AN INTEGRATED GIS-SPATIAL ANALYSIS OF ATLANTA'S URBAN STRUCTURE AND URBAN SPACE

by

YANBING TANG

(Under the Direction of Clifton W. Pannell)

ABSTRACT

This is an interdisciplinary study to examine Atlanta's urban structure and urban space by integrating GIS and spatial analysis. This dissertation is comprised of three separated topics. First, in terms of urban structure, the urban land use/land cover structures from 1990 to 2000 are analyzed. In order to get classified land use/land cover images, remotely sensed imagery and remote sensing technology are also employed. The second topic is to analyze urban poverty by applying spatial regression models. Third, in terms of urban space, the spatial distributions of population, race, and income are analyzed. During the whole process, GIS techniques and spatial statistics cooperate with each other so that some conclusions are derived. Specifically, this dissertation (1) adopts a hybrid approach to classify land use/land cover in Atlanta metropolitan area; (2) based on classified images, uses spatial metrics and spatial statistics to test if Atlanta's urban structure was more fragmented and had a random or quasi-random increase during the 1990s; (3) utilizes a series of spatial regression models to identify the factors and their contributions to urban poverty; and (4) uses surface maps, spatial cumulative distribution function (SCDF), and Kolmogorov-Smirnov (K-S) test to investigate urban space in terms of the spatial distributions of total population, Whites, Blacks, Asians, and the median household income. The classified images show that urban growth of the Atlanta metropolitan area consumed large amount of vegetative lands since forest and grassland/pasture/cropland both decreases in areas. Spatial metrics indicate the urban structure in the Atlanta metropolitan area was more fragmented during the 1990s. By Ripley's K-function and spatial Poisson point process model, the argument of random or quasi-random urban growth is not supported. By making comparison with conventional multivariate regression model, the spatial regression models are found to have higher $R^2$ and better incorporate spatial dependence. While the total population and whites were more unevenly distributed, blacks had a process of diverse distribution. SCDF of the median household income shows that the urban space of income was more polarized because low-income poor were more aggregated and the affluent are still segregated.

INDEX WORDS: GIS, Spatial Analysis, Urban Structure, Urban Space, Remotely Sensed Images, Land Use/Land Cover, Urban Poverty, Spatial Distribution, Atlanta Metropolitan Area

# AN INTEGRATED GIS-SPATIAL ANALYSIS OF ATLANTA'S URBAN STRUCTURE AND URBAN SPACE

By

YANBING TANG

B.S., Lanzhou University, P.R.China, 1997

M.S., Beijing Normal University, P.R.China, 2000

M.S., University of Georgia, 2003

A Dissertation Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

ATHENS, GEORGIA

2007

AN INTEGRATED GIS-SPATIAL ANALYSIS OF ATLANTA'S URBAN STRUCTURE

AND URBAN SPACE

by

YANBING TANG

Major Professor: Clifton W. Pannell

Committee: Steven R. Holloway
Chor-Pang Lo
Marguerite Madden
Kavita K. Pandit

Electronic Version Approved:

Maureen Grasso
Dean of the Graduate School
The University of Georgia
August 2007

# DEDICATION

To my parents and in-law parents

To Qingmin and Alan

## ACKNOWLEDGEMENTS

I am deeply indebted to my major professor Dr. Clifton W. Pannell. He has provided me with the academic and financial support during my study in the University of Georgia. He gives me his constant encouragement and confidence so that I can pursue a long way to the ultimate completion of this dissertation. I would also like to express my many thanks to my advisor committee members, Drs Steven Holloway, Chor-Pang Lo, Marguerite Madden, and Kavita Pandit. Their academic advice and guidance are greatly appreciated.

I also sincerely appreciate the financial support from Dr. Marguerite Madden through the Center for Remote Sensing and Mapping Science (CRMS) and from Dr. Steven Holloway through the Center for Family Research at the University of Georgia in the final stage of my dissertation research. I acknowledge the kind supports from Kate Blane, Emily Coffee, Emily Duggar, Jodie Guy, Audrey Hawkins, and Loretta Scott. I would also like to extend my appreciations to my friends, Polly Bass, Fuyuan Liang, Xu Bo, and Liang Zhou. They gave me opportunities to share happiness and sadness.

# TABLE OF CONTENTS

Page

# LIST OF TABLES

# LIST OF FIGURES

# CHAPTER 1

# INTRODUCTION

## Research background

The world has rapidly urbanized during the past decades while the share of urban population has increased from 5% in 1900 to nearly 50% in the early 21$^{st}$ century (Maktav et al., 2005). The rapid development of urbanization across the world has challenged the urban planners and managers who need particularly the information on urban land uses/land cover, housing characteristics, population growth, etc. Under this circumstance, traditional collecting methods (censuses and analog maps) cannot meet the needs for urban management purposes. Meanwhile, up-to-date information is particularly needed for the rural-urban fringe since this area changes rapidly. Recent developments in geospatial technologies and analytic techniques have resulted in many applications of geographical information system (GIS) and spatial analysis in various fields, such as forestry, ecology, water, wildlife, and urban studies.

Satellite images provide great data sources to monitor changes from continental to local scales. Urban remote sensing has the advantage that it supplies seamless, geographically extensive, and comprehensive built-up structures. As Longley (2002) noted, urban remote sensing is an important interdisciplinary field which measures and monitors the complexities of urban growth and change.

With the advances of remote sensing and GIS technologies, new urban changes can be detected in a timely and consistent manner (Rogan and Chen, 2004). As an example, Chen

(2002) developed a way to use census data in remote sensing and GIS contexts to derive data sources for human geography. The integration of remote sensing and GIS has proceeded in the following three ways (Treitz and Rogan, 2003; Wilkinson, 1996): (1) GIS can use remotely sensed data as input data for spatial analysis; (2) GIS can supply ancillary data in order to improve remote sensing data analysis; and (3) GIS data and remote sensing data can be used simultaneously for modeling.

Spatial data analysis deals with spatially referenced data and takes the spatial relationships or spatial interactions into account when data are analyzed. One of the reasons that spatial analysis has made rapid progress is the proliferation of digital data sources (Longley, 2000). Spatial statistics, especially geostatistics, has value for GIS analysis. Geostatistics can better understand the uncertainty and error in GIS-based spatial analysis, conduct interpolation and get estimates on error bounds, examine error propagation, and conduct data mining and spatial generalization (Burrough, 2001). Geostatistics has been applied in remote sensing data analysis on improving image classification, monitoring crop growth, conducting interpolation by kriging, designing optimal sampling schemes, and comparing two images with different spatial resolutions (Oliver et al., 2005).

During the past decade, there were rapid developments in the fields of remote sensing, GIS, and spatial analysis. It is within this framework that this dissertation examines Atlanta's urban structure and urban space by integrating GIS and spatial analysis. This is an interdisciplinary study which combines techniques from remote sensing, GIS, and spatial statistics into the application of urban studies. In particular, urban structure, urban poverty, and urban space, which are three of main topics in the field of urban geography, will be individually addressed in the following chapters.

**Study area**

The Atlanta metropolitan area, in this dissertation, comprises 13 counties. Southern Fulton County makes up most of the city of Atlanta. The other 12 counties are distributed around Fulton County (Figure 1.1). The fact that the Atlanta metropolitan area contains more counties than many other metropolitan areas in the U.S. largely reflects suburban sprawl, the result of high population growth and the opportunity for development to continue to develop outward without encountering legal or geographical barriers (Hartshorn and Ihlanfeldt, 2000).

Atlanta was the 13$^{th}$ largest metropolis in 1990 in the U.S. and has a relatively high share of blacks, which has averaged about 25% over the past 50 years. The figure was 29% in 2000 (Tables 1.1 and 1.2). Meanwhile, whites and blacks together comprise more than 95% of the total population of this large metropolitan region. In the 2000 census, people had the choice of identifying with more than one race; thus in 2000 whites and blacks made up about 91% of the total population.

Studies in racial segregation, especially between whites and blacks, have long been a focus of geography, demography, and social sciences in general (Alaba and Logan, 1991; Logan and Alba, 1993; McKinney and Schnare, 1989; Morrill, 1995; Stoll and Raphael, 2000). These studies argued that racial residential segregation accounted for differences in the quality of job search, suburbanization processes, and socioeconomic status. Spatial aggregation of whites and blacks in the Atlanta metropolitan area are obvious. Within the Atlanta metropolitan area, whites have generally settled in the northern suburbs and created an affluent sector in the northern part of the Atlanta metropolitan area. Meanwhile, blacks have formed generally poorer neighborhoods in many parts of southern Atlanta.

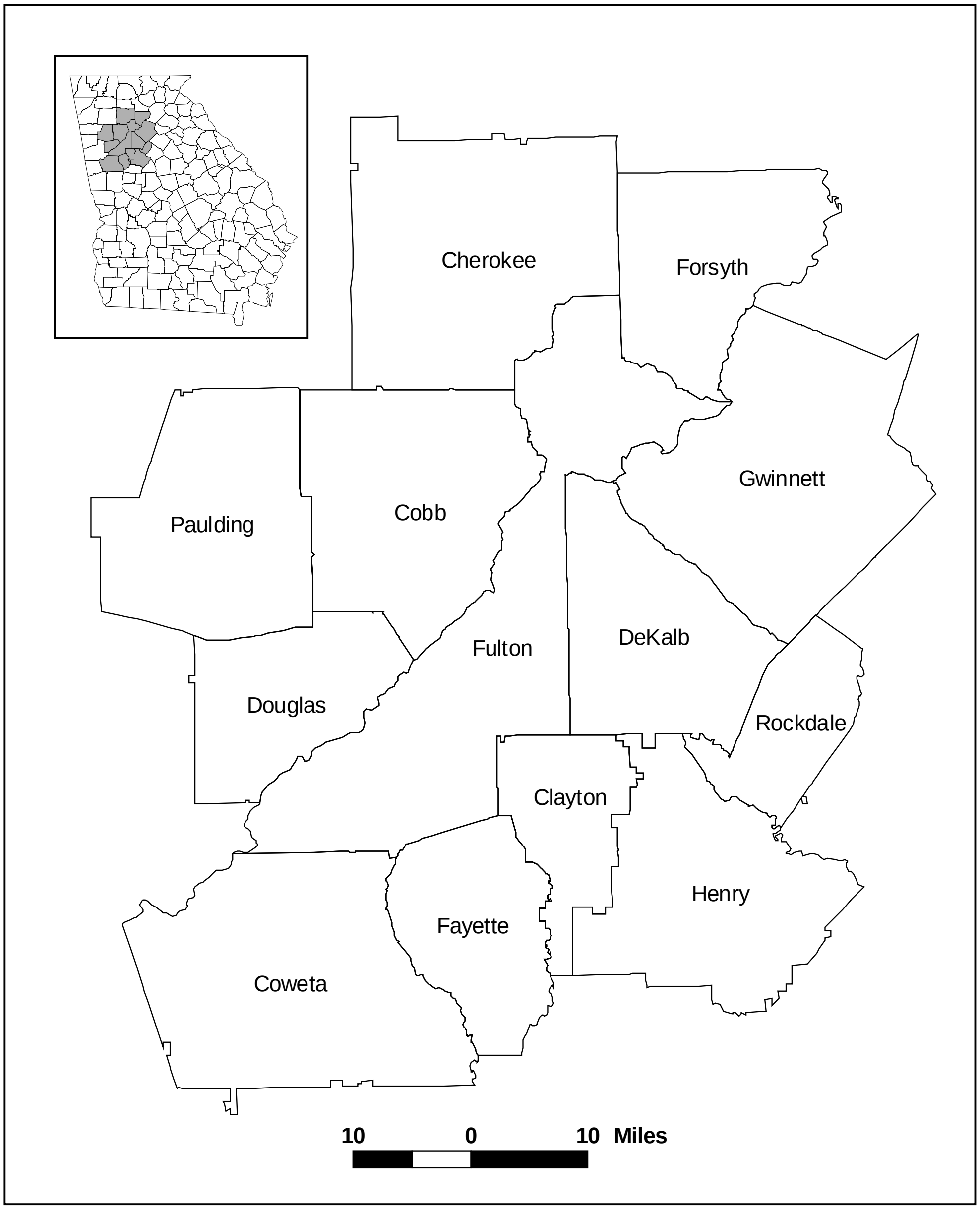



Figure 1.1 Study area: Atlanta metropolitan area

Table 1.1 The population in Atlanta MSA in 1990 and 2000

| | Total population | Whites | Blacks |
|---|---|---|---|
| 1990 | 2959950 | 2136169 | 746440 |
| 2000 | 4112198 | 2589888 | 1189179 |
| Growth rate | 38.9% | 21.2% | 59.3% |

Note: in 2000, the information of whites and blacks refers to one race of whites and Blacks

Table 1.2 The percentage of whites and blacks in the total population (%)

| | 1950 | 1960 | 1970 | 1980 | 1990 | 2000 |
|---|---|---|---|---|---|---|
| White | 76.52 | 77.32 | 78.31 | 75.08 | 72.11 | 62.98 |
| Black | 23.44 | 22.70 | 21.66 | 23.97 | 25.24 | 28.92 |

**Data sources**

There are three types of data used in this dissertation, which includes (1) remotely sensed imagery; (2) digital orthophoto quarter quadrangles (DOQQs) and digital raster graphics (DRGs); (3) metropolitan, county, and census tract boundary files; and (4) demographic and socioeconomic data.

Landsat TM and ETM+ images are the major data sources for land use/land cover classification. Landsat TM image in 1990 is from James Holt, a UGA alumnus of geography department. Dr. Lo kindly gave his Landsat ETM+ image in 2000 to make a comparison between two time spots. When Landsat images are processed, a Universal Transverse Mercator (UTM) map projection with GRS 1980, zone north 16 and is used for all digital data.

DOQQs and DRGs are used for georeferencing and accuracy assessment. DOQQs have spatial resolution of 1 m and DRGs have a scale of 1:24,000. DOQQs were borrowed from Institute of Ecology, University of Georgia and DRGs were downloaded from Georgia Clearinghouse (www.gis.state.ga.us). In order to keep all digital data in the same projection system, DOQQs and DRGs are converted into a UTM GRS 1980 NAD 83 zone N16 projection system and mosaiced while some of them have different projection systems from UTM.

In order to better depict the spatial distribution of population, race, and income variables, various boundary files at metropolitan, county, and census tract levels are downloaded from Georgia Clearinghouse (www.gis.state.ga.us). Again, the UTM projection system as above is imposed.

When urban poverty and urban space are analyzed, demographic and socioeconomic data are used. These data are downloaded from U.S. Census Bureau. This dissertation uses census data in 1990 and 2000 censuses. Specifically, all of data come from Summary File 1 (SF1) 100-

percent data and Summary File (SF3) sample data. By using ArcView and ArcGIS software, this nonspatial information is joined with digital boundary files.

**Research objectives**

The main objective of this dissertation is to use GIS together with remote sensing techniques and spatial analysis methods to study urban structure and urban space. Three separate topics will be addressed. The first topic includes: (1) adopting a hybrid approach to classify land use/land cover in Atlanta metropolitan area; (2) based on classified images, using spatial metrics and spatial statistics to test if Atlanta's urban structure was more fragmented and had a random or quasi-random increase during the 1990s. Second topic is to utilize a series of spatial regression models to identify the factors and their contributions to urban poverty. The third topic is to use surface maps and spatial cumulative distribution function (SCDF) to investigate urban space in terms of the spatial distributions of total population, whites, blacks, Asians, and the median household income.

This dissertation aims to make contributions in the following ways. First, by connecting geographical techniques and spatial analysis, this research brings the quantitative applications of spatial statistics in the field of urban geography, thus helping to better understand the theoretical and empirical issues in urban geography. Second, by addressing the arguments of post-modernism on urban structure and urban space, which had been largely qualitative, this dissertation brings a way to prove/disprove the arguments quantitatively. Third, by introducing various quantitative analyses, this dissertation hopes to bring more advanced applications of various methods in urban studies, some of which have never been applied in this field.

**Dissertation structure**

This dissertation has a total of seven chapters. Chapter 1 is an introduction on research background, study area, data, and objectives. Chapter 2 is a literature review on the applications of remote sensing, GIS, spatial statistics in urban studies. Chapter 3 is a case study of land use/land cover classification by a hybrid classification scheme for the Atlanta metropolitan area. Based on the results of Chapter 3, urban structure is analyzed in Chapter 4. Chapters 3 and 4 together address the issue of Atlanta's internal urban structure. Another two issues, urban poverty and urban space, are discussed in Chapters 5 and 6. Chapter 5 uses eight statistical models to explore the relationships between urban poverty rate and demographic and socioeconomic variables. In Chapter 5, the usefulness of spatial regression models is also discussed. Chapter 6 analyzes urban space by taking a look at the spatial distributions of population and income and explores the issue of urban polarization regarding race and income distributions. Chapter 7, which is the final chapter, is an overall summary and conclusion of this dissertation research.

Chapters 3-6 have their own introduction, literature review, methodology explanation, and conclusions and discussions. Chapter 7 summarizes the results from each individual chapter and points out some possible ways for further studies. Followed by these chapters, a comprehensive bibliography of literature is listed.

# CHAPTER 2

# GIS, REMOTE SENSING AND SPATIAL ANALYSIS FOR URBAN RESEARCH

## Introduction

This review chapter consults four types of literature: (1) the use of remote sensing and geographic information systems (GIS) for urban analysis; (2) spatial statistics and spatial analysis for urban research; (3) the integration of GIS and spatial analysis for urban analysis; and (4) urban structure and urban space. While this chapter conducts a general literature review, in the following chapters, each has its owns literature review covering its specific topics.

The literature on the uses of remote sensing and GIS for urban analysis outlines the current fields where remote sensing and GIS make contributions to the urban environment. The literature on spatial statistics and spatial analysis gives a general impression of how these spatial sciences are employed in urban analysis. The review section on the integration of GIS and spatial analysis for urban research shows current accomplishments in urban contexts when urban studies take advantage of both techniques and capabilities. The section of urban structure and urban space literature intends to depict some general arguments on urban structure and urban space from the Chicago School to the Los Angeles School.

## The use of remote sensing and GIS for urban analysis

From the late 1960s, GIS has been used as the computer tools for handling spatial data (Burrough and McDonnell, 1998). Nowadays, GIS has become a multi-billion-dollar industry and involved in data acquisition and dissemination, software development, and application (Goodchild and Haining, 2004). Since the first launch of Earth Resources Technology Satellite (ERTS) in 1972 and the availability of remotely sensed imagery, remote sensing and GIS has been closely used in the disciplines that study surface or near surface of the earth.

With the availability of high-spatial resolution imagery, it is expected that remote sensing data will receive an increasing acceptance for urban analysis (Treitz and Rogan, 2003). Remote sensing analysis usually converts raw reflectance data into useful quantitative information. In the process of urban remote sensing applications, the following three aspects have to be considered (Maktav et al., 2005): geometric resolution which can separate objects spatially, the spectral and radiometric resolution which are useful for distinguishing objects thematically, and temporal resolution which is useful for getting consistent updated image materials. There are two problems which further bring challenges for urban remote sensing (Longley, 2002): (1) which scale is best for a certain study and how to solve the issue of modifiable areal unit problem (MAUP); and (2) the fuzzy definition of geographical phenomena which is hard to tell one object from another. As a result, the spatial structure is identified with greater uncertainty when classification is conducted on high spectral resolution imagery (Longley, 2002).

When remote sensing data are taken as input data for GIS analysis, the spatial accuracy of the input data should be paid attention to. For example, when a thematic map is produced and further utilized for GIS analysis, the main sources of errors lie in boundary location, map geometry, and classification (Hord and Brooner, 1976). The errors can be compounded when overlay and other spatial analysis are conducted. Therefore, urban land surface classification brings an ultimate challenge to remote sensing due to the limitations of spectral data in the urban context, the quality of classifications, analysis methods, and modeling (Longley, 2002). In order to timely monitor urban changes, research methods have been required to be (1) reported in a timely manner; (2) to deal with data at a range of spatial scales; and (3) to evaluate statistical inference by sensitivity analysis (Goodchild and Longley, 1999). In order to better classify urban land use/land cover, various classification schemes as well as contextual information have been utilized. For example, geostatistics can be used to measure image texture and structure (Pesaresi and Bianchin, 2001) and pattern recognition is utilized for very high spatial resolution imagery (Barr and Barnsley, 1998).

Conventionally, GIS analyses are taken as exclusively deterministic and data are assumed to be exact (Burrough, 2001). At that time, the issue of data uncertainty and spatial-temporal variability were largely neglected in the context that market forces did not need to address these issues in many GIS applications (Burrough, 2001). Because GIS uses map layer and geometric transformations to represent schemes and conduct analysis, it has the drawbacks of temporal inflexibility and difficulty in handling overlapping features. Besides that, the fuzzy definition for relative or relational conceptualization of space poses another issue for the further development of GIS (Sui, 1998). The development of timely collecting and processing individual behavior data, together with the advancement of treating individuals at small geographic and temporal scales and new representation systems by internet GIS which facilitates the storage and dissemination of data, has brought great advantages for urban analysis in human dimensions (Longley, 2003).

Current integration between GIS and urban analysis is largely technical. In order to achieve a seamless integration, space and time need to be conceptualized so that the integration can reflect the urban reality in an appropriate spatial-temporal framework in information society (Sui, 1998). GIS can contribute to better understanding class, consumption and citizenship by differentiating between locations based on the identification of specific identities (Longley, 2003). With the establishment of digital data infrastructure, GIS can become the media through which additional specialized information can be added into data. These high value-added data can be utilized as sensitive indicators for commercial activities.

**Spatial statistics and spatial analysis for urban analysis**

Spatial analysis is a subfield of regional science and geography that takes spatial properties, which vary with geographic locations, into consideration (Miller and Wentz, 2003). Spatial analysis is primarily quantitative. It was not until the late 1960s that the analysis of spatial data began a quick development (Goodchild and Haining, 2004). The book *Statistics for Spatial Data* (Cressie, 1991) provides a first overview of the whole field.

Early spatial analysis mainly focused on testing spatial autocorrelation on regular lattices or irregular areal units. Since these data were largely observational, there were higher levels of uncertainty compared with experimental science, such as designed experimental data (Cressie, 1984). Before spatial statistics entered into a stage of rapid development, spatial pattern (randomness, clustering, or regularity) and spatial autocorrelation were largely used which emphasized the global properties in spatial data. With the development of localized statistics, such as Anselin's (1995) local indicators of spatial association (LISAs), the heterogeneity of spatial phenomena across the study area could be detected. By taking advantages of automated cartography and GIS, visualization for spatial data has been one of the dynamic areas in spatial analysis during the 1990s (Goodchild and Haining, 2004).

Spatial statistical models can be classified into geostatistical models, lattice models, and spatial point processes (Cressie, 1991). The spatial dependence structure is determined by the relative spatial locations between data points. As a result, errors in location may be compounded in spatial dependence structure, for example, which can further affect the attribute prediction by kriging. Geostatistics supplies a more robust way to detect data errors and outliers (Cressie, 1984). A central aspect of geostatistics is its ability to differentiate different kinds of spatial variations by incorporating spatial autocovariance structure into modeling, which is often represented by (semi)variogram (Burrough, 2001). Geostatistical methods and tools can be effectively useful for constructing a surface model based on sample points, which takes into account the spatial variations in the data structure (Felgueiras et al., 1999).

The spatial statistical models are used to test hypotheses so that the valid representations of reality can be derived. Spatial statistics often make the null hypothesis that spatial data or processes are stationary or homogeneous with the same mean and variance over the study area. However, in reality, this assumption is questionable. Besides that, spatial pattern is affected by size and shape of the study plot, which is known as edge effect. Fortunately, there are some corrections for edge effects specified to certain spatial statistical methods (Fortin et al., 2002). With the development of spatial statistics, the underlying variations of spatial data will be studied more thoroughly (Goodchild and Haining, 2004).

Spatial regression models with spatially correlated errors and spatial regression models with spatially averaged predictor and/or response variables have been used when spatial dependence and variations are accounted for into regression models. Spatial regression analysis usually utilizes sparse spatial weights to denote spatial dependence and variations. Nowadays, these matrices are largely intrinsically symmetric (Banerjee et al., 2000). Because the incapability to discovering the true structure of spatial dependence, the spatial weights matrix are normally subjective and arbitrary (Getis and Aldstadt, 2004).

As the increase of spatial data resolution, it is expected that spatial aggregations will be more flexible and better spatial scale can be detected so that the problem can be solved more correctly. However, as in the fine spatial scale, the observation with each zone will decrease, which brings challenge to measuring spatial variation and conducting inference (Goodchild and Haining, 2004). The rapid growth of Bayesian analysis supplies a way to solve this issue. Bayesian methods have the advantage on small sample size data analysis where conventional maximum-likelihood estimation and inference cannot get good results (LeSage et al., 2004). For Bayesian spatial analysis, Markov Chain Monte Carlo (MCMC) simulation is popular for fitting and getting inference for spatial regression models, which conducts simulation for samples based on posterior distributions of model parameters (Goodchild and Haining, 2004). Cowles (2003) gave an example that the Bayesian geostatistical model, which incorporates spatial correlation, can be used for comparing different measurement systems. In this case study, MCMC is used to derive unknown parameters.

Fortin et al. (2002) listed some functions that spatial statistics often use: nearest neighbor distance, Ripley's K function, blocked quadrant variance, join-count statistics, spatial autocorrelation coefficient, empirical and theoretical variogram, and Mantel test. There are some advances in software for spatial analysis. GeoDa by Anselin et al. (2006) is a free software which conducts the exploratory spatial data analysis and spatial regression analysis. Another software, SANET by Okabe et al. (2006), mainly focuses on network spatial analysis. S/S-plus and R are popular software packages for spatial data analysis. Especially, R is more and more popular as it is a free software under the terms of the Free Software Foundation's GNU General Public License in source code form (Bivand, 2006). Berman and Turner (1992) illustrates that GLIM, which is a traditional statistical package for non-spatial data analysis, can be used on Poisson process in space by using Dirichlet tessellations or Delaunay triangulations.

The concept of fractal dimension has changed the way we conduct research on cities (Sui, 1997). By taking the city as a physical structure which has an irregular or fragmented shape at different scales of measurement, city can be understood as a filling process over a two-dimensional space of connected points, lines, and polygons (Batty and Longley, 1994). In this way, cities are fractal in form and have a potential of infinite complexities.

**The integration of GIS and spatial analysis for urban analysis**

Both spatial analysis and GIS use the same geographic representation model; that is, they both use Euclidean space to construct their models. In the Euclidean model, geographic objects are represented as points, lines, and polygons, or as an intensity field/surface (Miller and Wentz, 2003). A lot of studies have been conducted to set up the bridge between GIS and spatial analysis (Fotheringham, 1991; Goodchild, 1992).

The development of geographic information science (GIScience) gets benefits from the development in GIS and the field of spatial data analysis (Goodchild and Haining, 2004). GIS can improve our technical capability to handle spatially referenced data and conceptualize and represent geographic reality in points, lines and polygons in the Euclidean space. GIS has values for spatial statistics in that GIS can act as spatial database, conduct geometric registration, supply exploratory spatial data analysis, examine spatial context, incorporate external information, and present the analysis results (Burrough, 2001).

With the development of object-oriented approach in GIS data modeling and component-based approach in aggregating reusable software components, the integration of GIS with other forms of software, especially statistical software, has been accelerated (Goodchild and Haining, 2004). During recent years, the capability of representing variation in space-time and in three dimensions has been improved in GIS. These features supply a solid basis for spatial data analysis, such as transformation, projection change and resampling, spatial analysis, and visualization. Besides that, the scripting languages and other third part programming language, such as Visual Basic for Applications, can greatly enhance the capability of GIS applications in more specialized contexts (Goodchild and Haining, 2004).

From the 1980s, the integration of GIS and spatial analysis in urban research has been developed quickly as more urban models were advanced to improve the analysis capabilities within GIS environment (Sui, 1998). The integration can conduct from data inventory and management to modeling and simulation. Sui (1994, 1998) identified four ways of integration between GIS and spatial analysis/modeling: the stand-alone module, macro programming, loose coupling, and full integration approaches. This integration greatly enhances the quantitative capabilities in urban analysis, which sets up a bridge between theory and practice (Sui, 1994). However, there are fundamental issues in spatial analysis when it is integrated with GIS: MAUP, spatial autocorrelation, and edge effects (Sui, 1997).

GIS applications in urban research have become more and more focused on setting up integrated databases, developing appropriate methods for urban analysis, and conducting simulations for fine-scale urban geographies (Longley, 2003). For example, Sui and Hugill (2002) used GIS-based Getis-Ord's G-statistic to conduct spatial analysis on neighborhood effects on voting by measuring spatial clustering of similar values.

What is needed now in urban research is a timely analysis exploring the increasingly heterogeneous structure of contemporary cities and the ways in which they make changes

(Longley, 2003). Today there are great improvement on depicting and examining the relationship between the built form and urban socio-economic functions and urban settlement hierarchies (Longley, 2003). More progress is expected when disaggregated small-area socio-economic data of urban systems are linked with digital data, such as built form.

**Urban structure and urban space**

Urban structure and urban space have been research topics for a long time since scholars were first interested in how cities grow and why certain spaces, such as rich and poor, evolved. the Chicago School has three famous urban structure models which have influenced urban geography development for more than half century. These three models are concentric zone model by Burgess (1925), sector model by Hoyt (1937), and multiple nuclei model by Harris and Ullman (1945).

Classical urban theory by the Chicago School has been challenged by the Los Angeles School in the last two decades. According to the Los Angeles School, postmodern city has a complete different trend in political, economic, and sociocultural life (Dear and Flusty, 1998). Regarding urban structure, the postmodern city should be a decentered and decentralized society which is due to flexible and disorganized capitalist accumulation. As a result, urban structure is fragmented yet constrained by the underlying economic principles. At the same time, the metropolis has a random or quasi-random growth where the development of one urban parcel has no relationship with the others (Dear and Flusty, 1998). This opinion is significantly different from the earlier Chicago School’s center-driven urban development.

Poulsen and Johnston (2002) summarized three interrelated concepts which are important to contemporary urban analysis. First, the classical Chicago School’s urbanism and urban theory, which are classical modernist visions of the industrial society, have been replaced by the postmodern Los Angeles School. Second, other modern urbanism has been superceded by postmodern urbanism. Third, Miami, instead of Los Angeles, should be taken as a paradigmatic model of postindustrial city.

Qualitative methods, such as in-depth interview, participant observation, and more and more discursive and representational analyses, are more and more used in contemporary urban geography to study urban structure and urban space. The problem of these qualitative methods is that the researchers seldom outline how they used these methods and the relationship of these qualitative methods to the theoretical tracks (Lees, 2003). This obscurity on research methods has brought obstacles for the formation and development of the Los Angeles School and indicated its fundamental weakness.

Postindustrial society refers to the socioeconomic environment of the contemporary age where the economy is service-based, and class structure is bifurcated into low- and high-end classes with different types of occupations. The working class declines in size and significance and the middle class gains more importance (Baum et al., 2002). Poulsen and Johnson (2002), based on the results on four cities (Los Angeles, Miami, Chicago, and New York), concluded that a modern-postmodern differentiation is more complex than a simple binary division. However, the examples of postmodern cities, in this case Los Angeles and Miami, have more degrees of heterogeneity than modern cities, in this case, Chicago and New York.

Income inequality in the United States has increased over the decades (Silver and Bures, 1997). However, the causes of this increasing difference are still under questions. The hypothesis from demographic and supply-side effects cannot explain the reality that income inequality persists within demographic categories, although increasing immigration and the number of female-headed families make contributions to the increased inequality. Meanwhile, the hypothesis from demand-side effects cannot explain the reality that income inequality has been increasing for all industries, although industrial restructuring has been proved to be partially influential. Other explanations include the declining unionization, economic globalization, technological innovation, and employment instability (Silver and Bures, 1997).

Sui (1999) argues that the issues talked by postmodern urban theory are not new regarding the world-city hypothesis, the dual-city theory, and the edge-city model. Instead, compared with the Chicago School which has had a long lasting influence on our understanding of how cities work, postmodernism has not formed a shared methodological procedures to validate and replicate its arguments.

There are still gaps to measure, model, and understand the syntax of urban space and the configuration of urban economic and social life (Longley, 2002). There exist some problems regarding urban models (Sui, 1998). First, as most of urban modeling sets assumptions based on industrial cities with targets of controlling land use and emphasizing the transportation lines, the informational cities have different urban forms and processes which cannot be fully taken into account in the conventional models. With the enhancement of measurement capability on what is going on in urban areas, urban theory will be developed and improved (Longley, 2000).

## Conclusions

At the present day, there is an increasing variety of applications of remote sensing and GIS for quick monitoring urban changes (Maktav et al., 2005). Technology advancement allows greater capabilities in examining the increased complexness in urban environment. Better conception and understanding of urban systems can be achieved by the integration of remote sensing, GIS and spatial analysis (Longley, 2002).

There remains more room for the applications of GIS and spatial analysis in urban structure and urban space. With the availability of rich and disaggregated data, new skills and techniques are needed to better investigate the heterogeneity and uncertainty in the data sets (Longley, 2003). However, the integration of GIS, spatial analysis, and urban analysis is largely technology-driven without adequate justification for the validity of the models and sensitivity analysis for the results. This drawback should be taken into consideration in the process of integrating GIS and spatial analysis in urban studies.

With the new form of urban development in postindustrial society, the informational cities should call for new models which incorporate multi-dimensional concepts of space and time and embody the urban complexness (Sui, 1998). As GIS and spatial analysis have much to give to each other, the integration between the two is expected to develop a new partnership with urban geography in the coming years.

# CHAPTER 3

# A HYBRID APPROACH FOR LAND USE/LAND COVER CLASSIFICATION

## Introduction

Urbanization, as a world-wide phenomenon, brings more and more population and activities into urban areas. Large number of migrants together with rapid increase of built-up areas make urban land an interesting and constant topic for many fields. As discussed by Wilson et al. (2003), urban growth has three categories: infill, expansion, and outlying urban growth. Compared with urban growth, urban sprawl is somewhat negative (Wilson et al., 2003) and elusive (Galster et al., 2001). Urban land use/land cover patterns change rapidly in the process of urban growth. Atlanta, as the largest metropolitan area in southeast U.S. has continuously changed its physical landscape as well as its socio-economic appearance during past decades (Yang and Lo, and 2002).

It is important to better understand the process and characteristics of urban changes since urban areas are human's big habitats (Weber et al., 2005). In order to better depict urban landscape evolutions, the integration of remote sensing and geographic information systems (GIS) has been widely employed and largely accepted as a powerful and effective tool. Remote sensing techniques facilitate the collection of multispectral, multiresolution, and multitemporal data and convert them into valuable information and sources for understanding and monitoring urban land use/land cover changes, especially for a large study area. Meanwhile, the development of GIScience and GIS technology provides a flexible and favorable environment for entering, analyzing, and displaying digital data, which are a benefit to urban analysis (e.g., Phinn et al., 2002; Weng, 2001). Moreover, for time-series information extraction on urban growth, spatial information and remotely sensed data are particularly useful when urban land use/land cover is of interest.

This chapter presents a time-series analysis using remotely sensed data to identify urban land use/land cover changes over a decade (from 1990 to 2000) in the Atlanta metropolitan area. This topic is of interest because the derived land use/land cover change information will be further used for urban structure analysis in chapter 4. Specifically, a hybrid image processing approach, which integrates unsupervised, supervised, and spectral mixture analysis (SMA) classification methods, will be used to extract information of six types of land use/land cover classes.

This chapter is organized as follows. The next section is a literature review on the use of remote sensing and GIS on urban analysis and image processing techniques. Then the sections on methods and results explain the classification scheme and present classification results. The section of conclusions and discussions is the last part of this chapter.

**Literature review**

Monitoring and mapping urban land use/land cover changes have been research topics for a long time (e.g. Madhavan et al., 2001; Martin and Howarth, 1989; Ridd, 1995; Thomas et al., 1987; Welch and Ehlers, 1987). Researchers focus on different aspects of urban analysis based on the integration of remote sensing and GIS in the following ways: (1) generating accurate urban land use/land cover maps (Clapham, 2003; Dong and Leblon, 2004; Treitz and Rogan, 2003; Zha et al., 2003); (2) developing new approaches (Erol and Akdeniz, 2005; Goovaerts et al., 2005; Song, 2005; Tompkins et al., 1997; Wu, 2004); or (3) discussing the (dis)advantages of certain techniques (Chang and Heinz, 2000; Dennison et al., 2004; Gilabert et al., 2000; Guindon et al., 2004; Ju et al., 2005; Rashed et al., 2005; Treitz and Rogan, 2003; Weber and Puissant, 2003).

Since the launch of the first Earth Resources Technology Satellite (ERTS) in 1972, remotely sensed data have been a useful and flexible source for detecting and monitoring changes in many fields, such as environmental protection, urban analysis, and policy formation. With the improvement of image processing techniques, especially together with GIS technologies, the usefulness and flexibility of remotely sensed data have received increasing acceptance, especially after the new generation of high-spatial resolution data (Treitz and Rogan, 2003). Two problems are closely related to remote sensing applications in urban analysis: the heterogeneity of urban area and inconsistent registration of image layers (Clapham 2003; Herold et al., 2004). Small (2005) found that urban reflectance is extremely variable at different spatial scale. The variability of urban reflectance can cause misclassification between urban and other land cover classes (Small, 2003).

There are a series of traditional image-analysis techniques: single-band analysis, color composite generation, band-to-band ratioing and vegetation indices, principal component analysis (PCA), and classification (Campbell, 1996; Schweik and Green, 1999). Of these, classification is one of the most commonly used techniques for remotely sensed imagery (Adams et al., 1995).

Conventional classification methods, including supervised and unsupervised classifications, are largely based on pixel-by-pixel classifiers. Computer-assisted image classification methods rely heavily upon brightness and spectral characteristics with limited use of image spatial content. Accordingly, classifiers advocated by this method generally work well in spectrally homogeneous areas, such as forests, but not in highly heterogeneous regions, such as urban landscapes (Yang and Lo, 2002). Additionally, these pixel-by-pixel classifiers generally have difficulty in producing satisfactory classification results when image spatial resolution increases (Casals-Carrasco et al., 2000). This situation is particularly serious for urban land use. New methods and procedures for classification have been developed and used in many studies. They include the support of classification by fuzzy set theory, neural network, geostatistics, and spectral mixture analysis (SMA).

The central idea of fuzzy set theory is that human understanding is imperfect and the phenomena in nature rarely fit perfectly the categories into which they are traditionally placed by Boolean logic (Brown, 1998). In image processing, fuzzy logic, unlike Boolean logic, admits and assigns partial membership values to objects and pixels when full memberships (0 or 1) are not applicable. As a result, the output can be taken as a series of probability surfaces representing the probability of membership to a specified class. Another technique is neural network, which is a complex mathematical structure with automaton characteristics (Tapiador and Casanova, 2003). Typical neural nets have three elements: an input layer consists of the source data; an output layer consists of the classes; and one or more hidden layers which are trained by backpropagation algorithm. This classification system involves huge computational cost. Furthermore, it is difficult to sharpen the network once it has been designed, which requires previous experience and knowledge of the mathematical basis of the network (Tapiador et al., 2003). Texture classification uses the spatial autocorrelation of digital numbers (DNs), which are calculated as variogram, to improve the classification accuracy (Chica-Olmo and Abarca-Hernandez, 2000). When texture classification is conducted, a new layer of texture information is usually computed and used as an image filter with the aim of increasing the accuracy of classification. Based on texture information, a number of techniques, such as the supervised maximum likelihood estimation algorithm and neural networks, can be used to classify pixels. Similarly, there is segment-based classification, for example, eCognition package (Definiens Imaging, 2004), which uses a bottom-up region merging technique where each pixel is originally classified as a segment and adjacent objects are merged based on certain rules.

