MEASURING THE EQUITY OF RECREATION OPPORTUNITY: A SPATIAL STATISTICAL APPROACH

By

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ABSTRACT

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Parks, playgrounds, trails, lakes and other public green and blue spaces are locally desirable land uses that provide recreation and open space opportunities in addition to various other environmental, social, health, and economic benefits. Access to recreation opportunities has been shown to have a substantial impact on individual and community health and well-being, especially in urban areas. Disparities in levels of access to recreation opportunities, whether in terms of age, race/ethnicity, income or other demographic or socioeconomic factors, represent an environmental justice concern. Level of access to recreation opportunities is based partially on the distribution of recreation opportunities. Assessing the level of environmental justice inherent in the distribution of recreation opportunities is, therefore, a valuable prerequisite for effective recreation planning and management. Assessment of results provides information for public leisure agencies that can help them allocate limited resources more equitably.

Such assessments have, in the past, focused on measuring the degree of equity associated with the distribution of access to recreation opportunities. Multivariate linear regression analyses using the ordinary least squares (OLS) method typically have employed; however, these approaches fail to explore important local variations in the relationships among variables caused by spatial effects such as spatial dependence (spatial autocorrelation) and spatial heterogeneity (spatial non-stationarity) that can lead to biased estimation results. Thus, the equity of recreation opportunities ideally should be examined using specialized research methods that incorporate spatial data.

The purpose of this study was to demonstrate the utility of spatial statistical techniques for assessing the distribution of recreation opportunities within the framework of environmental justice. To achieve this, the level of access to and the degree of equity inherent in the distribution of public beaches in the Detroit Metropolitan Area (DMA) were assessed. Results indicated that spatial statistical techniques have the potential to serve as a useful tool not only to assess the distribution of recreation opportunities, but also to deal with spatial effects when measuring the degree of equity inherent in the distribution of access to public beaches in the DMA. Specifically, results indicated substantial regional disparities in access to public beaches resulting from spatial clustering of public beaches in the DMA. Furthermore, the two local regression models based on a geographically weighted regression (GWR) approach explored spatially varying relationships between variables, with great improvements in model performance (as measured by R^2, $AIC_{c,}$ and Moran's I statistics of standardized residuals) over their corresponding global regression models based on the OLS approach. In addition to development of an improved approach to the measurement of equity, the findings of this study can help parks and recreation agencies better understand local patterns of equity by identifying the areas with inequitable access to public beaches, which corresponds with their residents' racial/ethnic and socioeconomic statuses and, thus, facilitate the formulation of appropriate policy solutions as and where needed.

I dedicate this work to my parents, both of whom have enriched my life with their love, sacrifice, support, and prayer.

이 논문을 지금까지 사랑으로 이끌어주시고 기도해주신 양가 부모님

(김제화, 하정숙 / 송화섭, 최명자)께 바칩니다.

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CHAPTER 1

INTRODUCTION

Background

"Everyone has the right to equal access to public service in his country"

(United Nations General Assembly, 1948, p. 4).

Access to recreation opportunities has been shown to have a substantial impact on individual and community health and well-being, especially in urban areas (Byrne, Wolch, & Zhang, 2009; Lee & Maheswaran, 2011; Sallis & Saelens, 2000). As Pred (1977) explained, overall quality of life within a city depends on access to multiple service types, including recreational open space opportunities. Providing and improving access to recreation opportunities has, therefore, been recognized as an essential responsibility of public leisure agencies in their quest to improve their residents' quality of life (Aukerman, 2011; Gilliland, Holmes, Irwin, & Tucker, 2006; Lofti & Koohsari, 2009; Sister, Wolch, & Wilson, 2010).

Parks, playgrounds, trails, lakes and other public green and blue spaces are locally desirable land uses (LDLUs) that provide recreation and open space opportunities in addition to various other environmental, social, health, and economic benefits (Porter, 2001; Taylor, Floyd, Whitt-Glover, & Brooks, 2007; Wendel, 2011). However, not all people have adequate access to LDLUs (Byrne et al., 2009). There has been growing concern that populations with low socioeconomic status as well as racial and ethnic minorities tend to be disproportionately denied the multiple benefits of access to LDLUs (Deng, Walker, & Strager, 2008). Disparities in levels of access to LDLUs, whether in terms of age, race/ethnicity, income or other socioeconomic or demographic factors, represent an environmental justice concern (Floyd & Johnson, 2002; Porter

& Tarrant, 2001; Tarrant & Cordell, 1999; Taylor et al., 2007). Assessing the level of environmental justice inherent in the distribution of LDLUs is, thus, a valuable prerequisite for effective recreation planning and management. Assessment of results provides information for public leisure agencies that can help them allocate limited resources more equitably (Byrne et al., 2009; Floyd & Johnson, 2002; Porter & Tarrant, 2001; Tarrant & Cordell, 1999).

To assess levels of environmental justice of LDLUs, previous studies have measured the degree of equity associated with the distribution of access to them. A fundamental question related to the equity of LDLUs is whether the distribution of access to them is indeed shared equitably among different demographic and socioeconomic groups (Nicholls, 2001). Numerous studies of the equity of LDLUs have attempted to determine whether disparities in level of access occur with regard to parks (Abercrombie, Sallis, Conway, Frank, Saelens, & Chapman, 2008; Boone, Buckley, Grove, & Sister, 2009; Byrne et al., 2009; Maroko, Maantay, Sohler, Grady, & Arno, 2009; Moore, Diez Roux, Evenson, McGinn, & Brines, 2008; Nicholls, 2001; Nicholls & Shafer, 2001; Omer, 2006; Sister et al., 2010; Talen, 1997, 1998; Wolch, Wilson, & Fehrenbach, 2005), urban trails (Estabrooks, Lee, & Gyurcsik, 2003; Lindsey, Maraj, & Kuan, 2001), playgrounds (Smoyer-Tomic, Hewko, & Hodgson, 2004; Talen & Anselin, 1998), golf courses (Deng et al., 2008), recreational forests (Tarrant & Cordell, 1999), and campsites (Porter & Tarrant, 2001).

Problem Statement

To measure the degree of equity inherent in the distribution of LDLUs, multivariate linear regression using the ordinary least squares (OLS) method typically has been employed (Deng et al., 2008; Porter & Tarrant, 2001; Tarrant & Cordell, 1999). OLS regression uses a global predictive model to capture the strength and significance of the statistical relationship between dependent and independent variables over an entire study area (Gilbert & Chakaraborty, 2011). However, spatial data such as the geographic locations of LDLUs, geographic proximity to LDLUs (e.g., distance or travel time between origin and destination), and spatially referenced census data may exhibit spatial effects, such as spatial dependence (spatial autocorrelation) and spatial heterogeneity (spatial non-stationarity) that can lead to biased estimation results using traditional multivariate techniques (Bailey & Gatrell, 1995; Brunsdon, Fotheringham, & Charlton, 1996; Fotheringham, Brunsdon, & Charlton, 2002; O'Sullivan & Unwin, 2003). Traditional OLS approaches also fail to explore important local variations in the relationships among variables caused by spatial dependence (Mennis & Jordan, 2005). Spatial dependence and spatial heterogeneity are unique characteristics whose consideration differentiates spatial data from non-spatial data, the latter of which are assumed to be stationary over space (Anselin & Getis, 1992). Thus, the equity of LDLUs, as represented by the relationship between the level of access to LDLUs and spatially referenced census data, ideally should be examined using specialized research methods that incorporate spatial data. To date, however, this typically has not been the case.

Purpose of the Study

The purpose of this study was to demonstrate the utility of spatial statistical techniques for assessing the distribution of recreation opportunities within the framework of environmental justice. Specifically, the level of access to and the degree of equity inherent in the distribution of public beaches in the Detroit Metropolitan Area (DMA) were assessed. Two measures of access to public beaches served as the dependent variables (allowing for comparison of the results of each); a series of fifteen demographic, socioeconomic and other characteristics were considered for use as independent variables. The unit of analysis was the census tract.

Objectives and Research Questions

Using a set of spatial statistical techniques such as point pattern analysis (PPA), exploratory spatial data analysis (ESDA), and geographically weighted regression (GWR) in a geographic information systems (GIS) environment, the following research objectives and questions were addressed. The first objective (O1) was to (1) assess the spatial distribution of public beaches and (2) determine levels of access to public beaches in the DMA. Spatial characteristics of public beach distribution (e.g., central tendency, dispersion, and spatial pattern) were calculated and used to describe the beaches' spatial distribution. Two different measures were used to determine levels of beach access; these then were used as the dependent variables in the measurement of the degree of equity inherent in the distribution. The research questions (R) can be stated as follows: O1R1: "What is the central tendency of the public beach distribution in the DMA?," O1R2: "How and to what extent are the public beaches dispersed?," O1R3: "Are the public beaches in the DMA spatially clustered?," and O1R4: "How is access to public beaches distributed across the DMA?"

The second objective (O2) was to explore the spatial patterns of access to public beaches relative to residents' demographic and socioeconomic status. The following questions were considered: O2R1: "Is there spatial autocorrelation associated with the distribution of access to public beaches and residents' demographic and socioeconomic status across the study area?," and O2R2: "If there is evidence of spatial autocorrelation, what is its nature and where is it evident?"

The third objective (O3) was to demonstrate the feasibility and utility of GWR when measuring the equity of access to public beaches and compare the results of this approach with those of traditional multivariate regression (OLS) techniques. A special focus of this objective was to assess whether the GWR model significantly improved on the traditional OLS regression model and whether it effectively dealt with spatial dependence and spatial heterogeneity in the data. The research questions can be stated as follows: O3R1: "What is the relationship between level of access to public beaches in the DMA and residents' demographic and socioeconomic status using OLS?," O3R2: "What is the relationship between level of access to public beaches in the DMA and residents' demographic and socioeconomic status using GWR?," O3R3: "How does the spatial relationship between level of access to public beaches and residents' demographic and socioeconomic status vary across the study area (using GWR) ?," and O3R4: "How well does the GWR approach perform in terms of model diagnostics compared to the traditional OLS approach?"

Assumptions of This Study

This study is based on several assumptions that might affect the results. The assumptions of this study are: (1) the distance threshold that residents are willing to travel for beach-based recreation activities in their local environment is 20 miles, based on the findings reported by Haas (2009); (2) populations are evenly distributed throughout census tracts and all areas in each census tract have the same demographic and socioeconomic characteristics; (3) the centroid of each census tract is used when identifying a 20-mile service area as well as calculating the distance to the nearest public beach for each census tract in the DMA; (4) residents can reach all public beaches within 20 miles of each census tract centroid; and (5) the level of attraction of all public beaches is the same and destination choice is determined by geographic distance. However, this study did not test any of these assumptions.

Delimitations

This study was delimited to identification of the degree of equity associated with the distribution of public beaches in the DMA, Michigan. The demographic and socioeconomic variables of the residential population were collected at the level of the census tract.

Significance of the Study

This study adds to the recreation, parks, and tourism literature via a number of methodological and practical contributions. It is one of relatively few efforts to respond to Floyd and Johnson's (2002) call for increased attention to environmental justice in the recreation, park, and tourism realm. Despite the importance of assessing the equity of recreation opportunity, assessments which can ultimately enhance the quality of life for local communities by informing decisions regarding the use and allocation of LDLUs (Tarrant & Cordell, 1999; Taylor et al., 2007), consideration of environmental justice issues remains relatively scarce in the recreation, park, and tourism literature. It is hoped that this study will stimulate recreation and tourism scholars into paying more attention to environmental justice, thereby extending the scope of the recreation, park, and tourism literature.

Methodologically, this study applied rigorous spatial statistical techniques (PPA, ESDA and GWR), to date rarely adopted in the recreation, park, and tourism literature. Since recreation and tourism are spatial phenomena (Hall & Page, 1999), the importance of spatial analysis to recreation and tourism has long been emphasized by recreation and tourism geographers (Barbier, 1984; Cooper, 1981; Hall & Page, 1999; Jensen-Verbeke, 1987; Kim & Fesenmaier, 1990; Mitchell & Murphy, 1991; Pearce, 1979; 1987; Raymond & Brown, 2007; Williams, 1998). Authors such as Hall (2012) have argued that future research in the realm of recreation and tourism geographies should employ a comprehensive spatial analysis approach. This study responded to this suggestion by applying a GIS-based spatial statistical approach to the analysis of equity. Further, the application of these techniques not only enabled more accurate measurement of the degree of equity inherent in the provision of recreation opportunities, it also allowed the scope of the research question to be broadened. Traditionally, the fundamental goal of equity-related research in the urban service delivery literature has been limited to identifying "who gets what" in the context of environmental or territorial justice (Talen, 1998, p. 22). This study, however, widened the focus from "who gets what" to "who gets what, where, and to what extent/how significantly." In addition to development of an improved approach to the measurement of equity, this study can also help parks and recreation agencies better understand local patterns of accessibility and equity and, thus, facilitate the formulation of locally appropriate policy solutions as and where needed.

The results of this study also offer practical insights and have implications for helping public leisure agencies provide and improve equitable access to public beaches. This study demonstrates spatial variations in map-based and statistical outcomes depending on the access and equity measures. Such findings may be used by public leisure agencies to allocate limited budgets more equitably by identifying vulnerable (low access) areas and populations. Moreover, the results of this study may facilitate a more informed decision making process because active stakeholder involvement, an essential part of the participatory approach, can be influenced positively by increased access to information (Trey & Clark, 2004; Yang, Madden, Kim, & Jordan, 2012). Information regarding spatial patterns of access to public beaches, residents' demographic and socioeconomic characteristics, and knowledge of the local variations in relationships among these variables could contribute to a spatial decision support system through the integration of Web-based GIS for more efficient community-based leisure planning.

Definitions of Terms

Several terms are defined to clarify their use in this dissertation:

- Accessibility: The ease with which a product, service, device, or environment can be reached or obtained (Lofti & Koohsari, 2009). As noted by Nicholls (2001), "it can thus be said to measure the relative opportunity for interaction or contact with a given phenomenon such as park" (p. 202).
- Aggregation error: "The error associated with representing an areal unit, which in turn represents spatially distributed individuals, by a single point" (Hewko, 2001, p. 23).
- Akaike information criterion (AIC): A measure of the relative quality of a statistical model, for a given set of data (Bozdogan, 1987). According to Fotheringham et al. (2002), models with smaller values of the AIC are preferable to models with higher values. However, if the difference in the AIC between two models is less than three, they are held to be equivalent in their explanatory power.
- Beach: A beach is a geographic landform along the coast of an ocean, sea, lake, or river (Orams, 1999)
- Community: A community is a social unit of any size that shares common values. A community-based approach is also referred to as a bottom-up or participatory approach that enables sharing of decision-making power, responsibility and risk between government and stakeholders (Fletcher, 2007).
- Ecological fallacy: A situation that can occur when a researcher or analyst makes an inference about an individual based on aggregate data for a group (Longley, Goodchild, Maguire, & Rhind, 2005, p. 98)

- <u>Edge effect</u>: The problem that "sites in the center of the study area can have nearby observations in all directions, whereas sites at the edges of the study area only have neighbors toward the center of the study area" (O'Sullivan & Unwin, 2003, p. 34).
- <u>Environmental justice:</u> "The fair and equitable distribution of both the environmental 'bads,' such as hazardous waste sites, and the environmental 'goods,' such as parks, open spaces, and recreation opportunities" (Maroko et al., 2009, p. 2). It is a broad conceptual construction or interpretive framework (Di Chiro, 1998).
- <u>Equity</u>: "The fairness or justice of a situation or distribution" (Nicholls, 2001, p. 202). An important concept within environmental justice (Lee, 2005). Inequities in the distribution of locally desirable land uses (LDLUs) have been recognized as an environmental injustice (Byrne et al., 2009; Sister et al., 2010).
- <u>Geographic information systems (GIS)</u>: A computer-based system designed to capture, store, manipulate, analyze, manage, and present all types of geographical data (Longley et al., 2005)
- <u>Kernel</u>: "A circle of influence or a circular area with a given radius around one particular regression point, and the given radius is called the bandwidth" (Yoo, 2012, p. 27).
- <u>Locally desirable land use (LDLU)</u>: A land use that is desirable to society and to local communities/neighbors. Public golf courses, urban parks, playgrounds, and recreational trails are examples of LDLUs (Tarrant & Cordell, 1999).
- <u>Locally unwanted land use (LULU)</u>: A land use that is useful to society, but objectionable to its neighbors. Incinerators, waste facilities, toxic release inventories, and landfills are examples of LULUs (Porter, 2001).

- Public beach: The landform along the shoreline of an ocean, sea, lake, or river, which is declared to be a public space by responsible authorities (Department of Environmental Quality [DEQ], 2013).
- Recreation opportunity: "An opportunity to engage in a preferred activity in a preferred setting to realize desired experience and benefit" (Driver, Brown, Stankey, & Gregoire, 1987, p. 204)
- Modifiable areal unit problem (MAUP): A statistical bias that can radically affect the results of statistical tests by the choice of district boundaries (O'Sullivan & Unwin, 2003).
- Spatial dependence (spatial autocorrelation): The extent to which the value of an attribute in one location is more likely to be similar to the value of an attribute in a nearby location than the value of an attribute in a distant location (O'Sullivan & Unwin, 2003). It is based on Tobler's (1970) First Law of Geography, which states that "everything is related to everything else, but near things are more related than distant things" (p. 236).
- Spatial heterogeneity (spatial non-stationarity): "A condition in which a simple global model cannot explain the relationship between some set of variables. The nature of the model must alter over space to reflect the structure within the data" (Brunsdon et al., 1996, p. 281). Refers to spatially varying relationships between variables based on "the tendency of geographic places and regions to be different from each other" (Longley et al., 2005, p. 98).

Organization of the Dissertation

The organization of this dissertation is as follows. Chapter 1 provides the general background of and justification for the study. In Chapter 2, a comprehensive literature review is presented. The literature review is divided into four parts. The first part discusses the framework of environmental justice and how it has been employed in the outdoor recreation and parks context. It includes a review of theoretical and empirical issues related to the traditional environmental justice framework as well as the role of recreation opportunities, in particular, public access to beaches, as LDLUs. The second part discusses accessibility and equity in the context of environmental justice, including their definition and measurement. The third part explains spatial effects such as spatial dependence and spatial heterogeneity and describes spatial statistical analysis as a tool for exploring spatial effects. Theoretical and empirical discussions of ESDA and GWR are summarized in an equity context. The final part of the literature review relates to GIS. Definitions and major functions of GIS are explained, and previous equity studies of LDLUs that have utilized GIS are reviewed. In Chapter 3, the study area and methodological issues related to data acquisition, preparation, and analysis are discussed. Chapter 4 describes the findings of the study. Chapter 5 includes a summary of the findings of the study, discusses their implications, and makes recommendations for practice. Study limitations are highlighted, and suggestions for future research proposed.

CHAPTER 2

LITERATURE REVIEW

The literature review is divided into four parts. The first part describes the framework of environmental justice, in general and in the context of outdoor recreation and parks. Part two explains the concepts of equity and accessibility in the context of environmental justice. The difference between environmental justice and equity is highlighted, and definition and measurement of these two concepts with respect to LDLUs is discussed. Part three discusses spatial effects and introduces spatial statistical analysis as a tool for exploring these effects, including techniques such as ESDA and GWR. Part four defines GIS and reviews previous applications of GIS techniques in park and recreation-related equity studies.

A Framework of Environmental Justice in Outdoor Recreation and Parks

Environmental Justice and Traditional Environmental Justice Research

Since the early 1980s, great attention has been paid to the notion of "environmental justice" in the United States (Floyd & Johnson, 2002). Environmental justice is a broad conceptual framework concerned with the inextricable link between social, political, economic, and environmental issues (Albrecht, 1995; Barakham, 1995). Bass (1998) defined the notion of environmental justice as "the fair treatment and meaningful involvement of all people regardless of race, color, sex, national origin, or income with respect to the development, implementation and enforcement of environmental laws, regulations, and policies" (p. 84). This definition views the environment as the places in which we live, work, and play (Di Chiro, 1998). "Fair treatment" implies that no group, due to political or economic disempowerment, is forced to bear disproportionate environmental burdens or costs of water or air pollution or of other environmental consequences resulting from regulatory operations or the execution of environmental policies and regulations (Taylor et al., 2007). The idea of environmental justice was originally based on the US Civil Rights Act of 1964, enacted to prohibit discrimination against racial, ethnic, national, and religious minorities and women (Porter, 2001; US Senate Committee on the Judiciary, 2013). Environmental justice traditionally referred to the equal enforcement of rules, regulations, decisions, and frameworks in the distribution of LULUs, such as incinerators, waste facilities, toxic release inventories, and landfills. Empirical studies of environmental justice, in terms of investigating the relationship between residents' demographic and socioeconomic variables and the location of LULUs, can be divided into three approaches.

The first approach has been to regard race as the dominant variable contributing to the siting of LULUs (Bullard, 1983; 1990; Mohai & Bryant, 1992; US Commission for Racial Justice and United Church of Christ, 1987; US General Accounting Office, 1983). For example, Bullard (1983) highlighted the location of six of eight incinerators and fifteen of seventeen landfills in predominantly African American communities in Houston, Texas. The US Commission for Racial Justice and United Church of Christ (1987) showed that zip code areas with more than one hazardous waste facility had an average of 38% nonwhite population compared to the national average of 16%.

The second approach, rather than focusing on the effect of race on the siting of LULUs, suggests another variable, income, as the essential factor contributing to their siting. Kriesel, Centner, and Keeler (1996) concluded that lower-income residents were more likely to be exposed to toxic releases in Georgia and Ohio. Similarly, Hamilton (1995) found that income was a more significant factor in explaining the capacity expansion of hazardous waste facilities than race.

The third approach has been to treat both race and income as significant and intertwined factors in the siting of LULUs (Costner & Thornton, 1990; Foreman, 1996; Glickman, 1994; Lavelle & Coyle, 1992; US Environmental Protection Agency, 1992). Lavelle and Coyle (1992) found clean-up of waste sites in poor and nonwhite communities took longer than in affluent neighborhoods. Costner and Thornton (1990) indicated that nonwhite and low-income populations have higher environmental risks or burdens resulting from exposure to air pollutants and hazardous waste facilities than other populations.

Locally Desirable Land Uses (LDLUs) and Environmental Justice

The original notion of environmental justice had the goal of protecting all communities from environmental costs or burdens arising from LULUs regardless of racial and economic composition (Tarrant & Cordell, 1999; Taylor et al., 2007). Following President Clinton's 1994 Executive Order 12898, titled "Federal Actions to Address Environmental Justice in Minority Populations and Low-Income Populations," all federal land management agencies were directed to assess any environmental impacts of their policies and practices in the context of environmental justice (Deng et al., 2008; Porter, 2001; Tarrant & Cordell, 1999). As Tarrant and Cordell (1999) noted, these environmental impacts can be classified into two types: environmental benefits and environmental costs. Examples of environmental benefits include the provision of open spaces for outdoor recreation and the provision of cleaner environments (Porter, 2001); environmental costs include noise, environmental pollution, crowding, and congestion associated with infrastructure and tourism development (Lundberg, Krishnamoorthy, & Stavenga, 1995).

As a result, the framework of environmental justice was expanded to encompass a more comprehensive definition that includes disparities not only in exposure to environmental costs from LULUs but also in access to environmental benefits from LDLUs. As Taylor et al. (2007) explained, access to LDLUs such as urban parks provides numerous environmental benefits, with psychological (e.g., stress reduction), social (e.g., open spaces for community interaction), and health (e.g., benefits of exercise) dimensions. Some authors such as Boone et al. (2009), Porter (2001), Tarrant and Cordell (1999) and Taylor et al. (2007) have suggested that environmental injustice can occur when certain groups or individuals receive an unfair amount of access to LDLUs. As Salazar (1998) noted, “a comprehensive concept of environmental justice must take account of environmental goods as well as bad” (p. 52). Accordingly, this more comprehensive framework of environmental justice has been used to explore disparities in levels of access to LDLUs with regard to parks (Abercrombie et al., 2008; Boone et al., 2009; Byrne et al., 2009; Maroko et al., 2009; Moore et al., 2008; Nicholls, 2001; Nicholls & Shafer, 2001; Omer, 2006; Sister et al., 2010; Talen, 1997, 1998; Wolch et al., 2005), urban trails (Estabrooks et al., 2003; Lindsey et al., 2001), playgrounds (Smoyer-Tomic et al., 2004; Talen & Anselin, 1998), golf courses (Deng et al., 2008), recreational forests (Tarrant & Cordell, 1999), and campsites (Porter & Tarrant, 2001).

Locally Desirable Land Uses (LDLUs) and Recreation Opportunity

Participants in outdoor recreation not only seek to participate in preferred activities, but also seek specific settings in order to enjoy special experiences and subsequent benefits (Aukerman, 2011; Aukerman, Haas, Lovejoy, & Welch, 2004; Clark & Stankey, 1979; Driver & Brown, 1978; Driver et al., 1987; Manning, 1985; Petengill & Manning, 2011; Stankey & Wood, 1982). As outlined by Driver et al. (1987), these four components (activities, settings, experiences, and benefits) constitute a recreation opportunity. A recreation opportunity can thus be defined as an opportunity to engage in a preferred activity in a preferred setting in order to realize desired experiences and achieve certain benefits (Manning, 1985). Pred (1977) specifically related the quality of life within a city to the accessibility of its residents to recreational open space opportunities. Driver et al. (1987) argued that the concept of recreation opportunity is based on Vroom's (1964) expectancy theory, which proposed that behavior is determined by the desirability of the expected outcome. Figure 1 depicts the key components of a recreation opportunity and the linkage between these four components. A number of types of LDLUs, such as parks, playgrounds, trails, golf courses, lakes and other public green and blue spaces, offer settings for recreation activities.

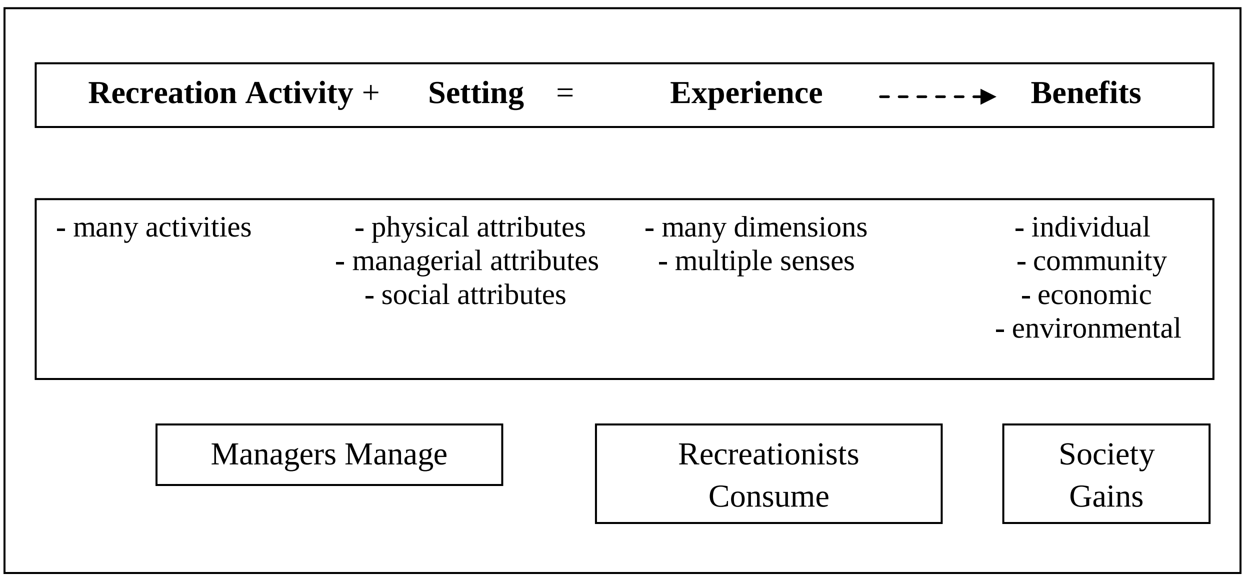

Figure 1. The components of a recreation opportunity (Aukerman et al., 2004, p. 4)

As suggested in figure 1, the role of public leisure agencies is to provide both recreation activities and settings that can contribute to the realization of particular types of experiences and subsequent benefits (Aukerman et al., 2004). As noted by Petengill and Manning (2011), "experiences are derived from recreation activities and [that] these activities are linked to the settings in which they occur" (p. 4). Providing access to recreation settings is an essential responsibility of public leisure agencies in their quest to improve their residents' quality of life.

