta, GA). Following image geometric rectification, the mosaic was spatially clipped to include only the thirteen-county area.

All Landsat scenes that were obtained had already been geometrically corrected and georeferenced, by USGS, to UTM projection (Zone 16N), the NAD83 horizontal datum, and the GRS80 ellipsoid. However, it is necessary to georeference all the images to ensure spatial compatibility among the images and the census tract boundaries, which would be overlaid on the resulting land-use and land-cover maps.

Ground control points (GCPs) were selected from DRGs, which were displayed side-by-side with the original Landsat image in the Geospatial Light Table feature of ERDAS Imagine 8.6. Simultaneously, image control points (ICPs) were selected from the Landsat image. These control points were carefully selected to ensure that the corresponding features could be identified, unambiguously, on both the DRG and the Landsat image. The final number of control points, and the resulting root mean squared error (RMSE), were 14 GCP with 10.0 meter RMSE (1984 TM); 13 GCP with 5.5 meter RMSE (1990 TM); 16 GCP with 12.5 meter RMSE (2000 ETM+ northern scene); and 16 GCP with 7.1 meter RMSE (2000 ETM+ southern scene).[*] In all three images, the RMSE is less than one-half the spatial resolution of one pixel. A first-order polynomial transformation was utilized, as the study area contained relatively even terrain relief. This is also the procedure followed by Lo and Yang (2000). Nearest Neighbor (NN) resampling was then conducted on the original Landsat scenes in order to preserve the original spectral values of the image pixels. The rectification of the final images was also visually checked by overlaying the 1990 census tract boundary file for the study area. In particular, an excellent fit was noted by observing the spatial coincidence among highways and the Chattahoochee River and the corresponding census tract boundaries, defined by those linear features.

Radiometric normalization was performed only on the 1984 Landsat TM scene. By visual inspection, it was determined that the 1990 Landsat TM and the 2000 Landsat

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[*] Two ETM+ scenes were obtained to provide full coverage of the study area, as ETM+ scenes could not be center-shifted. Each 2000 ETM+ scene was rectified separately, prior to creating a mosaic of both scenes.

ETM+ scenes displayed excellent contrast, which appeared to be roughly equivalent. Conversely, the image contrast of the 1984 TM scene appeared much lower, by comparison. This most likely is the result of atmospheric conditions during the time of the image collection. The 1990 scene was chosen as the reference image, as it was collected by the same sensor (Landsat 5) as the 1984 scene, thus reducing any sensor-specific variations in the two scenes. A histogram-match radiometric normalization was performed on the 1984 TM scene. The histogram-match procedure does not require the availability or use of *in situ* atmospheric data from the time of image collection.

The resampled images were then clipped to the spatial extent of the thirteen-county study area through the use of the Area-of-Interest and Subset functions in ERDAS Imagine 8.6. This allowed savings of processing time and computer memory for subsequent steps in the analysis. It also facilitated the creation of images and land-use and land-cover maps, as extraneous land areas were eliminated at this point.

Image Classification Scheme

The image classification scheme employed in this research is the same developed and utilized by Lo and Yang in their research (Yang, 2000; and Lo and Yang, 2000). This scheme was originally developed by Lo and Yang in order to be used with a computer-assisted classification approach for imagery with varying resolutions (30 meters and 79 meters). It is a variation of the well-known Anderson classification scheme, which was originally intended for land-use and land-cover mapping from manual interpretation of remotely-sensed satellite data (Anderson *et al*, 1976). Although the spatial resolutions of the images used in this study are consistent, this research utilized the same computer-assisted approach as used by Lo and Yang. Furthermore, it was desired to compare land-use and land-cover statistics to their previous Atlanta study; thus, a consistent classification scheme is necessary. Lastly, the scheme (Table 3.7) contained land-use and land-cover classes that were very appropriate for the current research study. In particular, the class entitled "Low-density urban use" corresponded extremely closely to residential areas, which is a primary class of interest to this author.

Image classification

An unsupervised ISODATA (Iterative Self-Organizing DATa Analysis) classification was utilized to identify clusters of spectrally-similar pixels in each Landsat scene. An unsupervised approach differs substantially from a supervised classification. In a supervised classification, spectral signature sets are developed for each targeted land-use and land-cover category by the analyst's selection of polygonal areas (or "training sites") known to correspond to each particular land-use and land-cover class. This requires the analyst to digitally select, *a priori*, a number of polygonal areas (in practice, usually five or more) that represent each category of interest. The training sites are used to train the classification algorithm: multivariate statistical parameters, such as the mean, standard deviation, and covariance/correlation matrices, are determined for each training site. The classification algorithm then evaluates and assigns every pixel to the particular class to which it has the highest likelihood of membership (Jensen, 1996; Lillesand and Kiefer, 2000).

An unsupervised classification does not make use of *a priori* land-cover information. Instead, pixels with similar spectral properties are grouped into a pre-determined number of clusters. This clustering is achieved through a computerized search for natural groupings of the pixels' spectral properties based on their distances in

Table 3.7. Land-use and land-cover classes and definitions used in this project. (Source: Yang, 2000).

Class #	**Class Name**	**Definitions**
1	High-Density Urban Use	Approximately 80 to 100 percent construction materials, e.g., asphalt, concrete, etc.; typically commercial and industrial buildings with large open roofs as well as large open transportation facilities, e.g., large airports, parking lots, and multilane interstate/state highways; with low percentage of residential development residing in the city cores.
2	Low-Density Urban Use	Approximately 50 to 80 percent construction materials; often residential development including most of single/multiple family houses and public rental housing estate as well as local roads and small open (transitional) space as can be always found in a residential area; with certain amount of vegetation cover (up to 20 percent).
3	Cultivated/Exposed Land	Areas of sparse vegetation cover (less than 20 percent) that are likely to change or be converted to other uses in the near future; including clearcuts, all quarry areas, cultivated land without crops, and barren rock or sand along river/stream beaches.
4	Cropland/Grassland	Characterized by high percentages of grasses, other herbaceous vegetation, and crops; including lands that are regularly mowed for hay and/or grazed by livestock, golf courses and city parks, and regularly tilled and planted cropland.
5	Forest	Including coniferous, deciduous, and mixed forests (90 to 100 percent).
6	Water	All areas of open water, generally with greater than 95 percent cover of water, including streams, rivers, lakes, and reservoirs.

multispectral feature space, defined by the spectral bands of the image data (i.e., a cluster analysis). The analyst manually assigns these spectral classes *a posteriori* to information classes of interest, such land-use/land-cover categories (Jensen, 1996).

In supervised and unsupervised classifications, assignments to land-use/land-cover categories is normally achieved through a hard partition of feature space. Each pixel is assigned to only one membership class. In contrast, a soft classification allows a fuzzy partition of feature space in which each pixel has a class membership value that corresponds to its correlation with each of the classes of interest. Fuzzy classifications take account of the heterogeneous and imprecise nature of land-cover, which is manifested in mixed pixels (Jensen, 1996; and Wang, 1990). However, to produce a final classification map from a fuzzy classification, a hard decision rule must be implemented. In the classification for this particular study, a hard classifier was utilized.

The supervised classification, while generally efficient from a time and computer-processing standpoint, is dependent upon the selection of “pure” training sites if a hard or crisp classifier is used. An analyst may take great pains to select an area known to be only residential or agricultural. However, by selecting a training area that contains multiple pixels, it is highly likely that the area will contain pixels that exhibit variation in spectral reflectances. This is especially problematic for sensors with higher spatial resolution (Irons *et al*, 1985; and Ehlers *et al*, 2003), as a training site of given spatial extent will have more pixels than would the same training area in which a sensor with coarser spatial resolution is used. This potentially can reduce the accuracy of the classification, as these reference signatures ideally should represent the mean spectral reflectance of a “pure” example of the category of interest. The requirement to have pure training sites is also problematic for built-up areas, such as residential areas, in which a typical residential parcel will contain pixels representing both vegetation (trees and grass) as well as impervious surfaces (roofs, sidewalks, driveways, and roads). The resulting signature set for that category will contain an averaged value for each spectral band; those mean spectral values contain information from pixels representing multiple objects: trees, grass, roofs, sidewalks, driveways, and roads. This is known as the mixed pixel problem.

The unsupervised ISODATA approach relies upon a computer algorithm to classify each pixel into a cluster of pixels in which all assigned pixels have similar spectral reflectance properties. The ISODATA routine begins by making an initial assignment of mean vectors in the feature space defined by the number of spectral bands of the image. The number of mean vectors corresponds to the number of clusters to be created. The mean vector assignment is made along an n-dimension vector that is constrained within a subset of the feature space, defined by the mean and standard deviation of each spectral band of the image. In the first iteration, each pixel is assigned to the cluster whose mean is closest in Euclidean distance. After all pixels have been assigned to a cluster in the first iteration, a new mean is calculated for each cluster based on the actual spectral locations of the assigned pixels. In the second, and all subsequent iterations, each pixel is compared to the new cluster means, and pixel reassignments are made if a different cluster mean is closer than the original cluster mean. Therefore, some pixels will move from one cluster to another, while others will remain in the previously assigned clusters. This process is repeated until a user-specified maximum number of iterations has been reached, or until there is very little change in cluster assignment from one iteration to the next. The analyst can specify this threshold (or convergence) value for determining the maximum percentage of pixels whose cluster assignment remains unchanged from one iteration to the next (Jensen, 1996).

Once the convergence threshold is reached, it is assumed that further iterations will result in little or no substantive improvement to the cluster assignments. Once the clusters have been formed, the analyst must then inspect the pixels in each cluster and make a determination as to which land-use or land-cover category that cluster belongs. This process continues until all clusters are categorized, after which the classification accuracy can be assessed through the use of reference data or "ground truth".

The ISODATA procedure in ERDAS Imagine 8.6 permits the user-specification of the number of target clusters, the maximum number of iterations, and the threshold convergence value. For this analysis, the number of target clusters varied, depending upon the type of imagery being analyzed: 60 clusters were specified for the two TM scenes, and 80 clusters were specified for the ETM+ scene. This is based upon previous assessments by Lo and Yang (Yang, 2000; Lo and Yang, 2000). In all cases, the convergence threshold was set to 0.99 and the maximum number of iterations was set to a high value of 80, to enable the convergence threshold to be reached first. All six non-thermal bands of the TM and ETM+ scenes were used for the classification. The clusters were displayed in ERDAS Imagine 8.6 as false color images, which facilitated their comparison to the original false color satellite image.

Clusters were assigned to one of the six land-use and land-cover categories, by a variety of assessment means. To facilitate the assessment, the false color ISODATA image was displayed alongside, and geographically linked to, the original satellite image in the Geospatial Light Table (ERDAS Imagine 8.6). In addition, the image was similarly linked to either a 1999 CIR DOQ or a DRG (dates varied). Initial assessments were often possible by examining the cluster at small scale (e.g., “zoomed out”), in which case both the relative situation, color, size, and shape of the clusters served to provide substantial information for manual interpretation. In this manner, the assignment of the clusters to categories is very similar to a manual image interpretation. Assessments made in this manner were always verified by an examination of the spectral reflectances of pixels within the cluster. That was accomplished by the use of the Inquire Cursor in Imagine. (The inquire cursor also pinpointed the corresponding areas in the original satellite image and in the DOQ and/or DRG; this provided a very precise means for comparing pixels to pixels.) The cluster’s spectral reflectance values were checked to ensure congruence with the category assignment. In many cases where it is difficult to select between two categories (e.g., forest and cropland/grassland), the examination of spectral reflectance values provided enough additional information to make an informed selection.

Cluster assignment proceeded in this manner until all clusters were either assigned to a land-use/land-cover category or unclassified. These unclassified clusters reflect the problem caused by mixed pixels. In the latter case, such clusters were masked from the original ISODATA image, and reprocessed through an additional application of the ISODATA algorithm. This process of “cluster busting” (Jensen, 1996) resulted in a larger set of clusters from the original subset of ambiguous clusters, in which the ISODATA algorithm was able to make finer distinctions among pixels based on mean spectral reflectances (e.g., ten ambiguous clusters were transformed into 30 new clusters, as a result of the second ISODATA iteration). In all cases where this was performed, the cluster busting process resulted in clusters that were classifiable into an appropriate land-use/land-cover category.

During the assignment of clusters to land-use/land-cover categories, there was occasionally some minor difficulty in selecting between two plausible categories. In the 1990 scene, most classification confusion occurred between the categories of High-Density Urban (HDU) and Low-Density Urban (LDU), and to a lesser extent between Cropland/Grassland and Forest. Similar results were obtained for the 1984 classification, which would be consistent with the use of the same satellite array (Landsat 5) for the acquisition of each scene. In the 2000 scene, most classification confusion occurred between the categories of Forest and Cropland/Grassland; and to a lesser extent between Cropland/Grassland and Cultivated/Exposed. In two cases out of eighty, there was some confusion between HDU and LDU. These instances of cluster assignment ease/difficulty should not be confused with assignment accuracy, as this cluster assignment refers specifically to the analyst’s decision-making process. The actual classification accuracy of the images is a separate issue and will be described in detail later. It should be noted now, however, that classification accuracies (and conversely categories with less than optimal classification accuracies) did not necessarily correspond to those classes for which analyst-assignment of clusters was easy or difficult.

Following initial assignment of clusters to land-use/land-cover categories, a spatial reclassification was performed in order to compensate for boundary errors in the dataset. Mis-classified areas can occur near the boundaries of land-use/land-cover areas. This is primarily due to the presence of spectral mixing within pixels (Booth and

Oldfield, 1989). This spectral mixing is also accompanied by the presence of small areas in the classified scene that represent anomalous noise or speckle. To remove both these problems, a 3 x 3 modal (or focal majority) filter was used in order to remove these isolated pixels, through modal smoothing. In order to preserve linear features important for urban analysis, such as roads, the modal filter was modified such that the four corners of the 3 x 3 matrix were disabled with an assigned value of 0 (the final filter resembled a rook's case cross).

Accuracy Assessment

Adequate reference data (or ground truth) were not available for all three classified scenes. Therefore, following the procedure employed by Lo and Yang (Yang, 2000; Lo and Yang, 2000), it was desired to assess the accuracy of at least one image of each sensor type. To that end, the 1990 TM image and the 2000 ETM+ image were assessed for classification accuracy. Excellent ground truth existed for the 2000 image and good reference data existed for the 1990 image. Color Infrared DOQs were primarily used for the 2000 scene, while color and Black-and-White aerial photographs were used for the 1990 scene. It is assumed that the accuracy assessment for the 1990 scene can serve as a proxy for the accuracy of the 1984 scene because of the use of the same classification process for both images and the use of the same satellite sensor (Landsat 5) to collect both images. Accuracy assessments are presented in the form of confusion matrices in Tables 3.8 (1990) and 3.9 (2000).

To conduct the accuracy assessments, 425 sample pixels were selected, with a minimum of 30 pixels per land-use/land-cover category, by stratified random sampling, from each of the 1990 and 2000 ISODATA images. The number of points chosen, 425,

Table 3.8. Accuracy assessment of ISODATA classification of 1990 Landsat TM scene.

Classified Data			Reference Data				Row Total	Users Accuracy
	High-Density Urban	Low-Density Urban	Cultivated/Exposed	Crop/Grassland	Forested Land	Water		
High-Density Urban	46	2	6	0	0	0	54	85.19
Low-Density Urban	7	63	0	0	2	0	72	87.50
Cultivated/Exposed	6	0	45	1	2	0	54	83.33
Crop/Grassland	0	0	2	62	0	0	64	96.88
Forested Land	0	0	0	0	131	0	131	100.00
Water	0	0	1	0	1	48	50	96.00
Column Total	59	65	54	63	136	48	425	
Producers Accuracy	77.97	96.92	83.33	98.41	96.32	100.00		92.94
								Overall Accuracy
Conditional Kappa								
High-Density Urban	0.8280							
Low-Density Urban	0.8524							
Cultivated/Exposed	0.8091							
Crop/Grassland	0.9633							
Forested Land	1.0000							
Water	0.9549							
Overall Kappa	0.9124							

Table 3.9. Accuracy assessment of ISODATA classification of 2000 Landsat ETM+ scene.

Classified Data			Reference Data				Row Total	Users Accuracy
	High-Density Urban	Low-Density Urban	Cultivated/Exposed	Crop/Grassland	Forested Land	Water		
High-Density Urban	46	0	4	0	2	0	52	88.46
Low-Density Urban	1	57	3	2	2	0	65	87.69
Cultivated/Exposed	6	2	41	5	2	0	56	73.21
Crop/Grassland	0	2	1	55	6	0	64	85.94
Forested Land	0	0	0	1	137	0	138	99.28
Water	1	0	0	0	2	47	50	94.00
Column Total	54	61	49	63	151	47	425	
Producers Accuracy	85.19	93.44	83.67	87.30	90.73	100.00		90.12
								Overall Accuracy
Conditional Kappa								
High-Density Urban	0.8678							
Low-Density Urban	0.8563							
Cultivated/Exposed	0.6972							
Crop/Grassland	0.8349							
Forested Land	0.9888							
Water	0.9325							
Overall Kappa	0.8759							

was determined by using the formula from Snedecor and Cochran (1967) as implemented by Lo and Watson (1998):

$$n = Z^2 \cdot p\,(1-p)/E^2 \qquad (3.1)$$

Where n = minimum number of sample points

p = expected population proportion (0.5, after Lo and Watson (1998))

Z = standard normal deviate (1.65 to correspond to 90% 2-tailed confidence level)

E = tolerable error (0.04 to correspond to a 4 % point deviation limitation)

Accuracy assessment was performed according to standard practice (Congalton, 1991). The following measures were computed: overall accuracy, producer's accuracy, user's accuracy, conditional Kappa, and overall Kappa.

For the 1990 scene, the overall accuracy of 92.94 is acceptable as it exceeded the minimum threshold of 85% set forth by Anderson *et al* (1976) for the classification of thematic data. Producer's accuracy ranged from 77.97% for HDU to 96.92% for LDU and 100% for water. This measure is an indication of the ability of the classifier to accurately assign a pixel to the correct category. In other words, it is a reflection of the sensitivity of the classification. It can also be thought of as the algebraic difference between a perfectly correct classification and the error of commission (for example, the total percentage of non-HDU pixels incorrectly assigned to the HDU category). Conversely, the user's accuracy is an indication of how accurately the resulting land-use/land-cover map reflects the true distribution of land-use/land-cover. It is a reflection of the specificity of the classification. It can be thought of as the algebraic difference between a perfectly correct classification and the error of omission (for example, the total percentage of HDU pixels not correctly assigned to the HDU category). In the 1990 scene, the user's accuracy ranged from 83.33% for cultivated/exposed land to 96.88% for cropland/grassland and 100% for water. The user's accuracy is less than the producer's accuracy for LDU, which indicates that while the classification very accurately assigned LDU pixels to the LDU category, it also assigned (erroneously) other categories' pixels to the LDU category. In other words, the classification is more sensitive than specific with respect to the LDU category. For HDU, the reverse was true: user's accuracy is higher than producer's accuracy, indicating that the classification is more specific than sensitive for HDU.

For the 2000 scene, generally similar results were observed. The overall accuracy is slightly lower, at 90.12%, but still quite acceptable. The patterns of producer's accuracy and user's accuracy were also similar to those from the 1990 image with a few notable exceptions. The producer's accuracy for HDU is higher, at 85.19%; the producer's and user's accuracies for cropland/grassland were both lower than those for 1990, at 83.67% and 85.94%; and the user's accuracy for cultivated/exposed land is a relatively low 73.21%. Accuracies for the LDU category were both good at 93.44% (producer's) and 87.69% (user's).

Conditional Kappa and overall Kappa statistics were computed for both scenes. The Kappa statistic is a superior measure to the overall accuracy percentage, because it takes into account the errors of omission and commission, which are obtained from the off-diagonal elements of the accuracy matrix; while the overall accuracy is based solely on the major diagonal of the accuracy matrix (Congalton, 1991). A review of the Kappa statistics indicated overall acceptable results for both images ($\text{Kappa}_{1990} = 0.9124$;

Kappa_{2000} = 0.8678). The only Kappa statistic of concern is the conditional Kappa for the cultivated/exposed category in the 2000 ETM+ scene, which is 0.6972. As previously mentioned, this category had a relatively low user's accuracy. These results indicate that the classification process had some difficulty in distinguishing between the cultivated/exposed category and one (or more) other category. When performing the manual assignment of clusters to land-use/land-cover categories, there was some difficulty in deciding between the cultivated/exposed category and the cropland/grassland category. The conditional Kappa statistic and the user's accuracy for the cropland/grassland category were the second lowest for the 2000 scene, which suggests that this may have been the category most often confused with cultivated/exposed land in the classification process. Despite these issues, the overall classifications were quite acceptable with respect to established standards (Anderson *et al*, 1976) and were quite suitable for subsequent analyses. These accuracy results compared favorably with the accuracies reported by Yang (2000) on his classification of a 1997/98 TM and a 1999 ETM+ scene.

Post-Accuracy Assessment Image Reclassification

Following the accuracy assessments, each classified image was examined for evidence of gross mis-classifications. There were five major misclassifications that were noted in the images: 1) Hartsfield International Airport; 2) Stone Mountain; 3) portions of western Paulding County; 4) roads throughout the entire scene area; and 5) clouds. Hartsfield International Airport's footprint consisted of a majority of impervious surface pixels interspersed with vegetation pixels (primarily grassy areas between runways and taxiways). The impervious surface pixels corresponding to runways, taxiways, and terminal buildings, were classified as either cultivated/exposed or as High-Density Urban. This highlights the difference between the definitions of land-cover and land-use: the former relates to 'the vegetational and artificial constructions covering the land surface' (Burley, 1961, quoted in Lo, 1986, p. 227), while land-use refers to 'man's activities on and in relation to the land, which are not directly visible from the imagery' (Lo, 1986, p. 227). Because the classification scheme definition for HDU encompasses airports, the Hartsfield-related cultivated/exposed pixels were manually reclassified to HDU pixels, to better reflect land-use.

The classification of Stone Mountain further illustrated the distinction between land-cover and land-use. In that case, both HDU and cultivated/exposed pixels were present. Some of the HDU pixels were valid, as there is a portion of Stone Mountain that has been developed into a commercial tourist attraction and monument. These pixels were isolated and retained as HDU pixels with the assistance of a CIR DOQQ; other HDU pixels corresponding to the granite mountain itself were manually changed to the cultivated/exposed category, to better reflect the land-cover of the mountain.

In the 1990 classification, a large area of western Paulding County is classified as Low-Density Urban (e.g., residential), and to a lesser extent as High-Density Urban and cultivated/exposed land. It is suspected that this remote area, in a rural county, was relatively or even completely unpopulated. Further investigation indicated that the majority of the area in question is in the Paulding Forest Wildlife Management Area, and was not populated, with the minor exception of the small village of Braswell. Comparisons of the 1984, 1990, and 2000 Landsat images further suggested that what was once an area of vigorous forest growth (1984), later was used for logging operations (circa 1990) with large tracts of timber having been extracted; the 2000 image indicated areas of timber regrowth. Because of this evidence, a manual reclassification was made to the 1990 classification; LDU pixels in that specific area were reclassified as forest land, while the small number of HDU pixels in that area were reclassified as cultivated/exposed land. In addition, there were a small number of pixels classified as cropland/grassland, which likely indicated very young forest regrowth at that time (1990). These pixels were reclassified as forest land. Examination of the 1990 reclassified area to the same areas in the 1984 and 2000 images indicated that the reclassified area was forested in 1984 and again in 2000.

It was noted that roads were variously classified in all three images. In many cases, the roads were classified as LDU, in others as cultivated/exposed, and in yet other cases as HDU. Given that the definition of HDU includes multilane interstate and state roads, road pixels were manually recoded to the HDU category. To facilitate this reclassification, a polyline vector layer of major Atlanta area roads was obtained (ESRI, Redlands, CA, 2002, from data updated and supplied by GDT, Inc.) and buffered to a width of 30 meters (corresponding to the width of one Landsat TM/ETM+ pixel). The resulting buffered road layer was converted to raster format and overlaid on top of the 2000 land-use/land-cover map, and areas of overlap were recoded to HDU.

The vector layer of roads was manually edited for the years 1990 and 1984 in order to remove roads that did not exist in 1990 and 1984 respectively. Reference data for both years was obtained in the form of regional highways maps for 1990 and 1983. The presence/absence of each federal, state, county, and local multilane primary highway was manually determined, and where necessary, roads were removed by manual editing in ArcInfo 8.2. The 1984 and 1990 road layers were each buffered, rasterized, and overlaid on top of the corresponding land-use/land-cover maps, and the HDU recoding was performed as previously described for 2000.

In the 1984 TM scene, there are many scattered cumulus clouds present in the southern portion of the scene. Comparison of the 1984 to the 1990 and 2000 scenes indicated that these were generally unpopulated, agricultural and forested areas. To remove the effects of the clouds from the classification, these areas were digitized as Areas-of-Interests ("aoi") in ERDAS Imagine. The 1990 land-use/land-cover map was clipped with the 1984 aoi's, and the resulting layer was overlaid on top the 1984 land-use/land-cover map, enabling the automatic recoding of the cloud-covered areas to the corresponding land-use/land-cover categories that existed in 1990.

Figures 3.3, 3.4, and 3.5 illustrate the original Landsat scenes for 1984, 1990, and 2000, respectively. Figures 3.6, 3.7, and 3.8 illustrate the land-use/land-cover maps, generated by the unsupervised ISODATA classifications for 1984, 1990, and 2000, respectively. County boundaries and 1990 census tract boundaries are depicted in these figures to facilitate inter-map comparisons.

Figures 3.9, 3.10, and 3.11 illustrate the land-use/land-cover maps for Gwinnett County, for 1984, 1990, and 2000. The Gwinnett County maps highlight the rapid changes in land-use and land-cover in the northern suburbs of Metropolitan Atlanta during the 1980's and 1990's. In particular, the loss of forested land and the increase in urbanized land-use (both high-density and low-density) is especially pronounced.

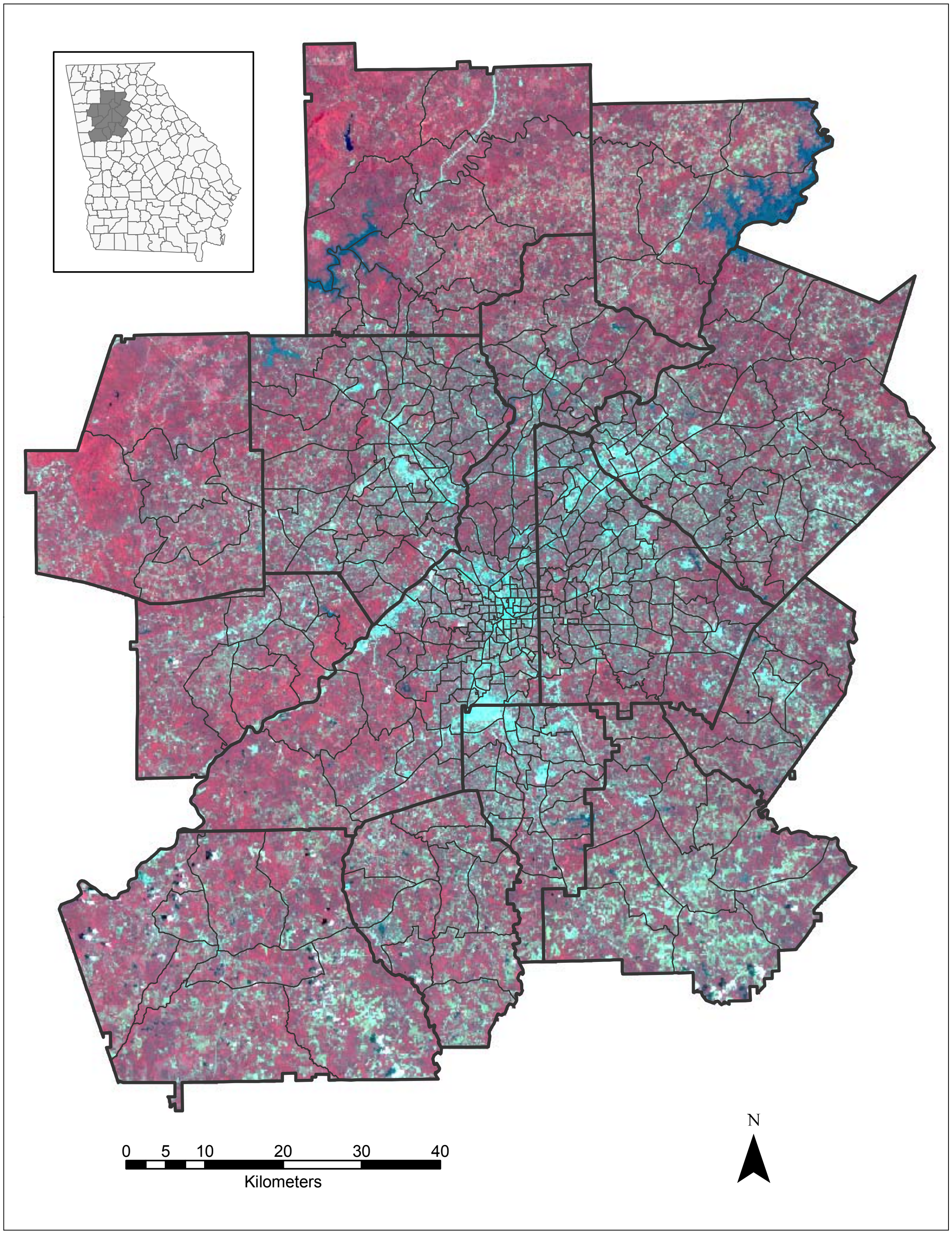

Figure 3.3. Landsat 5, Thematic Mapper, false color composite image, Metropolitan Atlanta, 20 June 1984.

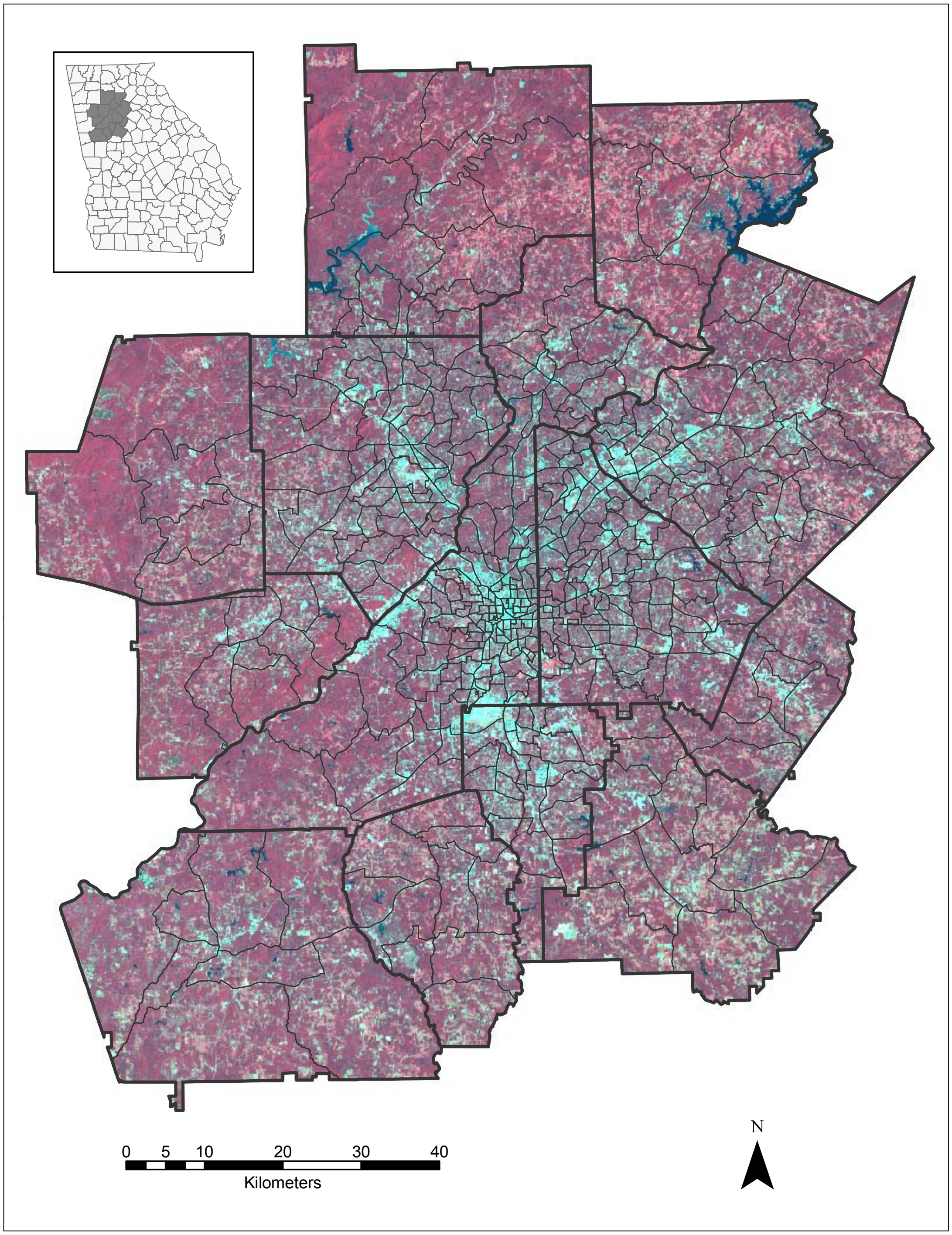

Figure 3.4. Landsat 5, Thematic Mapper, false color composite image, Metropolitan Atlanta, 25 September 1990.

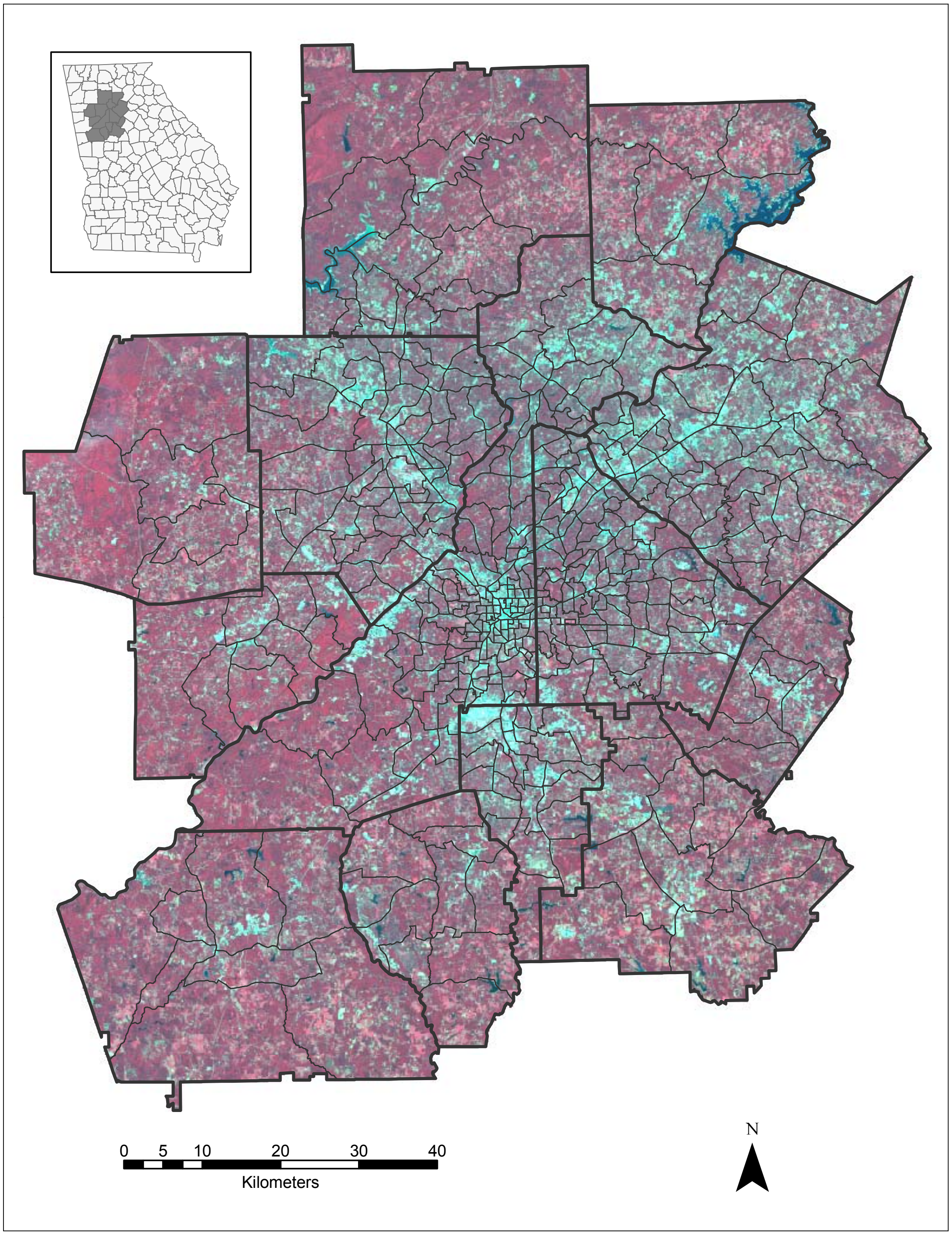

Figure 3.5. Landsat 7, Enhanced Thematic Mapper Plus, false color composite image, Metropolitan Atlanta, 28 September 2000.

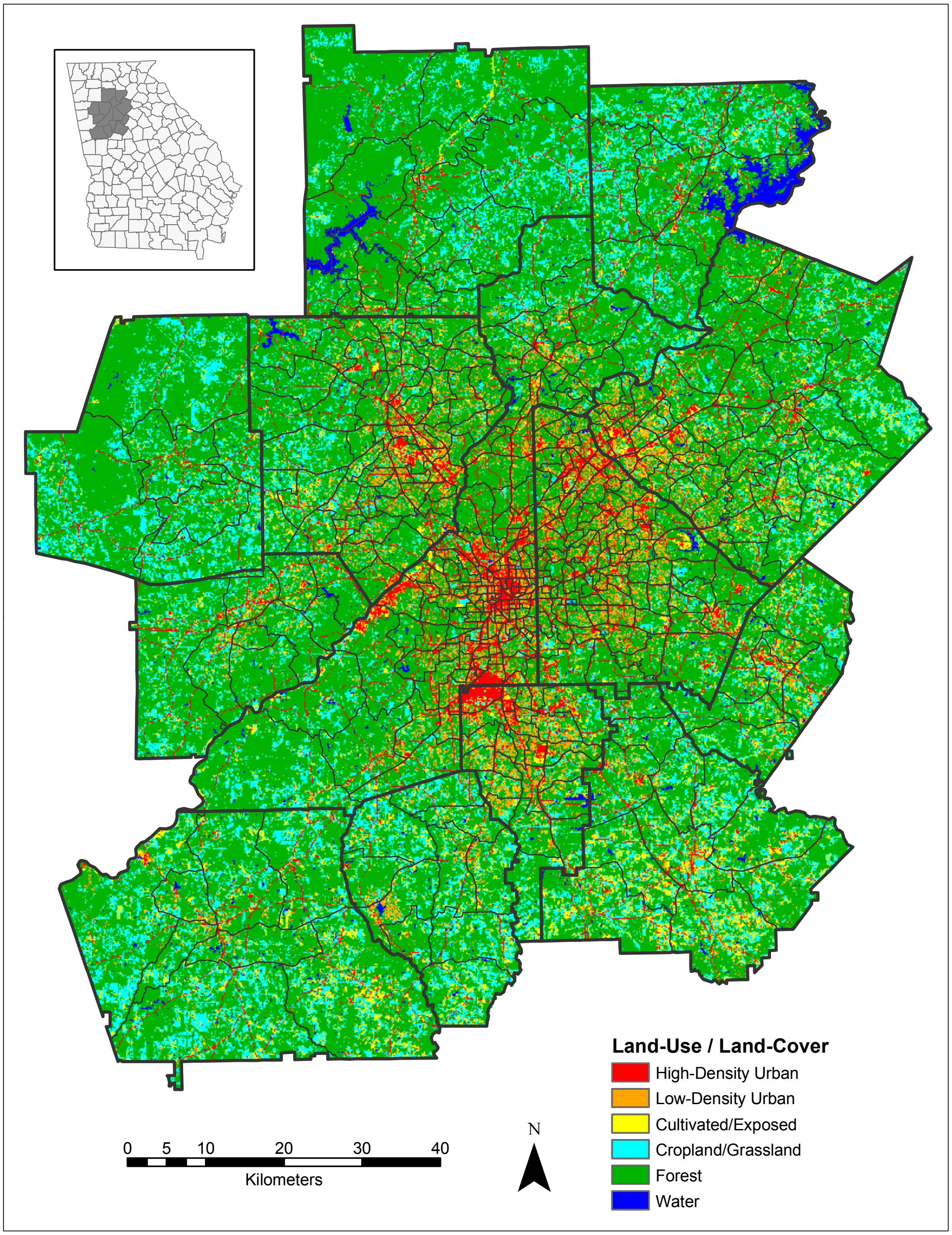

Figure 3.6. Land-use/Land-cover, Metropolitan Atlanta, 1984.

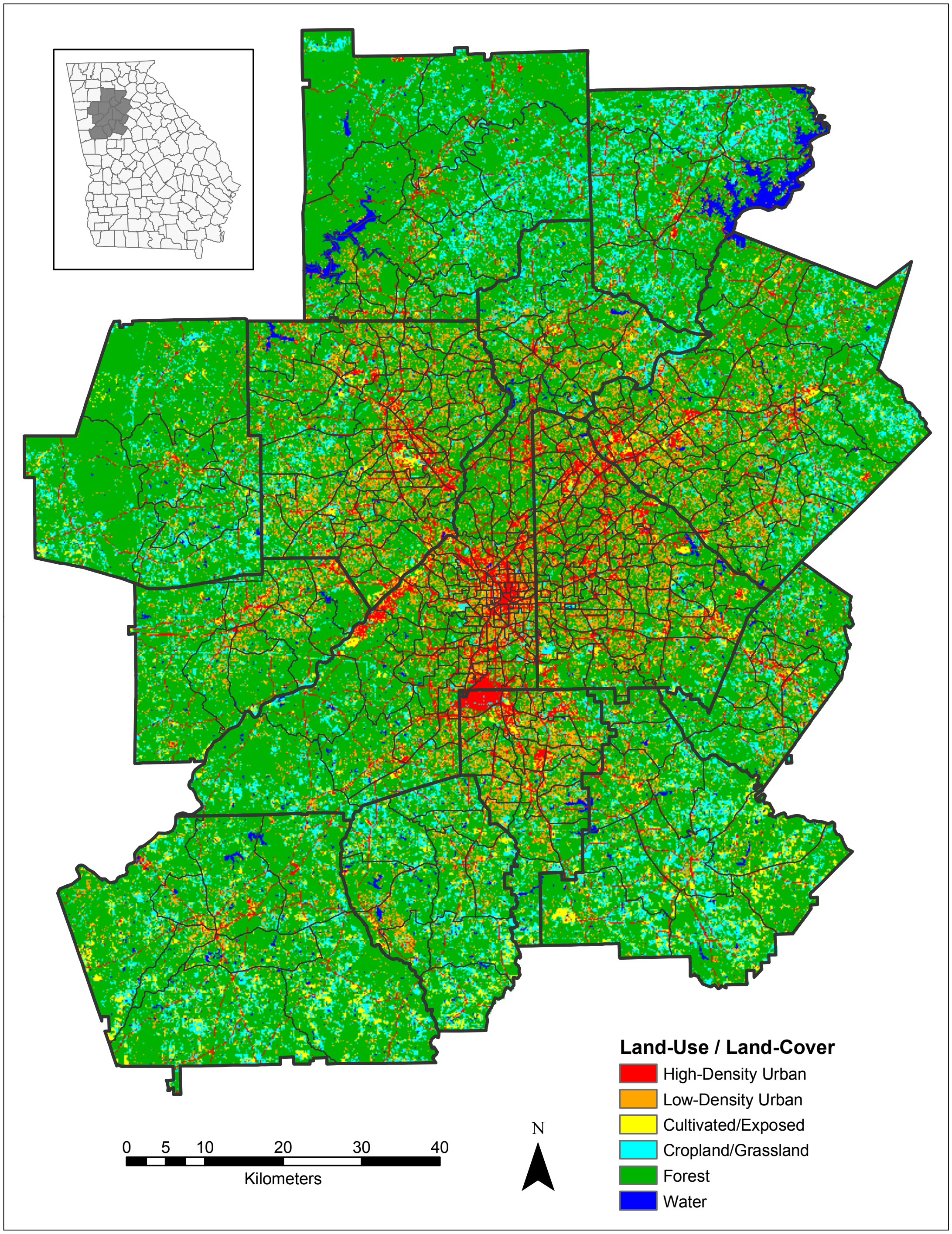

Figure 3.7. Land-use/Land-cover, Metropolitan Atlanta, 1990.

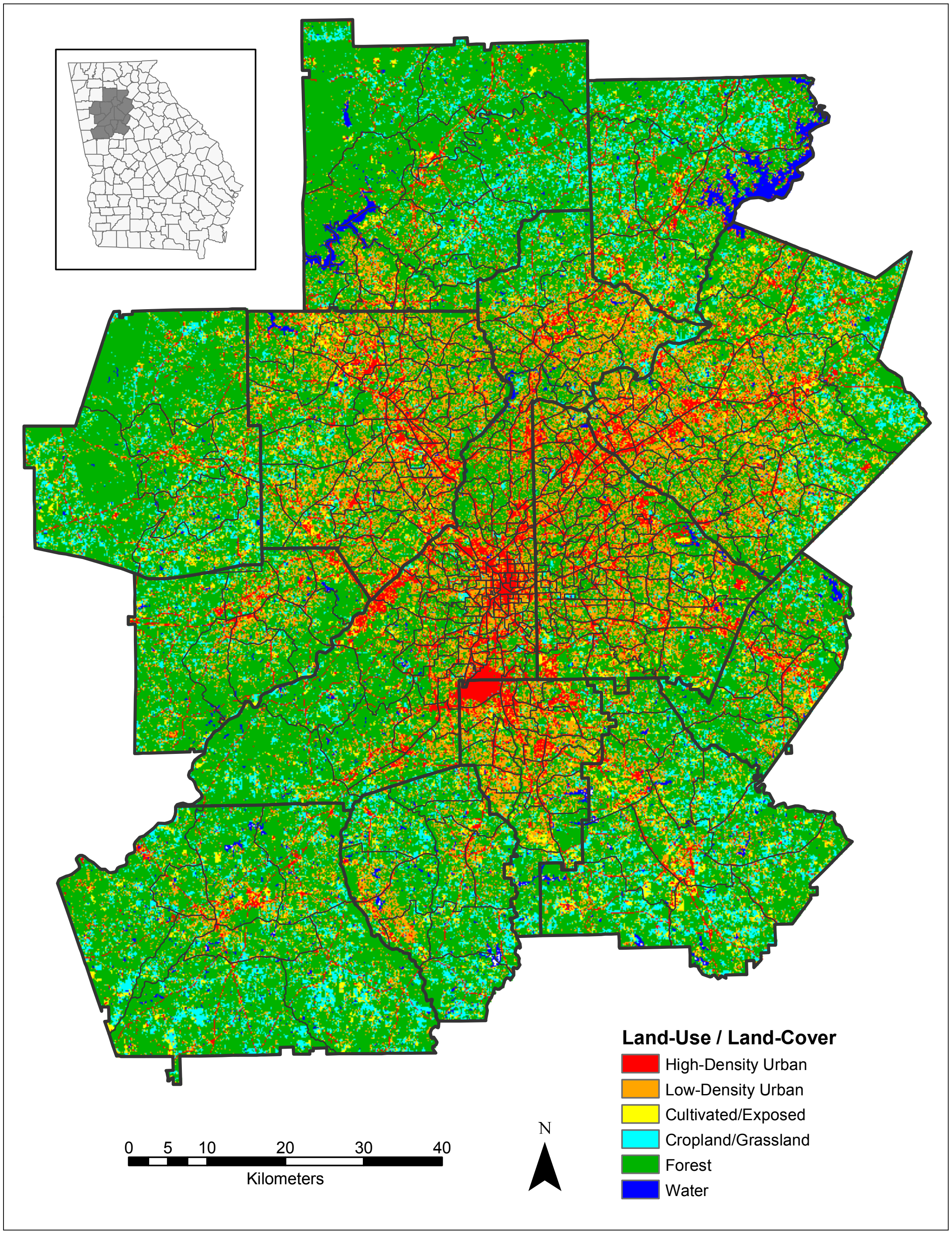

Figure 3.8. Land-use/Land-cover, Metropolitan Atlanta, 2000.

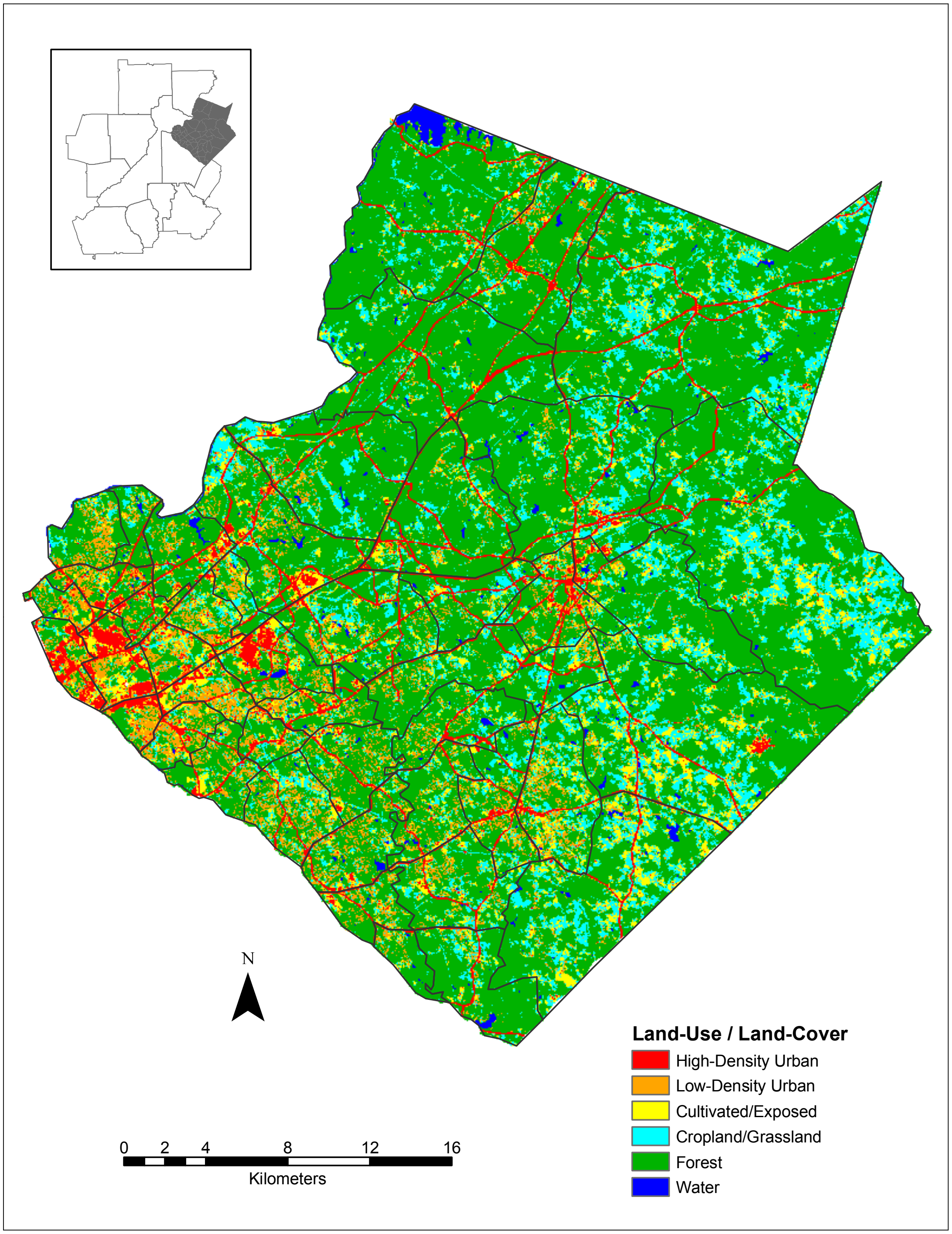

Figure 3.9. Land-use/Land-cover, Gwinnett County, 1984 (in 1990 census tracts).

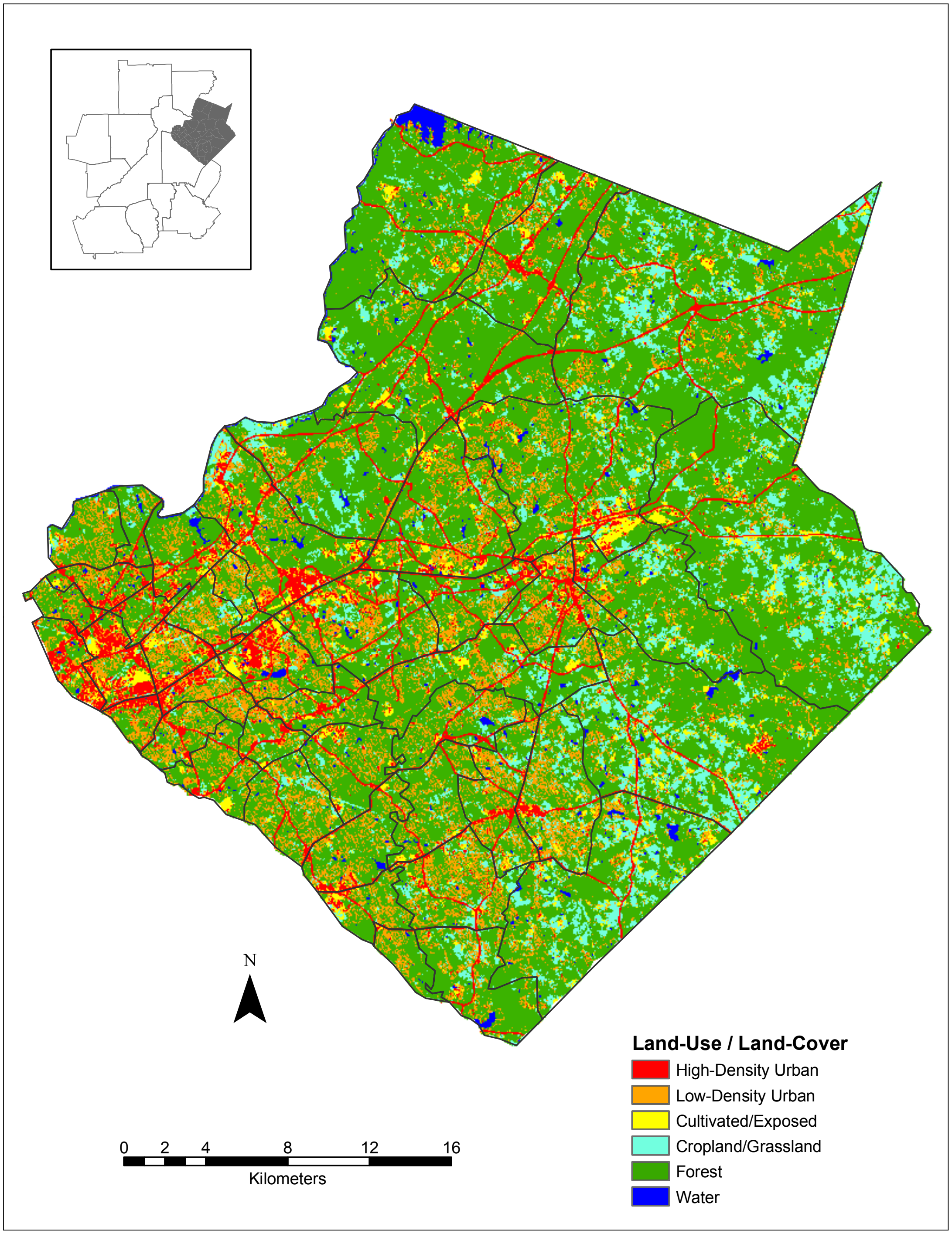

Figure 3.10. Land-use/Land-cover, Gwinnett County, 1990 (in 1990 census tracts).

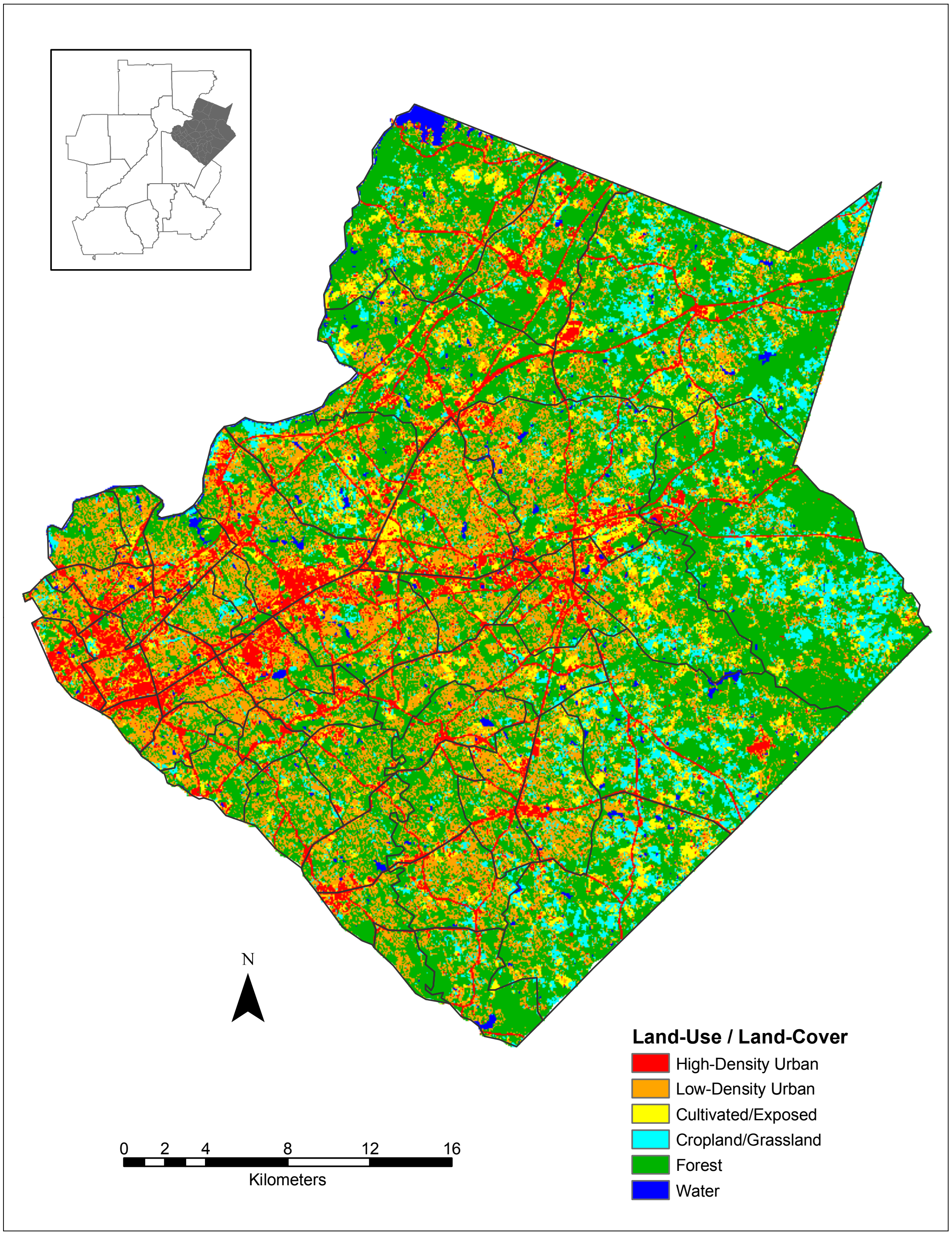

Figure 3.11. Land-use/Land-cover, Gwinnett County, 2000 (in 1990 census tracts).

Results and Discussion

Land-use/Land-cover Statistics

County-level and area-wide statistics

County-level land-use/land-cover statistics were extracted in ERDAS Imagine 8.6 through the Summary function. The final classified land-use/land-cover raster images for 1984, 1990, and 2000 were separately overlaid with a rasterized county boundary file. An output text report listed the number of pixels for each land-use/land-cover category along with their total area in hectares and their percentage of the total land area, by county. Table 3.10 presents the area-wide statistics from the 1984, 1990, and 2000 scene classifications. Table 3.11 illustrates changes in land-use/land-cover by area (in hectares) and by relative percentages. Figure 3.12 depicts these temporal changes in graphic format.

The area-wide statistics indicate an overall increase in urbanized land-use at the expense of vegetative land-cover. High-Density and Low-Density Urban land-use both increased at relatively constant rates throughout the 1980's and 1990's. The increase in Low-Density Urban land-use, most closely corresponding to residential development, is over 173% from 1984 through 2000. That percentage point increase is twice the percentage point increase in population for the entire thirteen-county area from 1980 through 2000 (1,989,613 to 3,698,679 population; an increase of 85.9%). On an area-wide basis, the net population density in 1980[*] is approximately 31 people per hectare of

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[*] 1980 net population density was computed using 1984 land-use/land-cover data, as no comparable land-use/land-cover data were available for 1980. Had 1980 land-use/land-cover data been used, the net population density likely would have been even higher, given the general trend of increased Low-Density Urban land-use during that period.

Table 3.10. Land-use/land-cover statistics, 1984-2000, Metropolitan Atlanta.

Land-use/Land-cover		**1984**	**1990**	**2000**
High-Density Urban	Hectares	67508	79733	96557
	% of total land area	6.45	7.61	9.28
Low-Density Urban	Hectares	64077	109366	174975
	% of total land area	6.12	10.43	16.72
Cultivated/Exposed	Hectares	57614	43088	52144
	% of total land area	5.51	4.11	4.98
Cropland/Grassland	Hectares	170924	118945	104890
	% of total land area	16.33	11.35	10.02
Forest	Hectares	668119	676258	595775
	% of total land area	63.84	64.52	56.90
Water	Hectares	18311	20736	21974
	% of total land area	1.75	1.98	2.10

Table 3.11. Changes in land-use/land-cover, 1984-2000, Metropolitan Atlanta.

Land-use/Land-cover		**Change: 1984-1990**	**Change: 1990-2000**	**Change: 1984-2000**
High-Density Urban	Hectares	12225	16824	29049
	% change	18.11	21.10	43.03
Low-Density Urban	Hectares	45289	65609	110898
	% change	70.68	59.99	173.07
Cultivated/Exposed	Hectares	-14526	9056	-5470
	% change	-25.21	21.02	-9.49
Cropland/Grassland	Hectares	-51979	-14055	-66034
	% change	-30.41	-11.82	-38.63
Forest	Hectares	8139	-80483	-72344
	% change	1.22	-11.90	-10.83
Water	Hectares	2425	1238	3663
	% change	13.24	5.97	20.00

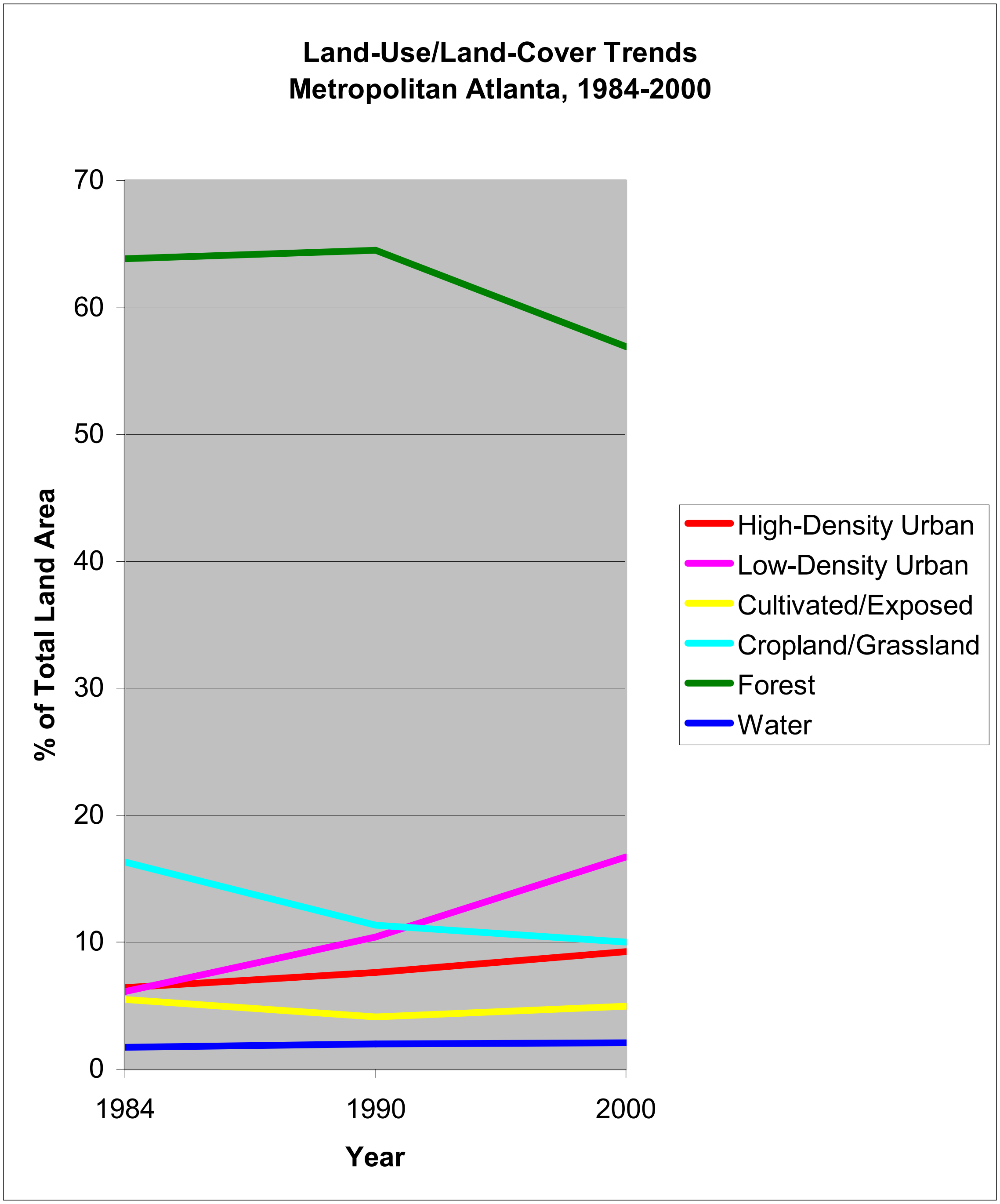

Figure 3.12. Temporal trends in land-use/land-cover, metropolitan Atlanta, Georgia, 1984-2000.

land-use, compared to a net population density of approximately 21 people per hectare of residential land-use in 2000. The greater relative increase in the percentage of land devoted to residential land-use compared to the increase in population tends to conform to widely-held conceptions of urban sprawl. Over the sixteen years for which land-use/land-cover data were available for this study (1984-2000), the amount of land devoted to urban/suburban land-use more than doubled from 12.57% to 26%.

The changes in cultivated/exposed land are more complex. The number of hectares of cultivated/exposed land decreased over the entire period. However, during 1984-1990 there is a 25% decrease in cultivated/exposed land, as opposed to a 21% increase during the 1990's. Because cultivated/exposed land often represents land in a transitional state prior to and during development, these trends suggest that the decrease from 1984-1990 may have been the result of the completion of urban/suburban development in the late 1980's. The increase in the 1990's may have been related to a subsequent building phase that began during the 1990's.

The largest percentage point decrease in any land-cover category is for cropland/grassland, followed by forested land. The decrease in cropland/grassland is greater during the 1980's than during the 1990's. The decrease in forested land was largely experienced during the 1990's, as there is a small net gain in forested land in the 1980's. These changes, together, suggest that the land-cover types most easily converted to urbanized land-use are agricultural lands and fields (e.g., cropland and grassland), because of lower clearance costs and the generally flatter terrain associated with these land-covers. On the other hand, forested land is more costly to clear for development, and would represent a secondary choice for developable land, compared to cropland/grassland, all things being equal. By the end of the study period, the percentage point loss in forested land eclipsed the percentage point loss in cropland/grassland, while the absolute loss in hectares is almost six-fold greater.

The changes in land-use and land-cover can be expressed in the form of average daily increases or decreases. For the period 1984-2000, the increase in High-Density Urban land-use is equivalent to approximately 5 hectares (12 acres) per day; and the increase in Low-Density Urban land-use is equivalent to approximately 19 hectares (46 acres) per day. The decrease in cropland/grassland is equivalent to approximately 10 hectares (24 acres) per day; and the decrease in forested land is approximately 12 hectares (29 acres) per day, on average. These general trends correspond quite closely to those reported by Yang (2002) although a direct comparison is not possible due to differing terminal dates of Yang's study and this present study. However, these results lend support to the findings reported by Yang with respect to changes in land-use/land-cover for the Metropolitan Atlanta area during the last three decades of the twentieth century.

Table 3.12 presents land-use/land-cover statistics, including each categories' percent of total land area, by county, for 1984, 1990, and 2000. Changes in land-use/land-cover, by county, are presented in Table 3.13. In relation to the overall trends for the thirteen-county area, county-level trends varied. The counties with the highest percentages of urbanized land-use (combined HDU and LDU) are listed in Table 3.14. There is a high degree of stability in the relative rankings of counties over the study period. DeKalb, Clayton, Cobb, Fulton, and Gwinnett Counties were the top five urbanized counties throughout the period, with only Fulton and Cobb Counties

Table 3.12. Land-use/land-cover statistics, by county, 1984-2000, Metropolitan Atlanta.

Cherokee		High-Density Urban	Low-Density Urban	Cultivated/Exposed	Cropland/Grassland	Forest	Water
1984	hectares	2940	1234	2197	16764	86554	2956
	% total area	2.61	1.10	1.95	14.88	76.84	2.62
1990	hectares	3908	4925	1321	12961	86603	2984
	% total area	3.47	4.37	1.17	11.50	76.84	2.65
2000	hectares	5039	8657	3360	11092	81419	3053
	% total area	4.47	7.69	2.98	9.85	72.30	2.71
Clayton		High-Density Urban	Low-Density Urban	Cultivated/Exposed	Cropland/Grassland	Forest	Water
1984	hectares	4815	5643	2866	5144	18574	482
	% total area	12.83	15.04	7.64	13.71	49.50	1.28
1990	hectares	5568	7486	2034	3556	18290	595
	% total area	14.84	19.95	5.42	9.48	48.74	1.59
2000	hectares	6572	10096	2512	2751	14961	605
	% total area	17.53	26.92	6.70	7.34	39.90	1.61
Cobb		High-Density Urban	Low-Density Urban	Cultivated/Exposed	Cropland/Grassland	Forest	Water
1984	hectares	8236	8980	4516	11671	54781	1292
	% total area	9.20	10.04	5.05	13.04	61.22	1.44
1990	hectares	10131	16517	3391	7100	51032	1327
	% total area	11.32	18.46	3.79	7.93	57.02	1.48
2000	hectares	12142	26314	4479	5548	39752	1245
	% total area	13.57	29.41	5.01	6.20	44.43	1.39
Coweta		High-Density Urban	Low-Density Urban	Cultivated/Exposed	Cropland/Grassland	Forest	Water
1984	hectares	3229	3841	7935	25433	74168	1121
	% total area	2.79	3.32	6.86	21.98	64.09	0.97
1990	hectares	3912	6407	7347	14561	81772	1807
	% total area	3.38	5.53	6.34	12.57	70.61	1.56
2000	hectares	4845	10075	5729	15545	77590	1908
	% total area	4.19	8.71	4.95	13.44	67.07	1.65
DeKalb		High-Density Urban	Low-Density Urban	Cultivated/Exposed	Cropland/Grassland	Forest	Water
1984	hectares	9915	11425	3208	5321	39865	635
	% total area	14.09	16.24	4.56	7.56	56.65	0.90
1990	hectares	11328	14219	2618	3514	39028	816
	% total area	15.84	19.88	3.66	4.91	54.57	1.14
2000	hectares	12767	20976	2850	2849	30045	896
	% total area	18.14	29.80	4.05	4.05	42.69	1.27

Table 3.12, continued.. Land-use/land-cover statistics, by county, 1984-2000, Metropolitan Atlanta.

Douglas		High-Density Urban	Low-Density Urban	Cultivated/Exposed	Cropland/Grassland	Forest	Water
1984	hectares	2337	2278	2026	8385	36426	545
	% total area	4.49	4.38	3.90	16.13	70.06	1.05
1990	hectares	2863	4831	2004	4734	36940	675
	% total area	5.50	9.28	3.85	9.10	70.97	1.30
2000	hectares	3481	6754	2410	4499	34082	773
	% total area	6.69	12.99	4.63	8.65	65.54	1.49
Fayette		High-Density Urban	Low-Density Urban	Cultivated/Exposed	Cropland/Grassland	Forest	Water
1984	hectares	1564	2326	4429	11801	30890	762
	% total area	3.02	4.49	8.55	22.79	59.67	1.47
1990	hectares	1982	4595	3434	8306	32361	1100
	% total area	3.83	8.87	6.63	16.04	62.50	2.12
2000	hectares	2511	7388	2530	7649	30339	1265
	% total area	4.86	14.30	4.90	14.80	58.70	2.45
Forsyth		High-Density Urban	Low-Density Urban	Cultivated/Exposed	Cropland/Grassland	Forest	Water
1984	hectares	3204	980	2201	13335	38627	5941
	% total area	4.98	1.52	3.42	20.74	60.08	9.24
1990	hectares	3754	2837	1443	12553	38183	5571
	% total area	5.83	4.41	2.24	19.51	59.34	8.66
2000	hectares	4663	6090	3580	9986	34632	5321
	% total area	7.26	9.48	5.57	15.54	53.88	8.28
Fulton		High-Density Urban	Low-Density Urban	Cultivated/Exposed	Cropland/Grassland	Forest	Water
1984	hectares	16199	12352	5452	16432	86805	1686
	% total area	11.66	8.89	3.92	11.83	62.48	1.21
1990	hectares	18258	18960	4052	11624	83906	2133
	% total area	13.14	13.65	2.92	8.37	60.39	1.54
2000	hectares	21149	29373	4952	8815	72169	2473
	% total area	15.22	21.14	3.56	6.34	51.95	1.78
Gwinnett		High-Density Urban	Low-Density Urban	Cultivated/Exposed	Cropland/Grassland	Forest	Water
1984	hectares	7432	8207	8146	16561	71806	1247
	% total area	6.55	7.24	7.18	14.60	63.32	1.10
1990	hectares	9529	15832	4330	13008	69220	1516
	% total area	8.40	13.96	3.82	11.47	61.02	1.34
2000	hectares	12722	28327	8180	10078	52498	1577
	% total area	11.22	24.98	7.21	8.89	46.30	1.39

Table 3.12, continued. Land-use/land-cover statistics, by county, 1984-2000, Metropolitan Atlanta.

Henry		High-Density Urban	Low-Density Urban	Cultivated/Exposed	Cropland/Grassland	Forest	Water
1984	hectares	3927	4128	9613	16964	48906	821
	% total area	4.66	4.89	11.39	20.11	57.97	0.97
1990	hectares	3982	5391	6997	13343	53504	1162
	% total area	4.72	6.39	8.29	15.81	63.41	1.38
2000	hectares	5109	9286	6465	13488	48405	1522
	% total area	6.06	11.02	7.67	16.00	57.44	1.81
Paulding		High-Density Urban	Low-Density Urban	Cultivated/Exposed	Cropland/Grassland	Forest	Water
1984	hectares	1929	874	2145	17225	59120	427
	% total area	2.36	1.07	2.63	21.08	72.34	0.52
1990	hectares	2417	3779	2727	9044	63217	587
	% total area	2.96	4.62	3.34	11.06	77.31	0.72
2000	hectares	2981	6356	3615	9202	58993	588
	% total area	3.65	7.78	4.42	11.26	72.18	0.72
Rockdale		High-Density Urban	Low-Density Urban	Cultivated/Exposed	Cropland/Grassland	Forest	Water
1984	hectares	1781	1808	2880	5888	21597	396
	% total area	5.19	5.26	8.38	17.14	62.87	1.15
1990	hectares	2101	3587	1390	4641	22202	463
	% total area	6.11	10.43	4.04	13.50	64.57	1.35
2000	hectares	2576	5283	1482	3388	20890	748
	% total area	7.50	15.37	4.31	9.86	60.79	2.18

Table 3.13. Changes in land-use/land-cover, by county, 1984-2000, Metropolitan Atlanta.

County	High-Density Urban	Low-Density Urban	Cultivated/Exposed	Crop/Grassland	Forested	Water
Cherokee						
% Change 1984-1990	32.82	299.65	-39.81	-22.73	0.05	0.99
% Change 1990-2000	29.04	75.81	154.30	-14.27	-5.94	2.19
% Change 1984-2000	71.37	602.39	53.08	-33.76	-5.90	3.21
Clayton						
% Change 1984-1990	15.94	32.81	-29.18	-31.02	-1.48	22.31
% Change 1990-2000	17.74	34.83	23.39	-22.66	-18.16	1.61
% Change 1984-2000	36.51	79.06	-12.63	-46.66	-19.37	24.25
Cobb						
% Change 1984-1990	23.04	83.84	-24.90	-39.11	-6.84	0.58
% Change 1990-2000	19.84	59.31	32.19	-21.90	-22.08	-6.48
% Change 1984-2000	47.45	192.88	-0.73	-52.45	-27.42	-5.91
Coweta						
% Change 1984-1990	21.12	67.25	-7.38	-42.66	10.15	60.27
% Change 1990-2000	23.79	57.07	-22.12	6.76	-5.03	5.87
% Change 1984-2000	49.92	162.73	-27.87	-38.79	4.61	69.65
Dekalb						
% Change 1984-1990	13.19	23.42	-21.11	-37.19	-3.76	24.48
% Change 1990-2000	13.65	48.62	12.56	-14.79	-21.71	13.49
% Change 1984-2000	28.65	83.43	-11.20	-46.48	-24.65	41.24
Douglas						
% Change 1984-1990	22.27	111.97	-1.34	-43.58	1.55	8.08
% Change 1990-2000	21.95	39.78	20.49	-4.74	-7.85	26.39
% Change 1984-2000	49.10	196.23	18.91	-46.26	-6.42	36.52
Fayette						
% Change 1984-1990	26.75	97.44	-22.36	-29.63	4.83	44.75
% Change 1990-2000	26.76	60.75	-26.48	-7.92	-6.27	15.14
% Change 1984-2000	60.65	217.43	-42.91	-35.20	-1.74	66.73
Forsyth						
% Change 1984-1990	18.21	189.35	-34.39	-5.84	-1.08	-7.04
% Change 1990-2000	24.49	114.53	148.29	-20.42	-9.33	-4.24
% Change 1984-2000	47.14	520.79	62.89	-25.07	-10.31	-10.97
Fulton						
% Change 1984-1990	12.95	53.47	-25.66	-29.30	-3.34	27.32
% Change 1990-2000	15.79	54.81	22.37	-24.12	-13.97	15.71
% Change 1984-2000	30.79	137.59	-9.04	-46.35	-16.84	47.28
Gwinnett						
% Change 1984-1990	28.42	80.88	-46.79	-21.46	-3.59	21.19
% Change 1990-2000	33.44	90.90	88.83	-22.54	-24.16	6.11
% Change 1984-2000	71.37	245.28	0.48	-39.16	-26.89	28.62

Table 3.13, continued. Changes in land-use/land-cover, by county, 1984-2000, Metropolitan Atlanta.

County	High-Density Urban	Low-Density Urban	Cultivated/Exposed	Crop/Grassland	Forested	Water
Henry						
% Change 1984-1990	1.61	30.58	-27.22	-21.33	9.43	41.83
% Change 1990-2000	28.03	72.33	-7.55	1.11	-9.54	30.59
% Change 1984-2000	30.08	125.00	-32.72	-20.46	-1.00	85.25
Paulding						
% Change 1984-1990	25.06	333.75	27.18	-47.54	6.87	37.24
% Change 1990-2000	23.15	67.98	32.56	1.73	-6.64	0.29
% Change 1984-2000	54.02	629.00	68.59	-46.64	-0.23	37.51
Rockdale						
% Change 1984-1990	17.52	98.55	-51.57	-21.25	2.76	16.83
% Change 1990-2000	22.99	47.13	6.19	-27.02	-5.90	61.60
% Change 1984-2000	44.57	192.07	-48.57	-42.53	-3.31	88.68

Table 3.14. Five most-urbanized counties, 1984-2000.

County	Rank (1984)	% Urban (1984)	Rank (1990)	% Urban (1990)	Rank (2000)	% Urban (2000)
DeKalb	1	30.33	1	35.72	1	47.94
Clayton	2	27.87	2	34.79	2	44.45
Fulton	3	20.55	4	26.79	4	36.36
Cobb	4	19.24	3	29.78	3	42.98
Gwinnett	5	13.79	5	22.36	5	36.20

exchanging positions after 1990. Likewise, the stability among the least urbanized counties is consistent. Paulding, Cherokee, Coweta, and Forsyth Counties were the least urbanized counties throughout the period, in that order, with no changes over time (Table 3.15).

Table 3.15. Four least-urbanized counties, 1984-2000.

County	Rank (1984)	% Urban (1984)	Rank (1990)	% Urban (1990)	Rank (2000)	% Urban (2000)
Paulding	1	3.43	1	7.58	1	11.43
Cherokee	2	3.71	2	7.84	2	12.16
Coweta	3	6.11	3	8.91	3	12.90
Forsyth	4	6.50	4	10.24	4	16.74

County-level urbanization trends are reflected in Table 3.16 and Figure 3.13. The statistics for rates of urbanization imply an interesting dynamic. The largest percentage point increases in urbanization occurred mainly among the less-urbanized counties, such as Paulding, Cherokee, and Forsyth (Figure 3.14). The notable exception is Gwinnett County, which ranked third in the rate of increase and fifth in the overall degree of urbanization. Together, both sets of statistics indicate that the highly urbanized core counties of DeKalb, Clayton, Cobb, Fulton, and Gwinnett continue to be the most highly urbanized. Yet the most recent increases in urbanization, on a percentage point basis, are associated with the surrounding suburban and rural counties, especially those in the northern arc.

Table 3.16. Urbanization, by county, by percentage change in urban land-use, 1984-2000.

County	% Urban (1984)	% Urban (1990)	% Urban (2000)	% Change 1984-1990	% Change 1990-2000	% Change 1984-2000	Rank: % Change (1984-2000)
Cherokee	3.71	7.84	12.16	111.32	55.10	227.76	2
Clayton	27.87	34.79	44.45	24.83	27.77	59.49	12
Cobb	19.24	29.78	42.98	54.78	44.33	123.39	6
Coweta	6.11	8.91	12.90	45.83	44.78	111.13	9
DeKalb	30.33	35.72	47.94	17.77	34.21	58.06	13
Douglas	8.87	14.78	19.68	66.72	33.03	121.78	7
Fayette	7.51	12.7	19.16	69.11	50.87	155.13	5
Forsyth	6.5	10.24	16.74	57.54	63.48	157.54	4
Fulton	20.55	26.79	36.36	30.36	35.72	76.93	11
Gwinnett	13.79	22.36	36.20	62.15	61.90	162.51	3
Henry	9.55	11.11	17.08	16.34	53.74	78.85	10
Paulding	3.43	7.58	11.43	120.99	50.79	233.24	1
Rockdale	10.45	16.54	22.87	58.28	38.27	118.85	8

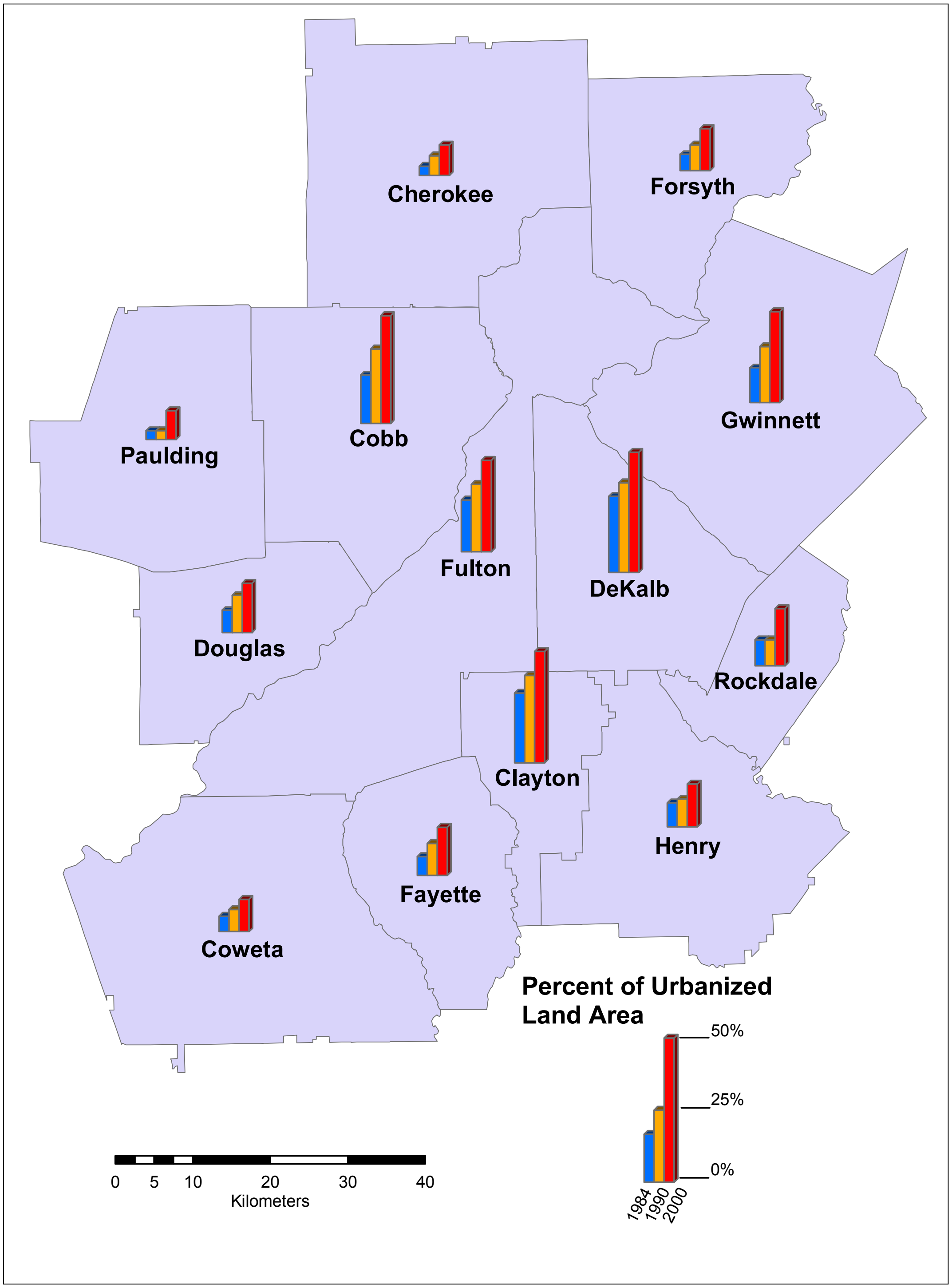

Figure 3.13. Percentages of urbanized land area, by county, metropolitan Atlanta, Georgia, 1984, 1990, and 2000.

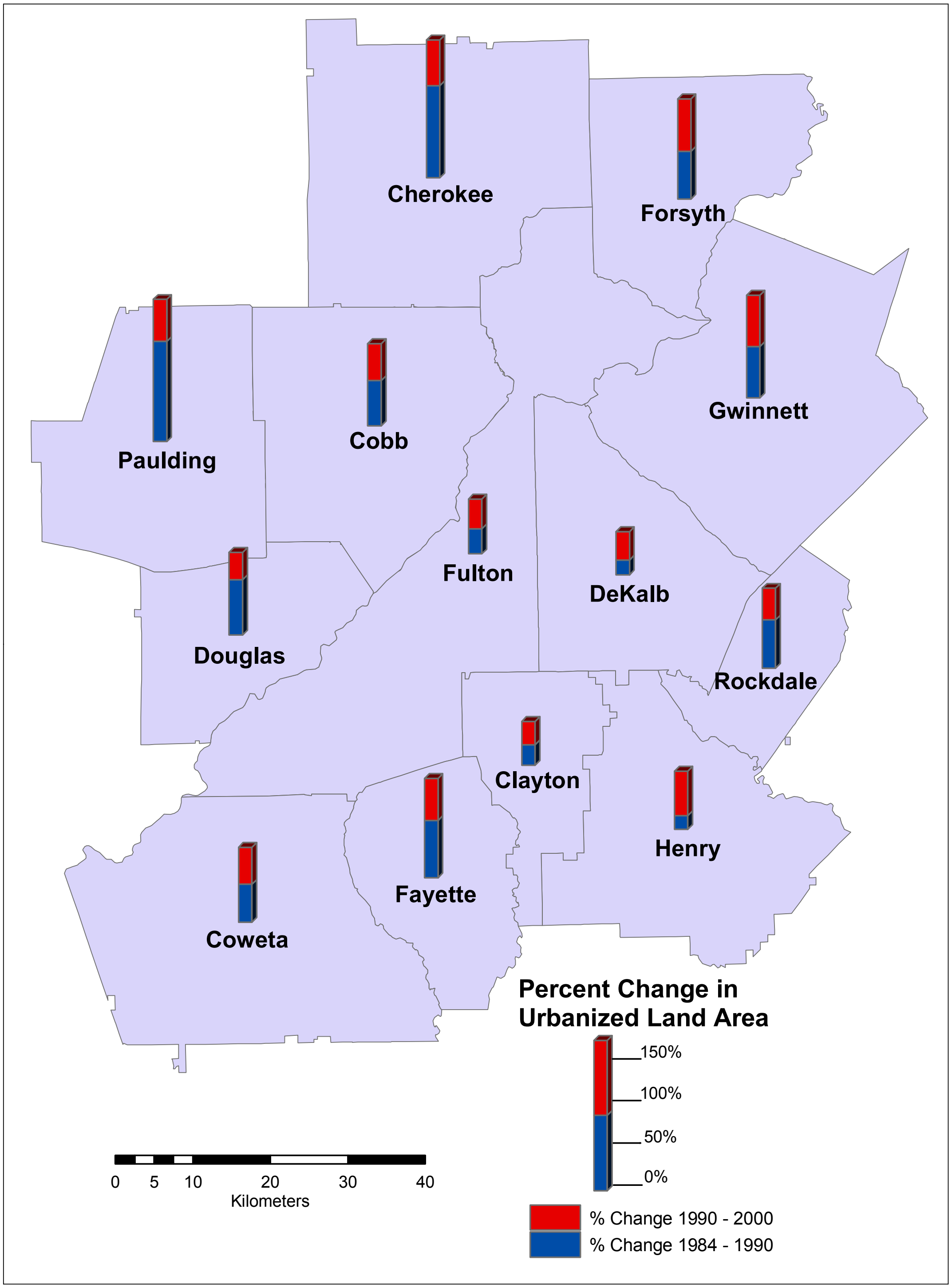

Figure 3.14. Percentage change in urbanized land area, by county, metropolitan Atlanta, Georgia, 1984 to 1990, and 1990 to 2000.

Census tract level land-use/land-cover statistics

Land-use/land-cover statistics were also extracted by census tract for 1984, 1990, and 2000. The same basic procedure used for the county-level data extraction was followed. Because of the large number (444) of census tracts in 1990[*] it was more efficient to extract the tract-level statistics separately for each county. To facilitate this process, county-specific boundary files were created from the area-wide boundary file. These county-specific boundary files were then rasterized for use as overlay files for the land-use/land-cover images in ERDAS Imagine 8.6. By using the Summary feature in Imagine for each of the thirteen counties, separate output text reports were produced. The land-use/land-cover statistics for each census tract were entered into a Microsoft Excel worksheet, which was exported as a database (.dbf) file to enable an attribute join procedure with the 1990 census tract boundary shapefile for use in ArcInfo 8.2.

Tables 3.17, 3.18, and 3.19 list tract-level land-use/land-cover statistics for Gwinnett County in 1984, 1990, and 2000. Table 3.20 lists the land-use/land-cover changes, by census tract in Gwinnett County, 1984-2000. These tables highlight the level of spatial detail for land-use/land-cover statistics that is obtainable by using the ISODATA procedure with the Landsat TM and ETM+ images.[**]

The extraction of census tract level land-use/land-cover statistics permits a much more detailed analysis of land use trends within a metropolitan region, such as Atlanta. As with most spatial data, analyses are often scale-dependent, where relationships that hold at one spatial scale often do not hold at another spatial scale. In this particular study, while the county-by-county land-use trends are valid, and general statements can

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[*] Because of the requirements of the mortality study to have all data expressed in terms of 1990 census tract boundaries, all tract level land-use/land-cover statistics were extracted for the 1990 census tract boundaries.

[**] Tract-level land-use/land-cover statistics for all counties are contained in Appendix A of this dissertation.

Table 3.17. Land-use/land-cover statistics, by census tract, for Gwinnett County, Georgia, 1984. (Land area in hectares.)

Tract Name	High-Density Urban	Low-Density Urban	Cultivated/ Exposed	Cropland/ Grassland	Forest	Water
501.01	248	157	153	553	4879	385
501.02	260	193	128	312	2630	18
502.02	312	106	171	493	4566	56
502.03	366	287	279	414	1942	52
502.04	221	160	139	537	2721	44
503.04	290	158	80	46	208	4
503.05	63	150	52	33	205	3
503.06	395	206	180	51	207	0
503.07	28	219	53	120	621	17
503.08	44	57	25	66	367	16
503.09	141	140	72	82	791	44
503.10	139	182	51	38	310	10
503.11	114	92	27	31	242	1
503.12	123	182	103	84	240	1
503.13	85	186	101	126	282	0
503.14	44	115	56	90	240	3
504.03	86	200	75	93	687	5
504.06	111	157	32	22	149	0
504.07	86	249	79	74	296	4
504.08	138	259	148	69	179	0
504.09	274	225	137	106	551	32
504.10	80	105	47	80	295	1
504.11	130	179	86	75	540	10
504.12	80	361	142	245	771	6
504.13	86	240	85	123	940	9
504.14	111	279	99	158	896	26
504.15	72	136	57	64	546	3
504.16	14	57	22	37	446	5
505.02	322	139	177	330	2590	20
505.03	302	180	309	902	4106	62
505.05	189	184	218	437	1918	14
505.06	246	233	229	454	1654	26
505.07	158	72	89	216	868	13
505.08	227	234	117	174	832	3
505.09	95	133	270	617	2306	19
506.01	466	211	637	2347	8598	62
506.02	181	173	929	2471	7680	23
507.04	140	191	708	1254	3274	84
507.05	260	270	877	1521	4532	56
507.06	104	135	87	183	1001	23
507.07	104	195	105	167	934	10
507.08	128	205	187	317	1216	8
507.09	83	72	88	211	1561	42
507.10	157	225	139	258	984	15
507.11	131	318	300	481	1004	12
508.98	1	1	0	0	2	0

Table 3.18. Land-use/land-cover statistics, by census tract, for Gwinnett County, Georgia, 1990. (Land area in hectares.)

Tract Name	High-Density Urban	Low-Density Urban	Cultivated/ Exposed	Cropland/ Grassland	Forest	Water
501.01	318	478	159	415	4635	372
501.02	359	397	118	261	2400	8
502.02	381	352	176	374	4340	79
502.03	598	548	204	258	1668	62
502.04	250	400	55	470	2581	68
503.04	287	153	52	24	262	8
503.05	69	114	10	11	296	6
503.06	434	200	156	42	206	2
503.07	35	280	21	46	649	26
503.08	57	80	1	39	372	24
503.09	181	196	53	48	745	49
503.10	180	177	21	11	329	13
503.11	133	86	20	18	250	2
503.12	185	234	69	47	195	3
503.13	87	227	33	89	343	1
503.14	54	168	28	55	237	5
504.03	105	257	48	41	685	8
504.06	125	128	8	8	198	2
504.07	108	249	9	32	383	7
504.08	203	294	28	34	230	4
504.09	321	330	128	53	454	41
504.10	95	144	22	47	299	2
504.11	149	213	36	35	575	11
504.12	93	449	32	132	892	8
504.13	99	289	46	71	971	10
504.14	144	368	36	70	927	26
504.15	89	189	51	36	507	2
504.16	24	128	6	10	407	6
505.02	448	629	197	199	2072	33
505.03	438	839	356	589	3558	83
505.05	235	461	132	280	1832	19
505.06	395	601	144	255	1414	32
505.07	245	239	56	117	746	14
505.08	303	397	57	119	706	5
505.09	132	338	124	503	2309	33
506.01	519	905	306	2150	8360	87
506.02	301	628	464	2176	7859	32
507.04	180	544	228	1183	3420	103
507.05	281	623	325	1491	4707	99
507.06	122	338	16	101	932	26
507.07	110	298	33	95	965	10
507.08	183	565	73	239	984	10
507.09	111	305	35	184	1384	43
507.10	205	428	64	174	896	14
507.11	157	564	94	376	1039	18
508.98	1	2	0	0	1	0

Table 3.19. Land-use/land-cover statistics, by census tract, for Gwinnett County, Georgia, 2000. (Land area in hectares.)

Tract Name	High-Density Urban	Low-Density Urban	Cultivated/ Exposed	Cropland/ Grassland	Forest	Water
501.01	412	1052	550	346	3670	346
501.02	493	657	232	200	1947	14
502.02	595	1227	552	301	2933	95
502.03	874	1051	206	142	996	69
502.04	458	1038	322	389	1547	69
503.04	338	223	32	20	166	8
503.05	82	232	14	33	135	9
503.06	544	287	70	31	105	2
503.07	58	466	22	43	439	29
503.08	92	209	43	21	191	18
503.09	257	409	86	55	409	57
503.10	235	317	52	13	100	14
503.11	169	145	24	16	152	3
503.12	221	313	38	31	125	6
503.13	113	316	25	68	255	3
503.14	68	249	15	38	171	6
504.03	121	400	43	39	532	9
504.06	135	210	4	5	114	2
504.07	111	376	18	34	243	6
504.08	218	407	16	18	131	4
504.09	419	488	60	31	296	33
504.10	105	220	23	29	228	3
504.11	185	364	37	32	389	11
504.12	101	610	38	89	756	11
504.13	125	517	69	57	708	9
504.14	161	537	53	63	729	29
504.15	118	273	24	20	436	3
504.16	21	170	2	9	377	1
505.02	655	1307	336	135	1111	34
505.03	695	1693	586	413	2388	89
505.05	292	934	259	179	1274	19
505.06	559	1060	166	131	891	35
505.07	313	450	77	49	516	13
505.08	356	568	70	76	508	10
505.09	193	662	399	390	1754	41
506.01	719	1805	1071	1827	6784	107
506.02	460	1229	783	1838	7087	47
507.04	200	966	592	950	2861	79
507.05	376	1163	646	1169	4047	112
507.06	170	587	46	49	655	26
507.07	137	458	58	64	786	9
507.08	202	790	100	167	783	13
507.09	112	420	48	120	1317	45
507.10	242	648	86	101	690	14
507.11	211	822	187	247	765	15
508.98	1	2	0	0	1	0

Table 3.20. Changes in land-use/land-cover, by census tract, for Gwinnett County, Georgia, 1984-2000. (Percentage changes.)

Tract Name	High-Density Urban	Low-Density Urban	Cultivated/ Exposed	Cropland/ Grassland	Forest	Water
501.01	65.93	568.58	260.50	-37.46	-24.77	-10.21
501.02	89.63	240.38	81.10	-35.94	-25.97	-21.34
502.02	90.78	1060.15	222.38	-38.93	-35.77	69.47
502.03	138.77	266.57	-26.17	-65.67	-48.71	33.75
502.04	107.01	548.69	131.91	-27.61	-43.15	56.32
503.04	16.49	41.37	-59.87	-56.47	-20.07	104.08
503.05	30.25	54.37	-73.15	-1.19	-34.13	194.31
503.06	37.70	39.51	-61.20	-38.89	-49.19	0.00
503.07	109.58	113.20	-58.18	-64.06	-29.34	72.85
503.08	110.30	263.69	70.87	-68.34	-47.97	13.10
503.09	82.42	192.42	18.85	-33.19	-48.28	28.68
503.10	68.59	73.98	1.42	-65.81	-67.78	40.60
503.11	48.87	56.87	-9.43	-48.20	-37.26	139.23
503.12	80.01	72.01	-63.22	-62.91	-47.96	537.62
503.13	33.21	70.28	-75.36	-45.82	-9.42	1810.83
503.14	54.33	116.35	-73.24	-57.59	-28.63	73.91
504.03	40.95	99.61	-42.39	-57.99	-22.60	73.95
504.06	21.86	33.86	-87.34	-76.89	-23.59	2464.10
504.07	29.42	51.20	-77.13	-53.91	-18.00	59.45
504.08	57.99	57.07	-89.16	-74.00	-26.81	920.41
504.09	53.13	116.43	-56.32	-70.86	-46.26	3.42
504.10	32.08	109.26	-51.43	-63.56	-22.68	218.81
504.11	42.75	103.63	-56.78	-57.13	-28.03	14.07
504.12	25.68	68.81	-73.21	-63.63	-1.91	79.89
504.13	44.68	115.86	-18.73	-53.75	-24.71	-0.18
504.14	45.23	92.35	-46.52	-60.06	-18.64	12.77
504.15	65.03	101.40	-57.66	-68.66	-20.11	19.57
504.16	49.64	199.91	-90.99	-75.93	-15.43	-81.78
505.02	103.37	837.62	89.97	-59.12	-57.11	73.47
505.03	130.49	838.89	89.47	-54.22	-41.85	44.61
505.05	54.86	407.59	18.75	-59.08	-33.57	39.28
505.06	127.36	355.85	-27.61	-71.15	-46.12	35.69
505.07	97.74	523.22	-13.70	-77.36	-40.57	0.49
505.08	56.96	142.63	-40.32	-56.22	-38.97	196.65
505.09	102.61	397.58	48.03	-36.81	-23.93	117.00
506.01	54.18	754.60	68.21	-22.14	-21.09	73.20
506.02	154.77	611.58	-15.72	-25.61	-7.72	101.17
507.04	43.32	405.81	-16.37	-24.27	-12.60	-6.26
507.05	44.50	330.72	-26.31	-23.13	-10.71	98.69
507.06	63.28	335.56	-47.14	-73.27	-34.58	12.04
507.07	31.19	134.71	-44.71	-61.69	-15.85	-8.89
507.08	58.36	286.22	-46.50	-47.29	-35.59	60.99
507.09	34.26	486.12	-45.72	-43.04	-15.64	7.89
507.10	54.18	188.09	-38.27	-60.82	-29.87	-6.50
507.11	60.48	158.88	-37.76	-48.68	-23.82	23.44
508.98	41.64	96.27	-100.00	-100.00	-36.22	0.00

be made about the overall growth and development patterns for metropolitan Atlanta, more-detailed data are needed in order to more-fully explore specific patterns.

Conclusion

This paper reported on the extraction of land-use/land-cover statistics at the census tract level for the thirteen-county metropolitan area of Atlanta, Georgia, for 1984, 1990, and 2000. These land-use and land-cover statistics were to be used as independent variables in a larger ecological study of mortality and as ancillary data for dasymetric mapping of population density and areal interpolation of census data for the study period.

The land-use/land-cover data were extracted from land-use/land-cover maps produced from Landsat TM and ETM+ images, which were classified through an unsupervised ISODATA approach. Classification accuracies for the 1990 and 2000 satellite images were 92.94% and 90.12%, which exceeded the minimum threshold of 85% set forth by Anderson *et al* (1976) for the classification of thematic data.

County-level and area-wide categorical land-use/land-cover statistics were consistent with data reported by Yang (2002) for the same study area. The overall similarities in land-use/land-cover statistics (between this study and Yang) as well as the acceptable classification accuracies, suggests that the unsupervised ISODATA approach is useful and may yield replicable results among different analysts. The data have succeeded in revealing the suburbanization of Atlanta with its problem of urban sprawl – that increasingly more land is being used further away from the Atlanta CBD for residential growth.

CHAPTER 4

DASYMETRIC ESTIMATION OF POPULATION DENSITY AND AREAL INTERPOLATION OF CENSUS DATA TO COMPENSATE FOR CENSUS GEOGRAPHY CHANGES, METROPOLITAN ATLANTA, 1980-2000[*]

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[*] Holt, J.B., Lo, C.P., and T.W. Hodler. To be submitted to *Cartography and Geographic Information Science*

Introduction

Dasymetric mapping of population density, and areal interpolation

Population mapping generally has two purposes: to cartographically portray the extent and density of population across an area of interest; and to derive quantitative estimates of population density for use in subsequent spatial analytical modeling tasks (Langford, 2003).

The computation of population density usually requires the standardization of population census data by enumeration areas. The usual manner of computing population density is to divide the total population for a given enumeration area by the total land area of that enumeration area. This is easily accomplished in a geographic information system (GIS), which can also easily display the results in the form of choroplethic maps. Choroplethic maps are familiar to, and easily interpreted by, most map users. Population densities are easily compared across areas in choroplethic maps.

Despite these advantages, there are several problems inherent in computing and displaying population densities in this manner (Langford, 2003). First, the traditional choroplethic method is subject to the Modifiable Areal Unit Problem (MAUP), as it does not account for inaccuracies due to scale and zonal effects. The population density for a given area will vary based solely upon the *scale* at which it is computed. A change in the areal extent of a given enumeration area will result in a change in population density, due to changes in land area, and most likely, concurrent changes in the total population within that enumeration area. The population density for a given area will vary based upon the manner in which the enumeration area is delineated (the *zonal* problem). For an area of given size, a change in the geographic boundaries of an enumeration area will most likely result in a change in the population within the enumeration; therefore the population density computed for that enumeration area will change based upon the change in population, despite the maintenance of constant land area.

A second limitation of choroplethic maps is that they give the impression of abrupt changes at the boundaries of administrative areas, while at the same time they represent population as a continuous variable across the entire land area. Population, comprised of individuals, is not a continuous phenomenon; however, population *density*, which is the number of persons per unit area, is continuous, because a value of population density can be computed for each discrete location. The traditional manner of population density computation results in positive values for population density at all locations. In reality, because some areas are unpopulated, the actual population density *within those areas* is zero. In the abstract, the traditional manner of computing population density overestimates population density in unpopulated and sparsely populated areas, while it underestimates population density in more-densely populated areas.

A third limitation of choroplethic maps is their sensitivity to the classification scheme adopted. By classifying data using different classification schemes (e.g., quantiles, equal-interval, Jenks' Optimal, etc.), different map patterns result. Often the difference in map patterns can be quite substantial and lead to different perceptions of patterns in the data.

Dasymetric mapping, like choroplethic mapping, is an area-based cartographic technique. The major difference is that dasymetric mapping divides the original administrative areas (or source zones) into smaller spatial units, onto which the sociodemographic variable of interest (e.g., population) is averaged to obtain a rate, such as population density. These smaller spatial units, which are subsets of the overall source zone, are those areas estimated to contain population, usually through the application of ancillary land-use data, often acquired through classification of remotely-sensed satellite images. This explicitly recognizes the fact that certain areas within an administrative area are populated, while others are not.

The smaller spatial units used in dasymetric mapping have greater interval consistency (i.e., less variation) in the density of the variable being mapped. Although there will still be some internal variation, it should be less than the variation in a choropleth map.

Dasymetric mapping is subject to some of the same limitations that accompany choroplethic mapping. It is vulnerable to the MAUP, and it still results in abrupt transitions at zonal boundaries. However, for dasymetric mapping, these transitions are a better reflection of the true underlying geography of the area compared to the transitions in choropleth maps, which are artifacts partially attributable to the arbitrary delineation of areal boundaries (Langford, 2003).

These limitations are offset by better visualizations of population patterns, due to the high degree of spatial disaggregation that can be achieved, especially if using high spatial resolution satellite imagery as the basis for ancillary land-use data; and by more precise estimates of population density for use in analytical procedures, such as areal interpolation (discussed below), where the estimates from dasymetric mapping have been shown to result in much higher accuracies in areal interpolation (Fisher and Langford, 1995).

Areal interpolation is closely related to dasymetric mapping of population densities. In many cases, data are collected and reported by administrative areas that are either designed for the convenience of data collection (but are not necessarily meaningful from an analysis standpoint), or that change over time, thus limiting temporal analyses of a particular phenomenon. In either of these cases, it would be desirable to represent the same data in different administrative units (e.g., in census tracts in lieu of zip codes). In other situations, data for some variables may be reported in one type of areal unit, while other data variables are reported in another, perhaps incompatible, type of areal unit. In that case, it would be desirable to have both data sets normalized to the same type of compatible areal unit. The process of areal interpolation involves the transformation of data from one areal unit, or zonation, to another, and is also called cross-area estimation (Fisher and Langford, 1996). Areal interpolation can be accomplished through dasymetric mapping techniques, simple areal weighting, the use of population-weighted centroids with a distance decay function, or through the use of a regression-based modeling approach, such as recently developed techniques by Yuan *et al* (1998).

