AN INTEGRATED GIS APPROACH TO URBAN ENVIRONMENTAL EQUITY ASSESSMENT

by

BYONG-WOON JUN

(Under the Direction of E. Lynn Usery)

ABSTRACT

In a research effort of improving the methodological basis in environmental equity research, this dissertation explored the integrated use of geographic information systems (GIS) and remote sensing for an urban environmental equity study in the Atlanta, Georgia, metropolitan area. The GIS were used to integrate, analyze, and visualize hazard-related, socioeconomic, and environmental data, and to assist in satellite image processing. Satellite remote sensing was employed to extract environmental data such as land use and cover, normalized difference vegetation index (NDVI), and surface temperature for the study area and to facilitate dasymetric representation of population, which was used to estimate the population at risk through intelligent areal interpolation. Three hypotheses were tested: 1) environmental equity analysis is sensitive to different spatial measures; 2) environmental risks in the Atlanta metropolitan area are disproportionately distributed among disadvantaged social groups in 1990 and 2000; and 3) quality of life assessment can complement environmental equity analysis in a metropolitan area. The results of environmental equity assessment were sensitive to the buffer distance used to determine the impact zones of toxic release inventory (TRI) facilities and the areal interpolation method used to estimate the population at risk, but not to the geographic scale and resolution used in the analyses. It is suggested that careful selection and justification of spatial measures are necessary. TRI facilities were inequitably distributed among people below poverty level and minority populations in metropolitan Atlanta in 1990 and 2000. Poverty was a relatively significant factor in explaining the relationship between distance to TRI facilities and socioeconomic characteristics in the metropolitan area in 1990 and 2000. The hot spots in the environmental inequities within the metropolitan area tended to be spatially clustered around a portion of the southern central city of Atlanta, midtown, and traditional centers of industry and population in 1990 and in 2000. These hot spots tended to move into the suburbs from 1990 to 2000. Spatially, the environmental inequity was significantly negatively correlated with the quality of life in the metropolitan area in 2000. This implies that quality of life assessment provides a more comprehensive perspective for examining urban environmental equity issues.

INDEX WORDS: Integrated GIS, Remote Sensing, Spatial Analysis and Modeling, Data Integration, Environmental Equity and Justice, Population Estimation, Areal Interpolation, Urban Quality of Life, Atlanta

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DEDICATION

This dissertation is dedicated to the memory of my parents who passed away during my study in Athens, Georgia.

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CHAPTER 1

INTRODUCTION

1.1 Research Background

The negative by-products of rapid technological and industrial development are environmental or technological hazards[1], such as pollution from toxic releases of industrial facilities, spills from transportation of hazardous materials, and contamination in landfills by hazardous wastes (Liverman, 1986; Cutter, 1993). These environmental hazards have impacts on people and places, and a community's vulnerability to these hazards is conceptualized as a function of human settlement pattern, demographics, and physical characteristics of the hazards (Cutter, 1996; Finco and Hepner, 1999). Liverman (1986) noted that urban areas are likely to be more vulnerable to these hazards where industries, transportation networks, and people are intermingled.

Research on the spatial distribution and impact of environmental risks and hazards has attracted the attention of geographers during the past three decades[2], but more recently this research has focused increasingly on the issue of environmental justice and equity, which has received considerable public scrutiny (Bowen *et al.*, 1995; Jerrett *et al.*, 2001; Margai, 2001; Maantay, 2002). Specifically, a number of empirical studies focusing on hazardous waste sites and toxic release facilities have investigated the relationship between socioeconomic

[1] Hereafter, the two terms will be used interchangeably.
[2] Berry's (1977) work on the differential impacts of pollution risks in urban areas is one of the few early detailed studies conducted by geographers.

characteristics and patterns of environmental risks and hazards. Inspired by the rise of the environmental justice movement, a national movement of grassroots environmental coalitions to call for equal protection of all people from environmental harms (Liu, 2001), some studies have indicated that these hazards are unevenly distributed among places and have disproportionate impacts on certain populations, primarily minorities and low-income communities (Bullard, 1983; US General Accounting Office, 1983; United Church of Christ Commission for Racial Justice, 1987; Bullard, 1990; Bryant and Mohai, 1992; Burke, 1993; Perlin *et al.*, 1995; Morello-Frosch *et al.*, 2001).

The call from the environmental justice movement and evidence from some of these studies have led to the formulation and implementation of environmental justice policies and strategies at the national level. A fundamental environmental justice policy was established through an executive order issued by President Clinton in 1994 that requires all federal agencies to adopt the principle of environmental justice in any program, policies, and activities. The U.S. Environmental Protection Agency (EPA) has also instituted a special office to oversee environmental justice issues at the national and state levels. The importance of environmental justice analysis and research has been embedded in several areas such as an intensified environmental justice movement, elevated public concerns, public policy actions, and research efforts over the past decade.

While environmental justice policies are formulated at the national and state levels, the debate on environmental justice[3] continues among different researchers and stakeholders (Been, 1994; Cutter, 1995; Anderton, 1996; Tiefenbacher and Hagelman, 1999). One of the primary

[3] Sheppard *et al.* (1999, p. 18) indicated that the environmental justice debate connotes “a national debate about the extent to which poor and communities of color are disproportionately exposed to environmental risks and hazards, about reasons for this, and possible remedial measures.”

reasons for its continuation is contrasting empirical evidence that either substantiates or refutes the existence of environmental inequity (Chakraborty and Armstrong, 1997a; Tiefenbacher and Hagelman, 1999). Though numerous studies to date have examined whether environmental hazards are distributed differently across racial and socioeconomic groups, conclusive and irrefutable evidence regarding the existence of inequity in the distribution of environmental hazards is absent in the existing literature due to methodological inconsistencies (Cutter, 1995; Perlin *et al.*, 1995). Specific methodological issues in environmental justice research have been noted in major areas relating to data and measurement, scale and resolution, and methods of analysis (Cutter, 1995; Perlin *et al.*, 1995; McMaster *et al.*, 1997; Sheppard *et al.*, 1999; Liu, 2001; Margai, 2001; Maantay, 2002). There has still been little consensus on how such an analysis should be made to obtain consistent and replicate results.

Empirical research on environmental justice has focused increasingly on geographic patterns and historical processes in urban areas. During the past decade, researchers have examined many cities such as Boston, Cleveland, Des Moines, Houston, Los Angeles, Minneapolis, Portland (Oregon), San Jose, St. Louis, and Tampa Bay (Holified, 2001), but a case study in the Atlanta metropolitan area, a rapidly suburbanizing and racially segregated urban area, remains lacking. Liu (2001) suggested that for environmental justice analysis in a metropolitan area, it appears to be more appropriate to assess quality of life by incorporating major environmental risks and amenities since environmental hazards affect human health and quality of life. This opens new possibilities for environmental justice research and provides a comprehensive perspective for examining environmental justice issues.

Geographic information systems (GIS) have been used to make valuable contributions to the understanding and solution of key socioeconomic and environmental problems such as facility management, public policy, natural resource management, and land cadastre (Maguire *et al.*, 1991). During the past decade, GIS have also been applied to the assessment of environmental risk generally and environmental equity specifically. Rejeski (1993) indicated that GIS help the risk analysis process move from its traditional focus on site-specific problems to a true macro-scale planning and policy tool so that GIS have the potential in regionalizing the risk analysis process. By allowing for data integration, spatial analysis and modeling, and visualization, GIS also provide great opportunity for environmental equity analysis (McMaster *et al.*, 1997). The recent development of remote sensing technology has provided invaluable biophysical data to be analyzed with GIS based socioeconomic data for environmental applications (Martin and Bracken, 1993; Wilkinson, 1996; Mesev, 2003). There exists much need for the integrated use of remotely sensed data and GIS data for environmental equity analysis. This opens up the potential for new forms of analysis.

The overall purpose of this dissertation is to improve the methodological basis of research on environmental equity. Specifically, this study explores the use of integrated GIS and remote sensing technologies and methodological issues in the assessment of urban environmental equity.

1.2 Research Objectives

The disproportionate burden of poor and minority communities with regard to environmental risks and hazards has been noted in many studies over the past two decades in the social sciences. In the context of examining the findings, the terms *environmental equity*, *environmental justice*, or *environmental racism* are commonly used. Environmental equity refers to an equal sharing of risk burdens, but not necessarily a reduction in the total burden of environmental degradation that has been criticized by environmental activists (Lavelle, 1994). Environmental justice is a more politically charged term that implies some remedial action to correct an injustice imposed on a specific group of people (Cutter, 1995) and should achieve adequate protection from harmful hazardous agents for everyone (Perlin *et al.*, 1995 and Harner *et al.*, 2002). The terms *environmental equity* and *environmental justice* are sometimes used synonymously (Brainard *et al.*, 2002). Environmental racism refers to the causes of perceived disproportionate environmental impacts on racial and ethnic minorities (McMaster *et al.*, 1997). In this dissertation, environmental equity analysis is used to examine the potential inequitable distribution of environmental risks and hazards with regard to the poor and minority populations.

The primary goal of this dissertation is to investigate the integrated use of GIS and remote sensing technologies for an urban environmental equity study. Specifically, this research attempts to develop an integrated GIS and remote sensing approach to delineate potential impact boundaries of toxic releases and to estimate population at risk, and then to examine the spatial and temporal relationships between the location of environmental hazards and the socioeconomic characteristics of the surrounding population in the Atlanta, Georgia, metropolitan area from 1990 to 2000.

The main hypothesis of this research is that the environmental risks and hazards in the Atlanta metropolitan area are disproportionately distributed among disadvantaged social groups such as the poor or minority populations. The secondary hypothesis is that environmental equity analysis is sensitive to different spatial measures. The third hypothesis is that quality of life assessment can be substituted for environmental equity analysis in a metropolitan area.

In this context, this research focuses on three research questions: (1) the methodological issues in environmental equity assessment, (2) the changing spatial patterns of environmental equity in the Atlanta metropolitan area, and (3) how quality of life relates to environmental inequity. To answer these questions, three research objectives are addressed as follows:

1) to explore alternative methods for identifying areas likely to be affected by toxic releases and estimating the socioeconomic characteristics of the population at risk;

2) to investigate the changing spatial patterns of environmental inequity; and

3) to assess quality of life in order to complement environmental equity analysis.

This dissertation contributes to the literature in four ways. By explicitly recognizing the advantages in using an integrated GIS and remote sensing approach to environmental equity assessment, this research makes a first contribution to the literature. This study will demonstrate a methodology for integrating GIS and remote sensing with spatial analysis and modeling to study the changing spatial patterns of environmental inequity in an urban environmental context. This attempt will make an improvement upon the method of estimating populations at risk.

The second contribution relates to the articulation of theoretical implications. Exploring the relationship between urban quality of life and environmental inequity, which has not been thoroughly studied, will add a new dimension to environmental equity research.

The third contribution of this study is general recommendations for public policy by making suggestions concerning residential and industrial planning. These may help reduce the human consequences of environmental risks and hazards and contribute to the formulation of equitable public policies. These also can help planners and decision-makers to be aware of any problem areas in the allocation of human services.

The fourth contribution of this study is that this research further extends our empirical understanding of the environment inequity in a different urban setting. A case study in the Atlanta metropolitan area provides a new insight into environmental equity study in a rapidly suburbanizing and racially segregated urban area.

1.3 Dissertation Structure

This dissertation is organized into eight chapters. Chapter One introduces the general research background and specifies the research objectives and significance. Chapter Two reviews the literature pertinent to this study on the integrated approach of GIS, remote sensing, spatial analysis and modeling for environmental equity studies. Chapter Three gives an introduction to the study area, the Atlanta metropolitan area, where the area’s geographic, demographic, and industrial settings are delineated. Chapter Four focuses on the methodology used to implement this research. Chapter Five explores the sensitivity of environmental equity analysis to different methods in impact area determination and population estimation. Chapter Six investigates the changing spatial relationship between the location of environmental hazards and the socioeconomic characteristics of the surrounding populations in the Atlanta metropolitan area from 1990 to 2000. Chapter Seven assesses urban quality of life to complement the environmental equity analysis and discusses the relationship between quality of life and environmental inequity in an urban setting. A summary and conclusions of the study are included in Chapter Eight. In this chapter, theoretical, methodological, policy, and application implications will also be discussed.

CHAPTER 2

LITERATURE REVIEW: INTEGRATED GIS APPROACH FOR ENVIRONMENTAL EQUITY STUDIES

2.1 Introduction

This research draws from two sources of academic work, environmental equity research and geographic information science. This chapter reviews the literature on the nature and scope of environmental equity research, GIS and environmental equity analysis, methodological issues in GIS-based environmental equity analysis, and integration of GIS and remotely sensed data. In the last section, trends in the literature are summarized.

2.2 The Nature and Scope of Environmental Equity Research

A growing research literature during the last two decades has explored the issue related to environmental equity analyzing the disproportionate distribution of environmental risks and hazards on people and places (Cutter, 1995; McMaster *et al.*, 1997; Maantay, 2002). The existing literature on environmental equity reveals two major areas of inquiry. One line of research examines the spatial association between the locations of environmental hazards and the racial and economic status of surrounding populations. This research area is referred to as outcome equity (Cutter, 1995). Two different types of sources of environmental hazards are generally used in the research. The first source is chronic hazards that are long-term, routine, polluting events that have gradual public health impacts on a given community. Emissions from fixed facilities such as toxic release inventory (TRI) facilities or toxic storage and disposal facilities (TSDFs) are good examples of chronic hazards. The second source is acute hazards that are short-term, nonroutine, accidental releases of hazardous materials that have immediate public health consequences for the affected population. Most studies have been conducted to either confirm or refute the existence of inequities based on chronic hazards such as toxic release facilities and hazardous waste sites (specifically, TRI facilities, TSDFs, and Superfund sites). In particular, the environmental justice movement and several studies have provided empirical evidence for the presence of inequities in low-income and minority communities (Berry, 1977; Bullard, 1983; US General Accounting Office, 1983; United Church of Christ, 1987; Bullard, 1990; Bryant and Mohai, 1992; Burke, 1993; Perlin *et al.*, 1995; Polluck and Vittas, 1995; Yandle and Burton, 1996). On the other hand, a relatively small number of studies has examined the existence of inequities with regard to acute hazards (Glickman, 1994; Cutter and Solecki, 1996; Charkraborty and Armstrong, 1996; Tiefenbacher and Hagelman, 1999; Chakraborty, 2001; Margai, 2001) since such accidental releases are random and uncontrollable in nature and may be explained by the notion of unpatterned inequity (Margai, 2001).

Although some studies have focused on the national and state levels, the majority of the research on environmental equity has been confined to urban areas because urban areas tend to be more vulnerable to environmental risks and hazards as indicated earlier by Liverman (1986) and most hazardous facilities are located near large population centers (Cutter and Tiefenbacher, 1991; Stockwell *et al.*, 1993). To date, researchers have examined a range of metropolitan studies such as a comparison of 13 U.S. metropolitan areas (Berry, 1977), Houston (Bullard, 1983), Detroit (Mohai and Bryant, 1992b), Los Angeles (Burke, 1993), Baton Rouge (Adeola, 1994), Pittsburgh (Glickman, 1994), Cleveland (Bowen *et al.*, 1995), Des Moines (Chakraborty and Armstrong, 1997), Minneapolis (McMaster *et al.*, 1997), and Baltimore (Boon, 2002).

Another line of research investigates the causal mechanisms that give rise to environmental inequity. This research area is referred to as process equity (Cutter, 1995). The research identifies four major factors that lead to the inequitable distribution of environmental hazards. The first group of researchers has argued that environmental hazards are disproportionately located in low-income and minority communities because of discriminatory siting practices, primarily based on racism (United Church of Christ, 1987; Bullard, 1990; Been, 1994; Liu, 1997). The second group of researchers has suggested that environmental inequity is the result of mutually conditioning forces of urbanization, industrialization, proximity to transportation networks, and population dynamics of the host communities (Bowen *et al.*, 1995; Cutter and Solecki, 1996; Chakrabory, 1999). Oakes *et al.* (1996) found that environmental inequities arise from the changes in the industrial structure of cities coupled with demographic changes within the communities after siting TSDFs. The third group of researchers has attributed the historical evolution of environmental inequities to institutional controls, gentrification processes, and public housing siting decisions (Liu, 1997; Cutter *et al.*, 2001). The fourth group of researchers has revealed that environmental inequity was compounded by the simultaneous evolution of racialized division of labor, class formation, and the deliberate and intentional practices of city planners (Pulido *et al.*, 1996; Pulido, 2000).

In addition, research into environmental equity addresses different dimensions of environmental equity and its determinants (Harner *et al.*, 2002). From the procedural equity perspectives, Bullard (1996) investigated such issues as unequal enforcement of environmental laws, exclusionary decision-making processes, and discriminatory zoning. Recently, research on environmental equity has also extended the analysis to certain other environmentally sensitive issues such as unwanted land uses (Liu, 1997), transportation system changes (Chakraborty *et al.*, 1999; Liu, 2001), urban sprawl (Liu, 2001), and even outdoor recreation sites (Tarrant and Cordell, 1999).

Research into outcome equity based on chronic hazards such as TRI sites in urban areas has been predominant in the literature over the past decade because of data availability and research feasibility. However, they have shown an ambiguity in results due to several methodological problems. Recently, GIS have shown the potential for the application in environmental equity analysis to complement traditional statistical analysis and improve analytical methods. This will be discussed in a later section.

2.3 GIS and Environmental Equity Analysis

Since their initial use for land and resource inventory in the early 1960s, GIS have been used to solve a variety of geographic problems ranging from socioeconomic to environmental problems during the last four decades (Longley *et al.*, 2001). In recent years, GIS have been used extensively for the assessment of environmental risk and equity (McMaster *et al.*, 1997; Nyerges *et al.*, 1997). The GIS exhibit the potential to enhance methods and to perform alternative technical approaches for environmental equity analysis. Specifically, GIS technology has provided four major capabilities for environmental equity analysis. First, GIS allow for the integration of different data sources such as data on locations of environmental hazards and population characteristics (McMaster *et al.*, 1997; Nyerges *et al.*, 1997; Sheppard *et al.*, 1999). For example, environmental hazards data such as TRI sites and hazardous waste facilities can be combined with socioeconomic data such as race, income, and age in a GIS environment through georeferencing such as coordinate transformation and reprojection. Second, GIS provide spatial analytical techniques such as buffering, overlay, distance-decay and neighborhood functions for proximity-based measurements at different spatial scales (Glickman, 1994; Pollock and Vittas, 1995; Chakraborty and Armstrong, 1997; Sheppard *et al.*, 1999; Cutter *et al.*, 2001). For example, a circular buffer from a fixed hazardous facility can be generated to delineate potential impact boundaries and overlaid with census units to estimate populations at risk. Third, GIS help the integration of spatial models such as plume dispersion models to accurately predict the environmental impact areas of potential exposure (Chakraborty and Armstrong, 1996; Finco and Hepner, 1999; Loibl and Orthofer, 2001). Fourth, GIS facilitate representing various data and analytical results in map form (McMaster *et al.*, 1997; Hodgson *et al.*, 2001; Maantay, 2002).

With the capabilities of GIS technology, a number of studies since the early 1990s have attempted to assess environmental equity, mostly utilizing data from toxic and hazardous waste facilities (McMaster *et al.*, 1997). Some GIS-based studies have provided empirical supports for the existence of environmental inequity across low-income and minority communities, but others have not. There have still been contradictory results in these and others studies. Their major focuses have been on methodological issues related to data and measurement (Chakraborty and Armstrong, 1997; McMaster *et al.*, 1997; Perlin *et al.*, 1999; Margai, 2001; Cutter *et al.*, 2002; Maantay, 2002), scale and resolution (Burke, 1993; Bowen *et al.*, 1995; Glickman *et al.*, 1995; Sui and Giardino, 1995; Cutter *et al.*, 1996; McMaster *et al.*, 1997; Underwood and Macey, 1998; Maantay, 2002), and methods of analysis (Burke, 1993; McMaster *et al.*, 1997; Sheppard *et al.*, 1999; Underwood and Macey, 1998; Liu, 2001; Maantay, 2002) rather than applications themselves.

In addition to methodological issues, GIS-based environmental equity studies address the importance of spatial accuracy of point-based environmental databases and standardized environmental justice indices. Scott *et al.* (1997) investigated the spatial accuracy of the U.S. EPA’s environmental hazards database and demonstrated the importance for accurate locations in environmental equity research. Surprisingly, they found that more than 50% of the facilities in South Carolina were initially located in the wrong census block groups. After the corrections, they observed there were significant differences in demographic characteristics around hazardous facilities. Harner *et al.* (2002) developed standardized environmental justice indices using GIS to make initial comparisons between cities. They identified comparative environmental risk index (CERI) as the best standardized environmental justice indicator.

Although the enthusiasm about the use of GIS in environmental equity assessment is high within the GIS research community, little consensus has been reached on how such an analysis should be made to gain consistent and replicable results. More details about these methodological issues will be discussed in the next section.

2.4 Methodological Issues in GIS-based Environmental Equity Analysis

Despite methodological inconsistencies that have caused contrasting results in environmental equity studies, the common GIS-based approach to environmental equity analysis is generally based on two major stages such as impact boundary delineation and population estimation and comparison. The first stage is to determine the geographic boundaries of areas potentially affected by environmental hazards. The second stage is to estimate and compare the characteristics of the population within impacted areas with the characteristics of the population in no impacted areas.

Several different techniques have been used in previous studies to define the spatial extent of the area potentially affected by environmental hazards. Most conventional statistical approaches to environmental equity use predefined administrative boundaries or census enumeration units (e.g. census tracts or block groups, zip codes) to represent impacted zones because data are readily available in these forms from U.S. Census Bureau (Glickman, 1995). For example, if a census enumeration unit hosts environmentally hazardous facilities, the enumeration unit is identified as an impacted zone. A major problem associated with this spatial coincidence approach is that the use of existence of a site as a surrogate for risk is problematic and edge effects are not taken into account (McMaster *et al.*, 1997; Chakraborty, 2001). For example, a person in an adjacent census tract that does not host any facilities may live closer to the hazard than another person in a census tract containing a hazardous facility. In spite of its ease with statistical comparisons, this spatial coincidence approach is based on the flimsy assumption that environmental risks and hazards are confined to the boundary of the enumeration unit hosting a facility.

With the emerging GIS technology, some researchers (Glickman, 1994; Zimmerman, 1994) suggested that GIS could represent more effectively the shape and size of the area affected by a hazardous facility through constructing a circular buffer of a specified radius centered at each hazardous site. Several recent studies have used GIS-based buffers around hazardous facilities to determine impacted areas (Glickman, 1994; Sui and Giardino, 1995; Chakraborty and Armstrong, 1997; McMaster *et al.*, 1997; Newmann *et al.*, 1998; Perlin *et al.*, 1999; Sheppard *et al.*, 1999). Although a circular buffer provides a more realistic delineation of the area potentially affected by environmental hazards, there are two limitations associated with its application in environmental equity analysis. First, the radius of the circle is often chosen arbitrarily (Chakraborty and Armstrong, 1997). Second, the construction of buffers around all facilities in a study area does not reflect the quantity or toxicity of the chemicals stored at each site (Chakraborty and Armstrong, 1997).

An alternative approach, known as geographic plume analysis (Chakraborty and Armstrong, 1995 and 1997; Glickman *et al.*, 1995), overcomes some of these limitations by using a chemical dispersion model in conjunction with a GIS database to identify the areas at risk. Three different models such as areal locations of hazardous atmospheres (ALOHA), industrial source complex long-term (ISCLT2), and COMPLEX1 were used as tools for estimating the movement and dispersion of gases in environmental equity analysis (Chakraborty and Armstrong, 1995 and 1997; Glickman *et* *al.*, 1995; Margai, 2001). This geographic plume analysis can account for the direction and the nature of distance decay of the diffusion of toxic chemicals released in the atmosphere. However, such models require an actual chemical release and entail simplifying assumptions (about average wind direction and topography in an area), which can lead to erroneous results (Sheppard *et al.*, 1999; Liu, 2001). These models are also much more time consuming to implement and more data-intensive than the circular buffer approach.

Most recently, advanced proximity analysis, known as the proximal exposure model, was used to improve the assessment of impacted areas based on a circular buffer or plumes (Cutter *et al.*, 2001). The proximal exposure model is based on a continuous functional distance from existing hazard sources to create risk surfaces and allows for considering the cumulative effect of multiple sources of risks with multiple hazards compared to other studies that modeled the wind-borne dispersal of a single hazard. This model is also more time-effective to implement than the geographic plume analysis. However, this model adopts a simplifying assumption that exposure does not vary with direction as a result of topography and dominant wind patterns. Another limitation of this model is that the selection of a threshold distance is subjective and the selection of a distance decay function is debatable.

The characteristics of the population at risk are typically estimated by overlaying the boundary of each impacted zone with the boundaries of census enumeration units that contain population characteristics. The analytical capabilities of GIS are used to extract data from these units. Since the census provides arbitrarily aggregated information, most environmental equity studies estimate the composition of the population at risk on the basis of predefined geographic units (e.g., census tracts or block groups) for which such data are available. However, there is a major problem associated with the use of aggregated census data for assessing risk exposure. Except for the use of census enumeration units to determine the areas at risk, the shape and size of an impacted zone (e.g., a circle or plume) usually does not coincide with underlying census enumeration units (e.g., census tracts or block groups). There are several methods for computing the composition of the population within an impacted buffer zone, namely polygon containment, centroid containment, and buffer containment as shown in Figure 2.1 (Chakraborty and Armstrong, 1997). The simplest method is polygon containment, which includes all census units that are adjacent to the buffer. The second method is centroid containment, which utilizes the idea of a point-in-polygon GIS operation. If a polygon has its centroid inside the buffer, it is included. The third method is buffer containment, which keeps the actual shape of the buffer and includes the population of census units that are contained completely within the buffer as well as the proportion of the population that is contained with the buffer for census units that are intersected by it. Since the polygon and centroid containment methods ignore edge effects described earlier in this section, the buffer containment method is more realistic. When the buffer containment method is used, areal interpolation (Goodchild and Lam, 1980; Goodchild *et al.*, 1993) techniques must be applied to transfer information from census units (source zone) to the areas at risk (target zone) as shown in Figure 2.2.

There are three major groups of areal interpolation methods, cartographic (simple areal weighting and intelligent areal weighting), regression, and surface methods as classified by Fisher and Langford (1995), which are useful to estimate the populations at risk. The simple areal weighting method, one of the cartographic methods, is achieved with two steps. The first step is to overlay the buffer units on the census enumeration units and determine the areas of intersection. In the second step, the populations of the buffer units are derived from the sum of the component portions of the census enumeration unit population. This method has been commonly used for estimating populations within buffer zones in the previous studies on environmental equity

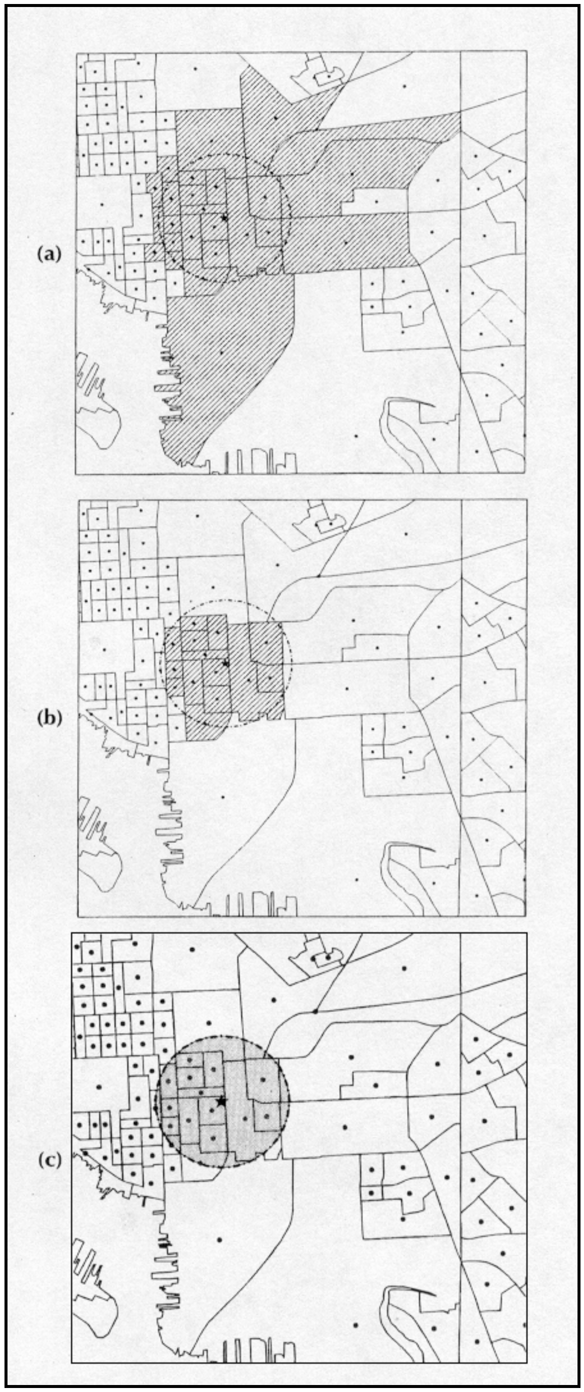


Figure 2.1 Methods for measuring demographic characteristics within a given proximity of a hazardous facility: (a) polygon containment, (b) centroid containment, (c) buffer containment (after Liu, 2001).

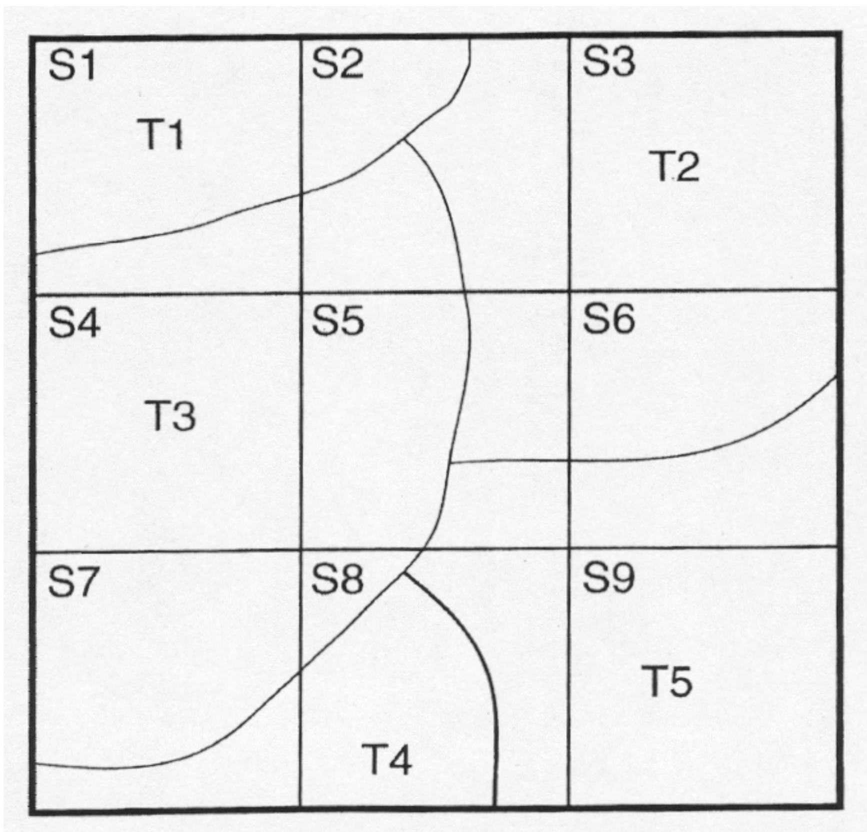


Figure 2.2 Source zones (S1 to S9) and target zones (T1 to T5) in areal interpolation (after Eicher, 1999).

assessment because it is simple to implement and the functionality it requires is present in almost every GIS. A key limitation of this approach is that this technique is based on the unrealistic assumption that population is distributed uniformly within each census enumeration unit.

An alternative cartographic method, known as intelligent areal interpolation (Langford *et al.*, 1991), overcomes this fundamental flaw by using ancillary data such as the distribution of land cover types in an integrated GIS framework to estimate the population at risk. This method is based on the principle of dasymetric mapping originally developed by Wright (1936), which uses knowledge of the locality to identify areas within buffer zones that have different population densities and allows refinement of the assumption of an even distribution. While improving the accuracy of population distribution, this method suffers from a weakness that the weighting scheme to assign population data to different classes of land cover within a census unit is subjectively determined.

Regression methods (Flowerdew and Green, 1989; Langford *et al.*, 1991; Goodchild *et al.*, 1993; Moxey and Allanson, 1994; Yuan *et al.*, 1997) as variants of intelligent areal interpolation are also suggested for overcoming the limitation in the simple areal weighting method. Based on the dasymetric mapping principle, these methods apply multivariate regression to examine the correlation between population counts from census and land cover types. A major limitation of these methods (especially for Langford *et al.*, 1991) is that the populations reported for target zones are not constrained to match the overall sum of the source units although some regression methods (Flowerdew and Green, 1989, Goodchild *et al.*, 1993) can handle the pycnophylactic property. Another limitation is that the selection of a regression method (ranging from linear regression to Poisson regression) is subjective.

A final group of methods, known as surface methods, has been proposed which are based on the mathematical assertion that population density should be viewed as a continuously varying probability distribution. The major step with these methods is to define the distribution surface and to use area-based statistics to approximate the surface. Once the distribution has been defined, integrating the volume under the surface gives one the population within any target zone. Tobler's (1979) smooth pycnophylactic interpolation and the methods developed by Martin (1989) and Bracken (1994) are examples of such methods. These methods create a dramatic visualization of the population density distribution, but it is not clear that they will give a good areal interpolation.

Recent GIS-based studies have indicated that the choice of the geographic scale of the study area (e.g., states, metropolitan areas, counties, municipalities) and the spatial resolution of data within that study area (e.g., zip codes, census tracts, block-groups) influence the results of the analysis (Bowen *et al.*, 1995; Sui and Giardino, 1995; Cutter *et al.*, 1996; McMaster *et al.*, 1997). This is frequently called the modifiable areal unit problem (MAUP) in geographic studies. Cutter *et al.* (1996) found in the case study of South Carolina that while some association between the location of toxic facilities and race and income exists at the county level, there is no such association at both the census tract and block group levels. Glickman (1994) revealed in his study on the Pittsburgh area that as the resolution was changed from block-groups to tracts to zip codes, the minority population became more important in explaining changes in the number of TRI sites, and per capita income and population density became less significant. Coarse spatial resolution data often do not allow for an accurate assessment of the different potential exposure of different subpopulations because of the heterogeneity of the population within these enumeration units. This problem can be addressed by using fine spatial resolution data, such as block groups and blocks, which are available in digital form since 1990.

In addition, other studies address the dependences of analytical results on the type of hazardous material information used, toxicity measures, and statistical methods. The paucity of a comprehensive hazards database is a major problem in environmental equity analysis. Many of the studies reported utilize only one hazards database to assess risk. McMaster *et al.* (1997) indicated that different sources of hazardous materials provide different results. Cutter *et al.* (2002) highlighted that the choice of the toxicity measure can alter (statistically and spatially) the results of environmental equity analyses and lead to erroneous conclusions. Greenberg (1993) illustrated that different statistics could lead to different findings about environmental equity because different statistics have different assumptions, advantages, and disadvantages. Furthermore, Sheppard *et al.* (1999) demonstrated the importance of a geographic randomization methodology for assessing the significance of results in environmental inequity studies.

2.5 Integration of GIS and Remotely Sensed Data

Since their introduction in the early 1960s, GIS have been seen as an important information technology both for the integration of data from different sources and techniques from different disciplines (Flowerdew, 1991; Shepherd, 1991; Martin, 1993; Burrough and McDonnell, 1998). The integration has been frequently made with remote sensing (RS), which provides large quantities of timely, accurate information relevant to aspects of environmental applications. According to Hinton (1996) and Wilkinson (1996), the integration between GIS and remote sensing can be mutually beneficial in one of three different ways: (1) remotely sensed data as an information source to GIS, (2) GIS as a tool for remotely sensed image processing, and (3) the combined use of GIS and remote sensing data for spatial analysis and modeling. Further, with special regard to the third view, Martin and Bracken (1993) also noted that such an integration provides researchers with the potential for the development of new database and increased analytical capabilities. In this context, the need for an integrated GIS approach for environmental equity studies is urgent because such an integration provides three major advantages: (1) remotely sensed data and census data can be integrated in a GIS framework for constructing detailed population models, (2) the integrated GIS approach is useful for integrating geographical data reported for different spatial units through intelligent areal interpolation, and (3) these benefits open up the potential for new forms of analysis in environmental equity studies.

Although the integrated use of remotely sensed data and GIS-based datasets has been explosively made for environmental applications such as land use and cover change detection and environmental degradation, the integration for socioeconomic applications such as urban planning, urban analysis, and urban growth detection has received relatively less attention, but has been rapidly developing in recent years (Martin and Bracken, 1993; Mesev, 2003). Several attempts have been made to integrate remotely sensed data with socioeconomic data or population related data in a GIS framework. The major emphases have been on three research areas: population estimation, quality of life assessment, and urban structure and function analysis. Some researchers have attempted to estimate urban population from high-resolution aerial photography (Lo, 1989) and remotely sensed imagery such as Landsat (Iisaka and Hegedus, 1982 (MSS); Langford *et al.*, 1991; Webster, 1996; Yuan *et al.*, 1997; Chen, 2002; Harvey, 2002a) and SPOT imagery (Lo, 1995; Webster, 1996). The attraction of these applications is that it should be possible to obtain a timely and accurate picture of the spatial distribution of population, and which is amenable to manipulation within GIS. These studies demonstrated that there is a degree of correlation between population or dwelling counts and various remote sensing indicators. Other researchers have assessed quality of life indicators in an urban environment by integrating biophysical variables (such as land use and cover, normalized difference vegetation index (NDVI), surface temperature) derived from Landsat TM imagery and socioeconomic variables (such as population density, per capita income, median home value, education level) extracted from census data (Weber and Hirsh, 1992; Lo, 1997; Lo and Faber, 1997). They found that satellite image data can complement census data by giving the environmental perspective in urban analysis. The third group of researchers has examined how the spatial information from classified remotely sensed images can be analyzed to reveal changes in the urban morphological structure based on urban density functions (Mesev *et al.*, 1996; Mesev, 1997; Mesev, 1999; Mesev, 2003). Particularly, these studies have demonstrated how urban measurements can be reliably and routinely extracted from a combination of satellite and socioeconomic data, and how these spatially extensive measurements are then analyzed for urban analysis.

Despite its benefits and recently growing applications, there have been various impediments for the closer integration between socioeconomic or population related data and remotely sensed data in a GIS environment because of dramatic differences in the intellectual traditions that produce and use the two kinds of data. The problems encountered in the integration are not only related to technical issues, but also to conceptual ones.

First, the raster-vector dichotomy is one of the technical impediments. This has been a long-standing problem in many GIS applications. Socioeconomic or population related data are represented as vector data structures in a GIS environment while remotely sensed data tend to be raster-oriented. Each of the methods of data representation has its advantages and disadvantages. Data conversion between raster and vector formats can introduce significant errors. Unlike many remotely sensed data such as land cover, zone-based population related data cannot be simply rasterized to provide meaningful map layers which are compatible with those derived from remote sensing. One possible solution to the dichotomy is to establish a mix of data structures such as the quad-tree data model (Burrough and McDonnell, 1998; Lo and Yeung, 2002). More recently, a feature-based or object-oriented GIS data model has been proposed to solve the problem of vector-raster dichotomy (Usery, 1996).

Second, another technical impediment is the problem of data uniformity (Ehlers *et al.*, 1989). Most socioeconomic or population related data are reliant on secondary datasets such as censuses and surveys. These data are clearly defined, collected and aggregated prior to input to the GIS. On the other hand, remotely sensed data, which contain a wealth of information about the environment, need to be interpreted before they can be used. Tracking errors of GIS-based socioeconomic data is difficult while remotely sensed data combine data collection and data processing together, and it is often easier to determine the errors. This lack of data uniformity made integration of GIS-based socioeconomic data and remotely sensed data difficult in the past. A new GIS data model as described above may be the solution for the integration.

Third, differences in areal units are a fundamental technical impediment (Martin and Bracken, 1993). Socioeconomic or population related data are aggregated to zonal systems such as census zones, postcodes, and administrative boundaries. The boundaries of census zones are arbitrarily imposed and do not relate to the underlying geography of the variable itself. On the other hand, remotely sensed data are disaggregated into pixels (e.g., 30 m for Landsat TM images). Therefore, pixels may be combined as necessary to produce a meaningful classification of land cover types, and to reconstruct such geographic entities as field or city. The boundaries created in this way are natural. Conceptually, two areal units are not compatible. One possible solution to the incompatibility in areal units involves aggregating pixel-based data to larger geographical units. However, this approach cannot reveal subunit variation in census data. In order to solve this problem, analogous approaches to satellite image classification might be used to unmix areally aggregated data (Mitchell *et al.*, 1998). A spatial micro-simulation model can be also used to spatially disaggregate spatially aggregate data within a spatial unit such as an urban district or a census tract (Spiekermann and Wegener, 2000).

Fourth, the decision on where to georeference individuals or other social units is an impediment to the integration (Liverman *et al.*, 1998). In some cases, a social unit has a natural object of georeference, but frequently this is not the case. Consider individuals, and assume that the substantive questions being examined involve the effect of individual behavior on some aspect of the land. To which pixel or pixels should the individual be linked? The question can be difficult to answer because people move although the land units represented by the pixels do not move. In order to overcome this obstacle, one can aggregate population data to larger geographic units.

Despite the difficulties outlined above, techniques are now available to facilitate the integrated use of socioeconomic data and remotely sensed data in a GIS environment. By integrating remotely sensed data and census data, detailed population models for use in an integrated GIS environment can be constructed and spur more socioeconomic applications.

2.6 Summary

Environmental equity analysis concerns the link between the spatial distribution of environmental hazards and the socioeconomic characteristics of population. The literature concerning environmental equity research reveals two major research areas: outcome and process equity. During the last two decades, much research has focused on outcome equity using chronic hazards such as TRI sites because of data availability and research feasibility. While empirical environmental equity research has focused increasingly on many urban areas such as Boston, Cleveland, Houston, Los Angeles, Minneapolis, Baltimore and the like, a case study of the Atlanta metropolitan area has been devoid in the literature, which is a rapidly suburbanizing and racially polarized urban area.

In spite of many studies applying GIS to the assessment of environmental equity, there is little consensus on how such an analysis should be performed to achieve consistent and replicable results. Many empirical studies concerning outcome equity have shown contrasting results in the existence of environmental inequity with respect to low-income and minority communities, which is mainly due to several methodological problems such as measurement of risk, estimation of populations at risk, and scale and resolution. The integrated use of socioeconomic and remotely sensed data in a GIS environment has the value to improve analytical methods in environmental equity studies. Further research remains to provide a more definitive solution of these methodological issues. This dissertation builds on the methodological critiques upon existing research to advance urban environmental equity studies.

CHAPTER 3

STUDY AREA: THE PARADOXICAL GEOGRAPHY OF METROPOLITAN ATLANTA

3.1 Introduction

The Atlanta, Georgia, metropolitan area is selected as the study area for this dissertation because of its biracial dichotomy between Whites and Blacks (Smith, 1985), one of the major manufacturing centers in the South (Hartshorn, 1997), water-quality issues related to urban development downstream of the upper Chattahoochee River, high acute airborne toxic release (Cutter and Solecki, 1996) and degenerated air quality, and high levels of urban inequality based on racial segregation (Smith, 1985; Sjoquist, 2000). The study area thus provides a unique urban setting for an environmental equity study. This chapter provides an overview of metropolitan Atlanta's geographic setting, socioeconomic, demographic, and industrial landscapes.

3.2 Geographic Setting

For this dissertation, the Atlanta metropolitan area is defined as the Atlanta region[1], which comprises ten counties (Cherokee, Clayton, Cobb, DeKalb, Douglas, Fayette, Fulton, Gwinnett, Henry, and Rockdale) and 64 cities in a twenty-county Metropolitan Statistical Area (MSA) defined by the Bureau of the Census's 1993 and 1999 June definition as is shown in Figures 3.1 and 3.2. The region has a total land area of approximately 7,825 km^2 (3,000 square

[1] The Atlanta region connotes the ten-county planning area of the Atlanta Regional Commission (ARC).

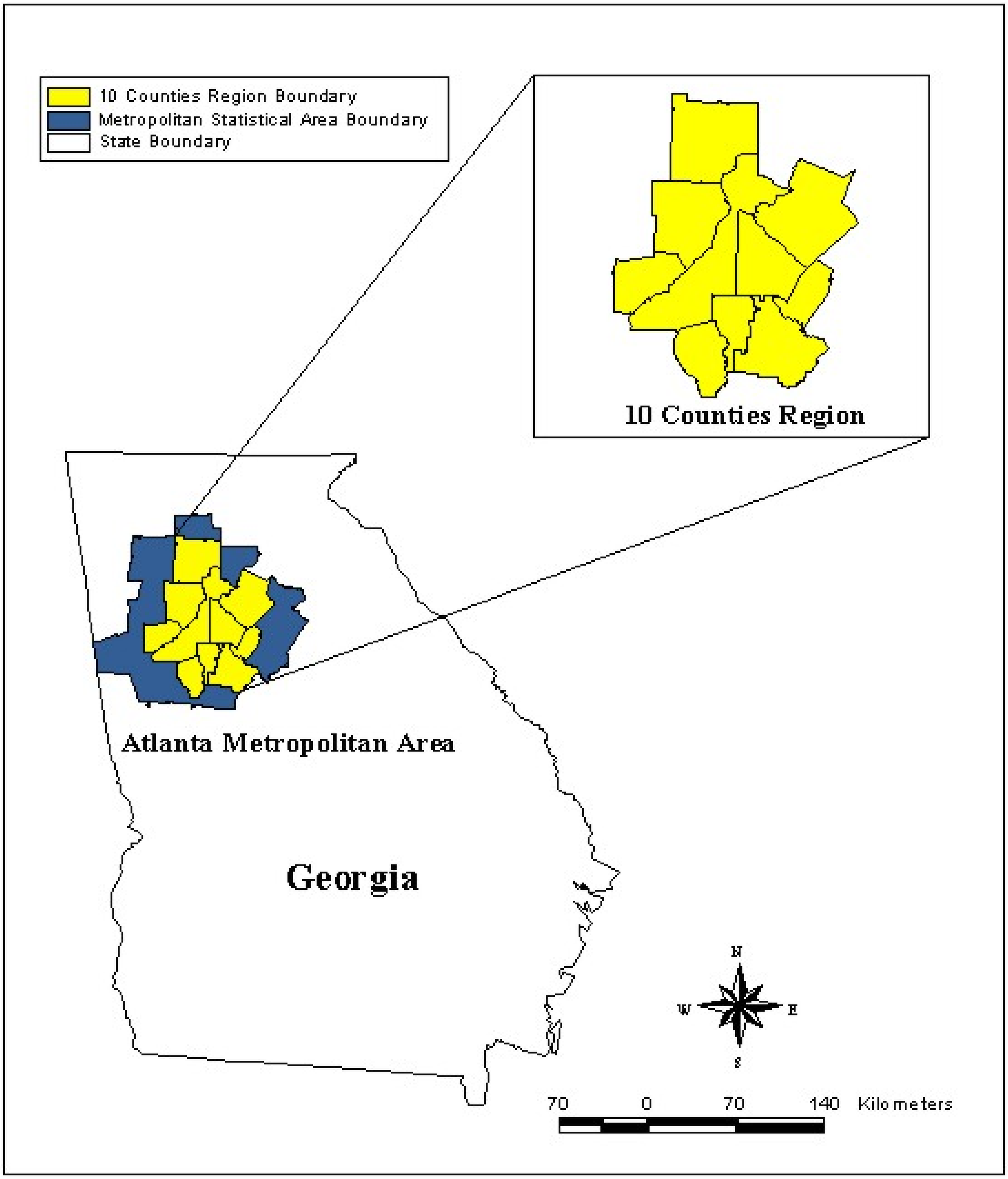


Figure 3.1 Location of the study area.