Recreation Opportunity and Environmental Justice

Authors such as Byrne et al. (2009) and Sallis and Saelens (2000) have argued that access to recreation opportunities is associated with the individual and community health and wellbeing of urban populations. If disparities in levels of access to recreation opportunities based on residents' demographic and socioeconomic status arise, they can be discussed in the context of environmental justice (Deng et al., 2008; Floyd & Johnson, 2002; Porter & Tarrant, 2001; Sister et al., 2010; Tarrant & Cordell, 1999; Taylor et al., 2007). When assessing the environmental justice aspects of recreation opportunities, determination of whether certain types of recreation settings, such as parks, trails, and wilderness areas, constitute LDLUs is first necessary (Taylor et al., 2007). For some communities, costs such as increased traffic, air and noise pollution, and crime have been caused by certain outdoor recreation activities at certain sites (Fridgen, 1984; McIntosh & Goeldner, 1990; Seaton, 1994). As Tarrant and Cordell (1999) explained, undesirable effects such as crowding also can be produced by excess numbers of visitors at campgrounds, trails, and other popular recreation destinations.

Despite some negative environmental costs being imposed by certain types of recreation settings, there is much evidence to suggest that recreation settings generally may be considered LDLUs because outdoor recreation sites such as parks are public goods that are provided as a matter of public policy (Taylor et al., 2007). As noted by Floyd and Johnson (2002), diverse types of outdoor recreation sites are provided by all levels of government, including municipal, county, state, and federal agencies. Moreover, a number of leisure and outdoor recreation studies have shown that the use of parks and outdoor recreation sites significantly improves the health and wellbeing of urban populations (Godbey, Caldwell, Floyd, & Payne, 2005; Lindsey et al., 2001; Wendell, 2011).

Public Beaches as Locally Desirable Land Uses (LDLUs)

Public beaches offer a variety of environmental, social, psychological, economic, and recreational benefits to local communities. Public beaches provide wildlife habitat as well as attractive landscapes that differ from terrestrial environments (Goodhead & Johnson, 1996; Jennings, 2007); they also can offer educational opportunities for local citizens. Public beaches may be used as places for residents to interact (Edgerton, 1979); as noted by Adolphs (1999), "humans are exceedingly social animals" (p. 469). Public beaches enable a variety of water- and land-based activities and offer natural settings in which to relax and reduce stress levels (Beatley, Brower, & Schwab, 2002; Jennings, 2007; Orams, 1999). Visitors to public beaches may be attracted by the promise of emotional well-being and physical fitness, which can contribute to reduced health care costs and lower levels of crime (Godbey, 1993; Meyer & Brightbill, 1964). Well designed and managed public beaches can bring economic benefits to local communities. The income generated through tourism, such as the payment of user fees and spending at concessions, can contribute to regional economic activity (Dixon, Oh, & Draper, 2012; Oh, Dixon, Mjelde, & Draper, 2008; Yang et al., 2012).

Since the 1960s, the increasing diversity of participants' preferences for outdoor recreation has been discussed by numerous leisure and recreation scholars (Aukerman, 2011; Aukerman et al., 2004; King, 1966; Manning, 1985; Shafer, 1969). According to Aukerman (2011), such diversity occurs not only between the participants in different recreation activities, but also among the participants within each activity itself. Providing a diversity of recreation opportunities to fulfill diverse participants' demands is therefore an essential responsibility of public leisure agencies (Aukerman, 2011; Aukerman et al., 2004). A diverse range of people visit beach areas with different motivations and expectations (Orams, 1999); the variety of water- and land-based recreational opportunities offered at public beaches can meet visitors' diverse and complex needs (Aukerman, 2011).

Public Access to Beaches and Environmental Justice

Beaches are an important type of LDLU due to their provision of ideal open spaces for diverse water- and land-based recreation opportunities (Brown, 1999; Elliott, 1976; Orams, 1999). The importance of public access to beaches has received much attention in various disciplines, including coastal management (Blizzard & Mangum, 2008; Fischer, 1988; Kline & Swallow, 1998; Oh et al., 2008; Oh, Draper, & Dixon, 2009; Pogue & Lee, 1999), law (Davison, 2006; Elliott, 1976; Kehoe, 1994; Negris, 1986; Pirkle, 1994; Poirier, 1996; Summerline, 1996), tourism (Dixon et al., 2012; Yang et al., 2012), environmental planning (Oehme, 1987), and resource economics (Whitehead, Dumas, Herstine, Hill, & Buerger, 2008). The issue of public access to beaches lends itself to examination within the framework of environmental justice for several reasons.

First, public access to beaches is a civil right that is based on the essence of the public trust doctrine, assuming that "the gifts of nature's bounty" should be preserved for the benefit of the whole population (Negris, 1986, p. 438). The source of the doctrine is an ancient principle of Roman law holding that "by the law of nature the air, running water, the sea, and consequently the shores of the sea were common to mankind" (Negris, 1986, p.438). Thus, a number of beach access movements have campaigned to protect the public's right to access beaches based on this doctrine (Davison, 2006; Negris, 1986; Oehme, 1987; Pirkle, 1994; Poirier, 1995; Summerlin, 1995).

Second, providing and improving public access to beaches for recreational purposes have been recognized as essential responsibilities of public leisure agencies in their response to the Coastal Zone Management Act (CZMA) of 1972 (Dixon et al., 2012; Pogue & Lee, 1999), which focuses on providing and improving public access to beaches for recreation purposes (National Oceanic and Atmospheric Administration [NOAA], 2013). For these reasons, emerging efforts to improve public access to beaches have precipitated a number of policies at the national (Kodama, 1996; Pogue & Lee, 1999), state (Delogu, 1993; Goodwin, 2000), regional (Sohngen, 1999), and local (Gardner, 1999; Marine Coastal Program, 2003; North Carolina Department of Environmental and Natural Resources, 2003; Scott, 1990; Spaeth, 1994) levels.

Equity and Accessibility in the Context of Environmental Justice

Environmental Justice and Equity

Equity is an important concept within the framework of environmental justice (Di Chiro, 1998). Because inequities in the distribution of LDLUs have been recognized as an environmental injustice (Bryne et al., 2009; Sister et al., 2010), environmental equity has been the most commonly used concept for assessing whether or not environmental (in)justice has occurred (Lee, 2005). Although much of the literature tends to use the term environmental equity interchangeably with environmental justice (Floyd & Johnson, 2002; Lee, 2005), some studies have distinguished the two (Liu, 2001; Zimmerman, 1994), as this one also will. Figure 2 shows the relationship between environmental justice and environmental equity.

According to Zimmerman (1994), environmental justice refers to the procedure or process used to ensure fair distribution while environmental equity refers to the outcome, the distribution of advantages and disadvantages across individuals and groups. Similarly, Liu (2001) noted that environmental equity emphasizes impacts on social groups while environmental justice focuses more on goals, policies, and regulations to ensure fair distribution of environmental burdens across those groups. Therefore, environmental justice focuses more on regulatory and policy-related issues while equity focuses on their outcomes for specific groups. The framework of environmental justice can therefore be employed as a theoretical background to understand (in)equities in the context of recreation and tourism (Camargo, Lane, & Jamal, 2007; Floyd & Johnson, 2002; Jamal & Camargo, 2014; Lee, 2005; Taylor et al., 2007).

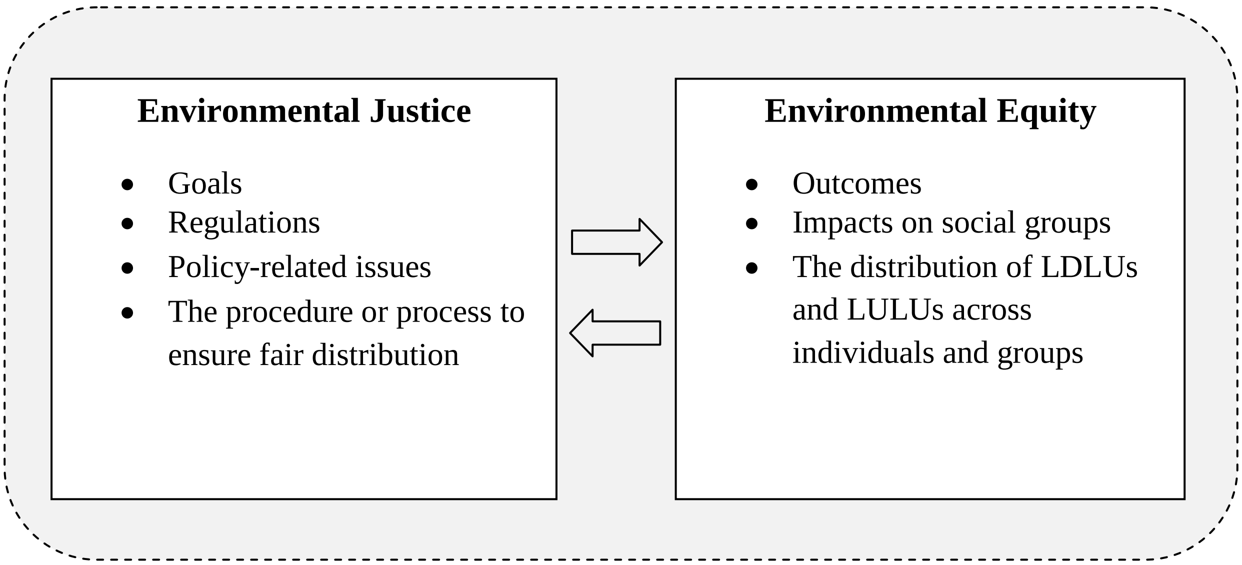

Figure 2. Environmental justice and environmental equity (Lee, 2005, p. 56)

The term 'equity' has been used as a prevailing concept in urban service delivery literature that asks questions such as "who benefits and why?" (Talen, 1997, p. 521) or "who gets what?" (Laswell, 1958, as cited in Crompton & Wicks, 1988, p. 288) in numerous contexts (Davies, 1968; Hay, 1995; Kinman, 1999; Nicholls, 2001; Nicholls & Shafer, 2001; Ogryczak, 2000; Smith, 1994; Talen & Anselin, 1998; Tsou, Hung, & Chang, 2005; Wicks & Crompton, 1986). Nicholls (2001) defined equity as "the fairness or justice of a situation or distribution" (p. 202). Wicks and Crompton (1986) described equity as "the perceived fairness of resource allocation patterns" (p. 342). However, equity is still an ambiguous concept due to the difficulties of establishing what is "just" or "fair" (Nicholls, 2001). Harvey (1988) explained this issue as "an ethical problem which cannot be resolved without making important moral decisions" (p. 99).

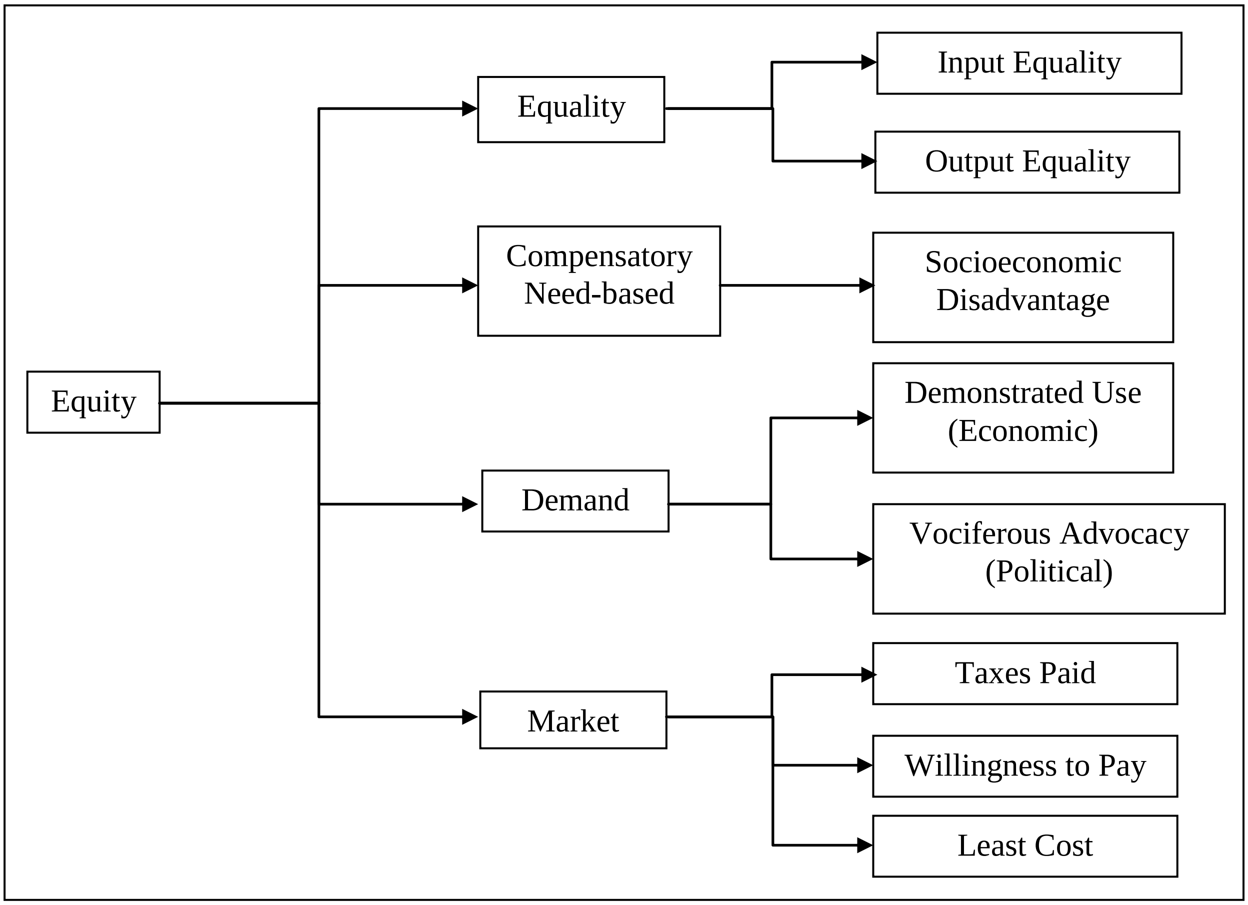

Figure 3. Types of equity (Nicholls, 2001, p. 203)

Although a single definition of equity has not yet been established and multiple, sometimes competing, interpretations abound, adoption of a definition of equity is a prerequisite to analysis of it (Nicholls, 2001). Typologies of equity such as those suggested by Lucy (1981) and Crompton and Wicks (1988) outlined four equity models that may be used with regard to the allocation of public services. These four models of equity are: (1) equality; (2) compensatory (Crompton & Wicks, 1988) or need (Lucy, 1981); (3) demand (including Lucy's category “preferences”); and (4) market (including Lucy’s category “willingness to pay”). Figure 3 illustrates the four models of equity that have been commonly employed in the parks and recreation literature.

First, equity can be defined according to two types of equality: input equality and output equality (Nicholls, 2001). Input equality refers to equal provision of public services, regardless of geographic area or the socioeconomic characteristics of residents (Wick & Crompton, 1986) while output equality is concerned with ensuring that the benefits received by residents as a result of public service provision are equal (Deng et al., 2008). Second, compensatory or need-based equity involves providing a given service to those who are deemed to need it the most (Davies, 1968; Lucy, 1981; Wicks & Crompton, 1986). Based on this premise, disadvantaged residents or the most needy groups or areas are awarded (compensated with) extra services (Deng et al., 2008). Third, demand-based equity involves providing resources to those who demonstrate an active interest in a service or facility (Nicholls, 2001). Demand can be demonstrated by use, as measured by the rate of participation, or via vociferous advocacy. Finally, market-based equity considers the potential influence of market forces on the distribution of services and resources. Wicks and Crompton (1986) argued that “a consumer has the necessary desire and resources to acquire a service at market price” (p. 346). Service distribution can thus be determined by the market, which can produce distributional inequity in service distribution if economically disadvantaged groups are less able to pay the necessary price (Deng et al., 2008)

Research Approach to the Equity of Recreation Opportunity

Among these four equity models, the compensatory or need-based model has most commonly been employed to measure the equity of LDLUs (Abercrombie et al., 2008; Boone et al., 2009; Byrne et al., 2009; Omer, 2006; Sister et al., 2010) because redistributing resources in a compensatory manner is the role of the public sector (Nicholls, 2001; Wicks & Crompton, 1986). Despite some debate regarding identification of who the most disadvantaged or needy groups are when employing the compensatory or need-based equity model, they have typically been defined according to demographic and socioeconomic characteristics such as race/ethnicity and income (Wicks & Crompton, 1986). Use of demographic and socioeconomic criteria is justified under the assumption of the "underclass hypothesis," that "systematic and deliberate discrimination exists against certain socio-economically disadvantaged groups and areas in the distribution of goods and services, resulting in their receiving fewer and/or poorer quality resources relative to more advantaged citizens" (Nicholls, 2001, p. 207). Recent empirical studies of LDLUs also have used other variables such as educational attainment (Deng et al., 2008; Estabrooks et al., 2003; Lindsey et al., 2001; Porter & Tarrant, 2001; Tarrant & Cordell, 1999), age (Abercrombie et al., 2008; Nicholls, 2001; Nicholls & Shafer, 2001; Smoyer-Tomic et al., 2004; Talen, 1997; Talen & Anselin, 1998), population density (Lindsey et al., 2001; Nicholls, 2001; Nicholls & Shafer, 2001; Maroko et al., 2009), vehicle ownership (Lindsey et al., 2001), language (Maroko et al., 2009), economic status (Estabrooks et al., 2003), and housing occupancy/value (Nicholls, 2001; Nicholls & Shafer, 2001) as proxies for or in addition to race/ethnicity and income.

With respect to outdoor recreation and parks, adopting such a compensatory or need-based equity model corresponds with the premise of social equity, one of the National Recreation and Park Association (NRPA)'s three core pillars (conservation, health & wellness, and social equity). According to Barbara Tulipane, NRPA's President and CEO (NRPA, 2014), universal access to public parks and recreation is not just a privilege but a right.

Accessibility and Its Relation to Equity

Although accessibility is a term commonly used in daily conversation, there is no universal agreement about its definition (Lotfi & Koohsari, 2009). Accessibility generally is referred to as the ease with which activities or services can be reached or obtained (Johnson, Gregory, Pratt, & Watts, 2000; Morris, Dumbie, & Wigan, 1979; Nicholls, 2001). Accessibility to goods and services is an important component of an urban system and a contributor to quality of life (Pacione, 1989; Pred, 1977; Nicholls, 2001). According to Pacione (1989), having close geographical accessibility to public services can contribute to personal welfare. Pred (1977) also emphasized the importance of accessibility with regard to public services, including extensive recreational open space opportunities for improving urban residents' quality of life. Accurately measuring levels of access to public services and facilities is, therefore, a prerequisite to effective urban planning and management.

It is imperative to clarify the distinction between accessibility, as defined by geographic relationships between locations, and equity, as explained by fair opportunity in service allocation and distribution (Cho, 2003). Specifically, accessibility is concerned more with efficiency (to maximize the efficiency of public service distribution while minimizing costs) while equity is more concerned with the impact of public service distribution on people who may use them (Nicholls, 2001). Many studies have explored issues related to accessibility and equity in the urban parks and recreation service literature (Deng et al., 2008; Estabrooks et al., 2003; Lindsey et al., 2001; Moore et al., 2008; Nicholls, 2001; Nicholls & Shafer, 2001; Omer, 2006; Porter & Tarrant, 2001; Sister et al., 2010; Smoyer-Tomic et al., 2004; Talen, 1997, 1998; Talen & Anselin, 1998; Tarrant & Cordell, 1999; Tsou et al., 2005). In those studies, the measurement of accessibility has served as a precursor to the measurement of the degree of equity inherent in the distribution of public services. As Talen and Anselin (1998) noted, "accessibility is a tool used to discover whether or not equity has been achieved, and the two concepts of accessibility and equity are the primary building blocks used to assess the spatial distribution or spatial pattern of public services" (p. 596).

Measuring the Accessibility of Recreation Opportunity

Accessibility can be measured subjectively and objectively (Tilt, Unfred, & Roca, 2007). Objective measures relate to characteristics of the physical environment while subjective measures depend upon the perceptions of citizens/users (Lotfi & Koohsari, 2009). In this study, accessibility was measured in an objective manner. Methods for measuring objective accessibility can be categorized into five different approaches: (1) the container approach; (2) the minimum distance approach; (3) the travel cost approach; (4) the spatial interaction model approach; and (5) the covering approach (Cho, 2003).

The container approach. The container approach is a common approach that defines accessibility according to the presence of LDLUs within a geographic unit, such as a census tract, zip code, or local neighborhood unit (e.g., the number of LDLUs or the total area of LDLUs within the geographic unit) (Lindsey et al., 2001; Zhang, Lu, & Holt, 2011). Formally, a container index Z_i^C is calculated as follows:

$$Z_i^C = \sum_j S_j, \ \ \forall_j \in I,$$

where Z_i^C is a container index for residential neighborhood i (in this case, a census tract), and the number or aggregate size, S_J, is summed for those LDLUs located within the boundaries I of i. This approach is based on the fundamental assumption that the benefits of LDLUs are allocated only to the constituents of the corresponding areal unit (Cho, 2003), and restricts accessibility to include only the number or area of LDLUs within that unit. The higher the number or the total area of LDLUs within each unit of analysis, the higher the level of accessibility to LDLUs enjoyed by residents of that unit. The container approach has been employed extensively in political science and urban planning due to its simplicity (Talen & Anselin, 1998; Lindsey et al., 2001). However, container-based measures have been criticized as unrealistic measures of accessibility because spatial externalities of surrounding units of analysis are excluded from consideration (Cho, 2003; Nicholls, 2001). The modifiable areal unit problem (MAUP), ecological fallacy, and edge effects are other methodological issues associated with the use of the container approach (Zhang et al., 2011).

The minimum distance approach. The minimum distance approach defines accessibility as the distance that neighborhood residents must travel to reach the nearest LDLU (Smoyer-Tomic et al., 2004). This distance is inversely related to accessibility. The minimum distance index Z_i^M is estimated as follows:

$$Z_i^M = \min \left| d_{ij} \right| ,$$

where Z_i^M is the index for minimum distance from residential neighborhood i to the nearest LDLU j. This approach assumes that residents always use the nearest LDLU with the least travel cost, as measured by distance or time (Talen & Anselin, 1998). However, in reality, residents do not always visit the nearest LDLU (Cho, 2003); the choice of LDLUs can be influenced by other factors, such as perceived or actual level of safety, environmental quality, size, quantity and quality of amenities, and general attractiveness (Zhang et al., 2011).

The travel cost approach. The travel cost approach is adapted from locational optimization models (Talen & Anselin, 1998) and defines accessibility according to the average or total distance between each residential neighborhood and all distributed LDLUs (Cho, 2003). The travel cost index Z_i^T is expressed as follows:

$$Z_i^T = \sum_j [d_{ij} / N],$$

where d_{ij} is the distance between a residential neighborhood i and LDLU location j, and N is the total number of LDLUs. The ease of interpreting the resulting value, expressed in a simple distance unit, is one of the advantages of using this approach (Talen & Anselin, 1998). The lower the total or average distance, the higher the level of the accessibility to LDLUs an area and its residents has. However, in reality, most residents do not interact with all LDLUs within a defined spatial area (Zhang et al., 2011).

The spatial interaction model approach. The spatial interaction model approach identifies levels of human interaction between origins (residential neighborhoods) and destinations (LDLUs). According to Zhang et al. (2011), gravity models have been employed extensively with the following assumptions: (1) “spatial interaction declines with a larger spatial separation (travel distance or time) between origins and destinations”; and (2) “spatial interaction increases with a greater demand at origins or with higher supply capacity and/or attractiveness at destinations” (p. 3). Thus, LDLUs are weighted by their size (or attractiveness) and “friction of distance” (Cho, 2003; Talen & Anselin, 1998). The gravity model index Z_i^G is measured as follows:

$$Z_i^G = \sum [S_j / d_{ij}^a],$$

where S_j reflects the number or size of LDLUs, and for each LDLU location j, d_{ij}^a is a distance decay factor, with distance d_{ij} between residential neighborhood i and LDLU j, and friction parameter a. However, the choice of the magnitude of the friction parameter a and the issue of self-potential when $d_{ij} = 0$ are two methodological problems to be considered when using the gravity model (Talen & Anselin, 1998).

The covering approach. The last approach is the covering approach, which defines accessibility within a certain service boundary measured not from residential neighborhoods to LDLUs but from LDLUs to residential neighborhoods (Cho, 2003). The basic assumption of this approach is that residents are said to be accessible to LDLUs if they are located within their service area, but they are deemed to have no access if they are not (Nicholls, 2001). Because a service boundary is defined by a critical radius or network distance, identification of the radius or distance is critical when delineating the service area of the LDLU (Omer, 2006). A number of LDLUs, including parks, are associated with recommended location criteria that include the definition of preferred service areas (Nicholls, 2001).

Because study results can be affected significantly by the type of accessibility measure selected (Talen & Anselin, 1998; Smoyer-Tomic et al., 2004), this choice is a substantial methodological issue when measuring the level of accessibility to LDLUs. Furthermore, the choice between Euclidean (straight-line) and network distance measures as well as aggregation error are other methodological issues (Lotfi & Koohsari, 2009; Nicholls, 2001; Smoyer-Tomic et al., 2004). Aggregation error refers to "the error associated with representing an areal unit, which in turn represents spatially distributed individuals, by a single point" (Hewko, 2001, p. 23). The degree of aggregation error depends upon the size of the spatial unit (Hewko, Smoyer-Tomic, & Hodgson, 2002); the larger the areal unit, the larger the aggregation error. In general, the centroids of spatial units, such as census blocks, census tracts, or ZIP codes, have been used as the origin of a residential neighborhood when calculating the distance from a residential neighborhood to an LDLU (Smoyer-Tomic et al., 2004). As a result, the centroid approach could produce considerable aggregation error in distance measures and, thus, interpretation of results (Hodgson, Shmulevitz, & Korkel, 1997). Hodgson et al. (1997) insisted that aggregation error can be reduced by minimally aggregating spatial units. However, the choice of spatial unit should be considered in combination with the acquisition of demographic and socioeconomic data, which may not be available at less aggregated levels (Hewko, 2001). In this study, census tracts are used as the unit of analysis and distance is measured along the actual street network.