Purpose

In a current research project of the impact of population growth patterns upon the health of metropolitan Atlanta residents (1980-2000), a more-precise estimate of population density is desired. Population densities previously have been correlated to social and health outcomes (Stephens, 1995; Tanaka *et al*, 1996; McDade and Adair, 2001; Rythönen *et al*, 2001). In the current Atlanta study, it is postulated that standard measures of population density would underestimate the true effects of high population density on the social environment and health.

An additional problem related to that analysis of population growth and health is the fact that census tract boundaries change over time. From 1980 to 2000, data from three decennial censuses were collected and analyzed. In 1980, the thirteen-county Metropolitan Atlanta area was comprised of 339 census tracts (Figure 4.1); in 1990, this increased to 444 census tracts (Figure 4.2); and in 2000, to 589 census tracts (Figure 4.3). Thus, in a 20-year period, the number of census tracts increased by approximately 74%. In most cases, the new census tracts were created by simply splitting existing tracts, usually by creating two new tracts out of one existing tract. In many cases, the split was 3:1 and in some cases 4:1. In a few cases, the creation of new tracts involved minor adjustments to existing tract boundaries. In a few other cases, even when new tracts were not created, the boundaries between adjacent tracts shifted. This is particularly problematic for Coweta County in the change from the 1980 tract boundaries to the 1990 tract boundaries, which involved significant changes.

For this research study, it is necessary to have all data for 1980, 1990, and 2000 normalized to 1990 census tract boundaries, as the analysis is between variables representing the social and physical environment in 1990 and the potential health outcomes experienced in the late 1990’s. Additional variables were added to that analysis: namely, the changes in the social and physical environment from 1980 to 2000. To add these change variables to the existing 1990 variables required the use of consistent census tract boundaries: in this case, 1990.

Because 1990 boundaries were used, it is necessary to account for census tract boundary changes by weighting the census data for 1980 and 2000. This is accomplished

Figure 4.1. Census Tracts, Metropolitan Atlanta, Georgia, 1980.

Figure 4.2. Census Tracts, Metropolitan Atlanta, Georgia, 1990.

Figure 4.3. Census Tracts, Metropolitan Atlanta, Georgia, 2000.

through areal interpolation based upon dasymetric mapping of population, derived from remotely sensed satellite ancillary data.

Previous research on dasymetric mapping and areal interpolation

Several attempts have been made to redress the problems inherent in the traditional methods of computing and mapping population densities, beginning with Wright, who in 1936 presented the earliest, and perhaps best known, account of dasymetric mapping in the English-language scientific literature[*]. Wright noted that the standard choroplethic representations of population density for Cape Cod, an area with which he was quite familiar, overrepresented the population density for areas that he knew to be uninhabited. He devised a mathematical adjustment to enable the recomputation of population densities based upon subjective assessments of relative population densities and distributions within the area. In Wright's method, an area's average population density is apportioned to sub-areas within the original area, based upon the relative densities of each sub-area (derived subjectively). His method had the attractive pycnophylactic property (Tobler, 1979) of preserving the overall total population.

Wright's concept is basically sound. However, his methodology involved purely subjective assessments of population distribution and density, which could result in completely different estimates of population from two or more analysts, due to differences in their estimates of relative population densities. This area of shortcoming is the key behind the dasymetric method: the use of ancillary data to determine the areal

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[*] Wright (1936) notes that the Russians originated the term "dasymetric" map, meaning "density measuring" (Wright, p. 104). However, Wright does not give a citation for that information. It can be implied, therefore, that Wright was not the first person to drive the concept of the dasymetric map; rather, he was the first to publish an article on dasymetric maps in an English-language journal.

extent of population within an administrative area. The ancillary data are necessary in order to apportion population to a more-narrowly defined area for density computations and mapping. In Wright's case, the ancillary data were subjective: his knowledge and experience. Others who followed Wright, improved upon both the types of ancillary data used, as well as the methodologies for computing population densities. Later researchers also had the benefit of using computerized cartography, GIS, and remotely-sensed satellite data. So while Wright may be criticized for his subjective manner of estimating ancillary data, he perceived shortcomings in traditional population density computations, and suggested a method for improvement. In fact, Wright's contributions to dasymetric mapping are so significant, that every scientific paper on dasymetric mapping and areal interpolation refers to Wright's original method.

Martin (1989) also acknowledged the shortcomings of the traditional method of population density computation. His solution is to disaggregate the population data from vector-based polygonal (object) representations to create an interpolated raster surface (field) of population density. The key to Martin's method is the use of a variable-kernel density estimator, which moved over a regular tessellation of grid cells and assigned to each grid cell a distance-decay weighted average of the sum of population-weighted centroids contained within the area of the kernel. Martin improved upon Wright by using objective ancillary data in the form of either a digitized map of populated areas or satellite imagery[*] in order to delineate populated and unpopulated areas. However, his method had three shortcomings: first, it relied upon the availability of population-weighted centroid data, produced by the Office of Population Censuses and Surveys in

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[*] Martin did not have access to suitable satellite imagery for this particular project; instead, he used a digitized map of residential areas.

the United Kingdom and not readily available for researchers in the United States or elsewhere, thus limiting the application. Second, it assumed that population density decreases away from the population-weighted centroids according to a predetermined distance-decay function. This is problematic because of the difficulty in selecting an appropriate distance-decay function; and because the distance-decay function is assumed to apply equally across the entire population surface. Finally, because the kernel is variable, the analyst must specify the parameters for the kernel (e.g., specifying the minimum number of centroids to be contained within the centroid); different parameters will yield different surface density estimates.

Martin (1996) expanded his 1989 work by devising a methodology for estimating the distance decay function. He calculated his distance decay function by computing the mean inter-centroid distances within a user-specified radius, at each centroid location. By doing this, Martin is able to create an indicator of the areal extent of zones surrounding each zonal centroid. Because this indicator is computed at each zonal centroid, it avoided the assumption of a constant distance decay function across the entire analysis area.

Langford *et al* (1991) developed a method for estimating the population of administrative units that were different from the original administrative units. This process, areal interpolation, is related to dasymetric mapping in that it usually involves the use of ancillary data to perform dasymetric adjustments to population density estimates. The major difference between dasymetric mapping and areal interpolation is that dasymetric mapping omits the final step of re-aggregating the data to preferred administrative boundaries (Eicher and Brewer, 2001). Langford and his colleagues' goal is to use census data collected at the census ward level to compute population estimates for 1 km x 1 km grid cells. To do this, they constructed a rasterized surface of population density, which relied upon ancillary data in the form of a land use/cover classification of a Landsat TM image of the area of interest. They overlaid their land use/cover map with rasterized census ward boundaries, and summed the number of pixels of each type of land use/cover in each ward. From that matrix, they used regression modeling to predict the relationship between pixel type and population, from which they could derive estimates of population based solely upon land use/cover types. Their accuracy is just over 85%, and their best model overestimated urban populations and underestimated rural populations. Their research is important in that it demonstrated the efficacy of using remotely-sensed satellite imagery for ancillary data to delineate residential areas, from which model population distributions could be modeled.

As opposed to Langford *et al* (1991) who focused on predicting population distributions for use in areal interpolation, Langford and Unwin (1994) focused on the cartographic representation of population density. They were attempting to create a cartographic product superior to the choroplethic map. Langford and Unwin created binary maps of occupied versus unoccupied areas, based upon land use/cover classifications of Landsat TM satellite imagery. They generated a raster surface in which the total population of each census ward was distributed equally to each of the occupied pixels in that census ward, with unoccupied pixels receiving no population. Langford and Unwin were dissatisfied with the appearance of the resulting dasymetric map, calling it a “poor cartographic product” (Langford and Unwin, p. 24) citing simultaneous contrast problems and too much fine spatial detail as the shortcomings. However, they argued that dasymetric data have great analytical value, and can be used to produce an interpolated surface map, which yields a discrete approximation to a continuous population density surface. The main advantages of Langford's and Unwin's approach were its inherent simplicity and ease of implementation in a raster GIS, and its adaptability to a variety of visualization techniques.

Fisher and Langford (1996) conducted an evaluation of the accuracy of the regression-based population methods first proposed by Langford *et al* (1991) and the binary dasymetric method as implemented by Langford and Unwin (1994) and in this current research project. Not only is the binary dasymetric method more accurate than all three variants of the 1991 regression-based areal interpolation methods, it is robust to errors in satellite image classification. Based on a sensitivity analysis of simulated errors in the form of reduced classification accuracies, they determined that the binary dasymetric method is relatively stable. They found that even with classification errors of 40%, the binary dasymetric method outperformed the regression-based areal interpolation methods. Since most land-use/land-cover classifications exceed 80% overall accuracy (Fisher and Langford, 1995, p. 302), this robustness to error should enable the binary dasymetric method to be accurately employed in most situations in which satellite-derived ancillary data is available.

In previous work, Fisher and Langford (1995) found that the binary dasymetric method is more accurate than a simple areal-weighted dasymetric method (which produced the worst accuracies), regression-based methods, and surface methods (such as Martin's). In addition, Fisher and Langford compared the binary dasymetric method to a dasymetric method based on three classes of land-use. They found that despite considerable increases in computational complexity, only a minor improvement in accuracy is achieved. For these reasons, they concluded that the binary dasymetric method is relatively accurate for areal interpolation, robust to error in land-use/land-cover classification, and represented a more-efficient tradeoff compared to a three-class dasymetric approach.

Donnay and Unwin (2001) extended the idea of using remote sensing data for use in determining population distribution by suggesting that satellite data are good enough to distinguish between several residential categories; and that each *residential* class should have a unique population density value associated with it. They derived equations for computing per-pixel population density estimates, based upon the density values associated with unique residential categories. They also suggested an alternative method of estimating population densities for all recognized land use categories (not just residential categories). They intended to advance the previous work by Langford *et al* (1991), where a regression model is used to estimate population densities for each land use category. The problem with the Langford *et al* 1991 regression-based approach is that it is possible to obtain negative population estimates for certain land use categories. As an alternate to that method, Donnay and Unwin reallocated population values to each land use class according to ratios that they believed represented plausible distributions of land use across the entire study area. For example, they assigned 80% of the population, in each district, to the Built-up area category, 15% of the population, in each district, to the Agricultural category, and 5% of the population, in each district, to the Other Lands category (excluding water bodies). They produced continuous interpolated surface models from the population-per-pixel counts through the use of a low-pass filtering algorithm (a local, approximate interpolator).

Eicher and Brewer (2001) conducted an accuracy assessment of dasymetric mapping and areal interpolation techniques employed *at the county level*. The produced dasymetric maps and areal interpolations of six socioeconomic variables for a relatively large area covering 159 counties in four states of the Mid-Atlantic region. Their ancillary land use data were adapted from existing USGS 1:7,500,000 scale land-use data included in the *National Atlas* (1970). They converted the polygon land use data into a raster grid with 1 km^2 grid cells and tested three different dasymetric techniques: 1) Grid Binary Method (Langford and Unwin, 1994); 2) Three-Class Method (similar to Donnay and Unwin, 2001); and 3) Limiting Variable Method, adapted from methodology previously utilized in a Ph.D. dissertation (McLeary, University of Wisconsin at Madison, 1969) and an unpublished Masters paper (Gerth, Ohio State University, 1993). The Limiting Variable Method is a variant of the Three-Class Method, in which there is a user-defined upper limit to the population density that can be assigned to any of a number (in this case, three) land use/cover categories. Any population exceeding the upper limit for a particular category is redistributed evenly to the other two categories.

By comparing the areally interpolated values derived from the three dasymetric methods to census data available at the block group level, Eicher and Brewer (2001) computed coefficients of variation for each method. They found that the Limiting Variable Method had the lowest overall mean coefficient of variation for all six socioeconomic variables. However, they acknowledge that the success of the Limiting Variable Method is subject to the correct selection of threshold values used for the upper limit of data values for each category, which they admitted is arbitrary for this particular exercise.

The method employed by Eicher and Brewer (2001) was applied to a relatively large region, which had existing land-use/land-cover data, and they utilized relatively coarse resolution grid cells (1 km^2). For a similar analysis of a single metropolitan area, the 1km^2 spatial resolution may be too coarse for observing and analyzing variations in population density within and among census tracts, or for facilitating dasymetric adjustments to census-derived data due to changes in census geography. In an Atlanta mortality study undertaken by this author, a pixel-based land-use/land-cover classification with 30-meter pixel resolution was derived, thus yielding relatively high-resolution ancillary data for small-area analyses. In addition, the derivation of percentages for the distribution of population to multiple land-use/land-cover classes is subjective, as is the determination of the upper threshold values for population within each land-use/land-cover class. Lastly, as Fisher and Langford (1996) determined, the slight increase in accuracy in using the three-class dasymetric method is more than offset by the increase in computational complexity. Although the concept of using more than one class of occupied land cover has great merit and is one of the two major areas of future research identified by Langford (2003), these techniques are still in the theoretical development stage. Because of these issues, the dasymetric method employed in this current research project differed from that recommended by Eicher and Brewer (2001) for county-level analyses, and followed the basic binary method described by Langford and Unwin (1994), evaluated by Fisher and Langford (1995 and 1996), and recommended by Langford (2003) in perhaps the most recent survey of dasymetric mapping and areal interpolation methods.

Data

Satellite imagery were obtained from the U.S. Geological Survey, EROS Data Center, for 1984 (LT5019036037084172, Landsat 5, Thematic Mapper, Path 019, Rows 036-037 (50% offset), acquired June 20, 1984); for 1990 (Scene ID: LT5019036037090268, Landsat 5, Thematic Mapper, Path 019, Rows 036-037 (50% offset), acquired September 25, 1990); and for 2000 (Scene ID: L71019036-03620000928, Path 019, Row 036, acquired September 28, 2000; and Scene ID: L71019037-03720000928, Path 019, Row 037, acquired September 28, 2000). These satellite images were used to derive land use/cover data for the period of the research project.[*]

Color infrared (CIR) digital orthophoto quadrangles (DOQs) of metropolitan Atlanta (February 1999) were used for ground truthing of satellite-derived land use/cover data for 2000. Black-and-white and color aerial photographs of portions of the metropolitan Atlanta area (particularly Gwinnett County, 1988 and 1989) were used for ground truthing of satellite-derived land use/cover data for 1990.

Road network data were obtained from the National Transportation Atlas Database: 2002, published by the U.S. Department of Transportation, Bureau of Transportation Statistics, and from ESRI (Environmental Systems Research Institute, Redlands, CA). These data were used to assist in classification of land use/cover.

County boundary files were obtained from the Digital Environmental Atlas of Georgia, Version 2, published jointly by the Georgia Geologic Survey and the U.S.

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[*] See Chapter 3 for details.

Geological Survey. Census tract boundary files were obtained from the U.S. Census Bureau for 1990 and 2000. For 1980, census tract boundaries were obtained from Geolytics, Inc., a retail provider of value-added U.S. decennial census data, which created the census tract boundaries based upon Census TIGER/Line Files, (no longer downloadable for 1980 from the Census Bureau). The 1980 Geolytics census tract boundaries were manually “cleaned” in a geographic information system (ArcInfo 8.2, Environmental Systems Research Institute, Redlands, California) in order to remove hundreds of small polygons corresponding to small-to-large bodies of water. The 1990 and 2000 census tract boundary files did not include such polygonal objects.

Socioeconomic and demographic data were obtained from Geolytics, Inc. Specifically, U.S. Census Long Form (SF-3) data were obtained for 1980, 1990, and 2000. This research project utilized selected original variables from the SF-3 as well as user-derived variables from the SF-3 data.

Methodology

Basic Procedure for Dasymetric Determination of Population Densities

The basic procedure used in this project closely follows the binary dasymetric procedure described by Langford and Unwin (1994) and Fisher and Langford (1995 and 1996). In this process, ancillary land-use/land-cover data were derived from a computer-assisted manual pixel-based classification of remotely-sensed satellite data. An example of the land-use/land-cover data is illustrated in Figure 4.4, which depicts Gwinnett County, in 1990. The ancillary data were used to differentiate residentially-occupied areas from unoccupied areas. The raster format land-use/land-cover map, in binary form (occupied vs. unoccupied), was overlaid with a census tract boundary file, which had

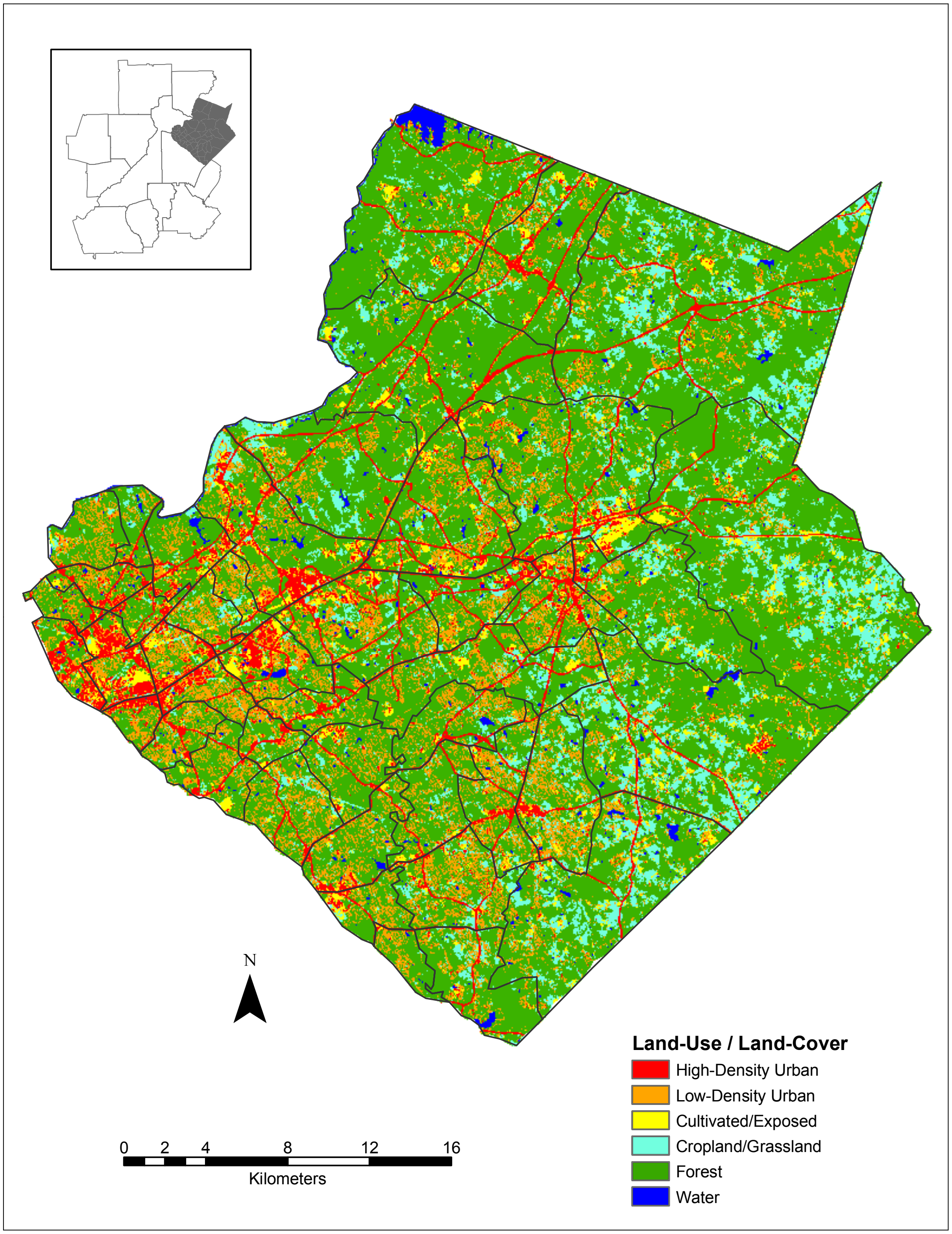

Figure 4.4. Land-use/land-cover, Gwinnett County, Georgia, 1990.

been transformed from the original vector shapefile format into a raster file. An example is shown in Figure 4.5, of Gwinnett County, for 1990. The number of residential land-use pixels per census tract were determined through the use of the Summary function in ERDAS Imagine 8.6 (Leica Geosystems, Inc., Atlanta, Georgia); these values were added as a separate attribute field in the census tract vector shapefile. The census tract shapefile was merged with a database file of census tract population, extracted from the Geolytics Long Form (SF-3) database. The population per residentially-occupied pixel, per census tract, is then determined by simple arithmetic calculation in ArcInfo 8.2. The areal unit of the land-use pixels was mathematically transformed from pixels (each representing an area 30 meters x 30 meters) into more commonly used land-area metrics, hectares and square kilometers. The resulting statistics represented the dasymetrically-derived population density for each census tract.

The basic methodology is used for three separate cases of population density determination: 1980, 1990, and 2000. Each year required a slightly different implementation of the dasymetric process in the GIS, as the population densities needed to be expressed in terms of the 1990 census tract boundaries. In addition, for 1980 and 2000, the dasymetric procedure is used as the basis for areal interpolation of census-derived data to 1990 census tract boundaries.

Application 1: 1990 population density in 1990 census tract boundaries

For the 1990 data, it is only necessary to compute census tract population densities; areal interpolation of 1990 census data is not necessary, given the use of 1990 census tract boundaries. To compute 1990 population densities, ancillary data were derived from the unsupervised classification of a 1990 Landsat Thematic Mapper (TM)

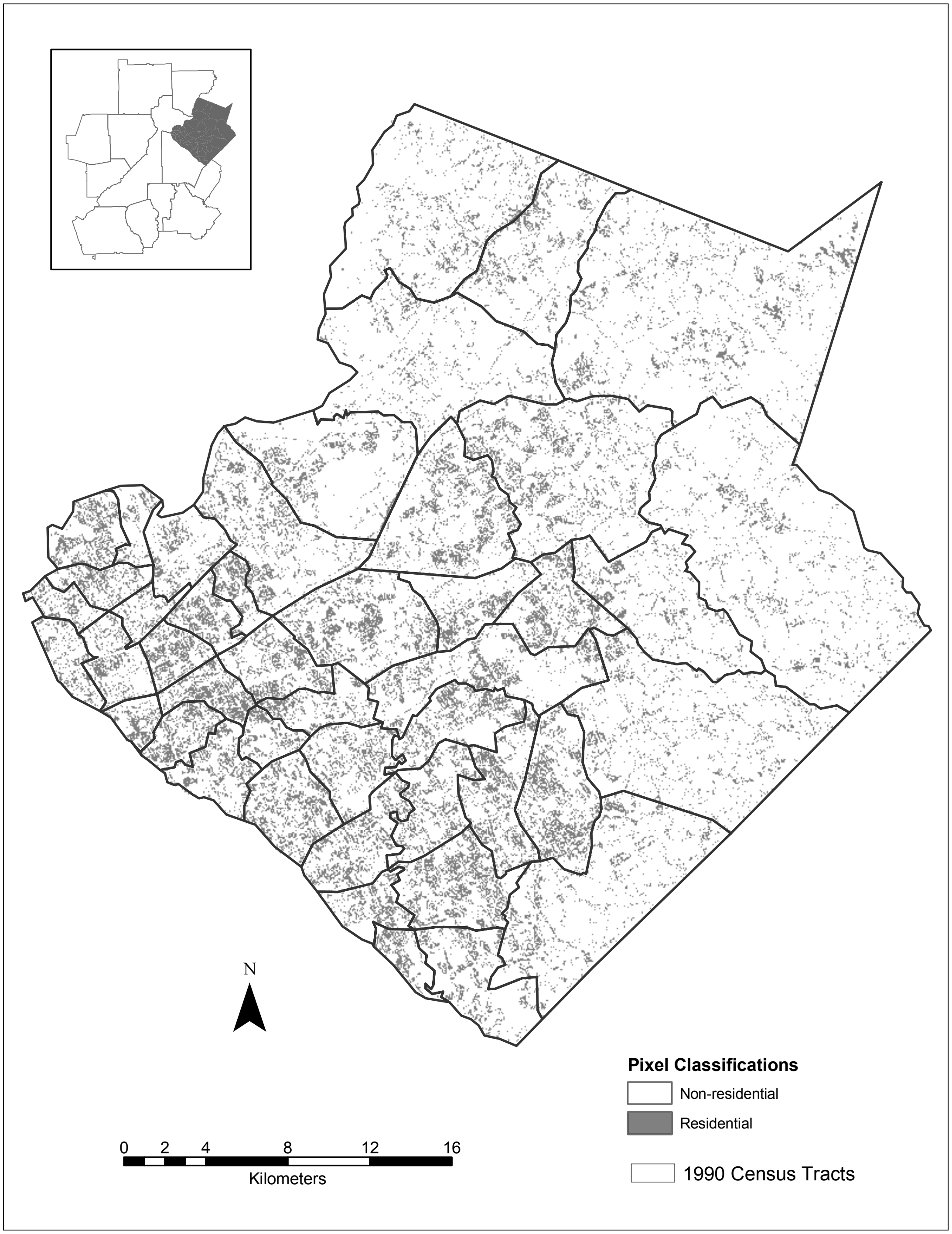

Figure 4.5. Residential versus non-residential pixel classifications, Gwinnett County, Georgia, 1990.

satellite image, with a scene acquisition date of September 25, 1990. The classification was performed in ERDAS Imagine 8.6 using the ISODATA procedure. Details of the classification are described in Chapter 3 of this dissertation. Overall accuracy for the classification is 92.94 percent. Producer's accuracy and user's accuracy for the Low-Density Urban category (which is associated with residential land-use) were 96.92 percent and 87.50 percent, respectively. In addition, the overall Kappa index of agreement is 0.9124 and the conditional Kappa for the Low-Density Urban category is 0.8524. Thus, the classification accuracies exceeded the commonly-accepted minimum thresholds for remotely-sensed data (Anderson *et al*, 1976), as well as the threshold determined necessary to ensure robustness to classification error of the binary dasymetric technique (Fisher and Langford, 1996).

Following the derivation of ancillary data, population density for 1990 was determined according to the basic procedure, outlined in the previous subsection. An example of dasymetric 1990 population density determination is highlighted in Figure 4.6, which illustrates the binary residential versus non-residential land-use in census tracts 501.02 and 502.02 in northwestern Gwinnett County, in 1990. The number of residential pixels within tracts 501.02 and 502.02 in 1990 were 4413 and 3915, respectively, and their 1990 populations were 8684 and 3047. To determine the dasymetric population densities for each tract, the tract populations were divided by their respective number of residential pixels, yielding densities of 1.97 people per pixel for tract 501.02 and 0.78 people per pixel for tract 502.02. The denominator was arithmetically transformed from pixels to square kilometers, in order to represent the data in units more suitable for analysis and interpretation. Thus, tract 501.02's density of 1.97

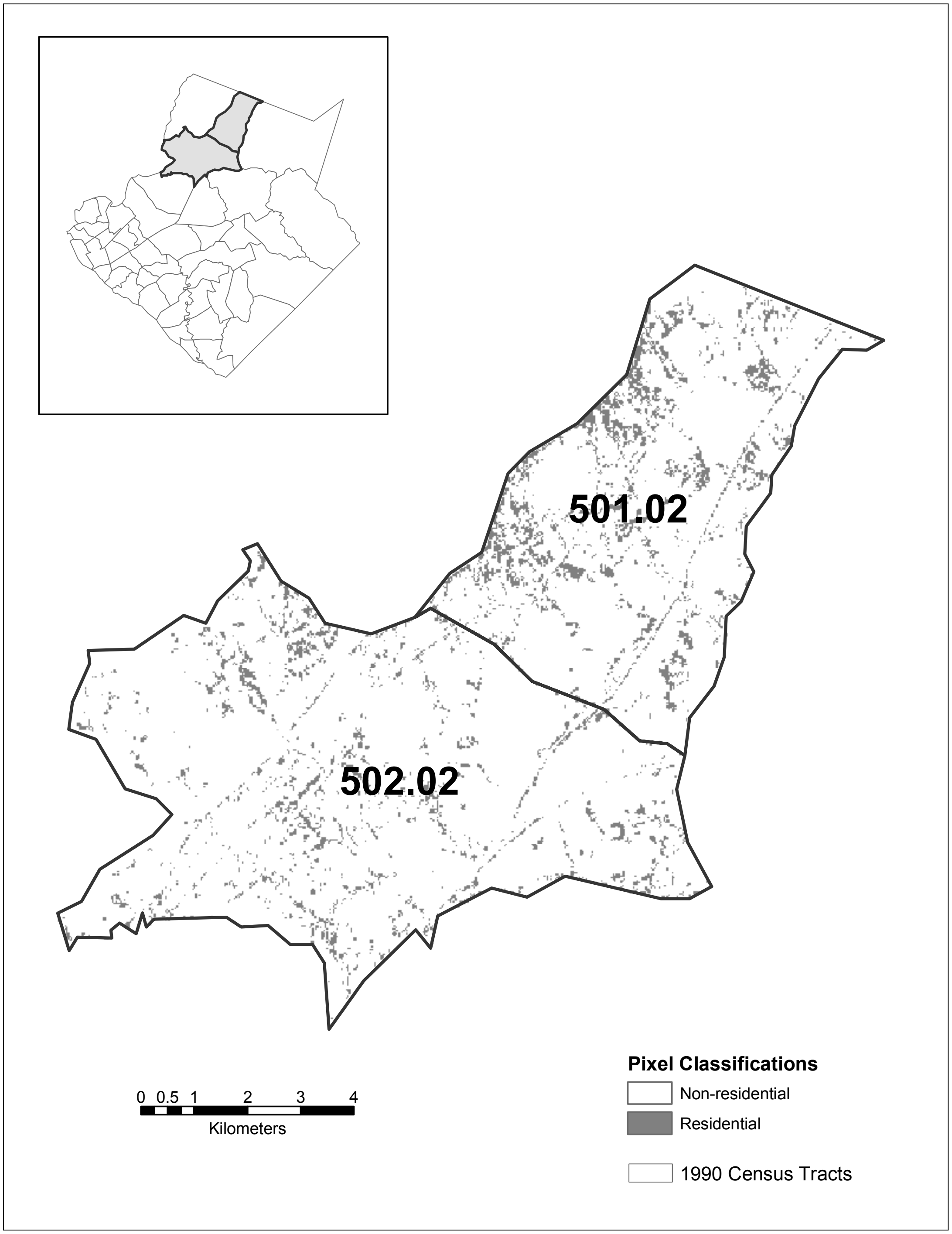

Figure 4.6. Residential versus non-residential pixel classifications, Census Tracts 501.02 and 502.02, Gwinnett County, Georgia, 1990.

people per pixel was multiplied by a conversion factor of 1111.11[*], to obtain a density of 2188.89 people per square kilometer. Similarly, tract 502.02's density of 0.78 people per pixel was transformed to a density of 866.67 people per square kilometer.[**]

To place these population densities in perspective: if a given residential area is comprised of single-family housing units, zoned for one-half acre lots, there are approximately 4.8 housing units per hectare (2 houses/acre x 2.4 acres/hectare). As there are 100 hectares per square kilometer, this translates to 480 housing units per square kilometer of residential area. If one assumes a population-to-housing unit density of two persons per housing unit, this would yield an estimated population density of 960 persons per square kilometer of residential area (480 housing units x 2 persons/housing unit). As a further comparison of these dasymetric population densities: if the population densities for tracts 501.02 and 502.02 had been calculated in the traditional manner of dividing each tract's total population by its total land area, their respective densities would have been 245.1 persons per square kilometer (8684 persons ÷ 35.43 km^2 total land area) and 53.4 persons per square kilometer (3047 persons ÷ 57.03 km^2 total land area). While the ordinal ranking of the two tracts remains the same (tract 501.02 is more densely populated than tract 502.02) the relative difference in population density is dramatically different between the methods of density computation. For the dasymetric method, tract 501.02 is roughly 2.5 times more densely populated than tract 502.02, while for the traditional method, tract 501.02 is roughly 4.5 times more densely populated than tract 502.02. Therefore, by not including unpopulated land areas in the calculations of

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[*] This conversion factor is the reciprocal of the number of square kilometers per pixel, which is 0.0009.

[**] Tract 501.02 corresponds to the city of Buford, which would be expected to have higher population densities than the more rural areas that comprised tract 502.02.

population density, the dasymetric method provides a more precise measure of population density within residential areas; and the variation in population density among tracts can be substantial.[*]

Application 2: 1980 and 2000 population densities in 1990 census tract boundaries

For the 1980 and 2000 data, it is necessary to compute census tract population densities, expressed in terms of the 1990 census tract boundaries. This involved a modification to the basic procedure that is used for 1990 population density determination. Essentially, the first step is to determine the population densities for 1980 in terms of the 1980 census tract boundaries, and the population densities for 2000 in terms of the 2000 census tract boundaries. The second step is to re-express the 1980 and 2000 population densities in terms of the 1990 census tract boundaries.

To compute the 1980 population densities, a June 20, 1984 Landsat TM scene is used to derive the ancillary data on residential land-use extent for 1980. The 1984 satellite image is a compromise as a satellite image with compatible spatial resolution (30 meters) did not exist for 1980.[**] The image is classified in the same manner as the 1990 image. An accuracy assessment was not conducted due to the lack of suitable ground truth data. However, as the image is of the same type and from the same satellite as the 1990 image, and because the same classification technique is used, the classification accuracies should be relatively similar to those for the 1990 image. In any case, it is most likely that the classification accuracy exceeds the minimum 60% threshold determined by

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[*] For the 1990 population data across the entire study area, the mean dasymetric population density is 4085 persons/km^2 (s.d.=4764); the mean choroplethic population density is 906 persons/km^2 (s.d.=925).

[**] A Landsat TM image from December, 1982 (the first year for which TM images were available) was acquired. However, because of poor radiometric contrast as well as seasonal incompatibility with the 1990 and 2000 Landsat images (winter versus summer), the 1982 image was not used.

Fisher and Langford (1996) determined to be necessary to ensure robustness to error of the binary dasymetric procedure.

Once the extent of Low-Density Urban (e.g., residential) land-use was determined, the land-use/land-cover map was converted into a binary map of residential versus non-residential pixels, as is the 1990 land-use/land-cover map. The 1984 binary map was overlaid with a rasterized map of 1980 census tract boundaries, and through the Summary function in ERDAS Imagine 8.6, the number of residential pixels, per census tracts, were determined. These values were entered as a separate attribute field in the 1980 census tract vector shapefile. The vector shapefile was merged with a database file containing 1980 tract populations. Population densities, for 1980 in terms of 1980 boundaries were computed by arithmetic operation in ArcInfo 8.2.

To express the 1980 population densities in terms of the 1990 census tract boundaries, additional processing was necessary. The 1984 binary land-use/land-cover map was combined with the 1980 census tract vector shapefile through the Matrix operation in ERDAS Imagine 8.6. This essentially recoded the land-use maps' individual pixel values (formerly binary – 0 and 1) to values representing the tract level population densities corresponding to each pixels' census tract[*]. The rasterized 1990 census tracts were then combined with the recoded land-use map via the Summary function in Imagine, and a report was exported as a .dat file (which could be converted into a Microsoft Excel file for data manipulation). The report contained the number of pixels of each attribute (density) for each 1990 census tract. For census tracts that experienced no

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[*] Because raster pixel values must be integers, it was first necessary to multiply the population densities by 100 in the vector shapefile. These "pseudo-densities" were used for the remaining steps of the procedure. At the completion, the pseudo-values were divided by 100 to return to density values expressed in the original, decimal format.

boundary changes from 1980 to 1990, each census tract contained only one summary number of pixels with an associated population density value. For census tracts that experienced boundary changes, each census tract contained more than one summary number of pixels, each with their associated population density values. In either case, the numbers of pixels were multiplied by their corresponding density values, and the resulting numbers were summed for each tract. The result was divided by the total number of residential pixels in each tract to derive the 1980 population density values in terms of the 1990 census tract boundaries. The Excel file, converted to a database (.dbf) file, was merged with the 1990 census tract vector shapefile; this added the 1980 dasymetric population density values as a separate attribute field in the 1990 shapefile.

For the 2000 population densities calculations, the same procedure was followed as for 1980. The 2000 ancillary land-use/land-cover data was derived from the ISODATA classification of a September 28, 2000 Landsat 7 ETM+ scene. Overall accuracy for the classification is 90.12 percent. Producer’s accuracy and user’s accuracy for the Low-Density Urban category (which is associated with residential land-use) were 93.44 percent and 87.69 percent, respectively. In addition, the overall Kappa index of agreement is 0.8759 and the conditional Kappa for the Low-Density Urban category is 0.8563. As with the 1990 ancillary data, the 2000 data exceeded the minimum thresholds for classification accuracy.

Areal Interpolation of Census Data

The objective in areal interpolation is to disaggregate data from one areal unit and reaggregate the same data to a different areal unit. In this research, it is necessary to express the 1980 and 2000 census-derived data in terms of the 1990 census tracts. To accomplish this, a form of areal interpolation is utilized.

In the study area, census tract boundaries were affected in three ways: 1) census tracts were split into two or more constituent tracts for the subsequent census (e.g., from 1980 to 1990); 2) census tracts had boundary shifts with neighboring tracts; and 3) census tracts were split into two or more constituent tracts and had concurrent boundary shifts with neighboring census tracts. The first case (a simple tract split) is the predominant form of tract change for the thirteen-county Metropolitan Atlanta area from 1980 through 2000. Figure 4.7 illustrates a typical situation in which a census tract from an earlier census is split into two census tracts for a subsequent census year. In this example, 1980 census tract 501 in northwestern Gwinnett County is split into two tracts, 501.01 and 501.02 for the 1990 census. Figure 4.8 illustrates a similar situation (a 2:1 split) for the 1990 to 2000 census years, in which 1990 census tract 501.01 is split into two tracts, 501.03 and 501.04, for the 2000 census. These two examples, from the same area of Gwinnett County, illustrate the rapid population growth in this suburban area, which resulted in the creation of new census tracts.

In a limited number of cases (8 for 1980-1990, and 15 for 1990-2000) census tract boundaries significantly shifted between adjacent tracts (the second and third cases). Figures 4.9, 4.10, and 4.11 illustrate a situation in which a census tract split occurred in conjunction with a tract boundary shift. In this example, 1990 census tract 501.02 split into census tracts 501.05 and 501.06 for the 2000 census. In addition, the new 2000 census tract 501.06 acquired land area from adjacent census tract 502.02. This change therefore also meant that 1990 census tract 502.02 is reduced in area for the 2000 census.

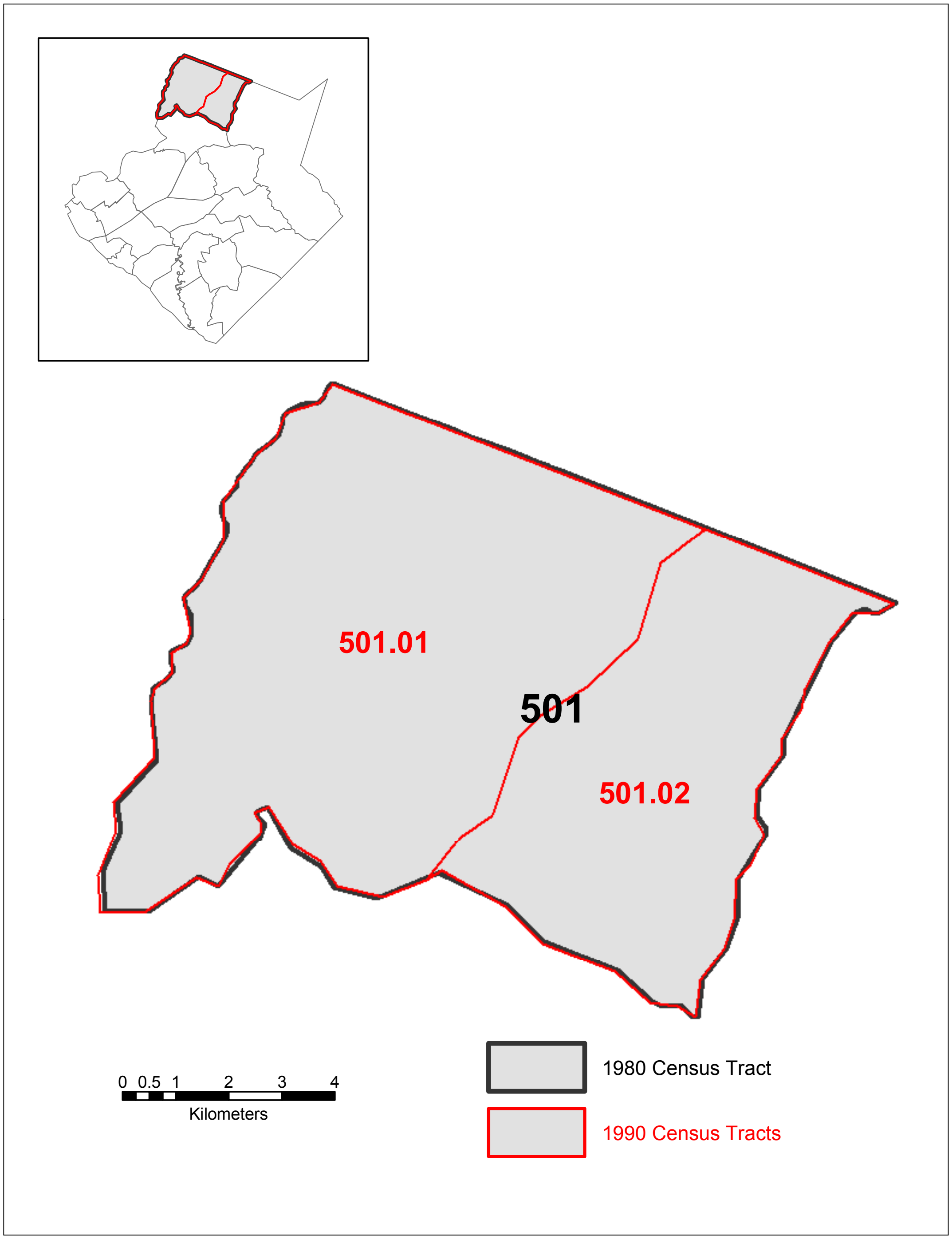

Figure 4.7. Census Tract Boundaries, Northwestern Gwinnett County, 1980 and 1990, illustrating a 2:1 tract split from 1980 to 1990.

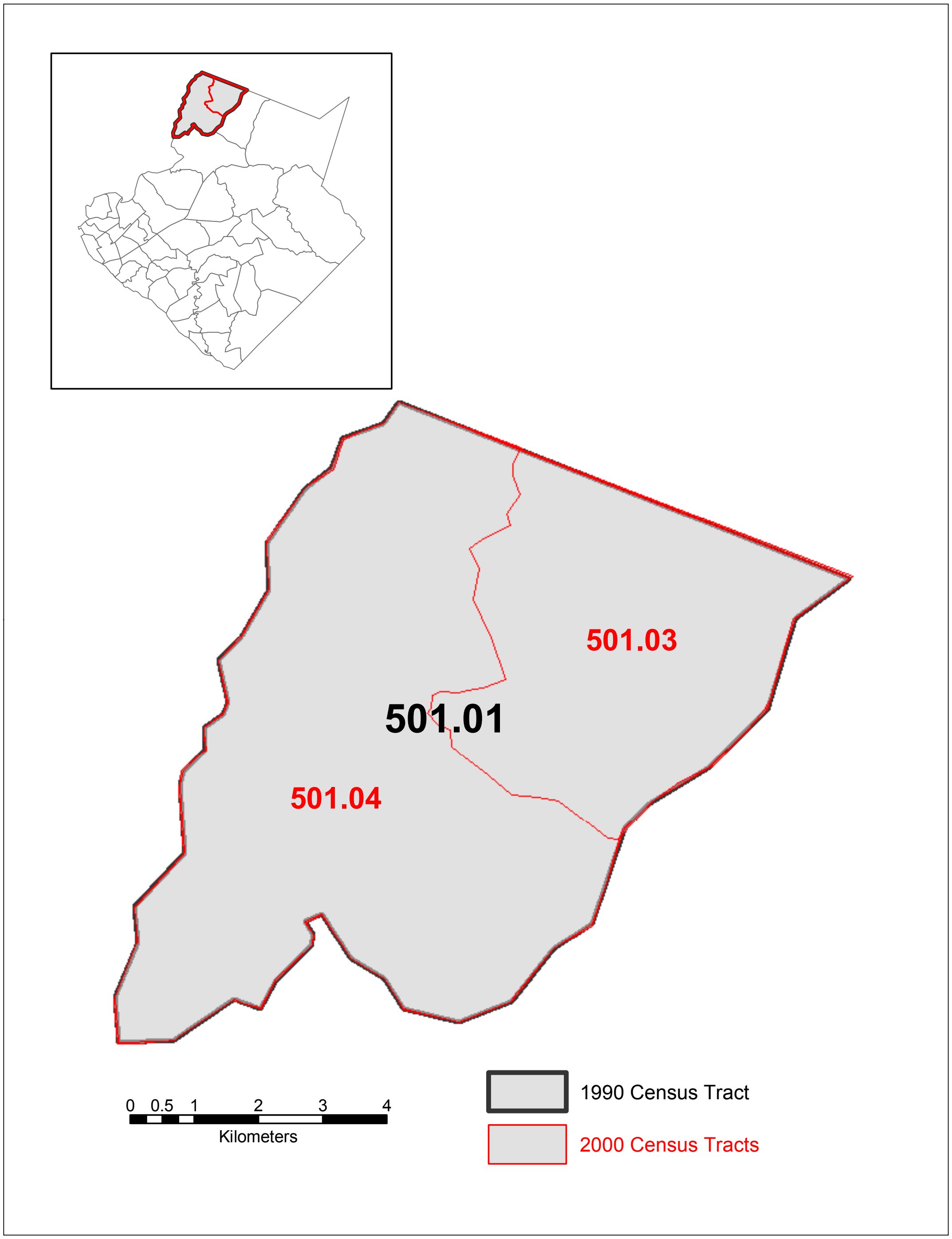

Figure 4.8. Census Tract Boundaries, Northwestern Gwinnett County, 1990 and 2000, illustrating a 2:1 tract split from 1990 to 2000.

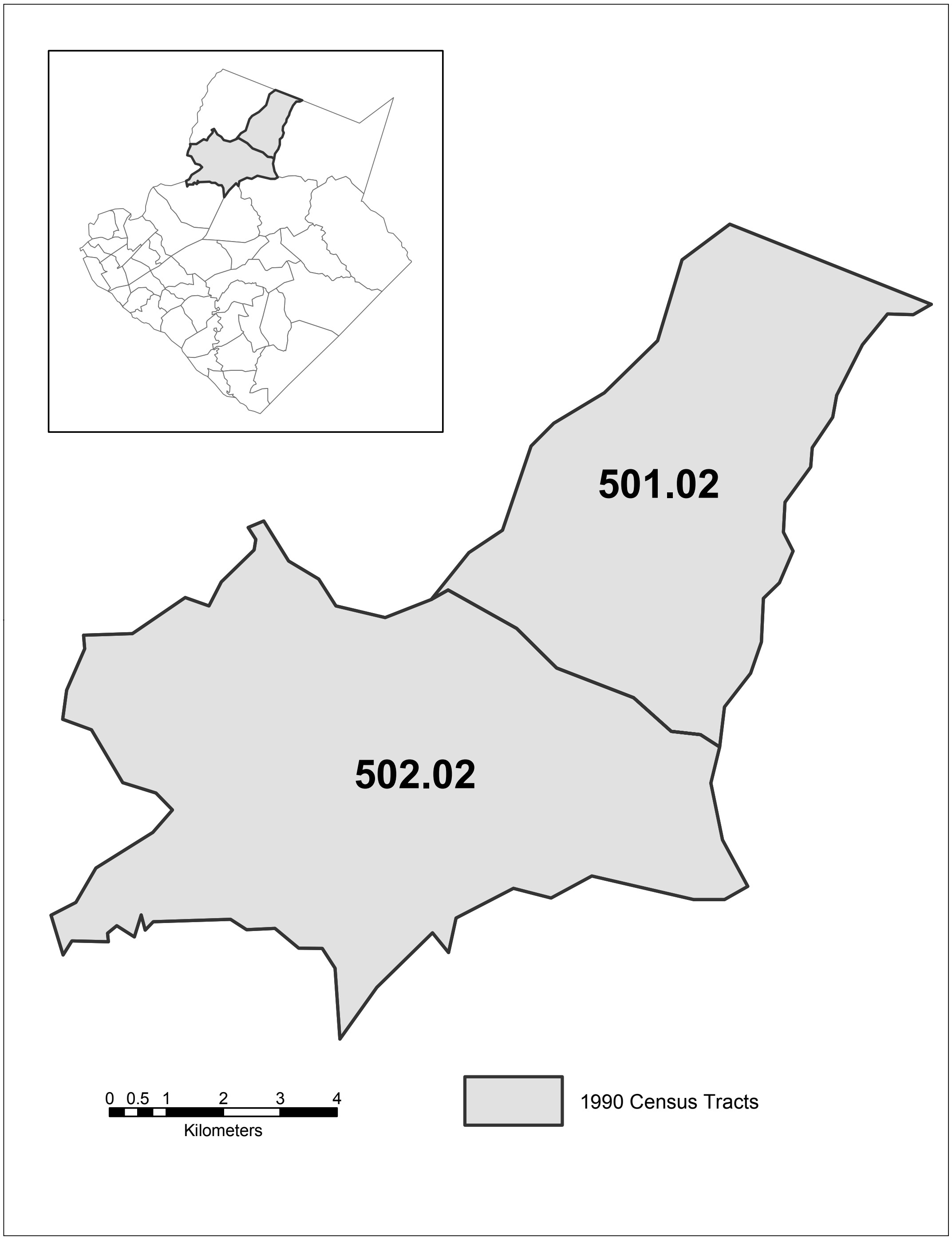

Figure 4.9. Census tract boundaries, northcentral Gwinnett County, 1990.

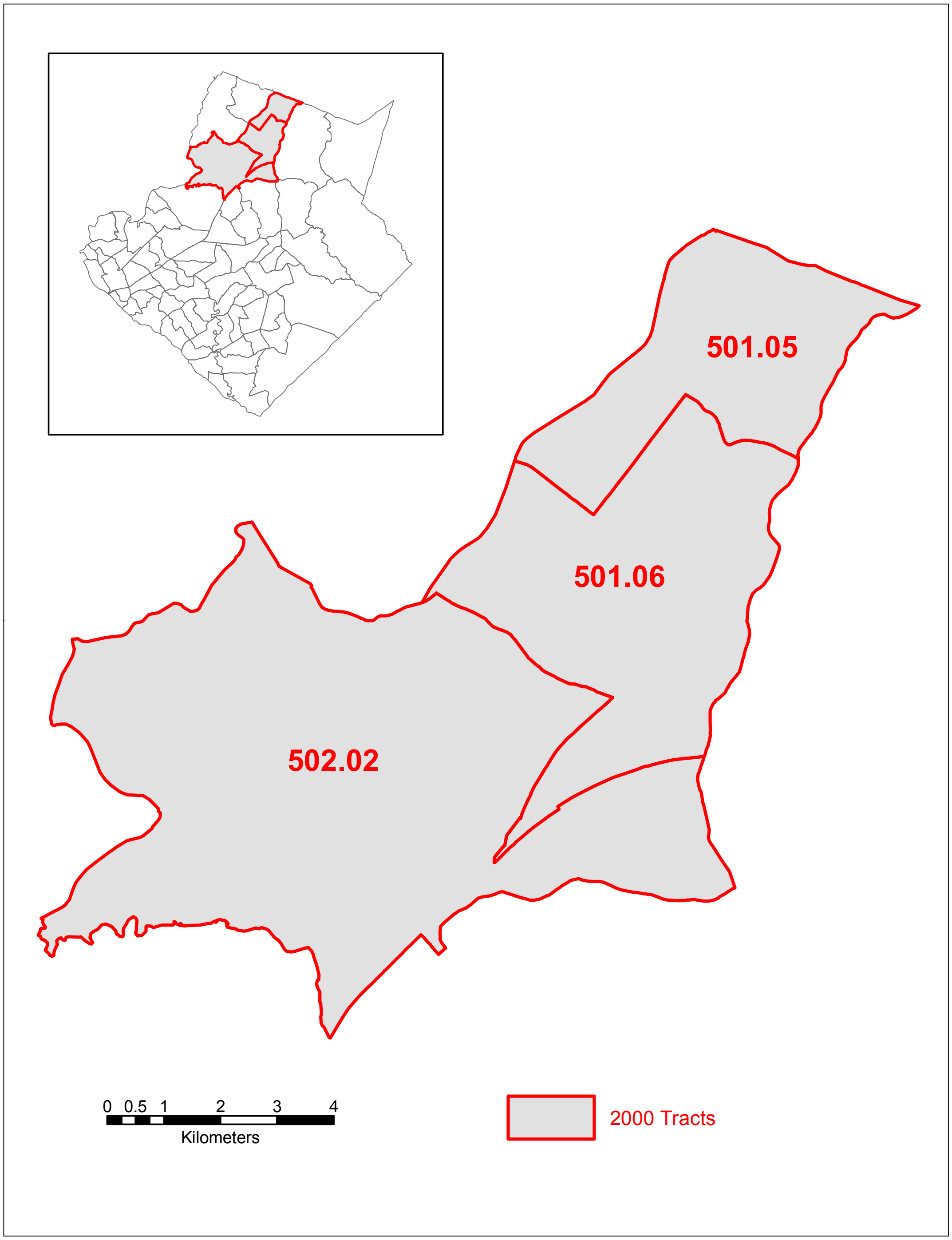

Figure 4.10. Census Tract Boundaries, Northcentral Gwinnett County, 2000.

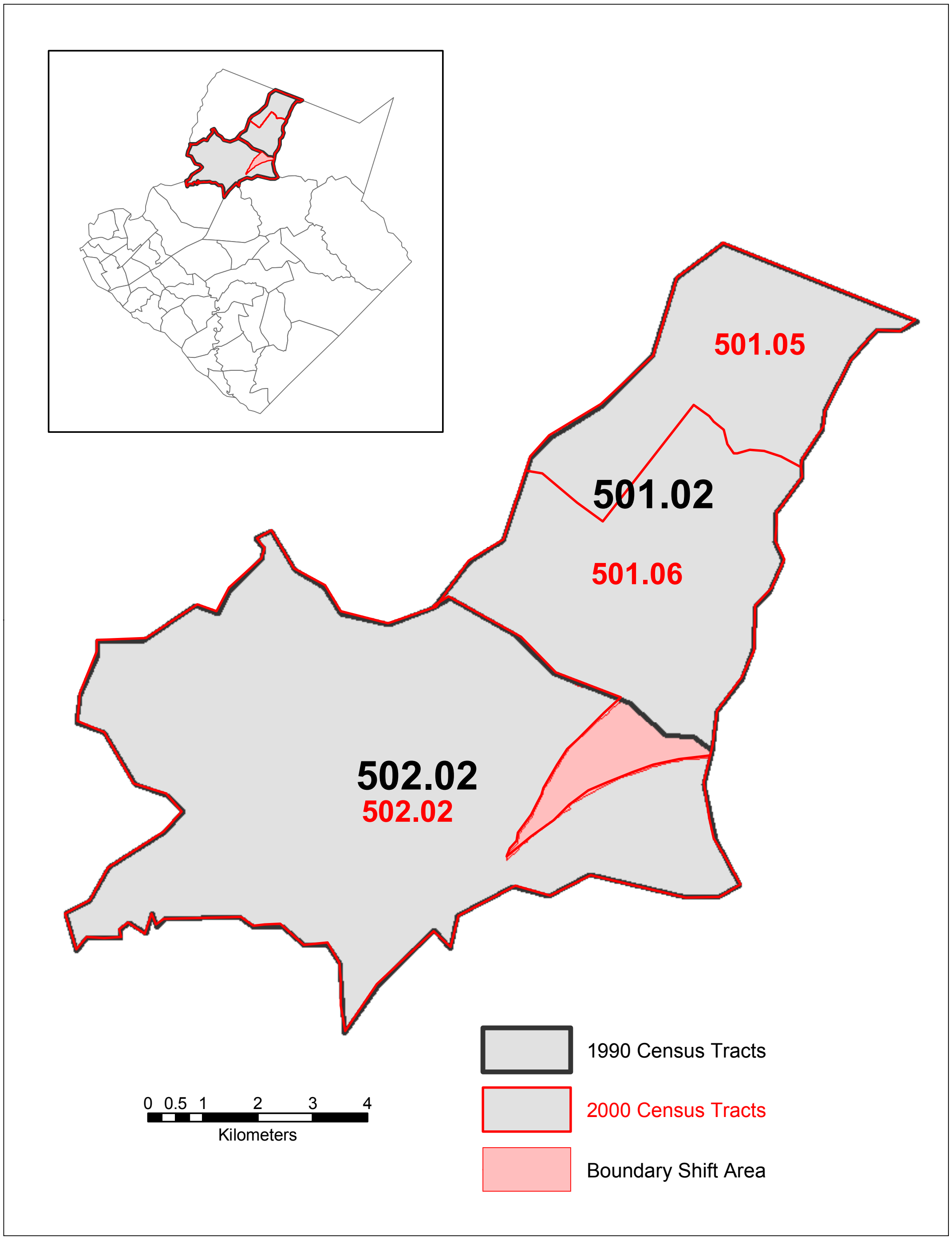

Figure 4.11. Census Tract Boundaries, Northcentral Gwinnett County, 1990 and 2000, illustrating census tract split in conjunction with census tract boundary shift.

Figure 4.11 highlights the boundary shift area: the area that 1990 tract 502.02 relinquished to the new 2000 tract 501.06, which was created out of 1990 tract 501.02.

The basic procedure for areal interpolation used in this research is to determine where changes occurred to census tract boundaries from 1980 to 1990 and from 1990 to 2000; determine the percentage of populated areas affected by those boundary changes in each impacted census tract; develop weights based on the percentage of affected populated areas; and apply the weights to 1980 and 2000 census-derived data in order to obtain estimates of the census data for 1980 and 2000 in terms of the 1990 census tract boundaries.

Census tract boundary changes from 1980 to 1990 were determined through the use of Tract Comparability Files; census tract boundary changes from 1990 to 2000 were determined through the use of Tract Relationship Files. Both datasets were originally published by the U.S. Census Bureau. The Tract Relationship Files are available on-line from the Census Bureau (www.census.gov/geo/www/relate/rel_tract.html), while the older data contained in the Tract Comparability Files are available on-line from the Socioeconomic Data and Applications Center (SEDAC) of the Center for International Earth Science Information Network (CIESEN) at Columbia University (www.sedac.ciesen.org).

The Census Tract Comparability/Relationship Files list tracts that experienced a significant change from one decennial census to the next. A significant change is defined as a change of 2.5 percent or greater in land area (Census Bureau, 2002). As an additional measure, 1980, 1990, and 2000 census tract boundary shapefiles were displayed in a GIS (ArcInfo 8.2), and differences in tract boundaries were confirmed by visual inspection. The results of the visual inspection of the GIS data were cross-checked with the information in the Census Tract Comparability/Relationship Files in order to determine the specific tract boundaries affected by changes, and to develop a table of the specific nature of those tract changes.

In the case of a census tract boundary shift, the percentages of populated areas affected by boundary changes in each impacted tract were determined through the application of the ancillary land-use/land-cover data derived for the dasymetric determination of census tract population densities, described previously. For a boundary shift from 1990 to 2000, the 1990 and 2000 tract boundary shapefiles were overlaid in a GIS (ArcInfo 8.2)[*]. The specific land areas affected by tract boundary shifts were determined through the use of the "Intersection" operation; each separate area was exported as a unique shapefile. In ERDAS Imagine 8.6, each shapefile was matrixed with a binary mask, representing residential pixels (coded as "1") and non-residential pixels (coded as "0"). This process was repeated for each intersection shapefile. Summary reports from Imagine provided the numbers of residential pixels that were contained within each of the intersection areas. For each instance of a boundary shift, the number of residential pixels in the shifted area was divided by the total number of residential pixels in census tract to which it originally belonged (this number was directly obtained from the attribute table of the 1990 tract boundary shapefile). The resulting percentage represented the residential land-use area that shifted from the original census tract to the receiving census tract.

The percentages of affected residential land-use, from the preceding step, were then used as interpolation weights for expressing 2000 census data in terms of 1990

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[*] This same process was repeated for the 1980 to 1990 tract boundary shifts.

census tract boundaries. This was accomplished through the multiplication of 2000 census data by the interpolation weights. Figures 4.12 through 4.17 illustrate the step-by-step procedure for interpolating census data, using DeKalb County census tracts 201 and 224.01 as examples. The census data used in the example are the number of persons living in poverty and the percentage of persons living in poverty.

In Figure 4.12, the portion of tract 201 that shifted to tract 224.01 from 1990 to 2000 is highlighted by the cross-hatched area. In Figure 4.13, the residential land-use pixels from 2000 are superimposed over the area of tracts 201 and 224.01. The number of residential land-use pixels in the portion of tract 201 that shifted to 224.01 is 105 pixels; the number of residential land-use pixels unaffected by the boundary shift is 484 pixels. As Figure 4.14 shows, these numbers correspond to 18% and 82% of the total number of residential pixels (589) for the entire land area of tract 201 in 2000. These percentages served as the dasymetric weights for the subsequent areal interpolation of the poverty data from their original 2000 boundaries to their 1990 boundaries.

Figure 4.15 depicts the population and poverty data for tracts 201 and 224.01 in terms of the 2000 tract boundaries, prior to areal interpolation. Figure 4.16 illustrates the weighting of the data for tract 201 in accordance with the dasymetric weights of 82% and 18%. Lastly, Figure 4.17 shows the resulting census data for tracts 201 and 224.01 after areal interpolation. These data were obtained by subtracting the data corresponding to the cross-hatched area from tract 201 (which lost the cross-hatched land area and the associated population within) and adding these data to 224.01 (which gained the cross-hatched land area and population).

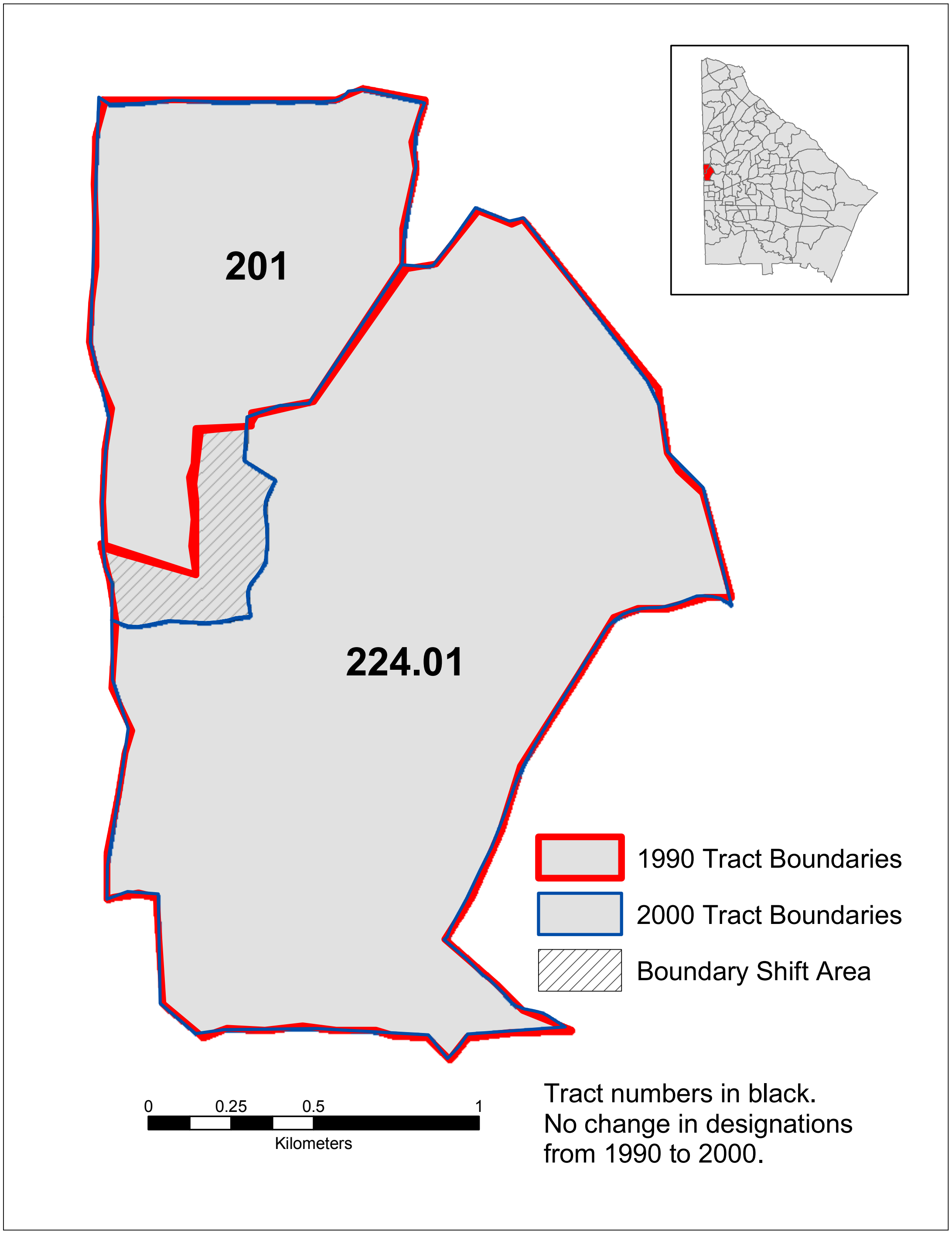


Figure 4.12. Boundary shift, census tracts 201 and 224.01, 1990 to 2000, DeKalb County, Georgia.

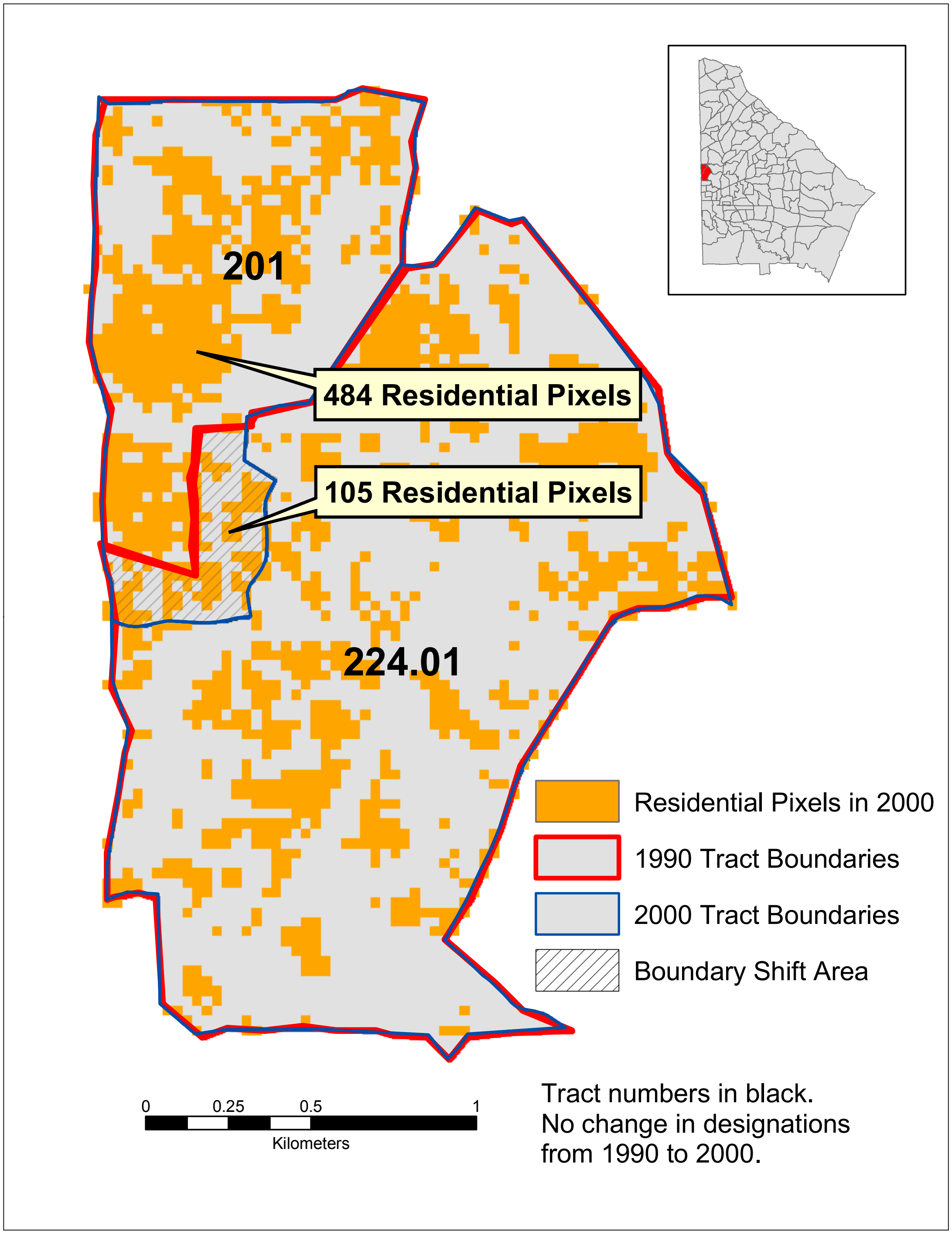


Figure 4.13. Residential land-use pixels, census tract 201, DeKalb County, Georgia, 2000; with 1990 and 2000 census tract boundaries.

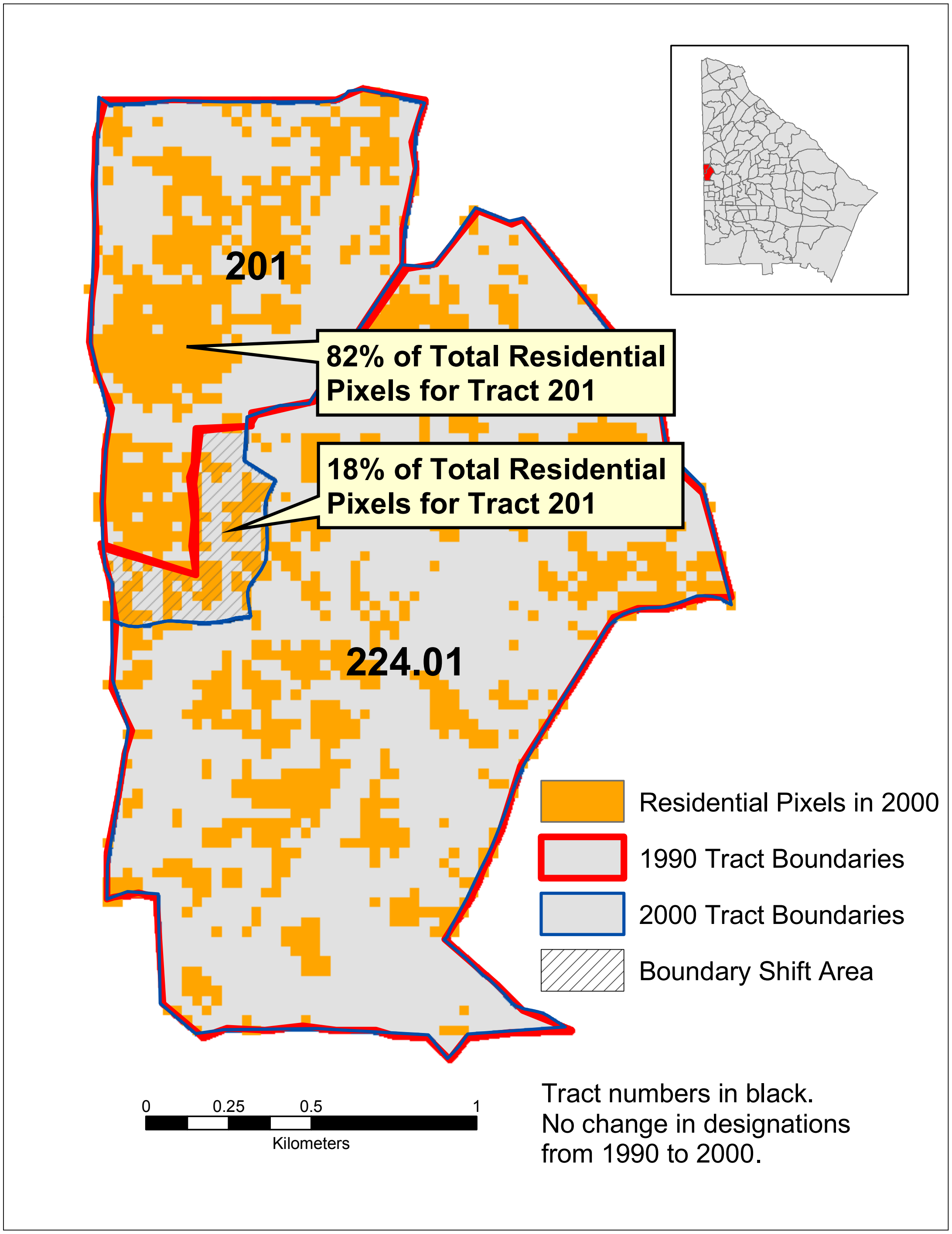


Figure 4.14. Residential land-use pixels, by subdivisions of census tract 201, DeKalb County, Georgia, 2000; with 1990 and 2000 census tract boundaries.

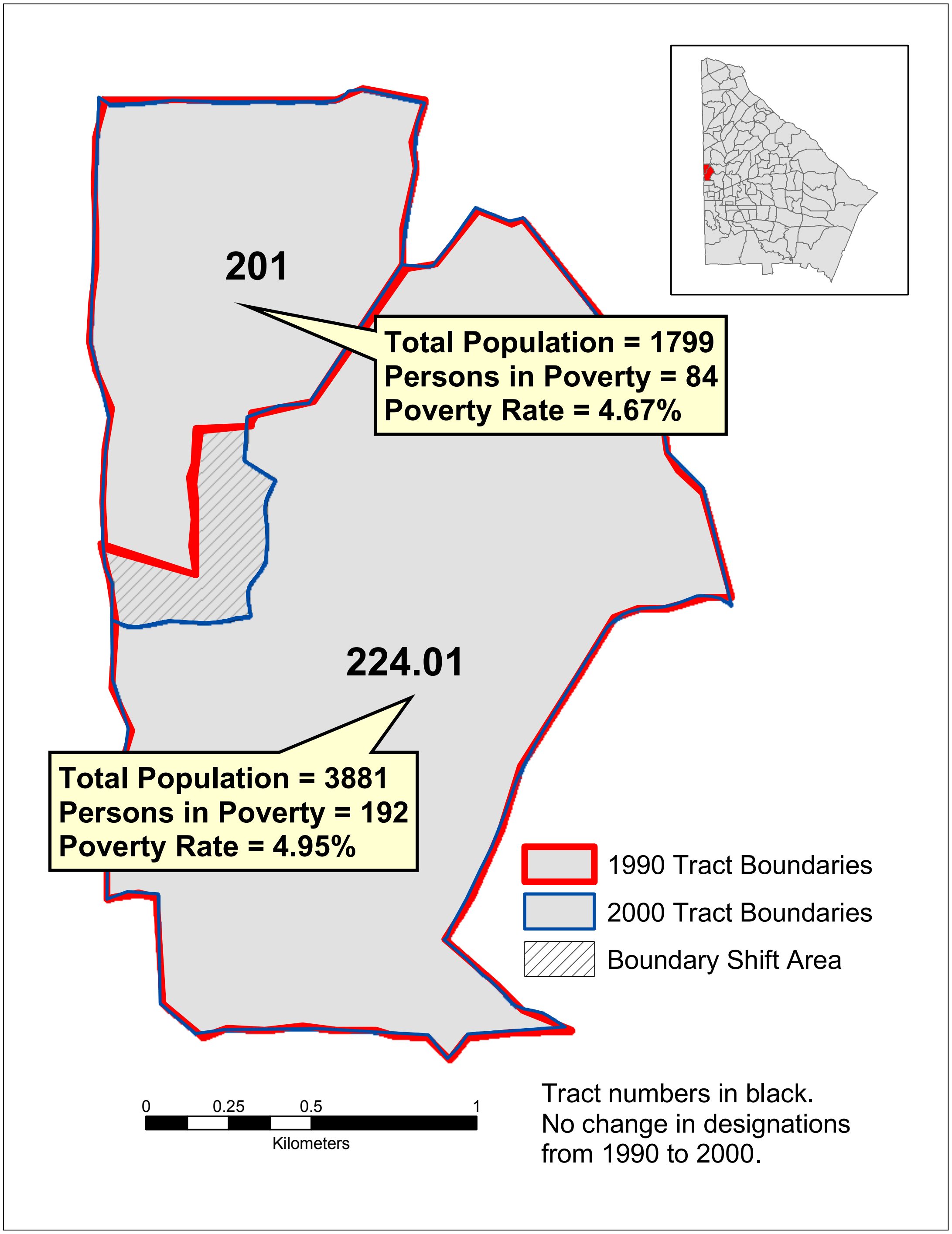


Figure 4.15. Population and poverty data, census tracts 201 and 224.01, DeKalb County, Georgia, 2000; data depicted for 2000 tract boundaries.

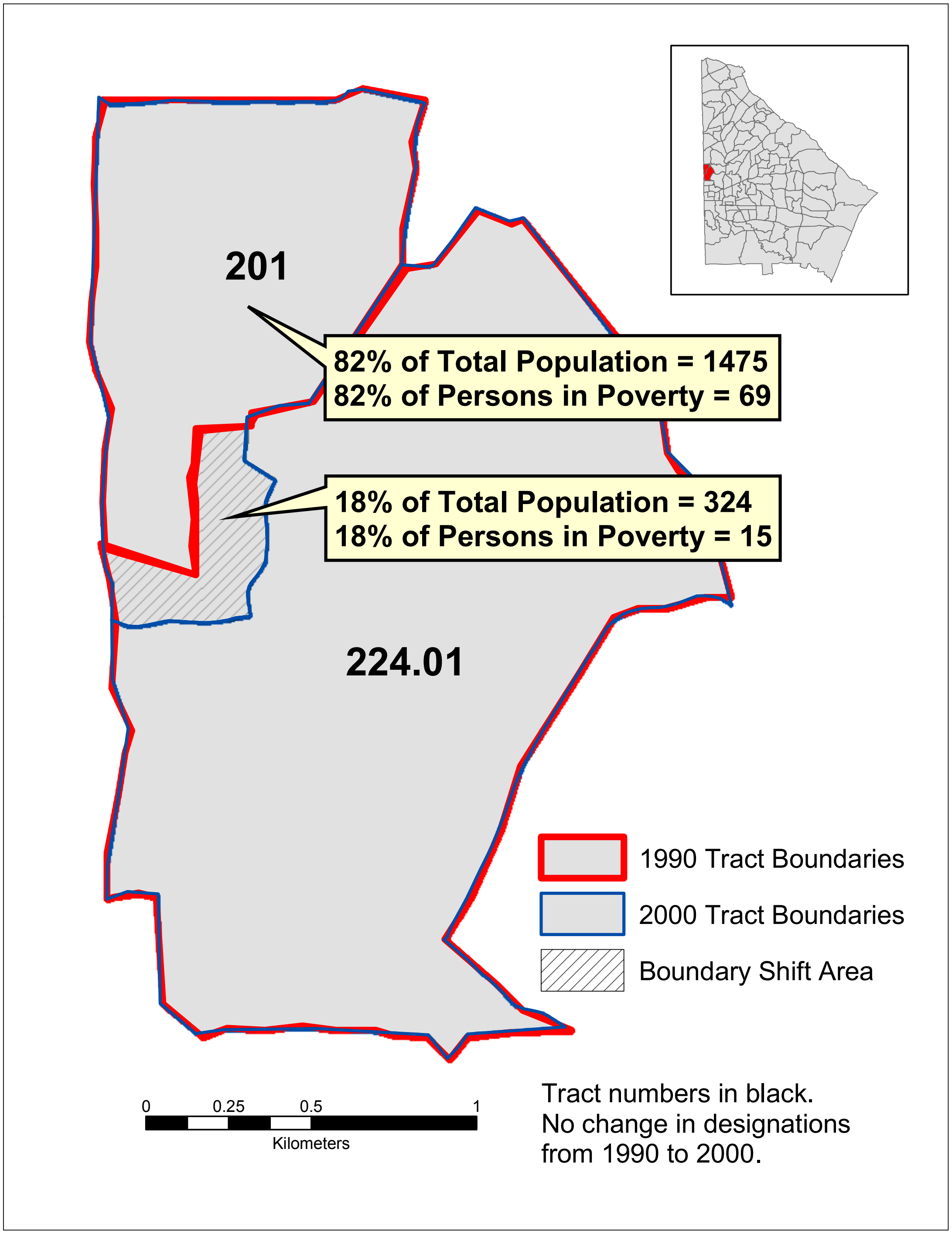


Figure 4.16. Population and poverty data, by subdivision of census tract 201, DeKalb County, Georgia, 2000; with 1990 and 2000 census tract boundaries.

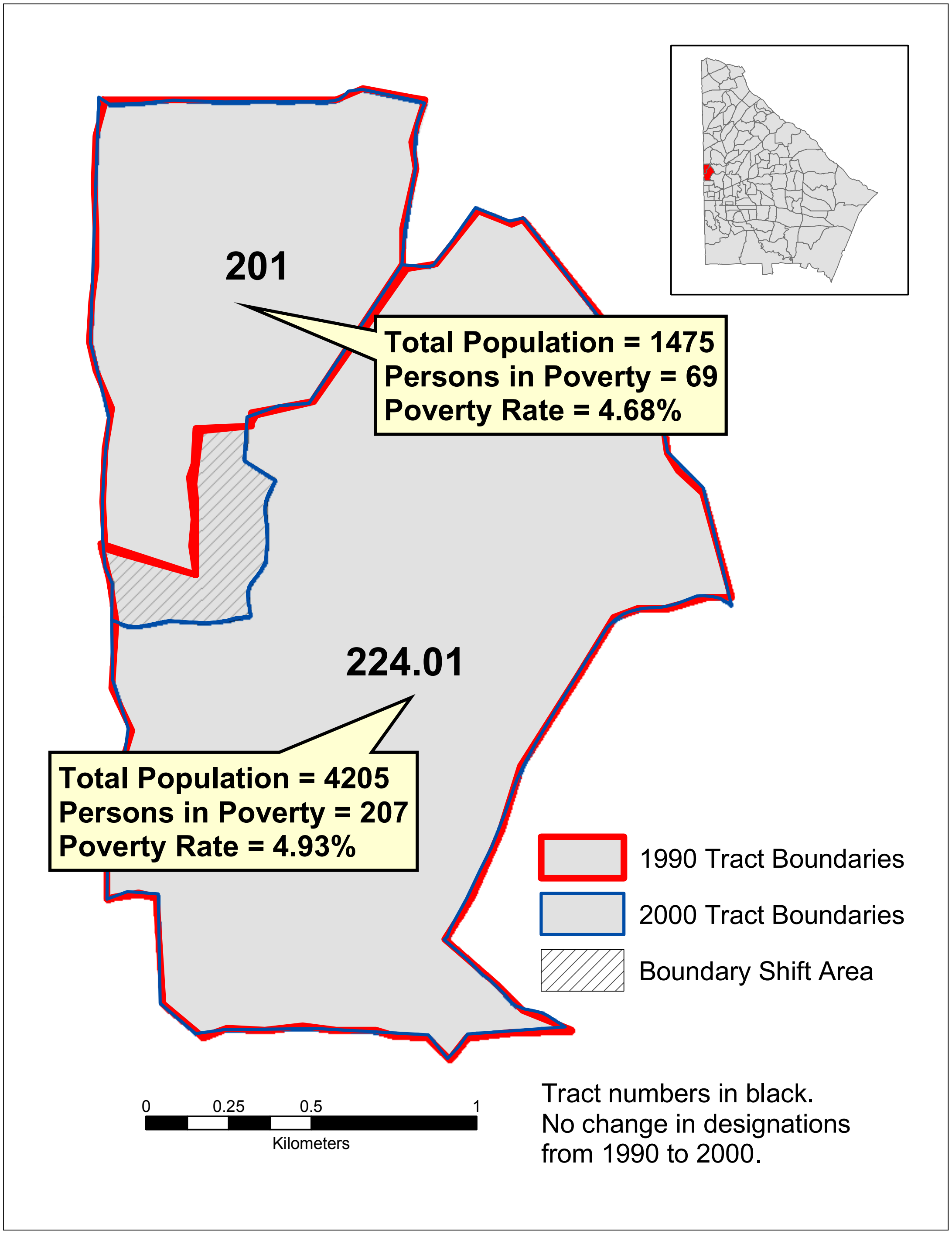


Figure 4.17. Population and poverty data, census tracts 201 and 224.01, DeKalb County, Georgia, 2000; data depicted for 1990 tract boundaries.

This procedure was followed for all instances in which tract boundaries shifted from 1980 to 1990 and from 1990 to 2000. In most of the 23 boundary shifts, the percentages of affected population were quite minor – generally less than 5% of a tract's populated area is included in a tract boundary shift. Therefore, the resulting modifications to the census tract data were relatively modest.

The vast majority of census geography changes were splits. In the case of simple (e.g., 2:1, 3:1, or 4:1, etc.) census tract splits, *from 1980 to 1990*, with no other shifts in tract boundaries, the areal interpolation process is unnecessary. Instead, the census data for each 1980 census tract were assigned to the corresponding 1990 constituent tracts. For example, if Gwinnett County's 1980 census tract 501 was split into two tracts for 1990 (tracts 501.01 and 501.02), each of the 1990 tracts is assigned the census data values for the 1980 census tract (tract 501). In this manner, the 1980 census data for 1980 tract 501 were expressed in terms of the 1990 census tract boundaries (tracts 501.01 and 501.02).

The case of simple census tracts splits, *from 1990 to 2000*, is handled differently because 1990 census tracts were used for this research project. Had 2000 census tracts been used, the same procedure for the 1980 to 1990 tract splits could have been used. In this case, the 1990 to 2000 changes were treated as though the 2000 census tracts were "back-aggregated" into the 1990 census tracts. For example, if Gwinnett County's 1990 census tract 501.01 was split into two tracts for 2000 (tracts 501.03 and 501.04), as illustrated in Figure 4.8, the data for tracts 501.03 and 501.04 were aggregated and assigned to 1990 tract 501.01. It is necessary to aggregate the appropriate denominator data (e.g., total population) as well as the numerator data (e.g., total number of white population) for each of the 2000 tracts; then the resulting percentages could be computed for the aggregated tracts. In this manner, the 2000 census data for 2000 census tracts 501.03 and 501.04 were expressed in terms of the 1990 census tract 501.01 boundaries.

Results and Discussion

Population Density

Census tract level population densities were estimated through the dasymetric procedure for all thirteen counties of the study area. In all cases, the dasymetrically-determined population densities exceeded the population densities computed through the conventional method. Dasymetric population density maps for 1980, 1990, and 2000 are illustrated in Figures 4.18, 4.19, and 4.20. The visual depictions of population densities for 1990 can be compared through Figure 4.21, a choropleth map, and Figure 4.19, a dasymetric map. In both maps, the data were assigned to five classes, using the Jenks' Optimal, or Natural Breaks, method. A visual comparison of the two maps readily indicates a difference in the outer counties. In particular, all census tracts in Douglas, Paulding, Forsyth, Rockdale, Coweta, Fayette, Henry, and (with one minor exception) Cherokee Counties are classed into the lowest class of population density in the choroplethic map. This suggests broad homogeneity of census tract population density throughout the outer suburban fringe. However, the dasymetric map of population densities for these same counties depicts areas with higher population densities within each county. These generally correspond to county seats, other small towns, or, especially in Paulding County, areas of new higher-density housing subdivisions. Therefore, the dasymetric map provides a greater degree of precision in differentiating areas of higher and lower relative population density within counties.

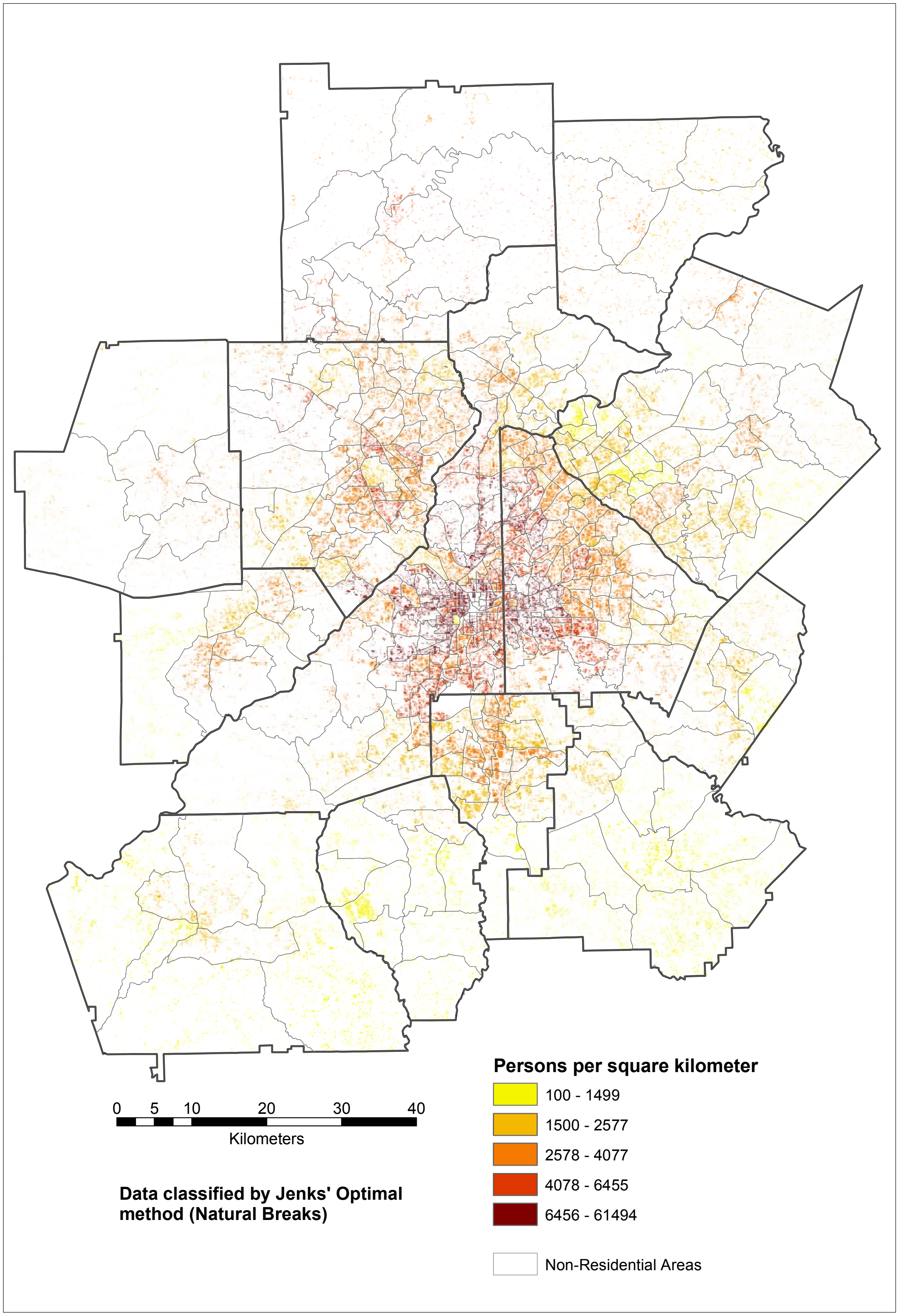


Figure 4.18. Dasymetric population density, metropolitan Atlanta, Georgia, 1980.

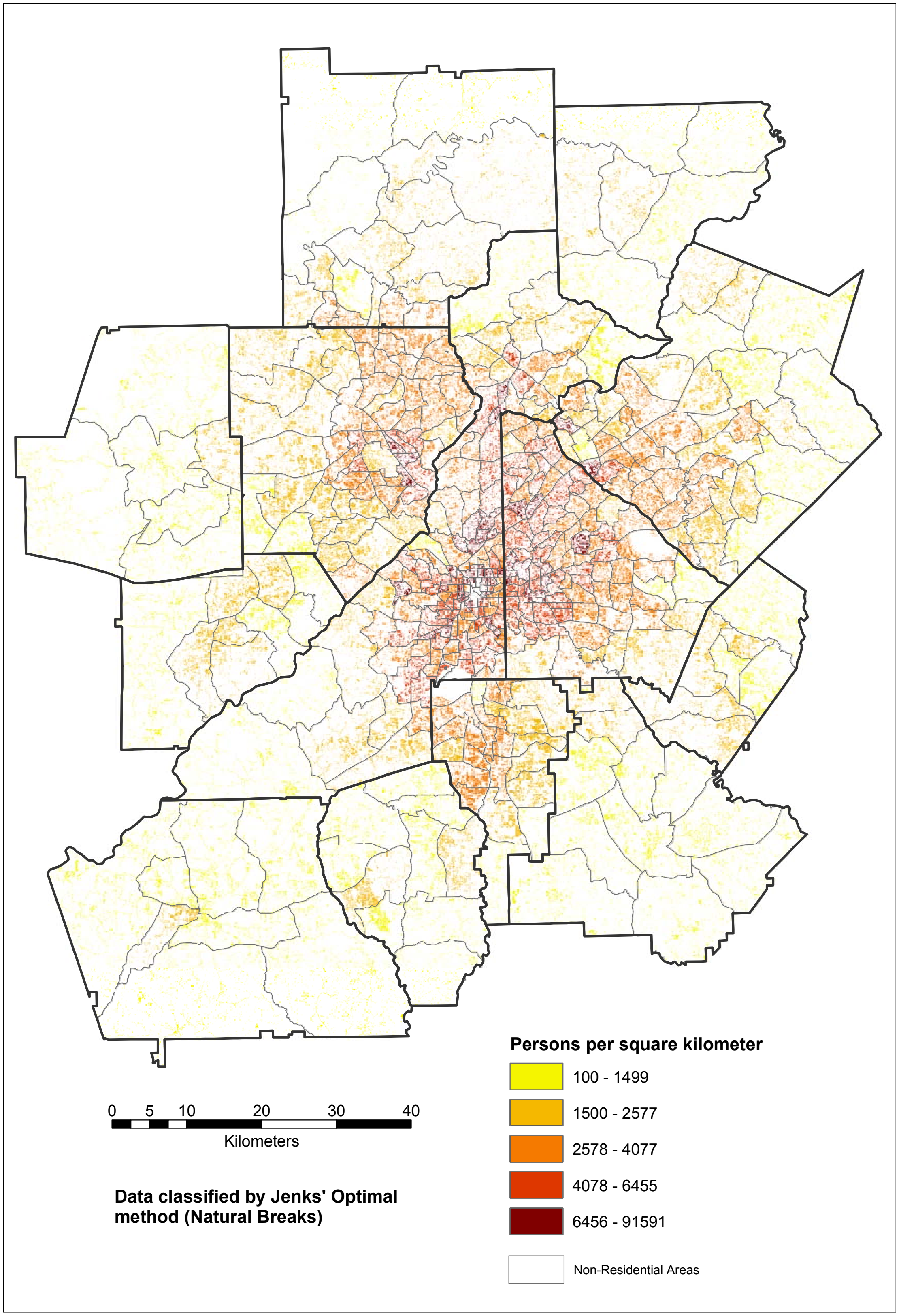
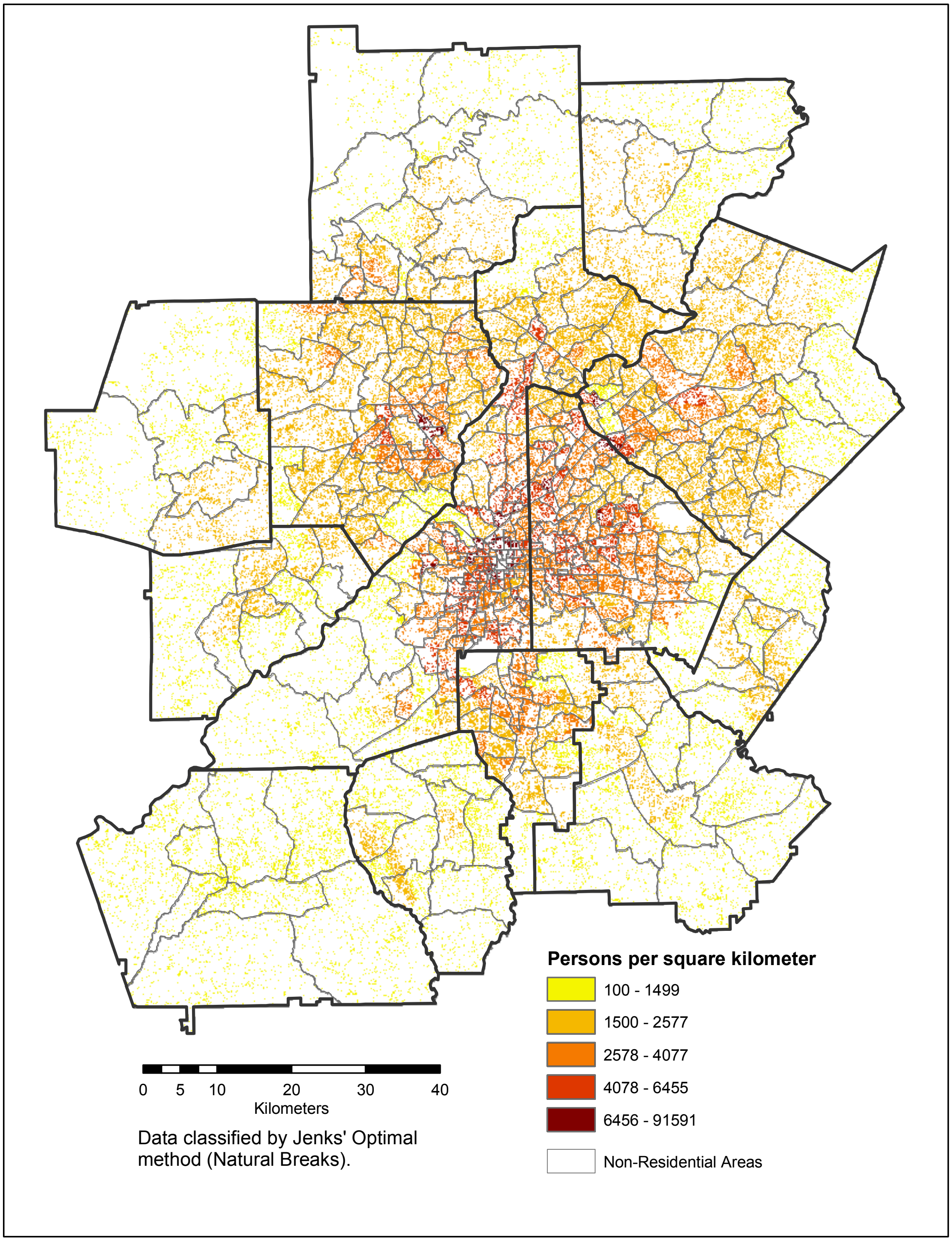


Figure 4.19. Dasymetric population density, metropolitan Atlanta, Georgia, 1990.



Data classified by Jenks' Optimal method (Natural Breaks).

Figure 4.20. Dasymetric population density, metropolitan Atlanta, Georgia, 2000.

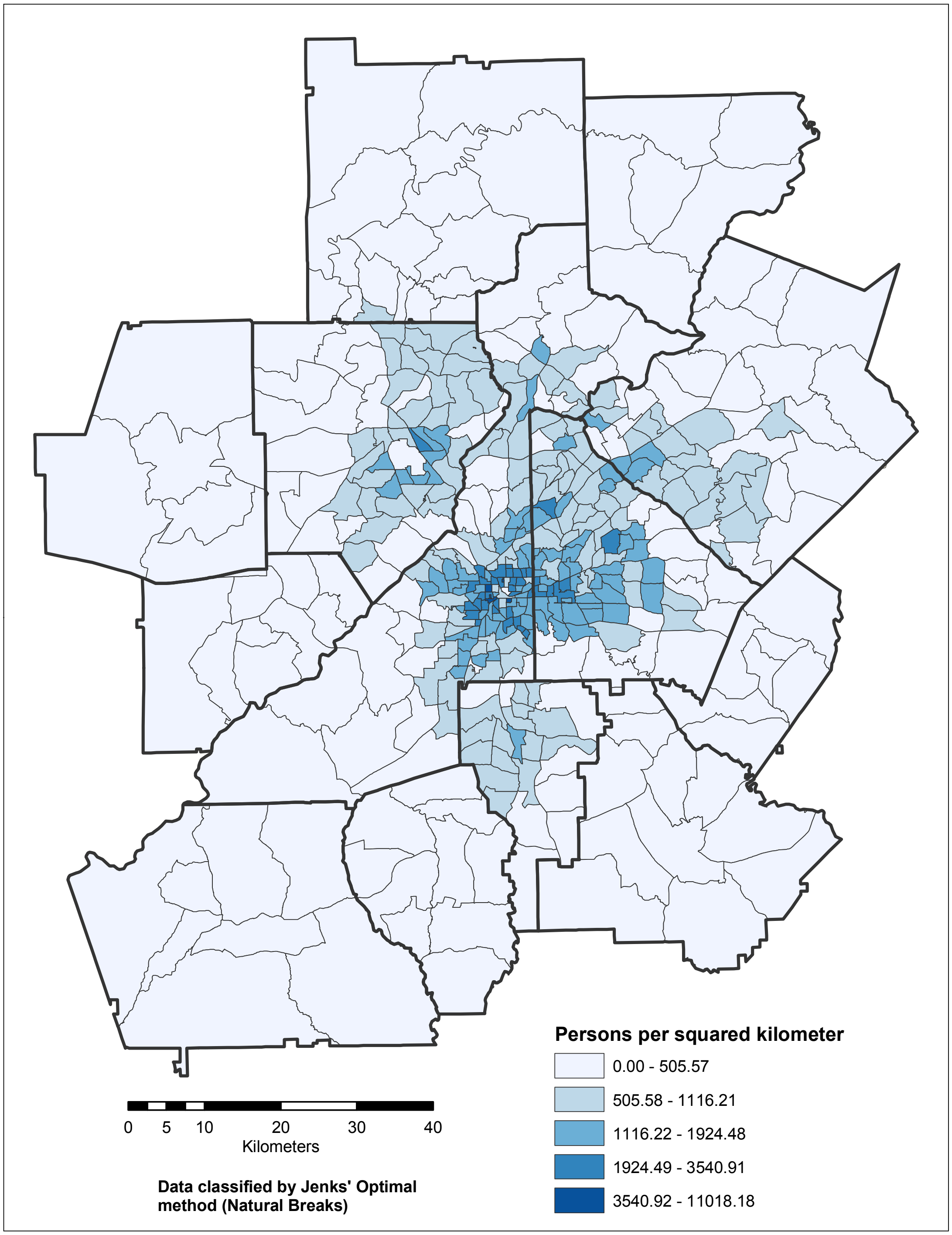


Figure 4.21. Choroplethic population density, metropolitan Atlanta, Georgia, 1990.

In addition, the dasymetric map provides an illustration of areas that are unpopulated. This is especially evident in the outer counties, where broad areas of non-residential land-use exist. This trait of the dasymetric map makes it quite suitable for the visual depiction of temporal changes to the landscape. By comparing dasymetric maps of population density for 1980, 1990, and 2000 (Figures 4.18, 4.19, and 4.20), an observer can note both the locations of new residential development as well as the changes in relative population density that are the result of that development. Table 4.1 compares the conventional and dasymetric population densities, by census tract, for Gwinnett County, for 1990.[*]

While dasymetric maps provide a greater degree of spatial precision in mapping population density, they are still subject to scale and aggregation effects, as with the case of choroplethic maps. Because the population is averaged over the number of residential land-use pixels found within a census tract, a change in the population and/or a change in the number of residential pixels as a result of changing census tract boundaries, will result in a change in the population density.

Populations change over time. Therefore, if the same census tract boundaries are maintained from one census to the next, and population increases with no increase in residential land-use area, then the population density will increase. On the other hand, if given the same census tract boundaries and the same population increase, but with an increase in residential land-use area, the population density may increase or decrease, depending upon the magnitudes of the population and land-use area increases, in relation to one another. For this reason, it appears that some census tracts in the suburban fringe

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[*] Population densities at the census tract level for all thirteen counties are contained in Appendix B.

Table 4.1. Population densities, choroplethic versus dasymetric, by census tract, Gwinnett County, Georgia, 1990.

Tract Number	**1990 Population**	**Choroplethic Population Density (persons per square kilometer)**	**Dasymetric Population Density (persons per square kilometer)**
501.01	8142	127.46	1700.00
501.02	8684	241.69	2188.89
502.02	3047	53.89	866.67
502.03	15462	463.77	2822.22
502.04	6616	173.38	1655.55
503.04	3288	430.37	2144.44
503.05	9605	1913.35	8422.21
503.06	2185	213.17	1088.89
503.07	7793	745.74	2777.77
503.08	1509	260.17	1888.89
503.09	3969	310.81	2022.22
503.10	4163	568.72	2355.55
503.11	1956	383.53	2277.77
503.12	7863	1089.06	3355.55
503.13	5718	729.34	2522.22
503.14	4406	818.96	2622.22
504.03	6971	617.45	2711.11
504.06	8379	1786.57	6544.44
504.07	11254	1426.36	4522.22
504.08	10986	1371.54	3733.33
504.09	9705	724.79	2944.44
504.10	4767	787.93	3311.11
504.11	5846	576.53	2744.44
504.12	11881	751.01	2644.44
504.13	9101	613.27	3144.44
504.14	10386	669.20	2822.22
504.15	4265	497.67	2255.55
504.16	3489	606.78	2722.22
505.02	12267	342.65	1955.55
505.03	12415	210.96	1477.78
505.05	11543	390.36	2500.00
505.06	16847	591.12	2800.00
505.07	6037	428.16	2522.22
505.08	11803	735.85	2977.77
505.09	5231	152.69	1544.44
506.01	8937	72.62	988.89
506.02	5521	48.22	877.78
507.04	7078	125.81	1300.00
507.05	6529	87.06	1044.44
507.06	10425	673.45	3088.88
507.07	8125	533.84	2722.22
507.08	12546	612.30	2222.22
507.09	5854	286.54	1922.22
507.10	10049	561.08	2344.44
507.11	10265	461.35	1822.22
508.98	2	100.00	100.00

counties experienced population increases concurrent with decreases in dasymetric population density, while other tracts with population increases experienced increases in dasymetric population density.

An example of the former case is the change in central Coweta County (specifically, census tract 1707) from 1990 to 2000. The population increased from 6458 in 1990 to 7139 in 2000 (an increase of 10.5%). For the same period, residential land-use increased from 4.04 km^2 to 5.10 km^2 (an increase of 26.2%). The resulting dasymetric population density decreased from 1600 persons/km^2 to 1400 persons/km^2. If this same 1990-to-2000 change is analyzed using the choroplethic method of calculating population density, the results would be exactly opposite: a 1990 density of 29 persons/km^2 (6458 persons ÷ 222.26 km^2 of total land area) compared to a 2000 density of 32 persons/km^2 (7139 persons ÷ 222.26 km^2 of total land area) indicates an increase in population density from 1990 to 2000. In the case of tract 1707, the decrease in dasymetric population density is most likely attributable to post-1990 new residents living in newly-constructed single-family houses built on relatively large lots (e.g., one acre or greater). This type of suburban development, where the percentage increase in population is less than the percentage increase in residential land-use area, is an example of urban sprawl.

An example of a dasymetric population density increase is census tract 1205 in southeastern Paulding County. Its population increased from 6809 to 14425 from 1990 to 2000 (an increase of 111.9%); while its residential land-use area increased from 5.47 km^2 to 8.89 km^2 (an increase of 62.5%). While population and residential land-use area grew substantially, population growth exceeded residential land-use growth. This may be attributable to the construction of single-family houses on smaller lots, the construction of multi-family housing units, and/or an influx of families with multiple children.

Table 4.2 lists the dasymetric population densities, by census tract, for an entire county, Gwinnett, in 1980, 1990, and 2000. Census tracts with decreasing population density, from either 1980-1990, 1990-2000, or 1980-2000, are indicative of areas experiencing urban sprawl during those periods.[*] This can be measured at the tract level because population increases and residential land use increases are incorporated into the dasymetric mapping process, whereas choroplethic techniques cannot account for changes in residential land use within tracts. Thus, dasymetric mapping can pinpoint areas of urban sprawl within counties (Figure 4.22), such as tracts further away from the Atlanta CBD, made accessible by multi-lane expressways (I 85, I 985, and Hwy 316).