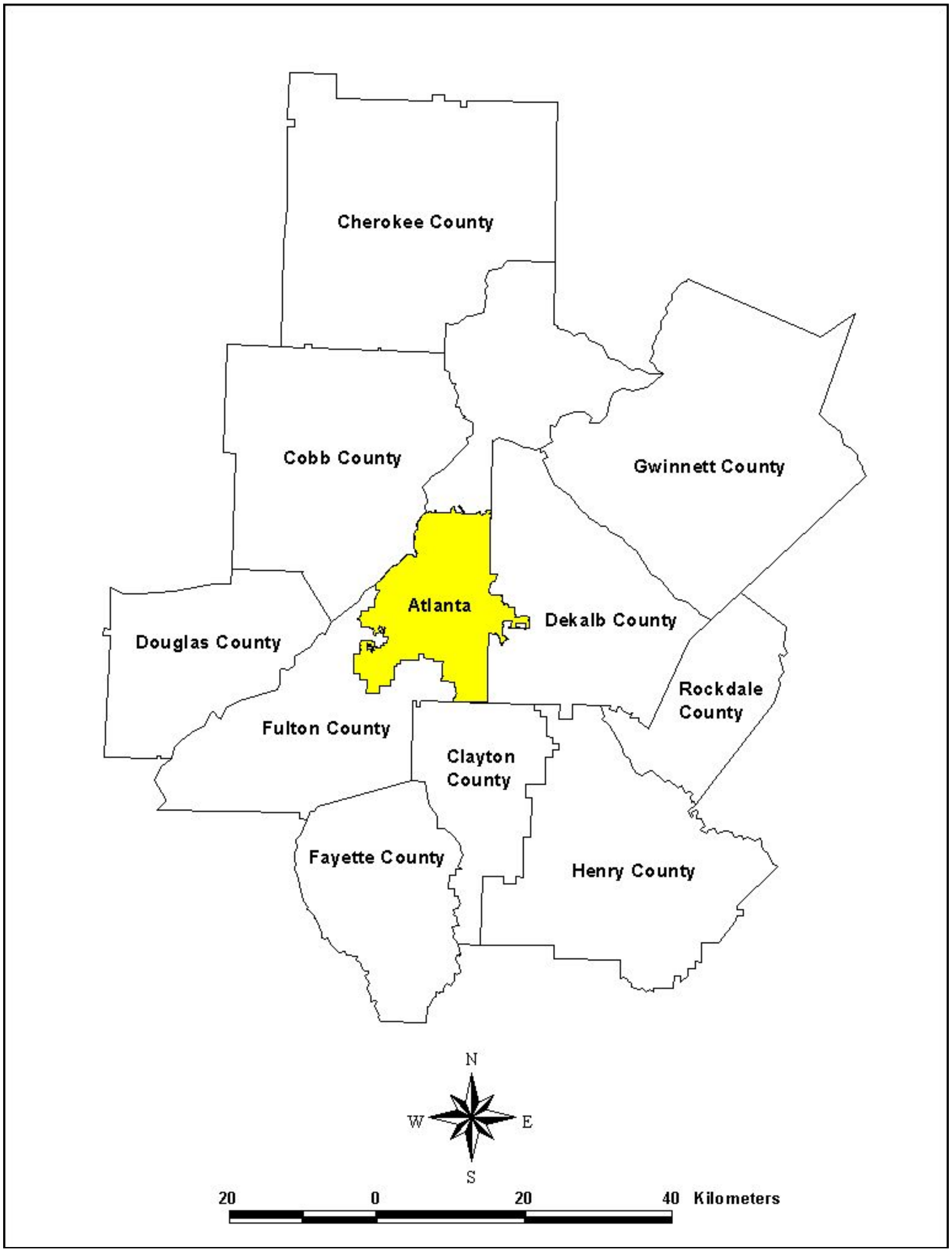


Figure 3.2 Atlanta city limits and 10 metro counties.

miles) and a total population of 3.4 million in 2000. The Atlanta metropolitan area is often known as the major trade, service, and transportation center for the southeastern United States. The city of Atlanta, which sits in the central part of a greater metropolitan area, lies across the county seat of the Fulton County and a small western portion of the Dekalb County.

The Atlanta metropolitan area spreads over the foothills of the Blue Ridge Mountains (Figure 3.3). The region's mean elevation is about 300 meters above sea level with the variation in local relief ranging from 30 to 100 meters. Atlanta is third in elevation to slightly higher Phoenix and mile-high Denver among major American cities. Its topography is rolling to hilly. The only major stream that runs through the metropolitan area is the Chattahoochee River from which Atlanta and many of its neighbors draw their municipal water supplies.

The region's elevation and southern location combine to make its climate quite mild. Its average annual rainfall is approximately 137 centimeters, which turns the rolling and wooded hills into a lush green from early spring to late fall. The region has a distinct change in seasons featuring moderate winters with rare snow and hot, humid summers with about 30 days over 92°F. Its average monthly temperatures remain consistent between about 47.0°F in the winter and 79.6°F in the summer. Its average relative humidity is around 70 percent.

3.3 Socioeconomic Landscape

For the past 30 years, Atlanta has been one of the fastest growing metropolitan areas in the nation[2]. In terms of population ranking, the Atlanta metropolitan area was the eleventh largest metropolitan area in the nation and the first one in the southeastern United States in 2000, having outpaced the Miami-Fort Lauderdale consolidated metropolitan area (CMSA) during the

[2] The Census of 2000 states that it is the second fastest growing metropolis in the nation between 1990 and 2000.

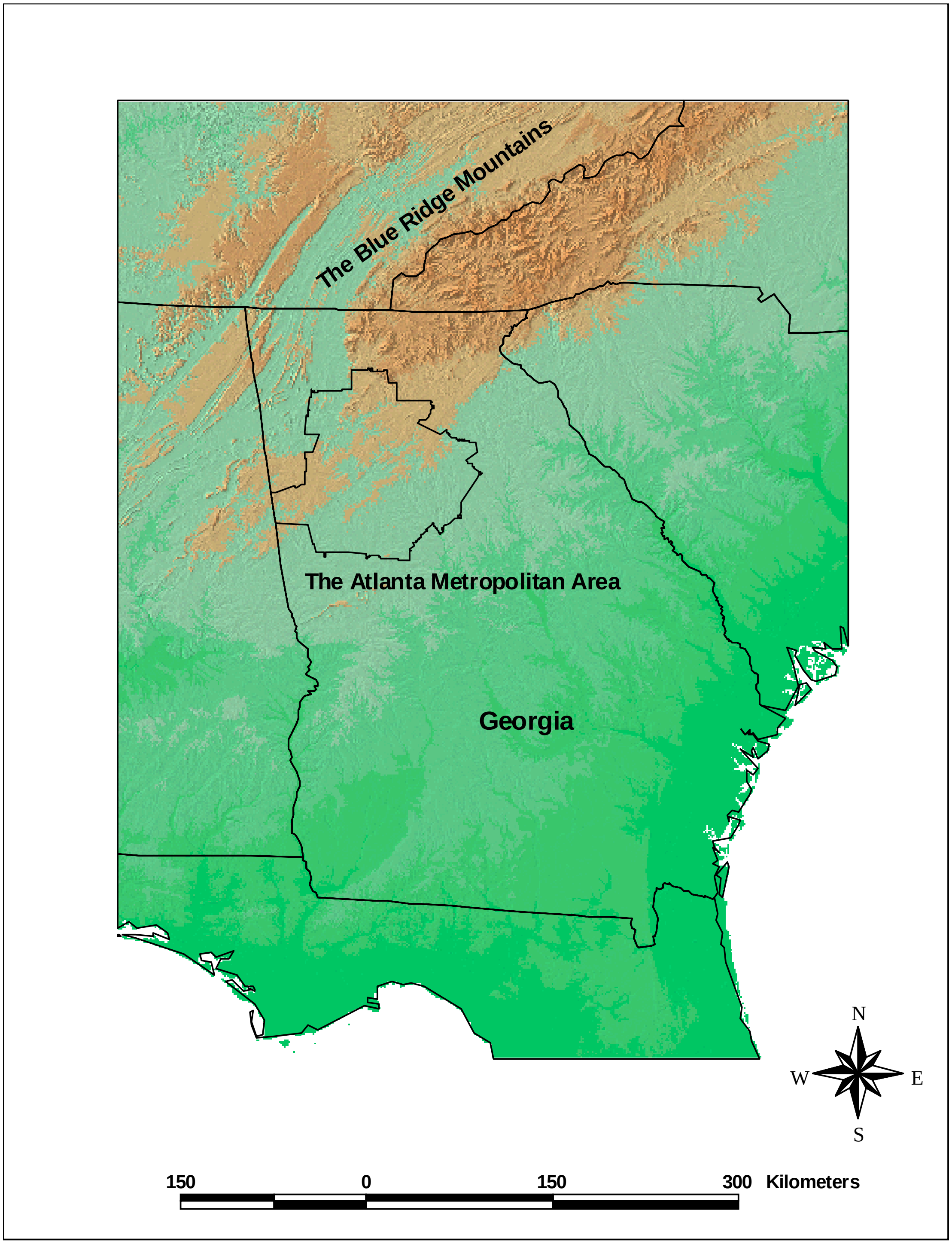


Figure 3.3 Topographic relief.

1990s. Atlanta's suburban counties, some of which are among the fastest growing in the United States, have helped to make the metropolitan area rank among the most populous in the country. Its population increased 27% between 1970 and 1980, 33% between 1980 and 1990, and 36.4% between 1990 and 2000. This high rate of population growth accompanied a substantial growth in retail, industrial, commercial, advanced services, and transportation services within the metropolitan area. The foundations of Atlanta's growth lie with rapidly expanding entrepreneurial and service jobs, as well as the expansion of high-technology industry, especially top-management office functions. The average employment growth rate of metropolitan Atlanta, especially in the service economy, is one of highest in the nation (Keating, 2001). The urbanization has pushed the peri-urban fringe farther and farther away from the original Atlanta urban core. The suburbanization trend of Atlanta in recent years suggests great expansion in the territorial extent of the city region.

Atlanta has always been a biracial city with significant White-Black segregation (Bayor, 1988; Hartshorn and Ihlanfeldt, 2000). Since the Civil War, Blacks have constituted at least one third of the city's population. As the region grew in the 20th century, the percentage of Blacks declined from 33% in 1900 to 26 % in 1990. At the same time, however, the percentage of Blacks within the city limits increased from 40% in 1900 to 67% in 1990 and to 61% in 2000. In other words, the metropolitan area has a high percentage of Blacks in the central city.

Figures 3.4 and 3.5 provide an indication of both the distribution of the population and the racial mix within each census block group in the Atlanta metropolitan area. The pattern is striking. The southern part of the city of Atlanta and south Dekalb County are predominantly Black. From south of Atlanta to East Point, College Park, Decatur, and south of Dekalb County, Blacks are clearly the predominant group both in 1990 and 2000. There are a few neighborhoods, such as

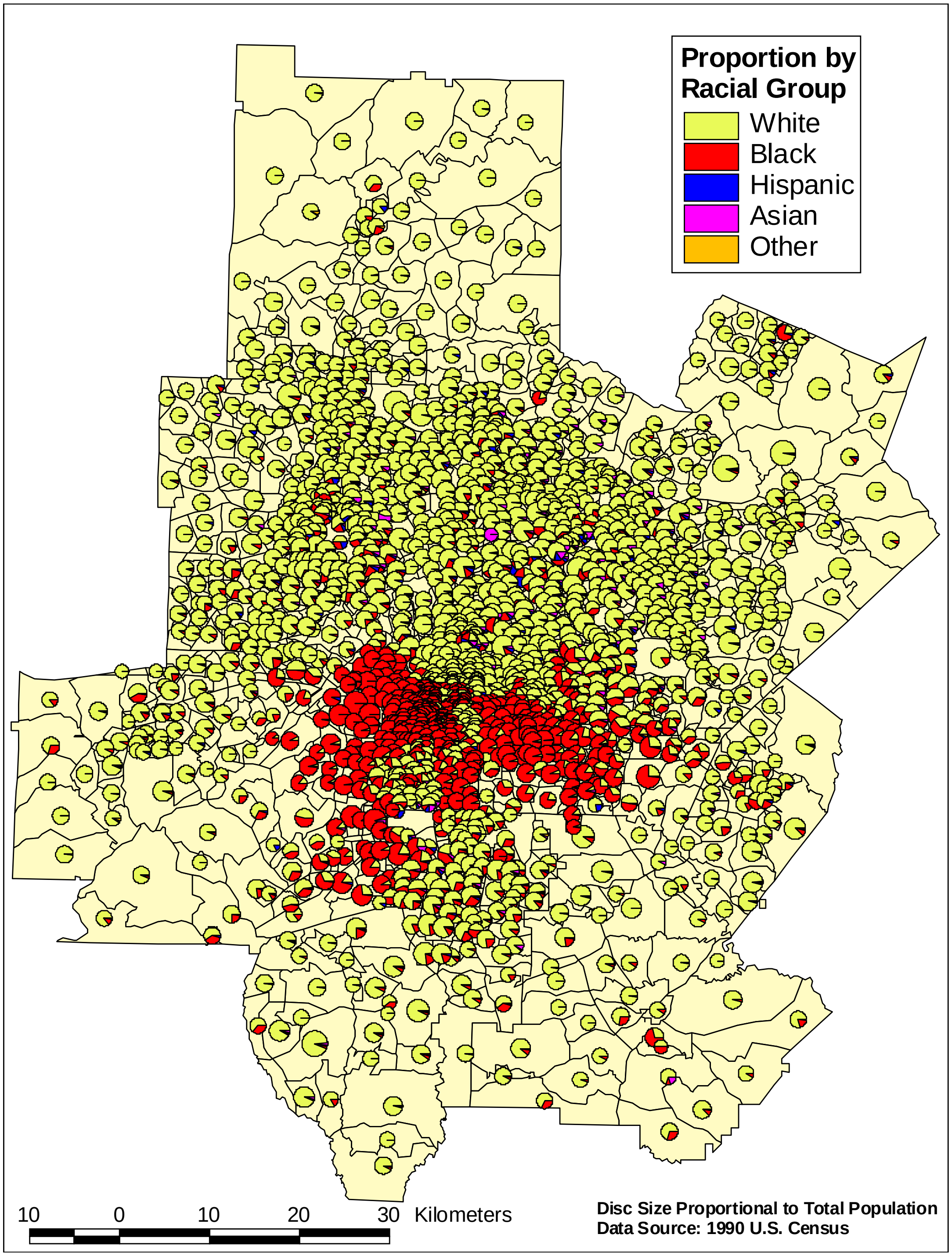


Figure 3.4 Racial and ethnic population patterns in 1990.

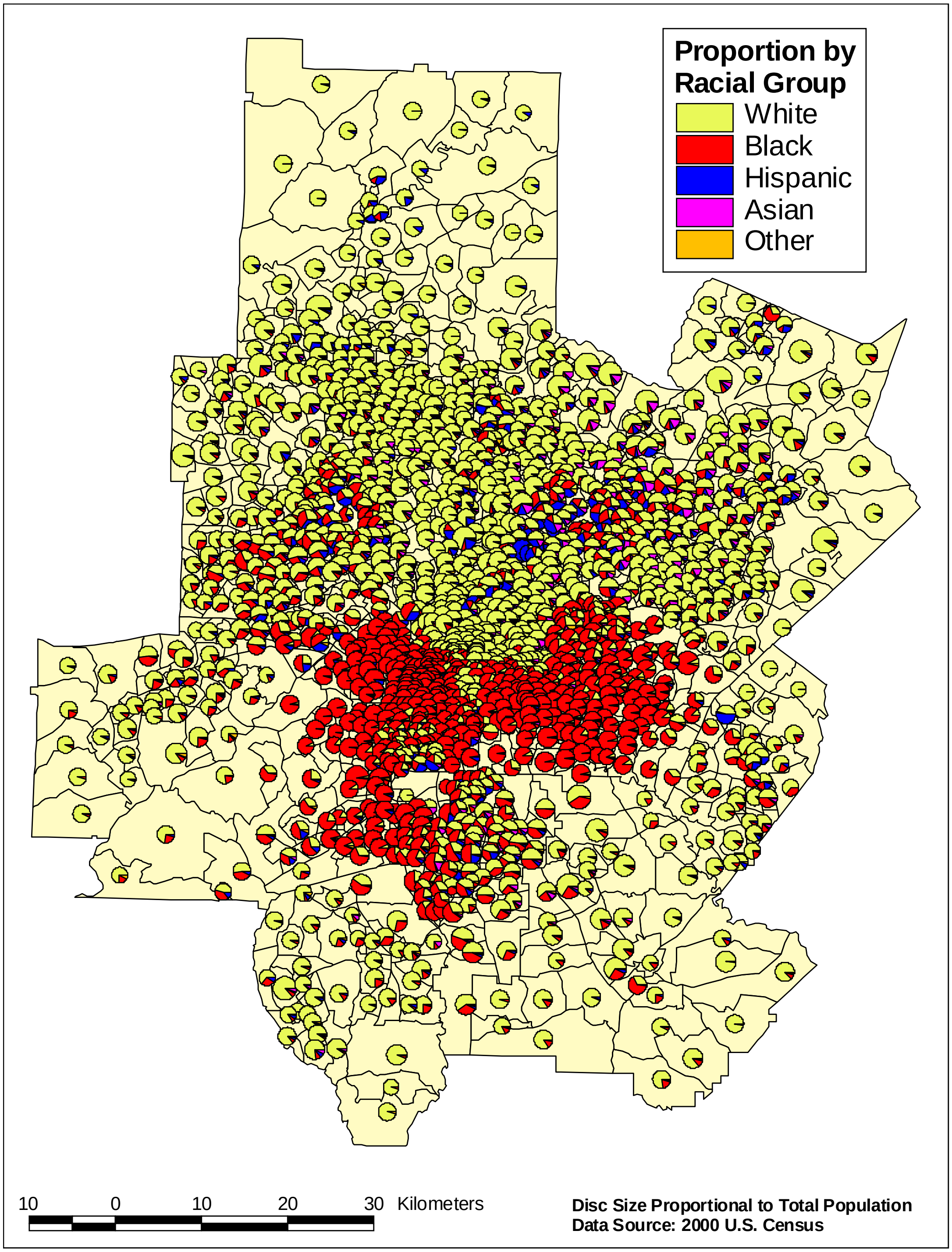


Figure 3.5 Racial and ethnic population patterns in 2000.

Marietta, Doraville, Norcross, Duluth, and northwest Gwinnett County, where Hispanics predominate, though these areas also include many Asians and some Blacks. In the remainder of the metropolitan area, Whites predominate.

The racial composition of the metropolitan area in 2000 is 55.4% White, 31.4% Black, 7.2% Hispanic, 3.7% Asian, and 2.0% other. Forty-five percent of metropolitan Atlanta's 3.4 million residents in 2000 are Black and other races. Figures 3.6 and 3.7 clearly present the spatial distribution of percentage minority[3] by census block group in the Atlanta metropolitan area. The geographic pattern is roughly that of the racial mix as shown in Figures 3.4 and 3.5. Among the nation's largest metropolitan areas, only Orlando matched Atlanta's Black population growth of 62 percent since 1960 (ARC, 2003). Asian population grew by 160 percent while the Hispanic population experienced even more dramatic growth with a 372 percent increase since 1990. The Atlanta metropolitan area, a booming center in the Sunbelt, has virtually no long-established ethnic enclave (Zhang, 1998).

The poverty rate for the Atlanta metropolitan area in 2000 was substantially lower than the average poverty rate for Georgia and the nation. Within the metropolitan area, 9.5 percent of the population was living under the poverty level[4], as compared with 12.1 percent for Georgia and 13.3 percent for the nation as a whole. Although in 2000 the region compares favorably with the state and the nation, there remain geographically concentrated pockets of poverty that have persisted over the past ten years. The largest concentration of high block group-level poverty rates within the metropolitan area remained within the central city of Atlanta. The Marietta area of Cobb County, the I-85/Buford Highway corridor between north DeKalb and south Gwinnett,

[3] The term refers to Black, Hispanics, Asian, and other races except White.
[4] The poverty status of an individual is determined by the Bureau of the Census, and is based on income and family structure. For more information on the determination of poverty status for the years 2000 and 1990, go to http://www.census.gov/hhes/poverty/threshld.html.

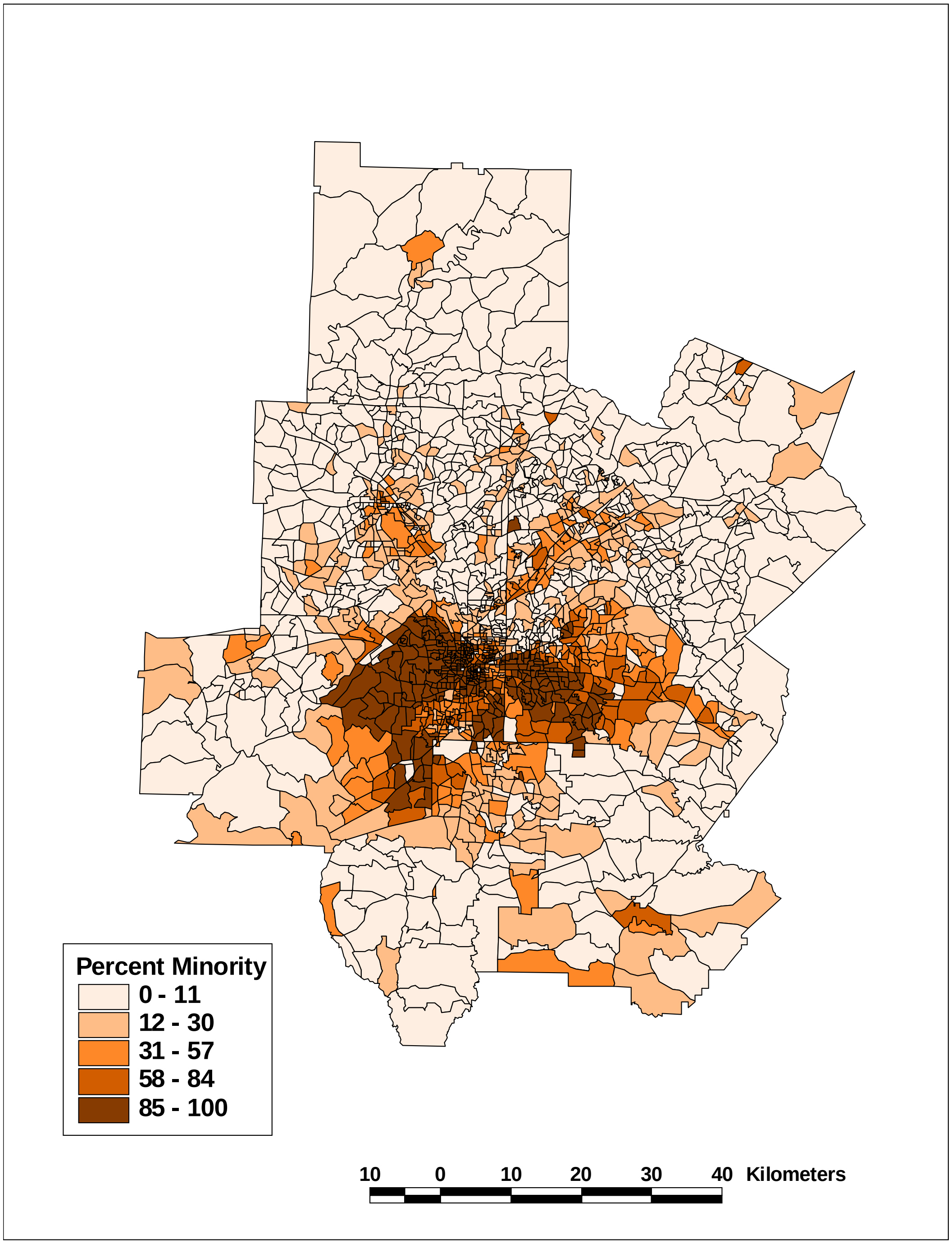


Figure 3.6 Percent minority in 1990.

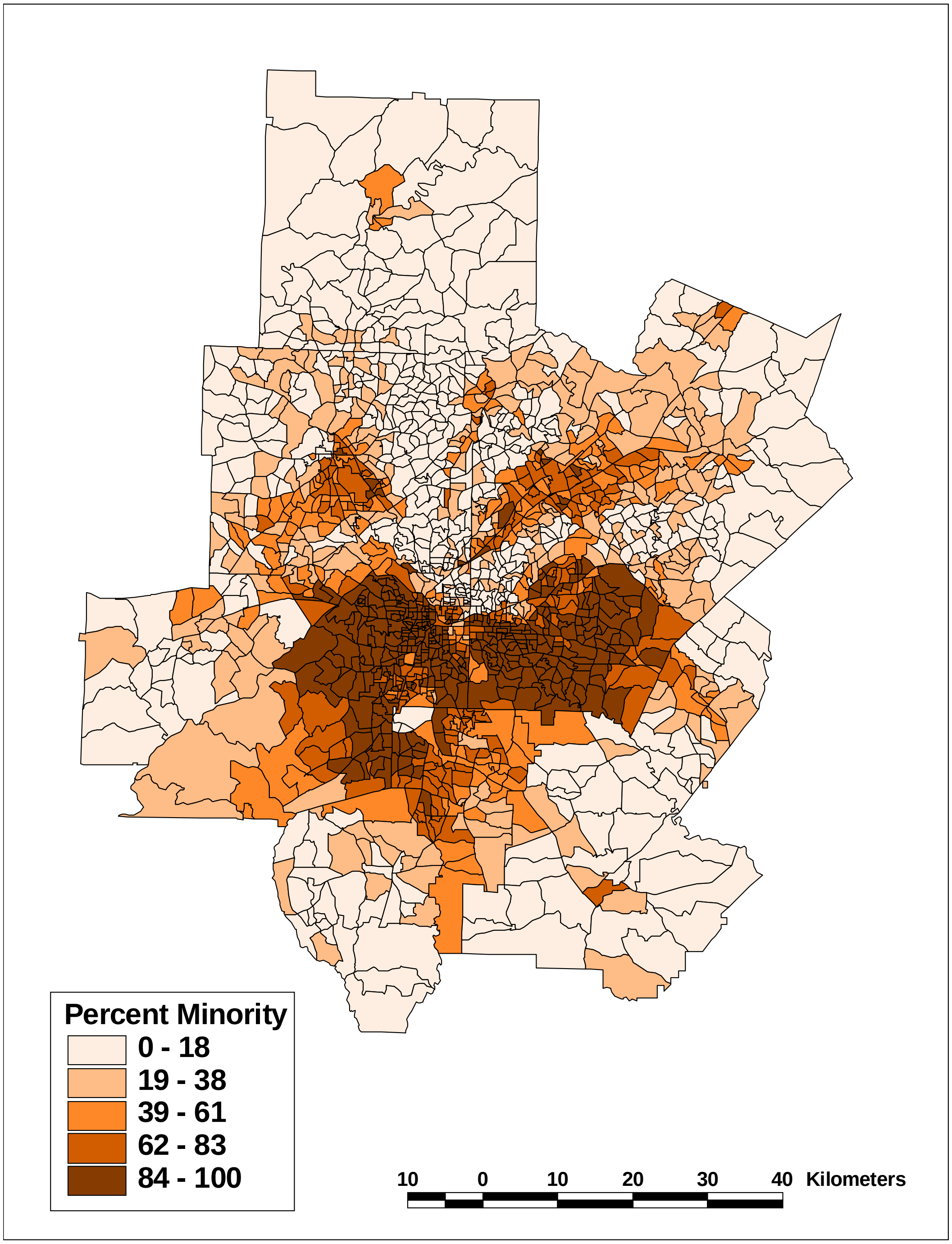


Figure 3.7 Percent minority in 2000.

the block groups along I-20 east of Atlanta, and north of Clayton represent four large areas of growing poverty in the Atlanta metropolitan area between 1990 and 2000 (Figures 3.8 and 3.9). These increases may be the result of the rapid changes in other demographic characteristics in these areas, such as substantial growth in immigrant populations.

3.4 Industrial Landscape

In terms of value added by manufacture, Atlanta is one of the three largest manufacturing centers in the southeastern United States (Hartshorn, 1997). Atlanta retains its strength in the transportation equipment manufacturing field as is shown in Table 3-1. The chemical industry is one of the top three leading manufacturing groups in the Atlanta region. This section describes the industrial landscape of the Atlanta metropolitan area based on the U.S. Environmental Protection Agency (EPA)'s Toxic Release Inventory (TRI) database.

The TRI database includes facilities within Standard Industrial Classification (SIC) numbers 2000-3999, whose emissions of any of a set of toxic chemicals exceeds prescribed thresholds. These SIC categories include food and tobacco processing; textile mill and apparel production; lumber, paper and furniture processing; printing; chemical processing; petroleum refining; rubber and plastics manufacture; leather, stone, clay, and glass industries; primary and fabricated metal industries; commercial machine and computer manufacturing; transportation equipment; analytical and optional goods; and miscellaneous manufacturing.

The TRI database used in this dissertation, which represents only airborne releases from hazardous facilities, contains 182 facilities in 1990 and 128 facilities in 2000 for the Atlanta metropolitan area. A total of 99 different chemicals in 1990 and 107 in 2000 are emitted by TRI facilities within the Atlanta metropolitan area. The pattern of TRI facilities in the metropolitan

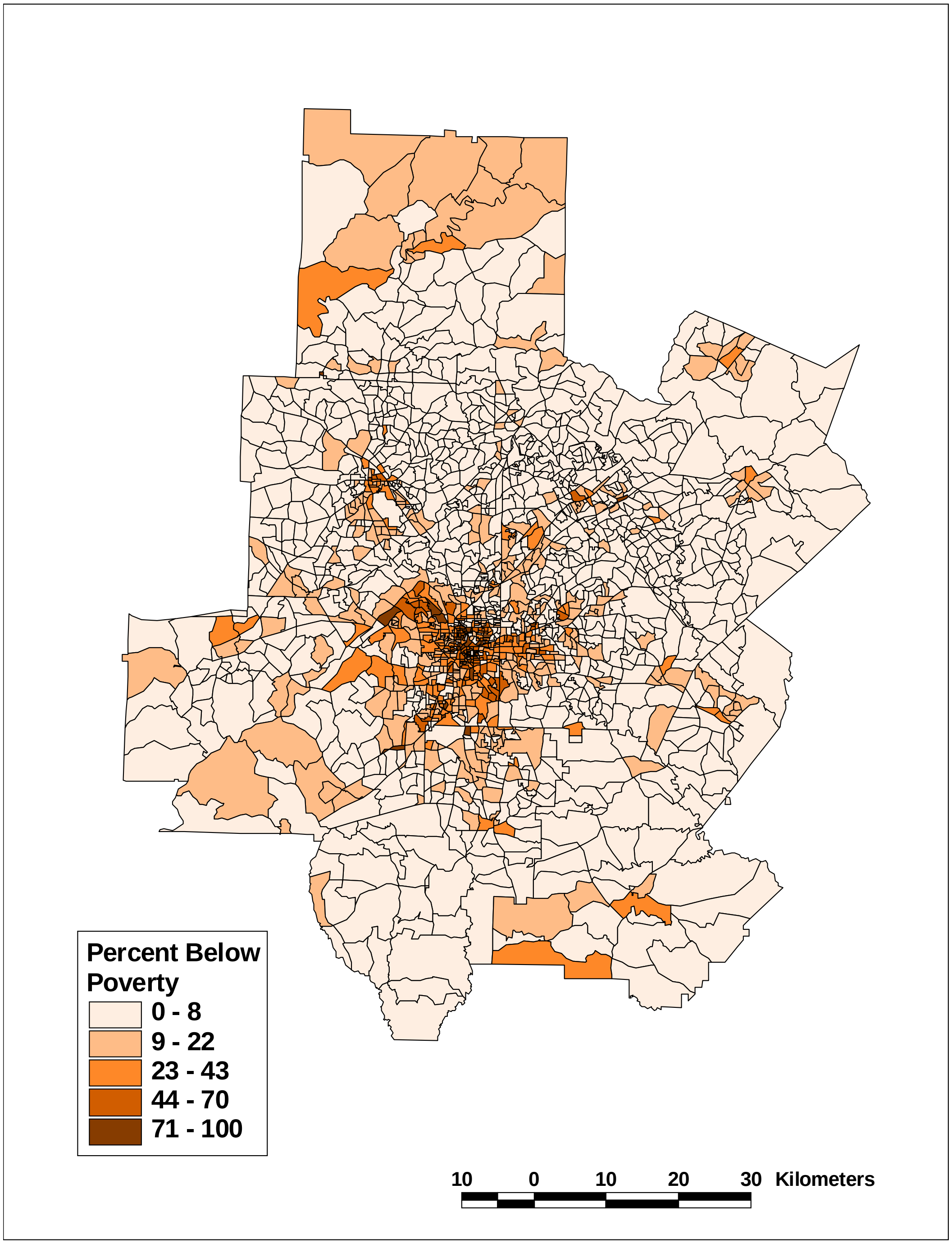


Figure 3.8 Percent below poverty in 1990.

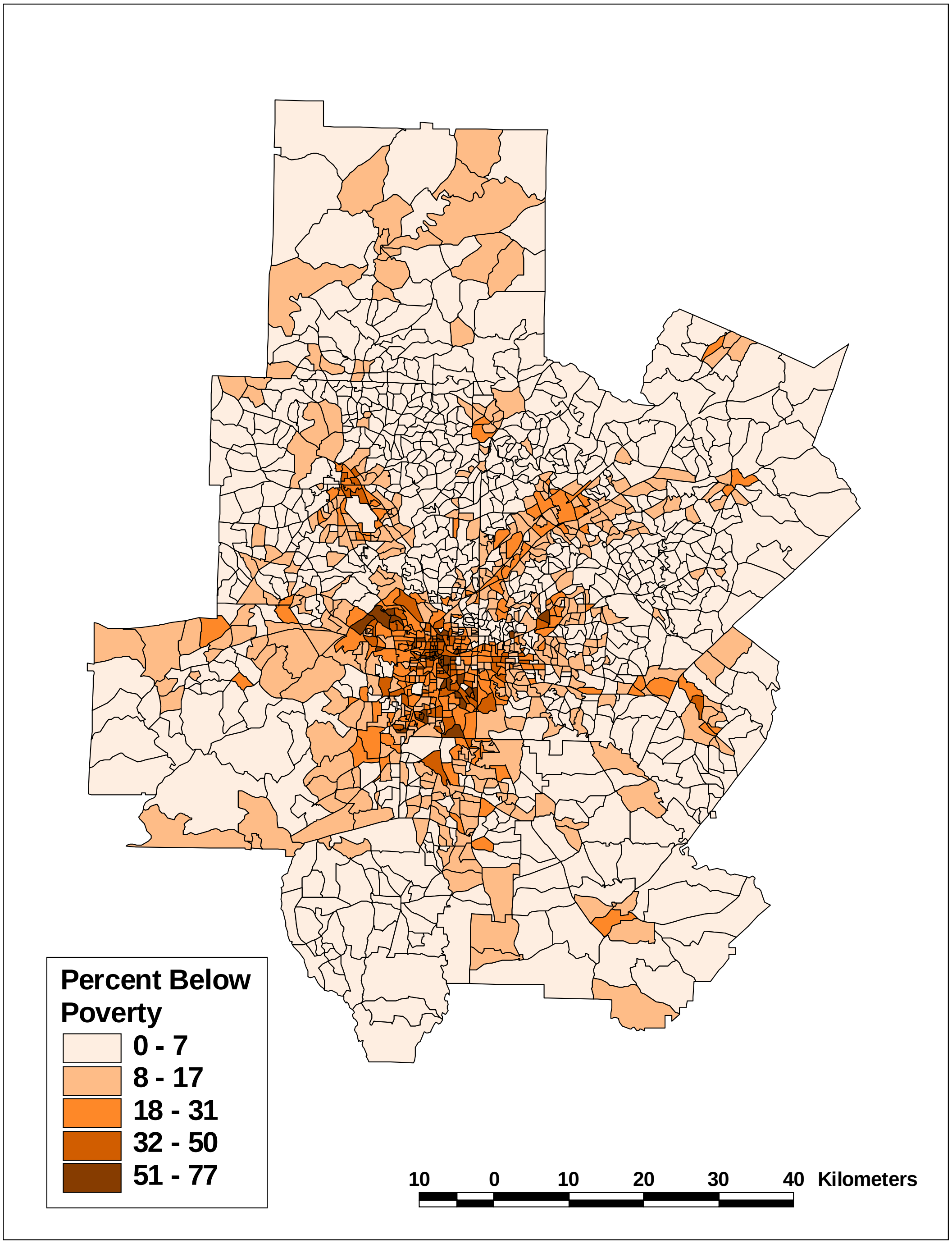


Figure 3.9 Percent below poverty in 2000.

Table 3.1 Top six manufacturing groups in metropolitan Atlanta, 1997 (in million dollars)

Rank	**Category**	**Value added total**
1	Transportation equipment	**4,205**
2	Food	**2,921**
3	Chemical	**2,035**
4	Computer & electronic product	**2,011**
5	Plastics & rubber products	**1,452**
6	Electrical equipment, appliance, & component	**1,292**
	Metro total	**22, 741**

Source: U.S. Economic Census – Manufacturing reports, 1997.

area is far from random. Most facilities are within major urban clusters of the metropolitan area. Large concentrations of facilities can be identified around the central city of Atlanta, southwest of Gwinnett, and along the Interstates 85, 285, 75, and 20 corridors. Figures 3.10 and 3.11 illustrate the geographic distribution of TRI facilities within the Atlanta metropolitan area. The major difference in the spatial distribution between 1990 and 2000 is that the number of TRI facilities relatively declined in the central city of Atlanta while increased around the suburbs.

3.5 Summary

The socioeconomic landscape deeply inherent in the Atlanta metropolitan area is paradoxical in relation to racial segregation and poverty. The region is strongly racially segregated in spite of a reputation for good race relations. The poverty rate of Blacks in the inner city is high despite the substantial economic growth over the past ten years.

The industrial landscape in the Atlanta metropolitan area is also paradoxical. In the face of rapid industrial growth, the metropolitan area as a major manufacturing center in the South experienced the severe degeneration of urban climate and air quality, particularly with regard to urban warming and the increases in ozone and emission of volatile organic compounds (VOCs) (SOS, 1995). This area is currently classified by the U.S. EPA in the category of serious nonattainment for ozone.

The paradoxical geography of metropolitan Atlanta, therefore, lies in extreme racial and economic, and environmental inequality. In such a paradoxical geography, the spatial relationship between TRI facility locations and socioeconomic characteristics will be investigated in the later chapters. This issue is the subject of this dissertation.

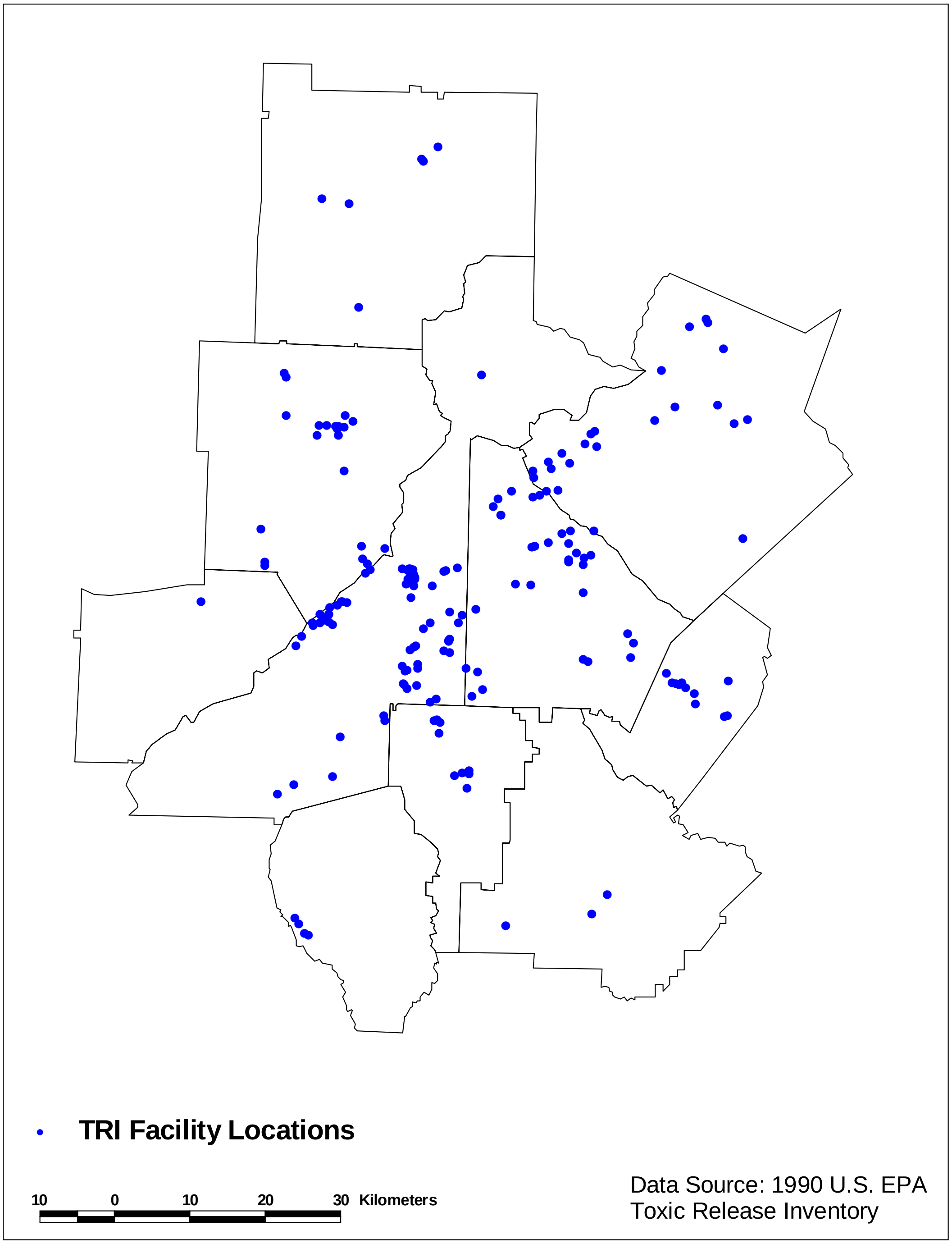


Figure 3.10 TRI facility locations in 1990.

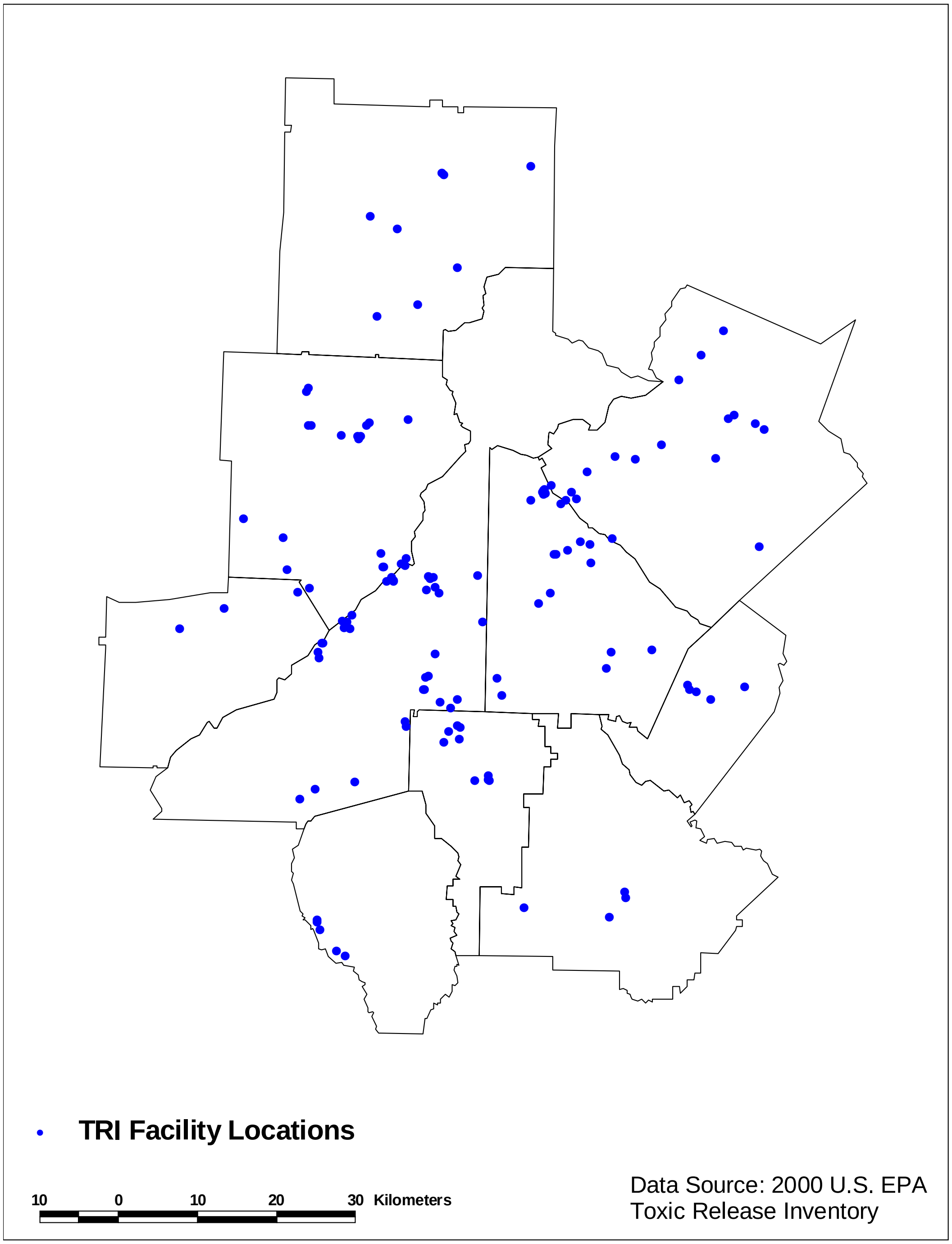


Figure 3.11 TRI facility locations in 2000.

CHAPTER 4

RESEARCH METHODOLOGY

4.1 Introduction

This chapter focuses on the research methodology used to accomplish the research objectives mentioned in Chapter One. The research approach can be summarized in five major stages as shown in Figure 4.1: (1) data collection, (2) information extraction from remotely sensed imagery, (3) exploratory sensitivity analysis, (4) environmental equity analysis, and (5) urban quality of life assessment. The analytical procedures used in this dissertation are based on an integrated GIS and remote sensing approach with spatial analysis and modeling techniques. The research procedures are illustrated in detail in Figure 4.2. In the first section, data collection and sources will be described. In the second section, the procedures for extracting land use and cover, normalized difference vegetation index (NDVI), and surface temperature from remotely sensed images will be presented. In the third section, the exploratory sensitivity analysis of environmental equity to spatial measures such as proximity, areal interpolators, and scale and resolution will be put forward. In the fourth section, the procedures used to perform the environmental equity analysis in this dissertation will be demonstrated. The final section will discuss the procedures employed for urban quality of life assessment.