Spectral mixture analysis (SMA) is commonly used in image analysis in recent years, which recognizes that a single pixel is typically made up of a number of varied spectral types (i.e., urban, water, soil, vegetation). Therefore, each image pixel is decomposed into several fractions of endmembers, which represent the varied spectral types, and the percentage of spectra for each spectral type/endmember in a single pixel is measured (Lobell et al., 2002; Small, 2005). Since endmember fractions are easier to interpret than DNs, the image interpretation based on these fractions is more intuitive (Adams et al., 1995; Collado et al., 2002). This method is especially suitable for hyperspectral image analysis (Gross and Schott, 1998). The key to SMA is the selection of endmembers (Lu and Weng, 2004; Song, 2005). Due to high heterogeneity of urban landscape, three or more endmembers are usually selected for urban analysis (Garcia-Haro et al., 1999; Meer and Jong, 2000; Roberts et al., 1998; Small, 2004; Theseira et al., 2003). SMA makes it possible to identify the subpixel components which facilitates a follow-up classification (Lu and Weng, 2004; Schweik and Green, 1999). However, a widely accepted limitation of SMA is that this technique uses linear unmixing of pixel reflectance and cannot incorporate non-linear mixing (Dennison and Roberts, 2003).

Because many of these enhanced techniques are highly demanding in terms of technical sophistication and expertise, their application to large-scale mapping and urban growth analysis remain largely experimental. In practice, researchers select an appropriate singular classification method or hybrid schemes based on their projects' requirements. Information from ancillary data sources has been widely shown to aid discrimination of classes that are difficult to classify using remotely sensed data. Newly developed methods, such as the use of landscape metrics for extracting spatial structure (Herold et al., 2002), have also been tested and improved. Nevertheless, further efforts will certainly be needed to solve practical problems in a productive environment.

Change detection is another important technique when land use/land cover changes are concerned, which is usually done to compare two or more images covering the same study area (Kaufmann and Seto, 2001). Jansen and Gregorio (2002) point out that land use/cover change detection aims to recognize two types of changes. One is the conversion from one land cover category to another, e.g. from urban to forest. The other is the modification within one category, e.g. from ordinary cultivated area to irrigated cultivated area. While conversion refers to an evident change, modifications are much less apparent and require greater details. When the categories for describing land use/cover are broader and fewer, there are fewer conversions from one class to another. Numerous change detection techniques are available which achieve different levels of success in monitoring land use/cover changes. Most of them are semi-automated because analysts still have to manually carry out many image processes such as image registration, threshold tuning, and change delineation (Dal and Khorram, 1999). This makes semi-automated techniques time-consuming, inconsistent, and difficult to apply to large-scale information systems, such as the International Earth Observing System.

The conventional change-detection techniques can be divided into two broad categories (Dal and Khorram, 1999): (1) change mask development (CMD), where only changes and nonchanges are detected and no categorical change information can be directly derived; and (2) categorical change extraction (CCE) where complete categorical changes are extracted. In the CMD category, changed and non-changed areas are delimitated by a preset threshold and the amount of change is a function of the threshold value (Dal and Khorram, 1999). The threshold has to be tuned and determined by experiments. This kind of technique cannot directly identify the nature of the changes. This category includes image differencing, image ratioing, image regression, normalized difference vegetation index (NDVI), Tasseled Cap Transformation, and multidate principal component analysis (PCA). As for CCE techniques, the explicit categorical changes can be detected directly based on the spectral reflectance of the data. There are mainly three techniques in this category: change vector analysis, post-classification comparison, and direct multidate classification (Dal and Khorram, 1999).

Researchers have developed some other change-detection techniques in order to better conduct their studies. Mask detection is the combination of pixel-by-pixel comparison and post-classification comparison (Pilon et al., 1988). This method can identify changes with higher accuracy, but it cannot exclude the misclassification within the change-detected areas, since it still uses conventional classification methods. A principal component analysis (PCA) of stacked multi-temporal images method is proposed by Li and Yeh (1998) to improve the accuracy of land use change detection. This procedure is opposite to the post-classification comparison method, which traditionally carries out land use classification for each image before change detection. The econometric change detection technique uses time series and panel techniques to identify the date of change for individual pixels (Kaufmann and Seto, 2001). The econometric technique is designed to identify the date of change from a time series of images, but many of statistical underlying assumptions, such as normality, may be inconsistent with the data collected by image sensors (Kaufmann and Seto, 2001). A neural-network-based land use/cover change-detection system considers both architectural and parameter selections (Dal and Khorram, 1999). This technique has the following advantages (Dal and Khorram, 1999): (1) providing complete categorical “from-to” changes; (2) not requiring statistical distribution; (3) easily incorporating additional information by adding input nodes; and (4) using two-date images simultaneously and free from accumulative errors, unlike the post-classification comparison.

Although these methods have been successful in monitoring changes for a myriad of applications, there is no consensus as to a ‘best’ change detection approach (Seto et al., 2002). The type of change detection method employed will largely depend on temporal and spatial resolutions of the data, time and computing constraints, and type of application (Weber et al., 2005).

**Study area, imagery, and reference data**

Atlanta metropolitan area is the largest metropolis in the southeast part of the U.S. 13 counties in Atlanta metropolitan area are studies in this chapter (Figure 3.1), which include: Cherokee, Clayton, Cobb, Coweta, Dekalb, Douglas, Fayette, Forsyth, Fulton, Gwinnett, Henry, Paulding, and Rockdale. These 13 counties can be incorporated into one Landsat scene (180 km *170 km), which supplies great convenience without the procedures of image fusion and enhancement when two or more image scenes are needed.

During the past 25 years, Atlanta has been one of the fastest growing metropolitan areas in the U.S. and becomes the largest commercial, industrial, and transportation center of the southeastern part of U.S. (Yang and Lo, 2002). Meanwhile, urban built-up areas have expanded quickly and consumed large areas of agricultural and forest land.

Table 3.1 lists the basic characteristics of images used in this chapter. In order to analyze urban growth change, 1990 and 2000 Landsat images were used in this study. These two images are both in September, which supply a good source of comparison between two dates. Only six bands were used in each year; that is, bands 1-5 and 7 for 1990 and 2000.

Reference data have several categories. First, the reference images are digital orthophoto quarter quadrangles (DOQQs), where 1993 DOQQs are black-n-white and 1999 DOQQs are color-infrared. Second, digital raster graphics (DRGs) in 1:24,000 were downloaded from Georgia GIS Clearinghouse (www.gis.state.ga.us). DRGs are used for the selection of ground control points (GCPs) for geometric registration of the Landsat images. Third, the boundary files for Atlanta metropolitan area are downloaded from U.S. Census of Bureau, which are used for better locating and interpreting the results.

## Methodology

This section introduces the procedure used for image processing. Figure 3.2 shows the flow chart for land use/land cover change analysis.

### *Geometric registration*

Accurate registration of images for change detection is vitally important (Treitz and Rogan, 2003). The precision requirement in the guidelines and specifications for image-to-image registration was 0.3 pixel in both directions (Ji et al., 2001). Two images are georeferenced to a Universal Transverse Mercator (UTM) map projection with GRS 1980, zone north 16 and NAD83. Ten ground control points (GCPs) are selected for each images with the root mean square error (RMSE) at less than a third of a pixel for each registration process. The images are

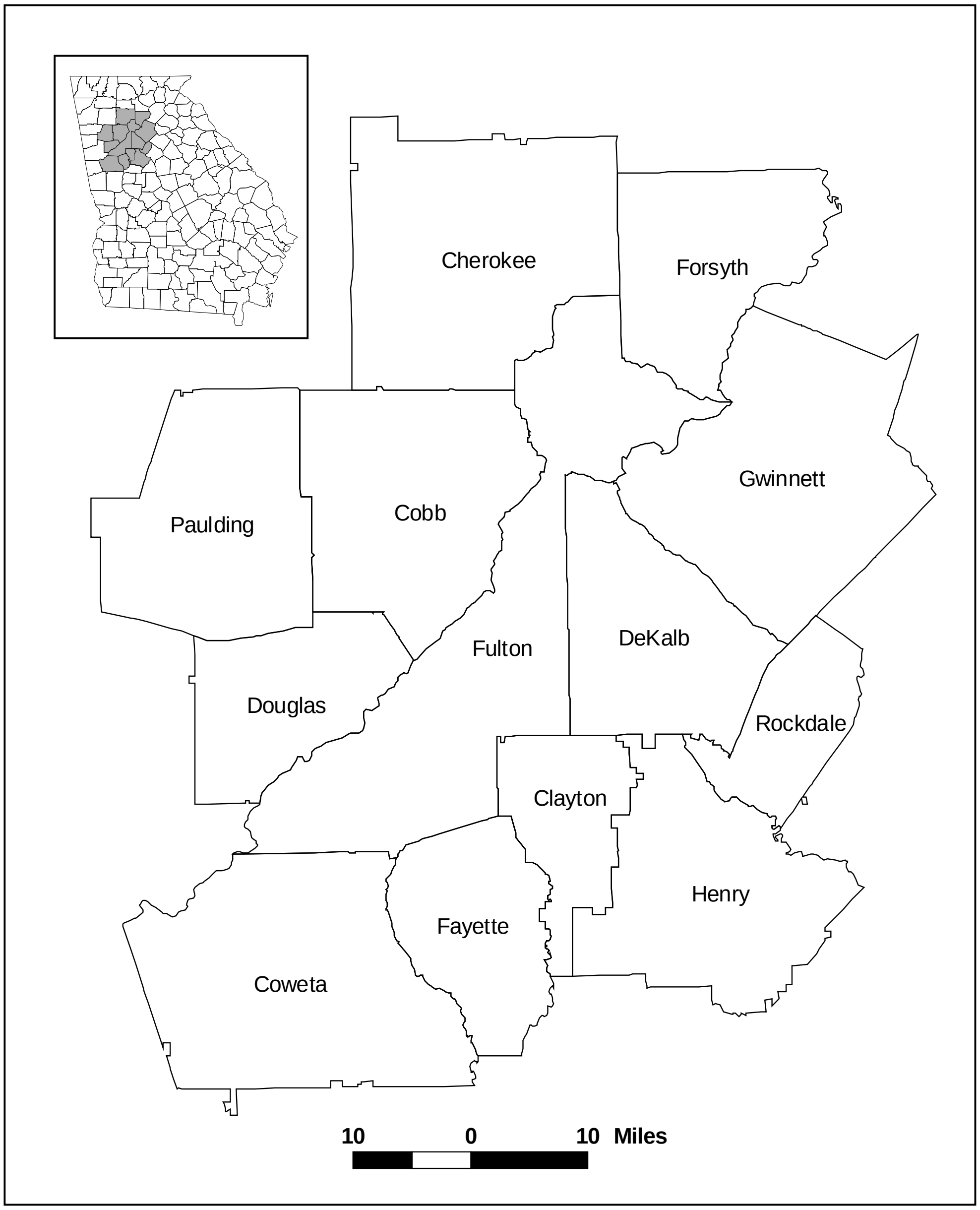



Figure 3.1 Study area: Atlanta metropolitan area

Table 3.1 Characteristics of Landsat imagery used for classification

| Date | 09/25/1990 | 09/28/2000 | 09/28/2000 |
|---|---|---|---|
| Type of imagery | TM | ETM+ | ETM+ |
| Landsat number | 5 | 7 | 7 |
| Spatial resolution (m) | 30 | 30 | 30 |
| Path # | 19 | 19 | 19 |
| Row # | 036-037 | 036 | 037 |
| Scene location | Center-shifted | North Atlanta | South Atlanta |

Table 3.2 Land use/land cover classification key (Source: Yang, 2000)

| No. | Classes | Definitions |
|---|---|---|
| 1 | Low-density urban | Areas with a mixture of 40 to 80 percent constructed materials (e.g. asphalt, concrete, etc.) and 20 to 60 percent vegetation of cover, including most of single/multiple family housing units, row houses, and public rental housing estates as well as local |
| 2 | High-density urban | Areas with a mixture of 80 to 100 percent constructed materials and/or less than 20 percent vegetation of cover, including industrial buildings with large open roofs as well as large open infrastructure (e.g. airports, parking lots, multilane interstate/s |
| 3 | Grassland /pasture/cropland | Areas dominated by grasses, herbaceous vegetation, and crops, including golf courses, airport grasses, industrials site grasses, lawns, city parks, lands planted for livestock grazing or the production of seed or hay crops, and planted and cultivated land |
| 4 | Forest | Areas characterized by tree cover including coniferous, deciduous, and mixed forests, with tree canopy accounting for 75 to 100 percent of cover. |
| 5 | Water | All areas of open water, typically with 85 percent or greater cover of water, including streams, rivers, lakes, and reservoirs. |
| 6 | Barren | Areas characterized by sparse vegetative covers, with little or no green vegetation cover (less than 25 percent of cover), including bare rocks, sand, clay, quarries, strips mines, gravel pits, cultivated land without crops, and forest clearcuts. |

resampled to 30m*30m pixels using a nearest neighbor resampling algorithm with a third-order polynomial.

*Radiometric calibration*

The DNs of two Landsat images were converted to normalized exo-atmospheric reflectance measures. The first step is to convert DNs to at-sensor spectral radiance by using the following equation (Markham and Barker, 1987):

$$L_{\lambda} = \left( \frac{LMAX_{\lambda} - LMIN_{\lambda}}{Q_{cal\max}} \right) Q_{cal} + LMIN_{\lambda} \tag{3.1}$$

where $L_{\lambda}$ is spectral radiance at the sensor's aperture in $W/(m^2 \cdot sr \cdot \mu m)$; $Q_{cal}$ is quantized calibrated pixel value in DNs; $Q_{calmin}$ is the minimum quantized calibrated pixel value (DN=0) corresponding to $LMIN_{\lambda}$; $Q_{calmax}$ is the maximum quantized calibrated pixel value (DN=255) corresponding to $LMAX_{\lambda}$; $LMIN_{\lambda}$ is spectral radiance that is scaled to $Q_{calmin}$ in $W/(m^2 \cdot sr \cdot \mu m)$; and $LMAX_{\lambda}$ is spectral radiance that is scaled to $Q_{calmax}$ in $W/(m^2 \cdot sr \cdot \mu m)$.

The next step is to convert at-sensor spectral radiance to planetary or exoatmospheric reflectance since this step can reduce between-scene variability by normalizing solar irradiance (Chander and Markham, 2003):

$$\rho P = \frac{\pi \cdot L_{\lambda} \cdot d^2}{ESUN_{\lambda} \cdot \cos\theta_s} \tag{3.2}$$

where $\rho P$ is unitless planetary reflectance; $L_{\lambda}$ is spectral radiance at the sensor's aperture; $d$ is earth-sun distance in astronomical units; $ESUN_{\lambda}$ is mean solar exoatmospheric irradiances; and $\theta_s$ is solar zenith angle in degrees.

The calibration parameters were obtained from Clander and Markham (2003) and image data header for Landsat-5 image in 1990. Meanwhile, from the manual by Landsat Project Science Office (1999) and image data header the calibration parameters for Landsat-7 image in 2000 can be derived. Here the atmospheric conditions within each image were assumed to be homogeneous so that no atmospheric corrections were carried for these two images.

After radiometric normalization, the area containing the Atlanta metropolitan area with 13 counties were masked out by using boundary files. In this way, only 13 counties are used for classification and change detection.

*Image classification*

This chapter uses a hybrid classification scheme which contains unsupervised classification, supervised classification, SMA, and then unsupervised classification again (Figure 3.2). Table 3.2 defines the classification keys used in this classification process. Six types of land use/land cover are identified: low-density urban, high-density urban, grassland/pasture/cropland, forest, water, and barren which is consistent with the work by Yang (2000) and Lo and Yang (2000).

<u>First-round unsupervised classification</u>

ISODATA (iterative self-organizing data analysis) classification was first used to identify clusters of spectrally similar pixels in each image. This process uses ENVI software which has the feature that can automatically identify the ideal number of classes based on the parameters for convergence criteria. In this step of image processing, the parameters are set as the following: change threshold is 0, minimum class distance is 0, maximum class standard deviation is 1, and

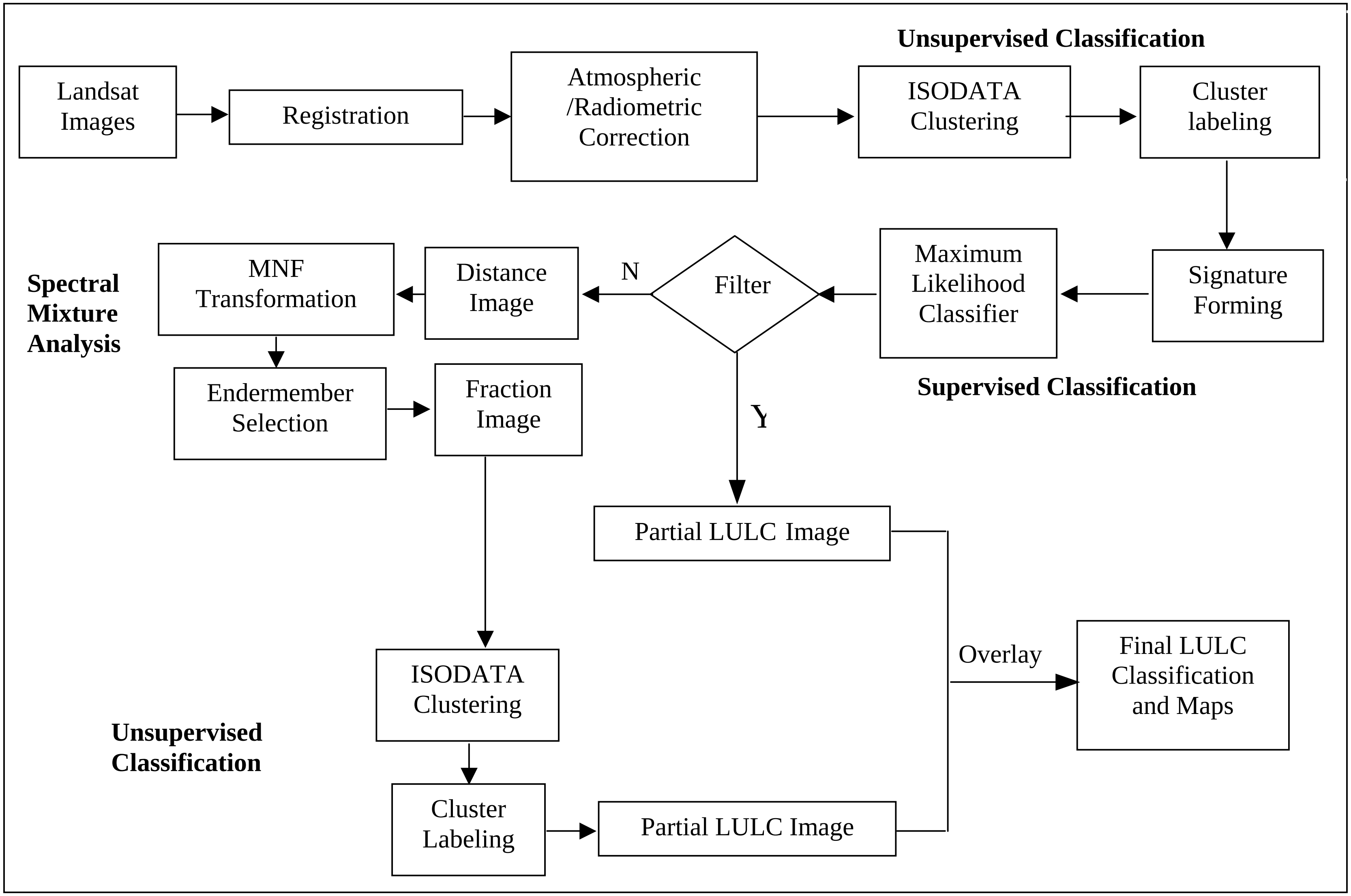



Figure 3.2 The flow chart of classification scheme

the number of classes has a range from 5 to 70. Based on these parameters for ISODATA, 37 classes were identified for 1990 image and 32 classes were formed for 2000 image. Based on these initial classification results, cluster labeling was conducted so that these classes were assigned to one of the six types of land use/land cover.

Supervised classification

Based on the results of unsupervised classification, area of interest (AOI) for each class was delineated. Supervised classification was then performed on the radiometrically-calibrated images for 1990 and 2000 respectively. During this process, a threshold was set so that when the pixel has a spectral distance from AOI greater than the cut-off value is set to be unclassified. In this research, a threshold value was set to 1. In this way, the resultant image contains the pixels having class type and the pixels having not been classified.

A mask was generated so that the unclassified pixels were covered in mask layer. A image that contains only unclassified pixels was further generated for 1990 and 2000 images (Figures 3.3 and 3.4). Those unclassified pixels are generally heterogeneous in nature so that traditional classification procedures cannot do well. In order to better classify these mixed spectral pixels, SMA method was used for linear unmixing of spectral signatures.

SMA method

SMA has the capability to identify subpixel measures so that a pixel can be composed by percentages of endmembers (Schweik and Green, 1999). Generally, the linear spectral mixture model for each pixel has the following form (Wu and Murray, 2003):

$$R_b = \sum_{i=1}^{N} f_i R_{i,b} + e_b \tag{3.3}$$

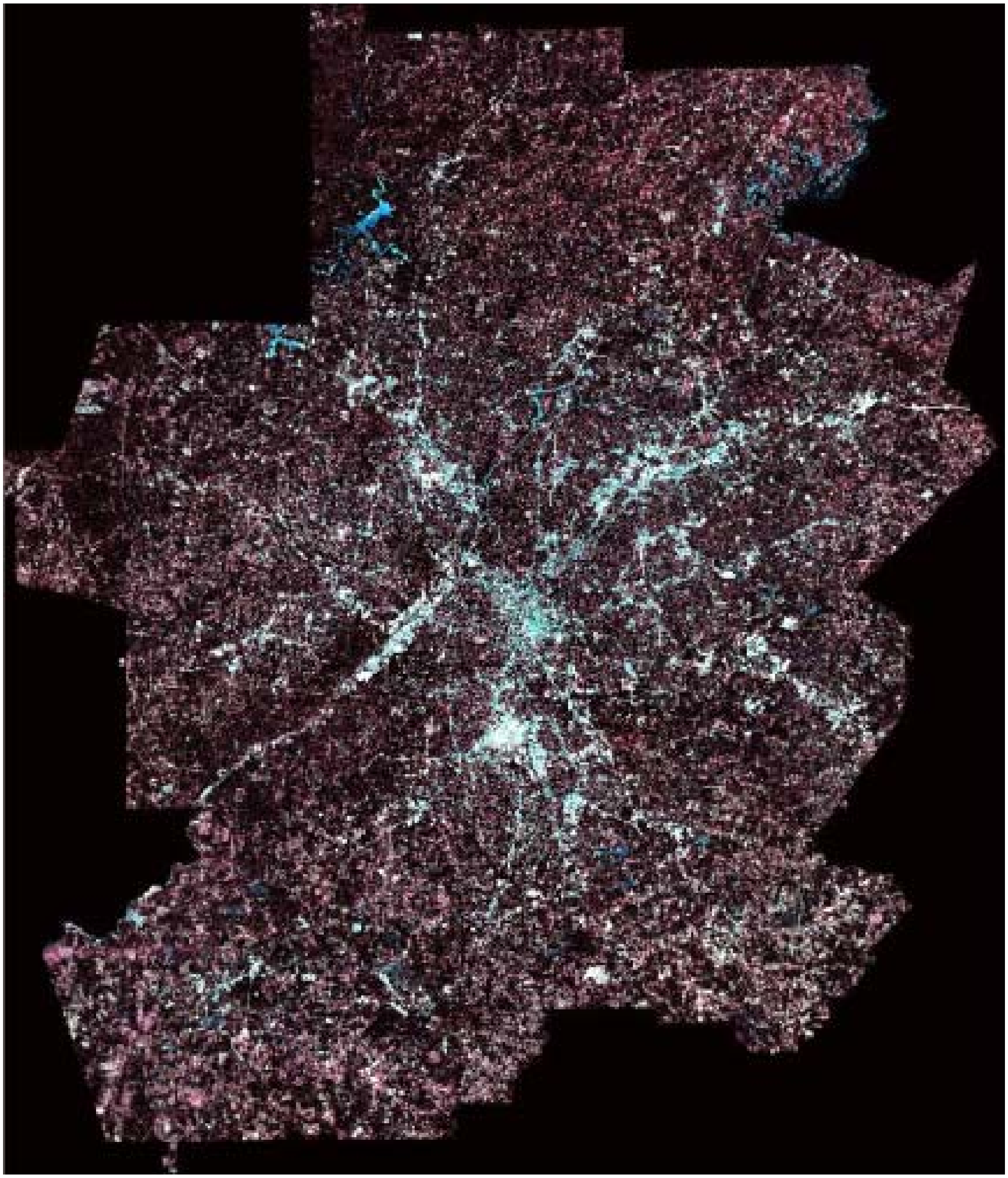


Figure 3.3 The unclassified pixels after first-round unsupervised and supervised classification procedures, 1990

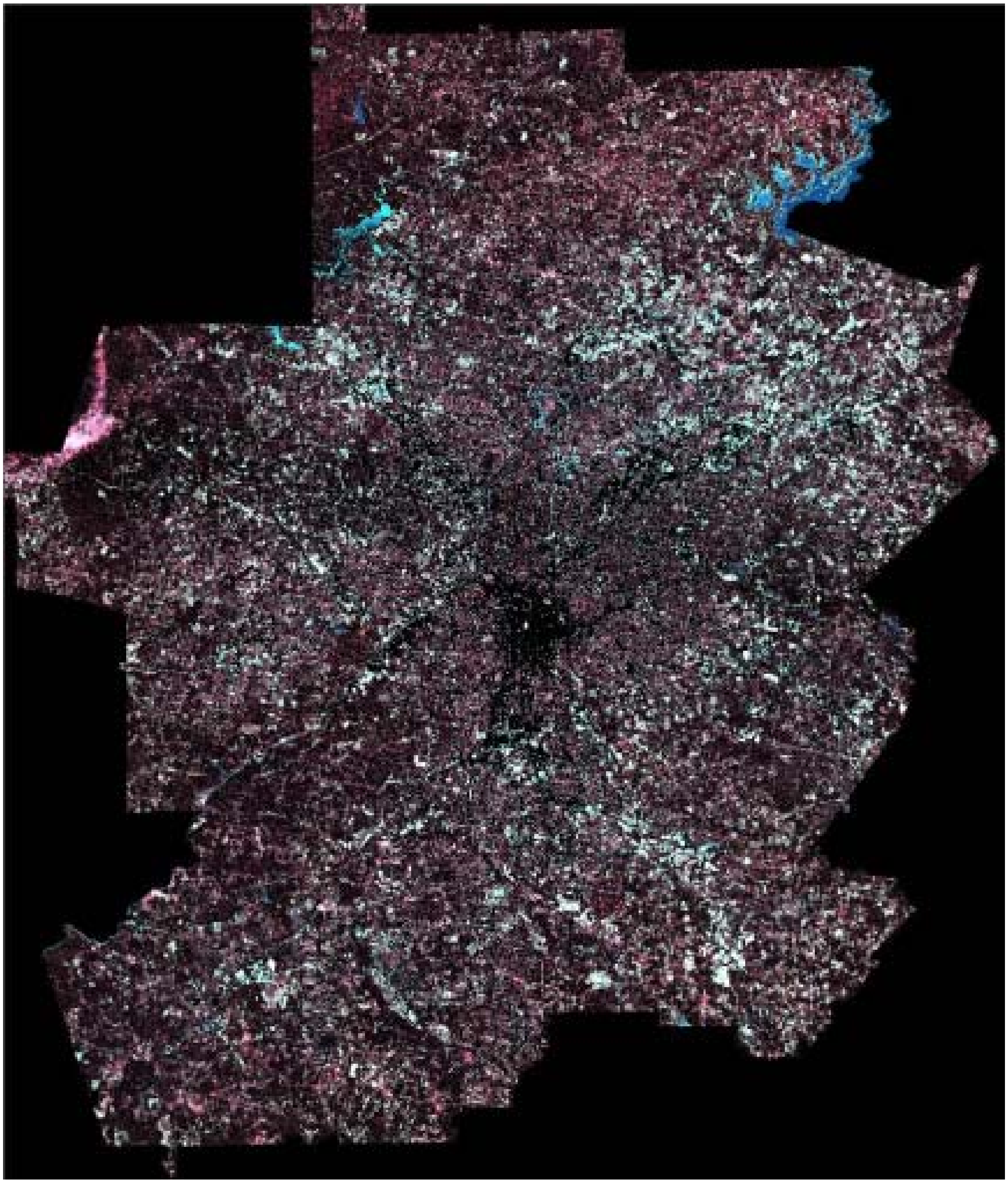


Figure 3.4 The unclassified pixels after first-round unsupervised and supervised classification procedures, 2000

where $R_b$ is the reflectance for each band $b$, $N$ is the number of endmembers, $f_i$ is the fraction of endmember $i$, $R_{i,b}$ is the reflectance of endmember $i$ in band $b$, and $e_b$ is the unmodeled residual.

In equation (3.3), $f_i$, $i$=1,2,…,$N$ are parameters to be estimated for each pixel. In reality, $f_i$ should meet the following conditions:

$$\sum_{i=1}^{N} f_i = 1 \quad and \quad f_i \geq 0 \tag{3.4}$$

In this way, the linear unmixing procedure is called constrained SMA. As stated in literature review section, the selection of endmembers is a critical part of SMA. Usually, there are three possible ways to determine endmembers (Schweik and Green, 1999): using spectrometer to collect known spectra from field or laboratory, borrowing known spectra from previous SMA work, or picking spectrally pure or extreme pixels from images being analyzed. In practice, the third method is usually taken.

In order to identify pure pixels and determine endmembers, scatter plot of feature space is a popular way. First, the image is transformed by principal component analysis (PCA) or minimum noise fraction (MNF) so that the highly correlated image bands are transformed into orthogonal bands. These uncorrelated bands are plotted into feature space and endmembers are selected based on pure pixels. In this chapter, MNF transformation was performed which has three steps (ENVI, 2000; Wu and Murray, 2003) ). First, a principal component transformation is performed to diagonalize the noise covariance matrix. Second, the noise covariance matrix is converted into an identity matrix by scaling the transformed dataset. Third, principal component analysis is conducted again on noise-whitened data.

Based on MNF transformation for each image, the first four MNF components were used for SMA and the last two were discarded since they contain high proportion of noise contents. From the scatter plots of MNF components, four endmembers were individually selected for

1990 and 2000 images and DOQQs were geographically linked for displaying. These four endmembers can be identified as vegetation (such as dense grass and cover crops), shade (such as clear and deep water), impervious surfaces (such as building roofs and roads), and soils (including dry soil and dark soil). The reflectance spectra for four endmembers in each image are plotted as Figures 3.5 and 3.6.

After endmembers were identified, the fraction of endmembers for each pixel can be computed by least squares techniques in order to minimize the error term eb based on equations (3.3) and (3.4). Model fitness is usually assessed by the residual term eb of the RMS over all image bands (Wu and Murray, 2003):

$$RMS = \left( \sum_{b=1}^{N} e_b^2 \Big/ N \right)^{1/2} \qquad (3.5)$$

Figures 3.7 and 3.8 show the residuals for 1990 and 2000 images after SMA procedure. The histogram distributions of RMS errors indicates that the residuals are generally small. Hence this procedure is acceptable for further image classification.

Second-round unsupervised classification

The generated fraction images for 1990 and 2000, where each fraction image has four layers (each layer denotes the fraction of one endmember), were further classified by unsupervised classification. ISODATA was used in the same way as the first round unsupervised classification. In this way, the unclassified pixels as a result of above supervised classification were assigned a land use/land cover type.

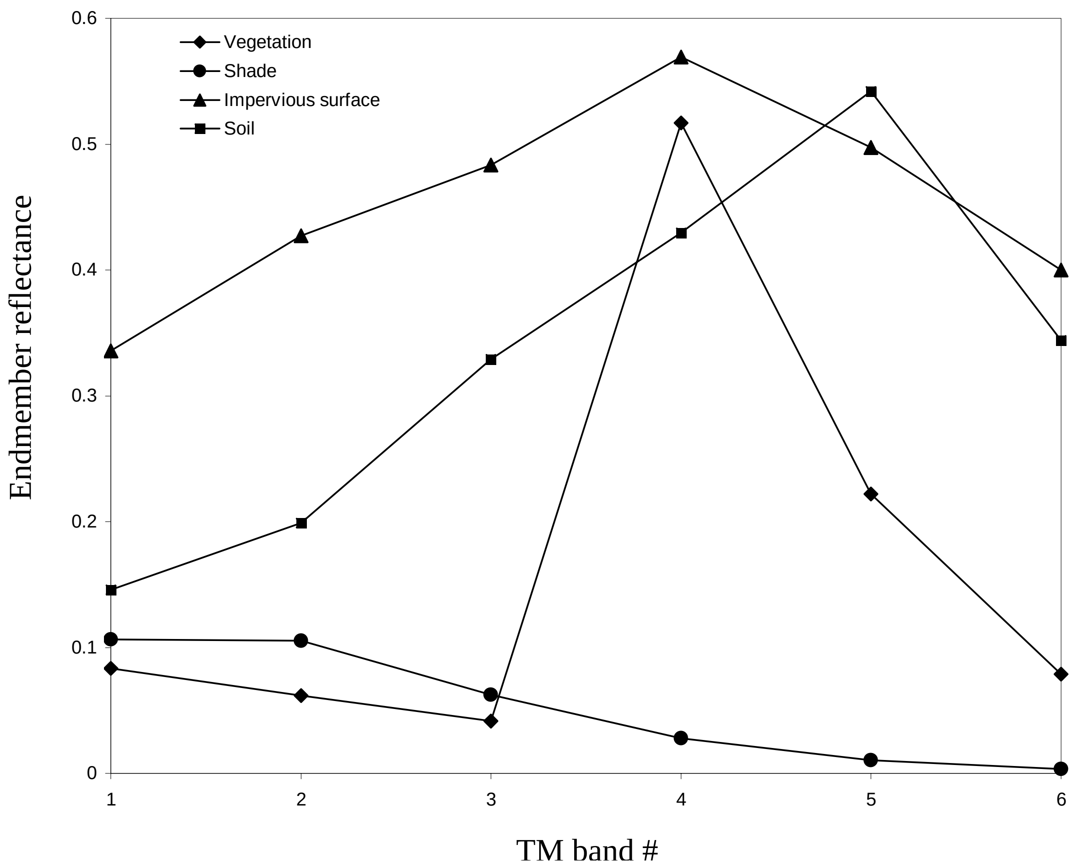



Figure 3.5 Endmember reflectance spectra for 1990 image

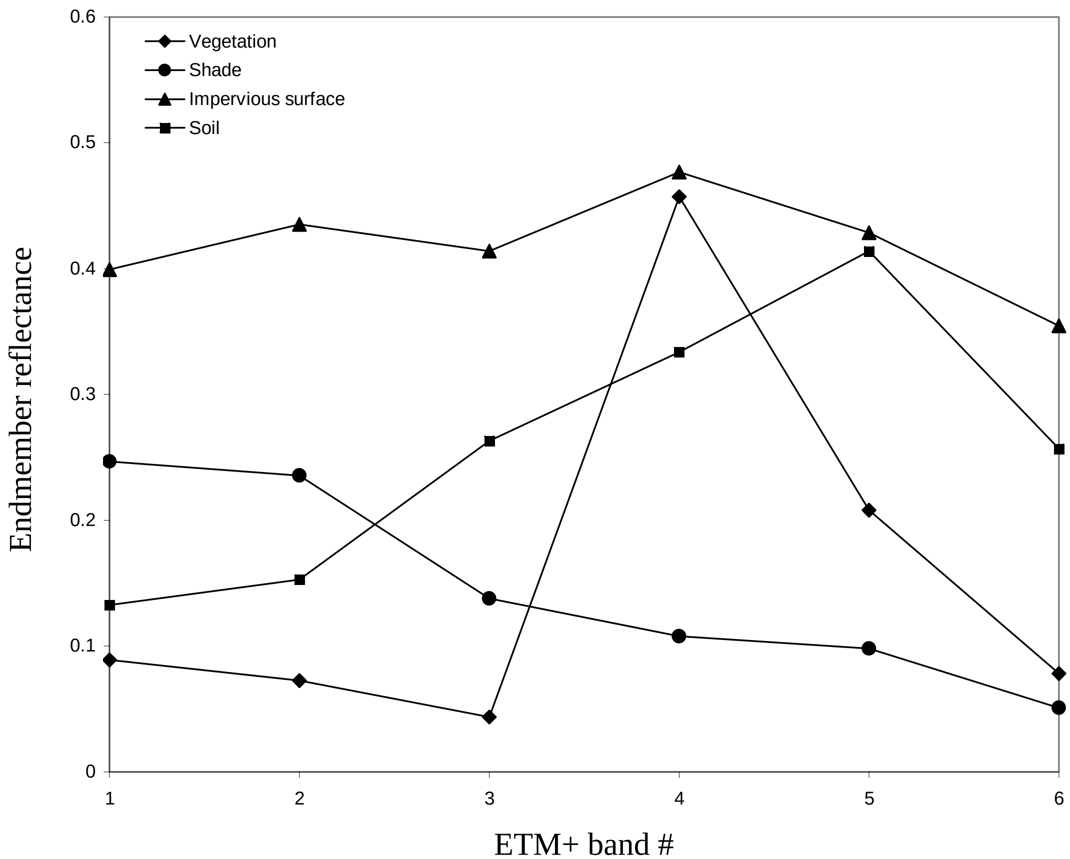
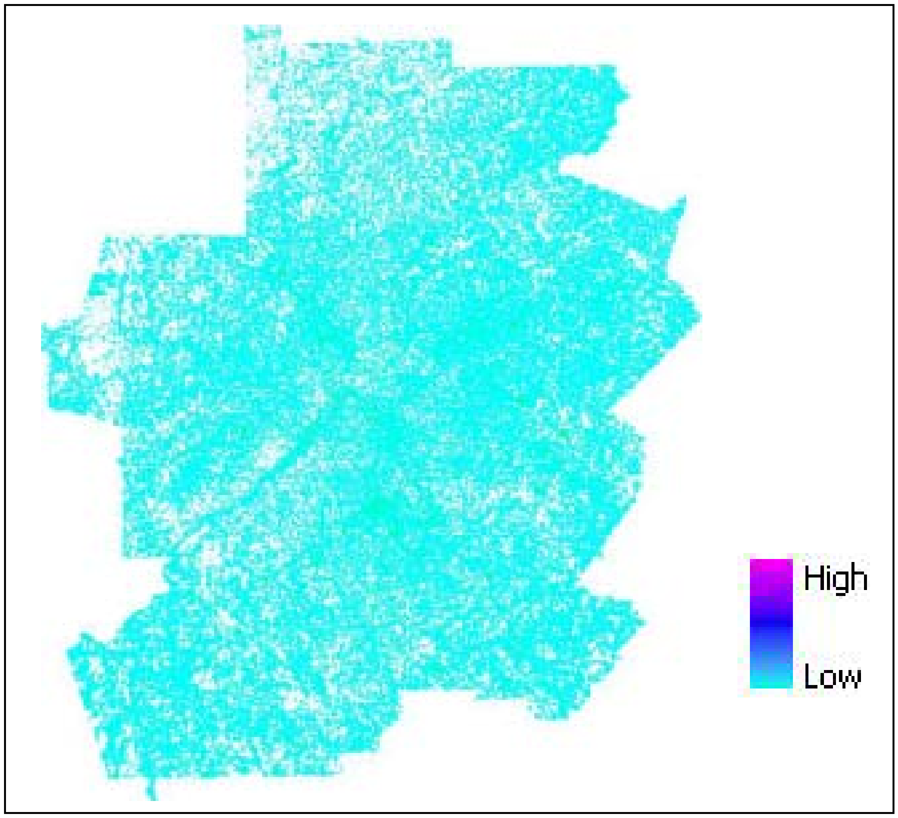
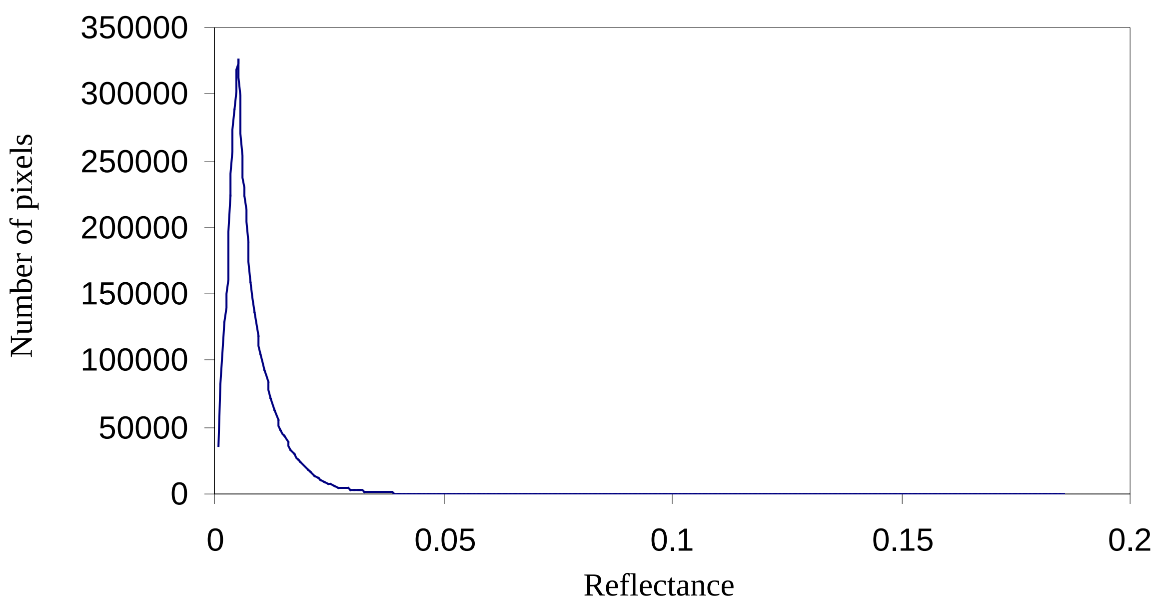



Figure 3.6 Endmember reflectance spectra for 2000 image



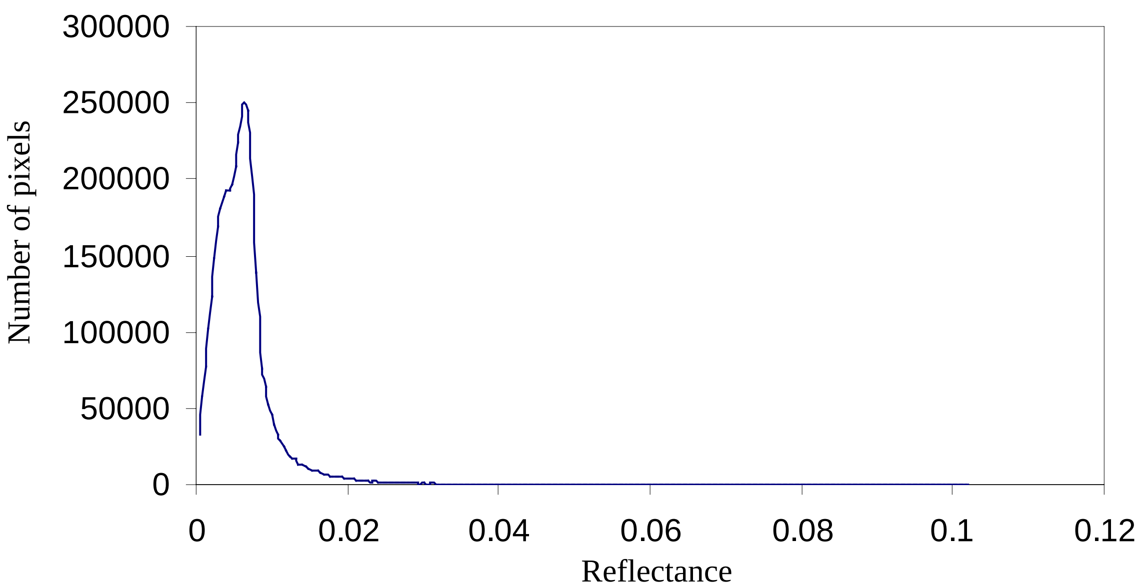

(a)




(b)

Figure 3.7 The RMS errors after SMA procedure for 1990 image: (a) the spatial distribution of RMS errors, and (b) the histogram distribution of RMS errors


(a)




(b)

Figure 3.8 The RMS errors after SMA procedure for 2000 image: (a) the spatial distribution of RMS errors, and (b) the histogram distribution of RMS errors

The next step was to overlay the results from supervised classification and second-round unsupervised classification. The resultant classification maps were the final products of land use/land cover classification for 1990 and 2000 Atlanta metropolitan area.