Areal Interpolation of Census Data

Census data for 1980 and 2000 were areally interpolated when boundary shifts occurred from one census to the next. This situation is relatively infrequent both in number of cases (8 for 1980-1990 and 15 for 1990-2000) and as a percentage of the overall number of census tracts (1.8% for 1980-1990 and 2.5% for 1990-2000). Furthermore, the percentages of affected population in these cases were generally small, especially for the 1990-2000 boundary shifts (1980-1990: range 0% to 47%; mean 23%; median 26.5%; and 1990-2000: range 0% to 18%; mean 6.5%; median 5%). Therefore, the overall impact on the total data set from census tract boundary shifts is modest.

The accuracy of the dasymetrically-derived areal interpolation weights were checked against population-based percentage changes that were included in the Tract

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[*] Provided that population has increased over that period.

Table 4.2. Changes in dasymetric population density, by census tract, Gwinnett County, Georgia, 1980-2000.

Tract Number	1980 Population Density	1990 Population Density	2000 Population Density	% Change 1980 to 2000
501.01	3417.72	1700.00	1700.00	-50.26
501.02	3417.72	2188.89	1555.55	-54.49
502.02	1531.65	866.67	1555.55	1.56
502.03	1898.74	2822.22	3000.00	58.00
502.04	1924.05	1655.55	1511.11	-21.46
503.04	1797.47	2144.44	1600.00	-10.99
503.05	1797.47	8422.21	5588.89	210.93
503.06	1797.47	1088.89	1511.11	-15.93
503.07	683.54	2777.77	1955.55	186.09
503.08	683.54	1888.89	1777.78	160.08
503.09	696.20	2022.22	1911.11	174.51
503.10	696.20	2355.55	1477.78	112.26
503.11	1518.99	2277.77	1566.67	3.14
503.12	1531.65	3355.55	3822.22	149.55
503.13	1518.99	2522.22	2177.78	43.37
503.14	1518.99	2622.22	2466.67	62.39
504.03	2367.09	2711.11	2400.00	1.39
504.06	2556.96	6544.44	6333.33	147.69
504.07	2556.96	4522.22	4255.55	66.43
504.08	1417.72	3733.33	3455.55	143.74
504.09	1405.06	2944.44	2411.11	71.60
504.10	1417.72	3311.11	2511.11	77.12
504.11	1405.06	2744.44	2600.00	85.05
504.12	2670.89	2644.44	1955.55	-26.78
504.13	2658.23	3144.44	2055.55	-22.67
504.14	2493.67	2822.22	2166.67	-13.11
504.15	2481.01	2255.55	1544.44	-37.75
504.16	2481.01	2722.22	2122.22	-14.46
505.02	1746.84	1955.55	2433.33	39.30
505.03	2886.08	1477.78	2055.55	-28.78
505.05	2784.81	2500.00	2166.67	-22.20
505.06	2493.67	2800.00	3411.11	36.79
505.07	2493.67	2522.22	2011.11	-19.35
505.08	2632.91	2977.77	2477.78	-5.89
505.09	2607.60	1544.44	1466.67	-43.75
506.01	2063.29	988.89	1500.00	-27.30
506.02	2063.29	877.78	1044.44	-49.38
507.04	1329.11	1300.00	1622.22	22.05
507.05	1139.24	1044.44	1355.56	18.99
507.06	2417.72	3088.88	2300.00	-4.87
507.07	2417.72	2722.22	1988.89	-17.74
507.08	1860.76	2222.22	2055.55	10.47
507.09	1860.76	1922.22	1622.22	-12.82
507.10	2139.24	2344.44	2011.11	-5.99
507.11	2139.24	1822.22	1644.44	-23.13
508.98	2556.96	100.00	6311.11	146.82

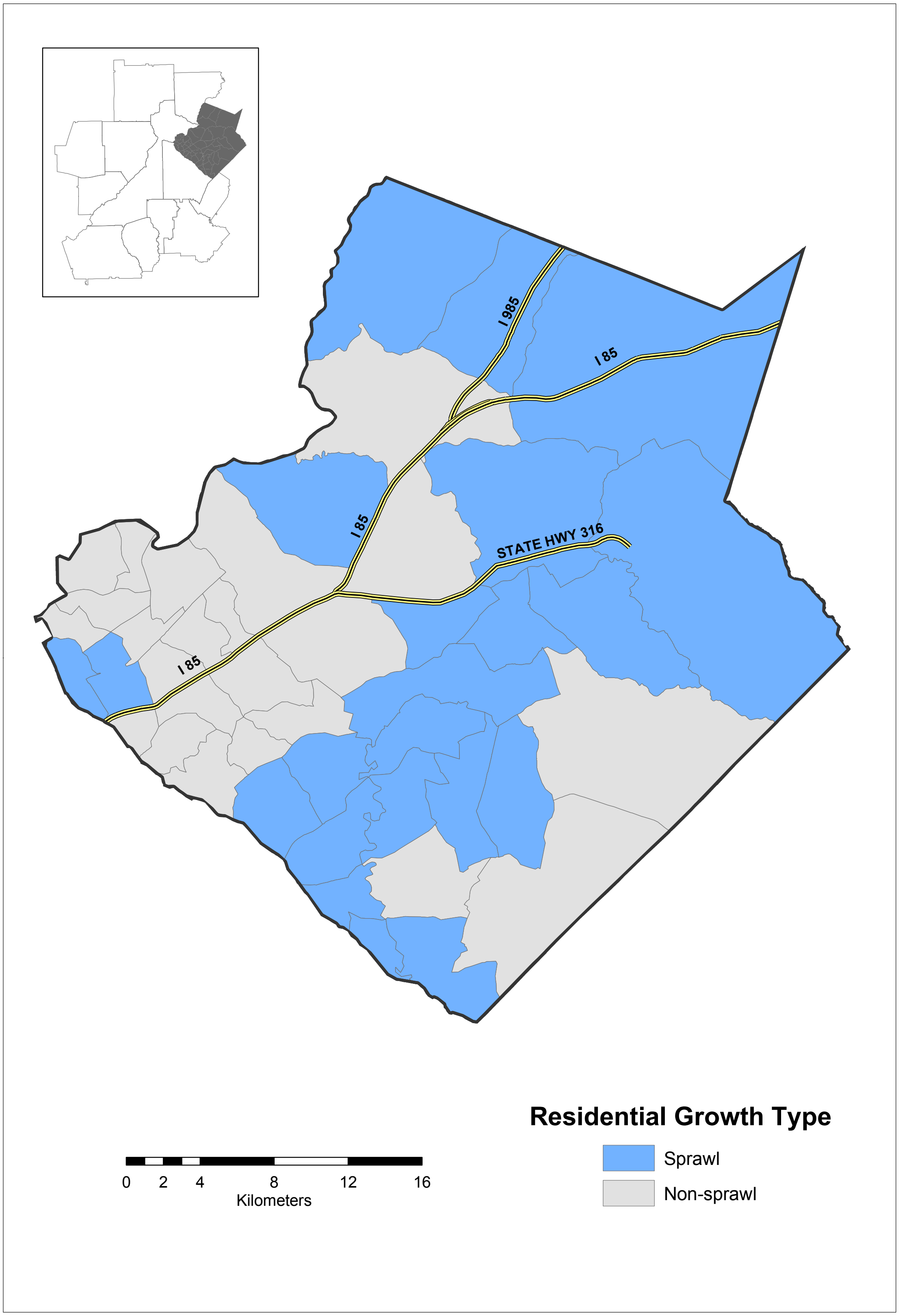

Figure 4.22. Urban sprawl, by 1990 census tract, Gwinnett County, Georgia, 1980-2000.

Comparability/Relationship Files.* Table 4.3 compares the percentages of affected population as determined by the dasymetric method to the percentages derived from the Tract Comparability/Relationship Files. The mean absolute difference between the two methods is 3.65%, with a range of 0% to 14%, and a median of 2%. Except for two outliers (tracts 230 and 57), the dasymetric satellite image-based method appeared to work satisfactorily.

The application of dasymetrically-derived areal interpolation weights is not limited to census tract boundary changes. Instead, this method is applicable across any types of geographic boundary (e.g., from census tracts to zip code tabulation areas; from census tracts to local school districts; and from zip code areas to telephone exchange prefix areas).

Conclusion

This paper reported on the application of satellite-derived ancillary land-use/land-cover data to map population densities using the dasymetric method. The dasymetric method accounts for the spatial distribution of population within administrative areas, yielding more precise density estimates while graphically representing the geographic distribution of populations. Dasymetric population density maps were presented for 1980, 1990, and 2000 for a rapidly-growing thirteen-county area corresponding to metropolitan Atlanta, Georgia, which succeeded in revealing more realistically the urban sprawl characteristics of growth than using the conventional choroplethic method. The more-precise dasymetric population densities were used in a separate analysis of the

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* These percentage changes could have been used to weight the census data for use in subsequent analyses, however, these percentages were not discovered until after data analysis. Therefore, data analysis for the larger Atlanta mortality study was performed using dasymetrically adjusted census data.

Table 4.3. Comparison of percentages of affected population from census tract boundary shifts: dasymetric method versus Tract Comparability/Relationship Files.

Affected Census Tracts	Census Years	Dasymetric Method (%)	Tract Comparability/ Relationship Files (%)	Difference (absolute)
107	1980-1990	0	0	0
218.05	1980-1990	33	35	2
230	1980-1990	40	53	13
312.04	1980-1990	8	4	4
314.03	1980-1990	0	2	2
807.98	1980-1990	22	22	0
1701	1980-1990	0	0	0
1702	1980-1990	10	17	7
1703	1980-1990	23	31	8
57	1990-2000	25	11	14
94.01	1990-2000	4	2	2
112.02	1990-2000	3	5	2
201	1990-2000	18	18	0
234.15	1990-2000	4	0	4
305.04	1990-2000	3	2	1
311.12	1990-2000	9	7	2
403.02	1990-2000	4	1	3
403.04	1990-2000	5	3	2
404.07	1990-2000	9	16	7
501.06	1990-2000	3	0	3
507.18	1990-2000	2	1	1
803.01	1990-2000	9	4	5
804.01	1990-2000	1	1	0
1403.03	1990-2000	4	2	2

effects of suburbanization on all-cause mortality for the metro Atlanta area (Chapter 6 of this dissertation).

The ancillary land-use/land-cover data were also used to derive adjustment weights for census data at the census tract level, where census tract boundary shifts made temporal data comparisons difficult. By determining the percentages of residential areas impacted by census tract boundary shifts, it is possible to re-weight the census data in order to estimate the census data in terms of the 1990 census tract boundaries, thus allowing all three years of census data (1980, 1990, and 2000) to be represented in one set of common census tracts (1990). Accuracy assessment of the dasymetrically-derived adjustment weights indicated a satisfactory level of accuracy for use in the Atlanta mortality research project. It was also discussed that this type of dasymetrically-derived areal interpolation is appropriate for many different types of geographic boundary aggregations, not just for census geography changes.

CHAPTER 5

A SPATIAL ANALYSIS OF MORTALITY, METROPOLITAN ATLANTA, GEORGIA, 1995-1999

Holt, J.B., Lo, C.P., Usery, E.L. and L.K. McCormick. To be submitted to *Social Science & Medicine*.

Introduction

The purpose of this paper is to describe the process of mapping and analyzing patterns of all-cause mortality in the thirteen-county Atlanta metropolitan area (Figures 5.1 and 5.2). This project is part of a larger research effort that assessed the relationship between observed patterns of mortality and potential explanatory variables in the physical and social environments.

The main goals of this project are to determine the feasibility of mapping mortality patterns at the level of the census tract; to identify potential patterns in the mortality data that differed significantly from the pattern of the underlying population; and to suggest relationships between any observed patterns and hypothesized explanatory variables. The results of this particular study were instrumental in assisting with the interpretation of results in the larger study, relating mortality outcomes with ecological factors.

Background

It is hypothesized that rapid population growth of metropolitan Atlanta (Table 5.1), especially through suburbanization from 1980-2000, had resulted in greater socioeconomic spatial variation, with increased polarization from the downtown urban core to the suburban fringe. Along with increased polarization, there had been a complex mixing of social class and socioeconomic position in the downtown urban core (as a result of gentrification) and in the outlying suburban fringe (as affluent households encroach on previously rural agricultural areas). These changes also have been manifested in changes to the physical and social environments of neighborhoods.

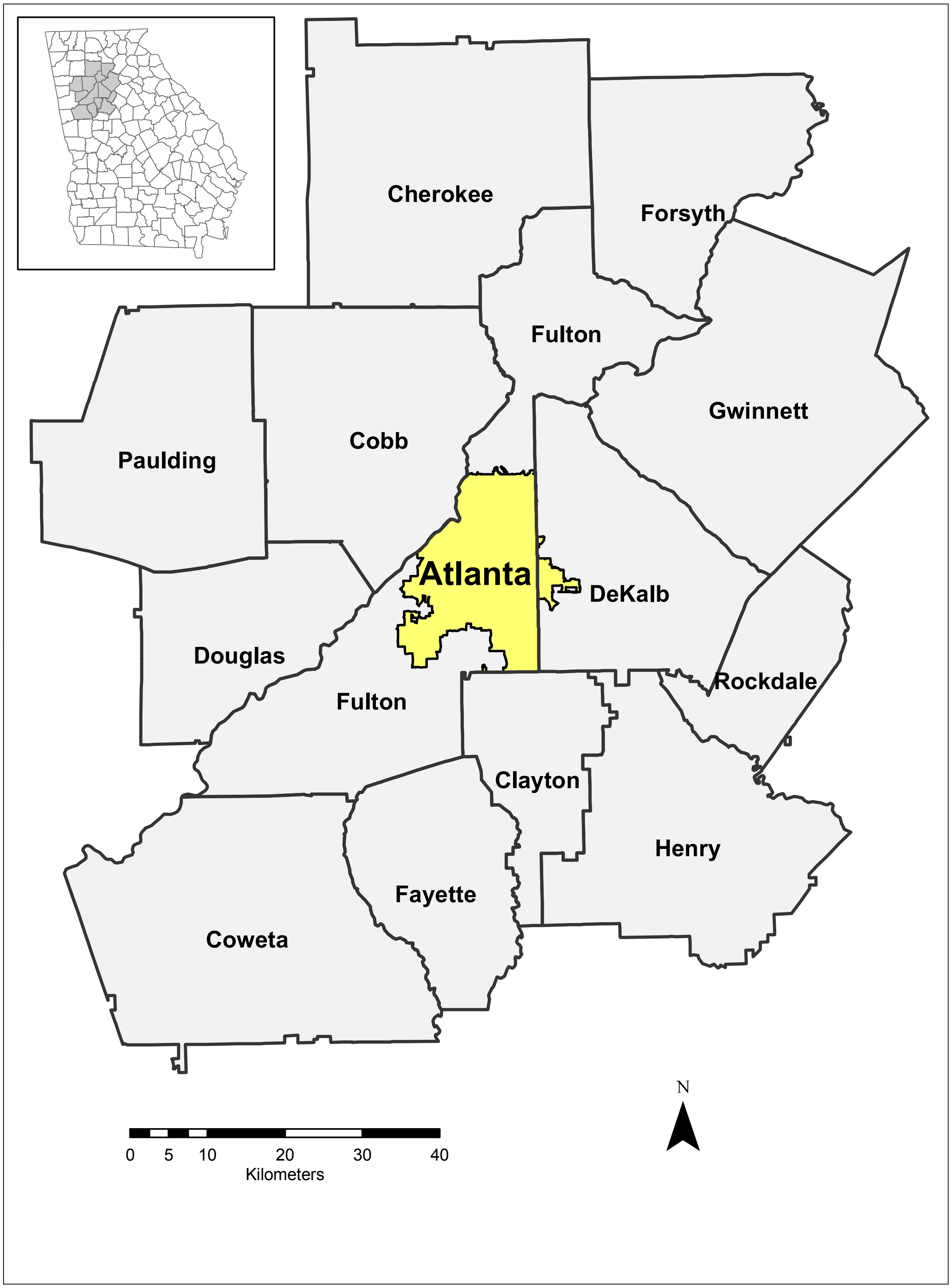

Figure 5.1. Thirteen-County Metropolitan Atlanta Study Area.

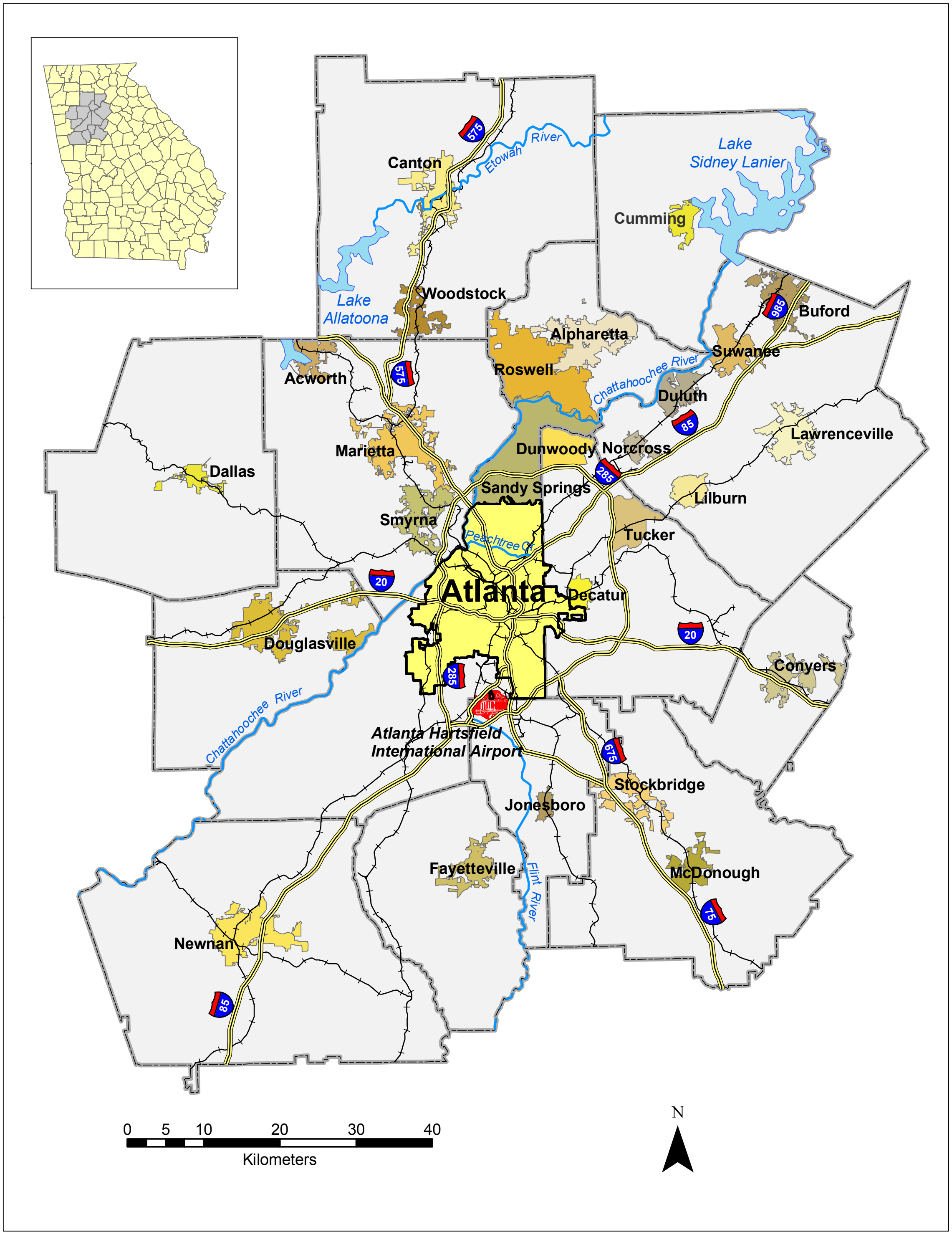

Figure 5.2. Principal cities, highways, railroads, and rivers, Metropolitan Atlanta, Georgia.

Previous public health research has demonstrated the linkages between health and measures of socioeconomic position, such as income, poverty, deprivation, wealth, and education (Osler *et al*, 2002; Sturm and Gresenz, 2002; Muller, 2002; Yen and Kaplan, 1999; Ben-Shlomo *et al*, 1996; Smith *et al*, 1996) . Significantly, these linkages hold at the individual, household, and neighborhood levels. Therefore, spatial patterns in health outcomes are likely to mirror spatial patterns of socioeconomic position, and may be explained to some degree by factors which are correlated to changes in the socioeconomic spatial pattern. These mortality patterns are complex and likely masked by aggregation of data at the county-level; only by examining spatial patterns at a finer spatial resolution, such as census tracts, can the complexity of these patterns be seen.

Table 5.1. Population Growth, 1980-2000, Metropolitan Atlanta (Source: U.S. Census Bureau, 2002).

County	**1980**	**1990**	**2000**	**% change 1980-2000**
Cherokee	51699	90204	141903	174.5
Clayton	150357	182052	236517	57.3
Cobb	297718	447745	607751	104.1
Coweta	39268	53853	89215	127.2
DeKalb	483024	545837	665865	37.9
Douglas	54573	71120	92174	68.9
Fayette	29043	62415	91263	214.2
Forsyth	27958	44083	98407	252.0
Fulton	589904	648951	816006	38.3
Gwinnett	166903	352910	588448	252.6
Henry	36309	58741	119341	228.7
Paulding	26110	41611	81678	212.8
Rockdale	36747	54091	70111	90.8
13-County Total	1989613	2653613	3698679	85.9

The first step in examining these relationships was to map the incidence of mortality for the study area. In doing so, three outcome measures were derived: 1) observed mortality events (unadjusted counts); 2) crude mortality rates (number of deaths per 100,000 population); and 3) Standardized Mortality Ratios (SMRs). These three measures are aggregated to the census tract level and were analyzed using methods appropriate for areally aggregated data; in addition, point data (locations of decedents' residences) were available for point pattern analysis.

Following the mapping of mortality incidence and calculation of crude mortality rates and SMRs, several measures of spatial analysis were computed, mapped (where possible) and interpreted, including: global indices of spatial autocorrelation (Moran's I and Geary's C); a Local Indicator of Spatial Association, or LISA (e.g., Local Moran); global measures of clustering (Nearest-Neighbor Analysis, K-order Neighbor Analysis, and Ripley's K-function); and local measures of clustering (Risk-adjusted Nearest-Neighbor Hierarchical Spatial Clustering and the Spatial Scan Statistic).

Computing and Mapping Mortality Incidence

The mortality data used for this study were obtained from the Georgia Division of Public Health, in Atlanta, Georgia. Data were obtained for 1980 through 1999; however, only data from 1995 through 1999, inclusive, contained a database field for the decedents' residential address. This information is necessary in order to geocode (address-match) the residential locations, from which point-level information were obtained and area-based rates computed at the census tract level. The database contained a total of 102,016 death records for the thirteen counties of the study area.

The data were geocoded through an iterative process, utilizing two software packages and two street file databases. The data were first converted from text files into Microsoft Access format for data manipulation, then saved as DBF files for incorporation into a geographic information system (GIS). The first geocoding iteration was performed in ArcInfo 8.2 ™ (Environmental Systems Research Institute, Redlands, CA) using the U.S. Census Bureau's 2000 TIGER Line Files as the street matching file. Initial match rates ranged from 58% (Paulding County) to 86% (Clayton County). There were many reasons for unmatched records, including: typographic errors, transpositions of street address numbers, abbreviations of street names, house addresses outside the address range in the TIGER database, street names not contained in the TIGER database (either due to the TIGER database not being up-to-date or because of the use of alternate or vernacular street names), no address reported in the address field, and addresses listed as "unknown".

Interactive matching was conducted on unmatched records. This involved human intervention in the process: for unmatched records, ArcInfo provides several possible "candidates" for matches; the analyst then must make an informed decision as to which candidate, if any, should be selected as the match. Through such an interactive and subjective process, success rates dramatically improved after generally three-to-four additional processing runs. The final success rate from geocoding with ArcInfo and TIGER Line Files ranged from 75% (Paulding County) to 92% (DeKalb County).

All records (matched and unmatched) were then geocoded with a second software application and database (Centrus Desktop 4.0 and Sagent Company's Address Coding Module). This was done in order to improve the overall geocoding rate as well as to serve as a check on the accuracy of the geocoding results from the ArcInfo/TIGER processing step. As in ArcInfo, Centrus also allows interactive matching. As a result, final match rates ranged from 58% (Paulding County) to 96% (Henry County).

The results from ArcInfo and Centrus were merged into one database file. Where both applications successfully geocoded a record and obtained identical or near-identical coordinates, that record was kept (with the associated latitude and longitude coordinates) in the database file. Where neither application geocoded a record, that record was exported into a separate database file for unmatched records. Where ArcInfo and Centrus both assigned a geocode, but the coordinates varied substantially, the Centrus geocode was assigned and the record was kept in the database. Centrus was thus used as the "gold standard" in this case as the Sagent Address Coding Module database is updated approximately every 90 days. Where only Centrus or ArcInfo assigned a geocode, that particular geocode was assigned and the record was kept in the database. In this manner, the final set of address-matched records was developed. Following the merger of ArcInfo and Centrus database information, the match rates for the area ranged from 83% (Paulding County) to almost 98% (Henry County).

Paulding County represented a special case, in that its match rate was significantly lower than that of the other twelve counties (Table 5.2). This is possibly due to the fact that Paulding County was a very rural county until recently, and has experienced a rapid increase in residential neighborhood construction, along with new roads to serve these neighborhoods. It is likely that the street file databases have not been kept as up-to-date in this county as with other more-developed counties. In order to interactively match records from Paulding County, a large scale paper map of the study

Table 5.2. Geocoding Match Rates (percentages).

County	**Number of Deaths**	**ArcInfo/TIGER Match Rate**	**Centrus/Sagent Match Rate**	**Final Match Rate (Combined with Interactive Matching)**
Cherokee	3,486	91.11	94.55	94.92
Clayton	6,106	91.52	94.28	96.61
Cobb	14,364	91.36	94.05	96.50
Coweta	2,807	88.31	91.34	96.62
DeKalb	20,451	92.68	93.75	96.84
Douglas	2,760	85.76	92.86	95.18
Fayette	2,081	89.14	94.15	96.00
Forsyth	2,122	88.27	92.55	96.09
Fulton	30,568	87.57	92.00	95.62
Gwinnett	10,014	90.94	93.50	95.72
Henry	2,946	91.17	95.82	97.79
Paulding	1,811	75.42	57.92	94.10
Rockdale	2,206	88.12	91.38	96.33
Total for Area	102,016	89.74	92.44	96.03

region was obtained (Atlanta Regional Wall Map, ADC Co., Alexandria, VA) along with a comprehensive Atlanta regional road atlas (also from ADC Co.). Fortunately, Paulding County contained only six census tracts in 1990, all of which covered relatively large areas. The 1990 census tract boundaries were carefully hand-drawn on the regional wall map. Streets for unmatched records were located in the road atlas and then cross-referenced to the regional wall map. If the street or road began and ended *entirely* within a census tract, that mortality record was then geocoded to the centroid of the census tract. This procedure worked exceptionally well for Paulding County (192 of 305 unmatched records), but it is unlikely that this would work as well in more-populated areas because of smaller census tract areas, as it is much more likely that streets would extend across multiple census tracts. As a result of this process, the final match rate for Paulding County is 94%. Table 5.2 details the match rates for all thirteen counties.

The results of the geocoding process are represented in Figure 5.3, which shows the locations of the geocoded residential addresses, for the period 1995-1999, in the thirteen-county area. Of the 97,966 successfully-geocoded records, 56 locations fell outside the thirteen-county area. This is most likely due to a discrepancy in listing the county of residence on the death certificate. For example, a decedent with a residential address of Loganville (the city limits extend across both Gwinnett and Walton Counties) may have a county of residence listed as “Gwinnett”, while in reality that portion of Loganville which contains their residence is in Walton County. When geocoded, the residential location would appear in Walton County. After removing these 56 records, the resulting file of geocoded deaths totaled 97,910 records.

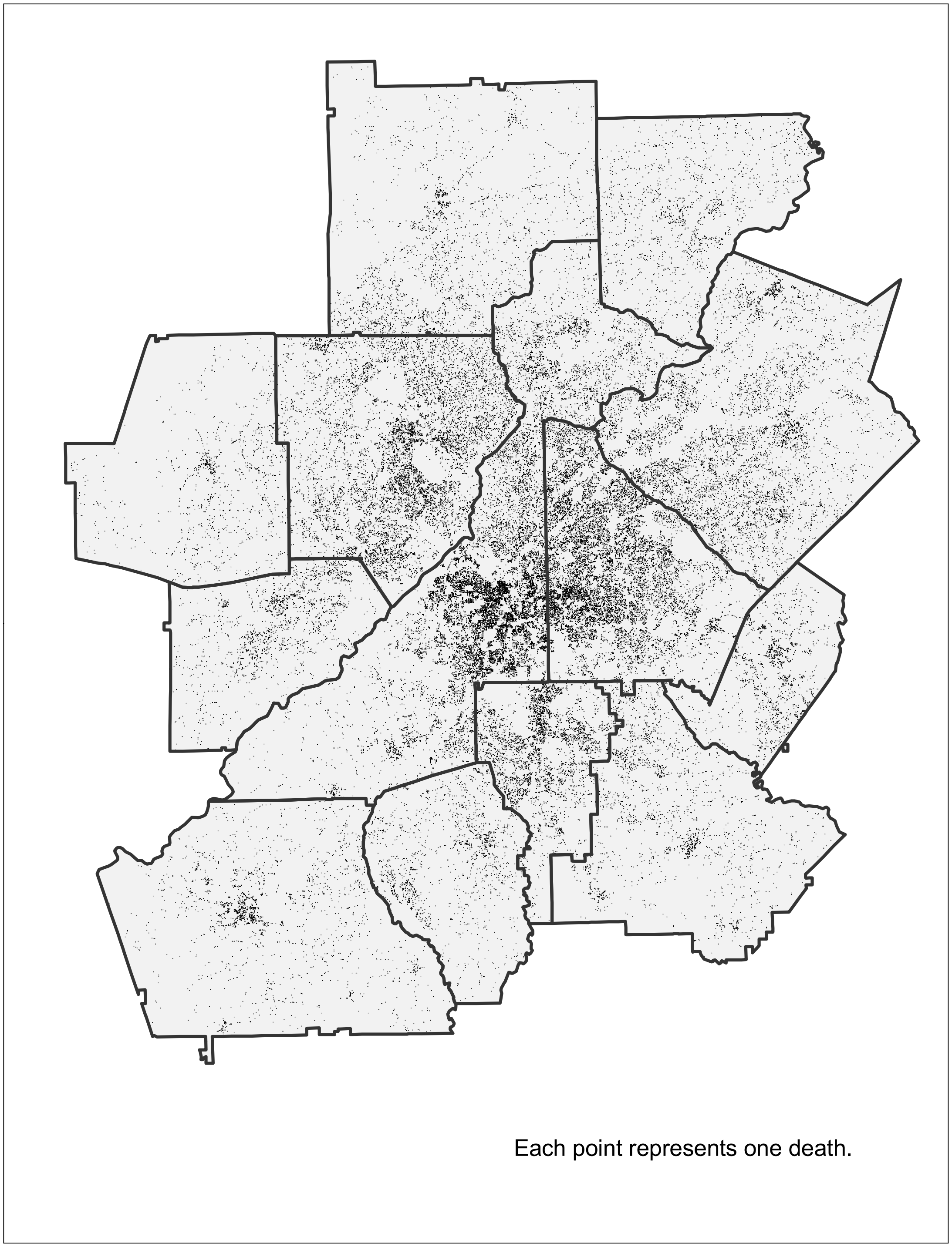

Figure 5.3. Geocoded Deaths, Metropolitan Atlanta, 1995-1999.

The next stage in mapping the mortality patterns was to construct a table and map of the crude mortality rates for each census tract. This was accomplished by dividing the count of geocoded deaths in each census tract by five and then by that tract's estimated 1997 population and multiplying by 100,000. The year 1997 is chosen as it represented the midpoint of the five-year span for which mortality data are available; its population represents the average population in each tract over the five-year span. This involved three distinct steps: 1) obtaining the total number of mortality events (e.g., geocoded addresses) in each tract; 2) estimating each tract's 1997 population; and 3) performing the rate calculation in a GIS.

The first step of obtaining the total number of deaths per tract was performed in ArcInfo 8.2 ™, using a spatial join procedure. A polygon layer, representing the 1990 census tracts, was spatially joined with the database file containing the geocoded mortality data. The resulting join was exported as a separate layer, which contained a field with the number of mortality events per record (e.g., per tract).

The second step of calculating the estimated 1997 tract-level populations involved an interpolation of tract level population from 1990 to 2000 (Yang, 2000). The 1990 and 2000 tract level populations were downloaded via the U.S. Census Bureau FactFinder website: (http://factfinder.census.gov). An annual rate of population change was determined by applying the following formula to the 1990 and 2000 population figures for each tract:

$$\%\mathrm{Inc} = e\ [(\ln(\mathrm{pop}_{2000}) - \ln(\mathrm{pop}_{1990})) / 10] - 1 \qquad (5.1)$$

Where the constant e equals 2.71828182845904, the base of the natural logarithm.

The rate of annual population change was applied in the following formula to determine the estimated 1997 population:

$$\text{Pop}_{1997} = \text{pop}_{1990} * [(1 + \%\text{Inc}) * 7] \qquad (5.2)$$

The estimated 1997 tract-level populations were tabulated in a Microsoft Excel worksheet, which was then exported as a DBF file to ArcInfo 8.2™, where it was merged with the existing layer of tract-level mortality counts. This enabled the calculation of the crude mortality rates directly within the GIS. The resulting tract-level crude mortality rates are depicted in Figure 5.4.[*] In a similar manner, age-group-specific population estimates were calculated for 1997; these estimates were used in computing indirectly age-adjusted mortality rates (described later).

In general, the crude mortality rates were highest in the inner city, the inner suburban areas, and in several isolated rural census tracts (e.g., in Forsyth, Cherokee, Paulding, Douglas, Coweta, and Rockdale Counties). Crude mortality rates were lowest in outer suburban areas, especially in Gwinnett, north Fulton, Cobb, and DeKalb Counties.

The crude mortality rate does not account for variations in the age structure of the underlying population at risk. In other words, in areas (tracts) with higher proportions of older adults, it is likely that the mortality rate will be higher than in areas with lower proportions of older adults. This is simply because age is a primary risk factor for death. This phenomenon can be illustrated by comparing the mortality rates for a state with a high proportion of senior citizens (Florida) to that with a lower proportion of senior citizens (California). One would expect that the mortality rate would be higher in

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[*] Data for Figures 5.3 and 5.4 were classified by quintiles, as recommended for epidemiological data by Brewer and Pickle (2002). Color schemes were chosen based on Brewer's *et al* (1997) recommendations, with color specifications derived from Brewer *et al* (2003).

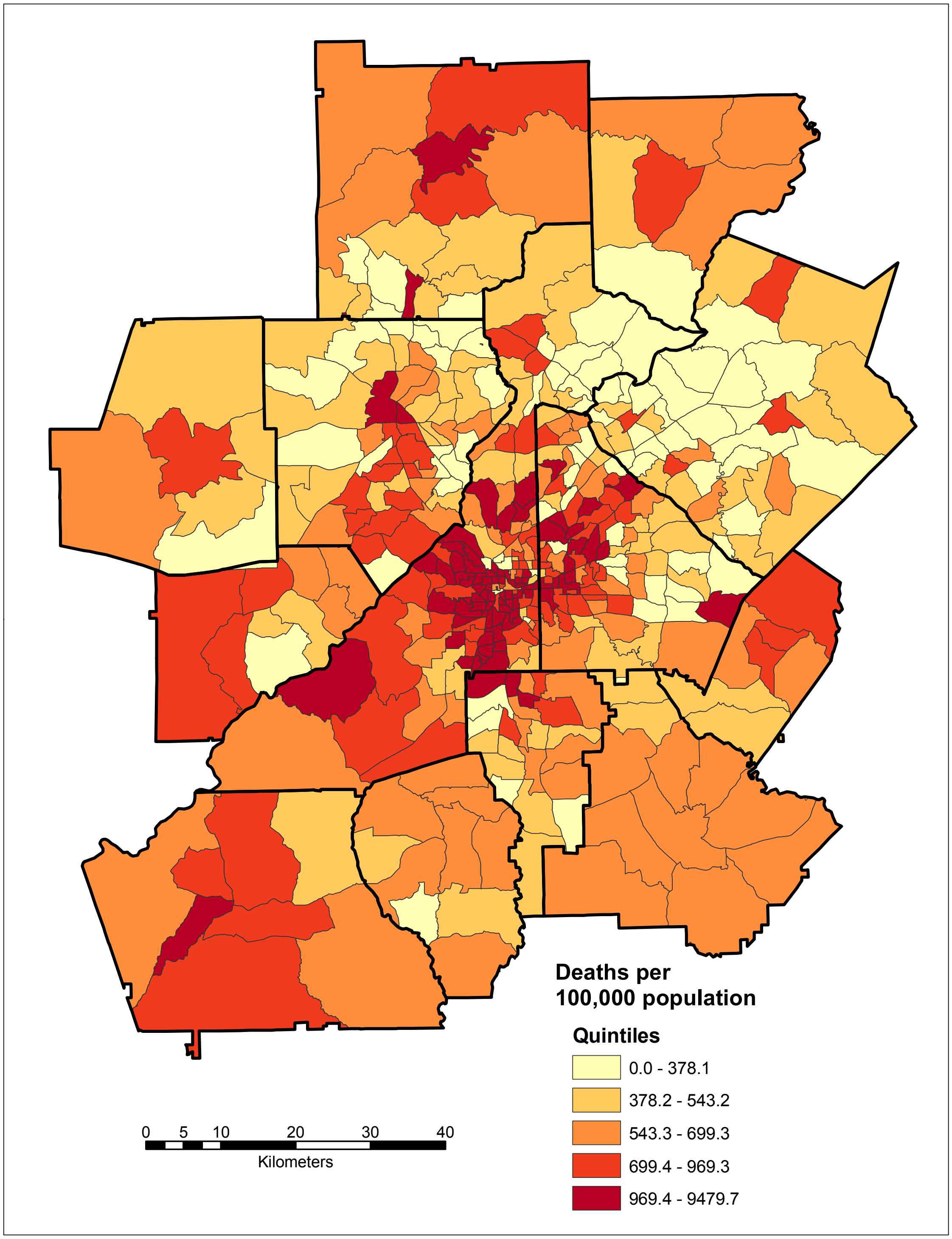

Figure 5.4. Crude Mortality Rates, Metropolitan Atlanta, 1995-1999.

Florida, all things being equal, given the higher proportion of older adults in that state. In order to be able to directly compare mortality rates among areas, it is necessary to correct for variations in the underlying age-structure. This is done through age-adjustment procedures (U.S. Department of Health and Human Services, 2001).

There are two options for computing age-adjusted mortality rates. In the first option, the observed tract-level age-specific (e.g., ages 15-24, 25-34, etc.) rates are multiplied by the proportion of the U.S. population represented by that age group, then summed, and the total is divided by the U.S. population, and multiplied by 100,000. The resulting rate is similar in form to the crude mortality rate (e.g., number of deaths per 100,000 population), but it has been adjusted to account for the unique population structure of that particular area. This direct method of age-adjustment is applicable only if there are sufficient numbers of deaths per age group within each tract to produce stable mortality rates. Where this is not possible, an alternate method of indirect age-adjustment is used (Friis and Sellers, 1999).

Indirect age-adjustment applies the age-specific death rates for the U.S. population to the age-specific populations within each census tract. In a sense, it is the opposite of the direct adjustment procedure. The indirect method was used for this study, given the lack of sufficient numbers of deaths, per age group, per census tract.

To begin the adjustment process, it was necessary to compute the average death rates for U.S. population per age-group. Mortality data were downloaded from the Centers for Disease Control and Prevention, National Center for Health Statistics website: (http://www.cdc.gov/nchs, accessed October 2, 2002). Data were available for all five years of the study period. These data were numerically averaged in order to estimate the mortality rate over the five-year period (Table 5.3). The age-specific rate estimates were then multiplied by tract-level 1997 age-specific population estimates. The results are the estimated number of deaths per age-group in each census tract, if those tracts were to experience the same death rate, per age-group, as the overall U.S. population.

Table 5.3. Crude Death Rates, U.S. Population, 1995-1999. (Source: National Center for Health Statistics.)

	Crude Death Rates (deaths per 100,000 population)					
Age	**1995**	**1996**	**1997**	**1998**	**1999**	**Average 1995-1999**
Under 5	183.6	179.0	175.2	177.3	175.2	178.06
5-14	22.5	21.7	20.8	19.9	19.2	20.82
15-24	95.3	89.6	86.2	82.3	81.2	86.92
25-34	141.3	126.7	115.0	109.6	108.3	120.18
35-44	240.8	221.3	203.2	199.6	199.2	212.82
45-54	460.1	445.9	430.8	423.5	427.3	437.52
55-64	1114.5	1094.1	1063.6	1030.7	1021.8	1064.94
65-74	2563.5	2538.4	2509.8	2495.1	2484.3	2518.22
75-84	5851.8	5803.1	5728.2	5703.2	5751.3	5767.52
85+	15469.5	15327.2	15345.2	15111.7	15476.1	15345.94

The estimates for each age-group are summed to obtain an overall expected number of deaths for each tract. The observed numbers of deaths per census tract are then divided by the estimated number of deaths in order to obtain a ratio of observed-to-expected deaths. This ratio is called the Standardized Mortality Ratio (SMR), a commonly-used index of mortality risk for an area. If a census tract has an SMR of 1.0, that census tract would have the same approximate mortality risk as that of the general U.S. population. If the SMR is greater than 1.0, then the mortality risk is greater than that of the U.S. population. If the SMR is less than 1.0, the mortality risk is lower than that of the U.S. population.[*]

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[*] Mortality data for all census tracts are contained in Appendix C.

SMRs can be mapped for visual comparison (Figure 5.5). Visual interpretation of Figure 5.5 suggests a pattern of mortality in which the highest rates were concentrated in the City of Atlanta and in southwest DeKalb County, while the lowest rates were concentrated in the suburban fringe (Gwinnett, north and east Cobb, Fayette, north Fulton, Forsyth, and north DeKalb Counties). Most of these areas are to the north of the study area, with the exception of Fayette County. Areas of elevated rates were also located in Cherokee, south Cobb, Paulding, Douglas, Coweta, Clayton, and parts of Rockdale and Henry Counties. Generally, these areas are more rural. This visual analysis suggested that potential covariates for age-adjusted mortality might include race, ethnicity, income, poverty, and urbanicity/rurality, due to the anticipated spatial distributions of those variables.

Standardized Mortality Ratios can also be tested for statistical significance, by first computing the standard error of each SMR, constructing confidence intervals (CI) for a specified confidence level (e.g., 95%), then determining whether the 95% CI includes the value 1.0.

Computing the standard errors of SMRs involves the following formula:

$$S_e (S_i) = \sqrt{(n_i/e_i)} \qquad (5.3)$$

Where: n_i = observed number of events (deaths) for the i^{th} area

e_i = expected number of events (deaths) for the i^{th} area

S_i = SMR for the i^{th} area

The standard error is influenced by both the observed number of case events (e.g., deaths) as well as the population in each area, as the population affects the calculation of the expected number of case events. In general, the smaller the number of observed

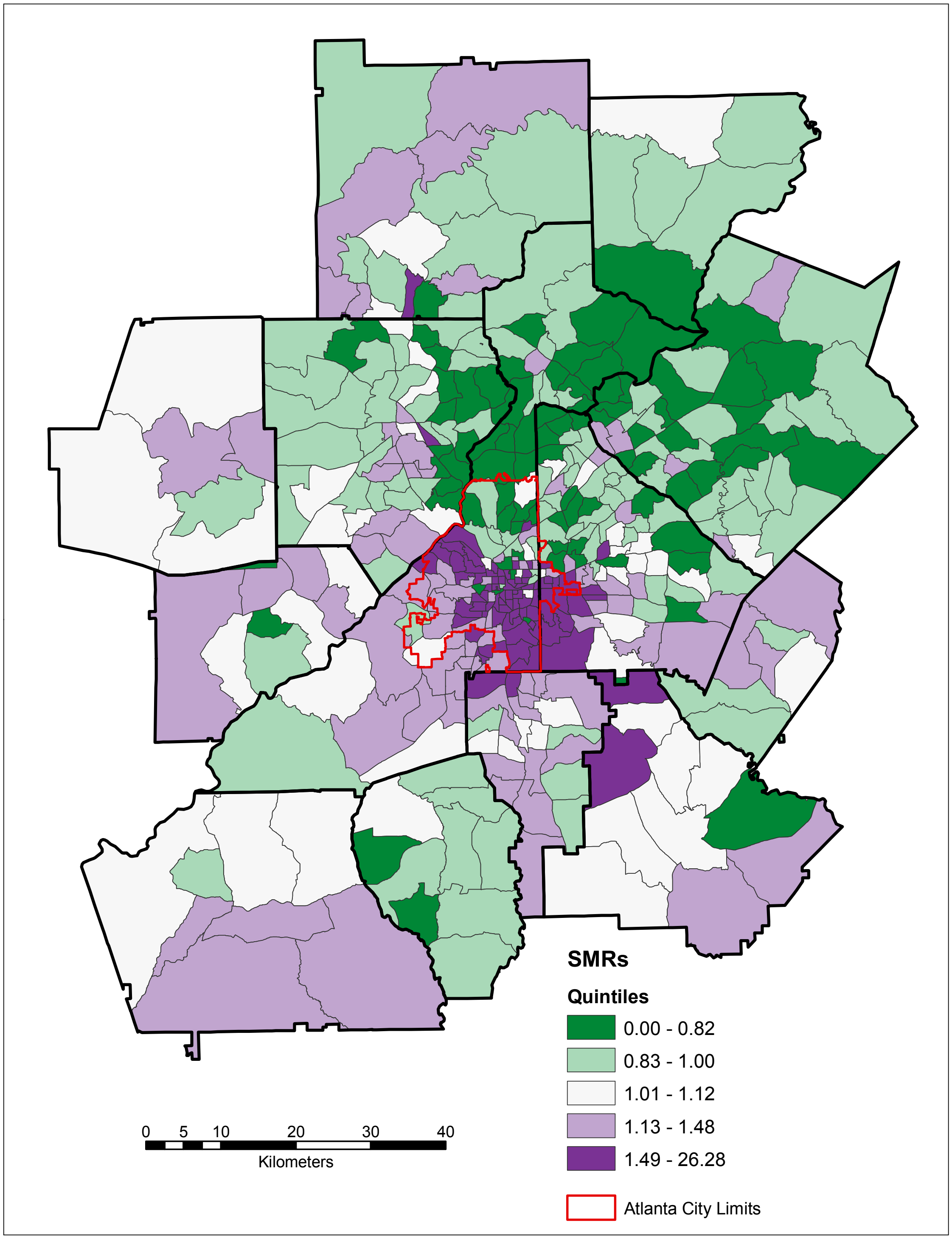

Figure 5.5. Standardized Mortality Ratios (SMRs), Metropolitan Atlanta, 1995-1999.

events, and the smaller the population of the area, the higher the resulting standard error of the estimated SMR. Figure 5.6 depicts the standard errors for the SMRs for the study area. The higher standard errors are found in the Atlanta Central Business District (CBD), around Hartsfield Airport, and in the less-populated areas in the surrounding counties. These areas have both lower observed counts of mortality as well as smaller populations.

Confidence intervals (CI) were constructed at the 95% level, by applying the following formulae to the Standardized Mortality Ratios (Kahn and Sempos, 1989):

$$SMR_{Ui} = SMR_i + 1.96 \sqrt{(SMR_i / e_i)} \qquad (5.4)$$

$$SMR_{Li} = SMR_i - 1.96 \sqrt{(SMR_i / e_i)} \qquad (5.5)$$

Where: SMR_{Ui} = upper confidence limit for SMR of the i^{th} area

SMR_{Li} = lower confidence limit for SMR of the i^{th} area

e_i = expected number of events (deaths) for the i^{th} area

Figure 5.7 depicts census tracts for which the 95% CI does not include the value 1.0. In other words, for those census tracts, either the upper limit of the 95% CI was less than 1.0 or the lower limit of the 95% CI was greater than 1.0. In either case, the SMRs can be said to be significantly different from unity at the 95% confidence level. Those tracts represent areas that have significantly elevated or reduced mortality risk, with respect to the overall U.S. population.

Having computed and mapped the point events (individual deaths) and the associated mortality rates for the study area, it was possible to conduct a preliminary assessment of spatial patterns in the data. Two statistical packages were utilized in the

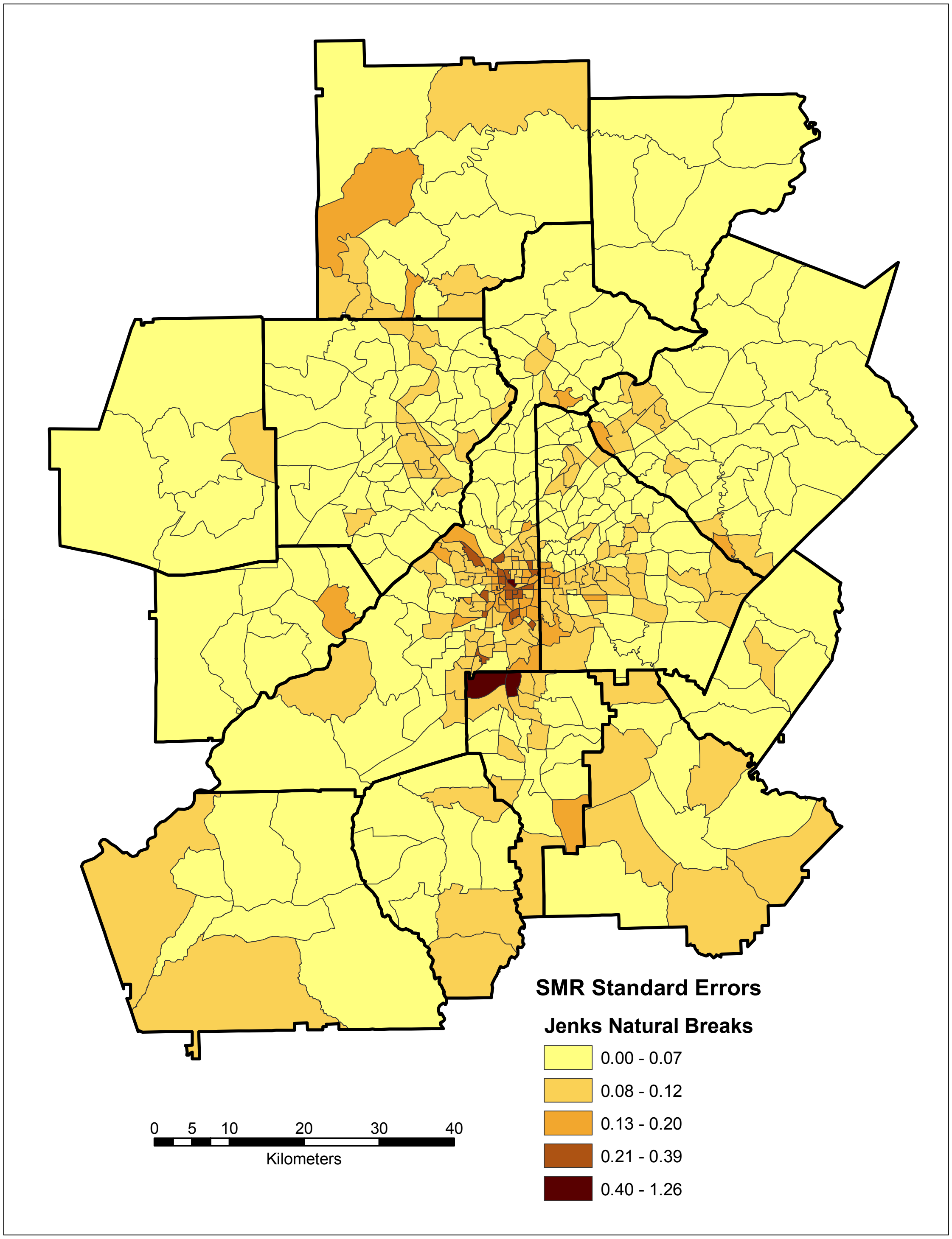

Figure 5.6. Standard Errors for Standardized Mortality Ratios, Metropolitan Atlanta, 1995-1999.

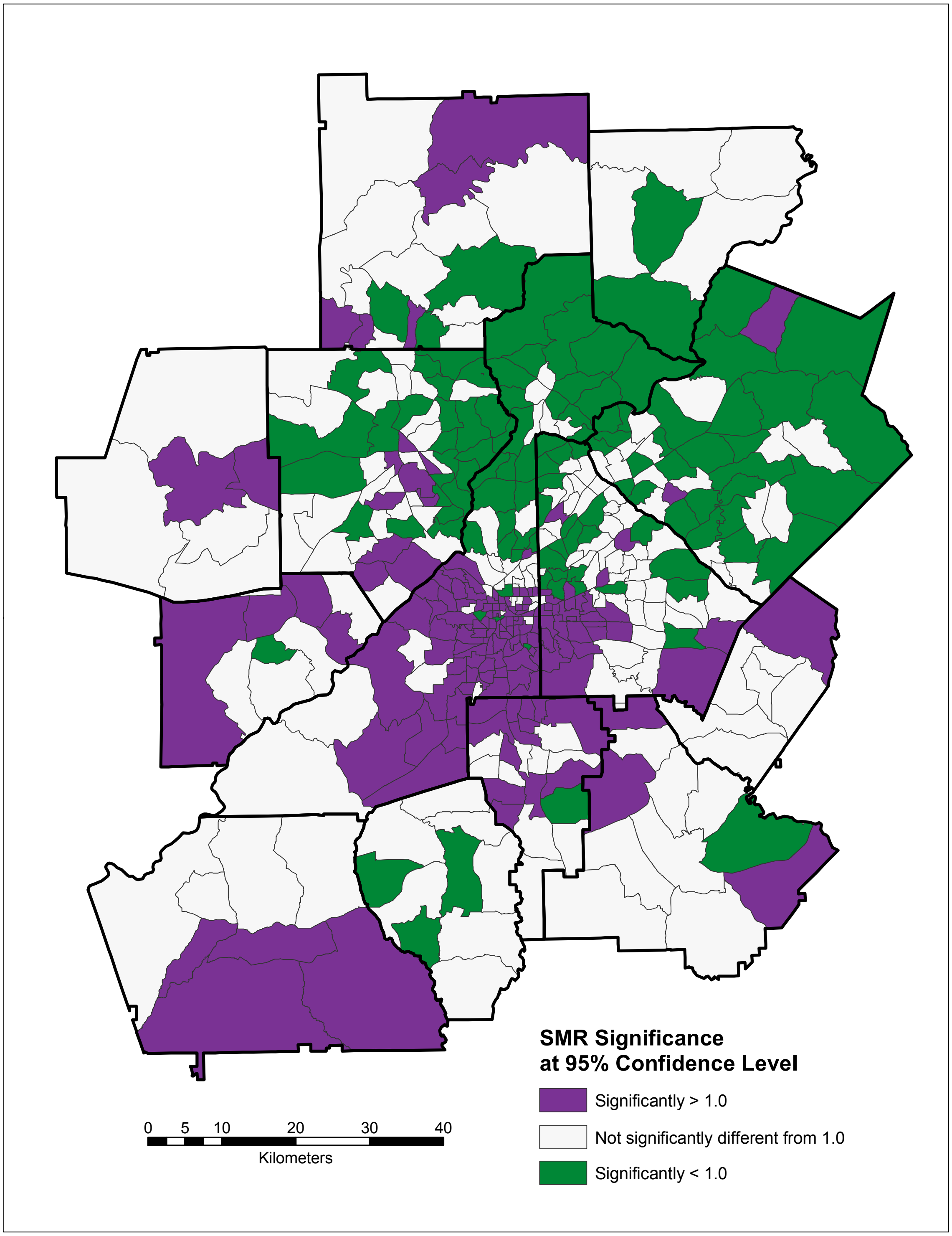

Figure 5.7. Standardized Mortality Ratio (SMR) Significance at 95% Confidence Level, Metropolitan Atlanta, 1995-1999.

procedures described below: The first, Crimestat II (Ned Levine & Associates, 2002), was developed under a contract from the National Institute of Justice, Office of Justice Programs, U.S. Department of Justice. Although originally intended for the analysis of crime incident locations, this is a very robust program that can be used with any point and area-level data for the analysis of spatial patterns. The second program, SaTScan 3.0 (Martin Kulldorff and the National Cancer Institute, 2002), is intended for use with health-related data, specifically to detect clusters of health events in space and time.

Five general types of spatial analyses are possible, using these two spatial statistical packages in combination with a GIS: 1) simple visual interpretation of point and areal patterns; 2) global indices of spatial autocorrelation (Moran's I and Geary's C); 3) a Local Indicator of Spatial Association (Local Moran); 4) global measures of clustering (Nearest-Neighbor Analysis, K-order Neighbor Analysis, and Ripley's K-function); and 5) local measures of clustering (Risk-adjusted Nearest-Neighbor Hierarchical Spatial Clustering and the Spatial Scan Statistic). The global and local measures of spatial autocorrelation used in this project were based on areally-aggregated data: mortality counts aggregated to the census tract level, crude mortality rates, and Standardized Mortality Ratios (SMRs). The global and local measures of clustering utilized point data: geocoded locations of decedents' residential address.

Assessment of Spatial Autocorrelation

Global Measures of Spatial Autocorrelation

Moran's I coefficient provides an assessment of the degree of spatial autocorrelation across the entire study area. Moran's I compares the value of a variable at any one location with the value of that variable at all other locations. Since Moran's I applies only to areal data, individual point data such as mortality events must first be aggregated into counts or rates. Moran's I can be defined by the following formula (Cliff and Ord, 1981):

$$I = \Sigma\Sigma W_{ij}C_{ij} / S^2\Sigma\Sigma W_{ij} \qquad (5.6)$$

Where: W_{ij} denotes locational similarities

C_{ij} denotes attribute similarities: $C_{ij} = (Z_i - \overline{Z})(Z_j - \overline{Z})$

S^2 denotes sample variance: $s^2 = \Sigma\ (Z_i - \overline{Z})^2 / N$

CrimeStat uses a distance matrix, rather than a contiguity matrix, for the measure of locational similarity (W_{ij}). Specifically, w_{ij} is equal to the inverse distance between locations i and j ($W_{ij} = 1/d_{ij}$).

As a measure to reduce the effects of scale on the computation of Moran's I, CrimeStat includes a user-selectable adjustment for small distances. Specifically, the numeric value for one mile is added to both the numerator and the denominator of the locational similarity calculation:

$$W_{ij} = (1 + 1\text{ mile})/(d_{ij} + 1\text{ mile}) \qquad (5.7)$$

This has the effect of forcing the minimum distance between points to be one mile in distance. This avoids the potential problem of two near points (e.g., 1000 yards) having a disproportionately high similarity weight. It is theoretically possible for two *very* near points to have a weight that approaches infinity. This scaling factor precludes those possibilities.*

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* In this data set, Moran's I coefficients were calculated both with and without the adjustment for small distances. The differences in the final statistic were negligible. The results reported here are those obtained using the adjustment.

The significance of the Moran's I coefficients can be estimated by comparing the coefficients to the Moran's I of a theoretical distribution and dividing by an estimate of the standard deviation:

$$Z(I) = (I - E(I)) / S_{E(I)} \tag{5.8}$$

Where: $Z(I)$ = standardized Moran's coefficient

I = computed Moran's I coefficient for the dataset

$E(I)$ = expected Moran's I coefficient for a theoretical random distribution

$S_{E(I)}$ = standard deviation for the theoretical random distribution

There are two possible assumptions regarding the theoretical distribution: first, the sampling distribution follows a normal distribution (the normality assumption); second, the sampling distribution follows a random distribution (the randomization assumption). Z-values are reported for both the normality assumption and the randomization assumption. The Z-values for the computed Moran's I coefficients can then be compared to a statistical table to determine their significance levels. In a similar manner, the Moran's I coefficients for two distributions (e.g., mortality counts and population) can be compared to each other to determine whether the differences in I values are statistically significant:

$$Z(I) = (I_{obs} - I_{pop})/S_{E(I)} \tag{5.9}$$

Where: I_{obs} = Moran's I for the observed mortality counts

I_{pop} = Moran's I for the tracts' populations

$S_{E(I)}$ = standard deviation for the theoretical random distribution

Table 5.4 lists the Moran's I calculations for this dataset. The Moran's I coefficient for the census tracts' populations (I_{pop}) indicates that the distribution of the estimated 1997 population exhibits moderately positive spatial autocorrelation at the census tract level (I = 0.186).

Table 5.4. Moran's I Coefficients, Census Tract Level.

Variable	**Moran's I**	**Expected I**	$S_{E(I)}$	**Z-value (normality)**	**Z-value (randomization)**	**Z-value (difference from I_{pop})**
1997 Estimated Population (by census tract)	0.186	-0.002	0.004	45.187	45.229	N/A
Observed Mortality Events (by census tract)	0.070	-0.002	0.004	17.451	17.455	-27.737
Crude Mortality Rates (by census tract)	0.100	-0.002	0.004	24.543	26.091	-20.644
Standardized Mortality Ratios (by census tract)	0.027	-0.002	0.004	7.008	8.292	-38.179

Three separate measures of Moran's I were calculated in order to assess spatial autocorrelation of mortality. First, Moran's I was calculated for the number of observed mortality events (deaths) per census tract. The results indicate a slight degree (I = 0.070) of spatial autocorrelation. Moran's I was then calculated for the crude mortality rates for each census tract (I = 0.100), and suggests a modest degree of positive spatial autocorrelation. The Moran's I for the Standardized Mortality Ratios (SMRs) is substantially lower at I = 0.027.

In all three cases, the computed Moran's I coefficients were less than that for the 1997 estimated population (all significant at 0.001). This suggests that mortality events, when aggregated to the level of the census tract, are less positively spatially autocorrelated than the underlying population structure of the study area, which is graphically depicted in Figure 5.8.

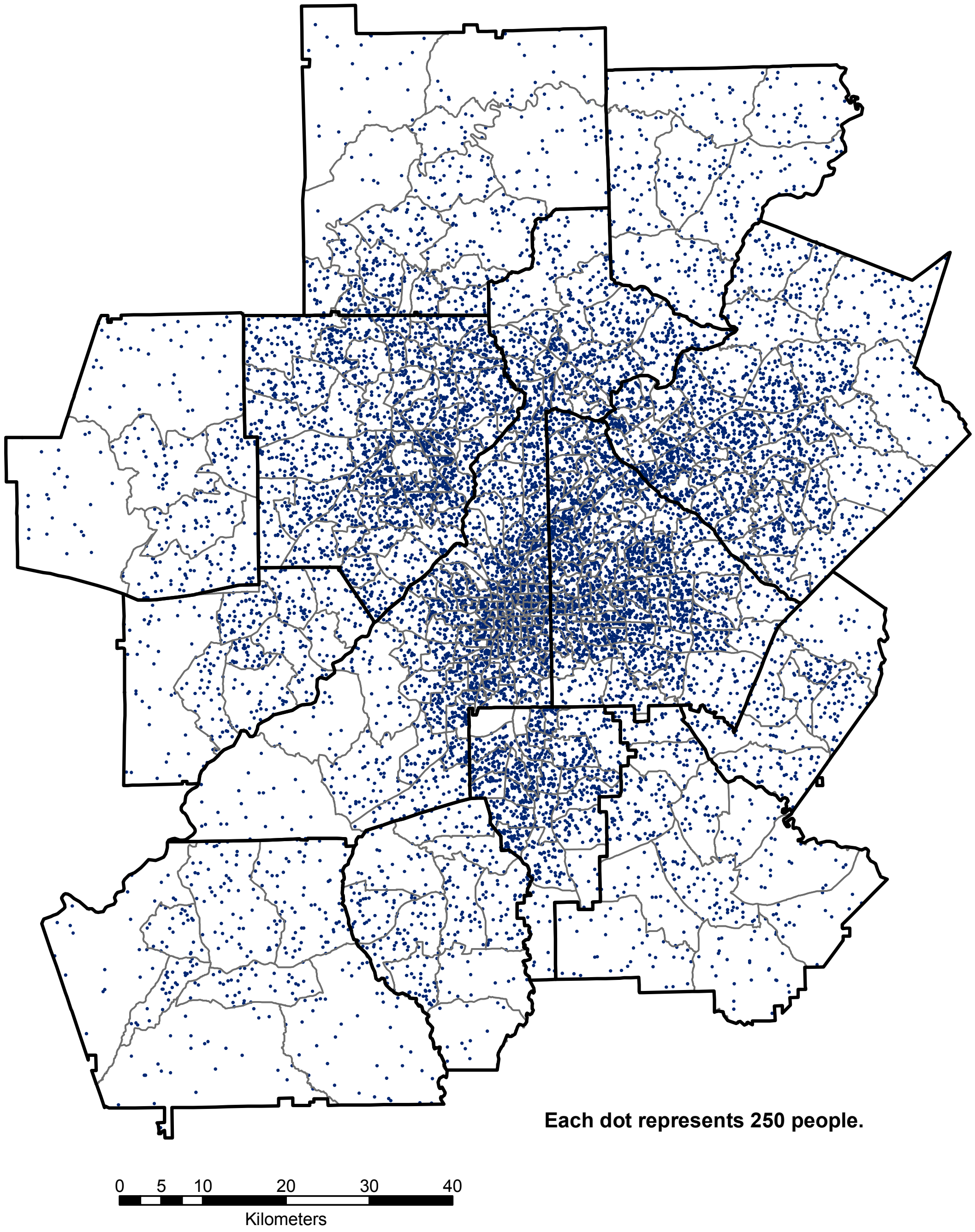

Figure 5.8. Population (Estimated), Metropolitan Atlanta, 1997.

Furthermore, the Moran’s I indices for each of the three measures of mortality, when compared to the Moran’s I for the 1997 estimated population, describe somewhat different relationships. The Moran’s I for observed mortality events does not account for the underlying population nor age structure of the census tracts. Therefore, its comparison to the Moran’s I for the 1997 estimated population is the most basic of the three comparisons. The comparison between Moran’s I for the crude mortality rates and the Moran’s I for the 1997 estimated population, controls for the population within each of the census tracts. In this case, even when controlling for census tract populations, there is a significant difference in spatial autocorrelation between mortality and population. Lastly, the SMRs represent an adjustment to the raw count data, taking into consideration the magnitude and the age structure of the underlying at-risk population. Consequently, the comparison of spatial autocorrelation between SMRs and 1997 estimated population is the most rigorous of the three comparisons, as it controlled for both population and age structure. In this case, the spatial autocorrelation for the SMRs is significantly lower than the spatial autocorrelation for the 1997 estimated population. This suggests that there is an underlying process affecting mortality within the study area, and that process results in a pattern of mortality that cannot be explained solely by the magnitude of census tract populations nor the age structure within each census tract.

Geary’s C ratio also assesses the degree of spatial autocorrelation, but is based on the deviations in intensities of each point location with one another, rather than on the cross-products of deviations from the mean, as in Moran’s I coefficient. While Moran’s I is considered more appropriate for measuring first-order spatial autocorrelation, Geary’s C is more sensitive to local clustering (Levine, 2002; and O’Sullivan and Unwin, 2003).

Both should be used in combination. Geary's C ratio is calculated as follows (Cliff and Ord, 1981):

$$C = (N-1) * [\Sigma\Sigma W_{ij} (Z_i - Z_j)^2] / 2 * (\Sigma\Sigma W_{ij}) \Sigma(Z_i - \overline{Z})^2 \qquad (5.10)$$

Where: N = number of observation locations (e.g., census tracts)

$W_{ij} = 1/d_{ij}$

Z_i = value of variable Z at the i^th location

Z_j = value of variable Z at the j^th location

$\overline{Z}$ = mean value of variable Z

Values of C less than 1.0 indicate positive spatial autocorrelation; values of C greater than 1.0 indicate negative spatial autocorrelation, or dispersion. As with the Moran's I coefficient, Crimestat II software provides an adjustment (identical in form) for small distances in the calculation of Geary's C ratios. The Geary's C ratios for this dataset are given in Table 5.5.

Table 5.5. Geary's C Ratios, Census Tract Level.

Variable	**Geary's C**	**Expected C**	**$S_{E(C)}$**	**Z-value (normality)**	**Z-value (difference from C_{pop})**
1997 Estimated Population (by census tract)	0.728	1.000	0.028	-9.635	N/A
Observed Mortality Events (by census tract)	0.897	1.000	0.028	-3.646	6.035
Crude Mortality Rates (by census tract)	1.037	1.000	0.028	1.310	11.038
Standardized Mortality Ratios (by census tract)	0.798	1.000	0.028	-7.156	2.500

The calculated Geary's C ratios suggest that the population of the study area tends to be positively spatially autocorrelated (C = 0.728). Likewise, the distribution of observed mortality events (deaths) and SMRs exhibit positive spatial autocorrelation at the level of the study area, although the degree of spatial autocorrelation is less than that of the population. The crude mortality rates, on the other hand, exhibit slightly negative spatial autocorrelation; however, this value is not significantly different from 1.0 (no autocorrelation) at the 95% confidence level (Z = 1.310). As with the results from the Moran's I calculations, the Geary's C indices suggest that mortality is less spatially autocorrelated than the underlying at-risk population *at the spatial scale of the entire study area* (all three mortality measures' C ratios differ significantly from that of the population at 95% confidence level).

To obtain a more precise indication of spatial autocorrelation at a spatial scale other than that of the entire area, it is possible to compute Moran's I and Geary's C at the county level, for mortality measures and for population counts. Comparisons can be made at the county level between spatial autocorrelation of mortality and spatial autocorrelation of the underlying county populations. These results of county-level Moran's I and Geary's C are given in Tables 5.6 and 5.7.

Unfortunately, while it is possible to compute measures of spatial autocorrelation at the county level, the relatively small numbers of census tracts per county result in very few counties' Moran's I coefficients and Geary's C ratios being statistically significant. This is verified by examining the Z scores for each county in Tables 5.6 and 5.7. Only those measures highlighted in red are significant at the 95% confidence level. Essentially, this applies to the most populated counties, and hence, those with larger numbers of census tracts: Cobb, DeKalb, Fulton, Gwinnett, and to a lesser extent, Clayton and Cherokee.

Table 5.6. Moran's I for Individual Counties.

County	**I (counts)**	**Z (counts)**	**I (crude rates)**	**Z (crude rates)**	**I (SMR)**	**Z (SMR)**	**I (pop)**	**Z (pop)**
Cherokee	0.062	1.535	-0.117	-0.810	-0.074	-0.223	-0.073	-0.186
Clayton	0.001	0.819	-0.021	0.479	-0.002	0.824	0.025	1.245
Cobb	**0.041**	**2.459**	**0.061**	**3.318**	**0.056**	**3.098**	**0.033**	**2.140**
Coweta	-0.102	0.257	-0.088	0.350	-0.115	0.172	0.034	1.112
DeKalb	0.004	0.917	**0.107**	**7.391**	**0.163**	**10.909**	**0.075**	**5.420**
Douglas	-0.176	-0.628	-0.171	-0.592	-0.130	-0.256	-0.163	-0.530
Fayette	-0.087	0.189	-0.032	0.649	-0.102	0.072	-0.052	0.459
Forsyth	-0.247	-0.222	-0.164	0.173	-0.148	0.248	-0.121	0.376
Fulton	**0.116**	**11.327**	**0.086**	**8.497**	**0.074**	**7.838**	**0.178**	**17.020**
Gwinnett	**0.134**	**5.009**	-0.016	0.185	-0.013	0.306	**0.056**	**2.529**
Henry	-0.109	-0.077	-0.037	0.529	-.065	0.307	-0.084	0.139
Paulding	-0.265	-0.291	-0.169	0.136	-0.167	0.144	-0.092	0.477
Rockdale	-0.294	-0.672	-0.030	0.722	-0.140	0.140	-0.269	-0.546

(Note: Values that are significant at 95% CI are depicted in **dark red**.)

Table 5.7. Geary's C for Individual Counties.

County	**C (counts)**	**Z (counts)**	**C (crude rates)**	**Z (crude rates)**	**C (SMR)**	**Z (SMR)**	**C (pop)**	**Z (pop)**
Cherokee	0.845	-1.483	**1.219**	**2.093**	1.182	1.742	1.098	0.941
Clayton	**0.863**	**-1.922**	**0.770**	**-3.225**	**0.795**	**-2.872**	**0.843**	**-2.203**
Cobb	**0.857**	**-3.116**	0.930	-1.513	1.086	1.873	**0.761**	**-5.202**
Coweta	1.034	0.301	0.957	-0.376	1.026	0.226	0.831	-1.484
DeKalb	1.018	0.514	0.940	-1.714	**0.882**	**-3.397**	**0.867**	**-3.833**
Douglas	1.082	0.941	1.019	0.221	0.984	-0.186	1.059	0.678
Fayette	0.993	-0.098	0.960	-0.521	0.990	-0.127	0.929	-0.931
Forsyth	1.090	0.813	0.963	-0.333	0.894	-0.953	0.848	-1.371
Fulton	**0.726**	**-5.499**	1.047	0.942	**1.299**	**6.017**	**0.456**	**-10.924**
Gwinnett	**0.787**	**-3.822**	1.069	1.236	1.052	0.926	0.916	-1.505
Henry	1.073	0.845	0.940	-0.698	0.983	-0.200	1.033	0.380
Paulding	1.115	0.697	1.062	0.379	1.100	0.608	0.811	-1.148
Rockdale	1.205	1.558	0.954	-0.348	0.931	-0.522	1.166	1.259

(Note: Values that are significant at 95% CI are depicted in **dark red**.)

For those counties whose calculated coefficients and ratios are significant, a comparison of Moran's I and Geary's C of disease counts, crude rates, and SMRs, to those of the underlying population allows an assessment of spatial autocorrelation of mortality relative to that of the population distribution. For Cherokee County, neither I nor C is significant for the population, thus limiting the validity of such a comparison. Likewise, for Gwinnett, Geary's C is not significant for population, so such a comparison is limited to Moran's I for Gwinnett.

DeKalb County exhibited the strongest evidence of positive spatial autocorrelation of mortality relative to population, while Fulton County exhibited the strongest evidence of negative spatial autocorrelation (or dispersion) of mortality relative to its population. Gwinnett and Clayton both exhibited lesser evidence of positive spatial autocorrelation, and Cherokee exhibited limited evidence of negative spatial autocorrelation. Cobb County had mixed results: while Moran's I coefficients suggest positive spatial autocorrelation (to a minor degree: the mortality coefficients were greater than the population coefficient, but all coefficients were just slightly greater than zero), Cobb's Geary C ratio suggests the opposite (mortality is higher than population, although both are below zero, which is an indication of positive spatial autocorrelation).

In general, the results of county-level measures of spatial autocorrelation are interesting, but inconclusive. Only for two counties, Fulton and DeKalb, were the results fairly clear-cut.

Local Indicator of Spatial Association

While both Moran's I and Geary's C provide global measures of spatial autocorrelation for the entire study area, it is useful to have an indication of spatial autocorrelation at local levels within the study area. Such measures are generally termed Local Indicators of Spatial Association or LISA (Anselin, 1995). One such LISA is Local Moran (I_L), which is defined as (Levine, 2002):

$$I_L = [(Z_i - \overline{Z})/S_Z^2] * \Sigma[W_{ij} * (Z_j - \overline{Z})] \qquad (5.11)$$

Where: $W_{ij} = 1/d_{ij}$

Z_i = value of variable Z at the ith location

Z_j = value of variable Z at the all other locations (where $i \neq j$)

$\overline{Z}$ = mean value of variable Z

S_Z^2 = sample variance

A high positive I_L indicates spatial clustering of similar values, while a high negative I_L indicates local clustering of dissimilar rates. Local Moran indices greater than two standard deviations above or below the mean I_L indicate statistical outliers. Observed I_L values for each tract can be compared to expected I_L values, variances can be computed, and the Local Moran statistic can be transformed to a standardized value.

As with the standard Moran's I, attribute similarity is constructed via a distance decay function, and an adjustment is made for small distances in order to prevent the potential for two very close observations having a disproportionately high influence on the overall measure.

Local Moran indices were computed for mortality events (counts), crude rates, and for Standardized Mortality Ratios (SMRs) for each census tract (n = 444). These results are graphically depicted in Figures 5.9, 5.10. and 5.11. It is possible to visually compare the maps of the significantly different crude rates and SMRs (Figures 5.10 and 5.11) with the respective maps of all the crude rates and SMRs (Figures 5.4 and 5.5). In

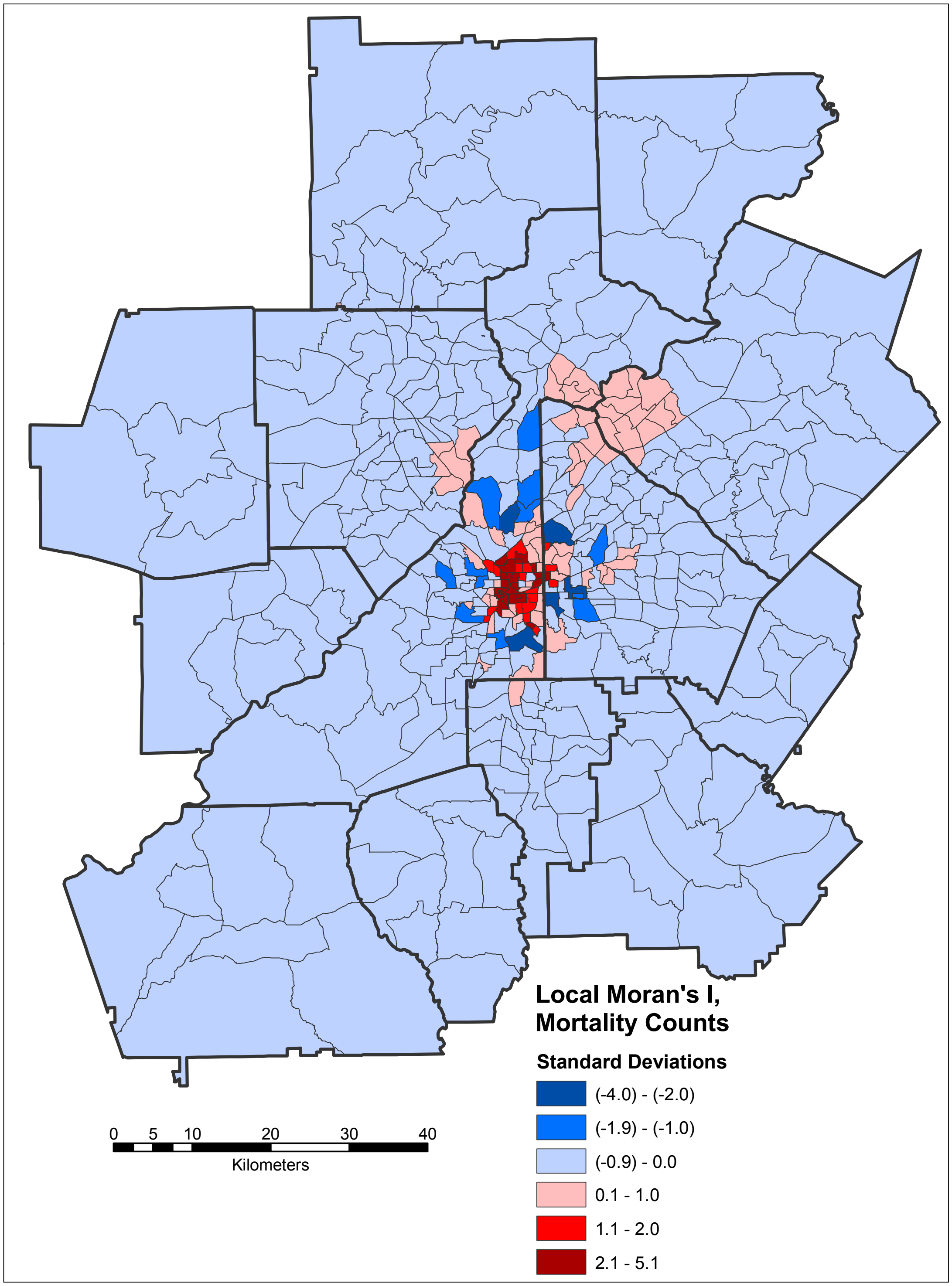

Figure 5.9. Local Moran Indices, Mortality Counts, Metropolitan Atlanta, 1995-1999.

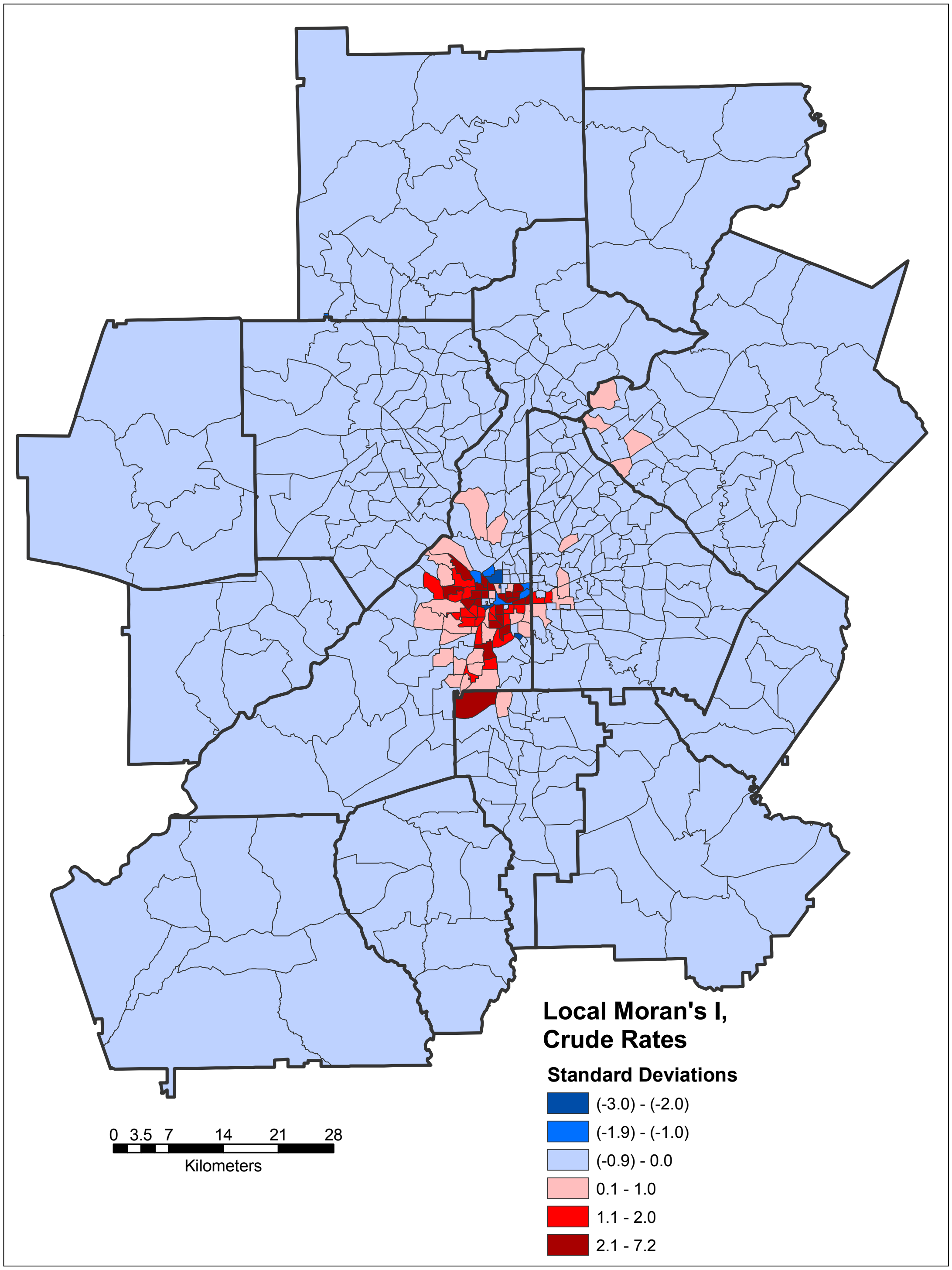

Figure 5.10. Local Moran Indices, Crude Mortality Rates, Metropolitan Atlanta, 1995-1999.

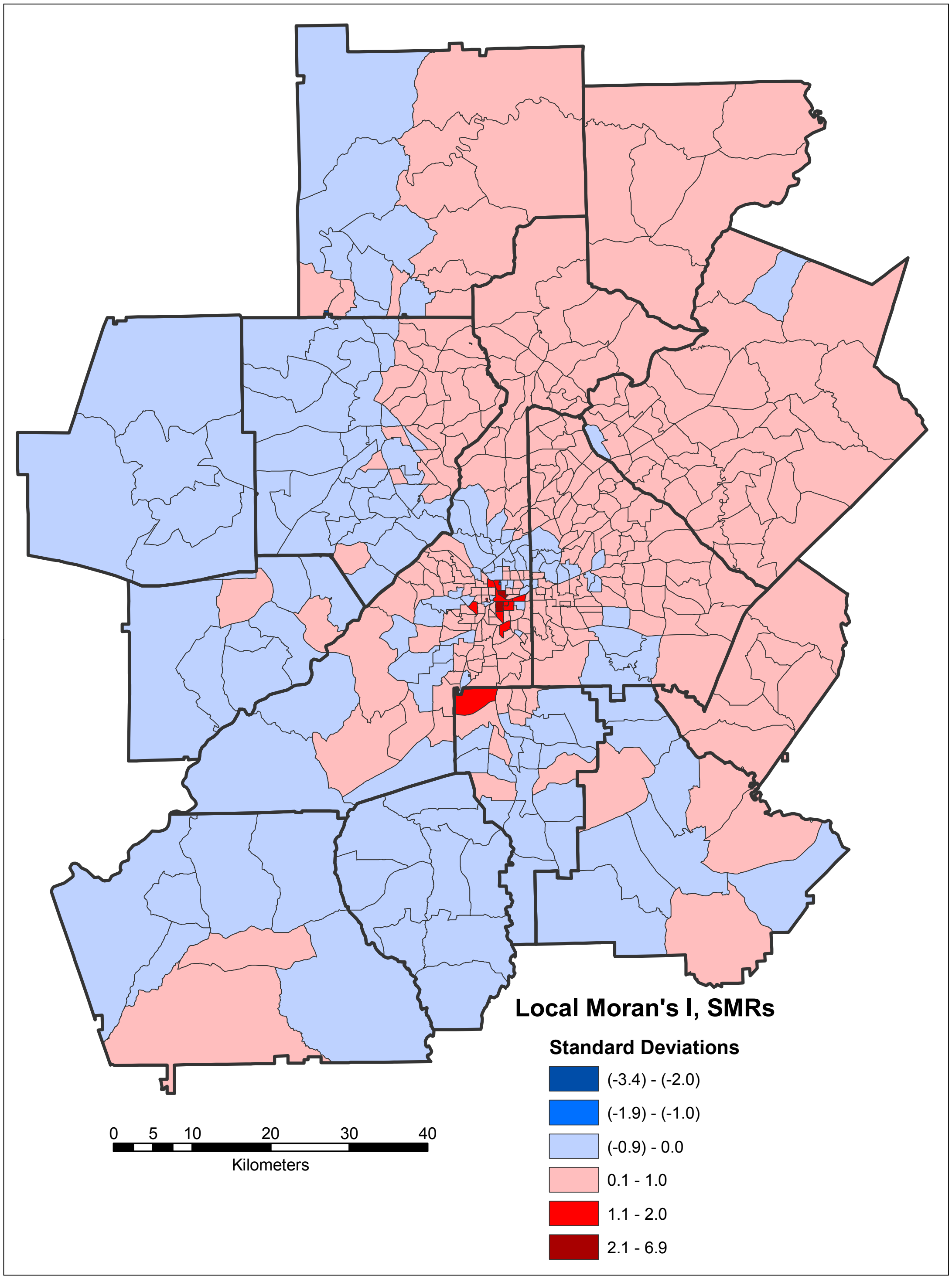

Figure 5.11. Local Moran Indices, Standardized Mortality Ratios (SMRs), Metropolitan Atlanta, 1995-1999.

doing so, it must be remembered that an individual tract's crude rates and SMRs are not being compared to only its immediate neighbors, but instead to all other crude rates and SMRs, albeit in a ratio inversely proportionate to the distance from that particular tract to all other tracts. Therefore, the visual inspection of tracts which are significantly different from neighboring/near tracts may not offer intuitive confirmation that the Local Moran calculations appear correct.

For I_L(counts), depicted in Figure 5.9, five tracts were < -2 standard deviations from the mean I_L(counts), which indicates that their mortality counts are significantly different from the mortality counts of neighboring/near tracts. Of these, one is located north of the downtown area in the extremely affluent, overwhelmingly-white neighborhood of Buckhead. The other four were located in a loose arc around the eastern and southeastern fringe of the central city. Conversely, twenty-five tracts were > +2 standard deviations from the mean I_L(counts), which indicates extremely high degrees of local spatial autocorrelation around those particular tracts. All of these tracts were concentrated in the central city. The indications of localized spatial autocorrelation based on mortality counts alone, as an indication of the spatial autocorrelation of mortality risk, however, are somewhat misleading, as the local moran indices do not account for the underlying population size and age distribution, which is the major risk factor for mortality.

The Local Moran indices for crude rates (Figure 5.10) take into account the population of each census tract. For I_L(crude rates), only four tracts were < -2 standard deviations from the mean I_L(crude rates), meaning that their crude rate is significantly different from the crude rates of neighboring/near tracts. These four tracts were dispersed throughout the downtown area, with no apparent pattern. Twenty-two tracts were > +2 standard deviations from the mean I_L(crude rates), which suggests local areas of extremely high spatial autocorrelation. Similar to the pattern for I_L(counts), all of these tracts were in the central city, with the addition of the census tract corresponding to the immediate vicinity of Hartsfield International Airport. This may be interpreted as indicating a high degree of homogeneity of crude mortality rates in the central city, and heterogeneity of crude mortality rates in the suburban counties.

The Local Moran indices for SMRs (Figure 5.11) take into account both the population and the age-structure of each census tract. As such, it is the most precise measure of the three Local Moran indices for suggesting the presence of localized spatially autocorrelated mortality risk. For I_L(SMRs), four tracts were < -2 standard deviations from the mean I_L(SMRs), which indicates that their SMRs are significantly different from the SMRs of neighboring/near tracts. Three of these tracts were located in the central city, and one is an extremely small tract (1990 population: 19) on the boundary between Cobb and Cherokee Counties. Eleven tracts were > +2 standard deviations from the mean I_L(SMRs), and were concentrated in the central city and in the census tract corresponding to Hartsfield International Airport. These indices suggest, as with the indices for crude rates, that the population mortality risk is spatially homogeneous in the central city of Atlanta, and is relatively heterogeneous in the surrounding suburbs. These indices also suggest that one or more of the potential explanatory variables for mortality risk may exhibit similar patterns of localized spatial autocorrelation.

Global Assessment of Clustering

Nearest Neighbor Analysis provides a global measure of the presence or absence of clustering (of point data, such as mortality events) across the entire study area. It does not provide information on the locations of potential clusters, but rather an indication of the *existence* of clustering. As such, it is a first order or first moment measure.

The Nearest Neighbor Index (NNI) is constructed by dividing the Mean Nearest Neighbor Distance (d) of an observed point pattern by the Expected Mean Nearest Neighbor Distance (d_{random}) of an independent random process:

$$NNI = d / d_{random} \qquad (5.12)$$

Where: d = Mean Nearest Neighbor Distance

d_{random} = Expected Mean Nearest Neighbor Distance

. The Mean Nearest Neighbor Distance (d) is obtained by calculating, for all points in a distribution, the distance from each point to its nearest neighbor; summing all these individual nearest-neighbor distances; and dividing by the total number of points in the distribution:

$$d = \Sigma d_{ij} / n \qquad (5.13)$$

Where: d_{ij} = distance from each point to its nearest neighbor

n = total number of points in the dataset

The Expected Mean Nearest Neighbor Distance (d_{random}) is obtained by the following equation:

$$d_{random} = 0.5 \sqrt{(a/n)} \qquad (5.14)$$

Where: a = area of the study region

n = total number of points in the dataset

If the observed point pattern is completely random, the Nearest Neighbor Index (NNI) would equal unity. If the observed point pattern is dispersed, relative to a random distribution, the NNI would exceed unity. If the observed point pattern is clustered, relative to a random distribution, the NNI would be less than unity. The significance of the NNI can be evaluated by converting the NNI to a standard normal deviate (z-score).

The Nearest Neighbor Index was computed for this data set (Table 5.7), and the result (NNI = 0.35) indicates the presence of clustering at the global level, in the context of first-neighbor distances. This result is significant at greater than the 99% level.

The Nearest Neighbor Index can be used to analyze the mean minimum distance between event pairs at k-orders. In other words, instead of computing the mean minimum distances between nearest points, the mean minimum distance can be computed for second-order neighbors, third-order neighbors, and so on until the k^{th}-order. The resulting indices indicate the degree of clustering within the dataset at discrete orders (or lags). This serves as a means of determining the scale dependency of clustering within the dataset. At each order, the Mean Nearest Neighbor Distance (d) can be compared to the Expected Mean Nearest Neighbor Distance (d_{random}), as shown in Figure 5.12, and a Nearest Neighbor Index (NNI) can be computed for each order (Figure 5.13).

Table 5.7. Nearest Neighbor Analysis.

Mean Nearest Neighbor Distance (d)	68.66 meters
Standard Deviation of d	126.03 meters
Minimum Distance Between Any Pair of Points	0 meters
Maximum Distance Between Any Pair of Points	150,433.79 meters
Expect Mean Nearest Neighbor Distance (d_{random})	196.36 meters
Nearest Neighbor Index (NNI)	0.35
Standard Error	0.33 meters
Test Statistic (z)	-388.9031
p-value (two tail)	0.0001

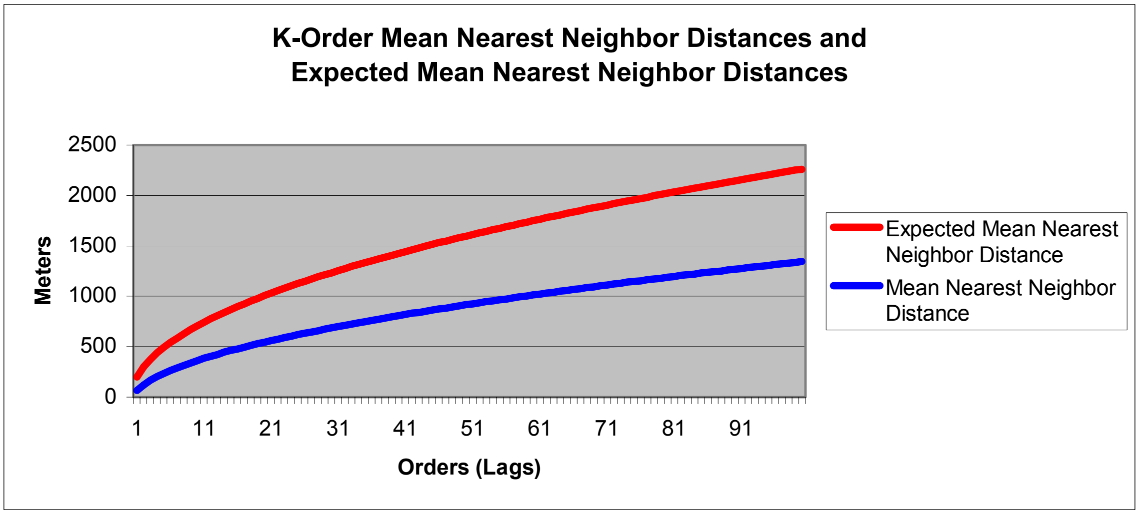

Figure 5.12. K-Order Mean Nearest Neighbor Distances and Expected Mean Nearest Neighbor Distances.

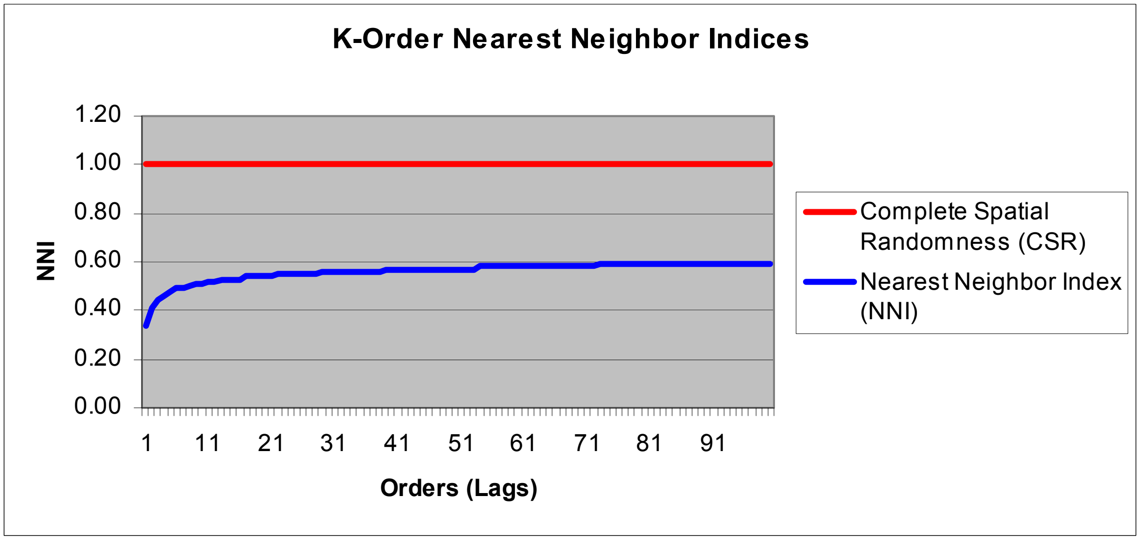

Figure 5.13. K-Order Nearest Neighbor Indices.

The Nearest Neighbor Indices for the observed events can be visually compared to the Nearest Neighbor Indices under the condition of Complete Spatial Randomness (CSR); these results are depicted in Figure 5.13, and indicate that there is clustering throughout the study area, at all orders. The degree of clustering is most pronounced at the level of nearest neighbors (roughly five lags), after which the degree of clustering gradually diminishes until reaching a threshold level of NNI = 0.59.

While the information from a Nearest Neighbor Analysis could be potentially useful, *it is not weighted for an underlying risk population*. Therefore, it only provides an indication that there are high volumes of events spatially clustered within the study area. It is highly likely that events, such as deaths, would naturally tend to be higher in areas with higher populations. Therefore, the indication of high volumes of deaths provides an incomplete assessment as to whether clustering of mortality really exists in comparison to the distribution of the population. In order to more fully assess the presence of clustering, it is necessary to have measures that take into account the underlying at-risk population distribution (Unwin, 1981; and O'Sullivan and Unwin, 2003). Two such measures, Ripley's K, and Risk-Adjusted Nearest Neighbor Hierarchical Spatial Clustering (a local measure of clustering), will be described in turn.

Ripley's K is a derivation of Nearest Neighbor Analysis. It summarizes spatial dependence over a wide range of scales, and uses the information of all events. Ripley's K, or "K-function" is a reduced second moment measure (Bailey and Gatrell, 1995) as it measures local clustering (e.g., second-order trends) while still being subject to first-order effects. To compute Ripley's K, a circle is placed over each point i, and the number of other points that are located within that circle are counted. The circle is enlarged, and the number of points within the circle are again counted. This process is repeated for each point i, for a total of 100 lags (the radius of each lag increment is determined by dividing the radius of a circle whose area is equal to the study area by 100). The results are summed across all points i and computed for all 100 lags.

The equation for computing $K(d_s)$ for each lag d_s is:

$$K(d_s) = (a / n) \sum\sum I(d_{ij}) \tag{5.15}$$

Where: $K(d_s)$ = Ripley's K for lag (d_s)

a = total area of the study

n = total number of events (points) in the study area

$I(d_{ij})$ = number of other points, j, found within distance d_s, summed over all points, I

In practice, $K(d_s)$ is transformed into a square root function, $L(d_s)$, to make the resulting plot of the K-function versus distance more linear. The transformation is computed as:

$$L(d_s) = \sqrt{[K(d_s) / \pi]} - d_s \tag{5.16}$$

The resulting K statistics (either K or L) can be graphed against distance (e.g., lags) to determine whether clustering exists, and if so, at any particular spatial extent. The graph of the computed $L(d_s)$ can also be compared to the $L(d_s)$ obtained from the Ripley's K analysis of an underlying risk population. In this manner, it is possible to assess the degree of clustering of mortality with respect to the degree of clustering of the underlying population. If the population tends to be clustered (which is normally the case in an urban area), then it would be expected that mortality should be clustered as well. However, if by inspection of the graphs of the K-functions for mortality events and for population it is determined that the K-function for mortality exceeds that for population, it can be determined that the degree of clustering for mortality is higher than would be expected, given the spatial pattern of the underlying population.

Figure 5.14 depicts the Ripley's K function (L) for mortality events; Figure 5.15 depicts the Ripley's K function (L) for the population; and Figure 5.16 depicts a

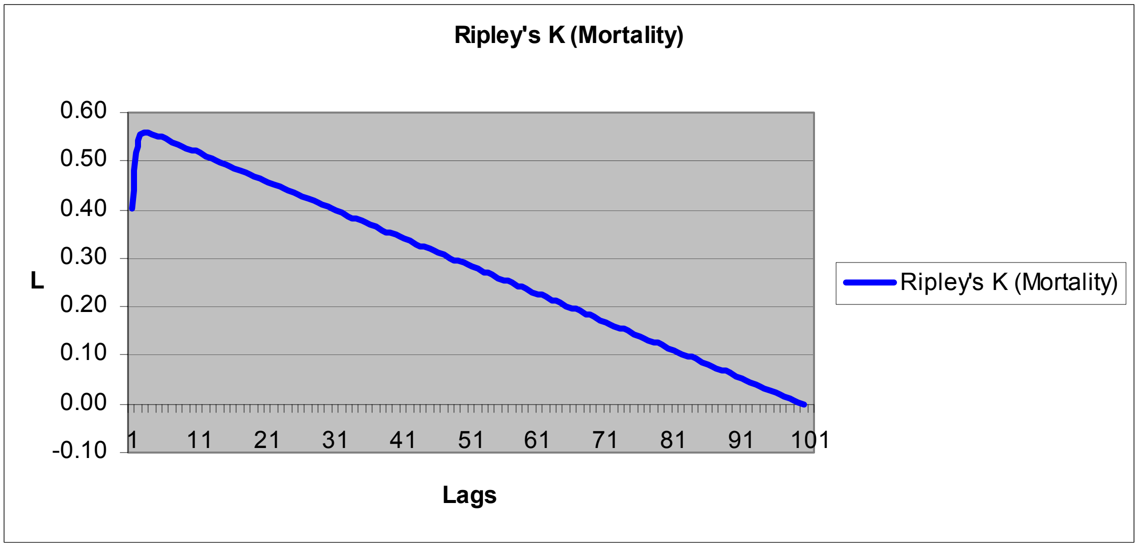

Figure 5.14. Ripley’s K for Mortality.

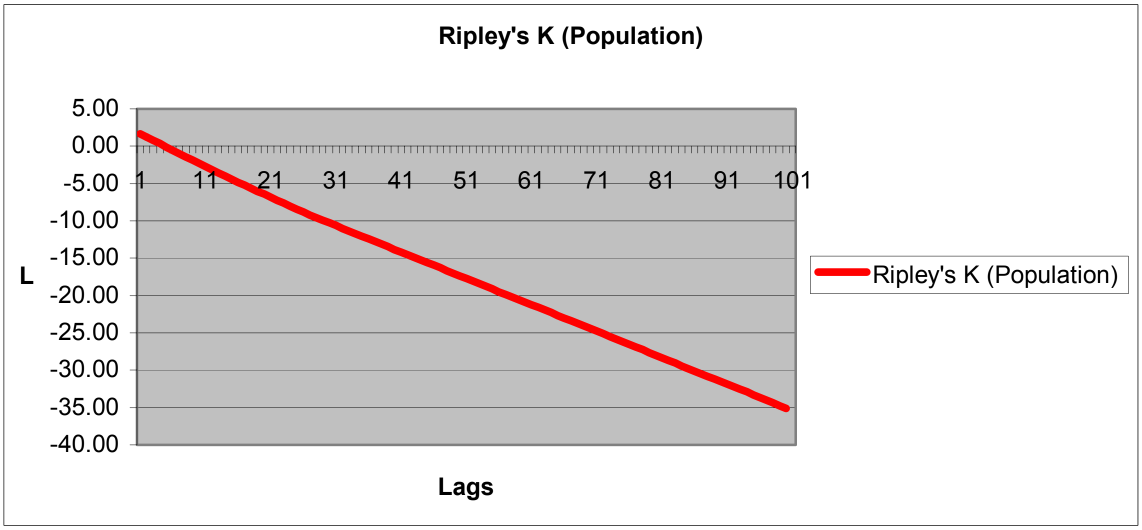

Figure 5.15. Ripley’s K for Population.

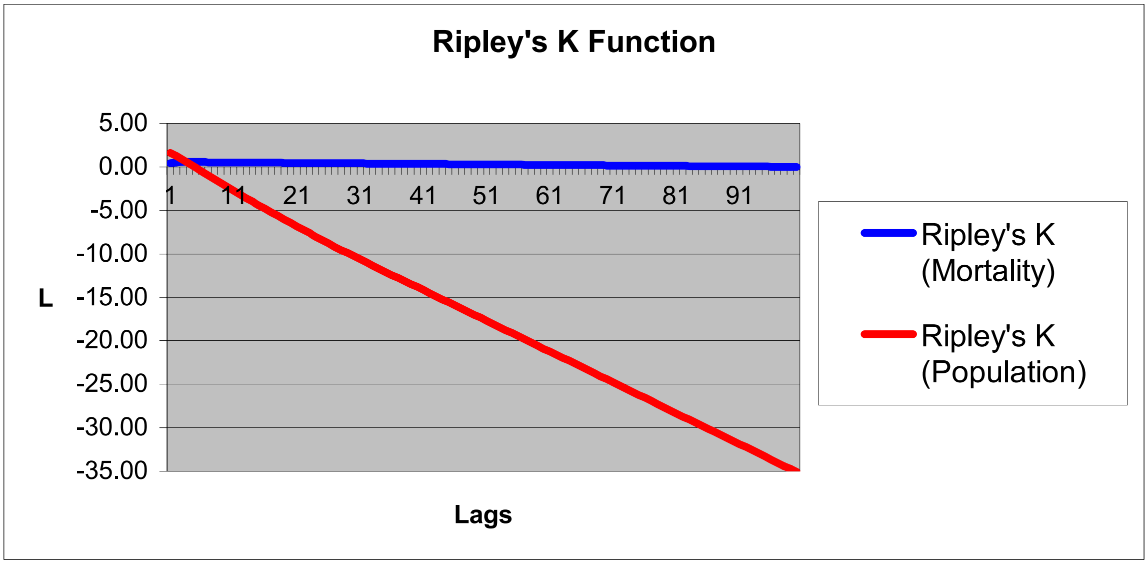

Figure 5.16. Comparison of Ripley's K (Mortality) Versus Ripley's K (Population).

comparison of the two functions. The Ripley's K function for mortality begins at a modest value (0.40) and climbs steeply to a high value of 0.56 at the fourth lag, after which the function falls off steadily to a value of zero.

For population, Ripley's K begins at a value of 1.65, after which the function falls off steadily to large negative values at the scale of the entire study area. This suggests that population is clustered at very short lags, but after a very low threshold (the fifth lag), no clustering exists.

The most useful interpretation is that of the comparison of the Ripley's K function for mortality versus that for the population (Figure 5.16). Up through the fourth lag, population is more clustered than mortality events. From the fifth lag onward, however, mortality has much higher K function values (L), which suggests that mortality is more clustered than the population at larger spatial extents (or smaller cartographic scales).

Local Measures of Clustering

The Risk-adjusted Nearest-neighbor Hierarchical Spatial Clustering algorithm in Crimestat II provides an indication of areas of high incidence, while taking into account the underlying population at risk. By accounting for a baseline variable (population), this algorithm provides a measure of risk rather than a measure of volume. As this is a hierarchical clustering algorithm, points are grouped together based on spatial proximity, with an adjustment to the groupings based on the distribution of the baseline variable, population.

First-order clusters are identified based on the number of observed points exceeding a user-specified minimum number of points within a clustering threshold distance. First-order clusters are then treated as points for the purpose of identifying second-order clusters, and so on, until no higher-order clusters are identified.

The clustering threshold distance is determined by the interaction of a user-specified threshold probability (the probability of grouping a pair of points by chance) and the grid cell density from a kernel density estimate of the baseline variable (population). As the threshold probability is fixed, the clustering threshold distance varies inversely over space with the density of the baseline variable: in areas with high population density, the clustering threshold distance is smaller. This means that in those areas, the density of observed events needs to be higher in order to exceed the threshold minimum number and be considered a cluster.