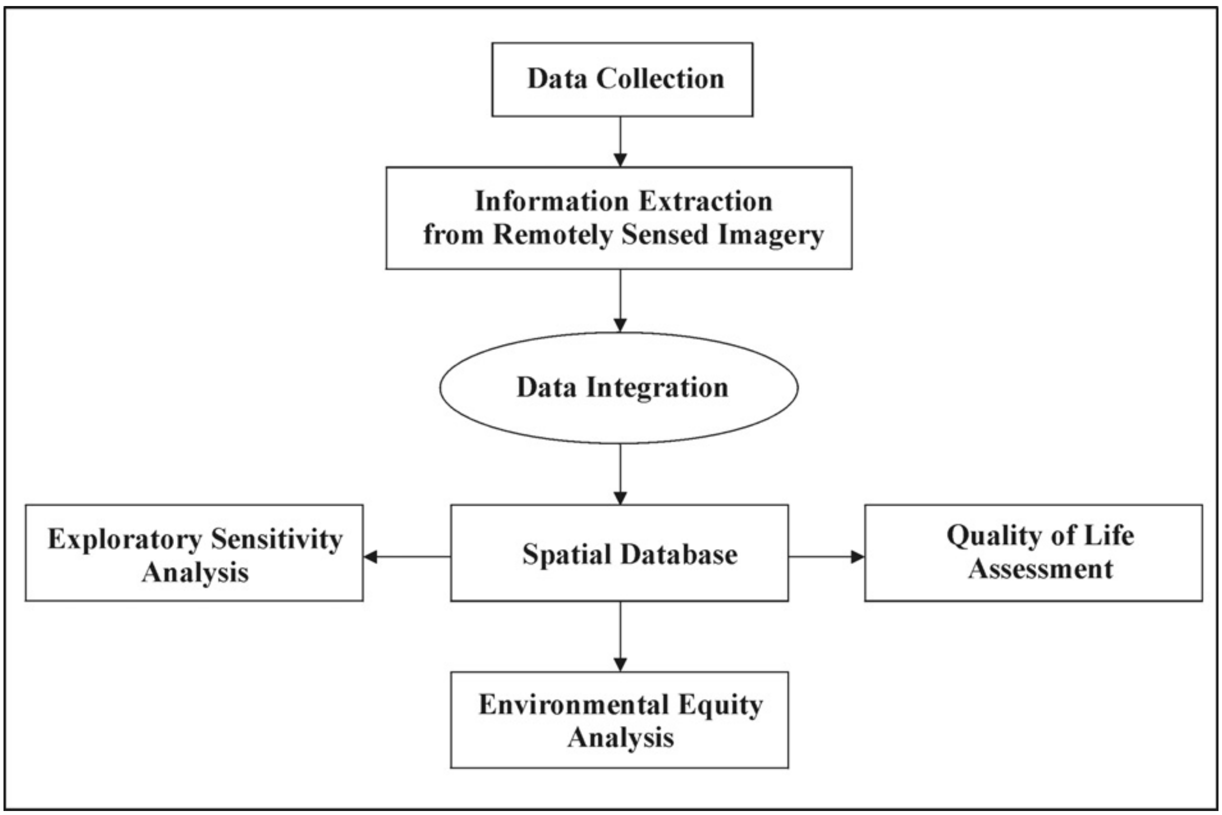


Figure 4.1 Research framework of the dissertation.

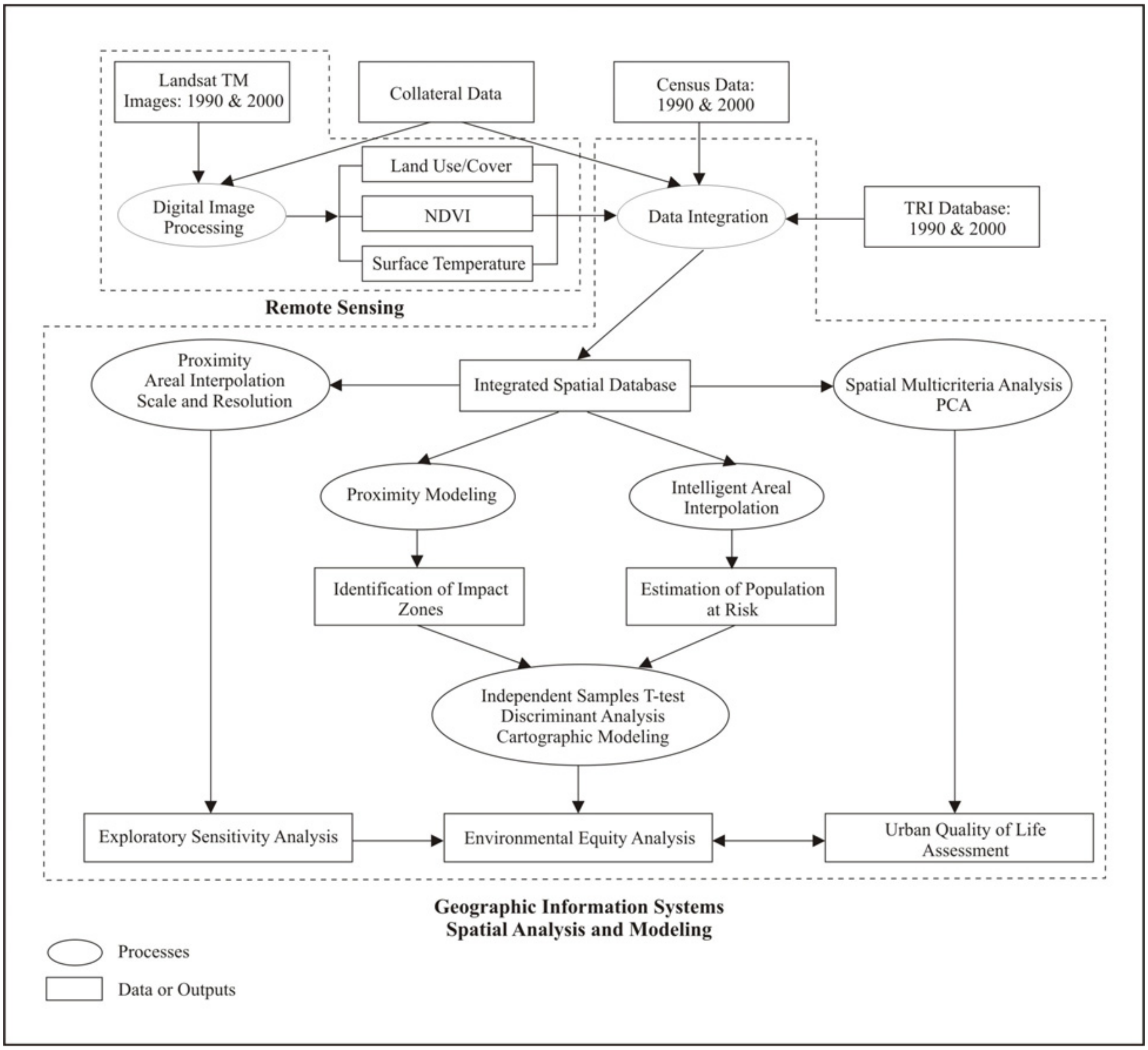


Figure 4.2 Research procedures of the dissertation.

4.2 Data Collection

This section describes the dataset and data sources acquired for this dissertation. The primary data sources include the U.S. Environmental Protection Agency's (EPA) Toxic Release Inventory (TRI) databases, Census TIGER/Line files and Census Summary Tape Files (STF3A), and Landsat Thematic Mapper (TM) images.

The TRI database, a national database of industrial facilities that release toxic and hazardous chemicals, contains a complete inventory of toxic release sites in all major U.S. cities. Under SARA’s Emergency Planning and Community Right-to-Know Act of 1986 (EPCRA), manufacturing facilities included in the Standard Industrial Classification (SIC) codes 20-39 with more than ten full-time employees must report to the U.S. EPA the annual amounts (including routine releases and accidental spills or leaks) of all listed chemicals that are released directly to the air, water, land or injected into underground wells. The inventory covers more than 300 chemicals and 20 categories of chemicals. The current reporting threshold is for facilities generating more than 25,000 pounds of toxics in manufacturing and processing uses and 100,000 pounds for other uses. For each toxic release site, this database provides detailed information (magnitude and frequency of emissions) about the type of chemicals released at each site and locational information in geographic coordinates. This database serves as one of the more reliable approximations of chronic toxic release currently available.

The 1990 and 2000 TRI databases for the Atlanta metropolitan area were obtained from the U.S. EPA. The industrial facilities released airborne emissions were extracted from the TRI databases to avoid the analytical complexity and then were used to determine the number and location of toxic facilities. The geographic locations of TRI facilities often are reported to EPA with varying degrees of accuracy and need to be verified for analysis below the county level

(Scott *et al.*, 1997). The location information for all TRI facilities used in this dissertation was verified for logical inconsistencies to help ensure that no TRI facilities were located in obviously incorrect locations, such as the middle of a water body and the outside of a county boundary. Several TRI facilities found incorrect in position were geocoded by an address matching method based on street address information.

Toxic chemical releases were measured both in raw pounds and in adjusted toxicity. The TRI reports the raw poundage of chemical releases. By scaling these data with modified Environmental Defense Fund (EDF) Scorecard (including 40 different chemical indexing systems) proposed by Cutter *et al.* (2001), a relative potential risk score (RPRS) was computed. The modified EDF Scorecard provides a simple average index for each chemical, which is computed by dividing the number of times the chemical is ranked above the 50th percentile (more hazardous than most substances) across all applicable indices by the total number of different indices for that particular chemical. Although using such a simple indicator glosses over uncertainties in measuring the complex toxicity indices, it does allow construction of a measure of relative risk when comparing two facilities in terms of the magnitude and toxicity of their releases. The modified EDF Scorecard was also selected in this dissertation because it includes a larger number of chemicals indexed than other toxicity indices. The mathematical notation for the RPRS is as follows:

$$RPRS_j = \sum_{i}^{n} (A_i \cdot T_i) \tag{4.1}$$

where $RPRS_j$ denotes the relative potential risk score for a given facility j; n is the number of chemicals released by a given facility j; A_i is the volume of chemical i (in pounds); and T_i is the toxicity measure of chemical i based on modified EDF Scorecard.

The demographic and socioeconomic data were collected at the census tract and block group levels from the 1990 and 2000 Census STF3A's. Data in STF3A are sample data (approximately 1 in 6 households), not entire (100%) population counts, and are aggregated to the block group level. The block group represents the smallest enumeration unit for which both racial and income information are available. The boundary files for census tract and block group levels were extracted from the 1990 and 2000 Census TIGER/Line files. The sociodemographic variables used in this dissertation include total population, population by race and ethnicity, population below poverty line, per capita income, median home value, and percent of college graduates.

Two Landsat 5 TM images of the Atlanta metropolitan area in digital form were acquired in 1990 and 2000. Since the study area lies across rows 36 and 37 in the Worldwide Reference System (WRS) employed for cataloging locations in path and row of Landsat scenes, the two scenes have been shifted by 50 percent in order to include the entire study area within single scenes. The Landsat scene of the year 1990 was acquired on October 27 in order to obtain a cloud-free image while the scene of the year 2000 was acquired on July 2 when vegetation is still growing so that the greenness of the environment could be accurately measured. Three major types of environmental data including land use and cover, NDVI, and surface temperature were extracted from the Landsat TM data. This will be discussed in the following section.

Finally, the reference data collected for land use and cover classification include: (1) U.S. Geological Survey (USGS) digital orthophotos derived from panchromatic National Aerial Photography Program (NAPP) imagery taken over the Atlanta metropolitan area in January to February 1993 at a scale of 1:40,000, (2) USGS digital orthophotos derived from color infrared NAPP imagery taken over the Atlanta metropolitan area in January 1999 at a scale of 1:40,000,

(3) land cover map of Georgia 1988-1990 generated by the ERDAS, Inc. for the Georgia Department of Natural Resources (GADNR) at a 30 m pixel resolution, (4) land cover map of Georgia 1992-1993 extracted from the National Land Cover Data (NLCD) built by the Multi-Resolution Land Characterization (MRLC) Consortium at a 30 m pixel resolution, (5) 1998 land cover map of Georgia produced by Natural Resource Spatial Analysis Laboratory, Institute of Ecology at the University of Georgia at a 30 m pixel resolution, (6) 1990 and 1999 land use and cover data of the Atlanta region compiled by Atlanta Regional Commission (ARC) at scales of 1:24,000 and 1:14,000, and (7) 7.5 minute topographic maps in Digital Raster Graphics (DRG) format at a scale of 1:24,000. In addition, several geographic reference data sets such as county and city boundaries, and roads were acquired for the aid in the stages of post-classification sorting and spatial analysis.

4.3 Information Extraction from Remotely Sensed Imagery

Three biophysical data sets for this research were derived from the Landsat TM data: (1) land use and cover, (2) NDVI, and (3) surface temperature. This section documents the procedures for extracting these data sets.

According to the ordering specifications, the 1990 Landsat TM image obtained from USGS had permanently been rectified and georeferenced to the Transverse Mercator projection cast on North American Datum (NAD) 1927 with a spatial resolution of 28.5 m. The Transverse Mercator projection was used to represent the entire study area on single map projection because its geographic extent spans zones 16 and 17 in the Universal Transverse Mercator (UTM) coordinate system. The georeferencing for this image was quite accurately performed by the USGS. This was verified by superimposing the vector-based county boundary over the study area onto the Landsat TM image. This image was thus used as the reference scene to which the 2000 Landsat TM image was registered. With thirteen control points, a first order polynomial equation was used for geometric correction. With the nearest neighbor resampling method, which was needed to avoid changes in the original pixel values, the 2000 Landsat TM image was resampled to 28.5 meters. The resultant root mean square error (RMSE)[1] was 0.44 pixels, which is quite acceptable for this dissertation. Each image was then atmospherically and radiometrically corrected using the image-based Cosine (Thetaz) (COST) model of Chavez (1996), which was implemented with the help of the Spatial Modeler in Imagine. The formula for this model is expressed as follows:

$$R_s = \frac{\pi * D^2 * (L_{sat} - L_{haz})}{ESUN * \cos^2 q} \tag{4.2}$$

where R_s is the corrected surface reflectance, D is the earth-sun distance in astronomical unit, L_{sat} is at-satellite spectral radiance in w.m^{-2}.ster^{-1}.mm^{-1}, and L_{haz} is upwelling atmospheric spectral radiance in w.m^{-2}.ster^{-1}.mm^{-1}, $ESUN$ is mean solar exoatmospheric irradiances, and q is solar zenith angle in degree. The image-based COST model was used in this research because of its relatively easy-to-use, cost-effective, and accurate radiometric calibration and correction procedure.

A modified version of the Anderson scheme of land use and cover classification (Anderson *et al.*, 1976) with mixed levels 1 and 2 was developed for this research as shown in Table 4.1. The six land use and cover categories in the scheme include: (1) residential, (2) commercial/industrial, (3) grassland/pasture/cropland, (4) forest, (5) water, and (6) barren. A hybrid approach was used for land use and cover classification. The hybrid approach has three

[1] As a good rule of thumb, the acceptable RMSE in the geometric correction is less than 0.5 in pixel.

Table 4.1 Land use and cover classification scheme and key

No.	Classes	Definitions
1	**Residential**	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 roads and small open space around a residential area.
2	**Commercial/ Industrial**	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/state highway, and railroad stations, etc.) and low percentage of residential development residing in the built-up areas.
3	**Grassland/ Pasture/ Cropland**	Areas dominated by grasses, herbaceous vegetation, and crops, including golf courses, airport grasses, industrial site grasses, lawns, city parks, lands planted for livestock grazing or the production of seed or hay crops, and planted and cultivated land with row crops, small grains, and fallow.
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 rock, sand, clay, quarries, strip mines, gravel pits, cultivated land without crops, and forest clearcuts.

Note: The percentage specified is visually determined on a per-pixel basis.

major steps as illustrated in Figure 4.3: (1) unsupervised training, (2) supervised classification, and (3) post-classification sorting. An unsupervised classification with the Iterative Self-Organizing Data Analysis (ISODATA) algorithm was initially used to extract unsupervised training areas from 60 natural spectral clusters of each Landsat TM image. Since the performance of this algorithm was found sensitive to sampling characteristics according to the intensive experiments carried out by author, the unsupervised clustering method was performed on the entire image, not a representative subset of each image. After the unsupervised classification, homogeneous spectral clusters were labeled as one of the most likely land use and cover classes with reference to ground truth data as described in Section 4.2 and then identified as unsupervised training areas. With the signatures developed from the unsupervised training areas selected, a supervised maximum likelihood classifier was then applied to classify the whole scene since it minimizes classification error for classes that are distributed in multivariate normal fashion (Richards and Jia, 1999).

The resultant land use and cover map had two major types of misclassification errors such as spectral confusion and boundary errors. The post-classification sorting was performed to reduce the misclassification errors and thus to improve classification accuracy. The spectral confusion causes different land use and cover classes to exhibit similar spectral reflectance characteristics. It is inevitable for an image in broad bands. For this research, three major kinds of spectral confusion were detected in the resultant land use and cover map. The first confusion was between water and shadows in urban built-up and forest areas. This was corrected using on-screen digitizing of the area of interest (AOI) to recode these shadows to commercial/industrial or forest class by referring to the false color composite (FCC) image and the DOQQs. The second was confusion between commercial/industrial (large open building rooftop, airfields, and

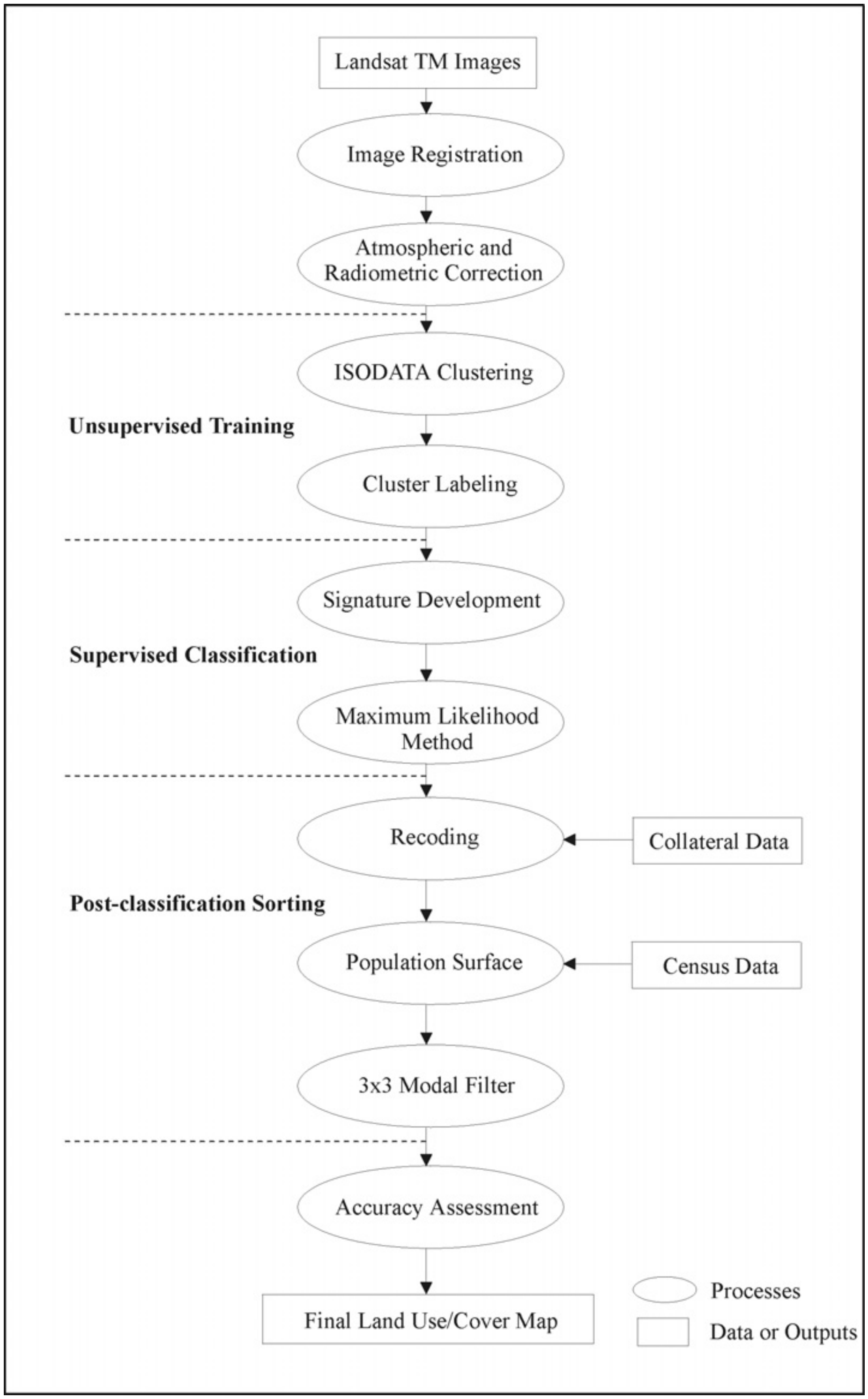


Figure 4.3 A hybrid approach for satellite image classification.

multilane highways) and barren (the exposed land including the sand area along a river, quarries, strip mines, and cultivated land without crops). This confusion was also resolved using the on-screen digitizing based on the AOI and recoding as described above. The third confusion was between residential and other built-up land covers, grassland or forest. A population surface generated based on census block group centroid as suggested by Mesev (1998) was applied to separate residential from other built-up land covers, grassland or forest. The population surface provides a spatially approximate contextual means to filter areas that are non-built and non residential. Finally, the boundary error is due to the occurrence of spectral mixing within a pixel and appears at class boundaries. This also produced small areas of anomalous pixels representing the noises within a class. A 3x3 modal filter with zero value at its four corner cells was used to remove these misclassified areas in the form of salt and pepper (Yang and Lo, 2002). The modal filter made it possible to preserve the linear features such as roads.

The accuracy of the land use and cover maps for 1990 and 2000 extracted from the Landsat TM images was assessed by the use of the ground truth or other reference data as stated in Section 4.2. Since field survey data are sometimes difficult and expensive to collect, it is an accepted practice that interpretation results of large-scale aerial photographs and existing maps can be treated as the reference data. In this research, the DOQQs, the 1:24,000-scale topographic maps, existing land use and cover maps, and the FCC formed from the VNIR bands of Landsat 5 TM were consulted as ground data. A stratified random sampling method was adopted based on the recommendation of Congalton (1991). As a good rule of thumb, he recommended a minimum of 50 samples for each land-use and cover category to produce an error matrix. For this research, 64 samples were selected for each land use and cover category. Two error matrices were produced as shown in Tables 4-2 and 4-3. The overall, producer’s, and user’s accuracy

Table 4.2 Error matrix for accuracy assessment of Landsat TM (October 27, 1990)

Classified Data	**Reference Data**							
	1	**2**	**3**	**4**	**5**	**6**	**RT**	**UA**
1	**51**	6	3	4	0	0	64	79.7%
2	4	**58**	1	0	0	1	64	90.6%
3	0	4	**59**	0	0	1	64	92.2%
4	0	0	1	**63**	0	0	64	98.4%
5	0	0	0	0	**64**	0	64	100.0%
6	0	2	17	3	1	**41**	64	64.1%
CT	55	70	81	70	65	43	**384**	
PA	92.7%	82.9%	72.8%	90.0%	98.5%	95.4%		
CK	0.7629	0.8854	0.9010	0.9809	1.0000	0.5953		
OA	**87.5%**							
KI	**0.8500**							

Note: 1-Residential; 2-Commercial/Industrial; 3-Grassland/Pasture/Cropland; 4-Forest; 5-Water; 6-Barren; CT-Column Total; RT-Row Total; PA-Producer's Accuracy; UA-User's Accuracy; CK-Conditional Kappa; OA-Overall Classification Accuracy; KI-Overall Kappa Index of Agreement.

Table 4.3 Error matrix for accuracy assessment of Landsat TM (July 02, 2000)

Classified Data	**Reference Data**							
	1	**2**	**3**	**4**	**5**	**6**	**RT**	**UA**
1	**54**	7	2	1	0	0	64	84.4%
2	0	**60**	4	0	0	0	64	93.8%
3	2	1	**58**	3	0	0	64	90.6%
4	3	0	0	**61**	0	0	64	95.3%
5	0	1	0	0	**63**	0	64	98.4%
6	5	5	9	0	0	**45**	64	70.3%
CT	55	70	81	70	65	43	**384**	
PA	84.4%	81.1%	79.5%	93.9%	100.0%	100.0%		
CK	0.8125	0.9226	0.8842	0.9436	0.9813	0.6637		
OA	**88.8%**							
KI	**0.8656**							

Note: 1-Residential; 2-Commercial/Industrial; 3-Grassland/Pasture/Cropland; 4-Forest; 5-Water; 6-Barren; CT-Column Total; RT-Row Total; PA-Producer's Accuracy; UA-User's Accuracy; CK-Conditional Kappa; OA-Overall Classification Accuracy; KI-Overall Kappa Index of Agreement.

were computed. Also calculated were kappa indices which incorporate the chance allocation of class labels (Jensen, 1996). The overall accuracy of land use and cover maps for 1990 and 2000 were determined to be 87.5 percent and 88.8 percent respectively. The kappa indices for the 1990 and 2000 maps were 0.85 and 0.8656 respectively. Apparently, these data are good enough to meet the minimum 85 percent accuracy recommended by the Anderson classification scheme (Anderson *et al.*, 1976), and thus are sufficient for environmental equity assessment.

The NDVI as a greenness measure is universally perceived to be a highly desirable quality of the morphological environment. The NDVI is a ratio transformation accentuating the contrast between the visible spectrum (0.4 – 0.7 μm), which more strongly reflects energy from soils and litter, and the near infrared spectrum (0.7 – 1.1 μm), which more strongly reflects energy from healthy green vegetation. For Landsat TM data, the NDVI is computed from TM band 4 (0.76 – 0.90 μm) and TM band 3 (0.63 – 0.69 μm), using the following formula:

$$\mathrm{NDVI} = \frac{\mathrm{TM}_4 - \mathrm{TM}_3}{\mathrm{TM}_4 + \mathrm{TM}_3} \tag{4.3}$$

The value varies from –1 to +1 as greenness increases. This ratio was quantified by using the Imagine software.

Band 6 (10.3 – 12.5 μm and at a spatial resolution of 120 m) of the Landsat TM data records thermal infrared emission from the land surface. It is an important physical variable in the sense that it can affect human comfort. Surface temperatures in a city are affected by the land use and cover types and are an important measurement to consider for the urban heat island phenomenon for which rural-urban differences are the greatest during the daytime (Lo *et al.*, 1997). Extraction of surface temperatures from the Landsat TM band 6 data required conversion of the spectral radiances (L) into at-satellite temperatures $T(K)$ by using the following equation proposed by Wukelic *et al.* (1989) for Landsat 5 TM band 6:

$$T(K) = \frac{K2}{\ln\left(\frac{K1}{L}+1\right)} \tag{4.4}$$

where $T(K)$ is effective at-satellite temperature in Kelvin, $K2$ is calibration constant 2 (=1260.56) in Kelvin, $K1$ is calibration constant 1 (=607.76) in w.m^{-2}.ster^{-1}.mm^{-1}, and L is spectral radiance in w.m^{-2}.ster^{-1}.mm^{-1}. This formula was applied to every pixel of the Landsat TM band 6 data with the help of the Spatial Modeler functionality in the Imagine.

The correction for emissivity (ε) was conducted according to the nature of land cover. In general, vegetated areas are given a value of 0.95 and non-vegetated areas 0.92 (Nichol, 1994). This differentiation is based on the NDVI image calculated as described above. The emissivity corrected surface temperature (T_s) is computed as follows (Nichol, 1994):

$$T_s = \frac{T(K)}{1+(\lambda T(K)/\alpha)\ln\varepsilon} \tag{4.5}$$

where λ is the wavelength of emitted radiance (= 11.5 μm), α is *hc*/*K* (1.438 * 10^{-2} mK), *K* is Stefan-Bolzmann's Constant (1.38 * 10^{-23} J/K), *h* is Planck's constant (6.26 * 10^{-34} J-sec), *c* is velocity of light (2.998 * 10^{8} m/sec), and ε is surface emissivity. These absolute temperatures were then converted into Celsius (C) by subtracting from them the temperature of the ice point (273.15 K) because people understand temperatures in interval scale better.

4.4 Exploratory Sensitivity Analysis

Based on the literature reviewed in Chapter Two, the results of environmental equity analysis vary dramatically depending on the method used. It is important to consider that an operational procedure for the environmental equity analysis is needed to formulate for ensuring accurate and effective results. In this regard, three experiments were completed to evaluate the effects of three spatial measures on the environmental equity analysis: (1) proximity, (2) areal interpolation, and (3) scale and resolution[2]. For these experiments, Fulton County was selected as a representative study area since the city of Atlanta is located in the county seat. As a data integration and analysis engine, GIS were used which produces results that can be rendered using map displays at various levels of information resolution. Three major data sets including demographic characteristics, the TRI database, and land use/cover for the study area in 1990 were integrated into a GIS environment through georeferencing. All of the original data were reprojected to the Transverse Mercator projection cast on NAD 1927 for these experiments. Two specific population characteristics, racial composition and poverty status, are collected for each census tract and block group, which were examined most frequently in environmental equity research. Based upon the geographic coordinates (latitude and longitude) for each site, the TRI data were imported into a GIS database and overlaid with the census tract and block group boundaries. Remotely sensed data were also coupled with the census tract and block group boundaries in the GIS environment.

The first experiment is to investigate the effect of different buffer distances on the environmental equity analysis. The selection of a threshold or buffer distance to identify the impact zones of a hazardous site becomes an important variable in determining whether or not environmental inequities exist. The review of literature in Chapter Two found that the threshold was set based on the reported releases, worst-case events, perceived effects, or modeled indirect

[2] Scale refers to the area covered by the analysis, such as states, regions, or urban areas while resolution refers to the enumeration units used, such as counties, tracts, or block groups.

effects and threshold distances for circles or plumes centered on the facility ranged from 0.5 miles to 5.0 miles (Cutter at al., 2001). Based on this review, six concentric half-mile wide circles with radii of 0.5, 1.0, 1.5, 2.0, 2.5 and 3.0 miles were generated around each TRI facility location, assuming that the TRI point location represented the center of the emission source. The concentric half-mile-wide rings were then overlaid on the census tract boundaries in order to estimate population counts within the study area. A simple areal weighting interpolation was used to estimate the population at a given point in time, for a specific geographic entity as shown in the following equation.

$$P_t = \sum_{r=1}^{q} \frac{A_{tsr} * P_{sr}}{A_{sr}} \tag{4.6}$$

where P_t is the estimated population of a target zone, q is the number of source zones which overlap with that target zone, P_{sr} is the population of the rth overlapping source zone, A_{sr} is the area of that rth source zone, and A_{tsr} is the area of geometric overlap between that rth source zone and the target zone. Finally, proximity ratios, as suggested by Sheppard *et al.* (1999), were computed to characterize environmental equity in the study area. A proximity ratio is the ratio of socioeconomic characteristics, such as percent minority and percent below poverty, within buffer and those outside the buffer. In this experiment, the study area, census tract boundaries, the simple areal weighting interpolation, and the proximity ratio were used as control factors to facilitate the analytical implementation while different buffer distances were employed as experimental factors.

The second experiment is to assess the effect of different areal interpolators on the environmental equity analysis. In this case, a concentric circle with one-mile radius to determine the impact zones of a hazardous site was drawn around each TRI facility location. The concentric one-mile-wide ring was then overlaid on the census tract boundaries in order to estimate population counts within the study area.

Different methods of areal interpolation were reviewed in Chapter Two. Based on this review, the following methods were selected for further assessment: (1) simple areal weighting (Lam, 1983), (2) intelligent areal weighting (Fisher and Langford, 1996), and (3) three regression models: simple, focused and shotgun models (Langford *et al.*, 1991). Unlike the simple areal weighting interpolation as expressed in Equation 4.6, the intelligent areal weighting interpolation adopts Wright's (1936) idea of dasymetric mapping for areal interpolation, which is guided by additional geographic information about the distribution of population derived from ancillary land use and cover data. The formula for the intelligent areal interpolation is as follows:

$$P_t = \sum_{r=1}^{q} \frac{R_t * P_{sr}}{R_{sr}} \qquad (4.7)$$

where P_t denotes the population of target zone; R_t is the residential area of target zone; P_{sr} is the total population of source zone, r; and R_{sr} is total residential area of source zone, r. In order to perform the intelligent areal interpolation, the land use and cover image of 1990 was reclassified to make a binary image with residential and non-residential classes. The regression methods use simple regression models and GIS techniques to enable areal interpolation to be inferred by the distribution of land use and cover types in both the source and target units. The general formula for three regression methods used in this experiment is expressed as follows:

$$P_i = \alpha_0 + \sum_{j=1}^{5} \alpha_j \cdot n_{j,i} \qquad (4.8)$$

where α is the regression coefficient, j is the number of land use and cover classes, P is the population in a given zone, n is the number of residential pixels in a given zone, and i is the zone index. The regression methods employ global information for the entire study area to estimate zone values. These methods were implemented in the GIS environment in order to estimate the socioeconomic characteristics of the population at risk. As mentioned above, proximity ratios were calculated to determine the environmental equity in the study area. In this experiment, the study area, census tract boundaries, one mile buffer distance, and the proximity ratio were used as control factors at the analytical convenience while different areal interpolators were employed as experimental factors.

The third experiment is to examine the effect of scale and resolution on the environmental equity analysis. The effect of the modifiable areal unit problem (MAUP) is notorious in geographic studies. The environmental equity analysis is not free from the MAUP issue. This experiment addresses the MAUP in the environmental equity analysis. With a one mile buffer distance and the simple areal weighting interpolation, the environmental equity was characterized in census tract and block group boundaries. Again, proximity ratios were quantified to test the environmental equity hypothesis in the study area. In this experiment, the study area, the simple areal weighting interpolation, one mile buffer distance, and the proximity ratio were used as control factors to avoid getting the analytical complexity while different resolutions such census tract and block group were employed as experimental factors.

4.5 Environmental Equity Analysis

The primary operational focus of environmental equity assessment has been placed on impact zone determination, population estimation, and comparison of socioeconomic characteristics. In taking three major steps in the environmental equity assessment, an integrated GIS database was developed first. The integrated GIS database was designed to include demographic and socioeconomic data from the census, hazard-related data from the TRI database, and biophysical data such as land use and cover derived from the satellite images. As implied by these various data, building the integrated database has been the most time-consuming and technology-driven work in the dissertation. Once the integrated GIS database was constructed, the three major steps in the environmental equity assessment were then taken on the basis of the insights shed by three methodological experiments discussed in Chapter Five.

Based on the first experiment in Chapter Five, a range of threshold distances from 0.5 to 3 miles was selected to delineate the impact zones of a hazardous site. The range of threshold distances was employed to test the sensitivity of the analysis to the half-mile distance. The radius size of the circle seems reasonable in the case of airborne toxic emissions in urban areas since it reflects the chronic hazard area. Furthermore, the maximum initial evacuation distance suggested by U.S. Department of Transportation for the most hazardous substances is approximately 500 meters. Six concentric half-mile wide circles with radii of 0.5, 1.0, 1.5, 2.0, 2.5 and 3.0 miles, respectively were generated around each TRI facility location. In doing so, there was an assumption that the TRI point location represented the center of the emission source. A circular buffer of a specified radius centered at each site was generated using a buffering function in the GIS environment.

To estimate the demographic and socioeconomic characteristics of the population at risk, the concentric half-mile-wide rings were overlaid onto census block group boundaries. As illustrated in Figure 2.1, there are three ways of computing the composition of the population within a circular buffer: (1) polygon containment, (2) centroid containment, and (3) buffer containment. The buffer containment method, which keeps the actual shape of the buffer, was used to measure demographic characteristics within a given proximity of a TRI facility since it is more realistic than the other two and considers boundary effects. The buffer containment method requires areal interpolation techniques of transferring information from census units (source zone) to impact zones (target zone) as shown in Figure 2.2. According to Fisher and Langford (1995), there are three major groups of areal interpolation: (1) cartographic methods (including simple areal weighting and intelligent areal weighting), (2) regression methods, and (3) surface methods (see Section 2.4 in Chapter Two for details). Sadahiro (2000) suggested two strategies to improve the accuracy of estimates in areal interpolation: (1) choosing an intelligent method and (2) employing enough small source zones. Based on his first strategy, an intelligent area weighting interpolation method was selected for this research because its performance is relatively accurate in areal interpolation and robust to error in a land use and cover classification (Fisher and Langford, 1995 and 1996). The intelligent areal weighting method used in this research is a variant of that expressed in Equation 4.7, which is extended to employ three classes of land use and cover.

This extended method involves two major steps to estimate the socioeconomic characteristics of the population at risk: (1) spatially disaggregating population data from census block group into individual pixels based on the principle of dasymetric mapping and (2) reaggregating population surfaces by a circular buffer. To spatially disaggregate population data from census block group into individual pixels by dasymetric mapping, the following equation proposed by Mennis (2003) was implemented:

$$P_{ubc} = \frac{F_{ubc} * P_b}{N_{ub}} \tag{4.9}$$

where P_{ubc} is population assigned to one grid cell of land use/cover class u in block group b and in county c, F_{ubc} is total fraction for land use/cover class u in block group b and in county c, P_b is population of block group b, and N_{ub} is the number of grid cells of land use/cover class u in block group b. The total fraction (F_{ubc}) is calculated as follows:

$$F_{ubc} = \frac{D_{uc} * A_{ub}}{\left[(D_{hc} * A_{hb}) + (D_{lc} * A_{lb}) + (D_{nc} * A_{nb})\right]} \tag{4.10}$$

where F_{ubc} is total fraction of land use/cover class u in block group b and in county c, D_{uc} is population density fraction of land use/cover class u in county c, A_{ub} is area ratio of land use/cover class u in block group b, D_{hc} is population density fraction of land use/cover class h in county c, D_{lc} is population density fraction of land use/cover class l in county c, D_{nc} is population density fraction of land use/cover class n in county c, A_{hb} is areal ratio of land use/cover class h in block group b, A_{lb} is area ratio of land use/cover class l in block group b, and A_{nb} is area ratio of land use/cover class n in block group b. The final step in areal interpolation was to enumerate the socioeconomic characteristics of the population at risk with the cross-tabulation and tabular calculation capabilities in GIS. Figure 4.4 shows the overall process to implement the extended intelligent areal weighting interpolation method in a GIS environment.

Based on Sadahiro's second strategy, census block group boundaries were chosen in this research since they are the smallest geographic unit in terms of data availability. The census block groups tend to be more homogenous in nature than census tracts or counties and small enough to provide high estimation accuracy in areal interpolation. A block group is a cluster of blocks within a census tract. These groups are generally composed of 250 to 550 housing units. Average block groups contain about 400 households.

The spatial-temporal relationships between the locations of TRI facilities and the socioeconomic characteristics of the population at risk in the Atlanta metropolitan area from 1990 to 2000 were examined by employing the analytical procedures as illustrated in Figure 4.2.

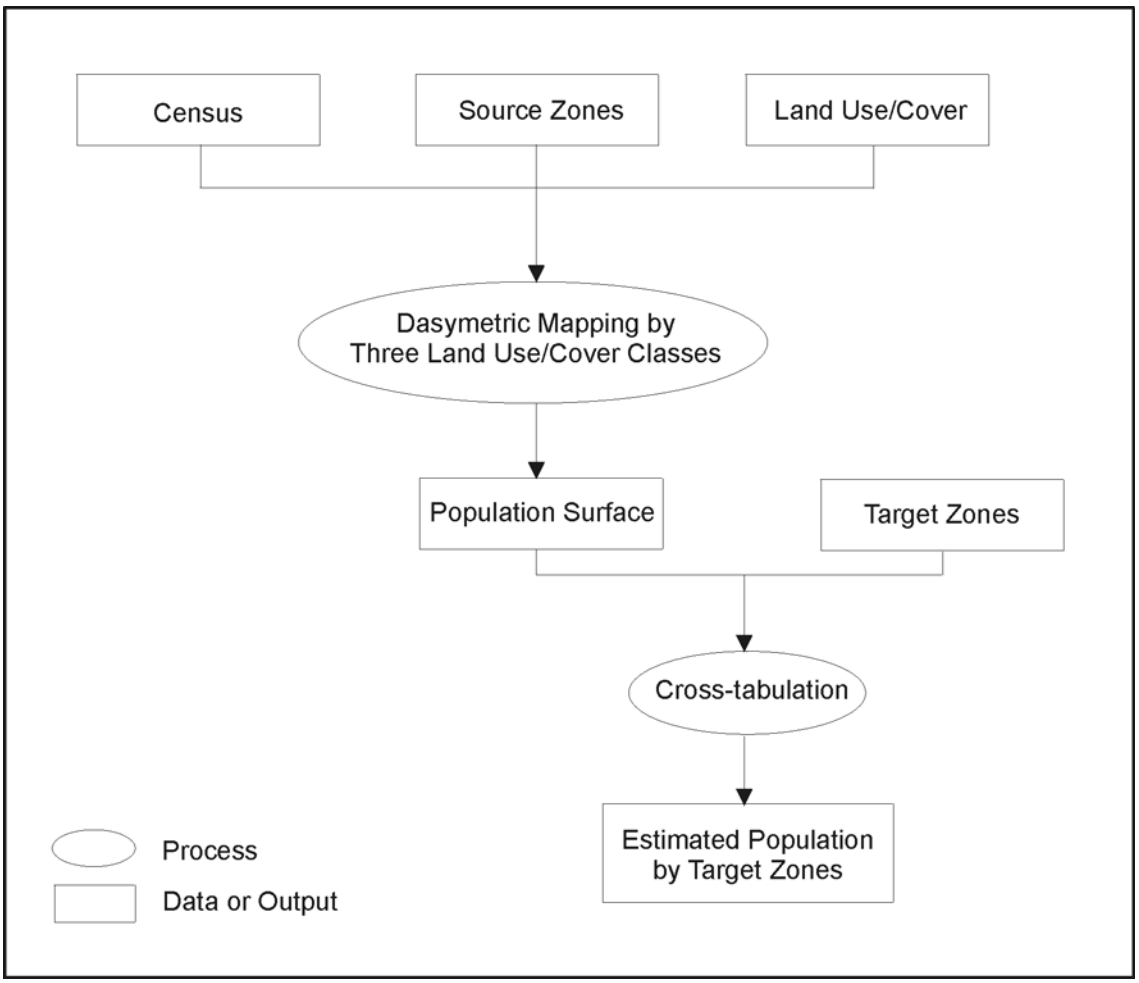


Figure 4.4 The process of the extended intelligent areal weighting interpolation method.

Two variables, percent minority and percent of people below poverty level, were selected to reflect the socioeconomic characteristics of the population. The most common approach used to characterize environmental equity is to compare the socio-economic characteristics of the population in neighborhoods that contain environmental hazards with populations in other similar neighborhoods that do not contain such hazards, or with those in larger areas such as entire county or state. The evidence of environmental equity in this research was gathered by comparing percent minority and percent of people below poverty level of the population within a threshold buffer with those outside the threshold buffer.

To determine the environmental equity, several analytical methods were applied in this research. First, a proximity ratio, the ratio of minority percent and below poverty percent within a buffer and those outside the buffer, was computed. If the ratio is above 1, there exists environmental inequity in a study area. Second, an independent samples t-test was used to test the statistical significance of the difference between the within buffer and the outside buffer means for each variable. Third, discriminant analysis was used to differentiate between the inside buffer and the outside buffer areas. This analysis is based on test of equality of group means, structure matrix, standardized function coefficient, and χ^2 statistics associated with Wilks' lambda. The test of equality of group means identifies significant variables of group differences between two groups. The structure matrix explains the loading of each variable for a linear discriminant function. The standardized function coefficient provides the relative contribution of each variable in explaining the group difference in the function. The χ^2 statistics in conjunction with Wilk's lambda and canonical correlation tests the overall significance of the discriminant function. Finally, an environmental equity model was developed in this research to detect the spatial clustering of hot spots in environmental equity as shown in Figure 4.5. This

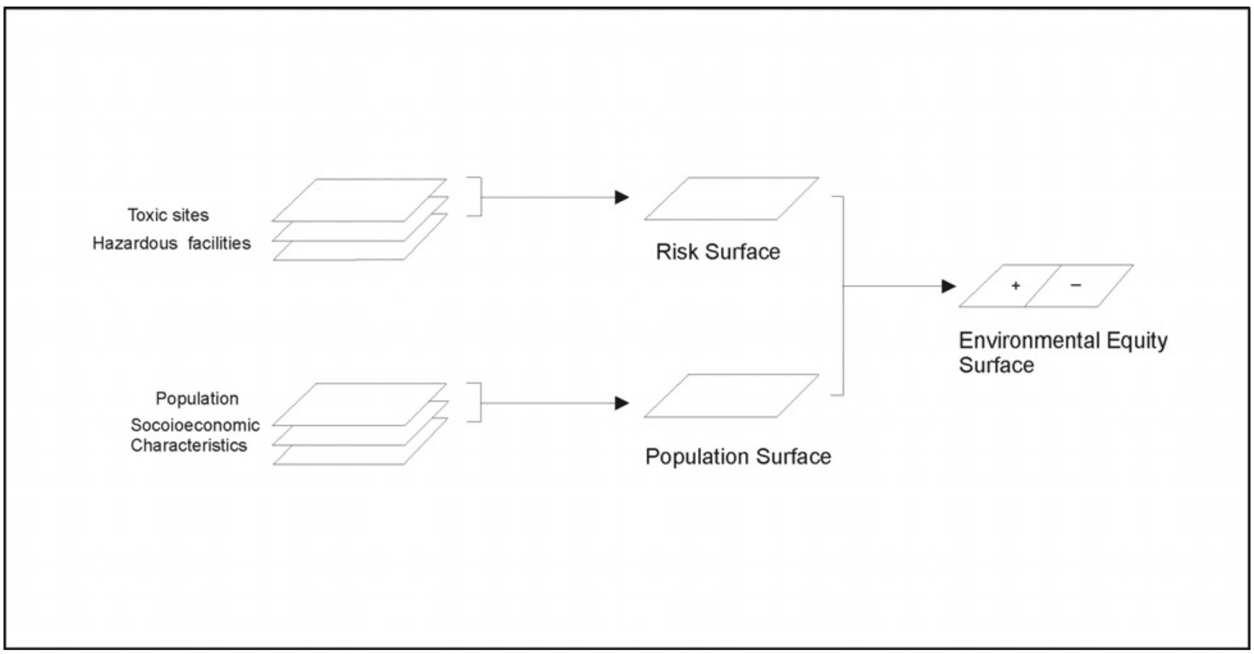


Figure 4.5 An approach to modeling environmental equity in a GIS context.

model provides us with the spatial variations in environmental equity within a defined urban region. The environmental equity model was implemented by linking a risk surface with a population surface. The risk surface was generated using the following equation proposed by Cutter *et al.* (2001):

$$CPE_i = \sum_{j=1}^{n}(1.0 - \frac{d_{ij}^{\,p}}{T_j^{\,p}}) \tag{4.11}$$

where CPE_i is cumulative proximal exposure to population in census unit i from distance to facility j at locations 1 through n (total number of facilities), d_{ij} is distance from population i to facility j, T_j is distance at which exposure is negligible for facility j, and p is rate of reduction of exposure at increasing distance from j. The CPE was then weighted by the RPRS for each TRI facility as expressed in Equation 4.1 in order to utilize the magnitude and the relative toxicity of release from TRI facilities. The population surface was constructed using Equations 4.9 and 4.10. Two surfaces were combined to create an environmental inequity surface using the weighted linear combination method in GIS environment. The spatial distribution of environmental inequity scores was then analyzed visually and statistically. For statistical analysis, Moran's I as a spatial autocorrelation index was used to measure the extent of spatial clustering among pixels with respect to environmental inequity scores. The Moran's I ranges from -1 when adjacent cells are very dissimilar to +1 when they are very much a like. Tests of significance were also performed under two null hypothesis assumptions such as the normality assumption and the randomization assumption. The form of Moran's I is formally given as follows:

$$\mathrm{I} = \frac{n}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(z_i - z_m)(z_j - z_m)}{\sum_i (z_i - z_m)^2} \tag{4.12}$$

where n is the total number of cells in an image, z_i is the value of the attribute of cell i, i = 1 to n, z_j is the value of the attribute of cell j, j = 1 to n, z_m is the mean cell value for the image, and w_{ij} is the similarity of i's location and j's location, w_{ij} = 1 if cells i and j are directly adjacent (4-adjacent) and 0 otherwise.

4.6 Quality of Life Assessment

The quality of life (QOL) in the Atlanta metropolitan area in 2000 was evaluated and mapped to complement environmental equity analysis. The three major data sets used were Landsat TM data, 2000 Census data, and the TRI database. The QOL was assessed based on demographic, economic, educational, housing, environmental, and hazard-related factors. Most of the criteria for QOL assessment were suggested by Lo and Faber (1997) while the hazard-related criterion was appended in this research since this is an obvious factor of environmental disamenity in urban areas.