*Accuracy assessment*

In order to assess accuracy of classification, a stratified random sampling method was applied. For estimating classification accuracy, a minimum of 50 samples for each land use/land cover type should be selected (Wu and Murray, 2003). A total of 420 samples were selected for each image. As DOQQs, which were taken as reference images, did not have complete coverage on the Atlanta metropolitan area, only 408 sample points were valid for 1990 image. Meanwhile, 420 sample points were all valid for 2000 image.

**Results and conclusions**

Tables 3.3, 3.4, 3.5, and 3.6 show the accuracy assessment results for classification. For 1990 image, the overall classification accuracy is 86.27% and overall Kappa is 0.834. For 2000 image, the overall classification accuracy is 87.38% and overall Kappa is 0.848. These statistics are generally acceptable for Landsat image classification.

Figures 3.9 and 3.10 show the classification maps for 1990 and 2000 Atlanta metropolitan area. Clearly, there was an expansion of urban land cover areas. Tables 3.7 and 3.8 have the summary of land use/land cover changes during the 1990s. Of six types of land use/land cover, low-density urban, high-density urban, water, and barren all had increases in areas, while

Table 3.3 Confusion matrix and accuracy assessment for 1990 imagery

| Classified image | Reference image | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | Row total | User's accuracy (%) |
| 1 | 54 | 3 | 3 | 4 | 0 | 2 | 66 | 81.82 |
| 2 | 4 | 53 | 0 | 3 | 2 | 1 | 63 | 84.13 |
| 3 | 1 | 1 | 56 | 10 | 0 | 0 | 68 | 82.35 |
| 4 | 2 | 1 | 1 | 80 | 0 | 1 | 85 | 94.12 |
| 5 | 0 | 0 | 2 | 4 | 56 | 0 | 62 | 90.32 |
| 6 | 0 | 2 | 7 | 1 | 1 | 53 | 64 | 82.81 |
| Column total | 61 | 60 | 69 | 102 | 59 | 57 | 408 | |
| Producer's accuracy (%) | 88.52 | 88.33 | 81.16 | 78.43 | 94.92 | 92.98 | | |
| Number of pixels correctly classified = 352<br>Overall classification accuracy = 86.27% | | | | | | | | |

Table 3.4 Kappa statistics for 1990 image classification

| LULC class | 1 | 2 | 3 | 4 | 5 | 6 | Overall |
|---|---|---|---|---|---|---|---|
| Kappa | 0.786 | 0.813 | 0.787 | 0.921 | 0.886 | 0.801 | 0.834 |

Table 3.5 Confusion matrix and accuracy assessment for 2000 imagery

| Classified image | Reference image | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | Row total | User's accuracy (%) |
| 1 | 57 | 1 | 3 | 6 | 1 | 0 | 68 | 83.82 |
| 2 | 5 | 53 | 3 | 4 | 0 | 2 | 67 | 79.10 |
| 3 | 3 | 0 | 59 | 4 | 0 | 2 | 68 | 86.76 |
| 4 | 1 | 0 | 2 | 83 | 1 | 0 | 87 | 95.40 |
| 5 | 0 | 0 | 0 | 3 | 62 | 0 | 65 | 95.38 |
| 6 | 0 | 1 | 4 | 7 | 0 | 53 | 65 | 81.54 |
| Column total | 66 | 55 | 71 | 107 | 64 | 57 | 420 | |
| Producer's accuracy (%) | 86.36 | 96.36 | 83.10 | 77.57 | 96.88 | 92.98 | | |
| Number of pixels correctly classified = 367 | | | | | | | | |
| Overall classification accuracy = 87.38% | | | | | | | | |

Table 3.6 Kappa statistics for 2000 image classification

| LULC Class | 1 | 2 | 3 | 4 | 5 | 6 | Overall |
|---|---|---|---|---|---|---|---|
| Kappa | 0.808 | 0.760 | 0.841 | 0.938 | 0.946 | 0.786 | 0.848 |

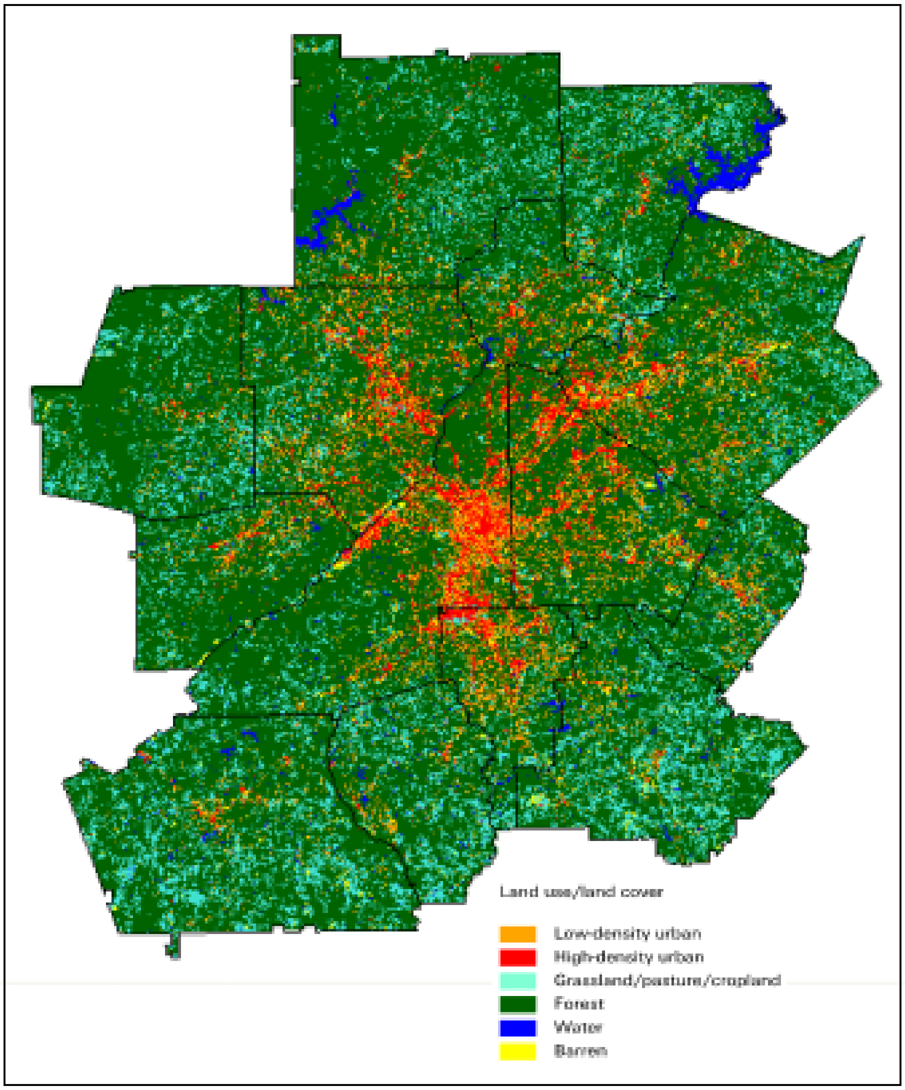



Figure 3.9 Land use/land cover, metropolitan Atlanta, 1990

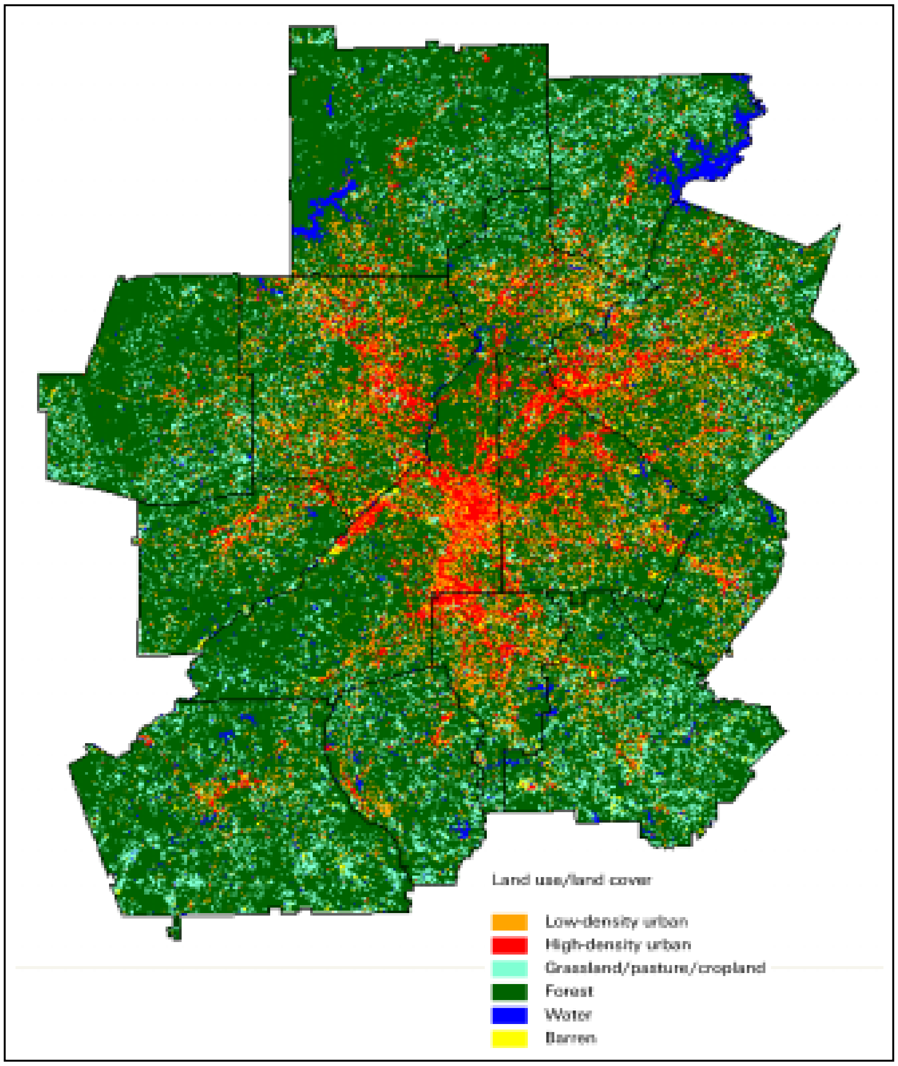



Figure 3.10 Land use/land cover, metropolitan Atlanta, 2000

Table 3.7 LULC statistics at metropolitan Atlanta

| Class | | 1990 | 2000 |
|---|---|---|---|
| Low-density urban | Sq. miles | 296.89 | 392.82 |
| | % of total land | 7.36 | 9.74 |
| High-density urban | Sq. miles | 136.96 | 231.76 |
| | % of total land | 3.39 | 5.75 |
| Grass/pasture/crop | Sq. miles | 549.63 | 461.37 |
| | % of total land | 13.63 | 11.44 |
| Forest | Sq. miles | 2941.83 | 2823.17 |
| | % of total land | 72.97 | 70.02 |
| Water | Sq. miles | 62.45 | 78.15 |
| | % of total land | 1.55 | 1.94 |
| Barren | Sq. miles | 43.91 | 44.66 |
| | % of total lan | 1.09 | 1.11 |

Table 3.8 Changes in LULC, 1990-2000

| Class | | Change |
|---|---|---|
| Low-density urban | Sq. miles | 95.93 |
| | % change | 32.31 |
| High-density urban | Sq. miles | 94.80 |
| | % change | 69.22 |
| Grass/pasture/crop | Sq. miles | -88.26 |
| | % change | -16.06 |
| Forest | Sq. miles | -118.66 |
| | % change | -4.03 |
| Water | Sq. miles | 15.70 |
| | % change | 25.14 |
| Barren | Sq. miles | 0.75 |
| | % change | 1.71 |

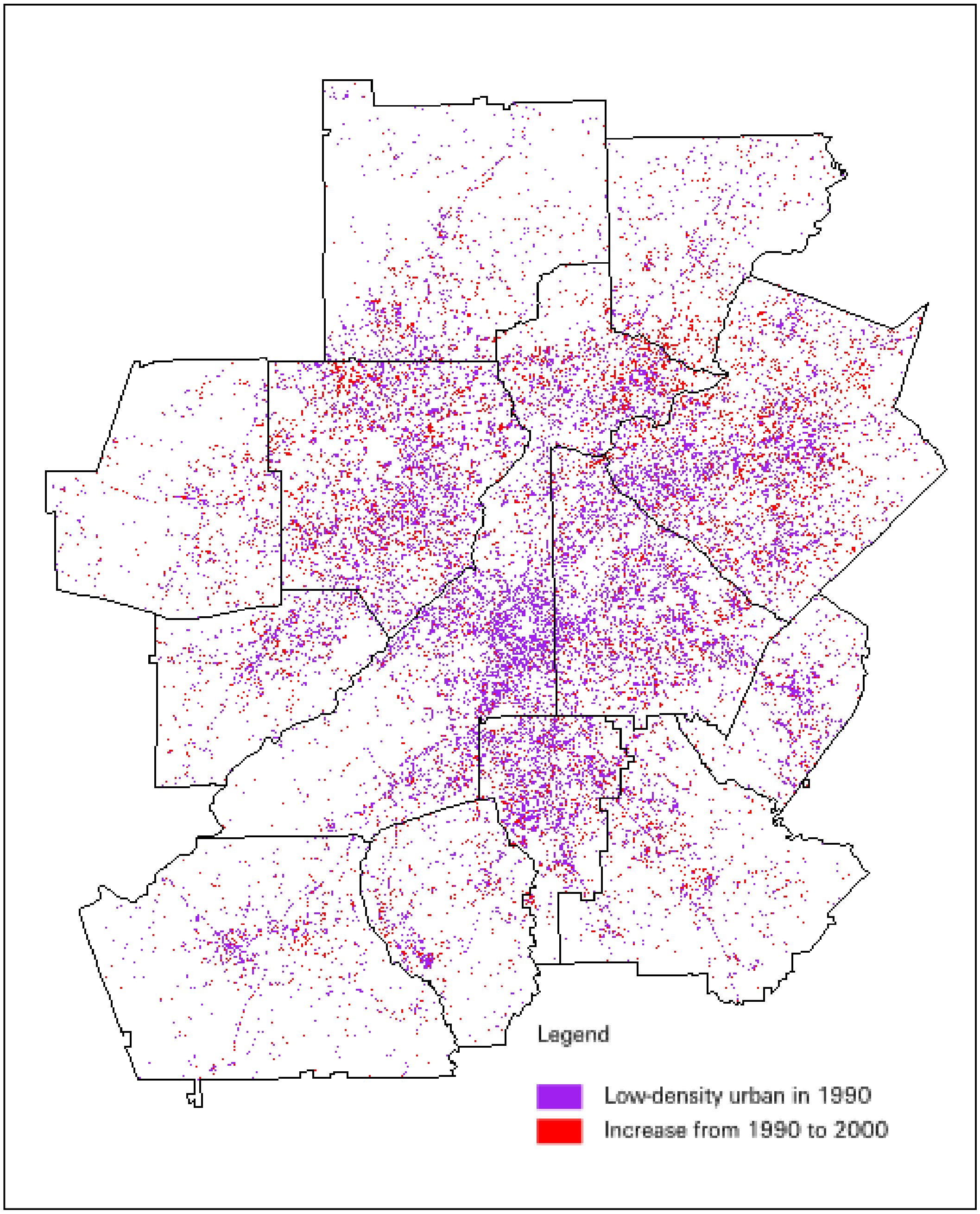



Figure 3.11 Low-density urban land use/land cover in 1990 and 2000

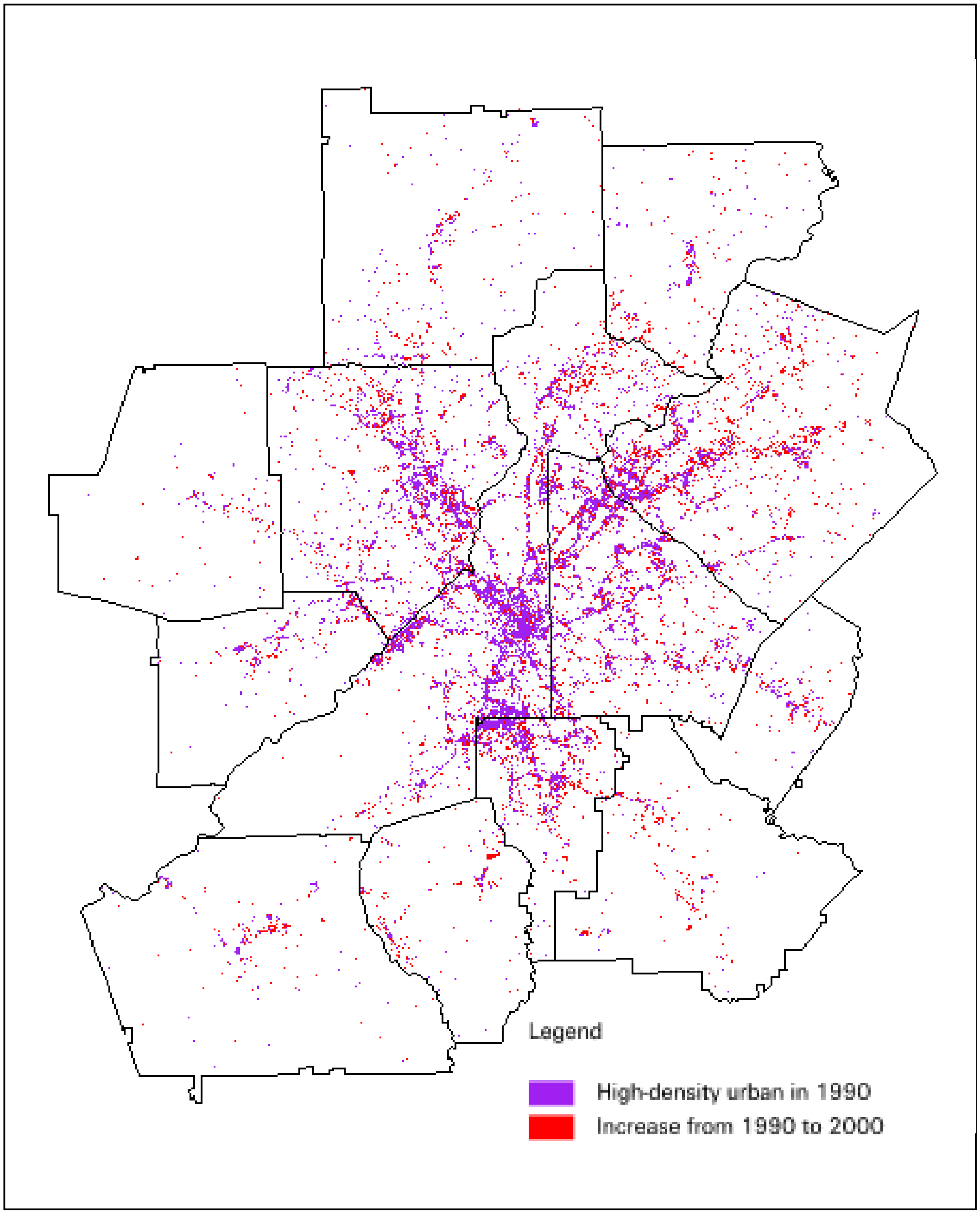



Figure 3.12 High-density urban land use/land cover in 1990 and 2000

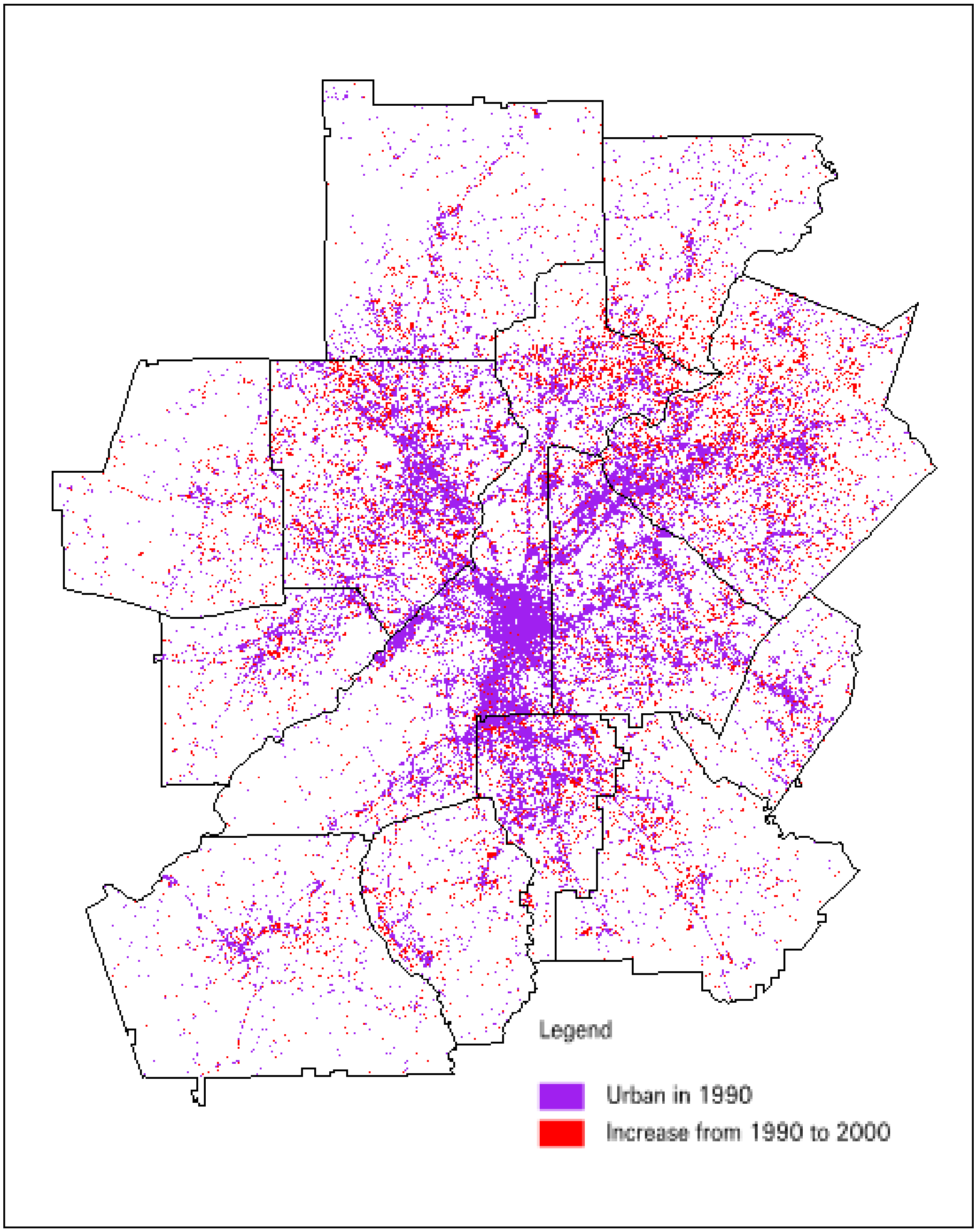



Figure 3.13 Urban land use/land cover in 1990 and 2000

grassland/pasture/cropland and forest had decreases. Clearly, the urban growth of Atlanta metropolitan area consumed large amount of vegetative lands.

In terms of absolute area with a unit of sq. miles, forest had the largest amount of decrease during the decade, followed by grassland/pasture/cropland. Even at this circumstance, forest was still the land cover type that had the largest percentage over the Atlanta metropolitan area although its share decreased sharply during the 1990s. Urban land cover had the second largest occupation in the Atlanta metropolitan area, a total of 10.75% in 1990 and 15.49% in 2000. Followed that, grassland/pasture/cropland had a decrease in percentage from 13.63% to 11.44%. Compared with urban and vegetative land cover, water and barren land had very small weights (1~2%) in overall metropolitan area and they did not have much change during the 1990s.

**Discussions**

This chapter uses a hybrid classification scheme to analyze land use/land cover for the Atlanta metropolitan area from 1990 and 2000. The results will be further used in the analysis of urban structure in chapter 4. Specifically, SMA method was introduced and applied in the image classification process. Together with unsupervised and supervised classification methods, land use/land cover maps were derived. According to accuracy assessment, the results were acceptable. However, as introduced in the methodology section, a cut-off value was used for supervised classification in order to mark those heterogeneous pixels, and the selection of threshold value is highly subjective. Different values were tried and intermediate results were evaluated in order to get a good cut-off value. In this way, the subjectivity can be reduced, but there is still possibility to get a better threshold.

SMA was used in this research for spectral unmixing of heterogeneous pixels and derived acceptable results. This proves that SMA is an effective approach for characterizing mixed feature areas, such as metropolitan area, although SMA has been largely used for vegetation analysis. During this process, the selection of endmembers is the key, which often involves a iterative process; that is, first selecting endmembers, deriving fraction images, evaluating the results, refining endmembers, and further testing their capabilities for representing heterogeneous landscape.

Even the classification maps are generally acceptable, when they were further used in other analysis, the error can be propagated. However, for large area, such as Atlanta metropolitan area, Landsat image is usually a good source since it has medium spatial resolution and wide coverage compared with other sources with high spatial resolution and narrow coverage. These classification errors should be taken into consideration when the results are used for further analysis.

# CHAPTER 4

# TEST ON POST-MODERNISM TREND FOR ATLANTA’S URBAN STRUCTURE

## Introduction

Local level applications, such as urban growth and land use changes, have more and more used remotely sensed images (Herold, 2001). This satellite remote sensing has the advantages of global coverage, short cycle, and low cost compared with field survey and visual interpretation of aerial photographs (Zhang et al., 2003). With the generation of high spatial and spectral resolution, satellite imagery has been more and more used in urban applications.

Urban internal structure is an interesting topic where the classical Chicago School posed several models on which many researches have been done to justify their applicability. With the shift to a service producing economy, polarization of the labor market into low- and high-wage sectors, and decentralization of jobs away from the central city, urban landscape has changed a lot across the U.S. cities. As a result, postmodern urbanism focuses on globalization, polarization, fragmentation, cultural hybrids, and cybercities, which can also be identified as the Los Angeles School (Dear and Flusty, 1998). Regarding urban structure, postmodern urbanism argues that urbanization is taking place on a quasi-random process, which overrides the traditional Chicago School’s point that center-driven agglomeration economies control and guide urban development (Dear and Flusty, 1998). However, as far as urban land use is concerned, no empirical study has been conducted to quantitatively prove or disprove this argument.

This chapter takes advantages of remote sensing and GIS techniques, as well as spatial statistics, to study Atlanta's urban internal structure from 1990 to 2000. Specifically, the land use/land cover classification results from chapter 3 are used in this chapter for the study area and data sources, several spatial metrics as well as statistical models of spatial point pattern and process will be used to test the fragmentation and random increase of urban growth in Atlanta metropolitan area.

This chapter is organized as follows. The next section is a literature review on urban structure, techniques of spatial metrics and spatial point pattern. Then the methodology part will introduce the methods used for urban analysis, which is followed by results section. The conclusions and discussions comprise the last section of this chapter.

**Urban structure, spatial metrics, and spatial point process**

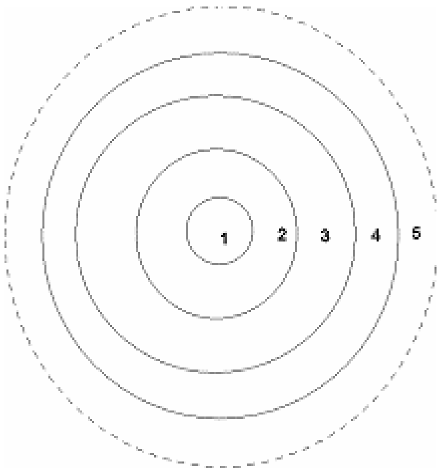
Over time there have been constant efforts by constructing models to understand how cities grow and evolve as they do and why certain areas are richer than others. For a long time there were three recognized models which exerted overwhelming influence on urban structure (Figure 4.1): concentric zone model by Burgess (1925), sector model by Hoyt (1937), and multiple nuclei model by Harris and Ullman (1945).

The Chicago School, based on especially empirical studies of Chicago, makes an analogy between the social development of the city and the evolution of the natural habitat among plants and animals through the process of biological invasion and succession. This Chicago School perspective focuses on the physical form of city and emphasizes human adjustment to the ecological conditions of urban life. In this way, the city can be taken as a social organism with distinct parts as a result of internal processes—competition, domination, invasion, and succession. During a process of expansion, succession, and “centralized decentralization” in the growth of the city, economic activities and the division of labor result in occupational differentiation and further produce a differentiation of community mentalities and social distance (Zorbaugh, 1929). Burgess’ concentric model (1925) (Figure 4.1a), based on Chicago, attempted to identify the outward expansion of the city in terms of socio-economic groupings of its inhabitants. There are five concentric rings. As people move out from the center, land use changes as distance from the center increases: central business district (CBD), wholesale, light manufacturing, low class housing, medium class housing, and high class housing.

Chicago School researchers in 1960s were also characterized as Chicago II, as they did not rely explicitly on those ecological analogies. Instead, Chicago II featured a belief that the processes of an economic reading of cities are useful to discover the general processes of urban evolution, which is largely a systematic quantitative approach (Shearmur and Charron, 2004). However, Chicago II researchers, like their predecessors, insist that urban form is a consequence of a variety of different types of competition. The transformation is taking place by way of various processes such as the bidding for land, religious and cultural similarities, and socioeconomic clustering. Spatial models were developed in order to better incorporate and explore urban data (Shearmur and Charron, 2004). Unlike Burgess’s concentric zone theory seen from an ecological perspective where cities continuously grow outwardly in concentric circles and the zone development is a result from competition for best locations, Hoyt (1937), taking the neoclassical economic perspective, thought urban development resulted from individual, rational, and economic pursuit for maximum economic benefits. While the classical Chicago School emphasized social competition for better locations and niches where people enjoy more similar interests, attitudes, and behavior, economic competition in a neoclassical economic perspective is to look for the minimum cost and maximum returns. As a result, Hoyt's sector model outlines that cities grow in sectors where each sector has different economic activities, and these sectors result from the effect of communication lines (Figure 4.1b). The high-rent areas are the most accessible along the main routes of transportation and mainly located on the periphery of the city, while low-rent sectors extend from the center to the periphery where the transportation is not very accessible. According to Hoyt (1937), the entire city can be taken as a circle and various neighborhoods are thought as sectors radiating out from one center.

When more urbanization takes place, Harris and Ullman (1945), also in neoclassical economic perspective, argued that cities should have more than one center (Figure 4.1c). Various activities look for their effective, desirable, and financially feasible locations for maximum revenue and similar activities located around minicenters within the large city. It incorporates the influence from the increasing suburbanization and the resulting outlying of population, business, and commercial hubs (Yeates, 1998). Meanwhile, it depicts the process that similar socioeconomic and cultural groups tend to cluster (Shearmur and Charron, 2004). The localized activities perform a specialized function for a large area and this concentration continuously grows until high labor cost and congestion counterbalance the concentrating forces. Therefore, the spatial distribution of these districts is more complex than that of monocentric city.

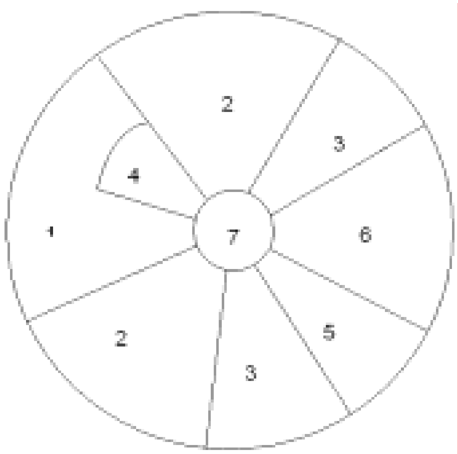
The above three models have most widespread influence on urban structure. There is another one, called urban realm model, developed by Vance in 1964. Later, Hartshorn and Muller (1989) summarized a suburban downtown model based on Atlanta's realization. In this model, single-centered metropolis is diversified into various sets of independent realms, where specialized goods and services are supplied by their own suburban mini-centers. As a result, the




Concentric Zone Model—Burgess (1925)

1- Central business district
2- Zone of transition
3- Zone of independent
workingmen's homes
4- Zone of better residences
5- Commuter's zone

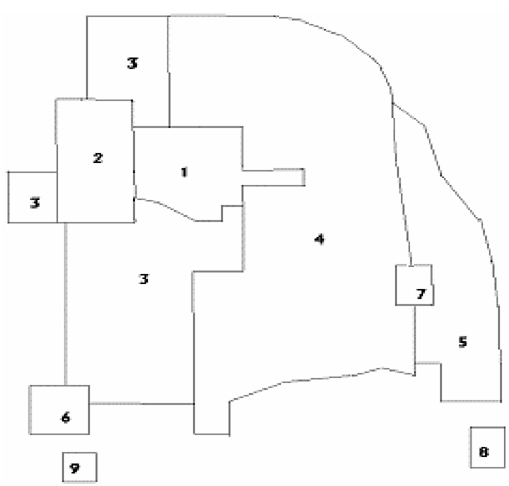
(a)




Sector Model –Hoyt (1939)

1-High rent residential
2-Intermediate rent residential
3- Low rent residential
4-Education and recreation
5-Transportation
6-Industrial
7-Core

(b)




Multiple nuclei model
—Harris and Ullman (1945)

1-CBD
2-Whole sale, light manufacturing;
3-Low-class residential
4-Medium-class residential
5-High-class residential
6-Heavy manufacturing
7-Outlying business district
8-Residential suburb
9-Industrial suburb;

(c)

Figure 4.1 Classical urban structure models metropolis can be taken as a composite of various small realms, where the small components are self-sufficient and independent of each other.