Measuring the Equity of Recreation Opportunity

The purpose of equity analysis is to investigate the existence and extent of relationships between levels of access to LDLUs and neighborhoods' demographic and socioeconomic status. A variety of different methods such as linear correlation (Gilliland et al., 2006; Omer, 2006; Sister et al., 2010; Smoyer-Tomic et al., 2004), equity mapping (Talen, 1997; 1998; Talen & Anselin, 1998; Tsou et al., 2005), and multivariate linear regression (Deng et al., 2008; Porter & Tarrant, 2001; Tarrant & Cordell, 1999) have been utilized for measuring the equity of recreation opportunities. Among these research methods, multivariate linear regression has been recognized as the most appropriate because linear correlation cannot be used to analyze the relationships between several variables simultaneously (Porter & Tarrant, 2001). Equity mapping is a useful visualization tool, but it cannot establish the sociopolitical processes that determine who benefits from and who pays for public resources (Talen, 1998). Multivariate linear regression, however, overcomes some of the limitations of linear correlation and equity mapping. Accordingly, the level of access to recreation opportunities has been used as the dependent variable in relation to spatially referenced demographic and socioeconomic census data, the independent variables (Talen & Anselin, 1998).

Deng et al. (2008) used logistic regression analysis to examine the distributional equity of public and private golf courses relative to Chinese residents and other disadvantaged groups in Calgary, Canada over a 10-year time span (1991-2001). Results indicated that Chinese residents were concentrated in several parts of Calgary over this period of time, and that they were more likely than Anglo-Canadians to reside in census tracts that did not contain, or were not near to, golf courses. However, the distributional inequity decreased during the study period, primarily due to the construction of new golf courses. Porter and Tarrant (2001) employed logistic regression analysis to determine whether inequities exist for certain socioeconomic and racial groups with respect to the distribution of federal tourism sites and campsites in Southern Appalachia. Results showed that the distribution of these federal tourism sites and campsites was advantageous to white populations and disadvantageous to minority populations. Tarrant and Cordell (1999) also used logistic regression analysis to determine the spatial relationships between outdoor recreation sites and census block group variables in northern Georgia. Results of their study suggested that there was a possible inequity with regard to household income, but not necessarily race, occupation, and/or ethnic heritage.

Spatial Effects and Spatial Statistical Analyses

Methodological Issues in Traditional Equity Research: Spatial Dependence and Spatial Heterogeneity

Ordinary least squares (OLS) is the most widely known and used regression method to model a dependent variable's association with a set of independent variables (Cui, 2010). To measure the degree of equity associated with a set of LULUs or LDLUs, multivariate linear regression analyses using the OLS method typically have been employed. This method is based on two critical assumptions: (1) the observations are independent of one another (Brunsdon et al., 1996); and (2) there is a stationary relationship among variables (Gilbert & Chakraborty, 2011). A stationary relationship refers to a spatially constant relationship between dependent and independent variables that is interpreted by average (global) parameter estimates across an entire study area. However, as Longley et al. (2005) stated, “spatial is special” (p. 5). The use of spatial data in a linear model leads to the potential for biased estimation results, due to the spatial dependence (spatial autocorrelation) and spatial heterogeneity (spatial non-stationarity) that make it difficult to meet the assumptions and requirements of traditional OLS regression (Brunsdon et al., 1996; Fotheringham et al., 2002).

Spatial dependence is the extent to which the value of an attribute in one location is more likely to be similar to the value of the attribute in a nearby location than the value of the attribute in a distant location (Fotheringham et al., 2002; O'Sullivan & Unwin, 2003). It is based on Tobler’s First Law of Geography, which states that “everything is related to everything else, but near things are more related than distant things” (Tobler, 1970, p. 236). Spatial dependence, often referred to as spatial autocorrelation, “is determined both by similarities in position, and by similarities in attributes” (Longley et al., 2005, p. 517). According to Anselin (1988), large residuals are likely to occur if geographic features are spatially autocorrelated when using non-spatial statistical methods such as OLS regression.

Spatial heterogeneity is referred to as spatial non-stationarity because “the relationships among the independent and dependent variables vary over space” (Mennis & Jordan, 2005, p. 249). In other words, every location has an intrinsic level of uniqueness with regard to the causal relationship between variables that may not be described by constant global parameter estimates. (Gilbert & Chakraborty, 2011; Fotheringham et al., 2002). When a lack of spatial uniformity or homogeneity is caused by the effects of spatial dependence and/or the relationships between the variables, spatial heterogeneity is likely to occur (Anselin & Getis, 1992). Spatial heterogeneity can thus be regarded as a special case of spatial dependence, and spatial dependence and heterogeneity often occur jointly (Anselin & Getis, 1992; Schooley, 2006). As noted by

Fotheringham et al. (2002), the coefficients of the model are related to spatial non-stationarity. Thus, when applied to a regression model, ignoring spatial heterogeneity gives rise to inaccurate results, such as biased parameter estimates and misleading significance tests (Anselin, 1988; Yoo, 2012; Zhang, Ma, & Guo, 2009). Traditionally, equity research based on linear statistical analyses has failed to account for these spatial effects. According to Cui (2010), researchers sometimes have violated the basic assumptions of OLS, including linearity, homoscedasticity, independence of residuals, and normality of residuals. Nevertheless, new research methods that address these spatial effects have remained underexploited by recreation and tourism researchers and practitioners in previous equity studies of LDLUs. The development and demonstration of improved research methods for measuring the equity of LDLUs is a substantial contribution of this study.

Spatial Statistical Analysis: A Tool for Exploring Spatial Effects

In recent years, great attention has been paid to the fact that the analysis of spatial data ideally should be conducted using specialized research methods that must be differentiated from those used to analyze non-spatial data (Getis, 2007; Gilbert & Charkraborty, 2011). Spatial statistical analysis has long been recognized as an effective research method to explore spatial effects such as spatial dependence and spatial heterogeneity (Anselin & Getis, 1992; Bailey & Gatrell, 1995; Cliff & Ord, 1973; Cressie, 1993; Diggle, 1983; Fortin, James, Mackenzie, Mellers, & Rayfield, 2012; Griffith, 1988; 2012; Ord & Getis, 1995; O’Sullivan & Unwin, 2003; Ripley, 1981; 1998; Rogerson, 2001). According to Bailey and Gatrell (1995), the purpose of spatial statistical analysis is to describe data, assess the degree of spatial dependence in data, and examine relationships among variables.

Although a number of spatial statistical techniques are based on the typical statistical analysis of non-spatial data, the most significant difference that distinguishes spatial statistical analyses from non-spatial statistics is the underlying assumption of spatial dependency among spatial data (Anselin & Getis, 1992). Thus, spatial statistics, and spatial statistical analysis, can provide both theoretical knowledge and analytical methods to account for effects such as spatial dependence and spatial heterogeneity, issues that have been regarded as serious methodological problems to be overcome in traditional environmental justice research (Gilbert & Chakraborty, 2011; Mennis & Jordan, 2005).

Spatial statistical techniques can be sub-divided into two types: descriptive and inferential (Rogerson, 2001). Descriptive spatial statistical methods are based on an exploratory approach designed in particular for large datasets and to suggest new hypotheses. Measuring and visualizing characteristics of spatial distributions (e.g., central tendency [mean center and median center], and dispersion [standard distance and standard deviational ellipse]) are major functions of descriptive spatial statistical methods.

Mean center is the most commonly used measure of central tendency for spatial data (Rogerson, 2001). It can be conceptualized as the center of gravity of a point pattern or spatial distribution that represents a point location consisting of the average x- and y-coordinates of all the features in the study area (Mitchell, 2005). The mean center (X_m , Y_m) is measured as follows:

$$X_m = \frac{\sum_{i=1}^{n} x_i}{n}, \quad Y_m = \frac{\sum_{i=1}^{n} y_i}{n},$$

where x_i and y_i are the coordinates for features i, and n is equal to the total number of features.

Median center is another spatial measure of central tendency. It is the location that minimizes Euclidean distance from it to all other features in the dataset (Rogerson, 2001). At each step (t) in the mathematical algorithm, a candidate median center ($X_{t,}$, Y_t) is found and then refined until it represents the location that minimizes the Euclidean distance, d, to all features in the dataset:

$$d_i^t = \sqrt{(x_i - x_t)^2 + (y_i - y_t)^2}$$

The median center is a measure of central tendency that is robust to spatial outliers (Burt & Barber, 1996). According to Kuhn and Kuenne (1962), the median center is a more practical and representative measure of central tendency than the mean center.

Standard distance can be conceptualized as the spatial equivalent of standard deviation (Mitchell, 2005). According to Rogerson (2001), it is the square root of the average squared distance of points to the mean center. The standard distance (S_d) is measured as follows:

$$S_d = \sqrt{\frac{\sum_{i=1}^{n}(x_i - x_m)^2 + \sum_{i=1}^{n}(y_i - x_m)^2}{n}}$$

where x_i and y_i are the coordinates for features i, $\{x_m, y_m\}$ represents the mean center for the features, and n is equal to the total number of features. As the two-dimensional equivalent of standard deviation, the standard distance measures the degree of absolute dispersion in point pattern data. It represents the standard deviation of the distance of each point from the mean center. As standard deviation, the standard distance is also sensitive to extreme or peripheral locations (Mitchell, 2005).

Standard deviational ellipse indicates the orientation and direction of distribution of a set of data in two dimensions. The standard deviational ellipse measures the degree of dispersion for a set of points or areas by calculating the standard distance separately in the x and y directions (Mitchell, 2005). It is estimated as follows:

$$SDE_x = \sqrt{\frac{\sum_{i=1}^{n}(x_i - x_m)^2}{n}}, \ SDE_y = \sqrt{\frac{\sum_{i=1}^{n}(y_i - y_m)^2}{n}},$$

where x_i and y_i are the coordinates for features i, $\{x_m, y_m\}$ represents the mean center for the features, and n is equal to the total number of features. Table 1 compares some basic nonspatial and spatial descriptive statistics.

Table 1.

Nonspatial and spatial descriptive statistics (Sahoo, n.d.)

Statistic	**Central tendency**	**Absolute dispersion**	**Relative dispersion**
Nonspatial	Mean Median	Standard deviation	Coefficient of variation
Spatial	Mean center Median center	Standard distance	Standard deviational ellipse (directional trend)

Exploratory spatial data analysis (ESDA) commonly has been used to visualize these descriptive statistical functions. In particular, ESDA can enhance the quality of the equity mapping approach by providing clues to possible causal relationships, by indicating the existence of spatial effects, and by mapping the locations of spatial clusters such as hot spots, cold spots, and spatial effects (Talen, 1998).

Inferential spatial statistical methods are based on a confirmatory approach designed to test hypotheses (Rogerson, 2001), including investigations of spatial relationships between features and the identification of spatial clusters of features or phenomena (Anselin, 1988; Anselin & Getis, 1992; Gatrell, Bailey, Diggle, & Rowlingson, 1996; Rogerson, 2001). Several methods of point pattern analysis (PPA) (e.g., nearest neighbor analysis [NNA] and Ripley's K-function analysis), ESDA (e.g., spatial autocorrelation analysis), and spatial econometric models (e.g., spatial error model, spatial lag model, spatial expansion model, spatial adaptive filtering, multilevel model, simultaneous autoregressive model, and geographically weighted regression [GWR]) have been recognized as confirmatory or inferential spatial statistical techniques.

PPA is a class of techniques that can be used to identify the pattern of a set of points in space (Bailey & Gatrell, 1995). PPA is used to determine whether the locations of these points, or events, are clustered randomly or regularly distributed (Bivand, 1998). As an inferential spatial statistical method, PPA is based on the hypothesis of complete spatial randomness (CSR), in which events are distributed independently according to a uniform probability distribution over the study area (Getis, 1999). The type of point pattern is judged by comparing the observed point pattern to the theoretical model of CSR (Wall, Dudycha, & Hutchinson, 1985). NNA and Ripley's K-function are the most commonly employed types of PPA. NNA examines the distances between each point and the closest point to it, and then compares these to expected values for a random sample of points. NNA calculates a nearest neighbor ratio (R) that is expressed as the ratio of the observed mean distance to the expected mean distance between the events. The R is given as follows:

$$R = \frac{D_o}{D_e},$$

where D_o is the observed mean distance between each event and its nearest neighbor and D_e is the expected mean distance between the events given the random pattern. D_o and D_e are calculated as follows:

$$D_o = \frac{\sum_{i=1}^{n} d_i}{n}, \; D_e = \frac{0.5}{\sqrt{\frac{n}{A}}}$$

where d_i equals the distance between event i and its nearest neighbor, N corresponds to the total number of events, and A is the area of a minimum enclosing rectangle around all events or a user-specified area. If the value of R is less than 1, the point pattern exhibits clustering. If the value of R is greater than 1, the point pattern exhibits a regular distribution, and if the value of R is 1, the point pattern exhibits CSR.

Ripley's K-function is another way to identify the spatial pattern of point data (Ripley, 1981). A distinguishing feature of this method from NNA is that it characterizes the patterns across multiple spatial scales. Ripley's K-function computes the expected value of the K(d) under CSR. The expected value of K(d) is as follow:

$$E[K(d)] = \frac{I\pi d^2}{I} = \pi d^2 \text{ (if a point pattern is CSR), } I = N/A$$

where K(d) is the average number of events inside a circle of radius d centered on an event, I is the mean density of events per unit area, N is the total number of events, and A is the study area. If the observed K(d) for a particular radius (d) is greater than the expected K(d) through the study area, the distribution is considered clustered at that radius, and if the observed K(d) for a particular radius (d) is smaller than the expected K(d), the distribution is considered dispersed at that radius. Among a number of variations of Ripley's K-function, a common transformation of the K-function, often referred to as L(d), is implemented as follows:

$$L(d) = \sqrt{\frac{A \sum_{i=1}^{n} \sum_{j=1, j \neq i}^{n} K_{i,j}}{\pi n(n-1)}}$$

where d is the distance, n is equal to the total number of events, A represents the study area and $K_{i,j}$ is a weight. If there is no edge correction, then the weight will be equal to one when the distance between I and j is less than d, and will equate to zero otherwise. Using a given edge correction method will modify $K_{i,j}$ slightly.

GWR is a local regression model that has become popular as a means of exploring spatial heterogeneity in the relationships among variables by fitting a regression equation to every feature in the dataset (Cahill & Mulligan, 2007; Patridge, Rickman, Ali, & Olfert, 2008; Waller, Zhu, Gotway, Gorman, & Gruenewald, 2007; Zhao & Park, 2004). GWR is discussed in more detail below.

These descriptive and inferential spatial statistical techniques also can be classified by the type of spatial data and by the purpose of spatial analysis. Bailey and Gatrell (1995) divided spatial statistical techniques into four categories depending upon the type of data, representing techniques for: (1) point pattern data; (2) spatially continuous data; (3) areal data; and (4) interaction data, while Scott and Janikas (2010) classified spatial statistical techniques into four categories by the purpose of spatial analysis, for (1) measuring geographic distributions; (2) analyzing patterns; (3) mapping clusters; and (4) modeling spatial relationships. Samples of relevant spatial statistical techniques sorted by spatial data type and by the purpose of spatial analysis are presented in Tables 2 and 3.

Table 2.

Classification of spatial statistical techniques (Adapted from Bailey & Gatrell, 1995)

Type of Spatial Data	Example of Spatial Statistical Technique
Point pattern data	Quadrat analysis Kernel estimation Nearest neighbor analysis K-function analysis
Geostatistical data (spatially continuous data)	Spatial moving averages Trend surface analysis Delauney triangulation Thiesen polygons Triangulated irregular network (TIN) Kernel estimation (for the values at sample point) Variograms Covariograms / kriging Principal components analysis / factor analysis Procrustes analysis Cluster analysis Canonical correlation
Area data (lattice data)	Spatial moving averages Kernel estimation Spatial autocorrelation (Moran’s I and Geary’s C) Spatial correlation and regression
Interaction data	Spatial interaction methods Augmented spatial interaction models

Table 3.

Classification of spatial statistical method by the purpose of spatial analysis

Purpose	Example of spatial statistical method
Measuring geographic distributions	Centrographic technique (standard deviational ellipse analysis)
Analyzing patterns	PPA (nearest neighbor analysis, Ripley's K-function) ESDA (using global Moran's I and Getis-Ord general G)
Mapping clusters	ESDA (using Anselin's local Moran's I and hot spot analysis)
Modeling spatial relationships	Spatial regression (econometric) models

Note: PPA (point pattern analysis), ESDA (exploratory spatial data analysis)

Exploratory Spatial Data Analysis (ESDA)

ESDA provides a set of specialized techniques that is useful in describing and visualizing spatial distributions, identifying atypical locations or spatial outliers, discovering patterns of spatial associations or clusters (e.g., hot spots and cold spots), and suggesting spatial regimes or other forms of spatial heterogeneity (Anselin, 1988). ESDA was extended from exploratory data analysis (EDA) (Turkey, 1977). The distinguishing characteristic of ESDA is its ability to reflect the spatial dependence of geographic data (Syabri, 2006) because, as previously described, the prevalence of spatial dependence may invalidate "the interpretation of methods based on an assumption of independence, which is the rule in mainstream EDA" (Anselin, 1999, p. 254).

Because the concept of spatial dependence is assessed generally both globally and locally (Anselin, 1995), ESDA also can be implemented to measure the degree of spatial dependence at two levels—the global and the local. Global Moran's I statistic (Moran, 1950) is the most commonly employed measure of spatial dependence, also known as spatial autocorrelation or spatial clustering at the global level. The global Moran's I is measured as follows:

$$I = \frac{N}{S_0} \sum_i \sum_j \frac{w_{ij}(x_i - \mu)(x_j - \mu)}{\sum_i (x_i - \mu)^2}, \ S_0 = \sum_i \sum_j w_{ij},$$

where w_{ij} is the matrix of weights such that, in some cases ($w_{ij} = 1$ if area i and area j are adjacent; otherwise, $w_{ij} = 0$), x_i is the attribute value of a specific variable at areal unit i (in this case, a census tract), x_j is the attribute value of a specific variable at areal unit j (in this case, a census tract), μ is the average attribute value of a specific variable, and N is the total number of areal units. Moran's I statistic ranges between -1 and 1. A value of 1 indicates a perfect positive autocorrelation that refers to patterns in which similar values tend to occupy adjacent locations. For example, high values tend to occur adjacent to high values and low values adjacent to low values. A value of 0 indicates no spatial autocorrelation (a random spatial pattern). A value of -1 indicates a perfect negative autocorrelation that refers to a pattern in which high values tend to be consistently located next to low values.

The global Moran's I statistic is a global measure of spatial autocorrelation that can indicate the existence of spatial autocorrelation but cannot identify the location and type of spatial clusters (Anselin, 1995). Thus, the local indicator of spatial autocorrelation (LISA) has been applied to identify the location and type of spatial clusters. LISA is calculated as follows:

$$I_i = \frac{(x_i - \mu)}{m_2} \sum_i w_{ij}(x_j - \mu), m_2 = \sum_i (x_i - \mu)^2 / N,$$

The results of LISA analysis can be presented in the forms of a Moran scatterplot and a Moran significance map with information incorporated about the significance of the local spatial autocorrelation or clusters. Generally, the results from both the scatterplot and the significance map are classified into five categories: high-high (HH); high-low (HL); low-high (LH); low-low (LL); and, not statistically significant. The five categories can be described as follows: (1) HH: clusters of locations with high values, indicating positive spatial autocorrelation, also called hot spots; (2) HL: clusters of locations with high values adjacent to locations with low values, indicating negative spatial autocorrelation, also called spatial outliers; (3) LH: clusters of locations with low values adjacent to locations with high values, indicating negative spatial autocorrelation, also called spatial outliers; (4) LL: clusters of locations with low values, indicating positive spatial autocorrelation, also called cold spots; and (5) not statistically significant: no clusters or spatial autocorrelation between locations.

Exploratory Spatial Data Analysis (ESDA) in the Context of Equity

The use of maps can play a pivotal role in elucidating variations in equity (Talen, 1998). Specifically, mapping the distribution of an accessibility measure to LDLUs and relevant socioeconomic characteristics represents an "equity mapping approach." Equity mapping has allowed exploratory analysis of variables to discover any spatial mismatch between residents' needs and public service provision by mapping the distribution of accessibility measures of LDLUs relative to the distribution of residents' demographic and socioeconomic characteristics (Deng et al., 2008; Porter & Tarrant, 2001; Talen & Anselin, 1998; Talen, 1998; Tarrant & Cordell, 1999; Tsou et al., 2005; Wolch, Wilson, & Fehrenbach, 2005). As explained by Talen (1998), exploring the spatial patterns of variable distributions is an essential procedure in the equity mapping approach. ESDA can enhance the equity mapping approach by indicating the existence of spatial association (autocorrelation) as well as mapping the locations of spatial clusters such as hot spots, cold spots, and spatial outliers.

The ESDA-based equity mapping approach has been employed in several analyses of recreation-related LDLUs. Talen (1997, 1998) produced "equity maps" to assess the social equity of park access in Pueblo, Colorado and Macon, Georgia. She used LISA to compare the spatial clustering of park access scores with the spatial clustering of selected socioeconomic variable distributions. Smoyer-Tomic et al. (2004) produced LISA significance maps to assess whether there is an association between neighborhood need and playground accessibility in Edmonton, Canada. Deng et al. (2008) used LISA to visualize the distribution of access to golf courses in Calgary, Canada.

As outlined by Anselin (1995), the degree of spatial dependence can be assessed at the global and local levels. The corresponding values contribute to the overall identification of spatial patterns of variable distribution in a complementary manner (Kang, Kim, & Nicholls, 2014; Yang & Wong, 2013; Zhang et al., 2011). Few empirical studies of LDLUs have explored the overall spatial patterns of variable distributions at the global and local levels simultaneously. Talen and Anselin (1998) used both global Moran's I and LISA to assess the sensitivity of spatial patterns of equity to different types of accessibility measure. Tsou et al. (2005) also used both global Moran's I and LISA to assess the spatial equity of urban facilities in Ren-de, Taiwan.

Effective equity mapping also should assess and visualize the spatial characteristics of LDLU distribution (e.g., central tendency, directional trend, absolute dispersion, and location pattern). Equity mapping studies to date have explored only spatial patterns of variable distributions in a visual manner without any full assessment of spatial characteristics of LDLUs.

Geographically Weighted Regression (GWR)

Among many statistical regression techniques, GWR recently has become popular for modeling spatial heterogeneous processes between variables (Charlton, Fotheringham, & Brunsdon, 2009). GWR is a local spatial statistical technique designed for exploring spatial heterogeneity, also known as spatial non-stationarity, in spatial data (Brunsdon et al., 1996; Fotheringham et al., 2002). GWR assumes that relationships between variables may differ from location to location. In other words, GWR generates a set of local regression coefficients for each observation point in the study area.

The traditional multiple linear regression model can be expressed as follows:

$$y_i = a_0 + \sum_{j=1}^{k} a_k x_{ik} + e_i, k = 1, \ldots\ldots, k,$$

where y_i is the vector of the estimated parameter for observation i, a_0 is the intercept parameter, a_k is the regression coefficient for the kth independent variable, x_{ik} is the value of the kth independent variable for observation i, and e_i is a random error term for observation i. The traditional multiple linear regression model is based on assumptions of independence and homogeneity such that the residuals should be both independent and drawn identically from a normal distribution with a mean of zero (Charlton et al., 2009). GWR extends the traditional multiple linear regression framework by allowing local parameters to be estimated as follows:

$$y_i = a_{io}(u_i, v_i) + \sum_{j=1}^{k} a_{ik}(u_i, v_i) x_{ik} + e_i, k = 1, \ldots, k,$$

where $(u_{i,} v_i)$ is the coordinate of the ith point in the study area, $a_{io}(u_{i,} v_i)$ is the intercept parameter at point i, $a_{ik}(u_{i,} v_i)$ is the local regression coefficient for the kth independent variable at point i, and a_{ik} is the value of the kth independent variable at point i. Thus, unlike linear multiple regression models, GWR can consider important local variations in relationships.

Based on Tobler's (1970) First Law of Geography, all observed data points in GWR are weighted by their spatial proximity from the regression point. In other words, observed data points closer to the regression point are weighted more heavily than observed data points located farther away (Fotheringham et al., 2002). The weight of an observed data point is thus at a maximum when an observed data point shares the same location as the regression point, and decreases as the distance between the two points increases.

In GWR, the weights of observed data points depend on the kernel chosen and the bandwidth for that kernel (Fotheringham et al., 2002). As explained by Yoo (2012), a kernel can be defined as a circle of influence or a circular area with a given radius around one particular regression point, and the given radius is called the bandwidth. The Gaussian kernel function and the bi-square kernel function are two types of kernel functions that are commonly used in GWR (Fotheringham et al., 2002; Charlton et al., 2009; Zhang & Shi, 2004).

The Gaussian kernel function also is referred to as a kernel with a fixed bandwidth because it is based on the assumption that the bandwidth at each regression point is constant across the study area (Fotheringham et al., 2002). The Gaussian kernel function is applied when the observed data points are reasonably regularly spaced in the study area. The weight for the Gaussian kernel function is estimated as follows:

$$w_{ij} = \exp[-(d_{ij} / b)^2],$$

where d_{ij} is the Euclidean distance between the regression point i and the data point j, and b is the bandwidth. At the regression point, the weight of a data point is unity and the weights decrease as the distance from the regression point increases. However, the weights of all the data points are non-zero, no matter how far they are from the regression point.

The bi-square kernel function is called a kernel with adaptive bandwidth because it permits use of variable bandwidth (Fotheringham et al., 2002). The bi-square kernel function is used when the observed data points are not regularly spaced but clustered in the study area. For example, the size of the bandwidth increases when the observed data points are widely spaced and decreases when the observed data points are clustered. The weight for the bi-square kernel function is estimated as follows:

$$w_{ij} = [1 - (d_{ij} / b)^2] \quad \text{when } d_{ij} \leq b$$

$$w_{ij} = 0 \quad \text{when } d_{ij} > b$$

At the regression point i, the weight of the data point is unity and falls to zero when the distance between i and j equals the bandwidth. When the distance is greater than the bandwidth, the weight of the data point is zero. The bandwidth is selected so that there is the same number of data points with non-zero weights at each regression point.

Choosing the bandwidth is very important because the results obtained from GWR largely depend upon that choice (Charlton et al., 2009; Fotheringham et al., 2002; Gilbert & Chakraborty, 2011). Bandwidth can be thought of as a smoothing parameter. A larger bandwidth can cause greater smoothing (Yoo, 2012). If the estimated parameters are similar in value across the study area, an over-smoothed model is applied, and if the estimated parameters include much local variation, an under-smoothed model is adopted. Somewhere between these two extremes is thus regarded as the best bandwidth (Fotheringham et al., 2002).