From the Landsat TM images, a land-use and cover map was extracted using a hybrid digital image classification as shown in Figure 4.3. From this land-use and cover map, the residential, commercial and industrial (urban use), and nonresidential (comprising grassland/pasture/cropland and forest) classes were extracted and water and barren classes were excluded using the reclassification method. From bands 3 and 4 of the Landsat TM data, NDVI was computed for each pixel using Equation 4.3. From band 6, the thermal infrared band, surface temperature for each pixel was also computed using Equations 4.4 and 4.5.

From the census data, the following variables were extracted at the census block group level: (1) population density, (2) per capita income, (3) median home value, and (4) percent of college graduates. From the TRI database, a risk surface was generated using Equation 4.11.

Three environmental variables, land use and cover, NDVI, and surface temperature, and the hazard-related variable, the risk surface, are per-pixel data while the socioeconomic variables such as population density, per capita income, median home value, and education level are per-zone data. Because of zone-based data aggregation's unrealistic assumption that all the socioeconomic variables are uniformly spatially distributed throughout the census block group, and analytical pitfalls such as the MAUP and spatial interpolation between incompatible zone systems, four socioeconomic variables were spatially disaggregated into individual pixels. Two demographic variables, population density and percent of college graduates, were transformed for each pixel using a spatial microsimulation model based on Equations 4.9 and 4.10. Two economic variables, per capita income and median home value, were interpolated for each pixel using a geostatistical modeling method known as inverse distance weighting (IDW) because unlike spatially extensive data such as population, these variables are spatially intensive data which are expected to have the same value in each part of a zone (Goodchild and Lam, 1980).

A spatial multicriteria analysis approach as illustrated in Figure 4.6 was taken in this research to integrate and transform environmental, hazard-related, and socioeconomic variables into a resultant QOL score for each pixel. The process involves six main stages. The first stage is the selection of evaluation criteria or measures that determine the scope of the analysis as described above. The second stage is to standardize each criterion map layer through a linear scale transformation method based on the minimum and maximum values as expressed in Equation 4.13:

$$y_i = \frac{(x_i - X_{min})}{(X_{max} - X_{min})} \tag{4.13}$$

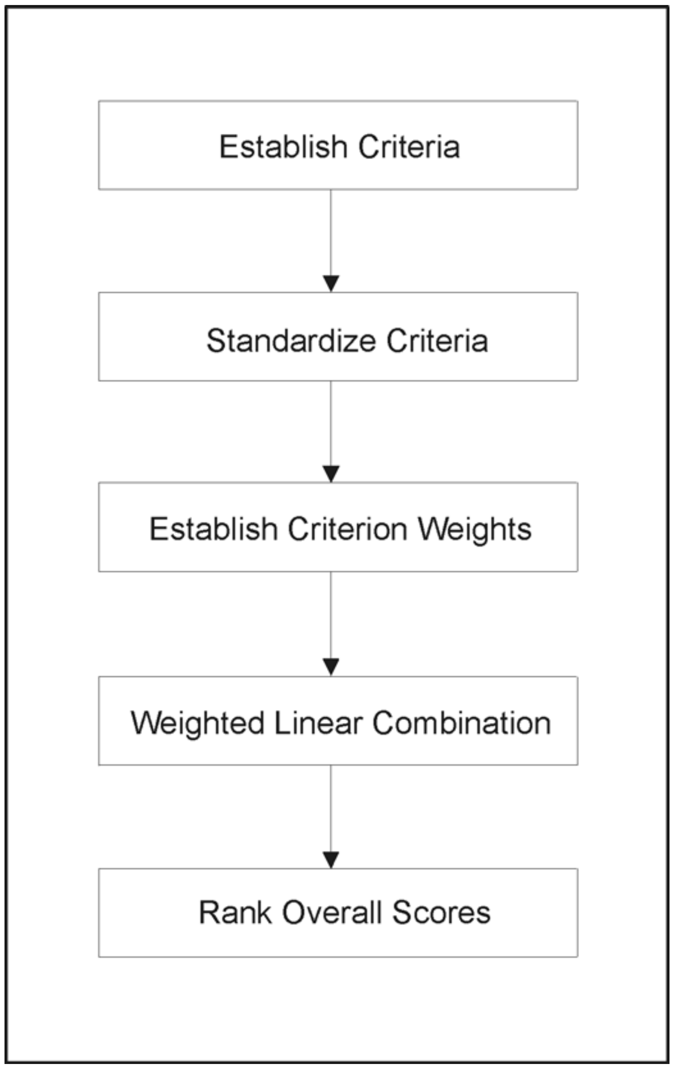


Figure 4.6 The process for spatial multicriteria analysis of QOL.

where y_i is the standardized score, x_i is the raw value, X_{max} is the maximum value, and X_{min} is the minimum value. The value of standardized scores ranges from 0 to 1. Because criteria are measured at the different scales, it is necessary that factors are standardized before combination. In the third stage, the evaluation criteria are compared pairwise using the analytical hierarchy process (AHP) developed by Saaty (1980) in order to generate the criterion weights. Although there are a variety of techniques for development of weights, Saaty's AHP appears as one of the most promising (Eastman *et al.*, 1995). The AHP approach allows one to assess the relative weight of multiple criteria in an intuitive manner. The weights sum to 1. In the fourth stage, the weighted standardized criteria are aggregated to generate the overall score using a decision rule based on a weighted linear combination (WLC) method. In the final stage, five ordinal levels are ranked according to the overall performance score.

The spatial multicriteria analysis is a subjective approach to determine the QOL score. To complement this approach, principal components analysis (PCA) as an alternative objective approach was used to integrate and transform the eight variables into a resultant QOL score for each pixel. According to Jensen (1996), there are two of the most common procedures for PCA: (1) standardized PCA and (2) unstandardized PCA. Since the standardized PCA function is not available in Imagine, the unstandardized PCA was used in this study. Before the analysis, all eight variables described above were stacked up and an image of eight layers was generated in the Imagine. PCA was then applied to the eight layers of image data using the Imagine.

The extent of spatial clustering among pixels with respect to quality of life scores based on two methods was measured by Moran's I. The resultant two QOL maps were visually and statistically compared with the environmental equity surface for 2000 in order to investigate spatial relationships among them. For statistical comparison, cross correlation analyses were performed for each pair of maps using the *correlation* function in the Imagine.

CHAPTER 5

EXPLORATORY SENSITIVITY ANALYSIS OF ENVIRONMENTAL EQUITY TO SPATIAL MEASURES

5.1 Introduction

In Chapter Two, several strategies and techniques for analyzing environmental equity were reviewed and considered. Many of the approaches have different advantages and disadvantages, assuming implicitly that complete information and data are available. However, the information and data available to the researcher are most often uncertain and imprecise in empirical studies. Moreover, conclusive and irrefutable evidence is not available in the existing literature on environmental equity studies due to methodological inconsistencies in data, measurement, scale/resolution, and method of analysis (McMaster *et al.*, 1997). A sensitivity analysis approach is used to handle uncertainties and the methodological inconsistencies in environmental equity analysis.

Sensitivity analysis is a technique for dealing with subjectivity and variability in model parameters (Lowry *et al.*, 1995). A sensitivity analysis assesses the variability of model results to changes in parameter values. In other words, the aim of the sensitivity analysis is to test the model for output over a range of legitimate uncertainty. Sensitivity analysis thus provides insight into the robustness of the model (Malczewski, 1999).

In order to develop an operational procedure for environmental equity analysis assuring accurate and effective results, this chapter explores the sensitivity of the analysis to three spatial measures using the combination of control and experimental factors as shown in Table 5.1: (1) proximity, (2) areal interpolation, and (3) scale and resolution. Because of the computational complexities in three experiments, Fulton County is chosen as a case study area considering that the majority of the city of Atlanta is located in this county. The first section evaluates the effect of different buffer distances on the environmental equity analysis. The second section investigates the effect of different areal interpolators. The third section assesses the effect of scale and resolution. A clear understanding of three spatial measures concerning the determination of impact zones and the estimation of the population at risk will be a first step toward identifying and measuring environmental inequities in metropolitan areas.

5.2 Sensitivity to Proximity

Previous studies on GIS-based analysis of environmental equity have usually relied on proximity modeling to represent the impact zones of a hazardous site because of its easy and economical operation (Liu, 2001). Proximity modeling, which is a spatial analytical technique for assessing proximity within a certain distance of a point, line, or area feature, has often implemented as circular buffer zones around a hazardous site. Previous studies set the threshold distance based on the reported releases, worst-case events, perceived effects, or modeled indirect effects, making the choice of a threshold or buffer distance an important parameter in characterizing environmental inequity. This section investigates how different buffer distances affect the results of environmental equity analysis using the experimental methods described in Section 4.4 of Chapter Four.

Table 5.1 Control and experimental factors for three experiments

Factor	Experiment 1	Experiment 2	Experiment 3
Study area	C	C	C
Proximity ratio	C	C	C
Buffer distance	E	C	C
Areal interpolator	C	E	C
Census boundary	C	C	E

Note: C stands for control factor while E connotes experimental factor.

Figure 5.1 shows the spatial distribution of 71 TRI facilities within the 146 census tracts of Fulton County in 1990. Thirty-nine percent of total TRI facilities in the Atlanta metropolitan area in 1990 were located in the Fulton County. Figure 5.2 represents six concentric half-mile wide circles with radii ranging from 0.5 to 3.0 miles around TRI facilities.

Table 5.2 indicates that minority residents comprise 66.1 to 69.5 percent of the population inside circular buffers, depending on the buffer distance, but only 18.9 to 50.9 percent of the population outside circular buffers. Similarly, about 19.5 to 24.8 percent of the population within these buffers are below the poverty level, as compared to only 4.7 to 14.1 percent for the rest of Fulton County.

The graph presented in Figure 5.3 illustrates the cumulative value of the percentages of minority and population below poverty within each buffer distance. It is noted that the percentages of minority and population below poverty drop slightly when larger buffer distances are used around the TRI sites.

To determine environmental inequity in the Fulton County, a proximity ratio, which is the ratio of the socioeconomic characteristics within buffer and those outside buffer, was computed for each circular buffer as shown in Table 5.2. If the proximity ratio exceeds 1, environmental inequity exists in the study area. For the percentage of minority, the proximity ratio ranges from 1.37 to 3.50. At the 3-mile buffer distance, the proximity ratio is highest while it is lowest at the half-mile buffer distance. For the percentage of population below poverty, the proximity ratio ranges from 1.75 to 4.16. Similarly, the highest proximity ratio is found at the 3-mile buffer distance while the lowest is found at the half-mile buffer distance. Extending the buffer distance from 0.5 to 3 miles makes remarkable difference to the proximity ratios as shown in Figure 5.4. The proximity ratio steadily increases as the buffer distance is extended to 3 miles.

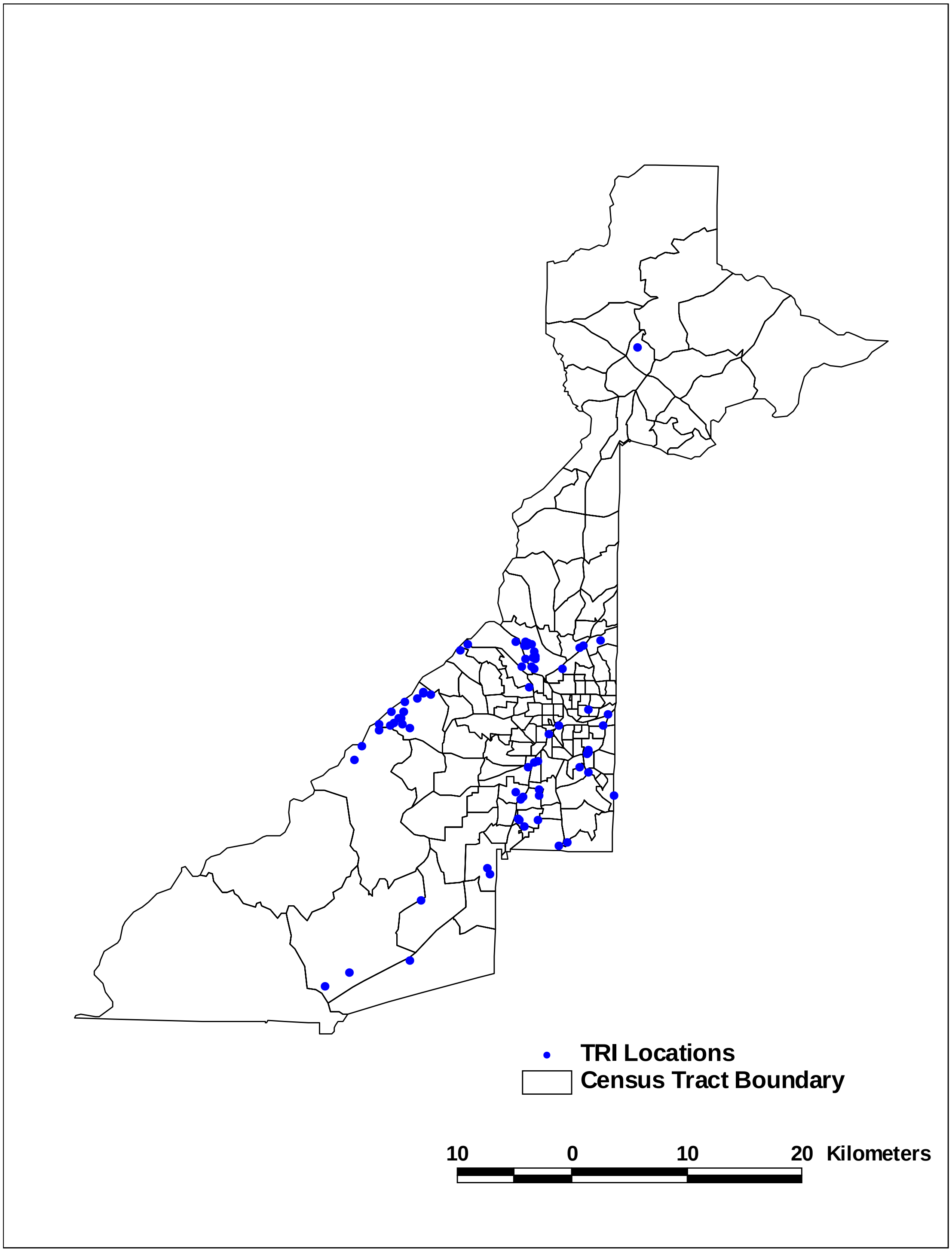


Figure 5.1 Spatial distribution of TRI facilities within the census tract boundaries of Fulton County in 1990.

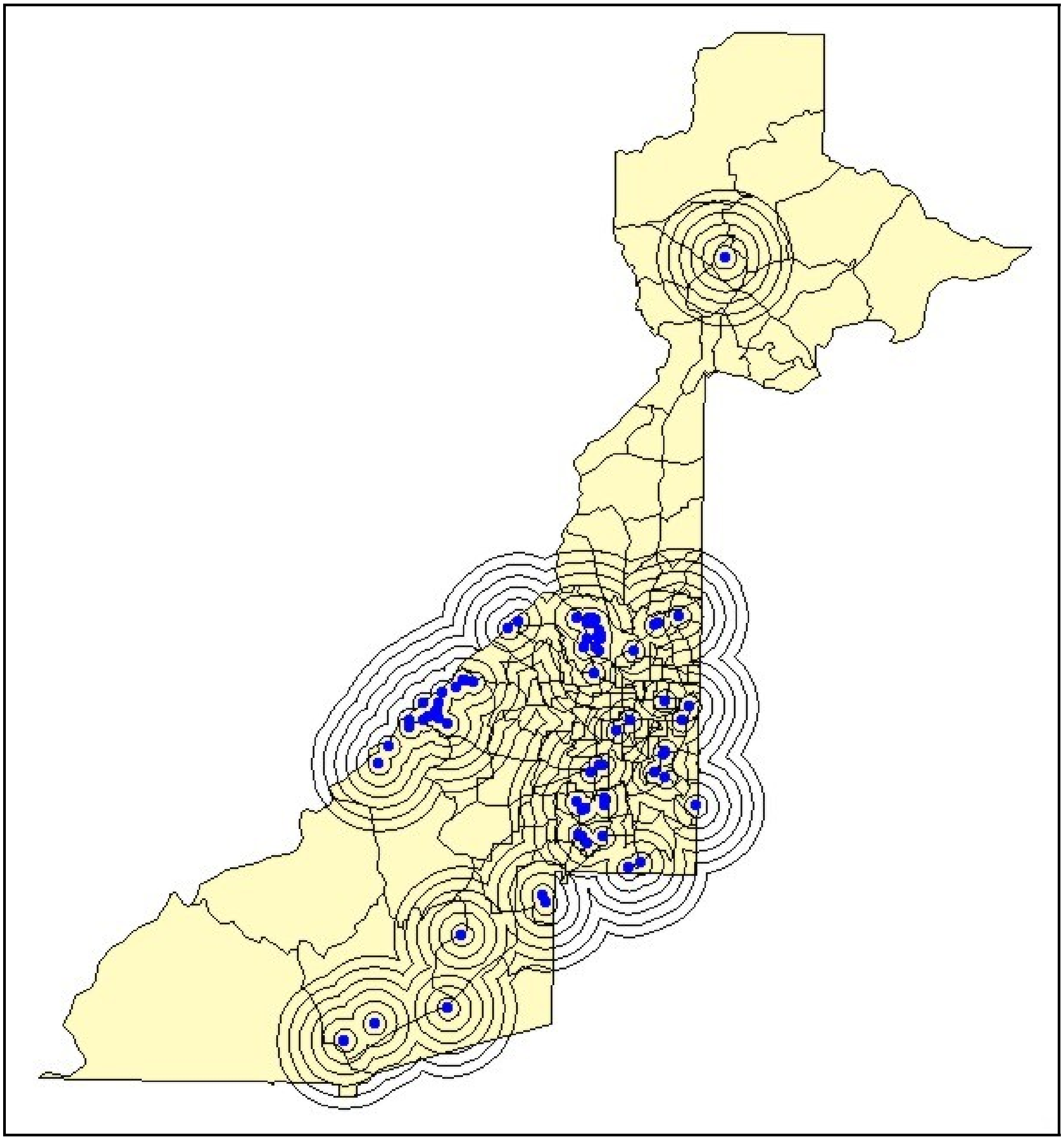


Figure 5.2 Circular buffer zones around TRI facilities in Fulton County.

Table 5.2 Comparison of the socioeconomic characteristics inside and outside circular buffers

Proximity measure	**Minority (%)**	**Below poverty (%)**
Inside 0.5 mile buffer	69.5	24.8
Outside 0.5 mile buffer	50.9	14.1
Proximity ratio	**1.37 (0.33)**	**1.75 (0.42)**
Inside 1 mile buffer	68.8	24.1
Outside 1 mile buffer	45.8	11.4
Proximity ratio	**1.50 (0.36)**	**2.11 (0.51)**
Inside 1.5 mile buffer	68.3	23.0
Outside 1.5 mile buffer	38.5	8.1
Proximity ratio	**1.77 (0.43)**	**2.84 (0.68)**
Inside 2 mile buffer	67.8	21.6
Outside 2 mile buffer	31.4	6.3
Proximity ratio	**2.16 (0.52)**	**3.43 (0.82)**
Inside 2.5 mile buffer	67.2	20.4
Outside 2.5 mile buffer	24.7	5.3
Proximity ratio	**2.72 (0.65)**	**3.85 (0.93)**
Inside 3 mile buffer	66.1	19.5
Outside 3 mile buffer	18.9	4.7
Proximity ratio	**3.50 (0.84)**	**4.16 (1)**

Note: The figures in parenthesis indicate the relative proximity ratio which is computed by dividing each proximity ratio by the maximum proximity ratio for comparison.

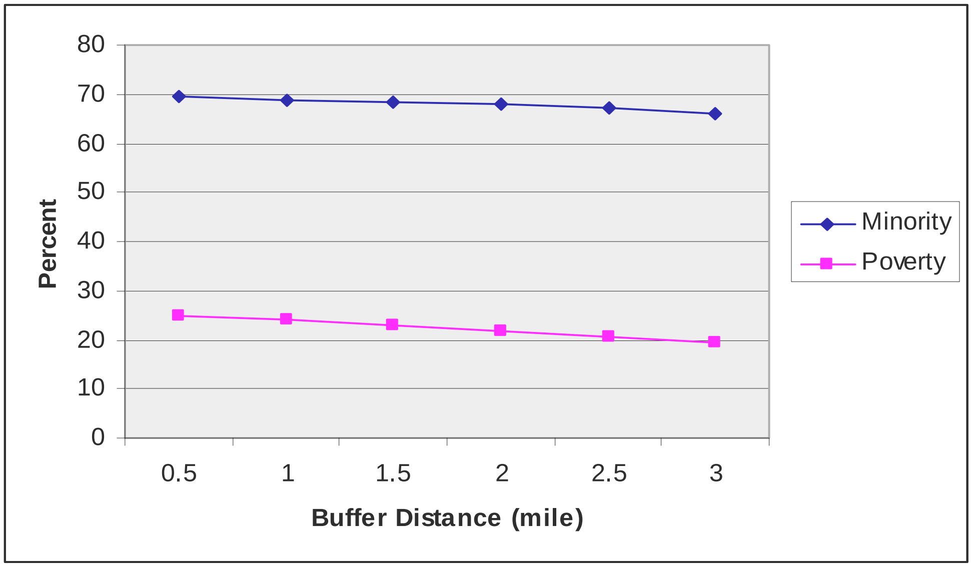


Figure 5.3 Relationship between buffer distance and socioeconomic characteristics.

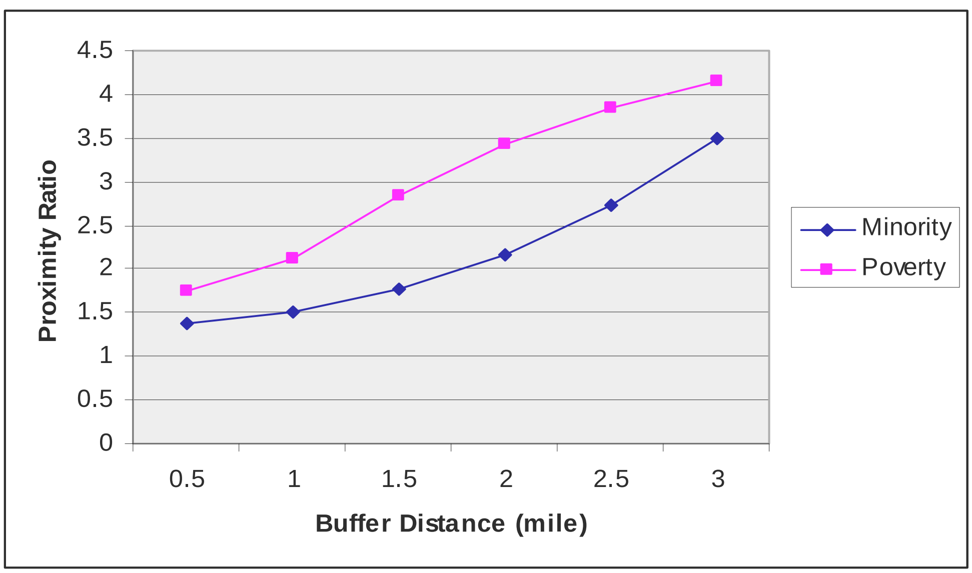


Figure 5.4 Relationship between buffer distance and proximity ratio.

To compare proximity ratios among different buffer distances by each variable, each proximity ratio was standardized by dividing it by the maximum proximity ratio found in Table 5.2. The standardized proximity ratio ranges from 0.33 to 1.00 as shown in Table 5.2. Figure 5.5 shows the relationship between buffer distance and standardized proximity ratio. At the half-mile buffer distance, the standardized proximity ratio is lowest for the percentage of minority while it is highest for the percentage of population below poverty at the 3-mile buffer distance. Through the pairwise comparisons between minority and poverty variables by buffer distance, it is found that poverty is a larger discriminating factor in explaining the relationship between distance to TRI facilities and socioeconomic characteristics in the Fulton County. This contrasts with the prevalence of ethnicity as the best predictor in previous studies (Underwood and Macey, 1998).

Irrespective of the buffer distance used, the proximity ratios are above 1 in all cases, except for the standardized proximity ratios as shown in Table 5.2. This means that some common patterns of environmental inequity based on minority and poverty status emerge for six buffer distances in the Fulton County. The findings also indicate that the results of environmental equity assessment are sensitive to the buffer distance used to determine the impact zones of TRI facilities.

5.3 Sensitivity to Areal Interpolation

Since the release of the 1990 U.S. Census data, a considerable amount of empirical research has applied GIS to environmental equity assessment. However, less attention has been given to estimating the population within environmental risk zones. As illustrated in Figure 2.1, there are three different methods for measuring demographic characteristics at risk: (1) polygon containment, (2) centroid containment, and (3) buffer containment. Most previous studies have

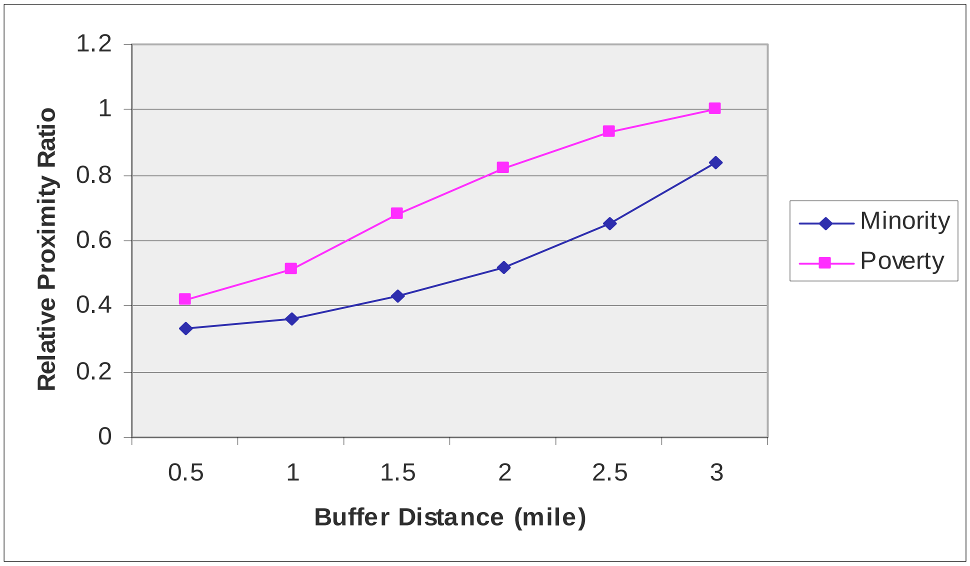
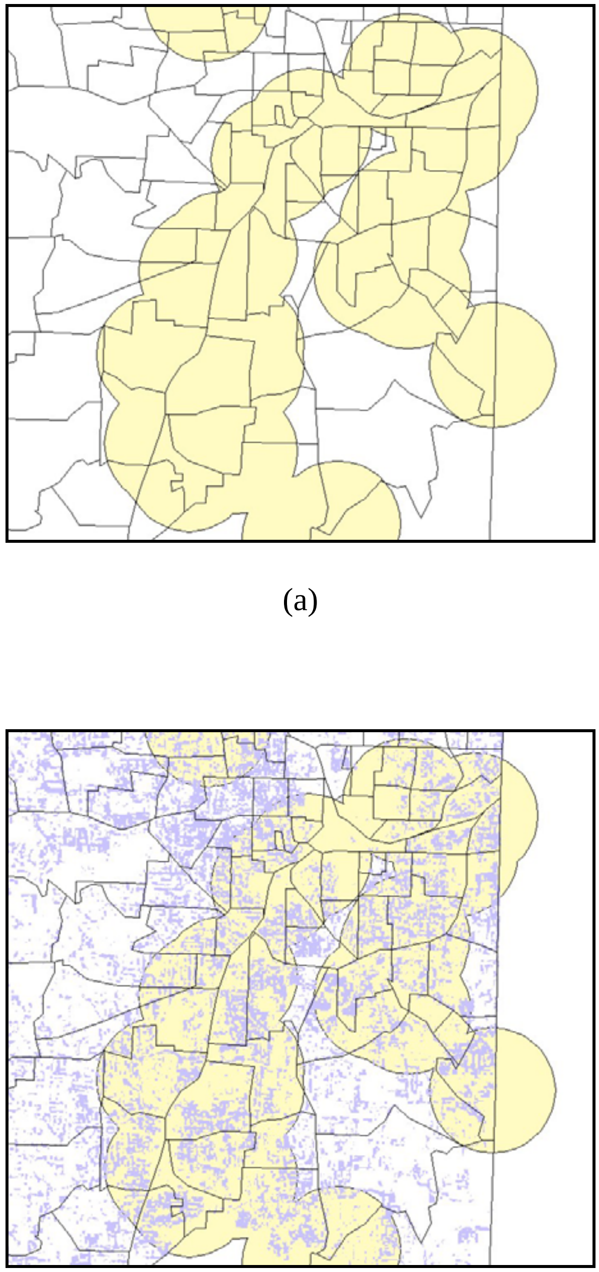


Figure 5.5 Relationship between buffer distance and standardized proximity ratio.

taken the polygon or centroid containment method because of its easy use. Some previous studies have used the buffer containment method which retains the original buffer shape because it is more realistic than the other two. The buffer containment method has commonly relied on a simple areal weighting interpolation method for quantifying the population at risk. Although this approach may be more sound and robust than the polygon and centroid containment methods, it may not be fully satisfactory since population is rarely assumed to be evenly distributed within a census enumeration unit. This limitation of the simple areal weighting interpolation can be overcome by intelligent areal interpolation methods, which are guided by additional geographic information about the distribution of population derived from ancillary land use and cover data as shown in Figure 5.6 (Jun, 2000).

This section evaluates the effect of different areal interpolators on the environmental equity analysis using the experimental methods described in Section 4.4 of Chapter Four. Based on the literature review of Chapter Two, the following areal interpolation methods were selected for sensitivity analysis: (1) simple areal weighting (Lam, 1983), (2) intelligent areal weighting (Fisher and Langford, 1996), and (3) three regression models: simple, focused and shotgun models (Langford *et al.*, 1991). Basically, the intelligent areal weighting interpolation method and three regression methods used in this experiment are typical examples of the intelligent areal interpolation method since they use land use and cover as ancillary data. The mathematical notation for the simple areal weighting interpolation was expressed in Equation 4.6 while the formula for the intelligent areal weighting interpolation method was described in Equation 4.7.

Three regression models, calibrated by ordinary least squares, linking population to the predictors are provided in Tables 5.3, 5.4, and 5.5. All the regression models are statistically significant at 0.05 level, except for one of the shotgun models relating population below poverty



(a)

(b)

Figure 5.6 Comparison of different areal interpolation methods: (a) circular buffers for simple areal weighting interpolation and (b) circular buffers for intelligent areal interpolation. Note that light purple clouds represent residential use in Figure 5.6 (b).

Table 5.3 Statistical summary for least squares simple model

Dependent variable	Predictor	Coefficient	Standard Error	t value	R^2	Adjusted R^2	p value
Pop90	Resid	3.103	0.115	27.069	0.835	0.834	0.000
Min90	Resid	1.394	0.132	10.596	0.436	0.433	0.000
Pov90	Resid	0.315	0.038	8.357	0.325	0.320	0.000

Note: Pop90-population in 1990; Min90-minority in 1990; Pov90-people below poverty in 1990; and Resid-the number of residential pixel. The two tailed p value is significant at 0.05 level.

Table 5.4 Statistical summary for least squares focused model

Dependent variable	Predictor	Coefficient	Standard error	t value	R^2	Adjusted R^2	p value
Pop90	Resid	2.769	0.179	15.5	0.841	0.839	0.000
	Indcom	0.357	0.148	2.410			
Min90	Resid	0.952	0.204	4.672	0.466	0.458	0.000
	Indcom	0.473	0.169	2.803			
Pov90	Resid	0.156	0.057	0.282	0.616	0.371	0.000
	Indcom	0.170	0.048	0.372			

Note: Pop90-population in 1990; Min90-minority in 1990; Pov90-people below poverty in 1990; Resid-the number of residential pixel; and Indcom-the number of industrial and commercial pixel. The two tailed p value is significant at 0.05 level.

Table 5.5 Statistical summary for least squares shotgun model

Dependent variable	Predictor	Coefficient	Standard error	T value	R^2	Adjusted R^2	p value
Pop90	Constant	1693.665	193.339	8.760	0.737	0.728	0.000
	Resid	2.553	0.178	14.381			
	Indcom	-0.024	0.117	-0.208			
	Gpc	-0.719	0.160	-4.492			
	Forest	0.035	0.022	1.610			
	Other	1.464	0.799	1.832			
Min90	Constant	1388.3	270.657	5.129	0.168	0.138	0.000
	Resid	0.854	0.249	3.438			
	Indcom	0.153	0.163	0.937			
	Gpc	-0.365	0.224	-1.629			
	Forest	0.036	0.031	1.177			
	Other	-1.498	1.118	-1.340			
Pov90	Constant	637.459	65.852	9.68	0.053	0.020	0.169*
	Resid	-0.022	0.060	-0.367			
	Indcom	0.086	0.040	2.173			
	Gpc	0.020	0.055	0.361			
	Forest	-0.004	0.008	-0.497			
	Other	-0.128	0.272	-0.472			

Note: Pop90-population in 1990; Min90-minority in 1990; Pov90-people below poverty in 1990; Resid-the number of residential pixel; Indcom-the number of industrial and commercial pixel; Gpc-the number of grassland/pasture/cropland pixel; Forest-the number of forest pixel; and Other-the number of water and barren pixel. The two tailed p value is significant at 0.05 level.
* This value is not significant at 0.05 level.

level to the carrier variables. The land use and cover map of Fulton County in 1990 used as collateral data for the intelligent areal interpolation is displayed in Figure 5.7.

In the simple model, the residential variable was regressed against population, minority, and population below poverty level in each census tract. The ordinary least squares models, with forced zero intercept term, are as follows:

$$\text{pop90} = 3.10 \text{ resid} \tag{5.1}$$

$$\text{min90} = 1.39 \text{ resid} \tag{5.2}$$

$$\text{pov90} = 0.32 \text{ resid} \tag{5.3}$$

This result implies that each pixel classified as residential will on average contain 3.10 people, 1.39 minority, and 0.32 people below poverty level. Table 5.3 gives the simple regression model in detail. Although the overall fit for population in 1990, at 83 percent, is good, minority and population below poverty level in 1990 are not well fitted at 43 and 32 percents.

As shown in Table 5.4, the ordinary least squares focused models are as follows:

$$\text{pop90} = 2.77 \text{ resid} + 0.36 \text{ indcom} \tag{5.4}$$

$$\text{min90} = 0.95 \text{ resid} + 0.47 \text{ indcom} \tag{5.5}$$

$$\text{pov90} = 0.16 \text{ resid} + 0.17 \text{ indcom} \tag{5.6}$$

In this model, the individual coefficients have a direct interpretation as the average density of people in each 28.5 m square pixel of the specified type. The models explained the variances of population, minority, and population below poverty level in 1990 at 84, 46, and 37 percents, respectively.

In the shotgun model, the ordinary least squares models, with intercept term, are expressed as follows:

$$\text{pop90} = 1693.67 + 2.55 \text{ resid} - 0.02 \text{ indcom} - 0.72 \text{ gpc} + 0.04 \text{ forest} + 1.46 \text{ other} \tag{5.7}$$

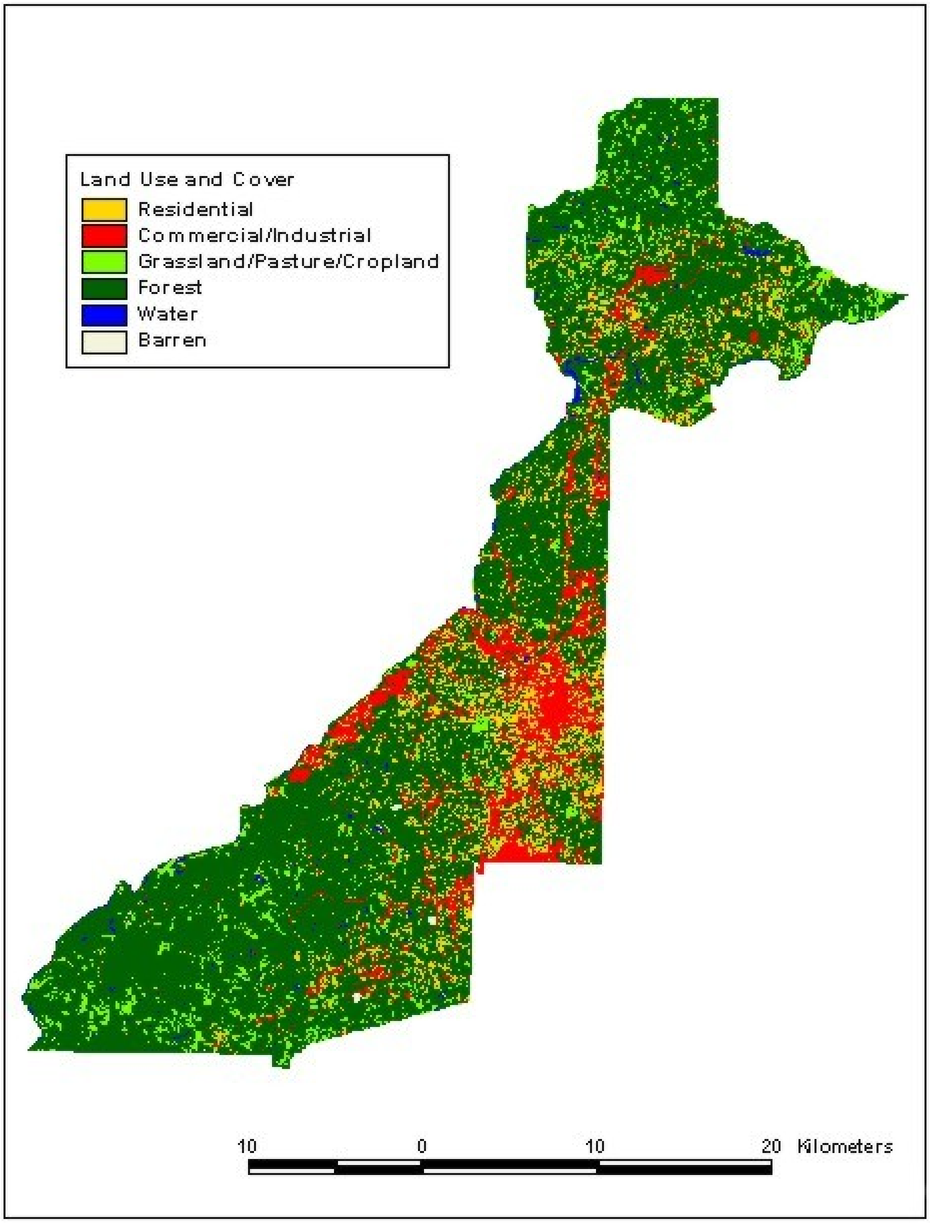


Figure 5.7 Land use and cover of Fulton County in 1990.

$$min90 = 1388.3 + 0.85\ resid + 0.15\ indcom - 0.37\ gpc + 0.04\ forest - 1.50\ other \quad (5.8)$$

$$pov90 = 637.46 - 0.02\ resid + 0.09\ indcom + 0.02\ gpc - 0.004\ forest - 0.13\ other \quad (5.9)$$

Unlike the simple and focused models, the shotgun model has an intercept constant. As shown in Table 5.5, the models accounted for the variances of population, minority, and population below poverty level in 1990 at 73, 14, and 2 percents, respectively.

Table 5.6 shows that the proportion of minority residents inside 1 mile buffer regions spans 52 to 77.5 percent, depending on the areal interpolation method, while that outside 1 mile buffer regions ranges 39.9 to 45.9 percent. Similarly, about 15.3 to 33.9 percent of the population within the buffer regions are below the poverty level, as compared to only 9.1 to 17.4 percent of the population outside the buffer regions.

Figure 5.8 illustrates the percentages of minority and population below poverty within one mile buffer distance by the areal interpolation method. The percentages of minority and population below poverty inside one mile buffer zones are consistently lower when the simple regression model is used. When the populations are estimated by the focused and shotgun regression models, the one mile buffer zones have the highest proportion of minority and population below poverty. The regression models tend to over or underestimate the population at risk, as compared to simple and intelligent areal weighting interpolation methods.

Table 5.6 also provides the proximity ratio to determine environmental inequity. The proximity ratio for the percentage of minority ranges from 1.30 to 1.93. Figure 5.9 illustrates that the proximity ratio is lowest when the population is estimated by the simple regression model while it is highest when the focused regression model is used for population estimation. The proximity ratio for the percentage of population below poverty comprises 1.58 to 2.79. Similarly,

Table 5.6 Comparison of the socioeconomic characteristics inside and outside one mile circular buffers by areal interpolation method

	Minority (%)					**Below Poverty (%)**				
	SAW	**IAW**	**R1**	**R2**	**R3**	**SAW**	**IAW**	**R1**	**R2**	**R3**
Inside 1 mile buffer	68.8	68.1	52.0	77.5	72.8	24.1	23.6	15.3	25.4	33.9
Outside 1 mile buffer	45.8	45.9	39.9	40.1	43.1	11.4	11.5	9.7	9.1	17.4
Proximity ratio	**1.50 (0.54)**	**1.48 (0.53)**	**1.30 (0.47)**	**1.93 (0.69)**	**1.69 (0.61)**	**2.11 (0.76)**	**2.05 (0.73)**	**1.58 (0.57)**	**2.79 (1)**	**1.95 (0.70)**

Note: SAW-simple areal weighting interpolation; IAW-intelligent areal weighting interpolation; R1-simple regression model; R2-focused regression model; and R3-shotgun regression model. The figures in parenthesis indicate the relative proximity ratio which is computed by dividing each proximity ratio by the maximum proximity ratio for comparison.

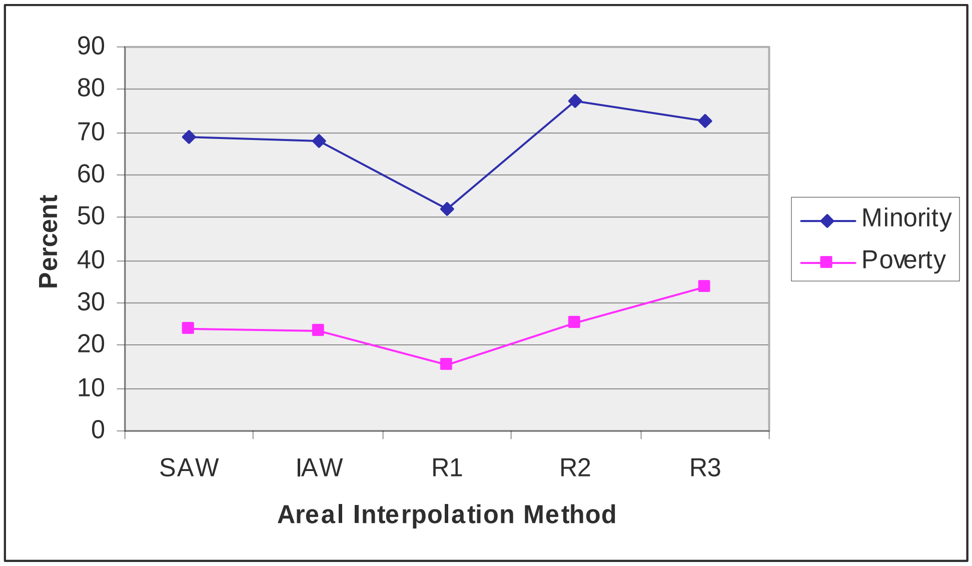


Figure 5.8 Relationship between areal interpolation method and socioeconomic characteristics.

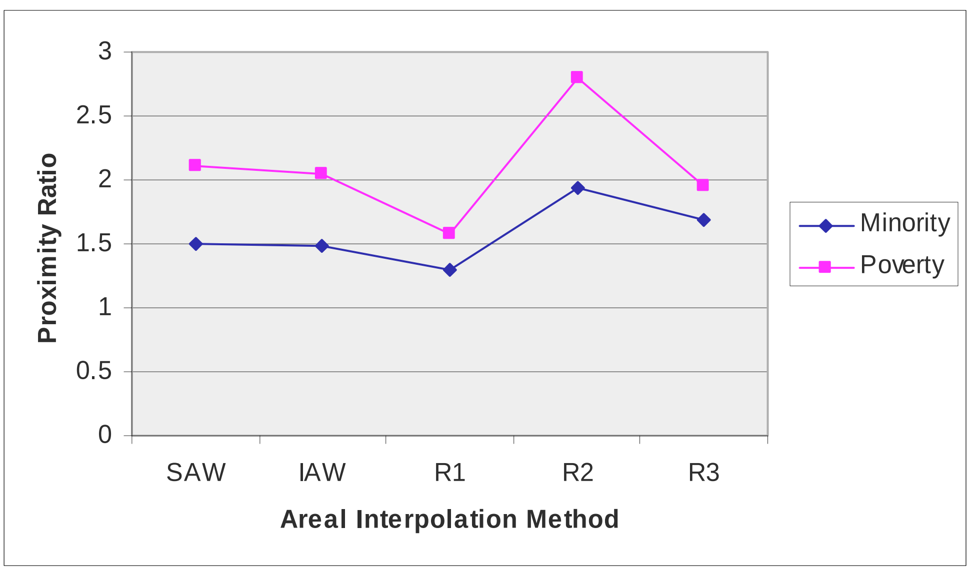


Figure 5.9 Relationship between areal interpolation method and proximity ratio.

the lowest proximity ratio is found at the simple regression model while the highest is found at the focused model.

In Table 5.6, the proximity ratios were also compared using the standardized proximity ratio. The standardized proximity ratio ranges from 0.47 to 1.00. When the population is estimated by the simple regression model, the standardized proximity ratio is lowest for the percentage of minority while it is highest for the percentage of population below poverty when the focused regression model is used. Based on the pairwise comparisons between minority and poverty factors by the areal interpolation method, it is found that poverty is a better predictor of environmental inequity in the Fulton County.

Regardless of the areal interpolation method used, the proximity ratios exceed 1 in all cases. In other words, there clearly exist some patterns of environmental inequity based on minority and poverty in the Fulton County. The findings from this experiment also indicate that the results of environmental equity assessment depend on the areal interpolation method used to estimate the population at risk.