The Chicago School and its successors had a consistent influence on urban research in the 20th century. The models of concentric zone, sector, and multiple nuclei of urban structure and their combinations influenced the factorial ecologies of intraurban structure, land-use models, urban scale economies and diseconomies, and urban designs (Dear and Flusty, 1998). During the past two decades, however, the Chicago School has been constantly challenged by the emerging Los Angeles School. While Chicago School holds the opinions that urban growth, control, and segregation begin in the (sub)center and emanate outward to form a series of concentrating forces, Los Angeles School argues that the prototypical post-modern city is less a tightly-linked, monocentric organism than a series of scattered processes that are overriding the traditional order of urban growth (Hackworth, 2005).

Postmodern urbanists think the contemporary city is a kind of new urban forms with fragmented, partitioned, less legible than previous urban forms (Beauregard and Haila, 2000). According to Dear (2003) and Dear and Flusty (1998), city evolves into a highly decentralized and chaotic entity, where global and local forces are fused, where social polarization is expanded, and where the periphery controls the urban core. Postmodernism permits the coexistence of dual or multiple representations, the combination of styles in architecture, and the multiplicity of landscapes as a result of plurality of cultures (Jackson, 1989). Based on the assumption that the built environment is a result and mediator of social relations, Knox (1991) argued that the new urban landscapes, which are derived from and interlinked with the economic restructuring and a philosophical, cultural and attitudinal shift from modernism to postmodernism, indicate the emergence of postmodern metropolis, such as Los Angeles. During this process, the production, consumption, and postmodern architecture give postmodern metropolis distinct characteristics from the modern cities. Dear (1996) examined the intentionality during the process of land use planning. He argues that the traditional practices are no longer suitable as they are defunct and irretrievable and they should be replaced by new legitimacies and intentionalities for postmodern cities. However, Beauregard and Haila (2000) objected to the notion that the postmodern city has replaced the modern city even though there are some changes to support the postmodern spatiality. Instead, there is only a more complex pattern mixed with historical trends and new forces, which is not completely distinct from previous forms.

Dear (2000) argued that the classical Chicago model is more and more being challenged by the Los Angeles School. Meanwhile, Miami and Los Angeles have been recognized as the paradigmatic models of postmodern cities (Poulsen and Johnston, 2002). As Lees (2003) identified that the new urban geography, which is largely concerned with the topics of social-spatial behaviors of ethnic groups in the postindustrial city, has mainly been explored in qualitative approaches, although this exploration, unlike the Chicago School, lacks shared methodological commitments to fieldwork, first-hand observation and ethnography. The criticism includes, for example, that Dear and Flusty got their conclusions just based on exaggeration of the power of academic interpretation which lacks more direct evidence. Another example is that Soja (2000) interpreted the city life by academic accounts, poems and secondary materials instead of through ethnographic research that defined the Chicago School. However, as a conclusion, Lees (2003) listed several advantages of an ethnographic approach for postmodern urban research: better understanding of the complexity of human life, dealing with cultural richness and complexity, and believing the socially constructed nature of phenomena and the key role of language during the interpretation process.

The post-modern urbanism arguments by the Los Angeles School have brought a number of challenges to urban geographers, especially on opinion of changing urban forms. According to the Los Angeles School, one of the most exciting aspects of the postmodern condition is the idea that the city has a radical break from past trend in political, economic, and socio-cultural life (Dear and Flusty, 1998). Postmodern urbanists focus not only on a specific city but also on the general urban processes, like restructuring through deindustrialization and reindustrialization, the birth of the information economy, and the decline of nation-states. As a result of increasingly flexible and disorganized capitalist accumulation, Los Angeles, as an exemplar of postmodern city, becomes a decentered and decentralized metropolis. Accordingly, urban structure is a complicated quilt and fragmented as well as constrained by the underlying economic rationality (Soja, 1989). Urban growth takes place on a quasi-random process; that is, the selection of urban development on one urban parcel is a random or quasi-random process. The development of this parcel is disjointed with the status of another parcel. In this way, the traditional center-driven urban development is not valid any more (Dear and Flusty, 1998).

The majority of postmodern arguments are based on detailed empirical knowledge of Los Angeles, rather than derived from tested hypotheses (Johnston *et al.*, 2006). Regarding urban spatial growth, there are few quantitative studies so far to test if the trend of postmodernism, i.e., the fragmentation and randomness of urban growth, is (un)applicable in typical post-modern (Los Angeles and Miami) and modern (Chicago) cities. The possible reasons are due to the lack of sufficient data and appropriate technologies. This chapter aims to test the underlying hypothesis of the postmodern city, namely the fragmentation and randomness of urban growth within the context of Atlanta metropolitan area. Some spatial matrices and spatial statistics are going to be used in order to do some empirical studies. While talking about Atlanta, the first question coming up in one's mind is whether Atlanta is a good case to study postmodern trend. While I admit that Atlanta is not a typical postmodern city by any means, it can be taken as a modern city to at least (dis)prove that the postmodern arguments are (un)applicable in Atlanta setting. The main reason I use Atlanta to do this case study is the data availability, namely I directly use the classified image results from chapter 3 as the urban land use/land cover and urban growth in 1990 and during the 1990s.

There are debates around the topics of what is sprawl, how to measure it, which type of land should be incorporated (Cutsinger et al., 2005; Ewing, 1997; Wolman et al., 2005). Generally, urban sprawl refers to the phenomenon or process which has characteristics of low-density development, segregated land uses, leapfrogging development, automobile-dependent development, employment deconcentration, homogeneous residential areas regarding race, ethnicity, and class (Heim, 2001; Johnston et al., 2003; Lopez and Hynes. 2003). Several scholars suggested that sprawl can be measured from various dimensions: density, concentration, nuclearity, proximity (Galster et al., 2001; Wolman, et al., 2005). However, Tsai (2005) pointed out that there are still gaps in the definitions of compactness and sprawl in a quantitative way. This chapter, however, does not measure sprawl in those dimensions. Instead, the land use/land cover maps derived from chapter 3 are taken as data sources, of which low-density urban and high-density urban are combined to denote urban land use in 1990 and 2000. By making comparison between these two dates, urban growth is measured by subtracting urban areas between two thematic images (Figures 3.9 and 3.10). In this way, urban growth incorporates low-density development around previous urban areas, segregated urban land uses, and leapfrog development. Figures 3.11, 3.12, and 3.13 depict the distributions of low-density urban, high-density urban, and the total urban increase from 1990 to 2000.

Spatial metrics, also called landscape metrics, are quantitative indices to describe landscape structure and pattern (Herold, 2001). Spatial metrics, which are commonly used in landscape ecology, have been applied to quantify structure and pattern, estimate landscape complexity, and perform texture analysis of satellite images (Herold et al., 2005; Parrinello and Vaughan, 2002).

The development of spatial metrics is derived from information theory measures and fractal geometry (Herold, 2001). The calculation of spatial metric is based on a thematic map which shows spatial patches classified as different categories (Herold et al., 2003), where patch is defined as a homogeneous region for a landscape, such as urban area (Herold et al., 2005). Patch-based land metrics, which include, but are not limited to, patch density, mean patch size, mean patch shape index, fractal dimension, contagion, and lacunarity, are often used to measure landscape complexness and fragmentation (Zeng and Wu, 2005).

As remote sensing can supply a good data source for large-area landscape study, the combination of remote sensing and landscape metrics has been a growing interest for many researchers (Herold et al., 2005). However, there are some problems existing in the application of spatial metrics. First, the input data from remote sensing analysis into spatial metrics have the issues of accuracy and scale. The data accuracy (which includes the definition of the classes and classification accuracy) and scale (which includes spatial and spectral resolution) directly affect landscape heterogeneity. Second, as there are many spatial metric indices, how to select the best ones is an issue when landscape is studied from different perspectives. When comparison among various subdivisions of a study area is conducted, how to define spatial domain is another issue

(Herold et al., 2005). Spatial discrimination and regional subdivision of urban space can be very different when different spatial domains are applied.

A spatial point process is defined as any stochastic model that generates a countable set of points in the plane (Ripley, 1977). A particular realization of such a process is called a spatial point pattern, which can also be understood as a set of data consisting of $n$ locations in an essentially planar region $A$ (Rowlingson and Diggle, 1993). In recent years, spatial statistical methodology has made big advances. Intensity, nearest-neighbor distribution function, the Ripley's K-function, and L-function are usually ways to describe spatial point process (Fajardo and Alaback, 2005; Haase, 1995; Podur et al., 2003; Walter, 2005). Several software packages have been developed and used for spatial point pattern analysis. Some notable R packages are available for analyzing spatial point data, which include the spatstat package by Baddeley and Turner (2005), the splancs package by Rowlingson et al. (2006), and the ptproc package by Peng (2003). Besides, SpPack is developed by Perry (2004) to study spatial point pattern using Visual Basic for Applications (VBA) programming language. Voroni diagrams and Delaunay tessellations are employed by Chiu (2003) to examine the dependence between spatial points.

Complete spatial randomness (CSR) is often assumed for the quantitative description of a spatial pattern. A formal definition of CSR is that the events in $A$ constitute a partial realization of a homogeneous Poisson process, which incorporates a fixed constant as intensity function (Diggle, 2003). There are a lot of applications which use statistics to identify spatial association, which takes into account the relative locations of observations (Leung et al., 2003). Moran's $I$ and Geary's $c$ are the most commonly used indices for the patterns of spatial association within one dataset. While Moran's $I$ and Geary's $c$ use Gaussian approximation under the assumption of first-order homogeneity, which in reality is often not true (Couteron et al., 2003), Kabos and

Csillag (2002) advanced a new method and algorithm that deal with first-order heterogeneity by using S-plus programming code.

## Methodology

In this chapter, three types of statistics are used to measure Atlanta's urban structure. Spatial metrics, specifically fractal dimension and contagion index, are used to measure fragmentation of urban structure. Ripley's K-function and spatial point process model are used to measure if Atlanta's urban growth from 1990 to 2000 is random or not.

*Spatial metrics*

Derived from the work of O'Neill et al (1988), some spatial metrics were developed (Herold et al., 2002). Of them, the contagion and fractal dimension are used in this chapter. The contagion index, which is a pixel-based metric, measures the extent to which landscape elements are aggregated or clumped (O'Neill *et al.,* 1988). Contagion has a range of 0 to 100. Higher values of contagion indicate landscapes having a few large and contiguous patches, whereas lower values characterize landscapes with many small patches. The more heterogeneous the urbanized area becomes, the lower the contagion index. The contagion index is computed by the random and conditional probabilities that a pixel of patch class *i* is adjacent to another patch class *k* (Herold et al*.,* 2002):

$$CONTAG = \left\{ 1 + \frac{1}{2\ln m} \left[ \left( \sum_{i=1}^{m} \sum_{k=1}^{m} p_i \frac{g_i}{\sum_{k=1}^{m} g_{ik}} \right) - \ln p_i \frac{g_{ik}}{\sum_{k=1}^{m} g_{ik}} \right] \right\} \times 100 \qquad (4.1)$$

where $m$ is the number of patch types (land use/land cover types in this dissertation), $p_i$ is the proportion of the landscape occupied by patch type $i$, and $g_{ik}$ is the number of adjacencies (joins) between pixels of patch types $i$ and $k$.

Fractal dimension is available for the analysis of the fractal structure of urban forms (Myint, 2003). Generally, fractal dimension for an urbanized area is between 1 and 2 (Longley and Mesev, 1997 and 2002). The urban fractal growth is taken as a space filling process—the process of urbanized areas filling the city map coverage (Shen, 2002). Meanwhile, the fractal dimension of urbanized areas is an indicator of the complexity or dispersion of urban form. A higher value of fractal dimension indicates a more complex or fragmented urban form (Read and Lam, 2002).

There are several types of definitions for calculating fractal dimension (Batty and Longley, 1988; Parrinello and Vaughan, 2002). This chapter describes the complexity and the fragmentation of a patch by a perimeter-area proportion. The fractal dimension can be applied as a derived metric called area-weighted mean patch fractal dimension (AWMPED) (Herold et al., 2002):

$$AWMPED = \sum_{i=1}^{m} \sum_{j=1}^{n} \left[ \left( \frac{2\ln(0.25 p_{ij})}{\ln a_{ij}} \right) \left( \frac{a_{ij}}{A} \right) \right] \qquad (4.2)$$

where $m$ is the number of patch types (classes), $n$ *is* the number of patches of a class, $p_{ij}$ is the perimeter of patch $ij$, $a_{ij}$ is the area of patch $ij$, $A$ is the total landscape area. The area weighted mean patch fractal dimension (AWMPFD) measures the fragmentation of each built-up patch, which is different from contagion index. Meanwhile, AWMPED averages the fractal dimensions of all patches by weighting larger land cover patches. This improves the measure of class patch fragmentation because the structure of smaller patches is often determined more by image pixel size than by characteristics of natural or manmade features found in the landscape.

*Testing for spatial association*

In this section, two types of spatial statistics are used to test spatial association between 1990 urban land cover and the increase during the 1990s. First, Ripley's K-function and the derived L-function are employed to test spatial independence between two datasets. Then, inhomogeneous point process model will be used to test the conditional spatial association between these two datasets. In both cases, R software is used, although the two tests use different packages: the former uses SPLANCS package while the latter uses SPATSTAT package.

<u>Ripley's K-function</u>

Ripley's K-function (1977) is usually used for testing spatial pattern of univariate variable or determining bivariate spatial association between two variables. Ripley's K-function is a second-order analysis of point patterns; that is, the variance of all point-to-point distances is used for the calculation of density functions (Haase, 1995). Specifically, theoretical K-function can be written as the follows:

$K(t) = (1/\lambda)$E[number of points within distance $t$ of an arbitrary point] (4.3)

where $\lambda$ is the intensity of the process. The unbiased estimator of $K(t)$ is given by (Ripley, 1976, 1981):

$$\hat{K}(t) = \frac{A}{n^2} \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} w_{ij}^{-1} I_t(u_{ij} \leq t) \qquad (4.4)$$

where $n$ is the number of points, $A$ is the area, $w_{ij}$ is a weighing factor for correcting edge effects, $u_{ij}$ is the distance between points $i$ and $j$, $I_t(u_{ij} \le t)$=1 if $u_{ij} \le t$, or 0 otherwise.

For the case with bivariate variables, the theoretical K-function (Equation (4.3)) measures the cross-covariance density of the bivariate point process (Diggle, 2003) and therefore reflects spatial interaction between two point datasets.

$$\begin{aligned} K_{12}(t) &= (1/\lambda_1)\text{E[number of type 1 points within distance } t \text{ of arbitrary type 2 point]} \\ &= (1/\lambda_2)\text{E[number of type 2 points within distance } t \text{ of arbitrary type 1 point]} \end{aligned} \tag{4.5}$$

where $\lambda_1$ and $\lambda_2$ are the intensities of the point processes. The unbiased estimator for bivariate K-function are given by (Ripley, 1977 and 1981)

$$\hat{K}_{12}^{(1)}(t) = \frac{A}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} w_{ij}^{-1} I_t(u_{ij}) \tag{4.6}$$

or

$$\hat{K}_{12}^{(2)}(t) = \frac{A}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} w_{ij}^{-1} I_t(u_{ij}) \tag{4.7}$$

where $n_1$ and $n_2$ are the numbers of points of types 1 and 2 respectively, other parameters have the same meanings as Equation (4.4).

After Ripley's K-function is calculated, $L$-function is usually derived which is a linearized version of Ripley's K-function. $L$-function has the following form (Bessag, 1977):

$$\hat{L}(t) = \sqrt{\hat{K}(t)/\pi} - t \tag{4.8}$$

where $t$ is distance. $L$-function scales K-function's variance to facilitate the test against the null hypothesis of complete spatial randomness for univariate variable or spatial independence for bivariate variables. Under null hypothesis, $L$-function has an expectation of zero for any value of $t$.

In practice, confidence intervals, which is also named as confidence envelopes, for K-function and *L*-function are derived from simulations (Fajardo and Alaback, 2005). If empirical *K(t)* and *L(t)* fall between confidence envelopes, the null hypothesis is not rejected. Otherwise, the spatial pattern is not random (i.e., clumped or regular) for univariate variable or is not spatially independent between two variables.

<u>Models of spatial point processes</u>

There are previous studies on the conditional spatial association of one point process on another spatial process or distribution (Berman, 1986; Berman and Diggle, 1989; Foxall and Baddeley, 2002). The SPATSTAT package for R software provides data structures and functions for fitting a variety of spatial statistical models via maximum pseudolikelihood function (Baddeley and Turner, 2000).

The spatial distribution of urban growth in Atlanta metropolitan area is modeled as a realization of an inhomogeneous Poisson process with some intensity function. The inhomogeneous Poisson process is a flexible model in that its intensity can be modeled as a function of spatial variables, another stochastic process, or its spatial coordinates (Rathbun and Cressie, 1994). While the null hypothesis is that the urban growth is a homogeneous Poisson process with a constant intensity, the alternative hypothesis is that urban growth is an inhomogeneous Poisson process with an intensity that depends on distance to the nearest urban land cover in 1990.

For the spatial Poisson point process model, the following assumption is made: let $G$ (1990 urban landcover) denote the geometric structure on a planar region, the point process $X$ (urban increase from 1990 and 2000) is conditionally Poisson given $G$, with intensity function

$$\lambda_{X|G}(u) = \rho(d(u,G))$$

where *d(u,G)* denotes the shortest distance from the point *u* to the nearest *G*, and $\rho$ is an unknown function.

The following hypotheses are made to construct models:

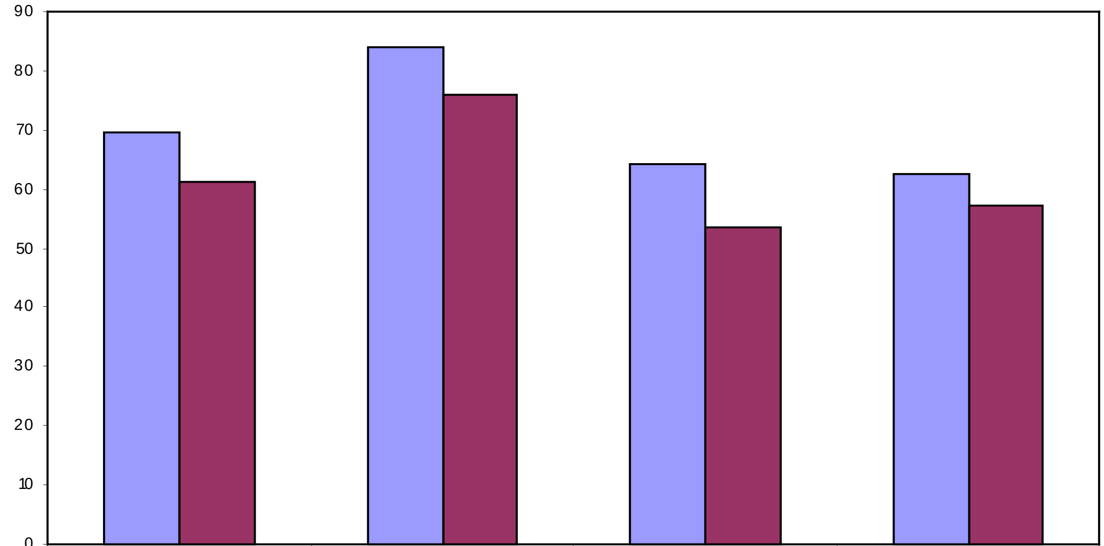
$$H_0: \quad \lambda(u) = \beta_1$$
$$H_1: \quad \lambda(u) = \beta_2 \exp(\alpha d)$$

where *d* is the distance from a point *u* to the nearest point in *G*, $\beta_1$,$\beta_2$, and $\alpha$ are parameters to be estimated. Under the assumption that the points, given the 1990 urban landcover, is a realization of an inhomogeneous Poisson processes, the likelihood ratio test can be used to test if the null hypothesis can be rejected or not rejected.

After the intensity for each point of urban growth is calculated, the inhomogeneous K-function is calculated based on formulas by Baddeley *et al*. (2000). Compared with conventional K-function with a constant intensity within a process and theoretical K-function under CSR process, the inhomogeneous K-function can inform if there is positive association between the urban growth, conditioned on the lineaments (Baddeley and Turner, 2006).

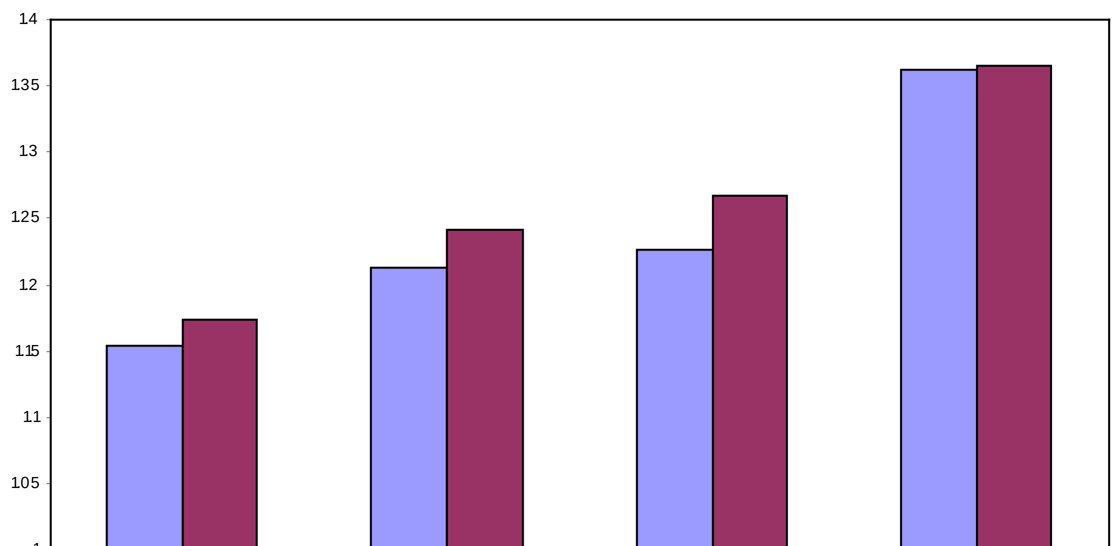
**Results**

The study area is the Atlanta metropolitan area as noted in chapter 3. The data sources for spatial metrics and spatial statistics are the thematic maps from chapter 3 (Figures 3.11, 3.12, 3.13). Non-urban types of land covers are combined so that only urban (which includes low-density urban, high-density urban, and total urban) and non-urban areas are derived from remotely sensed images. A public domain spatial metrics program, FRAGSTATS, which was




| | Low-density urban | High-density urban | Urban | Total metropolitan area |
|---|---|---|---|---|
| 1990 | 69.5561 | 84.1252 | 64.2472 | 62.7257 |
| 2000 | 61.3482 | 75.803 | 53.5451 | 57.2641 |

Figure 4.2 The values of contagion in 1990 and 2000




| | Low-density urban | High-density urban | Urban | Total metropolitan area |
|---|---|---|---|---|
| 1990 | 1.1538 | 1.2128 | 1.2267 | 1.3616 |
| 2000 | 1.1741 | 1.2418 | 1.2675 | 1.3657 |

Figure 4.3 The values of area-weighted mean patch fractal dimension in 1990 and 2000

developed in the mid-1990s and has been improved in the latest version 3, supplies a convenient way to calculate fractal dimension and AWMPFD (McGarigal et al., 2003).

Figures 4.2 and 4.3 show the results for spatial metrics. From 1990 to 2000, contagion indices for low-density urban, high-density urban, urban, and total metropolitan area decrease at various degrees (Figure 4.2), which indicates that these four types of land covers all had a fragmentation process during the 1990s. Meanwhile, the area-weighted mean patch fractal dimensions (Figure 4.3) all increase for these four types of land covers. The indices of AWMPED support the conclusion that Atlanta's urban landscapes were more fragmented from 1990 to 2000. This conclusion is not surprising since, in the process of urban growth, land use/cover are more differentiated according to economic rationality.

The total urban area has a very large size of data, which is a total of 1,834,256 nonzero pixels of urban areas in 2000 image (which is converted from the classified images in chapter 3) when spatial resolution is 30m. Because of the limitation of computer memory and the rather slow speed to process such a large dataset, a spatial resolution of 120m is selected and the classified image is resampled by nearest neighbor method. As a result, there are 78,062 pixels of urban area in 1990 image and 114,832 pixels of urban area in 2000 image. Of 2000 image, there are 36,770 pixels of urban growth from 1990 to 2000.

When Ripley's K-function and *L*-function are used for spatial pattern analysis, the results are usually presented as graphs with the *Khat* or *Lhat* plotted against the independent variable *t* (distance) (Haase, 1995). If the sample statistics *Khat* and/or *Lhat* fall into the simulation envelopes, the two datasets are spatially independent. Likewise, if *Khat* and *Lhat* lie above the upper limit of the confidence envelope, there exist positive relationship; and there is negative relationship if *Khat* and *Lhat* lie below the lower limit of the simulation envelope. Figures 4.4

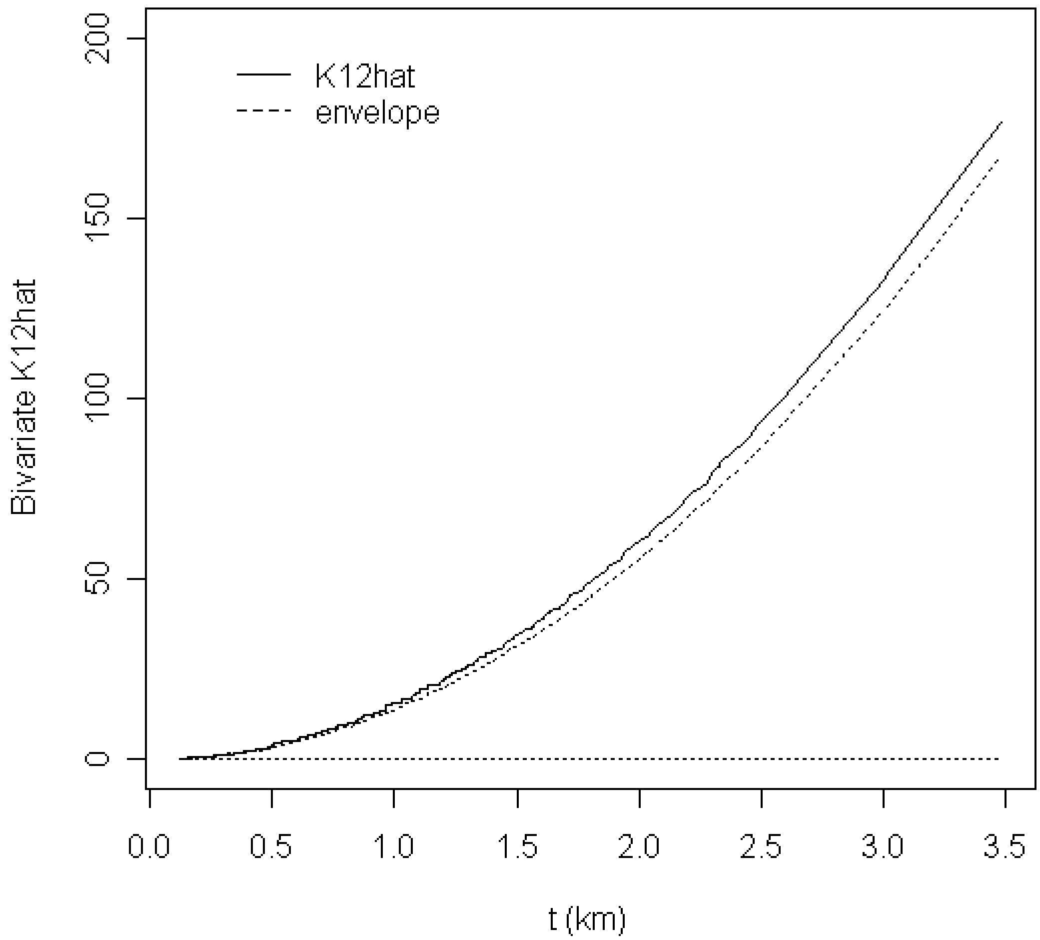



Figure 4.4 Estimated bivariate *K12hat* and simulation envelopes

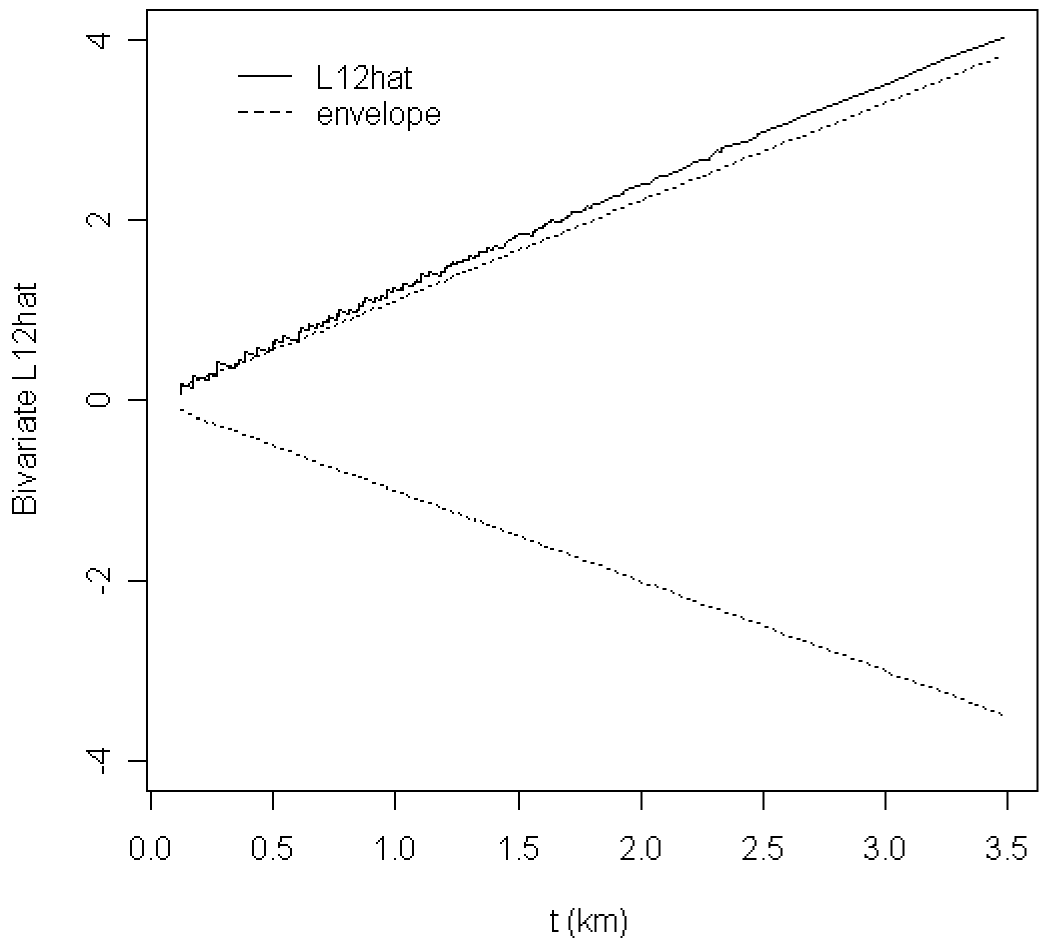



Figure 4.5    Estimated bivariate *L12hat* and simulation envelopes

and 4.5 show the results for *Khat* and *Lhat*. The solid lines in both graphs lie a little bit above the upper limit of confidence envelope (dashed line), which indicates that these two datasets are significantly positive related at the level of 0.01. In other words, urban growth during the 1990s was not spatially independent of urban area in 1990.

Based on the null and alternative hypotheses, spatial (in)homogeneous Poisson processes are constructed for testing the conditional spatial association between 1990 urban land cover and urban growth in the 1990s. This model uses the log pseudolikelihood ratio to test if null hypothesis is rejected. Under null hypothesis, the uniform intensity $\lambda(u)=3.521e^{-6}$. For alternative hypothesis, $\lambda(u)=-9.596*\exp(-0.0168*d)$. The log pseudolikelihood ratio test gets a

Deviance=80622 $\quad$ p-value $< 0.001$

which indicates that null hypothesis is rejected and urban growth during the 1990s was inhomogeneous and dependent on the distance from 1990 urban pixels.

Figure 4.6 depicts three types of K functions under different scenarios. Of which, the inhomogeneous K function is calculated by alternative hypothesis, conventional K function is determined by null hypothesis, and the theoretical K function under CSR is also given in order to made comparison. Since inhomogeneous K function lines falls far above two lines, a positive association between the urban growth pixels, conditioned on the 1990 urban pixels, is suggested. That means, the urban growth in 1990s not only depended on the distance from 1990 urban pixels, but also has positive association within itself.

**Conclusions and discussions**

This chapter uses data derived from remote sensing imagery to analyze urban structure. Since the Chicago School has for a long time influenced how we model cities and their internal

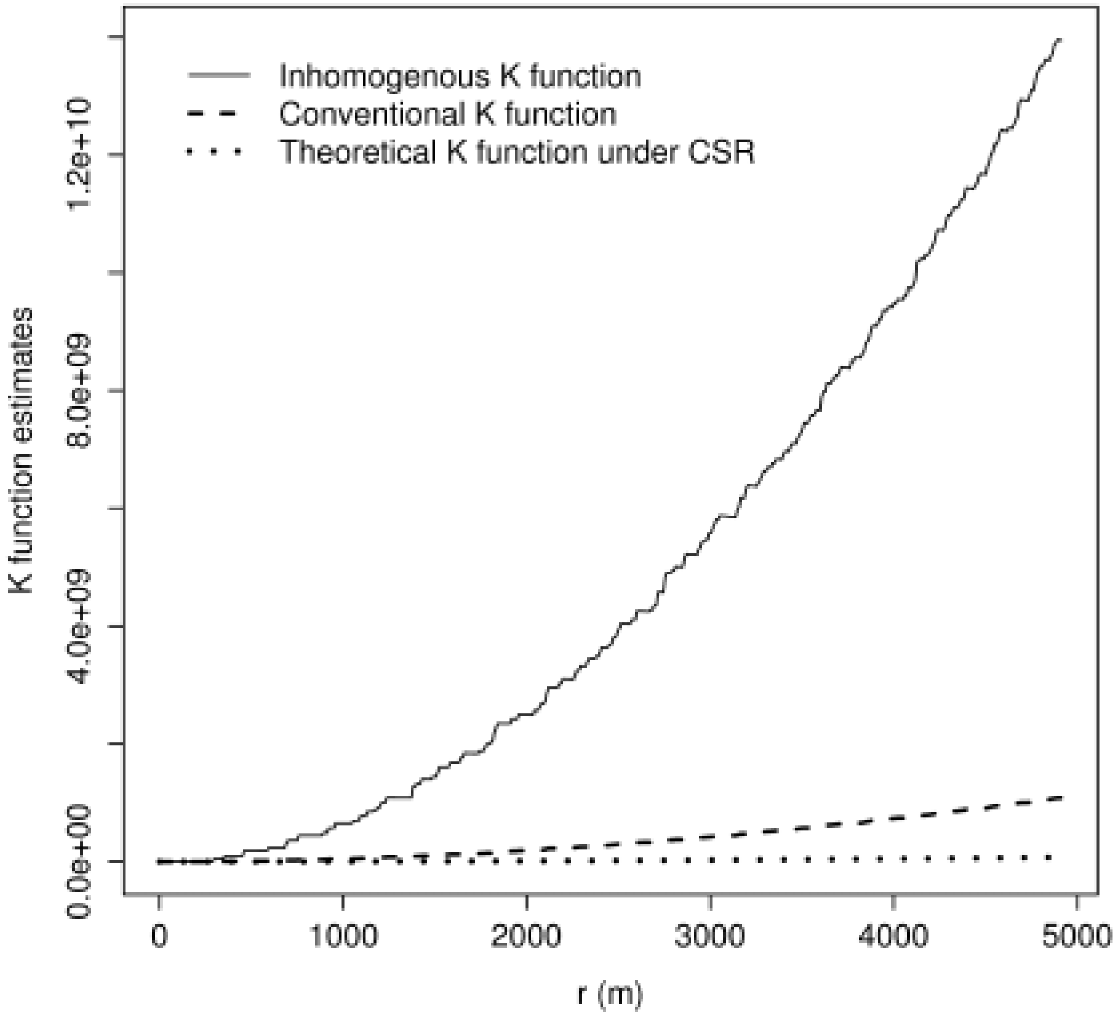



Figure 4.6 Inhomogeneous K function, conventional K function with uniform intensity, and theoretical K function under CSR.

structures and growth, previous studies on urban structure are largely concerned with the classical models by the Chicago School and its successors. Postmodern urbanism, by contrast, argues that the metropolis is more fragmented and has a random or quasi-random growth. However, this argument has not been tested quantitatively.

Spatial metrics and spatial statistics are used to analyze the changes in urban land use/land cover structure. Spatial metrics prove that Atlanta was more fragmented in 2000 than 1990, which proves the argument by post-modernism. Ripley's K-function and spatial Poisson point process model, however, reject the argument that urban growth is random or quasi-random, as these tests indicate that there are positive association between 1990 urban area and urban growth during the 1990s.

The bifurcated results from quantitative analyses in this chapter indicates that it is not self-evident that post-modern urbanism is applicable or inapplicable. To be intuitive, as any society evolves, it is expected that urban forms will be complicated. Thus, more fragmented urban use is not unique to post-modern cities. It is highly possible that modern cities have more fragmented urban functions when they enter into a highly competitive society.

However, the above results cannot be taken as the opinion that Atlanta does not have any feature of a postmodern city. First, a postmodern city has multi-dimension magnifications regarding the economic, social, cultural, and physical aspects. Other aspects should also be examined before this conclusion can be derived. Second, the methodology used in this chapter needs to be tested for other exemplar cities, especially Los Angeles, Miami, and Chicago. Based on the comparisons among these typical cities for post-modern and Chicago urbanisms, a better conclusion may be derived on the applicability of this methodology. Third, the data used for this analysis have intrinsic errors since the classification only has an approximately 85% overall accuracy. With image data mosaic, this error can be compounded. In order to get a robust conclusion, the tests should be conducted repeatedly on different scales and different resolutions. That is, MAUP should be taken into consideration when the conclusions are reached. Finally, as spatial statistics are growing quickly to better model reality, with the advancement of more powerful models, some further investigation can address this question more thoroughly. Although post-modernism largely uses qualitative methods to conduct research, its argument need to be proved or disproved quantitatively to some degree.

# CHAPTER 5

# EXPLORING ATLANTA'S URBAN POVERTY BY SPATIAL REGRESSION MODELS

## Introduction

Since Wilson's (1987) *The Truly Disadvantaged*, the growth of urban poverty concentration has been largely investigated (Cooke, 1998; Greene, 1991 and 1994; Hughes, 1990; Jargowsky, 1996, and 1997; Kasarda, 1993; Krivo et al., 1998; Massey and Denton 1993; Wilson, 1991 and 1996). One central question in urban poverty research concerns the persistence of the concentration of urban poverty----the causal relationships among poverty, segregation, and inequality. Many studies have used statistical models to explore the relationships among these factors (Jargowsky, 1996; Levernier, 2003; Levernier et al., 2000; Massey and Fischer, 2000). The majority of these studies treat urban poverty nonspatially in their multivariate statistical analyses; that is, no spatial effects are taken into consideration when they do ordinary least square (OLS) estimates. Generally, multivariate statistical models of spatial data assume spatial stationarity; that is, the causal relationship between independent and dependent variables do not vary over space. However, in reality, this assumption may not be appropriate since it is self-evident that spatial phenomena are not distributed evenly. There are known spatial dependence and heterogeneity among various spatial landscapes. This research investigates spatial nonstationarity in multivariate statistical models of urban poverty by using spatial econometrics. While conventional OLS regression produces a global predictive model, spatially-referenced econometric models can better account for spatial variations in model parameter estimates.