As explained by Fotheringham et al. (2002), three methods commonly have been used to determine the best bandwidth: (1) providing a user-supplied bandwidth; (2) selecting bandwidth that minimizes a cross-validation (CV) function, and (3) selecting bandwidth that minimizes the Akaike Information Criterion (AIC). Among these bandwidth selections, selecting a bandwidth that minimizes the AIC has most commonly been employed to determine the best bandwidth as well as to measure model performance (Fotheringham et al., 2002; Yoo, 2012). The AIC is a measure of relative model performance and is helpful for comparing different regression models (Bozdogan, 1987; Yamaoka, Nakagawa, & Uno, 1978). AIC deals with the trade-off between the goodness of fit of the model and the complexity of the model (Fotheringham et al., 2002). AICc is AIC with a correction for finite sample sizes (Bozdogan, 1987). This takes the following form:

$$AICc = 2n\log e\,(\hat{\sigma}) + n\log e(2\pi) + n[(n + tr(S)/(n—2 - tr(S)]$$

where n is the number of observations in the dataset, $\hat{\sigma}$ is the estimate of the standard deviation of the residuals, and tr(S) is the trace of the hat matrix. The AICc values can be used not only to compare models with different independent variables but also to compare the global model with a local GWR model (Charlton et al. 2009). If the difference between the two AICc values is more than three, the model with the lower AICc is considered better (Fotheringham et al., 2002).

In calibrating a GWR model, it is important to test whether the GWR offers an improvement over the global model with statistical significance. A Monte Carlo significance test has been widely employed to determine spatial non-stationarity against the null hypothesis that the parameter estimates are constant for all locations in the study area (Yoo, 2012).

Compared to the conventional and global regression model, there are two significant characteristics of GWR. The first is that it yields error terms (residuals) that are considerably smaller and less spatially dependent than residuals from a corresponding global regression model (Tu & Xia, 2008). The second significance of GWR is its ability to visualize spatial variations in regression diagnostics and model parameters within a study area (Gilbert & Chakraborty, 2011). Mapping regression diagnostics such as standardized residuals, the local r-square, parameter estimates, and t-statistic can play an important role in exploring how statistical relationships and their significance between the level of access to LDLUs and the demographic and socioeconomic characteristics of a residential population vary over space.

Geographically Weighted Regression (GWR) in the Context of Equity

The assumption of spatial stationary in multivariate linear regression using the OLS method has been strongly questioned and OLS regression models have not been able to capture important local variations in the relationships among variables. Although the analytical utility of GWR has been applied to analyze environmental inequities in the distribution of LULUs such as toxic air releases, air pollution, and coronary heart disease mortality, to date, only one study has used GWR to explore inequities in the distribution of LDLUs such as urban parks. In these studies, the statistical diagnostics of both GWR and OLS models were compared to assess whether or not the GWR model improved on the OLS model and effectively dealt with spatial effects such as spatial dependence and spatial heterogeneity in the data.

Mennis and Jordan (2005) applied GWR, in combination with conventional univariate and multivariate statistics, to model the density of toxic air releases in New Jersey. Results highlighted the effectiveness of the GWR model with higher R^2 and lower AIC. Gilbert and Chakraborty (2011) compared traditional global OLS and GWR, and found that GWR was the more appropriate approach to explore spatial variability in statistical relationships relevant to environmental justice analysis with respect to cumulative cancer risks from air toxics in Florida. Jephcote and Chen (2012) employed both GWR and OLS to investigate the environmental injustices of children's exposure to air pollution from road-transport in Leicester, UK. The findings showed significant statistical relationships between children's hospitalization rates and social-economic status, ethnic minorities, and road-transport emissions, suggesting GWR was more robust than the global OLS model. Gebreab and Diez Roux (2012) also compared GWR with OLS to explore racial disparities in coronary heart disease mortality between blacks and whites across the US. The authors concluded GWR was the most appropriate model to examine spatial heterogeneity with more desirable statistical results, including higher R^2, lower standardized residual, and lower AIC. Maroko et al. (2009) used both OLS and GWR to examine the statistical relationship between level of access to parks and residents' racial and ethnic status in New York City, US. The results indicated that the OLS model found a weak relationship with lower R^2 and higher AIC, while GWR suggested spatial non-stationarity, indicating disparities in accessibility that vary over space with higher R^2 and lower AIC.

Geographic Information Systems (GIS)

Definitions of GIS

Since 1963, when Roger Tomlinson first coined the term GIS (Dye & Shaw, 2007), GIS have become a technology with great potential to aid work in a variety of fields, including business marketing (Boyles, 2002; Grimshaw, 2000; Longley & Clarke, 1995; Mittal, Kamakura, & Govind, 2004), land use planning (Berke, Godschalk, Kaiser, & Rodriguez, 2006; Bocco, Mendoza, & Velazquez, 2001; Dai, Lee, & Zhang, 2001), environmental management (Aspinall & Pearson, 2000; Baker, Wiley, Seelbach, & Carlson, 2003; Talen & Anselin, 1998), park and recreation planning (Nicholls, 2001; Tarrant & Cordell, 1999), and tourism development and planning (Bahaire & Elliott-White, 1999; Brown & Weber, 2013; Hasse & Milne, 2005; McAdam, 1999), among others. A GIS is generally referred to as a computer-based system designed to capture, store, manipulate, analyze, and display spatially referenced and associated data and used to support spatial decision making (Longley et al., 2005). Lee (2001) described GIS as one of the most widely used decision aids to solve complex spatial planning and management problems.

Definitions of GIS have been determined by the meaning of the S in GIS. There have been three approaches. The first approach has been to define GIS as a GISystem [e.g., an information system] (Aronoff, 1989; Ducker, 1979; Smith, Menon, Starr, & Estes, 1987; Star & Estes, 1990). The system involves both hardware and software to solve specific spatial problems. The second approach has been to define GIS as GIScience, an area of information science (Goodchild, 1992). As explained by Longley et al. (2005), information science is defined as a discipline focusing on creation, collection, analysis, manipulation, storage, and classification of information, while GIS is the area concerned with the creation, collection, analysis, manipulation, storage, and classification of geographic information. The third approach has been to define GIS as GIStudies that focuses on the applications of spatial information and its impacts on our lives (Cowen, 1988; Pickles, 1995). This approach points out that most GIS definitions have ignored how GIS can change our lives as well as affect our society. From this perspective, the social context of geographic information has been discussed, including legal issues, privacy and confidentiality, and the economics of geographic information. In this study, GIS was defined as a GISystem that may be viewed as a sub-system of an information system.

Major Functions of GIS

The functions of GIS are four-fold: data input, data storage/management, data manipulation/analysis, and data output (Malczewski, 1999). Figure 4 illustrates the structure of a GIS.

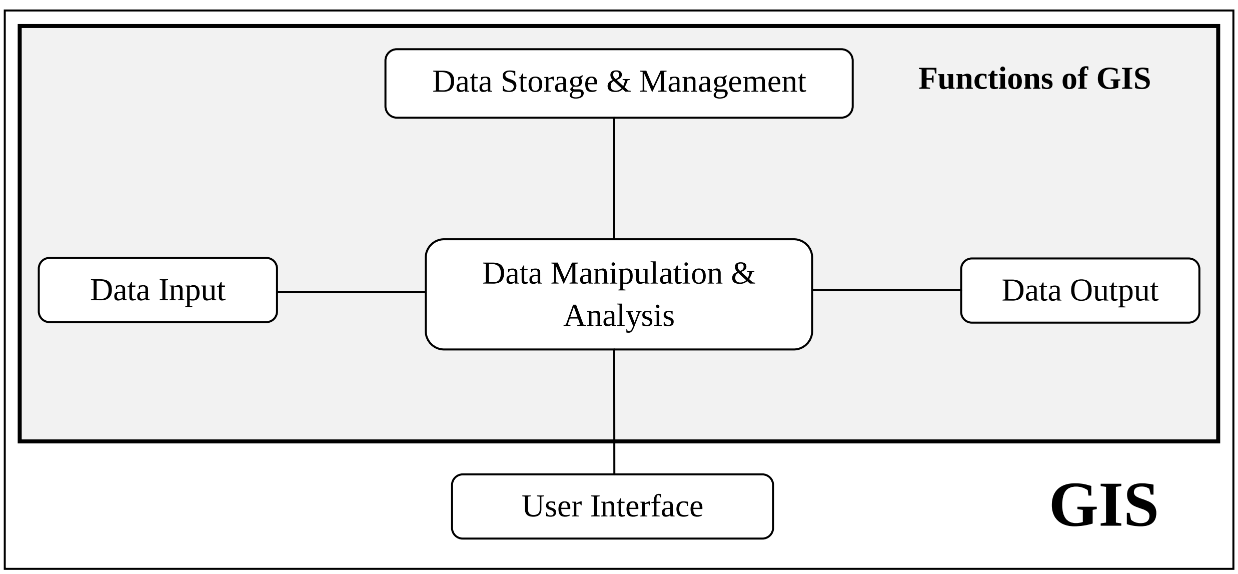

Figure 4. Structure of a GIS (Malczewski, 1999, p. 17)

Data input typically is referred to as "the process of identifying and gathering the data required for a specific application" (Malczewski, 1999, p. 17). In general, data input involves converting data from their raw or existing form into one that can be used by a GIS, which offers the efficiency of integrating a wide range of data and information sources into a format compatible with other devices, including digitizing, scanning, remote sensing (RS), and global positioning systems (GPS) (Longley et al., 2005). Vector and raster are two formats of data model representing geographic data in GIS environments (Malczewski, 1999). Data in vector models are entities represented by a point, line, or polygon (area) with specific coordinates, while data in raster models are stored in a two-dimensional matrix of uniform grid cells (pixels).

Data storage/management involves storing and retrieving data from the database and affects how efficiently the system performs operations with the data (Antennucci, Brown, Croswell, Kevany, & Archer, 1991; Aronoff, 1989). Most GIS systems are based on a database. Typically, the database is defined as “a collection of non-redundant data in a computer organized so that it can be expanded, updated, retrieved, and shared by various uses” (Malczewski, 1999, p. 25), while a GIS database can be thought of as a representation or model of real-world geographical systems with geographical entities and objects (Aronoff, 1989).

The distinguishing feature of GIS is its ability to perform an integrated analysis of spatial and attribute (non-spatial) data. Data manipulation and analysis are core functions of this process used to obtain useful information for specific applications. Overlay, neighborhood, and connectivity are three major types of analysis in GIS (Nicholls, 2002). These fundamental GIS operations can generate data for input into spatial decision analysis that can be a catalyst for decision making. Based on these basic functions, advanced functions, such as spatial statistical analysis, geo-simulation, spatial modeling, and web-based participatory GIS, are new methodological approaches used to interpret complex spatial problems. One of the outstanding features of GIS-based spatial analysis is its geographic intelligence or topology (Levine & Landis, 1989). As noted by Longley et al. (2005), “topology is the science and mathematics of relationships used to validate the geometry of vector entities, and for operations such as network tracing and tests of polygon adjacency" (p. 190). This geographical intelligence can distinguish GIS from other mapping systems such as computer-aided design (Aronoff, 1989).

Data output provides a way to see data or information. According to Martin (1991), "display" and "transfer" are two forms of data output from GIS. "Display" presents information to users in some form such as a map or table, while "transfer" transmits the information into another computer-based system for further processing and analysis (Malczewski, 1999). Output functions can be determined by users' needs and purposes. GIS can support data output with advanced visualization techniques, including three-dimensional (3D) display. This makes GIS more attractive than other information systems by providing advanced visualized information that can allow decision makers to examine quickly large amounts of data during decision making processes (Pundt & Brinkkotte-Runde, 2000).

GIS and Society

Such functions of GIS have successfully met many societal needs. GIS has contributed to the operation and management of utilities, transportation networks, cadastral infrastructure, and natural resources (Goodchild, 1992). In addition, a number of applications of GIS have expanded from government to the private sector, community groups, and individuals (Star & Estes, 1990; Martin, 1991). As explained by Craig, Harris, and Weiner (2002), these applications of GIS in our society bring significant benefits that can be measured in terms of efficiency (doing things more quickly and with less effort), effectiveness (doing things better), and equity (sharing benefits more widely and equally).

Although these benefits come with costs (technology development, data construction and staff training) (Craig et al., 2002), the future of GIS remains promising. The hardware, software, and data for GIS are becoming more available, more usable, and less expensive (Talen, 2000). As a result, society is able to share more geographic information that is essential for better decision making. Furthermore, GIS successfully has been incorporated into the Internet. Web-based GIS has led to active public participation that is the basis of a community-based approach to diverse social problems (Kingston, Carver, Evans, & Turton, 2000; Sieber, 2006).

GIS and Decision Making Processes

The ultimate aim of GIS is to support spatial decision making. GIS capabilities for supporting spatial decisions can be analyzed in the context of the decision-making process. Among a number of frameworks for analysis of the decision process, Simon's (1960) is the most widely used. This process can be divided into three major phases: intelligence, design, and choice. Figure 4 represents these three phases.

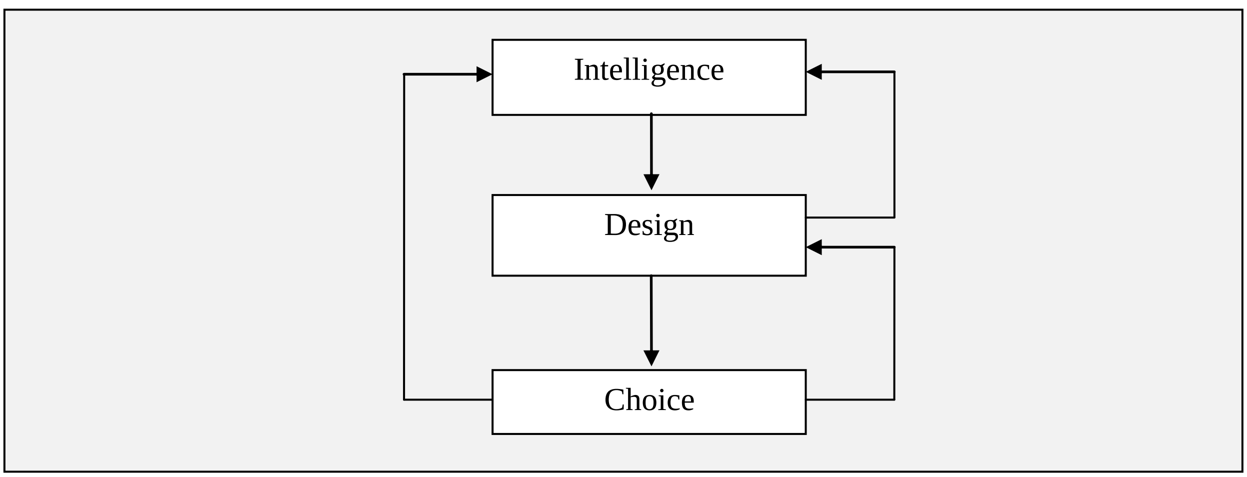

Figure 5. Three-phase decision-making process (Malczewski, 1999, p. 75)

Each stage of the decision-making process has a different purpose and requires different types of information. The intelligence phase defines the need for decision making or problem solving. The design phase prepares alternative courses of action. The choice phase involves evaluation of alternatives and selection of the most appropriate strategy. As a tool, GIS has played a pivotal role in supporting decision-making processes that include the intelligence, design, and choice phases.

Although GIS can provide important capabilities for manipulating and displaying spatial data, a number of GIS functions still lack the capabilities required to assist multiple decision makers come to consensual decisions. Feick and Hall (2002) insisted that “the capacity of commercial GIS to facilitate debate and achieve some measure of balance among different viewpoints has been identified as a major weakness” (p. 391). In particular, an intrinsic single-user perspective in commercial GIS software has disregarded the multi-interest character of the decision-making process and the socially constructed nature of data and analytical methods (Feick & Hall, 2002; Lee, 2001).

Malczewski (1999) stated that most GIS techniques tend to focus on supporting the first phase intelligence of the decision making-process with advanced spatial analysis and visualization. Meanwhile GIS has limitations in its ability to support the design and choice phases that require consideration of diverse viewpoints from different stakeholders. As noted by Densham (1991), “when different people are faced with the same spatial decision problem, they are likely to place different values on variables and relationships and select and use information in different ways” (p. 404). However, it is difficult to handle these situations using standard single user-based GIS. Hence, efforts to extend and integrate GIS technology with multiple criteria analysis are essential (Lee, 2001). Great attention has been given to GIS-based spatial decision support systems to overcome these weaknesses. In particular, multi-criteria decision analysis (MCDA) can be employed to reflect diverse decision makers’ preferences. The methodological integration of GIS and MCDA into multi-spatial decision support systems offers the potential to consider diverse decision makers’ preferences in order to solve complex spatial problems.

Spatial Analysis in GIS

The distinguishing characteristic of GIS that differentiates them from other information systems is their spatial analysis capabilities (Goodchild, 1987; Unwin, 1996). As Goodchild (1987, as cited in Lee, 2001, p. 16) stated, “the ability of a Geographic Information System to analyze spatial data is frequently seen as a key element in its definition, and has often been used as a characteristic which distinguishes the GIS from systems whose primary objective is map production.” Spatial analysis generally is referred to as spatial data manipulation, an ability to manipulate spatial data using a set of deterministic functions for extracting valuable meaning (Bailey, 1994; O’Sullivan & Unwin, 2003). Spatial queries, buffering, overlay, and the calculation of derivates on surfaces such as slope and aspect, are examples of deterministic functions (Unwin, 1996).

Because a GIS is a specialized tool for spatial analysis, definitions of spatial analysis should be discussed in the context of the analysis functions of GIS. Following the four functions of GIS as a GISystem (e.g., input, storage, analysis, and output) (Anselin & Getis, 1992), Anselin (1999) subdivided the analysis function of GIS into selection, manipulation, exploratory spatial data analysis (ESDA), and confirmatory spatial data analysis (CSDA). Figure 6 illustrates Anselin’s (1999) schematic overview of the interaction between different analytical functions of a GIS.

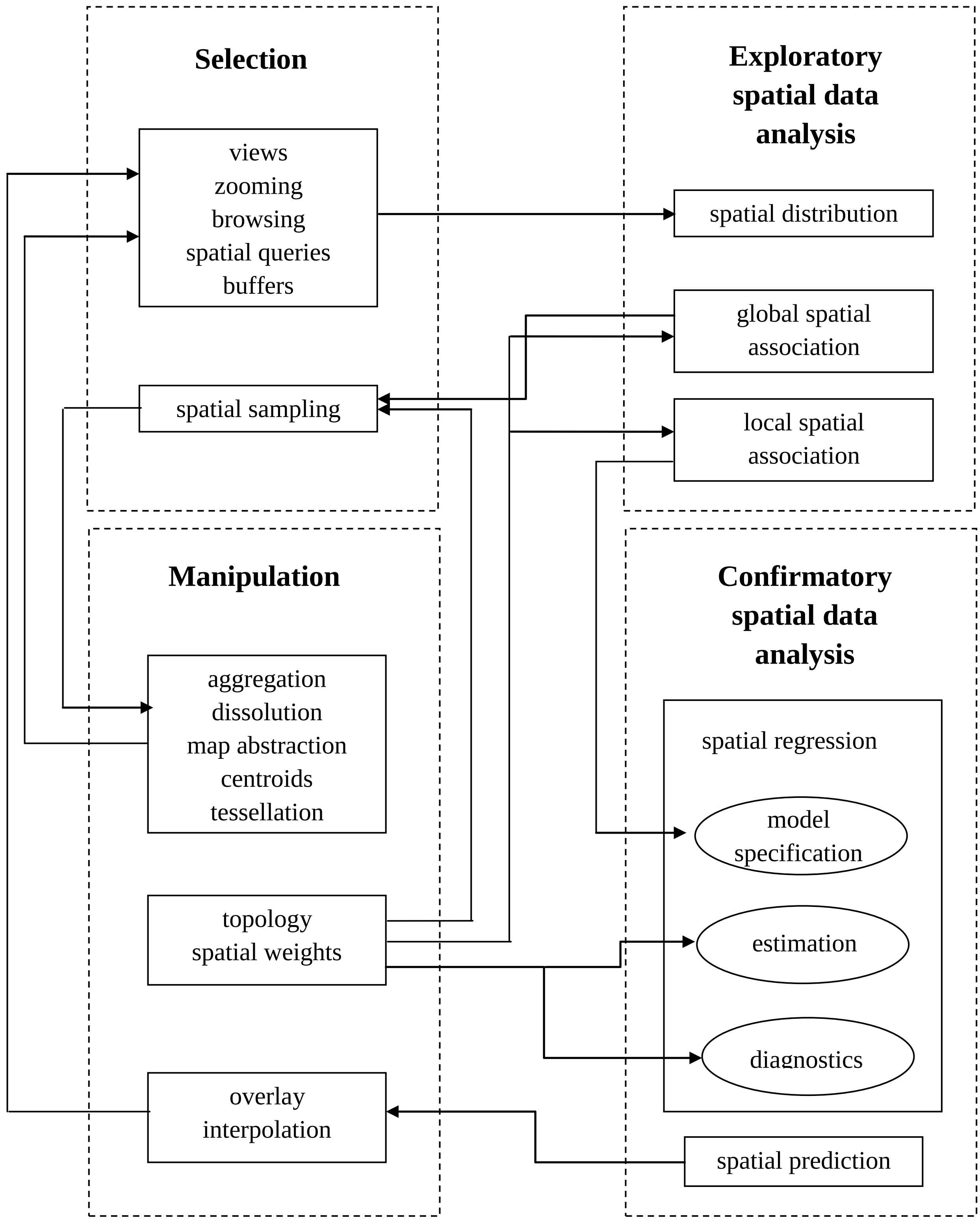

Figure 6. Spatial analysis in GIS (Anselin, 1999, p. 263)

Anselin's (1999) framework involves a sequence of activities that starts with selection and ends with CSDA. Spatial sampling of observational units from the database and the choice of the proper scale of analysis are two essential activities in the selection phase. The next phase is manipulation, the purpose of which is to convert the selected information into meaningful maps and surfaces; partitioning, aggregation, overlay, and interpolation procedures are major activities in the manipulation phase (Anselin & Getis, 1992). ESDA is an inductive approach that is based on "data-driven analysis" (Anselin, 1990) to let the data speak for themselves (Gould, 1981). In the ESDA phase, spatial distribution and spatial association should be assessed and explored at global and local levels in an exploratory manner. The final phase is CSDA based on "model-driven analysis" (Anselin, 1990), in which spatial regression models and spatial predictions can be implemented based on theoretical notions in a confirmatory manner.

Use of GIS Techniques in Equity Analyses of LDLUs

A number of GIS techniques have been employed in LDLU equity analyses of LDLUs. They can be grouped into two main types: (1) visualization, and (2) improvement of variable measurement.

Visualization. GIS allows the mapping of LDLUs, road and trail networks, and census data, thereby facilitating the visualization of the spatial relationships between LDLUs and potential users. Multiple researchers have used GIS to map levels of access to LDLUs (Boone et al., 2009; Gilliland et al., 2006; Lindsey et al., 2001; Marako et al., 2009; Nicholls, 2001; Nicholls & Shafer, 2001; Omer, 2006; Porter & Tarrant, 2001; Smoyer-Tomic et al., 2004; Talen, 1998; Talen & Anselin, 1998; Tarrant & Cordell, 1999; Tsou et al., 2005; Wolch et al., 2005).

Improvement of variable measurement. GIS-based spatial analyses such as network analysis and kernel density estimation (KDE) have been used to increase the accuracy of variable measurement. Network analysis allows the modeling of the actual travel distance between origins and destinations based on the locations of public rights of way and points of entry/egress; the measurement of levels of access is therefore improved in comparison to the traditional "as-the-crow flies" method to identify the total area of urban parks within a one-mile service area of the census blocks in her study area. Nicholls (2001) adopted GIS-based technology to evaluate accessibility and equity in a local park system; she specifically compared the simple radii buffering method (using straight line distance) with network analysis, and indicated that network analysis provided more realistic representations of service areas.

When measuring the degree of equity of LDLUs, factors such as the number of LDLUs (Abercrombie et al., 2008; Gilliland et al., 2006; Omer, 2006; Talen & Anselin, 1998) have been used as dependent variables to represent level of access. These traditional container-based measures cannot consider spatial externalities of other units of analysis or edge effects (Cho, 2003; Nicholls, 2001; Zhang et al., 2011). These limitations can be addressed using GIS-based KDE. KDE is a non-parametric way to estimate the probability density function of a random variable (O'Sullivan & Unwin, 2003). As a modified container method, KDE can overcome the methodological issues of traditional container-based measures; more recently, Maroko et al. (2009) and Moore et al. (2008) have employed KDE to calculate the density of urban parks.

GIS and Spatial Statistics: Essential Partners for Dealing with Spatial Effects

Spatial effects in spatial data analysis have been recognized as serious methodological issues when employing traditional statistical methods. As noted by Griffith and Layne (1999), "any spatial pattern embedded in data causes a number of measurement problems that affect the validity and robustness of traditional statistical description and inference methods when applied to this category of data" (vii). Brunsdon et al. (1996) further stated that classical statistics have failed to capture the locational information in its analysis of relationships between variables. Mennis and Jordan (2005) described the biased estimation results associated with employment of traditional multivariate techniques in previous environmental justice research.

Many scholars have focused on the importance of spatial statistical techniques as specialized techniques that can deal with spatial effects when analyzing spatial data. Getis (2007) stated that spatial data analysis requires specialized techniques that are differentiated from traditional statistical techniques. Brunsdon et al. (1996) described the misunderstanding or overgeneralizations about linkages among variables caused by employing traditional statistical techniques and suggested GWR as an exploratory tool for describing and mapping important local variations in the analysis of spatial data. Gilbert and Charkraborty (2011) criticized the lack of consideration of local statistical methods in environmental justice research and suggested local statistical techniques that are different from those used to analyze non-spatial data.

Because GIS functions can allow spatial statistical techniques to be complemented with innovative visualization, the integration of spatial statistical techniques within a GIS environment has been emphasized by geographers. Anselin and Getis (1992) reviewed a series of questions that need to be confronted in the analysis of spatial data, and the extent to which a GIS can facilitate their resolution in exploratory and confirmatory manners. Getis (1999) focused on the need of spatial statistical modules for a GIS to implement a number of exploratory and confirmatory spatial data analyses. Although several equity studies of LDLUs have employed GIS-based spatial statistical techniques such as ESDA (Deng et al., 2008; Smoyer-Tomic et al., 2004; Talen, 1997; 1998) and GWR (Maroko et al., 2009) to explore spatial effects such as spatial dependence and spatial heterogeneity, no studies have explored empirically these spatial effects simultaneously in exploratory and confirmatory manners. This study is the first study in the outdoor recreation to assess the distribution of LDLUs as well as to deal with these spatial effects together by employing a variety of spatial statistical techniques such as PPA, ESDA, and GWR, thereby making methodological contributions to the outdoor recreation, park, and tourism literature.

CHAPTER 3

METHODS

This chapter provides a description of the study area and of the research methods applied, including variable selection, data acquisition and preparation, data processing, and data analysis.