5.4 Sensitivity to Scale and Resolution

One of the long-standing problems latent in geographic studies is the MAUP. The MAUP issue refers to the fact that the results in geographic studies are highly sensitive to the scale and the zoning scheme (areal boundaries) used in the analysis (Openshaw, 1983). As portrayed in Figure 5.10, the scale effect refers to the inconsistency of analytical results derived from data recorded at different levels of partitioning for the same area while the zoning or aggregation effect refers to the variability of analytical results derived from data aggregated in different ways

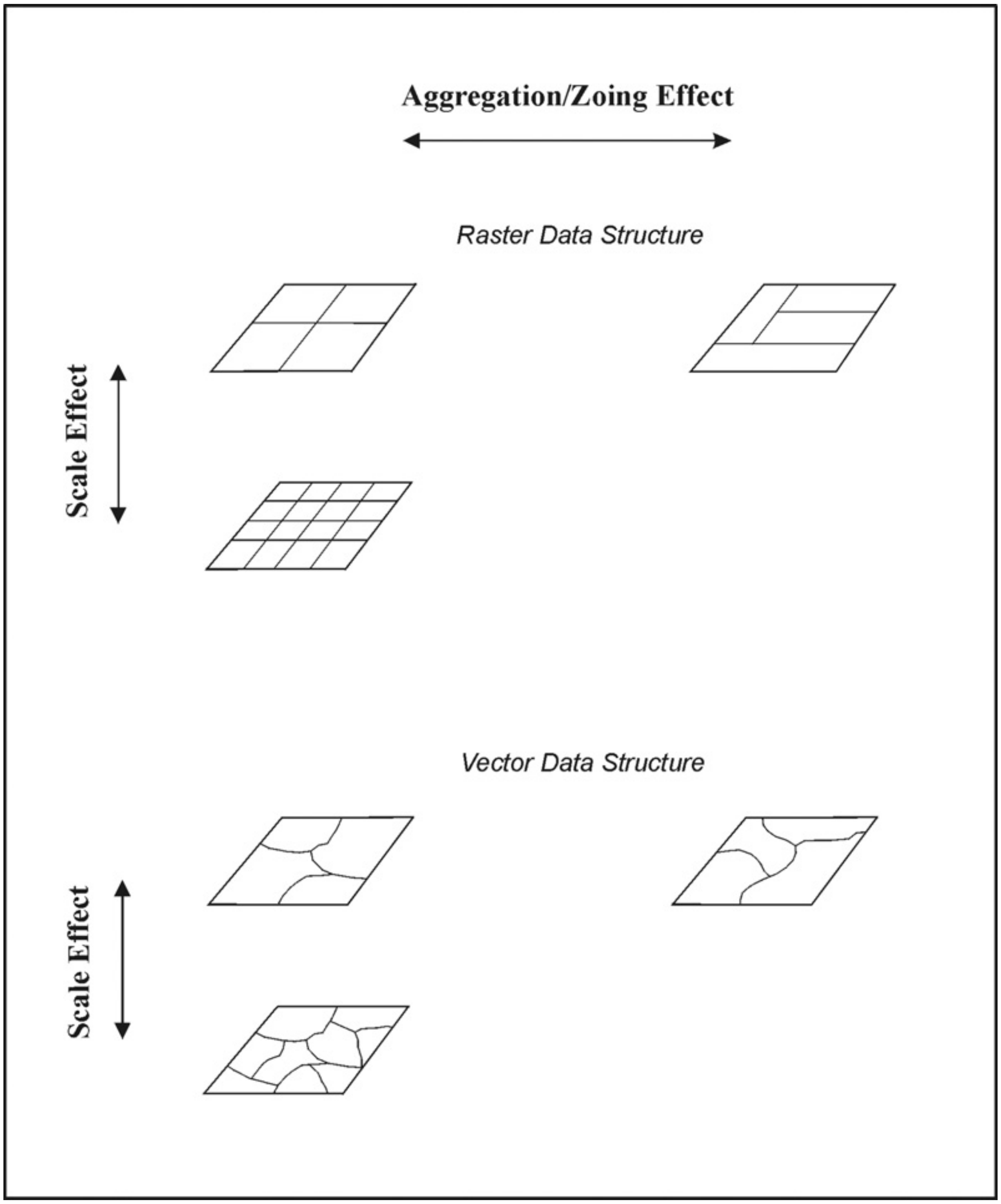


Figure 5.10 Two dimensions of the MAUP (after Wong, 1996).

and with the same number of areal units in different partitioning schemes for the same region (Wong, 1996).

Most previous studies on environmental equity analysis were based on an ad hoc selection of geographic scales and areal unit boundaries without a rational justification. Few studies addressed the effects of the MAUP in environmental equity analysis (Cutter *et al.*, 1996; McMaster *et al.,* 1997; Sui, 1999). It is not surprising that conflicting evidence has been documented in the literature. It is still not clear that to what degree the scale and areal unit of analysis may have over or underestimated the relationship between the distribution of TRI facilities and the socioeconomic characteristics of the population at risk. This section attempts to examine the effect of scale and resolution such as census tract and block group boundaries on the results of environmental equity analysis using the experimental methods described in Section 4.4 of Chapter Four.

Figure 5.11 shows the spatial distribution of TRI facilities over the census block group boundary of Fulton County in 1990, as compared to the census tract boundary in Figure 5.1. There are 636 census block groups in the Fulton County in 1990. With one mile buffer distance and the simple areal weighting interpolation method selected, environmental equity analysis was performed in both census tract and block group boundaries as shown in Figure 5.12.

Table 5.7 indicates that the proportion of minority residents inside one mile circular buffers comprises 68.8 to 69.2 percent, depending on the geographic scale and resolution, while that outside one mile circular buffers ranges from 45.8 to 46.0 percent. Similarly, the proportion of poor residents inside one mile buffers contains about 24.1 to 28.2 percent, as compared to only 11.4 to 13.1 percent of the population outside the buffer zones.

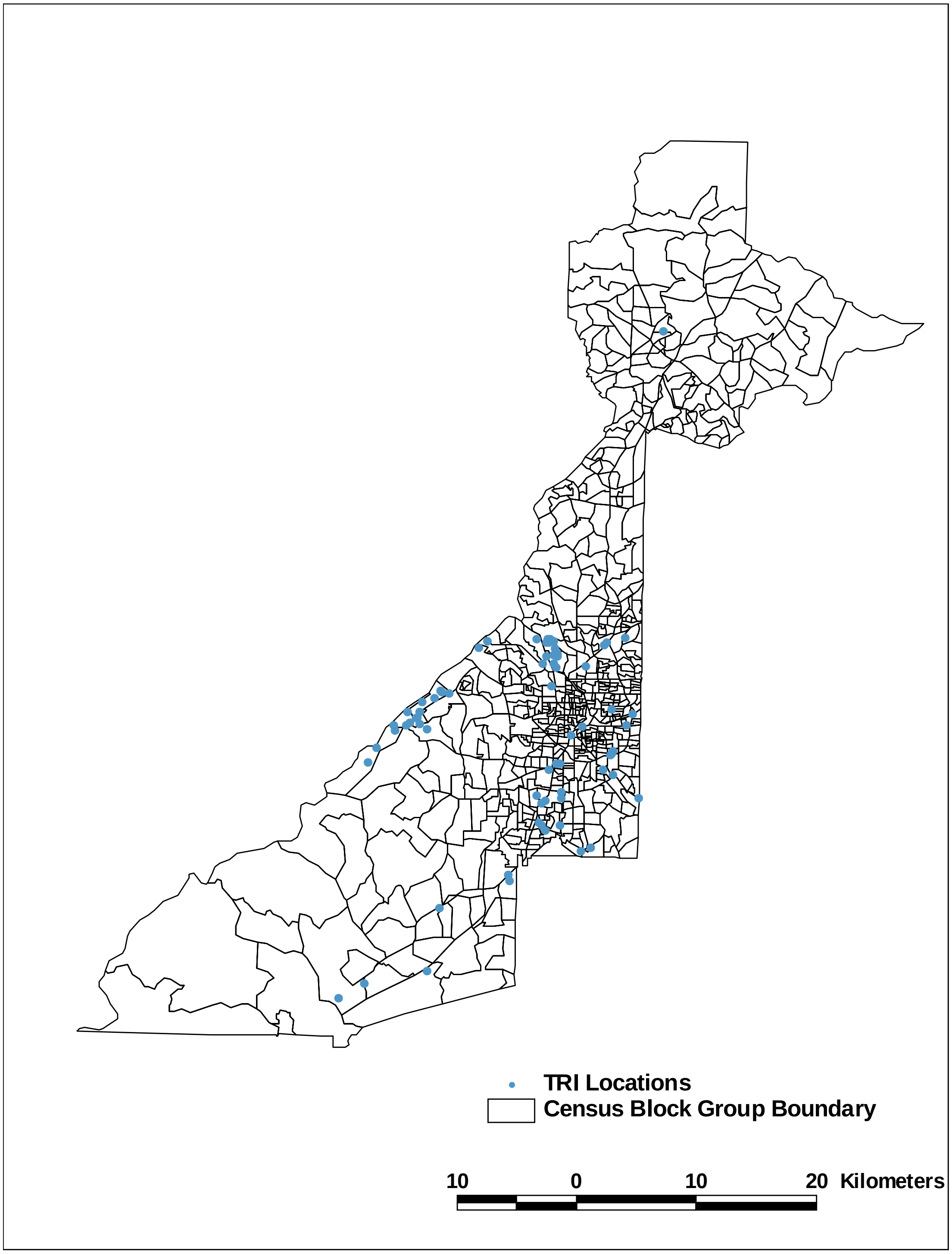
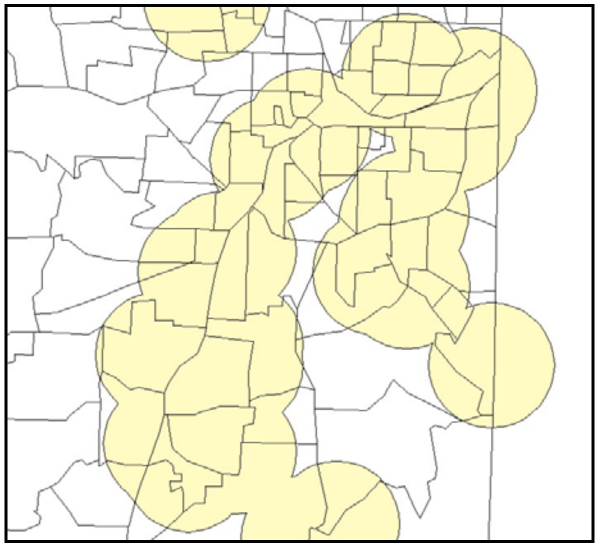
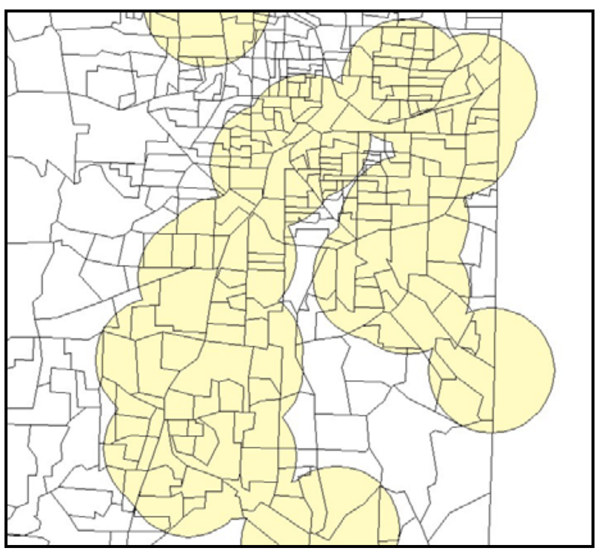


Figure 5.11 Spatial distribution of TRI facilities within the census block group boundaries of Fulton County in 1990.



(a)



(b)

Figure 5.12 Comparison of different scales and resolutions: (a) census tracts within circular buffers and (b) census block groups within circular buffers.

Table 5.7 Comparison of the socioeconomic characteristics inside and outside one mile circular buffers by geographic scale and resolution

	Minority (%)		**Below poverty (%)**	
	CT	**BG**	**CT**	**BG**
Inside 1 mile buffer	68.8	69.2	24.1	28.2
Outside 1 mile buffer	45.8	46.0	11.4	13.1
Proximity ratio	**1.50 (0.70)**	**1.50 (0.70)**	**2.11 (0.98)**	**2.15 (1)**

Note: CT-census tract and BG-census block group. The figures in parenthesis indicate the relative proximity ratio which is computed by dividing each proximity ratio by the maximum proximity ratio for comparison.

The percentages of minority and population below poverty within one mile buffer distance by geographic scale and resolution are represented in Figure 5.13. The percentages of minority and population below poverty inside one mile buffer zones are consistently lower when census tract is used. When census block group is used, the one mile buffer zones have the higher proportion of minority and population below poverty. The coarse scale and resolution of analysis tend to slightly average the percentage variables.

The proximity ratio is also provided in Table 5.7 to determine environmental inequity. The proximity ratio for the percentage of minority is 1.50. Figure 5.14 shows that the proximity ratio is very similar for both census tract and block group. This indicates that there is no scale effect on the percent of minority variable in this study area. The proximity ratio for the percentage of population below poverty ranges from 2.11 to 2.15. The proximity ratio is lower when census tract is used while the proximity ratio is slightly higher when census block group is used. This result indicates that there is some scale effect on the percentage of population below poverty variable in this study area, but the scale effect is very little.

The standardized proximity ratio was computed to compare the proximity ratios in Table 5.7. The standardized proximity ratio ranges from 0.7 to 1.00. When the population is estimated based on census tracts and block groups, the standardized proximity ratio is lowest for the percentage of minority while it is highest for the percentage of population below poverty when census block group is used. By pairwisely comparing minority and poverty factors by geographic scale and resolution, it is found that poverty is a better predictor for environmental inequity in the Fulton County.

In all cases, the proximity ratios exceed 1 with respect to the geographic scale and resolution used. That is, some patterns of environmental inequity based on minority and poverty

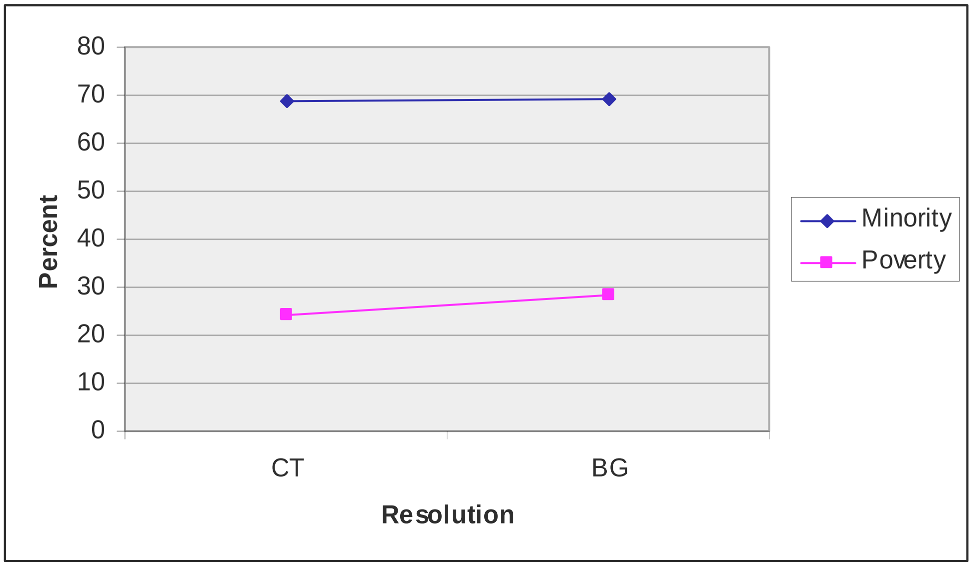


Figure 5.13 Relationship between geographic scale and resolution and socioeconomic characteristics (CT-census tract and BG-census block group).

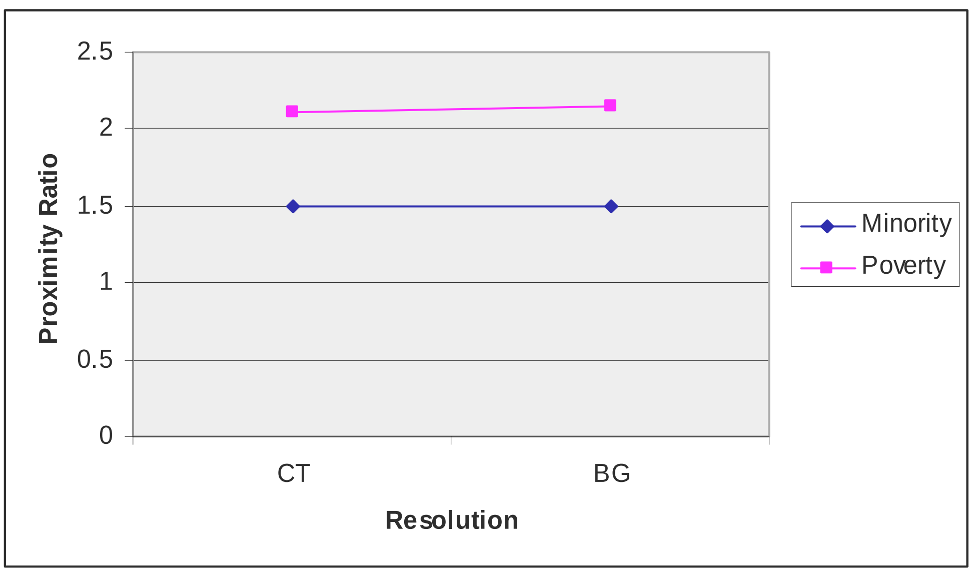


Figure 5.14 Relationship between geographic scale and resolution and proximity ratio (CT-census tract and BG-census block group).

clearly exist in the Fulton County. It is also found that the results of environmental equity assessment is little sensitive to the geographic scale and resolution used in the analyses and the effect of scale and resolution is very slight in this study area.

5.5 Concluding Discussion

Based on three experiments, general conclusions can be drawn as follows: First, in all cases, the proportion of racial minorities and the economically disadvantaged is consistently higher in populations residing within the buffer area around TRI facilities, as compared to the rest of Fulton County. This finding is consistent with other research that has shown TRI facilities to be distributed inequitably with regard to income and race (Burke, 1993; Bowen *et al.*, 1995; Pollock and Vittas, 1995). Second, regardless of different spatial measures of proximity, areal interpolation, and scale and resolution, the proximity ratio, which is a ratio to characterize environmental inequity, exceeds 1 in all cases. This means that there clearly exist some common patterns of environmental inequity based on minority and poverty in the Fulton County. Third, in all cases, poverty is a better predictor for environmental inequity in the Fulton County. This finding gets in contrast with the prevalence of ethnicity as the best predictor in previous studies (Underwood and Macey, 1998).

The findings from three experiments also indicate that the results of environmental equity assessment are sensitive to the buffer distance used to determine the impact zones of TRI facilities and the areal interpolation method used to estimate the population at risk, but not to the geographic scale and resolution used in the analyses. The effects of three spatial measures on environmental equity analysis were evaluated in two ways: (1) population proportion and (2) proximity ratio.

For proximity, it is found that the percentages of minority and population below poverty drop slightly when larger buffer distances are used around TRI facilities. The larger zones of analysis tend to average the proportions. As the buffer distance is extended from 0.5 to 3 miles, the proximity ratio increases.

In the case of areal interpolation, the percentages of minority and population below poverty within one mile buffer zones are consistently lower when the simple regression model is used while the one mile buffer zones have the highest proportion of minority and population below poverty when the focused and shotgun regression models are used. In general, regression models tend to over or underestimate the population at risk, as compared to simple and intelligent areal weighting interpolation methods. In all cases, the proximity ratio is lowest when the simple regression model is used while it is highest when the focused regression model is used.

With regard to scale and resolution, the percentages of minority and population below poverty inside one mile buffer zones are lower when census tracts are used while the one mile buffer zones have the slightly higher proportion of minority and population below poverty when census block group is used. The coarse geographic scale and resolution tend to average little the proportions. The proximity ratio is lower when census tract is used while the proximity ratio is a little higher when census block group is used. It is noted that although there is some scale effect on environmental equity analysis in the Fulton County, the effect is slight enough to ignore.

Environmental justice researchers may choose among several spatial measures to assess the environmental inequity posed to a community by industrial facilities. As demonstrated in this study, the consequences of these choices can alter statistically and spatially the results in environmental equity analysis and lead to erroneous conclusions. Careful selection and justification of spatial measures are, thus, necessary and caution should be paid in interpreting the results.

Three methodological experiments have shed insights on formulating an operational procedure for the environmental equity analysis ensuring accurate and effective results in Chapter Six. Based on the first experiment, a range of threshold distances from 0.5 to 3 miles to delineate the impact zones of TRI facilities needs to be used in order to test the sensitivity of environmental equity analysis to the half-mile distance. Based on the second experiment, it is necessary to determine an accurate areal interpolation method in order to estimate the population at risk. Sadahiro (2000) suggested two strategies to improve the accuracy of estimates in areal interpolation: (1) choosing an intelligent method and (2) employing the finest source zones. On the basis of his first strategy, an intelligent areal weighting interpolation method is recommended to employ for Chapter Six since its performance is relatively accurate in areal interpolation and robust to error in a land use and cover classification (Fisher and Langford, 1995 and 1996). Based on the third experiment, it is required to select an appropriate scale, dealing with the effects of the MAUP in environmental equity analysis. With his second strategy taken, census block group boundaries need to be selected in Chapter Six because they are the smallest geographic unit in terms of data availability. The census block groups tend to be more homogenous in nature than census tracts and fine enough to provide higher estimation accuracy in areal interpolation. This also provides a good rational justification in considering the MAUP issue.

CHAPTER 6

ENVIRONMENTAL EQUITY ANALYSIS IN METROPOLITAN ATLANTA, 1990-2000

6. 1 Introduction

During the past two decades, one of the recurring issues in the social sciences has concerned the inequity in the distribution of environmental risks with regard to socioeconomic characteristics (Brainard *et al.*, 2002). In this context, many empirical studies have been conducted to examine the geographic patterns and historical processes in various urban areas (Holifield, 2001). As a follow-up study, a preliminary work (Jun, 1999) was carried out for the Atlanta metropolitan area using the locations of TRI facilities in 1995 and the demographic data at the census block group level in 1990. This research showed clear evidence of environmental inequity based on ethnicity and poverty in the metropolitan area. However, further research in the study area needs to be continued at different time frames in order to reveal the changing spatial pattern of environmental inequity. A systematic case study in the Atlanta metropolitan area, a rapidly suburbanizing and racially segregated urban area, is also lacking in the literature. This case study will provide a new insight into environmental equity study in such a unique urban setting. Moreover, the data in the preliminary work are problematic because of outdated geodemographic data. Analyses are increasingly in error as the 1990 census data become dated (Jun, 1999). As stated in Chapter Three, the Atlanta metropolitan area is chosen as the study area because of the following reasons: (1) its biracial dichotomy between White and Black (Smith, 1985), (2) one of the major manufacturing centers in the South (Hartshorn, 1997), (3) water-quality issues related to urban development downstream of the upper Chattahoochee River, (4) high acute airborne toxic release (Cutter and Solecki, 1996) and degenerated air quality, and (5) strong existence of urban inequality based on racial segregation (Smith, 1985; Sjoquist, 2000).

Using the analytical procedures as illustrated in Figure 4.2 and the methodological strategies suggested in Chapter Five to improve environmental equity analysis, this chapter investigates the spatial and temporal relationships between the locations of TRI facilities and the socioeconomic characteristics of the population at risk in the Atlanta metropolitan area from 1990 to 2000. To estimate the population at risk, intelligent areal interpolation is first implemented through dasymetric representation of population by satellite imagery. The spatial patterns of environmental inequity in the metropolitan area are revealed by spatial and statistical analyses in an integrated environment of GIS and remote sensing. Subsequently, the spatial pattern change is examined with the integrated approach.

6.2 Intelligent Areal Interpolation by Dasymetric Population Representation

It is required to apply spatial interpolation methods for population estimation in the present study since impact zones represented as concentric buffers (target zone) and census boundaries (source zone) have different spatial bases. As explained in Section 4.5 of Chapter Four, an intelligent areal weighting interpolation method based on the principle of dasymetric mapping was used in this research to estimate the socioeconomic characteristics of the population at risk as well as to improve upon the methods of population data representation that are typically used in environmental equity research. This intelligent areal interpolation method is related to Langford and Unwin's (1994) use of remotely sensed imagery to redistribute population, Eicher and Brewer's (2001) grid three-class method, Mennis's (2003) empirical sampling and areal weighting techniques to overcome the weaknesses of previous approaches to dasymetric mapping, and Wright's (1936) initial dasymetric mapping technique. Like Eicher and Brewer (2001), this method employs three classes of land use and cover data as ancillary data to redistribute population to a raster grid. The land use and cover were initially extracted from the Landsat TM images using the digital image classification method shown in Figure 4.3. From these land use and cover data, the residential, commercial and industrial, and non-residential (comprising grassland/pasture/cropland and forest) classes were extracted as shown in Figures 6-1 and 6-2 and water and barren classes were excluded using the reclassification method. The resolution of land use and cover data is 28.5 meters. This grid cell resolution serves as the resolution for the final raster population surface since this was the original resolution of Landsat TM images acquired from USGS for this research.

As shown in Figure 4.4, this method involves two major stages to estimate the socioeconomic characteristics of the population at risk: (1) spatial disaggregation of population data from census block groups into individual pixels according to the principle of dasymetric mapping and (2) spatial reaggregation of population surfaces by circular buffers. In the first stage, Equation 4.9 proposed by Mennis (2003) was implemented to dasymetrically transfer population data from census block groups into individual pixels. Three factors play a controlling role in the spatial disaggregation process: (1) the population of the host block group of each grid cell, (2) the relative difference in population densities among the three classes of land use and cover, and (3) the percentage of total area of each block group occupied by each of the three classes of land use and cover. The relative difference in population densities among the three classes of land use and cover was determined from empirical measurement. Mennis (2003)

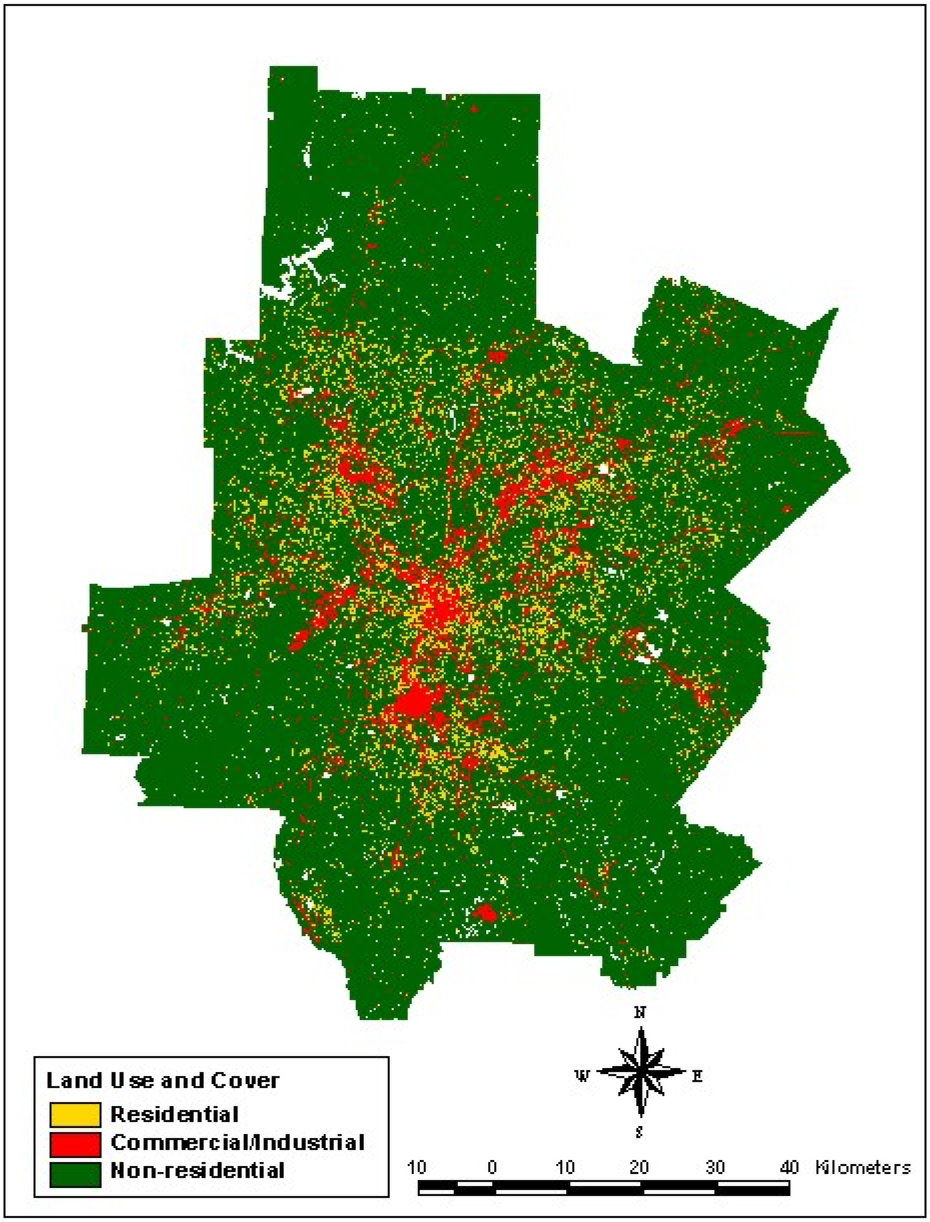


Figure 6.1 Land use and cover classes for metropolitan Atlanta, 1990.

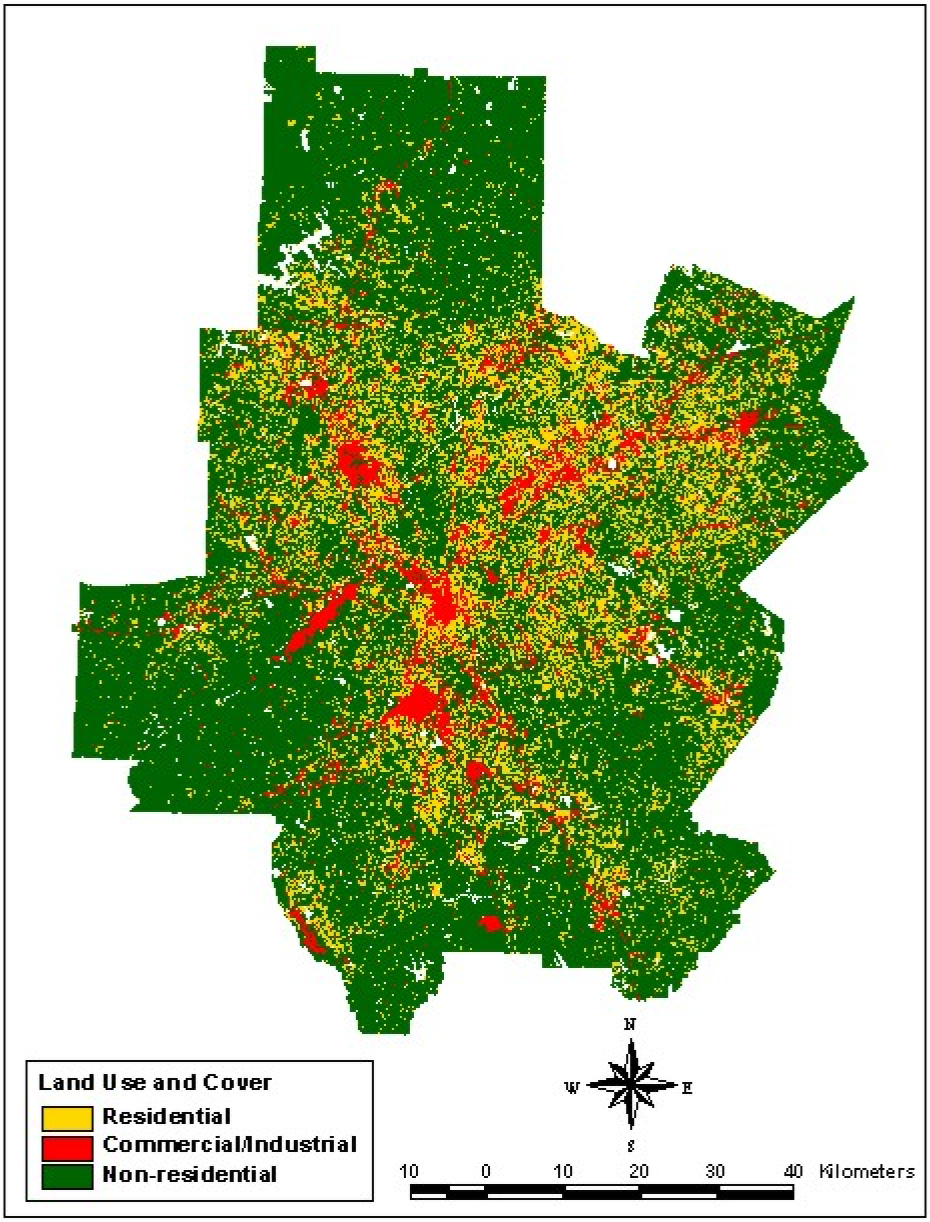


Figure 6.2 Land use and cover classes for metropolitan Atlanta, 2000.

suggested that the empirical measurement sample all block groups that are completely contained within each of the three classes of land use and cover. Although this sampling strategy mitigates the subjectivity of the assignment of a percentage of population to a given land use and cover class, this faces a practical problem that it is difficult to find block groups that lie entirely within a land use and cover class derived from the Landsat TM images. In order to tackle this problem, this study modified Mennis's sampling strategy by taking the concept of sampling threshold. In other words, the sampling process selected those block groups that are comprised of a certain percentage of each land use and cover class (i.e., 90-95 percent). The sampling threshold for each land use and cover class was determined independently for each county. As reported in Tables 6-1 and 6-2, a population density fraction was then calculated for each land use and cover class for each county. The population density fraction indicates the percentage of a block group's total population that should be assigned to a particular land use and cover class within the block group (Mennis, 2003). The population density fraction was computed by dividing a land use and cover class's population density by the sum of the population density values for all three classes of land use and cover. This can be expressed as:

$$D_{uc} = \frac{PD_{uc}}{(PD_{hc} + PD_{lc} + PD_{nc})} \tag{6.1}$$

where D_{uc} is population density fraction of land use/cover class u in county c, PD_{uc} is population density of land use/cover class u in county c, PD_{hc} is population density of land use/cover class h in county c, PD_{lc} is population density of land use/cover class l in county c, and PD_{nc} is population density of land use/cover class n in county c. This operation was performed for each individual county because the relative difference in population densities among the three classes

Table 6.1 Representative population densities for each land use and cover by county in Metropolitan Atlanta (1990)

County	LULC	Population	Area (km^2)	Population Density (persons/km^2)	Sum Density	Population Density Fraction
Cherokee	Resid	534	0.9522	560.83	837.17	0.67
	Comind	540	2.0926	258.06	837.17	0.31
	Nonresid	2273	124.3146	18.28	837.17	0.02
Clayton	Resid	2033	1.2959	1568.75	2250.64	0.70
	Comind	3872	6.5395	592.10	2250.64	0.26
	Nonresid	493	5.4905	89.79	2250.64	0.04
Cobb	Resid	443	0.3492	1268.63	1790.79	0.71
	Comind	108	0.2604	414.72	1790.79	0.23
	Nonresid	569	5.2958	107.44	1790.79	0.06
Dekalb	Resid	233	0.1021	2282.62	3898.04	0.59
	Comind	291	0.3447	844.10	3898.04	0.22
	Nonresid	443	0.5743	771.31	3898.04	0.20
Douglas	Resid	1251	1.8551	674.37	1032.54	0.65
	Comind	1660	5.0079	331.48	1032.54	0.32
	Nonresid	2011	75.3470	26.69	1032.54	0.03
Fayette	Resid	55	0.1468	374.6806	775.73	0.48
	Comind	197	0.5436	362.3827	775.73	0.47
	Nonresid	6063	156.7985	38.6675	775.73	0.05
Fulton	Resid	202	0.1281	1577.31	1992.40	0.79
	Comind	517	1.2988	398.05	1992.40	0.20
	Nonresid	2870	168.4380	17.04	1992.40	0.01
Gwinnett	Resid	157	0.1194	1315.16	1984.36	0.66
	Comind	15489	24.2690	638.22	1984.36	0.32
	Nonresid	1629	52.5766	30.98	1984.36	0.02
Henry	Resid	837	2.0676	404.81	575.53	0.70
	Comind	1267	9.7243	130.29	575.53	0.23
	Nonresid	1000	24.7366	40.43	575.53	0.07
Rockdale	Resid	2722	2.8991	938.91	1181.59	0.79
	Comind	409	2.0424	200.25	1181.59	0.17
	Nonresid	832	19.6082	42.43	1181.59	0.04

Note: LULC-land use and cover; Resid-residential; Comind-commercial and industrial; Nonresid-pasture, grassland, cropland, and forest.

Table 6.2 Representative population densities for each land use and cover by county in Metropolitan Atlanta (2000)

County	LULC	Population	Area (km^2)	Population Density (persons/km^2)	Sum Density	Population Density Fraction
Cherokee	Resid	1998	3.0280	659.85	1080.45	0.61
	Comind	799	2.0397	391.72	1080.45	0.36
	Nonresid	2174	75.2788	28.88	1080.45	0.03
Clayton	Resid	1792	1.0708	1673.48	2242.04	0.75
	Comind	1567	3.5189	445.31	2242.04	0.20
	Nonresid	5522	44.8002	123.26	2242.04	0.05
Cobb	Resid	1316	0.2086	6308.65	7221.69	0.87
	Comind	1239	1.7898	692.25	7221.69	0.10
	Nonresid	2277	10.3126	220.79	7221.69	0.03
Dekalb	Resid	4171	0.8171	5104.46	6886.39	0.74
	Comind	5673	4.6895	1209.72	6886.39	0.18
	Nonresid	856	1.4960	572.21	6886.39	0.08
Douglas	Resid	2042	1.1981	1704.34	2309.43	0.74
	Comind	2773	4.9397	561.37	2309.43	0.24
	Nonresid	1906	43.5972	43.72	2309.43	0.02
Fayette	Resid	2748	2.8719	956.87	1218.91	0.79
	Comind	2359	10.8737	216.95	1218.91	0.18
	Nonresid	2293	50.8503	45.09	1218.91	0.04
Fulton	Resid	655	0.1913	3424.80	4145.71	0.83
	Comind	587	0.8389	699.73	4145.71	0.17
	Nonresid	935	44.1478	21.18	4145.71	0.01
Gwinnett	Resid	737	0.6473	1138.59	1675.73	0.68
	Comind	762	1.6730	455.47	1675.73	0.27
	Nonresid	1615	19.7729	81.68	1675.73	0.05
Henry	Resid	10628	18.0222	589.72	750.85	0.79
	Comind	1320	10.7822	122.42	750.85	0.16
	Nonresid	1827	47.1971	38.71	750.85	0.05
Rockdale	Resid	1383	1.0618	1302.47	1980.92	0.66
	Comind	1070	1.6740	639.20	1980.92	0.32
	Nonresid	665	16.9440	39.25	1980.92	0.02

Note: LULC-land use and cover; Resid-residential; Comind-commercial and industrial; Nonresid-pasture, grassland, cropland, and forest.

of land use and cover varies from county to county. Figures 6-3 and 6-4 show the population density by block group for the Atlanta metropolitan area in 1990 and 2000.

Since the population density fraction above was computed under the unrealistic assumption behind Wright's initial dasymetric mapping technique that a given areal unit is evenly spatially partitioned among the three classes of land use and cover, the population density fraction needs to be adjusted by the difference in block group area occupied by each land use and cover class in order to improve the accuracy of the redistribution of population to a land use and cover class. This adjustment was made by calculating the area ratio for each land use and cover class for each block group. The area ratio represents the ratio of the percentage of area that a land use and cover class actually occupies within a block group to the expected percentage of 33.3% (Mennis, 2003). The area ratio for each land use and cover class within each block group was computed by dividing the number of grid cells (i.e., area) of a land use and cover class by a block group's total number of grid cells and then dividing the result by 33.3. This can be expressed as:

$$A_{ub} = \frac{\left(\frac{N_{ub}}{N_b}\right)}{0.33} \tag{6.2}$$

where A_{ub} is area ratio of land use/cover class u in block group b, N_{ub} is number of grid cells of land use/cover class u in block group b, and N_b is number of grid cells in block group b. This operation was performed for each land use and cover class in each individual block group.

The population density fraction and area ratio were then integrated into one term, referred to as the total fraction. The total fraction represents the fraction of a given block group's total population that should be assigned to a given land use and cover class within that block group, accounting for variation in both population density and area of the different land use and cover

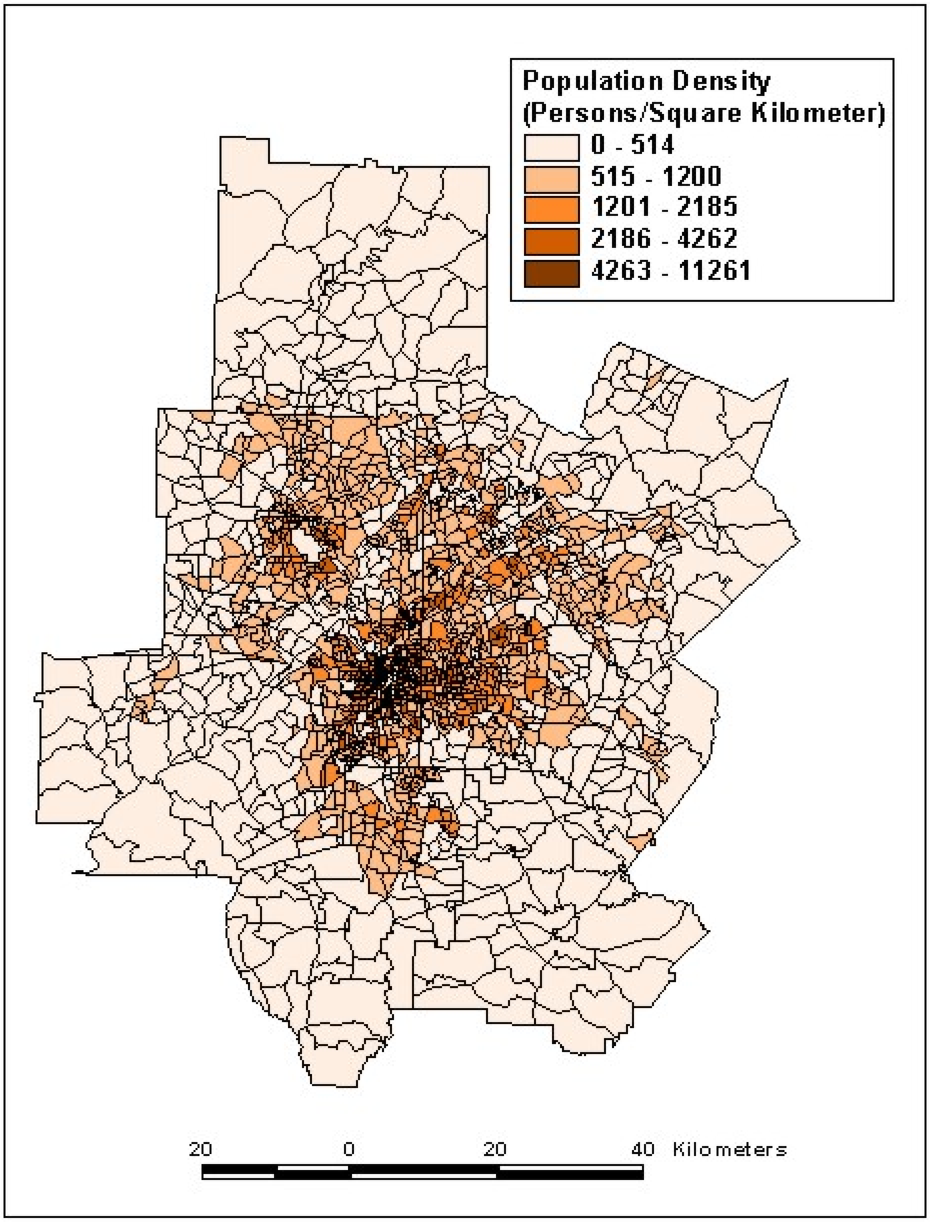


Figure 6.3 Population density by block group for metropolitan Atlanta, 1990.

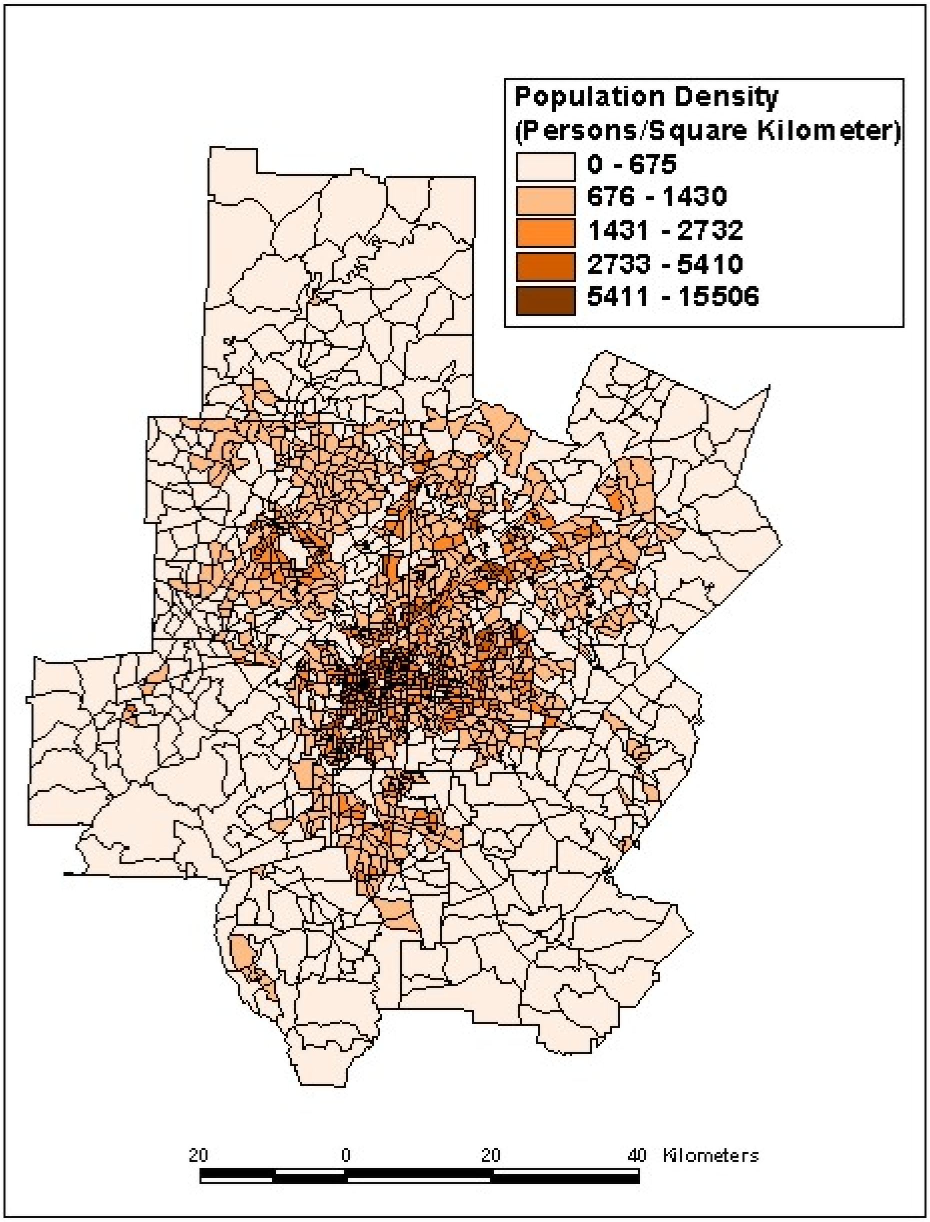


Figure 6.4 Population density by block group for metropolitan Atlanta, 2000.

classes (Mennis, 2003). As expressed in Equation 4.10, the total fraction was calculated by multiplying the population density fraction and area ratio of a given land use and cover class in a given block group and dividing that result by the result of the same expression for all three classes of land use and cover in that block group.

Once the total fraction for each land use and cover class for each block group was determined, a population portion assigned to each land use and cover class within each block group was evenly redistributed to the grid cells with each land use and cover class in each block group. The Equation 4.9 was implemented in ArcView GIS in order to spatially disaggregate population data from a given block group to a given grid cell within a given county.

Three raster grids were then generated with the operation described above. In the creation of the first grid, only the residential class was extracted from the three classes of land use and cover and then each residential grid cell was assigned its appropriate population value from each block group. The same procedure was performed for the commercial and industrial class and the non-residential class to generate the two other raster grids. The three grids were then merged to produce a composite population surface for the Atlanta metropolitan area. As an example, Figure 6.5 shows a map of the raster population surface for the Atlanta metropolitan area in 1990.