In this chapter, the causal relationships among poverty, demographic, and socio-economic variables are investigated. The primary purpose of this chapter is to understand the causes of poverty in the Atlanta metropolitan area. This analysis has two objectives. The first is to enhance statistical methodology in the analysis of urban poverty. Since spatial data analysis often differs from the non-spatial statistical analysis, issues of methodology can be a major concern of urban poverty study.  The second objective is to identify those variables that affect poverty rate and determine the strength of the influences. Particularly, the effects from demographic and socio-economic variables at the census tract level for the Atlanta metropolitan area will be investigated.

In the pages that follow, I first conduct a literature review on theoretical and empirical explanations of urban poverty. Then the data and study area are introduced. Analytically, I first use exploratory spatial data analyses to investigate some possible variables, then OLS model is employed to estimate poverty rate using demographic and socio-economic variables. Following the conventional multivariate regression, several spatial econometric models will be used to get coefficients when local contexts are incorporated. The section of conclusions and discussions is the final part of this chapter.

**Urban poverty: theoretical and empirical evidences**

A majority of previous research defined high-poverty neighborhoods based on a fixed cutoff, for example, the percentage of persons who live in families with income below the federal poverty line----40% has largely been used (Quillian, 1999). According to the official definition, a poverty threshold is set based on a family’s annual before-tax money income which excludes non-cash benefits such as public housing, Medicaid, and food stamps (Weber et al., 2005). Different-sized families have different thresholds. These poverty lines are adjusted annually by incorporating inflation, however, these figures have not been changed much during past decades (Weber et al., 2005).

This poverty definition has been criticized for a long time (Bishop et al., 1999; Brady, 2003; O'Boyle, 1999; Weber et al., 2005). O'Boyle (1999) pointed out four aspects of flawed poverty definition: the way how physical needs are defined and measured, the non-comprehensive definition of income for poor person or family, the inappropriateness of standard poverty line for different living-cost area, and insensitiveness of official standard poverty threshold for some people over others. Accordingly, Brady (2003) thought that ideal poverty measures should incorporate historical variation, use relative measures instead of absolute values, take poverty as social exclusion, measure the influence of taxes, transfers, and state benefits, and figure out the depth and inequality among the poor. With these criticisms, a number of new indices have been employed, for example, Sen index of poverty by Bishop et al., (1999), the Interval, Ordinal, and Sum of Ordinals by Brady (2003), and Foster-Greer-Thorbecke index by Cushing and Zheng (2000) and Jolliffe (2003).

Although this standard poverty statistic is widely criticized, it still retains widespread attention for the consistency of long-time use (Bishop et al., 1999; Quillian, 1999; Strait, 2000). Jargowsky and Bane (1991) checked visual appearances of neighborhoods with various poverty percentages. They made the conclusion that the neighborhoods with more than 40% poverty rates seem to be more dilapidated and more distressed than others.

Poverty is distributed unevenly across American landscape. Generally, this unevenness has four dimensions (Levernier, 2003; Weber et al, 2005). First, the areas with poverty rate of 20% or more concentrate in the South, particularly the Black Belt and Mississippi Delta, Appalachia, the lower Rio Grande Valley, and Indian Reservation areas in the Southwest and Great Plains. Second, poverty rates vary greatly. Usually lowest poverty rates can be found in the suburbs which are the fringe areas of large metropolises, whereas highest areas can be found in remote rural areas which are not adjacent to metropolitan areas. Third, rural areas tend to have high poverty rate and persistent poverty. Furthermore, less populous and more remotely-accessed counties tend to have persistent poverty.

The causes of poverty have long been an interesting topic for researchers in the fields of demography, sociology, geography, political science, and economics. A number of explanations have been suggested for the cause and persistence of poverty. Three explanations for the causes of high-level poverty predominate in the field (Quillian, 1999): the flight of middle-class black from mixed-income neighborhoods, racial segregation between Blacks and Whites, and spatial mismatches between inner-city residents and job locations.

In Wilson's (1987) *The Truly Disadvantaged*, one of the key reasons that cause the high-poverty neighborhoods is the flight of middle-classes residents from mixed-income neighborhoods to suburban areas, particularly, white-majority neighborhoods. The resultant landscape is that the disadvantaged poor blacks are more and more concentrated. Accompanying this flight, the demographic structure of poverty neighborhoods has been more and more prominent for the persistence of poverty, like the increased number of families headed by females (Blank and Hanratty, 1992; Wilson, 1987), and negative neighborhood effects associated with inner cities (Levernier et al., 2000.). This argument has been proved by Gramlich et al. (1992), Greene (1991), Jargowsky (1997), and Jargowsky and Bane (1991). However, this argument is also challenged by the theory of residential racial segregation.

Denton and Massey (1988) found that the residential segregation level for blacks with high-level socio-economic status does not differ much from blacks with low-level socio-economic status. Instead, African-Americans tend to live in predominately black neighborhoods after they abandoned the black poor in the inner city (Quillian, 1999). Massey and Denton (1993) insisted that racial segregation is the main cause of extremely poor neighborhoods by examining the racial disparities in the population of high-poverty neighborhoods. However, as Quillian (1999) pointed out, this racial segregation is important to understand the existence of high poverty in inner cities, it cannot explain the phenomenon that the number of poor neighborhoods over time has been increased while racial segregation has decreased over time (Farley and Frey, 1994; Jakubs, 1986).

The next explanation focuses on economic changes and its influence on poverty rates. Wilson (1987) emphasized that the increases of the number of high-poverty neighborhoods is a result from economic change which worsened the employment and earning prospects of blacks in the inner city. Particularly, the structural transformation of the U.S. economy from goods production to a service and information economy with a differentiated labor market which generates greater demands for high- and low-level skilled workers. As a result, the previous high-paying and unionized manufacturing jobs are lost in inner cities. The high-salary, non-unionized jobs are created for professionals and elites in central cities. Meanwhile, the number of inner-city factory jobs has declined and the wages and employment rates of inner-city residents decreased. This economic transformation bifurcated the middle class and income inequality expanded and poverty deepened. Sassen (1991) argued that the post-industrial economy, which leads to increasing income inequality, has a spatial stratification. This bifurcation of middle class is most prominent in large cities which are oriented toward the global economy. As a result, the residential segregation, class segregation, and the concentration of poor are more prominent in these global cities (John, 2002).

Wilson (1996) argued that the demand-side economic factors are the fundamental cause of increasing urban poverty, which includes the loss of manufacturing jobs, the shift in labor demand towards high-skilled occupations, and the decline of unions. Meanwhile, the supply-side low-skilled labor, which results from immigration and increased female labor force participation, have been responsible for low-paid wages (Topel, 1994). Accordingly, two hypotheses have been used for explanation of high-poverty neighborhoods. The spatial mismatch hypothesis, originally proposed by Kain (1968), argues that high unemployment rates among inner-city blacks are derived from the shift of jobs from urban central cities to suburban areas. The deindustrialization hypothesis emphasizes the decline of the inner-city factory employment opportunities. Massey and Denton (1993) found that, because of racial residential segregation, the inner-city blacks have a worse environment for job seeking. However, this argument is difficult to test given the non-availability of longitudinal data that can emphasize the influence from spatial mismatch and deindustrialization on the unemployment rate of inner-city residents. That is, this research needs the longitudinal data which can differentiate the employment changes based on demand-side job changes or resulting from class-selective migration (Quillian 1999).

The next explanation is somewhat hybrid. Massey and Fischer (2000) reexamined the causes of urban poverty and found that the interaction between economic restructuring and racial segregation is responsible for the concentrated urban poverty. As for segregation, Jargowsky (1996) pointed out that racial residential segregation is more influential than economic segregation by social class. His research found that neighborhoods are more heterogeneous along income than along the racial component. The interaction between racial segregation and the shifts of U.S. economic structure had different degrees of influence on the concentration of urban poverty. Before 1970, segregation played a predominate role. By 1990, however, economic restructuring had a larger effect on high-poverty neighborhoods (Massey and Fischer, 2000). Likewise, Freeman (2003) found that economic growth diminishes poverty, but the process is sensitive to the time period, the econometric circumstance, and the demographic characteristics. While the poverty rate has long been sensitive to the unemployment rate, its influence on the decline of poverty rates has decreased in recent decades (Freeman, 2003).

Weber et al. (2005) classifies quantitative research on poverty into two groups: community and contextual studies based on the research goals, data structure, and methodology. From Weber et al., (2005), community studies explore the relationship between aggregated poverty and demographic and economic structure within a community, for example, using county-level poverty rate and county demographic and economic characteristics. By contrast, contextual studies explain the relationship between individual poverty status and individual demographic variables and community social and economic structures, for example, using individual-level poverty data to explain the influence from individual educational attainment and neighborhood social-economic characteristics.

Levernier (2003) points out that the geographic differences of poverty rates may be caused by differential influence of particular causal factors, That is, for example, economic change may have different effects on poverty rate changes for residents living in central cities, suburbs, and rural areas. Thus, the causal relationship varies from place to place; that is, there is spatial nonstationarity. Mennis and Jordan (2005) thought there are two possible reasons for spatial nonstationarity. First, the multivariate regression models have missing variables which have global effects on poverty distribution. The other reason is nonstationary local contexts which generate locally-specific influence on poverty, like spatial clustering. Since spatial correlation and spatial dependence exist for poverty distribution, it violates the assumption that the phenomenon is independent and identically distributed (IID), where OLS analysis usually makes this assumption. Upon this issue, some spatial econometric models have sought ways to account for spatial dependence so that unbiased estimates of coefficients for the effects of local contextual influence can be derived (Weber et al., 2005).

Besides the problem of spatial dependence and spatial autocorrelation, another issue is the ecological fallacy (Weber et al, 2005). The conclusions based on individual-level data may not be extended for area-level inferences. For the aggregated data, like county or census tract level, the modifiable areal unit problem (MAUP) needs particular attention; that is, the conclusions based on a spatial aggregated level should be cautiously applied to another aggregated scale (Martin, 1996).

**Data and study area**

This research uses the same definition of high-poverty neighborhood as the majority of other studies: a census tract in which the poverty rate equals or exceeds 40%. Of which, poverty is defined based on standard definition by U.S. Census of Bureau. Although this definition has long been criticized, the consistency of this usage can help with the comparison of previous researches.

To investigate the causal relationships between concentrated urban poverty and demographic and socio-economic factors, the census tract level data from 2000 census are used. The variables are listed in Table 5.1. Many studies have been done on this topic by using similar variables (Jargowsky, 1996; Levernier, 2003; Levernier et al., 2000; Massey and Fischer, 2000).

Since different places have various place-specific characteristics, the causality of poverty may also be place-specific. For example, one area with a high poverty rate may largely be due to its demographic characteristics, while others may be attributed to the lack of economic opportunity. From the theory of racial segregation, high-level poverty results from racial residential segregation. The index of dissimilarity is usually used to denote the magnitude of racial residential segregation. In this chapter, I compute the index of dissimilarity by using census block data for each census tract. The index of dissimilarity is measured as the following expression (Massey and Denton, 1989):

$$D = \sum_{i=1}^{n} \frac{t_i \mid p_i - P \mid}{2TP(1-P)} \tag{5.1}$$

where $t_i$ and $p_i$ are the total population and the proportion of blacks in census block $i$, $T$ and $P$ are the population size and the proportion of blacks in the whole census tract, which is subdivided into $n$ blocks. This dissimilarity index varies between 0 and 1. The higher the index is, the greater the racial residential segregation is.

Based on literature review, some variables are incorporated into regression models in order to check their influence on poverty simultaneously. Poverty neighborhoods are expected to have high percentage of minority persons, which may be due to discrimination or racial preferences in hiring (Levernier et al., 2000). Since female-led families usually have lower income than others, this demographic characteristic should be expected to have a positive effect on poverty rate. Similarly, low educational attainment and employment in primary and secondary industries tend to generate poverty. Likewise, the neighborhoods having good social economic characteristics (like high employment rate, less migration) tend to have lower poverty rates.

This chapter still uses the Atlanta metropolitan area as the study area, which has 13 counties. In 2000, these 13 counties had a total of 589 census tracts (figure 3.1). These counties correspond to the ten counties comprising the Atlanta Regional Commission with the addition of Coweta, Forsyth, and Paulding Counties. This definition of Atlanta metropolitan area is somewhat different from the version that was defined by U.S. Census of Bureau, which has a total of 20 counties for the Atlanta metropolitan area in 2000. However, since chapter 1 uses these counties as study area and in order to keep consistency, I continue use these 13 counties as study area. These counties represent the major Atlanta metropolitan area.

## Methodology

### *Exploratory spatial data analysis*

As a first step in the analysis, exploratory spatial data analysis is conducted in order to describe and visualize spatial distributions of poverty rates as well as some variables. This step can discover patterns of spatial association and clusters, as well as spatial heterogeneity (Dall'erba, 2005). Specifically, choropleth maps are used first for spatial distribution visualization regarding poverty rates, demographic and socio-economic variables.

The next exploratory spatial data analysis will focus on the creation of the spatial weight matrix. Spatial statistics concern the data with points in some Euclidean space, usually $R^2$ or $R^3$ (Chang, 2004). Usually statistical analysis of spatial data is conducted from three perspectives: geostatistical data, point data, and lattice data (Cressie, 1991). Geostatistical data refer to continuous field, such as surface data. Point data refer to locations of individual events, such as the distribution of trees within a plot. The lattice data refer to the data structure where the units of observation are composed by discrete locations, which are either associated with a regular lattice or grid structure, like pixel-based raster image, or with an irregular lattice or polygon structure, like census tract polygons. This chapter uses lattice data models for spatial analysis. For lattice data, the predominated characteristics are spatial association or spatial dependence between values at different locations and the systematic variations of phenomena by location or spatial heterogeneity among values with different locations (Anselin, 1993).

The presence of spatial dependence and spatial heterogeneity violates the properties of standard multivariate regression analysis. Therefore, specialized diagnostic tests and estimation methods are needed. Of which, spatial weight matrix is usually employed into spatial statistical models. The underlying principle of spatial statistical analysis is the first law of geography (Tobler, 1979) where the values at close-by locations tend to be more correlated than values at locations that are far apart. Based on this law, the spatial clustering of spatial phenomena generates a loss of information compared with independent observations. One critical question for defining spatial weights matrix is to decide neighborhoods which are close by a given data point and influential. Nowadays, the selection of neighborhoods is largely subjective and arbitrary. There are several ways to set spatial weights. Getis and Aldstadt (2004) gave a comparison of some contiguity-based, distance-based, semivariance-based, and local statistic-based matrices. There is no consensus which type of spatial weights is more applicable and in which way spatial weights matrix is more appropriate for a specific dataset.

In this research, an inverse distance weights matrix will be used which defines weights based on inverse distance from a point. In order to find influential neighbors, a cut-off distance threshold needs to be set. For every census tract, if another census tract has a distance $d$ from this given census tract (which is calculated as the distance between two centroids) less than the threshold, the spatial weight for this pair of census tracts is $1/d$.

In order to decide the threshold distance, the semivarigram model is employed. Semivariograms can be calculated as (Cressie, 1991):

$$\gamma(h) = \frac{1}{2N}\sum_{i=1}^{N}[Z(x_i) - Z(x_{i+h})]^2 \qquad (5.2)$$

where $x_i$ is the location of census tract centroid, which is the coordinates of census tract centroid, $h$ is a vector of distance, $Z(x_i)$ is the data value of poverty rate at location $x_i$, and $N$ is the number of data pairs for a certain distance of $h$ units.

There are 6 general models for fitting spatial characteristics (Cressie, 1991): linear, spherical, exponential, rational quadratic, wave, and power semivariogram models. Semivariogram for poverty distribution is modeled by these models in turns and exponential model is found to be applicable for this set of data. Exponential semivariogram model is calculated by the following function (Cressie, 1991):

$$\gamma(h) = \begin{cases} 0, & h = 0 \\ C_0 + C\{1 - \exp(-|h|/a\ )\}, & h \neq 0 \end{cases} \qquad (5.3)$$

where $h$ is the lag distance, $C_0$ is the nugget effect, $C$ is equal to $(sill - C_0)$, and $a$ is the range. Four parameters, namely range, sill, nugget, and spatial dependence (calculated as *C/sill*) are used to depict the spatial characteristics of poverty rate. Range is the distance beyond which there are no spatial effects. In the following section, spatial weights are defined within the range; that is, only the pairs within the range are considered to have spatial dependence. Sill is the total degree of spatial variation for spatial phenomena. Nugget is the nearest variability of the attribute. Theoretically, nugget is equal to zero. However, nugget may present the close distance continuity of one attribute, or result from sampling errors, in which cases, nugget may not equal 0. Spatial dependence reflects the strength of spatial autocorrelation within the range.

The next part of exploratory spatial data analysis is about Moran's *I* index and Moran's scatterplot. In order to capture the global spatial autocorrelation of poverty rate in the Atlanta metropolitan area, Moran's *I* is computed as follows:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}^{*} x_i x_j}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j} \qquad (5.4)$$

where $W_{ij}$* is row-standarded spatial weights, $x_i$ and $x_j$ are poverty rates for census tracts *i* and *j* respectively, *n* is the total number of census tracts, i.e., 589. In order to test if the global Moran's *I* is statistically significant, 999 permutations are run to get inference. Theoretically, the expected *I* should be (Anselin, 1995):

$$E(I) = -\frac{1}{n-1} = -\frac{1}{589-1} = -0.0017$$

If the empirical *I* is larger than *E(I)*, there is positive spatial autocorrelation for the poverty rate. Likewise, smaller *I* indicates a negative spatial autocorrelation.

Moran scatterplot, on the other hand, expresses the poverty rate for each census tract on horizontal axis against the standard spatial weighted average which is the average poverty rates of defined neighborhoods (also called spatial lag) on vertical axis (Dall'erba, 2005). Moran scatterplot can be divided into four quadrants which indicate four types of local spatial autocorrelation between a census tract and its neighbors. Of which, quadrant I (the upper right corner) indicates census tracts have high poverty rates and surrounded by high poverty-rate neighbors; quadrant II (the upper left corner) indicates census tracts have low poverty rates and surrounded by high poverty-rate neighbors; quadrants III (the lower left corner) indicates census tracts have low poverty rates and surrounded by low poverty-rate neighbors; and quadrants IV (the lower right corner) indicates census tracts have high poverty rates but surrounded by low poverty-rate neighbors (Anselin, 1999).

*Spatial statistical modeling*

In order to make comparisons between conventional multivariate regression and spatial statistical regression, OLS is first conducted.

$$Y = X\beta + \varepsilon$$
$$\varepsilon \sim N(0, \sigma^2 I_n) \qquad (5.5)$$

where dependent variable $Y$ is poverty rate at census tract level, and the independent variables indicated in matrix form $X$ are defined as Table 5.1. The analysis has a total number of observations of 589, which is large enough to make inferences.

There are two different approaches to incorporate spatial effect into regression models (Gamerman and Moreira, 2004): one is to use spatial variations for coefficient estimates, the other is to directly incorporate spatial dependence structure, i.e. spatial weights matrix, into regression models. In this chapter, spatial regression models will use the second approach.

Several spatial statistical models will be introduced and applied with the data explained above. Specifically, the spatial autoregressive-regressive model, the spatial autoregressive error model, the spatial Durbin model, and the general spatial model are used. Based on the results of spatial statistical models as well as conventional regression model, best model for fitting the data in this case can be selected based on Akaike information criteria (AIC) which penalizes models with additional parameters among spatial models and $R^2$ between OLS and spatial models. Since all spatial models will use the same data and same set of variables, log-likelihood index can generate the same results for selecting best model since

AIC=-2*log-likelihood+2p

Table 5.1 Descriptions of variables used for analysis

| | |
|---|---|
| Dependent variable | |
| Poverty | Percent of persons who live in poor families in 1999 |
| Variables for demographic characteristics | |
| Black-poverty | The percentage of blacks in census tract which has poverty rate less than 40% |
| Female | Percent of families that are headed by a female, with no husband |
| Move | Percent of persons who were not in the same counties 5 years ago |
| Young-old | Percent of persons who are under 5 or over 65 years old |
| Variables for socio-economic characteristics | |
| Unemploy | Percent of persons who are 16 years or older and unemployed |
| Income | Median household income |
| Non-tertiary | Percent of persons who are employed in mining, construction, and |
| Education | Percent of no more than 12 years of educational attainment |
| Dissimilarity | The index of dissimilarity |

where $p$ is the number of independent variables. The selection criterion is that the smaller AIC the model is better. Hence, among these models, the best model should have the largest log-likelihood index.

The spatial autoregressive-regressive model includes both first-order spatial autoregressive model and traditional regression model, which has the following form (Anselin, 1988):

$$\begin{aligned} &Y = \rho WY + X\beta + \varepsilon \\ &\varepsilon \sim N(0, \sigma^2 I_n) \end{aligned} \qquad (5.6)$$

where $Y$ is an 589*1 vector indicating poverty rates for census tract level, $X$ is 589*11 matrix which contains a **1** vector (a vector composed of all 1's, which indicates intercept for regression analysis) and 10 independent variables, and $W$ is row-sum standarded weights matrix. The parameter $\rho$ is a coefficient on the spatially lagged dependent variable, i.e. $WY$. The parameter vector $\beta$ reflects the influence from independent variables $X$ on dependent variable $Y$. $\varepsilon$ is a normally distributed error term. Since spatially lagged dependent variable is incorporated into this model, the spatial autocorrelation is explained by this way.

The next model is termed as spatial autoregressive error model, where the disturbances have spatial dependence (Anselin, 1988):

$$\begin{aligned} &Y = X\beta + u \\ &u = \lambda Wu + \varepsilon \\ &\varepsilon \sim N(0, \sigma^2 I_n) \end{aligned} \qquad (5.7)$$

where $Y$, $X$, $\beta$, $W$, and $\varepsilon$ are defined as above. Spatial autoregressive error model puts spatial autocorrelation into disturbance vector $u$ and $\lambda$ is a coefficient on the spatially correlated errors. Spatial autocorrelation is explained by a first-order spatial autoregressive model. Finally, the error term $\varepsilon$ is assumed to be normally distributed. The difference between spatial autoregressive-regressive model and spatial autoregressive error model lies that the former takes autoregressive analysis on $Y$ directly, while the latter works on disturbance term $u$.

With reference to Durbin's time series model, a spatial Durbin model is introduced (Anselin, 1988):

$$\begin{aligned} &Y = \rho WY + X\beta_1 - \rho WX\beta_2 + \varepsilon \\ &\varepsilon \sim N(0, \sigma^2 I_n) \end{aligned} \tag{5.8}$$

where $WX$ indicates the explanatory variables constructed as average from neighboring census tracts, other parameters are the same as the above models.

The general spatial model includes both the spatial lag term and a spatially correlated disturbance term, which can be summarized as (Anselin, 1988):

$$\begin{aligned} &Y = \rho W_1 Y + X\beta + u \\ &u = \lambda W_2 u + \varepsilon \\ &\varepsilon \sim N(0, \sigma^2 I_n) \end{aligned} \tag{5.9}$$

where $W_1$ and $W_2$ are two spatial weights matrices, they can be equal or unequal, other parameters are used in the same way as above.

In sum, five models (OLS model, spatial autoregressive-regressive model, spatial autoregressive error model, spatial Durbin model, and general spatial model) will be tested in order to find relationships among poverty rate and explanatory variables. Meanwhile, spatial statistical models are conducted in order to get more accurate coefficients for parameters compared with conventional multivariate regression analysis. Since the general spatial model has two spatial weights matrices, which can be same or different, in order to derive as many as possible of testing results, the four combinations of spatial weights matrices are used, i.e., the permutations between the spatial weights matrix itself and the square of the spatial weight matrix are used for four patterns of the general spatial model.


Figure 5.1 Variables used in the analysis

Table 5.2 Exponential semivariogram model for poverty rate

| Nugget | Sill | Range | Spatial dependence |
|---|---|---|---|
| 138.06 | 191.76 | 10.55 | 0.28 |

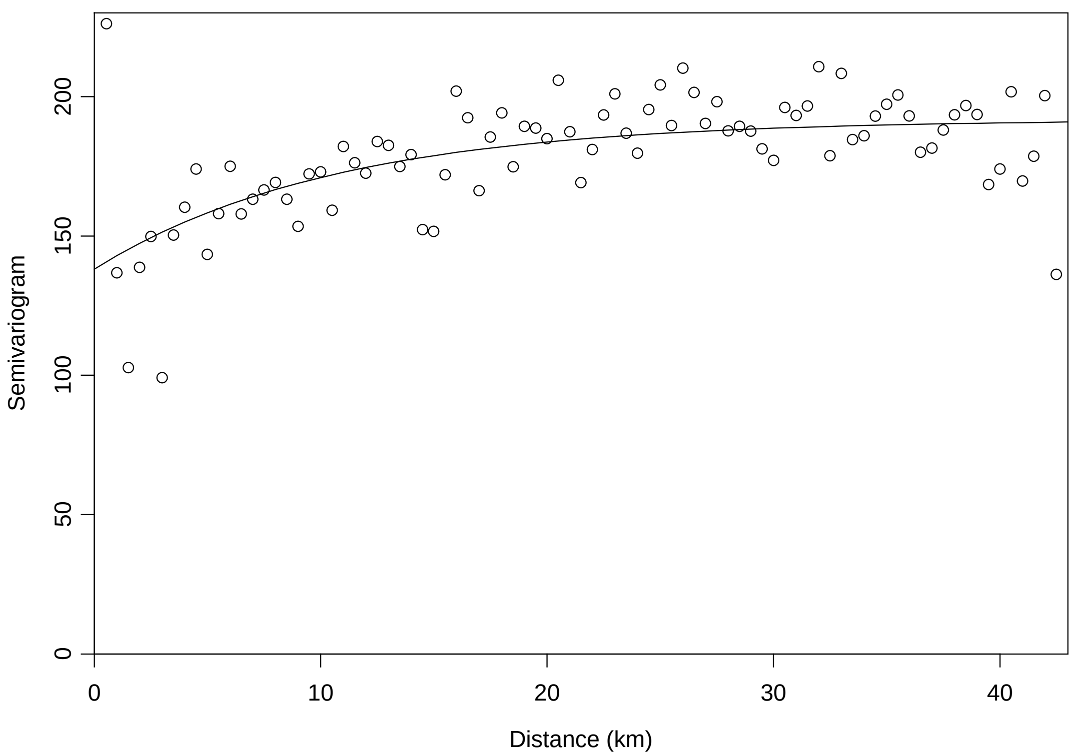



Figure 5.2 Exponential semivariogram fitting for poverty rate

**Results**

*Exploratory spatial data analysis*

Choropleth map is a traditional way to express spatial distribution. Figure 5.1 shows the distributions of 8 variables used in the later regression models. Generally, these variables are clustered in space by taking an eye examination. Poverty rates are higher in central city, lower in near suburbs, and a little bit higher again in outer suburbs which may be due to the fact that rural areas tend to have high percentage of poor people in their demographic structures. By direct comparison, poverty rate seems to be clearly positively related to blacks percentage, percent of female-headed families, unemployment rate, and lower educational attainment. Meanwhile, poverty rate is negatively related to mean household income, and percentage in primary and secondary industries. The relation between poverty rate and the percentage of moves beyond the county level seems to be unclear.

In order to better understand the spatial characteristics of poverty rate, empirical semivariogram is calculated based on equation (5.3) and the exponential semivariogram model is fitted. Table 5.2 lists the parameters for exponential model and figure 5.2 plots the semivariogram against distance. From Table 5.2, spatial autocorrelation for poverty rate has a range of 10.55 km, which is used later for cut-off threshold when spatial weights matrix is constructed. A bigger sill generally indicates greater spatial variation of poverty rate. Moreover, spatial dependence as calculated as (sill-nugget)/sill, which measures strength of spatial effect on poverty rate, has a value of 0.28. Since there is no other model fitted for comparison, I cannot get a conclusion as to how big the magnitude of spatial dependence is.

Based on threshold distance, a set of neighbors can be found for each census tract. An inverse-distance spatial weights matrix is constructed which can be displayed as figure 5.3. For

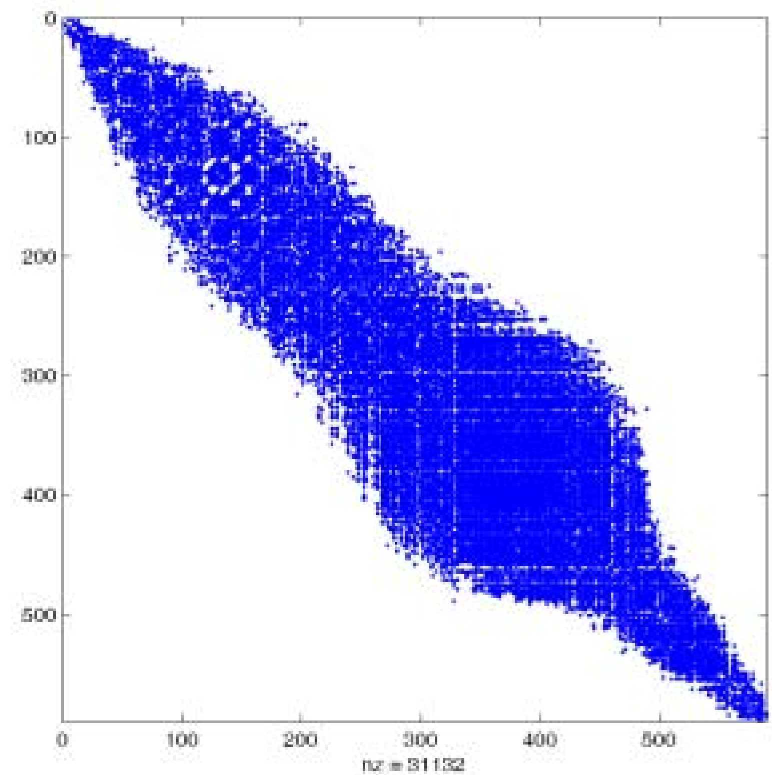



Figure 5.3 Spatial weights matrix based on inverse distance

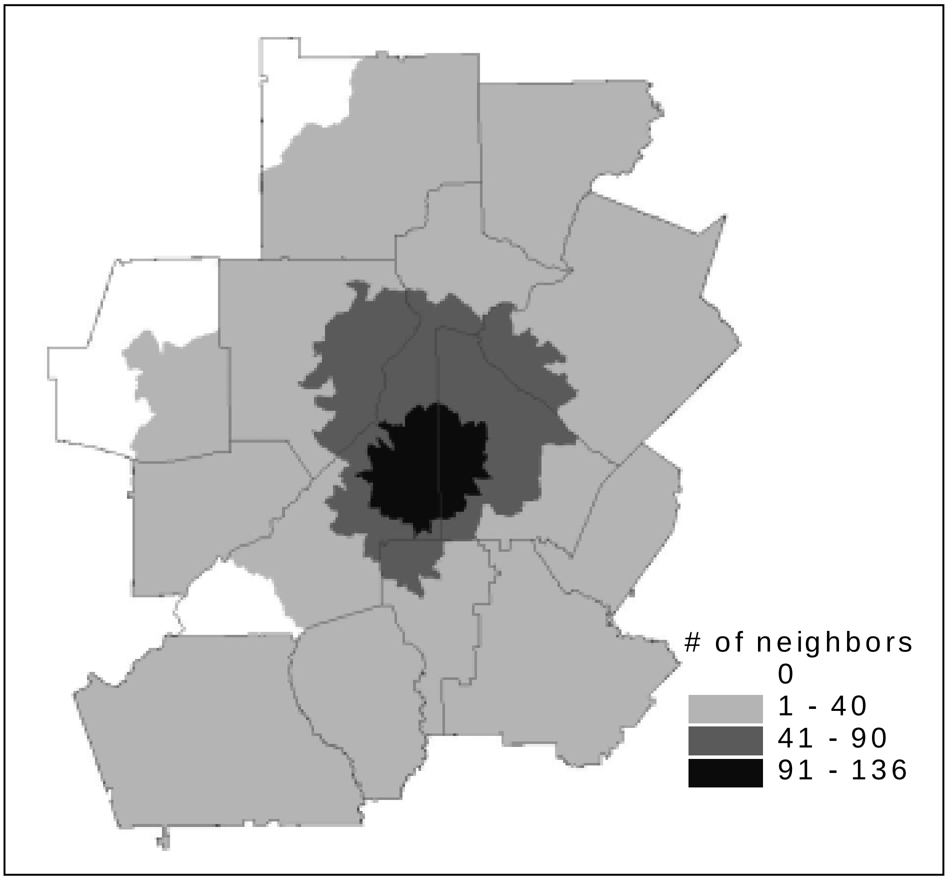



Figure 5.4 Number of neighbors for spatial weights matrix

589 census tracts, there are a total of 31132 neighbors within 10.55km, which is 8.97% of all pairs (589*589). Of which, two census tracts 1500 and 3200 have the largest number of neighbors, i.e., within 10.55 km there are 136 census tracts around each of them. At the same time, four census tracts 10400, 90200, 120100, and 120400 have no neighbor within 10.55 km. From figure 5.4, the census tracts having the largest number of neighbors locate in the central city and have small areas. Compared with small areas, large areas near the boundaries tend to have fewer neighbors.

By employing equation (5.4), global Moran's *I* is calculated. For poverty rate, the global Moran's *I* is 0.7035. With 999 random simulations which generate simulated Moran's *I* with mean –0.0021 and standard deviation 0.0266, the empirical global Moran's *I* for poverty rate has a *p*-value of 0.001. This small *p*-value indicates that poverty rate is highly correlated.

Figures 5.5 and 5.6 show the distribution of Moran's *I* for each census tract and its association with neighbor's Moran's *I*. Census tracts located in quadrants I and III refer to positive spatial autocorrelation, the spatial clusterings of similar values, whereas quadrants II and IV represent negative spatial autocorrelation, the spatial clusterings of dissimilar values (Figure 5.5). Quadrants I and III indicate that these poor census tracts are surrounded by poor census tracts, and rich are surrounded by rich. By contrast, quadrants II and IV indicate negative association, i.e., poor census tracts are surrounded by rich, and rich are surrounded by poor. Figure 5.6 is a linked map which shows the spatial distribution of these positive or negative associations, where the color has the same indication as that used in Figure 5.5. It is rather clear that central city is a place for higher concentration of poverty and suburbs are areas with lower poverty rates. Between them, there are some sporadic distributions of negative associations for poverty rates.

*Spatial statistical modeling*

Tables 5.3 and 5.4 list key features and fitted coefficients for OLS and spatial models. General spatial model (equation (5.9)) can have different specifications by setting different $W_1$ and $W_2$. In this chapter, inverse distance spatial weights matrix (which is called $W$) and $W^2$ (which equals to $W*W$) make four permutations and are applied into equation (5.9).

From table 5.3, all spatial models have larger $R^2$ than OLS model, which indicates that spatial models here can generally fit better for spatially-correlated poverty rate. Among seven spatial models, the best model can be selected based on larger log-likelihood and larger $R^2$. Meanwhile, the significance levels of $\rho$ and $\lambda$ should also be taken into consideration since they indicate if spatial-effect coefficients are significant or not. Based on these criteria, the best model seems to be the general spatial model with $W_1$=$W_2$=$W$ and $R^2$ of 0.8766 and significant $\rho$ and $\lambda$.

Table 5.4 shows the estimated coefficients for these eight models. Generally, the higher percentages of black percentage in non-highly-poor census tract, female-headed families, movers, kids and elders, unemployment rate, and bad educational attainment contribute to higher poverty rates. Likewise, higher household income and bigger percent of employment in primary and secondary industries indicate a lower poverty rate. Meanwhile, higher magnitude of racial residential segregation corresponds a higher level of poverty rate. However, in some models, dissimilarity index does not have a significant influence, which may be due to the fact that there are correlations among the independent variables, i.e., percentage of blacks, female-headed families, percentage of young kids and elder people, income, and low education attainment. The best model, which is selected as the general spatial model ($W$, $W$) has an insignificant coefficient for racial residential segregation.