Study Area: Detroit Metropolitan Area (DMA), Michigan

According to the U.S. Bureau of the Census (2010), southeast Michigan's DMA (also referred to as metro Detroit), is the 12th largest metropolitan area in the US. The DMA includes three counties (Oakland, Wayne, and Macomb) and had a population of 3,863,924 and an area of 1,958.96 square miles (3,463.2 km^2) in 2010. Table 4 describes the characteristics of each county in the DMA.

Table 4.

Characteristics of each county in the DMA (US Bureau of the Census, 2010)

	Oakland County	Wayne County	Macomb County
Population	1,202,362	1,820,584	840,978
Population under age 18 (%)	25.8%	28.4%	25.5%
Population over age 64 (%)	13.2%	12.6%	14.2%
Population density (/sq mi)	1,325/sq mi	2,706/sq mi	1,473/sq mi
Water area (%)	39.63 sq mi (4.6%)	60.60 sq mi (9.9%)	91.63 sq mi (19.1%)
Number of public beaches	169	5	4
Occupied housing units (%)	91.7%	85.5%	93.0%
Median household income ($)	$65,636	$41,504	$53,628
Median household value ($)	$177,600	$97,100	$134,700
White population (%)	77.2%	52.2%	85.3%
Black population (%)	13.6%	40.5%	8.6%
Asian population (%)	5.6%	2.5%	2.9%
Hispanic population (%)	3.4%	5.2%	2.2%
Population over 25 with university degree or higher (%)	42.7%	20.8%	22.1%
Population below the poverty line (%)	9.9%	23.7%	11.8%
Population with non-english spoken at home (%)	15.2%	20.3%	10.0%
Households without a vehicle (%)	5.4%	13.5%	6.4%

Because the results of spatial data analysis are sensitive to the nature of the areal unit employed (due to, e.g., the modifiable areal unit problem [MAUP], ecological fallacy, and aggregation error) (Hewko et al., 2002; O'Sullivan & Unwin, 2003; Smoyer-Tomic et al., 2004), the choice of areal unit is a substantial issue when applied to spatial statistical analysis. MAUP is a statistical bias that can radically affect the results of statistical tests due to the choice of district boundaries (O'Sullivan & Unwin, 2003); MAUP refers to the tendency of results to vary when the areal unit of analysis is changed (Porter, 2001). As noted by Longley et al. (2005), the notion of ecological fallacy references "a situation that can occur when a researcher or analyst makes an inference about an individual based on aggregate data for a group" (p. 98); the use of census data therefore tends to lend itself to this problem. Aggregation error refers to "the error associated with representing an areal unit, which in turn represents spatially distributed individuals, by a single point" (Hewko, 2001, p. 23). This study used the census tract as its unit of analysis because the census tract represents a good approximation of a neighborhood environment, with reliable social and economic data available from the U.S. Census Bureau (Estabrooks et al., 2003). A census tract is defined as a subdivision of a county with "a mean population of approximately 4,000 people that are relatively homogeneous in socioeconomic characteristics" (Moore et al., 2008, p. 17). Moreover, previous equity studies associated with the distribution of access to LDLUs have employed census tracts as their unit of analysis (Deng et al., 2008; Estabrooks et al., 2003; Lindsey et al., 2001; Moore et al., 2008; Talen & Anselin, 1998). There are 1,164 census tracts in the DMA. Figure 7 shows the locations of the 178 public beaches and the census tract boundaries within the DMA. All public beaches are owned and managed by the state of Michigan.

Recognizing the potential influence of the edge effect, public beaches outside of the DMA but within 20 miles of the centroid of a census tract within the DMA were also considered in a separate suite of analyses (n=59), based on the findings reported by Haas (2009). These additional beaches are shown in Figure 8.

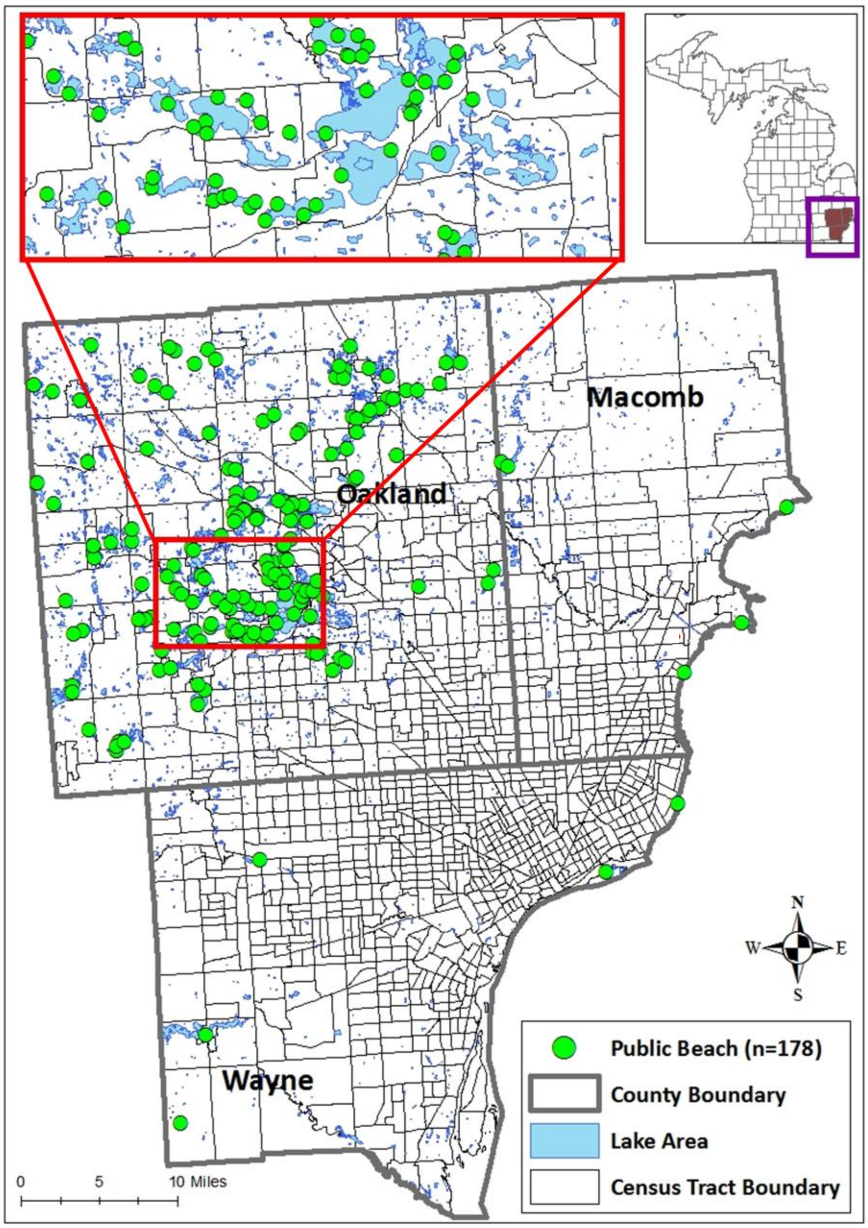

Figure 7. Study area: DMA (For interpretation of the references to color in this and all other figures, the reader is referred to the electronic version of this dissertation)

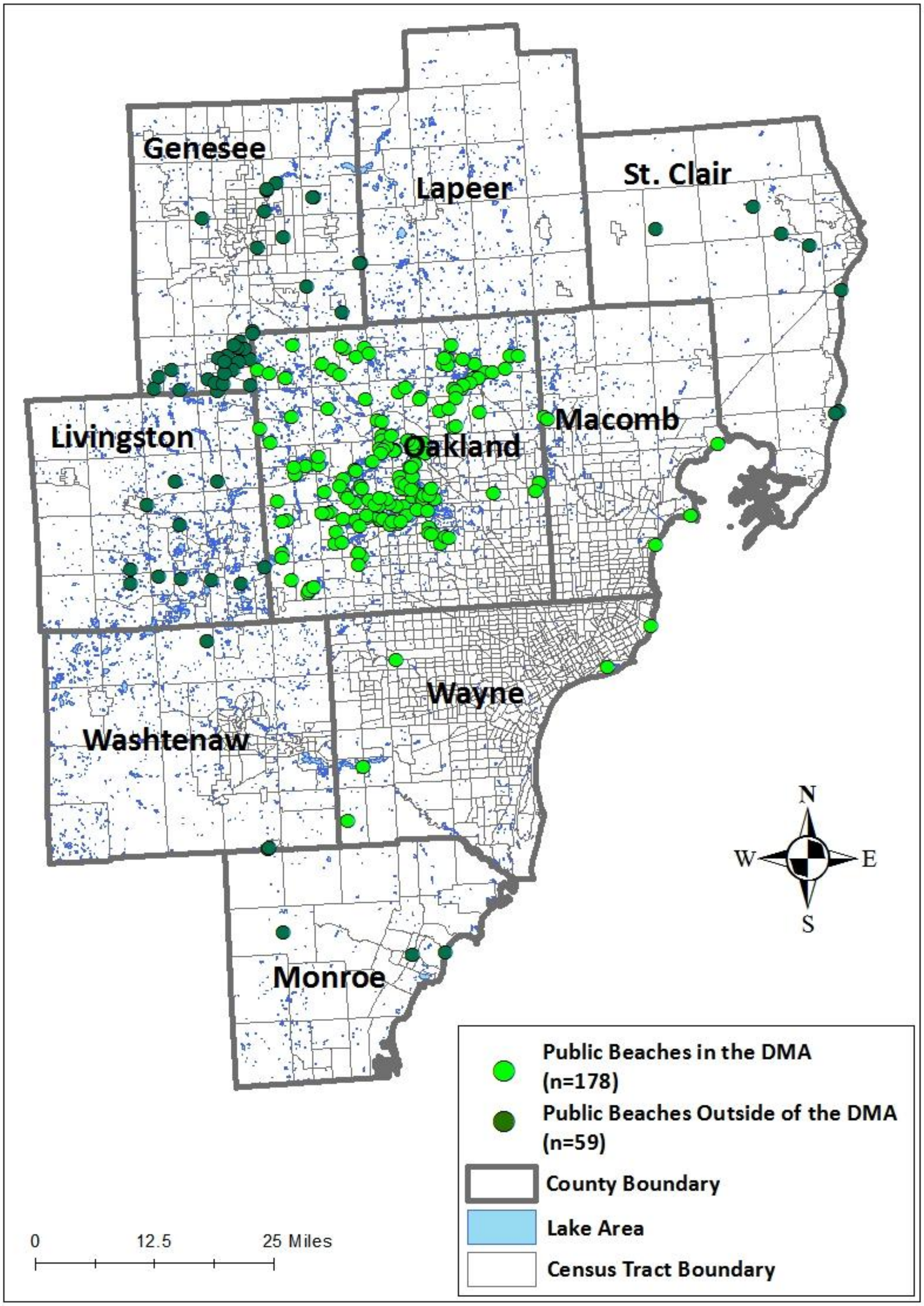

Figure 8. Study area, including public beaches outside of the DMA, but within 20 miles of the DMA

Variable Selection

In this section, selection of the dependent and independent variables is described.

The Dependent Variable

The dependent variable selected in this study was the level of access to public beaches. Access was measured in two manners: (1) the shortest road network distance from the residential centroid (in this case, census tract centroid) to the nearest public beach for each census tract in the DMA, and (2) the number of public beaches within 20 miles of each tract centroid.

These two dependent variables reflect two approaches to the measurement of access, (1) minimum distance, and (2) container. Use of the minimum distance approach recognizes that, although a neighborhood could interact with all the LDLUs in its local environment, most LDLUs such as parks are, in reality, mainly used by nearby residents (Zhang et al., 2011). Several previous equity studies associated with the distribution of LDLUs have employed the minimum distance approach to measure access to LDLUs (Byrne et al., 2009; Lotfi & Koohsari, 2009; Smoyer-Tomic et al., 2004; Talen, 1998; Talen & Anselin, 1998). Use of the container approach is justified because it is simple and efficient (Cho, 2003; Talen & Anselin, 1998). Other equity studies have employed the container approach to study the distribution of playgrounds (Talen & Anselin, 1998), urban parks (Abercrombie et al., 2008; Maroko et al., 2009; Omer, 2006; Talen, 1997; Wolch et al., 2005), swimming pools (Gilliland et al., 2006), fitness centers (Estabrooks et al., 2003), and tennis courts (Moore et al., 2003). The container approach sometimes has been criticized, however, due to an unrealistic assumption that all neighborhood residents use only LDLUs contained within a governmentally-defined areal unit such as a census tract (Lindsey et al., 2001). To overcome this limitation, one solution is to consider only LDLUs within a certain service area rather than within a government-defined unit (Talen, 1997). Based on a survey conducted by the Strategy Institute on behalf of the East Bay Regional Park District in October 2006 (Haas, 2009), it was estimated that 20 miles was the distance residents were willing to travel for beach-based recreation activities such as boating, fishing, and swimming. The number of public beaches within 20 network-distance miles of each census tract centroid was therefore utilized as the container measure. Use of two approaches, to date considered by only one other set of researchers (Nicholls, 2001; Nicholls & Shafer, 2001), enabled both the accessibility and equity findings to be compared and contrasted at each step of subsequent analysis. Due to its far superior representation of the actual landscape, only network distance was employed.

The Independent Variable

Selection of independent variables was based upon review of variables considered relevant in previous LDLU equity studies and limited to those available for census tracts. Table 5 lists the frequency of use of various possible independent variables in 22 previous park-related LDLU equity analyses.

Table 5.

Independent variables utilized in previous LDLU equity analyses

Variable	Description of variables	Times and % of times used (n=22)
Race/ethnicity		
White	Proportion (%) of White population	2 (9%)
Black	Proportion (%) of Black population	7 (31.8%)
Asian	Proportion (%) of Asian population	1 (4.5%)
Hispanic	Proportion (%) of Hispanic population	7 (31.8%)
Age		
Children	Proportion (%) of population under age 14	1 (4.5%)
Youth	Proportion (%) of population under age 18	5 (22.7%)
Older	Proportion (%) of population over age 64	2 (9.0%)

Table 5. *(cont'd)*

Variable	Description of variables	Times and % of times used (n=22)
Population density	Population per square mile	5 (22.7%)
Education		
University	Proportion (%) with a four-year univesity degree or higher	4 (18.1%)
High school	Proportion (%) within a high school diploma or higher	3 (13.6%)
Income	Median household income ($)	7 (31.8%)
Housing value	Median house price ($)	4 (18.1%)
Economic status	Proportion (%) of population below the poverty line	4 (18.1%)
Housing occupancy		
Owner	Proportion (%) of owner occupied housing units	2 (9.0%)
Renter	Proportion (%) of renter occupied housing units	2 (9.0%)
Vehicle ownership	Proportion (%) of households without a vehicle	2 (9.0%)
Others	Median contract rent ($); residents who have lived less than 5 years at current address (%); land area; proportion (%) of blue collar; proportion (%) of white collar; proportion (%) of vacant housing units; proportion (%) of population with non-English spoken at home; proportion (%) of the civilian unemployed; and average family size	1 (4.5%)

In this study, 14 demographic and socioeconomic variables were considered as potential independent variables to represent residents' needs with regard to access to public beaches. These independent variables relate to: (1) population density; (2) age (young and older); (3) race/ethnicity (four racial/ethnic groups); (4) housing value; (5) income; (6) educational attainment; (7) language; (8) vehicle ownership; (9) housing occupancy; and (10) economic status. Groups considered most likely to be in "need" of better than average access to public beaches were non-White (e.g., Black, Asian, and Hispanic groups) (Deng et al., 2008; Gilbert & Chakraborty, 2011; Nicholls, 2001; Wicks & Crompton, 1986), those earning low incomes (Estabrooks et al., 2003; Gilliland, Holmes, Irwin, & Tucker, 2006; Lindsey et al., 2001; Smoyer-Tomic et al., 2004), the young and the elderly (Nicholls, 2001; Nicholls & Shafer, 2001; Smoyer-Tomic et al., 2004; Talen, 1997; Talen & Anselin, 1998), those residing in more densely populated areas (Lindsey et al., 2001; Nicholls, 2001; Nicholls & Shafer, 2001; Maroko et al., 2009), those living in lower housing value (Lindsey et al., 2001; Talen, 1997; 1998), those having low educational attainment (Deng et al., 2008; Estabrooks et al., 2003; Lindsey et al., 2001; Porter & Tarrant, 2001; Tarrant & Cordell, 1999), those with non-English spoken at home (Maroko et al., 2009), those residing in lower proportion of housing occupied area (Nicholls, 2001; Talen, 1998), those residing in higher poverty rate area (Lindsey et al., 2001; Maroko et al., 2009), and those without a vehicle (Lindsey et al., 2001).

The choice of independent variables was based on data availability and prevalence of use in previous equity studies. In addition, water area (as a proportion of total area) was utilized as an additional independent variable in an effort to account for variations in the prevalence of lakes, and thus of water-based recreation opportunities, in each tract. Table 6 summarizes the dependent and independent variables and their operational definitions.

Data Acquisition

A variety of geographic and census data was required. All items listed in Table 6 were acquired from the U.S. Census Bureau (2010) at the level of the census tract. Table 7 summarizes the geographic data employed.

Table 6.

Dependent and independent variables

Variable	Operational definition	Abbreviation
Level of access to public beaches (DV)	(1) Shortest road network distance from tract centroid to the nearest public beach (in miles) (2) Number of public beaches within 20 miles of tract centroid	(1) DISTPB (2) NOPB
Population density (IV)	Population per square mile	POPD

Note: DV (dependent variable), IV (independent variable)

Table 6. *(cont'd)*

Variable	Operational definition	Abbreviation
Age (IV)	(1) Proportion (%) of population under age 18 (2) Proportion (%) of population over age 64	(1) AGE18 (2) AGE64
Race/ethnicity (IV)	(1) Proportion (%) of White population (2) Proportion (%) of Black population (3) Proportion (%) of Asian population (4) Proportion (%) of Hispanic population	(1) WHITE (2) BLACK (3) ASIAN (4) HISPAN
Housing value (IV)	Median housing value ($)	MHV
Income (IV)	Median household income ($)	MHI
Education (IV)	Proportion (%) of population with a four-year university degree or higher	EDU
Language (IV)	Proportion (%) of population with non-English spoken at home	LAN
Vehicle ownership (IV)	Proportion (%) of households without a vehicle	VEHIC
Housing occupancy (IV)	Proportion (%) of occupied housing units	HO
Economic status (IV)	Proportion (%) of population below the poverty line	ECON
Water area (IV)	Proportion (%) of water area	WATER

Note: IV (independent variable)

Table 7.

Dataset for analysis

Item	Type of data	Source	Date
Geographic data			
Public beach locations	Latitude and longitude	DEQ	2010
Michigan tract boundaries	Polygon	MGDL	2010
Michigan street network	Line	MGDL	2010

Note: DEQ: Department of Environmental Quality; MGDL: Michigan GIS Data Library

Data Processing and Analysis Tools

Various software programs were employed to organize data, build models, and visualize results. Non-spatial statistical analyses (e.g., frequencies, correlations and OLS regression) were performed using SPSS software (version 20.0) for Windows. ArcGIS (version 10.0) was used to display the study area and data spatially, and to calculate the dependent variables. Spatial statistical analyses, such as PPA, ESDA and GWR, were performed using ArcGIS (version 10.0), R, and GWR (version 4.0).

Data Preparation

After all the relevant geographic and census data had been collected, they were entered and integrated into the GIS environment in GIS shape file (.shp) form. As noted by Nicholls (2001), a shape file is a digital vector storage format for "the geographical representation of a theme or layer of spatial information" (p. 210). Shape files can describe a variety of geographic entities as points, lines, or polygons (Dong, 2008). In this study, shape files represent census tracts (as polygons), public beach locations (as points), and the street network (as lines). All shape files were projected and displayed in NAD 1983 Hotine Oblique Mercator.

Census Tract Boundaries and Data

To select only DMA boundaries, the shape file for all Michigan tract boundaries was clipped based on the DMA boundary polygon shape file using the geo-processing tool "Clip" in ArcGIS. The resulting shape file contained only the census tracts (n=1,164) located in the DMA. Census tract data (socioeconomic and demographic variables, and water area) were joined with corresponding census tract polygons using the geo-processing tool "Spatial Join" in ArcGIS.

Public Beach Locations

To represent access points to public beaches, information on the latitude and longitude of public beaches was acquired from the Department of Environmental Quality website (http://www.deq.state.mi.us/beach/) and converted into a point shape file using the geo-coding tool "Add XY data" in ArcGIS. The converted points then were relocated to the centroid of the parking lot for each public beach using the "Editing" tool in ArcGIS. If multiple parking lots existed at a single beach (as was the case for 19 [10.6%] of the beaches), the nearest parking lot to the beach was used. Google Earth was used to verify these locations.

Street Network Dataset

Building a network dataset is a prerequisite for performing network analysis using ArcGIS. The shape file for all streets within the DMA boundary and in adjacent counties to the DMA (St. Clair, Lapeer, Genesee, Livingston, Washtenaw, and Monroe Counties) was clipped using the geo-processing tool "Clip" in ArcGIS. Then, using the geo-processing tool "Network Dataset" in ArcCatalog, the clipped street line shape files were converted to a network dataset with junctions and edges. The resulting network dataset contained 220,525 junctions and 296,078 edges.

Data Analysis Procedures

Measuring the equity of access to public beaches in the DMA is a complex process that involves a sequence of activities. Figure 9 presents a methodological flowchart for data analyses. In addition, the more specific research questions and relevant research techniques, outcomes, and diagnostics that guide each step are outlined in Table 8.

Step 1: Conducting Descriptive Statistical Analysis for All Independent Variables

To check for missing or erroneously entered values, descriptive analysis of all independent variables was conducted. Tables of all independent variables' means, minimums, maximums, and standard deviations were created. Spurious entries and substantial outliers were corrected or removed. Lastly, choropleth maps that display the distribution of variables using different shades of color were created.

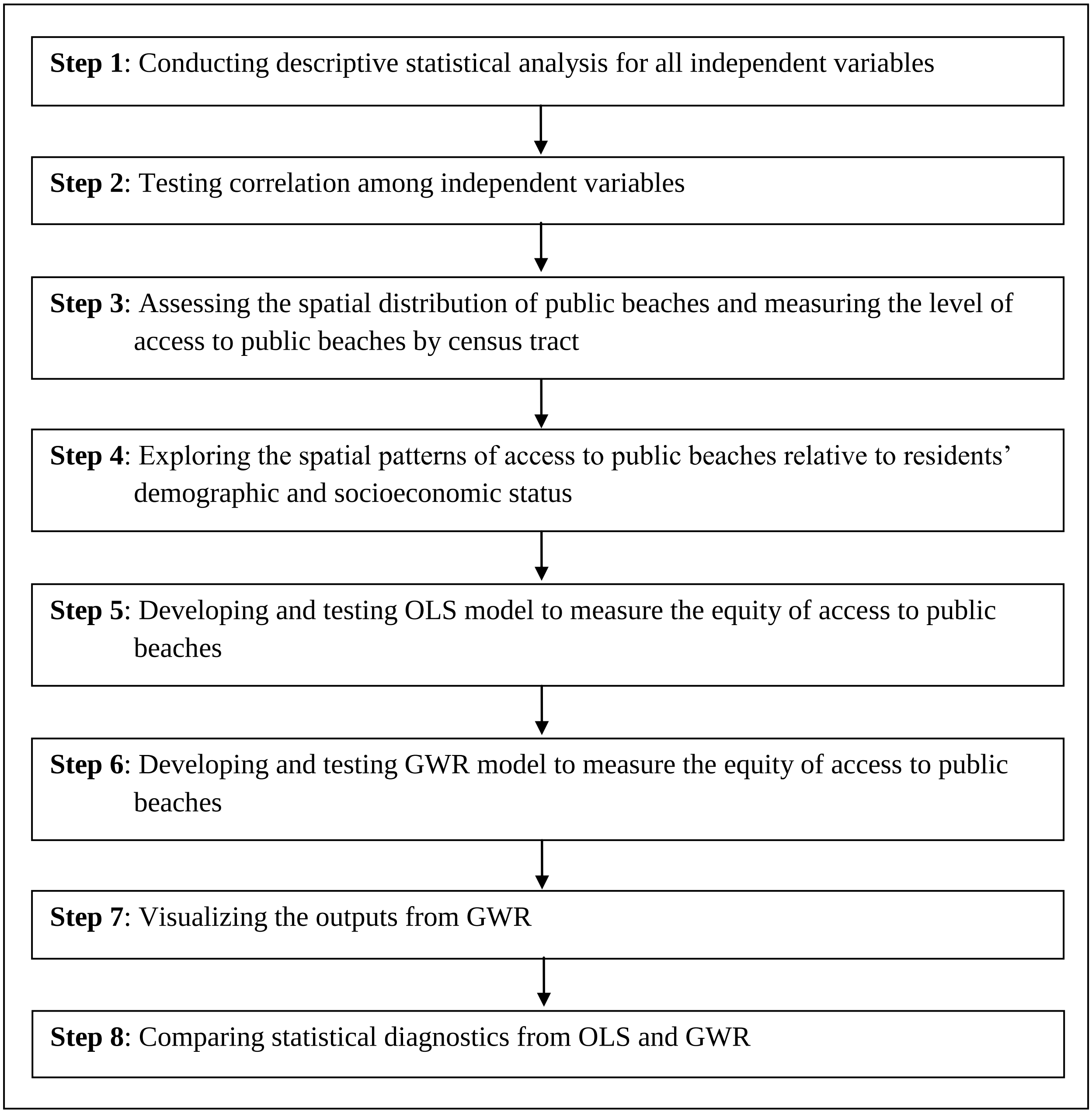

Figure 9. Methodological flowchart for data analyses

Table 8.

Objectives and relevant research questions

Objective/research question number	Step Number	Technique/outcome/diagnostic
O1R1	Step 3	Centrographic analyses for measuring the mean center and the median center/a map /no diagnostic
O1R2	Step 3	Centrographic analysis (standard deviational ellipse analysis for measuring the standard distance and the standard deviational ellipse)/a map/no diagnostic
O1R3	Step 3	PPA (nearest neighbor analysis [NNA] and Ripley's K-function analysis)/a graph and a table/NNA (nearest-neghbor ratio, z-score, and p-value) and Ripley's K-function analysis (K-value: L(d))
O1R4	Step 3	GIS-based network analysis/a map and a table/no diagnostic
O2R1	Step 4	ESDA (spatial autocorrelation analysis)/a table/global Moran's I statistic, z-score, and p-value
O2R2	Step 4	ESDA (LISA) /a map/local Moran's I statistic, z-score, and p-value
O3R1	Step 5	OLS regression/a table/coefficient estimates, t-values, VIFs, R^2, adjusted R^2, AIC_c, F-statistic, Joint Wald statistic, and Koenker (BP) statistic (Koenker's studentized Bruesch-Pagan statistic)
O3R2	Step 6	GWR /a table/ local coefficient estimates, local condition index, local R^2, and AIC_c
O3R3	Step 6 & Step 7	Monte carlo signifcance test and GIS-based mapping/a map/ local coefficient estimates and local R^2
O3R4	Step 8	ANOVA F-test, GIS-based ESDA (spatial autocorrelation analysis)/a table /R^2 and AIC_c (model performance), global Moran's I of regression residuals (model heteroskedasticity), and F-statistic

Note: O1R1: "What is the central tendency of the public beach distribution in the DMA?," O1R2: "How and to what extent are the public beaches dispersed?," O1R3: "Are the public beaches in the DMA spatially clustered?," O1R4: "How is access to public beaches distributed across the DMA?," O2R1: "Is there spatial autocorrelation associated with the distribution of access to public beaches and residents' demographic and socioeconomic status across the study area?," O2R2: "If there is evidence of spatial autocorrelation, what is its nature and where is it evident?," O3R1: "What is the relationship between level of access to public beaches in the DMA and residents' demographic and socioeconomic status using OLS?," O3R2: "What is the relationship between level of access to public beaches in the DMA and residents' demographic and socioeconomic status using GWR?," O3R3: "How does the spatial relationship between the level of access to public beaches and residents' demographic and socioeconomic status vary across the study area (using GWR)?," and O3R4: "How well does the GWR approach perform in terms of model diagnostics compared to the traditional OLS approach?"