The kernel density model for the baseline variable, population, is constructed by spatial interpolation using a normal kernel and an adaptive sampling interval (minimum number of points). A 50 x 50 cell grid is overlaid on the study area, and the kernel density estimate is calculated for the baseline variable. The kernel density estimates are rescaled so that their sum is equal to the sample size of the primary variable, mortality events (n = 97,910). This facilitates the comparison of the mortality distribution to the population distribution. For each of the 2,500 grid cells, a specific threshold distance is calculated for grouping a pair of points by chance (the confidence intervals are determined from the user-specified, and fixed, threshold probability). Pairs of observed points are selected for first-order clusters if they are closer together than their cell-specific threshold distance. However, first-order clusters are identified only if the number of points, thus selected, exceeds the user-specified minimum number of points. By specifying a higher minimum number, the likelihood of identifying a cluster decreases; by specifying a lower minimum number, the likelihood increases.

Two iterations of the Risk-adjusted Nearest-neighbor Hierarchical Spatial Clustering routine were processed on the mortality event data, using the study's population as the baseline variable. For the first iteration, the threshold minimum number of points was defined as 50 points per cluster, and the threshold probability was 95%. The kernel density estimate for the population variable is based on a normal kernel with an adaptive (minimum of 10 points) sampling interval. As a result of these parameters, 63 clusters were identified: 60 first-order and 3 second-order. For the second iteration, the threshold minimum number of points was doubled to 100 points per cluster, while the threshold probability remained the same (95% CI). The kernel density model of the population remained the same. For the second iteration, 11 clusters were identified: 10 first-order and 1 second order. Results from both iterations are depicted in Figure 5.17. The first-order clusters from the first iteration (minimum of 50 events per

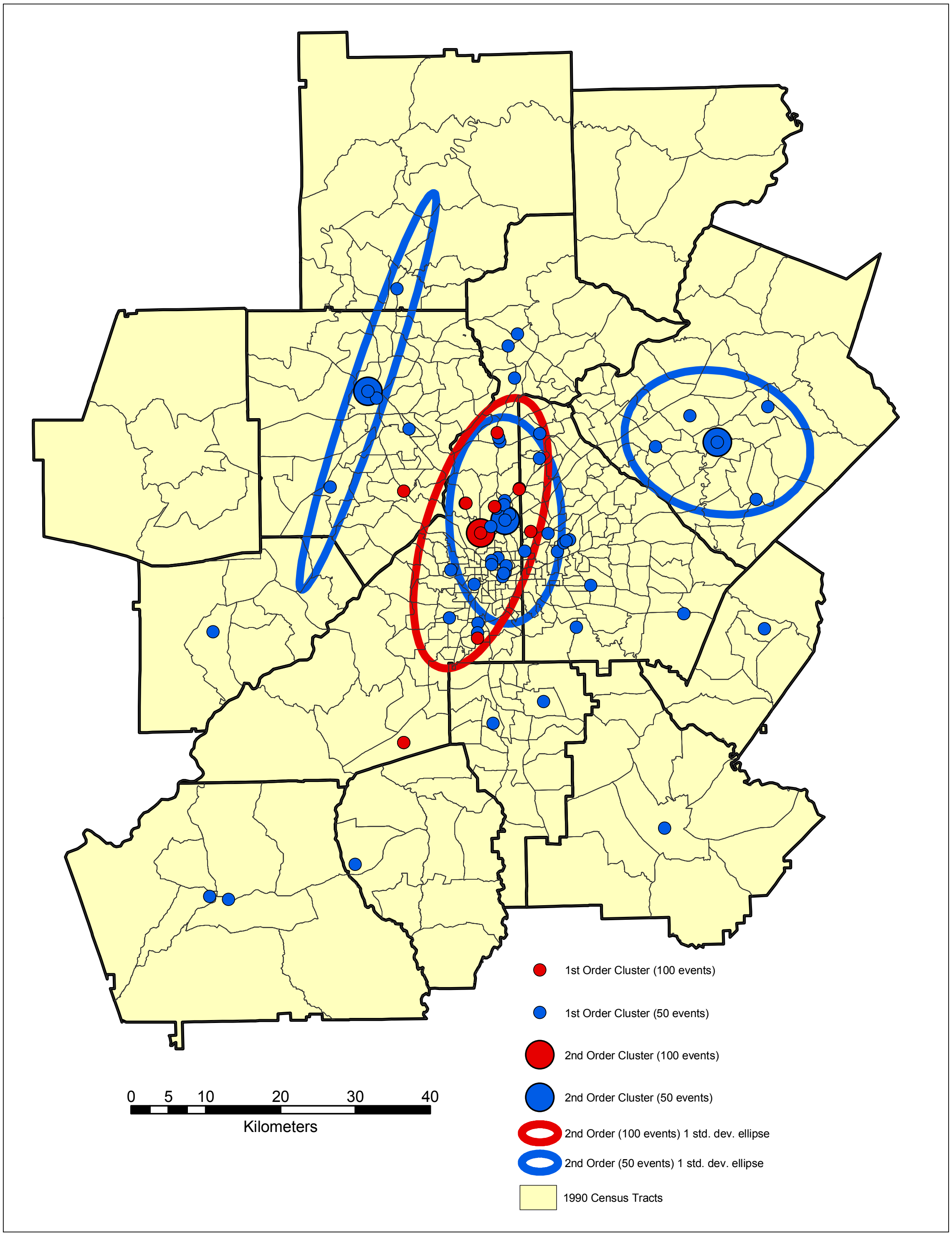

Figure 5.17. Mortality Clusters, Metropolitan Atlanta, 1995-1999.

cluster) are depicted as small blue points; second-order clusters from the first iteration are depicted as larger blue points surrounded by first standard deviation ellipses. For the second iteration (minimum of 100 events per cluster) the first- and second-order clusters (and the first standard deviation ellipse) are depicted in red.

For the first iteration (minimum 50 events), the three second-order clusters are located over the city of Atlanta (portions of Fulton and DeKalb Counties), southern Gwinnett County, and along an elongated ellipse stretching from central Cherokee County through Cobb County and extending into northeastern Douglas County. The second-order cluster over Atlanta is comprised of 43 first-order clusters, while the Gwinnett-based cluster contains only four first-order clusters, and the Cobb-centered cluster contains just three first-order clusters.

For the second iteration (minimum 100 events), there is only one second-order cluster, which is located over the city of Atlanta, and this cluster is generally spatially-coincident with the second-order cluster from the first iteration. This second-order cluster contains ten first-order clusters.

By comparing the locations of these clusters with the information on crude mortality rates (which are scaled by population), it is possible to determine that there is a fairly high degree of correspondence between the Atlanta-based second-order clusters and the highest crude mortality rates: 63 of 86 census tracts in the highest quintile for crude mortality rates have their geometric centroids within the first standard deviation ellipse for the second iteration’s (minimum 100 events) second-order cluster. By comparison, 51 of 86 census tract centroids (highest quintile) have their centroids within the first standard deviation ellipse for the first iteration's (minimum 50 events) second-order cluster. Therefore, the second-order clusters are good indicators of risk for mortality. While both second-order clusters correspond closely with crude mortality rates, the second-order cluster from the more-restrictive clustering criterion has a higher degree of correspondence with the pattern of crude mortality rates. Three-quarters of the census tracts with the highest rates of death are contained in the second-order cluster ellipse from the more-restrictive clustering iteration.

The SaTScan 3.0 software application (Martin Kulldorff and the National Cancer Institute, 2002) is designed to evaluate reported spatial (or space-time) clusters for statistical significance; to determine if disease outcomes are randomly distributed; and to assist in public health surveillance, specifically in the detection of significantly high or low health outcomes (morbidity and mortality).

SaTScan 3.0 is based on the spatial scan statistic, which functions by imposing a circular window on a map (either point or areal data) of a disease outcome variable (in this case, all-cause mortality). The circular window is first placed either over a point representing a case or the geometric centroid of an area for which disease rates have been aggregated (this is the method of operation for this particular data set). The window is moved, in turn, from case-to-case, or from centroid-to-centroid. At each point or centroid, the circular window is continuously expanded in size from zero to an upper limit, which is generally set to equal one-half of the area of the entire study area. Each circular window location and size combination (a very large number) is considered as a possible candidate for a cluster.

At each window location and size, SaTScan sums the counts and tests this result against an alternative hypothesis that the count is elevated within that particular scan circle, as compared to the expected count under the assumption of a Poisson distribution. SaTScan does this via a likelihood ratio test. The likelihood function (L) for each particular scan window is proportional to:

$$L \approx (n/\mu)^{n}([N-n]/[N-\mu])^{(N-n)} \quad (5.17)$$

Where: N = total number of cases in the entire area

n = number of cases within the scan window

μ = expected number of cases within the window (adjusted for covariates)

The expected number of cases within each window can be adjusted for covariates, such as age. For example, if the age-adjusted expected number of cases has been computed, this file can be used in SaTScan and the likelihood function uses these as the expected number of cases instead of the expected number generated from analysis of the underlying population distribution (which does not account for age). This procedure is used for the current study. The results, therefore, are based on an expected number of cases that had been determined through the indirect age-adjustment procedures described previously.

As SaTScan assesses a very large number of circular windows, the window that has the highest likelihood function is designated as the most likely cluster (i.e., least likely due to chance). To assess the significance of this cluster, SaTScan performs Monte Carlo simulations (1000) to generate a large random replication of the data set. The test statistic from the most likely cluster is compared to those from the Monte Carlo simulations in order to derive a p-value for significance. SaTScan also determines the presence of secondary clusters. These are based upon the next highest likelihood ratios. The results from SaTScan were exported as DBF files for subsequent analysis and display in a GIS.

For this dataset, four iterations of the SaTScan analysis were conducted, with each iteration using progressively less-restrictive criteria for the allowance of overlap among primary and secondary clusters. The first iteration allowed no geographic overlap among clusters (Figure 5.18). The second iteration allowed some limited degree of overlap, as long as no cluster centers were located within other clusters. The third iteration allowed overlap, as long as no cluster centers were located within the boundaries of more likely clusters, as determined by their likelihood ratios. The fourth iteration allowed overlap, but only as long as no cluster centers were located within the boundaries of less likely clusters.

As the clustering criteria become less restrictive, more clusters were identified. However, for all criteria, a clear pattern emerges in which the most likely cluster is located near the border of Fulton and Clayton Counties (coincident with Hartsfield Airport as the epicenter). Each of the four iterations of most likely clusters had slightly varying radii, but in all cases these clusters included downtown Atlanta. For the less restrictive clustering criteria, less likely clusters of high mortality were located in the southern half of the study area. The combination of these results tends to support a hypothesis that mortality occurs at a higher-than-expected rate in the downtown Atlanta area.

In another respect, there is a surprisingly high degree of correspondence in the results from the first three SaTScan iterations. In these three cases, the number of census

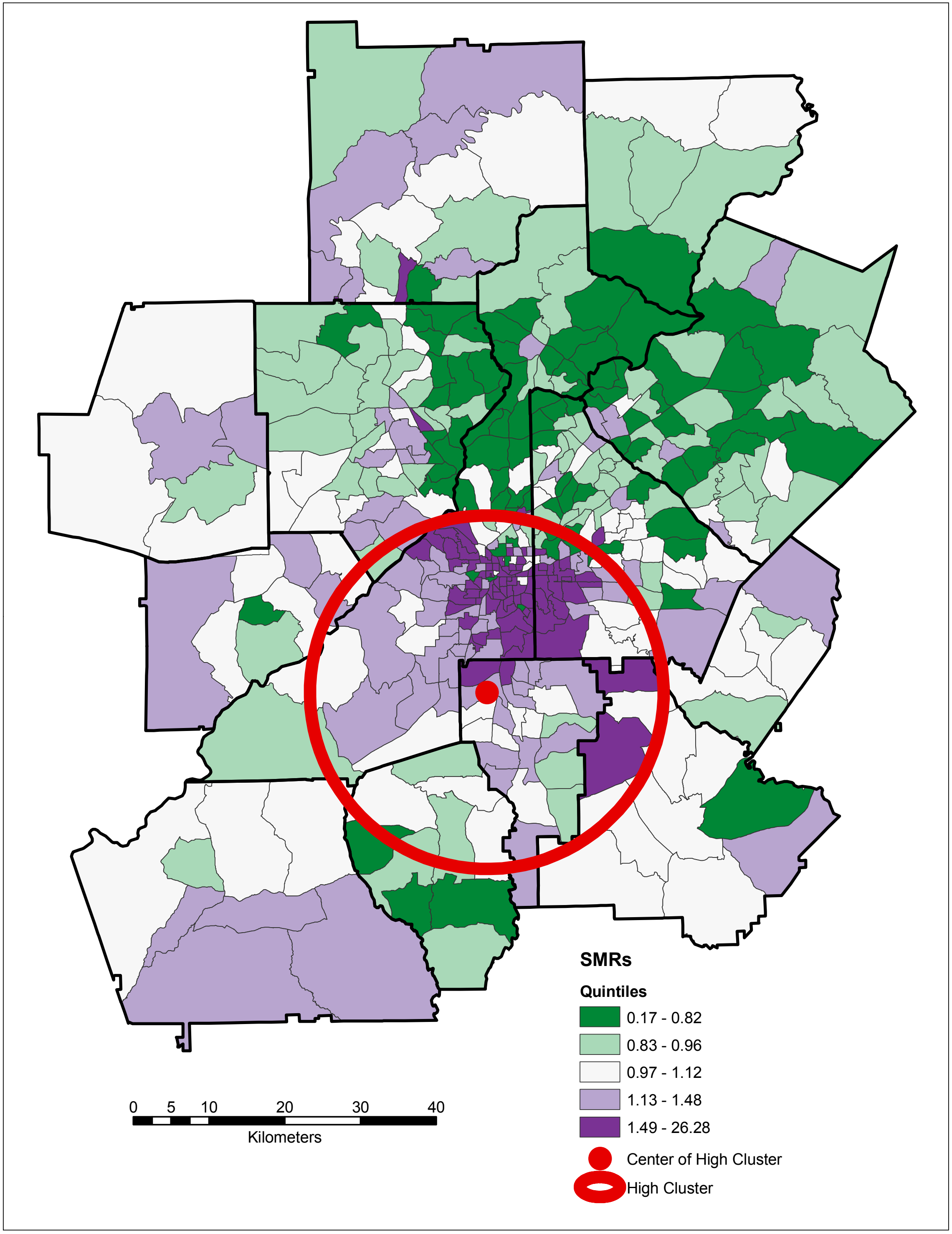

Figure 5.18. Mortality Clusters, Metropolitan Atlanta, 1995-1999, SaTScan 3.0.

tracts in the highest quintile (n = 86) that have their centroids within the primary cluster are identical (67 of 86). Only for the fourth, and least restrictive, iteration does the result differ slightly. In that case, 50 of the 86 census tract centroids are located within the primary cluster.

The results of the SaTScan analysis generally coincide with the results from the Risk-Adjusted Nearest-Neighbor Hierarchical Spatial Clustering analysis in Crimestat. In all cases, a cluster of higher-than-expected mortality was identified over the southern half of the City of Atlanta. These clusters were based upon an underlying risk structure: population distribution in CrimeStat; and age *and* population distribution in SaTScan.

Discussion

Cluster analysis, in general, can help assist in the determination of areas in which observed events are higher than would be expected, given a random or Poisson distribution. In this case, the events of interest were the incidence of mortality for metropolitan Atlanta, for a five-year period (1995-1999). Mortality data were mapped, after geocoding decedents' residential addresses. Then three summary measures were derived for each of the 444 census tracts (1990 boundaries) within the study area: counts, crude mortality rates, and Standardized Mortality Ratios. Each of these measures had application in subsequent analyses of mortality patterns.

The simplest spatial analysis is through visual interpretation of choropleth maps of each mortality summary measure. This interpretation, although subjective, does allow the discernment of potential patterns of mortality and the formulation of various hypotheses regarding the underlying causes of mortality patterns.

More objective analyses were possible through the application of two spatial statistical analysis software packages, CrimeStat II and SaTScan 3.0, in conjunction with a geographic information system, ArcInfo 8.2. Both applications took advantage of the spatial data in the dataset, either as point location data (mortality events – decedents' residential addresses) or as areally aggregated data (mortality events per tract, crude mortality rates, and Standardized Mortality Ratios). Four general types of objective analysis were conducted: 1) global indices of spatial autocorrelation; 2) a Local Indicator of Spatial Association; 3) global measures of the presence of clustering; and 4) local measures of the locations of clusters.

The global indices of spatial autocorrelation (Moran's I and Geary's C) both indicated varying degrees of spatial autocorrelation of the underlying population for the study area, along with some indication that mortality events were also spatially autocorrelated. However, the degree of spatial autocorrelation of the population is higher than that for mortality events. Therefore, any degree of spatial autocorrelation of mortality is likely due to the spatial autocorrelation of the underlying population distribution. This is an interesting result, and it is important for subsequent multivariate analysis of potential explanatory variables. Had the degree of spatial autocorrelation been greater, both in absolute terms as well as relative to the base population, the multivariate analysis would need to account for this. Otherwise, the resulting regression parameters would be overly precise (i.e., standard errors too high).

The attempt to perform Moran's I and Geary's C analyses at the county level resulted in mixed success. While this was intended to account for potential scale effects, many results were insignificant due to the small numbers of tracts within many counties.

For a few counties that had larger numbers of census tracts, the results were significant and interesting. DeKalb County exhibited the highest degree of spatial autocorrelation of mortality, while Fulton County exhibited the strongest evidence of dispersion of mortality. Gwinnett and Clayton Counties also exhibited some degree of positive spatial autocorrelation. Cherokee County exhibited limited evidence of negative spatial autocorrelation. Cobb County's results were mixed and inconclusive. None of the other counties' results were statistically significant, therefore, no further analysis was attempted. In all cases, the degree of spatial autocorrelation (positive or negative) is fairly low, and is considered to be an insignificant factor for subsequent multivariate analyses.

A Local Indicator of Spatial Association, Local Moran, was used to localize areas in which tracts had very similar rates compared to their surrounding tracts. Eleven tracts with extremely high Local Moran indices were concentrated in downtown Atlanta and in the immediate vicinity of Hartsfield International Airport. This suggests that the population mortality risk is spatially homogeneous in the central city of Atlanta, and is more heterogeneous in the surrounding suburbs. These indices also suggest that one or more of the potential explanatory variables for mortality risk may exhibit similar patterns of localized spatial autocorrelation.

Global measures of clustering (Nearest-Neighbor Analysis, K-Order Neighbor Analysis, and Ripley's K-function) provide an indication of whether clustering exists within the study area. All three operate on the principle of comparing the distances among points of data in an observed distribution to that of a random distribution. The resulting indices provide an indicator of whether the actual point pattern has clustering that would not otherwise be expected in a random, Poisson distribution. In all three instances, the global measures of clustering confirmed the probability that clustering existed in the data set. Nearest-Neighbor Analysis provides only a simple indication that there is clustering at the level of the first-order nearest-neighbor. K-Order Neighbor Analysis extends the comparisons to k-orders (in this case 100). As such, it is possible to infer some degree of scale effects on clustering at the level of the entire study area. In this instance, as with the first-order analysis, clustering is suggested throughout the area at all orders (lags).

The limitation to Nearest-Neighbor Analysis and K-Order Neighbor Analysis is that the underlying risk structure is not taken into account. Only by controlling for the spatial distribution of the underlying population can a more definitive statement be made regarding clustering of mortality vis-à-vis the population distribution. Ripley's K (or "K-Function") provides the means to compare a global measure of clustering of mortality to a measure of population clustering. In this case, mortality exhibited clustering throughout the majority of lags, while population exhibited clustering for only the first four lags. However, population is more clustered than mortality for the first four lags (or orders). Beginning with the fifth lag, the clustering of mortality became more pronounced than the clustering for population. In both cases (mortality and population), clustering tapered off with an increase in lags, indicating that the larger the area of analysis, the less the likelihood of clustering.

While all three global measures suggested the presence of clustering within the study area, it is more interesting to determine exactly where such clustering may exist. In the final two analyses, two local measures of clustering, Risk-adjusted Nearest-Neighbor

Hierarchical Spatial Clustering and the Spatial Scan Statistic, identified at least one cluster of higher-than-expected mortality. This cluster is located over the City of Atlanta, and in some analyses extended into southwestern DeKalb County and northern Clayton County. There is a close correspondence between these clusters and the number of census tracts in the highest quintile of mortality.

Conclusion

The mortality pattern of this study area can be characterized as not exhibiting significant spatial autocorrelation across the entire study area; however, county-level areas of positive and negative spatial autocorrelation may exist, but their degrees were fairly modest. In most cases where spatial autocorrelation of mortality is present, it is lesser in extent than the spatial autocorrelation of the underlying population. At the local level of analysis, there were a number of census tracts, mostly in downtown Atlanta and near Hartsfield International Airport, whose mortality counts/rates were significantly spatially autocorrelated with those of their nearby census tracts. At the global level, there was evidence of mortality clustering. When localized, this clustering appeared to be concentrated over Atlanta (downtown), southwest DeKalb County and north Clayton County, which contains Hartsfield International Airport.

This analysis is important for subsequent research[*] that examined the relationship of census tract level mortality to explanatory variables. First, it was determined that there is a substantial variation of mortality (the dependent variable) across the study area. Second, there were census tracts with significantly elevated mortality in the central portion of the study area, corresponding to the traditional Atlanta Central Business

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[*] See chapter 6 of this dissertation.

District (CBD). Third, the presence and potential impact of the spatial autocorrelation of mortality, at the scale of the study area, is relatively minimal.

The use of spatial statistics to analyze patterns of a public health outcome variable, such as mortality, can prove useful for investigating the spatial patterns of the outcome variable; for identifying areas with counts or rates that vary significantly from the expected pattern resulting from a random distribution of cases; and for generating hypotheses for causal relationships. The software necessary for such analyses are readily available free-of-charge, are easy to use, and can be readily integrated with a geographic information system (GIS) for data storage, manipulation, analysis, and display.

CHAPTER 6

ANALYSIS OF THE SOCIO-DEMOGRAPHIC AND PHYSICAL ENVIRONMENTAL IMPACTS ON MORTALITY IN THE ATLANTA METROPOLITAN AREA[*]

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[*] Holt, J.B. and C.P. Lo. To be submitted to ***Annals of the Association of American Geographers***

Introduction

The primary purpose of this study is to analyze the relationship between socio-demographic composition and physical environmental context and all-cause mortality, at the census tract level, for a rapidly-growing, major metropolitan city. Areally-aggregated socio-demographic variables, measures of land-use, and vegetative greenness are derived for each census tract in a thirteen-county area corresponding to metropolitan Atlanta, Georgia, for a twenty-year period, 1980-2000. The thirteen-county metropolitan area is depicted in Figures 6.1 and 6.2. All-cause mortality data for the metropolitan Atlanta area, for 1995-1999, were geocoded and aggregated to the census tract level. Exploratory data analyses were initially conducted for the socio-demographic and physical environmental data, followed by a multiple regression analysis of their relationships with the mortality data.

Atlanta was chosen for this analysis because it represented an area that underwent rapid suburbanization during the last two decades of the twentieth-century, typical of those cities described as “edge cities” (Garreau, 1991) and characterized in the urban geography literature under the “urban realms” model (Hartshorn and Muller, 1989). Atlanta was also chosen because of its historical patterns of residential segregation and land-use, which were hypothesized to influence the spatial distributions of socio-demographic and physical environmental variables.

A secondary purpose of this study is to determine the impact of suburbanization on the spatial distribution of socio-demographic variables, land-use, and vegetative greenness. It is hypothesized that suburbanization had led to changes in the spatial patterns of socio-demographic variables, which represented changes in the social

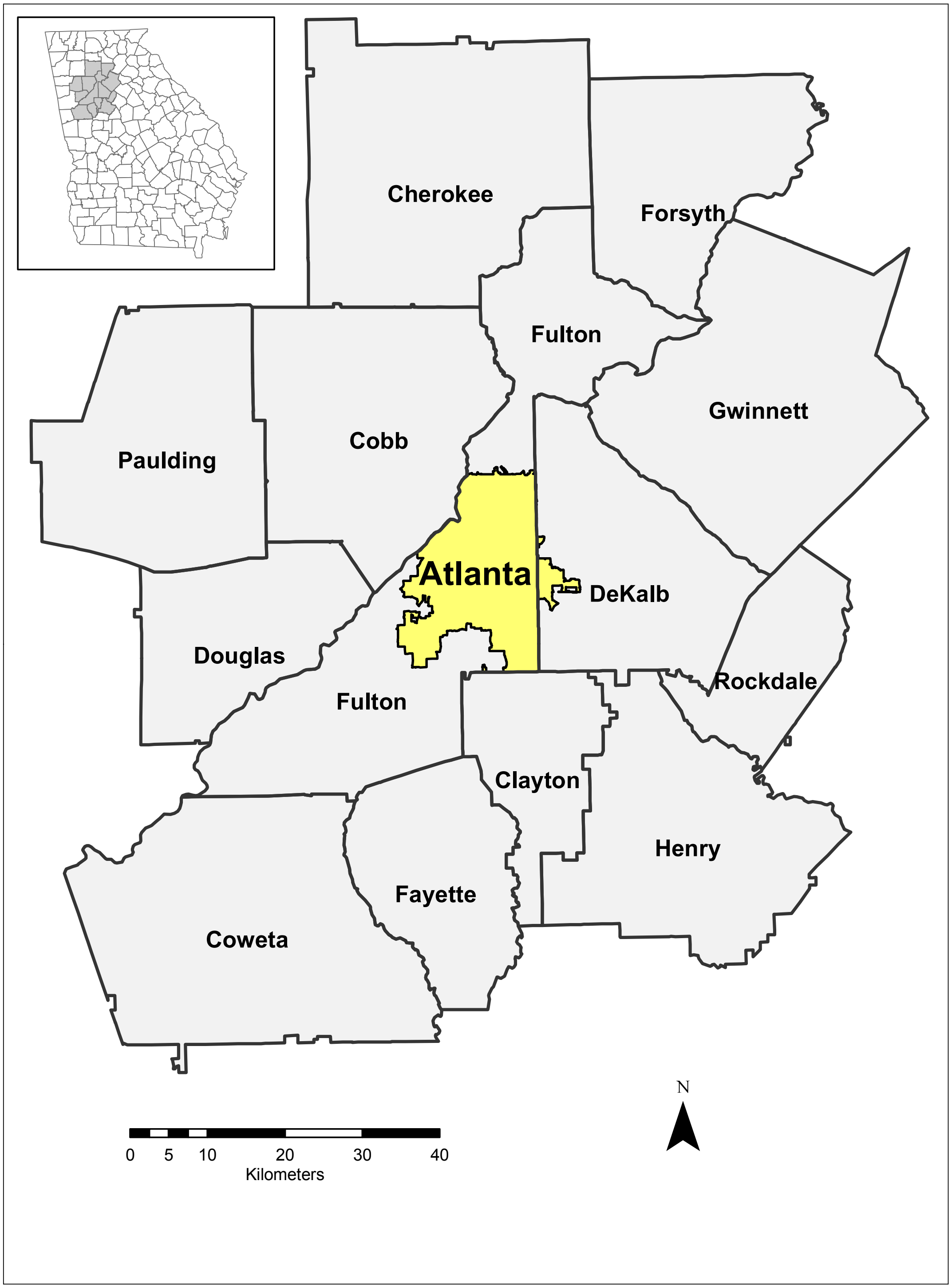

Figure 6.1. Thirteen-County Metropolitan Atlanta Study Area.

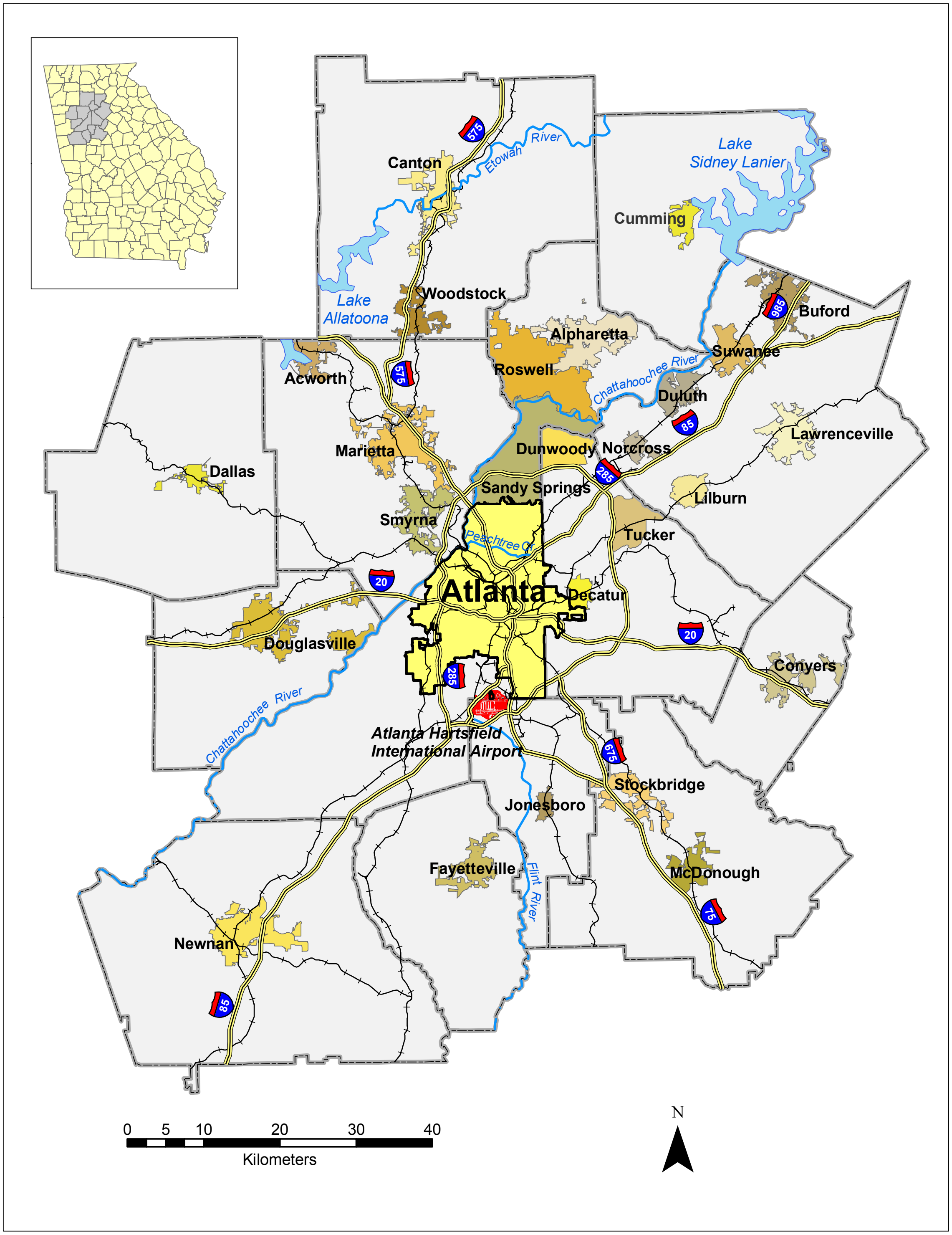

Figure 6.2. Principal cities, highways, railroads, and rivers, Metropolitan Atlanta, Georgia.

composition of neighborhoods (as represented by census tracts). These compositional changes possibly would be associated with all-cause mortality, although casual linkages could not be tested. The changes in the land-use and vegetative greenness spatial patterns were hypothesized to represent physical contextual changes of neighborhoods/census tracts.

Review of Previous Research

Ecological Studies and Area Effects

Many public health studies have examined the relationships between area-level variables (i.e., contextual and compositional variables[*]) and health outcomes. These studies have been ecological studies, including multilevel studies, which examine area-level relationships based upon aggregated data.

A representative sample of health-related ecological studies is listed in Table 6.1. Giggs (1983) and Meade (1983) represent early examples of ecological studies. Giggs studied the relationship between the ecological structure of the Nottingham Psychiatric Register Area and the incidence of schizophrenia from 1969-1973, in Nottingham, England. Independent variables were generated by a factor analysis of 62 variables which had been shown in previous research to be related to mental illness and mental health care. The resulting fifteen factors were grouped, by cluster analysis, into five major factors, which were used in subsequent regression analysis. Giggs argues that these methods produced both comprehensive and objective characterizations of the ecological areas in the study area for the period of his study. Based on his regression

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[*] Compositional influences refer to the aggregation of individuals' attributes, such as income, education, and occupational status, while contextual influences refer to the effects on a dependent variable due to the character of an area, over and above those effects that can be attributed to aggregated individual factors. Contextual influences include direct effects from the physical environment as well as indirect effects from the social environment, which influence individual behaviors.

analysis, Giggs found support for the hypothesis that social factors are largely responsible for the gradient pattern of schizophrenia incidence that characterized the study area.

Table 6.1. Selected Public Health Ecological Studies.

Authors	**Year**	**Outcomes of Interest**	**Notes**
Brimblecombe *et al*	1999	Mortality	Contextual variables, esp. housing tenure and deprivation
Duncan *et al*	1993	Smoking and alcohol consumption	Composition effects vice contextual effects
Duncan *et al*	1999	Smoking	Neighborhood deprivation
Ecob and Macintyre	2000	Health-related behaviors	Area-effects can vary based on age and household deprivation
Frolich *et al*	2002	Youth smoking initiation	Social structure at the neighborhood level
Giggs	1983	Schizophrenia	Factor analysis; intra-urban ecological structure
Goldsmith *et al*	1998	Mental illness and need for mental health services	Social area dimensions; Epi Catchment Area Survey
Gorman	1999	Low Birthweight	Contextual effects; interaction with ethnicity
Haynes and Gale	2000	Long-term illness ratio; Standardized mortality ratio	Social deprivation index
Huff and Gray	2001	Coronary heart disease mortality	Factor analysis; socioeconomic status index
Jones and Duncan	1995	Various	Area measures of deprivation and income variation
Meade	1983	Cardiovascular disease mortality	Factor analysis; contextual variables
Mustard *et al*	1999	Mortality	Ecological measures of SES as proxies for individual-level measures
Pampalon *et al*	1999	Health perception	Local area variations due to area-effects
Reidpath *et al*	2002	Obesity prevalence	Area measure of SES and density of fast-food restaurants
Subramanian *et al*	2003	Social Capital	Contextual differences in social capital

Meade (1983) conducted a factor analysis of cardiovascular disease mortality in Savannah, Georgia. Her analysis yielded groupings of census tracts that had similar factor scores and mortality rates. She argued that the spatial patterns that emerged from this data analysis would be useful for framing subsequent micro-level studies within the Savannah area.

Brimblecombe *et al* (1993) studied the relationship between housing tenure and mortality in Oxford, England. National studies had shown that there is a significant relationship between housing tenure (e.g., housing that is either tenant-owned, rented from the government, or rented from individuals) and mortality. However, this study revealed that the relationship did not hold at the local level. Instead, mortality is correlated with pockets of extreme deprivation. The extent to which this variable is related to housing tenure was limited by the historical local patterns of housing provision. Therefore, Brimblecombe *et al* argue that small-area studies are very important in confirming or refuting relationships found at higher-level units of analysis (e.g., national) and that local contextual variables are crucial to understanding local patterns of mortality.

Duncan *et al* (1993) applied multilevel modeling to the study of regional differences in smoking and alcohol consumption in the United Kingdom. They found that the major determinants of these behaviors were individual-level factors, and that geographic variations were a consequence of differing place composition (a type of area effect). While they did not deny the validity of contextual area effects, these were not substantiated in that particular study.

Jones and Duncan (1995), in another multilevel study, assessed the impact of contextual factors on a variety of health outcome measures, including heart disease and stroke, high blood pressure, and self-assessed health. They found that after controlling for a wide range of socio-structural, demographic, and behavioral variables, there remained an ecology of chronic illness that is related to area measures of deprivation and income variation.

There have been many additional studies in the past five years in which area-level contextual variables were analyzed in relation to health outcomes. Goldsmith *et al* (1998) analyzed the relationship between classic social area dimensions and the need for mental health services. Mustard *et al* (1999) examined the validity of using ecological measures of socioeconomic status in lieu of individual-level measures in the study of population health. They found that ecological measures can be useful proxies when individual-level income measures are not available.

Duncan *et al* (1999), in a multilevel study, determined that measures of neighborhood deprivation had an independent effect on health risk behavior, specifically smoking. They concluded that the character of the local neighborhood played a role in shaping health-related behavior. In another multilevel study, Gorman (1999) found that contextual effects had an independent effect on low birthweight, net of individuals variables. However, these contextual effects varied in their impact across different ethnic groups, which suggested the presence of interaction effects with respect to area and individual variables. Pampalon *et al* (1999) observed significant local area variations in individual health perception, which were over and above those attributable to individual and household variables.

Ecob and Macintyre (2000) found that the influence of area deprivation and other contextual effects on health related behaviors can vary by individuals' age and by household-level deprivation. Haynes and Gale (2000) used three common area-level indicators of social deprivation (Jarman index, Townsend index, and Carstairs index), derived from combinations of census measures, in order to assess differences in health between rural and urban areas. Huff and Gray (2001) derived an area-based index of socioeconomic status for Nottingham, England, in order to assess its relationship to coronary heart disease mortality. They computed their measures by principal components analysis, using indicators based on *a priori* knowledge. Their resulting index is similar to the Townsend index and the Carstairs index. They found that mortality rates, despite falling overall between 1982 and 1992, fell at differential rates between socioeconomic zones, with widening gaps between the most advantaged and the most disadvantaged areas. Reidpath *et al* (2002) studied the relationship between an area measure of socioeconomic status and the density of fast food outlets to the prevalence of obesity in Melbourne, Australia. In a multilevel study, Frolich *et al* (2002) determined that geographic area variations in youth smoking initiation were not fully explained by individual-level variables. Instead, the behavior was influenced by aspects of the social structure at the neighborhood level. Finally, in yet another example of a multilevel study, Subramanian *et al* (2003) found contextual effects in variations in neighborhood social capital, after controlling for individual demographics and socioeconomic characteristics.

Many of these studies, as mentioned, were multilevel studies, in which both individual and area variables are included in the model. The results from these studies are particularly noteworthy in that multilevel studies represent the most rigorous methodology by which to assess individual effects versus area effects. The fact that numerous multilevel studies have found evidence to support the presence of area-level effects (either compositional or contextual, or both) on health outcomes, including all-cause mortality, strongly suggests that area-level effects could be partly responsible for any geographic variations in health outcomes in the present Atlanta-based study.

This Atlanta-area study is an ecological study in the sense that relationships were analyzed among aggregated data. This type of study was chosen both because of data availability limitations as well as the desire to analyze influences on health that could potentially be attributed to area effects. No individual-level data were used in this study, particularly data related to individual health behaviors and health outcomes. Because of this limitation, it is not possible to conduct a multilevel analysis to separate out the specific impacts of individual factors versus area factors on health. Thus, the results of this study are particular to area effects alone. Furthermore, the area effects can be attributed to compositional or to contextual influences, but only to a limited degree. Any effects due to land-use and vegetative greenness would be contextual in nature. The effects due to the aggregated socio-demographic variables would not be attributable specifically as compositional or contextual, without the inclusion of individual-level data as in a multilevel study.

Impact of Socio-Demographic Variables on Health

There is a vast literature on the impact of specific socio-demographic variables on health. These variables typically include those that constitute the classical social area dimensions of social rank (income, occupation, education), lifestyle/urbanization (family composition and housing characteristics), and race/ethnicity (Goldsmith *et al*, 1998). Other variables include poverty, deprivation, wealth (often measured as median housing value), income inequality, and employment status. Most of these variables can be considered compositional variables, in that they represent the aggregation of individuals' characteristics for a given areal unit, such as a census tract.

Of all the potential explanatory variables for health outcomes, perhaps income and income-related measures have been the most studied. These variables usually take the form of average or median household income, family income, or individual income, per area. However, based on a seminal paper by Wilkinson (1992), the relative inequality of income has been the subject of recent intense study and debate. Therefore, these measures can be grouped into two categories: those that measure absolute income levels (e.g., median household income and poverty) and those that measure relative income distributions (e.g., Gini coefficient and Robin Hood Index).

A survey of the literature from the past decade indicates a consensus in support of the hypothesis that absolute income levels and poverty are significantly related to mortality. Recent studies that have indicated a significant relationship between the level of income and a variety of health measures include: Davey Smith *et al* (1996), McDonough *et al* (1997), Duncan *et al* (2002), and Osler *et al* (2002) on the relationship to all-cause mortality; Gorman (1999) on the relationship to low birthweight; Blakely *et al* (2001), and Shibuya *et al* (2002) on the relationship to self-rated health and quality-of-life; Goldsmith *et al* (1998) on the relationship to psychiatric disorders; Sturm and Gresenz (2002) on the relationship to chronic illnesses and mental disorders; and Gravelle *et al* (2002) on the relationship to life expectancy. McDonough *et al* (1997) also found a significant relationship between income stability and all-cause mortality, in addition to the effect of income levels on mortality.

The evidence in support of the hypothesis that income inequality is related to health is mixed, especially in light of many recent studies (2002-2003) that have shown a lack of support for the relative income hypothesis. Wilkinson (1992) presented early evidence of the potential linkage between area-based income inequality and health. Similar outcomes were attributed to income inequality in subsequent studies with respect to various health outcomes, for example: Kaplan *et al* (1996), Kennedy *et al* (1996), and Kawachi *et al* (1997) with respect to all-cause mortality; Gold *et al* (2002) with respect to teen births; Lynch *et al* (2001) with respect to infant mortality; and Kennedy *et al* (1996) with respect to cause-specific mortality.

However, later studies on income inequality demonstrated no significant effects on health outcomes, after controlling for other area-level variables, such as: average household or family income (Blakely *et al*, 2001; Sturm and Gresenz, 2002; and Blakely *et al*, 2003); per capita income (Gravelle *et al*, 2002; Shibuya *et al*, 2002; and Osler *et al*, 2002); educational attainment (Sturm and Gresenz, 2002; and Muller, 2002); and other demographic characteristics such as age, race, and ethnicity (Blakely *et al*, 2001; and Blakely *et al*, 2003).

Poverty is another measure that has been significantly linked to health outcomes, including all-cause mortality (Brimblecombe *et al*, 1999; Orford *et al*, 2002; Braveman and Tarimo, 2002; and Krieger *et al*, 2002); self-rated health (Kobetz *et al*, 2003); teen births (Gold *et al*, 2002); low birthweight and blood-lead levels in children (Krieger *et al*, 2003). Significant associations between wealth and health outcomes have been found by Krieger *et al*, 2002 and Duncan *et al,* 2002 (all-cause mortality); and Krieger *et al* 2003 (low birthweight and blood-lead levels in children).

Education has been shown to be significantly associated to health outcomes, such as all-cause mortality (Duncan *et al*, 2002; Krieger *et al*, 2002; Muller, 2002; Wong *et al*, 2002; and Osler and Prescott, 2003); chronic diseases and mental health (Sturm and Gresenz, 2002); self-reported morbidity (Krokstad *et al*, 2002); and low birthweight and blood-lead levels in children (Krieger *et al*, 2003).

Occupation has been linked to health outcomes by Barnett *et al* (1997); Gregorio *et al* (1997); Duncan *et al* (2002); Krieger *et al* (2002); and Krieger *et al* (2003). The relationship between unemployment and health has been demonstrated by Gorman (1999) with respect to low birthweight; and Brimblecombe *et al* (1999) with respect to all-cause mortality. However, more recently Kobetz *et al* (2003) failed to find a significant relationship between unemployment and self-rated health.

Impact of Urbanicity and Urbanization on Health

The degree to which an area is urbanized (e.g., urbanicity) and the rate at which an area is being urbanized (e.g., urbanization) are both potential contextual variables for explaining geographic variations in several health-related variables. Previous research has indicated significant relationships between urbanicity/urbanization and health, in which the impacts are both positive and negative. The following is a brief overview of previous theoretical and empirical work on urbanicity and urbanization.

Leviton (2000) proposed two conceptual frameworks for research and practice relating to urban health promotion: an urbanization framework and an inner-city ecology framework. The urbanization framework refers to the population growth of an urban area, with increases in the size of the urban area, increases in population density, population heterogeneity, changes in population mobility, changes in the industrial base (including deindustrialization), emerging issues of social justice, and spatial proximity of the rich and poor.

Leviton argues that urbanization is accompanied by increased anonymity, less socializing with neighbors, less involvement in community associations, separation from familiar connections and social supports, a loss of connectedness, and a decreased trust of others. All these factors negatively affect health directly and indirectly. At the same time, urbanization also confers benefits that positively affect health: the physical and human resources of the city, more affluent and middle-class neighborhoods, and easy access to diverse cultures, entertainment venues, and educational opportunities. One mechanism by which these factors can influence health is through the increase in leisure time physical activity, due to the availability of sidewalks and a variety of recreational choices. However, the presence and fear of crime, along with time pressures and the high costs of recreational facilities result in an unequal distribution of the benefits of urbanization among rich and poor. Likewise, the negative aspects of urbanization are not equally experienced by the population. This suggests an interaction effect between area-level social and physical attributes and individual-level characteristics.

Leviton's inner-city ecology framework focuses on issues unique to core central city areas: the concentration of the poor and minorities, deindustrialization, disinvestment in the downtown central business district, loss of inner city jobs, and relative isolation of the population from amenities and job opportunities in the surrounding suburban areas. The result is a concentration in the inner cities of low-income persons, with low social class. Low-income and low social class are well-known determinants of poor health and behaviors related to increased morbidity and mortality (Leviton, 2000).

Geronimus (2000) also focused on health problems unique to central cities. He argued that structural influences have resulted in modern ghettos in central cities. Modern urban environments developed under the influence of race-conscious policies. For example, highway construction and public housing projects isolated black neighborhoods. Racial covenants, discriminatory mortgage lending practices, and racial steering prevented blacks from moving to newly-developing suburban areas. White residents were offered government-subsidized low-interest home mortgage loans, which facilitated the migration of white residents to the suburbs. Publicly-funded transportation projects provided convenient links between suburban homes and employment and cultural/entertainment centers.[*]

Geronimus argued that economic restructuring led to a shift from a manufacturing to a service economy, which resulted in the loss of many high-paying unionized manufacturing jobs in the city, followed by high unemployment. The combined effect of housing policies/practices and economic restructuring was to prevent many blacks from escaping the poverty that resulted from the loss of jobs in the urban center. At the same time, there was a general lack of public and private investment in central urban areas, such as funds to maintain and supervise infrastructure, public housing and public parks. The inability of black residents to migrate out from the central city, combined with the decline of these areas, led to a further decline in the quality and value of housing stock.

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[*] Wyly and Holloway (1999) and Holloway and Wyly (2001) found evidence in support of these structural influences in metropolitan Atlanta, Georgia.

Therefore, a primary means of accumulating wealth through home ownership was denied to blacks.

As Geronimus noted, these factors are important to health through the strong associations between health and poverty. Those in poverty tend to be exposed to a greater extent to social, psychosocial, and physical factors that have been shown to be associated with increased morbidity and mortality. These factors include acute and chronic stress, overburdened or disrupted social supports, material deprivations, and exposure to hazards in the physical environment, such as toxins and pollutants. The psychosocial stresses often lead to increases in unhealthy behaviors, a lowered ability to access health information, health services, or technologies that could protect them from health exposures or to reduce their risks from such exposures. These negative influences resulting from poverty are often exacerbated for minorities, as their exposure to poverty is often prevalent across the lifespan, thus suggesting a cumulative health impact of persistent disadvantage.

The association between population density and health is often considered in the context of infectious diseases. As an example, Stephens (1995) reviewed previous studies of the association between population density in developing counties and potential health outcomes. In general, developing countries experience infectious and parasitic diseases to a much greater degree than do urban areas in more-industrialized countries. The transmission of infectious, parasitic, and respiratory diseases are often exacerbated by close proximity of human populations. Therefore, higher levels of population density (e.g., urbanicity) in developing countries contributes to an increased risk of the transmission of these diseases.

Tanaka *et al* (1996) found that mortality was positively correlated with population density, commercial-zone land area as a percentage of total land area, and urban land area as a percentage of total land area, in Tokyo, Japan. These relationships held even after adjustment for income and education. However, Tanaka noted that the relationship was not linear: as population density, urban area as a percentage of total area, and non-farmland and non-woodland area as a percentage of total land area increased, mortality decreased to a point; then mortality increased slightly as these indicators increased beyond that point. They also found that areas with a high proportion of residential land area and a low proportion of industrialized land area were related to low mortality rates. They concluded that residential-condition indicators concerning housing, land use, and local economic activities were related to age-adjusted mortality rates, both before and after adjusting for socio-economic levels of individual residents.

McDade and Adair (2001) noted the correlation between urbanicity and health outcomes. They specifically described population density as one of several measures that were positively correlated with urbanicity. Therefore, population density could serve as a proxy measure for urbanicity, which is significantly correlated to health.

Rythönen *et al* (2001) conducted a small-area analysis of health variations in Finland. They used population density as a measure for the degree of urbanization; their results indicated a significant correlation between population density and mortality. They also found that social and material deprivation were associated with mortality.

The evidence relating to the relationship between vegetative greenness and health is much more limited. In a study of the impact of walkable green spaces on longevity, Takano *et al* (2002) found a positive association among residents of Tokyo, after controlling for age, gender, marital status, baseline functional status, and socioeconomic status. They identified two important factors necessary for this positive relationship: the availability of walkable green spaces and streets, and a positive attitude to a person's own community (relating to their comfort with and willingness to use their surroundings for physical activity). Their findings suggest the operation of interaction effects in the sense that walkable green spaces are a necessary but not sufficient condition for the facilitation of healthy behaviors that lead to increased longevity. The concurrent presence of a favorable attitude towards the neighborhood environment is necessary in order for the walkable green spaces to have the desired effect on health behaviors.

Other researchers have noted the positive and the negative aspects of urbanicity or urbanization on health. Vögele (2000), in a retrospective study on the urbanization of Germany in the late 1800s and early 1900s, noted the positive impacts of urbanization or urbanicity on health, resulting from the systematic improvement of sanitary and hygiene infrastructure (e.g., water and sewer), disinfection, foodstuffs control, and municipal milk supply (which especially benefited infant health).

Verheij (1996) reviewed a number of previous studies on urbanicity and health, and also conducted a new study on the impact of urbanicity on mental health. Verheij noted that these studies all demonstrated both positive and negative impacts on health from urban living. However, these health-related environmental constraints and opportunities had effects that were dependent on the person who was living in that urban environment. In other words, there were interaction effects between area factors and individual characteristics. He cited the need for multilevel studies in order to more specifically analyze these interactions.

Hypotheses

There are two research hypotheses for this study: 1) the process of urbanization in metropolitan Atlanta, Georgia, from 1980 through 2000 has resulted in more dispersed spatial pattern of area-level variables that have been demonstrated by previous research to be significantly associated with poor health outcomes, specifically all-cause mortality; and 2) the spatial distribution of these area-level variables, in 1990, is significantly related to the spatial distribution of all-cause mortality, aggregated from 1995 through 1999. The second statement implies that the spatial patterning of all-cause mortality can be predicted, through regression modeling, by the spatial distribution of independent variables that are significantly associated with health.

Data and Methodology

Mortality data were obtained from the Georgia Division of Public Health, in Atlanta, Georgia. Data were obtained for 1980 through 1999; however, only data from 1995 through 1999, inclusive, contained a database field for the decedents' residential address, which is necessary for geocoding and computation of tract-level mortality rates.

Socioeconomic and demographic data were obtained from Geolytics, Inc., a retail provider of value-added U.S. decennial census data. Specifically, U.S. Census Long Form (SF-3) data were obtained for 1980, 1990, and 2000. This research project utilized selected original variables from the SF-3 as well as user-derived variables from the SF-3 data.

County boundary files were obtained from the Digital Environmental Atlas of Georgia, Version 2, published jointly by the Georgia Geologic Survey and the U.S. Geological Survey. Census tract boundary files were obtained from the U.S. Census

Bureau for 1990 and 2000. For 1980, census tract boundaries were obtained from Geolytics, Inc., which created the census tract boundaries based upon Census TIGER/Line Files, (no longer downloadable for 1980 from the Census Bureau). The 1980 Geolytics census tract boundaries were manually "cleaned" in a geographic information system (ArcInfo 8.2, Environmental Systems Research Institute, Redlands, California) in order to remove hundreds of small polygons corresponding to small-to-large bodies of water. The 1990 and 2000 census tract boundary files did not include such polygonal objects.

Satellite imagery were obtained from the U.S. Geological Survey, EROS Data Center, for 1984 (LT5019036037084172, Landsat 5, Thematic Mapper, Path 019, Rows 036-037 (50% offset), acquired June 20, 1984); for 1990 (Scene ID: LT5019036037090268, Landsat 5, Thematic Mapper, Path 019, Rows 036-037 (50% offset), acquired September 25, 1990); and for 2000 (Scene ID: L71019036-03620000928, Path 019, Row 036, acquired September 28, 2000; and Scene ID: L71019037-03720000928, Path 019, Row 037, acquired September 28, 2000). These satellite images were used to derive land use/cover data for the period of the research project.

Color infrared (CIR) digital orthophoto quadrangles (DOQs) of metropolitan Atlanta (February 1999) were used for ground truthing of satellite-derived land use/cover data for 2000. Black-and-white and color aerial photographs of portions of the metropolitan Atlanta area (particularly Gwinnett County, 1988 and 1989) were used for ground truthing of satellite-derived land use/cover data for 1990.

Road network data were obtained from the National Transportation Atlas Database: 2002, published by the U.S. Department of Transportation, Bureau of Transportation Statistics, and from ESRI (Environmental Systems Research Institute, Redlands, CA). These data were used to assist in classification of land use/cover.

Data Derivation and Adjustment of Census Geography Changes

The original mortality data obtained from the Georgia Division of Public Health consisted of individual records of decedents along with their last known residential street address. In order to derive area-based rates at the census tract level, it was necessary to geocode (address-match) the residential locations using a geographic information system (GIS). The original database contained a total of 102,016 death records for the thirteen counties of the study area.

The mortality data were geocoded through an iterative process, utilizing two software packages and two street file databases. The first geocoding iteration was performed in ArcInfo 8.2 ™ (Environmental Systems Research Institute, Redlands, CA) using the U.S. Census Bureau's 2000 TIGER Line Files as the street matching file. Interactive matching was conducted on unmatched records. All records (matched and unmatched) were then geocoded with a second software application and database (Centrus Desktop 4.0 and Sagent Company's Address Coding Module). This was done in order to improve the overall geocoding rate as well as to serve as a check on the accuracy of the geocoding results from the ArcInfo/TIGER processing step. As in ArcInfo, Centrus also allows interactive matching. The successfully matched addresses were merged from the ArcInfo and Centrus database information, resulting in match rates ranging from 83% (Paulding County) to almost 98% (Henry County). The resulting file of geocoded deaths totaled 97,910 records, for an overall geocoding rate of 96.03%. The spatial distribution of mortality is depicted in Figure 6.3.

The number of deaths per 1990 census were computed using ArcInfo 8.2, in which the point-level mortality data were spatially joined to the census tract boundary shapefile. Crude mortality rates (number of deaths per 100,000 population) were computed in the GIS, using 1997 estimates of census tract populations. In addition, the mortality rates were age-adjusted to account for variations in the age-structure of the census tract populations. Standardized Mortality Ratios (SMRs) were calculated using indirect age-adjustment procedures (U.S. Department of Health and Human Services, 2001), with estimated death rates per age-group for the U.S. population in 1997 as the reference data.[*] Figure 6.4 depicts the SMRs for metropolitan Atlanta (1995-1999).

Land-use/land-cover data were derived from unsupervised classifications of remotely-sensed satellite images of metropolitan Atlanta for 1984, 1990, and 2000. These three Landsat images were processed in ERDAS Imagine 8.6 (Leica Geosystems, Inc., Atlanta, Georgia) using the ISODATA procedure (Jensen, 1996), with classification accuracies exceeding the commonly-accepted minimum thresholds for remotely-sensed data (Anderson *et al*, 1976). Six categories of land-use/land-cover were used: high-density urban, low-density urban, cultivated or exposed land, cropland or grassland, forested land, and water. The high-density urban class represented predominantly commercial and industrial areas, while the low-density urban class represented mostly residential areas. After image classification, the extent of urbanized (high-density and

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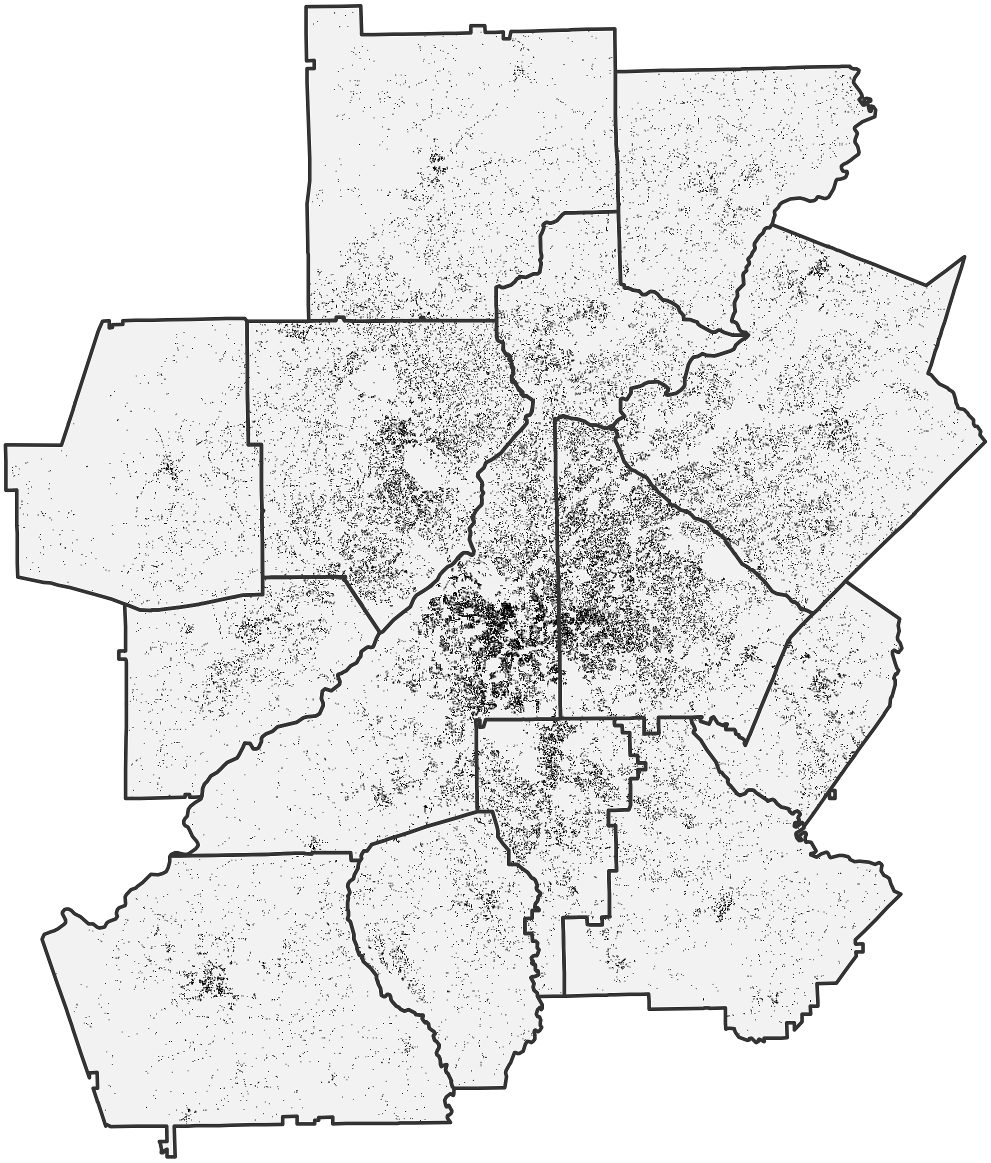
[*] Additional details of the geocoding and age-adjustment procedures are provided in Chapter 5 of this dissertation.



Each point represents one death.

Figure 6.3. Geocoded Deaths, Metropolitan Atlanta, 1995-1999.

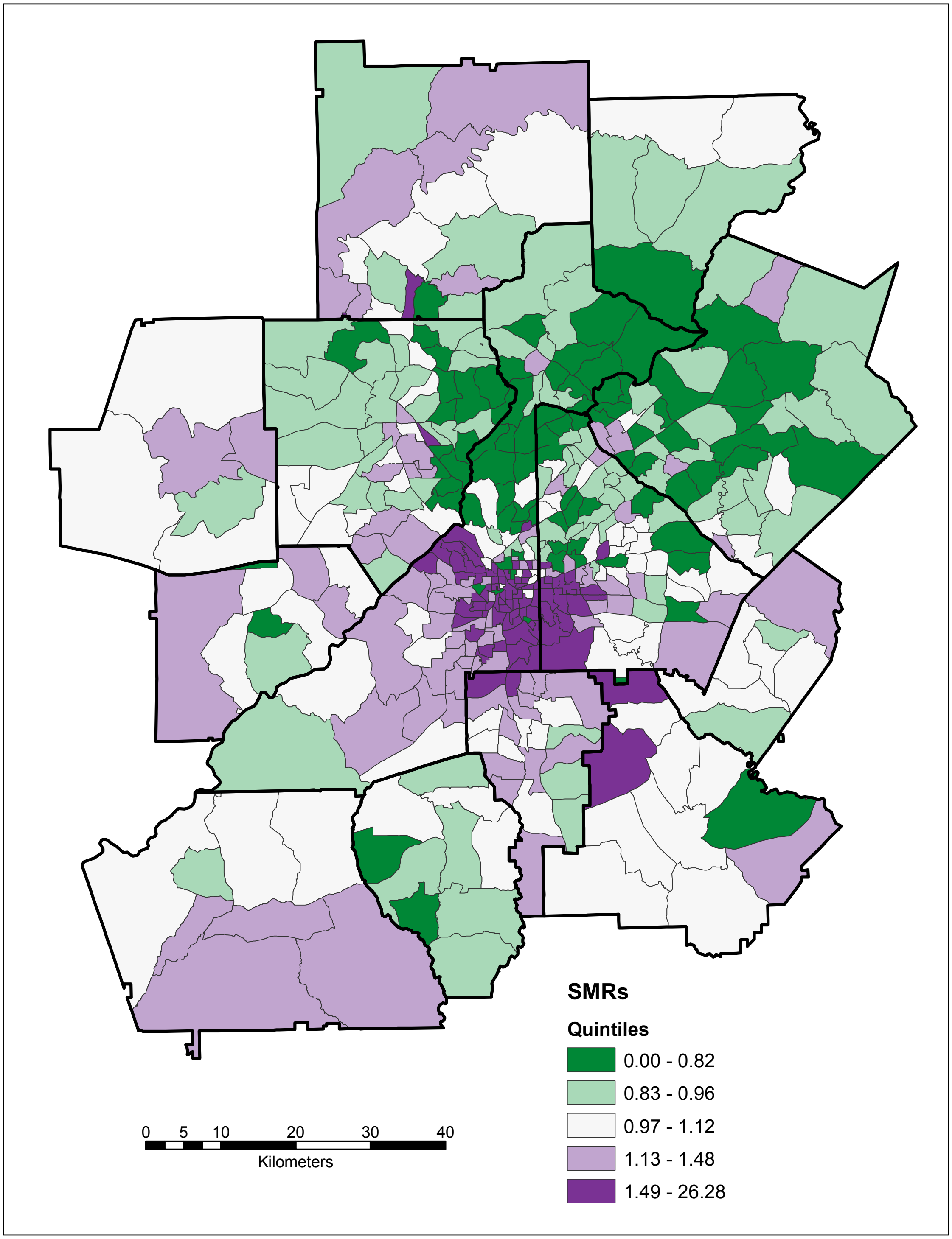


Figure 6.4. Standardized Mortality Ratios (SMRs), Metropolitan Atlanta, 1995-1999.

low-density urban classes) and residential areas (low-density class only) were determined and expressed as percentages of the total land area for each census tract.[*]

Vegetative indices were derived from 1984, 1990, and 2000 Landsat images in ERDAS Imagine. The Scaled Normalized Difference Vegetation Index (NDVI) represents a direct measure of the amount of aboveground green plants within the Instantaneous Field of View (IFOV) of the Landsat sensor (Weng and Lo, 2001). NDVI was scaled in order to reduce differences among the images due to non-systematic temporal variations in NDVI. This methodology is described in detail in Weng and Lo (2001). Figures 6.5, 6.6, and 6.7 depict Scaled NDVI for 1984, 1990, and 2000.[**]

The equation for calculating NDVI is (Jensen, 1996):

$$\mathrm{NDVI} = \frac{\text{NIR Band} - \text{Red Band}}{\text{NIR Band} + \text{Red Band}} \qquad (6.1)$$

The equation for the scaled NDVI is (Weng and Lo, 2001):

$$N^* = \frac{(\mathrm{NDVI} - \mathrm{NDVI}_O)}{(\mathrm{NDVI}_S - \mathrm{NDVI}_O)} \qquad (6.2)$$

Where:
NDVI_O = minimum NDVI value in the unscaled image
NDVI_S = maximum NDVI value in the unscaled image

The remaining independent variables were obtained or derived from 1980, 1990, and 2000 U.S. census data. These variables were selected based on the review of studies relating to mortality and other health outcomes, as described previously. The variables for 1990 are named and defined in Table 6.2.

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[*] See Chapter 3 for more details on land use/land cover mapping using Landsat images.

[**] Scaled NDVI values for all census tracts for 1984, 1990, and 2000 are contained in Appendix D.

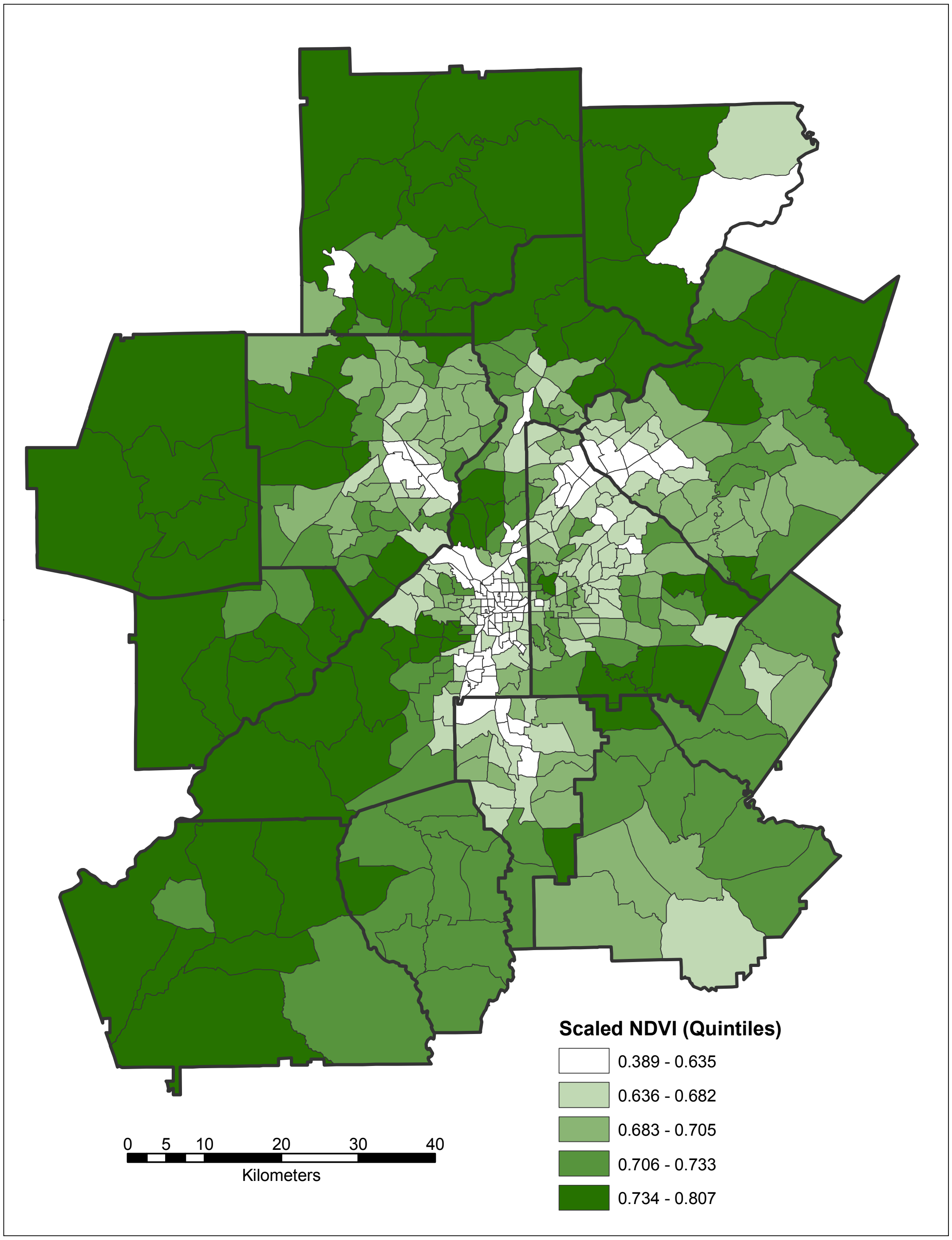

Figure 6.5. Scaled Normalized Difference Vegetation Index (NDVI), Metropolitan Atlanta, Georgia, 1984.

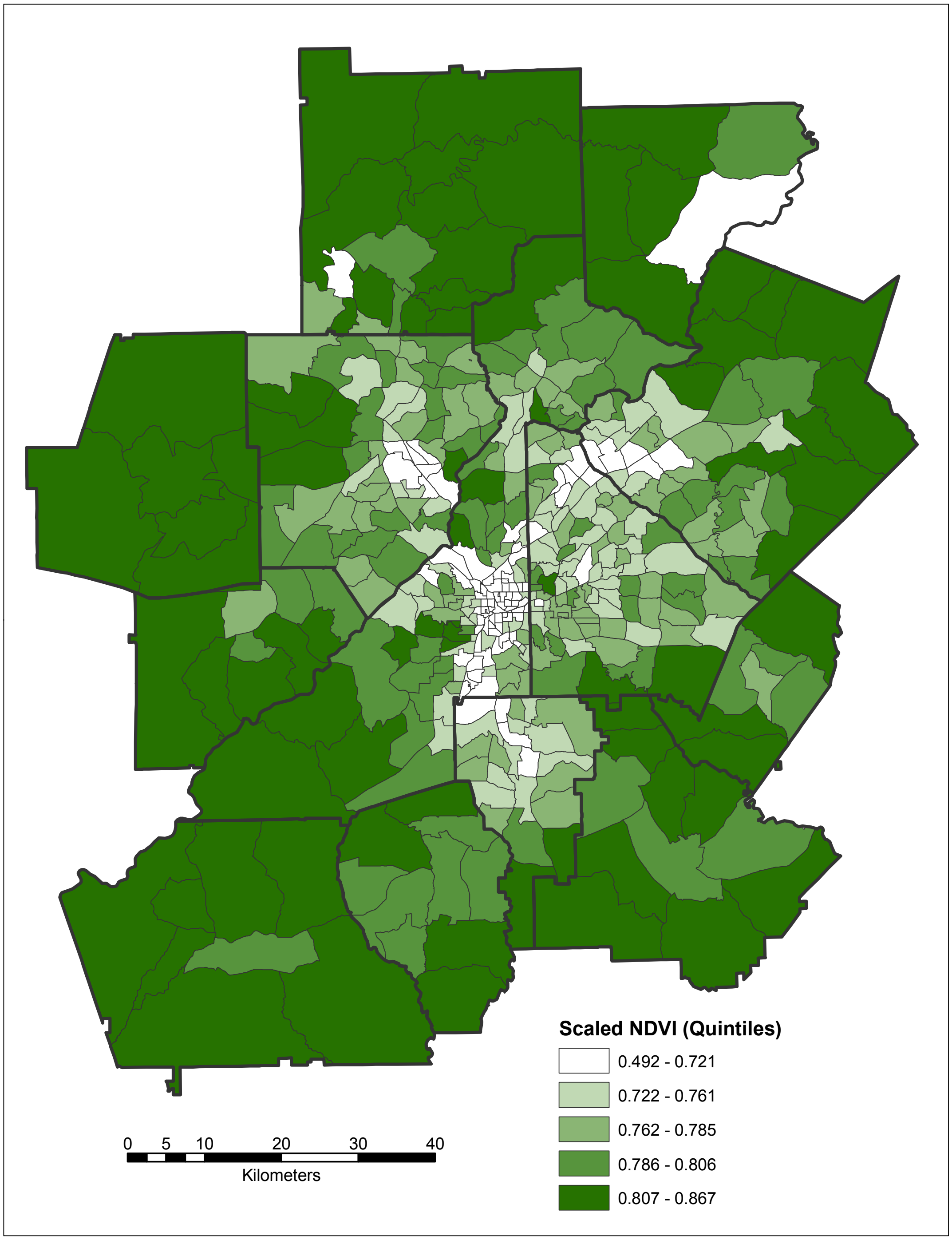

Figure 6.6. Scaled Normalized Difference Vegetation Index (NDVI), Metropolitan Atlanta, Georgia, 1990.

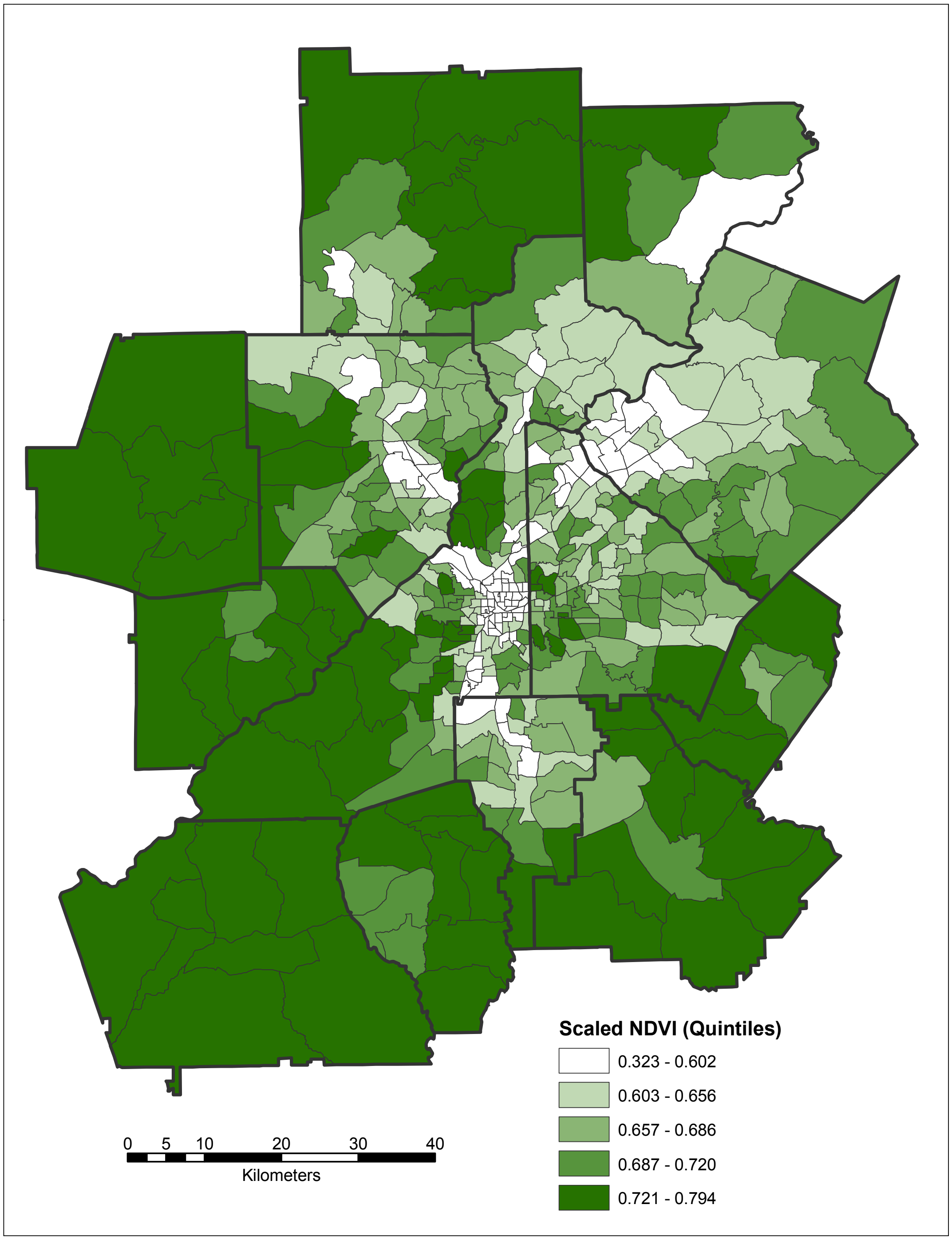

Figure 6.7. Scaled Normalized Difference Vegetation Index (NDVI), Metropolitan Atlanta, Georgia, 2000.

Table 6.2. Independent variables, 1990.

Variable Name	**Definition**	**Directly Obtained or Derived from Data**
PPOV	Percent of population living below the federal poverty line, 1990	Derived
MEDHHI	Median household income, 1990	Directly obtained
MDHSVL	Median housing value, 1990	Directly obtained
PUMP	Percentage of population over age 18 in the civilian workforce unemployed during past year (1989)	Derived
PHS	Percentage of population over age 25 with high school diploma or equivalent, 1990	Derived
PBCH	Percentage of population over age 25 with bachelors degree or higher, 1990	Derived
PUNOC	Percentage of housing units unoccupied, 1990	Derived
POWNOC	Percentage of housing units that were owner-occupied, 1990	Derived
PURB	Percentage of total land area that is urbanized (high-density and low-density urban land use), 1990	Derived
PHDU	Percentage of total land area that is high-density urban land use (e.g., commercial or industrial), 1990	Derived
PLDU	Percentage of total land area that is low-density urban land use (e.g., residential), 1990	Derived
POPDENS	Dasymetrically-derived population density., 1990	Derived
NDVI	Scaled Normalized Difference Vegetation Index, 1990	Derived
PBLK	Percentage of total population black, 1990	Derived
EXP_D	Number of expected deaths per census tract (based on indirect age-adjustment procedures), 1995-1999	Derived

Mortality data were only available for 1995 through 1999. Census and data were available for 1980, 1990, and 2000; while land-use/land-cover data were available for 1984[*], 1990, and 2000. To preserve temporal ordering, the cross-sectional analysis of the relationship between the independent variables and all-cause mortality data relied on independent variables derived from 1990 data. However, further analyses made use of data that represented changes in key variables from 1980 to 2000 (e.g., changes in population density, changes in urbanized land-area, changes in poverty rates, etc.). Because of the primary reliance upon 1990 data for analysis, all data (1980, 1984, 1990, and 2000) were calculated and referenced in terms of the 1990 census tract boundaries. This presented challenges with respect to changes in census tract boundaries from 1980 through 2000. In 1980, the thirteen-county metropolitan Atlanta area consisted of 339 census tracts. In 1990, because of population growth and the U.S. Census Bureau's desire to maintain relatively constant population sizes in each tract, the number of tracts grew to 444. In 2000, this number had expanded to 589. Thus, in a 20-year period, the number of census tracts increased by approximately 74%. In most cases, the new census tracts were created by simply splitting existing tracts, usually by creating two new tracts out of one existing tract. In many cases, the split was 3:1 and in some cases 4:1. In a few cases, the creation of new tracts involved minor adjustments to existing tract boundaries. In a few other cases, even when new tracts were not created, the boundaries between adjacent tracts shifted.

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[*] A Landsat Thematic Mapper (TM) image was acquired from December, 1982, the first year for which TM images were available. However, because of poor radiometric contrast as well as seasonal incompatibility with the 1990 and 2000 Landsat images (winter versus summer), the 1982 image was not used. Therefore, the 1984 image was used as a proxy for 1980 land-use/land-cover.

Because 1990 boundaries were used, it is necessary to account for census tract boundary changes by weighting the census data for 1980 and 2000. Census data for 1980 and 2000 were areally interpolated when boundary shifts occurred from one census to the next.[*] This situation is relatively infrequent (8 cases for 1980-1990 and 15 for 1990-2000) and represents a small percentage of the overall tracts (1.8% for 1980-1990 and 2.5% for 1990-2000). The percentages of affected population in these cases were small, especially for the 1990-2000 boundary shifts (1980-1990: range 0% to 47%; mean 23%; median 26.5%; and 1990-2000: range 0% to 18%; mean 6.5%; median 5%). Therefore, the overall impact on the total data set from census tract boundary shifts is modest.

The final set of 444 census tracts, corresponding to the 1990 census tract boundaries, was reduced to an analysis set of 431 tracts, to remove 4 tracts that were unpopulated in 1990 and 9 tracts in which the observed number of deaths over the five-year period (1995-1999) is less than 30. It is not possible to compute 1980-2000 change values for the independent variables in 23 census tracts, due to the unavailability of 1980 data variables for these tracts. These 23 tracts were kept in the analysis set, and their variables for the 1980-2000 changes were treated as missing values in the analysis.

Table 6.3 lists the descriptive statistics for the 1980 variables for the 408 census tracts for which 1980 census data are available. Tables 6.4 and 6.5 contain descriptive statistics for the 1990 and 2000 variables for the 431 census tracts in the analysis set.[**]

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[*] Details of the areal interpolation process are described in Chapter 4 of this dissertation.

[**] Data on median household income and median housing value were not utilized for 1980 and 2000 because of conceptual difficulties in performing areal interpolations on data that represented average values by area. Independent variables for all census tracts in the analysis set are contained in Appendix E.

Table 6.3. Descriptive statistics for 1980 variables.

Variable Name	Minimum	Maximum	Mean	Std. Deviation
PLDU80	0.21	67.00	17.0893	11.7773
PHDU80	0.12	98.30	17.8991	17.8215
PURB80	1.72	99.42	34.9885	24.9077
PPOV80	1.08	75.66	13.6820	14.6028
POPDENS80	354.43	184595.02	5503.9528	12773.5200
PUNOC80	0.00	30.08	6.9142	4.6872
POWNOC80	0.00	99.09	59.2709	25.3319
NDVI80	.389	0.807	0.67950	0.06167
PHS80	13.77	96.49	67.5057	17.7960
PBCH80	0.00	56.71	17.8832	13.6765
PUMP80	.00	25.95	6.0232	4.5111
PBLK80	.00	99.82	25.3919	35.0838

Table 6.4. Descriptive statistics for 1990 variables.

Variable Name	Minimum	Maximum	Mean	Std. Deviation
PLDU90	0.00	57.47	21.1645	10.7979
PHDU90	0.00	96.67	19.3117	17.5684
PURB90	3.47	100.00	40.4767	23.0494
PPOV90	0.000	88.00	13.5564	16.1117
POPDENS90	366.67	61499.92	4102.8048	4740.2531
PUNOC90	0.00	82.57	10.5277	7.6370
POWNOC90	0.00	90.11	47.4590	22.8129
NDVI90	.492	0.863	0.75856	0.05955
PHS90	22.10	100.00	76.9752	16.6636
PBCH90	0.00	72.30	25.8253	17.7888
PUMP90	0.00	41.00	6.3819	5.4335
MEDHHI90	4999	150001	36214.55	17503.56
PBLK90	.00	100.00	31.1152	35.8927
MEDHSVL90	0	500001	96009.75	60947.93

Table 6.5. Descriptive statistics for 2000 variables.

Variable Name	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
PLDU00	0.00	64.86	30.0192	12.6731
PHDU00	0.00	98.89	21.6663	18.4994
PURB00	5.37	100.00	51.6856	23.7703
PPOV00	0.52	75.43	13.0826	13.1715
POPDENS00	366.67	652221.96	5158.2087	31800.8037
PUNOC00	0.00	57.89	6.1604	5.1271
POWNOC00	0.00	99.27	60.7653	26.1355
NDVI00	0.323	0.794	.65674	0.07841
PHS00	30.43	98.78	79.9727	13.9389
PBCH00	0.00	60.02	20.1643	14.6902
PUMP00	0.00	89.72	7.0171	8.4045
PBLK00	0.00	100.00	37.8403	35.3532

Exploratory Factor Analysis

Fourteen potential explanatory variables for mortality had been identified through a comprehensive review of the public health literature. An exploratory factor analysis was conducted on these variables for 1990 as well as the variable for the number of expected deaths per tract, with SPSS 10 (SPSS, Inc., Chicago, Illinois), using an unweighted least squares extraction and Varimax rotation. Five factors were extracted and rotated. Of the five factors, three had Eigenvalues exceeding 1.0, and together these three factors explained 74.7% of the total variance. The total variance explained by all five factors is 84.8%. Rotated factor loadings, Eigenvalues, and percentages of explained variance are given in Table 6.6.

Factor 1 loads heavily (≥ ± 0.5) on four variables: percentage high-density urban land-use (HDU: 0.937), vegetative greenness index (NDVI: -0.905), percentage total urban land-use (PURB: 0.801), dasymetric population density (POPDENS: 0.656), and the percentage of housing units that were owner-occupied (POWNOC: -0.507). This

Table 6.6. Rotated factor loadings, Eigenvalues, and percentages of explained variance: factor analysis, 1990 data.

Variable	Factor				
	1	2	3	4	5
EXP_D	-.355	.153	-.243	-.158	.028
PLDU	.171	-.044	.191	**.964**	-.063
PHDU	**.937**	-.146	.185	.071	-.183
POPDENS	**.656**	.018	.145	-.056	-.167
PUNOC	.433	-.123	.267	.074	-.383
POWNOC	**-.507**	.171	-.219	-.074	**.798**
PHS	-.159	**.687**	**-.553**	-.036	.150
PBCH	.024	**.905**	-.288	.079	.030
PUMP	.255	-.382	**.741**	.213	-.152
MEDHHI	-.308	**.688**	-.259	-.156	.489
PBLK	.266	-.397	**.563**	.250	-.179
MEDHSVL	-.107	**.834**	-.114	-.116	.056
PPOV	.453	-.338	**.749**	.103	-.244
PURB	**.801**	-.133	.229	.499	-.165
NDVI	**-.905**	.120	-.144	-.210	.192
Initial Extraction:					
Eigenvalues	7.681	2.394	1.125	0.800	0.713
% of Variance	51.204	15.960	7.501	5.334	4.754
Cumulative % of Variance	51.204	67.164	74.666	80.000	84.754
After Varimax Rotation:					
Eigenvalues	3.840	3.001	2.240	1.430	1.295
% of Variance	25.602	20.007	14.934	9.534	8.630
Cumulative % of Variance	25.602	45.609	60.543	70.077	78.707

factor suggests an “urbanicity” construct. Factor 2 loads heavily on four variables: percentage over age 25 with bachelors degree or higher (PBCH: 0.905), median housing value (MEDHSVL: 0.834), median household income (MEDHHI: 0.688), and percentage over age 25 with a high school degree or equivalent (PHS: 0.687). This factor suggests a “socioeconomic status” construct. The third factor loads heavily on four variables: the percentage of persons living below the federal poverty line (PPOV: 0.749), the percentage of population over age 18 in the civilian workforce who experienced unemployment during the previous year (PUMP: 0.741), blacks as a percentage of total population (PBLK: 0.563), and the percentage over age 25 with a high school degree or equivalent (PHS: -0.553) . This factor suggests an “impoverished racial minority" construct. The fourth and fifth factors each loaded heavily on only one variable: percentage low-density urban land-use, and percentage of housing units that were owner-occupied, respectively. These factors suggest constructs of "residential development" and "residential stability".

The first three factors' constructs are congruent with the classical social area dimensions (Goldsmith *et al*, 1998). Factor 1, "urbanization/crowding" corresponds to "lifestyle/urbanization"; factor 2, "socioeconomic status" corresponds to "social rank"; and factor 3, "impoverished minority" corresponds to "race/ethnicity". Thus, the results from the factor analysis tend to support the analysis, by multiple regression, of variables that measure the three factor analysis constructs, which represent the three social area dimensions.

The only variables whose inclusion in regression modeling were not supported directly by the exploratory factor analysis were the expected numbers of deaths (EXP_D), and the percentage of housing units unoccupied (PUNOC). Because the number of expected deaths is derived from the indirect age-adjustment of mortality rates, it is a proxy measure for the age-distribution and population within each census tract. As age is a primary risk factor for death, it was deemed important to include this variable in subsequent regression modeling as a control.

The percentage of housing units unoccupied (PUNOC) was initially thought to be an indication of residential instability. However, it is likely that the percentage of housing units that were owner-occupied (POWNOC) variable is an adequate marker for the residential stability construct. In addition, the PUNOC variable may be misleading due to the possibility that certain census tracts may have large numbers of newly-constructed vacant houses awaiting purchase (e.g., builders' speculative housing units). In those cases, the PUNOC variable would not represent residential instability (and hence a census tract at increases risk for adverse health) but rather an area that is experiencing economic and population growth (and hence a census tract that may be at decreased risk for adverse health). Therefore, the PUNOC variable could have led to bias in the estimation of the relationship between the set of independent variables and the health outcome variable, and it was dropped from consideration for further analysis.

The exploratory factor analysis is therefore useful in helping to identify underlying constructs within the set of potential explanatory variables, and to identify variables that warranted closer scrutiny for inclusion in regression analysis. In this sense, the factor analysis supported the analysis of thirteen of the fifteen variables. Of the two variables not supported by the factor analysis, the EXP_D variable was determined to be critical enough to the outcome variable to warrant further analysis on its own merits.
The first three factor scores were also exported into the GIS database, from which the individual factors were mapped and analyzed for spatial patterns. Clear patterns emerged for each of the three factors (Figure 6.8). For factor 1, "urbanization", the more-heavily urbanized areas in the Central Business District (CBD) and the surrounding inner ring of suburban downtowns and commuting corridors all exhibited positive scores. For factor 2, "socioeconomic status", the more-affluent areas north of the CBD had positive scores, along with isolated areas to the southwest of Atlanta, such as Fayette County, Coweta County, and portions of southern Fulton County. For factor 3, "minority and poverty", two distinct patterns emerge: first, the poverty areas in the outer ring of counties are clearly delineated by positive scores; and second, the inner-city concentration of

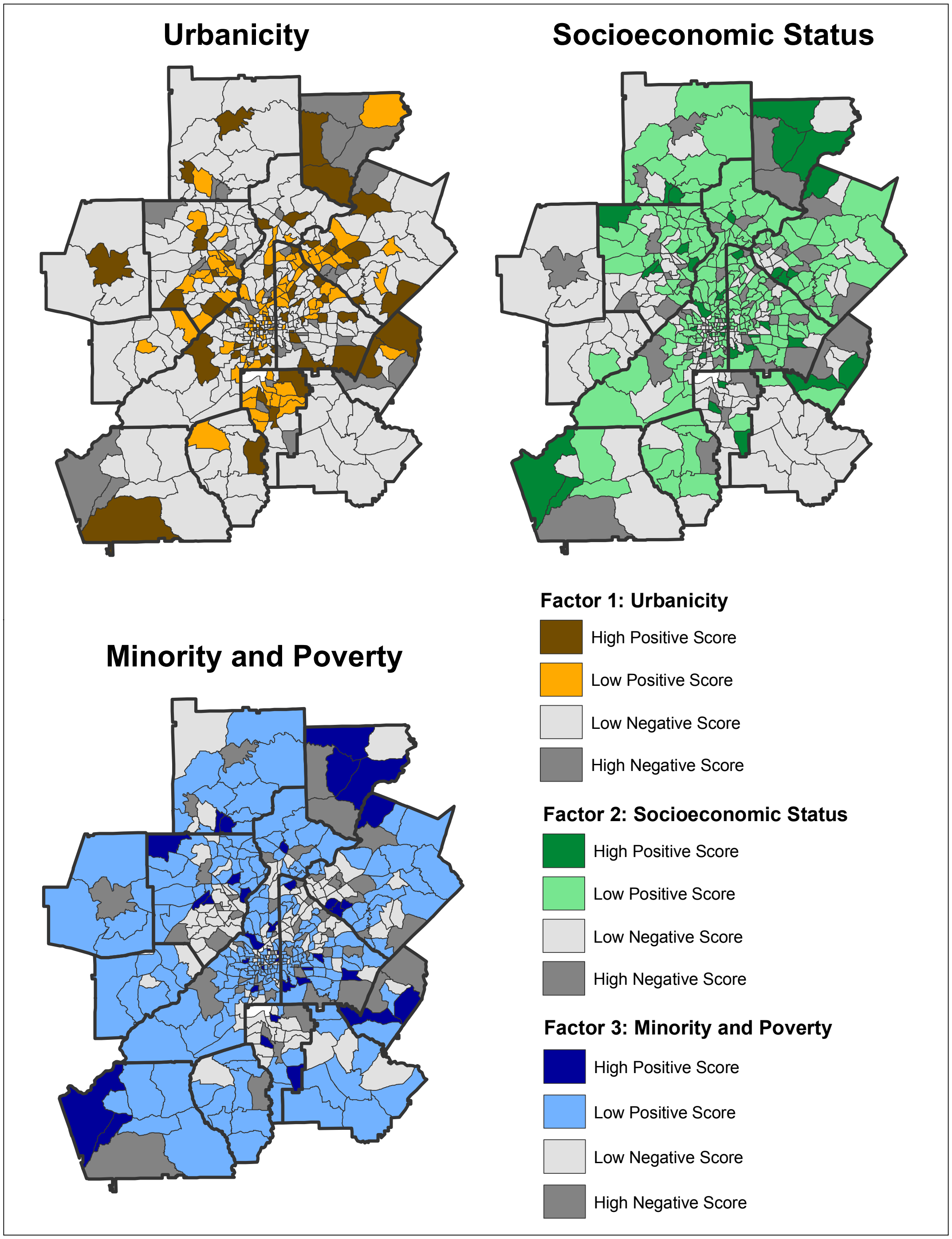

Figure 6.8. Factor scores from exploratory factor analysis, metropolitan Atlanta, Georgia, 1990.

minorities (blacks) is highlighted by positive scores. These observations suggest that there are spatial concentrations of each factor throughout the study area. If these factors, or individual variables that comprise these factors, are significantly associated with mortality, it would be expected that mortality would exhibit spatial patterns that correspond to the spatial patterns of these variables and factors.

Regression Analysis

Regression analysis was conducted using SPSS 10 statistical software. Independent variables were those initially selected from a review of previously-published public health studies and analyzed through exploratory factor analysis. A total of fourteen independent variables from 1990 were used in a series of regression models, with all-cause mortality (number of deaths per census tract, aggregated from 1995 through 1999) as the dependent variable.[*] Individual variables, rather than factor scores or index values (described later), were used in the regression analysis in order to analyze the specific effects of individual variables on the dependent variable.

A total of 62 models were analyzed. A set of models was analyzed to assess the independent effects of single variables on the dependent variable. A second set of models assessed the impact of each of these variables, while controlling for the age structure of each census tract, with the EXP_D variable as the control. Subsequent models analyzed different combinations of the independent variables. The analytic strategy was to first analyze the impact of socioeconomic variables, then the impact of race, and finally the impact of physical environmental variables.

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[*] Initially, Poisson Regression was considered. However, as the number of deaths per tract exceeded 30 in all but nine tracts (mean = 221 deaths/tract), Ordinary Least Squares regression was utilized. The distribution of mortality cases was slightly positively skewed; however, the data were not transformed in order to preserve the functional form of the relationship between the dependent and independent variables.

Diagnostics included the assessment of influential observations through DFFIT_S and DFBETA_S statistics, Leverage scores, Cook's D statistics, and visual interpretation of residual plots (Hamilton, 1992); heteroscedasticity through White's Test where suggested by visual interpretation of residual plots; and multicollinearity through Variance Inflation Factors, condition indices, and partial correlation matrices. Joint Partial F-tests assessed the significance of additional explanatory power for the inclusion of groups of variables to the models.

For selected models, regression residuals were saved and incorporated into the GIS database. The standardized residuals were mapped using a GIS and analyzed for the presence of significant spatial patterns, which may have suggested the omission of a significant explanatory variable (or set of variables) that would have been associated with a geographically-varying pattern of mortality.

Index Construction and Spatial Analysis

A composite index was constructed using the independent variables from the final regression model. This index is similar in concept to commonly-used deprivation indices (Jarman, 1983; Townsend *et al*, 1988; and Carstairs and Morris, 1989) which have been used to measure local and regional levels of socioeconomic deprivation, and which have been used in analyses of health outcomes. This composite index was constructed by standardizing the tract-level values for each variable; multiplying these standardized values by their corresponding standardized regression coefficients from the regression model; and then summing the resulting three values for an overall index value, per census tract.[*]

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[*] The educational attainment variable (PHS) and the urbanicity variable (PURB) were recoded into variables that reflected percentages of non-attainment (PNOHS and PNONURB). This was necessary in

Three separate composite indices were constructed: 1980, 1990, and 2000. The index scores for each census tract were incorporated into a GIS database for mapping and spatial analysis.[**] Spatial analysis of the indices consisted of visual interpretation of index patterns, computation of Moran's I (a global measure of spatial autocorrelation) and Local Moran's I (a Local Indicator of Spatial Autocorrelation, or LISA). Statistical analyses were performed using Crimestat II spatial analysis software (Ned Levine & Associates, 2002). It is hypothesized that the spatial patterns of potential explanatory variables for mortality became less concentrated due to urbanization processes from 1980 to 2000. Therefore, it is expected that measures of spatial autocorrelation would reflect a decreasing degree of concentration in the index scores from 1980 to 2000.

Results

Regression Analysis

Table 6.7 contains the regression coefficients for four Ordinary Least Squares (OLS) regression models: 1) individual bivariate regressions, unadjusted for other independent variables; 2) individual bivariate regressions, adjusted for age-distributions and tract populations (e.g., EXP_D); 3) a model with all fourteen independent variables; and 4) a model with independent variables for race (PBLK), urbanicity (PURB), educational attainment (PHS), and age-distribution and population (EXP_D).

Collinearity is problematic for many of these variables when included in the same model. Variables that were significant and whose coefficient signs were intuitive often became either non-significant (at P < .05) or had a coefficient sign change, or both, when

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order to ensure that associations between the standardized variables and the health outcome variable had the same direction (e.g., higher variable values reflected increased risks for negative health outcomes).

[**] Index scores for 1980, 1990, and 2000 for census tracts in the analysis set are contained in Appendix F.

Table 6.7. Ordinary Least Squares regression of all-cause mortality, 1995 through 1999 on socioeconomic, demographic, and environmental variables, 1990, metropolitan Atlanta, Georgia.

Independent Variable	**Model 1[a]**			**Model 2[b]**			**Model 3[c]**			**Model 4[d]**		
	b	**β**	**SE(b)**	**b**	**β**	**SE(b)**	**b**	**β**	**SE(b)**	**b**	**β**	**SE(b)**
PPOV	-1.564*	-0.212	0.358	1.319*	0.179	0.189	-1.403*	-0.190	0.407	…	…	…
MEDHHI	0.0002	0.036	0.000	-0.0016*	-0.234	0.000	-0.0005	-0.078	0.000	…	…	…
MDHSVL	0.0000	-0.005	0.000	-0.0004*	-0.230	0.000	0.0001	0.058	0.000	…	…	…
PUMP	-2.950*	-0.135	1.074	4.546*	0.208	0.532	-0.144	-0.007	0.873	…	…	…
PHS	0.0444	0.006	0.355	-1.950*	-0.273	0.157	-1.085*	-0.152	0.402	-1.302*	-0.181	0.173
PBCH	-0.843**	-0.126	0.329	-1.941*	-0.290	0.137	-1.119*	-0.168	0.325	…	…	…
POWNOC	1.122*	0.214	0.254	-0.354*	-0.067	0.135	0.234	0.045	0.206	…	…	…
PURB	-1.638*	-0.316	0.244	0.409*	0.079	0.141	…[e]	…	…	-0.473*	-0.091	0.123
PHDU	-2.179*	-0.323	0.317	0.268	0.040	0.182	-0.365	-0.054	0.444	…	…	…
PLDU	-1.622*	-0.147	0.542	0.974*	0.088	0.278	0.764*	-0.069	0.289	…	…	…
POPDENS	-0.0053*	-0.213	0.001	0.0003	0.011	0.001	0.0015**	0.059	0.001	…	…	…
NDVI	727.381*	0.364	92.297	-24.142	-0.012	54.542	220.481	0.110	132.296	…	…	…
PBLK	-0.163	-0.049	0.165	0.950*	0.285	0.074	0.697*	0.209	0.107	0.719*	0.215	0.088
EXP_D	0.795*	0.868	0.023	…	…	…	0.857*	0.936	0.019	0.873*	0.961	0.019

Note: **b** = unstandardized regression coefficient; **β** = standardized regression coefficient.

[a] Bivariate coefficients unadjusted for other independent variables.

[b] Bivariate coefficients adjusted for age-distribution and tract population (reflected in variable EXP_D).

[c] Includes all independent variables.

[d] Final regression model: includes PHS, PURB, PBLK, and EXP_D.

[e] PURB was excluded from the model due to extremely high Variance Inflation Factor (2.6E+07).

[*] P < .01

[**] P < .05

included in more highly-specified models. Collinearity was confirmed through high Variance Inflation Factors and examination of correlation matrices. Similar results were obtained between many models with different combinations of variables each representing socioeconomic, urbanicity, and race constructs. Because of collinearity, it was desired to include one variable for each of these three constructs in the model. The chosen variables would act as "indicator variables" as they would be explaining not only their own unique contributions to the model, but those of other highly-collinear variables whose effects on the dependent variable were quite similar to their own.

The model chosen as the best overall included variables for the percentage of blacks in the total population in 1990 (PBLK90); the percentage of population over age 25 with high school diplomas or equivalent in 1990 (PHS90); and percentage of total land area that was urbanized (high-density and low-density urban land use) in 1990 (PURB90). The expected number of deaths per tract (EXP_D) is a control variable. This model (Model 4 in Table 6.7) included one variable for each of the three social area dimensions, which also represented each of the first three factors from the exploratory factor analysis. In addition, the adjusted R^2 (0.846) is among the higher coefficients from all tested models, while at the same time this model had no problems with collinearity. Joint partial F-tests confirmed that the addition of each successive variable significantly improved upon the preceding, less complex regression models. All three independent variables exhibited robustness across a variety of model specifications, were conceptually easy to interpret, and their relationship to health outcomes, as well as potential causal pathways, have been previously supported in the literature.

The regression parameters of this model suggest that mortality at the census tract level for the thirteen county metropolitan Atlanta area, for 1995-1999, is positively associated with the number of black residents as a percentage of the total tract population; and negatively associated with the percentage of the population over age 25 with high school diploma or equivalent, and the percentage of total land area that was urbanized, when controlling for the age-distribution and population size for each tract. Thus, living in a census tract with higher percentages of black residents (PBLK) was a risk factor for high mortality rates, while living in a census tract with higher percentages of high school graduates (PHS) and/or a census tract with higher percentages of urbanized land use (PURB) were protective factors against high mortality rates, all other factors being equal. The relative magnitudes of these associations, as measured by their standardized regression coefficients, suggests that of the three variables, the race variable, PBLK, exerts the greatest influence on mortality ($\beta = 0.215$), followed by PHS ($\beta = -0.181$) and PURB ($\beta = -.091$).

Heteroscedasticity did not appear to be present as determined by visual examination of scatterplots of residuals versus predicted values and the independent variables.[*] Multicollinearity is not problematic in this model.

Table 6.8 contains predicted mortality counts for hypothetical census tracts. These results indicate that the worst-off hypothetical census tract would be 90% majority black, with a low (50%) high school completion rate, in a rural area (15% urban land-use). The best-off tract would be approximately 90% majority white, with a 90% high school completion rate, in an urban/suburban (65% urban land-use) area. The mortality

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[*] Weighted Least Squares regression (weight = population) using the same independent variables resulted in no substantive differences in regression coefficients, directions of the relationships to the dependent variable, or changes in significance.

Table 6.8. Predicted mortality counts for hypothetical census tracts, using coefficients from OLS regression model.

	Characteristics of Census Tracts (hypothetical)[a]											
	White Majority[b]				Racially Mixed[c]				Black Majority[d]			
	Low Education[e]		High Education[f]		Low Education		High Education		Low Education		High Education	
	Urban[g]	Rural[h]	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
Predicted Number of Deaths[i]	142	165	90	113	171	194	118	142	199	223	147	171

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[a] Age-distribution and population are held constant at the mean; mean expected deaths = 133, when all other variables held at their means.
[b] PBLK = 10%
[c] PBLK = 50%
[d] PBLK = 90%
[e] PHS = 50%
[f] PHS = 90%
[g] PURB = 65%
[h] PURB = 15%
[i] Rounded up to nearest whole number.

ratio between these two areas is 2.48-to-1 (223 versus 90 predicted deaths), and is a crude representation of area-level health disparities with respect to race, education, and urbanicity.

The model was analyzed for the presence of potentially influential observations, through examination of Leverage scores, Cook's D values, Standardized DFFIT, and Standardized DFBETAs (Hamilton, 1992). While no tracts exceeded the absolute cutoffs for identifying tracts as influential, several (generally 5% of total number of tracts) exceeded relative, size-adjusted, cutoffs. These tracts were removed from the analysis set and the regression was re-computed; this process was repeated for each diagnostic indicator. In all cases, the changes to the regression coefficients were modest, with no changes in significance at $P < .01$; and the relative magnitudes of the coefficients, as well as their signs, remained consistent. Adjusted R-squared values increased for each new model, except one (Leverage > 0.2), compared to the original model.

Regression residuals were exported to ArcInfo 8.2 for mapping of spatial patterns (Figure 6.9). Spatial autocorrelation of the residuals was assessed by computation of the Moran's I index; for this model, Moran's I = 0.0226. This indicated no spatial autocorrelation at the scale of the entire study area. Visual analysis suggested a pattern of mortality overestimation in the northeastern quadrant and underestimation south of downtown Atlanta. Yet one must be careful not to overinterpret results from a choropleth map because of the potential for perception bias due to areal variations in census tracts.

Regression residuals were checked for localized spatial autocorrelation through the computation of Local Moran Indices. The results, shown in Figure 6.10, suggest

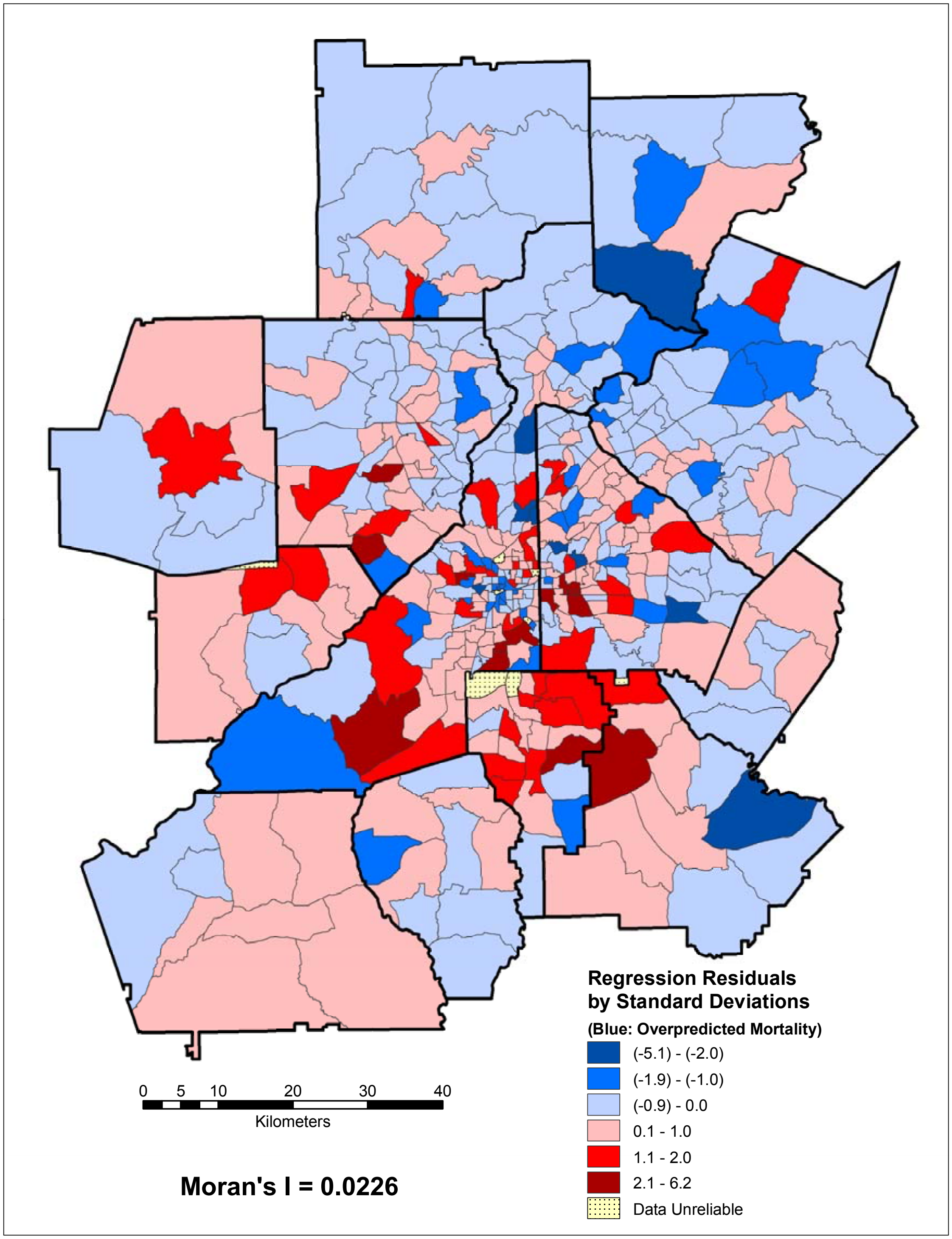


Figure 6.9. Regression Residuals from OLS regression of mortality, metropolitan Atlanta, Georgia, 1995-1999.