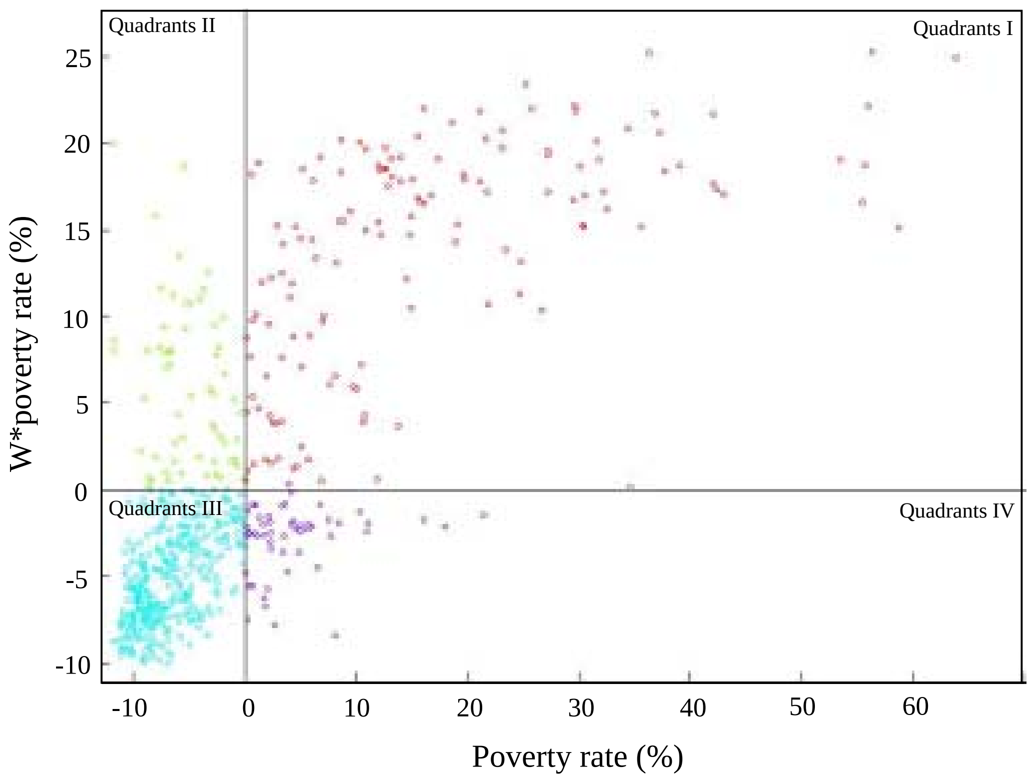



Figure 5.5 Moran scatterplot for poverty rate

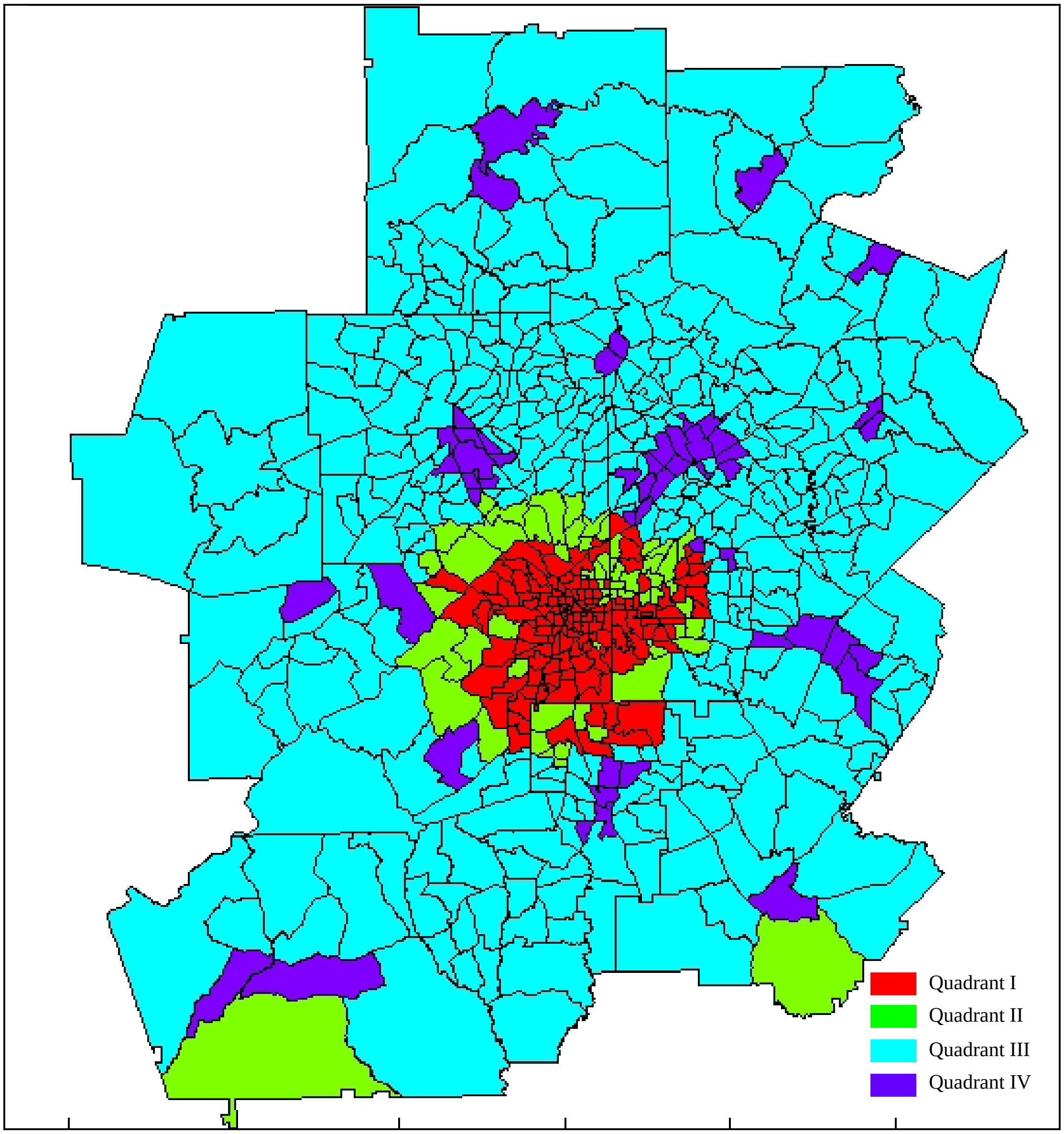



Figure 5.6 The distribution of Moran index

Table 5.3 Some key statistics for the fitted models

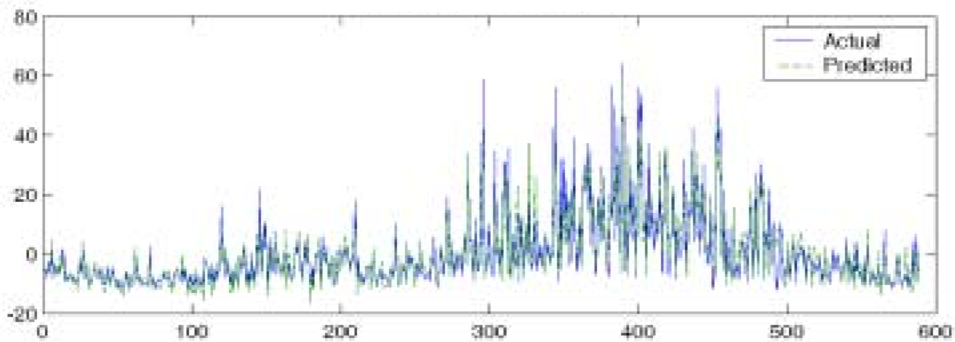
| | $R^2$ | Log-likelihood | $\rho$ | $\lambda$ |
|---|---|---|---|---|
| OLS model | 0.8524 | | | |
| Spatial autoregressive-regressive model | 0.8574 | -1529.67 | 0.2870*** | |
| Spatial autoregressive error model | 0.8766 | -1519.68 | | 0.7680*** |
| Spatial Durbin model | 0.8920 | -1464.22 | -0.1850 | |
| General spatial model ($W^2$,W) | 0.8767 | -1182.36 | 0.0044 | 0.7740*** |
| General spatial model (W, $W^2$) | 0.8706 | -1186.23 | 0.3290*** | 0.6840*** |
| General spatial model ($W^2$, $W^2$) | 0.8565 | -1213.36 | -0.0450 | 0.5950*** |
| General spatial model (W, W) | 0.8766 | -1177.14 | 0.2030*** | 0.6380*** |

Note: * means significant at 0.1 level, ** means significant at 0.01 level, ***means significant at 0.001 level.

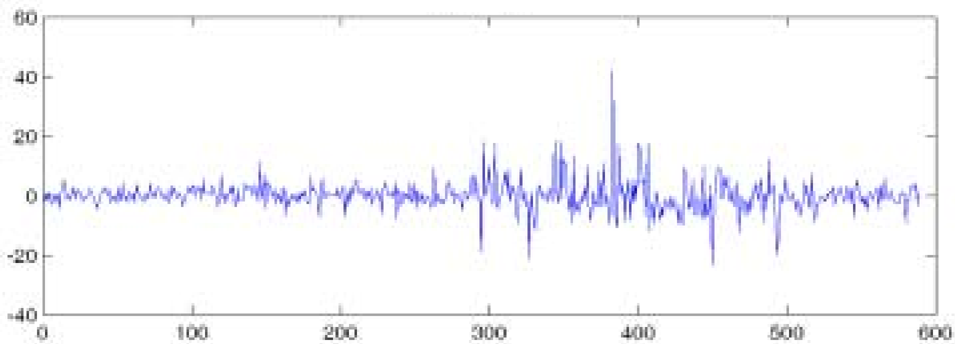
Table 5.4 The fitted coefficients for models

| | Intercept | % Black at non-poor tracts | Female | Move from another county | Young-old | Unem-ployed | Income | Non-tertiary-employ-ment | Low-educa-tion | Dissi-milar-ity |
|---|---|---|---|---|---|---|---|---|---|---|
| OLS model | -13.77 *** | 0.4119 *** | 0.1027 ** | 0.0637 ** | 0.0789 * | 0.4869 *** | -0.000029 * | -0.2345 *** | 0.3006 *** | 2.91 * |
| Spatial autoregressive-regressive model | -19.50 *** | 0.3584 *** | 0.0836 ** | 0.1120 *** | 0.1986 *** | 0.4289 *** | -0.000011 *** | -0.1218 ** | 0.2342 *** | 2.02 * |
| Spatial autoregressive error model | -16.91 *** | 0.3073 *** | 0.2090 *** | 0.0897 *** | 0.1499 ** | 0.3728 *** | -0.000046 *** | -0.1214 ** | 0.2309 *** | 1.69 |
| Spatial Durbin model | -20.94 *** | 0.2780 *** | 0.2528 *** | 0.1026 *** | 0.1930 *** | 0.3362 *** | -0.000044 ** | -0.0535 | 0.1909 *** | 1.34 |
| General spatial model ($W^2$,$W$) | -16.96 *** | 0.3070 *** | 0.2090 *** | 0.0898 *** | 0.1506 ** | 0.3724 *** | -0.000046 *** | -0.1206 ** | 0.2306 *** | 1.69 |
| General spatial model ($W$, $W^2$) | -18.06 *** | 0.3441 *** | 0.1017 ** | 0.1013 *** | 0.1965 *** | 0.4164 *** | -0.000025 *** | -0.1398 *** | 0.2348 *** | 1.76 |
| General spatial model ($W^2$, $W^2$) | -13.21 *** | 0.3958 *** | 0.1087 *** | 0.0550 ** | 0.0954 * | 0.4789 *** | -0.000042 *** | -0.2315 *** | 0.2958 *** | 2.46 * |
| General spatial model ($W$, $W$) | -17.99 *** | 0.3120 *** | 0.1826 *** | 0.1043 *** | 0.1768 *** | 0.3698 *** | -0.000037 *** | -0.1162 ** | 0.2259 *** | 1.73 |

Note: * means significant at 0.1 level, ** means significant at 0.01 level, ***means significant at 0.001 level.




(a)




(b)

Figure 5.7 Predicted values and residuals for general spatial model (W,W). (a) the predicted vs. actual poverty rate; and (b) residuals

The estimated coefficients (Table 5.4) have some differences among them, although the difference may not be huge. Spatial models can be used to better incorporate local dependence when parameters are estimated. Therefore, the errors tend to have less variations across space. Figure 5.7 shows predicted values and residuals for the general spatial model ($W$,$W$). Generally, this model fits well, especially for the first 300 observations. However, the residuals have bigger variations for the later 200 observations, which may be due to local variations not incorporated well into model fitting process.

**Conclusions and discussions**

This chapter uses exploratory spatial data analysis and spatial statistical modeling to analyze Atlanta's poverty rate. Choropleth map is first used to depict the spatial distribution of variables in the models. By applying semivariogram model to set threshold for selecting neighbors, an inverse distance spatial weights matrix is constructed. Moran's *I* and Moran scatterplot are used to test the existence of spatial autocorrelation and disclose the spatial positive (or negative) association of poverty rate across Atlanta metropolitan area. Central city is found to be the location for high poverty rate and positive association with its neighbors. As a comparison, suburban areas tend to concentrate no-poor people.

OLS model and seven spatial models are used to fit the causal relationship among poverty rates and demographic and socio-economic variables. The estimated coefficients indicate that all of these models generally agree with each other as far as the influence direction (the positive or negative sign of coefficients) is concerned. However, since spatial models can catch some degree of spatial dependence, they generate better $R^2$ than OLS model. Among spatial models, a general spatial model which takes the spatial lag and spatially correlated disturbance into consideration at the same time is found to be the best model. However, here at no means we should think that these demographic and socio-economic variables directly result in poverty. Instead, the statistical models just show that there are causal relationships among these variables.

Spatial weights matrix is used for fitting spatial models. There are many kinds of spatial weights matrix in academia and none of them has been definitely proved better than others. The selection of spatial weights matrix is largely subjective and arbitrary. If a different spatial weights matrix is constructed for this dataset, the results may be different, but I do not expect a large change on estimated coefficients since the coefficients among OLS and spatial models do not change much in this example. Using spatial model can better take spatial dependence and spatial variation into consideration when spatial phenomena are at issue.

Furthermore, since this chapter only uses census tract as the study scale and the results may have MAUP, it is somewhat questionable when the results are directly applied to other scales, such as county and census block levels. The applicability of various spatial regression models can be further tested in other scales.

# CHAPTER 6

# A DIFFERENT URBAN SPACE?----EXAMINIMG SPATIAL DISTRIBUTIONS OF POPULATION, RACE, AND INCOME IN THE 1990S

## Introduction

The geographic concentration of affluence and poverty throughout the world is a product of (sub)urbanization, rising income inequality, and increasing racial segregation, according to Massey (1996). This produces a radical change in the geographic basis of human society. The urban demographic landscape in most major North American cities has become racially and ethnically diversified (Fong and Shibuya, 2005). In 1900, whites had 88% of the total population in the U.S. while blacks had approximately 12%. Asian and other ethnic groups had less than 1%. However, in 2000, only 75% of the total population were whites while blacks still has the same level at 12%. Other racial and ethnic groups had about 13% which had the largest increase among ethnic groups. The racial and ethnic diversity is sufficiently demonstrated in large American cities, especially the ten largest cities (Grieco and Cassidy 2001; McKinnon 2001). This diversified demographic composition attracts researchers' attention on urban structures and processes (Fong and Shibuya, 2005).

During the 20$^{th}$ century, the urban internal distribution of population underwent enormous changes. These changes in urban settings can be mainly attributed to three factors (Price-Spratlen and Guest, 2002): the economic shifts in local and extralocal contexts, the personal preference of centrally located residential settlements, and the development of transportation networks. As a result, the outward population redistribution generates an increase of population share in the suburbs and a corresponding decrease of population share in the neighborhoods located in central cities. Furthermore, the issue of race was often related to the patterns of population redistribution as whites moved into metropolitan periphery areas and African-American neighborhoods having social disorders had different degrees of population loss (Price-Spratlen and Guest, 2002).

The measurement of spatial patterns has attracted much attention in academia as well as public policy designers (Johnston et al., 2003). Clusters of high poverty have made the disadvantaged individuals suffer more. Although the relationships between population redistribution and racial composition and income levels are known for a long time, there is little research that tests the difference statistically between overall spatial distributions in different years. To address this issue, this chapter compares quantitatively the spatial distributions of income and population for the Atlanta metropolitan area in 1990 and 2000.

This chapter is organized as follows. The next section is a literature review on urban space, mainly racial distribution and income disparities, in American metropolitan landscapes. Then data and methodology are introduced, followed by results section. The last section is conclusions and discussions.

**Racial distribution, income disparities, and urban space**

The contemporary American metropolitan areas are generally heterogeneous in terms of income levels, ethnic backgrounds, general life experiences, and built environment. When urban space is studied, especially racial segregation and income disparities are concerned, the census tract has been commonly taken as the neighborhood unit for quantitative studies. With 2500 to

8000 residents, the census tract is usually taken as homogeneous from indigenous experiences of the social and geographic landscapes (Pattillo, 2005).

Place and race have been identified as the determinants of opportunity structure in metropolitan area (Squires and Kubrin, 2005). Location can determine the quality of life and accessibility in the metropolitan America. Neighborhood influences educational resources, contacts, and benefits, which in turn affect people's opportunity structure, although individual intelligence and human capital are also important. The interactions among place, race and privilege are embodied by three social forces (Squires and Kubrin, 2005): sprawl, concentrated poverty, and segregation. Sprawl means the general process of urban outward expansion, low-density development of housing and commercial activities, as well as fiscal disparities among fragmented land parcels. During this process, the difference among income levels between central city and suburbs has been enlarged (Squires and Kubrin, 2005). Racial composition, as a result, also changes while racial segregation becomes a persistent feature in metropolitan areas although this pattern, measured by the index of dissimilarity, has decreased during the 1990s (Iceland et al., 2002). Furthermore, racial residential segregation has been taken as a connection with racial disparities in individual characteristics and neighborhood environment. As a result, residential segregation has negative effects on personal outcomes, such as health, school dropping out, and teenage pregnancy (Harding, 2003; Subramanian et al., 2005). Meanwhile, the spatial distribution of suburban ethnic businesses indicates ethnic retention and ethnic socialization (Fong et al., 2005).

Traditionally, racial composition at areal level has been measured by two major ways (Price-Spratlen and Guest, 2002). The first is to measure invasion, namely transitional in-migration, which shows significant number of people move into the area. The other is to measure succession which indicates that the in-migration group gradually dominates in the population composition in the neighborhoods. There are four theories concerning the relationship between population change and racial distribution.

Urban neighborhood life cycle theory by Hoover and Vernon (1962) aims to better understand the relationship between race and neighborhood population changes and argues that neighborhoods initially develop from a low density, and gradually increase their intensity through a regular sequence of land use change as they age. The land use change includes residential development in land use, subdivision of housing structure, and growing crowd of residential units. As the cycle takes place, population decreases in the neighborhood because the community is no longer desirable for residences. Accordingly, commercial activities begin to participate in neighborhood development and gradually dominate in land use (Price-Spratlen and Guest, 2002). In later stages of the life cycle, individuals with disadvantaged economic status and racial minorities tend to dominate in the neighborhood. Social status theory, from another perspective, explains the relationship between race and population change. African-American neighborhoods are concentrated with poverty and other forms of economic distress, which makes these low-status areas less attractive as places to live (Price-Spratlen and Guest, 2002). Consequently, these low-status areas are disproportionately undesirable for population relocation. The racial composition of low-status areas continues to be dominated by African-Americans with low economic class. The compression model suggests that because white neighborhoods are generally not friendly to potential African-American residents within the context of the metropolitan housing market, the African-American in-movement has to be accommodated in existing African-American neighborhoods thus bringing in a growing population (Price-Spratlen and Guest, 2002). Generally, the compression model was largely applied for the time periods before 1960s. The decompression model, as a comparison, has more influence on recent population distribution. This model posits that whites move outward for better housing opportunities and leave the abandoned older neighborhoods to in-moving African Americans, which brings the changes in racial composition and population distribution (Price-Spratlen and Guest, 2002). At the same time, African Americans with better socioeconomic status have opportunities to live in suburbs on a segregated basis through housing market guidance.

Iceland et al. (2005) found that residential patterns of African Americans across various socioeconomic groups still have persistent differences from non-Hispanic whites after a comprehensive view of economic and residential segregation for African Americans in U.S. metropolitan areas. According to Iceland et al. (2005), race has a dominant influence on prevailing residential patterns, while class is a secondary factor for this pattern. Their study supports spatial assimilation models in that the segregation level will decrease when socioeconomic status improves (Iceland et al., 2005). As some African Americans gained professional associations and are labeled as middle class, there are five areas which attract attention in the academic literature: racial and class segregation, the comparison between white and black middle-class neighborhoods, neighborhood racial preferences, black suburbanization, and the return of middle- and upper-class blacks to poor black neighborhoods (Pattillo, 2005).

Denton and Massey (1988) concluded that blacks were highly segregated from whites in the 1970s, although the dissimilarity index shows a slightly decrease. Meanwhile, blacks are also highly isolated from whites in the 1980s, although the racial segregation has declined slowly during the 1980s. The segregation between Hispanics and whites increased from 1970 to 1990 in 30 metropolitan areas with the largest Hispanic populations (Massey, 2001). Meanwhile, for

Asians, the dissimilarity index from whites decreased during the 1970s and later had an increasing trend in the 1990s (Fischer, 2003). There are five theories to explain the black-white residential segregation (Dawkins, 2004; Farley and Frey, 1994; Quillian, 2002): (1) the difference in affordability between whites and blacks due to household income differences; (2) different tastes for housing services and contextual demographic characteristics; (3) different accessibility to housing information; (4) racial prejudice which precludes the possibility to live in mixed racial neighborhoods; and (5) housing market discrimination which guides the location choices for blacks.

Branton and Jones (2005) found that the relationship between racial diversity and attitudes is conditioned on people's socioeconomic context. Crowder and South (2005) arrived at the conclusion that blacks and whites share more and more similarities in the moving rates between poor and nonpoor neighborhoods, which is largely driven by individual socioeconomic status and the shifting ecological conditions of metropolitan areas. However, during this process, race still remains a prominent factor in determining the possibility of residing or entering poor or non-poor neighborhoods, while class does not have significant influences (Crowder and South, 2005). One form of discrimination in the housing market is steering, where blacks are discriminated in the steering and lending market (Galster and Godfrey, 2005; Holloway, 1998). Krivo and Kaufman (2004) concluded that blacks and Hispanics receive less benefit from mortgage and housing characteristics than do whites which is a part of broader social and institutional processes of racial-ethnic stratification. As a result, this stratification gives whites an advantage over other racial groups.

Regardless of how income inequality is measured and whether household income or family income is investigated, inequality within the metropolitan context has risen (Madden, 1996; Silver and Bures, 1997). The extent of income poverty and the number of census tracts in extreme poverty have increased from 1970 to 1990 (Wilson, 1987), while at the same time the concentration of affluence grew more rapidly (Danziger, 1996). Fischer et al. (2004) found that the segregation for blacks decreased consistently from 1960 largely because neighborhoods were more integrated. At the same time, the class segregation based on income has been increasing which is largely due to the high clustering of the affluent (Sims, 1999). Moreover, the blacks with various socioeconomic statuses were highly segregated from non-Hispanic whites (Massey and Denton, 1988). At the same time, the affluent become more isolated than the poor which means that the affluent are more likely to live exclusively with other affluent households (Fischer, 2003). Earls (2000) concluded that a new set of demographic and geographical changes, which results in increasing gentrification in metropolitan areas, supply an additional contemporary explanation on urban poverty after his empirical study on Chicago.

As commonly understood, low-density development in the suburbanization process creates socioeconomic inequalities and racial and income segregation due to the fact that whites move away from central cities. Pendall and Carruthers (2003) found that fast urban growth in suburban areas was accompanied with less income segregation than those patterns found in moderately-dense urban forms. This phenomenon is due to the fact that the competition over individual sites in low-density regions is less fierce than that in high or growing density. Accordingly, there are fewer forces on sorting urban and suburban neighborhoods by class, and the low-density larger neighborhoods tend to share space with residents with lower-level socioeconomic status (Pendall and Carruthers, 2003). On the other hand, the very high-density metropolitan areas also had a process of less income segregation than moderately dense metropolitan areas. However, the income segregation level increased in those moderately dense metropolitan areas (Pendall and Carruthers, 2003).

The quantitative methods commonly used are dissimilarity index, the isolation index, and the entropy index when residential and class segregations are studied (Fischer, 2003; Iceland et al., 2005). Fischer et al. (2004) used the Theil index, where segregation can be decomposed into contributions arising from regional, metropolitan, city, place, and census tract levels. Now, the package STARS by Rey and Janikas (2006) can directly compute Theil index. When spatial concentration is studied, Johnston et al. (2003) found the threshold profiles give more of the geography than a single index.

None of above measures can test if the overall spatial distributions of income and population have statistically changed over time. To the best of my knowledge, no prior research considers the question that if the changes in spatial distributions of income, population, and race are statistically different from previous years. This chapter aims to address this question.

**Data and methodology**

This chapter uses data from U.S. Census of Bureau. Specifically, total population, whites, blacks, Asians, and the median household income at the census tract level in 1990 and 2000 are used. These data can be directly downloaded from the website of the U.S. Census Bureau (www.census.gov). After downloading, these attribute data were added into attribute tables of census tract boundary files, which was also downloaded from the U.S. Census of Bureau.

Representing data on an analog or digital map is the usual way in geographic analysis (Gluhih and Portnov, 2004). Traditional methods include symbols of varying size and color, clusters of data, contours, and charts. Population representation in GIS is usually done to construct digital boundary data for a set of zones, and tabular attributes of those zones store population characteristics (Martin, 1996). By these methods, the quantitative measures, such as counts, ratios, and ranks, can be represented on maps. GIS can be a great helper to urban studies which in part supplies a good means for representation: for example, Gluhih and Portnov (2004) developed a way of coordinate transformation to represent inter-urban disparities by bringing closer the locations with high values and moving away the places with low values.

3-dimensional display simulates spatial reality and allows the viewers to quickly grasp the changes in geographical reality.  Surface modeling supplies a good way to depict the spatial distribution of geographical information. The isometric distribution of the age structure by Coulson (1968) was the first illustration that used this method in population studies. Modern GIS software, such as Arc/Info and Surfer, have made surface modeling easier than ever. Surfaces are three-dimensional shaded renderings of a grid file, which provides an impressive visual interpretation of data. The geographic coordinates of the label point of census tract define *x* and *y* axes in the model: the demographic and income variables provide information for *z* axis. This process can be accomplished automatically in Surfer software. Meanwhile, the BLANK function in Surfer can cut off the margin outside the study area, and the base map of county boundaries can overlay with the surface map, which makes the resulting map more readable. This chapter uses a series of surface maps to display the distribution of demographic and economic variables over the Atlanta metropolitan area.

Corresponding to cumulative distribution function (CDF) for univariate variable, a spatial cumulative distribution function (SCDF) has been developed and some derived variations are also employed to study spatial distributions (Banerjee et al., 2004; Short et al., 2005; Wong, 2001; Zhu et al., 2002). The SCDF is a CDF constructed for a defined geographical region given a specific areal sampling size (Wong, 2001). SCDF is defined as (Banerjee et al., 2004):

$$F(w) = \Pr(s \in D : X(s) \leq w) = \frac{1}{D}\int_D Z_w(s)ds \qquad (6.1)$$

where $X(s)$ is the variable under investigation, $X(s)$, $s \in D$ is a spatial process, $w$ is a threshold value, $D$ is the total area, $Z_w(s)$=1 if $X(s) \leq w$, and 0 otherwise. When SCDF is computed, $w$ is set to a series of threshold values so that $F(w)$ is a random function which increases from 0 to 1 and is right-continuous.

Equation (6.1) is easily understood but difficult to compute in reality. When data in areal unit level are studied, the following equation is used to calculate SCDF (Banerjee et al., 2004):

$$\tilde{F}(w) = \frac{1}{D}\sum_{j=1}^{J} | B_j | Z_w(B_j) \qquad (6.2)$$

where $B_j$ are disjoint with union $D$, $D$ is the total area, $X(B_j)$, $j$=1,…$J$ is observation at areal $B_j$ (for example, the total population in census tract $j$), $J$ is the total number of census tracts, $Z_w(B_j)$=1 if $X(B_j)\ ) \leq w$, and 0 otherwise.

The Kolmogorov-Smirnov (K-S) test is usually used to measure if an empirical distribution is consistent with null hypothesis, or to compare two distributions to see if they are different (Loudin and Miettinen, 2003). The K-S test is a nonparametric test, which does not require explicit distributional assumptions about the underlying processes and independent of the shapes of the underlying distributions (Loudin and Miettinen, 2003; Rao and Goldsman, 1998). The test uses the maximum distance $d$ between the cumulative distribution functions as a measure of their similarity: it is necessary to consult K-S table with degrees of freedom to determine $p$-value, which in reality can be further used to explain if the difference between two distributions is statistically significant. SAS is used to calculate the SCDF and K-S test statistics and S-plus software is utilized to plot the SCDF, as it generates better-looking graphs than SAS.

**Results**

Since there are some changes on the boundaries of census tracts between census 1990 and 2000, some tracts in 2000 are merged to match with those in 1990. Moreover, a few census tracts in 1990 are merged or reclassified so that the tract boundaries are consistent with those in 2000. As a result, there are total of 436 common census tracts for conducting the mapping comparison in 1990 and 2000.

Figures 6.1, 6.2, 6.3, 6.4, 6.5 are surface maps of total population, whites, blacks, Asians, and the median household income in the Atlanta metropolitan area in 1990 and 2000. Generally, there are large numbers of total population and whites in the suburbs, large numbers of blacks locate in the central city, while Asians have residences in the northeastern part of the Atlanta metropolitan area near the central city. From 1990 to 2000, there were clear movements for total population and whites. Generally, total population and whites had migrations to northeastern and northwestern directions. By contrast, blacks also had some out-moving process, but the movement was from the central city to western part of the Atlanta metropolitan area. Asians, at the same time, mainly moved toward the northeastern part of Atlanta. As for the median household income, there were some summits in the southern part of the Atlanta metropolitan area in 2000 comprared with 1990.

In order to test if the spatial distributions of population and income between 1990 and 2000 had a significant difference, SCDF is used and K-S test is conducted. Because the numbers of total population, whites, blacks, and Asians as well as the values of the median household

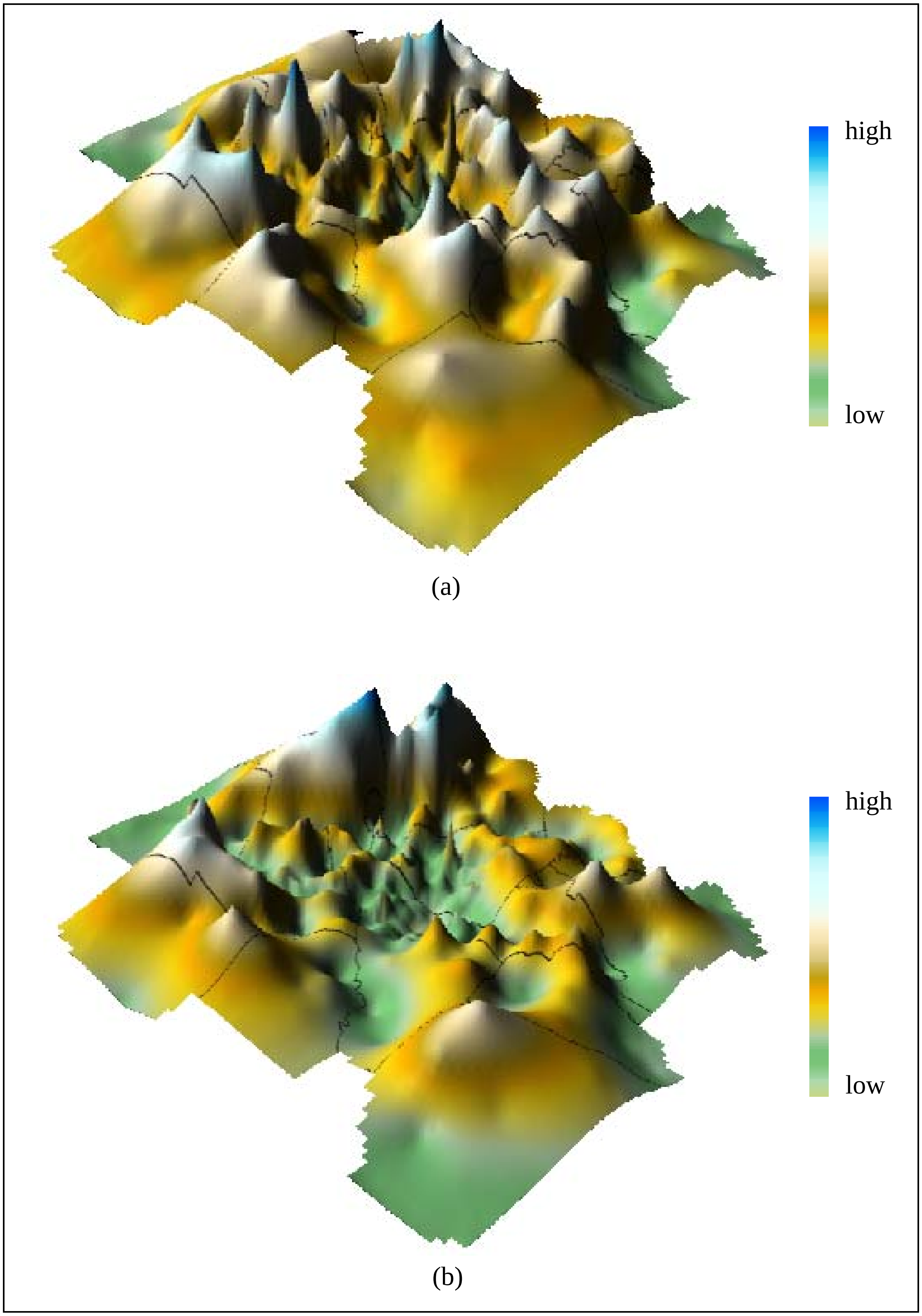



Figure 6.1 The surface maps of the total population in Atlanta metropolitan area in (a) 1990 and (b) 2000

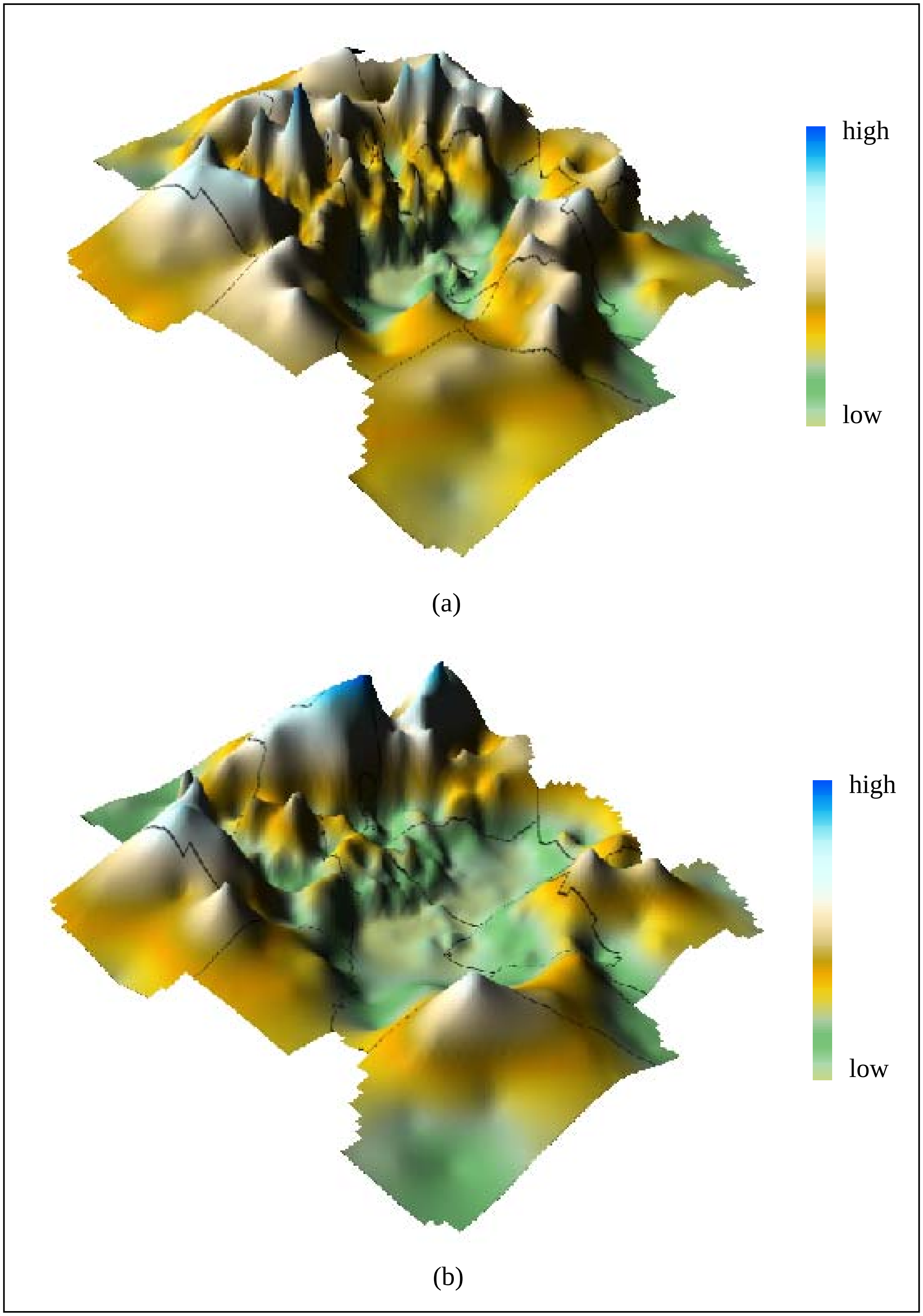



Figure 6.2 The surface maps of whites in Atlanta metropolitan area in (a) 1990 and (b) 2000

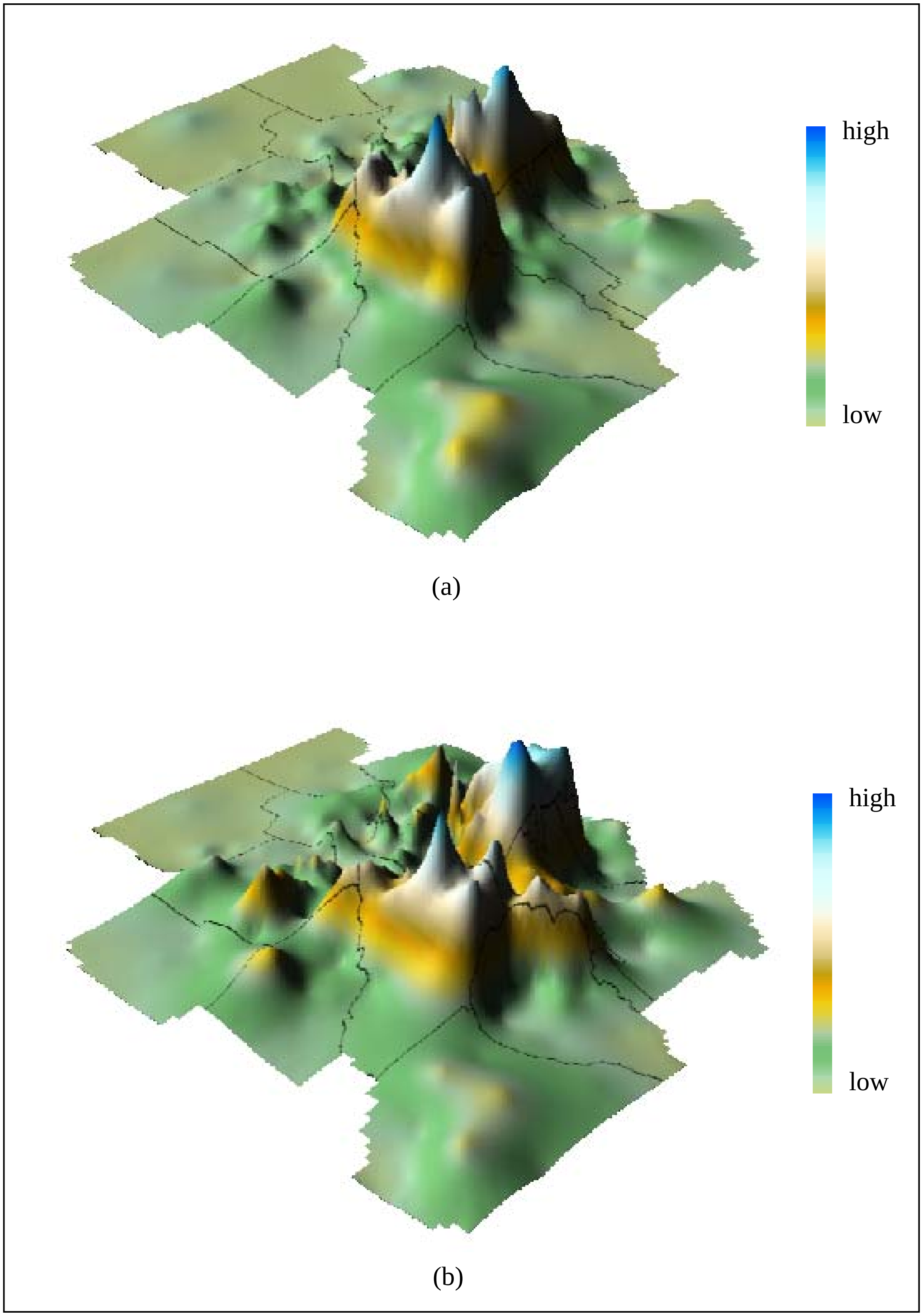



Figure 6.3 The surface maps of blacks in Atlanta metropolitan area in (a) 1990 and (b) 2000