Step 2: Testing Correlation among Independent Variables

Because all potential independent variables were continuous in nature, a correlation matrix was produced using Pearson's correlation coefficient. In cases in which the correlation exceeded 0.90, certain variables were deleted to avoid problems of multicollinearity. Variance inflation factors (VIFs) also were inspected.

Step 3: Assessing the Spatial Distribution of Public Beaches and Measuring the Level of Access to Them

Level of access to LDLUs is based on the distribution of LDLUs as well as on the population and the street network surrounding them (Talen, 1997). A two-step approach using spatial statistical techniques was applied to assess the spatial distribution of public beaches. First, centrographic analysis in combination with standard deviational ellipse analysis were used to describe their spatial characteristics (e.g., central tendency [e.g., mean and median center], dispersion [e.g., standard distance], and directional trend [e.g., standard deviational ellipse]). Second, PPA using nearest neighbor analysis and Ripley's K-function analysis were employed to explore the spatial patterns of public beaches. Network analysis was employed to calculate the shortest road network distance from each tract centroid to the nearest public beach and the number of public beaches within 20 miles of each tract centroid. The access measures were exported as a database file (.dbf) for the subsequent spatial autocorrelation tests and regression analyses.

Step 4: Exploring the Spatial Patterns of Access to Public Beaches relative to Residents' Demographic and Socioeconomic Status

Exploring the spatial patterns of variables is an essential procedure in the equity mapping approach. Spatial autocorrelation analyses using global Moran's I statistics and LISA using local Moran's I statistics were employed to reveal the spatial patterns of access to public beaches relative to residents' demographic and socioeconomic status.

Step 5: Developing and Testing OLS Model to Measure the Equity of Access to Public Beaches

Because an automated procedure (e.g., backwards, forwards, stepwise) may have immediately excluded some important variables (Burns & Burns, 2008), a conventional OLS regression model was built in a systematic manner. Coefficient estimates, t-values, and VIFs value were reported. The values of R^2, adjusted R^2, and AIC_c were used to assess model performance. Model significance was assessed using the Joint F and Joint Wald statistics. The value of the Koenker (BP) statistic also was employed to assess model stationarity.

Step 6: Developing and Testing GWR Model to Measure the Equity of Access to Public Beaches

The same dependent variable and set of independent variables from the global OLS model were utilized using GWR to explore spatial variations between dependent and independent variables. Because of the varying size and shape of census tracts as well as varying density of public beaches in the DMA, a bi-square kernel function (a kernel with adaptive bandwidth), which identifies a certain number of neighbors that maximizes model fit, was used. The optimal kernel size for this study was determined through an iterative statistical optimization process to minimize the AIC_c. Local coefficient estimates, local R^2, and local condition numbers were reported. Model performance was assessed using R^2 and AIC_c. The significance of the spatial variability in the local coefficient estimates was tested by conducting a Monte Carlo significance test (Fotheringham et al., 2002).

Step 7: Visualizing the Outputs from GWR

Statistical diagnostics (e.g., local coefficient estimates, and local R^2) from GWR were mapped using ArcGIS 10.0 to explore spatial heterogeneity.

Step 8: Comparing Statistical Diagnostics from OLS and GWR

To evaluate the relative effectiveness of GWR, statistical diagnostics (R^2, AIC_c, and Moran's I of regression residuals) from OLS and GWR were compared to assess whether the GWR model substantially improved the traditional OLS regression model as well as effectively dealt with spatial effects in the data. Lastly, analysis of variance (ANOVA) testing was performed to verify improvement in model fit of GWR over OLS regression.

Steps 4-8 were repeated using each of the two measures of access highlighted in Step 3.

CHAPTER 4

RESULTS

The purpose of this study was to demonstrate the utility of spatial statistical techniques for assessing the distribution of recreation opportunities within the framework of environmental justice via a case study of public beach access in the DMA. To achieve this purpose, three objectives and 10 more specific research questions were developed. In this section, descriptive statistics and correlation results for the independent variables are reported and each objective and related research questions are addressed.

Descriptive Statistics

Descriptive statistics for the independent variables are presented in Table 9; the sometimes substantial variability in the values of the independent variables across the census tracts in the DMA also is displayed in Figures 10 through 24. Maps were created using different natural break points in the data due to different range of each independent variable.

Table 9.

Descriptive statistics for each independent variable (n = 1,164)

Variable (unit)	Mean	SD	Minimum	Maximum
WHITE (%)	61.0	36.1	0.3	98.0
BLACK (%)	31.7	37.4	0.0	98.1
ASIAN (%)	2.8	4.7	0.0	53.3
HISPAN (%)	4.0	8.8	0.1	76.8
POPD (/sq mi)	4,200.9	2,521.8	90.9	18,404.6
MHI ($)	52,832	27,305	9,923	160,431
MHV ($)	128,322	83,322	13,400	674,900
AGE18 (%)	26.7	5.5	5.8	48.6
AGE64 (%)	13.4	5.1	1.0	42.7
EDU (%)	25.4	18.5	0.0	80.9
LAN (%)	12.9	12.0	0.0	86.4
ECON (%)	19.2	16.2	0.3	78.9
HO (%)	88.2	8.6	50.3	99.8

Table 9. *(cont'd)*

Variable (unit)	Mean	SD	Minimum	Maximum
VEHIC (%)	11.0	11.4	0.0	66.6
WATER (%)	2.5	8.4	0.0	62.8

In terms of race, the predominant racial groups in the DMA were white (mean: 61.0%) and black (mean: 31.7%). Figure 10 (p. 82) reveals the proportion (%) of White population by census tract. White population ranged from 0.3% to 98.0%. The majority of census tracts with the highest proportions of White population (i.e., greater than one standard deviation above the mean [97.1%]) were located in Oakland County, in the townships of Addison, Brandon, Lyon, and Rose, and in Macomb County, in the townships of Armada, Bruce, Lenox, and Ray.

The proportion of Black population by census tract is displayed in Figure 11 (p. 83). Black population ranged from 0.0% to 98.1%. The majority of census tracts with the highest proportions of Black population (i.e., greater than one standard deviation above the mean [69.1%]) were concentrated in Wayne County, in the cities of Detroit, Lincoln Park, and Southfield.

Figure 12 (p. 84) displays the proportion of Asian population by census tract. Asian population ranged from 0.0% to 53.3% with a mean of 2.8%. As displayed in Figure 12, the majority of census tracts with the highest proportions of Asian population (i.e., greater than one standard deviation above the mean [7.5%]) were located in Wayne County, in the cities of Allen Park, Dearborn, Detroit, Lincoln Park, and Romulus, and in Oakland County, in the cities of Pontiac and Troy.

The proportion of Hispanic population by census tract is displayed in Figure 13 (p. 85). Hispanic population (mean: 4.0%) ranged from 0.1% to 76.8%. The census tracts with the highest proportions of Hispanic population (i.e., greater than one standard deviation above the mean [12.8%]) were located in Wayne County, in the cities of Dearborn, Detroit, and Lincoln Park, and in Oakland County, in the cities of Auburn Hills and Pontiac.

Figure 14 (p. 86) displays population per square mile by census tract. Population density ranged from 90.9/sq mi to 18,404.6/sq mi, with a mean of 4,200.9/sq mi. The majority of exceptionally crowded census tracts (i.e., greater than one standard deviation above the mean [6,722.7/sq mi.]) were located in Wayne County, in the cities of Dearborn, Detroit, Lincoln Park, and Romulus.

Figures 15 (p. 87) and 16 (p. 88) display median household income and median housing value by census tract. Median household income ranged from $9,923 to $160,431 (mean: $52,832), while median housing value ranged from $13,400 to $674,900 (mean: $128,322). The majority of census tracts with the highest median household incomes (i.e., greater than one standard deviation above the mean [$80,137]) and with higher median housing value (i.e., greater than one standard deviation above the mean [$211,644]) were located in Oakland County, in the cities of Bloomfield Hills, Novi, and Troy and in the townships of Addison, Bloomfield, Independence, Lyon, Oakland, and West Bloomfield, and in Macomb County, in the townships of Chesterfield and Macomb. The census tracts with the lowest median household incomes (i.e., less than $25,188) and median housing values (e.g., less than $70,000) were concentrated in the city of Detroit, Wayne County.

The proportions of population under age 18 and over age 64 by census tract are displayed in Figures 17 (p. 89) and 18 (p. 90). The youth population varied from 5.8% to 48.6% (mean: 26.7 %) while over-64s accounted for between 1.0% and 42.7% of the population of each tract (mean: 13.4%). The majority of census tracts with the highest proportion of populations under age 18 (i.e., greater than one standard deviation above the mean [32.2%]) were located in

Wayne County, in the cities of Dearborn, Detroit, Ecorse, and Romulus, and in Oakland County, in the cities of Pontiac and Novi, while the majority of census tracts with the highest proportions of population over age 64 (i.e., greater than one standard deviation above the mean [18.5%]) were located in Oakland County, in the townships of Bloomfield, Southfield, and West Bloomfield; in Macomb County, in the cities of St. Clair Shores, Sterling Heights, and Warren; and, in Wayne County, in the cities of Livonia and Riverview.

Figure 19 (p. 91) displays the proportion of population with a 4-year university degree or higher by census tract. An average of about one quarter of residents (25.4%) held a 4-year university degree or higher, with a range from 0.0% to 80.9%. The majority of census tracts with the highest proportions of population with a university degree or higher (i.e., greater than one standard deviation above the mean [43.9%]) were located in Oakland County, in the cities of Farmington Hills, Royal Oak, Novi, and Troy and in the townships of Bloomfield, Independence, and West Bloomfield.

The proportion of population with non-English spoken at home by census tract is displayed in Figure 20 (p. 92). The proportion ranged from 0.0% to 86.4% (mean: 12.9%). The majority of census tracts with the highest proportions of population with non-English spoken at home (i.e., greater than one standard deviation above the mean [24.9%]) were located in Oakland County, in the cities of Novi and Troy, and in Wayne County, in the cities of Dearborn and Detroit.

Figure 21 (p. 93) displays the proportion of population below the poverty line by census tract. The population below the poverty line ranged from 0.3% to 78.9% (mean: 19.2%). The majority of census tracts with the highest proportions of population below the poverty line (i.e., greater than one standard deviation above the mean [35.4%]) were located in the city of Detroit, Wayne County.

The proportion of occupied housing units by census tract is displayed in Figure 22 (p. 94). The proportion of owner-occupied housing units ranged from 50.3% to 98.8% (mean: 88.2%). The majority of census tracts with the highest proportions of owner-occupied housing units (i.e., greater than one standard deviation above the mean [96.8%]) were located in Wayne County, in the cities of Detroit and Livonia; in Oakland County, in the cities of Novi, Rochester Hills, and Troy; and, in Macomb County, in the townships of Macomb and Shelby.

Figure 23 (p. 95) displays the proportion of households without a vehicle by census tract. The proportion of households without a vehicle ranged from 0.0% to 66.6%, with a mean of 11.0%. The majority of census tracts with the highest proportions of households without a vehicle (i.e., greater than one standard deviation above the mean [22.4%]) were located in the city of Detroit, Wayne County. These wide ranges in demographic and socioeconomic status across census tracts indicate potentially diverse levels of need for access to public beaches in the DMA.

Lastly, the proportion of water area by census tract is displayed in Figure 24 (p. 96). The proportion of water area varied from 0.0% to 62.8%, with a mean of 2.5%, suggesting potentially wide variations in level of access to water-based recreation opportunities. The majority of census tracts with the highest proportion of water area (i.e., greater than one standard deviation above the mean [10.9%]) were located in Oakland County, in the townships of Commerce, West Bloomfield, and White Lake. It should be noted that this proportion includes both public and private areas of water.

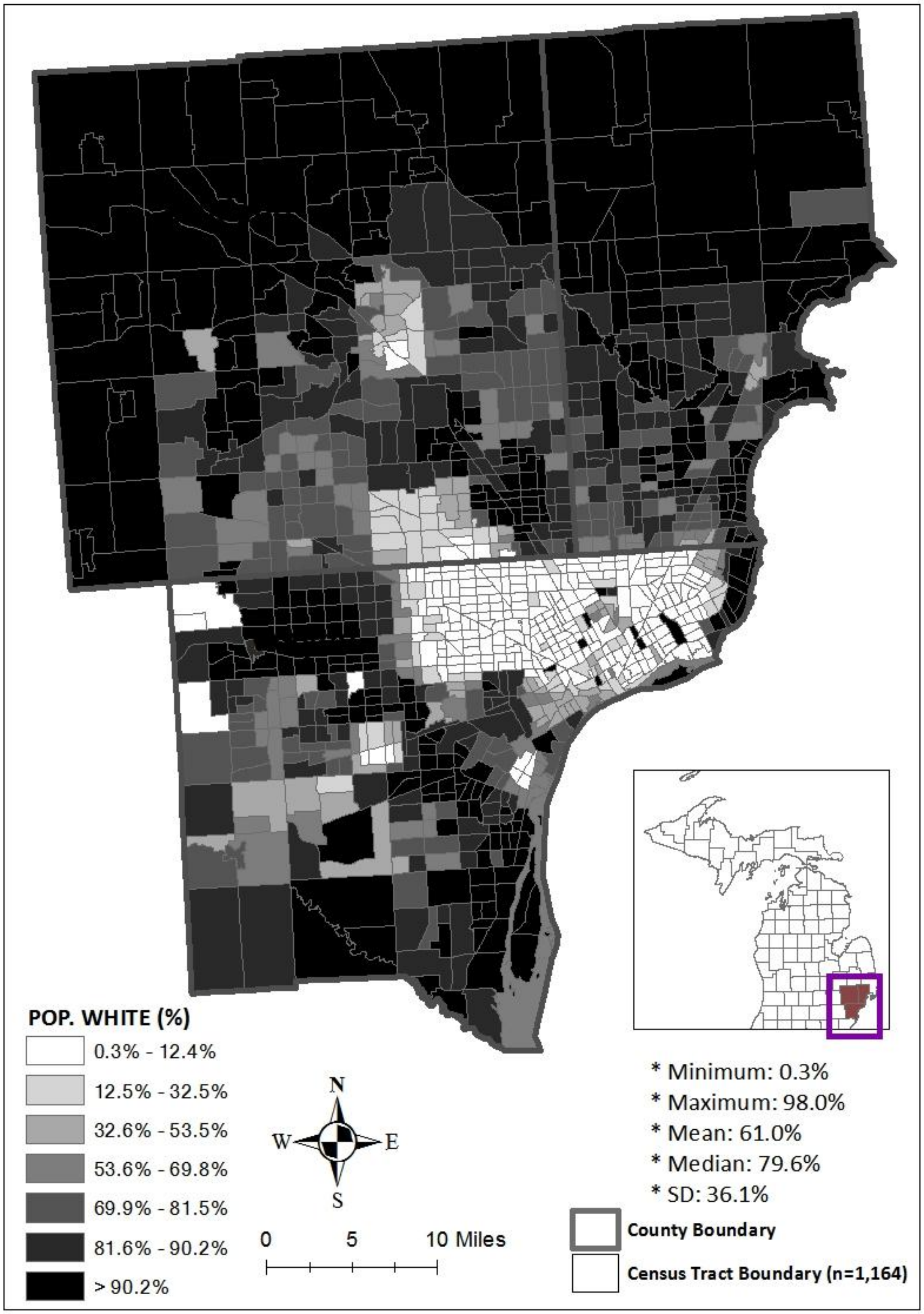

Figure 10. Proportion (%) of White population by census tract, DMA (2010)

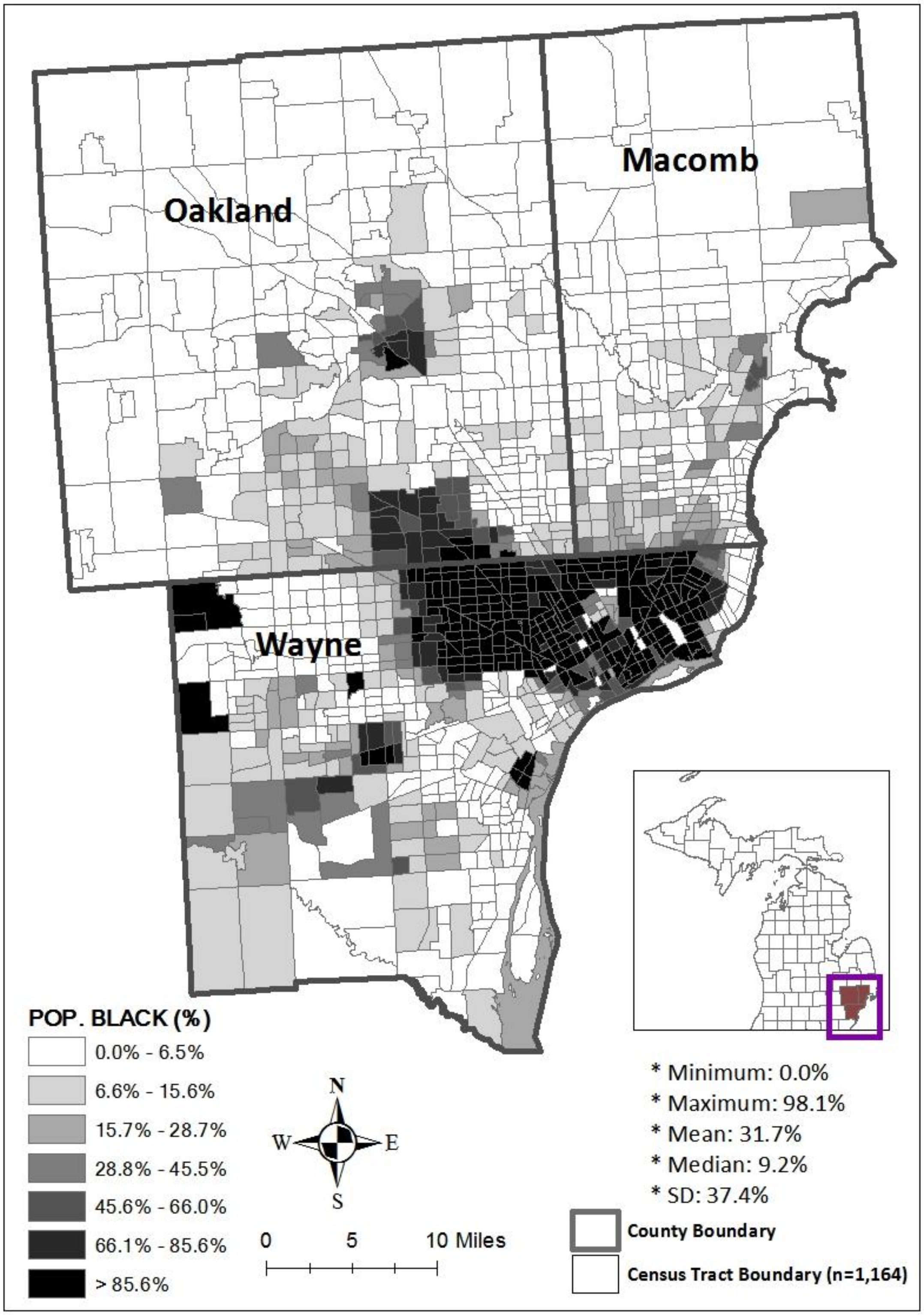

Figure 11. Proportion (%) of Black population by census tract, DMA (2010)

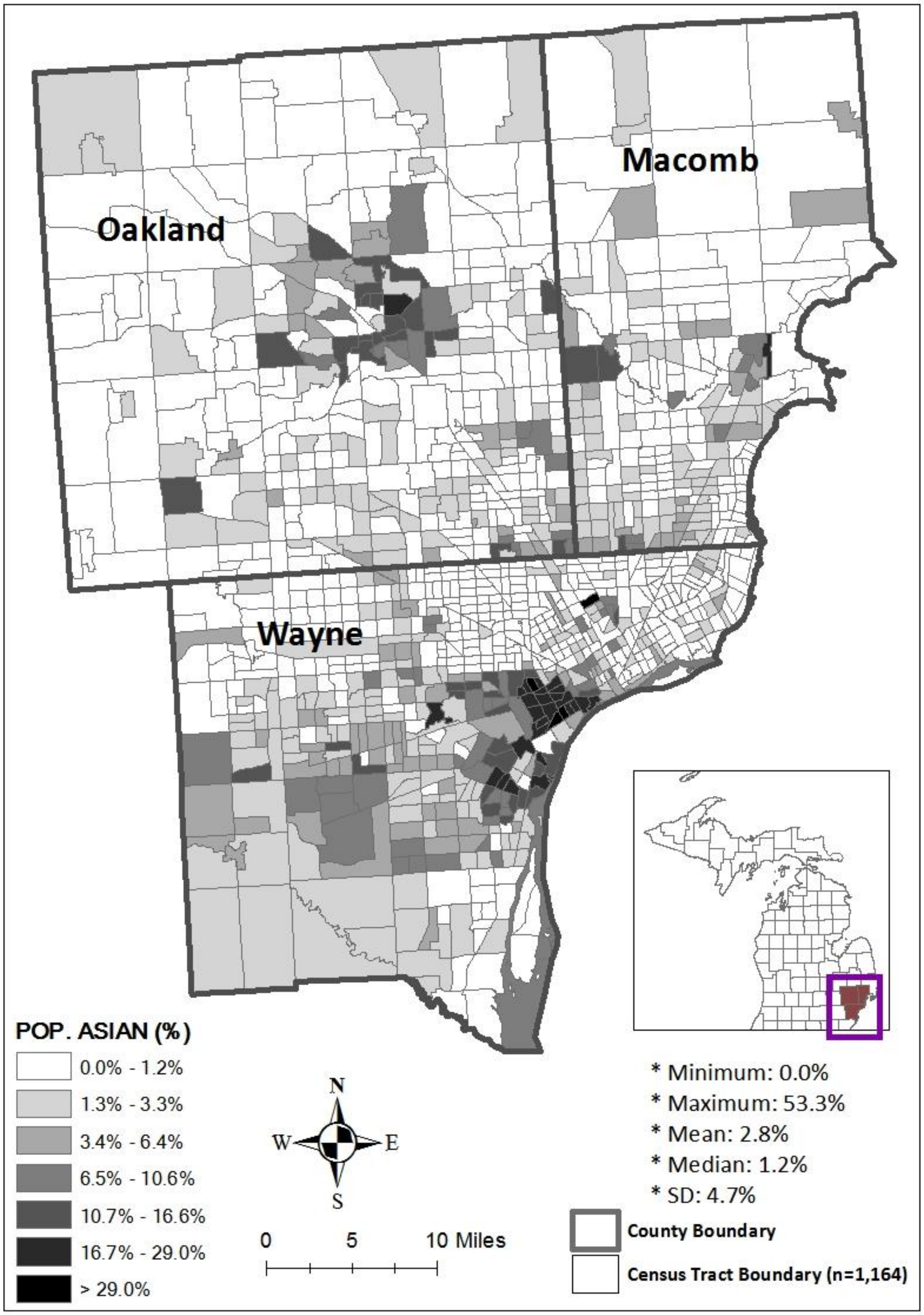

Figure 12. Proportion (%) of Asian population by census tract, DMA (2010)

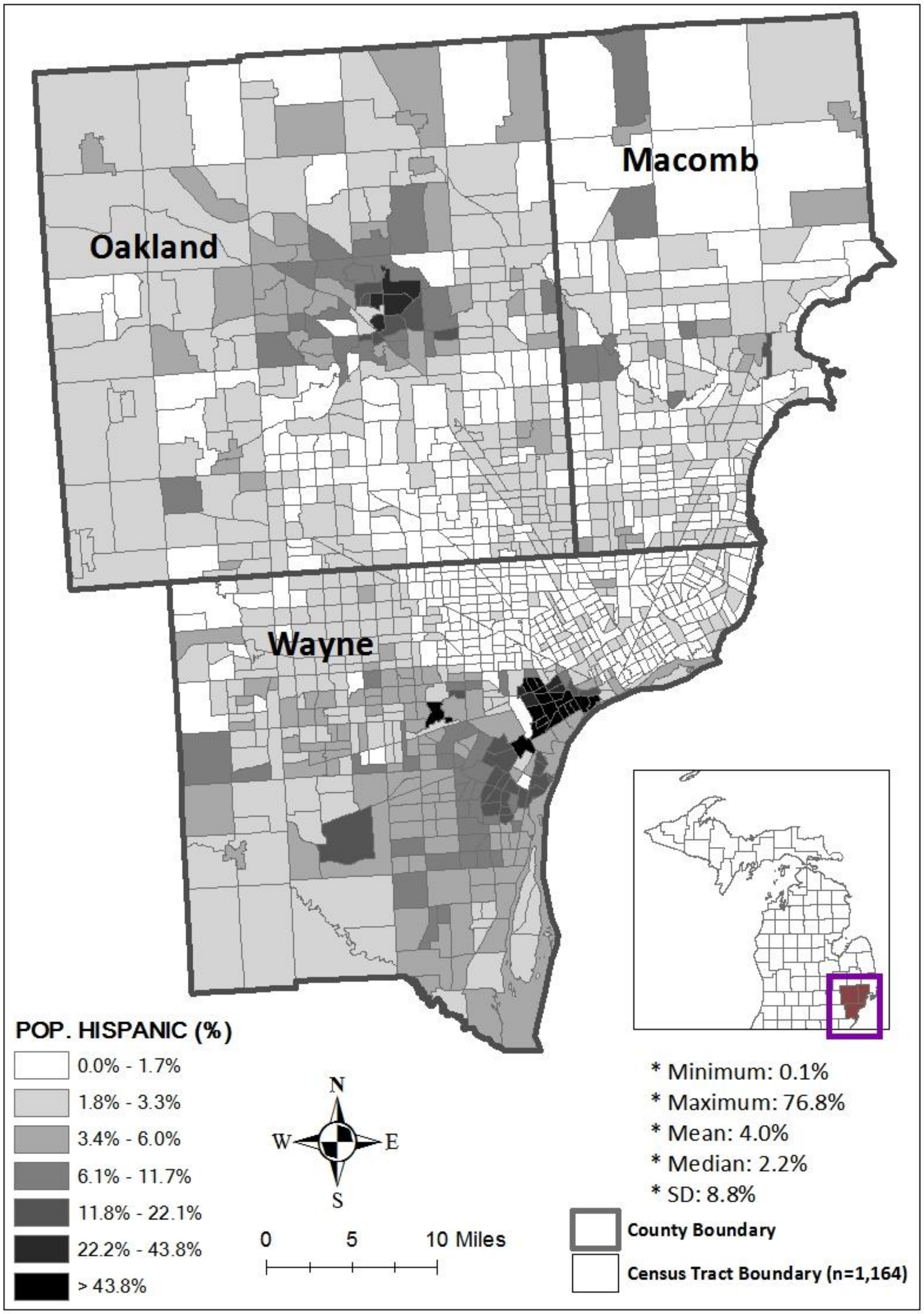

Figure 13. Proportion (%) of Hispanic population by census tract, DMA (2010)