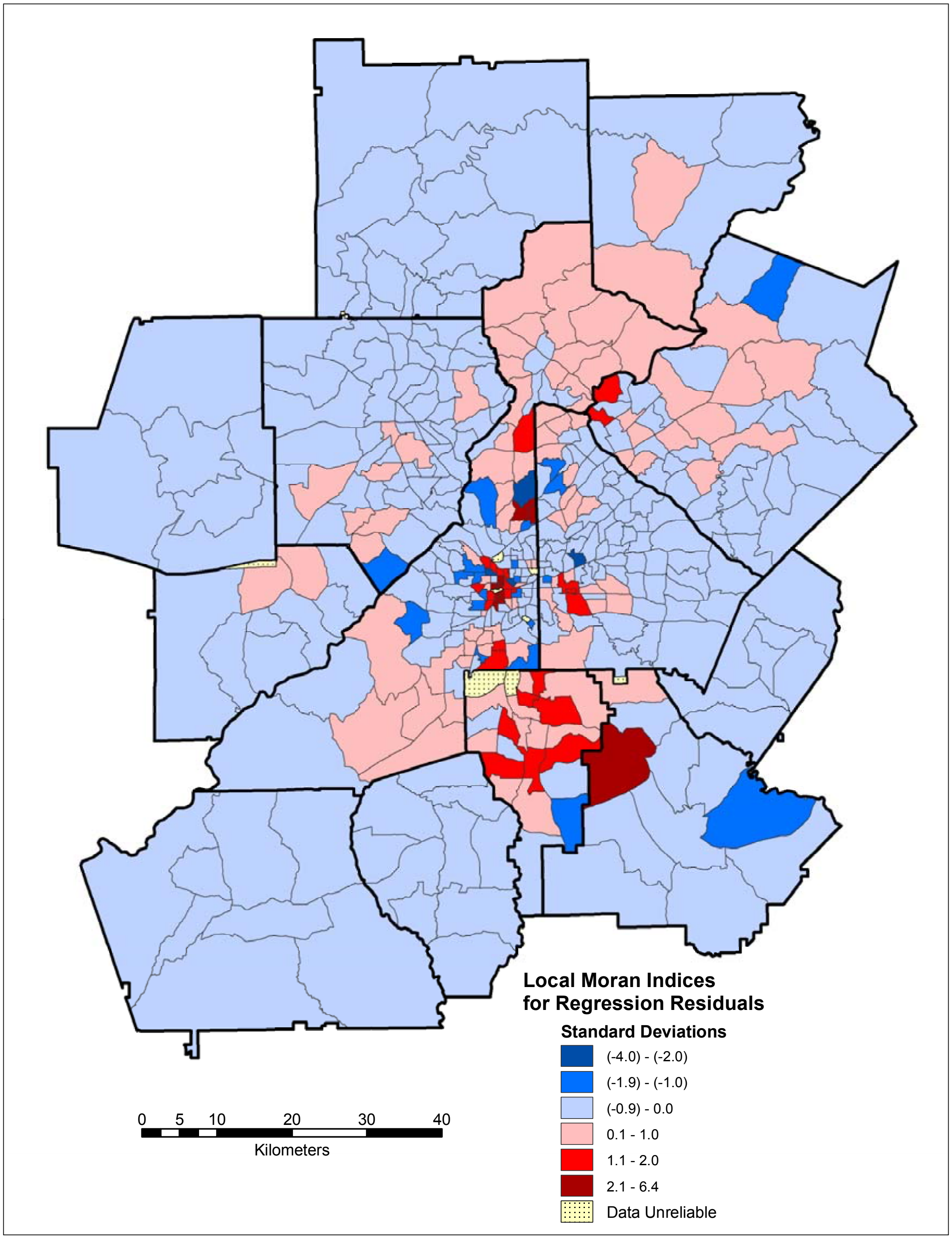


Figure 6.10. Local Moran indices for OLS regression residuals.

that there are three areas in which the regression residuals exhibit high degrees of localized spatial autocorrelation (> +2.00 standard deviations): 1) downtown Atlanta; 2) theBuckhead neighborhood, north of downtown Atlanta; and 3) the City of Stockbridge, in Henry County. These results suggest that there may be some unmeasured geographically-varying phenomenon that can potentially explain variations in mortality outcomes in these areas. However, since these areas were not large and represented a small proportion of the overall number of census tracts, the omission of such a variable or variables should not compromise the validity of the existing model.

Composite Indices and Spatial Analysis

The composite indices, described previously, for 1980, 1990, and 2000 were calculated and mapped in ArcInfo 8.2 (Figures 6.11, 6.12, and 6.13). Absolute changes in the composite indices were computed for 1980 through 1990 (Figure 6.14), for 1990 through 2000 (Figure 6.15) and for 1980 through 2000 (Figure 6.16). Moran's I for 1980, 1990, and 2000 were 0.2658, 0.2926, and 0.2437, respectively. These indices represent minor differences, yet they suggest an increased spatial concentration of the indexed values from 1980 to 1990, and a spatial dispersion of the indexed values from 1990 to 2000, with spatial dispersion over the entire period. This is congruent with the spatial pattern of urbanization for metro Atlanta during this period, in which outlying areas were rapidly developing, particularly around suburban downtowns or edge cities, such as Duluth, Roswell, Alpharetta, and Marietta.

A detailed examination of Figure 6.14 indicates that during the 1980s, the areas with positive changes to their composite index values (e.g., areas in relative decline, suggestive of an increased risk for adverse health) were located in a relatively

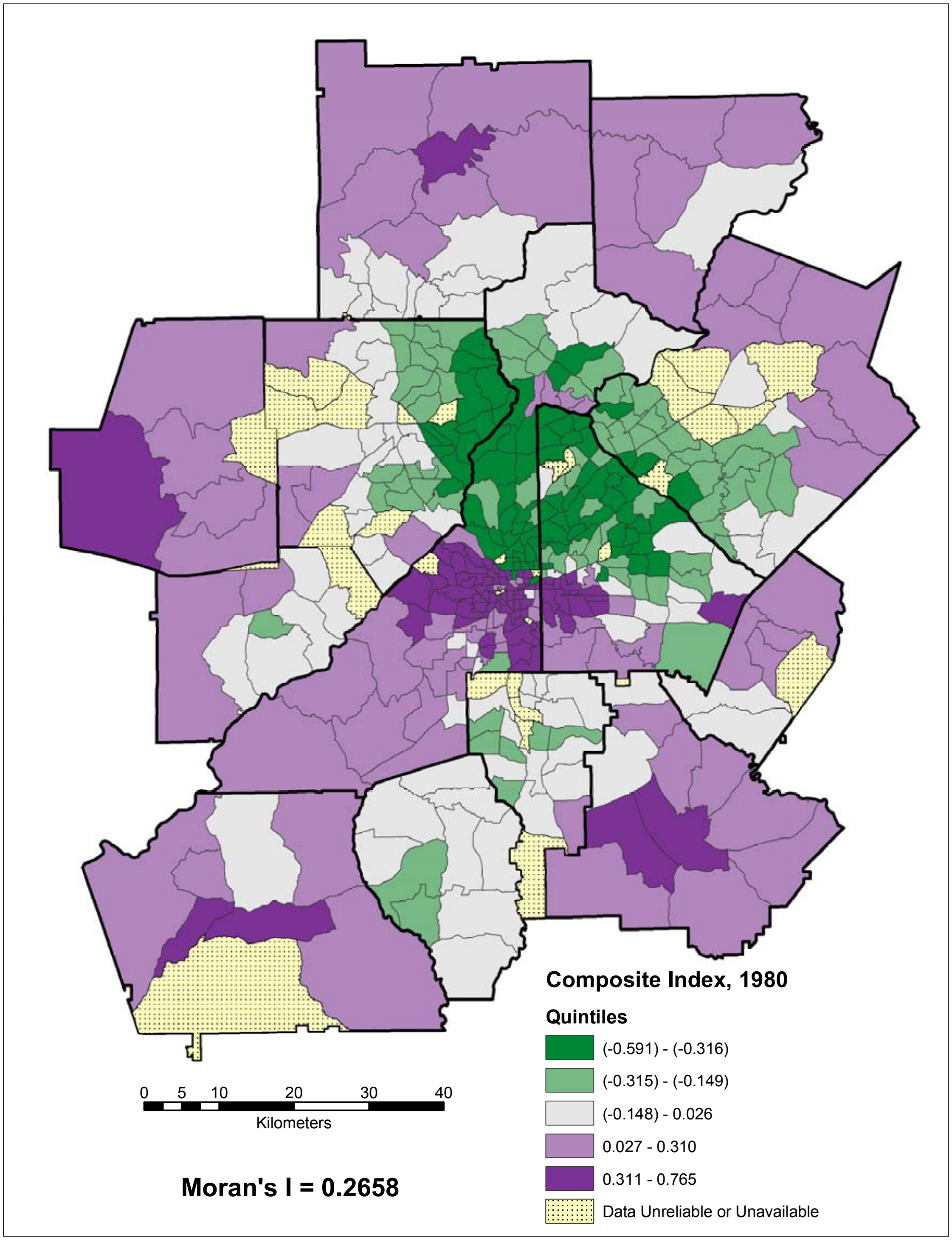


Figure 6.11. Composite Index, 1980.

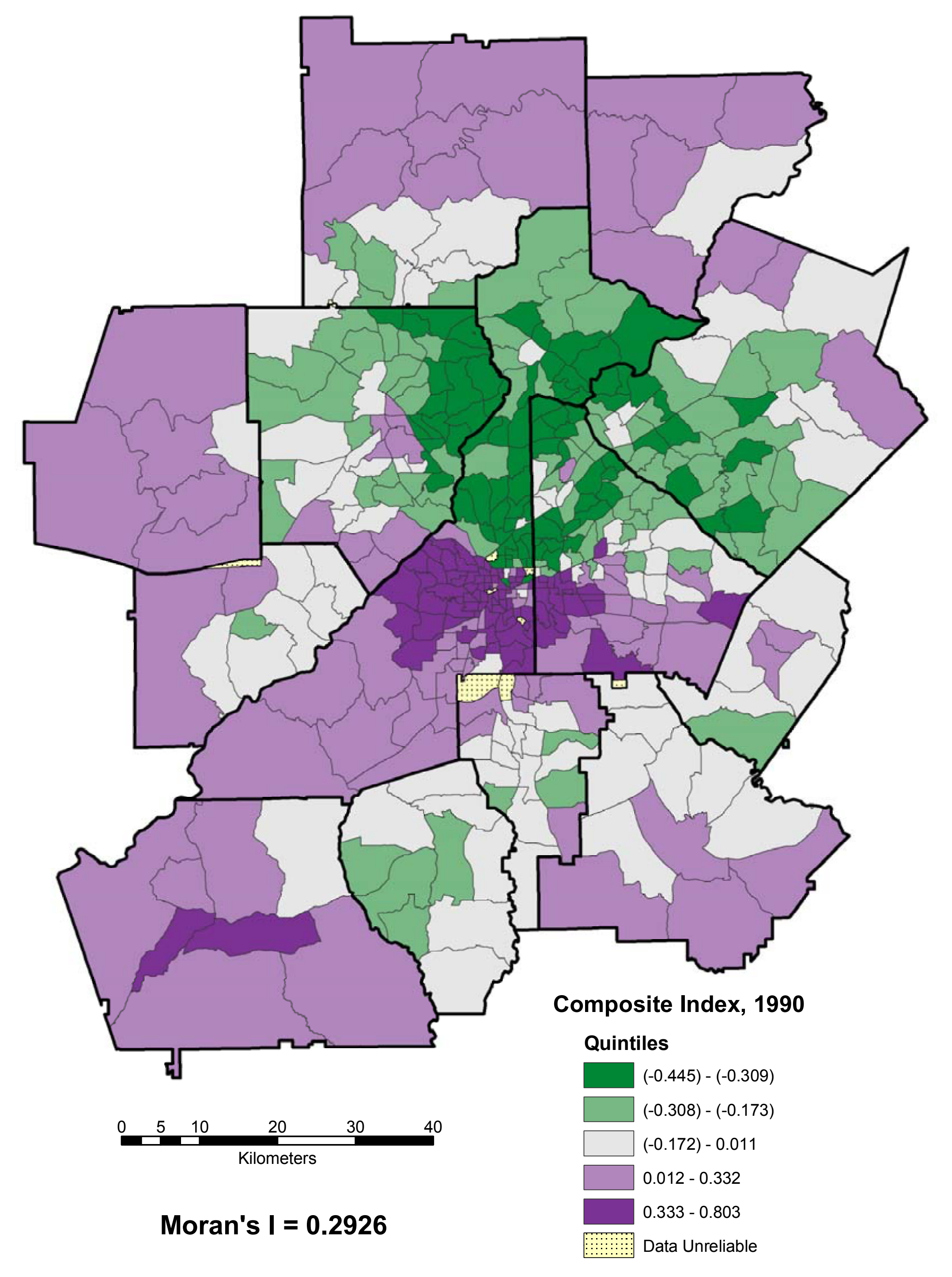


Figure 6.12. Composite Index, 1990.

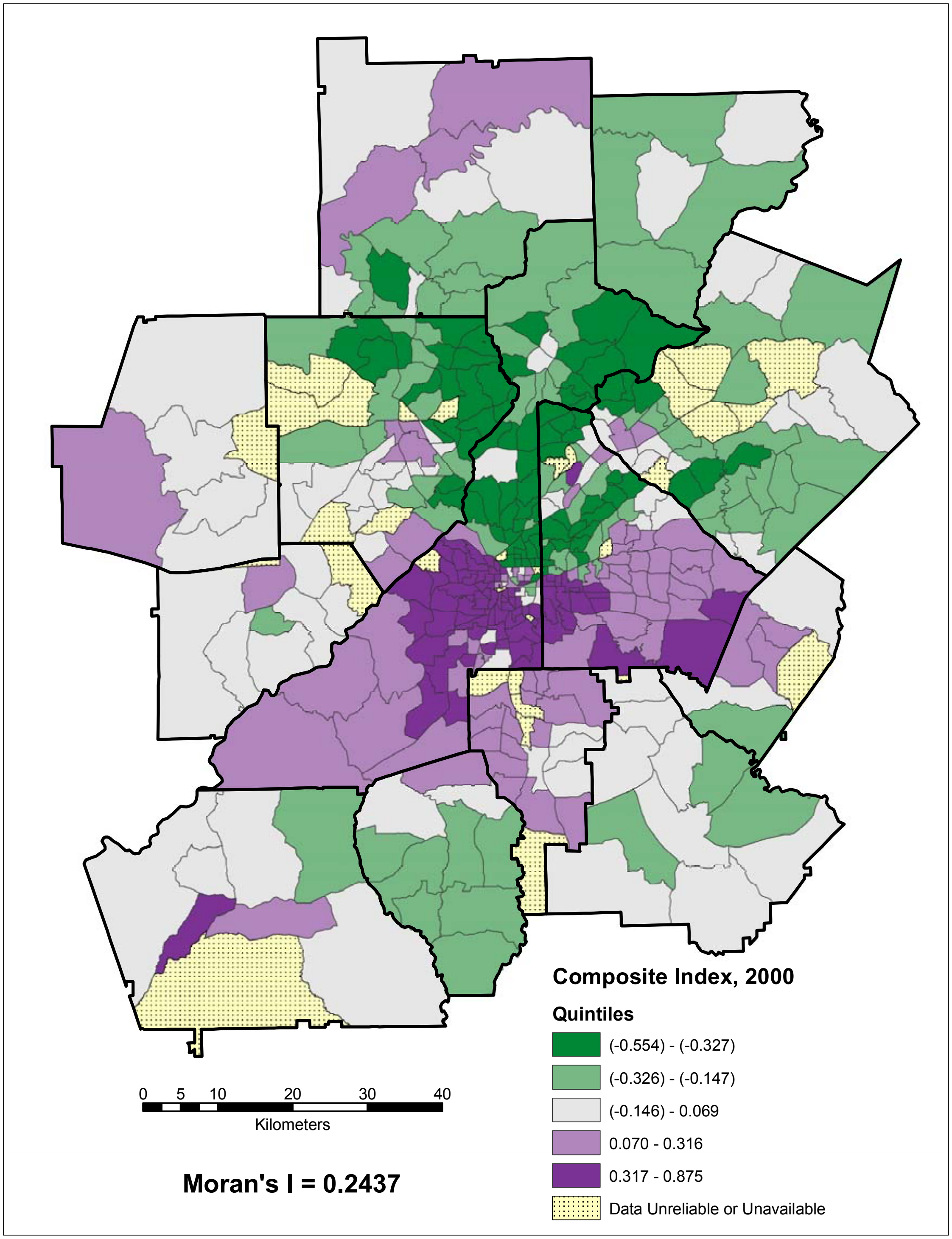
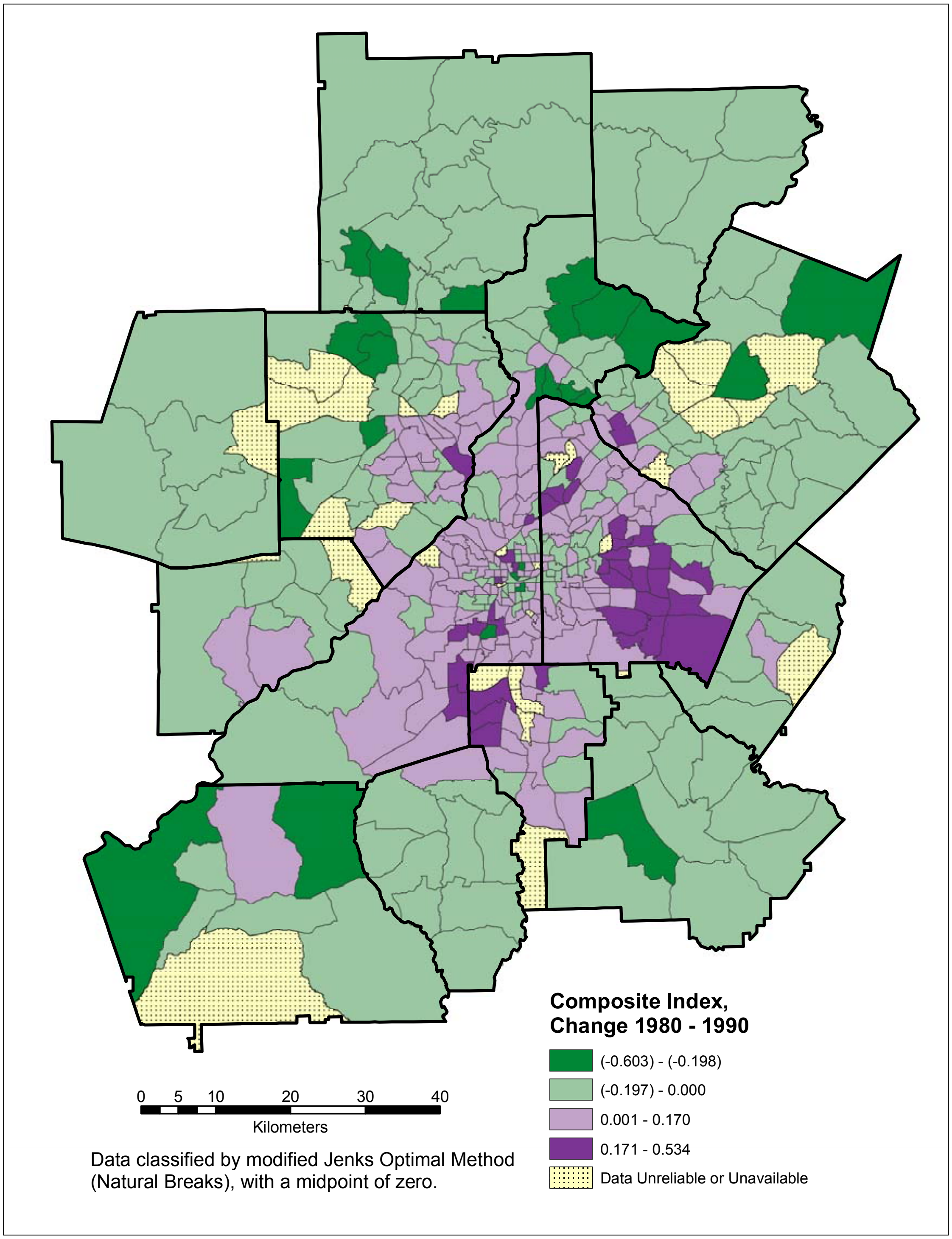


Figure 6.13. Composite Index, 2000.



Data classified by modified Jenks Optimal Method (Natural Breaks), with a midpoint of zero.

Figure 6.14. Composite Index, Change 1980-1990.

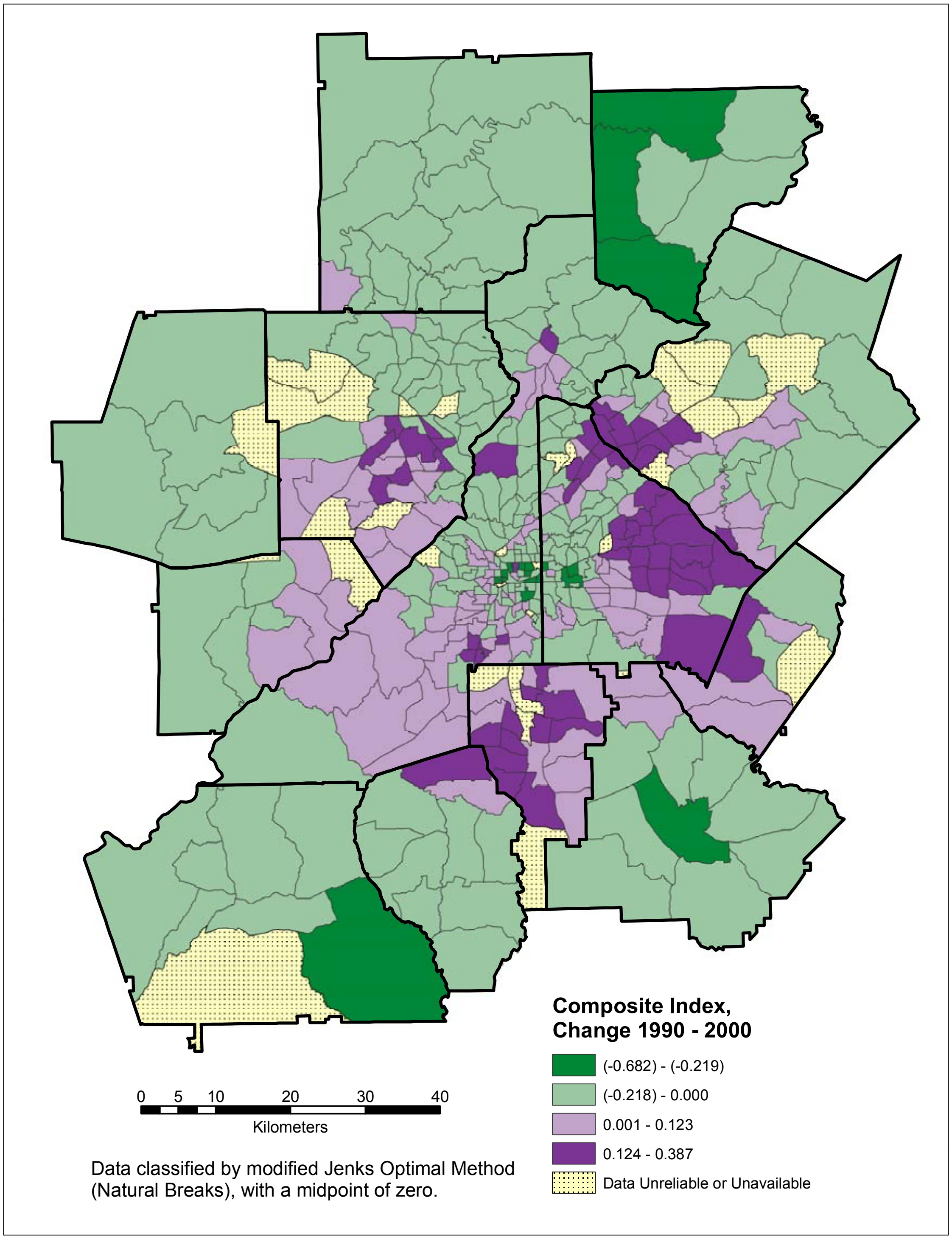


Figure 6.15. Composite Index, Change 1990-2000.

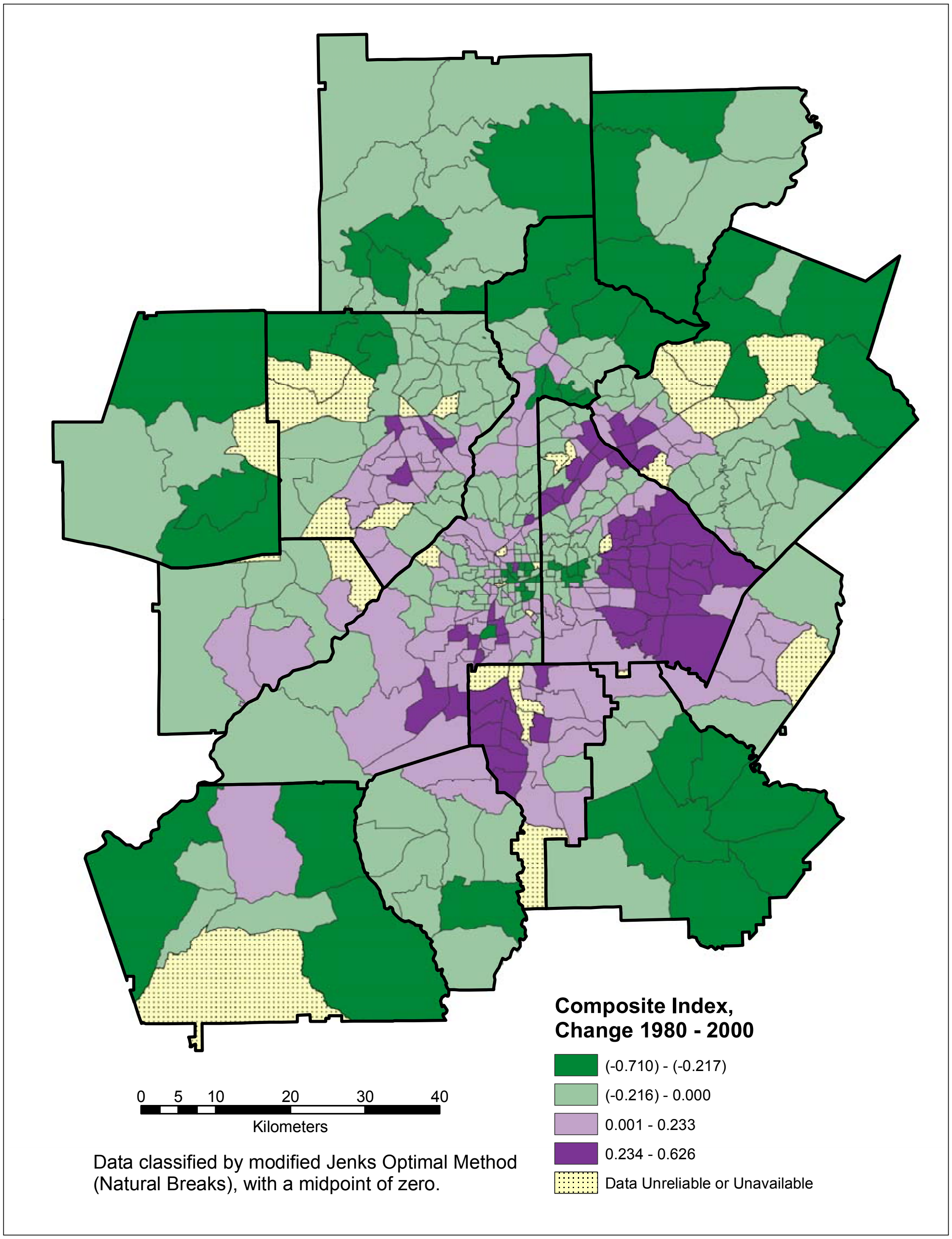


Figure 6.16. Composite Index, Change 1980-2000.

homogeneous area in the center of the thirteen-county area. Specifically, this area covered large portions of south Fulton County, including the cities of East Point, College Park, portions of Atlanta (especially the southern and western sides), and the Peachtree Road corridor running north through Buckhead into Sandy Springs; the majority of DeKalb County, especially the entire southern third of the county, extending north through Clarkston and Stone Mountain to Chamblee and Doraville; a small portion of Gwinnett County, adjoining DeKalb County, including the city of Norcross; the city of Smyrna and the southern portion of Marietta in Cobb County; most of the northern half of Clayton County, including the cities of Riverdale, Forest Park, and Morrow; and three isolated pockets in Rockdale, Coweta, and Douglas Counties.

Conversely, for the same decade (1980s), the areas in which the composite index decreased (indicating a decreased risk of adverse health), were located on the periphery of the region. These areas generally corresponded to newly-developing suburban areas as well as some rural areas that were beyond the leading edge of suburban development.

In Figure 6.15, the same type of trends can be visualized for the 1990s. In that decade, the areas in relative decline (suggestive of increased mortality risk) generally moved outward from the central city and appeared as a doughnut-shaped arrangement. While many of the areas of 1980s decline were still in decline in the 1990s, many previously-untouched areas were now included, such as: Lilburn, Lawrenceville, and Mountain Park in Gwinnett County; Powder Springs, Mableton, and a greater portion of Marietta and Smyrna in Cobb County; Roswell in north Fulton County; Lithia Springs and a large portion of Douglasville in Douglas County; all of Clayton County; Fayetteville in Fayette County; and the northern portion of Henry County.

Interestingly, areas that improved during the 1990s included many portions in the center of the region (e.g., Fulton and DeKalb Counties) that were in decline during the 1980s. These areas included many older neighborhoods that benefited from gentrification efforts and revitalization efforts tied to the 1996 Summer Olympic Games held in Atlanta. A significant area of southwest DeKalb County improved during the 1990s; this shift is coincident with the influx of a large number of middle- and upper-middle-class minority residents. The outer suburban areas continued to improve on their index scores, especially the outermost census tracts, which were experiencing rapid suburbanization during the latter half of the 1990s.

The temporal trend in composite index change can be thought of as an expanding wave, in which the areas of decline and improvement expanded radially outward, generally in the direction of the suburban downtowns (Hartshorn and Muller, 1989) along major transportation corridors, with a more pronounced emphasis to the north. While this was occurring, however, there was a backfill of improvement in many portions of the inner core as many residents were attracted to "inside-the-Perimeter" (i.e., I 285) living, perhaps as a backlash to suburbanization and commuter traffic congestion.

Finally, Figure 6.16 depicts the changes in the composite index for the entire twenty year period. Census tracts depicted in dark green were those that experienced the greatest absolute decreases in the composite index (which are suggestive of a decrease in mortality risk) over the twenty-year period. Conversely, the dark-purple areas are those in which the mortality risk increased the most, relative to all other census tracts, from 1980-2000. Areas that were relatively better-off at the end of the twenty-year period were concentrated in all the outer counties in the suburban fringe (with the exception of

Rockdale County), and the area east of downtown Atlanta. These results are congruent with the outer migration of affluent home-buyers to suburban downtowns as well as the influx of affluent residents into formerly depressed inner-city neighborhoods (e.g., gentrification).

There were four general areas that were worse-off at the end of the twenty-year period, relative to all other tracts: 1) southeast DeKalb County, including the cities of Stone Mountain and Clarkston; 2) the area surrounding Hartsfield International Airport in southern Fulton and northern Clayton Counties; 3) the city of Smyrna, in Cobb County; and 4) the Interstate 85 – Buford Highway corridor from Fulton County through DeKalb County and extending into the city of Norcross, in Gwinnett County.

As the temporal change data refer to relative changes over time in the three explanatory variables and not to absolute levels of those variables, it is not possible to directly compare the changes in the index to the Standardized Mortality Ratios for 1995-1999. However, these temporal changes may be suggestive of future mortality outcomes.

Conclusion

The results from this study offer support for the hypothesis that all-cause mortality in metropolitan Atlanta, Georgia, from 1995 through 1999, is significantly associated to areal measures of socioeconomic status, race, and urbanicity, which represent the three social area dimensions. Socioeconomic status, as measured by high school completion rates, and race, as measured by the percentage of blacks in the population, represent compositional variables in the sense that they are aggregations of individuals' attributes. It is possible that these variables could also represent contextual effects on a dependent variable due to the character of an area, over and above those effects that can be attributed to aggregated individual factors. However, this assertion cannot be tested without the inclusion of individual level data and analysis through multilevel modeling techniques. The urbanicity variable, as measured by percent of urbanized land-use, represents a contextual measure of the physical environment. This variable could have direct influences on health resulting from the physical environment as well as indirect effects from the social environment, which could influence individuals' health-related behaviors.

In this particular analysis, a number of alternative variables could have been selected to represent the social area dimensions. For the socioeconomic dimension, income, occupational status, wealth, poverty, and college education could have been included in the regression model in lieu of high school completion. These variables exhibited a great degree of collinearity and tend to measure the same construct. The income, occupational status, wealth, and poverty measures could suffer from bias due to the potential for reverse causality. That is, a person's health status could affect present income-earning potential and occupational status (and thus could lead to the person living in poverty), and wealth (if a health condition is severe enough to require large expenditures on health care). Education, however, is generally a precursor to major health events that would affect the other socioeconomic status indicators. Education is usually attained early in life before most adverse health conditions generally arise.

Of the two educational variables, the data for high school completion exhibited greater variation than the data for college completion, and the distribution is less skewed. Of the two measures, it is likely that the failure to attain a high school education would have more severe impacts on health than would the failure to attain a college education. For these reasons, the high school completion variable was chosen for this model.

For the race variable, the percentage of blacks in the total population is deemed the most appropriate measure for this study area, which has traditionally had a large black population. In addition, much of the distribution of majority and minority populations in Atlanta is a direct result from either overtly racial or race-conscious policies. Therefore, to measure the impact of urbanization of the distribution of sociodemographic variables, the variable relating to the black population is appropriate.[*]

For the urbanicity variable, the vegetative greenness index ($NDVI_S$) could have been used, as it exhibited high negative correlations with both the high-density urban land-use and the urban land-use variables. In other words, as an area is developed for urban land-uses, the land-cover categories most often affected (i.e., replaced) are cropland or grassland, followed by forested land. As this process occurs, the amount of aboveground green plants within the IFOV of the satellite is reduced. Hence, the $NDVI_S$ is also reduced. The urban land-use variable is chosen over the vegetative greenness index mainly because of its conceptual simplicity. As urban land-use represented the aggregation of commercial, industrial, and residential land-use categories, it is easier to visualize and to correlate with forces that drive urbanization processes.

With the urban land-use variable, it is possible to conceptualize an urban-rural dichotomy. This is particularly useful when looking at temporal changes in land-use for the Atlanta area. Specifically, most of the outer fringe counties (e.g., Coweta, Cherokee,

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[*] Categorical variables for race were tested in regression modeling. However, the difference between the categorical variables and the continuous variable for blacks as a percentage of total population was not significant. The continuous variable was chosen for the final model as it represented a more precise measure of the effect of race.

Forsyth, and Paulding) were rural in the 1980. As the urbanization process unfolded, these areas became rapidly suburbanized, as the growing (and generally affluent) population expanded outward in search of new residential housing opportunities. By 2000, the transition from rural to suburban land-use became quite clear and visually apparent from analysis of remotely-sensed satellite data. These changes were clearly reflected in the land-use statistics, such as urban land-use, derived from those satellite data. By choosing either high-density land-use (e.g., commercial and industrial) or low-density land-use (e.g., residential), the overall trend of urbanization would not have been as accurately captured. On the other hand, the composite measure of urban land-use adequately measured the outward expansion of the population, and the transition of rural areas to suburban areas.

The results from this study strongly suggest that areas that have a greater percentage of black residents, and have a lower high school completion rate, and that are rural experience a greater overall risk of adverse health outcomes. Conversely, areas that are predominantly white, and have a higher high school completion rate, and are either urban or suburban experience a lower overall risk of adverse health outcomes. These results are not surprising in that many previous studies have shown support for each of the three variables' relationships to a variety of health outcomes. It is also important not to over-interpret these results. As this is an ecological study, care must be taken to not attribute these relationships to individuals. Instead, these results suggest avenues for further research in order to better understand the complex relationships between individual and areal characteristics, individual behaviors, and the physical environment on health. With the inclusion of individual-level risk behavior and health outcomes data, it would be possible through multilevel modeling techniques to more precisely analyze such relationships and, more importantly, to suggest appropriate public health policies and interventions to improve the overall health status of the population and to reduce health disparities.

A final point is that the urban structural changes that have occurred in the Atlanta metropolitan area may be observed through the analysis of socioeconomic and demographic variables as well as some markers of the physical environment. The urbanization process of the late-1990s reflected dispersed growth, centered in the suburban counties, such as Gwinnett, Cobb, Forsyth, *north* Fulton, Coweta, Paulding, Henry, Douglas, and Cherokee. Likewise, the composite index of demographics, educational attainment, and degree of urbanicity followed this pattern of growth. The spatial patterns of 1980-1990 and 1990-2000 were indicative of an outward expansion of relatively better-off areas while substantial pockets of the central core were revitalized, especially in the 1990s.

This study is relatively unique in two ways. First, it represented the application of geographic information system (GIS) technology to the study of mortality at the census tract level. GIS is used to derive, store, analyze, and display health data, sociodemographic data, and land-use data. Without a GIS, it would have been nearly impossible to accurately geocode approximately 100,000 death events, and to derive census tract mortality rates from the geocoded data. The GIS is also instrumental in the analysis of remotely-sensed satellite data, particularly in the classification of land-use and land-cover categories and derivation of census tract level land-use statistics. Census tract boundary changes were quantified in a GIS and sociodemographic data were areally interpolated in a GIS by using dasymetric weights that were also derived in a GIS. New variables were derived within the GIS database and exported to statistical analysis packages for processing. The GIS is used to display the results from statistical analyses (both regression modeling as well as spatial statistical analysis) and to produce maps for visual representation of the data. In short, this study could not have been conducted without the use of a GIS.

The second unique aspect of this study is the use of remotely-sensed satellite data for the analysis of mortality in an urban area. While remote sensing has been demonstrated to be effective in other public health issues, such as infectious disease surveillance and prevention, the full potential of these data for application to non-infectious diseases has not yet been realized. The application to the study of mortality is indirect, in the sense that the data were used to quantify the changes to urban form and to quantify specific measures of land-use and land-cover that were thought to be associated with health outcomes. This study has demonstrated the effectiveness and relative ease in using remotely-sensed data for this purpose.

CHAPTER 7

CONCLUSION

The purpose of this dissertation is to use a geographic information system (GIS) and remotely-sensed satellite imagery to facilitate the small-area spatial analysis of a public health issue. The specific health issue is the spatial pattern of all-cause mortality in the Atlanta metropolitan area, from 1995 through 1999. While GIS and remote sensing have been used or advocated for use in public health research, it is believed that they have not been used together in the past to study small-area variations in all-cause mortality.

Most applications of remote sensing have been for the study of infectious diseases, especially those endemic to the tropics. Application of remote sensing to non-infectious diseases, such as chronic diseases or (more broadly) all-cause mortality, has been extremely limited or even non-existent. Most of the applications described in the literature have been conducted by academic researchers. The adoption of these techniques by public health practitioners has been lagging, most likely due to the absence of the necessary technical expertise.

The use of GIS in public health has been more prevalent; however, applications have generally been limited by the availability of data. Much public health mortality data are only available at aggregation levels higher than or equal to United States counties, and often only at the state level. Some applications are possible at finer spatial resolutions, such as census tracts, census block groups, or even at the individual (i.e., point) level. These applications typically rely upon the availability of individual, point-level data, such as are available in disease registries (either for individual-level studies, or to enable the geocoding and aggregation of cases to provide small-area disease counts or rates). Disease registries are quite rare in the United States; privacy concerns and logistical issues generally preclude the collection or the reporting of health-related data at the level of the individual. Mortality data, however, are not subject to confidentiality protections, and as such, were used in this study.

Another limiting factor in the conduct of small-area analysis is the temporal variability of census geography. The U.S. Bureau of the Census adjusts census tracts in an effort to maintain a range of population within each tract. Thus, for a given area, the numbers of census tracts and their spatial boundaries often change from one decennial census to the next. As this dissertation relied on the use of potential causal variables obtained from three decennial censuses, the issue of census tract geography changes is problematic. This issue is successfully addressed through the combined use of a GIS and remotely-sensed satellite imagery. Dasymetric population densities were computed in a GIS by using land-use/land-cover data derived from Landsat images of Atlanta; this enabled the areal interpolation of all census tract variables to a common census year geography (1990).

There were many uses of GIS in this dissertation. All data were stored, manipulated, analyzed, and visualized through use of two commercial GIS packages, ArcInfo 8.2 (Environmental Systems Research Institute, Redlands, CA) and ERDAS Imagine 8.6 (Leica Geosystems, Atlanta, GA). In many cases, data variables were derived/computed in the GIS from existing, stored data. The integration of a database within a GIS makes this type of operation possible, where it would have otherwise required data manipulation in a database/spreadsheet program to derive new variables. Individual point data (residential addresses of approximately 100,000 decedents) were accurately geocoded and aggregated to the census tract level by using a GIS. Land-use/land-cover statistics were extracted within a GIS, following the ISODATA classifications of Landsat images of Atlanta (also performed in a GIS). The interoperability of GIS software and spatial statistical programs, such as SaTScan and Crimestat II, facilitated spatial analyses of mortality and potential causal variables. The interoperability of GIS software and traditional statistical programs, such as SPSS, enabled the importation of data variables into SPSS for regression modeling, and the exportation of regression parameters (e.g., regression residuals) to the GIS for spatial analysis. Finally, the display of data for visualization is accomplished in a GIS. All maps were produced by ArcInfo 8.2 and exported as graphics files for inclusion in this dissertation.

Without a GIS, it would not have been possible to accurately and efficiently geocode the large number of individual mortality data; to compute mortality rates per census tract; to compute land-use/land-cover statistics; to perform a spatial analysis of mortality; to analyze regression residuals for spatial autocorrelation; or to efficiently visualize the results of all these processes. Without the remotely-sensed imagery, it would not have been possible to derive land-use/land-cover statistics for an area as large as the Atlanta metropolitan area. By extension, it would not have been possible to compute dasymetric population densities, nor to perform areal interpolation of census-derived data to 1990 census tract boundaries. Together, GIS and remote sensing technologies enabled the study of an important public health issue at the small-area level. This dissertation has shown that such studies are not only feasible, but can be accomplished in a relatively efficient manner.

Despite the many beneficial uses of a GIS for this study, there were a few substantial difficulties and inefficiencies. The most significant drawback to the use of GIS for public health is that there is no single GIS that is optimized for public health research. For this study, two commercial GISs were used (this in itself was an inefficiency, as no single GIS was adequate to perform all the GIS function required for this study). Both GISs are produced and mass-marketed towards the commercial (e.g., private sector) geospatial marketplace. Because of the many potential applications of GIS, these commercial GISs are not optimized for any particular application; and this is certainly the case with respect to public health.

The most severe limitation to commercial GISs is their lack of sophisticated spatial statistical and general statistical analysis capabilities. While these GISs are configured to export and import data files that are compatible with major statistical software packages, this requires extra data management and manipulation. In the present study, three separate statistical software applications were necessary, in addition to the two GISs.

A secondary inefficiency with respect to the use of GIS for this study was a general lack of user-friendliness, especially with one particular GIS package. The implication for public health use is that specialized training, and experience are both needed before a GIS can be used with relative ease and confidence. At present, this type of specialized expertise is not abundant in the public health workforce.

Despite these limitations and inefficiencies, GIS is an important tool for public health research that involves geospatial data. More expertise needs to be developed in order to more fully integrate these tools into mainstream public health research. It is unlikely that the major commercial GIS vendors will provide a product that is more suitably tailored for public health and/or statistical analysis. Thus, for the immediate future, public health researchers will need to develop expertise with several GISs and spatial statistical software applications, and be able to integrate these separate applications in order to conduct useful research.

A final caution is in order. There are many GIS enthusiasts in the public health workforce. Their expertise ranges from novice part-time users to trained experts. However, the field of public health is dominated by epidemiologists, who have successful, long-standing methods of conducting research and reporting results. The adoption of GIS as an integral part of public health faces an uphill struggle, as epidemiologists may naturally be skeptical of the usefulness of GIS. It is very important to not oversell the capabilities of GIS in the context of public health. Only by demonstrating successful applications of GIS can geographers earn the support and trust of the public health workforce at large. A few highly noticeable failures or under-achievements can bring doubt upon the geography discipline and GIS, and cause lasting harm to the effort to integrate geospatial techniques with public health research.

There were two substantive hypotheses in this dissertation: 1) the spatial distribution of selected area-level socio-demographic and physical environmental variables, in 1990, is significantly related to the spatial distribution of all-cause mortality, aggregated from 1995 through 1999; and 2) the process of urbanization in metropolitan Atlanta, Georgia, from 1980 through 2000 has resulted in more dispersed spatial pattern of those area-level variables that are significantly associated with poor health outcomes, specifically all-cause mortality.

In Chapter 6, three variables were chosen, through multiple regression modeling, to represent socio-demographic and physical environmental variables that were shown to be significantly related ($p < .01$) to the pattern of all-cause mortality in the Atlanta metropolitan area, from 1995 through 1999. These variables were the percentage of blacks in the total population in 1990 (PBLK90); the percentage of population over age 25 with high school diplomas or equivalent in 1990 (PHS90); and percentage of total land area that was urbanized (high-density and low-density urban land use) in 1990 (PURB90). The expected number of deaths per tract (EXP_D) is a control variable in the regression model. These results lend support to the first hypothesis.

Composite indices of the three explanatory variables from the regression analysis were constructed for 1980, 1990, and 2000. This enabled the mapping and visualization of point-in-time patterns of the indices as well as the analysis of temporal changes in the indices. Point-in-time analysis indicated that areas with positive index values (e.g., suggestive of higher mortality risk) were generally concentrated in the inner portions of the metropolitan area, corresponding to the traditional CBD and its immediate surroundings. Temporal analysis indicated that areas with increasing index values were initially located in the central city core (1980 to 1990), but over time moved outward, coincident with the general patterns of suburban growth (1990 to 2000). At the same time, areas with decreasing index values (e.g., suggestive of lower mortality risk) also expanded outward during both decades. However, during the 1990s there was a substantial backfill of decreasing index values in many portions of the CBD.

These observations suggest that three processes occurred during the growth of Atlanta during the 1980s and 1990s: 1) the spatial pattern of low-index value areas moved outward, coincident with the outward movement of population to newly suburbanized areas; 2) the spatial pattern of high-index value areas also moved outward, following the leading edge of the low-index value areas: and 3) during the 1990s as these two patterns expanded, portions of downtown Atlanta underwent vast improvement in index values (e.g., changed from positive index values to negative index values). The first two processes are generally related to suburbanization, while the third process is attributable to downtown revitalization and gentrification efforts. The overall trend, therefore suggested a transition from a state of spatially concentrated index values (positive values in the core, surrounded by negative values on the periphery) to a more dispersed state (negative values in the core and the outer periphery, surrounding an inner ring of positive values). These findings lend support to the second hypothesis.

There are at least three limitations to this study. First, as with all ecological studies, one must be careful not to suggest that these relationships hold at the individual level, thus avoiding the ecological fallacy. Second, the dependent variable, all-cause mortality, is a very broad measure of health outcomes. It is subject to confounding factors, such as different etiologies for different causes of death; and different temporal lags for onset of casual risk factors and onset of morbidity leading to mortality[*]. However, mortality data were readily available for this study (and not subject to human subjects protection), unlike morbidity data, which were not available. In addition, because the data were temporally aggregated to a five-year period, there were usually sufficient cases of mortality per census tract to be significant in statistical analysis. This may not have been the case had specific-cause mortality data been used. And lastly,

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[*] This is significant in that population migration patterns may be a confounding influence with respect to chronic diseases, which typically have a long lag period between risk factor adoption and disease, and between disease onset and death.

because mortality data at the individual level were only available back to 1995, it is not possible to conduct an analysis of mortality trends over time. As census and land-use/land-cover data were available from 1980 onwards, this lack of mortality data is the limiting factor in a full temporal analysis.

There are two broad avenues for future research that can build upon the results of this study. First, should additional mortality data become available, it may be possible to extend this analysis, both retrospectively and prospectively. This would enable the analysis of the trend of the relationship between socio-demographic and physical environmental factors and all-cause mortality, while enabling the comparison of the spatial patterns of mortality and urbanization. Second, if individual-level health risk factor data were available, it would be possible to include individual-level data along with area-level data in a multilevel modeling context.

The application of GIS and satellite remote sensing to public health issues offers much promise. Many useful public health GIS and remote sensing applications have already been documented and research continues on expanding these uses. As more public health scientists learn of the value of GIS and remote sensing through the documentation of successful applications, and with support from key public health leaders, GIS and remote sensing are likely to become more widely utilized within the field of public health.

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APPENDICES

APPENDIX A

LAND-USE/LAND-COVER DATA,
BY 1990 CENSUS TRACT BOUNDARIES

Table A.1. Land-use/land-cover data, metropolitan Atlanta, Georgia, 1984.

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
1.00	Fulton	38	76	1	11	197	0
2.00	Fulton	52	95	7	4	133	0
4.00	Fulton	36	40	7	26	49	5
5.00	Fulton	151	62	21	16	80	0
6.00	Fulton	78	44	11	2	13	1
7.00	Fulton	94	39	4	7	29	0
8.00	Fulton	56	31	2	5	3	0
10.95	Fulton	191	45	11	11	10	0
11.00	Fulton	23	18	2	2	3	0
12.00	Fulton	68	35	0	0	7	0
13.00	Fulton	70	42	3	2	15	0
14.00	Fulton	19	35	1	1	20	0
15.00	Fulton	25	62	1	1	22	0
16.00	Fulton	32	20	2	7	34	0
17.00	Fulton	69	35	1	3	14	0
18.00	Fulton	62	14	7	7	2	0
19.00	Fulton	89	1	0	0	0	0
20.00	Fulton	7	4	0	0	0	0
21.00	Fulton	67	15	2	1	1	0
22.00	Fulton	55	21	1	2	3	0
23.00	Fulton	40	53	3	6	15	0
24.00	Fulton	19	63	3	8	41	0
25.00	Fulton	41	38	1	2	6	0
26.00	Fulton	55	27	3	2	6	0
27.00	Fulton	82	0	8	0	0	0
28.00	Fulton	74	3	1	0	0	0
29.00	Fulton	44	22	3	2	4	0
30.00	Fulton	42	52	1	6	21	0
31.00	Fulton	20	36	1	2	21	0
32.00	Fulton	46	43	7	4	6	0
33.00	Fulton	55	10	5	1	0	0
35.00	Fulton	142	5	2	0	0	0
36.00	Fulton	29	7	1	1	1	0
37.00	Fulton	4	7	0	0	0	0
38.00	Fulton	35	33	2	5	6	0
39.00	Fulton	17	45	3	7	14	0
40.00	Fulton	43	57	3	8	51	0
41.00	Fulton	35	37	1	2	40	0
42.95	Fulton	65	37	5	8	16	0
43.00	Fulton	37	20	1	3	2	0
44.00	Fulton	65	14	6	2	2	0

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
46.95	Fulton	90	14	2	4	5	0
48.00	Fulton	26	9	1	1	0	0
49.95	Fulton	50	37	6	4	14	0
50.00	Fulton	66	38	10	3	15	0
52.00	Fulton	52	75	2	7	101	0
53.00	Fulton	32	80	5	17	85	0
55.01	Fulton	24	49	6	11	32	0
55.02	Fulton	51	71	7	10	30	0
56.00	Fulton	59	22	2	2	15	0
57.00	Fulton	32	26	2	2	4	0
58.00	Fulton	53	35	9	3	22	0
60.00	Fulton	32	59	1	2	76	0
61.00	Fulton	26	51	1	6	131	0
62.00	Fulton	36	27	4	3	35	0
63.00	Fulton	71	50	3	5	18	0
64.00	Fulton	47	38	4	6	27	0
65.00	Fulton	84	118	9	20	96	0
66.01	Fulton	69	55	3	7	46	0
66.02	Fulton	22	14	3	3	26	0
67.00	Fulton	109	92	23	37	92	2
68.01	Fulton	18	5	13	23	5	0
68.02	Fulton	14	16	12	17	15	0
69.00	Fulton	64	69	11	29	142	0
70.00	Fulton	166	159	41	83	431	0
71.00	Fulton	63	96	10	18	81	0
72.00	Fulton	171	148	46	46	499	1
73.00	Fulton	168	120	31	62	383	1
74.00	Fulton	74	63	6	11	71	0
75.00	Fulton	126	90	13	13	96	0
76.01	Fulton	132	86	18	72	136	0
76.02	Fulton	19	33	4	42	239	0
77.01	Fulton	198	136	17	36	744	5
77.02	Fulton	232	159	34	68	1125	86
78.02	Fulton	68	67	21	92	1091	28
78.03	Fulton	574	326	98	110	901	18
78.04	Fulton	135	109	15	22	174	0
79.00	Fulton	95	103	10	40	633	0
80.00	Fulton	36	54	5	53	405	0
81.01	Fulton	0	10	0	5	72	0
81.02	Fulton	99	102	48	112	375	0
82.01	Fulton	59	170	7	14	275	0
82.02	Fulton	152	112	108	68	258	4
83.01	Fulton	45	60	6	36	115	0

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
83.02	Fulton	38	50	5	14	84	0
84.00	Fulton	46	64	3	7	68	0
85.00	Fulton	68	44	5	21	231	0
86.01	Fulton	66	62	7	29	296	0
86.02	Fulton	93	48	101	25	192	3
87.01	Fulton	121	58	32	27	138	0
87.02	Fulton	92	100	26	33	161	0
88.00	Fulton	343	161	37	83	347	3
89.00	Fulton	420	302	40	43	304	20
90.00	Fulton	71	38	9	24	191	0
91.00	Fulton	87	78	7	25	139	0
92.00	Fulton	173	89	8	6	74	0
93.00	Fulton	51	60	4	3	134	1
94.01	Fulton	43	56	9	12	173	0
94.02	Fulton	101	31	10	3	19	0
95.00	Fulton	83	62	10	9	481	0
96.00	Fulton	170	123	18	8	195	0
97.00	Fulton	73	63	14	29	895	21
98.00	Fulton	211	81	20	45	1249	10
99.00	Fulton	102	46	7	56	589	0
100.00	Fulton	109	86	12	37	793	9
101.01	Fulton	125	116	28	24	704	4
101.03	Fulton	324	250	76	37	679	4
101.05	Fulton	149	170	85	35	216	8
101.06	Fulton	51	62	16	23	519	34
101.07	Fulton	12	43	10	69	406	14
101.08	Fulton	68	66	32	72	272	6
102.01	Fulton	222	166	44	52	1694	23
102.03	Fulton	76	124	67	133	954	144
102.04	Fulton	123	103	15	21	670	31
102.05	Fulton	133	100	16	24	402	1
103.01	Fulton	384	110	359	1263	6331	137
103.02	Fulton	748	268	360	814	5188	76
104.00	Fulton	325	205	773	3306	13779	204
105.03	Fulton	201	281	60	97	459	2
105.04	Fulton	347	317	322	1013	3070	39
105.05	Fulton	293	272	158	309	1499	13
105.06	Fulton	433	368	276	996	5643	103
106.01	Fulton	37	78	13	20	167	0
106.02	Fulton	289	262	35	69	453	3
107.00	Fulton	124	53	9	17	34	0
108.00	Fulton	561	119	11	19	126	0
109.00	Fulton	111	13	8	5	8	0

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
110.00	Fulton	81	88	26	20	60	0
111.00	Fulton	152	95	5	11	82	0
112.01	Fulton	136	100	14	17	113	1
112.02	Fulton	55	107	5	11	122	0
113.01	Fulton	31	152	5	24	278	0
113.02	Fulton	214	294	23	114	1063	2
114.03	Fulton	126	139	97	338	730	9
114.04	Fulton	123	104	75	76	194	4
114.05	Fulton	74	149	29	50	469	9
114.06	Fulton	91	82	32	60	767	65
114.07	Fulton	81	143	70	248	1211	30
114.08	Fulton	148	247	124	152	1055	16
114.09	Fulton	84	96	49	148	1668	39
114.10	Fulton	31	77	52	96	493	41
114.11	Fulton	33	139	31	40	478	44
115.00	Fulton	230	157	293	2163	7659	140
116.01	Fulton	321	185	202	800	3294	44
116.02	Fulton	256	72	119	460	3352	86
116.03	Fulton	229	79	226	1247	3667	90
201.00	DeKalb	6	22	0	1	64	0
202.00	DeKalb	24	17	2	13	103	0
203.00	DeKalb	17	39	1	19	116	0
204.00	DeKalb	19	38	1	4	36	0
205.00	DeKalb	29	63	5	5	74	0
206.00	DeKalb	26	35	5	10	27	0
207.00	DeKalb	15	42	1	7	64	0
208.00	DeKalb	65	75	12	16	239	0
209.00	DeKalb	118	105	5	20	180	0
211.00	DeKalb	66	80	15	41	482	15
212.02	DeKalb	92	114	12	23	487	10
212.04	DeKalb	210	68	70	41	47	0
212.05	DeKalb	84	253	22	39	446	4
212.07	DeKalb	145	146	51	13	336	0
212.08	DeKalb	159	90	7	5	97	0
212.09	DeKalb	91	85	20	64	215	2
212.10	DeKalb	64	168	20	33	359	7
212.11	DeKalb	33	97	14	38	314	10
212.12	DeKalb	113	140	21	15	175	0
213.01	DeKalb	213	75	14	9	59	1
213.02	DeKalb	178	231	34	32	151	0
213.03	DeKalb	207	147	33	11	72	0
213.04	DeKalb	240	181	65	22	236	28
214.01	DeKalb	98	120	19	49	203	0

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
214.02	DeKalb	61	134	17	16	218	0
214.03	DeKalb	76	119	15	20	272	0
214.04	DeKalb	80	111	21	19	151	0
215.00	DeKalb	141	196	18	22	534	1
216.01	DeKalb	83	118	8	13	477	6
216.02	DeKalb	34	58	9	10	199	1
216.03	DeKalb	91	72	13	14	185	0
217.02	DeKalb	230	218	30	24	513	6
217.03	DeKalb	62	85	4	10	367	1
217.04	DeKalb	181	187	24	27	312	0
218.05	DeKalb	78	246	20	32	243	2
218.06	DeKalb	285	189	92	61	490	2
218.08	DeKalb	53	106	3	7	127	4
218.09	DeKalb	106	252	16	44	455	14
218.10	DeKalb	180	161	34	16	262	9
218.98	DeKalb	101	128	32	23	231	1
219.02	DeKalb	168	173	40	67	1018	7
219.03	DeKalb	232	214	293	152	1553	174
219.04	DeKalb	118	122	39	31	155	3
219.05	DeKalb	122	199	50	36	294	13
220.01	DeKalb	75	118	12	28	207	2
220.02	DeKalb	94	199	57	29	246	2
220.04	DeKalb	34	151	9	15	177	3
220.05	DeKalb	82	110	17	15	119	0
221.00	DeKalb	69	77	16	31	153	1
222.00	DeKalb	199	162	24	53	255	0
223.01	DeKalb	72	101	5	15	232	0
223.02	DeKalb	57	89	9	13	196	0
224.01	DeKalb	39	48	4	4	188	0
224.02	DeKalb	36	78	8	13	189	6
224.03	DeKalb	44	23	1	35	378	0
225.00	DeKalb	70	53	11	12	146	0
226.00	DeKalb	65	51	3	13	170	0
227.00	DeKalb	32	48	5	10	140	0
228.00	DeKalb	50	30	1	7	175	0
229.00	DeKalb	55	53	9	37	213	1
230.00	DeKalb	27	38	11	6	87	1
231.01	DeKalb	48	80	5	15	212	0
231.02	DeKalb	50	93	8	11	90	0
231.03	DeKalb	119	255	23	43	319	1
231.05	DeKalb	120	117	33	40	194	1
231.06	DeKalb	98	118	23	28	222	1
232.03	DeKalb	168	113	86	176	620	7

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
232.04	DeKalb	35	126	14	66	424	5
232.05	DeKalb	49	235	53	82	509	12
232.06	DeKalb	61	169	21	63	416	2
232.07	DeKalb	82	174	49	127	596	5
233.02	DeKalb	188	102	91	205	2371	16
233.03	DeKalb	315	251	173	195	1014	39
233.05	DeKalb	73	66	43	182	1031	22
233.06	DeKalb	98	88	59	264	710	28
233.07	DeKalb	96	142	90	190	469	11
233.08	DeKalb	131	102	77	114	855	9
234.03	DeKalb	129	144	25	44	289	0
234.04	DeKalb	412	231	195	333	1847	15
234.05	DeKalb	237	80	83	241	2097	12
234.07	DeKalb	383	287	301	705	4630	65
234.08	DeKalb	275	306	53	128	1044	12
234.09	DeKalb	186	151	61	115	1486	9
235.01	DeKalb	47	72	5	13	101	0
235.02	DeKalb	59	163	13	28	177	0
235.03	DeKalb	145	280	19	48	385	0
236.00	DeKalb	86	171	19	98	435	12
237.00	DeKalb	88	74	9	22	280	0
238.01	DeKalb	32	80	8	25	283	3
238.02	DeKalb	145	97	128	169	426	1
238.03	DeKalb	56	103	6	25	300	6
239.98	DeKalb	9	9	4	19	124	0
301.98	Cobb	311	179	130	646	4124	431
302.03	Cobb	200	125	258	1383	3589	40
302.04	Cobb	223	229	118	357	2186	21
302.05	Cobb	334	167	175	315	1349	17
302.06	Cobb	175	128	129	514	3618	33
302.07	Cobb	393	96	162	1003	5153	84
303.02	Cobb	56	198	57	141	848	31
303.07	Cobb	67	158	91	183	1464	7
303.09	Cobb	81	157	45	82	793	13
303.10	Cobb	49	124	65	123	533	7
303.11	Cobb	72	94	51	148	473	12
303.12	Cobb	77	119	39	131	509	5
303.13	Cobb	71	145	48	146	512	7
303.14	Cobb	72	78	33	86	523	4
303.15	Cobb	93	180	35	113	604	5
303.16	Cobb	158	333	104	226	1334	19
303.17	Cobb	137	221	74	136	1157	39
303.18	Cobb	99	151	63	165	696	29

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
303.19	Cobb	47	48	19	43	538	61
303.20	Cobb	81	96	37	81	625	27
303.21	Cobb	379	235	79	28	343	38
304.01	Cobb	69	138	32	56	497	2
304.02	Cobb	68	164	21	32	366	3
304.04	Cobb	121	113	58	16	41	0
304.05	Cobb	130	137	27	23	140	1
304.06	Cobb	138	110	62	25	55	1
305.01	Cobb	185	158	79	193	787	11
305.02	Cobb	171	104	69	170	466	6
305.03	Cobb	179	164	84	94	665	8
306.00	Cobb	310	131	53	155	1548	20
307.00	Cobb	117	102	12	35	165	0
308.00	Cobb	175	129	42	43	130	0
309.01	Cobb	45	96	46	94	815	7
309.02	Cobb	82	81	27	73	242	3
309.03	Cobb	52	141	148	172	406	8
310.01	Cobb	528	252	183	143	452	5
310.02	Cobb	62	107	17	75	208	0
310.03	Cobb	120	251	33	94	428	2
311.01	Cobb	73	113	19	20	119	0
311.03	Cobb	109	187	33	56	452	0
311.05	Cobb	52	170	26	69	311	2
311.06	Cobb	125	101	26	162	465	15
311.07	Cobb	107	201	31	97	705	13
311.08	Cobb	52	109	18	47	112	0
311.09	Cobb	115	122	48	28	85	0
312.02	Cobb	280	176	130	125	943	49
312.03	Cobb	103	121	44	25	338	6
312.04	Cobb	76	117	41	70	632	27
313.01	Cobb	125	230	45	193	987	6
313.02	Cobb	159	208	81	252	2109	38
313.04	Cobb	107	245	46	131	906	3
313.05	Cobb	262	169	69	133	1406	31
314.03	Cobb	147	185	126	304	870	6
314.04	Cobb	84	157	44	145	447	7
314.98	Cobb	224	258	166	514	1636	30
315.01	Cobb	109	158	364	1010	2052	30
315.02	Cobb	200	312	354	744	1805	23
316.97	Cobb	0	0	0	0	0	0
316.98	Cobb	0	0	1	2	20	0
401.00	Clayton	1116	99	113	85	69	0
402.00	Clayton	355	264	125	121	703	8

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
403.01	Clayton	282	75	73	29	109	0
403.02	Clayton	51	155	14	35	262	4
403.03	Clayton	111	194	23	61	184	3
403.04	Clayton	98	147	33	49	104	0
403.05	Clayton	189	237	38	47	220	3
404.01	Clayton	203	511	161	247	761	20
404.02	Clayton	585	387	286	670	2198	18
404.03	Clayton	164	294	95	163	612	13
404.05	Clayton	129	180	36	30	248	0
404.06	Clayton	255	254	114	29	234	2
405.03	Clayton	68	245	46	73	347	0
405.04	Clayton	103	268	81	153	595	5
405.05	Clayton	66	305	87	147	529	4
405.06	Clayton	87	198	69	69	369	1
405.07	Clayton	91	317	166	245	757	15
405.08	Clayton	24	267	126	176	487	11
406.03	Clayton	143	324	150	279	1148	15
406.04	Clayton	246	317	79	147	548	8
406.05	Clayton	174	269	164	427	1499	214
406.06	Clayton	152	65	168	352	1755	44
406.07	Clayton	100	201	170	375	2051	34
406.08	Clayton	23	70	449	1135	2785	60
501.01	Gwinnett	248	157	153	553	4879	385
501.02	Gwinnett	260	193	128	312	2630	18
502.02	Gwinnett	312	106	171	493	4566	56
502.03	Gwinnett	366	287	279	414	1942	52
502.04	Gwinnett	221	160	139	537	2721	44
503.04	Gwinnett	290	158	80	46	208	4
503.05	Gwinnett	63	150	52	33	205	3
503.06	Gwinnett	395	206	180	51	207	0
503.07	Gwinnett	28	219	53	120	621	17
503.08	Gwinnett	44	57	25	66	367	16
503.09	Gwinnett	141	140	72	82	791	44
503.10	Gwinnett	139	182	51	38	310	10
503.11	Gwinnett	114	92	27	31	242	1
503.12	Gwinnett	123	182	103	84	240	1
503.13	Gwinnett	85	186	101	126	282	0
503.14	Gwinnett	44	115	56	90	240	3
504.03	Gwinnett	86	200	75	93	687	5
504.06	Gwinnett	111	157	32	22	149	0
504.07	Gwinnett	86	249	79	74	296	4
504.08	Gwinnett	138	259	148	69	179	0
504.09	Gwinnett	274	225	137	106	551	32

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
504.10	Gwinnett	80	105	47	80	295	1
504.11	Gwinnett	130	179	86	75	540	10
504.12	Gwinnett	80	361	142	245	771	6
504.13	Gwinnett	86	240	85	123	940	9
504.14	Gwinnett	111	279	99	158	896	26
504.15	Gwinnett	72	136	57	64	546	3
504.16	Gwinnett	14	57	22	37	446	5
505.02	Gwinnett	322	139	177	330	2590	20
505.03	Gwinnett	302	180	309	902	4106	62
505.05	Gwinnett	189	184	218	437	1918	14
505.06	Gwinnett	246	233	229	454	1654	26
505.07	Gwinnett	158	72	89	216	868	13
505.08	Gwinnett	227	234	117	174	832	3
505.09	Gwinnett	95	133	270	617	2306	19
506.01	Gwinnett	466	211	637	2347	8598	62
506.02	Gwinnett	181	173	929	2471	7680	23
507.04	Gwinnett	140	191	708	1254	3274	84
507.05	Gwinnett	260	270	877	1521	4532	56
507.06	Gwinnett	104	135	87	183	1001	23
507.07	Gwinnett	104	195	105	167	934	10
507.08	Gwinnett	128	205	187	317	1216	8
507.09	Gwinnett	83	72	88	211	1561	42
507.10	Gwinnett	157	225	139	258	984	15
507.11	Gwinnett	131	318	300	481	1004	12
508.98	Gwinnett	1	1	0	0	2	0
601.00	Rockdale	397	302	873	1679	6553	86
602.00	Rockdale	211	260	376	663	2570	109
603.02	Rockdale	307	344	396	847	2712	48
603.03	Rockdale	126	184	144	191	989	7
603.04	Rockdale	386	246	284	380	779	32
604.01	Rockdale	211	213	318	940	3767	70
604.02	Rockdale	143	258	490	1186	4226	44
701.02	Henry	154	112	209	709	2335	55
701.03	Henry	476	505	448	1063	4386	94
701.98	Henry	221	126	179	546	2424	17
702.01	Henry	167	196	496	1229	2961	79
702.02	Henry	103	175	545	1618	3036	22
702.03	Henry	276	399	923	1696	5781	122
703.01	Henry	414	231	1284	1495	4149	98
703.02	Henry	592	604	1012	1742	3688	47
704.02	Henry	286	416	765	1476	6003	27
704.98	Henry	558	824	1857	2483	6522	143
705.00	Henry	680	540	1895	2907	7620	117

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
801.98	Douglas	330	155	132	393	2942	107
802.00	Douglas	206	354	212	556	2062	50
803.00	Douglas	344	389	224	620	1821	14
804.00	Douglas	768	456	762	3891	15193	160
805.01	Douglas	193	329	238	1001	3562	39
805.03	Douglas	83	198	53	176	997	14
805.04	Douglas	135	146	158	744	4562	83
806.01	Douglas	169	165	172	629	3041	45
806.02	Douglas	101	77	46	245	1967	32
807.97	Douglas	0	0	0	0	0	0
807.98	Douglas	8	9	27	131	277	2
901.00	Cherokee	204	105	387	2612	14633	35
902.00	Cherokee	313	84	168	2476	18946	228
903.00	Cherokee	196	25	124	880	9791	1057
904.00	Cherokee	190	66	185	644	3554	12
905.00	Cherokee	563	99	314	3993	12702	130
906.00	Cherokee	319	133	112	970	4305	17
907.00	Cherokee	261	103	150	618	4063	415
908.00	Cherokee	241	90	281	2614	6327	88
909.01	Cherokee	3	54	81	466	1655	10
909.02	Cherokee	65	47	76	259	1500	20
909.03	Cherokee	65	72	62	302	1146	11
910.01	Cherokee	85	36	24	104	673	4
910.02	Cherokee	164	60	49	141	2667	130
910.03	Cherokee	106	98	61	99	625	14
911.01	Cherokee	19	43	33	76	1216	481
911.03	Cherokee	98	55	65	353	1945	297
911.98	Cherokee	50	61	24	151	787	5
912.98	Cherokee	0	2	2	8	19	0
1201.00	Paulding	300	146	443	4282	20754	79
1202.00	Paulding	237	97	195	963	2981	28
1203.00	Paulding	420	187	291	1808	6540	68
1204.00	Paulding	488	177	537	5038	18650	80
1205.00	Paulding	233	140	253	1793	4371	65
1206.98	Paulding	251	126	426	3340	5824	107
1301.00	Forsyth	438	171	405	2146	6010	1256
1302.00	Forsyth	614	147	443	3109	7591	92
1303.00	Forsyth	450	117	327	2848	5755	46
1304.00	Forsyth	599	171	302	1577	4917	44
1305.00	Forsyth	519	220	308	989	6684	4431
1306.00	Forsyth	583	155	415	2667	7670	73
1401.01	Fayette	166	200	310	1158	2372	56
1401.02	Fayette	137	176	300	614	1851	35

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
1402.01	Fayette	149	186	636	2233	3590	114
1402.02	Fayette	144	224	239	547	2800	64
1403.01	Fayette	170	518	378	822	3429	133
1403.02	Fayette	114	105	220	396	2245	41
1404.01	Fayette	217	278	464	1006	3017	77
1404.02	Fayette	152	260	466	1054	3244	47
1405.01	Fayette	151	178	556	1846	4297	83
1405.02	Fayette	164	202	859	2125	4044	112
1701.00	Coweta	319	670	1238	5417	14668	256
1702.00	Coweta	166	299	199	773	2410	61
1703.00	Coweta	506	433	676	2434	9261	113
1704.00	Coweta	519	339	879	2760	8914	121
1705.00	Coweta	731	1081	2775	5250	15744	215
1706.00	Coweta	268	307	362	1084	4563	129
1707.00	Coweta	67	249	252	845	2321	23
1708.00	Coweta	653	463	1554	6870	16287	203

Table A.2. Land-use/land-cover data, metropolitan Atlanta, Georgia, 1990.

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
1.00	Fulton	42	114	0	6	163	0
2.00	Fulton	60	110	2	4	116	1
4.00	Fulton	44	38	8	21	47	6
5.00	Fulton	158	74	3	11	83	2
6.00	Fulton	97	36	3	3	10	1
7.00	Fulton	103	45	8	5	14	0
8.00	Fulton	58	31	3	1	6	0
10.95	Fulton	182	50	15	8	11	1
11.00	Fulton	29	14	1	1	2	1
12.00	Fulton	70	32	2	0	6	0
13.00	Fulton	72	34	2	2	21	0
14.00	Fulton	22	34	3	2	18	0
15.00	Fulton	30	53	0	0	28	0
16.00	Fulton	36	31	3	12	13	0
17.00	Fulton	72	36	2	3	7	0
18.00	Fulton	60	22	4	4	2	0
19.00	Fulton	87	1	1	0	0	1
20.00	Fulton	5	6	0	0	0	0
21.00	Fulton	67	15	1	1	0	0
22.00	Fulton	51	24	2	3	1	0
23.00	Fulton	42	52	2	5	13	0
24.00	Fulton	26	70	4	4	31	0
25.00	Fulton	41	39	0	3	5	0
26.00	Fulton	49	23	16	3	1	0
27.00	Fulton	86	0	1	0	0	2
28.00	Fulton	73	4	0	0	0	0
29.00	Fulton	45	21	2	3	3	0
30.00	Fulton	42	45	4	5	26	0
31.00	Fulton	22	45	1	0	14	0
32.00	Fulton	54	40	3	3	4	0
33.00	Fulton	57	13	3	0	0	0
35.00	Fulton	139	4	2	0	0	1
36.00	Fulton	29	7	1	2	1	0
37.00	Fulton	6	6	0	0	0	0
38.00	Fulton	35	33	2	4	5	0
39.00	Fulton	20	50	1	4	12	0
40.00	Fulton	48	78	2	5	29	0
41.00	Fulton	38	53	0	2	22	0
42.95	Fulton	70	40	3	5	10	0
43.00	Fulton	38	18	3	2	2	0
44.00	Fulton	60	19	3	4	1	0
46.95	Fulton	96	13	2	2	2	0
48.00	Fulton	27	8	3	0	0	0
49.95	Fulton	59	38	1	5	10	0
50.00	Fulton	64	47	8	3	15	0
52.00	Fulton	48	87	9	7	86	0

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
53.00	Fulton	36	96	3	15	67	0
55.01	Fulton	25	62	3	11	19	0
55.02	Fulton	54	74	6	17	18	0
56.00	Fulton	61	27	0	3	10	0
57.00	Fulton	34	25	1	2	2	0
58.00	Fulton	60	41	1	3	15	0
60.00	Fulton	34	72	1	1	60	0
61.00	Fulton	27	76	0	3	113	0
62.00	Fulton	37	41	1	2	23	0
63.00	Fulton	75	55	2	5	13	0
64.00	Fulton	46	38	4	7	30	0
65.00	Fulton	83	133	8	16	85	0
66.01	Fulton	69	64	8	6	35	0
66.02	Fulton	23	20	0	2	22	0
67.00	Fulton	120	114	13	33	71	3
68.01	Fulton	13	11	20	15	5	0
68.02	Fulton	13	25	5	9	23	0
69.00	Fulton	58	83	8	33	130	0
70.00	Fulton	176	197	20	66	423	0
71.00	Fulton	58	111	8	14	76	0
72.00	Fulton	204	129	29	21	521	3
73.00	Fulton	181	124	21	56	379	1
74.00	Fulton	78	55	2	5	87	0
75.00	Fulton	132	86	11	11	98	0
76.01	Fulton	139	103	6	63	136	1
76.02	Fulton	19	57	5	34	221	0
77.01	Fulton	215	171	22	23	698	6
77.02	Fulton	258	206	42	54	1087	52
78.02	Fulton	76	170	20	39	1035	30
78.03	Fulton	559	355	110	58	914	30
78.04	Fulton	138	117	5	14	181	0
79.00	Fulton	107	153	21	28	572	1
80.00	Fulton	40	103	5	39	368	0
81.01	Fulton	0	20	1	1	66	0
81.02	Fulton	116	157	53	92	316	1
82.01	Fulton	60	179	4	13	270	0
82.02	Fulton	150	120	104	50	265	13
83.01	Fulton	44	84	20	17	96	0
83.02	Fulton	38	70	4	6	73	0
84.00	Fulton	49	69	4	5	59	0
85.00	Fulton	72	75	10	17	196	0
86.01	Fulton	69	110	7	20	254	1
86.02	Fulton	145	77	42	15	175	7
87.01	Fulton	129	78	19	25	124	2
87.02	Fulton	80	116	36	25	153	1
88.00	Fulton	357	191	67	61	288	9
89.00	Fulton	452	267	22	36	323	29
90.00	Fulton	79	45	2	19	187	0

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
91.00	Fulton	91	80	4	23	136	1
92.00	Fulton	180	90	6	2	73	0
93.00	Fulton	49	63	3	2	132	1
94.01	Fulton	51	69	7	4	159	1
94.02	Fulton	96	37	8	4	20	0
95.00	Fulton	92	84	2	7	459	3
96.00	Fulton	188	111	11	2	200	2
97.00	Fulton	73	121	7	26	837	30
98.00	Fulton	228	191	14	31	1140	15
99.00	Fulton	113	97	9	43	536	2
100.00	Fulton	130	113	19	26	746	11
101.01	Fulton	219	174	24	12	563	6
101.03	Fulton	391	213	17	19	724	12
101.05	Fulton	170	148	9	12	306	16
101.06	Fulton	59	88	1	7	515	31
101.07	Fulton	15	80	3	49	387	18
101.08	Fulton	68	145	1	33	263	7
102.01	Fulton	244	284	10	25	1597	41
102.03	Fulton	107	219	30	99	870	176
102.04	Fulton	123	138	4	6	630	62
102.05	Fulton	133	112	5	15	406	2
103.01	Fulton	404	299	169	920	6601	192
103.02	Fulton	905	543	427	416	5061	102
104.00	Fulton	424	780	525	2196	14372	303
105.03	Fulton	220	283	40	52	508	2
105.04	Fulton	424	623	260	713	3054	37
105.05	Fulton	369	365	110	141	1528	26
105.06	Fulton	570	659	271	624	5573	125
106.01	Fulton	44	91	5	12	164	0
106.02	Fulton	306	205	20	54	526	5
107.00	Fulton	140	55	2	12	29	0
108.00	Fulton	549	118	5	30	128	1
109.00	Fulton	115	16	5	4	5	0
110.00	Fulton	81	101	24	15	54	0
111.00	Fulton	160	91	14	7	73	0
112.01	Fulton	124	111	20	6	118	1
112.02	Fulton	60	121	6	6	106	0
113.01	Fulton	34	133	4	13	310	0
113.02	Fulton	242	304	34	75	1048	2
114.03	Fulton	150	281	27	239	729	14
114.04	Fulton	146	135	39	41	208	7
114.05	Fulton	107	162	17	31	455	10
114.06	Fulton	109	198	25	27	679	57
114.07	Fulton	90	322	18	154	1168	33
114.08	Fulton	187	430	26	52	1023	24
114.09	Fulton	146	424	85	142	1243	42
114.10	Fulton	49	154	20	81	433	51
114.11	Fulton	54	163	9	21	485	33

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
115.00	Fulton	279	762	173	1831	7423	176
116.01	Fulton	433	500	175	559	3124	51
116.02	Fulton	409	566	91	305	2881	93
116.03	Fulton	361	803	267	1130	2876	103
201.00	DeKalb	7	30	0	1	56	0
202.00	DeKalb	26	28	1	10	92	0
203.00	DeKalb	20	61	1	14	95	0
204.00	DeKalb	113	157	91	179	680	27
205.00	DeKalb	33	80	3	8	49	0
206.00	DeKalb	30	45	5	5	20	0
207.00	DeKalb	20	58	1	4	45	0
208.00	DeKalb	67	128	4	11	197	0
209.00	DeKalb	125	135	7	11	150	0
211.00	DeKalb	70	157	4	29	421	16
212.02	DeKalb	96	130	7	14	475	12
212.04	DeKalb	210	74	93	20	38	0
212.05	DeKalb	92	236	6	21	488	5
212.07	DeKalb	183	115	11	15	361	8
212.08	DeKalb	156	77	7	5	113	1
212.09	DeKalb	91	84	9	52	235	4
212.10	DeKalb	71	187	8	17	361	7
212.11	DeKalb	37	133	6	24	295	11
212.12	DeKalb	114	113	5	7	226	1
213.01	DeKalb	224	61	16	5	64	1
213.02	DeKalb	181	192	7	29	215	1
213.03	DeKalb	206	120	15	10	120	1
213.04	DeKalb	255	132	39	15	298	32
214.01	DeKalb	126	157	17	11	179	1
214.02	DeKalb	75	136	4	4	230	1
214.03	DeKalb	93	157	14	6	231	0
214.04	DeKalb	89	84	5	15	187	1
215.00	DeKalb	174	223	16	6	486	4
216.01	DeKalb	94	142	1	5	456	7
216.02	DeKalb	38	58	2	6	206	1
216.03	DeKalb	111	92	2	2	167	1
217.02	DeKalb	246	199	8	14	547	7
217.03	DeKalb	63	89	1	5	369	2
217.04	DeKalb	185	174	21	14	334	2
218.05	DeKalb	69	209	16	15	311	2
218.06	DeKalb	328	195	58	31	503	5
218.08	DeKalb	57	86	1	3	150	4
218.09	DeKalb	115	205	12	12	528	13
218.10	DeKalb	191	133	14	6	311	10
218.98	DeKalb	114	126	18	10	247	2
219.02	DeKalb	194	236	31	40	960	9
219.03	DeKalb	403	331	168	97	1446	177
219.04	DeKalb	118	129	19	10	188	4
219.05	DeKalb	134	169	12	14	363	16

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
220.01	DeKalb	88	111	5	9	226	3
220.02	DeKalb	107	197	4	12	305	3
220.04	DeKalb	48	120	2	5	211	4
220.05	DeKalb	86	88	7	11	150	1
221.00	DeKalb	90	96	22	18	122	1
222.00	DeKalb	225	170	22	27	248	2
223.01	DeKalb	77	114	7	13	213	1
223.02	DeKalb	68	75	3	10	207	1
224.01	DeKalb	41	61	1	3	179	0
224.02	DeKalb	55	76	6	11	175	7
224.03	DeKalb	46	50	0	30	356	1
225.00	DeKalb	72	73	3	7	135	0
226.00	DeKalb	70	64	1	8	162	0
227.00	DeKalb	33	78	2	5	115	0
228.00	DeKalb	52	45	4	7	155	0
229.00	DeKalb	64	74	5	19	207	1
230.00	DeKalb	26	43	1	4	94	2
231.01	DeKalb	50	87	2	9	210	0
231.02	DeKalb	46	82	3	7	114	1
231.03	DeKalb	135	260	21	23	321	1
231.05	DeKalb	132	114	30	20	208	2
231.06	DeKalb	117	113	18	12	228	1
232.03	DeKalb	222	191	97	112	538	8
232.04	DeKalb	47	152	9	41	419	6
232.05	DeKalb	72	323	16	28	488	11
232.06	DeKalb	67	198	4	25	436	3
232.07	DeKalb	107	310	24	76	511	7
233.02	DeKalb	235	339	161	103	2040	90
233.03	DeKalb	333	290	189	104	1028	43
233.05	DeKalb	101	235	35	117	904	26
233.06	DeKalb	113	157	91	179	680	27
233.07	DeKalb	130	280	63	104	414	12
233.08	DeKalb	193	216	79	73	717	8
234.03	DeKalb	145	150	21	22	294	1
234.04	DeKalb	453	331	176	200	1854	26
234.05	DeKalb	274	227	121	163	1947	15
234.07	DeKalb	413	615	325	601	4349	67
234.08	DeKalb	310	461	42	68	928	12
234.09	DeKalb	214	389	36	51	1311	7
235.01	DeKalb	50	88	1	4	93	0
235.02	DeKalb	62	168	5	16	189	0
235.03	DeKalb	156	295	13	22	391	2
236.00	DeKalb	88	235	8	61	414	13
237.00	DeKalb	95	101	12	11	256	0
238.01	DeKalb	26	115	17	16	249	3
238.02	DeKalb	184	138	112	185	346	1
238.03	DeKalb	56	136	4	16	284	0
239.98	DeKalb	10	25	2	14	114	0

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
301.98	Cobb	435	587	137	396	3952	328
302.03	Cobb	261	711	193	936	3435	54
302.04	Cobb	340	604	116	197	1845	30
302.05	Cobb	487	339	192	234	1072	35
302.06	Cobb	234	533	97	312	3384	36
302.07	Cobb	489	683	238	771	4606	97
303.02	Cobb	77	356	20	49	803	29
303.07	Cobb	107	480	27	75	1270	10
303.09	Cobb	109	265	13	37	731	17
303.10	Cobb	75	264	23	58	468	10
303.11	Cobb	91	185	42	61	458	14
303.12	Cobb	94	207	19	64	486	6
303.13	Cobb	89	229	14	81	514	5
303.14	Cobb	88	151	5	35	514	4
303.15	Cobb	101	272	10	49	591	5
303.16	Cobb	184	511	29	112	1311	25
303.17	Cobb	162	419	13	63	1059	49
303.18	Cobb	103	232	26	117	691	34
303.19	Cobb	48	97	10	29	515	60
303.20	Cobb	89	137	11	57	627	26
303.21	Cobb	409	176	18	15	435	47
304.01	Cobb	87	203	8	28	466	2
304.02	Cobb	75	170	15	15	374	4
304.04	Cobb	158	91	17	14	69	1
304.05	Cobb	149	116	8	7	176	3
304.06	Cobb	163	77	23	6	118	3
305.01	Cobb	274	280	50	93	703	16
305.02	Cobb	190	184	62	117	427	7
305.03	Cobb	232	256	43	60	589	13
306.00	Cobb	377	237	55	138	1393	17
307.00	Cobb	126	120	10	23	151	0
308.00	Cobb	201	138	30	31	119	1
309.01	Cobb	67	225	18	57	731	5
309.02	Cobb	95	114	12	39	246	3
309.03	Cobb	68	269	104	95	381	11
310.01	Cobb	412	274	241	192	444	5
310.02	Cobb	70	129	4	35	231	0
310.03	Cobb	121	338	23	45	399	2
311.01	Cobb	77	122	17	11	115	0
311.03	Cobb	131	255	15	19	422	1
311.05	Cobb	72	228	15	33	279	3
311.06	Cobb	151	203	42	70	418	12
311.07	Cobb	116	311	13	42	656	15
311.08	Cobb	56	130	8	12	130	2
311.09	Cobb	134	107	21	10	121	2
312.02	Cobb	391	335	94	74	755	54
312.03	Cobb	142	109	12	14	353	11
312.04	Cobb	86	204	17	41	585	28

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
313.01	Cobb	152	390	18	93	925	10
313.02	Cobb	199	392	174	182	1865	34
313.04	Cobb	137	397	42	65	793	3
313.05	Cobb	340	291	209	91	1110	30
314.03	Cobb	213	396	117	158	741	10
314.04	Cobb	96	217	29	85	451	8
314.98	Cobb	275	444	151	345	1590	26
315.01	Cobb	161	524	232	674	2095	38
315.02	Cobb	265	800	189	337	1825	26
316.97	Cobb	0	0	0	0	0	0
316.98	Cobb	0	3	0	1	19	0
401.00	Clayton	1189	82	7	84	116	0
402.00	Clayton	422	303	139	72	629	10
403.01	Clayton	281	67	65	37	120	0
403.02	Clayton	63	148	8	20	276	4
403.03	Clayton	115	207	18	33	202	2
403.04	Clayton	98	166	34	28	105	0
403.05	Clayton	191	210	85	40	205	3
404.01	Clayton	247	597	98	150	796	21
404.02	Clayton	628	562	216	548	2171	19
404.03	Clayton	210	380	80	74	581	13
404.05	Clayton	150	174	18	15	261	3
404.06	Clayton	293	251	56	19	268	5
405.03	Clayton	77	263	18	38	383	0
405.04	Clayton	147	332	51	96	569	7
405.05	Clayton	99	355	23	65	593	6
405.06	Clayton	113	300	22	38	316	2
405.07	Clayton	150	467	94	124	727	22
405.08	Clayton	42	381	51	99	517	5
406.03	Clayton	191	499	120	166	1071	14
406.04	Clayton	302	322	90	87	537	9
406.05	Clayton	190	594	99	315	1355	198
406.06	Clayton	140	120	160	299	1759	60
406.07	Clayton	166	475	139	303	1826	22
406.08	Clayton	64	231	343	806	2907	170
501.01	Gwinnett	318	478	159	415	4635	372
501.02	Gwinnett	359	397	118	261	2400	8
502.02	Gwinnett	381	352	176	374	4340	79
502.03	Gwinnett	598	548	204	258	1668	62
502.04	Gwinnett	250	400	55	470	2581	68
503.04	Gwinnett	287	153	52	24	262	8
503.05	Gwinnett	69	114	10	11	296	6
503.06	Gwinnett	434	200	156	42	206	2
503.07	Gwinnett	35	280	21	46	649	26
503.08	Gwinnett	57	80	1	39	372	24
503.09	Gwinnett	181	196	53	48	745	49
503.10	Gwinnett	180	177	21	11	329	13
503.11	Gwinnett	133	86	20	18	250	2

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
503.12	Gwinnett	185	234	69	47	195	3
503.13	Gwinnett	87	227	33	89	343	1
503.14	Gwinnett	54	168	28	55	237	5
504.03	Gwinnett	105	257	48	41	685	8
504.06	Gwinnett	125	128	8	8	198	2
504.07	Gwinnett	108	249	9	32	383	7
504.08	Gwinnett	203	294	28	34	230	4
504.09	Gwinnett	321	330	128	53	454	41
504.10	Gwinnett	95	144	22	47	299	2
504.11	Gwinnett	149	213	36	35	575	11
504.12	Gwinnett	93	449	32	132	892	8
504.13	Gwinnett	99	289	46	71	971	10
504.14	Gwinnett	144	368	36	70	927	26
504.15	Gwinnett	89	189	51	36	507	2
504.16	Gwinnett	24	128	6	10	407	6
505.02	Gwinnett	448	629	197	199	2072	33
505.03	Gwinnett	438	839	356	589	3558	83
505.05	Gwinnett	235	461	132	280	1832	19
505.06	Gwinnett	395	601	144	255	1414	32
505.07	Gwinnett	245	239	56	117	746	14
505.08	Gwinnett	303	397	57	119	706	5
505.09	Gwinnett	132	338	124	503	2309	33
506.01	Gwinnett	519	905	306	2150	8360	87
506.02	Gwinnett	301	628	464	2176	7859	32
507.04	Gwinnett	180	544	228	1183	3420	103
507.05	Gwinnett	281	623	325	1491	4707	99
507.06	Gwinnett	122	338	16	101	932	26
507.07	Gwinnett	110	298	33	95	965	10
507.08	Gwinnett	183	565	73	239	984	10
507.09	Gwinnett	111	305	35	184	1384	43
507.10	Gwinnett	205	428	64	174	896	14
507.11	Gwinnett	157	564	94	376	1039	18
508.98	Gwinnett	1	2	0	0	1	0
601.00	Rockdale	504	737	369	1283	6872	150
602.00	Rockdale	244	510	149	551	2641	95
603.02	Rockdale	344	582	312	634	2726	66
603.03	Rockdale	149	326	51	140	968	7
603.04	Rockdale	396	307	155	363	857	25
604.01	Rockdale	268	482	140	760	3800	68
604.02	Rockdale	196	643	214	910	4338	52
701.02	Henry	182	361	107	532	2327	62
701.03	Henry	573	888	385	629	4339	162
701.98	Henry	239	330	83	411	2432	20
702.01	Henry	208	396	356	865	3194	106
702.02	Henry	111	235	431	1390	3302	36
702.03	Henry	280	549	1194	1075	5908	197
703.01	Henry	385	363	591	1430	4743	160
703.02	Henry	601	697	563	1632	4108	86

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
704.02	Henry	324	389	851	774	6611	31
704.98	Henry	515	513	1155	2323	7726	155
705.00	Henry	564	670	1281	2282	8814	147
801.98	Douglas	435	438	194	244	2628	121
802.00	Douglas	249	664	217	326	1920	63
803.00	Douglas	417	610	195	364	1807	18
804.00	Douglas	912	1104	858	2081	16120	199
805.01	Douglas	264	589	159	573	3720	60
805.03	Douglas	107	338	28	101	937	11
805.04	Douglas	166	392	145	376	4657	94
806.01	Douglas	198	471	151	404	2939	57
806.02	Douglas	99	195	44	174	1912	46
807.97	Douglas	0	0	0	0	0	0
807.98	Douglas	16	30	13	91	300	6
901.00	Cherokee	398	482	156	1776	15098	75
902.00	Cherokee	456	341	125	1565	19519	258
903.00	Cherokee	231	188	66	265	10363	968
904.00	Cherokee	292	182	78	568	3501	28
905.00	Cherokee	619	447	156	3688	12721	174
906.00	Cherokee	375	328	94	885	4133	38
907.00	Cherokee	313	456	74	423	3944	401
908.00	Cherokee	293	515	193	2428	6095	119
909.01	Cherokee	25	205	29	409	1586	16
909.02	Cherokee	85	181	36	196	1438	23
909.03	Cherokee	89	253	44	187	1074	8
910.01	Cherokee	124	95	53	76	578	3
910.02	Cherokee	206	370	55	111	2362	105
910.03	Cherokee	130	200	65	41	549	13
911.01	Cherokee	54	253	11	18	1072	464
911.03	Cherokee	140	277	60	246	1808	285
911.98	Cherokee	78	147	25	74	744	6
912.98	Cherokee	0	5	1	5	18	0
1201.00	Paulding	506	859	732	1813	22034	93
1202.00	Paulding	288	500	197	615	2857	43
1203.00	Paulding	503	569	281	987	6896	85
1204.00	Paulding	520	716	702	2514	20409	112
1205.00	Paulding	291	546	259	1048	4606	106
1206.98	Paulding	309	589	556	2066	6415	148
1301.00	Forsyth	481	380	224	2229	5966	1168
1302.00	Forsyth	678	400	266	3123	7439	120
1303.00	Forsyth	528	399	157	2568	5817	71
1304.00	Forsyth	683	436	188	1337	4912	54
1305.00	Forsyth	698	698	198	918	6577	4067
1306.00	Forsyth	686	524	410	2378	7472	91
1401.01	Fayette	173	396	150	933	2527	81
1401.02	Fayette	160	356	201	405	1953	43
1402.01	Fayette	190	478	521	1636	3926	159
1402.02	Fayette	191	446	136	315	2741	184

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
1403.01	Fayette	236	667	236	466	3678	166
1403.02	Fayette	164	443	157	362	1956	41
1404.01	Fayette	284	598	273	691	3126	91
1404.02	Fayette	198	626	356	760	3202	77
1405.01	Fayette	175	324	496	1365	4635	121
1405.02	Fayette	211	261	908	1373	4617	137
1701.00	Coweta	532	1221	1627	2497	16320	381
1702.00	Coweta	234	433	166	502	2505	72
1703.00	Coweta	645	967	678	1260	9520	361
1704.00	Coweta	572	909	503	1479	9864	201
1705.00	Coweta	640	1033	1973	3939	17972	245
1706.00	Coweta	316	571	377	600	4618	232
1707.00	Coweta	119	404	242	431	2523	37
1708.00	Coweta	854	869	1781	3853	18450	278

Table A.3. Land-use/land-cover data, metropolitan Atlanta, Georgia, 2000.