This spatial disaggregation procedure preserves the pycnophylactic property (Tobler, 1979). In other words, the population of each block group is preserved in the transformation to raster surface. Therefore, any error introduced by this method is inherently limited to variation within each original individual areal unit. The results of the intelligent areal weighting interpolation method were a series of population surfaces that described the number of minorities and persons living below poverty level. Population surfaces of percents of each variable were

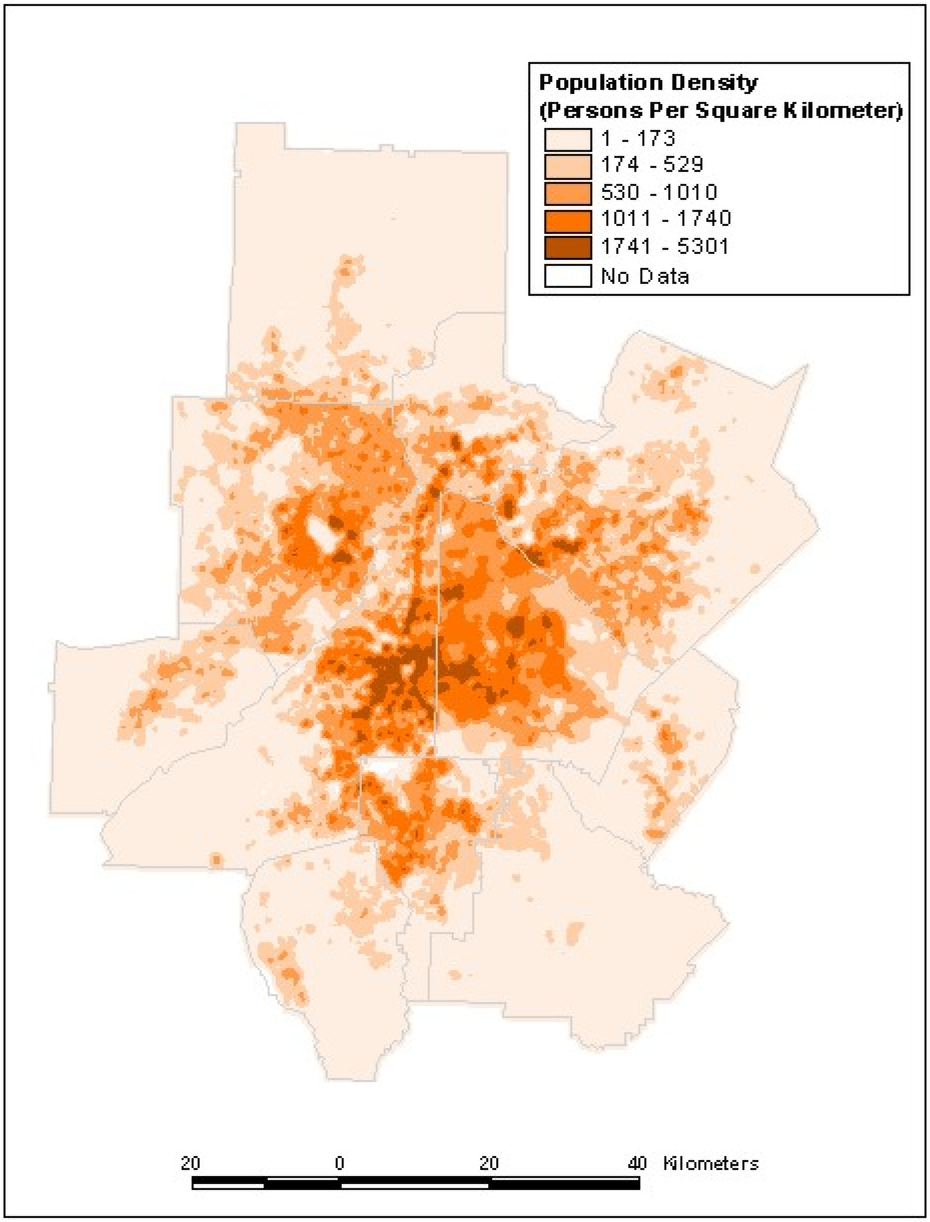


Figure 6.5 Raster surface of population for the Atlanta metropolitan area, 1990.

created by dividing the above count surfaces by a population surface that described the total population associated with each grid cell.

The second stage in areal interpolation was to enumerate the socioeconomic characteristics of the population at risk with the cross-tabulation and tabular calculation capabilities in GIS. Percentage of minorities and percentage of people below poverty level were tallied within each of the concentric buffers. These calculations are not averages of the values of the grid cells within each buffer, but reflect the character of the entire population within each buffer. As an example, Figure 6-6 shows the raster population surface within concentric buffers.

6.3 Spatial Patterns of Environmental Inequity

The spatial associations between the locations of TRI facilities and the socioeconomic characteristics of the population at risk in the Atlanta metropolitan area in 1990 and 2000 were revealed by spatial and statistical analyses in an integrated GIS and remote sensing environment. Two socioeconomic characteristics such as racial composition and poverty status were chosen for the analyses since they were examined most frequently in environmental equity research (Chakraborty, 2001). The specific variable used to reflect the racial composition is the percentage of minority. The minority includes the following census categories: Black, Hispanics, American Indian or Alaskan Native, Asian or Pacific Islander, and other race. Specific income characteristics are represented by the percentage of people below poverty level. The poverty level was determined by the incomes in 1989 (for 1990) and 1999 (for 2000) based on the census definition of poverty status (see Section 3.3 of Chapter Three for details). The environmental inequity hypothesis was tested by comparing the percentages of minorities and people below poverty level within a threshold buffer with those outside the threshold buffer.

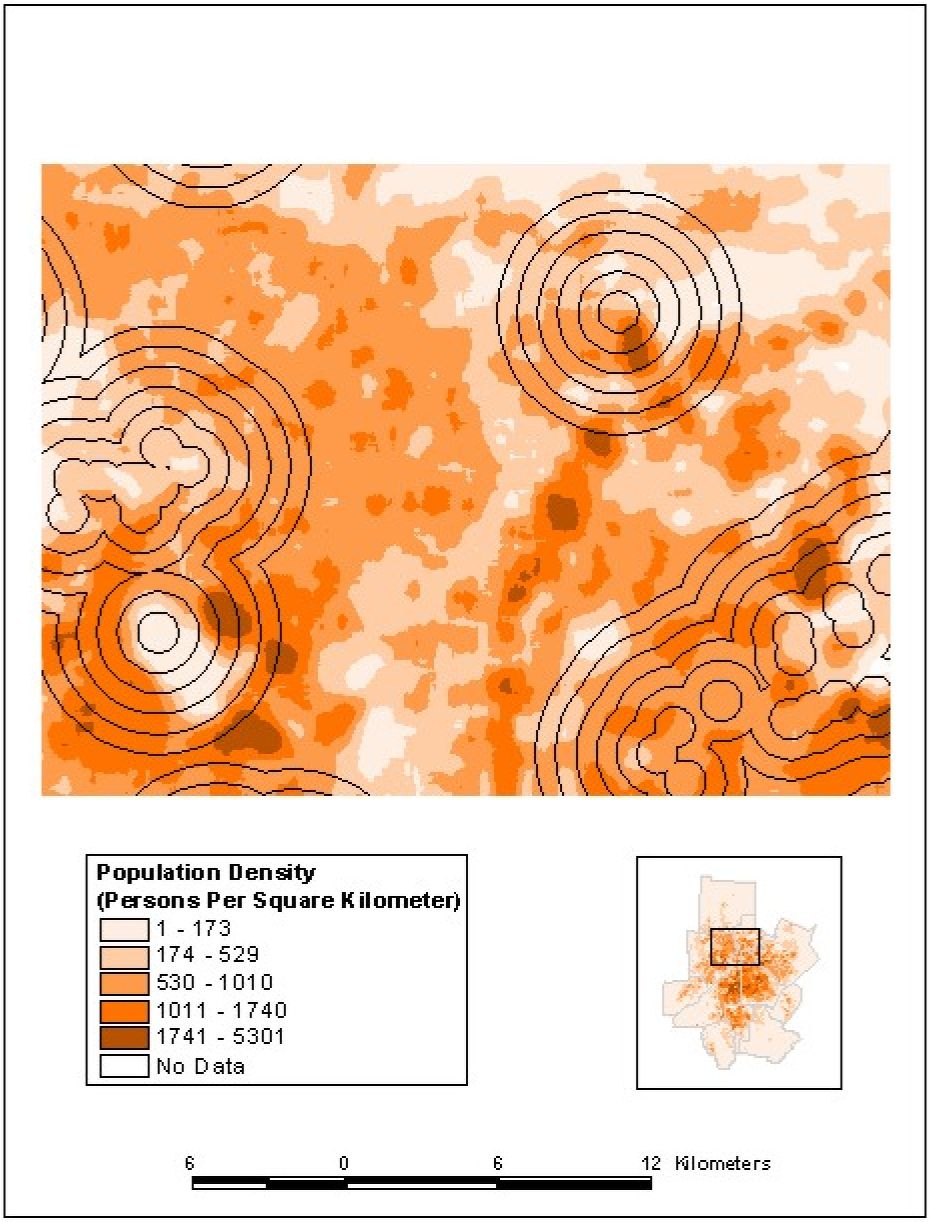


Figure 6.6 Raster population surface within circular buffers, 1990.

6.3.1 Spatial Pattern of 1990

Figure 6.7 shows the spatial distribution of 182 TRI facilities within the 1,837 census block groups of the Atlanta metropolitan area in 1990 and represents six concentric half-mile wide buffers with radii ranging from 0.5 to 3.0 miles around TRI facilities. The spatial distribution of TRI facilities in the metropolitan area is uneven, with a marked concentration around the central city of Atlanta, southwest of Gwinnett, Marietta, and along the Interstates 85, 285, 75, and 20 corridors.

Table 6.3 indicates that minorities comprise 39.1 to 48.8 percent of the population inside circular buffers, but only 16.6 to 30.1 percent of the population outside circular buffers, depending on the buffer distance. Similarly, about 12.3 to 19.1 percent of the population within these buffers are below the poverty level, as compared to only 4.2 to 8.9 percent for the rest of the Atlanta metropolitan area. In Figure 6.8, it is clear that the percentages of minorities and people below poverty drop slightly when larger buffer distances are used around the TRI sites.

A proximity ratio was also calculated for each circular buffer to compare the socioeconomic characteristics inside and outside circular buffers. The proximity ratio indicates the ratio of the socioeconomic characteristics inside and outside the buffer. If the proximity ratio exceeds 1, environmental inequity exists in the study area. For the percentage of minorities, the proximity ratio ranges from 1.62 to 2.36 with the buffer distance. At the 3-mile buffer distance, the proximity ratio is highest while it is lowest at the half-mile buffer distance. For the percentage of population below poverty, the proximity ratio ranges from 2.15 to 2.93. Likewise, the highest proximity ratio is found at the 3-mile buffer distance while the lowest is found at the half-mile buffer distance. As illustrated in Figure 6.9, the proximity ratios increase a little as the buffer distance is extended from 0.5 to 3 miles.

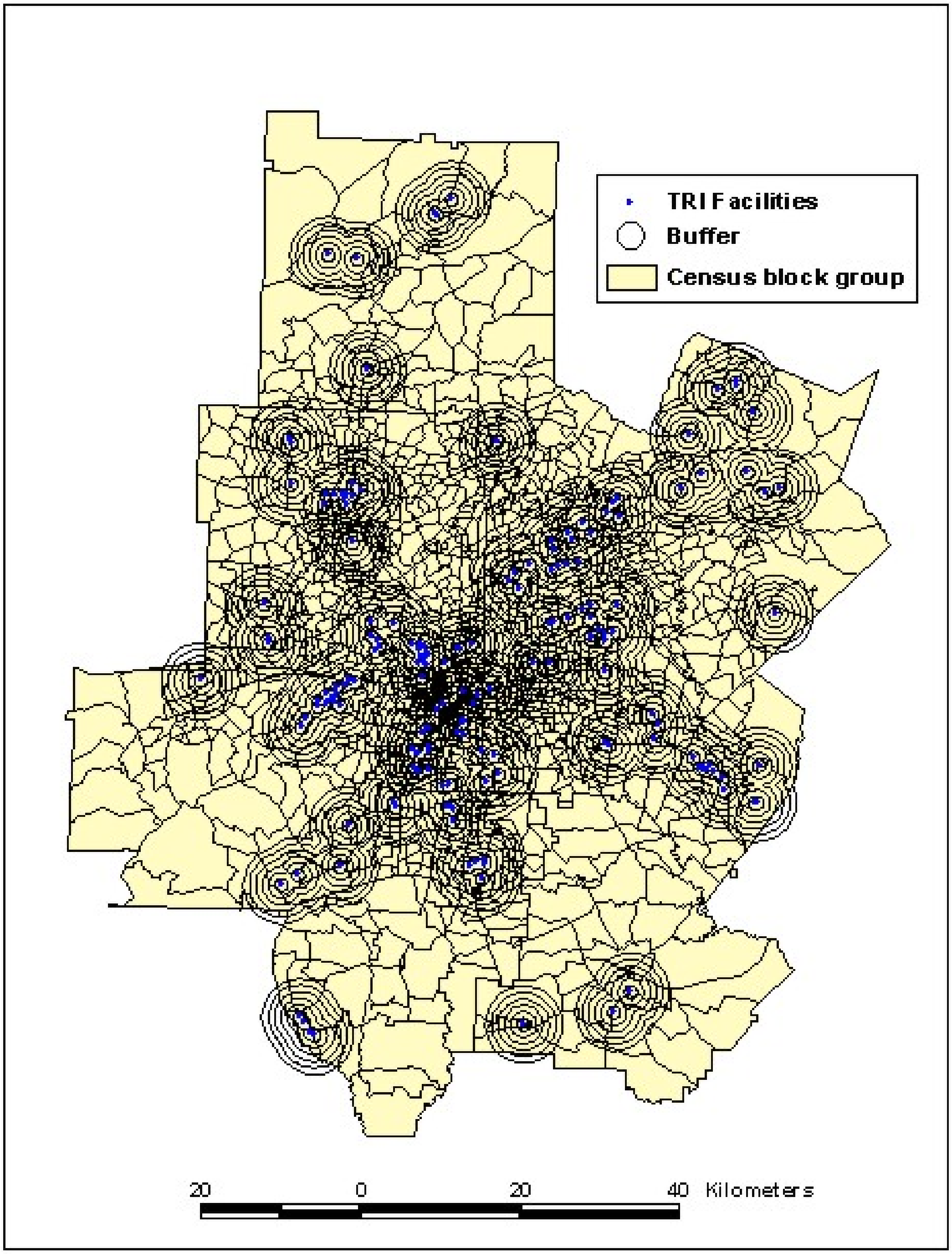


Figure 6.7 Spatial distribution of TRI facilities and circular buffers, 1990.

Table 6.3 Descriptive comparisons of the socioeconomic characteristics inside and outside circular buffers (1990)

Proximity measure	**Minority (%)**	**Below poverty (%)**
Inside 0.5 mile buffer	48.8	19.1
Outside 0.5 mile buffer	30.1	8.9
Proximity ratio	**1.62 (0.55)**	**2.15 (0.73)**
Inside 1 mile buffer	46.9	17.8
Outside 1 mile buffer	27.6	7.6
Proximity ratio	**1.70 (0.58)**	**2.34 (0.80)**
Inside 1.5 mile buffer	44.7	16.1
Outside 1.5 mile buffer	24.7	6.3
Proximity ratio	**1.81 (0.62)**	**2.56 (0.87)**
Inside 2 mile buffer	42.5	14.5
Outside 2 mile buffer	21.9	5.3
Proximity ratio	**1.94 (0.66)**	**2.74 (0.94)**
Inside 2.5 mile buffer	40.7	13.3
Outside 2.5 mile buffer	19.3	4.7
Proximity ratio	**2.11 (0.72)**	**2.83 (0.97)**
Inside 3 mile buffer	39.1	12.3
Outside 3 mile buffer	16.6	4.2
Proximity ratio	**2.36 (0.81)**	**2.93 (1)**

Note: The figures in parenthesis indicate the relative proximity ratio which is computed by dividing each proximity ratio by the maximum proximity ratio for comparison.

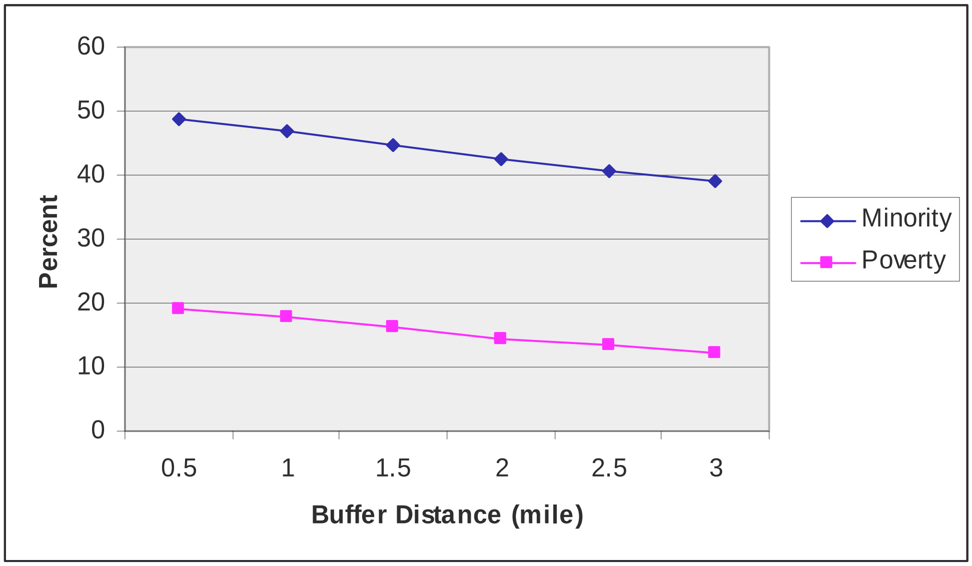


Figure 6.8 Relationship between buffer distance and socioeconomic characteristics (1990).

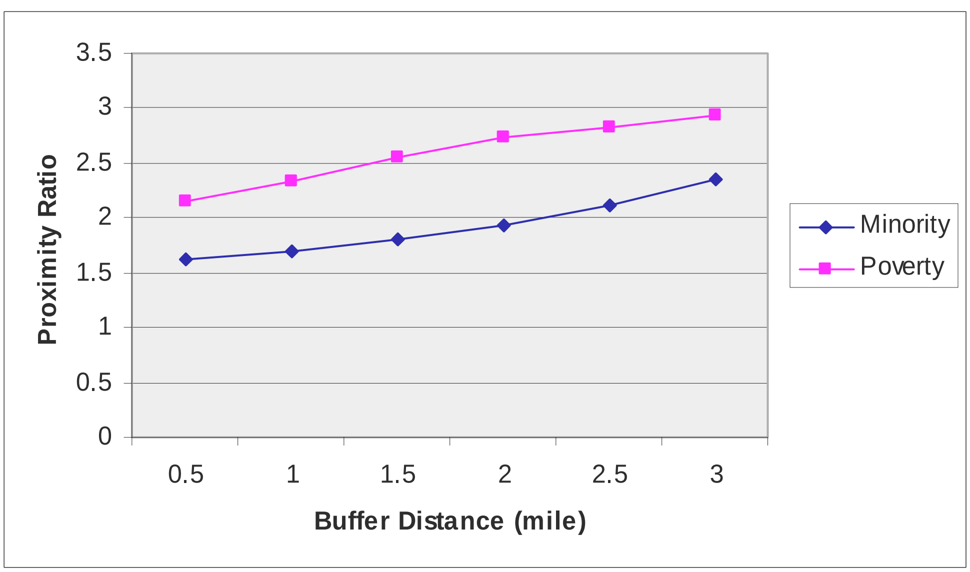


Figure 6.9 Relationship between buffer distance and proximity ratio (1990).

To compare proximity ratios among different buffer distances by each variable, each proximity ratio was standardized by dividing it by the maximum proximity ratio found in Table 6.3. The standardized proximity ratio ranges from 0.55 to 1.00 as reported in Table 6.3. At the half-mile buffer distance, the standardized proximity ratio is lowest for the percentage of minorities while it is highest for the percentage of population below poverty at the 3-mile buffer distance. Through the pairwise comparisons between minority and poverty variables by the buffer distance, it is found that poverty is a relatively significant factor to explain the relationship between distance to TRI facilities and socioeconomic characteristics in the Atlanta metropolitan area. This contrasts with the prevalence of ethnicity as the best predictor in previous studies at the state or county scale (Underwood and Macey, 1998). However, this is consistent with the fact that McMaster *et al.* (1997) and Bowen *et al.* (1995) found a stronger income-based rather than race-based pattern of environmental inequity at the intra-urban scale.

The descriptive results show that the proportions of minorities and persons below poverty are always larger inside circular buffers than outside circular buffers. In all the buffer distances used, the proximity ratios are also above 1 except for the standardized proximity ratios as shown in Table 6.3. These mean that there exists some spatial pattern of environmental inequity based on minority and poverty status in the Atlanta metropolitan area. These findings are consistent with other studies (Burke, 1993; Bowen *et al.*, 1995; Pollock and Vittas, 1995; Liu, 2001), which evidenced the inequity in the spatial distribution of TRI facilities with regard to income and race.

Independent samples t-tests were used to test the statistical significance of the difference between the within buffer and the outside buffer means for each variable. Three statistical assumptions concerning normal distribution, equal variance, and independence were checked by sample size, Q-Q plot, and Levene's test. The data under evaluation met all three assumptions.

As provided in Table 6.4, the t-tests show statistically significant differences in means between the inside buffer areas and the outside buffer areas for the percentages of minorities and persons below poverty level in all the buffer distances. As expected, the results show that minorities are more likely to reside within the circular buffers than outside the circular buffers. The results also present that the inside buffers contain a larger proportion of people below poverty level than do the outside buffers. It is meaningful to note that the percentage values reported in Table 6.4 are different from those in Table 6.3. This is explained by the fact that the percentage values in Table 6.3 reflect the character of the entire population within each buffer while those in Table 6.4 are averages of the values of the census block groups within each buffer. In Table 6.4, the percentage values for minorities and people below the poverty level peak at the one-mile buffer distance and then slightly decrease to the three-mile buffer distance. This curve shape is a little different from that depicted in Figure 6.8.

Discriminant analysis was further used to differentiate between the inside buffer and the outside buffer areas. As indicated from the test of equality of group means in Table 6.5, two independent variables, the percentages of minorities and people below poverty level, are significant indicators of group differences between areas of the inside buffer and the outside buffer in all the buffer distances. In examining the structure matrix, both minorities and people below poverty have positive loadings on a single linear function that maximizes the group differences in all the buffer distances. These figures suggest that the difference between the areas inside and outside the buffer is well characterized by the prevalence of minorities and people below poverty. The standardized function coefficients provide the relative importance of each independent variable in explaining the group differences in the discriminant function (Margai, 2001). These show that in all the buffer distances except for the three-mile, poverty provides the

Table 6.4 Statistical comparisons of the socioeconomic characteristics inside and outside circular buffers (1990)

Buffer distance	Variable	Mean		t-test
		Inside	Outside	
0.5 mile	n	459	1820	
	Min (%)	41.4	31.8	0.000
	Pov (%)	17.3	11.4	0.000
1 mile	n	746	1583	
	Min (%)	44.5	28.7	0.000
	Pov (%)	17.8	9.7	0.000
1.5 mile	n	998	1321	
	Min (%)	42.5	23.4	0.000
	Pov (%)	16.8	7.5	0.000
2 mile	n	1191	1079	
	Min (%)	40.2	22.2	0.000
	Pov (%)	15.1	6.2	0.000
2.5 mile	n	1328	912	
	Min (%)	38.5	20.1	0.000
	Pov (%)	14.2	5.2	0.000
3 mile	n	1461	754	
	Min (%)	37.4	17.4	0.000
	Pov (%)	13.5	4.6	0.000

Note: All t-test statistics are significant at 0.05 level.

Table 6.5 Discriminant analysis of the socioeconomic characteristics inside and outside circular buffers (1990)

Buffer distance	Variable	TEGM			Function Statistics				SFC
		Wilks	F	p	Wilks	CC	χ^2	p	
0.5 mile	Min (%)	0.989	26.326	0.000	0.981	0.136	42.776	0.000	0.327
	Pov (%)	0.983	40.170	0.000					0.772
1 mile	Min (%)	0.959	100.382	0.000	0.943	0.239	136.721	0.000	0.479
	Pov (%)	0.951	118.834	0.000					0.649
1.5 mile	Min (%)	0.936	158.462	0.000	0.909	0.301	220.057	0.000	0.488
	Pov (%)	0.924	190.800	0.000					0.656
2 mile	Min (%)	0.936	155.180	0.000	0.910	0.300	213.706	0.000	0.495
	Pov (%)	0.925	184.062	0.000					0.649
2.5 mile	Min (%)	0.939	144.706	0.000	0.911	0.298	208.230	0.000	0.475
	Pov (%)	0.925	181.661	0.000					0.673
3 mile	Min (%)	0.930	166.174	0.000	0.911	0.299	206.655	0.000	0.591
	Pov (%)	0.932	160.630	0.000					0.561

Note: TEGM-test of equality of group means, Wilks-Wilks' lambda, CC-canonical correlation, SFC-standardized function coefficients, Min-the percent of minority, and Pov-the percent of population below poverty. All F and χ^2 statistics are significant at 0.05 level.

better explanation for the variation between the two areas. The overall significance of the discriminant function in all the buffer distances is good, as evidenced by the χ^2 statistics associated with the Wilks' lambda. However, the model explains only 14 percent of the variance between the areas inside and outside the buffer at the half-mile buffer distance while 24 percent at the one-mile buffer distance. From 1.5 to 3 miles, the model captures approximately 30 percent of the observed differences between the two areas. It is also noted that the standardized function coefficients may not reliably assess the relative influence of the independent variables because of the presence of multicollinearity between the two independent variables diagnosed by Pearson's correlation ($0.577 \leq r \leq 0.608$). The inclusion of other socioeconomic variables also might contribute further in explaining the observed differences between the two areas.

Finally, an environmental equity model was developed in this research to detect the spatial clustering of hot spots in environmental inequity as illustrated in Figure 4.5. The environmental equity model was implemented in a GIS environment by combining risk and population surfaces as described in Section 4.5 of Chapter Four. Figure 6.10 represents the spatial distribution of standardized relative risk scores of TRI facilities in the metropolitan area. To determine the standardized relative potential risk score, the relative risk score for each facility calculated with Equation 4.1 was divided by the maximum risk score for any facility in the metropolitan area. Unlike the simple spatial distribution in Figure 6.7, Figure 6.10 shows that there is a considerable geographic variability in relative risk of TRI facilities within the metropolitan area. This variability is a function of the specific types of chemicals and quantities released by each individual facility. One facility stands out around Marietta in the metropolitan area. The combination of a large quantity and higher toxicity of chemical releases pushes the Lockheed aeronautical system facility into the top position in the metropolitan area. Figure 6.11

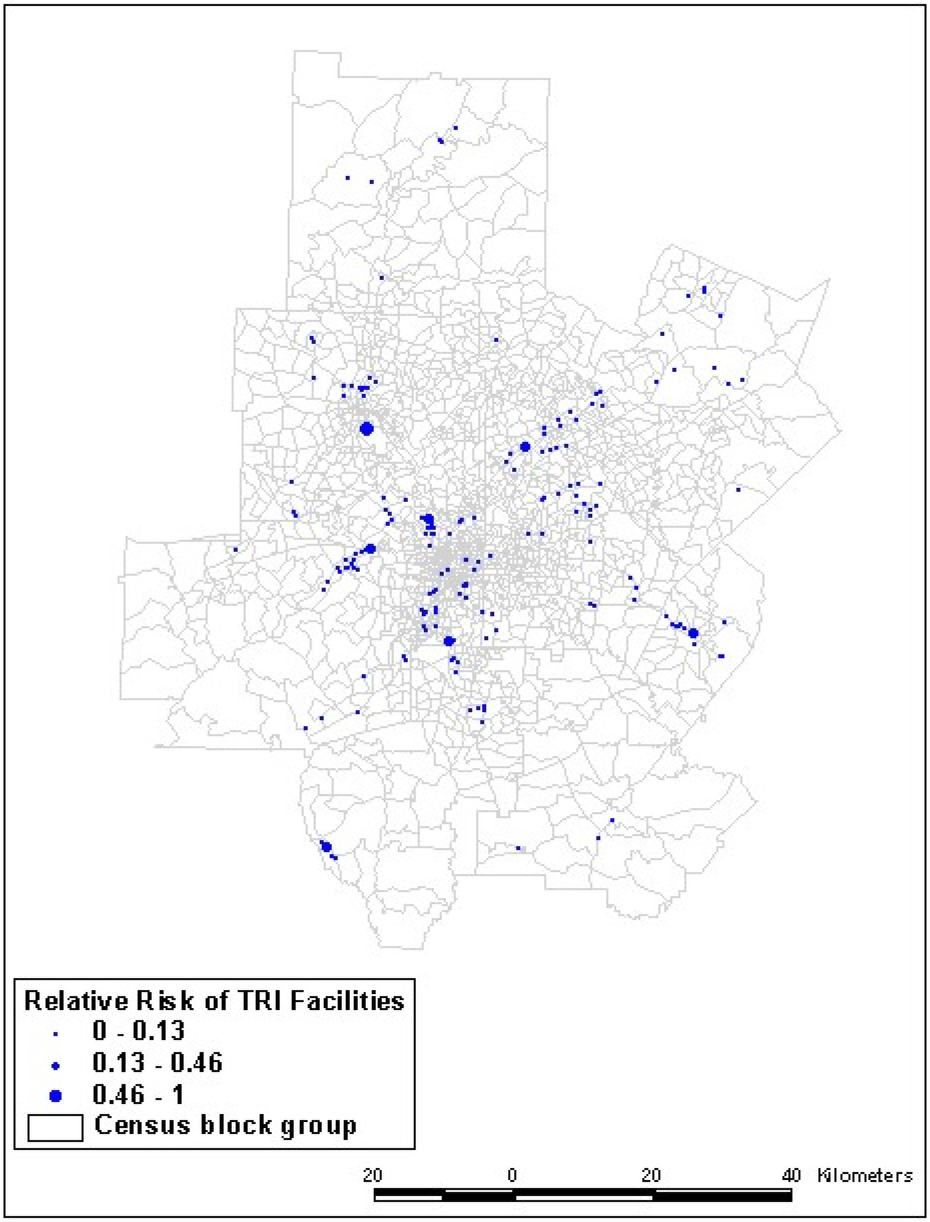


Figure 6.10 Spatial distribution of relative risk of TRI facilities in 1990.

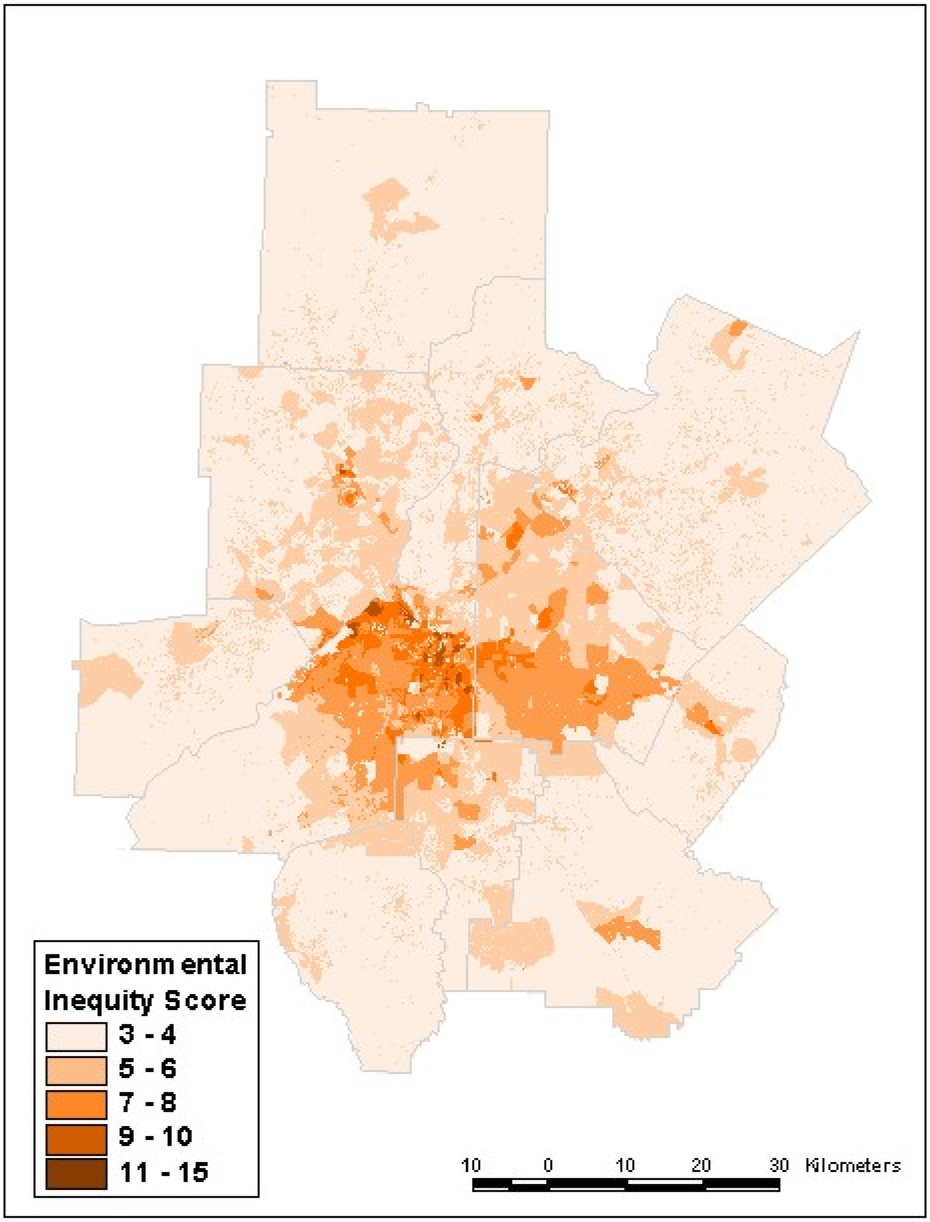


Figure 6.11 Environmental inequity surface in 1990.

shows the environmental inequity surface in the metropolitan area. In the environmental inequity surface, it is found that there is also a considerable spatial variation in environmental inequity within the Atlanta metropolitan area. The hot spots in environmental inequity in the metropolitan area are spatially clustered around the top portion of the southern central city of Atlanta, Decatur, Norcross, Marietta, and the intersection of Interstates 85, 75, and 20 (midtown). These hot spots are spatially coincident with traditional centers of industry and population in the Atlanta metropolitan area. In other words, these spatial clusters are better characterized by the combination of closer proximity to TRI facilities, higher percentage of minorities, and larger percentage of people below the poverty level. The extent of spatial clustering among cells with respect to environmental inequity scores was measured by Moran's I, a spatial autocorrelation index. The resultant spatial autocorrelation coefficient was 0.98 for only pixels covering metropolitan Atlanta. This represents that the environmental inequity scores were strongly spatially clustered, which confirmed the spatial pattern identified from the visual inspection.

6.3.2 Spatial Pattern of 2000

Figure 6.12 shows the spatial distribution of 128 TRI facilities within the 1563 census block groups of the Atlanta metropolitan area in 2000 and depicts six concentric half-mile wide buffers with radii ranging from 0.5 to 3.0 miles around TRI facilities. TRI facilities within the metropolitan area are mainly concentrated around the central city of Atlanta, southwest of Gwinnett, Marietta, and along the Interstates 85, 285, 75, and 20 corridors. Figure 6.13 presents that there is a considerable spatial variability in relative risk of TRI facilities within the metropolitan area. A facility around Smyrna remarkably stands out. In terms of the combination

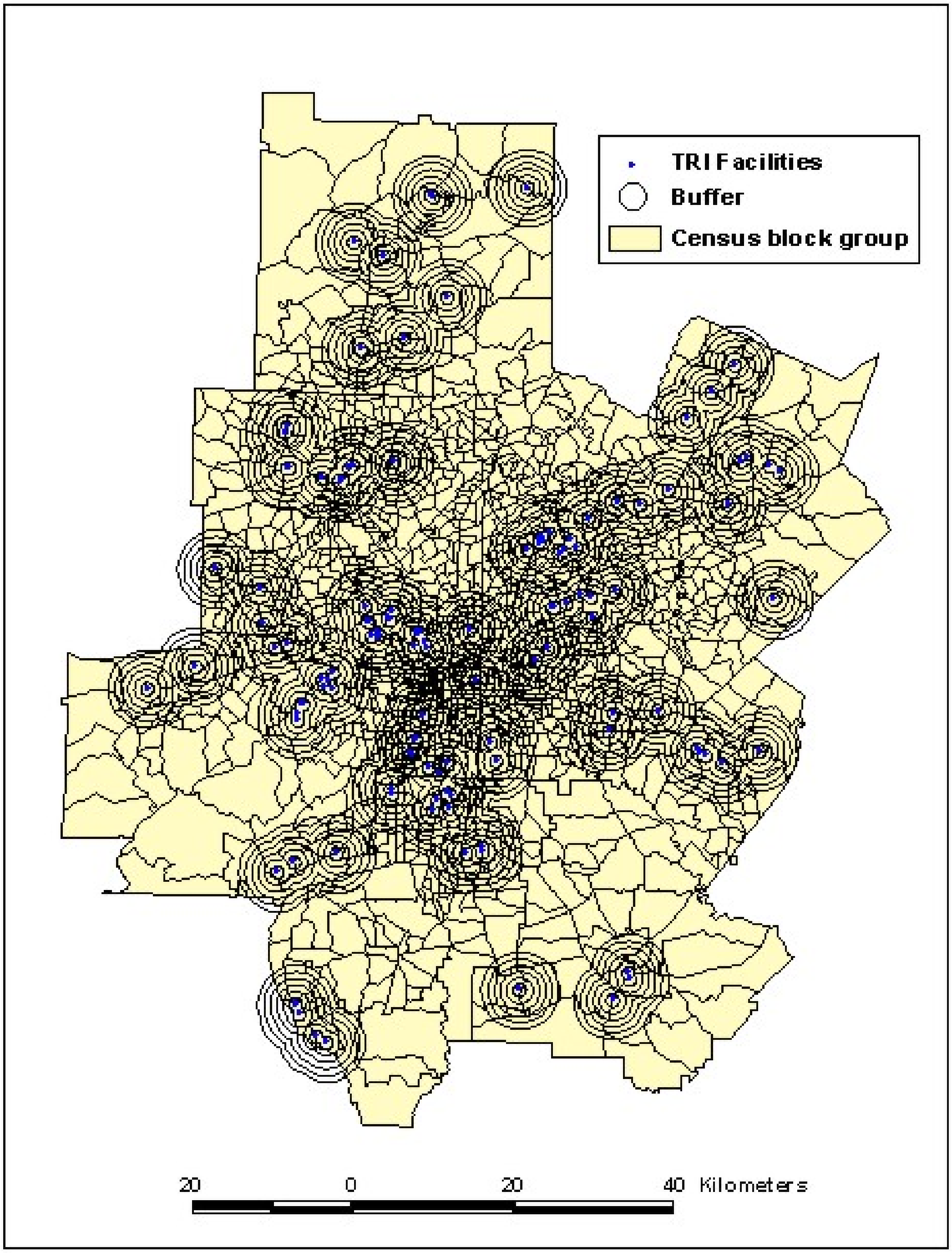


Figure 6.12 Spatial distribution of TRI facilities and circular buffers, 2000.

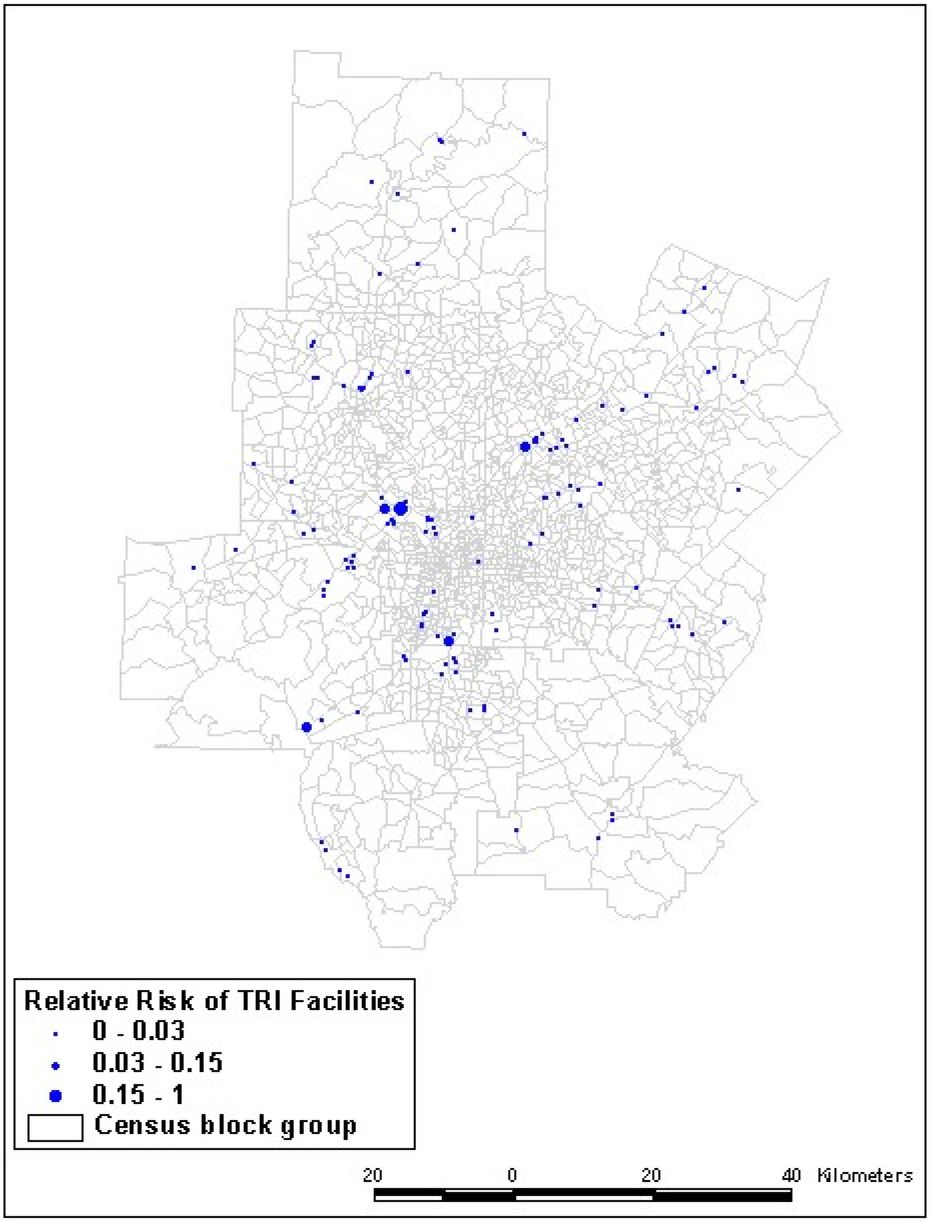


Figure 6.13 Spatial distribution of relative risk of TRI facilities in 2000.

of quantity and toxicity of chemical release, the McDomough/Atkinson steam electronic generating facility is the largest emitter in the metropolitan area.

Table 6.6 indicates that minorities occupy 49.2 to 57.3 percent of the population inside circular buffers, but 34.7 to 44.1 percent of the population outside circular buffers, depending on the buffer distance. Likewise, people below the poverty level range from 10.4 to 13.3 percent of the population within these buffers, as compared to only 6.0 to 9.1 percent outside these buffers. In Figure 6.14, it appears that the percentages of minorities and population below poverty peak at the half-mile buffer distance and then slightly decline before plateauing at the one-mile buffer distance.

To compare the socioeconomic characteristics inside and outside circular buffers, a proximity ratio was also computed for each circular buffer as reported in Table 6.6. For the percentage of minorities, the proximity ratio ranges from 1.12 to 1.42. At the 3-mile buffer distance, the proximity ratio is highest while it is lowest at the one-mile buffer distance. For the percentage of population below poverty, the proximity ratio ranges from 1.18 to 1.73. Similarly, the highest proximity ratio is found at the 3-mile buffer distance while the lowest is found at the one-mile buffer distance. As depicted in Figure 6.15, the proximity ratio slightly drops from 0.5 to 1 miles while it steadily increases from 1 to 3 miles.

For comparison, each proximity ratio was standardized by dividing it by the maximum proximity ratio found in Table 6.6. The standardized proximity ratio ranges from 0.65 to 1.00 as reported in Table 6.6. At the one-mile buffer distance, the standardized proximity ratio is lowest for the percentage of minorities while it is highest for the percentage of population below poverty at the 3-mile buffer distance. Through the pairwise comparisons between minority and poverty variables by the buffer distance, it is found that poverty is a relatively important factor in

Table 6.6 Descriptive comparisons of the socioeconomic characteristics inside and outside circular buffers (2000)

Proximity measure	**Minority (%)**	**Below poverty (%)**
Inside 0.5 mile buffer	57.3	13.3
Outside 0.5 mile buffer	44.1	9.1
Proximity ratio	**1.30 (0.75)**	**1.46 (0.84)**
Inside 1 mile buffer	49.4	10.7
Outside 1 mile buffer	44.1	9.1
Proximity ratio	**1.12 (0.65)**	**1.18 (0.68)**
Inside 1.5 mile buffer	50.4	10.9
Outside 1.5 mile buffer	43.1	8.7
Proximity ratio	**1.17 (0.68)**	**1.25 (0.72)**
Inside 2 mile buffer	50.2	11.1
Outside 2 mile buffer	41.2	8.0
Proximity ratio	**1.22 (0.71)**	**1.39 (0.80)**
Inside 2.5 mile buffer	49.5	10.9
Outside 2.5 mile buffer	38.6	7.0
Proximity ratio	**1.28 (0.74)**	**1.56 (0.90)**
Inside 3 mile buffer	49.2	10.4
Outside 3 mile buffer	34.7	6.0
Proximity ratio	**1.42 (0.82)**	**1.73 (1)**

Note: The figures in parenthesis indicate the relative proximity ratio which is computed by dividing each proximity ratio by the maximum proximity ratio for comparison.

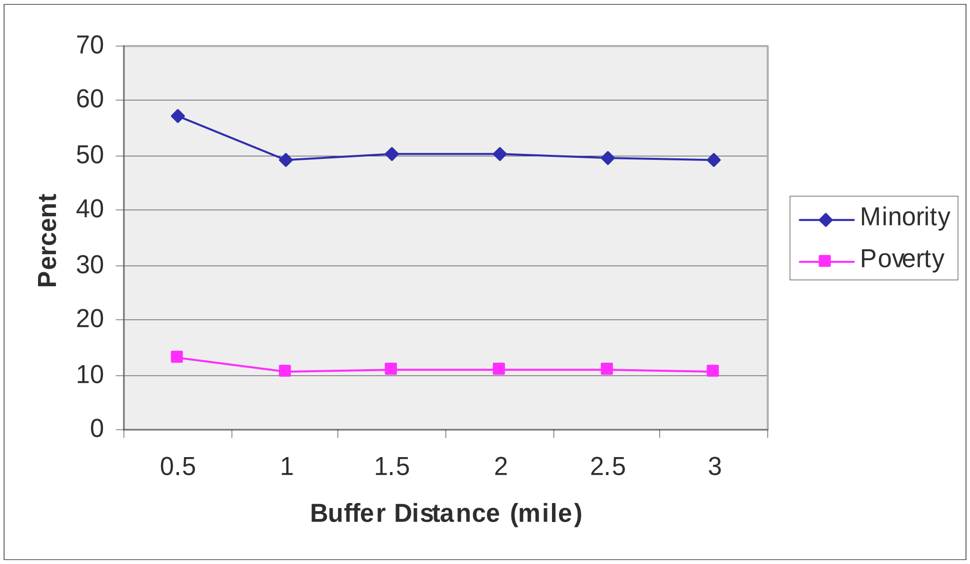


Figure 6.14 Relationship between buffer distance and socioeconomic characteristics (2000).