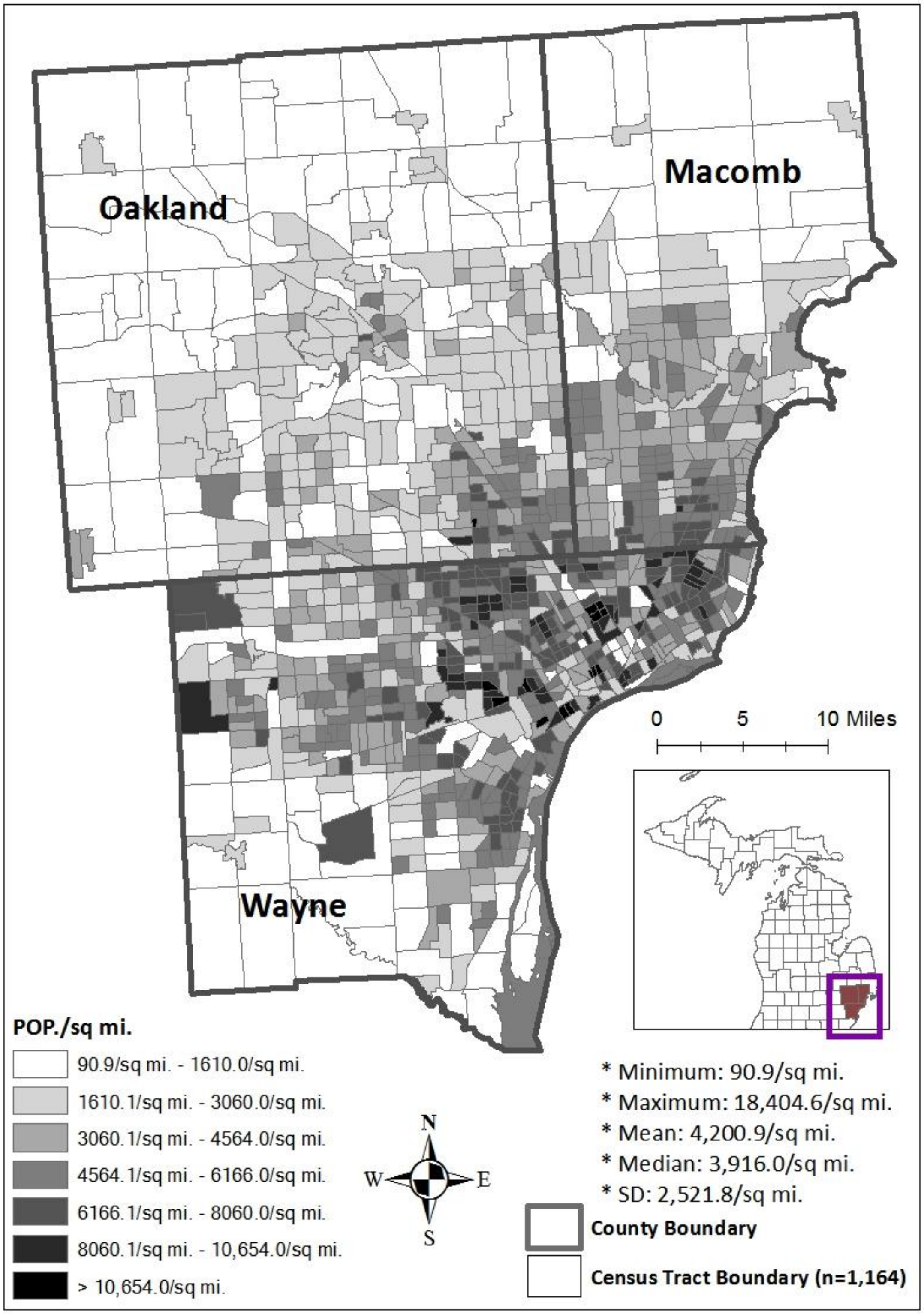

Figure 14. Population per square mile by census tract, DMA (2010)

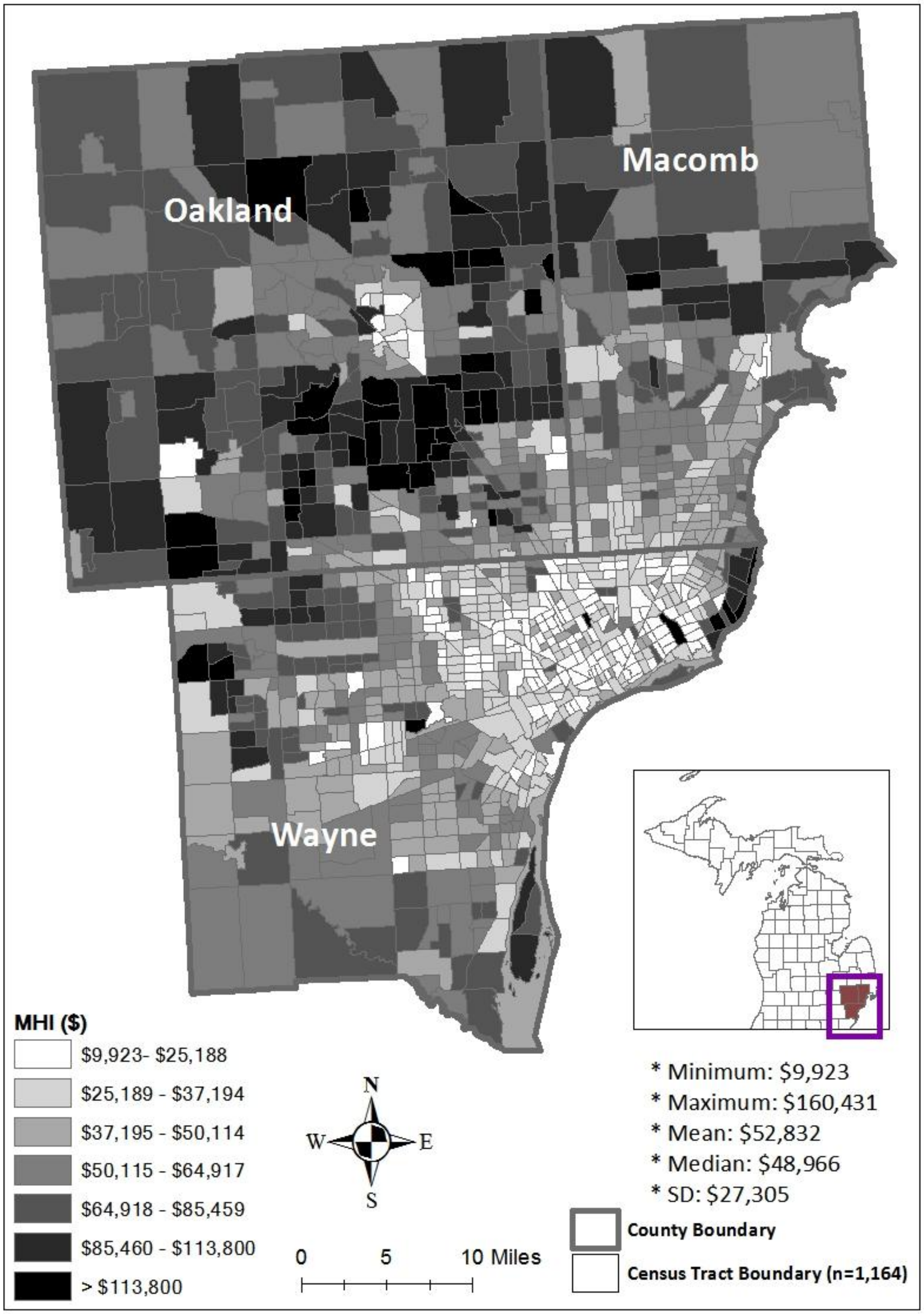

Figure 15. Median household income ($) by census tract, DMA (2010)

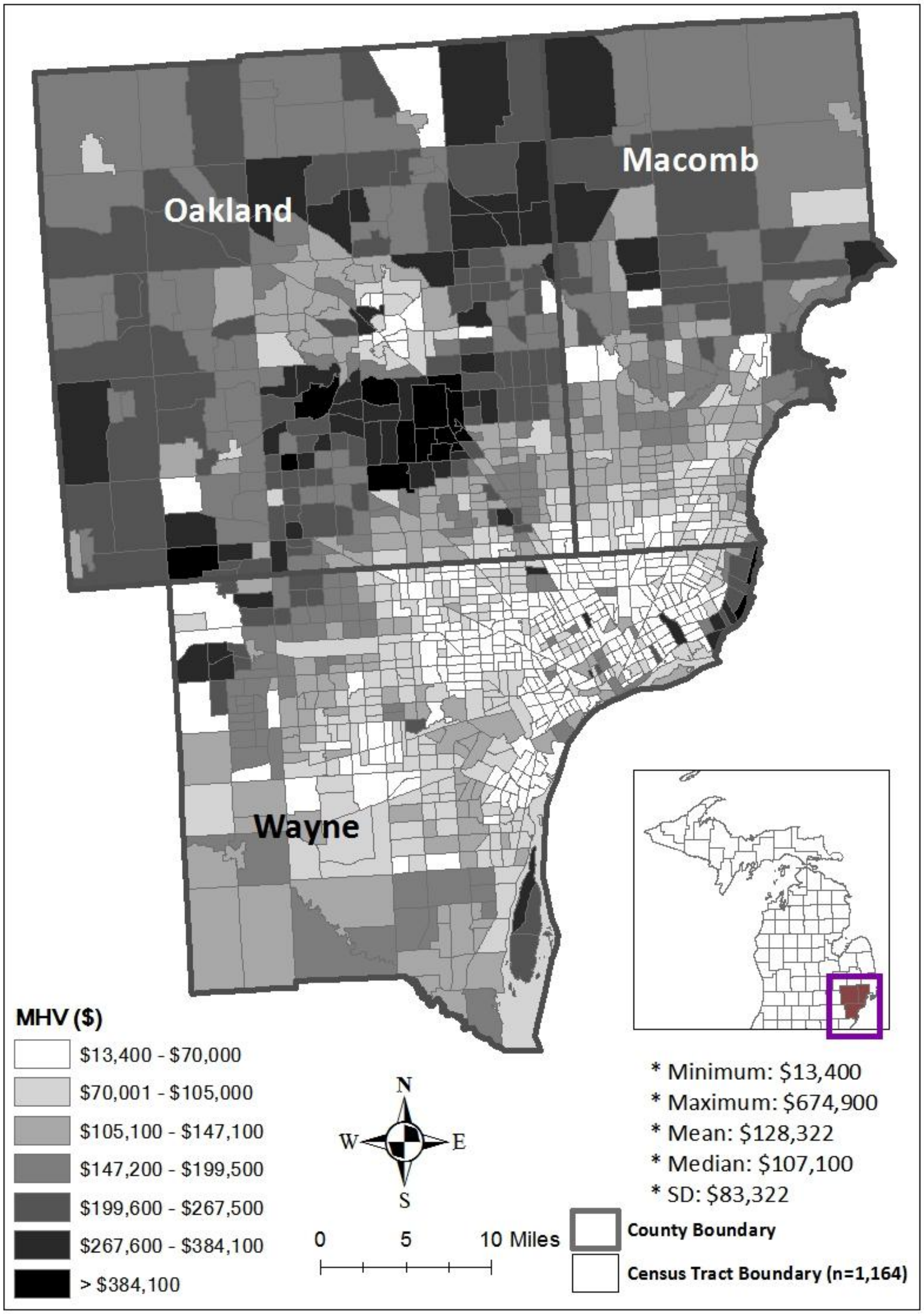

Figure 16. Median housing value ($) by census tract, DMA (2010)

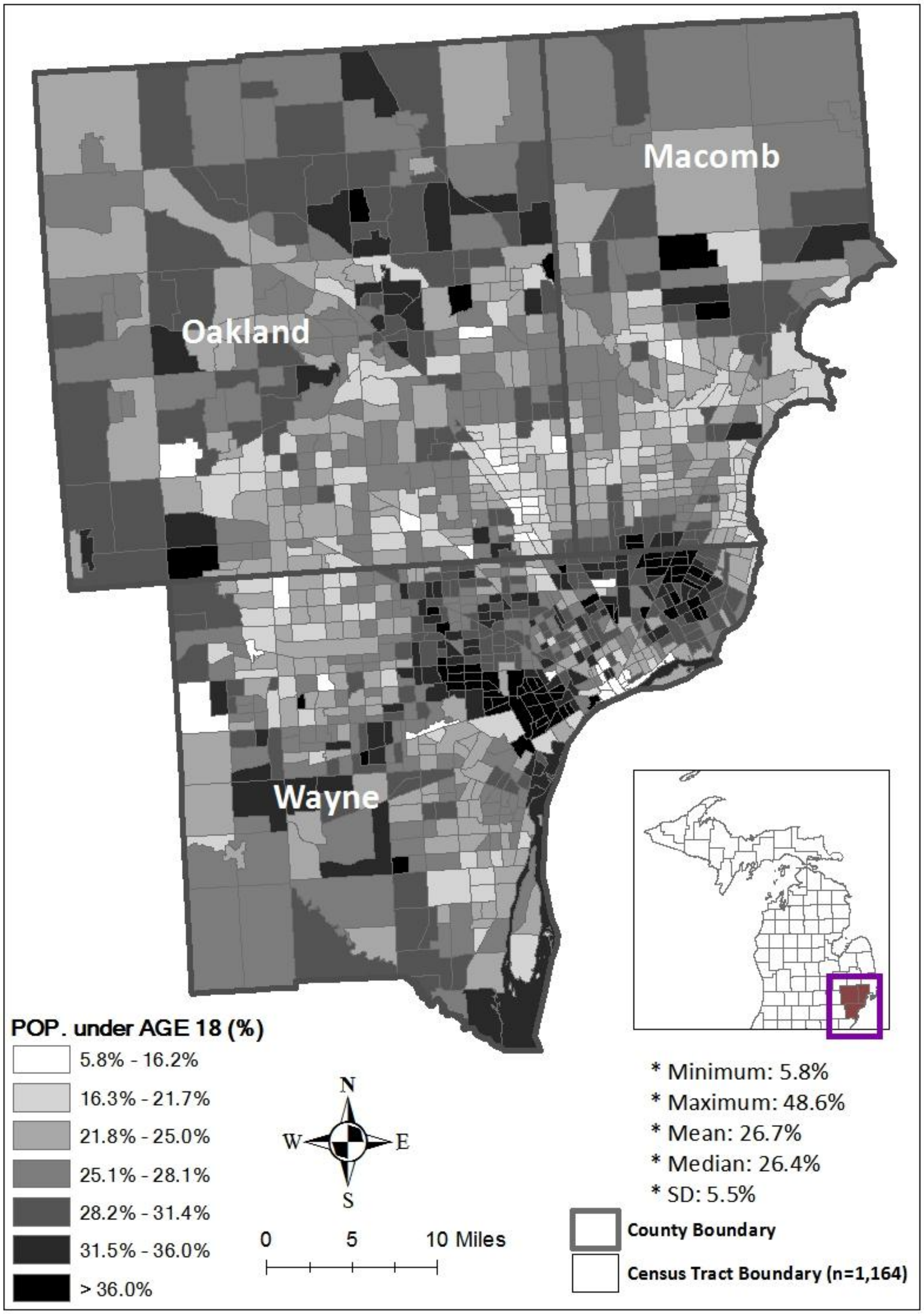

Figure 17. Proportion (%) of population under age 18 by census tract, DMA (2010)

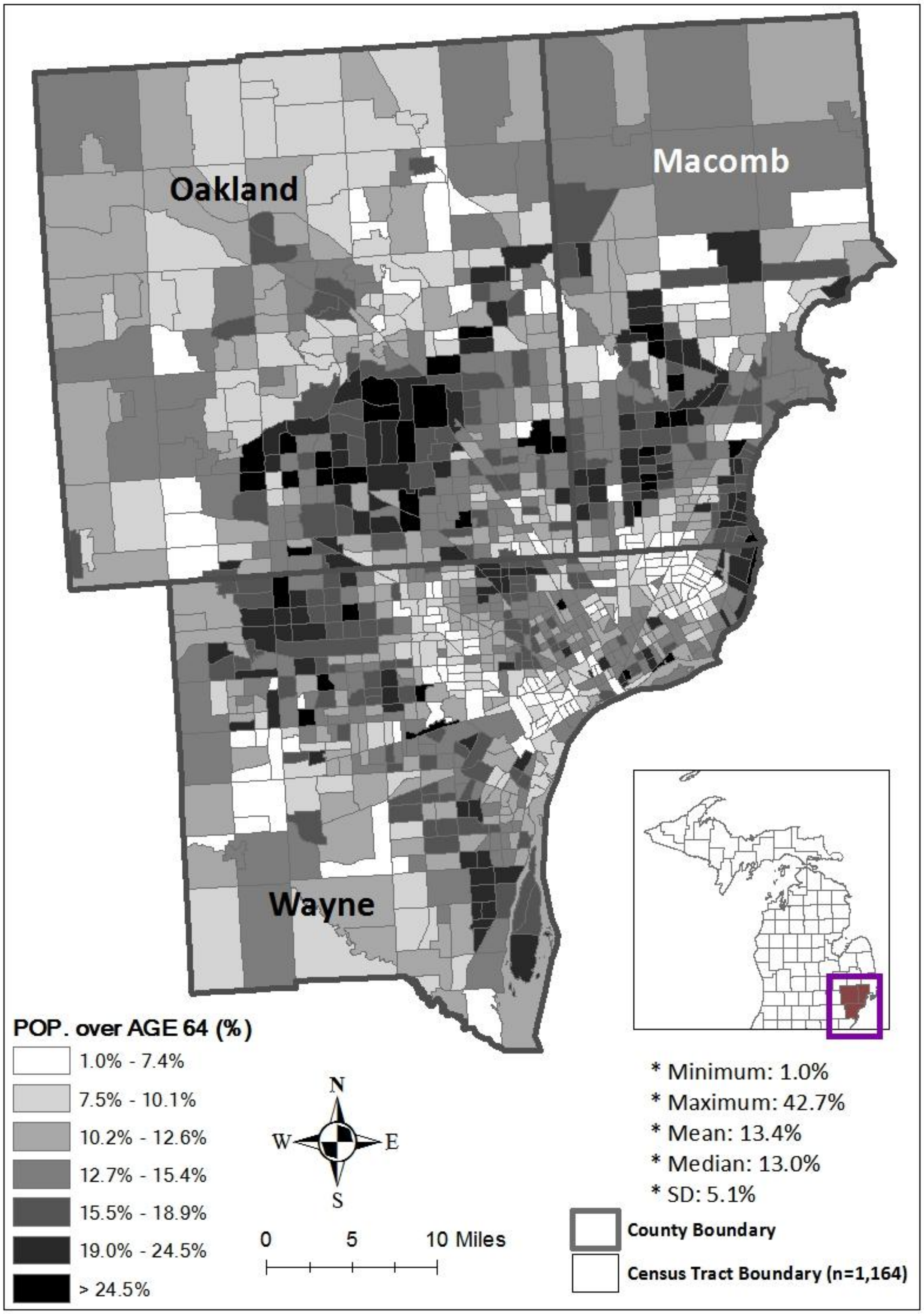

Figure 18. Proportion (%) of population over age 64 by census tract, DMA (2010)

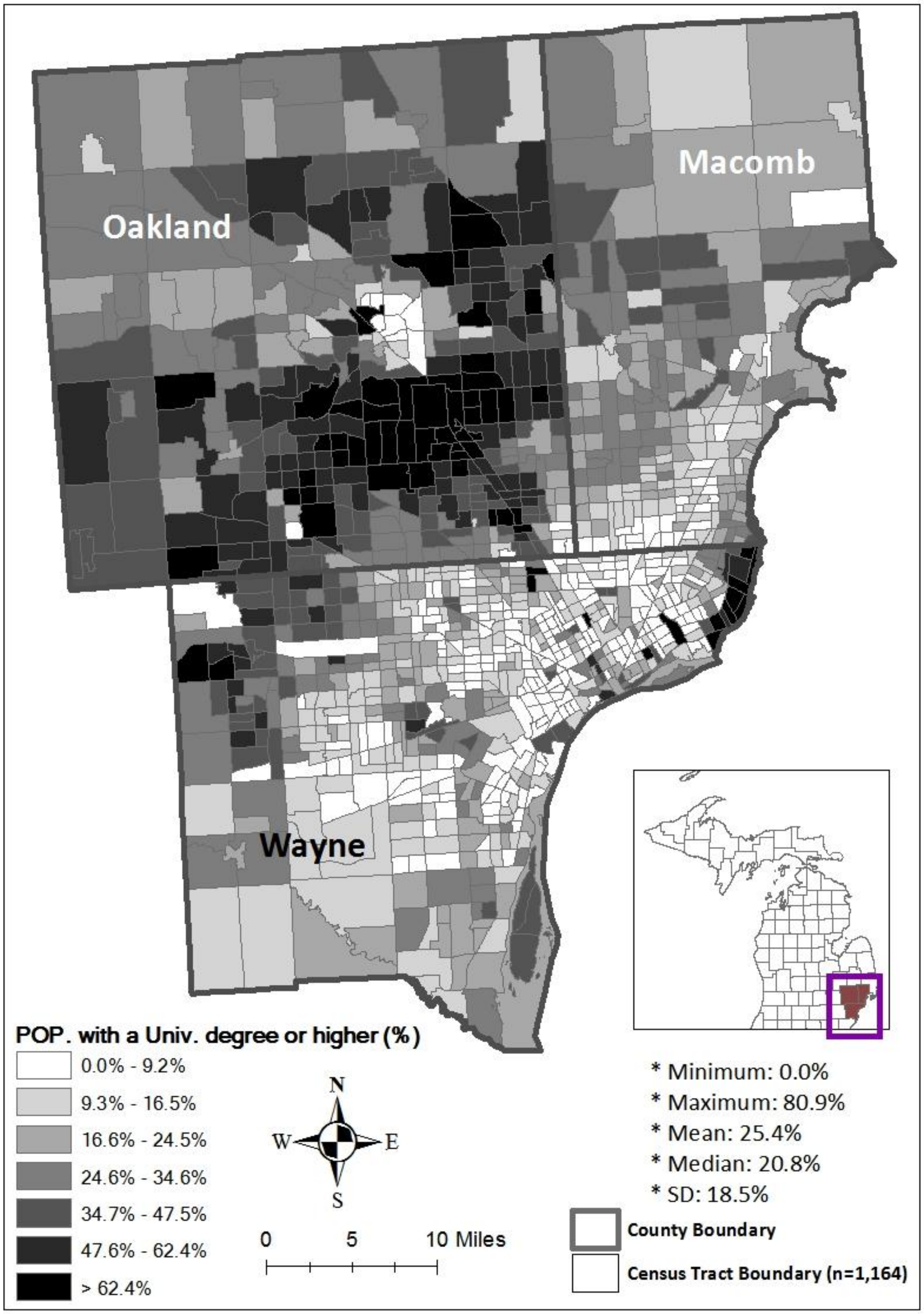

Figure 19. Proportion (%) of population with a four-year university degree or higher by census tract, DMA (2010)

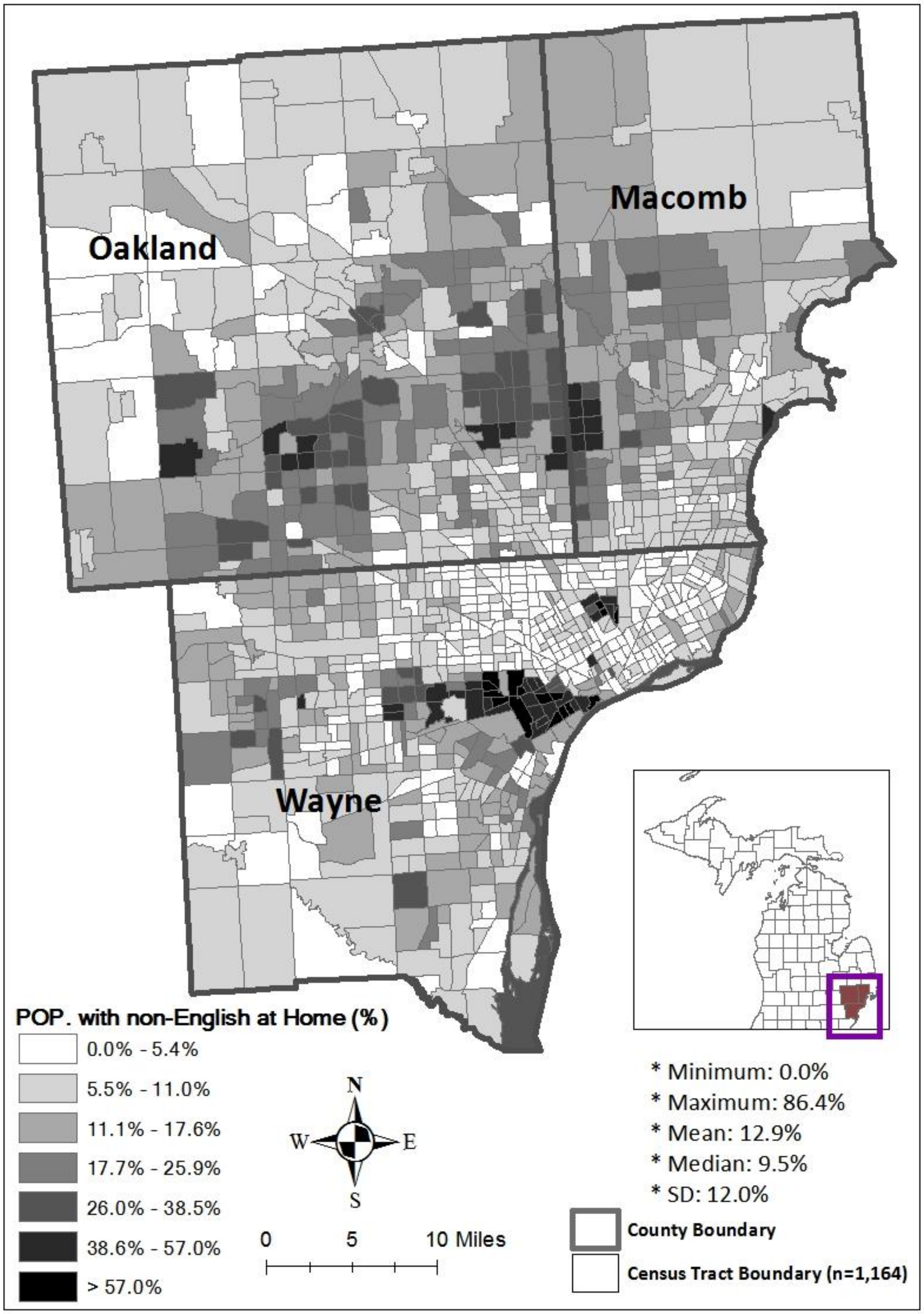

Figure 20. Proportion (%) of population with non-English spoken at home by census tract, DMA (2010)