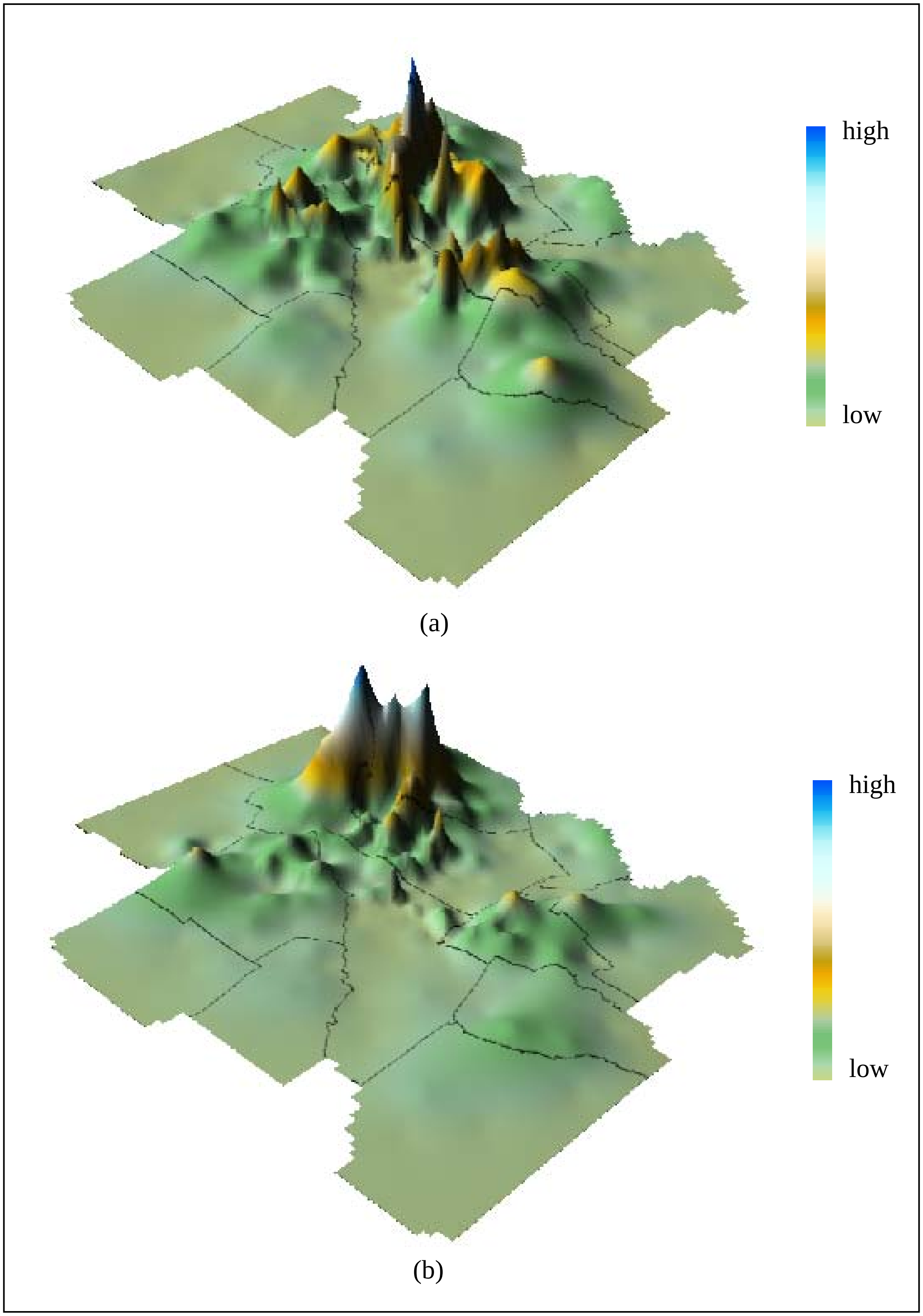



Figure 6.4 The surface maps of Asians in Atlanta metropolitan area in (a) 1990 and (b) 2000

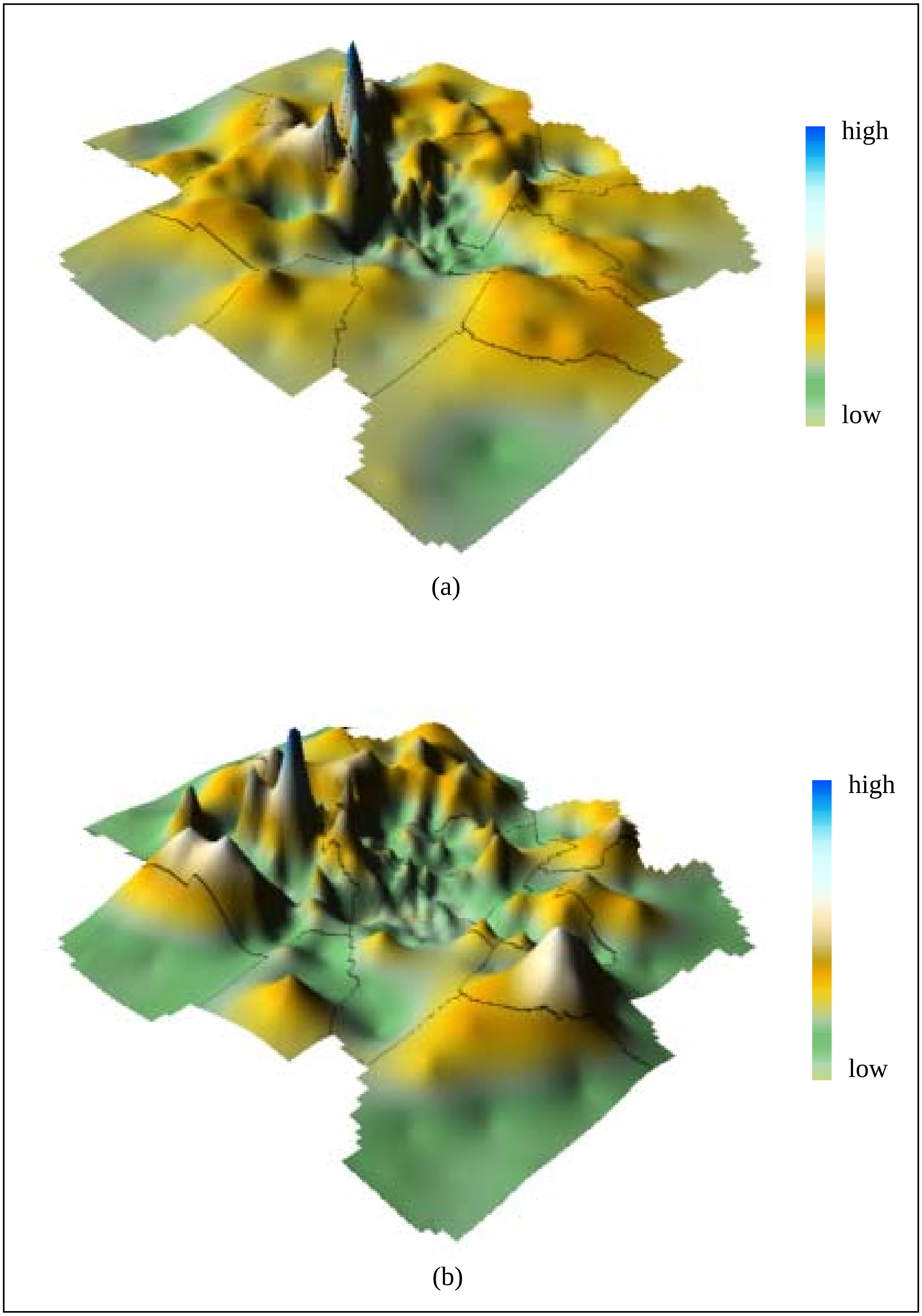



Figure 6.5    The surface maps of the median household income in Atlanta metropolitan area in (a) 1990 and (b) 2000

Table 6.1 The minimum and maximum values of population and income across all census tracts in Atlanta metropolitan area

| | | Minimum | Maximum | Range |
|---|---|---|---|---|
| Total population (persons) | 1990 | 162 | 17,724 | 17,562 |
| | 2000 | 18 | 38,742 | 38,724 |
| Whites (persons) | 1990 | 2 | 16,763 | 16,761 |
| | 2000 | 11 | 30,856 | 30,845 |
| Blacks (persons) | 1990 | 0 | 12,409 | 12,409 |
| | 2000 | 6 | 17,101 | 17,105 |
| Asians (persons) | 1990 | 0 | 1,145 | 1,145 |
| | 2000 | 0 | 5,443 | 5,443 |
| The median household income ($) | 1990 | 4,999 | 150,001 | 145,002 |
| | 2000 | 4,705 | 379,410 | 374,705 |

income had large ranges across all of census tracts in 1990 and 2000 (Table 6.1), in order to better make comparison between two years, the scaled values are used for population and income variables. The values of population and income variables for each year are first multiplied by 100 then divided by the maximum values in their corresponding years. For example, suppose a census tract had a total population *x* in 1990, then the scaled value of total population for this census tract in 1990 is ($x$*100/17724), another example, if a census tract had a median household income *y* in 2000, then the scaled median household income for this census tract is ($y$*100/379410). By this way, all variables are converted into values having a range from 0 to 100.

When SCDF is computed, the threshold value *w* in equation (6.2) is set to have a range from 0 to 100, which is corresponding to the scaled values of population and income variables. Specifically, *w* changes from 0 to 100 with a step of 2.5. For each w, the SCDF can be computed. After all threshold values are examined, the SCDF is plotted as figures 6.6, 6.7, 6.8, 6.9, and 6.10.

For SCDF plot, a slope of 45 degree indicates the even distribution over all land parcels. All of the SCDF plots are skewed to the left, which indicates that the population and income over Atlanta metropolitan area are unevenly distributed and agglomerated. Moreover, compared with total population and whites, the distributions of blacks and Asians were more unevenly distributed as their SCDFs have bigger shifts to the left. The SCDF plots of total population and whites (Figures 6.6 and 6.7) in 2000 both shift to the left with steeper slopes than those in 1990, which means that total population and whites generally occupied low-density urban parcels and were more aggregated in 2000 than 1990. However, blacks had a process of more even

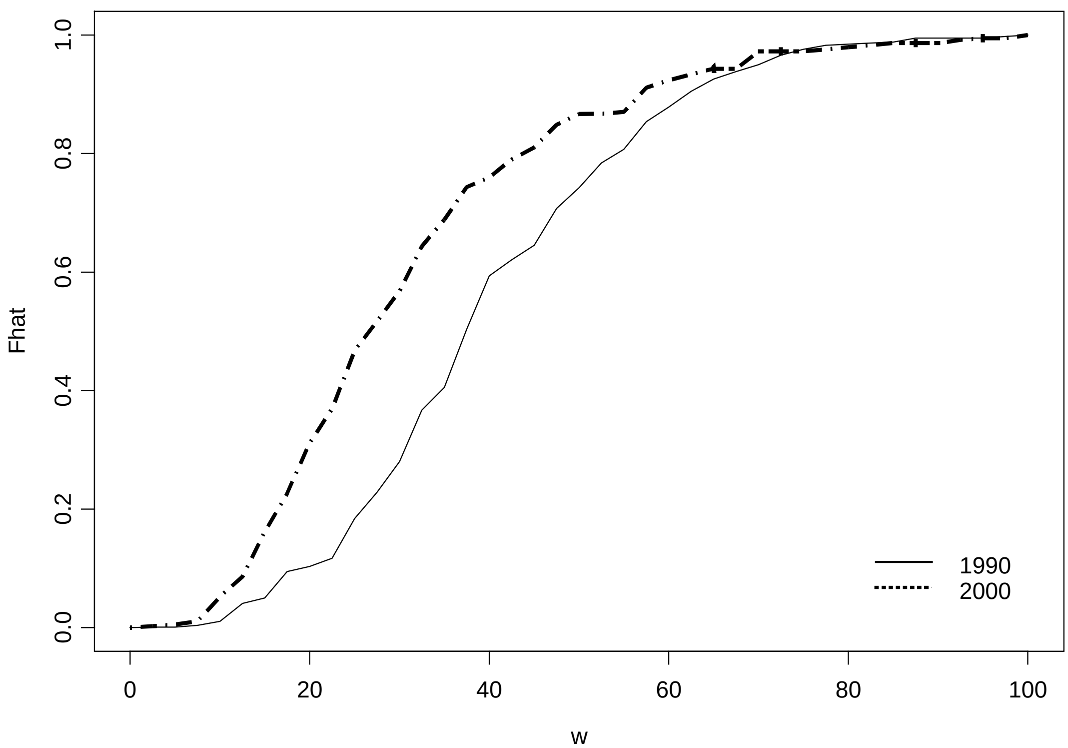



Figure 6.6 Spatial CDF for total population in 1990 and 2000

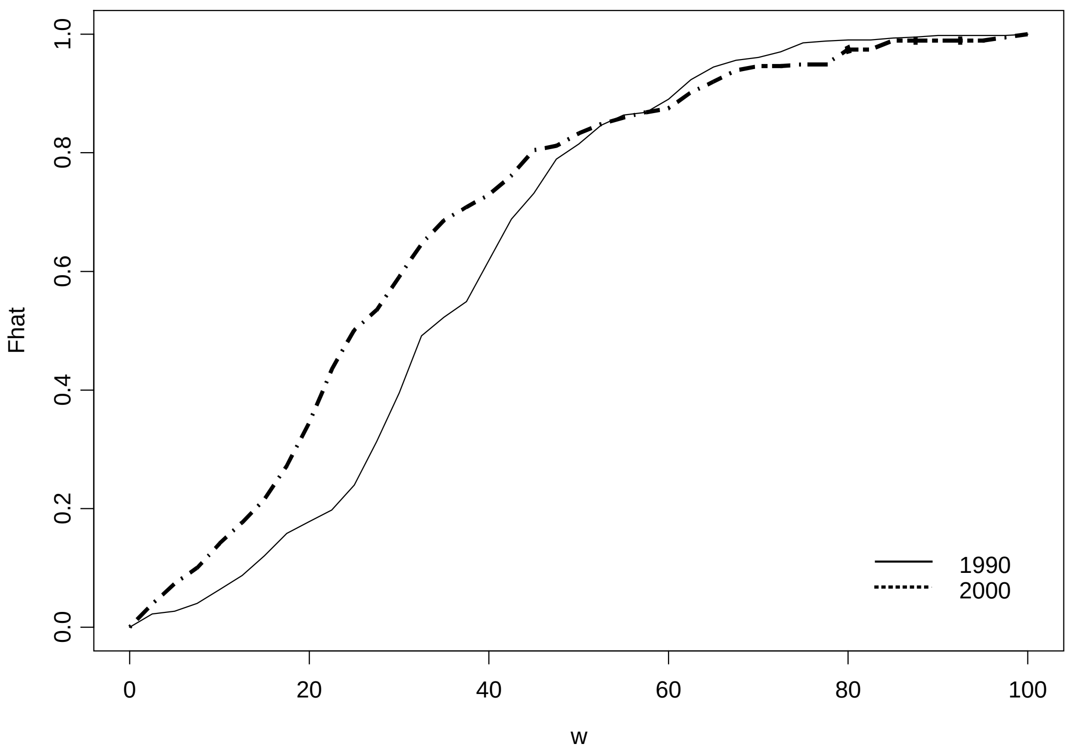



Figure 6.7    Spatial CDF for whites in 1990 and 2000

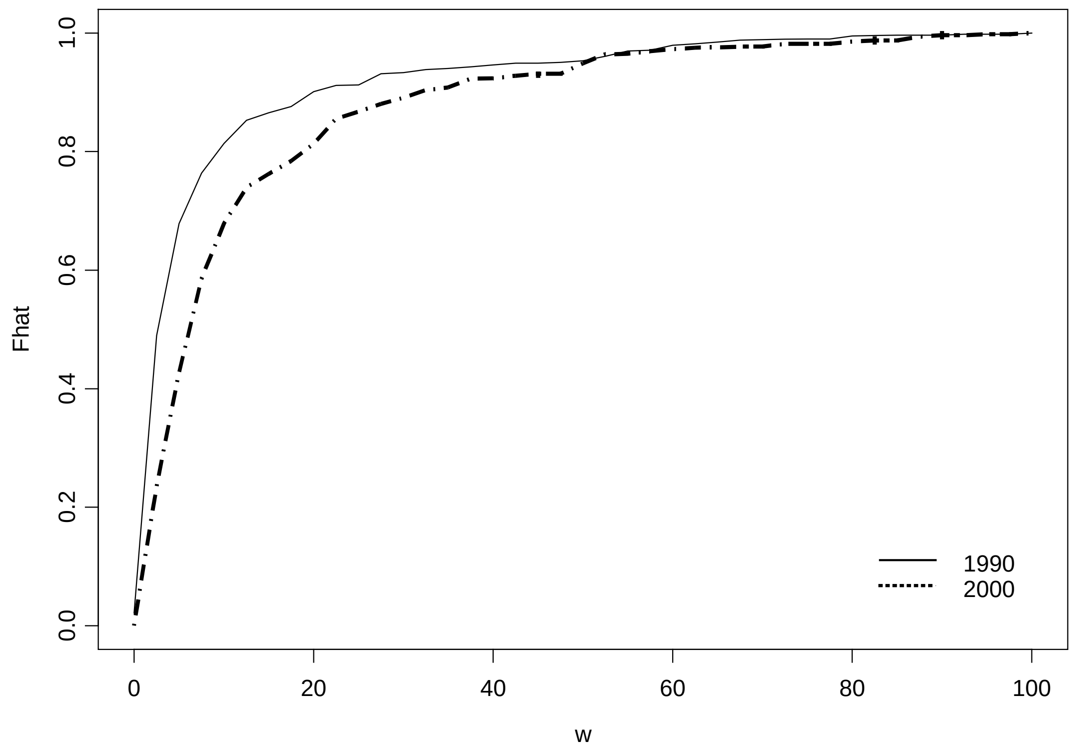



Figure 6.8 Spatial CDF for blacks in 1990 and 2000

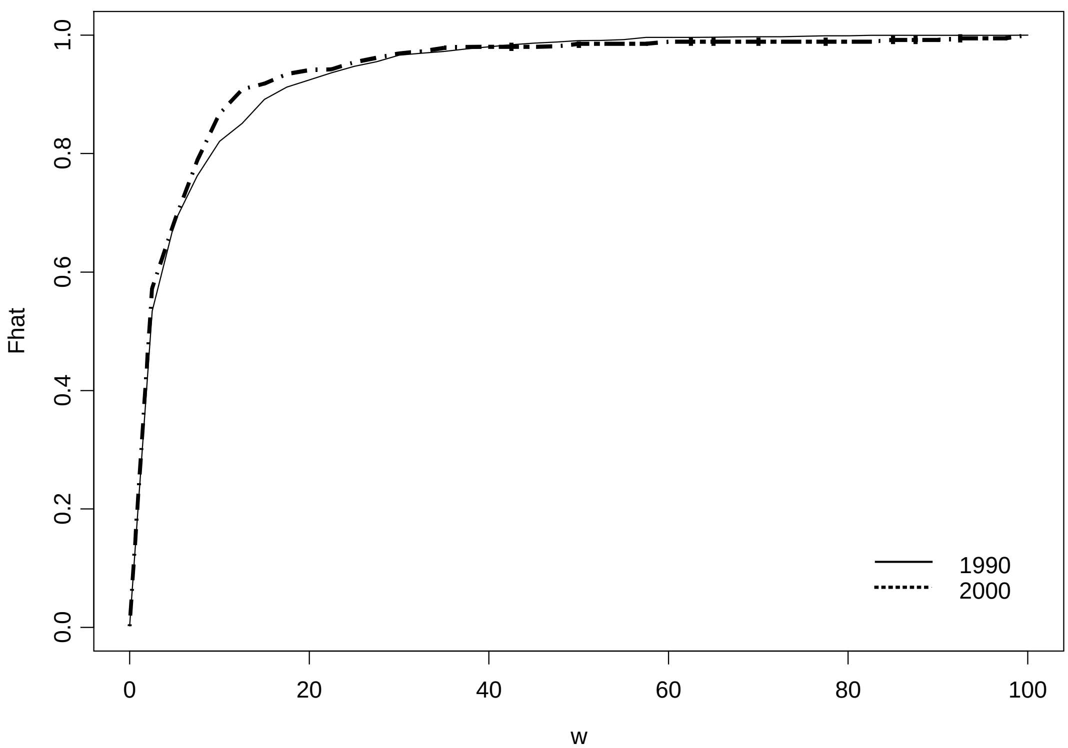



Figure 6.9    Spatial CDF for Asian in 1990 and 2000

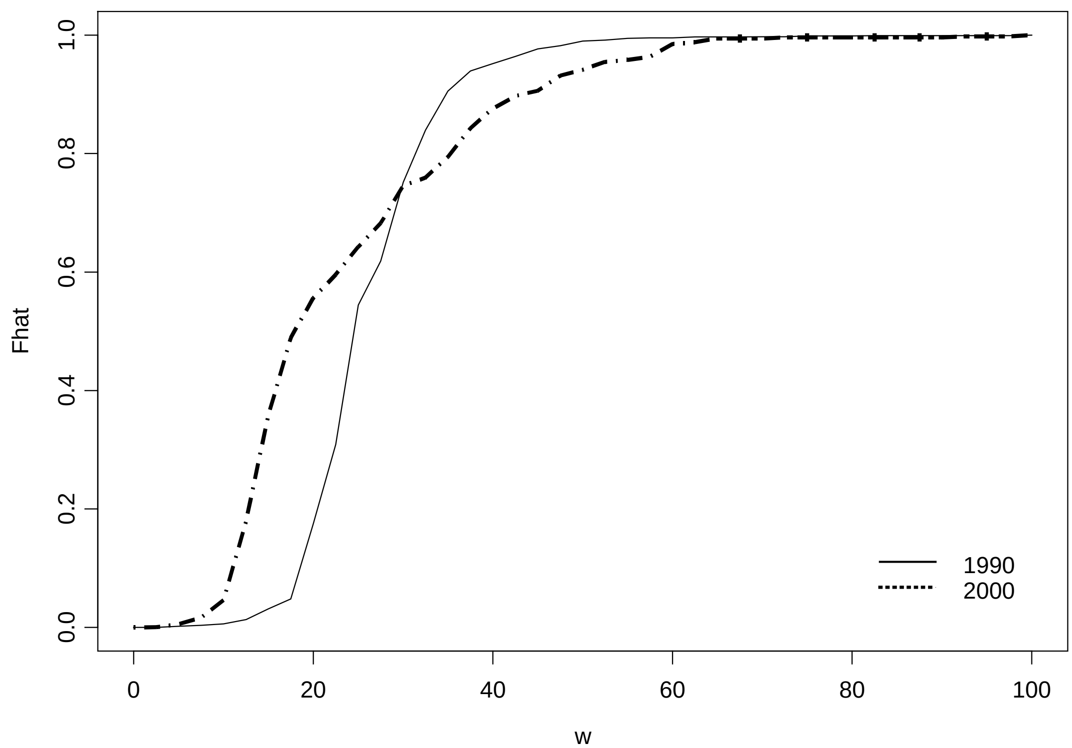



Figure 6.10 Spatial CDF for the median household income in 1990 and 2000

Table 6.2 The K-S test for spatial distributions of population, race, and income

| | Maximum difference d | p-value |
|---|---|---|
| Total population | 0.2885 | <0.001 |
| Whites | 0.2606 | <0.001 |
| Blacks | 0.2555 | <0.001 |
| Asians | 0.0575 | 0.4304 |
| The median household income | 0.4404 | <0.001 |

distribution during the 1990s as the SCDF in 2000 had a right shift compared with 1990. Asians, as they are always highly aggregated, had a little trend to concentrate in some areas during the 1990s. The median household income, however, indicates a different story. For low-income households, which had their income less than 30% of the maximum median household income across the Atlanta metropolitan area, were more aggregated in 2000 than 1990. Meanwhile, those households having 30%-65% of maximum median household income were more diversely distributed in 2000 than in 1990. In both years, the affluent were constantly highly aggregated.

Table 6.2 shows the K-S test statistics and the associated *p*-values. For total population, Whites, Blacks, and the median household income, the spatial distributions in 2000 all were statistically different from their corresponding distributions in 1990 as the *p*-values are less than 0.001. Asians, however, did not change their spatial distribution much as its associated *p*-value is much bigger than 0.1.

**Conclusions and discussions**

This chapter presents a case study of population, race, and income distributions and their changes within the Atlanta metropolitan area for 1990 and 2000. During the 1990s, the process of suburbanization and relocation has changed Atlanta's urban space and the spatial distributions of total population, whites, blacks, and the median household income all had a statistically different presence in 2000 than in 1990. The spatial distributions of total population and whites were more aggregated in the 1990s, while blacks had an inverse process. Asians, by comparison, did not change much in their spatial distributions during the 1990s. The spatial distribution of the median household income indicates the urban space of income distribution had been more polarized as poor people were more agglomerated and the affluent still highly segregated. It is possible, from another perspective, to look at the ethnical distribution and changes based on the division of Latino and Hispanic lines. That is, instead of using whites, blacks, Asians divisions, the racial and ethnical distribution can be studied by exploring the spatial variability of Latino/Hispanic and non-Latino/Hispanic ethnicities.

High-income whites and low-income blacks both live in the central city of the Atlanta metropolitan area, although whites are dominant to the north and blacks to the south (Hartshorn and Ihlanfeldt, 2000). For high-income whites, living in the central city saves commuting time and cost; most use private schools for their children’s education. Low-income blacks continue to be concentrated within the central city because of racial discrimination in the suburban housing market and access to less expensive public housing in the central city, as well as accessibility to public transportation.

This chapter gets the conclusions based on data at the census tract level. The issue of ecological fallacy is still present because successive aggregation of regionalized variables tends to increase correlations. Another issue is the use of SCDF. As there are other forms to compute SCDF, especially several derivations, more tests are needed to confirm the conclusions in this chapter.

In this chapter, surface models and SCDF are used to examine the spatial distributions of population, race, and income variables. This study can be further explored to study the polarized city in contemporary society, which may supply more empirical proofs or disputes for the arguments of postmodern urbanism. As more quantitative techniques are used together with GIS and spatial analysis, a detailed description of urban space is possible which can supply a good complementariness for qualitative study in urban geography studies.

# CHAPTER 7

# CONCLUSIONS AND DISCUSSIONS

This dissertation research aims to integrate GIS and spatial analysis to analyze Atlanta's urban structure and urban space. Three separated topics are addressed. First, in terms of urban structure, the urban land use/land cover structures from 1990 to 2000 are analyzed. In order to get classified land use/land cover images, remotely sensed imagery and remote sensing technology are also employed. The classified urban images are used as source data and analyzed by statistical procedures in order to empirically test postmodernism arguments. In terms of urban space, urban poverty and the spatial distributions of population, race, and income are analyzed respectively by analyzing U.S. census data. During the whole process, GIS techniques and spatial statistics cooperate with each other so that some conclusions are derived.

As defined by Sui (1998), there are four different approaches to integrate GIS and spatial analysis: embedding GIS functions into spatial analysis packages, embedding spatial analysis functions into GIS packages, loose-coupling, and tight coupling. While the first two are easily understood at the first glance, the latter two need to be explained. Loose-coupling integration refers to the approach which involves separate GIS package and statistical package. When data need transferring between different interfaces, ASCII, binary data, or spreadsheet formats are usually used. Tight-coupling integration refers to the approach which embeds certain spatial analysis functions with GIS software package via either GIS macro or conventional programming. However, such programming languages are usually not enough for sophisticated models. In this dissertation, the integration is loose coupling, according to above definitions. After database has been constructed within GIS packages, it is converted into statistical packages such as SAS, S-plus, or R. After statistical models are fitted, sometimes the results are converted into GIS packages again for visualization.

Chapter 3 uses a mixed classification scheme to classify land use/land cover in the Atlanta metropolitan area. During the classification process, unsupervised, supervised, and spectral mixture analysis (SMA) are used in turn in order to better discriminate objects from spectral information. Six types of land use/land cover are defined and classified: low-density urban, high-density urban, grassland/pasture/cropland, forest, water, and barren land. The hybrid approach generates classified images with overall accuracy greater than 85%. The classified images show that urban growth of the Atlanta metropolitan area consumed large amount of vegetative land since forest and grassland/pasture/cropland both decreases in areas.

Chapter 4 aims to test statistically the postmodernism argument on urban structure. Postmodern urbanism, which labels itself radically different from Chicago School, argues that postmodern city is more decentered and decentralized with the increasing flexible and disorganized capitalist accumulation. As far as urban structure is concerned, postmodernism thinks that urban land use is fragmented but at the same time is partially constrained by the underlying economic rationality. Meanwhile, urban growth has characteristics of random or quasi-random increase. The classified images from Chapter 3 are used to test this argument. While spatial metrics are used to test fragmentation, statistical models of spatial point pattern and process are used to test random or quasi-random increase. The statistics of contagion index and area-weighted mean patch fractal dimension (AWMPED) both indicate the urban structure was more fragmented during the 1990s. While Ripley’s K-function and spatial point process models indicates that the argument of random or quasi-random urban growth in the Atlanta metropolitan area is not supported. In order to better quantitatively test the post-modern argument regarding urban increase and urban development, more empirical studies are needed for other North America or worldwide cities

Chapter 5 analyzes urban poverty by taking into account spatial dependence and spatial variation of poverty distribution. Since traditional multivariate regression models neglect spatial dependence within the data, the results cannot incorporate the influence from spatial variations. This chapter has two sections of analyses: exploratory spatial data analysis and spatial regression modeling. In the section on exploratory spatial data analysis, urban poverty is found to be spatially dependent. With the help of semivariogram which calculates the range of spatial dependence, a spatial weights matrix is constructed based on inverse distance. Moran scatterplot shows the poor people tend to live in the central city surrounded by poor people, while nonpoor reside in suburbs largely surrounded by non-poor. There are a few census tracts scatted over the Atlanta metropolitan area which are poor/non-poor but surrounded by non-poor/poor. By incorporating a spatial weights matrix into regression analysis, the spatial autoregressive-regressive model, the spatial autoregressive error model, the spatial Durbin model, and the general spatial model are used to explore the relationship between urban poverty and demographic and socioeconomic variables. By making comparison with conventional multivariate regression model, the general spatial model is found to have higher $R^2$ and to better incorporate spatial dependence. Poverty rate is positively related with the percentage of blacks living in non-highly-poor census tract, the percentage of female-headed families, movers, unemployment rate, and bad educational attainment. Racial residential segregation, which is denoted by dissimilarity index, is found to be insignificant in the selected best model.

Regarding the issue if the spatial distributions of population, race, and income had statistically significant changes, spatial cumulative distribution function (SCDF) and Kolmogorov-Smirnov (K-S) test are used in chapter 6. By surface models of the total population, whites, blacks, and Asians for 1990 and 2000, the total population and whites were found to move north, blacks moved west, and Asians moved northeast. The surface models of the median household income shows there were big increase of income in some parts of southern Atlanta. SCDF and K-S test show that the spatial distributions of the total population, whites, blacks, and the median household income were statistically different from 1990 to 2000. However, where Asians were found, they did not have much difference in their spatial distributions. While the total population and whites were more unevenly distributed, blacks had a process of diverse distribution. SCDF of the median household income shows that the urban space of income was more polarized because low-income poor were more aggregated and the affluent are still segregated.

There are several issues which need more consideration or further investigations. First, the modifiable areal unit problem (MAUP) affects the applicability of results from census tract level to other scales. In order to better justify urban structure and urban space, it is expected to use other scales as well to investigate the urban changes. It has no consensus on which scale is the best for a specific topic on urban structure and urban space, while at the same time the researches are constrained by the availability of data. With the increasing data sources of high-resolution imagery data as well as other detailed socioeconomic data, the topics on urban structure and urban space can be studied more thoroughly.

Second, the results from data analysis may contain errors. The analysis of urban structure is based on classified images from Chapter 3. As there are errors existing within the classified images, the errors can be compounded in the later analyses. When data are converted from one interface to another in order to integrate GIS and spatial analysis, the error can be created during this process. Furthermore, because of the limitation of computer's memory, only resampled images with resolution of 120 m are used. A different result may be possible if a different resolution or spatial scale is used for the same analysis. There are still possibilities that the errors exist in census data, which are used in the analyses of urban poverty and the spatial distributions of population, race, and income. Although the existence of data errors is the reality, the data used in this dissertation are generally acceptable for the topics of urban structure and urban space.

Third, regarding urban theory on urban structure and urban space, Atlanta is found to have a more fragmented urban form and have a more polarized income space. These findings support the arguments of postmodern urbanism. However, as a city is multi-dimensional on demographic, economic, political, social, and cultural perspectives, the results from this dissertation cannot derive the opinion that Atlanta has a trend of postmodern city. Instead, the spatial point process shows that the random urban growth in Atlanta is not applicable as the model shows that the urban increase tends to depend on the distance from the existing urban area and the positive correlation within itself. More empirical studies are needed to quantitatively test the various arguments of postmodern urban theory, especially for the typical cities: Los Angeles and Miami.

Fourth, urban space can be studied in more details. This dissertation only considers one race at a time when spatial distribution of racial residence is analyzed. In future, the research, which can take several races into consideration at the same time and incorporate their interactive relationships, is needed. Moreover, the polarized urban space regarding the combined race and income factors, such as white affluent and black poor, is possible to give more hints on the contemporary metropolitan area.

This dissertation can derive the following conclusions at the technological, theoretical, and application levels. At the technological level, several spatial statistical techniques and models are integrated with GIS packages via loose-coupling approach. This integration demonstrates that the integration of GIS and spatial analysis can help address issues which are impossible to be accomplished when a single package is used. Meanwhile, the capabilities of GIS and spatial analysis are enhanced when new developments of technologies in their own fields are incorporated into the integration process.

At the theoretical level, the arguments by postmodernism on urban structure and urban space are examined. Although there are evidences for postmodern urbanism (fragmentation and polarization), the contradictory outcome between the reality of Atlanta's status as a mixed industrial/postindustrial city and the statistical results lead us to reconsider the question if there is a postmodern society. Nowadays, postmodern urbanism largely uses qualitative approaches to support its arguments. This dissertation, in part, supplies a quantitative approach to test its arguments.

At the application level, several spatial statistical methods are introduced for studying urban environment. These methods can be further applied to other contexts. In some cases, these methods can be modified so that the derivations can be better applied into various scenarios. This dissertation is a case study on urban structure and urban space. The comparisons among different cities with different economic, social, and cultural backgrounds will be more intuitive to better understand the contemporary world.

# REFERENCES


Adams, J.B., Sabol, D.E., Kapos, V., Filho, R.A., Roberts, D.A., Smith, M.O., Gillespie, A.R. 1995. Classification of multispectral images based on fractions of endmembers: Application to land-cover change in the Brazilian Amazon. *Remote Sensing of Environment*. 52: 137-154.

Alba, R.D., and Logan, J.R. 1991. Variations on two themes: Racial and ethnic patterns in the attainment of suburban residence. *Demography*. 28: 431-453.

Anselin, L. 1988. *Spatial Econometrics: Methods and Models*. Dordrecht: Kluwer Academic Publishers.

Anselin, L. 1993. Discrete space autoregressive models. In M.F. Goodchild, B.O. Parks, and L.T. Steyaert (eds) *Environmental Modeling with GIS*. NY: Oxford University Press, pp. 454-469.

Anselin, L. 1995. Local indicator of spatial association—LISA. *Geographical Analysis*. 27: 93-115.

Anselin, L. 1999. Interactive techniques and exploratory spatial data analysis. In P.A. Longley, M.F. Goodchild, D.J. Maguire, D.W. Rhind (eds,) *Geographic Information System: Principles, Techniques, Management, and Applications*. New York: Wiley, pp. 251-264.

Anselin, L., Syabri, I., and Kho, Y. 2006. GeoDa: An introduction to spatial data analysis. *Geographical Analysis*. 38: 5-22.

Baddeley, A., Moller, J., and Waagepetersen, R. 2000. Non- and semi-parametric estimation of interaction in inhomogeneous point patterns. *Statistica Neerlandica*. 54(3): 329-350.

Baddeley, A. and Turner, R. 2000. Practical maximum pseuolikelihood for spatial point patters. *The Australian & New Zealand Journal of Statistics*. 42(3): 283-322.

Baddeley, A., and Turner, R. 2005. Spatstat: An *R* package for analyzing spatial point patterns. *Journal of Statistical Software.* 12: 1-42.

Baddeley, A., and Turner, R. 2006. Modelling spatial point patterns in R, in A. Baddeley, P. Gregori, J. Mateu, R. Stoica, and D. Stoyan (eds) Case Studies in Spatial Point Process Modeling. New York: Springer, pp. 23-74.

Banerjee, S., Carlin, B.P., and Gelfand, A.E. 2004. *Hierarchical Modeling and Analysis for Spatial Data*. New York: Chapman & Hall/CRC.

Banerjee, S., Gelfand, A.E., and Polasek, W. 2000. Geostatistical modeling for spatial interaction data with application to postal service performance. *Journal of Statistical Planning and Inference*. 90: 87-105.

Barr, S.L., and Barnsley, M.J. 1998. A syntactic pattern recognition paradigm for the derivation of second-order thematic information from remotely-sensed images. In P. Atkinson, and N. Tate (eds,) *Advances in Remote Sensing and GIS Analysis*. Chichester: John Wiley, pp. 167-184.

Batty, M., and Longley, P.A. 1988. The morphology of urban land use. *Environment and Planning B: Planning and Design*. 15: 461-488.

Batty, M., and Longley, P.A. 1994. *Fractal Cities: A geometry of form and function*. London: Academic Press.

Baum, S., Mullins, P., Stimson, R., and O'Connor, K. 2002. Communities of the postindustrial city. *Urban Affairs Review*. 37(3): 322-357.

Beauregard, R.A., and Haila, A. 2000. The unavoidable continuities of the city. In P. Marcuse and R.v. Kampen (eds,) *Globalizing Cities: A New Spatial Order?* pp. 22-36.

Berman, M. 1986. Testing for spatial association between a point process and another stochastic process. *Applied Statistics*. 35(1): 54-62.

Berman, M., and Diggle, P. 1989. Estimates weighted integrals of the second-order intensity of a spatial point process. *Journal of the Royal Statistical Society—Series B*. 51(1): 81-92.

Berman, M., and Turner, T.R. 1992. Approximating point process likelihoods with GLIM. *Applied Statistics*. 41(1): 31-38.

Bessag, J. 1977. Contribution to the discussion of Dr. Ripley's paper. *Journal of the Royal Statistical Society*----*Series B*. 39: 193-195.

Bishop, J.A., Formby, J.P., and Zheng, B. 1999. Distribution sensitive measures of poverty in the United States. *Review of Social Economy*. LVII(3): 306-343.

Bivand, R. 2006. Implementing spatial data analysis software tools in R. *Geographical Analysis.* 38: 23-40.

Blank, R.M., and Hanratty, M. 1992. Down and out in North America: Recent trends in poverty rates in the United States and Canada. *Quarterly Journal of Economics*. 107: 232-254.

Brady, D. 2003. Rethinking the sociological measurement of poverty. *Social Forces*. 81(3): 715-752.

Branton, R.P., and Jones, B.S. 2005. Reexamining racial attitudes: The conditional relationship between diversity and socioeconomic environment. *American Journal of Political Science*. 49(2): 359-372.

Brown, D. 1998. "Classification and boundary vagueness in mapping resettlement forest types". *International Journal of Geographic Information Science*. 12: 105-129.

Burgess, E.W. 1925. The growth of the city: An introduction to a research project. In R.E. Park, E.W. Burgess, and R.D. McKenzie (eds.) *The City*. Chicago: University of Chicago Press, pp. 47-62.