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
1.00	Fulton	43	147	0	5	131	0
2.00	Fulton	64	147	0	4	77	0
4.00	Fulton	49	59	7	22	23	4
5.00	Fulton	163	102	3	13	50	0
6.00	Fulton	100	41	3	4	1	0
7.00	Fulton	109	50	4	3	9	0
8.00	Fulton	63	33	1	1	1	0
10.95	Fulton	195	60	6	3	2	0
11.00	Fulton	32	15	0	0	0	0
12.00	Fulton	75	35	0	0	0	1
13.00	Fulton	74	49	1	0	7	0
14.00	Fulton	23	45	1	1	6	1
15.00	Fulton	32	72	0	0	7	0
16.00	Fulton	39	39	5	4	8	0
17.00	Fulton	74	41	1	1	2	0
18.00	Fulton	63	24	1	2	1	0
19.00	Fulton	88	1	0	0	0	0
20.00	Fulton	5	6	0	0	0	0
21.00	Fulton	68	15	1	0	0	0
22.00	Fulton	53	25	2	2	0	0
23.00	Fulton	43	56	1	6	8	0
24.00	Fulton	28	82	1	4	21	0
25.00	Fulton	42	42	1	0	2	0
26.00	Fulton	63	24	4	0	0	0
27.00	Fulton	89	0	0	0	0	1
28.00	Fulton	73	4	0	0	0	0
29.00	Fulton	48	25	2	0	0	0
30.00	Fulton	46	56	2	4	15	0
31.00	Fulton	23	51	0	1	8	0
32.00	Fulton	56	43	2	3	1	0
33.00	Fulton	58	14	1	0	0	0
35.00	Fulton	141	4	0	0	0	0
36.00	Fulton	30	8	1	1	0	0
37.00	Fulton	6	6	0	0	0	0
38.00	Fulton	38	38	1	1	0	0
39.00	Fulton	20	55	1	4	6	0
40.00	Fulton	48	91	1	4	18	0
41.00	Fulton	38	60	0	2	15	0
42.95	Fulton	72	48	2	3	5	0
43.00	Fulton	39	20	3	1	0	0
44.00	Fulton	61	21	3	2	1	0
46.95	Fulton	99	16	0	1	0	0
48.00	Fulton	28	9	1	0	0	0
49.95	Fulton	59	44	2	2	5	0
50.00	Fulton	68	55	3	4	6	0
52.00	Fulton	54	106	4	7	66	0

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
53.00	Fulton	39	120	3	10	45	0
55.01	Fulton	28	73	4	7	9	0
55.02	Fulton	58	81	6	13	13	0
56.00	Fulton	62	34	1	0	5	0
57.00	Fulton	34	28	1	1	1	0
58.00	Fulton	61	46	1	3	9	0
60.00	Fulton	35	90	0	1	42	0
61.00	Fulton	27	93	0	3	96	0
62.00	Fulton	38	48	0	1	18	0
63.00	Fulton	77	63	1	3	6	0
64.00	Fulton	49	45	3	5	23	0
65.00	Fulton	88	153	8	12	63	0
66.01	Fulton	74	76	3	5	25	0
66.02	Fulton	23	22	0	1	20	0
67.00	Fulton	125	134	12	20	59	4
68.01	Fulton	17	13	16	15	3	0
68.02	Fulton	13	29	4	6	22	0
69.00	Fulton	61	101	13	22	113	0
70.00	Fulton	189	245	18	54	376	0
71.00	Fulton	65	126	4	8	64	0
72.00	Fulton	236	158	25	23	463	1
73.00	Fulton	189	165	10	59	337	3
74.00	Fulton	82	76	1	5	64	0
75.00	Fulton	139	102	2	5	87	2
76.01	Fulton	144	132	10	53	106	2
76.02	Fulton	20	71	2	37	205	1
77.01	Fulton	223	258	39	24	582	8
77.02	Fulton	275	271	28	82	967	75
78.02	Fulton	81	289	60	40	865	35
78.03	Fulton	623	480	71	37	778	38
78.04	Fulton	141	146	2	7	159	1
79.00	Fulton	122	222	7	20	510	2
80.00	Fulton	41	133	6	45	330	0
81.01	Fulton	0	26	0	2	59	0
81.02	Fulton	124	195	14	93	306	2
82.01	Fulton	64	233	4	13	212	0
82.02	Fulton	164	162	53	54	249	19
83.01	Fulton	45	101	5	30	80	0
83.02	Fulton	39	82	2	7	61	0
84.00	Fulton	50	85	0	3	46	0
85.00	Fulton	76	92	4	13	185	0
86.01	Fulton	71	130	3	19	236	1
86.02	Fulton	169	101	21	17	145	9
87.01	Fulton	140	96	13	20	105	3
87.02	Fulton	94	142	19	37	117	2
88.00	Fulton	388	253	41	51	230	11
89.00	Fulton	478	365	14	16	231	25
90.00	Fulton	80	70	0	18	163	1

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
91.00	Fulton	102	110	1	20	101	2
92.00	Fulton	186	114	3	3	44	0
93.00	Fulton	52	95	0	2	100	2
94.01	Fulton	70	103	3	2	113	1
94.02	Fulton	107	47	4	1	5	1
95.00	Fulton	99	144	1	6	395	1
96.00	Fulton	211	155	3	5	139	2
97.00	Fulton	76	203	7	17	751	39
98.00	Fulton	246	327	14	37	981	14
99.00	Fulton	116	154	4	48	475	4
100.00	Fulton	197	251	8	24	555	12
101.01	Fulton	248	298	10	12	416	14
101.03	Fulton	479	400	21	16	445	17
101.05	Fulton	204	276	9	6	144	22
101.06	Fulton	63	147	6	7	443	37
101.07	Fulton	15	133	8	36	336	24
101.08	Fulton	74	204	8	18	203	10
102.01	Fulton	261	478	12	29	1373	50
102.03	Fulton	125	339	30	105	694	207
102.04	Fulton	127	212	3	7	536	78
102.05	Fulton	139	189	5	20	321	1
103.01	Fulton	437	463	280	818	6368	219
103.02	Fulton	1091	881	369	277	4720	116
104.00	Fulton	514	1085	584	1815	14269	320
105.03	Fulton	239	385	50	34	393	4
105.04	Fulton	570	914	335	451	2798	42
105.05	Fulton	451	500	93	109	1362	25
105.06	Fulton	729	912	372	467	5211	132
106.01	Fulton	45	109	3	12	147	0
106.02	Fulton	361	270	31	38	409	5
107.00	Fulton	152	61	2	10	13	0
108.00	Fulton	565	150	5	23	87	1
109.00	Fulton	120	18	2	2	3	0
110.00	Fulton	90	122	17	7	40	0
111.00	Fulton	170	108	5	9	52	1
112.01	Fulton	129	133	10	8	99	1
112.02	Fulton	64	143	3	5	84	0
113.01	Fulton	37	188	8	14	246	2
113.02	Fulton	271	402	20	54	953	6
114.03	Fulton	182	469	83	119	574	14
114.04	Fulton	205	209	33	17	110	4
114.05	Fulton	127	257	18	19	347	12
114.06	Fulton	121	324	29	20	543	58
114.07	Fulton	121	530	72	88	932	42
114.08	Fulton	245	740	62	47	616	31
114.09	Fulton	183	839	82	127	790	61
114.10	Fulton	66	298	27	69	280	49
114.11	Fulton	60	242	8	6	404	45

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
115.00	Fulton	356	1498	467	1444	6675	203
116.01	Fulton	772	1194	352	320	2122	83
116.02	Fulton	707	1460	345	156	1576	103
116.03	Fulton	529	1850	399	674	1984	104
201.00	DeKalb	7	43	0	1	43	0
202.00	DeKalb	27	42	1	7	80	0
203.00	DeKalb	21	80	1	14	75	0
204.00	DeKalb	20	54	4	4	18	0
205.00	DeKalb	35	92	2	5	39	0
206.00	DeKalb	33	51	1	6	14	1
207.00	DeKalb	21	72	1	3	30	0
208.00	DeKalb	69	165	5	10	161	0
209.00	DeKalb	129	165	4	11	119	0
211.00	DeKalb	84	249	5	28	314	18
212.02	DeKalb	107	229	14	14	358	12
212.04	DeKalb	231	86	66	26	27	0
212.05	DeKalb	97	381	3	20	339	8
212.07	DeKalb	262	230	16	9	161	14
212.08	DeKalb	165	106	3	5	80	0
212.09	DeKalb	98	122	6	53	192	4
212.10	DeKalb	78	295	21	29	221	6
212.11	DeKalb	39	244	23	52	135	12
212.12	DeKalb	126	184	3	4	145	5
213.01	DeKalb	240	91	4	4	32	1
213.02	DeKalb	191	251	6	21	156	1
213.03	DeKalb	217	162	8	7	75	1
213.04	DeKalb	291	233	25	5	183	33
214.01	DeKalb	147	212	13	5	112	2
214.02	DeKalb	86	205	3	3	150	2
214.03	DeKalb	99	186	8	6	200	3
214.04	DeKalb	99	141	6	8	125	2
215.00	DeKalb	192	324	9	9	373	4
216.01	DeKalb	97	227	1	7	365	9
216.02	DeKalb	40	94	6	8	162	2
216.03	DeKalb	119	130	1	4	119	2
217.02	DeKalb	260	325	9	10	408	8
217.03	DeKalb	66	162	1	7	290	3
217.04	DeKalb	205	266	7	17	233	3
218.05	DeKalb	79	288	14	16	222	3
218.06	DeKalb	381	277	41	55	363	4
218.08	DeKalb	60	131	2	3	100	4
218.09	DeKalb	120	289	6	56	402	13
218.10	DeKalb	207	219	7	6	210	15
218.98	DeKalb	124	192	10	9	177	4
219.02	DeKalb	211	357	32	43	811	15
219.03	DeKalb	512	467	152	93	1205	192
219.04	DeKalb	132	189	10	13	122	3
219.05	DeKalb	144	259	7	9	274	16

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
220.01	DeKalb	91	145	3	11	187	4
220.02	DeKalb	115	298	5	9	197	4
220.04	DeKalb	50	173	1	5	156	5
220.05	DeKalb	92	128	6	5	110	1
221.00	DeKalb	98	128	7	18	98	1
222.00	DeKalb	250	234	11	16	183	1
223.01	DeKalb	82	156	4	9	174	1
223.02	DeKalb	70	118	2	9	162	3
224.01	DeKalb	43	84	1	3	153	1
224.02	DeKalb	67	116	9	7	124	7
224.03	DeKalb	46	81	1	32	322	0
225.00	DeKalb	76	101	1	4	110	0
226.00	DeKalb	71	100	0	7	125	0
227.00	DeKalb	34	103	1	5	90	0
228.00	DeKalb	54	67	2	6	134	0
229.00	DeKalb	65	99	5	12	188	1
230.00	DeKalb	28	57	1	6	77	1
231.01	DeKalb	52	115	2	12	178	1
231.02	DeKalb	48	111	3	10	80	1
231.03	DeKalb	141	327	11	26	254	1
231.05	DeKalb	151	173	18	11	152	1
231.06	DeKalb	128	182	5	9	165	2
232.03	DeKalb	292	309	124	86	349	7
232.04	DeKalb	51	221	14	22	360	6
232.05	DeKalb	73	403	13	33	403	13
232.06	DeKalb	73	260	11	16	369	2
232.07	DeKalb	111	427	13	65	411	7
233.02	DeKalb	327	639	205	93	1613	91
233.03	DeKalb	451	421	101	68	886	61
233.05	DeKalb	111	427	108	111	637	24
233.06	DeKalb	137	292	112	140	544	21
233.07	DeKalb	147	383	58	62	340	13
233.08	DeKalb	224	402	137	48	468	8
234.03	DeKalb	155	217	22	17	220	1
234.04	DeKalb	591	535	262	164	1465	23
234.05	DeKalb	308	513	271	125	1507	24
234.07	DeKalb	544	989	381	415	3959	82
234.08	DeKalb	331	671	70	77	656	16
234.09	DeKalb	240	574	126	53	1005	11
235.01	DeKalb	51	101	1	5	77	1
235.02	DeKalb	64	205	4	23	144	0
235.03	DeKalb	164	374	16	21	301	1
236.00	DeKalb	92	286	7	69	352	13
237.00	DeKalb	102	139	9	26	198	2
238.01	DeKalb	27	141	12	26	218	3
238.02	DeKalb	211	183	95	100	372	5
238.03	DeKalb	59	165	10	19	243	0
239.98	DeKalb	11	36	2	8	109	0

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
301.98	Cobb	583	1183	385	335	3077	261
302.03	Cobb	293	1230	336	757	2920	53
302.04	Cobb	458	1204	326	114	1004	27
302.05	Cobb	777	607	260	110	568	38
302.06	Cobb	271	1083	221	247	2733	41
302.07	Cobb	600	1408	362	594	3827	92
303.02	Cobb	89	506	25	35	647	32
303.07	Cobb	128	662	41	49	1074	14
303.09	Cobb	132	441	23	23	534	18
303.10	Cobb	84	342	23	48	389	11
303.11	Cobb	106	297	38	42	349	18
303.12	Cobb	100	298	21	45	406	6
303.13	Cobb	98	340	21	79	387	6
303.14	Cobb	104	275	26	28	360	4
303.15	Cobb	111	412	11	27	463	5
303.16	Cobb	197	799	27	96	1029	25
303.17	Cobb	188	653	10	25	832	55
303.18	Cobb	108	419	21	91	533	31
303.19	Cobb	51	180	10	25	437	57
303.20	Cobb	98	246	16	35	532	21
303.21	Cobb	458	318	25	6	253	40
304.01	Cobb	97	289	11	21	373	3
304.02	Cobb	83	263	5	16	283	3
304.04	Cobb	178	127	7	7	31	1
304.05	Cobb	158	176	4	5	115	2
304.06	Cobb	184	138	13	3	46	6
305.01	Cobb	300	436	52	74	540	13
305.02	Cobb	244	338	69	50	278	7
305.03	Cobb	258	396	33	56	435	13
306.00	Cobb	429	450	90	98	1128	22
307.00	Cobb	138	165	8	23	97	0
308.00	Cobb	223	177	24	22	73	1
309.01	Cobb	76	313	31	39	637	5
309.02	Cobb	98	153	6	45	204	3
309.03	Cobb	87	401	82	59	290	8
310.01	Cobb	535	352	153	192	332	4
310.02	Cobb	76	171	15	23	183	0
310.03	Cobb	126	414	23	43	317	2
311.01	Cobb	86	153	9	13	81	1
311.03	Cobb	146	348	19	20	309	1
311.05	Cobb	76	304	7	28	213	3
311.06	Cobb	162	292	27	69	334	12
311.07	Cobb	129	472	21	38	480	14
311.08	Cobb	63	178	13	8	74	1
311.09	Cobb	146	156	16	12	60	6
312.02	Cobb	475	548	118	62	455	46
312.03	Cobb	178	241	11	10	188	12
312.04	Cobb	119	380	34	30	370	27

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
313.01	Cobb	162	488	20	90	819	8
313.02	Cobb	243	628	204	129	1606	37
313.04	Cobb	154	514	42	62	665	2
313.05	Cobb	456	451	139	64	931	30
314.03	Cobb	274	596	126	144	486	9
314.04	Cobb	100	284	38	78	381	4
314.98	Cobb	356	653	311	259	1228	26
315.01	Cobb	194	802	260	585	1846	37
315.02	Cobb	299	1161	210	260	1491	21
316.97	Cobb	0	0	0	0	0	0
316.98	Cobb	0	3	0	0	19	0
401.00	Clayton	1268	97	17	27	70	0
402.00	Clayton	510	439	129	75	413	9
403.01	Clayton	349	92	32	13	83	1
403.02	Clayton	74	178	14	18	229	4
403.03	Clayton	128	253	14	26	153	3
403.04	Clayton	122	193	22	18	77	0
403.05	Clayton	234	257	52	27	160	5
404.01	Clayton	297	724	104	102	659	24
404.02	Clayton	766	838	349	326	1846	20
404.03	Clayton	292	511	115	52	356	13
404.05	Clayton	162	215	8	16	217	3
404.06	Clayton	325	310	33	19	202	4
405.03	Clayton	93	315	35	25	309	2
405.04	Clayton	170	483	86	72	386	4
405.05	Clayton	103	460	31	60	481	7
405.06	Clayton	135	348	31	21	254	2
405.07	Clayton	188	640	176	72	492	16
405.08	Clayton	49	490	62	63	422	9
406.03	Clayton	288	698	165	125	769	17
406.04	Clayton	340	411	82	53	449	10
406.05	Clayton	219	795	125	249	1149	185
406.06	Clayton	164	190	162	217	1736	68
406.07	Clayton	201	743	421	232	1308	25
406.08	Clayton	95	416	247	843	2741	174
501.01	Gwinnett	412	1052	550	346	3670	346
501.02	Gwinnett	493	657	232	200	1947	14
502.02	Gwinnett	595	1227	552	301	2933	95
502.03	Gwinnett	874	1051	206	142	996	69
502.04	Gwinnett	458	1038	322	389	1547	69
503.04	Gwinnett	338	223	32	20	166	8
503.05	Gwinnett	82	232	14	33	135	9
503.06	Gwinnett	544	287	70	31	105	2
503.07	Gwinnett	58	466	22	43	439	29
503.08	Gwinnett	92	209	43	21	191	18
503.09	Gwinnett	257	409	86	55	409	57
503.10	Gwinnett	235	317	52	13	100	14
503.11	Gwinnett	169	145	24	16	152	3

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
503.12	Gwinnett	221	313	38	31	125	6
503.13	Gwinnett	113	316	25	68	255	3
503.14	Gwinnett	68	249	15	38	171	6
504.03	Gwinnett	121	400	43	39	532	9
504.06	Gwinnett	135	210	4	5	114	2
504.07	Gwinnett	111	376	18	34	243	6
504.08	Gwinnett	218	407	16	18	131	4
504.09	Gwinnett	419	488	60	31	296	33
504.10	Gwinnett	105	220	23	29	228	3
504.11	Gwinnett	185	364	37	32	389	11
504.12	Gwinnett	101	610	38	89	756	11
504.13	Gwinnett	125	517	69	57	708	9
504.14	Gwinnett	161	537	53	63	729	29
504.15	Gwinnett	118	273	24	20	436	3
504.16	Gwinnett	21	170	2	9	377	1
505.02	Gwinnett	655	1307	336	135	1111	34
505.03	Gwinnett	695	1693	586	413	2388	89
505.05	Gwinnett	292	934	259	179	1274	19
505.06	Gwinnett	559	1060	166	131	891	35
505.07	Gwinnett	313	450	77	49	516	13
505.08	Gwinnett	356	568	70	76	508	10
505.09	Gwinnett	193	662	399	390	1754	41
506.01	Gwinnett	719	1805	1071	1827	6784	107
506.02	Gwinnett	460	1229	783	1838	7087	47
507.04	Gwinnett	200	966	592	950	2861	79
507.05	Gwinnett	376	1163	646	1169	4047	112
507.06	Gwinnett	170	587	46	49	655	26
507.07	Gwinnett	137	458	58	64	786	9
507.08	Gwinnett	202	790	100	167	783	13
507.09	Gwinnett	112	420	48	120	1317	45
507.10	Gwinnett	242	648	86	101	690	14
507.11	Gwinnett	211	822	187	247	765	15
508.98	Gwinnett	1	2	0	0	1	0
601.00	Rockdale	564	1090	368	1118	6377	390
602.00	Rockdale	290	753	181	406	2450	109
603.02	Rockdale	503	954	395	443	2298	68
603.03	Rockdale	171	416	63	64	915	13
603.04	Rockdale	499	419	124	163	874	25
604.01	Rockdale	289	694	123	586	3746	79
604.02	Rockdale	260	957	228	608	4230	64
701.02	Henry	195	533	162	429	2185	67
701.03	Henry	834	1504	731	477	3267	138
701.98	Henry	265	547	211	345	2116	30
702.01	Henry	248	674	371	878	2842	113
702.02	Henry	150	517	394	1339	3039	64
702.03	Henry	376	912	493	1599	5580	229
703.01	Henry	498	673	702	1246	4389	150
703.02	Henry	767	1260	830	1118	3632	80

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
704.02	Henry	367	680	593	1130	6146	56
704.98	Henry	717	980	1022	2396	7003	250
705.00	Henry	692	1006	956	2531	8206	345
801.98	Douglas	571	608	222	173	2363	116
802.00	Douglas	293	832	186	289	1772	67
803.00	Douglas	502	807	219	280	1586	18
804.00	Douglas	1081	1668	904	2107	15212	266
805.01	Douglas	289	734	163	531	3550	96
805.03	Douglas	152	490	72	119	671	17
805.04	Douglas	199	641	297	424	4169	100
806.01	Douglas	242	656	233	361	2676	51
806.02	Douglas	135	271	98	139	1789	37
807.97	Douglas	0	0	0	0	0	0
807.98	Douglas	17	47	16	76	294	5
901.00	Cherokee	552	782	412	1650	14450	115
902.00	Cherokee	608	584	442	1499	18791	290
903.00	Cherokee	336	420	230	296	9914	876
904.00	Cherokee	369	338	162	420	3323	38
905.00	Cherokee	752	833	492	3140	12353	235
906.00	Cherokee	417	546	126	691	4017	57
907.00	Cherokee	407	851	350	343	3264	397
908.00	Cherokee	354	875	423	2023	5819	149
909.01	Cherokee	33	312	62	304	1531	26
909.02	Cherokee	101	329	44	123	1334	29
909.03	Cherokee	140	401	106	89	903	15
910.01	Cherokee	153	156	64	36	516	4
910.02	Cherokee	320	953	227	163	1475	71
910.03	Cherokee	180	276	67	37	421	18
911.01	Cherokee	64	351	21	22	956	458
911.03	Cherokee	176	410	86	188	1689	267
911.98	Cherokee	77	232	44	63	650	8
912.98	Cherokee	0	8	2	5	13	0
1201.00	Paulding	620	1503	608	1856	21313	122
1202.00	Paulding	332	778	265	578	2516	31
1203.00	Paulding	602	884	441	983	6328	82
1204.00	Paulding	705	1164	1028	2842	19098	117
1205.00	Paulding	357	891	354	1002	4166	87
1206.98	Paulding	365	1136	919	1941	5572	149
1301.00	Forsyth	572	697	405	1853	5789	1098
1302.00	Forsyth	733	675	516	2494	7461	129
1303.00	Forsyth	584	843	497	2079	5450	88
1304.00	Forsyth	783	783	390	1084	4501	69
1305.00	Forsyth	955	1452	570	785	5583	3793
1306.00	Forsyth	1036	1640	1202	1691	5848	144
1401.01	Fayette	192	555	167	684	2584	79
1401.02	Fayette	245	522	171	345	1789	47
1402.01	Fayette	259	765	418	1334	3978	157
1402.02	Fayette	265	904	201	308	2175	158

Census Tract	County	High-Density Urban (ha)	Low-Density Urban (ha)	Cultivated/ Exposed (ha)	Cropland/ Grassland (ha)	Forest (ha)	Water (ha)
1403.01	Fayette	290	1061	223	462	3222	172
1403.02	Fayette	232	762	237	280	1575	39
1404.01	Fayette	308	947	277	576	2859	95
1404.02	Fayette	273	905	217	705	3054	65
1405.01	Fayette	212	542	273	1309	4524	225
1405.02	Fayette	235	425	346	1646	4579	228
1701.00	Coweta	698	1702	1112	2692	15938	406
1702.00	Coweta	234	554	148	462	2468	45
1703.00	Coweta	901	1567	744	1341	8493	366
1704.00	Coweta	692	1730	766	1381	8727	227
1705.00	Coweta	826	1701	1406	4411	17178	278
1706.00	Coweta	389	973	351	742	4042	211
1707.00	Coweta	130	506	197	435	2444	44
1708.00	Coweta	975	1342	1005	4081	18300	331

APPENDIX B

DASYMETRIC POPULATION DENSITIES,
BY 1990 CENSUS TRACT BOUNDARIES

Table B.1. Dasymetric population densities, metropolitan Atlanta, Georgia, 1980-2000.

Census Tract	**County**	**1980 (persons/km^2)**	**1990 (persons/km^2)**	**2000 (persons/km^2)**
1.00	Fulton	5303.80	3444.44	2811.11
2.00	Fulton	4835.45	4422.22	3811.11
4.00	Fulton	4949.37	4066.66	3166.67
5.00	Fulton	184595.02	3466.66	3555.55
6.00	Fulton	3037.98	3711.11	7400.00
7.00	Fulton	6886.08	7744.43	6866.66
8.00	Fulton	7075.95	4888.88	4722.22
10.95	Fulton	11113.93	12922.21	14844.44
11.00	Fulton	8835.45	10188.88	16311.10
12.00	Fulton	10911.40	9799.99	11922.22
13.00	Fulton	8582.28	9977.76	8022.22
14.00	Fulton	3531.65	5499.99	4911.11
15.00	Fulton	6113.93	7344.43	5444.44
16.00	Fulton	6455.70	3211.11	3633.33
17.00	Fulton	8113.93	7499.99	5733.33
18.00	Fulton	11468.36	11255.54	15066.66
19.00	Fulton	60582.31	61499.92	20322.21
20.00	Fulton	39417.74	20199.97	20611.10
21.00	Fulton	13974.69	18044.42	15622.22
22.00	Fulton	11151.90	7644.43	3855.55
23.00	Fulton	6848.10	5566.66	4933.33
24.00	Fulton	5455.70	3577.77	3022.22
25.00	Fulton	11746.84	9899.99	4733.33
26.00	Fulton	7177.22	3877.77	5355.55
27.00	Fulton	159278.56	34466.62	652221.96
28.00	Fulton	78443.08	47755.49	73877.75
29.00	Fulton	7430.38	6022.21	5488.89
30.00	Fulton	3139.24	3700.00	3400.00
31.00	Fulton	6050.64	3922.22	3144.44
32.00	Fulton	3962.03	3100.00	3511.11
33.00	Fulton	30835.46	18133.31	17711.10
35.00	Fulton	11215.20	26355.52	86077.74
36.00	Fulton	10582.28	9133.32	16044.44
37.00	Fulton	17911.40	6799.99	20022.21
38.00	Fulton	10329.12	8166.66	7833.33
39.00	Fulton	6556.97	4733.33	4533.33
40.00	Fulton	4974.69	3333.33	3411.11
41.00	Fulton	6822.79	4677.77	4400.00
42.95	Fulton	1341.77	6188.88	4966.66
43.00	Fulton	9037.98	19066.64	12677.77
44.00	Fulton	17721.53	10833.32	8088.89
46.95	Fulton	9721.52	9722.21	7377.77
48.00	Fulton	20430.39	24477.75	26299.99

Census Tract	County	1980 (persons/km^2)	1990 (persons/km^2)	2000 (persons/km^2)
49.95	Fulton	6000.00	5344.44	4722.22
50.00	Fulton	5392.41	3588.88	3400.00
52.00	Fulton	5189.88	4266.66	3344.44
53.00	Fulton	4278.48	3200.00	2377.78
55.01	Fulton	5835.45	4277.77	3366.67
55.02	Fulton	6392.41	4822.22	1855.55
56.00	Fulton	8734.18	5988.88	4600.00
57.00	Fulton	5974.69	5699.99	4144.44
58.00	Fulton	5493.67	4077.77	5022.22
60.00	Fulton	8645.57	5977.77	4911.11
61.00	Fulton	10101.27	6077.77	4477.78
62.00	Fulton	7037.98	4299.99	3133.33
63.00	Fulton	5329.12	3899.99	3288.89
64.00	Fulton	6443.04	7699.99	6344.44
65.00	Fulton	3670.89	3544.44	3044.44
66.01	Fulton	4215.19	3633.33	3255.55
66.02	Fulton	11848.11	7133.32	5833.33
67.00	Fulton	5607.60	3722.22	2855.55
68.01	Fulton	24303.81	12611.09	18222.22
68.02	Fulton	11531.65	8055.55	5700.00
69.00	Fulton	4911.39	4311.11	3166.67
70.00	Fulton	5493.67	4622.22	3977.78
71.00	Fulton	5329.12	3999.99	3055.55
72.00	Fulton	4797.47	2988.89	2600.00
73.00	Fulton	5860.76	5422.22	4455.55
74.00	Fulton	5227.85	5822.21	5433.33
75.00	Fulton	4240.51	4244.44	3844.44
76.01	Fulton	9126.59	7199.99	5233.33
76.02	Fulton	9835.45	4955.55	4133.33
77.01	Fulton	7164.56	4433.33	3333.33
77.02	Fulton	4455.70	3433.33	2888.89
78.02	Fulton	8430.38	3188.88	2177.78
78.03	Fulton	2696.20	2288.89	1955.55
78.04	Fulton	8455.70	6888.88	5222.22
79.00	Fulton	5012.66	2888.89	2055.55
80.00	Fulton	11835.45	6055.55	4211.11
81.01	Fulton	13544.31	5999.99	4700.00
81.02	Fulton	6822.79	4055.55	3477.78
82.01	Fulton	4101.27	3388.88	2411.11
82.02	Fulton	4556.96	3222.22	2700.00
83.01	Fulton	7556.97	4577.77	3888.89
83.02	Fulton	7544.31	4133.33	3288.89
84.00	Fulton	8556.97	6788.88	6644.44
85.00	Fulton	12898.74	6111.10	4855.55
86.01	Fulton	10417.73	5277.77	4544.44

Census Tract	County	1980 (persons/km^2)	1990 (persons/km^2)	2000 (persons/km^2)
86.02	Fulton	8354.43	4344.44	3522.22
87.01	Fulton	6759.50	3566.66	444.44
87.02	Fulton	4658.23	3711.11	2888.89
88.00	Fulton	2000.00	1433.33	1211.11
89.00	Fulton	2797.47	3666.66	3400.00
90.00	Fulton	8556.97	7711.10	5255.55
91.00	Fulton	8316.46	7722.21	6588.89
92.00	Fulton	3531.65	3333.33	3522.22
93.00	Fulton	7025.32	7266.66	5400.00
94.01	Fulton	5607.60	4955.55	4944.44
94.02	Fulton	5696.21	7777.77	9344.44
95.00	Fulton	9898.74	8277.77	5222.22
96.00	Fulton	5645.57	6533.32	5633.33
97.00	Fulton	4556.96	2544.44	1944.44
98.00	Fulton	7468.36	3455.55	2366.67
99.00	Fulton	7278.48	3988.88	3011.11
100.00	Fulton	8012.66	6411.10	3444.44
101.01	Fulton	6443.04	4266.66	4055.55
101.03	Fulton	3316.46	4611.11	3566.67
101.05	Fulton	2278.48	6922.21	4911.11
101.06	Fulton	2202.53	3800.00	2522.22
101.07	Fulton	2202.53	2122.22	1844.44
101.08	Fulton	2202.53	2188.89	1866.67
102.01	Fulton	5126.58	3922.22	2844.44
102.03	Fulton	4582.28	5333.33	4055.55
102.04	Fulton	4582.28	3733.33	2244.44
102.05	Fulton	4582.28	4055.55	2400.00
103.01	Fulton	2797.47	1011.11	688.89
103.02	Fulton	2810.13	1644.44	1100.00
104.00	Fulton	1936.71	700.00	588.89
105.03	Fulton	3126.58	3277.77	2611.11
105.04	Fulton	2518.99	2066.66	1655.55
105.05	Fulton	2481.01	2444.44	2033.33
105.06	Fulton	2860.76	1633.33	1322.22
106.01	Fulton	5987.34	3844.44	3844.44
106.02	Fulton	4936.71	4944.44	4033.33
107.00	Fulton	6025.32	4433.33	3900.00
108.00	Fulton	5050.64	4644.44	4166.67
109.00	Fulton	6316.46	4444.44	4111.11
110.00	Fulton	5012.66	3933.33	3622.22
111.00	Fulton	3088.61	2977.77	2655.55
112.01	Fulton	5835.45	4833.33	4255.55
112.02	Fulton	4518.99	3822.22	4188.89
113.01	Fulton	3810.13	3977.77	2900.00
113.02	Fulton	5075.95	4799.99	4288.89

Census Tract	County	1980 (persons/km^2)	1990 (persons/km^2)	2000 (persons/km^2)
114.03	Fulton	2772.15	2133.33	1855.55
114.04	Fulton	2772.15	5022.22	5222.22
114.05	Fulton	2772.15	2566.66	2577.78
114.06	Fulton	2772.15	3000.00	2411.11
114.07	Fulton	2772.15	2266.66	1777.78
114.08	Fulton	1670.89	2933.33	2333.33
114.09	Fulton	1670.89	2200.00	2155.55
114.10	Fulton	1670.89	2700.00	2088.89
114.11	Fulton	1670.89	4288.88	3300.00
115.00	Fulton	3215.19	1400.00	1466.67
116.01	Fulton	2379.75	1766.66	1811.11
116.02	Fulton	2367.09	1644.44	2100.00
116.03	Fulton	2354.43	1088.89	2211.11
201.00	DeKalb	6417.72	4488.88	3388.89
202.00	DeKalb	13050.64	7677.77	5188.89
203.00	DeKalb	7620.26	5033.33	4066.67
204.00	DeKalb	5898.74	11266.65	3788.89
205.00	DeKalb	7139.24	4288.88	3500.00
206.00	DeKalb	3835.44	4511.11	4044.44
207.00	DeKalb	8012.66	4511.11	3666.67
208.00	DeKalb	15506.34	7399.99	3844.44
209.00	DeKalb	7215.19	5444.44	3955.55
211.00	DeKalb	7025.32	4333.33	3322.22
212.02	DeKalb	5025.32	4122.22	2400.00
212.04	DeKalb	5037.98	5555.55	6088.89
212.05	DeKalb	3708.86	3644.44	2300.00
212.07	DeKalb	2088.61	2411.11	3100.00
212.08	DeKalb	4367.09	3200.00	2288.89
212.09	DeKalb	4354.43	5588.88	4244.44
212.10	DeKalb	3759.50	2888.89	1777.78
212.11	DeKalb	3772.15	3244.44	1877.78
212.12	DeKalb	3759.50	4622.22	3933.33
213.01	DeKalb	2481.01	4411.11	4044.44
213.02	DeKalb	3139.24	3366.66	3511.11
213.03	DeKalb	3291.14	3855.55	3933.33
213.04	DeKalb	3063.29	5933.33	4488.89
214.01	DeKalb	5367.09	4777.77	6000.00
214.02	DeKalb	6569.62	6544.44	6033.33
214.03	DeKalb	5632.91	3455.55	3377.78
214.04	DeKalb	5468.36	6755.55	6277.78
215.00	DeKalb	4772.15	4566.66	4188.89
216.01	DeKalb	6873.42	5422.22	3544.44
216.02	DeKalb	5291.14	5899.99	3844.44
216.03	DeKalb	4329.12	4322.22	4244.44
217.02	DeKalb	3405.06	4533.33	3255.55

Census Tract	County	1980 (persons/km^2)	1990 (persons/km^2)	2000 (persons/km^2)
217.03	DeKalb	3670.89	4744.44	2822.22
217.04	DeKalb	3670.89	2722.22	1933.33
218.05	DeKalb	2911.39	2977.77	2255.55
218.06	DeKalb	3164.56	2533.33	1988.89
218.08	DeKalb	2417.72	4922.22	3511.11
218.09	DeKalb	2822.79	3355.55	2322.22
218.10	DeKalb	2822.79	2988.89	1900.00
218.98	DeKalb	2417.72	6455.55	5711.11
219.02	DeKalb	2518.99	3144.44	2544.44
219.03	DeKalb	3544.31	3322.22	2800.00
219.04	DeKalb	3379.75	5044.44	4133.33
219.05	DeKalb	3392.41	5966.66	4722.22
220.01	DeKalb	3759.50	3666.66	2588.89
220.02	DeKalb	5670.89	7855.55	6600.00
220.04	DeKalb	3759.50	3788.88	3433.33
220.05	DeKalb	3772.15	3866.66	3455.55
221.00	DeKalb	4696.20	3500.00	2944.44
222.00	DeKalb	3113.93	3533.33	3366.67
223.01	DeKalb	5037.98	4711.11	3344.44
223.02	DeKalb	4101.27	5411.10	3555.55
224.01	DeKalb	8518.99	6888.88	4922.22
224.02	DeKalb	6075.95	5988.88	3888.89
224.03	DeKalb	15164.56	6955.55	4966.66
225.00	DeKalb	8835.45	6188.88	5000.00
226.00	DeKalb	9126.59	7233.32	4877.78
227.00	DeKalb	11303.80	6166.66	4100.00
228.00	DeKalb	11810.13	7333.32	5644.44
229.00	DeKalb	6911.40	5555.55	4277.78
230.00	DeKalb	5518.99	4599.99	3488.89
231.01	DeKalb	7000.00	6311.10	4700.00
231.02	DeKalb	3658.23	3944.44	3244.44
231.03	DeKalb	4012.66	3811.11	3300.00
231.05	DeKalb	3949.37	5977.77	5588.89
231.06	DeKalb	3949.37	5433.33	4177.78
232.03	DeKalb	2556.96	2777.77	2844.44
232.04	DeKalb	3126.58	4066.66	3100.00
232.05	DeKalb	3113.93	3544.44	3188.89
232.06	DeKalb	3227.85	3455.55	2988.89
232.07	DeKalb	3215.19	3777.77	3477.78
233.02	DeKalb	1075.95	1088.89	1588.89
233.03	DeKalb	2012.66	1533.33	1100.00
233.05	DeKalb	2607.60	2700.00	2511.11
233.06	DeKalb	2569.62	1233.33	1822.22
233.07	DeKalb	1848.10	2844.44	3066.67
233.08	DeKalb	1848.10	3833.33	3600.00

Census Tract	County	1980 (persons/km^2)	1990 (persons/km^2)	2000 (persons/km^2)
234.03	DeKalb	5873.42	5577.77	4111.11
234.04	DeKalb	2607.60	1900.00	1711.11
234.05	DeKalb	5759.50	3211.11	2911.11
234.07	DeKalb	2797.47	1844.44	1700.00
234.08	DeKalb	4113.93	2933.33	2733.33
234.09	DeKalb	4113.93	2466.66	2466.67
235.01	DeKalb	6189.88	4733.33	3655.55
235.02	DeKalb	5278.48	4955.55	3844.44
235.03	DeKalb	4177.22	3988.88	3244.44
236.00	DeKalb	6620.26	4577.77	3611.11
237.00	DeKalb	8759.50	5811.10	4588.89
238.01	DeKalb	6683.55	4255.55	3355.55
238.02	DeKalb	3772.15	3166.66	2455.55
238.03	DeKalb	6050.64	4677.77	3655.55
239.98	DeKalb	5772.15	1211.11	2911.11
301.98	Cobb	4012.66	1811.11	2033.33
302.03	Cobb	3911.39	1811.11	1855.55
302.04	Cobb	1594.94	2244.44	2444.44
302.05	Cobb	1569.62	1711.11	1655.55
302.06	Cobb	4886.08	2111.11	2177.78
302.07	Cobb	4898.74	1855.55	1877.78
303.02	Cobb	2430.38	2955.55	2488.89
303.07	Cobb	2430.38	2911.11	2466.67
303.09	Cobb	2455.70	3711.11	2533.33
303.10	Cobb	2924.05	2877.77	2322.22
303.11	Cobb	2924.05	2933.33	2100.00
303.12	Cobb	2924.05	2922.22	2211.11
303.13	Cobb	2924.05	2677.77	2077.78
303.14	Cobb	3278.48	3433.33	2488.89
303.15	Cobb	3278.48	3222.22	2388.89
303.16	Cobb	3632.91	3466.66	2333.33
303.17	Cobb	3632.91	3577.77	2733.33
303.18	Cobb	3493.67	2577.77	1733.33
303.19	Cobb	3493.67	3333.33	2188.89
303.20	Cobb	2810.13	3733.33	2433.33
303.21	Cobb	2708.86	5388.88	3766.67
304.01	Cobb	3544.31	3577.77	2677.78
304.02	Cobb	4443.04	4433.33	2933.33
304.04	Cobb	3392.41	8211.10	6755.55
304.05	Cobb	3392.41	4655.55	3900.00
304.06	Cobb	3367.09	7955.55	6988.89
305.01	Cobb	3405.06	2666.66	1933.33
305.02	Cobb	3417.72	2222.22	1766.67
305.03	Cobb	3405.06	3355.55	2788.89
306.00	Cobb	3734.18	3000.00	2166.67

Census Tract	County	1980 (persons/km^2)	1990 (persons/km^2)	2000 (persons/km^2)
307.00	Cobb	5544.31	3633.33	3222.22
308.00	Cobb	4215.19	3166.66	2866.67
309.01	Cobb	3987.34	2833.33	2522.22
309.02	Cobb	3987.34	4755.55	4733.33
309.03	Cobb	3987.34	3422.22	3222.22
310.01	Cobb	2101.27	1766.66	1622.22
310.02	Cobb	5556.96	4311.11	4355.55
310.03	Cobb	4000.00	2911.11	2866.67
311.01	Cobb	4202.53	3533.33	3355.55
311.03	Cobb	4430.38	3666.66	3033.33
311.05	Cobb	4012.66	3255.55	3211.11
311.06	Cobb	3430.38	2377.77	2488.89
311.07	Cobb	3354.43	2455.55	2233.33
311.08	Cobb	2962.03	3833.33	3044.44
311.09	Cobb	2987.34	6966.66	4266.66
312.02	Cobb	2177.22	1788.89	1488.89
312.03	Cobb	3405.06	5277.77	3000.00
312.04	Cobb	3481.01	3477.77	2488.89
313.01	Cobb	3151.90	2366.66	1888.89
313.02	Cobb	2949.37	1588.89	1444.44
313.04	Cobb	2265.82	2300.00	2122.22
313.05	Cobb	6506.33	3166.66	2766.67
314.03	Cobb	2924.05	2233.33	2222.22
314.04	Cobb	2936.71	1922.22	1777.78
314.98	Cobb	2417.72	1488.89	1522.22
315.01	Cobb	2417.72	1255.55	1233.33
315.02	Cobb	2417.72	1888.89	1877.78
316.97	Cobb	0.00	0.00	0.00
316.98	Cobb	0.00	0.00	3000.00
401.00	Clayton	4303.80	4066.66	33.33
402.00	Clayton	2341.77	3455.55	2855.55
403.01	Clayton	2506.33	633.33	488.89
403.02	Clayton	3822.79	3411.11	3277.78
403.03	Clayton	3341.77	3011.11	3066.67
403.04	Clayton	3240.51	2422.22	2677.78
403.05	Clayton	3215.19	3500.00	3233.33
404.01	Clayton	2493.67	2288.89	2177.78
404.02	Clayton	2025.32	1733.33	1577.78
404.03	Clayton	2683.55	2400.00	2466.67
404.05	Clayton	3746.84	4022.22	3977.78
404.06	Clayton	3151.90	3122.22	2955.55
405.03	Clayton	3139.24	3022.22	2877.78
405.04	Clayton	2860.76	3422.22	3166.67
405.05	Clayton	2329.12	2377.77	2044.44
405.06	Clayton	2924.05	2644.44	2566.67

Census Tract	County	1980 (persons/km^2)	1990 (persons/km^2)	2000 (persons/km^2)
405.07	Clayton	2303.80	2644.44	2622.22
405.08	Clayton	2303.80	2788.89	2666.67
406.03	Clayton	2000.00	1944.44	2133.33
406.04	Clayton	2949.37	2877.77	2511.11
406.05	Clayton	2430.38	1655.55	1511.11
406.06	Clayton	746.84	1111.11	1800.00
406.07	Clayton	696.20	1611.11	2433.33
406.08	Clayton	1240.51	611.11	1300.00
501.01	Gwinnett	3417.72	1700.00	1700.00
501.02	Gwinnett	3417.72	2188.89	1555.55
502.02	Gwinnett	1531.65	866.67	1555.55
502.03	Gwinnett	1898.74	2822.22	3000.00
502.04	Gwinnett	1924.05	1655.55	1511.11
503.04	Gwinnett	1797.47	2144.44	1600.00
503.05	Gwinnett	1797.47	8422.21	5588.89
503.06	Gwinnett	1797.47	1088.89	1511.11
503.07	Gwinnett	683.54	2777.77	1955.55
503.08	Gwinnett	683.54	1888.89	1777.78
503.09	Gwinnett	696.20	2022.22	1911.11
503.10	Gwinnett	696.20	2355.55	1477.78
503.11	Gwinnett	1518.99	2277.77	1566.67
503.12	Gwinnett	1531.65	3355.55	3822.22
503.13	Gwinnett	1518.99	2522.22	2177.78
503.14	Gwinnett	1518.99	2622.22	2466.67
504.03	Gwinnett	2367.09	2711.11	2400.00
504.06	Gwinnett	2556.96	6544.44	6333.33
504.07	Gwinnett	2556.96	4522.22	4255.55
504.08	Gwinnett	1417.72	3733.33	3455.55
504.09	Gwinnett	1405.06	2944.44	2411.11
504.10	Gwinnett	1417.72	3311.11	2511.11
504.11	Gwinnett	1405.06	2744.44	2600.00
504.12	Gwinnett	2670.89	2644.44	1955.55
504.13	Gwinnett	2658.23	3144.44	2055.55
504.14	Gwinnett	2493.67	2822.22	2166.67
504.15	Gwinnett	2481.01	2255.55	1544.44
504.16	Gwinnett	2481.01	2722.22	2122.22
505.02	Gwinnett	1746.84	1955.55	2433.33
505.03	Gwinnett	2886.08	1477.78	2055.55
505.05	Gwinnett	2784.81	2500.00	2166.67
505.06	Gwinnett	2493.67	2800.00	3411.11
505.07	Gwinnett	2493.67	2522.22	2011.11
505.08	Gwinnett	2632.91	2977.77	2477.78
505.09	Gwinnett	2607.60	1544.44	1466.67
506.01	Gwinnett	2063.29	988.89	1500.00
506.02	Gwinnett	2063.29	877.78	1044.44

Census Tract	County	1980 (persons/km^2)	1990 (persons/km^2)	2000 (persons/km^2)
507.04	Gwinnett	1329.11	1300.00	1622.22
507.05	Gwinnett	1139.24	1044.44	1355.56
507.06	Gwinnett	2417.72	3088.88	2300.00
507.07	Gwinnett	2417.72	2722.22	1988.89
507.08	Gwinnett	1860.76	2222.22	2055.55
507.09	Gwinnett	1860.76	1922.22	1622.22
507.10	Gwinnett	2139.24	2344.44	2011.11
507.11	Gwinnett	2139.24	1822.22	1644.44
508.98	Gwinnett	2556.96	100.00	6311.11
601.00	Rockdale	1683.55	922.22	722.22
602.00	Rockdale	2531.65	1700.00	1622.22
603.02	Rockdale	1291.14	1433.33	1411.11
603.03	Rockdale	2405.06	2466.66	2200.00
603.04	Rockdale	2405.06	1377.78	1133.33
604.01	Rockdale	2139.24	1533.33	1255.56
604.02	Rockdale	2139.24	1644.44	1455.55
701.02	Henry	1898.74	1777.78	1700.00
701.03	Henry	1898.74	1355.55	1611.11
701.98	Henry	1898.74	2066.66	1733.33
702.01	Henry	746.84	1144.44	1466.67
702.02	Henry	734.18	877.78	1055.56
702.03	Henry	734.18	488.89	766.67
703.01	Henry	898.73	800.00	1155.56
703.02	Henry	898.73	1266.67	1788.89
704.02	Henry	354.43	477.78	822.22
704.98	Henry	367.09	855.55	855.56
705.00	Henry	822.79	922.22	977.78
801.98	Douglas	2974.68	1466.66	1600.00
802.00	Douglas	2683.55	1588.89	1433.33
803.00	Douglas	2329.12	1922.22	1844.44
804.00	Douglas	1379.75	755.55	666.67
805.01	Douglas	2670.89	1833.33	1455.55
805.03	Douglas	2810.13	2122.22	2088.89
805.04	Douglas	2810.13	1588.89	1433.33
806.01	Douglas	2544.31	1477.78	1500.00
806.02	Douglas	2544.31	1477.78	1388.89
807.97	Douglas	0.00	0.00	0.00
807.98	Douglas	2139.24	444.44	1588.89
901.00	Cherokee	3265.82	900.00	677.78
902.00	Cherokee	2911.39	1255.55	966.67
903.00	Cherokee	5898.74	1155.55	744.44
904.00	Cherokee	5189.88	2188.89	1366.67
905.00	Cherokee	4721.52	1566.66	1111.11
906.00	Cherokee	4696.20	2133.33	1866.67
907.00	Cherokee	3746.84	1777.78	1511.11

Census Tract	County	1980 (persons/km^2)	1990 (persons/km^2)	2000 (persons/km^2)
908.00	Cherokee	5481.02	1944.44	1888.89
909.01	Cherokee	3924.05	2377.77	1900.00
909.02	Cherokee	3924.05	2611.11	2222.22
909.03	Cherokee	3924.05	2611.11	2066.67
910.01	Cherokee	3721.52	2100.00	1488.89
910.02	Cherokee	3734.18	1266.67	2611.11
910.03	Cherokee	3721.52	2655.55	2133.33
911.01	Cherokee	4278.48	1744.44	1633.33
911.03	Cherokee	4278.48	1966.66	1722.22
911.98	Cherokee	4278.48	3577.77	2900.00
912.98	Cherokee	4278.48	155.56	2466.67
1201.00	Paulding	2278.48	766.67	955.56
1202.00	Paulding	3734.18	1677.78	1555.55
1203.00	Paulding	3341.77	1388.89	1333.33
1204.00	Paulding	2075.95	711.11	600.00
1205.00	Paulding	3202.53	1244.44	1622.22
1206.98	Paulding	3721.52	1166.67	1911.11
1301.00	Forsyth	2088.61	1388.89	1388.89
1302.00	Forsyth	2329.12	1355.55	1433.33
1303.00	Forsyth	3468.36	1744.44	2111.11
1304.00	Forsyth	3607.60	2133.33	1988.89
1305.00	Forsyth	2506.33	1455.55	1322.22
1306.00	Forsyth	3303.80	1333.33	1655.55
1401.01	Fayette	1658.23	1500.00	1211.11
1401.02	Fayette	1658.23	1466.66	1066.67
1402.01	Fayette	1417.72	1122.22	1044.44
1402.02	Fayette	1417.72	1388.89	1500.00
1403.01	Fayette	911.39	1677.78	1288.89
1403.02	Fayette	911.39	1144.44	1433.33
1404.01	Fayette	1493.67	1422.22	1311.11
1404.02	Fayette	1493.67	1533.33	1422.22
1405.01	Fayette	810.13	911.11	844.44
1405.02	Fayette	810.13	888.89	711.11
1701.00	Coweta	746.84	366.67	366.67
1702.00	Coweta	1670.89	1322.22	1166.67
1703.00	Coweta	1632.91	1022.22	1122.22
1704.00	Coweta	544.30	911.11	1300.00
1705.00	Coweta	531.65	633.33	700.00
1706.00	Coweta	2240.51	1244.44	1088.89
1707.00	Coweta	1392.41	1600.00	1400.00
1708.00	Coweta	873.42	622.22	533.33

APPENDIX C

MORTALITY DATA, BY 1990 CENSUS TRACT BOUNDARIES

Table C.1. Mortality data, metropolitan Atlanta, Georgia, 1995-1999.

Census Tract	County	Deaths	Crude Death Rate (deaths/100,000 population)	Expected Deaths	Standardized Mortality Ratio (SMR)	SMR Standard Error	Lower Limit 95% CI	Upper Limit 95% CI
1.00	Fulton	143	700.37	158.46	0.90	0.08	0.75	1.05
2.00	Fulton	176	668.63	162.72	1.08	0.08	0.92	1.24
4.00	Fulton	61	749.39	74.00	0.82	0.11	0.62	1.03
5.00	Fulton	103	616.63	110.68	0.93	0.09	0.75	1.11
6.00	Fulton	28	258.63	23.00	1.22	0.23	0.77	1.67
7.00	Fulton	61	347.34	59.48	1.03	0.13	0.77	1.28
8.00	Fulton	121	1574.75	67.42	1.79	0.16	1.48	2.11
10.95	Fulton	37	88.85	49.62	0.75	0.12	0.51	0.99
11.00	Fulton	58	524.83	46.92	1.24	0.16	0.92	1.55
12.00	Fulton	156	821.79	103.07	1.51	0.12	1.28	1.75
13.00	Fulton	135	722.36	97.41	1.39	0.12	1.15	1.62
14.00	Fulton	55	535.71	30.96	1.78	0.24	1.31	2.25
15.00	Fulton	164	799.00	113.31	1.45	0.11	1.23	1.67
16.00	Fulton	22	350.58	21.99	1.00	0.21	0.58	1.42
17.00	Fulton	246	1914.98	111.88	2.20	0.14	1.92	2.47
18.00	Fulton	134	842.45	131.59	1.02	0.09	0.85	1.19
19.00	Fulton	47	647.95	60.68	0.77	0.11	0.55	1.00
20.00	Fulton	59	0.00	0.00	0.00	0.00	0.00	0.00
21.00	Fulton	106	1148.00	48.83	2.17	0.21	1.76	2.58
22.00	Fulton	98	1523.39	34.38	2.85	0.29	2.29	3.41
23.00	Fulton	254	1836.44	108.93	2.33	0.15	2.05	2.62
24.00	Fulton	236	1904.27	167.93	1.41	0.09	1.23	1.58
25.00	Fulton	171	1422.87	88.39	1.93	0.15	1.64	2.22
26.00	Fulton	64	1045.85	34.13	1.88	0.23	1.42	2.33
27.00	Fulton	54	2486.83	5.85	9.23	1.26	6.77	11.69
28.00	Fulton	229	1789.70	124.06	1.85	0.12	1.61	2.08
29.00	Fulton	196	2990.84	87.83	2.23	0.16	1.92	2.54
30.00	Fulton	37	400.03	37.91	0.98	0.16	0.66	1.29
31.00	Fulton	149	1801.76	70.03	2.13	0.17	1.79	2.47
32.00	Fulton	108	1542.29	46.04	2.35	0.23	1.90	2.79
33.00	Fulton	206	1659.50	134.89	1.53	0.11	1.32	1.74
35.00	Fulton	74	578.14	37.74	1.96	0.23	1.51	2.41
36.00	Fulton	47	805.73	48.17	0.98	0.14	0.70	1.25
37.00	Fulton	50	1017.00	20.97	2.38	0.34	1.72	3.05
38.00	Fulton	73	612.45	43.95	1.66	0.19	1.28	2.04
39.00	Fulton	166	1375.87	111.64	1.49	0.12	1.26	1.71
40.00	Fulton	252	1691.74	311.74	0.81	0.05	0.71	0.91
41.00	Fulton	162	1274.30	59.09	2.74	0.22	2.32	3.16
42.95	Fulton	162	1304.53	112.95	1.43	0.11	1.21	1.66
43.00	Fulton	13	88.13	22.16	0.59	0.16	0.27	0.91
44.00	Fulton	110	1210.89	55.63	1.98	0.19	1.61	2.35

Census Tract	County	Deaths	Crude Death Rate (deaths/100,000 population)	Expected Deaths	Standardized Mortality Ratio (SMR)	SMR Standard Error	Lower Limit 95% CI	Upper Limit 95% CI
46.95	Fulton	97	1639.30	31.40	3.09	0.31	2.47	3.70
48.00	Fulton	83	765.41	37.08	2.24	0.25	1.76	2.72
49.95	Fulton	119	1169.89	53.18	2.24	0.21	1.84	2.64
50.00	Fulton	114	1231.64	102.94	1.11	0.10	0.90	1.31
52.00	Fulton	169	953.75	94.83	1.78	0.14	1.51	2.05
53.00	Fulton	134	909.97	83.36	1.61	0.14	1.34	1.88
55.01	Fulton	147	1197.78	82.53	1.78	0.15	1.49	2.07
55.02	Fulton	172	2036.12	58.38	2.95	0.22	2.51	3.39
56.00	Fulton	164	1995.92	65.67	2.50	0.19	2.12	2.88
57.00	Fulton	84	1203.24	54.87	1.53	0.17	1.20	1.86
58.00	Fulton	92	893.68	59.70	1.54	0.16	1.23	1.86
60.00	Fulton	263	1229.99	158.38	1.66	0.10	1.46	1.86
61.00	Fulton	272	1233.19	158.06	1.72	0.10	1.52	1.93
62.00	Fulton	92	1120.04	58.07	1.58	0.17	1.26	1.91
63.00	Fulton	189	1920.31	100.88	1.87	0.14	1.61	2.14
64.00	Fulton	74	500.42	42.20	1.75	0.20	1.35	2.15
65.00	Fulton	253	1079.41	156.50	1.62	0.10	1.42	1.82
66.01	Fulton	146	1207.42	99.97	1.46	0.12	1.22	1.70
66.02	Fulton	79	1138.36	33.02	2.39	0.27	1.86	2.92
67.00	Fulton	264	1325.08	123.73	2.13	0.13	1.88	2.39
68.01	Fulton	5	46.14	30.14	0.17	0.07	0.02	0.31
68.02	Fulton	58	594.79	31.08	1.87	0.25	1.39	2.35
69.00	Fulton	161	952.28	71.98	2.24	0.18	1.89	2.58
70.00	Fulton	411	873.08	213.79	1.92	0.09	1.74	2.11
71.00	Fulton	186	913.56	120.93	1.54	0.11	1.32	1.76
72.00	Fulton	101	496.67	62.69	1.61	0.16	1.30	1.93
73.00	Fulton	240	667.87	142.76	1.68	0.11	1.47	1.89
74.00	Fulton	330	1716.72	179.34	1.84	0.10	1.64	2.04
75.00	Fulton	327	1728.02	245.90	1.33	0.07	1.19	1.47
76.01	Fulton	275	774.19	228.53	1.20	0.07	1.06	1.35
76.02	Fulton	143	1004.74	89.22	1.60	0.13	1.34	1.87
77.01	Fulton	307	740.72	228.62	1.34	0.08	1.19	1.49
77.02	Fulton	254	672.83	235.86	1.08	0.07	0.94	1.21
78.02	Fulton	186	613.38	187.27	0.99	0.07	0.85	1.14
78.03	Fulton	328	730.34	246.08	1.33	0.07	1.19	1.48
78.04	Fulton	341	879.78	235.89	1.45	0.08	1.29	1.60
79.00	Fulton	298	1355.44	246.39	1.21	0.07	1.07	1.35
80.00	Fulton	338	1150.35	210.59	1.60	0.09	1.43	1.78
81.01	Fulton	71	1224.83	51.37	1.38	0.16	1.06	1.70
81.02	Fulton	313	963.23	268.16	1.17	0.07	1.04	1.30
82.01	Fulton	482	1657.30	365.15	1.32	0.06	1.20	1.44
82.02	Fulton	208	991.50	123.49	1.68	0.12	1.46	1.91
83.01	Fulton	357	1857.59	170.92	2.09	0.11	1.87	2.31

Census Tract	County	Deaths	Crude Death Rate (deaths/100,000 population)	Expected Deaths	Standardized Mortality Ratio (SMR)	SMR Standard Error	Lower Limit 95% CI	Upper Limit 95% CI
83.02	Fulton	210	1480.56	183.86	1.14	0.08	0.99	1.30
84.00	Fulton	324	1250.62	212.19	1.53	0.08	1.36	1.69
85.00	Fulton	325	1373.58	191.25	1.70	0.09	1.51	1.88
86.01	Fulton	340	1170.68	224.22	1.52	0.08	1.36	1.68
86.02	Fulton	132	746.19	58.65	2.25	0.20	1.87	2.63
87.01	Fulton	82	2634.52	23.44	3.50	0.39	2.74	4.26
87.02	Fulton	217	1045.98	128.76	1.69	0.11	1.46	1.91
88.00	Fulton	183	1268.46	107.24	1.71	0.13	1.46	1.95
89.00	Fulton	244	425.87	244.91	1.00	0.06	0.87	1.12
90.00	Fulton	111	623.16	119.38	0.93	0.09	0.76	1.10
91.00	Fulton	255	739.18	261.92	0.97	0.06	0.85	1.09
92.00	Fulton	161	859.87	136.75	1.18	0.09	1.00	1.36
93.00	Fulton	150	643.02	228.90	0.66	0.05	0.55	0.76
94.01	Fulton	141	550.75	274.91	0.51	0.04	0.43	0.60
94.02	Fulton	106	568.62	61.56	1.72	0.17	1.39	2.05
95.00	Fulton	590	1603.93	729.20	0.81	0.03	0.74	0.87
96.00	Fulton	418	1025.99	764.72	0.55	0.03	0.49	0.60
97.00	Fulton	124	679.31	162.40	0.76	0.07	0.63	0.90
98.00	Fulton	511	1387.40	517.44	0.99	0.04	0.90	1.07
99.00	Fulton	125	582.00	194.75	0.64	0.06	0.53	0.75
100.00	Fulton	497	1215.96	485.12	1.02	0.05	0.93	1.11
101.01	Fulton	231	444.56	313.16	0.74	0.05	0.64	0.83
101.03	Fulton	569	895.57	799.42	0.71	0.03	0.65	0.77
101.05	Fulton	200	322.73	212.24	0.94	0.07	0.81	1.07
101.06	Fulton	89	489.80	98.56	0.90	0.10	0.72	1.09
101.07	Fulton	45	509.92	47.09	0.96	0.14	0.68	1.23
101.08	Fulton	39	215.84	84.49	0.46	0.07	0.32	0.61
102.01	Fulton	338	522.68	433.92	0.78	0.04	0.70	0.86
102.03	Fulton	328	497.77	409.91	0.80	0.04	0.71	0.89
102.04	Fulton	140	575.31	181.59	0.77	0.07	0.64	0.90
102.05	Fulton	161	715.95	234.30	0.69	0.05	0.58	0.79
103.01	Fulton	168	1073.06	151.09	1.11	0.09	0.94	1.28
103.02	Fulton	357	763.06	268.95	1.33	0.07	1.19	1.47
104.00	Fulton	206	677.17	234.82	0.88	0.06	0.76	1.00
105.03	Fulton	286	582.00	210.19	1.36	0.08	1.20	1.52
105.04	Fulton	654	905.75	598.58	1.09	0.04	1.01	1.18
105.05	Fulton	277	569.66	224.02	1.24	0.07	1.09	1.38
105.06	Fulton	535	916.74	424.98	1.26	0.05	1.15	1.37
106.01	Fulton	222	1127.68	149.72	1.48	0.10	1.29	1.68
106.02	Fulton	211	395.43	157.00	1.34	0.09	1.16	1.53
107.00	Fulton	135	1113.46	117.89	1.15	0.10	0.95	1.34
108.00	Fulton	373	1251.24	284.47	1.31	0.07	1.18	1.44
109.00	Fulton	48	1323.06	25.11	1.91	0.28	1.37	2.45

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110.00	Fulton	261	1206.32	170.02	1.54	0.10	1.35	1.72
111.00	Fulton	167	1198.19	112.86	1.48	0.11	1.26	1.70
112.01	Fulton	237	844.62	155.49	1.52	0.10	1.33	1.72
112.02	Fulton	252	879.99	200.50	1.26	0.08	1.10	1.41
113.01	Fulton	270	996.17	236.40	1.14	0.07	1.01	1.28
113.02	Fulton	433	528.63	378.53	1.14	0.05	1.04	1.25
114.03	Fulton	310	800.25	380.19	0.82	0.05	0.72	0.91
114.04	Fulton	131	275.49	145.31	0.90	0.08	0.75	1.06
114.05	Fulton	203	715.05	179.41	1.13	0.08	0.98	1.29
114.06	Fulton	163	454.59	220.52	0.74	0.06	0.63	0.85
114.07	Fulton	356	814.08	430.24	0.83	0.04	0.74	0.91
114.08	Fulton	189	238.77	293.06	0.64	0.05	0.55	0.74
114.09	Fulton	200	270.21	287.35	0.70	0.05	0.60	0.79
114.10	Fulton	95	344.36	143.90	0.66	0.07	0.53	0.79
114.11	Fulton	120	311.80	167.02	0.72	0.07	0.59	0.85
115.00	Fulton	462	524.11	550.17	0.84	0.04	0.76	0.92
116.01	Fulton	398	480.82	472.90	0.84	0.04	0.76	0.92
116.02	Fulton	282	264.95	359.18	0.79	0.05	0.69	0.88
116.03	Fulton	292	235.41	427.48	0.68	0.04	0.60	0.76
201.00	DeKalb	56	684.66	62.71	0.89	0.12	0.66	1.13
202.00	DeKalb	88	805.15	55.39	1.59	0.17	1.26	1.92
203.00	DeKalb	113	714.95	77.93	1.45	0.14	1.18	1.72
204.00	DeKalb	46	428.95	44.67	1.03	0.15	0.73	1.33
205.00	DeKalb	222	1357.66	147.45	1.51	0.10	1.31	1.70
206.00	DeKalb	90	844.84	51.54	1.75	0.18	1.39	2.11
207.00	DeKalb	223	1706.86	97.47	2.29	0.15	1.99	2.59
208.00	DeKalb	493	1387.45	284.82	1.73	0.08	1.58	1.88
209.00	DeKalb	441	1315.89	254.28	1.73	0.08	1.57	1.90
211.00	DeKalb	265	685.61	299.38	0.89	0.05	0.78	0.99
212.02	DeKalb	145	534.34	191.47	0.76	0.06	0.63	0.88
212.04	DeKalb	62	240.49	68.19	0.91	0.12	0.68	1.14
212.05	DeKalb	216	494.70	290.39	0.74	0.05	0.64	0.84
212.07	DeKalb	189	703.83	259.51	0.73	0.05	0.62	0.83
212.08	DeKalb	79	649.77	85.77	0.92	0.10	0.72	1.12
212.09	DeKalb	328	1298.95	303.74	1.08	0.06	0.96	1.20
212.10	DeKalb	154	588.32	213.82	0.72	0.06	0.61	0.83
212.11	DeKalb	126	562.97	178.89	0.70	0.06	0.58	0.83
212.12	DeKalb	209	640.89	226.60	0.92	0.06	0.80	1.05
213.01	DeKalb	61	363.14	64.33	0.95	0.12	0.71	1.19
213.02	DeKalb	226	568.96	224.14	1.01	0.07	0.88	1.14
213.03	DeKalb	139	470.34	123.15	1.13	0.10	0.94	1.32
213.04	DeKalb	151	310.73	169.99	0.89	0.07	0.75	1.03
214.01	DeKalb	180	331.56	179.65	1.00	0.07	0.86	1.15

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214.02	DeKalb	260	466.61	263.83	0.99	0.06	0.87	1.11
214.03	DeKalb	237	821.23	200.00	1.18	0.08	1.03	1.34
214.04	DeKalb	126	325.70	160.69	0.78	0.07	0.65	0.92
215.00	DeKalb	630	1024.58	718.38	0.88	0.03	0.81	0.95
216.01	DeKalb	299	751.86	393.07	0.76	0.04	0.67	0.85
216.02	DeKalb	310	1706.13	335.05	0.93	0.05	0.82	1.03
216.03	DeKalb	285	1138.73	389.79	0.73	0.04	0.65	0.82
217.02	DeKalb	326	650.10	368.42	0.88	0.05	0.79	0.98
217.03	DeKalb	228	1025.59	320.94	0.71	0.05	0.62	0.80
217.04	DeKalb	236	942.27	258.66	0.91	0.06	0.80	1.03
218.05	DeKalb	296	931.37	252.80	1.17	0.07	1.04	1.30
218.06	DeKalb	151	569.33	223.40	0.68	0.06	0.57	0.78
218.08	DeKalb	185	819.60	210.45	0.88	0.06	0.75	1.01
218.09	DeKalb	328	976.21	361.46	0.91	0.05	0.81	1.01
218.10	DeKalb	189	927.50	204.28	0.93	0.07	0.79	1.06
218.98	DeKalb	178	365.54	191.72	0.93	0.07	0.79	1.06
219.02	DeKalb	225	532.99	234.12	0.96	0.06	0.84	1.09
219.03	DeKalb	356	405.44	318.55	0.80	0.05	0.71	0.90
219.04	DeKalb	148	402.25	147.47	1.00	0.08	0.84	1.17
219.05	DeKalb	252	438.54	245.89	1.02	0.06	0.90	1.15
220.01	DeKalb	160	832.82	180.64	0.89	0.07	0.75	1.02
220.02	DeKalb	299	322.39	279.59	1.07	0.06	0.95	1.19
220.04	DeKalb	147	548.44	151.19	0.97	0.08	0.82	1.13
220.05	DeKalb	101	473.51	93.85	1.08	0.11	0.87	1.29
221.00	DeKalb	188	1051.30	114.13	1.65	0.12	1.41	1.88
222.00	DeKalb	445	1240.68	460.68	0.97	0.05	0.88	1.06
223.01	DeKalb	282	1073.39	343.77	0.82	0.05	0.72	0.92
223.02	DeKalb	153	740.14	161.15	0.95	0.08	0.80	1.10
224.01	DeKalb	172	865.98	200.53	0.86	0.07	0.73	0.99
224.02	DeKalb	83	364.21	203.91	0.41	0.04	0.32	0.49
224.03	DeKalb	126	654.07	190.53	0.66	0.06	0.55	0.78
225.00	DeKalb	310	1242.29	257.42	1.20	0.07	1.07	1.34
226.00	DeKalb	193	781.07	407.45	0.47	0.03	0.41	0.54
227.00	DeKalb	274	1278.42	165.99	1.65	0.10	1.46	1.85
228.00	DeKalb	126	697.79	101.22	1.24	0.11	1.03	1.46
229.00	DeKalb	183	876.14	138.16	1.32	0.10	1.13	1.52
230.00	DeKalb	97	878.67	104.52	0.83	0.09	0.66	1.01
231.01	DeKalb	240	880.09	130.14	1.84	0.12	1.61	2.08
231.02	DeKalb	132	755.47	121.77	1.08	0.09	0.90	1.27
231.03	DeKalb	342	653.57	244.63	1.40	0.08	1.25	1.55
231.05	DeKalb	141	321.70	180.26	0.78	0.07	0.65	0.91
231.06	DeKalb	134	377.44	128.75	1.04	0.09	0.86	1.22
232.03	DeKalb	131	344.13	137.88	0.95	0.08	0.79	1.11

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232.04	DeKalb	189	566.44	179.39	1.05	0.08	0.90	1.20
232.05	DeKalb	248	404.12	227.88	1.09	0.07	0.95	1.22
232.06	DeKalb	202	543.66	176.00	1.15	0.08	0.99	1.31
232.07	DeKalb	213	306.50	222.19	0.96	0.07	0.83	1.09
233.02	DeKalb	139	369.89	141.21	0.98	0.08	0.82	1.15
233.03	DeKalb	232	1020.70	190.84	1.22	0.08	1.06	1.37
233.05	DeKalb	127	280.22	164.87	0.77	0.07	0.64	0.90
233.06	DeKalb	82	422.82	77.34	1.06	0.12	0.83	1.29
233.07	DeKalb	190	370.70	191.82	0.99	0.07	0.85	1.13
233.08	DeKalb	173	275.05	246.95	0.70	0.05	0.60	0.80
234.03	DeKalb	202	462.17	159.65	1.27	0.09	1.09	1.44
234.04	DeKalb	265	652.82	164.89	1.61	0.10	1.41	1.80
234.05	DeKalb	291	467.86	261.85	1.11	0.07	0.98	1.24
234.07	DeKalb	414	554.33	360.05	1.15	0.06	1.04	1.26
234.08	DeKalb	455	547.14	422.84	1.08	0.05	0.98	1.17
234.09	DeKalb	275	433.06	244.46	1.12	0.07	0.99	1.26
235.01	DeKalb	174	909.53	98.86	1.76	0.13	1.50	2.02
235.02	DeKalb	275	688.57	194.68	1.41	0.09	1.25	1.58
235.03	DeKalb	422	700.99	353.46	1.19	0.06	1.08	1.31
236.00	DeKalb	444	841.96	282.64	1.57	0.07	1.42	1.72
237.00	DeKalb	252	810.80	155.37	1.62	0.10	1.42	1.82
238.01	DeKalb	190	785.17	122.32	1.55	0.11	1.33	1.77
238.02	DeKalb	125	558.41	79.90	1.56	0.14	1.29	1.84
238.03	DeKalb	266	873.51	156.33	1.70	0.10	1.50	1.91
239.98	DeKalb	19	0.00	0.00	0.00	0.00	0.00	0.00
301.98	Cobb	454	482.89	495.02	0.92	0.04	0.83	1.00
302.03	Cobb	359	373.06	399.47	0.90	0.05	0.81	0.99
302.04	Cobb	367	314.27	456.12	0.80	0.04	0.72	0.89
302.05	Cobb	172	408.91	197.97	0.87	0.07	0.74	1.00
302.06	Cobb	345	365.98	379.11	0.91	0.05	0.81	1.01
302.07	Cobb	434	410.05	518.97	0.84	0.04	0.76	0.91
303.02	Cobb	179	300.39	214.69	0.83	0.06	0.71	0.96
303.07	Cobb	215	274.77	258.22	0.83	0.06	0.72	0.94
303.09	Cobb	211	394.40	230.66	0.91	0.06	0.79	1.04
303.10	Cobb	146	377.78	140.12	1.04	0.09	0.87	1.21
303.11	Cobb	102	338.25	129.70	0.79	0.08	0.63	0.94
303.12	Cobb	186	579.95	168.25	1.11	0.08	0.95	1.26
303.13	Cobb	177	514.86	200.74	0.88	0.07	0.75	1.01
303.14	Cobb	106	335.58	154.59	0.69	0.07	0.56	0.82
303.15	Cobb	185	385.90	234.38	0.79	0.06	0.68	0.90
303.16	Cobb	381	419.22	526.23	0.72	0.04	0.65	0.80
303.17	Cobb	303	357.39	368.11	0.82	0.05	0.73	0.92
303.18	Cobb	198	576.82	229.28	0.86	0.06	0.74	0.98

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303.19	Cobb	93	500.72	116.28	0.80	0.08	0.64	0.96
303.20	Cobb	82	289.51	117.05	0.70	0.08	0.55	0.85
303.21	Cobb	95	168.72	143.84	0.66	0.07	0.53	0.79
304.01	Cobb	175	460.55	214.65	0.82	0.06	0.69	0.94
304.02	Cobb	265	684.63	308.35	0.86	0.05	0.76	0.96
304.04	Cobb	183	410.49	112.67	1.62	0.12	1.39	1.86
304.05	Cobb	144	505.21	161.40	0.89	0.07	0.75	1.04
304.06	Cobb	68	163.66	99.45	0.68	0.08	0.52	0.85
305.01	Cobb	241	595.55	287.54	0.84	0.05	0.73	0.94
305.02	Cobb	161	604.73	154.16	1.04	0.08	0.88	1.21
305.03	Cobb	243	472.56	257.59	0.94	0.06	0.82	1.06
306.00	Cobb	547	1200.69	620.31	0.88	0.04	0.81	0.96
307.00	Cobb	281	1125.04	203.38	1.38	0.08	1.22	1.54
308.00	Cobb	177	731.52	168.27	1.05	0.08	0.90	1.21
309.01	Cobb	213	584.32	229.96	0.93	0.06	0.80	1.05
309.02	Cobb	296	894.83	254.85	1.16	0.07	1.03	1.29
309.03	Cobb	221	374.02	251.10	0.88	0.06	0.76	1.00
310.01	Cobb	197	746.17	143.67	1.37	0.10	1.18	1.56
310.02	Cobb	269	786.73	239.23	1.12	0.07	0.99	1.26
310.03	Cobb	413	745.21	320.41	1.29	0.06	1.16	1.41
311.01	Cobb	174	739.27	148.50	1.17	0.09	1.00	1.35
311.03	Cobb	324	618.19	360.92	0.90	0.05	0.80	1.00
311.05	Cobb	227	494.75	226.80	1.00	0.07	0.87	1.13
311.06	Cobb	169	519.82	183.05	0.92	0.07	0.78	1.06
311.07	Cobb	452	951.24	500.96	0.90	0.04	0.82	0.99
311.08	Cobb	147	555.57	117.12	1.26	0.10	1.05	1.46
311.09	Cobb	82	235.16	108.59	0.76	0.08	0.59	0.92
312.02	Cobb	201	547.59	196.57	1.02	0.07	0.88	1.16
312.03	Cobb	96	283.46	121.20	0.79	0.08	0.63	0.95
312.04	Cobb	168	393.67	238.24	0.71	0.05	0.60	0.81
313.01	Cobb	358	771.34	290.45	1.23	0.07	1.10	1.36
313.02	Cobb	296	730.89	247.80	1.19	0.07	1.06	1.33
313.04	Cobb	463	893.95	351.11	1.32	0.06	1.20	1.44
313.05	Cobb	168	296.50	190.75	0.88	0.07	0.75	1.01
314.03	Cobb	411	705.42	462.46	0.89	0.04	0.80	0.97
314.04	Cobb	200	821.87	188.10	1.06	0.08	0.92	1.21
314.98	Cobb	305	696.72	286.79	1.06	0.06	0.94	1.18
315.01	Cobb	209	487.69	213.72	0.98	0.07	0.85	1.11
315.02	Cobb	480	485.70	458.57	1.05	0.05	0.95	1.14
316.97	Cobb	5	0.00	0.00	1.00	0.00	0.00	0.00
316.98	Cobb	5	0.00	0.00	1.00	0.00	0.00	0.00
401.00	Clayton	41	9479.72	5.29	7.76	1.21	5.38	10.13
402.00	Clayton	215	370.42	162.18	1.33	0.09	1.15	1.50

Census Tract	County	Deaths	Crude Death Rate (deaths/100,000 population)	Expected Deaths	Standardized Mortality Ratio (SMR)	SMR Standard Error	Lower Limit 95% CI	Upper Limit 95% CI
403.01	Clayton	23	1668.62	5.50	4.18	0.87	2.47	5.89
403.02	Clayton	203	690.55	160.77	1.26	0.09	1.09	1.44
403.03	Clayton	287	789.09	194.53	1.48	0.09	1.30	1.65
403.04	Clayton	244	1031.80	166.57	1.46	0.09	1.28	1.65
403.05	Clayton	244	598.09	200.77	1.22	0.08	1.06	1.37
404.01	Clayton	587	772.70	545.14	1.08	0.04	0.99	1.16
404.02	Clayton	350	587.99	288.78	1.21	0.06	1.09	1.34
404.03	Clayton	257	457.93	273.01	0.94	0.06	0.83	1.06
404.05	Clayton	262	653.69	238.97	1.10	0.07	0.96	1.23
404.06	Clayton	199	454.31	187.35	1.06	0.08	0.91	1.21
405.03	Clayton	311	717.53	236.00	1.32	0.07	1.17	1.46
405.04	Clayton	240	335.95	244.64	0.98	0.06	0.86	1.11
405.05	Clayton	231	506.76	223.40	1.03	0.07	0.90	1.17
405.06	Clayton	177	409.62	174.89	1.01	0.08	0.86	1.16
405.07	Clayton	343	448.16	269.42	1.27	0.07	1.14	1.41
405.08	Clayton	230	373.38	192.11	1.20	0.08	1.04	1.35
406.03	Clayton	383	582.46	292.65	1.31	0.07	1.18	1.44
406.04	Clayton	331	650.57	272.58	1.21	0.07	1.08	1.35
406.05	Clayton	315	558.53	357.22	0.88	0.05	0.78	0.98
406.06	Clayton	40	310.52	44.26	0.90	0.14	0.62	1.18
406.07	Clayton	279	399.25	248.60	1.12	0.07	0.99	1.25
406.08	Clayton	96	526.61	83.90	1.14	0.12	0.92	1.37
501.01	Gwinnett	380	543.21	420.75	0.90	0.05	0.81	0.99
501.02	Gwinnett	414	818.70	325.89	1.27	0.06	1.15	1.39
502.02	Gwinnett	151	277.79	216.45	0.70	0.06	0.59	0.81
502.03	Gwinnett	422	332.70	520.42	0.81	0.04	0.73	0.89
502.04	Gwinnett	201	332.15	216.43	0.93	0.07	0.80	1.06
503.04	Gwinnett	87	497.05	69.41	1.25	0.13	0.99	1.52
503.05	Gwinnett	122	208.04	207.20	0.59	0.05	0.48	0.69
503.06	Gwinnett	86	491.83	76.19	1.13	0.12	0.89	1.37
503.07	Gwinnett	91	207.13	173.42	0.52	0.06	0.42	0.63
503.08	Gwinnett	45	335.34	65.90	0.68	0.10	0.48	0.88
503.09	Gwinnett	109	342.98	128.63	0.85	0.08	0.69	1.01
503.10	Gwinnett	103	459.41	139.36	0.74	0.07	0.60	0.88
503.11	Gwinnett	106	969.31	106.51	1.00	0.10	0.81	1.18
503.12	Gwinnett	105	200.77	136.80	0.77	0.07	0.62	0.91
503.13	Gwinnett	125	381.63	145.60	0.86	0.08	0.71	1.01
503.14	Gwinnett	71	256.33	94.46	0.75	0.09	0.58	0.93
504.03	Gwinnett	208	478.52	226.11	0.92	0.06	0.79	1.04
504.06	Gwinnett	105	180.05	147.76	0.71	0.07	0.57	0.85
504.07	Gwinnett	202	279.62	254.86	0.79	0.06	0.68	0.90
504.08	Gwinnett	165	254.07	178.87	0.92	0.07	0.78	1.06
504.09	Gwinnett	117	212.94	171.03	0.68	0.06	0.56	0.81

Census Tract	County	Deaths	Crude Death Rate (deaths/100,000 population)	Expected Deaths	Standardized Mortality Ratio (SMR)	SMR Standard Error	Lower Limit 95% CI	Upper Limit 95% CI
504.10	Gwinnett	207	782.96	170.37	1.22	0.08	1.05	1.38
504.11	Gwinnett	265	638.87	291.91	0.91	0.06	0.80	1.02
504.12	Gwinnett	277	463.61	350.83	0.79	0.05	0.70	0.88
504.13	Gwinnett	179	351.80	272.34	0.66	0.05	0.56	0.75
504.14	Gwinnett	320	568.58	374.20	0.86	0.05	0.76	0.95
504.15	Gwinnett	109	517.87	110.68	0.98	0.09	0.80	1.17
504.16	Gwinnett	66	377.27	56.68	1.16	0.14	0.88	1.45
505.02	Gwinnett	299	249.33	390.10	0.77	0.04	0.68	0.85
505.03	Gwinnett	388	302.45	506.07	0.77	0.04	0.69	0.84
505.05	Gwinnett	242	281.53	309.84	0.78	0.05	0.68	0.88
505.06	Gwinnett	434	302.02	512.98	0.85	0.04	0.77	0.93
505.07	Gwinnett	134	336.85	174.85	0.77	0.07	0.64	0.90
505.08	Gwinnett	491	731.18	529.54	0.93	0.04	0.85	1.01
505.09	Gwinnett	170	428.36	178.47	0.95	0.07	0.81	1.10
506.01	Gwinnett	364	379.22	415.70	0.88	0.05	0.79	0.97
506.02	Gwinnett	229	455.27	262.82	0.87	0.06	0.76	0.98
507.04	Gwinnett	294	474.98	337.26	0.87	0.05	0.77	0.97
507.05	Gwinnett	229	375.04	285.91	0.80	0.05	0.70	0.90
507.06	Gwinnett	173	278.68	217.69	0.79	0.06	0.68	0.91
507.07	Gwinnett	176	391.70	207.19	0.85	0.06	0.72	0.97
507.08	Gwinnett	236	311.05	273.17	0.86	0.06	0.75	0.97
507.09	Gwinnett	132	404.29	129.54	1.02	0.09	0.85	1.19
507.10	Gwinnett	310	524.22	333.84	0.93	0.05	0.83	1.03
507.11	Gwinnett	411	663.73	423.85	0.97	0.05	0.88	1.06
508.98	Gwinnett	2	0.00	0.00	0.00	0.00	0.00	0.00
601.00	Rockdale	277	737.36	235.99	1.17	0.07	1.04	1.31
602.00	Rockdale	355	641.39	318.12	1.12	0.06	1.00	1.23
603.02	Rockdale	347	594.00	331.13	1.05	0.06	0.94	1.16
603.03	Rockdale	394	877.88	421.55	0.93	0.05	0.84	1.03
603.04	Rockdale	208	926.54	185.80	1.12	0.08	0.97	1.27
604.01	Rockdale	212	519.25	219.29	0.97	0.07	0.84	1.10
604.02	Rockdale	311	483.99	341.31	0.91	0.05	0.81	1.01
701.02	Henry	215	535.85	207.14	1.05	0.07	0.91	1.19
701.03	Henry	568	576.84	286.38	1.98	0.08	1.82	2.14
701.98	Henry	223	515.08	149.64	1.49	0.10	1.29	1.69
702.01	Henry	220	564.88	211.35	1.04	0.07	0.90	1.18
702.02	Henry	113	548.70	106.32	1.06	0.10	0.87	1.26
702.03	Henry	153	572.64	387.44	0.39	0.03	0.33	0.45
703.01	Henry	159	550.28	144.15	1.10	0.09	0.93	1.27
703.02	Henry	597	699.32	589.37	1.01	0.04	0.93	1.09
704.02	Henry	118	625.70	99.70	1.25	0.11	1.03	1.47
704.98	Henry	211	602.86	185.23	1.12	0.08	0.97	1.28
705.00	Henry	297	688.32	273.49	1.08	0.06	0.96	1.21

Census Tract	County	Deaths	Crude Death Rate (deaths/100,000 population)	Expected Deaths	Standardized Mortality Ratio (SMR)	SMR Standard Error	Lower Limit 95% CI	Upper Limit 95% CI
801.98	Douglas	279	655.33	259.25	1.08	0.06	0.95	1.20
802.00	Douglas	371	653.21	326.87	1.14	0.06	1.02	1.25
803.00	Douglas	535	745.31	476.47	1.12	0.05	1.03	1.22
804.00	Douglas	365	713.45	316.83	1.15	0.06	1.03	1.27
805.01	Douglas	423	778.90	397.65	1.06	0.05	0.96	1.17
805.03	Douglas	177	389.77	215.22	0.82	0.06	0.70	0.94
805.04	Douglas	156	378.09	169.53	0.92	0.07	0.78	1.06
806.01	Douglas	212	476.16	196.95	1.08	0.07	0.93	1.22
806.02	Douglas	106	601.83	76.88	1.38	0.13	1.12	1.64
807.97	Douglas	5	0.00	0.00	0.00	0.00	0.00	0.00
807.98	Douglas	13	0.00	0.00	0.00	0.00	0.00	0.00
901.00	Cherokee	213	859.23	177.79	1.20	0.08	1.04	1.36
902.00	Cherokee	150	575.99	170.15	0.88	0.07	0.74	1.02
903.00	Cherokee	95	690.93	77.45	1.23	0.13	0.98	1.47
904.00	Cherokee	264	1173.70	221.19	1.19	0.07	1.05	1.34
905.00	Cherokee	289	679.20	296.48	0.97	0.06	0.86	1.09
906.00	Cherokee	382	839.53	389.51	0.98	0.05	0.88	1.08
907.00	Cherokee	253	450.46	249.17	1.02	0.06	0.89	1.14
908.00	Cherokee	305	429.95	341.18	0.89	0.05	0.79	0.99
909.01	Cherokee	147	521.18	123.06	1.19	0.10	1.00	1.39
909.02	Cherokee	99	306.45	117.66	0.84	0.08	0.68	1.01
909.03	Cherokee	193	504.35	257.91	0.75	0.05	0.64	0.85
910.01	Cherokee	144	1305.66	79.59	1.81	0.15	1.51	2.10
910.02	Cherokee	226	302.75	268.99	0.84	0.06	0.73	0.95
910.03	Cherokee	107	354.21	98.62	1.08	0.10	0.88	1.29
911.01	Cherokee	92	360.44	95.10	0.97	0.10	0.77	1.17
911.03	Cherokee	177	541.50	126.35	1.35	0.10	1.14	1.55
911.98	Cherokee	170	522.15	127.84	1.38	0.10	1.18	1.59
912.98	Cherokee	3	3157.89	0.11	26.28	15.17	-3.46	56.01
1201.00	Paulding	271	476.33	252.20	1.07	0.07	0.95	1.20
1202.00	Paulding	260	475.94	211.26	1.23	0.08	1.08	1.38
1203.00	Paulding	459	877.05	382.38	1.20	0.06	1.09	1.31
1204.00	Paulding	210	670.69	196.10	1.07	0.07	0.93	1.22
1205.00	Paulding	237	411.52	251.17	0.94	0.06	0.82	1.06
1206.98	Paulding	285	367.74	279.17	1.02	0.06	0.90	1.14
1301.00	Forsyth	232	575.64	234.70	0.99	0.06	0.86	1.12
1302.00	Forsyth	257	635.79	245.55	1.05	0.07	0.92	1.17
1303.00	Forsyth	318	476.62	335.79	0.95	0.05	0.84	1.05
1304.00	Forsyth	470	713.57	552.36	0.85	0.04	0.77	0.93
1305.00	Forsyth	455	574.67	484.69	0.94	0.04	0.85	1.02
1306.00	Forsyth	289	320.94	391.34	0.74	0.04	0.65	0.82
1401.01	Fayette	214	669.69	221.76	0.96	0.07	0.84	1.09
1401.02	Fayette	164	606.00	165.57	0.99	0.08	0.84	1.14

Census Tract	County	Deaths	Crude Death Rate (deaths/100,000 population)	Expected Deaths	Standardized Mortality Ratio (SMR)	SMR Standard Error	Lower Limit 95% CI	Upper Limit 95% CI
1402.01	Fayette	221	622.61	204.18	1.08	0.07	0.94	1.23
1402.02	Fayette	264	489.35	358.71	0.74	0.05	0.65	0.82
1403.01	Fayette	368	573.97	392.09	0.94	0.05	0.84	1.03
1403.02	Fayette	115	262.62	175.47	0.66	0.06	0.54	0.78
1404.01	Fayette	376	677.81	418.96	0.90	0.05	0.81	0.99
1404.02	Fayette	378	645.41	391.70	0.97	0.05	0.87	1.06
1405.01	Fayette	101	501.49	120.96	0.83	0.08	0.67	1.00
1405.02	Fayette	80	567.35	84.74	0.94	0.11	0.74	1.15
1701.00	Coweta	187	680.64	170.18	1.10	0.08	0.94	1.26
1702.00	Coweta	236	754.69	251.24	0.94	0.06	0.82	1.06
1703.00	Coweta	521	705.18	488.66	1.07	0.05	0.97	1.16
1704.00	Coweta	367	444.90	364.45	1.01	0.05	0.90	1.11
1705.00	Coweta	337	674.72	298.86	1.13	0.06	1.01	1.25
1706.00	Coweta	403	851.88	322.45	1.25	0.06	1.13	1.37
1707.00	Coweta	363	1048.00	305.11	1.19	0.06	1.07	1.31
1708.00	Coweta	287	873.30	221.81	1.29	0.08	1.14	1.44

APPENDIX D

SCALED NORMALIZED DIFFERENCE VEGETATION INDICES ($NDVI_S$), BY 1990 CENSUS TRACT BOUNDARIES

Table D.1. Scaled Normalized Difference Vegetation Indices ($NDVI_S$), metropolitan Atlanta, Georgia, 1984-2000.

Census Tract	County	1984	1990	2000
1.00	Fulton	0.714	0.776	0.709
2.00	Fulton	0.678	0.737	0.662
4.00	Fulton	0.640	0.709	0.599
5.00	Fulton	0.590	0.681	0.570
6.00	Fulton	0.544	0.621	0.486
7.00	Fulton	0.571	0.632	0.507
8.00	Fulton	0.556	0.646	0.516
10.95	Fulton	0.518	0.605	0.450
11.00	Fulton	0.573	0.619	0.418
12.00	Fulton	0.549	0.615	0.454
13.00	Fulton	0.593	0.666	0.539
14.00	Fulton	0.641	0.704	0.577
15.00	Fulton	0.637	0.698	0.589
16.00	Fulton	0.682	0.725	0.600
17.00	Fulton	0.581	0.645	0.522
18.00	Fulton	0.560	0.618	0.507
19.00	Fulton	0.417	0.504	0.344
20.00	Fulton	0.520	0.613	0.402
21.00	Fulton	0.477	0.567	0.407
22.00	Fulton	0.523	0.612	0.472
23.00	Fulton	0.625	0.702	0.622
24.00	Fulton	0.655	0.729	0.640
25.00	Fulton	0.615	0.691	0.558
26.00	Fulton	0.558	0.602	0.446
27.00	Fulton	0.389	0.492	0.323
28.00	Fulton	0.481	0.550	0.405
29.00	Fulton	0.546	0.632	0.491
30.00	Fulton	0.605	0.682	0.571
31.00	Fulton	0.628	0.692	0.595
32.00	Fulton	0.558	0.626	0.519
33.00	Fulton	0.503	0.567	0.432
35.00	Fulton	0.427	0.518	0.362
36.00	Fulton	0.523	0.605	0.458
37.00	Fulton	0.594	0.619	0.485
38.00	Fulton	0.612	0.674	0.508
39.00	Fulton	0.641	0.716	0.618
40.00	Fulton	0.670	0.731	0.633
41.00	Fulton	0.659	0.722	0.626
42.95	Fulton	0.569	0.650	0.517
43.00	Fulton	0.545	0.632	0.468
44.00	Fulton	0.528	0.621	0.493
46.95	Fulton	0.553	0.598	0.455

Census Tract	County	1984	1990	2000
48.00	Fulton	0.566	0.619	0.484
49.95	Fulton	0.617	0.684	0.557
50.00	Fulton	0.571	0.654	0.537
52.00	Fulton	0.668	0.742	0.653
53.00	Fulton	0.675	0.752	0.655
55.01	Fulton	0.648	0.726	0.622
55.02	Fulton	0.603	0.693	0.570
56.00	Fulton	0.577	0.666	0.521
57.00	Fulton	0.559	0.654	0.550
58.00	Fulton	0.561	0.653	0.535
60.00	Fulton	0.678	0.736	0.653
61.00	Fulton	0.716	0.788	0.722
62.00	Fulton	0.618	0.708	0.627
63.00	Fulton	0.575	0.660	0.554
64.00	Fulton	0.595	0.684	0.585
65.00	Fulton	0.644	0.724	0.632
66.01	Fulton	0.610	0.689	0.581
66.02	Fulton	0.653	0.739	0.670
67.00	Fulton	0.630	0.714	0.621
68.01	Fulton	0.613	0.691	0.593
68.02	Fulton	0.632	0.748	0.683
69.00	Fulton	0.681	0.779	0.687
70.00	Fulton	0.682	0.769	0.694
71.00	Fulton	0.636	0.726	0.642
72.00	Fulton	0.687	0.764	0.677
73.00	Fulton	0.689	0.772	0.697
74.00	Fulton	0.634	0.722	0.632
75.00	Fulton	0.622	0.700	0.613
76.01	Fulton	0.653	0.738	0.646
76.02	Fulton	0.738	0.817	0.760
77.01	Fulton	0.734	0.795	0.717
77.02	Fulton	0.716	0.791	0.719
78.02	Fulton	0.754	0.818	0.740
78.03	Fulton	0.656	0.733	0.635
78.04	Fulton	0.663	0.752	0.675
79.00	Fulton	0.743	0.809	0.733
80.00	Fulton	0.741	0.815	0.755
81.01	Fulton	0.744	0.821	0.761
81.02	Fulton	0.701	0.770	0.716
82.01	Fulton	0.695	0.775	0.701
82.02	Fulton	0.653	0.737	0.660
83.01	Fulton	0.702	0.771	0.709
83.02	Fulton	0.692	0.768	0.702
84.00	Fulton	0.666	0.733	0.661
85.00	Fulton	0.713	0.779	0.718

Census Tract	County	1984	1990	2000
86.01	Fulton	0.724	0.798	0.736
86.02	Fulton	0.648	0.720	0.622
87.01	Fulton	0.627	0.701	0.602
87.02	Fulton	0.656	0.739	0.659
88.00	Fulton	0.622	0.688	0.584
89.00	Fulton	0.600	0.678	0.570
90.00	Fulton	0.701	0.788	0.704
91.00	Fulton	0.656	0.724	0.609
92.00	Fulton	0.595	0.662	0.556
93.00	Fulton	0.693	0.767	0.677
94.01	Fulton	0.686	0.734	0.634
94.02	Fulton	0.550	0.621	0.472
95.00	Fulton	0.721	0.790	0.709
96.00	Fulton	0.624	0.697	0.579
97.00	Fulton	0.739	0.808	0.742
98.00	Fulton	0.741	0.804	0.729
99.00	Fulton	0.736	0.804	0.732
100.00	Fulton	0.725	0.786	0.674
101.01	Fulton	0.715	0.766	0.658
101.03	Fulton	0.666	0.756	0.618
101.05	Fulton	0.621	0.727	0.579
101.06	Fulton	0.712	0.809	0.695
101.07	Fulton	0.723	0.805	0.704
101.08	Fulton	0.696	0.789	0.663
102.01	Fulton	0.737	0.808	0.733
102.03	Fulton	0.692	0.755	0.655
102.04	Fulton	0.708	0.787	0.711
102.05	Fulton	0.685	0.778	0.681
103.01	Fulton	0.761	0.834	0.784
103.02	Fulton	0.740	0.798	0.729
104.00	Fulton	0.760	0.829	0.786
105.03	Fulton	0.668	0.758	0.659
105.04	Fulton	0.731	0.805	0.719
105.05	Fulton	0.711	0.787	0.703
105.06	Fulton	0.744	0.811	0.747
106.01	Fulton	0.690	0.776	0.713
106.02	Fulton	0.660	0.752	0.649
107.00	Fulton	0.606	0.696	0.586
108.00	Fulton	0.545	0.654	0.539
109.00	Fulton	0.521	0.606	0.480
110.00	Fulton	0.612	0.696	0.598
111.00	Fulton	0.598	0.675	0.570
112.01	Fulton	0.628	0.716	0.651
112.02	Fulton	0.661	0.739	0.663
113.01	Fulton	0.710	0.796	0.721

Census Tract	County	1984	1990	2000
113.02	Fulton	0.732	0.799	0.734
114.03	Fulton	0.706	0.803	0.648
114.04	Fulton	0.641	0.723	0.538
114.05	Fulton	0.689	0.774	0.636
114.06	Fulton	0.708	0.772	0.658
114.07	Fulton	0.717	0.805	0.669
114.08	Fulton	0.700	0.781	0.630
114.09	Fulton	0.743	0.786	0.646
114.10	Fulton	0.699	0.778	0.641
114.11	Fulton	0.680	0.772	0.662
115.00	Fulton	0.757	0.834	0.715
116.01	Fulton	0.734	0.806	0.629
116.02	Fulton	0.749	0.801	0.607
116.03	Fulton	0.743	0.799	0.642
201.00	DeKalb	0.721	0.780	0.712
202.00	DeKalb	0.732	0.796	0.724
203.00	DeKalb	0.706	0.778	0.702
204.00	DeKalb	0.672	0.745	0.636
205.00	DeKalb	0.663	0.737	0.657
206.00	DeKalb	0.619	0.693	0.610
207.00	DeKalb	0.679	0.738	0.645
208.00	DeKalb	0.699	0.779	0.690
209.00	DeKalb	0.686	0.758	0.673
211.00	DeKalb	0.714	0.779	0.672
212.02	DeKalb	0.704	0.791	0.691
212.04	DeKalb	0.555	0.633	0.513
212.05	DeKalb	0.682	0.782	0.667
212.07	DeKalb	0.652	0.745	0.571
212.08	DeKalb	0.602	0.691	0.567
212.09	DeKalb	0.686	0.773	0.683
212.10	DeKalb	0.684	0.781	0.672
212.11	DeKalb	0.698	0.782	0.656
212.12	DeKalb	0.642	0.742	0.627
213.01	DeKalb	0.557	0.638	0.493
213.02	DeKalb	0.626	0.737	0.632
213.03	DeKalb	0.572	0.673	0.552
213.04	DeKalb	0.600	0.691	0.558
214.01	DeKalb	0.656	0.703	0.593
214.02	DeKalb	0.670	0.747	0.648
214.03	DeKalb	0.682	0.751	0.673
214.04	DeKalb	0.640	0.731	0.623
215.00	DeKalb	0.704	0.751	0.674
216.01	DeKalb	0.703	0.783	0.698
216.02	DeKalb	0.708	0.786	0.706
216.03	DeKalb	0.673	0.733	0.644

Census Tract	County	1984	1990	2000
217.02	DeKalb	0.664	0.754	0.649
217.03	DeKalb	0.710	0.795	0.704
217.04	DeKalb	0.654	0.736	0.632
218.05	DeKalb	0.662	0.768	0.675
218.06	DeKalb	0.645	0.726	0.616
218.08	DeKalb	0.665	0.762	0.668
218.09	DeKalb	0.682	0.778	0.695
218.10	DeKalb	0.635	0.730	0.619
218.98	DeKalb	0.655	0.739	0.631
219.02	DeKalb	0.721	0.797	0.718
219.03	DeKalb	0.686	0.761	0.673
219.04	DeKalb	0.623	0.725	0.613
219.05	DeKalb	0.644	0.745	0.657
220.01	DeKalb	0.675	0.773	0.694
220.02	DeKalb	0.656	0.749	0.655
220.04	DeKalb	0.670	0.764	0.684
220.05	DeKalb	0.647	0.739	0.640
221.00	DeKalb	0.677	0.741	0.661
222.00	DeKalb	0.642	0.719	0.612
223.01	DeKalb	0.681	0.755	0.672
223.02	DeKalb	0.683	0.758	0.670
224.01	DeKalb	0.733	0.789	0.725
224.02	DeKalb	0.693	0.745	0.631
224.03	DeKalb	0.760	0.824	0.764
225.00	DeKalb	0.674	0.753	0.662
226.00	DeKalb	0.685	0.758	0.660
227.00	DeKalb	0.701	0.778	0.683
228.00	DeKalb	0.716	0.792	0.700
229.00	DeKalb	0.688	0.781	0.696
230.00	DeKalb	0.657	0.762	0.663
231.01	DeKalb	0.697	0.782	0.704
231.02	DeKalb	0.650	0.757	0.653
231.03	DeKalb	0.670	0.760	0.682
231.05	DeKalb	0.654	0.733	0.639
231.06	DeKalb	0.676	0.747	0.664
232.03	DeKalb	0.700	0.751	0.632
232.04	DeKalb	0.707	0.795	0.715
232.05	DeKalb	0.692	0.776	0.710
232.06	DeKalb	0.708	0.798	0.718
232.07	DeKalb	0.708	0.774	0.699
233.02	DeKalb	0.742	0.781	0.679
233.03	DeKalb	0.666	0.746	0.640
233.05	DeKalb	0.736	0.800	0.692
233.06	DeKalb	0.712	0.786	0.685
233.07	DeKalb	0.689	0.763	0.674

Census Tract	County	1984	1990	2000
233.08	DeKalb	0.713	0.774	0.647
234.03	DeKalb	0.679	0.757	0.661
234.04	DeKalb	0.711	0.788	0.680
234.05	DeKalb	0.763	0.814	0.712
234.07	DeKalb	0.739	0.810	0.728
234.08	DeKalb	0.706	0.779	0.686
234.09	DeKalb	0.745	0.800	0.708
235.01	DeKalb	0.673	0.762	0.685
235.02	DeKalb	0.678	0.770	0.688
235.03	DeKalb	0.685	0.769	0.692
236.00	DeKalb	0.697	0.785	0.722
237.00	DeKalb	0.717	0.785	0.698
238.01	DeKalb	0.721	0.798	0.739
238.02	DeKalb	0.686	0.766	0.690
238.03	DeKalb	0.709	0.797	0.728
239.98	DeKalb	0.743	0.811	0.745
301.98	Cobb	0.705	0.782	0.644
302.03	Cobb	0.742	0.810	0.728
302.04	Cobb	0.734	0.791	0.611
302.05	Cobb	0.700	0.756	0.556
302.06	Cobb	0.757	0.819	0.713
302.07	Cobb	0.762	0.816	0.725
303.02	Cobb	0.700	0.785	0.672
303.07	Cobb	0.734	0.802	0.692
303.09	Cobb	0.701	0.786	0.658
303.10	Cobb	0.701	0.776	0.666
303.11	Cobb	0.688	0.771	0.645
303.12	Cobb	0.701	0.781	0.662
303.13	Cobb	0.703	0.791	0.670
303.14	Cobb	0.715	0.801	0.661
303.15	Cobb	0.697	0.789	0.664
303.16	Cobb	0.695	0.783	0.681
303.17	Cobb	0.693	0.779	0.659
303.18	Cobb	0.700	0.796	0.700
303.19	Cobb	0.714	0.788	0.698
303.20	Cobb	0.724	0.807	0.730
303.21	Cobb	0.605	0.702	0.571
304.01	Cobb	0.700	0.787	0.708
304.02	Cobb	0.687	0.779	0.691
304.04	Cobb	0.555	0.655	0.525
304.05	Cobb	0.637	0.721	0.626
304.06	Cobb	0.566	0.664	0.532
305.01	Cobb	0.691	0.761	0.631
305.02	Cobb	0.674	0.753	0.592
305.03	Cobb	0.687	0.762	0.667

Census Tract	County	1984	1990	2000
306.00	Cobb	0.733	0.802	0.682
307.00	Cobb	0.647	0.738	0.619
308.00	Cobb	0.619	0.699	0.577
309.01	Cobb	0.738	0.802	0.726
309.02	Cobb	0.684	0.771	0.679
309.03	Cobb	0.670	0.753	0.664
310.01	Cobb	0.611	0.705	0.599
310.02	Cobb	0.690	0.782	0.688
310.03	Cobb	0.692	0.769	0.688
311.01	Cobb	0.640	0.725	0.634
311.03	Cobb	0.684	0.765	0.671
311.05	Cobb	0.683	0.763	0.679
311.06	Cobb	0.710	0.775	0.697
311.07	Cobb	0.712	0.791	0.701
311.08	Cobb	0.652	0.739	0.632
311.09	Cobb	0.594	0.686	0.570
312.02	Cobb	0.682	0.738	0.612
312.03	Cobb	0.671	0.748	0.614
312.04	Cobb	0.707	0.790	0.665
313.01	Cobb	0.720	0.797	0.730
313.02	Cobb	0.746	0.806	0.720
313.04	Cobb	0.713	0.785	0.713
313.05	Cobb	0.734	0.769	0.678
314.03	Cobb	0.705	0.762	0.661
314.04	Cobb	0.700	0.787	0.711
314.98	Cobb	0.710	0.786	0.678
315.01	Cobb	0.717	0.796	0.724
315.02	Cobb	0.701	0.779	0.702
316.97	Cobb	0.766	0.000	0.000
316.98	Cobb	0.794	0.867	0.784
401.00	Clayton	0.513	0.624	0.475
402.00	Clayton	0.666	0.736	0.613
403.01	Clayton	0.555	0.656	0.507
403.02	Clayton	0.690	0.780	0.694
403.03	Clayton	0.651	0.742	0.650
403.04	Clayton	0.629	0.724	0.614
403.05	Clayton	0.629	0.703	0.594
404.01	Clayton	0.671	0.761	0.670
404.02	Clayton	0.696	0.785	0.682
404.03	Clayton	0.689	0.759	0.637
404.05	Clayton	0.662	0.743	0.655
404.06	Clayton	0.612	0.702	0.602
405.03	Clayton	0.682	0.774	0.683
405.04	Clayton	0.693	0.776	0.667
405.05	Clayton	0.687	0.783	0.702

Census Tract	County	1984	1990	2000
405.06	Clayton	0.684	0.756	0.668
405.07	Clayton	0.682	0.758	0.651
405.08	Clayton	0.681	0.769	0.695
406.03	Clayton	0.705	0.777	0.672
406.04	Clayton	0.675	0.745	0.651
406.05	Clayton	0.687	0.766	0.686
406.06	Clayton	0.739	0.820	0.761
406.07	Clayton	0.729	0.797	0.688
406.08	Clayton	0.726	0.808	0.750
501.01	Gwinnett	0.733	0.807	0.667
501.02	Gwinnett	0.741	0.813	0.673
502.02	Gwinnett	0.752	0.822	0.647
502.03	Gwinnett	0.688	0.754	0.573
502.04	Gwinnett	0.739	0.821	0.641
503.04	Gwinnett	0.599	0.690	0.560
503.05	Gwinnett	0.648	0.754	0.613
503.06	Gwinnett	0.569	0.651	0.510
503.07	Gwinnett	0.698	0.782	0.653
503.08	Gwinnett	0.711	0.794	0.601
503.09	Gwinnett	0.688	0.760	0.585
503.10	Gwinnett	0.645	0.727	0.533
503.11	Gwinnett	0.657	0.746	0.578
503.12	Gwinnett	0.635	0.705	0.583
503.13	Gwinnett	0.656	0.769	0.634
503.14	Gwinnett	0.673	0.762	0.633
504.03	Gwinnett	0.696	0.783	0.693
504.06	Gwinnett	0.617	0.723	0.602
504.07	Gwinnett	0.646	0.759	0.653
504.08	Gwinnett	0.601	0.707	0.598
504.09	Gwinnett	0.630	0.700	0.568
504.10	Gwinnett	0.681	0.771	0.665
504.11	Gwinnett	0.676	0.768	0.653
504.12	Gwinnett	0.684	0.795	0.710
504.13	Gwinnett	0.694	0.795	0.688
504.14	Gwinnett	0.686	0.781	0.684
504.15	Gwinnett	0.698	0.781	0.687
504.16	Gwinnett	0.732	0.803	0.745
505.02	Gwinnett	0.738	0.786	0.603
505.03	Gwinnett	0.733	0.790	0.631
505.05	Gwinnett	0.721	0.807	0.660
505.06	Gwinnett	0.703	0.772	0.608
505.07	Gwinnett	0.714	0.781	0.611
505.08	Gwinnett	0.684	0.759	0.609
505.09	Gwinnett	0.722	0.811	0.659
506.01	Gwinnett	0.740	0.834	0.695

Census Tract	County	1984	1990	2000
506.02	Gwinnett	0.734	0.829	0.714
507.04	Gwinnett	0.706	0.810	0.714
507.05	Gwinnett	0.705	0.812	0.707
507.06	Gwinnett	0.708	0.794	0.687
507.07	Gwinnett	0.701	0.798	0.703
507.08	Gwinnett	0.705	0.778	0.692
507.09	Gwinnett	0.742	0.805	0.740
507.10	Gwinnett	0.699	0.785	0.677
507.11	Gwinnett	0.685	0.788	0.675
508.98	Gwinnett	0.671	0.752	0.672
601.00	Rockdale	0.723	0.814	0.737
602.00	Rockdale	0.711	0.805	0.727
603.02	Rockdale	0.704	0.790	0.689
603.03	Rockdale	0.705	0.791	0.712
603.04	Rockdale	0.656	0.762	0.662
604.01	Rockdale	0.731	0.818	0.755
604.02	Rockdale	0.726	0.816	0.747
701.02	Henry	0.733	0.815	0.748
701.03	Henry	0.719	0.792	0.683
701.98	Henry	0.740	0.823	0.741
702.01	Henry	0.716	0.807	0.734
702.02	Henry	0.714	0.816	0.747
702.03	Henry	0.712	0.795	0.749
703.01	Henry	0.696	0.809	0.731
703.02	Henry	0.687	0.795	0.703
704.02	Henry	0.716	0.811	0.753
704.98	Henry	0.673	0.810	0.731
705.00	Henry	0.701	0.810	0.749
801.98	Douglas	0.749	0.798	0.723
802.00	Douglas	0.718	0.787	0.722
803.00	Douglas	0.709	0.784	0.702
804.00	Douglas	0.756	0.828	0.773
805.01	Douglas	0.746	0.823	0.763
805.03	Douglas	0.735	0.802	0.700
805.04	Douglas	0.777	0.842	0.780
806.01	Douglas	0.757	0.820	0.759
806.02	Douglas	0.781	0.841	0.792
807.97	Douglas	0.732	0.000	0.000
807.98	Douglas	0.734	0.816	0.759
901.00	Cherokee	0.783	0.854	0.763
902.00	Cherokee	0.807	0.863	0.785
903.00	Cherokee	0.738	0.817	0.719
904.00	Cherokee	0.774	0.848	0.748
905.00	Cherokee	0.772	0.854	0.757
906.00	Cherokee	0.762	0.836	0.742

Census Tract	County	1984	1990	2000
907.00	Cherokee	0.725	0.793	0.664
908.00	Cherokee	0.758	0.837	0.734
909.01	Cherokee	0.752	0.830	0.726
909.02	Cherokee	0.752	0.826	0.712
909.03	Cherokee	0.743	0.807	0.670
910.01	Cherokee	0.748	0.796	0.662
910.02	Cherokee	0.763	0.808	0.649
910.03	Cherokee	0.708	0.774	0.632
911.01	Cherokee	0.603	0.694	0.587
911.03	Cherokee	0.698	0.774	0.669
911.98	Cherokee	0.752	0.817	0.698
912.98	Cherokee	0.715	0.811	0.690
1201.00	Paulding	0.785	0.843	0.778
1202.00	Paulding	0.751	0.814	0.739
1203.00	Paulding	0.755	0.828	0.762
1204.00	Paulding	0.784	0.852	0.794
1205.00	Paulding	0.744	0.819	0.754
1206.98	Paulding	0.745	0.818	0.747
1301.00	Forsyth	0.682	0.795	0.695
1302.00	Forsyth	0.748	0.841	0.754
1303.00	Forsyth	0.748	0.844	0.731
1304.00	Forsyth	0.744	0.834	0.719
1305.00	Forsyth	0.571	0.682	0.556
1306.00	Forsyth	0.752	0.835	0.680
1401.01	Fayette	0.724	0.816	0.757
1401.02	Fayette	0.716	0.799	0.722
1402.01	Fayette	0.719	0.808	0.747
1402.02	Fayette	0.734	0.797	0.700
1403.01	Fayette	0.719	0.800	0.720
1403.02	Fayette	0.730	0.797	0.707
1404.01	Fayette	0.715	0.802	0.723
1404.02	Fayette	0.723	0.801	0.744
1405.01	Fayette	0.729	0.819	0.757
1405.02	Fayette	0.715	0.809	0.762
1701.00	Coweta	0.738	0.813	0.767
1702.00	Coweta	0.724	0.807	0.759
1703.00	Coweta	0.747	0.807	0.739
1704.00	Coweta	0.741	0.819	0.748
1705.00	Coweta	0.716	0.819	0.764
1706.00	Coweta	0.736	0.800	0.738
1707.00	Coweta	0.735	0.809	0.759
1708.00	Coweta	0.743	0.823	0.774

APPENDIX E

SOCIODEMOGRAPHIC AND PHYSICAL ENVIRONMENTAL VARIABLES, BY 1990 CENSUS TRACT BOUNDARIES

Table E.1. Sociodemographic variables, metropolitan Atlanta, Georgia, 1980.