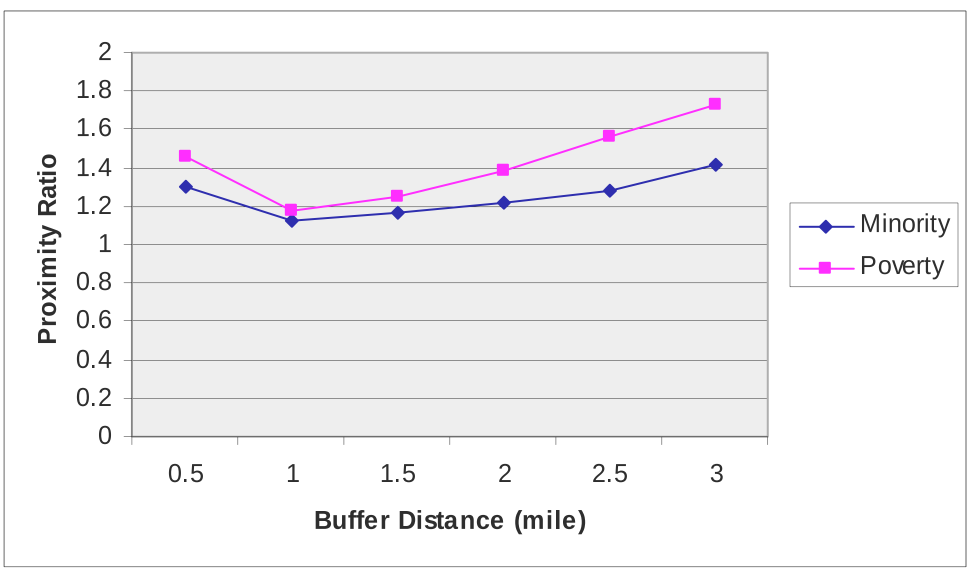


Figure 6.15 Relationship between buffer distance and proximity ratio (2000).

explaining the relationship between proximity to TRI facilities and socioeconomic characteristics in the Atlanta metropolitan area. This contrasts with the prevalence of race as the best predictor in some previous studies (Underwood and Macey, 1998) while this is consistent with other studies (Bowen *et al.*, 1995; McMaster *et al.*, 1997) that found a stronger income-based rather than race-based pattern of environmental inequity at the intra-urban scale.

The descriptive results show that the proportions of minorities and people below poverty level are always larger inside circular buffers than outside circular buffers. In all the buffer distances except for the standardized proximity ratios, the proximity ratios are also above 1. These findings indicate that there is a spatial pattern of environmental inequity based on minority and poverty status in the Atlanta metropolitan area. This is consistent with other studies (Burke, 1993; Bowen *et al.*, 1995; Pollock and Vittas, 1995; Liu, 2001) used TRI facilities.

Independent samples t-tests were used to examine the statistical significance of the difference between the within buffer and the outside buffer means for each variable. The data under investigation met three statistical assumptions concerning normal distribution, equal variance, and independence. Table 6.7 shows statistically significant difference in means between the areas inside and outside buffer for the percentages of minorities and persons below poverty level in all the buffer distances except for the half-mile buffer distance. The results show that minorities are more likely to reside within the circular buffers than outside the circular buffers and a larger proportion of people below the poverty level lives inside the circular buffers. It is needed to note that the percentage values in Table 6.7 are averages of the values of the census block groups within each buffer while those in Table 6.6 reflect the character of the entire population within each buffer. In Table 6.7, the percentage values for minorities and people

Table 6.7 Statistical comparisons of the socioeconomic characteristics inside and outside circular buffers (2000)

Buffer distance	Variable	Mean		t-test
		Inside	Outside	
0.5 mile	n	267	1561	
	Minority (%)	49.3	46.4	0.186*
	Poverty (%)	11.6	10.7	0.266*
1 mile	n	447	1524	
	Minority (%)	51.9	45.8	0.001
	Poverty (%)	12.6	10.5	0.001
1.5 mile	n	680	1395	
	Minority (%)	52.0	44.8	0.000
	Poverty (%)	12.5	10.0	0.000
2 mile	n	913	1194	
	Minority (%)	52.2	43.0	0.000
	Poverty (%)	13.0	9.2	0.000
2.5 mile	n	1082	977	
	Minority (%)	51.8	39.7	0.000
	Poverty (%)	12.8	7.7	0.000
3 mile	n	1208	789	
	Minority (%)	51.2	34.5	0.000
	Poverty (%)	12.2	6.0	0.000

Note: *The t-test statistic is not significant at 0.05 level.

below the poverty level peak at the two-mile buffer distance and then slightly decrease to the three-mile buffer distance. This curve shape is little different from that depicted in Figure 6.14.

Discriminant analysis was further used to differentiate between the inside buffer and the outside buffer areas. As evidenced from the test of equality of group means in Table 6.8, two independent variables, the percentages of minorities and people below the poverty level, are significant indicators of group differences between areas of the inside buffer and the outside buffer in all the buffer distances except for the half-mile buffer distance. In examining the structure matrix, both minorities and people below poverty have positive loadings on a single linear function that maximizes the group differences in all the buffer distances. These figures suggest that the difference between the areas inside and outside buffer is well characterized by the prevalence of minorities and people below poverty. The standardized function coefficients provide the relative importance of each independent variable in explaining the group differences in the discriminant function. These show that from 0.5 to 1 miles, minority provides the better explanation for the variation between the two areas while poverty does from 2 to 3 miles. Interestingly, at the one and half-mile buffer distance, minority and poverty have similar explanation power. The overall significance of the discriminant function in all the buffer distances except for the half-mile buffer distance is good, as indicated by the χ^2 statistics associated with the Wilks' lambda. However, the model explains only 3 to 28 percent of the variance between the areas inside and outside buffer, depending on the buffer distance. The larger the buffer distance, the larger proportion the model captures of the observed differences between the two areas. It is also noted that the standardized function coefficients may not reliably evaluate the relative influence of the independent variables because of the presence of multicollinearity between the two independent variables diagnosed by Pearson's correlation

Table 6.8 Discriminant analysis of the socioeconomic characteristics inside and outside circular buffers (2000)

Buffer distance	Variable	TEGM			Function Statistics				SFC
		Wilks	F	p	Wilks	CC	χ^2	p	
0.5 mile	Min (%)	0.999	1.581	0.209*	0.999	0.031	1.773	0.412*	0.692
	Pov (%)	0.999	1.237	0.266*					0.415
1 mile	Min (%)	0.994	11.150	0.001	0.993	0.082	13.386	0.001	0.598
	Pov (%)	0.995	10.382	0.001					0.518
1.5 mile	Min (%)	0.990	20.338	0.000	0.988	0.110	25.199	0.000	0.557
	Pov (%)	0.990	20.381	0.000					0.559
2 mile	Min (%)	0.983	37.439	0.000	0.975	0.158	52.905	0.000	0.422
	Pov (%)	0.978	47.501	0.000					0.687
2.5 mile	Min (%)	0.969	65.367	0.000	0.951	0.220	102.268	0.000	0.340
	Pov (%)	0.955	97.009	0.000					0.761
3 mile	Min (%)	0.943	120.049	0.000	0.920	0.282	165.473	0.000	0.456
	Pov (%)	0.931	148.146	0.000					0.669

Note: TEGM- test of equality of group means, Wilks-Wilks' lambda, CC-canonical correlation, SFC-standardized function coefficients, Min-the percent of minority, and Pov-the percent of population below poverty.
*The F and χ^2 statistics are not significant at 0.05 level.

($0.577 \leq r \leq 0.595$). The model also might be subject to the bias due to misspecification of other socioeconomic variables.

Finally, an environmental equity model was generated to detect the spatial clustering of hot spots in environmental inequity. Figure 6.16 represents the environmental inequity surface in the Atlanta metropolitan area. In the environmental inequity surface, it is found that there is a considerable spatial variability in environmental inequity within the Atlanta metropolitan area. The hot spots in environmental inequity in the metropolitan area are spatially clustered around the top portion of the southern central city of Atlanta, Tri-Cities, Norcross, Marietta/Smyrna, Conyer, and midtown. These hot spots are spatially coincident with traditional centers of industry and population in the Atlanta metropolitan area. In other words, these spatial clusters are better characterized by the mix of closer proximity to TRI facilities, higher percentage of minorities, and larger percentage of people below poverty level. The extent of spatial clustering among cells with respect to environmental inequity scores was evaluated by Moran's I. The resultant spatial autocorrelation coefficient was 0.98 for only pixels covering metropolitan Atlanta. This confirmed the spatial pattern indicated from the visual inspection that the environmental inequity scores were strongly spatially clustered.

6.4 Spatial Pattern Change in Environmental Inequity

The changing spatial pattern of environmental inequity was examined in the Atlanta metropolitan area from 1990 to 2000. This study does not attempt to establish the dates of establishment of industry or residential districts because establishing the timing of residential or industrial development does not reveal the multitude of factors that create landscapes of inequity (Cutter *et al.*, 2001). Instead, this research takes a snapshot approach to examine some of the

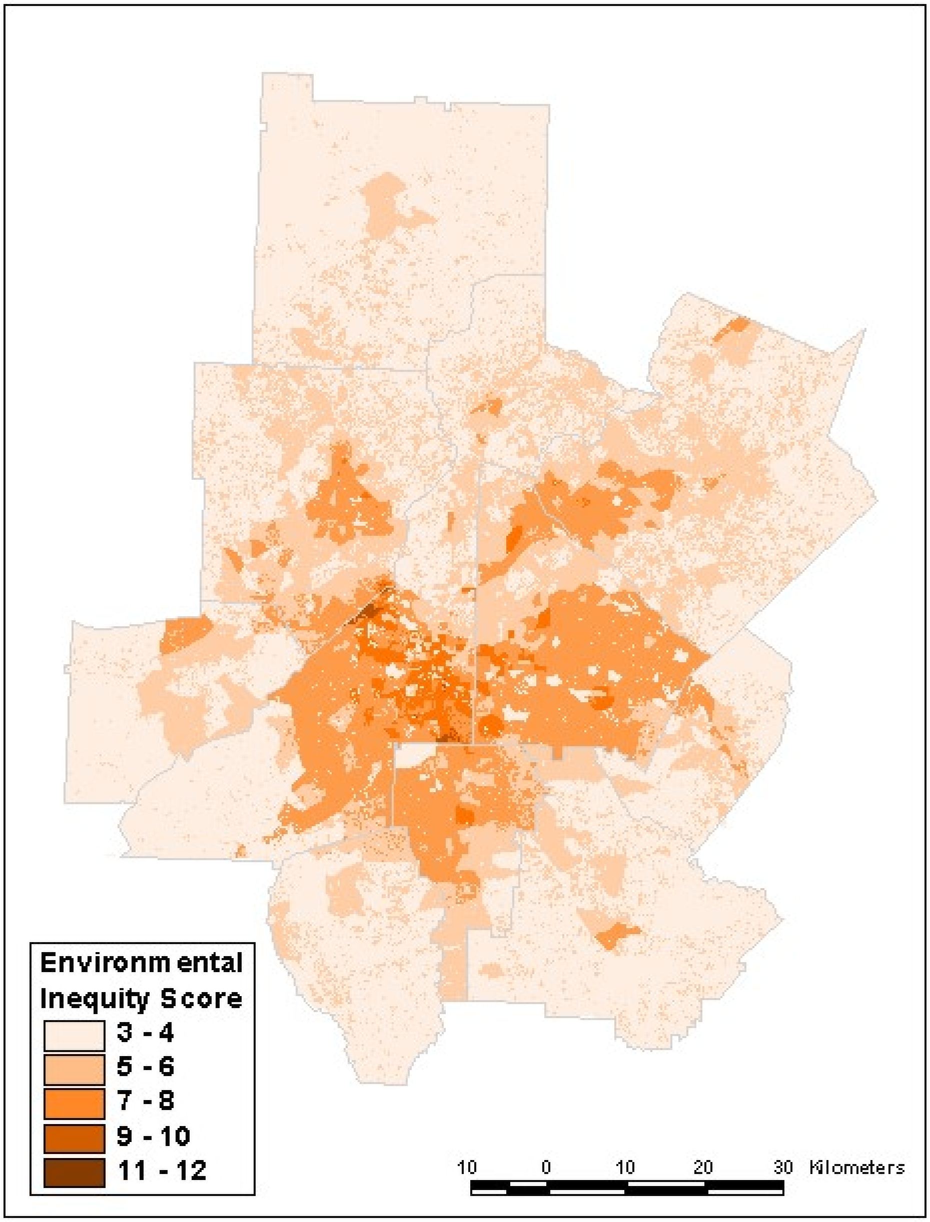


Figure 6.16 Environmental inequity surface in 2000.

broader changes that took place in the spatial patterns of environmental inequity within the metropolitan area.

Figures 6.11 and 6.16 represent environmental inequity surfaces in the Atlanta metropolitan area in 1990 and 2000. From visual comparison, it is found that there is some temporal variability in environmental inequity within the Atlanta metropolitan area between 1990 and 2000. The hot spots in environmental inequity in the metropolitan area were changed over time. These hot spots were spatially clustered around a small top portion of the southern central city of Atlanta, midtown, Decatur, a small portion of Norcross and Marietta, and Conyers in 1990 while they were concentrated on a large top portion of the southern central city of Atlanta, Tri-Cities, Norcross, Marietta/Smyrna, and a portion of Conyers in 2000. A correlation analysis between Figure 6.11 and 6.16 was also performed in Imagine. The result exhibited that the correlation coefficient was 0.86 or a coefficient of determination of 74 percent for only pixels covering metropolitan Atlanta. In other words, the two maps were moderately correlated, which confirmed the change in the spatial pattern from the visual comparison.

The spatial pattern change in environmental inequity may be partially associated with the dual development of industrial and residential geography in the Atlanta metropolitan area from 1990 to 2000. Note that the hot spots in environmental inequity are spatially coincident with traditional centers of industry and population in the metropolitan area. As Figures 3.10 and 3.11 show, the major difference in the spatial distributions of TRI facilities between 1990 and 2000 is that the number of TRI facilities relatively decreased in the central city of Atlanta and traditional industrial centers such as north Dekalb County and the western part of Gwinnett County while increased around the suburbs. Overall, the total number of TRI facilities declined from 182 in 1990 to 128 in 2000. This may be in part explained by the suburbanization of TRI facilities.

Figures 6.10 and 6.13 portray that there is a significant temporal variation in relative risk of TRI facilities within the metropolitan area between 1990 and 2000, depending on the quantity and toxicity of each facility. The location of the largest emitter in the metropolitan area was changed over time from Marietta to Smyrna.

The Atlanta metropolitan area is very racially segregated. As shown in Figures 3.4 and 3.5, the southern part of the city of Atlanta and south Dekalb County are predominantly Black neighborhoods. From south of Atlanta to East Point, College Park, Decatur, and south of Dekalb County, Blacks were clearly the predominant group in 1990 and 2000. There are a few neighborhoods, such as Marietta, Doraville, Norcross, Duluth, and northwest Gwinnett County, where Hispanics predominate. Whites predominate in the rest of the metropolitan area.

There exist spatially concentrated pockets of poverty that have persisted over the past ten years. The largest concentration of high block group-level poverty rates within the metropolitan area remained located within the central city of Atlanta. The poverty rate of Blacks in the inner-city is high. The Marietta area of Cobb County, the I-85/Buford Highway corridor between north DeKalb and south Gwinnett, the block groups along I-20 east of Atlanta, and north of Clayton represent four large areas of growing poverty in the Atlanta metropolitan area between 1990 and 2000 as shown in Figures 3.8 and 3.9. These increases may be the result of the rapid changes in other demographic characteristics in these areas, such as substantial growth in immigrant populations.

6.5 Summary

The spatial and temporal relationships between proximity to TRI facilities and the socioeconomic characteristics of the population at risk in the Atlanta metropolitan area from

1990 to 2000 were investigated by spatial and statistical analyses in an integrated GIS and remote sensing environment. Specifically, an intelligent areal interpolation was used through dasymetric representation of population by satellite imagery to estimate the socioeconomic characteristics of the population at risk as well as to improve upon the methods of population data representation in environmental equity research.

The descriptive results show that the proportions of minorities and people below poverty are always larger inside circular buffers than outside circular buffers and the proximity ratios are also always above 1 within all the buffer distances. This means that there are consistently spatial patterns of environmental inequity based on minority and poverty status in the Atlanta metropolitan area. Through the pairwise comparisons of standardized proximity ratios, it is found that poverty is a relatively significant factor in explaining the relationship between distance to TRI facilities and socioeconomic characteristics in the Atlanta metropolitan area.

The statistical results confirm that minorities and people below poverty level are more likely to reside within the circular buffers than outside the circular buffers in the Atlanta metropolitan area from 1990 to 2000. Independent samples t-tests show statistically significant difference in means between the areas inside and outside buffer for the percentages of minorities and persons below poverty level within all the buffer distances, except for the half-mile buffer distance in 2000. Discriminant analyses indicate that poverty provides the better explanation for the variation between the two areas within all the buffer distances, except for the three-mile buffer distance in 1990 and from half to one-mile buffer distances in 2000. For the exceptional cases, minority is the better explanation variable. Interestingly, at the one and half-mile buffer distance in 2000, minority and poverty have similar explanation power. The findings from this study are consistent with other studies (Bowen *et al.*, 1995; McMaster *et al.*, 1997) that found a stronger income-based rather than race-based pattern of environmental inequity at the intra-urban scale.

By visually comparing environmental inequity surfaces generated by spatial modeling, it is found that there are considerable spatial and temporal variations in environmental inequity within the Atlanta metropolitan area between 1990 and 2000. The hot spots in environmental inequity within the metropolitan area were spatially clustered around a large top portion of the southern central city of Atlanta, midtown, Decatur, and Marietta in 1990 while they were concentrated on a small top portion of the southern central city of Atlanta, Tri-Cities, Norcross, Smyrna, and Conyers in 2000. These hot spots are spatially coincident with traditional centers of industry and population in the metropolitan area. The spatial pattern change in environmental inequity may be in part explained by the dual development of industrial and residential geography in the Atlanta metropolitan area from 1990 to 2000.

CHAPTER 7

URBAN QUALITY OF LIFE ASSESSMENT IN THE ENVIRONMENTAL EQUITY CONTEXT

7.1 Introduction

Since early 1990, environmental justice policies have tried to create environmental equity within society, which is the concept that all people should bear a proportionate share of environmental costs such as pollution and health risk and rejoice at equal access to environmental amenties (Harner *et al.*, 2002). The importance of environmental justice analysis and research has been demonstrated in the environmental justice policies. Research concerns for environmental justice have been mainly focused on human health effects from environmental hazards. Recently, attention has also been given to multiple dimensions of impacts from environmental hazards such as environmental, social, and economic impacts, in addition to health risk (Liu, 2001).

Urban environmental justice issues are salient. Toxic sites tend to be correlated with low income and minority locations in urban areas (Cutter, 1995). Most toxic release and transfer sites are near large population centers (Stockwell *et al.*, 1993). Research focus for urban environmental justice has been largely confined to potential exposure to toxic sites. However, the research focus has recently expanded to certain other environmentally sensitive issues such as a zone of urban blight, open space, parks, transportation systems, and urban sprawl (Liu, 2001; Harner, *et al.*, 2002). Liu (2001) suggested that it is necessary to incorporate major environment risks and amenities for urban environmental justice analysis. Further, Holifield (2001) pointed out the need to broaden the usual conception of environment in order to open new possibilities in environmental justice research. Therefore, it is apparent that the final goal of urban environmental justice analysis needs to be extended to include and evaluate the quality of life (QOL) of people.

The QOL is a concept that has no consensus definition. Various indicators consisting of both objective and subjective elements can be used to quantify it (Bederman and Hartshorn, 1984). Even though there is no single definition and no broadly accepted method to measure QOL, it appears clear from the literature that some consensual objective indicators such as income, housing, and education have been widely used to measure the QOL (Wallace, 1971; Smith, 1973; Liu, 1976). The majority of previous QOL evaluation studies utilized only socioeconomic indicators from census data as exemplified by the works of Liu (1976) and Bederman and Hartshorn (1984). With increasing concern about environmental issues, biophysical data from remotely sensed images have been employed for QOL assessment. The inclusion of environmental data has allowed for taking a more complete picture of the QOL by relating environmental quality to social quality (Lo and Faber, 1997). Environmental equity studies in the last decade have provided meaningful research insight into the use of potential risk from toxic release facilities as a negative indicator in QOL assessment. The inclusion of industrial hazard-related data will enable us to link the environmental and social qualities to the context of environmental justice. The applicability of both environmental and hazard-related data as indicators of urban quality of life needs to be tested in a larger city such as Atlanta in order to complement environmental equity analysis. The QOL assessment can help planners and decision-makers to be aware of any problem areas in the allocation of human services.

This chapter assesses the quality of life in the Atlanta metropolitan area in 2000 in the context of environmental justice. This research integrates environmental and socioeconomic factors with a hazard-related factor for urban quality of life assessment. Previous literature related to QOL assessment is first reviewed. Urban quality of life is then assessed with the methodology described in Section 4.6 of Chapter Four. The relationship of environmental equity to quality of life is also explored by visual and statistical analyses. Subsequently, implications of urban quality of life assessment to environmental equity analysis are addressed.

7.2 Previous Related Studies

The QOL assessment by itself is not a new research topic. Early insights can be traced to a French sociologist Chombart de Lauwe who laid out the conceptual framework for integrating the biophysical characteristics of the environment in social studies and developed the concept of social space (consisting of the morphological environment and the sociocultural environment) in 1952 (Lo and Faber, 1997). He had an interest in the use of aerial photography, which can be used to extract the biophysical characteristics. However, it was not until the 1960s and 1970s that remote sensing was actually used for social analysis. Some studies in the 1960s and 1970s took advantage of aerial photography for social analysis in the city. Green (1957) pioneered the research to link physical data derived from the aerial photographs to socioeconomic data. He used aerial photography to examine the social structure of Birmingham, Alabama. Subsequently, his work was expanded by Mumbower and Donoghue (1976) and Metivier and McCoy (1971). Mumbower and Donoghue (1976) used aerial photography to study urban poverty in nine U.S. and Puerto Rican metropolitan areas. Metivier and McCoy (1971) employed aerial photography to interpret housing density as an indicator of poverty in Lexington, Kentucky. All these studies are pertained in one way or another to urban QOL assessment.

Recent advances in satellite remote sensing and GIS technologies help streamline the integration of biophysical data from the remotely sensed images with socioeconomic data from the census (Martin and Bracken, 1993). Such a digital approach allows for a more detailed characterization of the urban landscape than that based solely on census data. Forster (1983) developed a residential quality index in the city of Sydney, Australia, using spectral reflectance data derived from Landsat MSS images. He employed house size and vegetation content as a positive indicator of quality and roads and nonresidential buildings as a negative indicator. Weber and Hirsch (1992) measured the urban life quality of Strasbourg, France, by combining the high-resolution SPOT XS image data with cartographic and census data. Most recently, Lo (1997) and Lo and Faber (1997) demonstrated the usefulness of Landsat TM image in conjunction with census data for QOL assessment in a small city in Georgia with emphasis on NDVI as a desirable quality indicator of urban morphological environment. Lo argued that satellite image data could complement census data in providing an environmental perspective for the QOL assessment. The review of all the literature indicates that urban quality was measured with the use of scales or indices which coupled the socioeconomic with environmental data for a complete evaluation.

There is a fundamental technical problem, namely differences in areal units, underlying urban quality of life assessments. Socioeconomic data are aggregated to zonal systems such as census zones while environmental data from remotely sensed images are disaggregated into pixels (e.g., 30 m for Landsat TM images). Conceptually, these two areal units are not compatible. Most previous studies aggregated pixel-based data to zonal units to tackle the incompatibility problem in areal units. However, this approach cannot reveal subunit variation in zonal units. Urban models have become increasingly disaggregated in space, time, and substantive elements (Spiekermann and Wegener, 2000). In order to solve this problem, a spatial microsimulation model can be used to spatially disaggregate data within a spatial unit such as a census tract and a census block group (Spiekermann and Wegener, 2000). Model results can be assessed through multicriteria evaluation techniques that are sensitive to equity, environmental, and efficiency criteria (Malczewski, 1999).

7.3 Urban Quality of Life Assessment

The QOL in the Atlanta metropolitan area in 2000 was evaluated to complement environmental equity analysis using the methodology demonstrated in Section 4.6 of Chapter Four. The QOL was assessed based on demographic, economic, educational, housing, environmental, and hazard-related factors. As mentioned in Section 4.6 of Chapter Four, three environmental variables including land use and cover, NDVI, and surface temperatures were extracted from Landsat TM data while four socioeconomic variables including population density, per capita income, percent college graduates, and median home value were derived from census data. A hazard-related variable, cumulative potential relative exposure to TRI facilities, was extracted from the TRI database. The environmental data were included in the QOL assessment to provide an environmental perspective. Most of the socioeconomic data were selected on the basis of the commonly agreed set of variables used by social scientists to objectively measure the degree of crowding in an area, the income level, and the housing condition of the population living in it (Lo and Faber, 1997). A hazard-related criterion was adopted in this research since this is an obvious factor of environmental disamenity in urban areas and this also makes it possible to frame the QOL assessment within the context of environmental justice.

Three environmental variables and a hazard-related variable are per-pixel data while four socioeconomic variables are zonal data. There are two data aggregation methods available to solve this analytical problem, namely differences in areal units: (1) pixel-based approach and (2) zone-based approach (Martin and Bracken, 1993). The zone-based approach mostly used in previous studies aggregates pixel-based data to zonal units in order to fix this problem while the pixel-based approach spatially disaggregates zonal data to individual pixel. The zone-based approach unrealistically assumes that all the socioeconomic variables are uniformly distributed within zonal units and also has analytical pitfalls such as MAUP and spatial interpolation between incompatible zone systems. Besides, this approach cannot reveal microscale variation in zonal units. This research, therefore, took the pixel-based approach to spatially disaggregate the four socioeconomic variables into individual pixels, as described in Section 4.6 of Chapter Four.

Finally, two approaches were employed to integrate and transform environmental, hazard-related, and socioeconomic variables into a resultant QOL score for each pixel: (1) spatial multicriteria analysis (SMA) and (2) principal components analysis (PCA). The former is selected as a representative method from multicriteria evaluation techniques while the latter is from multispectral remote sensing image analysis.

7.3.1 Spatial Multicriteria Analysis

The SMA is the actual decision making procedure of applying a decision rule to meet a specific objective on the basis of multiple and conflicting criteria (Malczewski, 1999). Two of the most common procedures for SMA are weighting linear combination (WLC) and concordance-discordance analysis (CDA) (Carver, 1991). In the former, each factor is multiplied by a weight and then summed to arrive at a final suitability index. This process can be expressed as follows:

$$S = \sum w_i * x_i \tag{7.1}$$

where S is suitability, w_i is the weight of factor i, and x_i is the criterion score of factor i. In the latter, each pair of alternatives is analyzed for the degree to which one out ranks the other on the specified criteria. The CDA is computationally impractical when a large number of alternatives is present (i.e., with raster data where every pixel is an alternative) (Eastman *et al.*, 1995). However, WLC is very straightforward in a raster GIS. In this regard, a SMA based on WLC, as illustrated in Figure 4.6, was used to integrate and transform the eight variables into a resultant QOL score for each pixel.

As indicated above, this research identified eight factors as being relevant to the determination of the QOL in the Atlanta metropolitan area in 2000. The eight factors are illustrated in Figure 7.1 to Figure 7.8, respectively. The eight factors are divided into two major groups for the QOL assessment: (1) positive factor and (2) negative factor. The positive factor includes NDVI, percentage of college graduates, per capita income, and median home value. The higher values in the positive factors represent more desirable to the QOL. The negative factor contains urban use, surface temperatures, population density, and cumulative potential relative exposure to TRI facilities. The higher values in the negative factors indicate less desirable to the QOL. Unlike other negative factors, the value of the urban use variable was assigned to one of 10 rank scores, with 2 being the commercial and industrial class and 10 being the residential class so that the value was reversed before standardization in order to reflect the undesirability to the QOL.

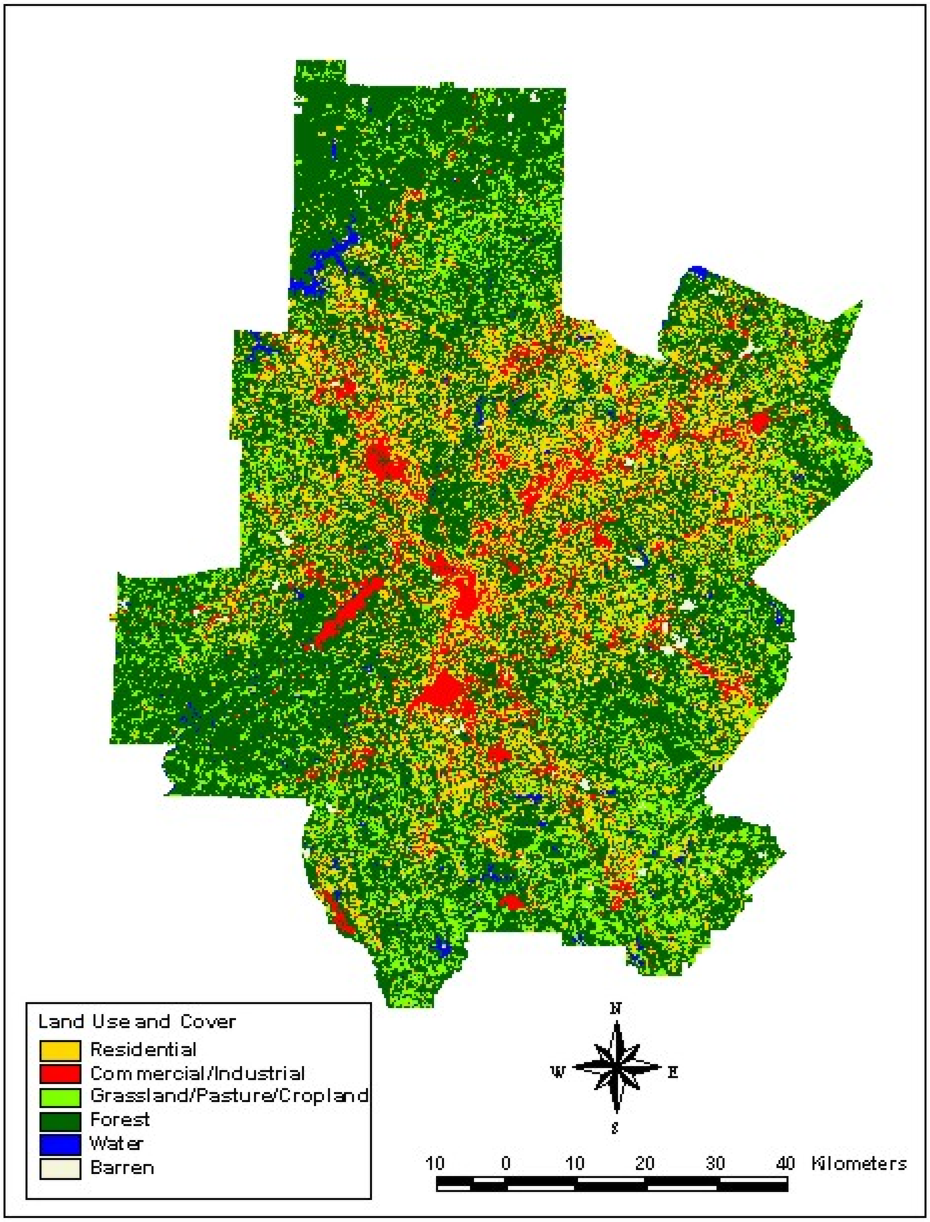


Figure 7.1 Land use and cover, 2000.

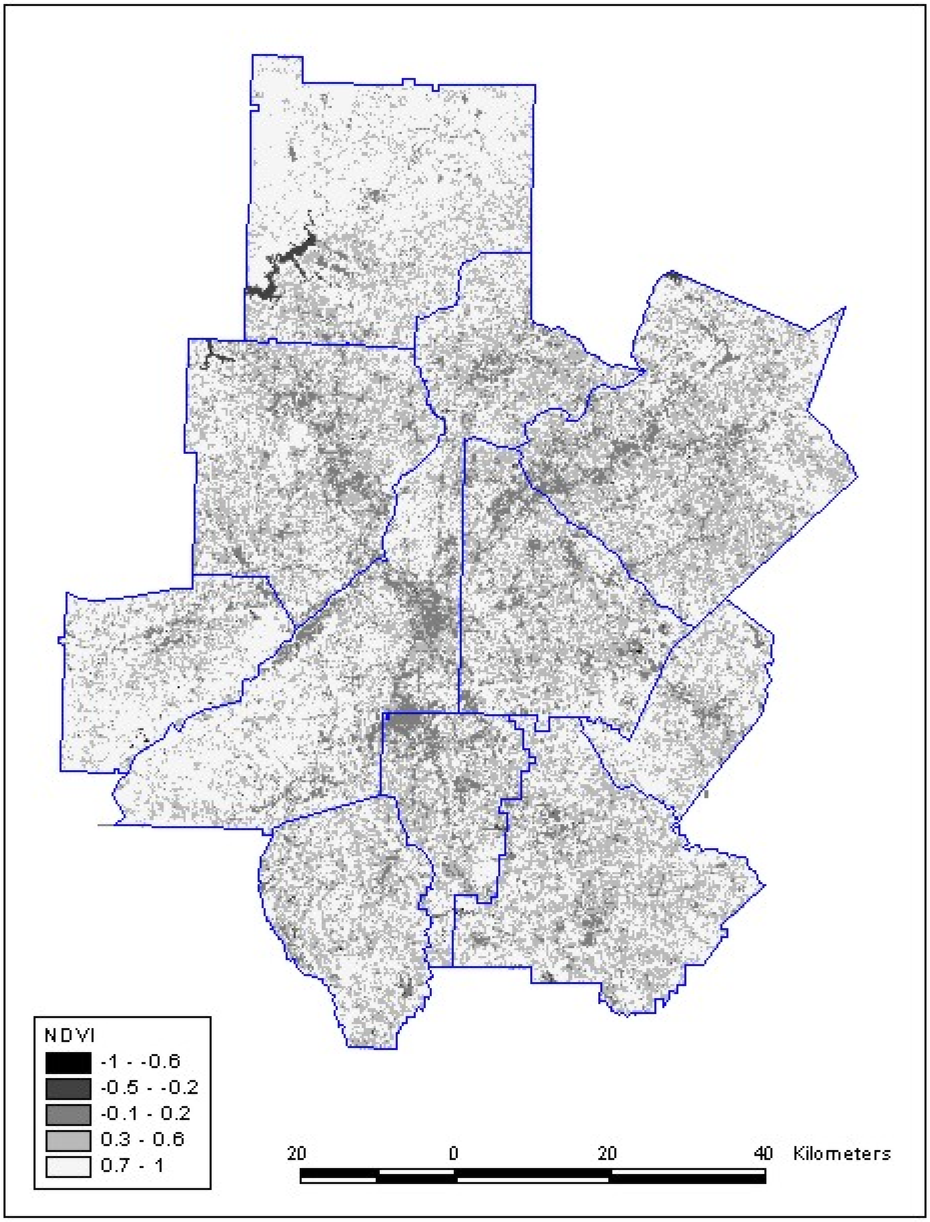


Figure 7.2 NDVI, 2000.

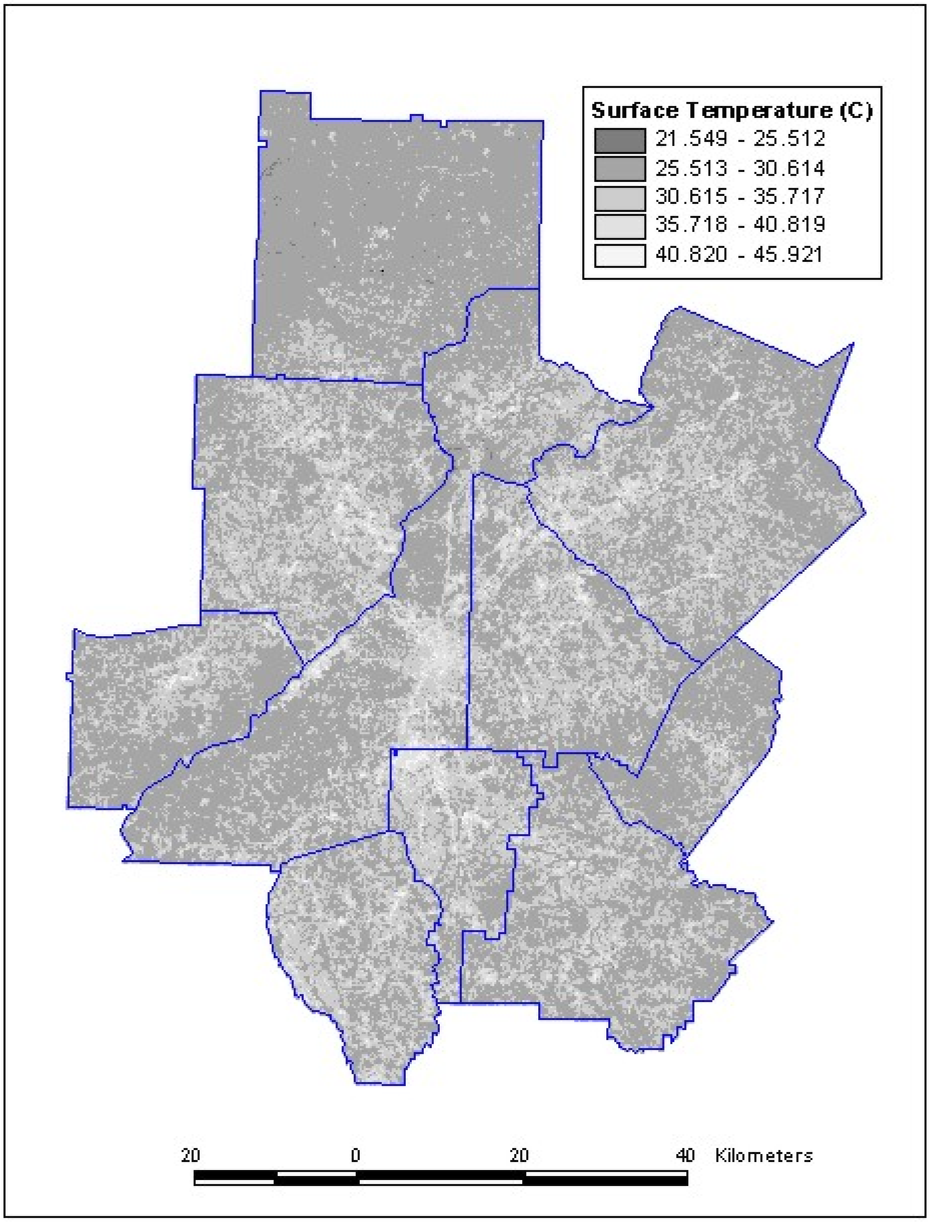


Figure 7.3 Apparent surface temperatures, 2000.

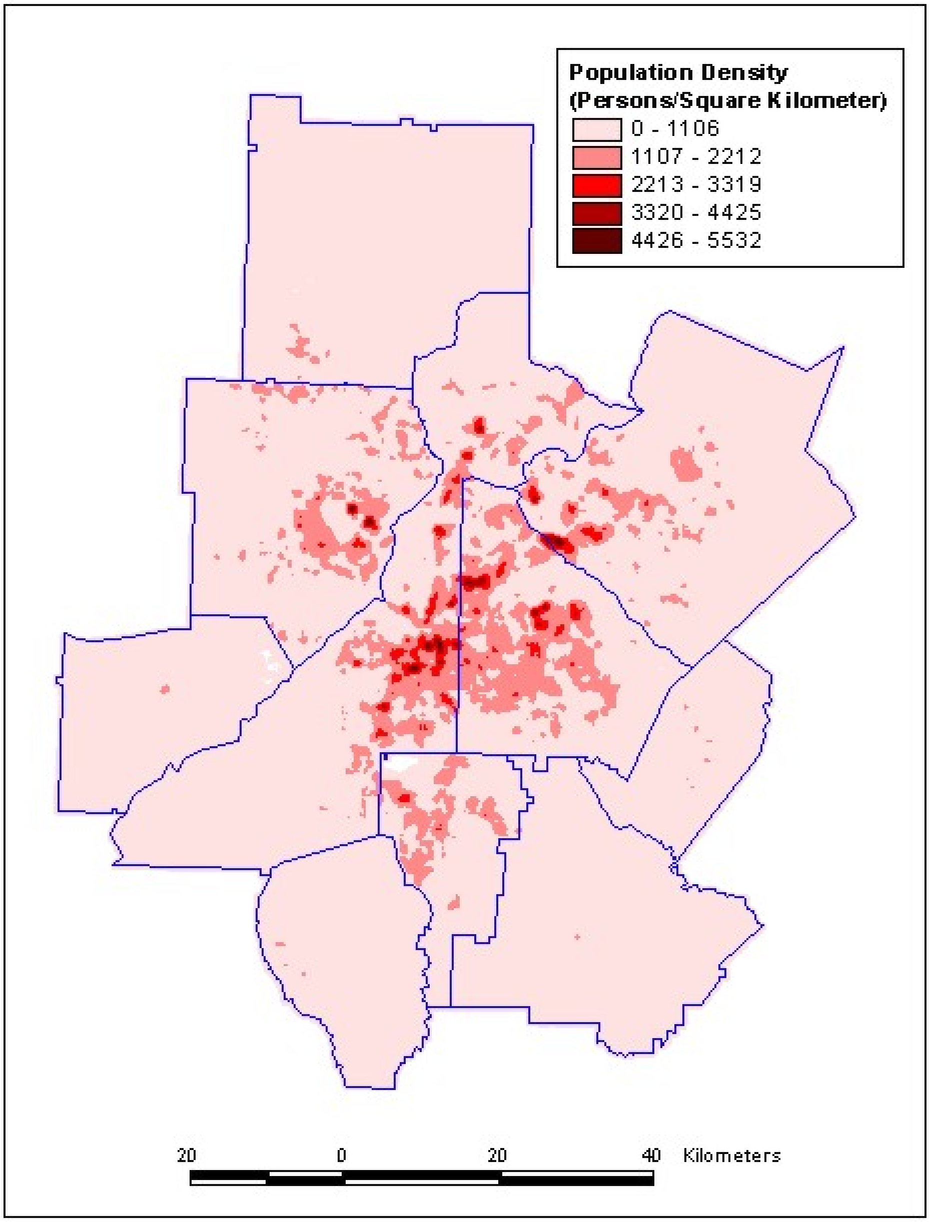


Figure 7.4 Population density, 2000.

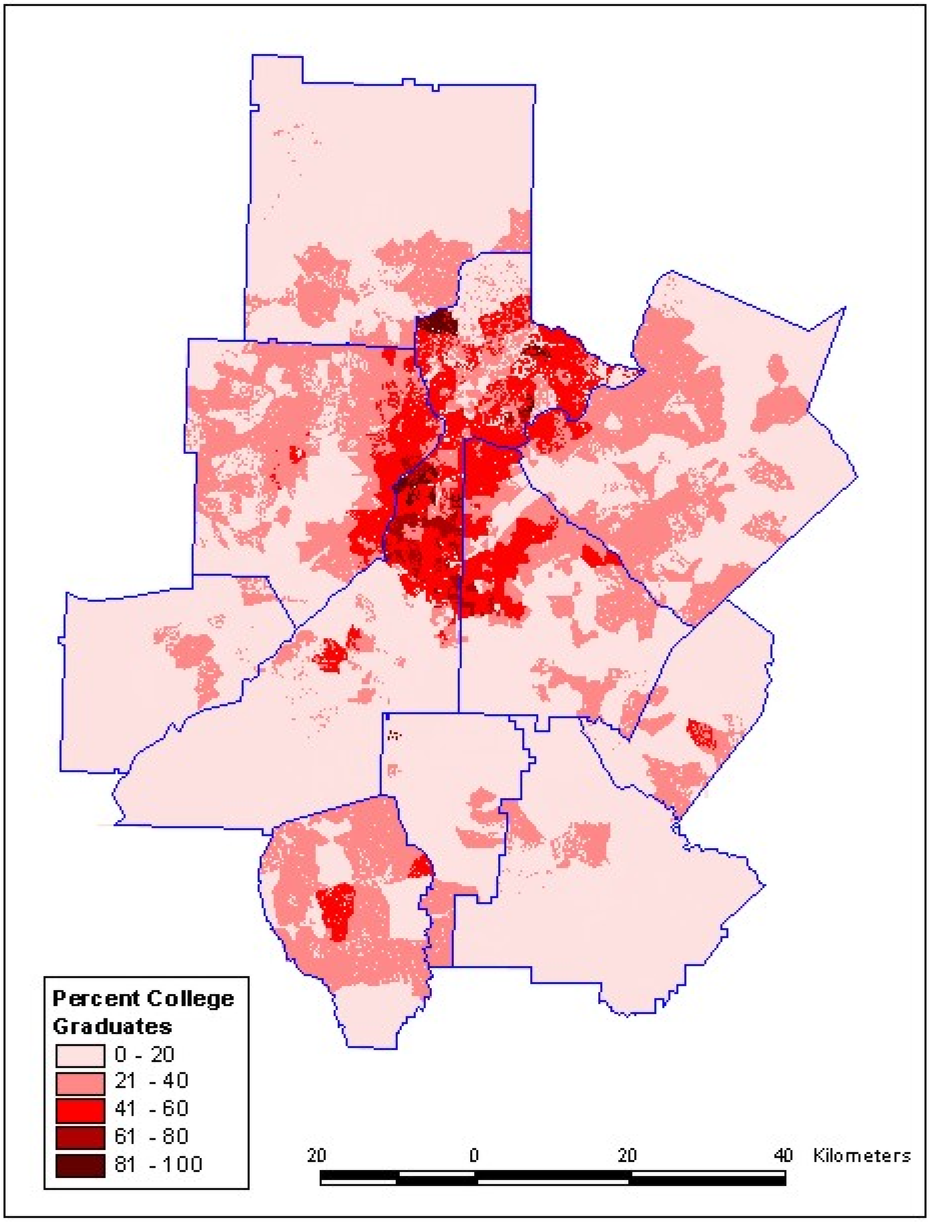


Figure 7.5 Percent college graduates, 2000.

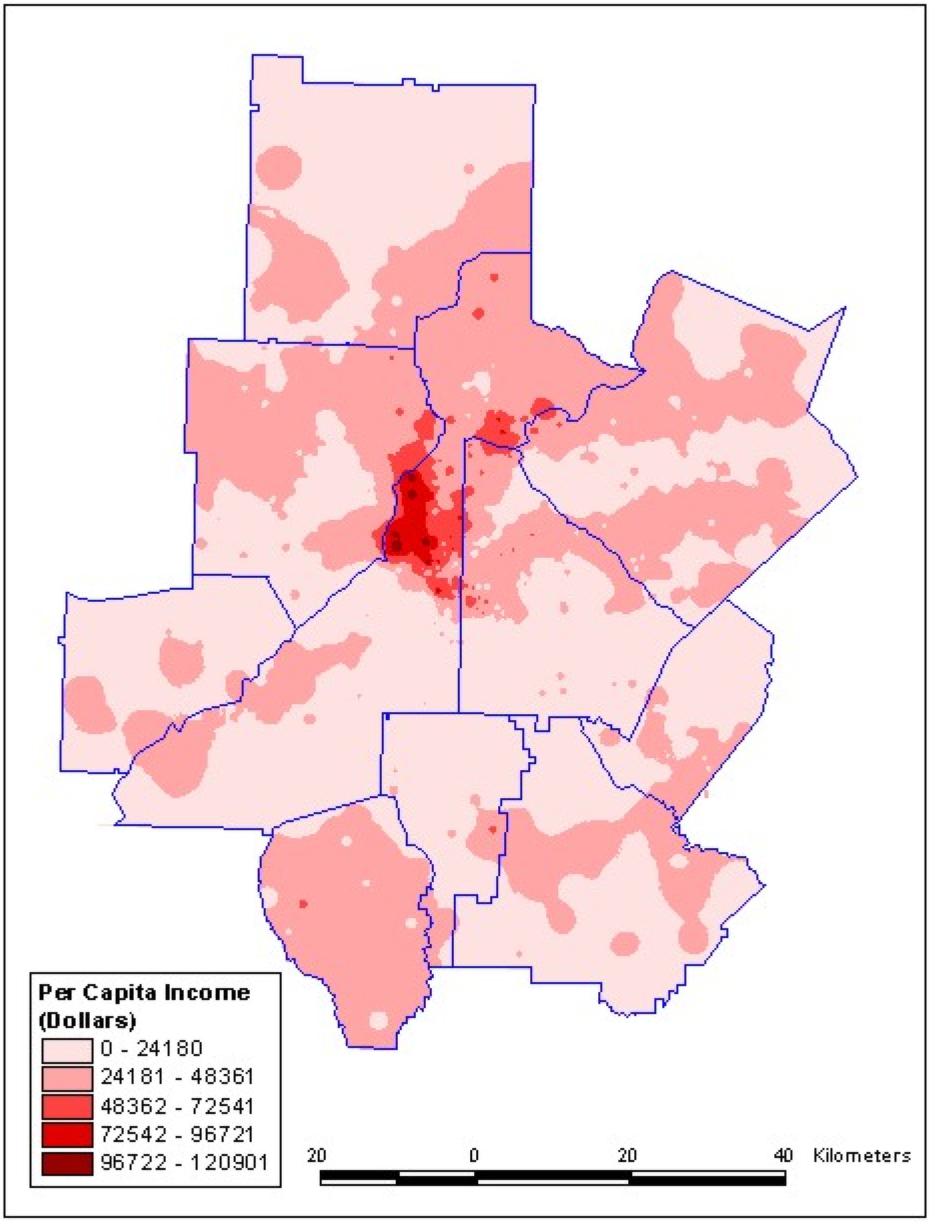


Figure 7.6 Per capita income, 2000.