Burrough, P.A. 2001. GIS and geostatistics: Essential partners for spatial analysis. *Environmental and Ecological Statistics*. 8: 361-377.

Burrough, P.A., and McDonell, R.A. 1998. *Principles of Geographical Information Systems*. Oxford, Oxford University Press.

Campbell, J.B. 1996. *Introduction to Remote Sensing*. New York: Guiford.

Casals-Carrasco, P., Kubo, S., and Madhavan, B.B. 2000. Application of spectral mixture analysis for terrain evaluation studies. *International Journal of Remote Sensing*. 21(16): 3039-3055.

Chander, G., and Markham, B. 2003. Revised Landsat-5 TM radiometric calibration procedures and postcalibration dynamic ranges. *IEEE Transactions on Geoscience and Remote Sensing*. 41(11): 2674-2677.

Chica-Olmo, M., and Abarca-Hernandez, F. 2000. Computing geostatistical image texture for remotely sensed data classification. *Computers & Geosciences*. 26: 373-383.

Chang, C., and Heinz, D. 2000. Constrained subpixel target detection for remotely sensed imagery. *IEEE Tractions on Geoscience and Remote Sensing*. 38(3): 1144-1159.

Chang, T. 2004. Spatial Statistics. *Statistical Science*. 19(4): 624-635.

Chen, K. 2002. An approach to linking remotely sensed data and areal census data. *International Journal of Remote Sensing.* 23(1): 37-48.

Chiu, S.N. 2003. Spatial point pattern analysis by using Voronoi diagrams and Delaunay tessellations—A comparative study. *Biometrical Journal*. 45(1): 367-376.

Clapham, W.B. 2003. Continuum-based classification of remotely sensed imagery to describe urban sprawl on a watershed scale. *Remote Sensing of Environment*. 86: 322-340.

Collado, A.D., Chuvieco, E., and Camarasa, A. 2002. Satellite remote sensing analysis to monitor desertification processes in the crop-rangeland boundary of Argentina. *Journal of Arid Environments*. 52: 121-133.

Cooke, T.J. 1999. Geographic context and concentrated urban poverty within the United States. *Urban Geography.* 20: 552-566.

Coulson, M.C. 1968. The Distribution of Population Age Structures in Kansas City. *Annals of the American Association of Geographers.* 58: 155-176.

Couteron, P., Seghieri, J., and Chadeuf, J. 2003. A test for spatial relationships between neighboring plants in plots of heterogeneous plant density. *Journal of Vegetation Science*. 14: 163-172.

Cowles, M.K. 2003. Efficient model-fitting and model-comparison for high-dimension Bayesian geostatistical models. *Journal of Statistical Planning and Inference*. 112: 221-239.

Cressie, N.A.C. 1984. Toward resistant geostatistics. In G. Verly, M. David, A.G. Journel, and A. Marechal (eds.) *Geostatistics for natural resources characterization*. Dordrecht: Reidel, pp. 21-44.

Cressie, N.A.C. 1991. *Statistics for Spatial Data*. Canada: John Wiley & Sons, Inc.

Crowder, K., and South, S.J. 2005. Race, class, and changing patterns of migration between poor and nonpoor neighborhoods. *American Journal of Sociology*. 110(6): 1715-1763.

Cushing, B., and Zheng, B. 2000. Re-evaluating differences in poverty among central city, suburban and nonmetro areas of the U.S. *Applied Economics*. 32: 653-660.

Cutsinger, J., Galster, G., Wolman, H., Hanson, R., and Towns, D. 2005. Verifying the multi-dimensional nature of metropolitan land use: Advancing the understanding and measurement of sprawl. *Journal of Urban Affairs*. 27(3): 235-259.

Dal, X.L., and Khorram, S. 1999. Remotely sensed change detection based on artificial neural networks. *Photogrammetric Engineering & Remote Sensing*. 65(10): 1187-1194.

Dall'erba, S. 2005. Distribution of regional income and regional funds in Europe 1989-1999: An exploratory spatial data analysis. *The Annals of Regional Science*. 39: 121-148.

Danziger, S. 1996. Comment on "The age of extremes: Concentrated affluence and poverty in the twenty-first century". *Demography*. 33(4): 413-416.

Dawkins, C.J. 2004. Recent evidence on the continuing causes of black-white residential segregation. *Journal of Urban Affairs*. 26(3): 379-400.

Dear, M. 1996. In the city, time becomes visible: Intentionality and urbanism in Los Angeles, 1781-1991. In A. Scott and E. Soja (eds.) *City: Los Angeles and Urban Theory at the End of the Twentieth Century*. Los Angeles: University of California Press, pp. 76-99.

Dear, M. 2000. *The Postmodern Urban Condition*. Oxford: Blackwell.

Dear, M., and Flusty, S. 1998. Postmodern urbanism. *Annals of the Association of American Geographers*. 88(1): 50-72.

Definiens Imaging. 2004. *eCognition User Guide*. Germany.

Dennison, P.E., Halligan, K.Q., and Roberts, D.A. 2004. A comparison of error metrics and constraints for multiple endmember spectral mixture analysis and spectral angle mapper. *Remote Sensing of Environment*. 93: 359-367.

Dennison, P.E., and Roberts, D.A. 2003. Endmember selection for multiple endmember spectral mixture analysis using endmember average RMSE. *Remote Sensing of Environment*. 87: 123-135.

Denton, N.A., and Massey, D.S. 1988. Residential segregation of Blacks, Hispanics and Asians by socioeconomic status and generation. *Social Science Quarterly*. 69: 797-817.

Diggle, P.J. 2003. *Statistical Analysis of Spatial Point Patterns*. New York: Oxford University Press.

Dong, P., and Leblon, B. 2004. Rock unit discrimination on Landsat TM, SIR-C and radarsat images using spectral and textual information. *International Journal of Remote Sensing*. 25: 3745-3768.

Earls, F. 2000. Urban poverty: Scientific and ethical considerations. *Annals of the American Academy of Political and Social Science*. 572: 53-65.

ENVI, 2000. *ENVI User's Guide*. Research Systems Inc., Boulder, Colorado.

Erol, H., and Akdeniz, F. 2005. A per-field classification method based on mixture distribution models and an application to Landsat Thematic Mapper data. *International Journal of Remote Sensing*. 26(6): 1229-1244.

Ewing, R. 1997. Is Los Angeles-style sprawl desirable? *Journal of the American Planning Association*. 63: 107-126.

Fajardo, A., and Alaback, P. 2005. Effects of natural and human disturbances on the dynamics and spatial structure of *Nothofagus glauca* in south-central Chile. *Journal of Biogeography*. 32: 1811-1825.

Farley, R., and Frey, W.H. 1994. Changes in the segregation of Whites from Blacks during the 1980s: Small steps toward a more integrated society. *American Sociological Review*. 59(1): 23-45.

Felgueiras, C.A., Monteiro, A.M.V., Camargo, E.C.G., and Fuks, S.D. 1999. Integrating geostatistical tools in geographical information systems. *Geoinfo*. www.geoinfo.info/geoinfo1999/papers/carlos.pdf. (Accessed on 03/01/06).

Fischer, C.S., Stockmayer, G., Stiles, J., and Hout, M. 2004. Distinguishing the geographic levels and social dimensions of U.S. metropolitan segregation, 1960-2000. *Demography*. 41(1): 37-59.

Fischer, M.J. 2003. The relative importance of income and race in determining residential outcomes in U.S. urban areas, 1970-2000. *Urban Affairs Review*. 38(5): 669-696.

Fong, E., and Shibuya, K. 2005. Multiethnic cities in North America. *Annual Review of Sociology*. 31: 285-304.

Fong, E., Luk, C., and Ooka, E. 2005. Spatial distribution of suburban ethnic businesses. *Social Science Research*. 34: 215-235.

Fortin, M.J., Dale, M.R.T., and Hoef, J. 2002. Spatial analysis in ecology. http://www.nceas.ucsb.edu/scicomp/Dloads/SpatialAnalysisEcologists/SpatAnalEcolFortin.pdf. (Accessed on 03/01/06).

Fotheringham, A.S. 1991. GIS and spatial analysis: An NCGIA research initiative. *Environment and Planning A*. 23: 1390-1391.

Foxall, R., and Baddeley, A. 2002. Nonparametric measures of association between a spatial point process and a random set, with geological applications. *Applied Statistics*. 51: 165-182.

Freeman, D.G. 2003. Poverty and the macroeconomy: Estimates from U.S. regional data. *Contemporary Economic Policy*. 21(3): 358-371.

Galster, G., and Godfrey, E. 2005. By words and deeds: Racial steering by real estate agents in the U.S. in 2000. *Journal of the American Planning Association*. 71(3): 251-268.

Galster, G., Hanson, R., Ratcliffe, M.R., Wolman, H., Colman, S., and Freihage, J. 2001. Wrestling sprawl to the ground: Defining and measuring an elusive concept. *Housing Policy Debate*. 12(4): 681-717.

Gamerman, D., and Moreira, A.R.B. 2004. Multivariate spatial regression models. *Journal of Multivariate Analysis*. 91: 262-281.

Garcia-Haro, F.J., Gilabert, M.A., and Melia, J. 1999. Extraction of endmembers from spectral mixtures. *Remote Sensing of Environment*. 68: 237-253.

Getis, A., and Aldstadt, J. 2004. Constructing the spatial weights matrix using a local statistic. *Geographical Analysis*. 36(2): 91-104.

Gilabert, M.A., Garcia-Haro, F.J., and Melia, J. 2000. A mixture modeling to estimate vegetation parameters for heterogeneous canopies in Remote Sensing. *Remote Sensing of Environment*. 72: 328-345.

Gluhih, R., and Portnov, B.A. 2004. Visualization of the spatial patterns of inter-urban income disparities using coordinate transformations. *International Journal of Geographical Information Science*. 18(3): 281-297.

Goodchild, M.F. 1992. Analysis. In R.E. Abler, M.G. Marcus, and J.M. Olson (eds.) *Geography's Inner Worlds*. New Brunswick, NJ: Rutgers University Press, pp.138-162.

Goodchild, M.F., and Haining, R.P. 2004. GIS and spatial data analysis: Converging perspectives. *Papers in Regional Science*. 83: 363-385.

Goodchild, M.F., and Longley, P.A. 1999. The future of GIS and spatial analysis. In P.A. Longley, M.F. Goodchild, D.J. Maguire, and D.W. Rhind (eds.) *Geographical Information Systems: Principles, Techniques, Management and Applications*. New York: Wiley, Vol. 1, pp. 567-580.

Goovaerts, P., Jacquez, G.M., and Marcus, A. 2005. Geostatistical and local cluster analysis of high resolution hyperspectral imagery for detection of anomalies. *Remote Sensing of Environment*. 95: 351-367.

Gramlich, E., Laren, D., and Sealand, N. 1992. Moving into and out of poor areas. *Journal of Policy Analysis and Management*. 11: 273-287.

Greene, R.P. 1991. Poverty concentration measures and the urban underclass. *Economic Geography*. 67: 240-252.

Greene, R.P. 1994. Poverty-area instability: The case of Chicago. *Urban Geography*. 15: 362-375.

Grieco, E.M., and Cassidy, R.C. 2001. *Overview of Race and Hispanic Origin*. 2000 brief. Washington, D.C.: U.S. Census Bureau. http://www.census.gov/prod/2001pubs/c2kbr01-3.pdf. (Accessed on 05/01/06)

Gross, H.N., and Schott, J.R. 1998. Application of spectral mixture analysis and image fusion techniques for image sharpening. *Remote Sensing of Environment*. 63: 85-94.

Guindon, B., Zhang, Y., and Dillabaugh, C. 2004. Landsat urban mapping based on a combined spectral-spatial methodology. *Remote Sensing of Environment*. 92: 218-232.

Haase, P. 1995. Spatial pattern analysis in ecology based on Ripley's K-function: Introduction and methods of edge correction. *Journal of Vegetation Science*. 6(4): 575-582.

Hackworth, J. 2005. Emergent urban forms, or emergent post-modernisms? A comparison of large U.S. metropolitan areas. *Urban Geography*. 26(6): 484-519.

Harding, D.J. 2003. Counterfactual models of neighborhood effects: The effect of neighborhood poverty on dropping out and teenage pregnancy. *American Journal of Sociology*. 109(3): 676-719.

Harris, C., and Ullman, E.L. 1945. The nature of cities. *The Annals of the American Academy of Political and Social Sciences*. 242: 7-17.

Hartshorn, T. A. and Ihlanfeldt, K. R. 2000. Growth and Change in Metropolitan Atlanta. In D.L. Sjoquist (ed.) *The Atlanta Paradox.* New York: Russell Sage Foundation, pp. 15-41.

Hartshorn, T. A. and Muller, P. O. 1989. Suburban downtowns and the transformation of metropolitan Atlanta's business landscape. *Urban Geography*. 10(4): 375-395.

Heim, C.E. 2001. Leapfrogging, urban sprawl, and growth management. *American Journal of Economics and Sociology*. 60: 245-283.

Herold, M. 2001. Remote sensing and spatial metrics—A new approach for the description of structures and changes in urban areas. http://www.geogr.uni-jena.de/~c5hema/pub/studpriz_herold_270.pdf. (Accessed on 03/01/06).

Herold, M., Couclelis, H., and Clarke, K.C. 2005. The role of spatial metrics in the analysis and modeling of urban land use change. *Computers, Environment and Urban Systems*. 29: 369-399.

Herold, M., Goldstein, N.C., and Clarke, K.C. 2003. The spatiotemporal form of urban growth: Measurement, analysis and modeling. *Remote Sensing of Environment*. 86: 286-302.

Herold, M., Roberts, D.A., Gardner, M.E., and Dennison, P.E. 2004. Spectrometry for urban area remote sensing—Development and analysis of a spectral library from 350-2400nm. *Remote Sensing of Environment*. 91: 304-319.

Herold, M., Scepan, J., and Clarke, K.C. 2002. The use of remote sensing and landscape metrics to describe structures and changes in urban land uses. *Environment and Planning A*. 34: 1443-1458.

Holloway, S.R. 1998. Exploring the neighborhood contingency of race discrimination in mortgage lending in Columbus, Ohio. *Annals of the Association of American Geographers*. 88(2): 252-276.

Hoover, E.M., and Vernon, R. 1962. *Anatomy of a Metropolis: The Changing Distribution of People and Jobs within the New York Metropolitan Region*. Garden City, NJ: Doubleday.

Hord, R.M., and Brooner, W., 1976. Land-use map accuracy criteria. *Photogrammetric Engineering and Remote Sensing*. 42(5): 671-677.

Hoyt, H. 1937. City growth and mortgage risk. *Insured Mortgage Protfolio 1(7) and 1(10)*. Reprinted in H. Hoyt (ed.) *According to Hoyt: Fifty Years of Homer Hoyt. Articles on Law, Real Estate Cycle, Economic Base, Sector Theory, Shopping Centers, Urban Growth, 1916-1966*. Washington, DC: Homer Hoyt, pp. 587-598.

Hughes, M.A. 1990. Formation of the impacted ghetto: Evidence from large metropolitan areas: 1970-1980. *Urban Geography*. 11: 265-284.

Iceland, J., Sharpe, C., and Steinmetz, E. 2005. Class differences in African American residential patterns in US metropolitan areas: 1990-2000. *Social Science Research*. 34: 252-266.

Jackson, K.T. 1985. *Crabgrass Frontier*. Oxford: Oxford University Press.

Jakubs, J.F. 1986. Recent racial segregation in the U.S. SMSAs. *Urban Geography*. 7: 146-163.

Jansen, L.J.M., and Gregorio, A.D. 2002. Parametric land cover and land-use classifications as tools for environmental change detection. *Agriculture, Ecosystems & Environment*. 91: 89–100.

Jargowsky, P.A. 1996. Take the money and run: Economic segregation in U.S. metropolitan areas. *American Sociological Review*. 61(6): 984-998.

Jargowsky, P.A. 1997. *Poverty and place: Ghettos, barrios, and the American city*. New York: Russell Sage Foundation.

Jargowsky, P.A., and Bane, M.J. 1991. Ghetto poverty in the United States. In C. Jencks and P.E. Peterson, (eds.) *The Urban Underclass*. Washington D.C.: The Brookings Institute, pp. 235-273.

Ji, C.Y., Liu, Q., Sun, D., Wang, S., Lin, P., and Li, X. 2001. Monitoring urban expansion with remote sensing in China. *International Journal of Remote Sensing*. 22(8): 1441–1455.

John, C.S. 2002. The concentration of affluence in the United States, 1990. *Urban Affairs Review*. 37(4): 500-520.

Johnston, R., Poulsen, M., and Forrest, J. 2006. Modern and post-modern cities and ethnic residential segregation: Is Los Angeles different? *Geoforum*. 37: 318-330.

Johnston, R., Voas, D., and Poulsen, M. 2003. Measuring spatial concentration: The use of threshold profiles. *Environment and Planning B*. 30: 3-14.

Jolloffe, D. 2003. On the relative well-being of the nonmetropolitan poor: An examination of alternate definitions of poverty during the 1990s. *Southern Economic Journal*. 70: 295-311.

Ju, J., Gopal, S., and Kolaczyk, E.D. 2005. On the choice of spatial and categorical scale in remote sensing land cover classification. *Remote Sensing of Environment*. 96(1): 62-77.

Kabos, S., and Csillag, F. 2002. The analysis of spatial association on a regular lattice by join-count statistics without the assumption of first-order homogeneity. *Computers & Geosciences*. 28: 901-910.

Kain, J.F. 1968. Housing segregation, Negro employment, and metropolitan decentralization. *Quarterly Journal of Economics*. 82: 175-197.

Kasarda, J.D. 1993. Inner-city concentrated poverty and neighborhood distress, 1970 to 1990. *Housing Policy Debate*. 4: 253-302.

Kaufmann, R.K., and Seto, K.C. 2001. Change detection, accuracy, and bias in a sequential analysis of Landsat imagery in the Pearl River Delta, China: econometric techniques. *Agriculture, Ecosystems & Environment*. 85: 95–105.

Knox, P. 1991. The restless urban landscape: Economic and sociocultural change and the transformation of metropolitan Washington, D.C. *Annals of the Association of American Geographers*. 81(2): 181-209.

Krivo, L.J., and Kaufman, R.L. 2004. Housing and wealth inequality: Racial-ethnic differences in home equity in the United States. *Demography*. 41(3): 585-605.

Krivo, L.J., Peterson, R.D., Rizzo, H., and Reynolds, J.R. 1998. Race, segregation, and the concentration of disadvantage: 1980-1990. *Social Problems*. 45(1): 61-80.

Landsat Project Science Office. 1999. Landsat 7 Science Data Users Handbook. http://ltpwww.gsfc.nasa.gov/IAS/handbook/handbook_htmls/chapter11/chapter11.html. (Accessed on 03/01/06)

Lees, L. 2003. Urban geography: 'New' urban geography and the ethnographic void. *Progress in Human Geography*. 27(1): 107-113.

LeSage, J.P., Pace, R.K., and Tiefelsdorf, M. 2004. Methodological developments in spatial econometrics and statistics. *Geographical Analysis*. 36(2): 87-89.

Leung, Y., Mei, C.L., and Zhang, W.X. 2003. Statistical test for local patterns of spatial association. *Environment and Planning A*. 35: 725-744.

Levernier, W. 2003. An analysis of poverty in the American South: How are metropolitan areas different from nonmetropolitan areas? *Contemporary Economic Policy*. 21(3): 372-382.

Levernier, W., Partridge, M.D., and Rickman, D.S. 2000. The causes of regional variations in U.S. poverty: A cross-county analysis. *Journal of Regional Science*. 40(3): 473-497.

Li, X., and Yeh, A.G.O. 1998. Principal component analysis of stacked multi-temporal images for the monitoring of rapid urban expansion in the Pearl River Delta. *International Journal of Remote Sensing*. 19: 1501-1518.

Lobell, D.B., Asner, G.P., Law, B.E., and Treuhaft, R.N. 2002. View angle effects on canopy reflectance and spectral mixture analysis of coniferous forests using AVIRIS. *International Journal of Remote Sensing*. 23(11): 2247-2262.

Logan, J.R., and Alba, R.D. 1993. Loational returns to human capital: Minority access to suburban community resources. *Demography*. 30: 243-268.

Longley, P. 2000. Spatial analysis in the new millennium. *Annals of the Association of American Geographers*. 90(1): 157-165.

Longley, P.A. 2002. Geographical information systems: Will developments in urban remote sensing and GIS lead to 'better' urban geography? *Progress in Human Geography*. 26(2): 231-239.

Longley, P.A. 2003. Geographical information systems: developments in socio-economic data infrastructures. *Progress in Human Geography*. 27(1): 114-121.

Longley, P.A., and Mesev, V. 1997. Beyond analogue models: Space filling and density measurement of an urban settlement. *Papers in Regional Science*. 76(4): 409-427.

Longley, P.A., and Mesev, V. 2002. Measurement of density gradients and space-filling in urban systems. *Papers in Regional Science*. 81: 1-28.

Lopez, R. and Hynes, H.P. 2003. Sprawl in the 1990s: Measurement, distribution, and trends. *Urban Affairs Review*. 38(3): 325-355.

Loudin, J.D., and Miettinen, H.E. 2003. A multivariate method for comparing N-dimensional distributions. *Phystat2003*. September: 8-11.

Lu, D., and Weng, Q. 2004. Spectral mixture analysis of the urban landscape in Indianapolis with Landsat ETM+ imagery. *Photogrammetric Engineering & Remote Sensing*. 70(9): 1053-1062.

Madden, J.F. 1996. Changes in the distribution of poverty across and within the US metropolitan areas, 1979-89. *Urban Studies*. 33(9): 1581-1600.

Madhavan, B.B., Kubo, S., Kurisaki, N., and Sivakumar, T.V.L.N. 2001. Appraising the anatomy and spatial growth of the Bangkok metropolitan area using a vegetation-imperious-soil model through remote sensing. *International Journal of Remtoe Sensing.* 22: 789-806.

Maktav, D., Erbek, F.S., and Jurgens, C. 2005. Remote sensing of urban areas. *International Journal of Remote Sensing*. 26(20): 655-659.

Markham, B.L., and Barker, J.L. 1987. Thematic mapper bandpass solar exoatmospheric irradiances. *International Journal of Remote Sensing*. 8(3): 517-523.

Martin, D. 1996. An assessment of surface and zonal models of population. *International Journal of Geographical Information Systems*. 10(8): 973-989.

Martin, L.R.G., and Howarth, P.J. 1989. Change detection accuracy assessment using SPOT multispectral imagery of the rural-urban fringe. *Remote Sensing of Environment*. 30: 55-66.

Massey, D.S. 1996. The age of extremes: Concentrated affluence and poverty in the twenty-first century. *Demography*. 33: 395-412.

Massey, D.S. 2001. Residential segregation and neighborhood conditions in U.S. metropolitan areas. In N.J. Smelser, W.J. Wilson, and F. Mitchell. (eds) *America Becoming: Racial Trends and Their Consequences*. Washington, D.C.: National Academy Press, pp. 391-434.

Massey, D.S. and Denton, N.A. 1993. *American Apartheid: Segregation and the Making of the Underclass*. Cambridge, M.A.: Harvard University Press.

Massey, D.S., and Fischer, M. 2000. How segregation concentrates poverty. *Ethnic and Racial Studies*. 23(4): 670-691.

McKinney, S. and Schnare, A.B. 1989. Trends in Residential Segregation by Race: 1960-1980. *Journal of Urban Economics.* 26: 269-280.

McKinnon J. 2001. *The Black Population: 2000.* Census 2000 Brief. Washington, DC: U.S. Census Bureau. http://www.census.gov/prod/2001pubs/c2kbr01-5.pdf. (Accessed 05/01/06)

Mennis, J.L., and Jordan, L. 2005. The distribution of environmental equity: Exploring spatial nonstationarity in multivariate models of air toxic releases. *Annals of the Association of American Geographers*. 95(2): 249-268.

Meer, F.V.D., and Jong, S.M.D. 2000. Improving the results of spectral unmixing of Landsat thematic mapper imagery by enhancing the orthogonality of end-members. *International Journal of Remote Sensing*. 21(15): 2781-2797.

Miller, H.J., and Wentz, E.A. 2003. Representation and spatial analysis in geographical information systems. *Annals of the Association of American Geographers*. 93(3): 574-594.

Morrill, R. 1995. Racial Segregation and Class in a Liberal Metropolis. *Geographical Analysis*. 27: 22-41.

Myint, S.W. 2003. Fractal approaches in texture analysis and classification of remotely sensed data: Comparisons with spatial autocorrelation techniques and simple descriptive statistics. *International Journal of Remote Sensing*. 24(9): 1925-1947.

O'Boyle, E.J. 1999. Distribution sensitive measures of poverty in the United States: Comment. *Review of Social Economy*. LVII(3): 344-350.

O'Neill, R.V., Krummel, J.R., Gardner, R.H., Sugihara, G., Jackson, B., Deangelis, D.L., Milne, B.T., Turner, M.G., Zygmunt, B., Christensen, S.W., Dale, V.H., and Graham, R.L. 1988. Indices of landscape pattern. *Landscape Ecology*. 1: 153-162.

Okabe, A., Okunuki, K., and Shiode, S. 2006. SANET: A toolbox for spatial analysis on a network. *Geographical Analysis*. 38(1): 57-66.

Oliver, M.A., Shine, J.A., and Slocum, K.R. 2005. Using the variogram to explore imagery of two different spatial resolutions. *International Journal of Remote Sensing*. 26(15): 3225-3240.

Parrinello, T., and Vaughan, R.A. 2002. Multifractal analysis and feature extraction in satellite imagery. *International Journal of Remote Sensing*. 23(9): 1799-1825.

Pattillo, M. 2005. Black middle-class neighborhoods. *Annual Review of Sociology*. 31: 305-329.

Pendall, R., and Carruthers, J.I. 2003. Does density exacerbate income segregation? Evidence from U.S. metropolitan areas, 1980-2000. *Housing Policy Debate*. 14(4): 541-589.

Peng, R.D. 2003. Multi-dimensional Point Process Models in R. *Journal of Statistical Software*. 8(16): 1-27.

Perry, G.L.W. 2004. SpPack: Spatial point pattern analysis in Excel using Visual Basic for Applications (VBA). *Environmental Modelling & Software*. 19: 559-569.

Pesaresi, M., and Bianchin, A. 2001. Recognizing settlement structure using mathematical morphology and image texture. In J.P. Donnay, M.J. Barnsley, and P.A. Longley (eds.) *Remote Sensing and Urban Analysis*. London: Taylor and Francis, pp. 55-67.

Phinn, S., Stanford, M., Scarth, P., Murray, A.T., and Shyy, P.T. 2002. Monitoring the composition of urban environments based on the vegetation-impervious surface-soil (VIS) model by subpixel analysis techniques. *International Journal of Remote Sensing*. 23(20): 4131-4153.

Pilon, P.G., Howarth, P.J., and Bullock, R.A. 1988. An enhanced classification approach to change detection in semi-arid environments. *Photogrammetric Engineering and Remote Sensing*. 54: 1709-1716.

Podur, J., Martell, D.L., and Csillag, F. 2003. Spatial patterns of lightning-caused forest fires in Ontario, 1976-1998. *Ecological Modelling*. 164: 1-20.

Poulsen, F., and Johnston, R. 2002. From Modern to Post-modern? *Cities*. 19(3): 161-172.

Price-Spratlen, T., and Guest, A.M. 2002. Race and population change: A longitudinal look at Cleveland neighborhoods. *Sociological Forum*. 17(1): 105-136.

Quillian, L. 1999. Migration patterns and the growth of high-poverty neighborhoods, 1970-1990. *American Journal of Sociology*. 10591): 1-37.

Quillian, L. 2002. Why is Black-White residential segregation so persistent? Evidence on three theories from migration data. *Social Science Research*. 31: 197-229.

Rao, L., Goldsman, D. 1998. Development and applications of a validation framework for traffic simulation models. In D.J. Medeiros, E.F. Watson, J.S. Carson, and M.S. Manivannan (eds.) *Proceedings of the 1998 Winter Simulation Conference*, pp: 1079-1086.

Rashed, T., Weeks, J.R., Stow, D., and Fugate, D. 2005. Measuring temporal compositions of urban morphology through spectral mixture analysis: Toward a soft approach to change analysis in crowded cities. *International Journal of Remote Sensing*. 26: 699-718.

Rathbun, S.L., and Cressie, N. 1994. Asymptotic properties of estimators for the parameters of spatial inhomogeneous poisson point processes. *Advances in Applied Probability*. 26: 122-154.

Read, J.M., and Lam, N.S-N. 2002. Spatial methods for characterizing land cover and detecting land-cover changes for the tropics. *International Journal of Remote Sensing*. 23(12): 2457-2474.

Rey, S.J., and Janikas, M.V. 2006. STARS: Space-time analysis of regional systems. *Geographical Analysis*. 38: 67-86.

Ridd, M.K. 1995. Exploring a V-I-S (Vegetation-impervious-soil) model for urban ecosystem analysis through remote sensing comparative anatomy for cities. *International Journal of Remote Sensing*. 16: 2165-2185.

Ripley, B.D. 1976. The second-order analysis of stationary point processes. *Journal of Applied Probability*. 13: 255-266.

Ripley, B.D. 1977. Modelling spatial patterns. *Journal of the Royal Statistical Societ*----*Series B*. 39: 172-212.

Ripley, B.D. 1981. *Spatial Statistics*. New York: Wiley.

Roberts, D.A., Gardner, M., Church, R., Ustin, S., Scheer, G., and Green, R.O. 1998. Mapping chaparral in the Santa Monica Mountains using multiple endmember spectral mixture models. *Remote Sensing of Environment*. 65: 267-279.

Rogan, J., and Chen, D. 2004. Remote sensing technology for mapping and monitoring land-cover and land-use change. *Progress in Planning*. 61: 301-325.

Rowlingson, B.S., and Diggle, P.J. 1993. Splancs: Spatial point pattern analysis code in S-plus. *Computers & Geosciences*. 19(5): 627-655.

Rowlingson, B., Diggle, P., and Bivand, R. 2006. *The Splancs Package*, version 2.01-17, http://cran.r-project.org/doc/packages/splancs.pdf. (Accessed on 06/01/2006)

Sassen, S. 1991. *The Global City: New York, London, Tokyo*. Princeton, NJ: Princeton University of Press.

Schweik, C.M., Green, G.M. 1999. The use of spectral mixture analysis to study human incentives, actions, and environmental outcomes. *Social Science Computer Review*. 17(1): 40-63.

Seto, K.C., Woodcock, C.E., Song, C., Huang, X., Lu, J., and Kaufmann, R.K. 2002. Monitoring land-use change in the Pearl River Delta using Landsat TM. *International Journal of Remote Sensing.* 23(10): 1985–2004.

Shearmur, R. and Charron, M. 2004. From Chicago to L.A. and back again: A Chicago-inspired quantitative analysis of income distribution in Montreal. *The Professional Geographer*. 56(1): 109-126.

Shen, G. 2002. Fractal dimension and fractal growth of urbanized areas. *International Journal of Geographical Information Science*. 16(5): 419-437.

Short, M., Carlin, B.P., and Gelfand, A.E. 2005. Bivariate spatial process modeling for constructing indicator or intensity weighted spatial CDFs. *Journal of Agricultural, Biological, and Environmental Statistics*. 10(3): 259-275.

Silver, H., and Bures, R. 1997. Dual cities? Sectoral shifts and metropolitan income inequality, 1980-1990. *The Service Industries Journal*. 17(1): 69-90.

Sims, M. 1999. High-status residential segregation among racial and ethnic groups in five metro areas, 1980-1990. *Social Science Quarterly*. 80(3): 556-573.

Small, C. 2003. High spatial resolution spectral mixture analysis of urban reflectance. *Remote Sensing of Environment*. 88: 170-186.

Small, C. 2004. The landsat ETM+ spectral mixing space. *Remote Sensing of Environment*. 93: 1-17.

Small, C. 2005. A global analysis of urban reflectance. *International Journal of Remote Sensing*. 26(4): 661-681.

Soja, E. 1989. *Postmodern Geographies: The Reassertion of Space in Critical Social Theory*. London: Verson.

Soja, E. 2000. *Postmetropolis: Critical Studies of Cities and Regions*. Oxford: Blackwell.

Song, C. 2005. Spectral mixture analysis for subpixel vegetation fractions in the urban environment: How to incorporate endmember variability? *Remote Sensing of Environment*. 95: 248-263.

Squires, G.D., and Kubrin, C.E. 2005. Privileged places: Race, uneven development and the geography of opportunity in urban America. *Urban Studies*. 42(1): 47-68.

Stoll, M. A. and Raphael, S. 2000. Racial Differences in Spatial Job Search Patterns: Exploring the Causes and Consequences. *Economic Geography*. 76: 201-223.

Strait, J.B. 2000. An examination of extreme urban poverty: The effect of metropolitan employment and demographic dynamics. *Urban Geography*. 21(6): 514-542.

Subramanian, S.V., Acevedo-Garcia, D., and Osypuk, T.L. 2005. Racial residential segregation and geographical heterogeneity in black/white disparity in poor-self-rated health in the US: A multilevel statistical analysis. *Social Science & Medicine*. 60: 1667-1679.

Sui, D.Z. 1994. GIS and urban studies: positivism, post-postitivism, and beyond. *Urban Geography*. 15: 258-278.

Sui, D.Z. 1997. Reconstructing urban reality: From GIS to electroplis. *Urban Geography*. 18: 74-89.

Sui, D.Z. 1998. GIS- based urban modeling: Practice, problems, and prospects. *International Journal of Geographical Information Science*. 12(7): 651-671.

Sui, D.Z. 1999. Postmodern urbanism disrobed: Or why postmodern urbanism is a dead end for urban geography. *Urban Geography*. 20: 403-411.

Sui, D.Z., and Hugill, P. 2002. A GIS-based spatial analysis on neighborhood effects and voter turn-out: A case study in College Station, Texas. *Political Geography*. 21: 159-173.

Tapiador, F.J., and Casanova, J.L. 2003. Land use mapping methodology using remote sensing for the regional planning directives in Segovia, Spain. *Landscape & Urban Planning*. 62: 103–115.

Theseira, M.A., Thomas, G., Taylor, J.C., Gelmmell, F., and Varjo, J. 2003. Sensitivity of mixture modeling to end-member selection. *International Journal of Remote Sensing*. 24: 1559-1575.

Thomas, I.L., Benning, V., and Ching, N.P. 1987. *Classification of Remotely Sensed Images*. Bristol: J.W. Arrowsmith Ltd.

Tobler, W. 1979. Cellular geography. In S. Gale and G. Olsson (eds.) *Philosophy in Geography*. Dordrech1: Reidel, pp. 379-386.

Tompkins, S., Mustard, J.F., Pieters, C.M., and Forsyth, D.W. 1997. Optimization of endmembers for spectral mixture analysis. *Remote Sensing of Environment*. 59: 472-489.

Topel, R.H. 1994. Regional labor markets and the determination of wage inequality, *American Economic Review*. 84: 17-22.

Treitz, P., and Rogan, J. 2003. Remote sensing for mapping and monitoring land-cover and land-use change—an introduction. *Progress in Planning*. 61: 269-279.

Tsai, Y. 2005. Quantifying urban form: Compactness versus ‘sprawl’. *Urban Studies*. 42(1): 141-161.

Vance, J. E., 1964. *Geography and Urban Evolution in the San Francisco Bay Area*. Berkeley, CA: University of California, Institute of Governmental Studies.

Walter, C., McBratney, A.B., Rossel, R.A.V., and Markus, J.A. 2005. Spatial point-process statistics: Concepts and application to the analysis of lead contamination in urban soil. *Environmetrics*. 16: 339-355.

Weber, B., Jensen, L., Miller, K., Mosley, J., and Fisher, M. 2005. A critical review of rural poverty literature: Is there truly rural effect? *International Regional Science Review*. 28(4): 381-414.

Welch, R., and Ehlers, M., 1987. Merging multi-resolution SPOT HRV and Landsat-TM data. *Photogrammetic Engineering and Remote Sensing*. 52: 301-303.

Weber, C., and Puissant, A. 2003. Urbanization pressure and modeling of urban growth: Example of the Tunis metropolitan area. *Remote Sensing of Environment*. 86: 341-352.

Weng, Q. 2001. Modeling urban growth effects on surface runoff with the integration of remote sensing and GIS. *Environmental Management*. 28(6): 737-748.

Wong, D.W.S. 2001. Location-specific cumulative distribution function (LSCDF): A alternative to spatial correlation analysis. *Geographical Analysis*. 33(1): 76-93.

Wilkinson, G.G. 1996. A review of current issues in the integration of GIS and remote sensing data. *International Journal of Geographical Information Systems*. 10: 85-101.

Wilson, W.J. 1987. *The Truly Disadvantaged: The Inner City, The Underclass, and Public Policy*. Chicago: The University of Chicago Press.

Wilson, W.J. 1991. Studying inner-city social dislocations: The challenge of public agenda research. *American Sociological Review*. 56: 1-14.

Wilson, W.J. 1996. *When Work Disappears: The World of the New Urban Poor*. New York, NY: Alfred A. Knopf.

Wilson, E.H., Hurd, J.D., Civco, D.L., Prisloe, M.P., and Arnold, C. 2003. Development of a geospatial model to quantify, describe and map urban growth. *Remote Sensing of Environment*. 86: 275-285.

Wolman, H., Galster, G., Hanson, R., Ratcliffe, M., Furdell, K., and Sarzynski, A. 2005. The fundamental challenge in measuring sprawl: Which land should be considered? *Professional Geographer*. 57(1): 94-105.

Wu, C. 2004. Normalized spectral mixture analysis for monitoring urban composition using ETM+ imagery. *Remote Sensing of Environment*. 93: 480-492.

Wu, C., and Murray, A. 2003. Estimating impervious surface distribution by spectral mixture analysis. *Remote Sensing of Environment*. 84: 493-505.

Yang, X., 2000. *Integrating image analysis and dynamic spatial modeling with GIS in a rapidly suburbanizing environment*. University of Georgia Dissertation.

Yang, X., and Lo, C.P. 2000. Relative radiometric normalization performance for change detection from multi-data satellite images. *Photogrammetric Engineering & Remote Sensing*. 66: 967-980.

Yang, X., and Lo, C.P. 2002. Using a time series of satellite imagery to detect land use and land cover changes in the Atlanta, Georgia metropolitan area. *International Journal of Remote Sensing.* 23(9): 1775–1798.

Yeates, M. 1998. *The North American City*. New York: HarperCollins.

Zeng, H., and Wu, X.B. 2005. Utilities of edge-based metrics for studying landscape fragmentation. *Computers, Environment and Urban Systems*. 29: 159-178.

Zha, Y., Gao, J., and Ni, S. 2003. Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. *International Journal of Remote Sensing*. 24(3): 583-594.

Zhang, Q., Wang, J., Gong, P., and Shi, P. 2003. Study of urban spatial patterns from SPOT panchromatic imagery using texture analysis. *International Journal of Remote Sensing*. 24(21): 4137-4160.

Zhu, J., Lahiri, S.N., and Cressie, N. 2002. Asymptotic inference for spatial CDFs over time. *Statistica Sinica*. 12: 843-861.

Zorbaugh, H.W. 1929 *The Gold Coast and the Slum: A Sociological Study of Chicago'e Near North Side*. Chicago: University of Chicago Press.