Census Tract	County	PLDU80	PHDU80	PURB80	PPOV80	POPDENS80	PUNOC80	POWNOC80	NDVI80	PHS80	PBCH80	PUMP80	PBLK80
1.00	Fulton	23.54	11.75	35.29	5.16	5303.80	7.53	70.28	0.714	83.67	46.40	7.70	0.48
2.00	Fulton	32.70	17.80	50.50	7.65	4835.45	24.67	46.40	0.678	88.09	43.23	4.24	2.82
4.00	Fulton	24.49	22.26	46.75	10.61	4949.37	2.58	35.41	0.640	92.35	47.49	3.97	4.71
5.00	Fulton	18.79	45.73	64.52	5.14	184595.02	3.15	43.21	0.590	86.57	50.86	1.90	3.94
7.00	Fulton	22.29	54.47	76.77	3.83	6886.08	6.24	44.44	0.571	45.14	2.04	5.09	68.62
8.00	Fulton	32.00	57.60	89.60	49.66	7075.95	0.72	15.50	0.556	36.03	1.94	3.78	97.24
10.95	Fulton	16.88	71.38	88.26	6.18	11113.93	6.09	12.45	0.518	95.12	10.54	21.57	5.65
11.00	Fulton	38.36	48.38	86.74	31.01	8835.45	10.11	4.63	0.573	83.43	22.76	3.43	28.52
12.00	Fulton	31.50	61.38	92.88	16.95	10911.40	5.98	21.73	0.549	80.86	34.80	3.35	24.52
13.00	Fulton	32.26	53.15	85.40	19.97	8582.28	5.22	6.51	0.593	83.70	31.98	1.85	17.95
14.00	Fulton	45.70	24.86	70.55	20.19	3531.65	3.50	24.78	0.641	84.70	36.61	2.81	11.75
15.00	Fulton	56.74	22.81	79.55	18.52	6113.93	5.07	21.03	0.637	80.13	36.20	4.90	10.65
17.00	Fulton	28.90	56.69	85.60	46.71	8113.93	3.05	19.89	0.581	46.40	5.27	2.70	88.71
18.00	Fulton	15.52	66.17	81.69	58.74	11468.36	4.32	7.10	0.560	28.26	4.37	3.80	95.16
19.00	Fulton	1.12	98.30	99.42	22.09	60582.31	5.51	0.94	0.417	79.64	39.36	8.31	16.57
20.00	Fulton	33.55	63.45	97.00	65.81	39417.74	4.36	0.00	0.520	46.43	2.50	6.64	58.26
21.00	Fulton	17.06	78.86	95.92	75.66	13974.69	4.62	1.30	0.477	31.27	2.52	3.33	74.12
22.00	Fulton	25.74	67.37	93.11	62.58	11151.90	9.80	5.89	0.523	33.58	1.53	5.71	99.79
23.00	Fulton	45.35	34.41	79.76	39.25	6848.10	1.42	24.96	0.625	39.79	2.90	3.28	99.53
24.00	Fulton	47.22	13.87	61.08	23.06	5455.70	6.09	40.14	0.655	56.12	12.32	1.47	99.76
25.00	Fulton	43.03	46.42	89.45	39.37	11746.84	16.44	13.86	0.615	54.27	2.82	9.26	99.61
26.00	Fulton	29.51	58.92	88.43	50.71	7177.22	10.70	12.33	0.558	27.27	1.12	1.23	99.29
27.00	Fulton	0.52	90.64	91.15	36.42	159278.56	4.49	0.00	0.389	48.40	15.88	5.32	33.38
28.00	Fulton	3.36	95.71	99.08	42.23	78443.08	8.10	16.25	0.481	53.71	13.01	6.15	85.98
29.00	Fulton	29.79	58.64	88.43	48.03	7430.38	8.29	9.33	0.546	28.05	3.10	4.42	97.79
30.00	Fulton	42.29	34.70	76.99	17.10	3139.24	9.32	38.95	0.605	87.02	43.96	4.25	10.70
31.00	Fulton	45.01	24.98	69.99	35.03	6050.64	4.62	32.67	0.628	28.18	2.45	3.45	94.17
32.00	Fulton	40.46	43.05	83.51	48.22	3962.03	3.64	26.12	0.558	13.77	1.12	2.65	36.83
33.00	Fulton	14.49	76.76	91.25	47.65	30835.46	10.65	1.72	0.503	29.18	1.21	12.90	99.12
35.00	Fulton	3.34	95.61	98.95	66.67	11215.20	9.57	0.00	0.427	26.26	2.10	4.08	81.50

Census Tract	County	PLDU80	PHDU80	PURB80	PPOV80	POPDENS80	PUNOC80	POWNOC80	NDVI80	PHS80	PBCH80	PUMP80	PBLK80
36.00	Fulton	16.90	75.38	92.28	24.72	10582.28	4.95	11.04	0.523	71.91	5.62	3.15	97.07
37.00	Fulton	67.00	32.09	99.09	71.69	17911.40	4.08	0.61	0.594	27.91	1.38	4.20	98.89
38.00	Fulton	41.33	42.59	83.93	21.09	10329.12	5.33	21.17	0.612	75.46	10.18	5.94	98.86
39.00	Fulton	51.78	19.78	71.56	34.49	6556.97	9.59	35.17	0.641	48.94	9.12	8.44	98.58
40.00	Fulton	34.94	26.52	61.46	21.16	4974.69	2.88	73.40	0.670	56.92	13.41	0.64	98.76
41.00	Fulton	32.31	30.13	62.44	33.50	6822.79	4.13	30.27	0.659	61.38	10.67	3.87	93.53
42.95	Fulton	28.22	49.63	77.85	61.39	1341.77	6.41	7.26	0.569	49.88	13.09	1.58	87.12
44.00	Fulton	15.94	73.32	89.26	64.67	17721.53	6.31	7.02	0.528	24.55	2.07	4.83	99.60
46.95	Fulton	12.14	78.47	90.61	62.55	9721.52	4.22	5.45	0.553	25.79	0.00	4.03	97.82
48.00	Fulton	24.39	73.39	97.78	72.23	20430.39	7.65	2.41	0.566	35.48	2.30	2.93	95.82
49.95	Fulton	33.62	44.99	78.61	28.71	6000.00	3.96	26.72	0.617	38.93	11.16	2.46	56.09
50.00	Fulton	28.63	50.13	78.76	24.19	5392.41	5.87	41.22	0.571	46.19	14.79	3.49	10.16
52.00	Fulton	31.76	21.97	53.72	20.32	5189.88	4.01	55.91	0.668	49.09	8.48	1.83	35.84
53.00	Fulton	36.30	14.75	51.05	32.18	4278.48	3.45	42.59	0.675	45.12	6.92	3.96	61.36
55.01	Fulton	39.78	20.05	59.83	50.45	5835.45	4.62	21.35	0.648	30.12	0.39	7.29	98.48
55.02	Fulton	42.33	30.15	72.48	60.62	6392.41	3.45	10.68	0.603	30.47	1.62	4.92	97.58
56.00	Fulton	22.42	58.80	81.22	55.48	8734.18	5.74	12.03	0.577	28.56	1.42	2.43	96.40
57.00	Fulton	40.03	48.94	88.97	49.45	5974.69	2.19	27.26	0.559	32.62	1.86	7.28	98.65
58.00	Fulton	28.51	43.67	72.18	27.25	5493.67	5.95	35.73	0.561	47.08	5.84	5.28	79.01
60.00	Fulton	34.82	18.54	53.36	23.17	8645.57	6.01	53.39	0.678	57.01	8.04	5.52	97.28
61.00	Fulton	23.92	11.96	35.88	19.65	10101.27	4.98	74.14	0.716	53.44	6.66	5.28	96.22
62.00	Fulton	25.91	34.12	60.04	32.89	7037.98	6.55	39.21	0.618	41.59	5.99	4.07	86.93
63.00	Fulton	34.11	47.84	81.95	43.65	5329.12	2.83	36.78	0.575	34.04	2.85	0.70	94.43
64.00	Fulton	31.04	38.24	69.28	53.57	6443.04	8.86	14.67	0.595	28.77	1.28	3.25	62.04
65.00	Fulton	36.07	25.65	61.72	19.76	3670.89	3.79	69.21	0.644	56.51	7.62	7.65	59.69
66.01	Fulton	30.75	38.28	69.03	12.82	4215.19	2.98	54.06	0.610	54.63	7.46	6.50	36.89
66.02	Fulton	20.53	32.63	53.16	38.40	11848.11	3.04	38.76	0.653	48.51	1.39	6.50	87.71
67.00	Fulton	25.98	30.85	56.83	40.12	5607.60	3.86	30.38	0.630	41.36	3.06	3.00	75.21
68.02	Fulton	21.82	19.28	41.11	48.00	11531.65	5.58	20.24	0.632	46.56	1.31	5.68	99.11
69.00	Fulton	22.07	20.22	42.30	23.23	4911.39	5.92	45.92	0.681	51.32	3.86	3.15	51.54
70.00	Fulton	18.10	18.81	36.91	24.15	5493.67	12.92	54.19	0.682	49.27	3.45	24.05	68.54
71.00	Fulton	35.98	23.40	59.38	49.22	5329.12	10.31	47.34	0.636	41.32	3.19	6.02	97.30

Census Tract	County	PLDU80	PHDU80	PURB80	PPOV80	POPDENS80	PUNOC80	POWNOC80	NDVI80	PHS80	PBCH80	PUMP80	PBLK80
72.00	Fulton	16.29	18.74	35.04	37.85	4797.47	13.59	28.16	0.687	51.23	2.95	11.36	87.46
73.00	Fulton	15.67	21.96	37.63	25.61	5860.76	16.82	42.64	0.689	64.02	5.95	11.19	87.14
74.00	Fulton	28.16	32.72	60.88	11.89	5227.85	6.89	30.65	0.634	53.11	5.68	3.45	48.79
75.00	Fulton	26.67	37.18	63.86	19.46	4240.51	2.51	38.17	0.622	47.92	7.64	3.01	31.61
76.01	Fulton	19.39	29.70	49.09	19.65	9126.59	4.99	10.46	0.653	83.18	18.14	3.50	84.43
76.02	Fulton	9.68	5.58	15.26	14.77	9835.45	9.12	64.05	0.738	79.05	20.44	10.78	91.74
77.01	Fulton	11.93	17.40	29.33	14.85	7164.56	18.62	40.37	0.734	82.38	22.59	2.82	94.05
77.02	Fulton	9.34	13.60	22.94	11.60	4455.70	16.12	39.48	0.716	81.63	20.93	7.72	87.82
78.02	Fulton	4.91	4.98	9.89	25.08	8430.38	4.09	54.61	0.754	68.48	16.37	7.57	85.31
78.03	Fulton	16.09	28.32	44.42	18.83	2696.20	5.43	41.94	0.656	72.31	8.53	12.03	98.27
78.04	Fulton	23.93	29.65	53.58	30.96	8455.70	8.39	26.96	0.663	63.05	6.90	3.63	99.28
79.00	Fulton	11.69	10.76	22.45	6.32	5012.66	9.10	87.18	0.743	80.80	33.90	2.72	96.80
80.00	Fulton	9.85	6.51	16.36	19.07	11835.45	7.46	78.79	0.741	64.22	10.84	11.62	94.16
81.01	Fulton	11.32	0.35	11.67	11.54	13544.31	5.71	90.02	0.744	78.74	11.53	3.41	98.30
81.02	Fulton	13.89	13.40	27.29	23.48	6822.79	8.90	35.11	0.701	74.23	15.95	10.78	99.39
82.01	Fulton	32.33	11.19	43.52	10.33	4101.27	6.36	73.48	0.695	75.32	26.37	8.89	99.10
82.02	Fulton	n/a	n/a	n/a	n/a	4556.96	n/a	n/a	0.653	n/a	n/a	n/a	n/a
83.01	Fulton	22.83	17.27	40.10	30.01	7556.97	7.41	43.43	0.702	57.47	7.47	3.24	99.31
83.02	Fulton	26.23	19.91	46.14	33.24	7544.31	3.91	40.33	0.692	49.95	9.57	0.85	99.26
84.00	Fulton	34.24	24.39	58.63	30.36	8556.97	8.93	27.94	0.666	49.69	6.07	3.82	99.18
85.00	Fulton	11.82	18.41	30.23	31.66	12898.74	3.23	49.67	0.713	52.65	3.97	11.76	98.31
86.01	Fulton	13.47	14.25	27.71	35.56	10417.73	7.72	39.26	0.724	48.41	2.96	13.17	98.47
86.02	Fulton	10.49	20.07	30.56	63.95	8354.43	2.01	17.45	0.648	38.64	1.07	3.18	98.25
87.01	Fulton	15.47	32.09	47.56	70.19	6759.50	5.87	3.94	0.627	34.69	1.61	11.38	99.82
87.02	Fulton	24.27	22.32	46.58	48.71	4658.23	4.93	38.96	0.656	45.89	1.48	8.46	98.04
88.00	Fulton	16.51	35.18	51.68	18.83	2000.00	2.85	53.00	0.622	37.23	2.65	3.96	20.62
89.00	Fulton	26.78	37.23	64.01	15.89	2797.47	2.74	26.31	0.600	79.91	37.31	5.38	5.79
90.00	Fulton	11.49	21.38	32.87	5.15	8556.97	3.03	74.95	0.701	91.86	56.71	2.63	2.02
91.00	Fulton	23.19	26.10	49.29	11.28	8316.46	9.86	19.00	0.656	90.00	47.06	14.55	4.76
92.00	Fulton	25.45	49.46	74.91	11.58	3531.65	4.84	32.57	0.595	83.02	33.17	3.66	3.25
93.00	Fulton	23.80	20.22	44.02	6.54	7025.32	10.65	41.66	0.693	88.77	43.74	5.76	3.04
94.01	Fulton	18.97	14.82	33.80	9.34	5607.60	10.75	18.70	0.686	83.50	33.13	5.92	4.13

Census Tract	County	PLDU80	PHDU80	PURB80	PPOV80	POPDENS80	PUNOC80	POWNOC80	NDVI80	PHS80	PBCH80	PUMP80	PBLK80
94.02	Fulton	18.88	61.48	80.36	9.34	5696.21	10.75	18.70	0.550	83.50	33.13	5.92	4.13
95.00	Fulton	9.60	12.91	22.51	3.54	9898.74	6.64	43.08	0.721	89.67	47.85	15.00	0.77
96.00	Fulton	23.90	33.07	56.97	14.51	5645.57	2.73	29.18	0.624	88.90	39.72	4.71	4.08
97.00	Fulton	5.74	6.67	12.42	2.13	4556.96	3.27	91.61	0.739	94.08	48.39	3.48	3.39
98.00	Fulton	5.02	13.05	18.06	3.36	7468.36	10.59	85.30	0.741	90.18	49.98	7.17	1.59
99.00	Fulton	5.80	12.71	18.52	1.08	7278.48	4.14	82.72	0.736	94.05	54.59	2.58	0.88
100.00	Fulton	8.27	10.46	18.73	4.71	8012.66	4.16	75.05	0.725	89.62	45.93	23.35	0.79
101.01	Fulton	11.63	12.50	24.13	5.72	6443.04	2.09	44.94	0.715	91.14	44.82	2.07	1.10
101.03	Fulton	18.23	23.67	41.90	3.15	3316.46	3.65	46.46	0.666	91.47	40.81	9.36	1.23
101.05	Fulton	25.64	22.50	48.14	12.66	2278.48	1.86	70.10	0.621	50.97	4.79	1.45	23.34
101.06	Fulton	8.83	7.28	16.11	12.66	2202.53	1.86	70.10	0.712	50.97	4.79	1.45	23.34
101.07	Fulton	7.81	2.19	10.01	12.66	2202.53	1.86	70.10	0.723	50.97	4.79	1.45	23.34
101.08	Fulton	12.79	13.08	25.87	12.66	2202.53	1.86	70.10	0.696	50.97	4.79	1.45	23.34
102.01	Fulton	7.56	10.10	17.66	5.79	5126.58	4.54	55.99	0.737	94.15	48.50	4.09	2.53
102.03	Fulton	8.29	5.06	13.35	3.79	4582.28	3.82	77.67	0.692	92.41	46.54	4.37	1.10
102.04	Fulton	10.74	12.74	23.48	3.79	4582.28	3.82	77.67	0.708	92.41	46.54	4.37	1.10
102.05	Fulton	14.76	19.72	34.48	3.79	4582.28	3.82	77.67	0.685	92.41	46.54	4.37	1.10
103.01	Fulton	1.28	4.47	5.75	11.64	2797.47	6.53	82.65	0.761	71.16	17.88	7.35	49.01
103.02	Fulton	3.60	10.04	13.63	11.64	2810.13	6.53	82.65	0.740	71.16	17.88	7.35	49.01
104.00	Fulton	1.10	1.75	2.85	12.66	1936.71	1.86	70.10	0.760	50.97	4.79	1.45	23.34
105.03	Fulton	25.50	18.25	43.75	6.09	3126.58	9.59	59.34	0.668	82.67	20.68	3.10	31.12
105.04	Fulton	6.20	6.80	13.00	7.76	2518.99	3.88	85.89	0.731	76.06	18.88	7.94	49.56
105.05	Fulton	10.70	11.51	22.20	10.17	2481.01	12.01	64.42	0.711	69.85	14.46	3.91	35.25
105.06	Fulton	4.70	5.54	10.24	9.85	2860.76	3.28	65.04	0.744	54.96	8.65	1.71	15.12
106.01	Fulton	24.81	11.78	36.59	31.49	5987.34	4.33	37.98	0.690	56.08	12.66	3.46	40.72
106.02	Fulton	23.58	26.03	49.61	15.50	4936.71	4.83	22.43	0.660	77.99	17.47	4.46	69.55
107.00	Fulton	22.27	51.92	74.18	11.74	6025.32	6.48	32.34	0.606	54.87	9.41	4.30	5.92
108.00	Fulton	14.29	67.13	81.42	8.91	5050.64	3.97	49.46	0.545	56.82	7.84	2.14	3.08
109.00	Fulton	8.76	77.15	85.91	18.78	6316.46	8.66	38.90	0.521	32.08	2.70	6.81	14.29
110.00	Fulton	31.93	29.42	61.35	29.15	5012.66	4.97	32.16	0.612	44.43	4.96	3.16	59.38
111.00	Fulton	27.41	44.06	71.47	29.15	3088.61	4.97	32.16	0.598	44.43	4.96	3.16	59.38
112.01	Fulton	26.39	35.71	62.10	24.87	5835.45	13.66	31.17	0.628	54.96	7.07	11.90	45.44

Census Tract	County	PLDU80	PHDU80	PURB80	PPOV80	POPDENS80	PUNOC80	POWNOC80	NDVI80	PHS80	PBCH80	PUMP80	PBLK80
112.02	Fulton	35.54	18.42	53.96	10.99	4518.99	12.40	51.53	0.661	52.63	7.54	2.19	9.16
113.01	Fulton	31.01	6.37	37.38	4.86	3810.13	14.04	85.61	0.710	75.13	19.08	14.49	31.09
113.02	Fulton	17.18	12.50	29.69	11.64	5075.95	6.53	82.65	0.732	71.16	17.88	7.35	49.01
114.03	Fulton	9.66	8.74	18.40	3.37	2772.15	4.30	64.31	0.706	80.19	29.39	4.21	1.66
114.04	Fulton	18.06	21.36	39.42	3.37	2772.15	4.30	64.31	0.641	80.19	29.39	4.21	1.66
114.05	Fulton	19.08	9.45	28.53	3.37	2772.15	4.30	64.31	0.689	80.19	29.39	4.21	1.66
114.06	Fulton	7.47	8.30	15.77	3.37	2772.15	4.30	64.31	0.708	80.19	29.39	4.21	1.66
114.07	Fulton	8.00	4.52	12.52	3.37	2772.15	4.30	64.31	0.717	80.19	29.39	4.21	1.66
114.08	Fulton	14.15	8.51	22.66	4.60	1670.89	10.04	70.78	0.700	91.59	39.05	4.01	1.22
114.09	Fulton	4.60	4.03	8.63	4.60	1670.89	10.04	70.78	0.743	91.59	39.05	4.01	1.22
114.10	Fulton	9.79	3.92	13.70	4.60	1670.89	10.04	70.78	0.699	91.59	39.05	4.01	1.22
114.11	Fulton	18.13	4.33	22.46	4.60	1670.89	10.04	70.78	0.680	91.59	39.05	4.01	1.22
115.00	Fulton	1.48	2.16	3.64	7.97	3215.19	7.99	81.56	0.757	65.88	21.42	1.93	0.04
116.01	Fulton	3.81	6.63	10.44	6.43	2379.75	2.01	78.07	0.734	61.65	16.09	1.01	3.29
116.02	Fulton	1.66	5.90	7.57	6.43	2367.09	2.01	78.07	0.749	61.65	16.09	1.01	3.29
116.03	Fulton	1.43	4.14	5.57	6.43	2354.43	2.01	78.07	0.743	61.65	16.09	1.01	3.29
201.00	DeKalb	23.77	6.17	29.94	5.29	6417.72	2.48	79.67	0.721	87.97	46.25	2.79	1.01
202.00	DeKalb	10.77	14.94	25.70	9.68	13050.64	6.55	28.10	0.732	90.40	55.14	8.59	3.26
203.00	DeKalb	20.24	8.74	28.98	16.64	7620.26	3.87	56.31	0.706	71.45	36.21	2.98	18.27
204.00	DeKalb	38.40	19.36	57.76	16.45	5898.74	6.34	32.06	0.672	76.74	31.79	9.00	13.36
205.00	DeKalb	35.84	16.71	52.55	32.35	7139.24	3.09	40.72	0.663	40.31	2.55	4.72	98.26
206.00	DeKalb	34.17	24.97	59.15	45.53	3835.44	6.85	25.34	0.619	30.91	1.49	2.21	99.40
207.00	DeKalb	32.76	11.43	44.19	34.01	8012.66	4.40	37.70	0.679	45.41	4.50	2.08	98.98
208.00	DeKalb	18.32	16.05	34.37	35.61	15506.34	3.00	54.19	0.699	42.30	4.47	3.08	95.49
209.00	DeKalb	24.47	27.54	52.01	24.20	7215.19	7.44	60.14	0.686	47.17	7.16	9.81	84.13
211.00	DeKalb	11.44	9.48	20.92	9.72	7025.32	13.40	48.34	0.714	80.34	31.12	16.27	19.63
212.02	DeKalb	15.46	12.45	27.90	2.72	5025.32	4.26	84.06	0.704	90.82	44.97	13.95	0.28
212.04	DeKalb	15.48	48.16	63.64	14.56	5037.98	3.09	17.11	0.555	72.23	11.05	2.25	5.83
212.05	DeKalb	29.82	9.86	39.68	2.91	3708.86	6.84	93.49	0.682	94.67	50.76	3.34	0.58
212.07	DeKalb	21.10	20.94	42.03	1.93	2088.61	7.65	94.34	0.652	89.24	39.87	12.26	0.20
212.08	DeKalb	n/a	n/a	n/a	n/a	4367.09	n/a	n/a	0.602	n/a	n/a	n/a	n/a
212.09	DeKalb	n/a	n/a	n/a	n/a	4354.43	n/a	n/a	0.686	n/a	n/a	n/a	n/a

Census Tract	County	PLDU80	PHDU80	PURB80	PPOV80	POPDENS80	PUNOC80	POWNOC80	NDVI80	PHS80	PBCH80	PUMP80	PBLK80
212.10	DeKalb	25.81	9.79	35.60	1.79	3759.50	3.58	82.21	0.684	89.71	40.13	4.16	1.17
212.11	DeKalb	19.10	6.60	25.70	1.79	3772.15	3.58	82.21	0.698	89.71	40.13	4.16	1.17
212.12	DeKalb	30.18	24.35	54.52	1.79	3759.50	3.58	82.21	0.642	89.71	40.13	4.16	1.17
213.01	DeKalb	20.21	57.46	77.68	11.89	2481.01	2.57	33.67	0.557	70.16	13.52	3.81	20.53
213.02	DeKalb	36.97	28.45	65.42	11.06	3139.24	4.88	58.81	0.626	82.36	22.20	6.76	1.87
213.03	DeKalb	31.31	43.98	75.29	11.89	3291.14	2.57	33.67	0.572	70.16	13.52	3.81	20.53
213.04	DeKalb	23.41	31.09	54.49	2.39	3063.29	11.69	44.22	0.600	80.54	22.28	21.98	4.99
214.01	DeKalb	24.43	20.05	44.48	15.48	5367.09	13.71	22.23	0.656	88.88	32.85	6.45	5.53
214.02	DeKalb	29.96	13.75	43.71	10.13	6569.62	5.02	25.84	0.670	86.58	30.41	3.42	2.59
214.03	DeKalb	23.71	15.20	38.90	7.92	5632.91	2.71	54.92	0.682	73.49	16.38	6.73	1.14
214.04	DeKalb	29.08	21.04	50.12	7.39	5468.36	15.06	27.44	0.640	88.48	30.59	22.07	4.44
215.00	DeKalb	21.46	15.44	36.90	9.94	4772.15	3.51	46.71	0.704	88.17	44.88	2.55	2.23
216.01	DeKalb	16.69	11.82	28.51	6.51	6873.42	9.61	60.15	0.703	89.29	36.74	7.61	1.62
216.02	DeKalb	18.58	10.99	29.57	3.13	5291.14	2.94	66.10	0.708	89.80	42.26	3.18	1.74
216.03	DeKalb	19.18	24.29	43.48	3.21	4329.12	1.39	63.92	0.673	87.16	36.16	2.36	1.85
217.02	DeKalb	21.32	22.49	43.81	4.26	3405.06	6.86	55.87	0.664	92.35	37.55	4.32	1.03
217.03	DeKalb	16.07	11.77	27.83	1.74	3670.89	4.35	84.63	0.710	84.57	37.05	4.69	0.92
217.04	DeKalb	25.58	24.78	50.36	1.74	3670.89	4.35	84.63	0.654	84.57	37.05	4.69	0.92
218.05	DeKalb	39.57	12.58	52.14	3.59	2911.39	3.97	63.46	0.662	82.77	26.74	2.51	1.60
218.06	DeKalb	16.88	25.44	42.32	4.44	3164.56	3.76	65.69	0.645	79.87	23.90	2.81	2.06
218.08	DeKalb	35.36	17.67	53.03	1.85	2417.72	4.38	58.94	0.665	88.65	32.52	1.89	0.67
218.09	DeKalb	28.41	11.93	40.34	2.35	2822.79	5.12	89.91	0.682	83.85	32.02	3.40	0.07
218.10	DeKalb	24.28	27.18	51.46	2.35	2822.79	5.12	89.91	0.635	83.85	32.02	3.40	0.07
218.98	DeKalb	24.80	19.52	44.32	1.85	2417.72	4.38	58.94	0.655	88.65	32.52	1.89	0.67
219.02	DeKalb	11.78	11.39	23.17	4.56	2518.99	3.86	59.01	0.721	87.93	33.29	4.73	0.53
219.03	DeKalb	8.18	8.86	17.05	5.95	3544.31	2.86	57.15	0.686	71.59	21.59	10.58	9.32
219.04	DeKalb	25.98	25.26	51.25	4.27	3379.75	3.81	36.25	0.623	82.24	26.16	2.10	1.36
219.05	DeKalb	27.88	17.05	44.94	4.27	3392.41	3.81	36.25	0.644	82.24	26.16	2.10	1.36
220.01	DeKalb	26.68	16.96	43.63	1.78	3759.50	4.00	88.46	0.675	77.57	19.88	6.63	0.09
220.02	DeKalb	31.75	15.04	46.79	5.77	5670.89	3.93	16.77	0.656	85.54	25.54	4.48	5.76
220.04	DeKalb	38.78	8.73	47.50	7.13	3759.50	8.73	43.61	0.670	86.09	26.06	11.46	4.80
220.05	DeKalb	31.95	23.89	55.84	7.13	3772.15	8.73	43.61	0.647	86.09	26.06	11.46	4.80

Census Tract	**County**	**PLDU80**	**PHDU80**	**PURB80**	**PPOV80**	**POPDENS80**	**PUNOC80**	**POWNOC80**	**NDVI80**	**PHS80**	**PBCH80**	**PUMP80**	**PBLK80**
221.00	DeKalb	n/a	n/a	n/a	n/a	4696.20	n/a	n/a	0.677	n/a	n/a	n/a	n/a
222.00	DeKalb	23.37	28.72	52.09	7.74	3113.93	19.26	60.20	0.642	64.70	16.76	4.22	3.89
223.01	DeKalb	23.80	16.86	40.65	5.45	5037.98	13.27	54.78	0.681	78.73	30.72	11.71	0.23
223.02	DeKalb	24.53	15.59	40.13	2.39	4101.27	4.69	73.00	0.683	87.98	37.39	6.29	0.46
224.01	DeKalb	16.89	13.89	30.78	7.64	8518.99	4.64	52.23	0.733	85.18	49.44	5.74	1.64
224.02	DeKalb	23.64	10.98	34.62	6.12	6075.95	16.72	18.55	0.693	96.49	26.99	0.00	3.34
224.03	DeKalb	4.86	9.06	13.92	5.50	15164.56	4.41	67.46	0.760	88.75	52.56	8.34	0.50
225.00	DeKalb	18.14	24.05	42.20	18.77	8835.45	4.43	51.49	0.674	77.62	34.04	3.36	27.99
226.00	DeKalb	16.97	21.53	38.50	9.39	9126.59	17.72	35.84	0.685	73.69	32.95	25.11	2.22
227.00	DeKalb	20.62	13.58	34.20	25.19	11303.80	16.12	57.10	0.701	51.81	9.13	4.22	85.66
228.00	DeKalb	11.42	19.08	30.50	5.21	11810.13	12.29	66.70	0.716	78.56	24.76	3.50	43.00
229.00	DeKalb	14.42	14.87	29.29	18.37	6911.40	4.94	56.90	0.688	64.38	12.07	2.66	45.43
230.00	DeKalb	22.32	16.09	38.42	11.08	5518.99	4.28	72.33	0.657	75.86	26.26	4.45	24.63
231.01	DeKalb	22.24	13.35	35.59	22.66	7000.00	3.27	59.28	0.697	61.17	7.69	3.73	70.92
231.02	DeKalb	36.91	19.83	56.74	2.85	3658.23	3.52	89.73	0.650	88.81	42.26	6.46	1.19
231.03	DeKalb	33.54	15.71	49.25	10.34	4012.66	6.95	66.97	0.670	67.44	10.52	7.28	25.52
231.05	DeKalb	23.09	23.69	46.78	6.79	3949.37	6.95	31.12	0.654	87.07	31.01	6.01	14.36
231.06	DeKalb	23.98	20.10	44.08	6.79	3949.37	6.95	31.12	0.676	87.07	31.01	6.01	14.36
232.03	DeKalb	9.68	14.34	24.02	3.37	2556.96	5.04	69.40	0.700	84.97	28.82	5.66	24.10
232.04	DeKalb	18.82	5.26	24.08	2.16	3126.58	5.84	91.45	0.707	88.16	34.22	3.44	0.59
232.05	DeKalb	25.00	5.19	30.18	2.16	3113.93	5.84	91.45	0.692	88.16	34.22	3.44	0.59
232.06	DeKalb	23.11	8.40	31.51	4.16	3227.85	9.23	91.17	0.708	85.60	26.51	2.43	2.51
232.07	DeKalb	16.80	7.94	24.73	4.16	3215.19	9.23	91.17	0.708	85.60	26.51	2.43	2.51
233.02	DeKalb	3.43	6.31	9.74	9.13	1075.95	4.24	83.98	0.742	69.18	12.55	5.07	9.32
233.03	DeKalb	12.64	15.87	28.51	21.58	2012.66	28.52	56.73	0.666	47.10	4.06	3.64	38.92
233.05	DeKalb	4.65	5.16	9.81	3.99	2607.60	4.27	88.89	0.736	79.57	26.76	2.36	4.99
233.06	DeKalb	7.10	7.84	14.94	3.99	2569.62	4.27	88.89	0.712	79.57	26.76	2.36	4.99
233.07	DeKalb	14.20	9.62	23.81	5.92	1848.10	5.08	58.28	0.689	72.05	15.58	9.49	12.60
233.08	DeKalb	7.91	10.18	18.10	5.92	1848.10	5.08	58.28	0.713	72.05	15.58	9.49	12.60
234.03	DeKalb	22.86	20.42	43.28	9.41	5873.42	4.42	40.42	0.679	82.73	16.76	6.72	91.76
234.04	DeKalb	7.61	13.59	21.20	3.92	2607.60	13.45	69.88	0.711	76.44	13.09	9.18	55.66
234.05	DeKalb	2.91	8.60	11.51	14.07	5759.50	6.67	37.74	0.763	78.03	15.97	5.48	66.47

Census Tract	County	PLDU80	PHDU80	PURB80	PPOV80	POPDENS80	PUNOC80	POWNOC80	NDVI80	PHS80	PBCH80	PUMP80	PBLK80
234.07	DeKalb	4.51	6.01	10.52	4.27	2797.47	4.15	54.00	0.739	82.31	20.19	2.43	6.07
234.08	DeKalb	16.84	15.10	31.94	4.45	4113.93	5.32	78.84	0.706	83.07	21.14	4.24	44.48
234.09	DeKalb	7.53	9.26	16.79	4.45	4113.93	5.32	78.84	0.745	83.07	21.14	4.24	44.48
235.01	DeKalb	30.11	19.76	49.87	18.39	6189.88	6.96	64.93	0.673	59.83	6.65	8.89	80.61
235.02	DeKalb	37.06	13.34	50.40	12.94	5278.48	3.40	63.03	0.678	68.86	9.61	5.95	88.68
235.03	DeKalb	31.91	16.50	48.42	8.51	4177.22	2.83	75.32	0.685	78.76	16.48	3.78	64.48
236.00	DeKalb	20.82	10.47	31.29	12.12	6620.26	5.39	71.95	0.697	61.47	7.84	3.12	93.85
237.00	DeKalb	15.75	18.61	34.36	22.84	8759.50	13.00	51.59	0.717	51.04	5.63	9.26	94.30
238.01	DeKalb	18.46	7.48	25.94	15.36	6683.55	3.80	59.01	0.721	65.68	7.57	4.51	82.25
238.02	DeKalb	10.06	15.05	25.11	12.67	3772.15	1.97	31.92	0.686	69.21	9.27	2.34	68.50
238.03	DeKalb	20.74	11.38	32.12	12.40	6050.64	16.03	88.47	0.709	65.74	7.92	6.60	87.42
301.98	Cobb	3.08	5.34	8.42	13.17	4012.66	30.08	75.37	0.705	50.94	9.05	13.35	4.67
302.03	Cobb	2.24	3.57	5.81	5.32	3911.39	6.70	83.64	0.742	74.26	17.37	6.92	4.83
302.04	Cobb	7.29	7.13	14.42	5.89	1594.94	8.03	76.88	0.734	65.03	11.53	9.98	3.44
302.05	Cobb	7.10	14.15	21.25	5.89	1569.62	8.03	76.88	0.700	65.03	11.53	9.98	3.44
302.06	Cobb	n/a	n/a	n/a	n/a	4886.08	n/a	n/a	0.757	n/a	n/a	n/a	n/a
302.07	Cobb	n/a	n/a	n/a	n/a	4898.74	n/a	n/a	0.762	n/a	n/a	n/a	n/a
303.02	Cobb	14.88	4.17	19.05	2.36	2430.38	3.08	89.23	0.700	91.46	22.37	1.36	1.10
303.07	Cobb	8.02	3.40	11.42	2.36	2430.38	3.08	89.23	0.734	91.46	37.91	1.36	1.10
303.09	Cobb	13.41	6.92	20.33	2.36	2455.70	3.08	89.23	0.701	91.46	37.91	1.36	1.10
303.10	Cobb	13.76	5.44	19.20	3.11	2924.05	7.09	89.83	0.701	83.33	22.37	4.81	0.99
303.11	Cobb	11.03	8.49	19.51	3.11	2924.05	7.09	89.83	0.688	83.33	22.37	4.81	0.99
303.12	Cobb	13.51	8.78	22.29	3.11	2924.05	7.09	89.83	0.701	83.33	22.37	4.81	0.99
303.13	Cobb	15.60	7.63	23.23	3.11	2924.05	7.09	89.83	0.703	83.33	22.37	4.81	0.99
303.14	Cobb	9.82	9.02	18.85	1.23	3278.48	6.77	91.72	0.715	86.59	30.65	2.21	0.97
303.15	Cobb	17.46	9.06	26.52	1.23	3278.48	6.77	91.72	0.697	86.59	30.65	2.21	0.97
303.16	Cobb	15.31	7.25	22.56	1.57	3632.91	4.22	91.36	0.695	94.35	44.11	4.16	1.25
303.17	Cobb	12.51	7.76	20.27	1.57	3632.91	4.22	91.36	0.693	94.35	44.11	4.16	1.25
303.18	Cobb	12.59	8.22	20.81	2.52	3493.67	24.97	92.75	0.700	93.97	46.82	8.70	0.50
303.19	Cobb	6.36	6.25	12.61	2.52	3493.67	24.97	92.75	0.714	93.97	46.82	8.70	0.50
303.20	Cobb	10.10	8.60	18.70	5.64	2810.13	2.41	10.48	0.724	95.58	43.57	3.87	3.89
303.21	Cobb	21.31	34.41	55.72	5.64	2708.86	2.41	10.48	0.605	95.58	43.57	3.87	3.89

Census Tract	County	PLDU80	PHDU80	PURB80	PPOV80	POPDENS80	PUNOC80	POWNOC80	NDVI80	PHS80	PBCH80	PUMP80	PBLK80
304.01	Cobb	n/a	n/a	n/a	n/a	3544.31	n/a	n/a	0.700	n/a	n/a	n/a	n/a
304.02	Cobb	25.02	10.44	35.46	2.93	4443.04	8.31	71.57	0.687	85.44	30.12	12.25	0.51
304.04	Cobb	32.51	34.55	67.06	5.34	3392.41	3.36	27.44	0.555	83.09	23.97	4.86	2.93
304.05	Cobb	29.89	28.30	58.19	5.34	3392.41	3.36	27.44	0.637	83.09	23.97	4.86	2.93
304.06	Cobb	28.15	35.41	63.56	5.34	3367.09	3.36	27.44	0.566	83.09	23.97	4.86	2.93
305.01	Cobb	11.21	13.10	24.31	4.48	3405.06	3.67	70.70	0.691	74.66	20.41	6.29	7.03
305.02	Cobb	10.52	17.36	27.88	4.48	3417.72	3.67	70.70	0.674	74.66	20.41	6.29	7.03
305.03	Cobb	13.77	14.96	28.73	4.48	3405.06	3.67	70.70	0.687	74.66	20.41	6.29	7.03
306.00	Cobb	5.92	13.99	19.91	9.73	3734.18	15.82	72.07	0.733	63.89	20.51	25.95	8.84
307.00	Cobb	n/a	n/a	n/a	n/a	5544.31	n/a	n/a	0.647	n/a	n/a	n/a	n/a
308.00	Cobb	24.82	33.70	58.51	18.49	4215.19	6.30	21.60	0.619	52.09	7.57	10.94	10.89
309.01	Cobb	8.71	4.04	12.75	8.41	3987.34	6.50	59.72	0.738	69.76	18.44	5.27	7.98
309.02	Cobb	15.99	16.14	32.13	8.41	3987.34	6.50	59.72	0.684	69.76	18.44	5.27	7.98
309.03	Cobb	15.19	5.59	20.78	8.41	3987.34	6.50	59.72	0.670	69.76	18.44	5.27	7.98
310.01	Cobb	16.10	33.79	49.88	13.83	2101.27	21.14	35.18	0.611	50.07	7.95	12.27	4.13
310.02	Cobb	22.80	13.17	35.97	16.63	5556.96	2.90	32.91	0.690	56.09	5.66	0.68	5.01
310.03	Cobb	27.03	12.94	39.98	4.16	4000.00	10.40	59.98	0.692	72.19	8.81	9.32	1.03
311.01	Cobb	32.80	21.37	54.17	9.62	4202.53	3.58	42.95	0.640	63.07	10.40	2.96	1.35
311.03	Cobb	22.33	13.04	35.37	4.03	4430.38	4.00	54.21	0.684	71.76	15.96	3.39	2.26
311.05	Cobb	27.01	8.25	35.26	5.26	4012.66	5.35	48.17	0.683	77.69	13.15	10.36	3.22
311.06	Cobb	11.27	13.94	25.21	6.44	3430.38	1.77	88.66	0.710	76.50	13.27	3.12	0.43
311.07	Cobb	17.38	9.28	26.67	3.07	3354.43	12.63	81.53	0.712	78.14	21.20	4.45	0.38
311.08	Cobb	32.20	15.26	47.46	8.42	2962.03	4.40	28.63	0.652	73.01	18.97	9.82	13.04
311.09	Cobb	30.65	28.90	59.56	8.42	2987.34	4.40	28.63	0.594	73.01	18.97	9.82	13.04
312.02	Cobb	10.35	16.47	26.82	5.87	2177.22	3.42	51.87	0.682	61.70	16.33	2.36	4.07
312.03	Cobb	19.03	16.20	35.23	5.53	3405.06	4.60	38.65	0.671	88.59	44.70	5.27	1.80
312.04	Cobb	12.17	7.84	20.01	5.41	3481.01	4.55	39.89	0.707	87.25	42.40	5.12	1.84
313.01	Cobb	n/a	n/a	n/a	n/a	3151.90	n/a	n/a	0.720	n/a	n/a	n/a	n/a
313.02	Cobb	7.29	5.57	12.87	6.43	2949.37	14.38	72.42	0.746	49.49	4.93	8.11	2.54
313.04	Cobb	17.02	7.42	24.44	5.54	2265.82	17.81	74.62	0.713	57.04	8.60	19.58	2.77
313.05	Cobb	8.17	12.67	20.84	9.56	6506.33	2.24	45.77	0.734	59.96	8.58	3.05	8.60
314.03	Cobb	11.32	9.00	20.32	3.59	2924.05	6.92	87.68	0.705	67.38	8.34	2.49	1.08

Census Tract	County	PLDU80	PHDU80	PURB80	PPOV80	POPDENS80	PUNOC80	POWNOC80	NDVI80	PHS80	PBCH80	PUMP80	PBLK80
314.04	Cobb	17.76	9.50	27.26	3.59	2936.71	6.92	87.68	0.700	67.38	8.34	2.49	1.08
314.98	Cobb	n/a	n/a	n/a	n/a	2417.72	n/a	n/a	0.710	n/a	n/a	n/a	n/a
315.01	Cobb	4.25	2.93	7.19	5.98	2417.72	3.60	84.58	0.717	60.36	6.70	2.06	7.88
315.02	Cobb	9.08	5.81	14.89	5.98	2417.72	3.60	84.58	0.701	60.36	6.70	2.06	7.88
402.00	Clayton	16.75	22.53	39.28	6.74	2341.77	7.10	30.92	0.666	79.76	18.21	10.51	32.26
403.02	Clayton	29.75	9.79	39.54	12.16	3822.79	3.81	55.23	0.690	50.57	4.26	5.64	3.30
403.03	Clayton	33.68	19.27	52.95	11.74	3341.77	18.39	56.85	0.651	56.80	3.74	8.82	7.26
403.04	Clayton	34.11	22.74	56.84	9.66	3240.51	3.90	58.82	0.629	55.51	3.07	2.93	18.07
403.05	Clayton	n/a	n/a	n/a	n/a	3215.19	n/a	n/a	0.629	n/a	n/a	n/a	n/a
404.01	Clayton	26.85	10.67	37.52	6.93	2493.67	13.04	61.88	0.671	67.18	8.01	5.51	7.08
404.02	Clayton	9.34	14.12	23.46	4.64	2025.32	3.54	74.58	0.696	60.58	4.76	4.03	11.59
404.03	Clayton	21.92	12.23	34.15	4.97	2683.55	5.41	88.39	0.689	74.03	10.54	9.27	2.19
404.05	Clayton	n/a	n/a	n/a	n/a	3746.84	n/a	n/a	0.662	n/a	n/a	n/a	n/a
404.06	Clayton	28.60	28.72	57.32	6.15	3151.90	4.87	50.76	0.612	70.18	6.73	5.18	2.90
405.03	Clayton	31.45	8.73	40.18	8.98	3139.24	6.30	55.93	0.682	64.16	6.43	5.71	0.99
405.04	Clayton	22.24	8.55	30.79	5.44	2860.76	1.19	52.94	0.693	78.55	13.29	9.18	7.23
405.05	Clayton	26.80	5.80	32.60	9.45	2329.12	9.31	66.12	0.687	81.80	15.38	11.01	1.82
405.06	Clayton	24.97	10.97	35.94	9.41	2924.05	18.21	63.14	0.684	69.07	8.57	18.51	2.12
405.07	Clayton	19.92	5.72	25.64	5.81	2303.80	3.37	83.09	0.682	70.40	8.41	3.90	1.48
405.08	Clayton	24.47	2.20	26.67	5.81	2303.80	3.37	83.09	0.681	70.40	8.41	3.90	1.48
406.03	Clayton	15.74	6.95	22.68	4.07	2000.00	9.15	87.65	0.705	75.47	12.98	16.51	8.67
406.04	Clayton	23.57	18.29	41.86	13.19	2949.37	4.13	59.42	0.675	56.68	6.10	2.36	6.51
406.05	Clayton	9.79	6.33	16.13	7.70	2430.38	8.45	82.22	0.687	71.09	16.24	8.33	10.98
406.06	Clayton	2.56	5.99	8.56	5.02	746.84	9.47	69.14	0.739	54.30	1.99	4.33	20.08
406.07	Clayton	6.86	3.41	10.27	7.08	696.20	4.55	89.23	0.729	71.38	11.96	6.95	3.87
406.08	Clayton	n/a	n/a	n/a	n/a	1240.51	n/a	n/a	0.726	n/a	n/a	n/a	n/a
501.01	Gwinnett	2.47	3.89	6.36	13.31	3417.72	4.95	68.52	0.733	48.31	6.14	3.84	10.02
501.02	Gwinnett	5.45	7.34	12.79	13.31	3417.72	4.95	68.52	0.741	48.31	6.14	3.84	10.02
502.02	Gwinnett	1.85	5.47	7.32	9.65	1531.65	4.95	80.89	0.752	58.84	5.61	3.56	6.82
502.03	Gwinnett	n/a	n/a	n/a	n/a	1898.74	n/a	n/a	0.688	n/a	n/a	n/a	n/a
502.04	Gwinnett	n/a	n/a	n/a	n/a	1924.05	n/a	n/a	0.739	n/a	n/a	n/a	n/a
503.04	Gwinnett	20.09	36.96	57.06	5.79	1797.47	7.66	37.26	0.599	72.93	20.36	10.74	2.48

Census Tract	County	PLDU80	PHDU80	PURB80	PPOV80	POPDENS80	PUNOC80	POWNOC80	NDVI80	PHS80	PBCH80	PUMP80	PBLK80
503.05	Gwinnett	29.64	12.42	42.06	5.79	1797.47	7.66	37.26	0.648	72.93	20.36	10.74	2.48
503.06	Gwinnett	19.80	38.02	57.82	5.79	1797.47	7.66	37.26	0.569	72.93	20.36	10.74	2.48
503.07	Gwinnett	20.68	2.62	23.30	2.38	683.54	1.36	75.33	0.698	85.90	37.60	1.73	0.75
503.08	Gwinnett	9.98	7.60	17.57	2.38	683.54	1.36	75.33	0.711	85.90	37.60	1.73	0.75
503.09	Gwinnett	11.00	11.08	22.09	2.38	696.20	1.36	75.33	0.688	85.90	37.60	1.73	0.75
503.10	Gwinnett	24.92	19.07	43.99	2.38	696.20	1.36	75.33	0.645	85.90	37.60	1.73	0.75
503.11	Gwinnett	18.23	22.39	40.62	5.14	1518.99	5.01	58.35	0.657	75.07	16.72	4.77	2.91
503.12	Gwinnett	24.83	16.75	41.57	5.14	1531.65	5.01	58.35	0.635	75.07	16.72	4.77	2.91
503.13	Gwinnett	23.82	10.89	34.71	5.14	1518.99	5.01	58.35	0.656	75.07	16.72	4.77	2.91
503.14	Gwinnett	21.00	8.04	29.04	5.14	1518.99	5.01	58.35	0.673	75.07	16.72	4.77	2.91
504.03	Gwinnett	n/a	n/a	n/a	n/a	2367.09	n/a	n/a	0.696	n/a	n/a	n/a	n/a
504.06	Gwinnett	33.38	23.57	56.95	3.01	2556.96	8.11	40.49	0.617	80.99	19.75	3.69	0.86
504.07	Gwinnett	31.60	10.90	42.50	3.01	2556.96	8.11	40.49	0.646	80.99	19.75	3.69	0.86
504.08	Gwinnett	32.67	17.40	50.07	4.12	1417.72	17.00	74.85	0.601	73.24	14.00	4.68	0.28
504.09	Gwinnett	17.00	20.63	37.64	4.12	1405.06	17.00	74.85	0.630	73.24	14.00	4.68	0.28
504.10	Gwinnett	17.32	13.10	30.42	4.12	1417.72	17.00	74.85	0.681	73.24	14.00	4.68	0.28
504.11	Gwinnett	17.54	12.72	30.26	4.12	1405.06	17.00	74.85	0.676	73.24	14.00	4.68	0.28
504.12	Gwinnett	22.51	5.01	27.52	2.02	2670.89	8.76	92.67	0.684	87.51	28.02	7.56	0.11
504.13	Gwinnett	16.14	5.82	21.96	2.02	2658.23	8.76	92.67	0.694	87.51	28.02	7.56	0.11
504.14	Gwinnett	17.79	7.07	24.86	2.66	2493.67	3.82	90.12	0.686	80.13	20.40	1.43	0.06
504.15	Gwinnett	15.47	8.16	23.64	2.66	2481.01	3.82	90.12	0.698	80.13	20.40	1.43	0.06
504.16	Gwinnett	9.74	2.41	12.15	2.66	2481.01	3.82	90.12	0.732	80.13	20.40	1.43	0.06
505.02	Gwinnett	3.90	9.00	12.90	4.44	1746.84	4.39	80.83	0.738	64.79	8.49	4.81	4.40
505.03	Gwinnett	n/a	n/a	n/a	n/a	2886.08	n/a	n/a	0.733	n/a	n/a	n/a	n/a
505.05	Gwinnett	6.22	6.37	12.59	2.21	2784.81	7.48	89.97	0.721	76.91	12.68	5.85	0.17
505.06	Gwinnett	n/a	n/a	n/a	n/a	2493.67	n/a	n/a	0.703	n/a	n/a	n/a	n/a
505.07	Gwinnett	n/a	n/a	n/a	n/a	2493.67	n/a	n/a	0.714	n/a	n/a	n/a	n/a
505.08	Gwinnett	14.74	14.28	29.02	13.88	2632.91	6.95	60.98	0.684	54.83	11.68	6.68	6.32
505.09	Gwinnett	3.87	2.77	6.64	13.88	2607.60	6.95	60.98	0.722	54.83	11.68	6.68	6.32
506.01	Gwinnett	1.71	3.79	5.50	8.59	2063.29	16.84	82.80	0.740	52.71	5.41	10.42	4.36
506.02	Gwinnett	1.51	1.58	3.08	8.59	2063.29	16.84	82.80	0.734	52.71	5.41	10.42	4.36
507.04	Gwinnett	3.38	2.47	5.85	8.44	1329.11	4.96	87.74	0.706	67.98	14.97	3.73	2.75

Census Tract	County	PLDU80	PHDU80	PURB80	PPOV80	POPDENS80	PUNOC80	POWNOC80	NDVI80	PHS80	PBCH80	PUMP80	PBLK80
507.05	Gwinnett	3.59	3.46	7.05	6.40	1139.24	6.54	78.61	0.705	59.58	11.03	4.44	3.59
507.06	Gwinnett	8.79	6.79	15.57	1.66	2417.72	8.33	91.92	0.708	84.93	28.09	19.60	0.02
507.07	Gwinnett	12.88	6.89	19.77	1.66	2417.72	8.33	91.92	0.701	84.93	28.09	19.60	0.02
507.08	Gwinnett	9.93	6.19	16.12	5.44	1860.76	4.09	90.63	0.705	77.33	15.47	2.27	7.54
507.09	Gwinnett	3.48	4.06	7.54	5.44	1860.76	4.09	90.63	0.742	77.33	15.47	2.27	7.54
507.10	Gwinnett	12.65	8.83	21.48	2.44	2139.24	4.19	91.84	0.699	79.76	17.63	1.50	0.18
507.11	Gwinnett	14.13	5.85	19.98	2.44	2139.24	4.19	91.84	0.685	79.76	17.63	1.50	0.18
601.00	Rockdale	3.06	4.01	7.07	13.98	1683.55	3.51	83.39	0.723	58.69	4.19	5.14	2.93
602.00	Rockdale	6.21	5.05	11.25	6.47	2531.65	7.51	83.47	0.711	59.16	9.33	17.30	8.94
603.02	Rockdale	n/a	n/a	n/a	n/a	1291.14	n/a	n/a	0.704	n/a	n/a	n/a	n/a
603.03	Rockdale	11.19	7.70	18.89	11.07	2405.06	9.21	62.59	0.705	56.60	9.58	2.65	17.77
603.04	Rockdale	11.67	18.33	30.00	11.07	2405.06	9.21	62.59	0.656	56.60	9.58	2.65	17.77
604.01	Rockdale	3.86	3.82	7.68	3.99	2139.24	7.64	89.26	0.731	73.84	15.65	5.37	2.31
604.02	Rockdale	4.07	2.26	6.33	3.99	2139.24	7.64	89.26	0.726	73.84	15.65	5.37	2.31
701.02	Henry	3.14	4.32	7.46	8.01	1898.74	5.34	82.70	0.733	62.72	9.83	5.88	6.45
701.03	Henry	7.24	6.82	14.06	8.01	1898.74	5.34	82.70	0.719	62.72	9.83	5.88	6.45
701.98	Henry	3.58	6.28	9.86	8.01	1898.74	5.34	82.70	0.740	62.72	9.83	5.88	6.45
702.01	Henry	3.82	3.26	7.08	5.51	746.84	9.28	81.50	0.716	55.76	8.73	9.36	7.64
702.02	Henry	3.19	1.88	5.06	5.51	734.18	9.28	81.50	0.714	55.76	8.73	9.36	7.64
702.03	Henry	4.34	3.00	7.34	5.51	734.18	9.28	81.50	0.712	55.76	8.73	9.36	7.64
703.01	Henry	3.01	5.39	8.40	17.77	898.73	1.70	67.33	0.696	48.86	9.44	4.90	42.20
703.02	Henry	7.86	7.70	15.56	17.77	898.73	1.70	67.33	0.687	48.86	9.44	4.90	42.20
704.02	Henry	4.63	3.19	7.82	9.81	354.43	5.03	77.32	0.716	49.86	5.08	3.91	23.80
704.98	Henry	6.65	4.51	11.16	9.81	367.09	5.03	77.32	0.673	49.86	5.08	3.91	23.80
705.00	Henry	3.92	4.94	8.87	12.08	822.79	7.31	75.64	0.701	54.76	7.57	5.39	16.61
801.98	Douglas	n/a	n/a	n/a	n/a	2974.68	n/a	n/a	0.749	n/a	n/a	n/a	n/a
802.00	Douglas	10.28	5.99	16.27	6.78	2683.55	4.98	79.70	0.718	56.64	6.16	2.56	0.78
803.00	Douglas	11.40	10.09	21.49	14.98	2329.12	5.34	60.71	0.709	48.10	5.81	4.83	16.54
804.00	Douglas	2.15	3.62	5.76	8.67	1379.75	8.10	81.20	0.756	45.17	6.04	8.84	9.76
805.01	Douglas	6.13	3.60	9.73	4.54	2670.89	17.63	86.30	0.746	71.28	10.14	3.95	1.33
805.03	Douglas	13.00	5.44	18.44	3.79	2810.13	1.64	89.95	0.735	75.48	12.39	3.03	1.73
805.04	Douglas	2.51	2.31	4.82	3.79	2810.13	1.64	89.95	0.777	75.48	12.39	3.03	1.73

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806.01	Douglas	3.91	3.99	7.91	5.86	2544.31	14.00	85.51	0.757	60.50	8.22	14.15	0.80
806.02	Douglas	3.11	4.11	7.21	5.86	2544.31	14.00	85.51	0.781	60.50	8.22	14.15	0.80
901.00	Cherokee	0.58	1.13	1.72	12.66	3265.82	3.74	75.70	0.783	38.10	7.22	2.01	1.23
902.00	Cherokee	0.38	1.41	1.79	18.09	2911.39	9.05	69.21	0.807	51.49	7.45	4.91	0.36
903.00	Cherokee	0.21	1.62	1.83	10.46	5898.74	2.79	85.92	0.738	48.71	4.94	3.08	0.00
904.00	Cherokee	1.43	4.09	5.52	15.84	5189.88	4.60	72.14	0.774	36.04	4.16	3.77	16.42
905.00	Cherokee	0.55	3.16	3.71	10.35	4721.52	6.12	79.58	0.772	42.38	5.96	13.95	0.02
906.00	Cherokee	2.27	5.44	7.71	14.70	4696.20	13.25	68.47	0.762	44.29	8.90	10.15	4.08
907.00	Cherokee	1.84	4.66	6.50	7.65	3746.84	7.45	76.12	0.725	51.46	6.44	3.50	0.08
908.00	Cherokee	0.93	2.50	3.44	6.30	5481.02	3.80	83.24	0.758	62.26	10.94	3.18	0.02
909.01	Cherokee	2.37	0.12	2.49	6.11	3924.05	6.38	85.94	0.752	65.06	12.46	4.29	2.09
909.02	Cherokee	2.40	3.31	5.71	6.11	3924.05	6.38	85.94	0.752	65.06	12.46	4.29	2.09
909.03	Cherokee	4.34	3.90	8.24	6.11	3924.05	6.38	85.94	0.743	65.06	12.46	4.29	2.09
910.01	Cherokee	3.93	9.15	13.08	9.77	3721.52	17.11	78.24	0.748	64.72	11.17	8.38	1.02
910.02	Cherokee	1.88	5.10	6.98	9.77	3734.18	17.11	78.24	0.763	64.72	11.17	8.38	1.02
910.03	Cherokee	9.73	10.58	20.31	9.77	3721.52	17.11	78.24	0.708	64.72	11.17	8.38	1.02
911.01	Cherokee	2.31	1.00	3.31	10.31	4278.48	20.39	76.59	0.603	63.63	8.56	14.27	0.30
911.03	Cherokee	1.96	3.48	5.44	10.31	4278.48	20.39	76.59	0.698	63.63	8.56	14.27	0.30
911.98	Cherokee	5.66	4.63	10.29	10.31	4278.48	20.39	76.59	0.752	63.63	8.56	14.27	0.30
1201.00	Paulding	0.56	1.15	1.72	14.52	2278.48	5.22	81.28	0.785	45.70	1.92	4.20	0.03
1202.00	Paulding	n/a	n/a	n/a	n/a	3734.18	n/a	n/a	0.751	n/a	n/a	n/a	n/a
1203.00	Paulding	2.01	4.51	6.52	9.60	3341.77	5.64	67.23	0.755	46.82	5.59	3.43	5.80
1204.00	Paulding	0.71	1.95	2.66	12.68	2075.95	9.97	76.74	0.784	35.70	3.51	3.97	11.02
1205.00	Paulding	2.05	3.40	5.45	14.15	3202.53	3.13	84.46	0.744	45.09	4.88	4.07	6.51
1206.98	Paulding	1.25	2.49	3.74	13.16	3721.52	3.40	83.08	0.745	44.34	3.34	3.68	0.86
1301.00	Forsyth	1.64	4.20	5.84	9.42	2088.61	2.97	67.55	0.682	50.98	8.23	1.70	0.03
1302.00	Forsyth	1.23	5.12	6.34	16.06	2329.12	3.66	78.91	0.748	44.75	4.89	3.35	0.00
1303.00	Forsyth	1.22	4.72	5.94	8.34	3468.36	5.85	81.66	0.748	50.92	3.91	4.95	0.00
1304.00	Forsyth	2.24	7.87	10.11	11.64	3607.60	5.92	71.01	0.744	50.46	9.22	20.62	0.00
1305.00	Forsyth	1.67	3.95	5.62	8.43	2506.33	4.54	62.40	0.571	68.53	14.14	3.28	0.00
1306.00	Forsyth	1.34	5.04	6.38	11.04	3303.80	7.13	74.25	0.752	47.84	4.70	5.56	0.00
1401.01	Fayette	4.70	3.90	8.60	4.38	1658.23	5.76	88.73	0.724	74.43	17.26	23.81	1.98

Census Tract	County	PLDU80	PHDU80	PURB80	PPOV80	POPDENS80	PUNOC80	POWNOC80	NDVI80	PHS80	PBCH80	PUMP80	PBLK80
1401.02	Fayette	5.64	4.39	10.03	4.38	1658.23	5.76	88.73	0.716	74.43	17.26	23.81	1.98
1402.01	Fayette	2.69	2.16	4.85	5.54	1417.72	11.99	84.44	0.719	69.11	12.99	9.15	3.63
1402.02	Fayette	5.58	3.58	9.16	5.54	1417.72	11.99	84.44	0.734	69.11	12.99	9.15	3.63
1403.01	Fayette	9.51	3.11	12.62	3.50	911.39	7.39	77.43	0.719	82.72	21.06	2.36	2.82
1403.02	Fayette	3.35	3.66	7.01	3.50	911.39	7.39	77.43	0.730	82.72	21.06	2.36	2.82
1404.01	Fayette	5.50	4.29	9.79	6.15	1493.67	11.95	83.27	0.715	72.56	14.02	10.99	7.19
1404.02	Fayette	4.97	2.92	7.89	6.15	1493.67	11.95	83.27	0.723	72.56	14.02	10.99	7.19
1405.01	Fayette	2.50	2.12	4.62	7.74	810.13	10.66	83.71	0.729	63.99	7.30	5.13	6.28
1405.02	Fayette	2.69	2.19	4.88	7.74	810.13	10.66	83.71	0.715	63.99	7.30	5.13	6.28
1701.00	Coweta	2.97	1.41	4.38	14.30	746.84	5.11	76.11	0.738	48.73	7.75	4.36	23.07
1702.00	Coweta	7.65	4.25	11.90	11.79	1670.89	11.16	74.42	0.724	54.20	12.69	11.76	15.50
1703.00	Coweta	3.23	3.77	7.00	13.32	1632.91	15.84	99.09	0.747	72.27	17.56	16.71	12.67
1704.00	Coweta	2.51	3.84	6.34	15.25	544.30	5.51	73.19	0.741	49.69	6.84	8.56	24.18
1705.00	Coweta	4.19	2.83	7.02	15.25	531.65	5.51	73.19	0.716	49.69	6.84	8.56	24.18
1706.00	Coweta	4.57	3.99	8.57	27.24	2240.51	0.00	56.06	0.736	44.33	8.08	0.00	42.78
1707.00	Coweta	6.63	1.78	8.41	19.73	1392.41	6.58	68.49	0.735	49.44	9.23	6.89	43.94
1708.00	Coweta	n/a	n/a	n/a	n/a	873.42	n/a	n/a	0.743	n/a	n/a	n/a	n/a

Table E.2. Sociodemographic variables, metropolitan Atlanta, Georgia, 1990.

Census Tract	County	PLDU90	PHDU90	PURB90	PPOV90	POPDENS90	PUNOC90	POWNOC90	NDVI90	PHS90	PBCH90	PUMP90	MEDHHI90	PBLK90	MEDHSVL90
1.00	Fulton	35.08	12.92	48.00	5.00	3444.44	6.87	57.96	0.776	96.40	68.80	2.50	60763	0.41	184200
2.00	Fulton	37.54	20.48	58.02	5.70	4422.22	8.78	43.20	0.737	94.50	58.60	4.80	42127	4.71	162300
4.00	Fulton	23.17	26.83	50.00	13.00	4066.66	16.88	16.37	0.709	95.60	71.80	3.40	40417	7.82	500001
5.00	Fulton	22.36	47.73	70.09	5.00	3466.66	24.90	32.43	0.681	93.90	61.50	4.00	45300	7.28	262900
7.00	Fulton	25.71	58.86	84.57	15.00	7744.43	14.07	46.18	0.632	51.00	7.10	2.10	20000	81.60	37200
8.00	Fulton	31.31	58.59	89.90	44.90	4888.88	33.74	10.40	0.646	34.20	0.80	13.90	10318	98.92	23400
10.95	Fulton	18.73	68.16	86.89	40.40	12922.21	11.95	9.76	0.605	84.60	48.20	5.40	14929	12.00	94700
11.00	Fulton	29.17	60.42	89.58	18.50	10188.88	20.35	2.71	0.619	87.90	40.70	8.90	20824	27.44	105100
12.00	Fulton	29.09	63.64	92.73	12.70	9799.99	21.73	3.13	0.615	90.90	42.10	4.10	20979	24.63	169300
13.00	Fulton	25.95	54.96	80.92	20.70	9977.76	15.68	13.39	0.666	83.10	42.60	4.90	26939	26.28	137500
14.00	Fulton	43.04	27.85	70.89	12.50	5499.99	9.90	16.66	0.704	93.60	52.70	6.20	24049	17.93	132700
15.00	Fulton	47.75	27.03	74.77	11.20	7344.43	11.19	15.93	0.698	87.50	57.40	4.60	24494	13.77	143100
17.00	Fulton	30.00	60.00	90.00	44.50	7499.99	19.90	14.61	0.645	44.50	5.10	10.00	9849	89.42	46900
18.00	Fulton	23.91	65.22	89.13	40.30	11255.54	15.86	7.36	0.618	63.70	26.00	12.80	12967	79.66	99500
19.00	Fulton	1.11	96.67	97.78	46.80	61499.92	50.51	1.28	0.504	95.40	10.80	2.20	23672	72.74	67500
20.00	Fulton	54.55	45.45	100.00	88.00	20199.97	20.99	0.00	0.613	23.80	1.30	28.10	4999	94.16	0
21.00	Fulton	17.86	79.76	97.62	69.90	18044.42	7.22	0.00	0.567	38.10	5.60	24.90	4999	83.61	0
22.00	Fulton	29.63	62.96	92.59	78.50	7644.43	13.37	4.89	0.612	40.30	1.80	25.10	4999	99.62	16900
23.00	Fulton	45.61	36.84	82.46	32.50	5566.66	26.07	18.70	0.702	58.40	5.10	13.50	15413	99.69	33400
24.00	Fulton	51.85	19.26	71.11	21.30	3577.77	28.93	31.50	0.729	57.60	10.00	12.00	15717	99.72	44800
25.00	Fulton	44.32	46.59	90.91	58.10	9899.99	21.62	9.56	0.691	50.20	2.70	19.40	7073	99.28	37600
26.00	Fulton	25.00	53.26	78.26	48.60	3877.77	29.06	10.52	0.602	34.50	1.20	19.90	8496	98.28	22200
27.00	Fulton	0.00	96.63	96.63	15.80	34466.62	0.00	0.00	0.492	100.00	24.00	14.40	21250	43.72	0
28.00	Fulton	5.19	94.81	100.00	47.60	47755.49	13.51	0.62	0.550	58.20	11.90	4.80	8257	93.78	55000
29.00	Fulton	28.38	60.81	89.19	45.90	6022.21	30.05	12.82	0.632	22.10	2.00	24.00	8636	96.67	36100
30.00	Fulton	36.89	34.43	71.31	4.10	3700.00	9.87	29.60	0.682	94.70	57.30	2.90	33365	11.81	117100
31.00	Fulton	54.88	26.83	81.71	26.40	3922.22	18.99	25.70	0.692	48.30	6.20	12.90	16221	96.17	32800
32.00	Fulton	38.46	51.92	90.38	35.30	3100.00	23.39	26.76	0.626	33.90	5.80	4.00	15000	29.91	34000
33.00	Fulton	17.81	78.08	95.89	64.10	18133.31	11.20	1.58	0.567	36.60	5.50	21.40	4999	97.38	37100
35.00	Fulton	2.74	95.21	97.95	78.00	26355.52	82.57	0.00	0.518	45.70	12.10	0.00	5632	90.16	0

Census Tract	County	PLDU90	PHDU90	PURB90	PPOV90	POPDENS90	PUNOC90	POWNOC90	NDVI90	PHS90	PBCH90	PUMP90	MEDHHI90	PBLK90	MEDHSVL90
36.00	Fulton	17.50	72.50	90.00	30.50	9133.32	5.98	1.14	0.605	66.70	22.70	8.70	8712	91.81	47500
37.00	Fulton	50.00	50.00	100.00	85.30	6799.99	72.81	0.00	0.619	28.00	0.00	41.00	4999	94.87	0
38.00	Fulton	41.77	44.30	86.08	44.60	8166.66	19.63	13.70	0.674	53.00	17.90	33.20	8953	99.66	20000
39.00	Fulton	57.47	22.99	80.46	38.10	4733.33	13.69	28.99	0.716	59.70	15.30	10.90	13125	97.82	35600
40.00	Fulton	48.15	29.63	77.78	27.40	3333.33	7.79	62.65	0.731	62.30	21.90	12.20	16637	98.53	52000
41.00	Fulton	46.09	33.04	79.13	23.60	4677.77	19.14	29.26	0.722	64.00	19.70	13.20	21640	97.67	48900
42.95	Fulton	31.25	54.69	85.94	54.60	6188.88	7.01	9.32	0.650	51.90	11.80	17.30	7003	95.45	65500
44.00	Fulton	21.84	68.97	90.80	75.30	10833.32	15.65	5.63	0.621	38.70	2.20	19.80	4999	96.19	25000
46.95	Fulton	11.30	83.48	94.78	64.60	9722.21	20.57	3.51	0.598	37.60	1.90	24.00	7735	98.48	41300
48.00	Fulton	21.05	71.05	92.11	69.20	24477.75	7.85	1.18	0.619	38.00	3.30	33.30	5136	98.43	61500
49.95	Fulton	33.63	52.21	85.84	37.70	5344.44	14.41	35.70	0.684	66.40	32.00	8.10	22143	56.36	85500
50.00	Fulton	34.31	46.72	81.02	17.70	3588.88	22.92	32.42	0.654	58.80	22.40	2.10	23355	20.44	71200
52.00	Fulton	36.71	20.25	56.96	29.10	4266.66	9.51	47.89	0.742	61.50	21.80	8.70	20067	49.41	58100
53.00	Fulton	44.24	16.59	60.83	27.40	3200.00	12.11	47.76	0.752	62.20	22.80	11.80	24811	62.71	63100
55.01	Fulton	51.67	20.83	72.50	51.10	4277.77	30.89	19.47	0.726	42.90	3.60	14.20	11223	92.88	38300
55.02	Fulton	43.79	31.95	75.74	69.30	4822.22	16.17	9.93	0.693	48.80	3.50	22.40	5209	96.65	35800
56.00	Fulton	26.73	60.40	87.13	58.00	5988.88	25.28	10.19	0.666	30.50	0.50	17.60	6763	94.35	35700
57.00	Fulton	39.06	53.13	92.19	48.20	5699.99	16.69	18.33	0.654	42.30	0.80	13.60	10272	95.59	23500
58.00	Fulton	34.17	50.00	84.17	34.20	4077.77	20.06	33.89	0.653	50.50	12.00	14.40	16229	92.10	45300
60.00	Fulton	42.86	20.24	63.10	26.70	5977.77	8.79	41.97	0.736	59.50	13.30	12.60	19399	98.70	49700
61.00	Fulton	34.70	12.33	47.03	17.30	6077.77	7.49	63.51	0.788	66.10	12.50	10.40	23293	97.23	49200
62.00	Fulton	39.42	35.58	75.00	34.20	4299.99	12.61	35.61	0.708	50.80	7.40	14.30	18875	92.82	41900
63.00	Fulton	36.67	50.00	86.67	40.40	3899.99	19.05	28.92	0.660	41.80	2.40	15.80	9956	99.68	33000
64.00	Fulton	30.40	36.80	67.20	51.00	7699.99	7.70	9.71	0.684	28.70	0.40	18.00	11250	57.25	39700
65.00	Fulton	40.92	25.54	66.46	18.20	3544.44	11.74	54.26	0.724	66.40	12.00	12.20	23547	84.39	52900
66.01	Fulton	35.16	37.91	73.08	26.80	3633.33	9.56	53.75	0.689	56.50	17.70	11.40	19432	69.08	49600
66.02	Fulton	29.85	34.33	64.18	33.70	7133.32	11.51	24.64	0.739	57.50	4.80	10.00	16220	93.18	42500
67.00	Fulton	32.20	33.90	66.10	38.70	3722.22	20.46	28.56	0.714	49.90	4.50	12.60	14661	85.31	37300
68.02	Fulton	33.33	17.33	50.67	67.90	8055.55	3.99	10.94	0.748	48.00	1.50	20.00	5701	97.46	47800
69.00	Fulton	26.60	18.59	45.19	20.60	4311.11	9.45	37.94	0.779	52.10	10.30	9.80	22272	59.04	43000
70.00	Fulton	22.34	19.95	42.29	29.40	4622.22	8.48	45.37	0.769	60.70	4.20	12.60	22689	82.77	47600
71.00	Fulton	41.57	21.72	63.30	53.80	3999.99	5.27	38.73	0.726	47.90	3.50	22.30	12925	98.74	42700

Census Tract	County	PLDU90	PHDU90	PURB90	PPOV90	POPDENS90	PUNOC90	POWNOC90	NDVI90	PHS90	PBCH90	PUMP90	MEDHHI90	PBLK90	MEDHSVL90
72.00	Fulton	14.22	22.49	36.71	42.40	2988.89	18.80	29.30	0.764	62.40	7.20	13.20	16136	96.16	54700
73.00	Fulton	16.27	23.75	40.03	30.50	5422.22	10.48	33.18	0.772	61.90	7.90	9.10	19770	92.77	51700
74.00	Fulton	24.23	34.36	58.59	21.10	5822.21	13.74	21.11	0.722	59.40	4.90	17.10	20435	65.99	44200
75.00	Fulton	25.44	39.05	64.50	17.60	4244.44	6.30	31.45	0.700	52.70	6.40	4.60	15717	58.73	54400
76.01	Fulton	22.99	31.03	54.02	21.30	7199.99	15.05	8.54	0.738	75.40	13.60	11.20	18652	87.96	61700
76.02	Fulton	16.96	5.65	22.62	16.80	4955.55	9.13	46.41	0.817	81.50	20.10	12.90	30027	98.31	64300
77.01	Fulton	15.07	18.94	34.01	20.70	4433.33	26.47	35.05	0.795	79.10	23.10	8.70	28726	96.83	74100
77.02	Fulton	12.12	15.19	27.31	13.70	3433.33	12.84	32.34	0.791	78.20	20.80	8.30	23558	95.45	69300
78.02	Fulton	12.41	5.55	17.96	26.20	3188.88	14.26	52.91	0.818	80.50	22.40	12.00	30574	93.22	79900
78.03	Fulton	17.52	27.59	45.11	14.80	2288.89	11.63	48.06	0.733	75.70	14.70	9.50	28630	97.35	67300
78.04	Fulton	25.71	30.33	56.04	38.30	6888.88	19.71	20.32	0.752	62.60	4.80	13.10	15628	99.19	53300
79.00	Fulton	17.35	12.13	29.48	6.20	2888.89	5.37	79.13	0.809	85.00	39.10	5.30	44505	98.23	91100
80.00	Fulton	18.56	7.21	25.77	9.10	6055.55	6.41	66.68	0.815	74.20	15.70	5.90	32393	97.13	57100
81.01	Fulton	22.73	0.00	22.73	9.60	5999.99	5.29	78.19	0.821	76.90	11.10	12.30	31650	98.96	59300
81.02	Fulton	21.36	15.78	37.14	20.50	4055.55	16.89	25.18	0.770	71.20	18.60	9.70	20588	99.62	71400
82.01	Fulton	34.03	11.41	45.44	14.40	3388.88	6.13	64.58	0.775	75.70	27.90	6.70	27634	99.65	70200
82.02	Fulton	17.09	21.37	38.46	35.50	3222.22	24.18	34.97	0.737	54.50	6.50	12.20	17310	99.84	49700
83.01	Fulton	32.18	16.86	49.04	30.30	4577.77	12.04	35.54	0.771	57.60	9.70	12.30	15426	100.00	43600
83.02	Fulton	36.65	19.90	56.54	35.20	4133.33	30.88	36.21	0.768	55.50	11.00	10.10	14699	99.17	45400
84.00	Fulton	37.10	26.34	63.44	33.80	6788.88	25.67	23.83	0.733	46.60	9.80	12.70	16891	99.10	43000
85.00	Fulton	20.27	19.46	39.73	26.90	6111.10	14.04	39.50	0.779	57.70	7.10	10.40	16757	99.21	41500
86.01	Fulton	23.86	14.97	38.83	36.50	5277.77	12.82	34.70	0.798	49.30	2.90	12.10	16262	97.88	40900
86.02	Fulton	16.70	31.45	48.16	67.40	4344.44	9.23	13.98	0.720	42.20	1.00	23.10	4999	99.73	43700
87.01	Fulton	20.69	34.22	54.91	86.50	3566.66	25.04	3.29	0.701	35.90	0.00	32.10	4999	98.83	37000
87.02	Fulton	28.22	19.46	47.69	46.50	3711.11	11.19	34.26	0.739	49.40	2.50	15.10	9884	98.33	43000
88.00	Fulton	19.63	36.69	56.32	30.30	1433.33	15.31	44.13	0.688	43.90	9.90	11.70	20380	37.58	47100
89.00	Fulton	23.65	40.04	63.68	17.50	3666.66	20.39	25.09	0.678	87.50	51.20	3.70	32202	18.08	98500
90.00	Fulton	13.55	23.80	37.35	9.50	7711.10	8.96	54.83	0.788	94.70	65.70	1.20	45691	6.05	184300
91.00	Fulton	23.88	27.16	51.04	9.60	7722.21	15.70	11.79	0.724	92.40	58.60	1.90	31007	11.87	274200
92.00	Fulton	25.64	51.28	76.92	15.70	3333.33	15.72	30.07	0.662	88.80	46.20	6.00	30149	18.01	130600
93.00	Fulton	25.20	19.60	44.80	6.70	7266.66	9.03	32.23	0.767	95.50	58.10	3.90	38347	7.22	172400
94.01	Fulton	23.71	17.53	41.24	6.50	4955.55	14.78	20.70	0.734	94.30	56.90	4.20	46760	4.84	163800

Census Tract	County	PLDU90	PHDU90	PURB90	PPOV90	POPDENS90	PUNOC90	POWNOC90	NDVI90	PHS90	PBCH90	PUMP90	MEDHHI90	PBLK90	MEDHSVL90
94.02	Fulton	22.42	58.18	80.61	17.10	7777.77	5.85	0.40	0.621	73.10	28.50	5.90	22500	22.70	187500
95.00	Fulton	12.98	14.22	27.20	4.10	8277.77	16.50	29.42	0.790	95.00	58.00	3.30	49103	1.01	500001
96.00	Fulton	21.60	36.58	58.17	11.20	6533.32	14.80	19.41	0.697	94.40	51.50	3.20	30115	7.73	191100
97.00	Fulton	11.06	6.67	17.73	0.80	2544.44	5.41	82.27	0.808	98.80	65.60	1.50	120191	0.72	365800
98.00	Fulton	11.80	14.08	25.88	2.30	3455.55	4.94	70.18	0.804	95.60	64.70	2.00	93421	0.84	365400
99.00	Fulton	12.13	14.12	26.25	2.10	3988.88	13.97	56.47	0.804	97.10	70.10	2.80	79034	1.89	308400
100.00	Fulton	10.81	12.44	23.25	4.90	6411.10	6.96	56.08	0.786	95.70	60.80	2.90	60675	2.04	202600
101.01	Fulton	17.43	21.94	39.38	8.40	4266.66	13.03	41.66	0.766	94.40	52.10	5.80	40630	9.92	187700
101.03	Fulton	15.48	28.42	43.90	3.80	4611.11	19.12	29.07	0.756	94.80	49.50	2.80	42395	4.32	166500
101.05	Fulton	22.39	25.72	48.11	6.20	6922.21	14.03	8.95	0.727	96.80	38.60	3.40	34121	16.00	99100
101.06	Fulton	12.55	8.42	20.97	2.00	3800.00	10.00	42.26	0.809	95.60	55.50	1.60	51660	4.07	285500
101.07	Fulton	14.49	2.72	17.21	0.00	2122.22	5.00	83.50	0.805	97.80	61.80	1.50	150001	0.00	432500
101.08	Fulton	28.05	13.15	41.20	1.60	2188.89	3.71	89.36	0.789	99.40	66.60	4.60	104854	2.53	318200
102.01	Fulton	12.90	11.09	23.99	5.80	3922.22	9.14	48.64	0.808	95.90	57.80	2.40	51424	8.56	300600
102.03	Fulton	14.59	7.13	21.72	5.70	5333.33	12.05	22.61	0.755	96.00	57.10	2.90	40946	9.05	254100
102.04	Fulton	14.33	12.77	27.10	1.80	3733.33	2.99	88.03	0.787	98.30	65.40	2.20	110323	0.14	303400
102.05	Fulton	16.64	19.76	36.40	4.10	4055.55	5.87	60.89	0.778	92.80	51.80	4.40	57308	4.32	174200
103.01	Fulton	3.48	4.71	8.19	6.40	1011.11	7.18	61.54	0.834	74.80	11.60	5.60	45409	19.36	86400
103.02	Fulton	7.28	12.14	19.43	12.60	1644.44	7.52	69.72	0.798	83.70	31.30	8.20	43690	79.60	87300
104.00	Fulton	4.19	2.28	6.47	8.90	700.00	5.90	54.41	0.829	62.20	9.10	4.40	31641	20.23	74000
105.03	Fulton	25.61	19.91	45.52	7.10	3277.77	10.53	42.21	0.758	84.10	21.60	6.50	32326	86.89	72500
105.04	Fulton	12.19	8.30	20.49	5.40	2066.66	7.68	60.00	0.805	86.20	23.10	5.10	36980	75.76	78500
105.05	Fulton	14.38	14.53	28.91	10.60	2444.44	12.76	35.14	0.787	84.80	23.20	8.00	31895	74.95	72000
105.06	Fulton	8.42	7.29	15.71	9.90	1633.33	7.94	53.58	0.811	70.30	10.20	5.50	30164	30.57	74500
106.01	Fulton	28.80	13.92	42.72	34.00	3844.44	15.61	33.68	0.776	67.00	19.40	5.60	17781	56.94	64700
106.02	Fulton	18.37	27.42	45.79	21.50	4944.44	24.15	12.81	0.752	77.30	16.30	9.80	23722	86.88	83900
107.00	Fulton	23.11	58.82	81.93	20.10	4433.33	13.02	24.41	0.696	62.10	12.80	6.30	20417	36.30	50400
108.00	Fulton	14.20	66.06	80.26	11.80	4644.44	11.27	41.16	0.654	58.10	12.90	8.50	24865	10.40	54600
109.00	Fulton	11.03	79.31	90.34	31.50	4444.44	14.05	32.03	0.606	39.10	1.30	10.70	17330	23.33	53500
110.00	Fulton	36.73	29.45	66.18	36.30	3933.33	13.80	26.96	0.696	51.60	3.40	16.90	15642	77.37	48700
111.00	Fulton	26.38	46.38	72.75	9.90	2977.77	9.49	58.76	0.675	62.10	11.60	6.10	26978	31.50	57600
112.01	Fulton	29.21	32.63	61.84	34.10	4833.33	14.36	27.99	0.716	59.90	8.80	12.30	18027	69.46	50600

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112.02	Fulton	40.47	20.07	60.54	16.20	3822.22	11.93	42.78	0.739	66.20	11.20	9.40	23097	40.41	53300
113.01	Fulton	26.92	6.88	33.81	4.10	3977.77	4.54	80.20	0.796	82.30	27.30	4.90	38661	65.32	68800
113.02	Fulton	17.83	14.19	32.02	13.30	4799.99	19.65	29.24	0.799	85.10	26.00	7.10	30607	84.11	82000
114.03	Fulton	19.51	10.42	29.93	4.30	2133.33	9.88	72.54	0.803	93.20	42.20	2.50	61686	0.47	148500
114.04	Fulton	23.44	25.35	48.78	6.00	5022.22	15.01	13.60	0.723	93.50	32.90	2.70	32753	12.88	85000
114.05	Fulton	20.72	13.68	34.40	8.90	2566.66	8.33	40.97	0.774	80.50	33.50	3.80	32766	10.74	110000
114.06	Fulton	18.08	9.95	28.04	2.90	3000.00	11.74	48.09	0.772	94.20	44.60	2.60	51200	6.04	135100
114.07	Fulton	18.04	5.04	23.08	2.30	2266.66	4.97	77.12	0.805	87.60	43.50	1.60	57080	2.29	134900
114.08	Fulton	24.68	10.73	35.42	2.10	2933.33	5.29	70.23	0.781	95.90	52.80	2.20	57426	3.04	122000
114.09	Fulton	20.37	7.01	27.38	2.70	2200.00	10.03	44.77	0.786	97.20	53.90	3.00	54478	2.57	200200
114.10	Fulton	19.54	6.22	25.76	1.90	2700.00	11.45	54.66	0.778	96.30	53.80	3.20	67278	3.14	199900
114.11	Fulton	21.31	7.06	28.37	0.40	4288.88	17.63	61.54	0.772	95.70	54.30	3.20	63081	3.69	140300
115.00	Fulton	7.16	2.62	9.78	3.40	1400.00	6.06	72.91	0.834	87.60	42.50	3.30	66438	0.99	196700
116.01	Fulton	10.33	8.94	19.27	4.20	1766.66	7.68	58.87	0.806	86.80	33.50	1.90	44173	1.97	113200
116.02	Fulton	13.03	9.41	22.44	2.70	1644.44	9.68	51.26	0.801	94.20	45.10	2.40	51064	2.80	138600
116.03	Fulton	14.49	6.52	21.01	2.00	1088.89	8.76	79.79	0.799	96.30	54.70	2.40	72282	0.74	208100
201.00	DeKalb	31.91	7.45	39.36	6.10	4488.88	4.29	75.49	0.780	94.70	68.00	0.90	58342	4.48	198100
202.00	DeKalb	17.83	16.56	34.39	7.20	7677.77	10.99	26.33	0.796	94.50	68.00	2.90	40714	11.86	181500
203.00	DeKalb	31.94	10.47	42.41	13.20	5033.33	5.43	54.39	0.778	86.80	56.00	5.40	37234	15.88	113100
204.00	DeKalb	12.59	9.06	21.65	16.60	11266.65	10.89	28.68	0.745	88.90	52.90	6.30	28438	17.05	103700
205.00	DeKalb	46.24	19.08	65.32	37.30	4288.88	18.86	34.97	0.737	52.50	5.00	19.20	14663	98.43	40700
206.00	DeKalb	42.86	28.57	71.43	47.10	4511.11	10.89	16.02	0.693	51.70	6.80	18.30	11809	97.66	34000
207.00	DeKalb	45.31	15.63	60.94	26.40	4511.11	20.47	35.89	0.738	54.20	5.90	10.50	19496	96.81	41700
208.00	DeKalb	31.45	16.46	47.91	43.10	7399.99	11.78	43.42	0.779	44.50	6.60	18.00	13494	95.90	48200
209.00	DeKalb	31.54	29.21	60.75	26.00	5444.44	9.75	50.38	0.758	56.90	7.40	11.30	20560	88.77	47100
211.00	DeKalb	22.53	10.04	32.57	15.20	4333.33	7.84	47.14	0.779	87.70	47.00	5.30	41448	19.00	179900
212.02	DeKalb	17.71	13.08	30.79	3.10	4122.22	5.22	73.01	0.791	96.90	54.60	2.70	66833	1.21	161600
212.04	DeKalb	17.01	48.28	65.29	35.40	5555.55	14.54	10.84	0.633	48.80	12.10	14.30	20573	24.31	73000
212.05	DeKalb	27.83	10.85	38.68	0.40	3644.44	2.52	87.59	0.782	97.10	63.10	3.20	84862	0.56	213700
212.07	DeKalb	16.59	26.41	43.00	2.20	2411.11	19.50	58.06	0.745	94.10	55.90	2.10	65812	0.61	163800
212.08	DeKalb	21.45	43.45	64.90	7.70	3200.00	6.80	68.63	0.691	84.70	35.60	6.20	43269	2.11	101800
212.09	DeKalb	17.68	19.16	36.84	15.40	5588.88	9.15	29.06	0.773	85.40	41.80	3.00	30393	13.69	112900

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212.10	DeKalb	28.73	10.91	39.63	1.60	2888.89	1.45	87.59	0.781	96.30	58.00	3.80	72834	1.02	172100
212.11	DeKalb	26.28	7.31	33.60	1.50	3244.44	6.49	82.92	0.782	93.90	50.70	1.50	68008	0.65	147900
212.12	DeKalb	24.25	24.46	48.71	1.90	4622.22	12.68	33.09	0.742	91.00	42.90	2.40	41051	9.94	148100
213.01	DeKalb	16.44	60.38	76.82	11.30	4411.11	14.81	17.16	0.638	77.00	23.70	5.40	30408	26.19	72900
213.02	DeKalb	30.72	28.96	59.68	8.60	3366.66	11.57	50.27	0.737	84.90	30.60	4.40	36016	14.95	85100
213.03	DeKalb	25.42	43.64	69.07	5.50	3855.55	6.91	34.65	0.673	81.00	20.70	5.60	31338	17.73	80900
213.04	DeKalb	17.12	33.07	50.19	8.50	5933.33	15.27	22.20	0.691	91.40	36.60	3.70	34023	25.04	88600
214.01	DeKalb	31.98	25.66	57.64	16.70	4777.77	14.33	16.49	0.703	80.80	34.30	5.30	28112	30.75	116200
214.02	DeKalb	30.22	16.67	46.89	12.80	6544.44	13.80	20.12	0.747	85.50	35.80	4.80	29559	22.31	85400
214.03	DeKalb	31.34	18.56	49.90	4.70	3455.55	9.22	50.78	0.751	83.20	24.90	3.30	32705	4.47	80300
214.04	DeKalb	22.05	23.36	45.41	10.30	6755.55	16.44	23.49	0.731	90.40	33.00	6.50	30888	40.80	89600
215.00	DeKalb	24.53	19.14	43.67	7.90	4566.66	16.49	30.73	0.751	93.10	51.20	3.70	36276	8.81	130400
216.01	DeKalb	20.14	13.33	33.48	8.70	5422.22	9.52	56.01	0.783	92.40	48.20	3.70	44990	13.83	142900
216.02	DeKalb	18.65	12.22	30.87	1.70	5899.99	5.58	53.64	0.786	93.70	50.30	2.60	46888	0.99	128000
216.03	DeKalb	24.53	29.60	54.13	7.40	4322.22	17.52	29.81	0.733	91.20	50.80	2.90	34069	4.50	110800
217.02	DeKalb	19.49	24.09	43.58	4.70	4533.33	6.98	39.93	0.754	95.00	47.10	2.60	43253	7.27	147800
217.03	DeKalb	16.82	11.91	28.73	1.50	4744.44	1.33	88.32	0.795	96.90	54.60	2.50	64176	0.76	161900
217.04	DeKalb	23.84	25.34	49.18	4.10	2722.22	4.48	63.33	0.736	88.60	45.90	3.40	42436	6.09	118300
218.05	DeKalb	33.60	11.09	44.69	5.30	2977.77	4.62	64.12	0.768	85.50	31.40	3.80	43322	8.06	93600
218.06	DeKalb	17.41	29.29	46.70	4.80	2533.33	11.47	48.60	0.726	84.60	29.90	3.30	42894	10.85	135700
218.08	DeKalb	28.57	18.94	47.51	1.80	4922.22	5.04	59.04	0.762	94.70	46.40	2.80	52319	2.40	136600
218.09	DeKalb	23.16	12.99	36.16	1.30	3355.55	4.38	80.22	0.778	89.60	42.10	4.70	53996	1.77	116800
218.10	DeKalb	20.00	28.72	48.72	1.40	2988.89	4.32	75.54	0.730	94.40	47.40	2.30	57631	1.02	137000
218.98	DeKalb	24.37	22.05	46.42	5.40	6455.55	11.21	25.93	0.739	95.50	47.80	3.00	33796	14.02	90600
219.02	DeKalb	16.05	13.20	29.25	5.30	3144.44	13.21	32.63	0.797	95.10	45.90	4.40	42760	17.67	236400
219.03	DeKalb	12.62	15.37	27.99	4.40	3322.22	6.75	61.66	0.761	81.90	28.40	3.80	39641	17.57	83100
219.04	DeKalb	27.56	25.21	52.78	6.80	5044.44	8.63	34.44	0.725	91.10	36.70	3.20	33662	28.81	95900
219.05	DeKalb	23.87	18.93	42.80	11.70	5966.66	11.32	28.80	0.745	83.80	27.00	7.00	30814	36.71	82200
220.01	DeKalb	25.11	19.91	45.02	3.80	3666.66	3.31	72.98	0.773	83.20	30.40	2.40	40833	1.85	83100
220.02	DeKalb	31.37	17.04	48.41	11.30	7855.55	14.54	15.31	0.749	88.80	28.40	5.40	28005	55.43	83200
220.04	DeKalb	30.77	12.31	43.08	5.10	3788.88	8.67	63.20	0.764	91.40	30.10	3.40	46910	24.32	101800
220.05	DeKalb	25.66	25.07	50.73	13.00	3866.66	22.53	25.08	0.739	80.70	33.90	6.70	27921	43.44	93200

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221.00	DeKalb	27.51	25.79	53.30	37.40	3500.00	15.54	28.13	0.741	55.80	7.70	13.70	15642	83.30	45800
222.00	DeKalb	24.50	32.42	56.92	8.00	3533.33	8.99	35.30	0.719	78.10	29.60	5.10	30220	13.36	70800
223.01	DeKalb	26.82	18.12	44.94	9.60	4711.11	3.66	44.88	0.755	87.30	48.00	2.00	33846	1.81	93100
223.02	DeKalb	20.60	18.68	39.29	6.90	5411.10	6.50	43.76	0.758	92.00	49.50	2.60	34351	6.91	94600
224.01	DeKalb	21.40	14.39	35.79	7.20	6888.88	6.55	41.36	0.789	92.70	60.60	2.50	37586	4.32	162200
224.02	DeKalb	23.03	16.67	39.70	23.50	5988.88	14.47	13.29	0.745	93.10	55.90	5.70	17676	7.23	128400
224.03	DeKalb	10.35	9.52	19.88	7.70	6955.55	6.02	65.67	0.824	96.40	72.30	1.90	56955	0.52	170100
225.00	DeKalb	25.17	24.83	50.00	22.20	6188.88	5.61	42.35	0.753	82.30	48.50	4.70	29824	28.92	129000
226.00	DeKalb	20.98	22.95	43.93	10.10	7233.32	6.83	32.52	0.758	85.70	48.70	3.50	25615	5.77	115400
227.00	DeKalb	33.48	14.16	47.64	23.40	6166.66	10.55	51.58	0.778	62.20	16.30	10.20	21613	81.25	55100
228.00	DeKalb	17.11	19.77	36.88	14.60	7333.32	7.93	60.95	0.792	89.20	48.10	4.80	35575	37.81	88300
229.00	DeKalb	20.00	17.30	37.30	9.70	5555.55	8.78	61.94	0.781	73.90	25.80	8.40	29623	59.17	59300
230.00	DeKalb	25.29	15.29	40.59	5.10	4599.99	6.47	50.33	0.762	89.40	50.70	4.90	33669	9.21	121700
231.01	DeKalb	24.30	13.97	38.27	22.10	6311.10	13.73	45.87	0.782	65.10	8.20	10.40	24828	85.83	54100
231.02	DeKalb	32.41	18.18	50.59	6.70	3944.44	4.61	40.97	0.757	86.20	28.40	7.40	29505	49.39	88600
231.03	DeKalb	34.17	17.74	51.91	10.70	3811.11	8.36	55.32	0.760	74.80	11.20	8.70	30885	66.47	58300
231.05	DeKalb	22.53	26.09	48.62	7.60	5977.77	14.44	36.17	0.733	82.30	24.80	5.40	29831	56.67	84600
231.06	DeKalb	23.11	23.93	47.03	12.80	5433.33	13.33	22.36	0.747	85.20	28.40	6.30	27998	67.49	83900
232.03	DeKalb	16.35	19.01	35.36	8.00	2777.77	11.85	38.59	0.751	88.40	27.30	6.10	35203	82.36	87200
232.04	DeKalb	22.55	6.97	29.53	2.60	4066.66	5.63	78.51	0.795	93.70	41.10	6.30	51283	21.49	92300
232.05	DeKalb	34.43	7.68	42.11	3.60	3544.44	4.83	70.97	0.776	93.40	39.00	4.80	45683	34.84	86600
232.06	DeKalb	27.01	9.14	36.15	5.90	3455.55	4.20	79.89	0.798	85.30	22.40	3.50	41250	36.26	78400
232.07	DeKalb	29.95	10.34	40.29	2.10	3777.77	11.37	52.23	0.774	91.90	40.30	3.90	43585	55.61	93300
233.02	DeKalb	11.42	7.92	19.34	1.60	1088.89	7.58	84.99	0.781	90.70	34.80	3.30	52880	20.00	108200
233.03	DeKalb	14.59	16.76	31.35	14.50	1533.33	6.93	31.99	0.746	55.10	5.00	4.60	22070	49.01	56800
233.05	DeKalb	16.57	7.12	23.70	1.30	2700.00	10.75	74.06	0.800	92.20	37.50	3.80	51872	17.86	96200
233.06	DeKalb	12.59	9.06	21.65	6.50	1233.33	4.89	84.03	0.786	75.70	20.10	5.10	46250	26.13	92800
233.07	DeKalb	27.92	12.96	40.88	5.40	2844.44	5.86	78.50	0.763	88.60	28.50	2.90	42038	50.55	78100
233.08	DeKalb	16.80	15.01	31.80	8.10	3833.33	17.97	38.29	0.774	87.00	22.10	6.10	30946	70.32	73700
234.03	DeKalb	23.70	22.91	46.60	11.60	5577.77	12.40	39.96	0.757	81.50	16.30	7.00	28876	96.02	68200
234.04	DeKalb	10.89	14.90	25.79	3.80	1900.00	12.35	66.53	0.788	79.30	13.90	9.30	36308	77.88	70700
234.05	DeKalb	8.26	9.97	18.24	8.90	3211.11	9.34	44.17	0.814	80.40	16.40	6.00	32782	87.00	76300

Census Tract	County	PLDU90	PHDU90	PURB90	PPOV90	POPDENS90	PUNOC90	POWNOC90	NDVI90	PHS90	PBCH90	PUMP90	MEDHHI90	PBLK90	MEDHSVL90
234.07	DeKalb	9.65	6.48	16.14	3.30	1844.44	7.68	49.88	0.810	85.80	25.90	6.00	39593	56.45	85200
234.08	DeKalb	25.32	17.02	42.34	4.90	2933.33	12.44	66.47	0.779	84.80	26.30	6.50	43379	85.28	91300
234.09	DeKalb	19.37	10.66	30.03	3.70	2466.66	7.13	81.77	0.800	90.00	30.00	6.20	46865	86.57	88600
235.01	DeKalb	37.29	21.19	58.47	24.50	4733.33	7.29	53.58	0.762	61.50	7.40	15.30	24643	91.36	49700
235.02	DeKalb	38.18	14.09	52.27	10.50	4955.55	3.85	55.07	0.770	73.90	12.90	10.20	31927	94.47	64500
235.03	DeKalb	33.56	17.75	51.31	7.50	3988.88	5.80	67.12	0.769	83.10	18.80	9.90	37961	84.87	73500
236.00	DeKalb	28.69	10.74	39.44	12.40	4577.77	7.18	60.07	0.785	64.20	8.30	12.80	28697	96.91	55600
237.00	DeKalb	21.26	20.00	41.26	28.70	5811.10	12.39	45.07	0.785	57.20	4.70	8.90	21747	97.29	48100
238.01	DeKalb	27.00	6.10	33.10	14.70	4255.55	12.51	52.11	0.798	65.70	10.00	8.00	28450	92.09	58600
238.02	DeKalb	14.29	19.05	33.33	22.30	3166.66	9.13	27.17	0.766	70.00	8.20	14.70	21837	72.42	60600
238.03	DeKalb	27.42	11.29	38.71	10.50	4677.77	6.57	75.03	0.797	70.40	7.50	8.40	31788	95.17	58500
301.98	Cobb	10.06	7.46	17.51	7.40	1811.11	11.93	55.08	0.782	71.50	14.50	4.70	34661	3.84	84900
302.03	Cobb	12.72	4.67	17.39	1.30	1811.11	5.04	77.04	0.810	85.60	34.40	2.90	54675	4.18	113400
302.04	Cobb	19.28	10.86	30.14	2.40	2244.44	5.44	77.17	0.791	89.00	34.90	2.50	49430	4.81	93700
302.05	Cobb	14.37	20.64	35.01	6.90	1711.11	19.65	46.03	0.756	89.50	32.40	4.10	41073	3.87	110300
302.06	Cobb	11.60	5.09	16.69	3.80	2111.11	5.48	73.00	0.819	86.90	25.10	4.40	47335	2.34	93800
302.07	Cobb	9.92	7.10	17.02	3.90	1855.55	6.84	70.55	0.816	90.80	35.80	3.30	53370	2.57	120100
303.02	Cobb	26.69	5.77	32.46	1.30	2955.55	4.26	85.59	0.785	97.20	49.20	4.10	67654	2.91	142000
303.07	Cobb	24.38	5.43	29.81	2.10	2911.11	3.65	85.39	0.802	95.90	47.20	3.10	62585	2.47	123000
303.09	Cobb	22.61	9.30	31.91	2.10	3711.11	3.19	83.79	0.786	96.30	46.60	3.60	59724	2.93	117100
303.10	Cobb	29.40	8.35	37.75	2.00	2877.77	7.25	69.85	0.776	91.40	31.10	3.30	50122	4.34	97900
303.11	Cobb	21.74	10.69	32.43	2.90	2933.33	3.27	79.71	0.771	92.20	37.30	2.40	51976	2.26	101700
303.12	Cobb	23.63	10.73	34.36	4.10	2922.22	4.23	78.20	0.781	89.90	29.30	3.00	50553	3.36	95800
303.13	Cobb	24.57	9.55	34.12	1.10	2677.77	4.25	79.49	0.791	90.00	30.10	3.30	54257	4.61	92500
303.14	Cobb	18.95	11.04	29.99	2.30	3433.33	4.02	80.68	0.801	89.70	39.10	2.40	54420	3.02	98100
303.15	Cobb	26.46	9.82	36.28	2.30	3222.22	3.18	82.56	0.789	94.60	48.60	3.20	62454	3.59	131100
303.16	Cobb	23.53	8.47	32.00	1.80	3466.66	3.18	83.06	0.783	97.50	55.00	3.00	72559	2.49	145300
303.17	Cobb	23.74	9.18	32.92	1.50	3577.77	2.84	87.12	0.779	97.80	57.70	1.90	77006	2.05	164600
303.18	Cobb	19.29	8.56	27.85	2.30	2577.77	3.69	85.69	0.796	96.70	58.00	4.30	81000	1.47	208800
303.19	Cobb	12.78	6.32	19.10	2.00	3333.33	5.72	65.31	0.788	96.30	52.30	1.30	58077	0.50	125700
303.20	Cobb	14.47	9.40	23.86	2.40	3733.33	13.56	29.36	0.807	98.30	64.00	1.40	58745	2.35	259600
303.21	Cobb	16.00	37.18	53.18	7.80	5388.88	22.19	2.67	0.702	96.00	49.70	3.50	29087	23.90	81800

Census Tract	County	PLDU90	PHDU90	PURB90	PPOV90	POPDENS90	PUNOC90	POWNOC90	NDVI90	PHS90	PBCH90	PUMP90	MEDHHI90	PBLK90	MEDHSVL90
304.01	Cobb	25.57	10.96	36.52	4.00	3577.77	6.12	60.63	0.787	92.60	43.30	4.50	48113	4.92	132400
304.02	Cobb	26.03	11.49	37.52	2.50	4433.33	8.48	59.30	0.779	92.70	41.50	3.40	45194	4.21	106200
304.04	Cobb	26.00	45.14	71.14	14.70	8211.10	16.63	3.54	0.655	93.40	32.80	5.30	26435	23.99	55500
304.05	Cobb	25.27	32.46	57.73	6.30	4655.55	14.73	32.76	0.721	87.50	28.10	4.30	32868	7.48	71900
304.06	Cobb	19.74	41.79	61.54	5.40	7955.55	24.48	5.16	0.664	93.90	45.30	3.80	34772	22.98	85100
305.01	Cobb	19.77	19.35	39.12	3.40	2666.66	3.44	71.49	0.761	83.00	28.00	3.70	43919	5.97	89100
305.02	Cobb	18.64	19.25	37.89	3.60	2222.22	12.80	65.00	0.753	85.70	29.00	1.10	46853	7.87	95300
305.03	Cobb	21.46	19.45	40.91	10.00	3355.55	7.40	36.01	0.762	84.40	31.60	4.10	33525	12.24	84200
306.00	Cobb	10.69	17.00	27.70	7.50	3000.00	12.89	40.86	0.802	83.00	33.00	4.00	35011	5.77	97500
307.00	Cobb	27.91	29.30	57.21	31.70	3633.33	14.95	31.34	0.738	59.90	15.50	9.80	16737	45.99	70600
308.00	Cobb	26.54	38.65	65.19	30.40	3166.66	13.36	18.29	0.699	54.90	8.70	9.20	14196	24.32	58700
309.01	Cobb	20.40	6.07	26.47	2.10	2833.33	9.71	56.56	0.802	93.60	43.90	4.60	41875	6.28	132400
309.02	Cobb	22.40	18.66	41.06	17.40	4755.55	11.75	27.21	0.771	71.90	17.80	11.50	19600	25.52	70800
309.03	Cobb	28.99	7.33	36.31	10.40	3422.22	10.02	38.48	0.753	84.00	21.70	4.20	34564	14.97	86200
310.01	Cobb	17.47	26.28	43.75	16.40	1766.66	18.19	22.26	0.705	60.50	10.50	10.60	22441	11.14	58300
310.02	Cobb	27.51	14.93	42.43	15.00	4311.11	21.62	22.50	0.782	59.80	8.60	7.60	22108	15.39	59500
310.03	Cobb	36.42	13.04	49.46	9.60	2911.11	10.86	53.47	0.769	72.70	11.20	4.70	34384	10.08	70500
311.01	Cobb	35.67	22.51	58.19	13.00	3533.33	13.35	36.57	0.725	68.10	13.90	4.70	27874	14.29	63500
311.03	Cobb	30.25	15.54	45.79	7.50	3666.66	7.15	44.68	0.765	85.60	31.70	4.10	35426	16.79	80100
311.05	Cobb	36.19	11.43	47.62	6.90	3255.55	15.84	42.44	0.763	81.80	19.60	6.00	32146	14.46	74800
311.06	Cobb	22.66	16.85	39.51	2.00	2377.77	7.79	66.24	0.775	83.60	17.00	5.60	42459	5.82	85500
311.07	Cobb	26.97	10.06	37.03	4.40	2455.55	8.13	65.52	0.791	84.10	28.00	4.10	44766	5.22	98900
311.08	Cobb	38.46	16.57	55.03	12.50	3833.33	11.69	27.97	0.739	81.20	30.30	6.30	31168	30.40	62400
311.09	Cobb	27.09	33.92	61.01	5.20	6966.66	13.42	11.21	0.686	93.90	48.00	3.50	29978	23.42	72700
312.02	Cobb	19.67	22.96	42.63	6.30	1788.89	14.54	23.99	0.738	87.60	37.40	3.70	32018	18.36	86200
312.03	Cobb	17.00	22.15	39.16	5.20	5277.77	16.42	13.17	0.748	96.00	58.80	3.00	34464	11.34	103100
312.04	Cobb	21.23	8.95	30.18	2.90	3477.77	8.61	38.69	0.790	91.80	52.10	2.20	44635	7.19	207600
313.01	Cobb	24.56	9.57	34.13	4.80	2366.66	5.00	73.23	0.797	79.30	23.10	2.80	42574	3.73	83200
313.02	Cobb	13.77	6.99	20.77	8.30	1588.89	9.30	55.32	0.806	67.10	12.50	8.30	31733	7.11	71800
313.04	Cobb	27.63	9.53	37.16	5.90	2300.00	4.85	65.70	0.785	67.30	12.70	4.30	34081	16.40	72200
313.05	Cobb	14.05	16.42	30.47	11.40	3166.66	16.88	15.77	0.769	80.80	13.90	6.90	28122	56.16	73100
314.03	Cobb	24.22	13.03	37.25	4.90	2233.33	8.17	61.53	0.762	79.70	19.80	3.70	40910	10.04	76200

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314.04	Cobb	24.49	10.84	35.33	2.20	1922.22	2.87	79.83	0.787	76.10	13.70	4.00	40855	0.00	78300
314.98	Cobb	15.68	9.71	25.40	10.00	1488.89	6.93	58.15	0.786	65.50	10.40	5.90	29602	9.16	61100
315.01	Cobb	14.07	4.32	18.39	2.50	1255.55	5.03	77.45	0.796	85.00	16.00	3.90	43880	3.21	83200
315.02	Cobb	23.24	7.70	30.94	2.50	1888.89	4.77	76.17	0.779	80.80	20.90	4.10	43355	15.26	81600
402.00	Clayton	19.24	26.79	46.03	11.80	3455.55	13.27	16.71	0.736	83.40	18.20	8.90	27390	72.99	68700
403.02	Clayton	28.52	12.14	40.66	14.90	3411.11	10.93	45.19	0.780	60.70	3.70	7.30	24639	22.22	51600
403.03	Clayton	35.88	19.93	55.81	19.70	3011.11	7.55	48.19	0.742	63.90	6.20	10.90	23659	34.93	55200
403.04	Clayton	38.52	22.74	61.25	13.30	2422.22	11.86	51.83	0.724	59.70	5.80	7.70	21989	21.52	47800
403.05	Clayton	28.61	26.02	54.63	12.00	3500.00	8.65	36.59	0.703	73.00	8.80	7.40	26766	25.09	61600
404.01	Clayton	31.27	12.94	44.21	8.50	2288.89	7.53	52.99	0.761	74.10	11.60	6.20	35270	15.21	68400
404.02	Clayton	13.56	15.15	28.72	8.00	1733.33	8.10	66.37	0.785	70.50	11.80	5.10	35481	15.80	67100
404.03	Clayton	28.40	15.70	44.10	7.20	2400.00	9.37	52.06	0.759	85.90	17.60	4.50	36910	11.18	70500
404.05	Clayton	28.02	24.15	52.17	8.60	4022.22	9.86	24.15	0.743	72.10	14.50	7.20	28479	18.91	62200
404.06	Clayton	28.14	32.85	60.99	8.30	3122.22	10.54	37.95	0.702	76.90	12.50	5.20	31996	18.82	62000
405.03	Clayton	33.76	9.88	43.65	5.50	3022.22	8.00	44.55	0.774	70.90	9.50	5.80	31046	18.27	62200
405.04	Clayton	27.62	12.23	39.85	4.90	3422.22	10.90	29.18	0.776	86.10	23.40	6.00	31877	59.68	81800
405.05	Clayton	31.11	8.68	39.79	6.20	2377.77	7.54	61.61	0.783	87.80	20.90	3.10	42103	33.16	85100
405.06	Clayton	37.93	14.29	52.21	9.90	2644.44	8.41	55.19	0.756	79.70	11.90	4.70	37018	18.48	70600
405.07	Clayton	29.48	9.47	38.95	6.00	2644.44	10.60	50.51	0.758	80.50	15.20	4.10	35717	14.60	69400
405.08	Clayton	34.79	3.84	38.63	3.70	2788.89	6.98	66.02	0.769	85.40	17.70	3.10	40409	16.25	69300
406.03	Clayton	24.21	9.27	33.48	3.80	1944.44	8.25	61.58	0.777	79.90	19.50	4.50	45197	11.33	79400
406.04	Clayton	23.90	22.42	46.33	14.90	2877.77	7.96	37.82	0.745	65.10	9.30	5.50	24850	13.54	59700
406.05	Clayton	21.59	6.91	28.50	8.60	1655.55	2.73	79.73	0.766	85.40	27.20	4.60	51539	9.80	104600
406.06	Clayton	4.73	5.52	10.24	1.80	1111.11	14.14	64.83	0.820	67.60	4.90	6.40	46964	32.99	87800
406.07	Clayton	16.21	5.66	21.87	2.40	1611.11	3.61	70.23	0.797	76.30	13.00	3.80	40597	7.13	73100
406.08	Clayton	5.11	1.42	6.53	0.90	611.11	6.24	68.81	0.808	79.80	12.50	3.60	50526	2.17	101600
501.01	Gwinnett	7.50	4.99	12.48	8.50	1700.00	10.38	54.09	0.807	68.20	14.20	5.10	35548	1.90	83300
501.02	Gwinnett	11.21	10.13	21.34	13.00	2188.89	9.19	40.62	0.813	63.20	7.90	4.90	26495	12.84	69100
502.02	Gwinnett	6.17	6.68	12.86	3.50	866.67	9.56	71.17	0.822	77.50	23.40	3.40	45625	1.87	115800
502.03	Gwinnett	16.42	17.91	34.33	3.20	2822.22	10.38	36.79	0.754	91.80	33.20	2.30	39722	5.35	95200
502.04	Gwinnett	10.46	6.54	17.00	1.20	1655.55	3.09	72.60	0.821	85.10	31.50	4.00	52498	3.73	129900
503.04	Gwinnett	19.47	36.51	55.98	3.30	2144.44	17.55	21.06	0.690	81.80	31.40	2.90	31849	10.83	67400