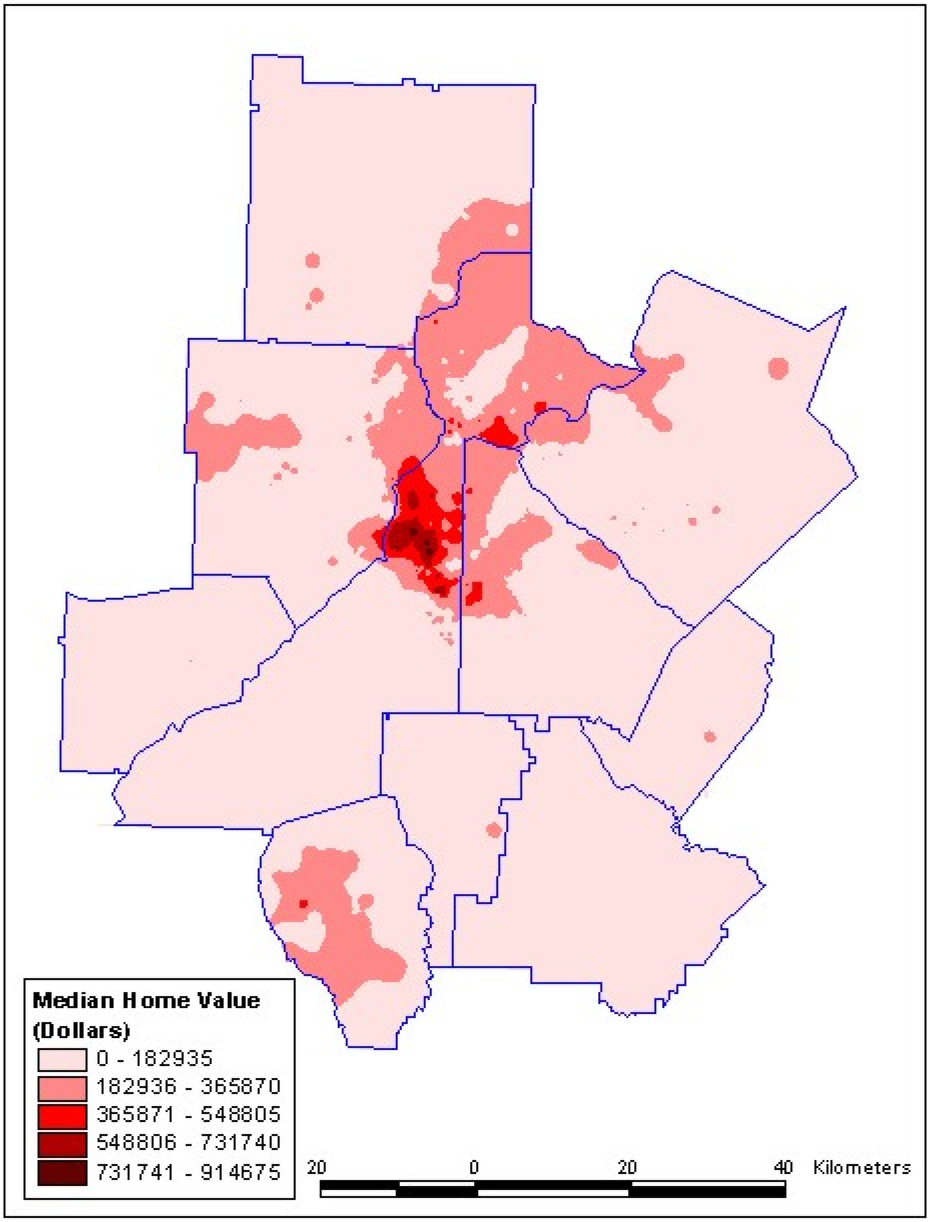


Figure 7.7 Median home value, 2000.

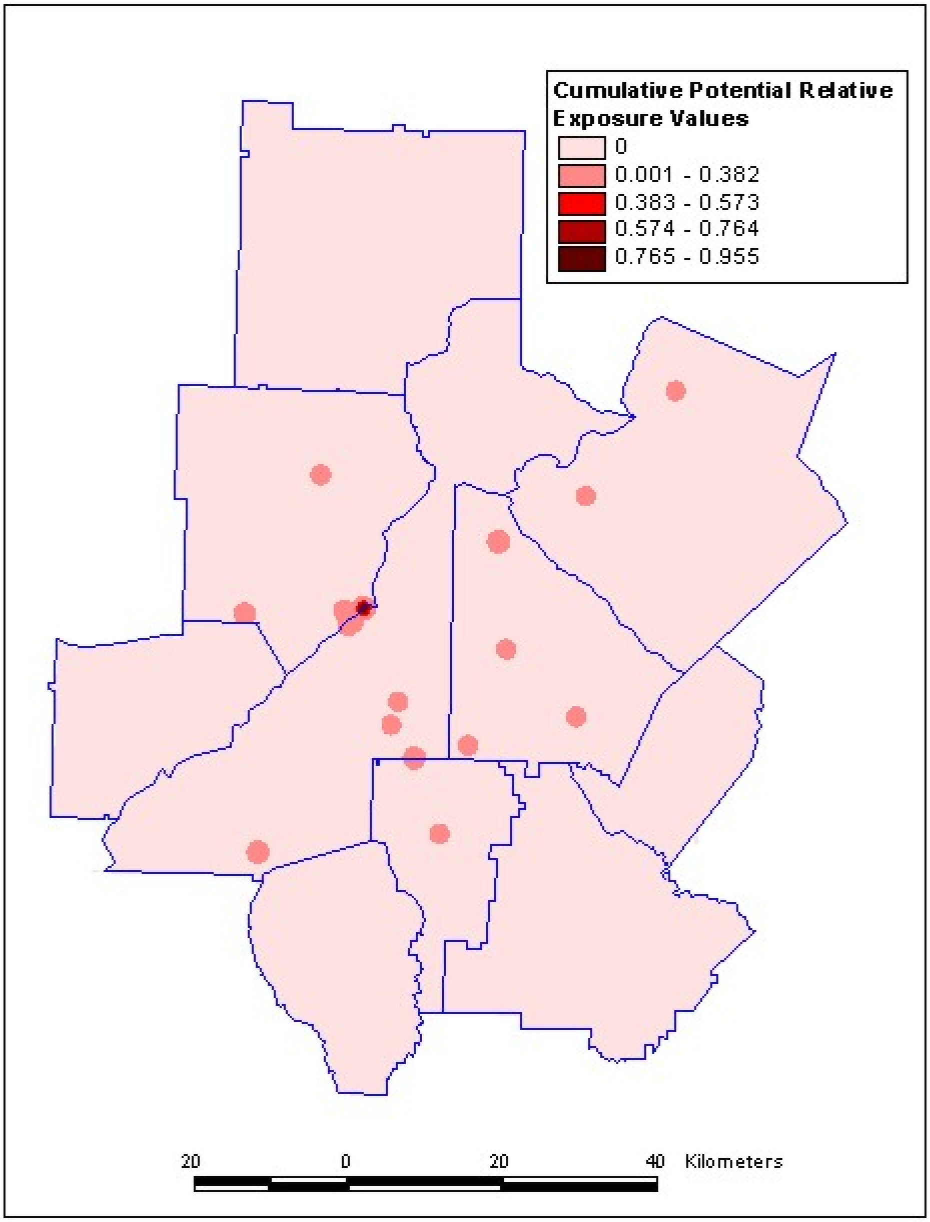


Figure 7.8 Cumulative potential relative exposure values to TRI facilities, 2000.

Because criteria are measured at the different scales, it is necessary that factors are standardized before combination. The eight factors were standardized to a consistent numeric range of 0 to 1. Standardization was achieved by undertaking a linear scale transformation method based on the minimum and maximum values, as expressed in Equation 4.12. In case of the negative factors, the numeric scales were reversed to reflect the undesirability to the QOL.

In the next stage, the evaluation criteria were compared pairwise using the analytical hierarchy process (AHP) developed by Saaty (1980) in order to generate the criterion weights. The AHP approach allows one to assess the relative weight of multiple criteria in an intuitive manner. In the SMA based on WLC method, it is necessary that the weights sum to 1. In Saaty's technique, these weights can be derived by taking the principal eigen vector of a square reciprocal matrix of pairwise comparison. The comparisons concern the relative importance of the two criteria involved in determining the QOL. Ratings are provided on a nine-point continuous scale (Figure 7.9). For example, if one thought that NDVI was moderately more important than percent college graduates in determining the QOL, one would enter a 3 on this scale. If the inverse was the case (percent college graduates was moderately more important than NDVI), one would enter 1/3. In developing the weights, a person compared every possible pairing and entered the ratings into a pairwise comparison matrix (Table 7.1). Because the matrix is symmetrical, only the lower triangular half actually needs to be filled in. The remaining cells are then simply the reciprocals of the lower triangular half. Since no empirical evidence exists about the relative efficacy of a pair of factors, a person's perception was mainly used and Bederman and Hartshorn's (1984) weights were considered. The principal eigen vector of the pairwise comparison matrix was computed to produce a best fit set of weights (Table 7.2). This computation was performed using a special module named *weight* in Idrisi. The highest weight is

Less important				More important				
Extremely	Very strongly	Strongly	Moderately	Equally important	Moderately	Strongly	Very strongly	Extremely
1/9	1/7	1/5	1/3	1	3	5	7	9

Figure 7.9 The continuous rating scale used for AHP pairwise comparison.

Table 7.1 A pariwise comparison matrix for assessing the comparative importance of factors

	LULC	NDVI	TEMP	POPD	EDU	PINCO	HOME	RISK
LULC	1							
NDVI	5	1						
TEMP	5	1	1					
POPD	1/5	1/7	1/5	1				
EDU	3	1/3	1/3	5	1			
PINCO	5	3	3	7	3	1		
HOME	5	3	3	7	3	1	1	
RISK	7	5	5	9	5	5	3	1

LULC-Urban use; NDVI-NDVI; TEMP-Surface temperatures; POPD-Population density; EDU-Percent college graduates; PINCO-Per capita income; HOME-Median home value; RISK-Cumulative potential relative exposure.

Table 7.2 Weights for factors and consistency ratio

Factors	Weights
Urban use	0.0340
NDVI	0.0950
Surface temperatures	0.0909
Population density	0.0178
Percent college graduates	0.0563
Per capita income	0.1624
Media home value	0.1681
Cumulative potential relative exposure	0.3756
Consistency ratio	**0.08**

0.3756 for the hazard-related factor while the lowest is 0.0178 for the population density factor. To determine the degree of consistency that has been used in developing the ratings, a consistency ratio was also produced as shown in Table 7.2. The consistency ratio (CR) has been used in developing the ratings, a consistency ratio was also produced as shown in Table 7.2. The consistency ratio (CR) indicates the probability that the matrix ratings were randomly generated. If matrices have CR ratings greater than 0.10, these should be re-evaluated. With several re-evaluations, the acceptable CR, 0.08, was achieved in this research. Since each variable was judged in regard to whether it is desirable or not, the SMA is more subjective than PCA, but this approach provides a logically coherent procedure that would be comprehensible to the majority of decision makers.

Once the weights were established, each criteria map was multiplied by its weight in ArcView GIS. The weighted standardized criteria were then aggregated to generate the overall quality of life score using a decision rule based on the WLC method. This operation was achieved by the GIS overlay (add) function in ArcView GIS. Because the weights sum to 1 and the criteria were standardized from 0 to 1, the resultant QOL score ranges from 0 to 1. The best QOL score is 1 while the worst is 0.

Figure 7.10 shows the overall QOL score map generated by the SMA based on the WLC method. The highest QOL score was found around Roswell, Alphretta, and the northern parts of Fulton County along Georgia 400 whereas the lowest QOL score was found around Smyrna in Cobb County. The areas with the highest QOL score are characterized by the higher NDVI, the lower surface temperature, the highest per capita income, the highest median home value, very high percentage of college graduates, lower population density, lower percentage of urban use, and no relative risk from TRI facilities. In contrast, the places with the lowest QOL score are

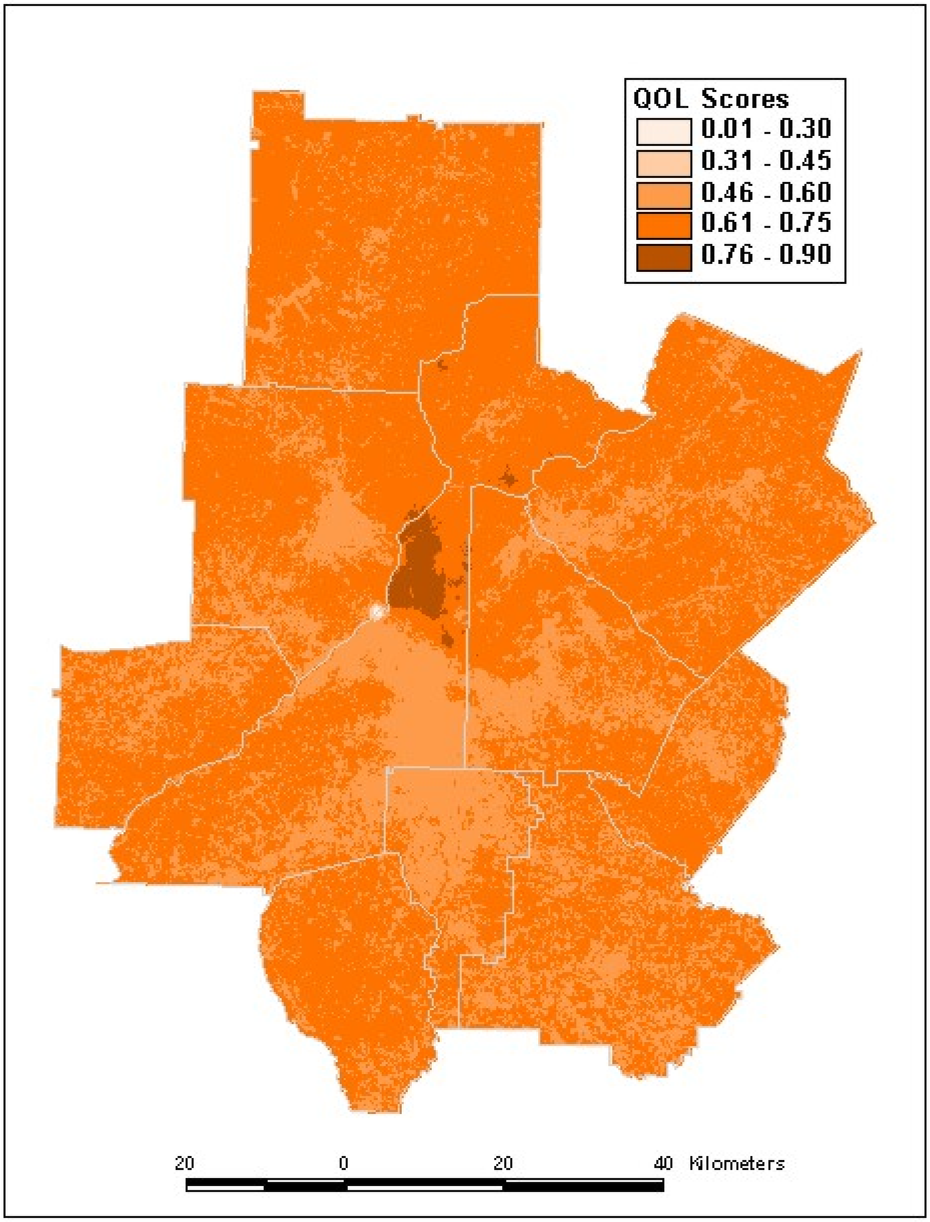


Figure 7.10 Urban quality of life scores based on SMA, 2000.

characterized by the highest relative risk from TRI facilities, higher surface temperature, higher percentage of urban use, lower NDVI, higher population density, lower per capita income, lower median home value, and lower percentage of college graduates. The major urbanized areas and the southern central city of Atlanta showed relatively lower QOL scores than their counterparts. Intermediate QOL scores were found farther away from major roads than the areas with lower QOL scores. Median home values, per capita income, and education attainment were slightly lower than those of the areas with the highest QOL score while NDVI and surface temperatures were generally similar. In average, no relative risk was found in the areas with intermediate QOL scores. The extent of spatial clustering among cells with respect to quality of life scores was assessed by Moran's I, a spatial autocorrelation statistic. The result showed that the spatial autocorrelation coefficient was 0.99 for only pixels covering metropolitan Atlanta. This indicates a strong similarity in the spatial patterning of the quality of life scores.

7.3.2 Principal Components Analysis

The PCA has proved to be valuable in the analysis of multispectral remotely sensed data (Jensen, 1996). The PCA is a data transformation technique which can convert a large number of correlated data into a smaller number of uncorrelated components whose axes in attribute space are rotated with respect to the original attribute space. The main reasons to transform the data in PCA are to compress data by eliminating redundancy, to emphasize the variance within the original data, and to make the data more interpretable. Generally, the first two or three components explain a high proportion of the variance in the original data whereas the remaining components describe progressively less of the variance and can be dropped. In this respect, PCA is also used to integrate and transform the eight variables into a resultant QOL score for each pixel. The PCA can be an alternative objective approach to complement SMA, a subjective approach.

There are two common procedures for PCA: (1) standardized PCA and (2) unstandardized PCA (Jensen, 1996). Standardized PCA is based on the computation of eigen values from a correlation matrix while unstandardized PCA is computed from a covariance matrix. The unstandardized PCA was used in this study since Imagine provides only the unstandardized PCA function. All eight variables described in Section 7.3.1 were stacked up and an image of eight layers was generated in the Imagine. The PCA was then applied to the eight layers of image data using the Imagine.

The cross correlation among the eight variables, as reported in Table 7.3, indicates that NDVI is negatively correlated with urban use (r = -0.8899), surface temperature (r = -0.9762), population density (r = -0.9682), and relative risk from TRI facilities (r = -0.9724). This implies that NDVI is a versatile environmental quality variable. In Table 7.3, it is clear that NDVI is positively correlated with per capita income (r = 0.8480), median home value (r = 0.7542), and percentage of college graduates (r = 0.4729). The implication is that NDVI also appears to be a good indicator of socioeconomic characteristics of an urban area. These results are consistent with those found in previous study by Lo and Faber (1997). It is also worthy to note that relative risk from TRI facilities is negatively correlated with NDVI (r = -0.9724), percentage of college graduates (r = -0.5040), per capita income (r = -0.8655), and median home value (r = -0.7731), but positively correlated with urban use (r = 0.8774), surface temperature (r = 0.9509), and population density (r = 0.9856). This suggests that relative risk from TRI facilities is also another versatile indicator of environmental and socioeconomic quality of an urban area. In other words, this gives a new insight into urban environmental justice analysis.

Table 7.3 Correlation matrix of variables

	LULC	**NDVI**	**TEMP**	**POPD**	**EDU**	**PINCO**	**HOME**	**RISK**
LULC	1							
NDVI	-0.8899	1						
TEMP	0.8694	-0.9762	1					
POPD	0.8515	-0.9682	0.9549	1				
EDU	-0.5123	0.4729	-0.4436	-0.4510	1			
PINCO	-0.7789	0.8480	-0.8350	-0.8517	0.6822	1		
HOME	-0.6976	0.7542	-0.7436	-0.7517	0.7057	0.9183	1	
RISK	0.8774	-0.9724	0.9509	0.9856	-0.5040	-0.8655	-0.7731	1

LULC-Urban use; NDVI-NDVI; TEMP-Surface temperatures; POPD-Population density; EDU-Percent college graduates; PINCO-Per capita income; HOME-Median home value; RISK-Cumulative potential relative exposure.

As shown in Table 7.4, the PCA identified two principal components which describe over 95 percent of total variance of the original data. The first principal component explained 93 percent of total variance of the original variables while the second principal component accounted for only 3 percent. The first principal component showed strong positive loadings on four variables such as NDVI, per capita income, median home value, and percentage of college graduates whereas very strong negative loadings on four variables such as urban use, surface temperature, population density, and relative risk. The second principal component exhibited very weak positive loading on urban use, surface temperature, population density, and relative risk. On the other hand, the second component represented very weak negative loadings on NDVI, percentage of college graduates, per capita income, and median home value. In Table 7.4, the communality for each variable revealed that the two principal components together accounted for the following: (1) an extremely high proportion of the variance of urban use, NDVI, surface temperature, population density, and relative risk, (2) a moderately high proportion of the variance of per capita income and median home value, and (3) a low proportion of the variance of percentage of college graduates. In other words, the two principal components reflected very strongly the environmental and hazard-related characteristics and strongly the socioeconomic characteristics of the Atlanta metropolitan area.

Figure 7.11 illustrates the relative positions of the eight variables plotted in a graph according to their component loadings in component 1 (X axis) and component 2 (Y axis). The resulting component pattern indicates two dichotomous relationships between the cluster of environmental variables and the cluster of socioeconomic variables, and between the cluster of desirable indicators and the cluster of undesirable indicators. The cluster of the socioeconomic or desirable variables includes NDVI, per capita income, median home value, and percentage of

Table 7.4 Principal component loadings

Variables	Component Loadings		Communality
	PC1	PC2	
LULC	-0.9147	0.3846	0.98
NDVI	0.9879	-0.0316	0.98
TEMP	-0.9730	0.0534	0.95
POPD	-0.9851	0.1375	0.99
EDU	0.5072	-0.3658	0.39
PINCO	0.8738	-0.0551	0.77
HOME	0.7801	-0.0945	0.62
RISK	-0.9911	0.0684	0.99
Eigen Value	0.8416	0.0299	
Variance (%)	92.6	3.30	

LULC-Urban use; NDVI-NDVI; TEMP-Surface temperatures; POPD-Population density; EDU-Percent college graduates; PINCO-Per capita income; HOME-Median home value; RISK-Cumulative potential relative exposure; PC1-Principal component 1; PC2-Principal component 2.

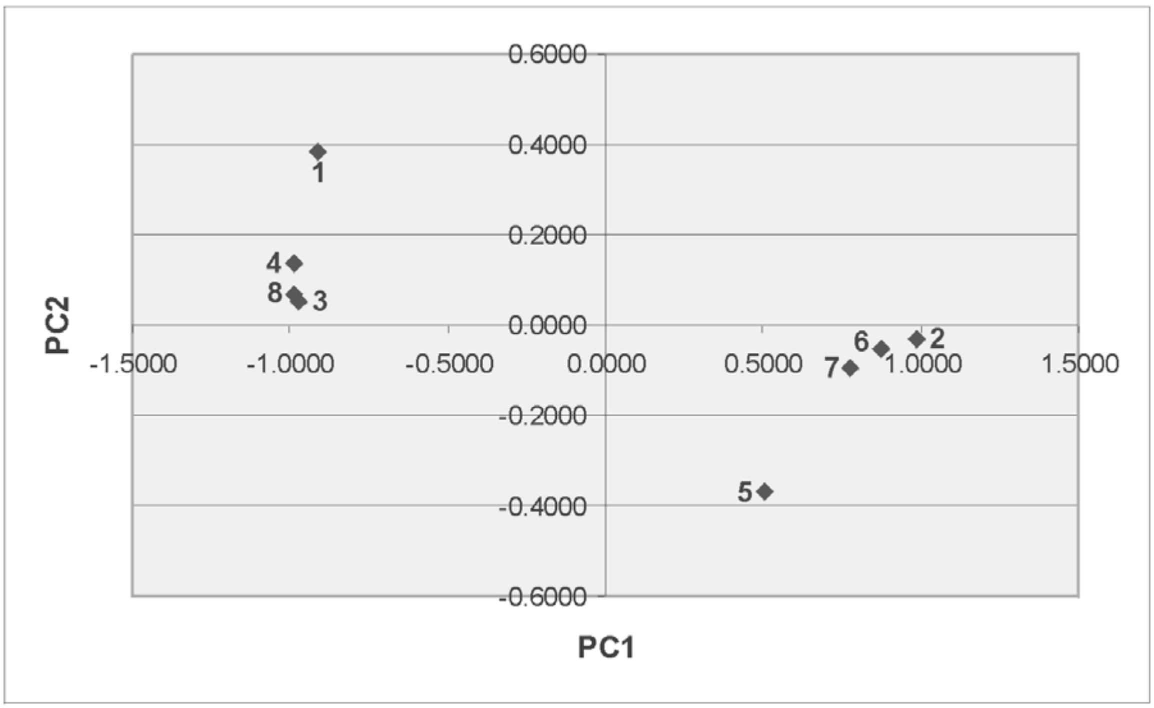


Figure 7.11 A scatter plot of principal components 1 and 2.

1-Urban use; 2-NDVI; 3-Surface temperatures; 4-Population density;
5-Percent college graduates; 6-Per capita income; 7-Median home value;
8- Cumulative potential relative exposure; PC1-Principal component 1;
PC2-Principal component 2.

college graduates whereas the cluster of the environmental or undesirable variables consists of urban use, surface temperature, population density, and relative risk. It is interesting to note that NDVI is much closer to the socioeconomic cluster than the environmental one. In contrast, population density is much closer to the environmental cluster than the socioeconomic one.

Because the first principal component explained 93 percent of the total variance of the eight variables and reflected very strongly both environmental and socioeconomic variables, this first component was used to create a QOL score map. Figure 7.12 shows the QOL score map based on the first principal component scores. The resultant QOL score ranges from 0.01 to 2.46. A higher level of QOL is associated with a higher principal component score. The map exhibited high QOL areas around Roswell, Alphretta, and the northern parts of Fulton County along Georgia 400, and low QOL areas around Smyrna, downtown Atlanta, and Hartsfield-Jackson International Airport. A sectoral pattern of spatial variation in QOL was also detected along major roads. This indicates that it is necessary to control highways, urban use, vegetation cover, and location of industrial facilities. The extent of spatial clustering among cells with respect to quality of life scores was quantified by Moran’s I. The result exhibited that the spatial autocorrelation coefficient was 0.99 for only pixels covering metropolitan Atlanta. This represents a strong similarity in the spatial patterning of the quality of life scores.

According to a map comparison between Figure 7.12 and Figure 7.10, it was found that the spatial patterns were very similar. In order to verify the spatial similarity, a correlation analysis between the QOL score map based on PCA and the QOL score map based on SMA was performed in the Imagine. The resulted correlation coefficient was 0.99 or a coefficient of determination of 98 percent for only pixels covering the Atlanta metropolitan area. The two maps are spatially strongly correlated.

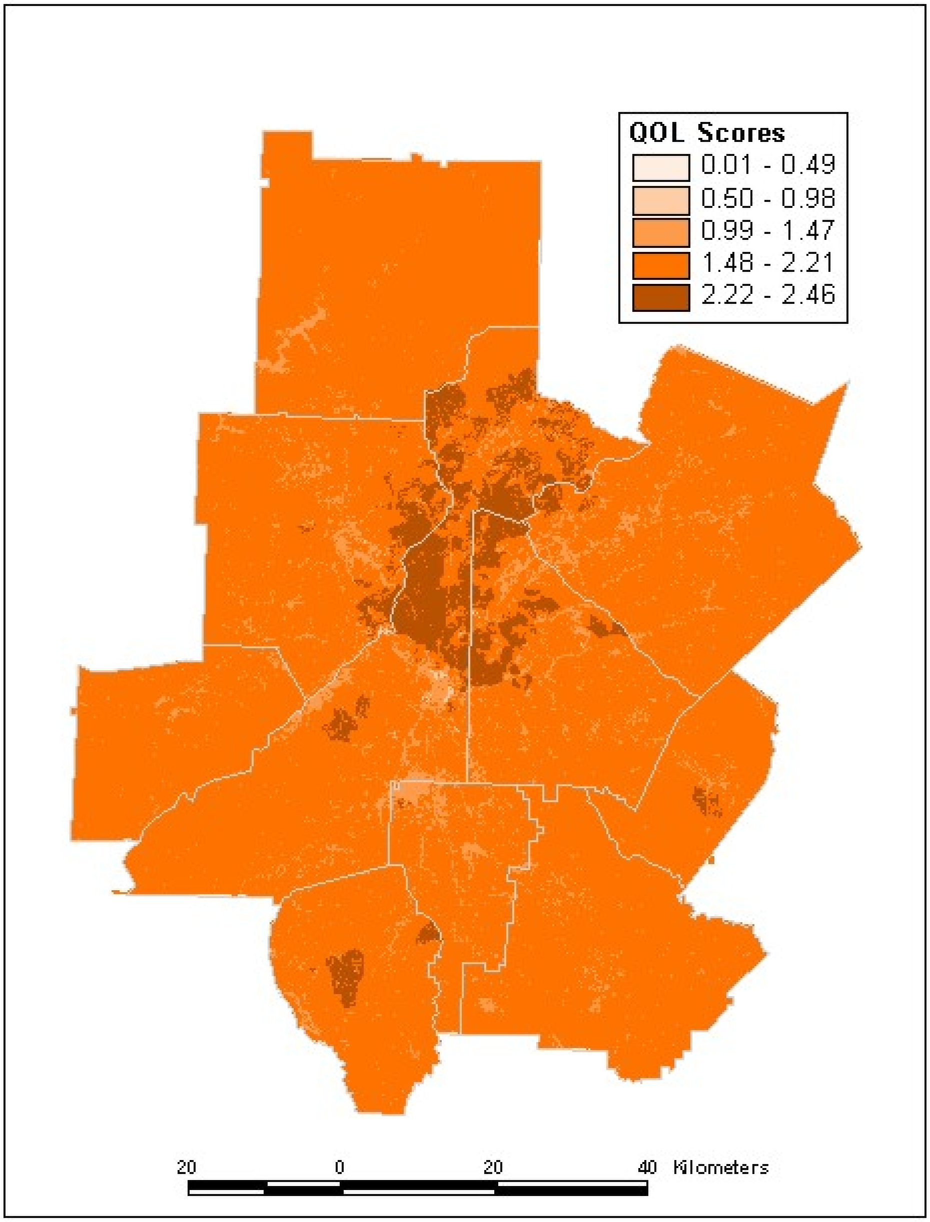


Figure 7.12 Urban quality of life scores based on PCA, 2000.

7.4 Implications for Environmental Equity Analysis

The relationship between environmental inequity and quality of life was explored by visual and statistical analyses. In order to investigate the spatial relationship between them, the two QOL score maps were visually compared with the environmental inequity surface for 2000, which was generated in Section 6.3.2 of Chapter Six. Two pairs of visual comparisons between Figure 6.16 and Figure 7.10, and between Figure 6.16 and Figure 7.12 revealed that the spatial patterns were inversed. In other words, the areas with higher environmental inequity scores appeared around those with lower QOL scores while the places with lower environmental inequity scores occurred around those with higher QOL scores.

The reverse spatial relationship between them was statistically verified. This was achieved by performing correlation analyses between the environmental inequity score map and the QOL score maps of the study area using the *correlation* function in the Imagine. The results from the correlation analyses indicated that the correlation coefficient between the environmental inequity score map and the QOL score map based on SMA was -0.70 or a coefficient of determination of 49 percent for only pixels covering the Atlanta metropolitan area whereas the correlation coefficient between the environmental inequity score map and the QOL score map based on PCA was -0.69 or a coefficient of determination of 48 percent. Since the two QOL score maps are positively strongly correlated as indicated in Section 7.3, the correlation analysis results between them are very similar. The statistical results confirm that environmental inequity scores are significantly negatively correlated with QOL scores in the Atlanta metropolitan area in 2000.

The visual and statistical analyses address implications of urban QOL assessment to environmental equity analysis. It is clearly noted that at least in this area, urban QOL assessment can complement environmental equity analysis and the QOL assessment provides a more comprehensive perspective for examining environmental justice issues in an urban area.

7.5 Summary

The QOL in the Atlanta metropolitan area in 2000 was assessed and mapped to complement environmental equity analysis. For the QOL assessment, this study integrated three environmental factors including land use and cover, NDVI, and surface temperatures from the Landsat TM image and four socioeconomic factors such as population density, per capita income, percent college graduates, and median home value from the census data with a hazard-related factor from the TRI data. The environmental factors and a hazard-related factor as an obvious indicator of environmental disamenity were included in the QOL assessment to provide an environmental perspective and to frame the QOL assessment within the environmental justice context. Unlike most previous studies using the zone-based approach, this study employed the pixel-based approach to solve the incompatibility problem in areal units among environmental, hazard-related, and socioeconomic data. This choice was made due to the zone-based approach's uniformity assumption about the spatial distribution of data, analytical pitfalls such as MAUP and spatial interpolation problem between incompatible zone systems, and inability not to reveal sub-unit variation in zonal units. Therefore, the four socioeconomic variables aggregated by census block groups were spatially disaggregated into individual pixels using the methodological framework developed in this research.

Two approaches, SMA and PCA, were employed to integrate and transform environmental, hazard-related, and socioeconomic variables into a resultant QOL score for each pixel. In the SMA based on the WLC method, each factor was multiplied by a weight developed by the AHP process and then summed to generate a overall QOL score for each pixel. The SMA based on the WLC method was an appropriate tool for the large data handling needs for raster GIS. The PCA of the eight variables identified two variable clusters. One is the cluster of the socioeconomic or desirable variables including NDVI, per capita income, median home value, and percentage of college graduates. Another is the cluster of the environmental or undesirable variables consisting of urban use, surface temperature, population density, and relative risk. The PCA also revealed that NDVI and relative risk from TRI facilities were two versatile indicators of environmental and socioeconomic quality of an urban area. The SMA is more subjective than the PCA, but the SMA provides a logically coherent procedure that would be comprehensible to the majority of decision makers. Based on the two approaches for the QOL assessment, the highest QOL score was found around Roswell, Alphretta, and the northern parts of Fulton County along Georgia 400 whereas the lowest QOL score was found around Smyrna of Cobb County, downtown Atlanta, and Hartsfield-Jackson International Airport.

The spatial association between environmental inequity and QOL was examined by visual and statistical analyses. It was found that the spatial cluster of higher environmental inequity scores appeared around that of lower QOL scores while the spatial cluster of lower environmental inequity scores occurred around that of higher QOL scores. In other words, the environmental inequity was significantly negatively correlated with the QOL in the Atlanta metropolitan area in 2000. The implications addressed that QOL assessment can be substituted for environmental equity analysis in an urban area and provides a more complete perspective for examining urban environmental justice issues. Replication of this research in other cities will be required to examine the role of environmental risks in the spatial variation of QOL.

CHAPTER 8

SUMMARY AND CONCLUSIONS

8.1 Summary

This dissertation was motivated by the following research background. First, one of recurring issues in the social sciences during the last two decades has concerned the inequity in the spatial distribution of environmental risks and hazards with regard to socioeconomic characteristics of populations. The importance of environmental justice analysis and research has been demonstrated in environmental justice policies, which have tried to generate environmental equity in the society. Although environmental justice policies have been formulated at the national and state levels, environmental justice debate has continued among different researchers and stakeholders. The main reason for its continuation is conflicting empirical evidence on whether environmental inequity exists or not. Generalized evidence is devoid in the existing literature due to methodological inconsistencies. Specific methodological issues addressed in environmental justice research were identified in three major areas including data and measurement, scale and resolution, and methods of analysis (McMaster *et al.*, 1997). Little consensus has been made on how such an analysis must be conducted to obtain reliable results.

Second, GIS have been recently used to make valuable contributions to the understanding and solution of key socioeconomic and environmental problems. With their powerful functionalities of data integration, spatial analysis, modeling, and visualization, GIS also offer great opportunity for environmental equity analysis. The recent development of remote sensing technology has provided invaluable biophysical data to be analyzed with socioeconomic data for environmental applications. The integrated use of socioeconomic and remotely sensed data in a GIS environment has exhibited new potential to improve analytical methods in environmental equity studies.

Third, urban environmental justice issues are salient. While empirical environmental equity research has focused increasingly on many urban areas such as Boston, Cleveland, Houston, Los Angeles, Minneapolis, Baltimore and the like, a systematic case study of the Atlanta metropolitan area, which is a rapidly suburbanizing and racially segregated urban area, has been void in the literature. The selection of the Atlanta metropolitan area as a study area was justified on the basis of its following characteristics: biracial dichotomy between White and Black, one of major manufacturing centers in the South, water-quality issues related to urban development downstream of the upper Chattahoochee River, high acute airborne toxic release and degenerated air quality, and strong existence of urban inequality based on racial segregation. Metropolitan Atlanta thus provides a unique urban setting for environmental equity study.

In this research context, the primary goal of this dissertation was to investigate the integrated use of GIS and remote sensing technologies for an urban environmental equity study in the Atlanta metropolitan area. Three hypotheses were formulated: environmental equity analysis is sensitive to different spatial measures; environmental risks and hazards in the Atlanta metropolitan area are disproportionately distributed among disadvantaged social groups such as the poor or minority populations; and quality of life assessment can complement environmental equity analysis in a metropolitan area. Three research questions were addressed in this research: the methodological issues in environmental equity assessment, the spatial and temporal patterns of environmental inequity in the Atlanta metropolitan area, and the relationship between quality of life and environmental inequity. With respect to these hypotheses and research questions, three research objectives were established. The first objective was to explore alternative methods for determining potential impact areas of toxic releases and estimating populations at risk. The second was to examine the spatial and temporal relationships between the spatial distribution of TRI facilities and the racial and economic characteristics of populations in the Atlanta, Georgia metropolitan area from 1990 to 2000. The third was to evaluate urban quality of life in order to complement environmental equity analysis.

These research objectives were accomplished in four major stages: data integration, exploratory sensitivity analysis, environmental equity analysis, and urban quality of life assessment. The analytical procedures underlying this dissertation were based on an integrated GIS and remote sensing approach with spatial analysis and modeling techniques. In the integrated approach, GIS were used as a data integration and analysis engine.

The first stage of the research was to integrate environmental data from the Landsat TM images and hazard-related data from the TRI database with socioeconomic data from the census data. Two Landsat 5 TM images were acquired for the Atlanta metropolitan area in 1990 and 2000. Three biophysical datasets were derived from the Landsat TM data: land use and cover, NDVI, and surface temperature. Reference data in support of land use and cover mapping were collected, which includes orthophotos, land use and cover maps, DRGs, roads, and administrative boundaries. The TRI databases for 1990 and 2000 were acquired from U.S. EPA. Toxic chemical releases were measured both in raw pounds and in adjusted toxicity. Socioeconomic data were collected at the census tract and block group levels from the 1990 and 2000 Census STF3A's. Six specific socioeconomic variables were extracted from the census data: percentage of minority, percentage of people below poverty level, population density, percentage of college graduates, per capita income, and median home value. Three major data sets were integrated into a spatial database in a GIS environment through georeferencing.

The second stage was to explore the sensitivity of environmental equity analysis to three spatial measures including proximity, areal interpolation, and scale and resolution. This stage was implemented to develop an operational procedure for the environmental equity analysis assuring accurate and effective results. Three experiments were completed to evaluate the effects of the three spatial measures. Because of the computational complexities in the three experiments, Fulton County was chosen as a case study area considering that the majority of the city of Atlanta is located in this county. Three major datasets including socioeconomic characteristics (percentage of minority and percentage of people below poverty level for each census tract and block group), TRI database, and land use and cover for the study area in 1990 were integrated in a GIS environment. Different proximity modeling and areal interpolation techniques were used for impact area determination of toxic releases and estimation of the population at risk. In the three experiments, GIS were used for data integration, spatial analysis and modeling, and cartographic visualization. The effects of three spatial measures on environmental equity analysis were determined in two ways, population proportion and proximity ratio. The findings from three experiments indicated that the results of environmental equity assessment are sensitive to the buffer distance used to determine the impact zones of TRI facilities and the areal interpolation method used to estimate the population at risk, but not to the geographic scale and resolution used in the analyses. It was suggested that careful selection and justification of spatial measures be necessary and caution must be paid in interpreting the results.

The third stage was to investigate the spatial and temporal relationships between the spatial distribution of TRI facilities and the socioeconomic characteristics of the population at risk in the Atlanta metropolitan area from 1990 to 2000. An integrated GIS and remote sensing approach was used to perform spatial and statistical analyses of environment inequity. Insights from the three methodological experiments in the second stage helped formulate an operational procedure for the environmental equity analysis ensuring accurate and effective results. Based on the first experiment, a range of threshold distances from 0.5 to 3 miles was selected to delineate the impact zones of TRI facilities. The range of threshold distances was used to test the sensitivity of environmental equity analysis to the half-mile distance. Based on the second experiment, an intelligent areal weighting interpolation was implemented through dasymetric representation of population by satellite imagery to estimate the socioeconomic characteristics of the population at risk as well as to improve upon the methods of population data representation in environmental equity research. In this implementation, GIS were used to enable areal interpolation to be informed by the distribution of land use and cover classes derived from the Landsat TM images. Based on the third experiment and Sadahiro's (2000) second strategy, census block group boundaries were chosen since they are the smallest geographic unit in terms of data availability and also fine enough to provide higher estimation accuracy in areal interpolation. This provides a good rational justification in considering the MAUP issue.

Several analytical methods including proximity ratio, independent samples t-test, discriminant analysis, and surface modeling were used to determine the spatial and temporal relationships between the locations of TRI facilities and the socioeconomic characteristics of the population at risk. Descriptive and statistical results showed that minorities and people below poverty level were more likely to reside within the circular buffers than outside the circular buffers in the Atlanta metropolitan area in 1990 and 2000. It was also found that poverty was a relatively significant factor in explaining the relationship between distance to TRI facilities and socioeconomic characteristics in the Atlanta metropolitan area in 1990 and 2000. The findings from this study are consistent with other studies that found a stronger income-based rather than race-based pattern of environmental inequity at the intra-urban scale. Environmental inequity surfaces for 1990 and 2000 were generated by spatial modeling. They were compared visually and statistically. Some spatial and temporal variations in environmental inequity were revealed within the Atlanta metropolitan area between 1990 and 2000. The hot spots in environmental inequity within the metropolitan area tended to be spatially clustered around a large top portion of the southern central city of Atlanta, midtown, Decatur, and Marietta in 1990 while they tended to be concentrated on a small top portion of the southern central city of Atlanta, Tri-cities, Norcross, Smyrna, and Conyers in 2000. These hot spots were spatially coincident with traditional centers of industry and population in the metropolitan area. The temporal change of the spatial pattern in environmental inequity may be partially explained by the dual development of industrial and residential geography in the Atlanta metropolitan area from 1990 to 2000.

The fourth stage was to assess and map the quality of life in the Atlanta metropolitan area in 2000 in order to complement environmental equity analysis. For quality of life assessment, this research combined three environmental factors including land use and cover, NDVI, and surface temperatures from the Landsat TM image and four socioeconomic factors including population density, per capita income, percent college graduates, and median home value from the census data with a hazard-related factor from the TRI data. A pixel-based approach for data integration was employed to solve the incompatibility problem in areal units among environmental, hazard-related, and socioeconomic data. Thus, the four socioeconomic variables aggregated by census block groups were spatially disaggregated into individual pixels. This approach helped reveal sub-unit variation in zonal units and achieve a more seamless integration between the raster image data and the vector census data. Two techniques, SMA and PCA, were employed to integrate and transform environmental, hazard-related, and socioeconomic variables into a resultant quality of life score for each pixel. Specifically, these two techniques were selected on the basis of the large data handling needs for the pixel-based approach. The SMA is more subjective than the PCA, but the SMA provides a logically coherent procedure that would be comprehensible to the majority of decision makers. The results from quality of life assessments based on the two techniques revealed that higher quality of life scores were found around Roswell, Alphretta, and the northern parts of Fulton County along Georgia 400 whereas lower quality of life scores were found around Smyrna of Cobb County, downtown Atlanta, and Hartsfield-Jackson International Airport. The spatial relationship between environmental equity and quality of life was also investigated by visual and statistical analyses. It was found that higher environmental inequity scores were spatially clustered around areas with lower qualify of life scores while lower environmental inequity scores were spatially concentrated around places with higher quality of life scores. This indicates that the environmental inequity is significantly negatively correlated with the quality of life in the Atlanta metropolitan area in 2000. The implication is that quality of life assessment can be substituted for environmental equity analysis in an urban area and provides a more complete perspective for examining urban environmental justice issues.

8.2 Conclusions

This dissertation has resulted in the following implications of its empirical findings in the light of the technological, theoretical, policy, and application aspects. First, this research demonstrated the value of the integrated use of GIS and remote sensing for urban environmental equity assessment. Specifically, this study developed an integrated GIS and remote sensing approach to estimate the population at risk and to evaluate and map the quality of life in the study area. In the integrated approach, GIS were employed to allow areal interpolation to be informed by the geographic distribution of land use and cover classes derived from the Landsat TM images. This operation improved the methods of population data representation previously used in environmental equity research. As a data integration and analytical engine, GIS helped incorporate hazard-related, socioeconomic and environmental data necessary for environmental equity analysis and quality of life assessment. The GIS technology also allowed for spatial analysis and modeling, and cartographic visualization in the environmental equity analysis and quality of life assessment. The technology of remote sensing provided large quantities of timely, accurate environmental data to be analyzed with socioeconomic data for the environmental equity analysis and the quality of life assessment. This remote sensing technology enables us to examine environmental equity and quality of life issues more frequently and realistically than based on solely on socioeconomic data from the static census data by bringing environmental perspectives to the analyses. The integrated approach provides the potential for the development of new database and thus a new form of analysis in environmental equity studies.

Second, this research explored the spatial relationship between quality of life and environmental equity. This topic has not been thoroughly studied in environmental equity research. The empirical findings of this dissertation imply that quality of life assessment can complement environmental equity analysis in an urban area. This empirical result is consistent with the recent theoretical suggestions in environmental equity studies that it is necessary to use the wider concept of environment in environmental justice research and that it is needed to perform multiple dimensions of environmental justice analysis in a metropolitan area. Therefore, this exploration has brought new research possibilities to environmental equity research and has provided a comprehensive perspective for investigating urban environmental justice issues.

Third, this research addresses general recommendations concerning residential and industrial planning. This research methodology and the associated findings can be used by planners and decision makers to find out any problem areas in the allocation of human services in the Atlanta metropolitan area. This may help make a contribution towards building sustainable communities in the problem areas in the Atlanta metropolitan area. These may also provide benchmarks for detailed and neighborhood-scale analysis of environmental equity and quality of life.

Fourth, this research established an empirical case study of the Atlanta metropolitan area. This study revealed the spatial patterns of the environment inequity and the quality of life in the Atlanta metropolitan area. These improve our understanding of the environmental inequity and the quality of life in a rapidly suburbanizing and racially segregated urban area. The conceptual and technical frameworks developed in the present study may be applicable to other metropolitan areas in order to examine the role of environmental risks in the spatial variation of quality of life.

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