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503.05	Gwinnett	22.53	13.64	36.17	5.50	8422.21	11.52	12.21	0.754	93.80	41.60	4.20	34141	21.58	108200
503.06	Gwinnett	19.23	41.73	60.96	15.50	1088.89	17.25	49.24	0.651	61.10	1.90	8.20	34238	8.48	56300
503.07	Gwinnett	26.49	3.31	29.80	0.90	2777.77	4.35	88.63	0.782	96.30	59.70	3.20	82414	0.99	195600
503.08	Gwinnett	13.96	9.95	23.91	2.90	1888.89	0.97	88.39	0.794	97.40	46.30	0.70	69615	1.92	154900
503.09	Gwinnett	15.41	14.23	29.64	1.60	2022.22	8.54	43.03	0.760	95.20	42.80	1.10	43804	5.62	155600
503.10	Gwinnett	24.21	24.62	48.84	1.10	2355.55	6.34	49.75	0.727	95.60	47.50	2.60	48594	6.29	117100
503.11	Gwinnett	16.90	26.13	43.03	11.00	2277.77	6.81	45.21	0.746	78.80	24.60	0.60	31558	24.19	105500
503.12	Gwinnett	31.92	25.24	57.16	5.10	3355.55	14.22	29.03	0.705	82.60	24.50	3.90	34241	17.34	82100
503.13	Gwinnett	29.10	11.15	40.26	9.30	2522.22	7.58	60.65	0.769	89.20	29.70	3.40	46151	7.46	92900
503.14	Gwinnett	30.71	9.87	40.59	3.30	2622.22	2.22	71.75	0.762	89.90	35.30	1.60	47380	1.54	88900
504.03	Gwinnett	22.47	9.18	31.64	2.70	2711.11	7.98	56.56	0.783	89.80	36.50	1.90	45942	3.44	98700
504.06	Gwinnett	27.29	26.65	53.94	6.90	6544.44	15.13	19.57	0.723	88.30	32.80	2.80	33676	20.38	78200
504.07	Gwinnett	31.60	13.71	45.30	3.90	4522.22	13.27	33.84	0.759	88.90	35.50	3.20	38424	11.45	93700
504.08	Gwinnett	37.07	25.60	62.67	3.90	3733.33	10.63	29.23	0.707	88.40	24.40	3.90	35905	9.42	82500
504.09	Gwinnett	24.87	24.19	49.06	3.10	2944.44	9.61	50.67	0.700	92.50	37.10	3.00	43307	8.29	90600
504.10	Gwinnett	23.65	15.60	39.24	3.00	3311.11	7.96	42.07	0.771	80.20	27.30	4.80	36711	3.24	80000
504.11	Gwinnett	20.90	14.62	35.53	5.10	2744.44	5.19	50.91	0.768	84.60	21.80	1.90	39636	1.37	88400
504.12	Gwinnett	27.96	5.79	33.75	2.00	2644.44	2.02	85.45	0.795	91.70	38.80	3.20	58433	0.06	110600
504.13	Gwinnett	19.45	6.66	26.11	2.10	3144.44	2.87	84.74	0.795	92.50	40.20	2.40	59788	1.12	123200
504.14	Gwinnett	23.42	9.17	32.59	1.50	2822.22	2.80	71.99	0.781	89.90	31.90	2.10	50969	0.81	105400
504.15	Gwinnett	21.62	10.18	31.81	2.10	2255.55	2.31	85.57	0.781	92.90	37.00	2.10	62047	0.80	134600
504.16	Gwinnett	22.03	4.13	26.16	4.40	2722.22	4.09	59.23	0.803	93.00	32.70	2.70	44899	2.41	94500
505.02	Gwinnett	17.58	12.52	30.10	4.20	1955.55	5.91	65.21	0.786	87.50	30.20	3.40	48533	2.93	98000
505.03	Gwinnett	14.31	7.47	21.78	2.20	1477.78	4.30	80.35	0.790	87.20	24.70	2.30	49803	1.75	98400
505.05	Gwinnett	15.58	7.94	23.52	4.60	2500.00	5.42	74.75	0.807	88.30	23.50	3.70	47538	2.09	88500
505.06	Gwinnett	21.15	13.90	35.06	3.40	2800.00	11.27	38.32	0.772	88.10	28.60	3.80	37018	5.94	90100
505.07	Gwinnett	16.87	17.29	34.16	2.50	2522.22	5.44	71.06	0.781	92.40	32.60	2.30	49330	2.18	89300
505.08	Gwinnett	25.02	19.09	44.11	8.40	2977.77	7.62	40.36	0.759	73.30	23.70	4.80	32129	6.39	94500
505.09	Gwinnett	9.83	3.84	13.67	8.40	1544.44	6.29	56.37	0.811	70.30	11.10	4.50	34076	3.50	80800
506.01	Gwinnett	7.34	4.21	11.55	3.80	988.89	3.19	71.15	0.834	79.70	16.30	4.20	42108	2.59	89000
506.02	Gwinnett	5.48	2.63	8.11	6.70	877.78	4.38	64.07	0.829	71.80	11.70	3.70	39795	4.24	81900
507.04	Gwinnett	9.61	3.18	12.80	2.60	1300.00	5.03	72.52	0.810	86.40	25.90	3.80	50422	2.10	113800

Census Tract	County	PLDU90	PHDU90	PURB90	PPOV90	POPDENS90	PUNOC90	POWNOC90	NDVI90	PHS90	PBCH90	PUMP90	MEDHHI90	PBLK90	MEDHSVL90
507.05	Gwinnett	8.28	3.73	12.01	4.10	1044.44	5.15	69.15	0.812	82.20	18.60	2.60	46006	1.13	94800
507.06	Gwinnett	22.02	7.95	29.97	0.50	3088.88	5.20	85.30	0.794	92.80	41.00	2.60	60786	0.46	124000
507.07	Gwinnett	19.72	7.28	27.00	2.00	2722.22	2.91	84.50	0.798	93.00	38.30	1.70	56454	1.19	112200
507.08	Gwinnett	27.51	8.91	36.42	2.00	2222.22	4.89	78.42	0.778	91.50	29.00	2.40	47474	1.93	92000
507.09	Gwinnett	14.79	5.38	20.17	1.40	1922.22	8.68	70.57	0.805	88.50	24.80	3.10	46879	5.81	94000
507.10	Gwinnett	24.03	11.51	35.54	3.20	2344.44	8.94	62.33	0.785	86.80	28.00	2.30	45690	1.15	104000
507.11	Gwinnett	25.09	6.98	32.07	3.30	1822.22	3.16	81.58	0.788	88.30	22.40	2.90	49122	0.52	91300
601.00	Rockdale	7.43	5.08	12.52	5.10	922.22	5.59	64.22	0.814	70.60	12.50	2.80	40737	1.95	78900
602.00	Rockdale	12.17	5.82	18.00	6.10	1700.00	7.32	61.01	0.805	75.10	13.70	4.50	38803	8.73	84800
603.02	Rockdale	12.48	7.38	19.85	4.10	1433.33	12.58	48.03	0.790	85.30	27.40	3.90	42717	6.99	97900
603.03	Rockdale	19.87	9.08	28.95	10.80	2466.66	12.61	40.79	0.791	69.60	11.90	5.50	29785	15.09	65000
603.04	Rockdale	14.60	18.83	33.43	19.30	1377.78	9.67	42.27	0.762	63.40	11.80	3.80	23042	29.43	72600
604.01	Rockdale	8.74	4.86	13.59	2.50	1533.33	4.01	76.74	0.818	82.50	20.10	2.60	43727	2.37	85000
604.02	Rockdale	10.12	3.09	13.21	2.20	1644.44	4.14	79.51	0.816	87.20	24.00	4.00	47450	2.11	97100
701.02	Henry	10.11	5.10	15.21	1.80	1777.78	3.35	82.02	0.815	82.80	11.80	3.90	46585	2.22	87600
701.03	Henry	12.73	8.21	20.94	4.40	1355.55	6.39	59.54	0.792	75.50	10.90	3.80	36424	5.91	79700
701.98	Henry	9.39	6.80	16.19	5.20	2066.66	6.09	67.66	0.823	73.40	15.40	4.30	40545	9.40	80300
702.01	Henry	7.73	4.06	11.79	4.50	1144.44	4.07	52.72	0.807	74.60	8.10	3.80	39441	1.79	85700
702.02	Henry	4.27	2.02	6.29	0.60	877.78	4.53	66.21	0.816	79.00	9.90	4.60	45417	3.08	94500
702.03	Henry	5.97	3.04	9.01	3.00	488.89	4.89	64.46	0.795	78.10	18.30	0.40	43355	2.79	94400
703.01	Henry	4.73	5.02	9.75	6.00	800.00	4.95	66.54	0.809	80.00	11.40	2.90	48812	1.34	94900
703.02	Henry	9.07	7.82	16.89	11.20	1266.67	8.17	54.88	0.795	63.30	9.10	6.10	29362	29.61	70200
704.02	Henry	4.33	3.61	7.94	3.90	477.78	7.27	50.00	0.811	69.20	11.00	2.90	36359	15.87	72300
704.98	Henry	4.14	4.16	8.30	6.60	855.55	8.39	38.69	0.810	66.20	9.50	5.90	32864	15.23	69300
705.00	Henry	4.87	4.10	8.97	12.40	922.22	4.67	46.07	0.810	67.70	5.50	4.70	30845	11.14	68800
801.98	Douglas	10.79	10.71	21.50	7.30	1466.66	18.18	32.65	0.798	69.70	11.80	4.30	31830	8.48	78500
802.00	Douglas	19.31	7.24	26.55	7.20	1588.89	3.85	60.71	0.787	71.20	11.10	4.80	36723	4.27	70900
803.00	Douglas	17.88	12.23	30.11	14.80	1922.22	9.63	43.34	0.784	63.20	9.30	8.00	27872	18.13	69100
804.00	Douglas	5.19	4.29	9.48	7.00	755.55	4.71	49.64	0.828	59.50	7.80	5.40	33146	7.81	70500
805.01	Douglas	10.98	4.92	15.90	3.70	1833.33	3.13	70.08	0.823	75.90	10.20	4.80	42861	3.58	74000
805.03	Douglas	22.21	7.03	29.24	2.80	2122.22	13.65	58.53	0.802	86.80	23.80	4.00	41883	4.18	85000
805.04	Douglas	6.72	2.85	9.57	4.40	1588.89	5.76	71.41	0.842	81.50	13.70	4.10	42775	4.80	73300

Census Tract	County	PLDU90	PHDU90	PURB90	PPOV90	POPDENS90	PUNOC90	POWNOC90	NDVI90	PHS90	PBCH90	PUMP90	MEDHHI90	PBLK90	MEDHSVL90
806.01	Douglas	11.16	4.69	15.85	2.70	1477.78	8.10	70.69	0.820	81.20	14.50	3.50	43446	7.50	73800
806.02	Douglas	7.89	4.01	11.90	3.70	1477.78	8.83	57.74	0.841	71.40	9.20	4.50	36694	5.24	63600
901.00	Cherokee	2.68	2.21	4.89	14.00	900.00	6.24	49.97	0.854	50.90	9.00	4.70	26303	0.53	58500
902.00	Cherokee	1.53	2.05	3.58	7.60	1255.55	17.09	41.28	0.863	65.10	16.10	3.00	35115	0.00	87400
903.00	Cherokee	1.56	1.91	3.47	17.60	1155.55	7.39	50.57	0.817	64.70	8.90	4.50	29375	0.00	70000
904.00	Cherokee	3.91	6.28	10.20	8.60	2188.89	6.45	42.43	0.848	53.70	6.40	4.70	22737	16.26	58900
905.00	Cherokee	2.51	3.48	5.99	8.20	1566.66	5.30	55.15	0.854	64.50	11.70	3.80	34500	0.00	89100
906.00	Cherokee	5.60	6.41	12.01	10.70	2133.33	8.52	55.61	0.836	62.70	13.30	2.90	29119	4.62	69200
907.00	Cherokee	8.13	5.58	13.71	3.80	1777.78	4.47	65.98	0.793	75.00	17.10	2.70	39913	0.39	82400
908.00	Cherokee	5.34	3.04	8.38	3.00	1944.44	4.71	66.85	0.837	79.90	23.00	3.30	43543	0.56	95100
909.01	Cherokee	9.03	1.10	10.13	3.70	2377.77	4.23	74.63	0.830	85.00	29.30	2.30	48646	0.33	93900
909.02	Cherokee	9.24	4.34	13.58	2.10	2611.11	4.84	79.43	0.826	89.60	28.30	3.90	46801	1.10	89300
909.03	Cherokee	15.29	5.38	20.66	4.30	2611.11	6.80	64.93	0.807	83.20	20.10	4.50	41102	3.02	86900
910.01	Cherokee	10.23	13.35	23.57	3.50	2100.00	9.42	51.67	0.796	75.60	13.40	3.20	32609	2.58	73200
910.02	Cherokee	11.53	6.42	17.95	3.20	1266.67	14.72	64.35	0.808	89.90	27.30	3.20	49219	1.23	100000
910.03	Cherokee	20.04	13.03	33.07	7.50	2655.55	7.54	51.39	0.774	79.50	21.10	7.20	38939	0.66	93800
911.01	Cherokee	13.51	2.88	16.40	4.00	1744.44	9.44	74.24	0.694	87.60	27.40	3.70	50480	0.00	93400
911.03	Cherokee	9.84	4.97	14.81	3.10	1966.66	6.79	66.48	0.774	81.10	16.70	5.20	44038	0.97	86000
911.98	Cherokee	13.69	7.26	20.95	7.20	3577.77	9.14	48.72	0.817	81.20	14.50	3.70	35716	0.55	79700
1201.00	Paulding	3.30	1.94	5.24	10.20	766.67	6.19	50.62	0.843	64.70	8.60	4.00	35779	1.09	77300
1202.00	Paulding	11.11	6.40	17.51	4.70	1677.78	5.82	68.06	0.814	74.40	12.00	3.40	37684	2.54	73400
1203.00	Paulding	6.10	5.39	11.50	14.10	1388.89	4.47	49.93	0.828	59.40	7.80	5.70	28051	6.49	62500
1204.00	Paulding	2.87	2.08	4.95	8.20	711.11	7.03	45.38	0.852	52.80	3.90	5.20	29495	8.34	57800
1205.00	Paulding	7.96	4.25	12.21	11.20	1244.44	7.54	50.96	0.819	61.70	5.20	6.40	31135	4.93	65500
1206.98	Paulding	5.85	3.06	8.91	4.50	1166.67	5.40	60.60	0.818	67.50	6.20	4.20	34298	1.21	65800
1301.00	Forsyth	3.64	4.60	8.24	6.60	1388.89	15.29	41.55	0.795	65.60	10.70	3.40	32409	0.00	81400
1302.00	Forsyth	3.33	5.64	8.96	9.40	1355.55	4.21	42.52	0.841	57.70	8.60	3.70	36215	0.00	76000
1303.00	Forsyth	4.18	5.53	9.72	8.10	1744.44	7.65	51.21	0.844	64.70	17.50	4.30	36578	0.00	102400
1304.00	Forsyth	5.73	8.98	14.70	7.00	2133.33	7.73	46.58	0.834	61.10	12.50	5.40	31933	0.00	90700
1305.00	Forsyth	5.31	5.31	10.61	4.30	1455.55	18.71	54.21	0.682	81.60	24.70	3.00	43455	0.00	119100
1306.00	Forsyth	4.53	5.93	10.47	6.80	1333.33	4.35	46.25	0.835	65.80	12.30	3.60	35180	0.00	92100
1401.01	Fayette	9.30	4.06	13.36	2.70	1500.00	5.40	67.79	0.816	84.70	25.00	2.70	49673	16.14	122500

Census Tract	County	PLDU90	PHDU90	PURB90	PPOV90	POPDENS90	PUNOC90	POWNOC90	NDVI90	PHS90	PBCH90	PUMP90	MEDHHI90	PBLK90	MEDHSVL90
1401.02	Fayette	11.42	5.13	16.55	0.40	1466.66	3.08	76.86	0.799	86.10	23.90	1.90	53840	5.29	118200
1402.01	Fayette	6.92	2.75	9.67	2.50	1122.22	9.02	47.90	0.808	76.50	11.70	2.40	45413	1.62	115200
1402.02	Fayette	11.11	4.76	15.87	4.20	1388.89	7.59	60.03	0.797	88.80	36.30	4.30	54620	7.14	136200
1403.01	Fayette	12.24	4.33	16.57	2.80	1677.78	7.21	60.58	0.800	91.90	28.60	4.50	48148	2.75	107300
1403.02	Fayette	14.19	5.25	19.44	0.40	1144.44	3.54	90.11	0.797	95.10	43.40	3.80	54788	2.64	127600
1404.01	Fayette	11.81	5.61	17.42	3.00	1422.22	3.96	77.70	0.802	88.00	29.10	1.40	55238	4.02	132500
1404.02	Fayette	11.99	3.79	15.79	2.70	1533.33	7.18	64.50	0.801	83.90	19.80	4.00	45830	5.05	104400
1405.01	Fayette	4.55	2.46	7.01	2.50	911.11	5.49	64.87	0.819	83.20	18.70	1.80	48886	2.87	131300
1405.02	Fayette	3.48	2.81	6.29	6.40	888.89	7.45	57.45	0.809	77.30	9.40	5.40	42500	3.68	87600
1701.00	Coweta	5.41	2.36	7.76	8.80	366.67	7.59	48.07	0.813	67.40	9.20	2.70	35566	6.26	66300
1702.00	Coweta	11.07	5.98	17.05	7.70	1322.22	5.95	56.27	0.807	66.60	14.30	3.70	32380	9.85	64700
1703.00	Coweta	7.20	4.80	12.00	11.00	1022.22	7.92	44.86	0.807	74.80	21.00	5.60	34467	24.54	78700
1704.00	Coweta	6.72	4.23	10.95	3.30	911.11	7.07	59.74	0.819	74.50	12.70	4.40	41520	7.25	90700
1705.00	Coweta	4.00	2.48	6.48	7.30	633.33	8.52	44.16	0.819	67.50	9.10	5.30	34109	20.36	68100
1706.00	Coweta	8.50	4.71	13.21	23.70	1244.44	7.72	41.59	0.800	56.00	10.30	7.00	21262	44.26	50000
1707.00	Coweta	10.76	3.17	13.92	19.30	1600.00	5.62	56.42	0.809	64.00	12.70	8.00	26733	49.85	59700
1708.00	Coweta	3.33	3.27	6.61	10.00	622.22	7.27	45.27	0.823	63.00	12.30	5.60	28466	11.11	52700

Table E.3. Sociodemographic variables, metropolitan Atlanta, Georgia, 2000.

Census Tract	County	PLDU00	PHDU00	PURB00	PPOV00	POPDENS00	PUNOC00	POWNOC00	NDVI00	PHS00	PBCH00	PUMP00	PBLK00
1.00	Fulton	45.09	13.19	58.28	3.06	2811.11	5.55	76.14	0.709	97.66	60.02	1.86	1.32
2.00	Fulton	50.34	21.92	72.26	4.42	3811.11	5.39	54.99	0.662	95.28	53.77	1.81	4.41
4.00	Fulton	35.98	29.88	65.85	5.36	3166.67	8.00	63.96	0.599	97.50	54.22	2.40	7.56
5.00	Fulton	30.82	49.24	80.06	15.87	3555.55	14.31	43.89	0.570	92.24	50.36	6.48	18.43
7.00	Fulton	28.57	62.29	90.86	4.74	6866.66	9.21	60.51	0.507	49.76	3.39	2.33	83.35
8.00	Fulton	33.33	63.64	96.97	25.70	4722.22	25.64	19.84	0.516	42.92	2.74	21.13	94.96
10.95	Fulton	22.56	73.31	95.86	4.66	14844.44	7.97	12.37	0.450	97.06	13.19	89.72	10.69
11.00	Fulton	31.91	68.09	100.00	8.52	16311.10	14.72	35.79	0.418	94.87	47.26	5.07	18.60
12.00	Fulton	31.53	67.57	99.10	15.09	11922.22	18.49	29.78	0.454	91.61	41.78	3.60	18.36
13.00	Fulton	37.40	56.49	93.89	12.87	8022.22	6.49	32.98	0.539	86.52	40.94	2.18	21.44
14.00	Fulton	58.44	29.87	88.31	7.80	4911.11	13.07	26.88	0.577	97.22	57.63	3.43	14.53
15.00	Fulton	64.86	28.83	93.69	12.53	5444.44	6.72	27.52	0.589	94.07	48.09	2.12	8.51
17.00	Fulton	34.45	62.18	96.64	33.93	5733.33	13.47	21.63	0.522	71.61	11.48	18.05	80.96
18.00	Fulton	26.37	69.23	95.60	26.79	15066.66	12.22	31.37	0.507	80.94	32.71	5.64	58.71
19.00	Fulton	1.12	98.88	100.00	44.09	20322.21	21.65	10.59	0.344	63.74	17.81	29.06	68.70
20.00	Fulton	54.55	45.45	100.00	44.09	20611.10	21.65	10.59	0.402	63.74	17.81	29.06	68.70
21.00	Fulton	17.86	80.95	98.81	43.58	15622.22	5.54	8.34	0.407	78.94	16.79	15.17	69.45
22.00	Fulton	30.49	64.63	95.12	66.47	3855.55	7.80	6.01	0.472	49.45	5.33	21.22	99.48
23.00	Fulton	49.12	37.72	86.84	34.76	4933.33	26.59	27.37	0.622	55.18	2.25	13.58	98.57
24.00	Fulton	60.29	20.59	80.88	30.24	3022.22	20.81	47.35	0.640	60.22	6.09	17.69	98.61
25.00	Fulton	48.28	48.28	96.55	37.50	4733.33	22.31	21.92	0.558	59.72	6.87	35.03	97.68
26.00	Fulton	26.37	69.23	95.60	30.75	5355.55	13.38	9.63	0.446	81.67	14.46	31.20	97.14
27.00	Fulton	0.00	98.89	98.89	26.39	652221.96	13.25	20.44	0.323	90.67	37.30	7.25	41.87
28.00	Fulton	5.19	94.81	100.00	29.12	73877.75	9.20	7.96	0.405	63.99	8.73	14.20	75.71
29.00	Fulton	33.33	64.00	97.33	26.34	5488.89	25.86	20.90	0.491	74.82	20.78	13.19	74.11
30.00	Fulton	45.53	37.40	82.93	5.88	3400.00	4.69	53.15	0.571	94.27	48.39	0.62	11.04
31.00	Fulton	61.45	27.71	89.16	20.04	3144.44	13.26	42.28	0.595	69.05	9.98	7.22	76.54
32.00	Fulton	40.95	53.33	94.29	20.34	3511.11	12.20	31.16	0.519	79.67	26.14	7.36	31.81
33.00	Fulton	19.18	79.45	98.63	54.58	17711.10	7.94	3.69	0.432	48.74	5.75	20.68	95.66

Census Tract	County	PLDU00	PHDU00	PURB00	PPOV00	POPDENS00	PUNOC00	POWNOC00	NDVI00	PHS00	PBCH00	PUMP00	PBLK00
35.00	Fulton	2.76	97.24	100.00	26.15	86077.74	15.68	24.45	0.362	60.78	12.92	34.94	71.75
36.00	Fulton	20.00	75.00	95.00	22.88	16044.44	0.00	10.44	0.458	88.25	8.69	64.31	90.80
37.00	Fulton	50.00	50.00	100.00	75.43	20022.21	0.00	0.00	0.485	47.82	0.00	55.28	100.00
38.00	Fulton	48.72	48.72	97.44	40.97	7833.33	14.03	11.03	0.508	89.01	5.72	11.21	97.61
39.00	Fulton	63.95	23.26	87.21	41.29	4533.33	13.47	29.77	0.618	60.85	4.46	20.36	100.00
40.00	Fulton	56.17	29.63	85.80	18.75	3411.11	4.63	66.29	0.633	65.17	11.90	17.19	99.68
41.00	Fulton	52.17	33.04	85.22	34.89	4400.00	9.86	31.22	0.626	65.31	8.57	15.77	95.41
42.95	Fulton	36.92	55.38	92.31	48.65	4966.66	18.74	16.47	0.517	62.09	7.96	15.97	95.44
44.00	Fulton	23.86	69.32	93.18	67.87	8088.89	12.92	8.26	0.493	55.09	0.00	34.45	95.38
46.95	Fulton	13.79	85.34	99.14	53.59	7377.77	5.30	9.65	0.455	39.59	5.91	17.14	75.44
48.00	Fulton	23.68	73.68	97.37	65.17	26299.99	4.51	5.37	0.484	49.89	4.38	33.22	95.98
49.95	Fulton	39.29	52.68	91.96	20.39	4722.22	5.81	67.21	0.557	80.93	39.31	2.92	48.50
50.00	Fulton	40.44	50.00	90.44	19.89	3400.00	12.34	45.59	0.537	81.24	30.93	6.86	25.32
52.00	Fulton	44.73	22.78	67.51	16.26	3344.44	7.65	64.77	0.653	75.67	23.63	8.13	44.40
53.00	Fulton	55.30	17.97	73.27	17.95	2377.78	12.53	64.32	0.655	78.24	24.19	7.15	49.48
55.01	Fulton	60.33	23.14	83.47	39.01	3366.67	18.66	31.83	0.622	52.23	2.69	14.07	93.48
55.02	Fulton	47.37	33.92	81.29	39.00	1855.55	23.02	37.08	0.570	46.36	2.27	37.62	88.63
56.00	Fulton	33.33	60.78	94.12	46.18	4600.00	11.99	21.71	0.521	38.62	1.58	30.18	92.71
57.00	Fulton	43.08	52.31	95.38	37.59	4144.44	19.14	24.09	0.550	45.80	0.69	19.73	99.51
58.00	Fulton	38.33	50.83	89.17	27.76	5022.22	15.45	43.16	0.535	57.63	5.19	14.36	69.42
60.00	Fulton	53.57	20.83	74.40	22.60	4911.11	6.32	49.81	0.653	68.14	6.07	16.23	96.72
61.00	Fulton	42.47	12.33	54.79	25.03	4477.78	7.38	71.02	0.722	66.24	5.99	10.31	98.29
62.00	Fulton	45.71	36.19	81.90	33.47	3133.33	11.51	38.85	0.627	54.59	6.45	10.79	100.00
63.00	Fulton	42.00	51.33	93.33	42.35	3288.89	22.24	36.67	0.554	58.11	1.27	18.42	99.42
64.00	Fulton	36.00	39.20	75.20	54.14	6344.44	3.98	15.10	0.585	36.60	2.22	23.50	67.46
65.00	Fulton	47.22	27.16	74.38	24.37	3044.44	9.87	64.44	0.632	71.58	6.27	10.91	91.36
66.01	Fulton	41.53	40.44	81.97	23.59	3255.55	9.72	53.15	0.581	68.97	6.21	14.89	85.78
66.02	Fulton	33.33	34.85	68.18	29.06	5833.33	12.73	29.38	0.670	65.55	1.45	11.02	92.95
67.00	Fulton	37.85	35.31	73.16	41.72	2855.55	14.59	36.18	0.621	60.83	4.27	11.90	87.88
68.02	Fulton	39.19	17.57	56.76	67.33	5700.00	6.04	22.06	0.683	55.26	0.00	31.89	98.33
69.00	Fulton	32.58	19.68	52.26	27.35	3166.67	12.52	44.29	0.687	63.17	7.17	12.03	62.06
70.00	Fulton	27.78	21.43	49.21	36.14	3977.78	6.77	51.19	0.694	61.82	4.94	15.39	78.22

Census Tract	County	PLDU00	PHDU00	PURB00	PPOV00	POPDENS00	PUNOC00	POWNOC00	NDVI00	PHS00	PBCH00	PUMP00	PBLK00
71.00	Fulton	47.19	24.34	71.54	53.63	3055.55	5.32	41.49	0.642	55.12	2.75	24.47	99.24
72.00	Fulton	17.44	26.05	43.49	35.18	2600.00	7.20	31.96	0.677	70.51	1.44	12.22	91.71
73.00	Fulton	21.63	24.77	46.40	28.39	4455.55	5.28	37.22	0.697	65.53	1.73	11.37	94.27
74.00	Fulton	33.33	35.96	69.30	39.01	5433.33	8.42	25.86	0.632	40.86	1.93	14.53	50.19
75.00	Fulton	30.27	41.25	71.51	23.55	3844.44	4.45	30.77	0.613	63.76	5.38	16.70	80.66
76.01	Fulton	29.53	32.21	61.74	31.03	5233.33	11.93	11.52	0.646	72.34	6.11	11.21	91.65
76.02	Fulton	21.13	5.95	27.08	16.89	4133.33	5.20	59.41	0.760	75.89	10.22	8.49	95.50
77.01	Fulton	22.75	19.66	42.42	23.84	3333.33	4.65	53.30	0.717	77.05	13.28	10.47	96.75
77.02	Fulton	15.96	16.20	32.16	16.84	2888.89	7.32	37.11	0.719	77.21	10.11	10.21	95.23
78.02	Fulton	21.09	5.91	27.01	6.47	2177.78	2.84	77.32	0.740	88.79	28.37	5.25	96.51
78.03	Fulton	23.68	30.74	54.42	16.28	1955.55	6.41	50.60	0.635	80.01	11.33	7.83	92.72
78.04	Fulton	32.02	30.92	62.94	37.29	5222.22	12.93	28.50	0.675	62.69	3.15	14.92	95.19
79.00	Fulton	25.14	13.82	38.96	6.24	2055.55	1.62	87.76	0.733	84.90	29.39	5.20	97.31
80.00	Fulton	23.96	7.39	31.35	20.36	4211.11	5.27	74.89	0.755	72.67	11.14	12.01	95.58
81.01	Fulton	29.89	0.00	29.89	12.87	4700.00	0.00	80.43	0.761	76.55	11.55	12.38	98.62
81.02	Fulton	26.57	16.89	43.46	26.65	3477.78	9.13	33.81	0.716	75.22	13.10	10.35	89.98
82.01	Fulton	44.30	12.17	56.46	18.52	2411.11	5.90	70.64	0.701	80.31	19.51	5.57	98.60
82.02	Fulton	n/a	n/a	n/a	n/a	2700.00	n/a	n/a	0.660	n/a	n/a	n/a	n/a
83.01	Fulton	38.70	17.24	55.94	24.95	3888.89	9.51	43.22	0.709	66.96	4.20	14.42	98.28
83.02	Fulton	42.93	20.42	63.35	24.44	3288.89	18.20	52.41	0.702	72.98	5.82	12.11	97.67
84.00	Fulton	46.20	27.17	73.37	50.59	6644.44	20.84	29.59	0.661	60.65	3.84	24.43	96.95
85.00	Fulton	24.86	20.54	45.41	25.57	4855.55	7.69	47.00	0.718	58.06	1.92	20.01	93.18
86.01	Fulton	28.26	15.43	43.70	41.30	4544.44	7.48	40.11	0.736	58.88	4.34	17.40	97.75
86.02	Fulton	21.86	36.58	58.44	70.46	3522.22	3.71	16.82	0.622	48.62	1.73	25.89	98.34
87.01	Fulton	25.46	37.14	62.60	25.00	444.44	57.89	39.42	0.602	35.11	0.00	21.05	93.27
87.02	Fulton	34.55	22.87	57.42	44.23	2888.89	10.73	42.01	0.659	54.81	2.31	23.70	98.68
88.00	Fulton	25.98	39.84	65.81	30.48	1211.11	14.30	49.45	0.584	63.07	11.89	14.95	49.80
89.00	Fulton	32.33	42.34	74.67	14.68	3400.00	5.22	41.24	0.570	89.07	38.00	3.15	23.03
90.00	Fulton	21.08	24.10	45.18	4.19	5255.55	4.06	65.60	0.704	97.28	57.42	0.61	3.22
91.00	Fulton	32.74	30.36	63.10	12.15	6588.89	8.82	32.31	0.609	93.81	41.27	6.92	14.61
92.00	Fulton	32.57	53.14	85.71	12.18	3522.22	6.92	36.37	0.556	86.85	37.87	3.22	16.94
93.00	Fulton	37.85	20.72	58.57	4.59	5400.00	8.86	50.74	0.677	96.01	52.13	2.45	2.10

Census Tract	County	PLDU00	PHDU00	PURB00	PPOV00	POPDENS00	PUNOC00	POWNOC00	NDVI00	PHS00	PBCH00	PUMP00	PBLK00
94.01	Fulton	35.27	23.97	59.25	9.00	4944.44	15.51	32.52	0.634	96.18	51.04	3.06	11.39
94.02	Fulton	28.48	64.85	93.33	20.02	9344.44	15.62	6.96	0.472	66.99	21.50	6.62	10.70
95.00	Fulton	22.29	15.33	37.62	5.09	5222.22	11.79	57.54	0.709	93.83	45.39	2.49	3.30
96.00	Fulton	30.10	40.97	71.07	11.12	5633.33	11.49	41.52	0.579	94.14	42.40	3.70	6.75
97.00	Fulton	18.57	6.95	25.53	2.72	1944.44	8.67	72.34	0.742	98.39	57.69	0.70	2.16
98.00	Fulton	20.20	15.19	35.39	2.44	2366.67	6.34	73.56	0.729	96.35	52.25	2.74	1.58
99.00	Fulton	19.23	14.48	33.71	3.41	3011.11	8.33	70.16	0.732	97.39	51.86	1.65	1.83
100.00	Fulton	23.97	18.82	42.79	4.32	3444.44	12.94	77.29	0.674	95.56	49.88	3.37	3.11
101.01	Fulton	29.86	24.85	54.71	7.86	4055.55	15.02	38.22	0.658	92.25	40.94	1.58	7.04
101.03	Fulton	29.03	34.76	63.79	7.26	3566.67	10.65	39.84	0.618	93.49	37.60	2.92	10.25
101.05	Fulton	41.75	30.86	72.62	8.15	4911.11	7.30	18.30	0.579	92.10	30.34	4.92	29.17
101.06	Fulton	20.91	8.96	29.87	2.82	2522.22	5.38	56.94	0.695	95.81	37.50	1.87	12.65
101.07	Fulton	24.09	2.72	26.81	1.69	1844.44	2.26	98.92	0.704	96.91	45.96	0.00	1.87
101.08	Fulton	39.46	14.31	53.77	1.22	1866.67	3.63	84.73	0.663	96.92	51.45	1.56	3.88
102.01	Fulton	21.70	11.85	33.55	8.08	2844.44	4.95	66.92	0.733	80.37	39.20	3.34	7.25
102.03	Fulton	22.60	8.33	30.93	5.91	4055.55	6.95	29.27	0.655	95.25	40.96	2.60	15.66
102.04	Fulton	22.01	13.19	35.20	2.10	2244.44	1.67	98.47	0.711	96.62	51.38	2.59	2.06
102.05	Fulton	28.00	20.59	48.59	6.05	2400.00	6.26	81.39	0.681	94.91	41.56	2.18	7.37
103.01	Fulton	5.39	5.09	10.48	2.20	688.89	4.40	80.59	0.784	83.64	10.91	3.78	40.82
103.02	Fulton	11.82	14.64	26.46	8.75	1100.00	6.18	90.40	0.729	87.37	25.77	4.03	87.58
104.00	Fulton	5.84	2.77	8.60	8.98	588.89	4.17	74.30	0.786	73.11	7.43	2.82	30.62
105.03	Fulton	34.84	21.63	56.47	10.57	2611.11	3.68	58.70	0.659	79.60	12.12	8.18	90.82
105.04	Fulton	17.89	11.15	29.04	6.36	1655.55	4.54	72.68	0.719	84.07	12.16	6.44	80.55
105.05	Fulton	19.69	17.76	37.44	10.91	2033.33	6.65	46.75	0.703	81.56	8.88	6.02	84.84
105.06	Fulton	11.66	9.32	20.98	10.59	1322.22	5.34	66.20	0.747	73.31	8.07	7.00	47.07
106.01	Fulton	34.49	14.24	48.73	33.57	3844.44	7.24	36.78	0.713	64.15	10.60	9.47	65.70
106.02	Fulton	24.24	32.41	56.64	16.58	4033.33	5.28	16.97	0.649	80.71	9.37	8.47	90.80
107.00	Fulton	25.63	63.87	89.50	14.32	3900.00	10.55	30.49	0.586	65.85	8.64	5.56	62.36
108.00	Fulton	18.05	67.99	86.04	17.82	4166.67	6.42	47.71	0.539	65.76	7.27	5.44	26.34
109.00	Fulton	12.41	82.76	95.17	26.38	4111.11	11.34	26.36	0.480	40.45	3.53	21.03	31.05
110.00	Fulton	44.20	32.61	76.81	41.76	3622.22	7.57	31.90	0.598	48.62	3.51	17.65	74.34
111.00	Fulton	31.30	49.28	80.58	12.34	2655.55	6.26	67.95	0.570	80.71	12.89	7.46	57.00

Census Tract	County	PLDU00	PHDU00	PURB00	PPOV00	POPDENS00	PUNOC00	POWNOC00	NDVI00	PHS00	PBCH00	PUMP00	PBLK00
112.01	Fulton	35.00	33.95	68.95	33.12	4255.55	9.05	31.90	0.651	68.97	5.62	7.79	81.83
112.02	Fulton	47.83	21.40	69.23	20.47	4188.89	8.14	46.56	0.663	63.27	7.49	7.20	55.85
113.01	Fulton	37.98	7.47	45.45	3.69	2900.00	3.47	83.61	0.721	85.63	13.78	7.38	81.78
113.02	Fulton	23.56	15.89	39.45	18.66	4288.89	6.10	34.03	0.734	82.63	11.24	9.19	92.40
114.03	Fulton	32.55	12.63	45.18	2.64	1855.55	2.08	89.29	0.648	94.25	34.54	3.53	3.70
114.04	Fulton	36.16	35.47	71.63	12.05	5222.22	5.05	18.87	0.538	72.56	14.84	5.41	15.30
114.05	Fulton	32.95	16.28	49.23	14.38	2577.78	5.10	41.22	0.636	76.09	27.58	3.80	10.80
114.06	Fulton	29.59	11.05	40.64	2.99	2411.11	3.80	72.97	0.658	94.94	37.03	1.47	5.55
114.07	Fulton	29.69	6.78	36.47	4.92	1777.78	2.65	91.01	0.669	91.07	38.27	6.55	3.31
114.08	Fulton	42.50	14.07	56.58	1.82	2333.33	1.78	79.01	0.630	94.27	34.94	2.39	6.60
114.09	Fulton	40.30	8.79	49.09	2.95	2155.55	3.57	71.48	0.646	95.43	38.25	2.79	7.72
114.10	Fulton	37.77	8.37	46.13	2.68	2088.89	5.03	73.15	0.641	95.52	40.72	2.82	8.19
114.11	Fulton	31.63	7.84	39.48	3.27	3300.00	2.94	74.78	0.662	87.98	35.30	2.30	8.43
115.00	Fulton	14.07	3.34	17.42	3.09	1466.67	3.16	94.41	0.715	93.21	37.83	2.26	2.84
116.01	Fulton	24.65	15.94	40.59	5.30	1811.11	6.52	71.07	0.629	92.93	33.71	3.23	6.32
116.02	Fulton	33.59	16.26	49.85	3.13	2100.00	5.09	65.61	0.607	96.19	40.42	2.50	6.57
116.03	Fulton	33.39	9.55	42.94	2.47	2211.11	3.11	86.15	0.642	96.10	42.76	2.46	5.86
201.00	DeKalb	45.74	7.45	53.19	4.67	3388.89	3.59	74.20	0.712	86.06	50.54	1.79	3.95
202.00	DeKalb	26.75	17.20	43.95	6.42	5188.89	8.62	41.05	0.724	96.35	59.98	4.47	4.08
203.00	DeKalb	41.88	10.99	52.88	9.86	4066.67	4.31	67.88	0.702	93.22	52.36	2.22	14.89
204.00	DeKalb	54.00	20.00	74.00	6.88	3788.89	6.51	46.05	0.636	95.31	44.77	1.59	8.61
205.00	DeKalb	53.18	20.23	73.41	26.11	3500.00	15.87	51.78	0.657	58.96	6.45	14.73	89.18
206.00	DeKalb	48.11	31.13	79.25	37.98	4044.44	7.24	27.23	0.610	51.15	2.54	15.29	97.64
207.00	DeKalb	56.69	16.54	73.23	26.80	3666.67	12.48	43.08	0.645	55.20	7.98	11.16	80.64
208.00	DeKalb	40.24	16.83	57.07	17.28	3844.44	7.90	68.11	0.690	63.21	11.27	11.70	80.79
209.00	DeKalb	38.55	30.14	68.69	18.12	3955.55	8.23	60.02	0.673	63.43	9.71	12.30	80.54
211.00	DeKalb	35.67	12.03	47.71	9.33	3322.22	3.79	52.86	0.672	91.23	35.11	4.98	19.74
212.02	DeKalb	31.20	14.58	45.78	2.40	2400.00	2.31	86.38	0.691	94.50	47.58	1.84	3.33
212.04	DeKalb	19.72	52.98	72.71	29.68	6088.89	2.16	6.62	0.513	30.43	4.92	5.60	2.91
212.05	DeKalb	44.93	11.44	56.37	1.56	2300.00	1.42	96.84	0.667	97.59	50.14	2.37	0.81
212.07	DeKalb	33.24	37.86	71.10	5.32	3100.00	13.88	32.87	0.571	93.73	49.20	1.48	5.67
212.08	DeKalb	n/a	n/a	n/a	n/a	2288.89	n/a	n/a	0.567	n/a	n/a	n/a	n/a

Census Tract	County	PLDU00	PHDU00	PURB00	PPOV00	POPDENS00	PUNOC00	POWNOC00	NDVI00	PHS00	PBCH00	PUMP00	PBLK00
212.09	DeKalb	n/a	n/a	n/a	n/a	4244.44	n/a	n/a	0.683	n/a	n/a	n/a	n/a
212.10	DeKalb	45.38	12.00	57.38	2.57	1777.78	1.47	96.49	0.672	98.28	41.42	2.04	0.48
212.11	DeKalb	48.32	7.72	56.04	2.46	1877.78	2.05	95.92	0.656	97.04	43.33	1.84	2.09
212.12	DeKalb	39.40	26.98	66.38	5.82	3933.33	4.94	39.94	0.627	89.12	37.51	5.49	10.35
213.01	DeKalb	24.46	64.52	88.98	16.17	4044.44	3.78	20.34	0.493	72.39	22.54	6.96	20.81
213.02	DeKalb	40.10	30.51	70.61	15.00	3511.11	3.42	57.99	0.632	61.69	13.55	2.80	10.34
213.03	DeKalb	34.47	46.17	80.64	16.17	3933.33	2.69	42.22	0.552	53.43	8.17	6.44	13.48
213.04	DeKalb	30.26	37.79	68.05	12.28	4488.89	3.90	25.54	0.558	75.26	17.71	3.95	25.47
214.01	DeKalb	43.18	29.94	73.12	14.09	6000.00	5.37	25.20	0.593	59.92	25.68	3.85	12.53
214.02	DeKalb	45.66	19.15	64.81	12.61	6033.33	3.58	30.15	0.648	76.02	22.51	5.59	25.67
214.03	DeKalb	37.05	19.72	56.77	7.62	3377.78	5.33	47.87	0.673	88.43	38.64	3.51	6.01
214.04	DeKalb	37.01	25.98	62.99	22.08	6277.78	5.07	30.08	0.623	56.54	14.77	6.70	17.82
215.00	DeKalb	35.57	21.08	56.64	11.69	4188.89	5.01	39.67	0.674	94.14	49.62	4.79	7.20
216.01	DeKalb	32.15	13.74	45.89	8.01	3544.44	6.81	67.12	0.698	87.30	39.12	3.64	10.75
216.02	DeKalb	30.13	12.82	42.95	5.49	3844.44	6.55	57.73	0.706	96.15	48.37	2.15	3.74
216.03	DeKalb	34.67	31.73	66.40	17.53	4244.44	3.93	33.60	0.644	94.65	43.58	4.18	7.35
217.02	DeKalb	31.86	25.49	57.35	8.24	3255.55	3.86	52.79	0.649	89.66	37.17	2.20	10.15
217.03	DeKalb	30.62	12.48	43.10	4.60	2822.22	1.69	93.20	0.704	95.57	45.31	0.98	0.13
217.04	DeKalb	36.39	28.04	64.43	2.64	1933.33	3.09	78.16	0.632	92.88	37.30	2.63	10.42
218.05	DeKalb	46.30	12.70	59.00	5.30	2255.55	2.76	73.41	0.675	82.53	23.94	2.84	23.71
218.06	DeKalb	24.71	33.99	58.70	6.33	1988.89	3.81	54.46	0.616	80.98	21.70	5.03	27.74
218.08	DeKalb	43.67	20.00	63.67	2.98	3511.11	2.34	66.74	0.668	92.83	31.74	2.89	10.33
218.09	DeKalb	32.62	13.54	46.16	3.35	2322.22	2.31	92.04	0.695	91.85	31.00	1.65	2.27
218.10	DeKalb	32.98	31.17	64.16	2.34	1900.00	3.18	92.48	0.619	96.84	44.52	2.15	3.76
218.98	DeKalb	37.21	24.03	61.24	11.28	5711.11	5.90	33.13	0.631	86.35	22.47	3.74	39.51
219.02	DeKalb	24.30	14.36	38.67	4.17	2544.44	3.71	38.54	0.718	90.55	25.68	5.74	56.01
219.03	DeKalb	17.82	19.53	37.35	8.07	2800.00	4.67	69.93	0.673	83.94	16.34	4.85	70.28
219.04	DeKalb	40.30	28.14	68.44	9.39	4133.33	5.32	39.57	0.613	87.02	16.90	5.48	67.02
219.05	DeKalb	36.53	20.31	56.84	13.43	4722.22	5.97	38.06	0.657	84.67	11.93	7.86	74.65
220.01	DeKalb	32.88	20.63	53.51	3.18	2588.89	2.47	83.34	0.694	87.87	24.77	3.81	10.53
220.02	DeKalb	47.45	18.31	65.76	19.36	6600.00	5.79	20.68	0.655	77.87	12.35	7.26	63.80
220.04	DeKalb	44.36	12.82	57.18	11.32	3433.33	5.32	71.42	0.684	82.29	17.21	5.21	63.79

Census Tract	County	PLDU00	PHDU00	PURB00	PPOV00	POPDENS00	PUNOC00	POWNOC00	NDVI00	PHS00	PBCH00	PUMP00	PBLK00
220.05	DeKalb	37.43	26.90	64.33	16.53	3455.55	2.30	31.99	0.640	70.94	13.99	5.82	61.73
221.00	DeKalb	n/a	n/a	n/a	n/a	2944.44	n/a	n/a	0.661	n/a	n/a	n/a	n/a
222.00	DeKalb	33.67	35.97	69.64	10.29	3366.67	5.02	34.71	0.612	84.08	27.81	5.27	25.46
223.01	DeKalb	36.62	19.25	55.87	6.22	3344.44	4.76	64.05	0.672	94.48	40.44	2.91	4.40
223.02	DeKalb	32.42	19.23	51.65	9.62	3555.55	3.95	53.85	0.670	93.65	44.44	2.36	7.84
224.01	DeKalb	29.47	15.09	44.56	4.93	4922.22	4.65	56.77	0.725	97.03	59.30	1.16	4.18
224.02	DeKalb	35.15	20.30	55.45	7.72	3888.89	4.88	21.26	0.631	98.78	20.11	6.11	9.07
224.03	DeKalb	16.80	9.54	26.35	4.07	4966.66	2.53	78.13	0.764	96.60	59.24	0.88	5.14
225.00	DeKalb	34.59	26.03	60.62	19.60	5000.00	2.89	58.32	0.662	89.49	44.59	4.23	24.82
226.00	DeKalb	33.00	23.43	56.44	5.75	4877.78	4.44	51.67	0.660	92.09	43.78	5.16	5.25
227.00	DeKalb	44.21	14.59	58.80	9.19	4100.00	9.78	64.21	0.683	75.78	21.41	4.65	66.67
228.00	DeKalb	25.48	20.53	46.01	9.15	5644.44	5.35	68.50	0.700	93.30	31.63	9.34	29.16
229.00	DeKalb	26.76	17.57	44.32	14.99	4277.78	4.44	70.04	0.696	82.23	24.00	3.97	52.69
230.00	DeKalb	33.53	16.47	50.00	5.49	3488.89	4.11	67.83	0.663	93.99	41.33	3.10	22.97
231.01	DeKalb	31.94	14.44	46.39	22.52	4700.00	11.44	58.22	0.704	68.28	7.79	8.33	90.29
231.02	DeKalb	43.87	18.97	62.85	13.66	3244.44	3.34	44.49	0.653	84.11	19.31	4.51	63.92
231.03	DeKalb	43.03	18.55	61.58	12.88	3300.00	5.42	65.71	0.682	74.85	7.44	7.03	80.29
231.05	DeKalb	34.19	29.84	64.03	12.08	5588.89	2.76	43.52	0.639	70.20	10.30	4.89	66.24
231.06	DeKalb	37.07	26.07	63.14	11.89	4177.78	3.18	25.45	0.664	82.31	12.08	7.72	83.84
232.03	DeKalb	26.48	25.02	51.50	9.47	2844.44	4.49	50.32	0.632	88.20	13.06	4.89	93.54
232.04	DeKalb	32.79	7.57	40.36	4.29	3100.00	2.58	92.09	0.715	90.04	22.16	4.58	74.48
232.05	DeKalb	42.96	7.78	50.75	7.79	3188.89	2.67	82.98	0.710	89.61	15.67	5.26	85.55
232.06	DeKalb	35.57	9.99	45.55	7.55	2988.89	3.18	88.56	0.718	81.69	8.66	5.43	79.04
232.07	DeKalb	41.30	10.74	52.03	6.44	3477.78	3.47	63.07	0.699	91.46	19.45	6.64	91.95
233.02	DeKalb	21.53	11.02	32.55	3.71	1588.89	3.03	95.65	0.679	91.80	23.50	2.99	84.55
233.03	DeKalb	21.18	22.69	43.86	16.42	1100.00	8.67	61.61	0.640	70.30	6.97	6.21	67.14
233.05	DeKalb	30.11	7.83	37.94	2.50	2511.11	3.28	91.51	0.692	91.04	24.57	5.95	84.59
233.06	DeKalb	23.43	11.00	34.43	2.82	1822.22	2.43	95.02	0.685	88.94	16.06	6.12	88.81
233.07	DeKalb	38.19	14.66	52.84	4.73	3066.67	2.34	90.64	0.674	86.73	12.20	4.98	88.65
233.08	DeKalb	31.24	17.40	48.64	8.04	3600.00	4.91	55.93	0.647	87.91	12.43	6.34	93.88
234.03	DeKalb	34.34	24.53	58.86	10.94	4111.11	4.15	44.96	0.661	81.30	9.38	6.69	93.76
234.04	DeKalb	17.60	19.44	37.04	8.50	1711.11	3.68	78.74	0.680	88.43	10.04	5.20	90.16

Census Tract	County	PLDU00	PHDU00	PURB00	PPOV00	POPDENS00	PUNOC00	POWNOC00	NDVI00	PHS00	PBCH00	PUMP00	PBLK00
234.05	DeKalb	18.67	11.21	29.88	8.34	2911.11	3.50	75.11	0.712	85.00	13.84	6.94	96.37
234.07	DeKalb	15.53	8.54	24.07	6.80	1700.00	3.88	75.29	0.728	87.35	16.92	5.10	87.29
234.08	DeKalb	36.85	18.18	55.02	7.04	2733.33	3.09	82.14	0.686	85.42	17.07	6.46	92.38
234.09	DeKalb	28.57	11.95	40.52	4.47	2466.67	2.65	94.26	0.708	89.18	17.86	4.64	94.57
235.01	DeKalb	42.80	21.61	64.41	25.52	3655.55	6.69	67.11	0.685	66.23	3.98	13.59	94.17
235.02	DeKalb	46.59	14.55	61.14	11.06	3844.44	2.45	60.98	0.688	75.85	6.96	7.93	97.11
235.03	DeKalb	42.65	18.70	61.35	7.53	3244.44	2.02	73.67	0.692	81.43	9.59	7.38	93.37
236.00	DeKalb	34.92	11.23	46.15	14.34	3611.11	5.93	67.40	0.722	68.26	5.52	16.19	94.53
237.00	DeKalb	29.20	21.43	50.63	36.35	4588.89	6.63	45.21	0.698	67.04	3.91	10.58	94.35
238.01	DeKalb	33.02	6.32	39.34	22.62	3355.55	8.13	60.83	0.739	68.79	6.06	9.91	86.07
238.02	DeKalb	18.94	21.84	40.79	19.99	2455.55	4.86	33.46	0.690	73.18	4.49	9.02	78.43
238.03	DeKalb	33.27	11.90	45.16	16.11	3655.55	3.71	82.34	0.728	73.39	3.51	11.20	96.62
301.98	Cobb	20.31	10.01	30.32	5.75	2033.33	4.47	81.39	0.644	84.54	17.81	3.22	10.77
302.03	Cobb	22.01	5.24	27.25	2.51	1855.55	2.97	94.81	0.728	91.28	27.45	2.92	10.60
302.04	Cobb	38.43	14.62	53.05	2.80	2444.44	4.56	85.33	0.611	92.38	25.24	2.17	11.64
302.05	Cobb	25.72	32.92	58.64	9.05	1655.55	6.31	38.35	0.556	91.08	20.34	2.42	8.39
302.06	Cobb	n/a	n/a	n/a	n/a	2177.78	n/a	n/a	0.713	n/a	n/a	n/a	n/a
302.07	Cobb	n/a	n/a	n/a	n/a	1877.78	n/a	n/a	0.725	n/a	n/a	n/a	n/a
303.02	Cobb	37.93	6.67	44.60	0.52	2488.89	1.55	96.51	0.672	94.72	37.70	3.61	4.79
303.07	Cobb	33.64	6.50	40.14	1.05	2466.67	1.49	94.27	0.692	94.26	32.63	2.46	2.83
303.09	Cobb	37.66	11.27	48.93	2.22	2533.33	1.65	94.10	0.658	93.32	36.89	2.35	4.18
303.10	Cobb	38.13	9.36	47.49	1.21	2322.22	2.44	84.27	0.666	88.27	20.65	2.99	8.35
303.11	Cobb	34.94	12.47	47.41	1.25	2100.00	1.93	93.35	0.645	90.95	26.82	3.29	6.42
303.12	Cobb	34.02	11.42	45.43	4.38	2211.11	2.34	88.79	0.662	89.15	20.62	2.24	7.01
303.13	Cobb	36.52	10.53	47.05	3.11	2077.78	1.87	89.55	0.670	93.82	19.56	1.96	9.06
303.14	Cobb	34.50	13.05	47.55	1.34	2488.89	2.40	91.51	0.661	93.39	28.76	2.37	6.08
303.15	Cobb	40.04	10.79	50.83	2.12	2388.89	1.58	93.82	0.664	94.53	33.46	3.32	3.52
303.16	Cobb	36.77	9.07	45.84	2.22	2333.33	1.36	95.19	0.681	96.34	39.44	2.41	3.24
303.17	Cobb	37.04	10.66	47.70	1.36	2733.33	0.99	98.16	0.659	96.05	44.74	2.42	1.96
303.18	Cobb	34.83	8.98	43.81	2.12	1733.33	2.17	97.01	0.700	95.29	46.06	1.63	2.65
303.19	Cobb	23.68	6.71	30.39	3.30	2188.89	1.57	92.28	0.698	96.59	37.46	2.32	1.90
303.20	Cobb	25.95	10.34	36.29	5.61	2433.33	5.95	52.46	0.730	96.08	42.78	2.59	5.14

Census Tract	County	PLDU00	PHDU00	PURB00	PPOV00	POPDENS00	PUNOC00	POWNOC00	NDVI00	PHS00	PBCH00	PUMP00	PBLK00
303.21	Cobb	28.91	41.64	70.55	8.73	3766.67	10.46	9.02	0.571	93.97	36.87	3.40	27.37
304.01	Cobb	n/a	n/a	n/a	n/a	2677.78	n/a	n/a	0.708	n/a	n/a	n/a	n/a
304.02	Cobb	40.28	12.71	52.99	6.09	2933.33	3.72	71.63	0.691	94.34	31.77	1.91	10.59
304.04	Cobb	36.18	50.71	86.89	22.72	6755.55	6.16	13.42	0.525	80.24	20.43	8.11	43.46
304.05	Cobb	38.26	34.35	72.61	7.44	3900.00	4.17	41.05	0.626	91.30	25.63	3.24	19.99
304.06	Cobb	35.38	47.18	82.56	11.86	6988.89	6.60	9.37	0.532	84.73	22.40	7.73	44.08
305.01	Cobb	30.81	21.20	52.01	4.72	1933.33	3.15	81.35	0.631	89.06	18.31	4.30	10.50
305.02	Cobb	34.28	24.75	59.03	5.40	1766.67	3.21	82.92	0.592	92.30	24.93	4.54	13.97
305.03	Cobb	33.25	21.66	54.91	10.65	2788.89	3.70	44.95	0.667	86.63	23.02	3.54	19.39
306.00	Cobb	20.30	19.35	39.65	6.31	2166.67	6.58	48.50	0.682	87.31	22.50	3.08	11.49
307.00	Cobb	n/a	n/a	n/a	n/a	3222.22	n/a	n/a	0.619	n/a	n/a	n/a	n/a
308.00	Cobb	34.04	42.88	76.92	30.93	2866.67	5.94	19.55	0.577	59.58	6.73	7.98	24.80
309.01	Cobb	28.43	6.90	35.33	4.73	2522.22	2.73	70.65	0.726	91.53	31.05	2.81	18.02
309.02	Cobb	30.06	19.25	49.31	18.59	4733.33	6.70	38.82	0.679	62.16	9.20	6.43	26.85
309.03	Cobb	43.26	9.39	52.64	7.24	3222.22	3.66	67.43	0.664	79.03	13.49	3.45	39.10
310.01	Cobb	22.45	34.12	56.57	12.20	1622.22	6.64	37.07	0.599	53.70	5.85	7.10	22.54
310.02	Cobb	36.54	16.24	52.78	18.93	4355.55	3.18	37.20	0.688	61.53	4.88	7.02	31.18
310.03	Cobb	44.76	13.62	58.38	8.94	2866.67	3.19	60.92	0.688	76.17	10.11	6.53	31.86
311.01	Cobb	44.61	25.07	69.68	13.83	3355.55	4.94	44.33	0.634	68.74	9.88	7.46	22.10
311.03	Cobb	41.28	17.32	58.60	6.25	3033.33	6.10	56.84	0.671	83.46	24.55	4.59	22.01
311.05	Cobb	48.18	12.04	60.22	11.59	3211.11	5.50	54.68	0.679	74.83	13.40	2.44	34.47
311.06	Cobb	32.59	18.08	50.67	5.14	2488.89	2.28	78.67	0.697	80.42	15.20	6.05	29.44
311.07	Cobb	40.90	11.18	52.08	7.03	2233.33	3.07	75.92	0.701	86.99	23.97	6.52	18.64
311.08	Cobb	52.82	18.69	71.51	14.08	3044.44	4.96	43.42	0.632	77.71	21.72	5.78	45.25
311.09	Cobb	39.39	36.87	76.26	11.26	4266.66	6.46	20.06	0.570	83.76	29.31	6.19	32.32
312.02	Cobb	32.16	27.88	60.04	8.69	1488.89	6.55	32.32	0.612	92.23	31.62	3.53	36.80
312.03	Cobb	37.66	27.81	65.47	7.73	3000.00	9.71	22.21	0.614	97.00	45.58	3.76	14.76
312.04	Cobb	39.58	12.40	51.98	3.75	2488.89	5.12	48.88	0.665	95.25	46.73	1.50	9.06
313.01	Cobb	n/a	n/a	n/a	n/a	1888.89	n/a	n/a	0.730	n/a	n/a	n/a	n/a
313.02	Cobb	22.06	8.54	30.59	10.02	1444.44	5.72	82.68	0.720	77.40	17.94	4.38	34.89
313.04	Cobb	35.72	10.70	46.42	6.68	2122.22	2.56	80.87	0.713	77.93	10.42	4.86	41.53
313.05	Cobb	21.78	22.02	43.80	10.93	2766.67	9.45	35.21	0.678	77.72	8.94	7.24	66.24

Census Tract	County	PLDU00	PHDU00	PURB00	PPOV00	POPDENS00	PUNOC00	POWNOC00	NDVI00	PHS00	PBCH00	PUMP00	PBLK00
314.03	Cobb	36.45	16.76	53.21	5.81	2222.22	2.88	69.80	0.661	85.78	16.36	6.04	37.52
314.04	Cobb	32.09	11.30	43.39	4.73	1777.78	3.97	79.03	0.711	80.64	12.84	3.86	22.69
314.98	Cobb	n/a	n/a	n/a	n/a	1522.22	n/a	n/a	0.678	n/a	n/a	n/a	n/a
315.01	Cobb	21.54	5.21	26.75	2.78	1233.33	3.08	93.27	0.724	85.14	13.78	2.68	17.18
315.02	Cobb	33.73	8.69	42.42	7.08	1877.78	2.37	88.60	0.702	84.62	16.36	3.40	37.15
402.00	Clayton	27.87	32.38	60.25	11.64	2855.55	5.92	26.97	0.613	83.88	9.92	6.89	81.31
403.02	Clayton	34.43	14.31	48.74	14.99	3277.78	5.64	48.88	0.694	63.63	2.92	8.47	36.88
403.03	Clayton	43.85	22.18	66.03	22.09	3066.67	5.09	49.09	0.650	59.15	3.84	6.60	47.56
403.04	Clayton	44.68	28.24	72.92	11.31	2677.78	4.40	57.39	0.614	56.81	4.66	4.95	35.00
403.05	Clayton	n/a	n/a	n/a	n/a	3233.33	n/a	n/a	0.594	n/a	n/a	n/a	n/a
404.01	Clayton	37.91	15.55	53.46	9.78	2177.78	4.85	59.27	0.670	74.88	5.85	5.98	42.51
404.02	Clayton	20.22	18.48	38.70	7.19	1577.78	4.36	82.53	0.682	79.59	7.79	5.76	45.53
404.03	Clayton	38.16	21.81	59.97	10.04	2466.67	3.88	62.95	0.637	78.10	9.34	5.24	42.74
404.05	Clayton	n/a	n/a	n/a	n/a	3977.78	n/a	n/a	0.655	n/a	n/a	n/a	n/a
404.06	Clayton	34.71	36.39	71.11	12.11	2955.55	5.74	44.47	0.602	68.49	5.18	4.88	44.52
405.03	Clayton	40.44	11.94	52.37	9.81	2877.78	4.14	49.71	0.683	78.54	6.67	7.59	56.71
405.04	Clayton	40.22	14.15	54.37	7.26	3166.67	6.44	34.19	0.667	89.35	13.29	4.37	84.57
405.05	Clayton	40.28	9.02	49.30	8.09	2044.44	3.54	71.97	0.702	83.05	12.92	6.49	70.52
405.06	Clayton	43.99	17.07	61.06	11.64	2566.67	3.66	63.50	0.668	79.20	7.02	6.80	59.94
405.07	Clayton	40.40	11.87	52.27	8.37	2622.22	4.42	67.06	0.651	78.09	7.19	4.85	60.00
405.08	Clayton	44.75	4.47	49.22	9.03	2666.67	4.17	76.20	0.695	80.68	6.82	6.00	66.34
406.03	Clayton	33.85	13.97	47.82	8.26	2133.33	3.86	65.89	0.672	82.77	13.95	3.96	37.55
406.04	Clayton	30.56	25.28	55.84	16.43	2511.11	6.01	49.06	0.651	72.74	7.34	6.49	34.10
406.05	Clayton	29.21	8.05	37.25	4.61	1511.11	2.50	89.74	0.686	88.01	20.12	4.57	25.19
406.06	Clayton	7.49	6.46	13.95	5.70	1800.00	12.76	90.33	0.761	62.82	4.35	6.08	27.45
406.07	Clayton	25.36	6.86	32.22	9.02	2433.33	3.49	87.02	0.688	83.58	10.14	4.07	47.34
406.08	Clayton	n/a	n/a	n/a	n/a	1300.00	n/a	n/a	0.750	n/a	n/a	n/a	n/a
501.01	Gwinnett	16.50	6.46	22.96	5.27	1700.00	4.34	85.07	0.667	81.76	18.00	3.27	5.25
501.02	Gwinnett	18.54	13.91	32.46	7.15	1555.55	4.53	65.99	0.673	69.88	9.67	3.76	8.76
502.02	Gwinnett	21.51	10.43	31.95	1.85	1555.55	9.22	85.69	0.647	92.97	31.06	1.33	7.34
502.03	Gwinnett	n/a	n/a	n/a	n/a	3000.00	n/a	n/a	0.573	n/a	n/a	n/a	n/a
502.04	Gwinnett	n/a	n/a	n/a	n/a	1511.11	n/a	n/a	0.641	n/a	n/a	n/a	n/a

Census Tract	County	PLDU00	PHDU00	PURB00	PPOV00	POPDENS00	PUNOC00	POWNOC00	NDVI00	PHS00	PBCH00	PUMP00	PBLK00
503.04	Gwinnett	28.34	42.95	71.28	16.77	1600.00	7.26	27.52	0.560	71.45	13.78	3.53	21.97
503.05	Gwinnett	45.94	16.24	62.18	12.11	5588.89	3.76	19.80	0.613	84.31	20.08	7.00	38.95
503.06	Gwinnett	27.62	52.36	79.98	16.44	1511.11	4.08	60.68	0.510	49.07	7.03	6.94	13.96
503.07	Gwinnett	44.09	5.49	49.57	1.08	1955.55	1.12	98.76	0.653	96.96	47.75	3.22	1.98
503.08	Gwinnett	36.41	16.03	52.44	1.61	1777.78	1.89	99.27	0.601	94.54	43.31	1.69	1.27
503.09	Gwinnett	32.13	20.19	52.32	4.62	1911.11	2.69	71.29	0.585	94.71	40.69	1.87	9.30
503.10	Gwinnett	43.37	32.15	75.51	7.11	1477.78	1.89	61.35	0.533	93.72	31.43	3.54	19.01
503.11	Gwinnett	28.49	33.20	61.69	13.85	1566.67	4.85	81.15	0.578	86.21	22.90	12.33	22.68
503.12	Gwinnett	42.64	30.11	72.75	19.30	3822.22	3.75	39.88	0.583	57.56	8.61	5.80	24.04
503.13	Gwinnett	40.51	14.49	55.00	5.69	2177.78	2.09	78.57	0.634	80.12	21.50	4.16	14.42
503.14	Gwinnett	45.52	12.43	57.95	4.04	2466.67	2.12	89.39	0.633	83.31	21.86	3.84	10.73
504.03	Gwinnett	n/a	n/a	n/a	n/a	2400.00	n/a	n/a	0.693	n/a	n/a	n/a	n/a
504.06	Gwinnett	44.68	28.72	73.40	14.04	6333.33	5.68	28.11	0.602	70.44	16.14	4.91	29.38
504.07	Gwinnett	47.72	14.09	61.80	11.29	4255.55	3.49	43.96	0.653	69.57	14.27	5.02	22.72
504.08	Gwinnett	51.26	27.46	78.72	13.04	3455.55	4.48	42.22	0.598	76.54	10.74	5.04	26.67
504.09	Gwinnett	36.77	31.57	68.35	7.58	2411.11	3.62	56.74	0.568	81.53	17.20	2.73	27.00
504.10	Gwinnett	36.18	17.27	53.45	8.46	2511.11	3.07	59.46	0.665	79.37	12.98	3.87	16.57
504.11	Gwinnett	35.76	18.17	53.93	5.89	2600.00	3.44	55.86	0.653	81.42	14.78	2.72	16.02
504.12	Gwinnett	38.01	6.29	44.30	2.70	1955.55	1.72	94.29	0.710	92.79	27.98	2.33	3.66
504.13	Gwinnett	34.81	8.42	43.23	2.07	2055.55	2.34	94.56	0.688	93.16	33.94	2.21	4.24
504.14	Gwinnett	34.16	10.24	44.40	2.39	2166.67	3.34	86.38	0.684	89.07	22.81	3.44	7.36
504.15	Gwinnett	31.24	13.50	44.74	0.93	1544.44	1.19	95.03	0.687	91.61	29.01	2.27	16.01
504.16	Gwinnett	29.31	3.62	32.93	7.51	2122.22	4.44	92.00	0.745	86.84	13.03	5.58	27.15
505.02	Gwinnett	36.53	18.31	54.84	4.03	2433.33	2.29	83.20	0.603	90.61	24.56	1.75	11.61
505.03	Gwinnett	n/a	n/a	n/a	n/a	2055.55	n/a	n/a	0.631	n/a	n/a	n/a	n/a
505.05	Gwinnett	31.59	9.87	41.46	4.93	2166.67	1.77	89.72	0.660	89.23	19.29	3.57	16.50
505.06	Gwinnett	n/a	n/a	n/a	n/a	3411.11	n/a	n/a	0.608	n/a	n/a	n/a	n/a
505.07	Gwinnett	n/a	n/a	n/a	n/a	2011.11	n/a	n/a	0.611	n/a	n/a	n/a	n/a
505.08	Gwinnett	35.77	22.42	58.19	12.21	2477.78	2.82	51.01	0.609	73.58	11.25	4.03	14.05
505.09	Gwinnett	19.25	5.61	24.86	7.02	1466.67	3.11	84.25	0.659	77.31	12.94	3.98	11.25
506.01	Gwinnett	14.66	5.84	20.50	2.50	1500.00	3.40	94.39	0.695	87.75	15.73	2.50	4.16
506.02	Gwinnett	10.74	4.02	14.76	2.82	1044.44	3.73	93.53	0.714	85.45	16.56	2.73	4.14

Census Tract	County	PLDU00	PHDU00	PURB00	PPOV00	POPDENS00	PUNOC00	POWNOC00	NDVI00	PHS00	PBCH00	PUMP00	PBLK00
507.04	Gwinnett	17.10	3.54	20.64	2.15	1622.22	2.86	95.82	0.714	88.96	18.70	3.97	7.48
507.05	Gwinnett	15.48	5.00	20.48	2.74	1355.56	2.58	91.20	0.707	89.40	17.08	1.86	4.06
507.06	Gwinnett	38.29	11.09	49.38	1.35	2300.00	2.03	96.09	0.687	93.51	31.27	3.42	4.24
507.07	Gwinnett	30.29	9.06	39.35	3.14	1988.89	1.75	90.53	0.703	93.20	25.66	2.66	6.77
507.08	Gwinnett	38.44	9.83	48.27	2.63	2055.55	2.51	83.71	0.692	88.69	18.30	2.25	17.31
507.09	Gwinnett	20.37	5.43	25.80	3.40	1622.22	6.02	91.78	0.740	86.78	17.59	3.08	16.48
507.10	Gwinnett	36.38	13.59	49.97	3.16	2011.11	3.49	77.30	0.677	88.88	20.58	2.87	7.87
507.11	Gwinnett	36.58	9.39	45.97	3.90	1644.44	2.93	91.25	0.675	89.61	18.09	2.88	6.11
601.00	Rockdale	11.00	5.69	16.70	6.02	722.22	5.88	80.91	0.737	76.37	11.46	4.00	5.80
602.00	Rockdale	17.98	6.92	24.90	11.08	1622.22	3.44	77.18	0.727	72.48	13.02	5.17	22.43
603.02	Rockdale	n/a	n/a	n/a	n/a	1411.11	n/a	n/a	0.689	n/a	n/a	n/a	n/a
603.03	Rockdale	25.33	10.41	35.75	15.23	2200.00	6.47	48.86	0.712	70.03	8.26	4.65	29.81
603.04	Rockdale	19.91	23.72	43.63	12.66	1133.33	4.74	57.34	0.662	72.01	9.97	5.69	30.26
604.01	Rockdale	12.58	5.24	17.82	3.64	1255.56	2.78	89.91	0.755	85.96	11.95	4.65	11.96
604.02	Rockdale	15.08	4.10	19.17	4.51	1455.55	2.63	93.39	0.747	87.84	17.87	2.62	6.61
701.02	Henry	14.93	5.46	20.39	1.96	1700.00	1.49	93.92	0.748	85.50	9.30	3.03	7.86
701.03	Henry	21.64	12.00	33.64	6.22	1611.11	4.23	75.68	0.683	84.06	14.78	2.59	17.02
701.98	Henry	15.57	7.54	23.11	2.80	1733.33	3.65	89.99	0.741	86.86	13.33	2.34	38.68
702.01	Henry	13.15	4.84	17.99	3.84	1466.67	4.79	84.37	0.734	83.05	12.77	1.33	5.84
702.02	Henry	9.39	2.73	12.12	3.26	1055.56	2.47	95.79	0.747	88.65	12.49	2.92	3.08
702.03	Henry	9.92	4.09	14.02	1.82	766.67	3.33	95.04	0.749	89.23	14.19	1.67	3.35
703.01	Henry	8.79	6.50	15.29	2.04	1155.56	3.16	95.86	0.731	91.52	16.26	2.16	5.66
703.02	Henry	16.39	9.98	26.37	7.75	1788.89	4.99	77.33	0.703	79.80	13.58	3.81	23.13
704.02	Henry	7.58	4.09	11.67	4.81	822.22	4.59	94.66	0.753	82.27	7.99	2.84	5.86
704.98	Henry	7.92	5.80	13.72	5.03	855.56	4.29	90.78	0.731	75.99	5.12	3.31	11.17
705.00	Henry	7.32	5.04	12.36	5.97	977.78	5.95	86.52	0.749	74.96	6.28	2.74	10.30
801.98	Douglas	n/a	n/a	n/a	n/a	1600.00	n/a	n/a	0.723	n/a	n/a	n/a	n/a
802.00	Douglas	24.19	8.52	32.71	7.52	1433.33	5.05	86.96	0.722	78.62	8.16	3.83	17.43
803.00	Douglas	23.65	14.71	38.36	14.12	1844.44	6.94	62.67	0.702	72.45	7.72	5.78	29.78
804.00	Douglas	7.85	5.09	12.94	5.96	666.67	6.59	89.71	0.773	75.94	8.50	3.09	9.14
805.01	Douglas	13.69	5.39	19.08	6.07	1455.55	3.78	86.35	0.763	80.28	8.06	3.19	7.10
805.03	Douglas	32.22	9.99	42.21	3.32	2088.89	5.66	70.98	0.700	88.67	18.65	3.01	12.76

Census Tract	County	PLDU00	PHDU00	PURB00	PPOV00	POPDENS00	PUNOC00	POWNOC00	NDVI00	PHS00	PBCH00	PUMP00	PBLK00
805.04	Douglas	10.99	3.41	14.41	3.18	1433.33	3.22	91.17	0.780	85.75	15.16	4.04	14.44
806.01	Douglas	15.55	5.74	21.28	5.48	1500.00	3.56	83.05	0.759	83.72	13.96	3.86	15.83
806.02	Douglas	10.98	5.47	16.44	8.56	1388.89	3.63	77.38	0.792	78.69	11.46	3.74	22.68
901.00	Cherokee	4.35	3.07	7.43	6.69	677.78	5.36	87.14	0.763	66.81	8.77	1.68	0.97
902.00	Cherokee	2.63	2.74	5.37	6.06	966.67	9.94	85.30	0.785	77.47	12.41	4.05	0.33
903.00	Cherokee	3.48	2.78	6.26	6.55	744.44	4.80	87.90	0.719	69.44	10.71	3.59	0.78
904.00	Cherokee	7.27	7.94	15.20	13.05	1366.67	5.36	52.14	0.748	58.60	6.46	6.89	9.56
905.00	Cherokee	4.68	4.22	8.90	6.07	1111.11	4.08	86.91	0.757	79.79	13.94	3.53	0.37
906.00	Cherokee	9.33	7.12	16.45	9.12	1866.67	4.70	72.34	0.742	70.63	12.69	1.67	2.50
907.00	Cherokee	15.16	7.25	22.42	3.94	1511.11	5.09	87.97	0.664	84.86	16.00	1.66	1.32
908.00	Cherokee	9.07	3.67	12.74	4.72	1888.89	3.17	91.81	0.734	87.75	19.69	2.47	0.81
909.01	Cherokee	13.76	1.46	15.21	3.83	1900.00	3.77	91.65	0.726	87.68	17.43	4.02	1.96
909.02	Cherokee	16.79	5.15	21.94	3.45	2222.22	2.13	92.67	0.712	92.29	22.86	1.45	3.87
909.03	Cherokee	24.24	8.46	32.71	4.70	2066.67	4.14	78.29	0.670	84.11	13.84	1.49	3.62
910.01	Cherokee	16.79	16.47	33.26	8.28	1488.89	5.40	59.59	0.662	79.74	5.99	4.00	5.32
910.02	Cherokee	29.70	9.97	39.67	2.45	2611.11	5.01	85.96	0.649	91.97	28.32	2.47	2.33
910.03	Cherokee	27.63	18.02	45.65	7.61	2133.33	5.55	65.11	0.632	79.68	12.98	3.40	3.41
911.01	Cherokee	18.75	3.42	22.17	2.78	1633.33	6.76	91.80	0.587	91.10	17.35	2.39	2.48
911.03	Cherokee	14.56	6.25	20.81	5.67	1722.22	3.30	89.38	0.669	81.32	11.18	2.95	1.82
911.98	Cherokee	21.60	7.17	28.77	6.90	2900.00	4.66	83.95	0.698	82.07	9.59	3.63	2.70
1201.00	Paulding	5.78	2.38	8.16	3.26	955.56	3.41	91.62	0.778	82.89	10.68	1.47	3.17
1202.00	Paulding	n/a	n/a	n/a	n/a	1555.55	n/a	n/a	0.739	n/a	n/a	n/a	n/a
1203.00	Paulding	9.48	6.46	15.94	8.56	1333.33	6.43	66.84	0.762	74.49	6.88	3.66	7.80
1204.00	Paulding	4.66	2.83	7.49	10.23	600.00	5.60	86.90	0.794	65.70	3.10	2.29	5.61
1205.00	Paulding	12.99	5.21	18.20	6.39	1622.22	3.47	88.81	0.754	79.90	8.16	3.82	7.65
1206.98	Paulding	11.27	3.62	14.89	4.08	1911.11	2.73	93.58	0.747	84.41	9.27	2.17	11.34
1301.00	Forsyth	6.69	5.49	12.19	9.57	1388.89	10.67	84.73	0.695	74.20	11.33	4.54	0.00
1302.00	Forsyth	5.62	6.10	11.73	3.79	1433.33	4.40	88.43	0.754	84.71	17.40	1.91	0.00
1303.00	Forsyth	8.84	6.12	14.96	3.74	2111.11	2.83	91.39	0.731	85.37	22.38	1.59	0.18
1304.00	Forsyth	10.29	10.29	20.58	10.25	1988.89	4.38	75.24	0.719	73.06	12.91	2.16	2.07
1305.00	Forsyth	11.05	7.27	18.32	3.73	1322.22	8.79	88.94	0.556	87.97	22.92	1.82	0.30
1306.00	Forsyth	14.19	8.96	23.15	4.25	1655.55	2.69	93.69	0.680	88.87	30.75	1.71	1.02

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1401.01	Fayette	13.03	4.51	17.53	3.80	1211.11	4.38	94.29	0.757	85.76	21.54	2.42	45.78
1401.02	Fayette	16.74	7.86	24.59	2.50	1066.67	2.85	95.24	0.722	87.64	20.45	2.61	24.17
1402.01	Fayette	11.07	3.75	14.82	3.13	1044.44	3.40	90.08	0.747	86.42	18.68	2.95	7.10
1402.02	Fayette	22.54	6.61	29.14	1.99	1500.00	5.36	80.58	0.700	92.49	32.21	2.43	7.05
1403.01	Fayette	19.54	5.34	24.88	1.88	1288.89	3.22	86.16	0.720	91.93	24.53	2.75	4.79
1403.02	Fayette	24.38	7.42	31.81	3.14	1433.33	3.57	83.06	0.707	94.26	30.81	1.81	6.12
1404.01	Fayette	18.71	6.08	24.79	1.54	1311.11	2.39	91.72	0.723	93.68	22.78	2.37	16.40
1404.02	Fayette	17.34	5.23	22.57	3.53	1422.22	4.26	77.69	0.744	89.19	17.66	3.87	11.45
1405.01	Fayette	7.65	2.99	10.64	2.77	844.44	2.51	94.40	0.757	92.11	18.95	2.28	4.24
1405.02	Fayette	5.70	3.15	8.85	3.24	711.11	3.00	93.52	0.762	87.71	11.73	0.54	1.28
1701.00	Coweta	7.55	3.10	10.64	5.25	366.67	5.43	87.45	0.767	79.86	9.50	4.83	6.58
1702.00	Coweta	14.17	5.98	20.15	7.29	1166.67	3.86	71.96	0.759	72.58	11.62	4.25	13.21
1703.00	Coweta	11.68	6.72	18.40	7.27	1122.22	6.62	64.91	0.739	81.59	18.14	3.57	20.16
1704.00	Coweta	12.79	5.12	17.91	2.65	1300.00	4.15	93.87	0.748	88.45	17.24	1.96	7.63
1705.00	Coweta	6.59	3.20	9.79	5.20	700.00	3.50	88.13	0.764	83.53	10.22	3.19	11.63
1706.00	Coweta	14.51	5.80	20.30	17.73	1088.89	7.16	62.59	0.738	68.17	9.78	6.14	34.31
1707.00	Coweta	13.47	3.46	16.93	15.18	1400.00	5.23	64.98	0.759	70.72	8.06	6.63	50.60
1708.00	Coweta	n/a	n/a	n/a	n/a	533.33	n/a	n/a	0.774	n/a	n/a	n/a	n/a

APPENDIX F

COMPOSITE INDEX SCORES,
BY 1990 CENSUS TRACT BOUNDARIES

Table F.1. Composite index scores, metropolitan Atlanta, Georgia, 1980-2000.

Census Tract	**County**	**Index 1980**	**Index 1990**	**Index 2000**
1.00	Fulton	-0.3193	-0.4276	-0.4787
2.00	Fulton	-0.4031	-0.4198	-0.4821
4.00	Fulton	-0.4197	-0.3809	-0.4659
5.00	Fulton	-0.4316	-0.4445	-0.3848
7.00	Fulton	0.3450	0.4190	0.5202
8.00	Fulton	0.5706	0.6852	0.6567
10.95	Fulton	-0.5911	-0.3814	-0.5543
11.00	Fulton	-0.3246	-0.3313	-0.4924
12.00	Fulton	-0.3468	-0.3931	-0.4493
13.00	Fulton	-0.3896	-0.2534	-0.3459
14.00	Fulton	-0.3853	-0.3783	-0.5035
15.00	Fulton	-0.3796	-0.3541	-0.5221
17.00	Fulton	0.4283	0.5158	0.2074
18.00	Fulton	0.6628	0.2534	-0.0468
19.00	Fulton	-0.4089	-0.1620	0.2167
20.00	Fulton	0.1933	0.7273	0.2167
21.00	Fulton	0.4479	0.5183	0.0340
22.00	Fulton	0.5984	0.6139	0.6098
23.00	Fulton	0.5836	0.4605	0.5630
24.00	Fulton	0.4910	0.5136	0.5222
25.00	Fulton	0.4059	0.5126	0.4633
26.00	Fulton	0.6745	0.7235	0.1864
27.00	Fulton	0.0368	-0.3869	-0.2884
28.00	Fulton	0.2900	0.3575	0.2578
29.00	Fulton	0.6573	0.8033	0.1210
30.00	Fulton	-0.4382	-0.4297	-0.4679
31.00	Fulton	0.6996	0.5495	0.2401
32.00	Fulton	0.4288	0.2578	-0.1955
33.00	Fulton	0.6444	0.6266	0.5813
35.00	Fulton	0.5334	0.4765	0.2733
36.00	Fulton	0.2050	0.2935	0.0655
37.00	Fulton	0.6271	0.6868	0.6151
38.00	Fulton	0.2115	0.5039	0.0897
39.00	Fulton	0.5167	0.4429	0.4990
40.00	Fulton	0.4754	0.4300	0.4478
41.00	Fulton	0.3945	0.4012	0.4213
42.95	Fulton	0.4118	0.4900	0.4353
44.00	Fulton	0.7004	0.6167	0.5200
46.95	Fulton	0.6720	0.6271	0.5674
48.00	Fulton	0.5375	0.6330	0.5736
49.95	Fulton	0.3201	0.0927	-0.0973
50.00	Fulton	-0.0442	-0.0305	-0.2417
52.00	Fulton	0.1809	0.2146	0.0358

Census Tract	County	Index 1980	Index 1990	Index 2000
53.00	Fulton	0.3920	0.2747	0.0136
55.01	Fulton	0.7445	0.6227	0.5809
55.02	Fulton	0.6897	0.5704	0.6327
56.00	Fulton	0.6695	0.7072	0.7076
57.00	Fulton	0.6156	0.5691	0.6551
58.00	Fulton	0.4084	0.4911	0.3394
60.00	Fulton	0.4944	0.5182	0.4348
61.00	Fulton	0.5861	0.5014	0.5430
62.00	Fulton	0.5569	0.5282	0.5982
63.00	Fulton	0.6001	0.6214	0.5068
64.00	Fulton	0.4921	0.5737	0.6455
65.00	Fulton	0.2302	0.3425	0.3576
66.01	Fulton	0.0774	0.3273	0.3267
66.02	Fulton	0.5183	0.5011	0.4673
67.00	Fulton	0.4963	0.5259	0.4760
68.02	Fulton	0.6536	0.6819	0.6744
69.00	Fulton	0.2999	0.4208	0.3628
70.00	Fulton	0.4477	0.4877	0.4933
71.00	Fulton	0.6279	0.6416	0.6259
72.00	Fulton	0.5553	0.5745	0.4903
73.00	Fulton	0.4174	0.5458	0.5583
74.00	Fulton	0.1975	0.3337	0.5051
75.00	Fulton	0.1289	0.3371	0.3998
76.01	Fulton	0.1693	0.3171	0.3977
76.02	Fulton	0.3788	0.4389	0.5084
77.01	Fulton	0.3098	0.4108	0.4436
77.02	Fulton	0.3007	0.4380	0.4708
78.02	Fulton	0.4619	0.4361	0.3522
78.03	Fulton	0.3816	0.4070	0.3353
78.04	Fulton	0.4465	0.5157	0.5374
79.00	Fulton	0.3677	0.3742	0.3611
80.00	Fulton	0.5369	0.4972	0.5334
81.01	Fulton	0.4366	0.4916	0.5091
81.02	Fulton	0.4317	0.5004	0.4200
82.01	Fulton	0.3604	0.4201	0.3609
82.02	Fulton	n/a	0.6749	n/a
83.01	Fulton	0.5506	0.6015	0.5294
83.02	Fulton	0.6029	0.5895	0.4215
84.00	Fulton	0.5598	0.6572	0.5347
85.00	Fulton	0.6276	0.6319	0.6495
86.01	Fulton	0.6797	0.7169	0.6745
86.02	Fulton	0.7646	0.7678	0.7519
87.01	Fulton	0.7522	0.8031	0.8748
87.02	Fulton	0.6337	0.6840	0.6798
88.00	Fulton	0.2088	0.3316	0.2354

Census Tract	County	Index 1980	Index 1990	Index 2000
89.00	Fulton	-0.3521	-0.2840	-0.2953
90.00	Fulton	-0.3818	-0.3329	-0.4123
91.00	Fulton	-0.4053	-0.3256	-0.3645
92.00	Fulton	-0.4384	-0.3500	-0.3475
93.00	Fulton	-0.3850	-0.3632	-0.4540
94.01	Fulton	-0.2890	-0.3513	-0.4001
94.02	Fulton	-0.4573	-0.1676	-0.1649
95.00	Fulton	-0.3306	-0.3277	-0.3396
96.00	Fulton	-0.4265	-0.4005	-0.4484
97.00	Fulton	-0.3211	-0.3332	-0.3586
98.00	Fulton	-0.3144	-0.3301	-0.3738
99.00	Fulton	-0.3588	-0.3410	-0.3790
100.00	Fulton	-0.3163	-0.3134	-0.3822
101.01	Fulton	-0.3489	-0.3135	-0.3608
101.03	Fulton	-0.4156	-0.3703	-0.3905
101.05	Fulton	0.1030	-0.3355	-0.2871
101.06	Fulton	0.2187	-0.2908	-0.2763
101.07	Fulton	0.2408	-0.3249	-0.3466
101.08	Fulton	0.1834	-0.4200	-0.4361
102.01	Fulton	-0.3462	-0.2779	-0.1293
102.03	Fulton	-0.3225	-0.2671	-0.2542
102.04	Fulton	-0.3591	-0.3680	-0.3735
102.05	Fulton	-0.3989	-0.3196	-0.3691
103.01	Fulton	0.2196	0.0763	0.1285
103.02	Fulton	0.1912	0.3116	0.3159
104.00	Fulton	0.2666	0.2230	0.2042
105.03	Fulton	-0.1452	0.2507	0.3208
105.04	Fulton	0.1485	0.2569	0.3034
105.05	Fulton	0.0857	0.2339	0.3304
105.06	Fulton	0.1482	0.1646	0.2586
106.01	Fulton	0.2046	0.2582	0.3867
106.02	Fulton	0.1242	0.3223	0.3060
107.00	Fulton	-0.1404	0.0293	0.1898
108.00	Fulton	-0.2039	-0.0824	-0.0232
109.00	Fulton	0.0958	0.1615	0.2916
110.00	Fulton	0.3490	0.4581	0.5310
111.00	Fulton	0.3124	0.0353	0.0022
112.01	Fulton	0.1535	0.3372	0.3510
112.02	Fulton	-0.0246	0.0945	0.2581
113.01	Fulton	-0.0478	0.1817	0.2293
113.02	Fulton	0.1331	0.2755	0.3569
114.03	Fulton	-0.2164	-0.3225	-0.3710
114.04	Fulton	-0.2923	-0.3222	-0.1241
114.05	Fulton	-0.2530	-0.1405	-0.1122
114.06	Fulton	-0.2069	-0.2912	-0.3508

Census Tract	County	Index 1980	Index 1990	Index 2000
114.07	Fulton	-0.1951	-0.2247	-0.3003
114.08	Fulton	-0.3473	-0.3568	-0.3961
114.09	Fulton	-0.2966	-0.3423	-0.3753
114.10	Fulton	-0.3149	-0.3228	-0.3623
114.11	Fulton	-0.3466	-0.3231	-0.2404
115.00	Fulton	-0.0318	-0.1808	-0.2582
116.01	Fulton	0.0061	-0.2032	-0.3204
116.02	Fulton	0.0165	-0.2895	-0.3951
116.03	Fulton	0.0237	-0.3191	-0.3722
201.00	DeKalb	-0.3391	-0.3505	-0.2963
202.00	DeKalb	-0.3335	-0.2831	-0.3905
203.00	DeKalb	-0.0626	-0.2072	-0.3166
204.00	DeKalb	-0.2501	-0.1413	-0.4625
205.00	DeKalb	0.6687	0.5827	0.5069
206.00	DeKalb	0.7450	0.5626	0.6368
207.00	DeKalb	0.6530	0.5715	0.5012
208.00	DeKalb	0.6971	0.7204	0.4622
209.00	DeKalb	0.5130	0.4935	0.4138
211.00	DeKalb	-0.1127	-0.1590	-0.2413
212.02	DeKalb	-0.3646	-0.3608	-0.3788
212.04	DeKalb	-0.2746	0.1618	0.3256
212.05	DeKalb	-0.4433	-0.3978	-0.4738
212.07	DeKalb	-0.4005	-0.3823	-0.4501
212.08	DeKalb	n/a	-0.3581	n/a
212.09	DeKalb	n/a	-0.1841	n/a
212.10	DeKalb	-0.3758	-0.3901	-0.4884
212.11	DeKalb	-0.3400	-0.3432	-0.4575
212.12	DeKalb	-0.4441	-0.3135	-0.3445
213.01	DeKalb	-0.2114	-0.1728	-0.1529
213.02	DeKalb	-0.4064	-0.2601	-0.0143
213.03	DeKalb	-0.2028	-0.2378	0.0719
213.04	DeKalb	-0.3291	-0.2298	-0.0805
214.01	DeKalb	-0.3719	-0.1101	0.0124
214.02	DeKalb	-0.3651	-0.1708	-0.0766
214.03	DeKalb	-0.2275	-0.2688	-0.3268
214.04	DeKalb	-0.3953	-0.1025	0.1268
215.00	DeKalb	-0.3585	-0.3233	-0.3909
216.01	DeKalb	-0.3431	-0.2448	-0.2415
216.02	DeKalb	-0.3512	-0.3283	-0.3863
216.03	DeKalb	-0.3747	-0.3706	-0.4334
217.02	DeKalb	-0.4324	-0.3528	-0.3184
217.03	DeKalb	-0.2985	-0.3556	-0.4023
217.04	DeKalb	-0.3799	-0.3136	-0.3842
218.05	DeKalb	-0.3642	-0.2508	-0.1491
218.06	DeKalb	-0.2971	-0.2317	-0.1030

Census Tract	County	Index 1980	Index 1990	Index 2000
218.08	DeKalb	-0.4314	-0.3952	-0.3813
218.09	DeKalb	-0.3419	-0.3003	-0.3534
218.10	DeKalb	-0.3821	-0.4053	-0.4752
218.98	DeKalb	-0.4000	-0.3273	-0.1062
219.02	DeKalb	-0.3173	-0.2333	0.0303
219.03	DeKalb	-0.0777	-0.0880	0.2088
219.04	DeKalb	-0.3572	-0.2132	0.0316
219.05	DeKalb	-0.3344	-0.0472	0.1534
220.01	DeKalb	-0.2916	-0.2661	-0.2789
220.02	DeKalb	-0.3458	-0.0062	0.1370
220.04	DeKalb	-0.3599	-0.2065	0.1136
220.05	DeKalb	-0.3900	-0.0033	0.2169
221.00	DeKalb	n/a	0.5003	n/a
222.00	DeKalb	-0.1707	-0.1865	-0.1979
223.01	DeKalb	-0.2914	-0.3098	-0.4100
223.02	DeKalb	-0.3795	-0.3063	-0.3618
224.01	DeKalb	-0.3106	-0.3162	-0.4007
224.02	DeKalb	-0.4255	-0.3176	-0.4332
224.03	DeKalb	-0.2922	-0.3172	-0.3203
225.00	DeKalb	-0.1096	-0.1077	-0.2361
226.00	DeKalb	-0.2211	-0.2642	-0.3766
227.00	DeKalb	0.5412	0.4414	0.2079
228.00	DeKalb	0.0188	-0.0750	-0.2015
229.00	DeKalb	0.1789	0.2196	0.0931
230.00	DeKalb	-0.0999	-0.2693	-0.2644
231.01	DeKalb	0.3499	0.4754	0.4985
231.02	DeKalb	-0.4431	-0.0245	0.0700
231.03	DeKalb	-0.0501	0.1983	0.2950
231.05	DeKalb	-0.3062	0.0701	0.2558
231.06	DeKalb	-0.2965	0.1126	0.2173
232.03	DeKalb	-0.1413	0.2163	0.2482
232.04	DeKalb	-0.3225	-0.1957	0.1469
232.05	DeKalb	-0.3445	-0.1587	0.1828
232.06	DeKalb	-0.3118	-0.0401	0.2614
232.07	DeKalb	-0.2873	-0.0065	0.1950
233.02	DeKalb	-0.0275	-0.1331	0.2178
233.03	DeKalb	0.3112	0.3805	0.3366
233.05	DeKalb	-0.1580	-0.1795	0.2072
233.06	DeKalb	-0.1766	0.0562	0.2736
233.07	DeKalb	-0.0859	-0.0050	0.2308
233.08	DeKalb	-0.0652	0.1704	0.2648
234.03	DeKalb	0.2413	0.3310	0.3088
234.04	DeKalb	0.1539	0.3231	0.2787
234.05	DeKalb	0.2419	0.3975	0.3883
234.07	DeKalb	-0.1808	0.1582	0.3233

Census Tract	County	Index 1980	Index 1990	Index 2000
234.08	DeKalb	-0.0216	0.2457	0.2626
234.09	DeKalb	0.0332	0.2462	0.2839
235.01	DeKalb	0.3731	0.4694	0.4807
235.02	DeKalb	0.3332	0.3804	0.3901
235.03	DeKalb	0.0886	0.2263	0.2953
236.00	DeKalb	0.5082	0.5493	0.5264
237.00	DeKalb	0.6031	0.6193	0.5237
238.01	DeKalb	0.4122	0.5281	0.4922
238.02	DeKalb	0.2928	0.3590	0.3831
238.03	DeKalb	0.4221	0.4751	0.4786
301.98	Cobb	0.1281	-0.0213	-0.1475
302.03	Cobb	-0.0921	-0.1693	-0.2221
302.04	Cobb	-0.0407	-0.2515	-0.3271
302.05	Cobb	-0.0654	-0.2817	-0.3523
302.06	Cobb	n/a	-0.1919	n/a
302.07	Cobb	n/a	-0.2334	n/a
303.02	Cobb	-0.3337	-0.3600	-0.3679
303.07	Cobb	-0.3062	-0.3385	-0.3575
303.09	Cobb	-0.3383	-0.3481	-0.3704
303.10	Cobb	-0.2546	-0.3098	-0.2749
303.11	Cobb	-0.2557	-0.3105	-0.3206
303.12	Cobb	-0.2657	-0.2866	-0.2867
303.13	Cobb	-0.2691	-0.2790	-0.3388
303.14	Cobb	-0.2857	-0.2695	-0.3541
303.15	Cobb	-0.3134	-0.3429	-0.3971
303.16	Cobb	-0.3740	-0.3640	-0.4028
303.17	Cobb	-0.3658	-0.3735	-0.4142
303.18	Cobb	-0.3687	-0.3456	-0.3856
303.19	Cobb	-0.3391	-0.3132	-0.3559
303.20	Cobb	-0.3555	-0.3416	-0.3514
303.21	Cobb	-0.4892	-0.2977	-0.3142
304.01	Cobb	n/a	-0.3142	n/a
304.02	Cobb	-0.3372	-0.3236	-0.3582
304.04	Cobb	-0.4128	-0.3395	-0.1012
304.05	Cobb	-0.3807	-0.3266	-0.3348
304.06	Cobb	-0.4001	-0.3136	-0.1376
305.01	Cobb	-0.1489	-0.2153	-0.2884
305.02	Cobb	-0.1618	-0.2275	-0.3340
305.03	Cobb	-0.1649	-0.1983	-0.2127
306.00	Cobb	-0.0150	-0.1719	-0.2133
307.00	Cobb	n/a	0.2095	n/a
308.00	Cobb	-0.0247	0.0971	0.0797
309.01	Cobb	-0.0526	-0.2772	-0.2090
309.02	Cobb	-0.1226	0.0172	0.1646
309.03	Cobb	-0.0816	-0.1591	0.0162

Census Tract	County	Index 1980	Index 1990	Index 2000
310.01	Cobb	-0.0165	0.0391	0.2167
310.02	Cobb	-0.0202	0.0781	0.1867
310.03	Cobb	-0.2192	-0.1201	-0.0151
311.01	Cobb	-0.1783	-0.0789	-0.0256
311.03	Cobb	-0.1905	-0.2019	-0.1701
311.05	Cobb	-0.2426	-0.1829	0.0114
311.06	Cobb	-0.2123	-0.2242	-0.0548
311.07	Cobb	-0.2341	-0.2235	-0.2112
311.08	Cobb	-0.1780	-0.1064	0.0003
311.09	Cobb	-0.2217	-0.3088	-0.1757
312.02	Cobb	-0.0486	-0.2012	-0.1930
312.03	Cobb	-0.3594	-0.3209	-0.4128
312.04	Cobb	-0.2909	-0.2668	-0.3756
313.01	Cobb	n/a	-0.1702	n/a
313.02	Cobb	0.1128	0.0333	0.0938
313.04	Cobb	-0.0022	0.0249	0.0690
313.05	Cobb	0.0190	0.1538	0.2374
314.03	Cobb	-0.1003	-0.1475	-0.0811
314.04	Cobb	-0.1254	-0.1639	-0.0726
314.98	Cobb	n/a	0.0450	n/a
315.01	Cobb	0.0598	-0.1729	-0.1012
315.02	Cobb	0.0320	-0.1021	-0.0280
402.00	Clayton	-0.0931	0.1699	0.1924
403.02	Clayton	0.0106	0.1179	0.2115
403.03	Clayton	-0.0743	0.1035	0.2699
403.04	Clayton	-0.0069	0.0438	0.1942
403.05	Clayton	n/a	-0.0502	n/a
404.01	Clayton	-0.1223	-0.0827	0.0870
404.02	Clayton	0.0224	0.0199	0.1025
404.03	Clayton	-0.2090	-0.2333	0.0232
404.05	Clayton	n/a	-0.0694	n/a
404.06	Clayton	-0.2501	-0.1557	0.1136
405.03	Clayton	-0.1408	-0.0273	0.1345
405.04	Clayton	-0.2095	0.0825	0.1662
405.05	Clayton	-0.2826	-0.1003	0.1763
405.06	Clayton	-0.1668	-0.1534	0.1137
405.07	Clayton	-0.1468	-0.1343	0.1613
405.08	Clayton	-0.1506	-0.1751	0.1802
406.03	Clayton	-0.1406	-0.1269	-0.0225
406.04	Clayton	-0.0378	-0.0052	0.0520
406.05	Clayton	-0.0589	-0.1757	-0.1266
406.06	Clayton	0.1923	0.2299	0.2939
406.07	Clayton	-0.0858	-0.0692	0.0881
406.08	Clayton	n/a	-0.0775	n/a
501.01	Gwinnett	0.1956	0.0215	-0.1194

Census Tract	County	Index 1980	Index 1990	Index 2000
501.02	Gwinnett	0.1724	0.1083	0.0168
502.02	Gwinnett	0.0676	-0.0795	-0.2818
502.03	Gwinnett	n/a	-0.2944	n/a
502.04	Gwinnett	n/a	-0.1653	n/a
503.04	Gwinnett	-0.2790	-0.2381	-0.0667
503.05	Gwinnett	-0.2248	-0.2222	-0.0875
503.06	Gwinnett	-0.2818	-0.0510	0.1324
503.07	Gwinnett	-0.2963	-0.3519	-0.4327
503.08	Gwinnett	-0.2756	-0.3349	-0.4175
503.09	Gwinnett	-0.2919	-0.3108	-0.3685
503.10	Gwinnett	-0.3711	-0.3858	-0.3826
503.11	Gwinnett	-0.2381	-0.0725	-0.2123
503.12	Gwinnett	-0.2415	-0.2108	0.1162
503.13	Gwinnett	-0.2167	-0.2767	-0.1621
503.14	Gwinnett	-0.1962	-0.3223	-0.2369
504.03	Gwinnett	n/a	-0.2744	n/a
504.06	Gwinnett	-0.3686	-0.2402	-0.0152
504.07	Gwinnett	-0.3164	-0.2684	-0.0023
504.08	Gwinnett	-0.2708	-0.3435	-0.1295
504.09	Gwinnett	-0.2259	-0.3412	-0.1511
504.10	Gwinnett	-0.1998	-0.2028	-0.1332
504.11	Gwinnett	-0.1992	-0.2469	-0.1644
504.12	Gwinnett	-0.3316	-0.3240	-0.3495
504.13	Gwinnett	-0.3115	-0.2961	-0.3464
504.14	Gwinnett	-0.2493	-0.2956	-0.2796
504.15	Gwinnett	-0.2449	-0.3246	-0.2583
504.16	Gwinnett	-0.2033	-0.2936	-0.0831
505.02	Gwinnett	-0.0268	-0.2470	-0.3117
505.03	Gwinnett	n/a	-0.2187	n/a
505.05	Gwinnett	-0.1724	-0.2351	-0.2128
505.06	Gwinnett	n/a	-0.2541	n/a
505.07	Gwinnett	n/a	-0.3199	n/a
505.08	Gwinnett	0.0257	-0.1285	-0.0940
505.09	Gwinnett	0.1066	0.0044	-0.0325
506.01	Gwinnett	0.1192	-0.0934	-0.1926
506.02	Gwinnett	0.1279	0.0147	-0.1419
507.04	Gwinnett	-0.0433	-0.1729	-0.1874
507.05	Gwinnett	0.0408	-0.1310	-0.2140
507.06	Gwinnett	-0.2634	-0.3185	-0.3741
507.07	Gwinnett	-0.2786	-0.3045	-0.3163
507.08	Gwinnett	-0.1425	-0.3206	-0.2266
507.09	Gwinnett	-0.1115	-0.2010	-0.1227
507.10	Gwinnett	-0.2326	-0.2718	-0.2950
507.11	Gwinnett	-0.2272	-0.2782	-0.3002
601.00	Rockdale	0.0453	-0.0039	-0.0242

Census Tract	County	Index 1980	Index 1990	Index 2000
602.00	Rockdale	0.0637	-0.0313	0.0988
603.02	Rockdale	n/a	-0.1583	n/a
603.03	Rockdale	0.1176	0.0242	0.1352
603.04	Rockdale	0.0774	0.1621	0.0832
604.01	Rockdale	-0.1107	-0.1326	-0.1106
604.02	Rockdale	-0.1058	-0.1830	-0.1732
701.02	Henry	0.0264	-0.1431	-0.1404
701.03	Henry	0.0026	-0.0646	-0.1146
701.98	Henry	0.0177	-0.0019	0.0265
702.01	Henry	0.1042	-0.0448	-0.1131
702.02	Henry	0.1115	-0.0623	-0.1790
702.03	Henry	0.1032	-0.0651	-0.1918
703.01	Henry	0.3873	-0.0973	-0.2110
703.02	Henry	0.3614	0.2288	0.0052
704.02	Henry	0.2626	0.1154	-0.0792
704.98	Henry	0.2505	0.1421	0.0258
705.00	Henry	0.1646	0.0980	0.0385
801.98	Douglas	n/a	0.0112	n/a
802.00	Douglas	0.0187	-0.0507	-0.0398
803.00	Douglas	0.1844	0.1070	0.0946
804.00	Douglas	0.2272	0.1629	0.0166
805.01	Douglas	-0.0990	-0.0636	-0.0743
805.03	Douglas	-0.1695	-0.2284	-0.2321
805.04	Douglas	-0.1203	-0.0912	-0.0794
806.01	Douglas	0.0108	-0.0957	-0.0710
806.02	Douglas	0.0134	0.0104	0.0540
901.00	Cherokee	0.2575	0.2275	0.1012
902.00	Cherokee	0.1192	0.0776	-0.0297
903.00	Cherokee	0.1443	0.0823	0.0712
904.00	Cherokee	0.3606	0.2746	0.2296
905.00	Cherokee	0.2002	0.0746	-0.0721
906.00	Cherokee	0.1927	0.0990	0.0285
907.00	Cherokee	0.1007	-0.0653	-0.1813
908.00	Cherokee	0.0046	-0.0958	-0.1843
909.01	Cherokee	-0.0065	-0.1585	-0.1855
909.02	Cherokee	-0.0181	-0.2163	-0.2572
909.03	Cherokee	-0.0273	-0.1637	-0.1963
910.01	Cherokee	-0.0482	-0.0966	-0.1324
910.02	Cherokee	-0.0262	-0.2358	-0.3300
910.03	Cherokee	-0.0743	-0.1873	-0.1906
911.01	Cherokee	-0.0067	-0.2128	-0.2518
911.03	Cherokee	-0.0144	-0.1311	-0.1273
911.98	Cherokee	-0.0319	-0.1588	-0.1614
1201.00	Paulding	0.1747	0.0822	-0.0907
1202.00	Paulding	n/a	-0.0604	n/a

Census Tract	County	Index 1980	Index 1990	Index 2000
1203.00	Paulding	0.1829	0.1479	0.0151
1204.00	Paulding	0.3400	0.2555	0.1443
1205.00	Paulding	0.2084	0.1109	-0.0627
1206.98	Paulding	0.1861	0.0387	-0.0839
1301.00	Forsyth	0.1076	0.0541	-0.0163
1302.00	Forsyth	0.1672	0.1356	-0.1472
1303.00	Forsyth	0.1076	0.0579	-0.1667
1304.00	Forsyth	0.0971	0.0769	-0.0206
1305.00	Forsyth	-0.0654	-0.1261	-0.2114
1306.00	Forsyth	0.1365	0.0432	-0.2366
1401.01	Fayette	-0.1219	-0.0697	0.1063
1401.02	Fayette	-0.1271	-0.1645	-0.0805
1402.01	Fayette	-0.0453	-0.0579	-0.1357
1402.02	Fayette	-0.0609	-0.1792	-0.2669
1403.01	Fayette	-0.2131	-0.2423	-0.2580
1403.02	Fayette	-0.1928	-0.2884	-0.3052
1404.01	Fayette	-0.0746	-0.1961	-0.2065
1404.02	Fayette	-0.0678	-0.1395	-0.1726
1405.01	Fayette	0.0230	-0.1113	-0.2098
1405.02	Fayette	0.0221	-0.0404	-0.1661
1701.00	Coweta	0.2815	0.0756	-0.0404
1702.00	Coweta	0.1521	0.0702	0.0574
1703.00	Coweta	-0.0269	0.0936	-0.0059
1704.00	Coweta	0.2720	-0.0065	-0.1697
1705.00	Coweta	0.2696	0.1671	-0.0516
1706.00	Coweta	0.4352	0.4122	0.2456
1707.00	Coweta	0.3926	0.3587	0.3289
1708.00	Coweta	n/a	0.1572	n/a