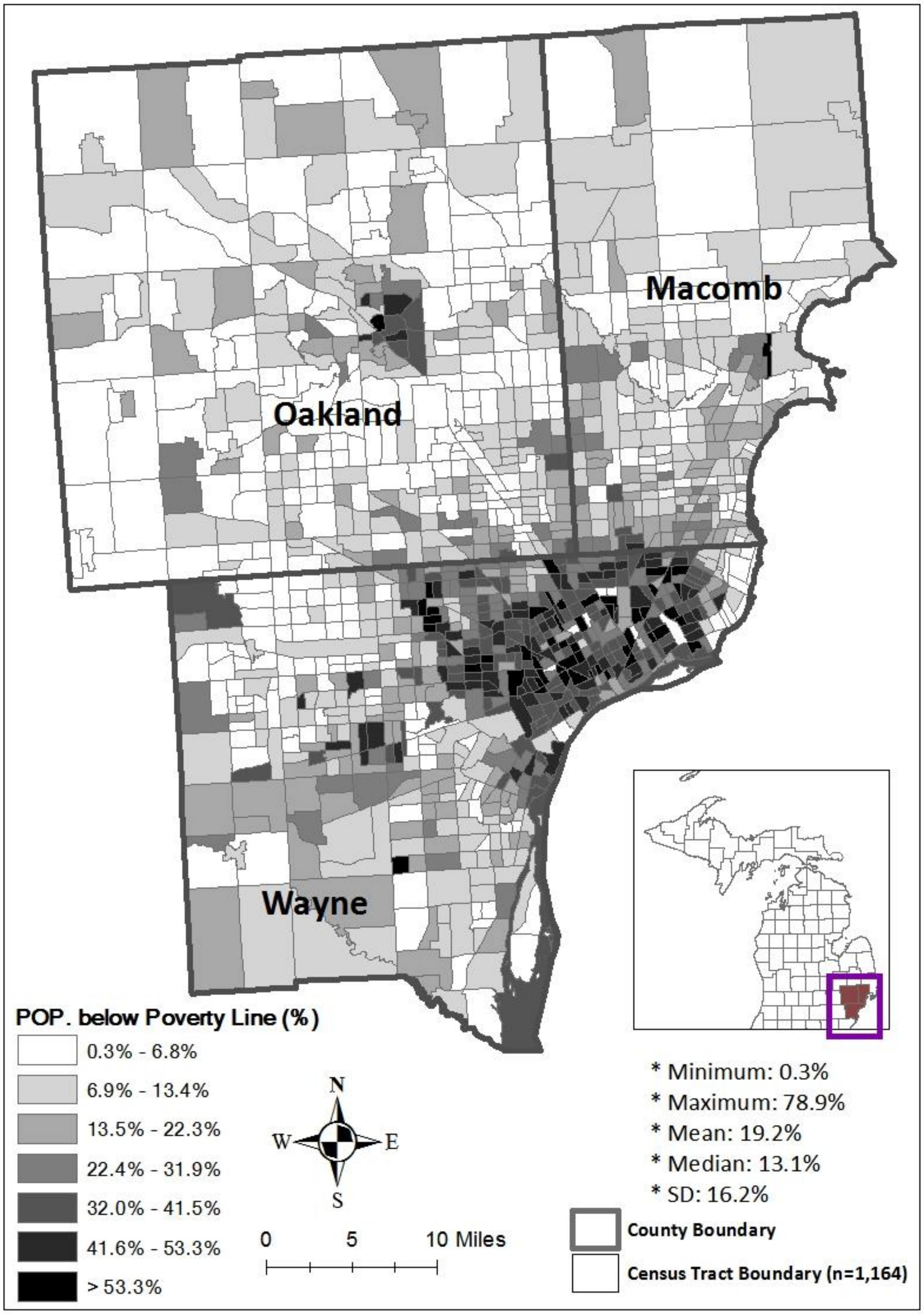

Figure 21. Proportion (%) of population below the poverty line by census tract, DMA (2010)

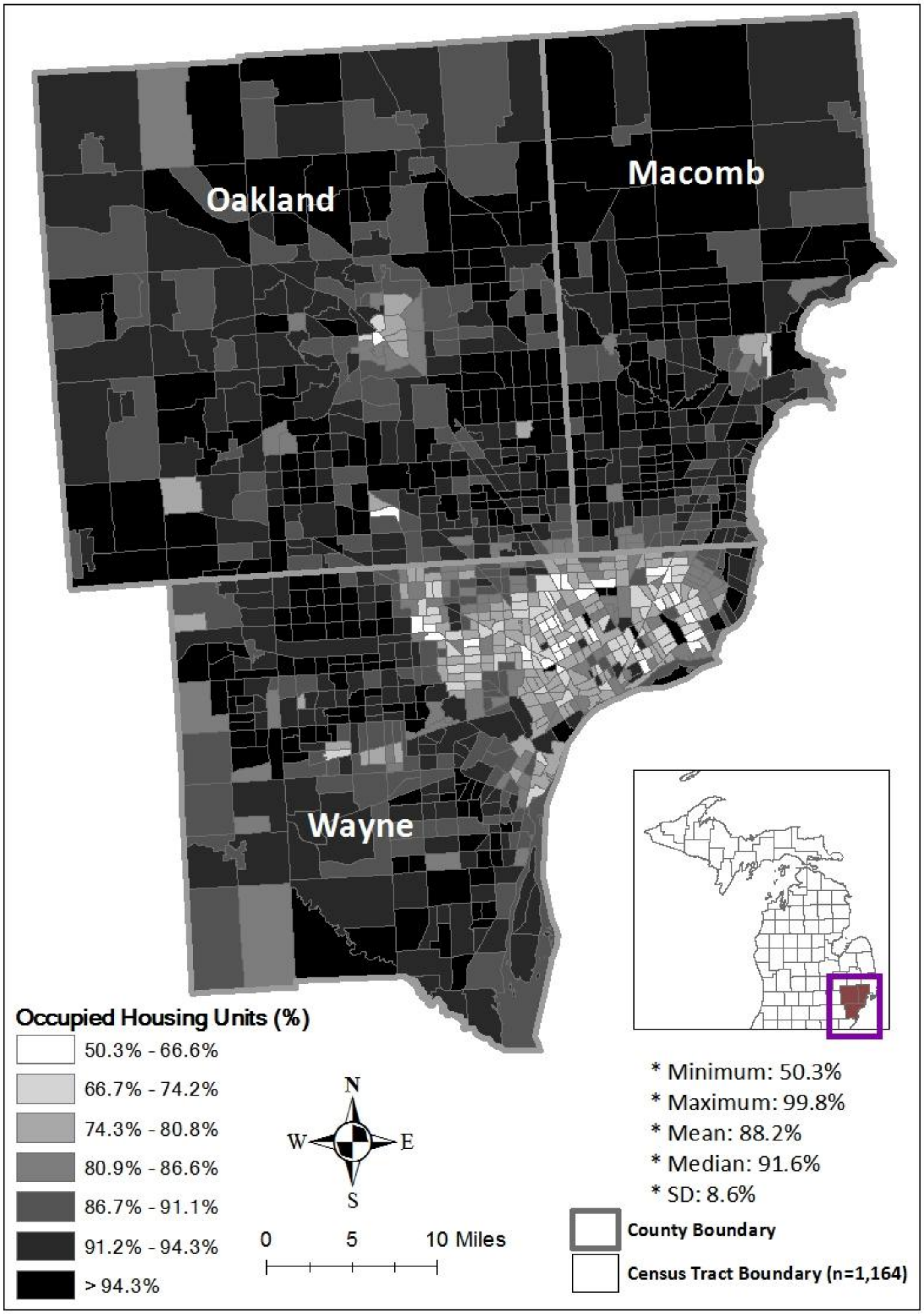

Figure 22. Proportion (%) of occupied housing units by census tract, DMA (2010)

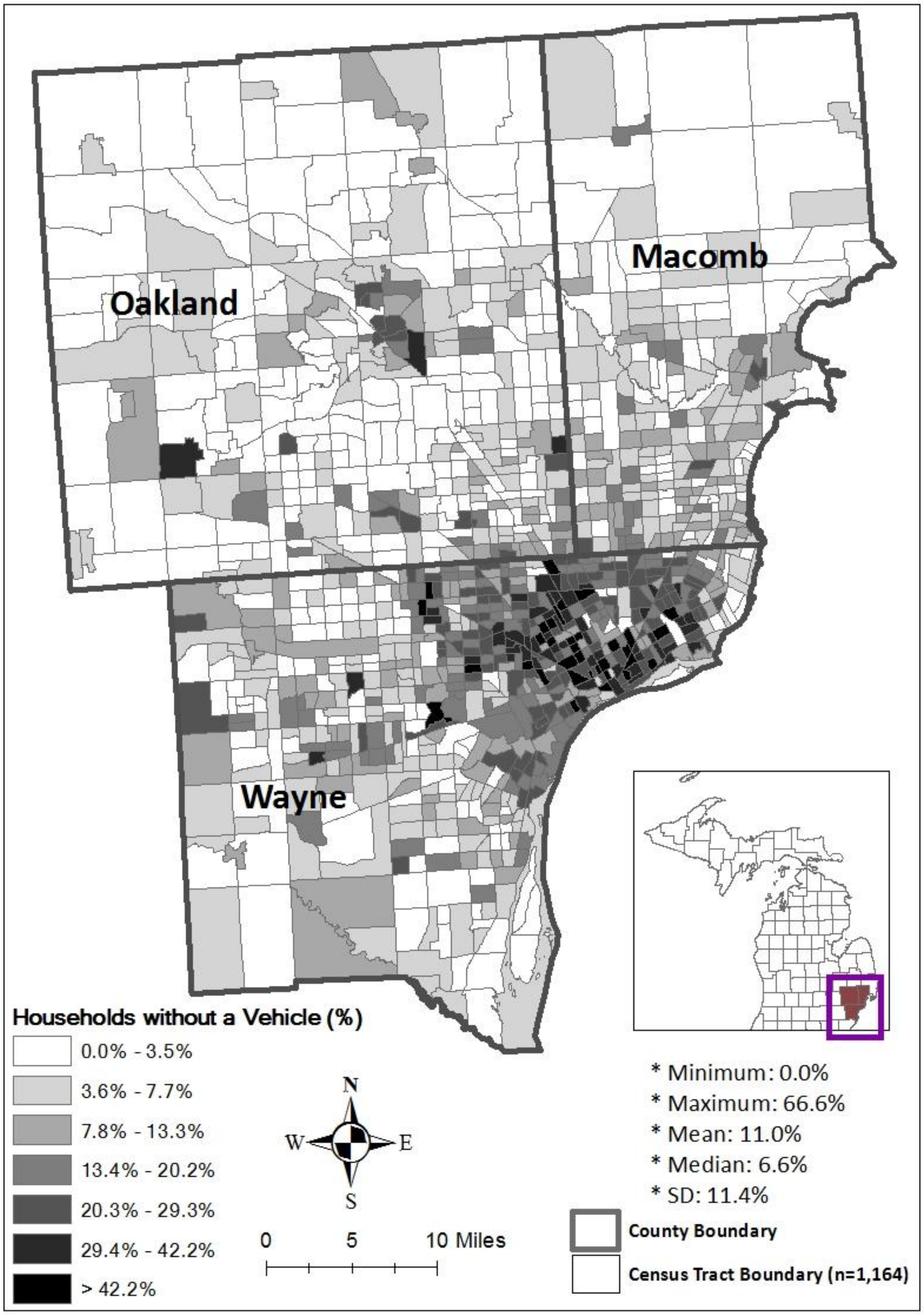

Figure 23. Proportion (%) of households without a vehicle by census tract, DMA (2010)

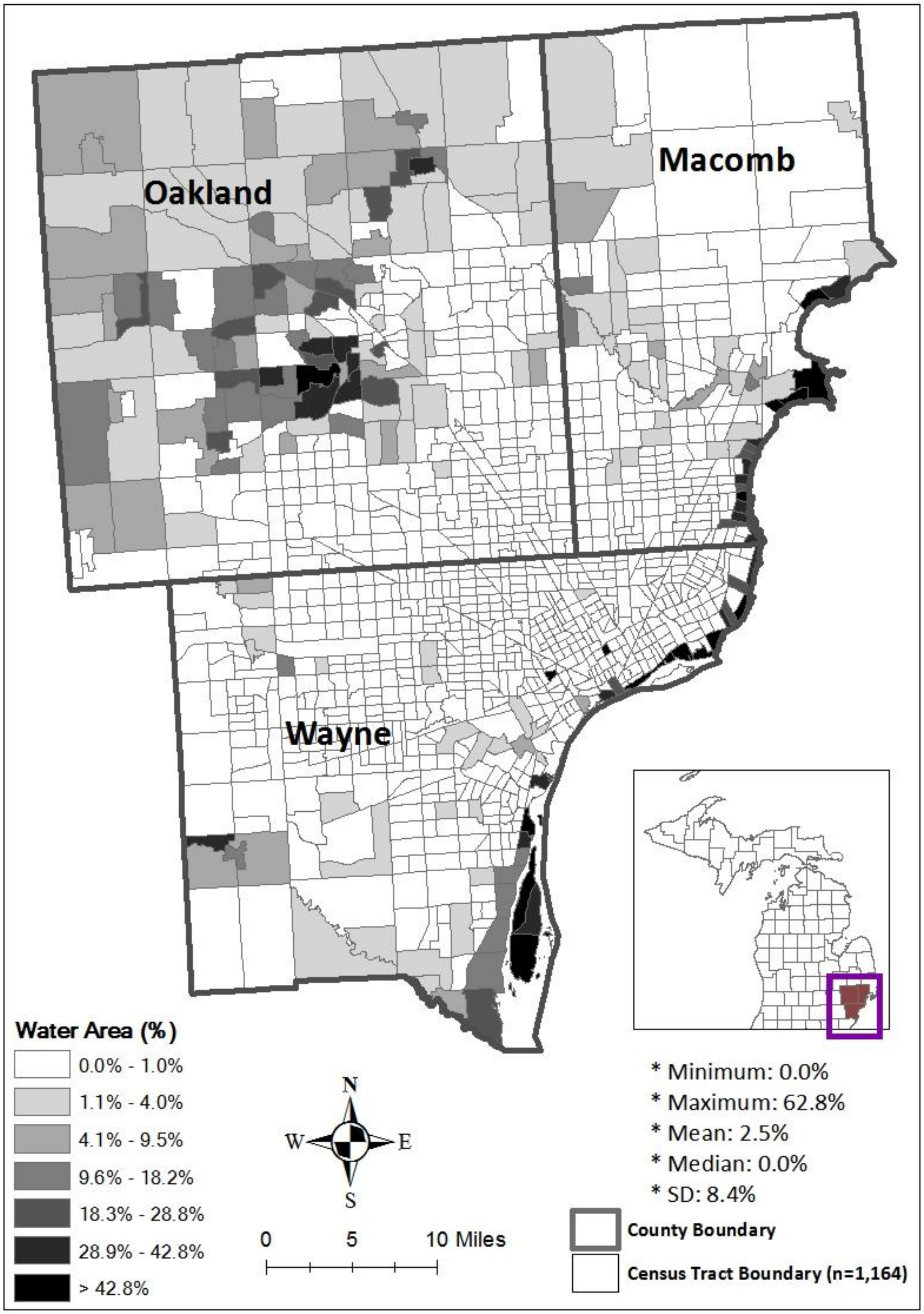

Figure 24. Proportion (%) of water area by census tract, DMA (2010)

Description of Correlation Matrix

Table 10 presents correlation results for the independent variables. Significant correlations (over 0.50) are summarized in Table 11. In this study, the WHITE (proportion of White population by census tract) variable was excluded for two reasons. First, the strongest correlation was between the proportions of WHITE and BLACK (proportion of Black population by census tract) in each census tract (-0.983, $p < 0.01$). The WHITE variable also showed high levels of correlation with five other economic variables (e.g., MHI: median household income by census tract [0.602, $p < 0.01$], MHV: median housing value by census tract [0.516, $p < 0.01$], ECON: proportion of population below the poverty line by census tract [-0.743, $p < 0.01$], HO: proportion of occupied housing units by census tract [0.762, $p < 0.01$], and VEHIC: proportion of households without a vehicle by census tract [-0.700, $p < 0.01$]). Second, the White population has not been recognized as a minority group in previous environmental justice studies. Therefore, the variable WHITE was excluded from further analysis.

Table 10.

Correlation matrix for independent variables

Variable	WHITE	BLACK	AISAN	HISPAN	POPD	MHI	MHV	AGE18	AGE64	EDU	LAN	ECON	HO	VEHIC	WATER
WHITE	1.00	-0.983**	-0.020**	0.034**	-0.417**	0.602**	0.516**	-0.332**	0.183**	0.435**	0.255**	-0.743**	0.762**	-0.700**	0.159**
BLACK	-0.983**	1.00	-0.098**	-0.149**	0.391**	-0.592**	-0.513**	0.290**	-0.141**	-0.442**	-0.376**	0.711**	-0.742**	0.682**	-0.141**
ASIAN	-0.020**	-0.098**	1.00	0.776**	0.391**	-0.592**	-0.513**	0.320**	-0.318**	-0.299**	0.471**	0.308**	-0.196**	0.131**	-0.057**
HISPAN	0.034**	-0.149**	0.776**	1.00	0.164**	-0.304**	-0.294**	0.259**	-0.224**	-0.199**	0.471**	0.177**	-0.137**	0.081**	-0.031
POPD	-0.417**	0.391**	0.164**	0.153**	1.00	-0.448**	-0.438**	0.246**	-0.154**	-0.333**	0.096**	0.423**	-0.333**	0.357**	-0.278**
MHI	0.602**	-0.592**	-0.304**	-0.164**	-0.448**	1.00	0.877**	-0.171**	0.180**	0.831**	0.153**	-0.764**	0.644**	-0.679**	0.157**
MHV	0.516**	-0.513**	0.294**	-0.168**	-0.438**	0.877**	1.00	-0.222**	0.233**	0.833**	0.192**	-0.611**	0.527**	-0.493**	0.202**
AGE18	0.159**	0.290**	0.320**	0.259**	-0.278**	0.157**	0.202**	1.00	-0.638**	-0.313**	0.203**	0.449**	-0.347**	0.166**	-0.171**
AGE64	-0.332**	-0.141**	-0.318**	-0.224**	0.246**	-0.171**	-0.222**	-0.638**	1.00	0.243**	-0.093**	-0.294**	0.266**	-0.060**	0.095**
EDU	0.183**	-0.442**	-0.299**	0.477**	-0.154**	0.160**	0.232**	0.203**	0.243**	1.00	0.198**	-0.626**	0.510**	-0.491**	-0.491**
LAN	0.435**	-0.376**	0.471**	-0.299**	-0.333**	0.831**	0.833**	0.133**	-0.093**	0.198**	1.00	-0.027**	0.168**	-0.149**	-0.045**
ECON	0.255**	0.711**	0.308**	0.177**	0.096**	0.153**	0.192**	0.449**	-0.294**	-0.626**	-0.027	1.00	-0.787**	0.790**	-0.146**
HO	-0.743**	-0.742**	-0.196**	-0.137**	0.423**	-0.764**	-0.611**	-0.347**	0.266**	0.510**	0.168**	-0.787**	1.00	-0.720**	0.075*
VEHIC	0.762**	0.682**	0.131**	-0.196**	-0.333**	0.644**	0.527**	0.075*	-0.060**	-0.491**	-0.149**	0.790**	-0.720**	1.00	-0.122**
WATER	-0.700**	-0.141**	-0.057**	-0.031**	0.357**	-0.679**	-0.493**	-0.171**	0.095**	0.133**	-0.045	-0.146**	0.075*	-0.122**	1.00

Note: **: correlation is significant at the 0.01 level (2-tailed); * correlation is significant at the 0.05 level (2-tailed)

Table 11.

Summary of correlations (over 0.50) for independent variables

Variable	WHITE	BLACK	ASIAN	HISPAN	MHI	MHV	AGE18	AGE64	EDU	ECON	HO	VEHIC	WATER
WHITE	1.0	--			+	+				-	++	-	
BLACK	--	1.0			-	-				+	-	+	
ASIAN			1.0	++		-							
HISPAN			++	1.0									
MHI	+	-			1.0	++			++	--	+	-	
MHV	+	-			++	1.0			++	-	+		
AGE18							1.0	-					
AGE64							-	1.0					
EDU									1.0	-	+		
ECON		+							-	1.0	--	++	
HO	-	-			-	-			+	--	1.0	-	
VEHIC	++	+			+	+				++	-	1.0	
WATER	-				-								1.0

Note: + indicates positive correlation > 0.50 and < 0.75; ++ indicates positive correlation > 0.75; - indicates negative correlation > 0.50 and < 0.75; -- indicates negative correlation > 0.75

Addressing the Objectives and Research Questions

Objective One (O1): Assessing the Spatial Distribution of Public Beaches and Determining Levels of Access to Public Beaches in the DMA

The first objective of the study was to (1) assess the spatial distribution of public beaches and (2) determine levels of access to public beaches in the DMA. This objective included four research questions; findings related to these are discussed below.

O1R1: "What is the central tendency of the public beach distribution in the DMA?" The mean and median centers of the distribution of public beaches are shown in Figure 25. Both the mean and the median center are located in Waterford township, Oakland County, though the mean center is located approximately 0.5 miles north of the median center.

As also seen in Figure 25, the mean and median centers of the study area are located in the cities of Oak Park, Oakland County (mean center) and Detroit, Wayne County (median center), while the mean and median centers of the distribution of public beaches are located about 17.1 miles northwest of these points. These findings confirm the visual suggestion that public beaches in the DMA are concentrated in the northwest of the study area.

O1R2: "How and to what extent are the public beaches dispersed?" The standard distance and the standard deviational ellipse were identified to measure the degree of beach dispersion; these also are shown in Figure 25. The majority of the public beaches in the DMA (n=168, 94.3%) are concentrated in Oakland County. More than one third of the census tracts in Oakland County are located within the standard distance (n=145, 38.9%) and the standard deviational ellipse (n=138, 37.0%) of the 178 public beaches, while none of either Macomb or Wayne Counties falls within these areas. The standard deviational ellipse indicated a northeastward shift in the distribution's mean center and standard distance. These findings again imply that public beaches in the DMA are spatially concentrated in Oakland County.

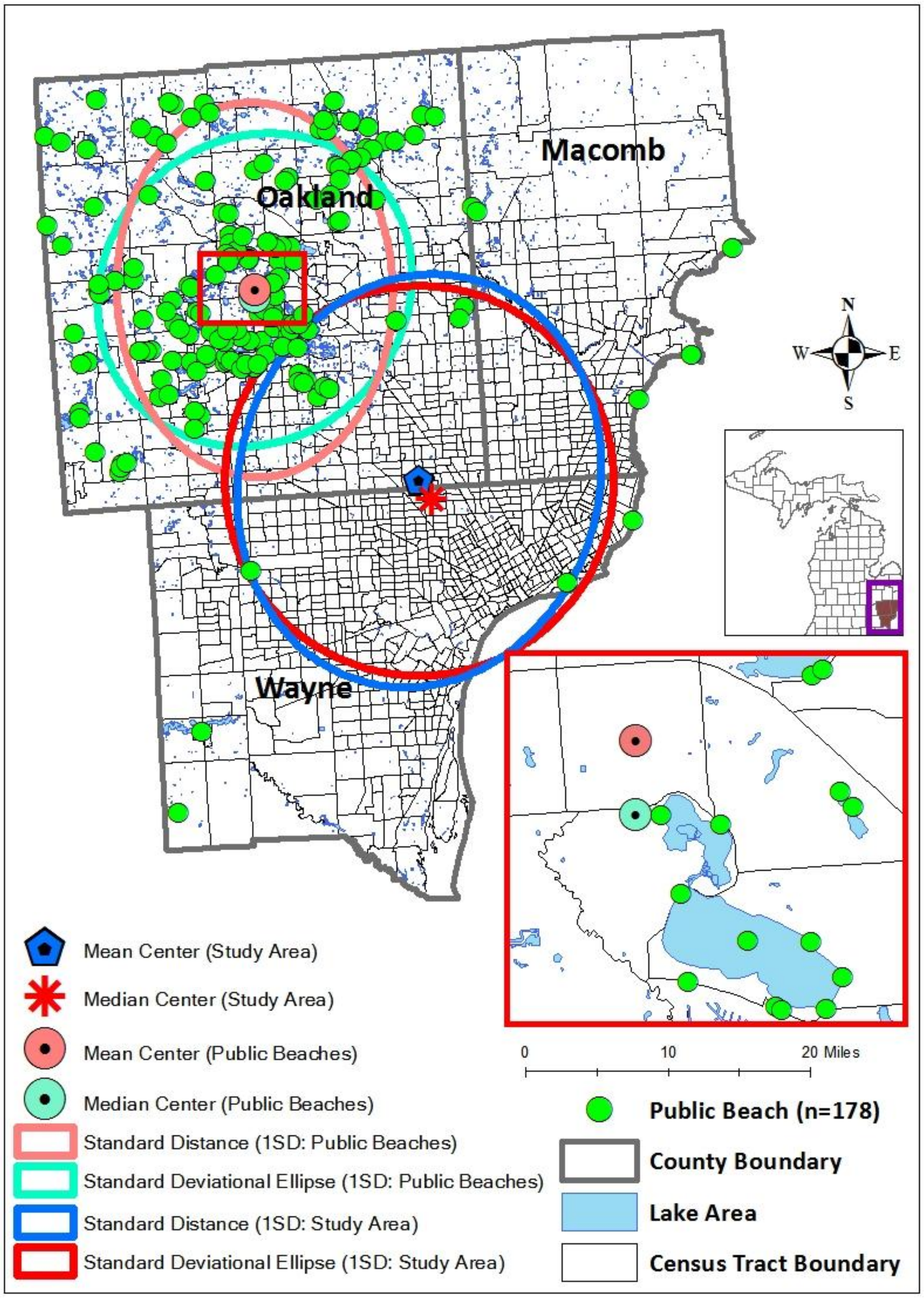

Figure 25. Spatial characteristics of public beach distribution (central tendency and dispersion)

O1R3: "Are the public beaches in the DMA spatially clustered?" The nearest neighbor ratio (NNR) and K-value [L(d)] were calculated to identify the extent of spatial clustering of public beaches. NNR results showed that the spatial distribution of public beaches is significantly clustered (NNR: 0.52; z-score: -12.12; $p < 0.01$) (Table 12).

Table 12.

Summary of nearest neighbor analysis

Observed mean distance	Expected mean distance	NNR	z-score	p-value
0.01	0.03	0.52	-12.12	< 0.01

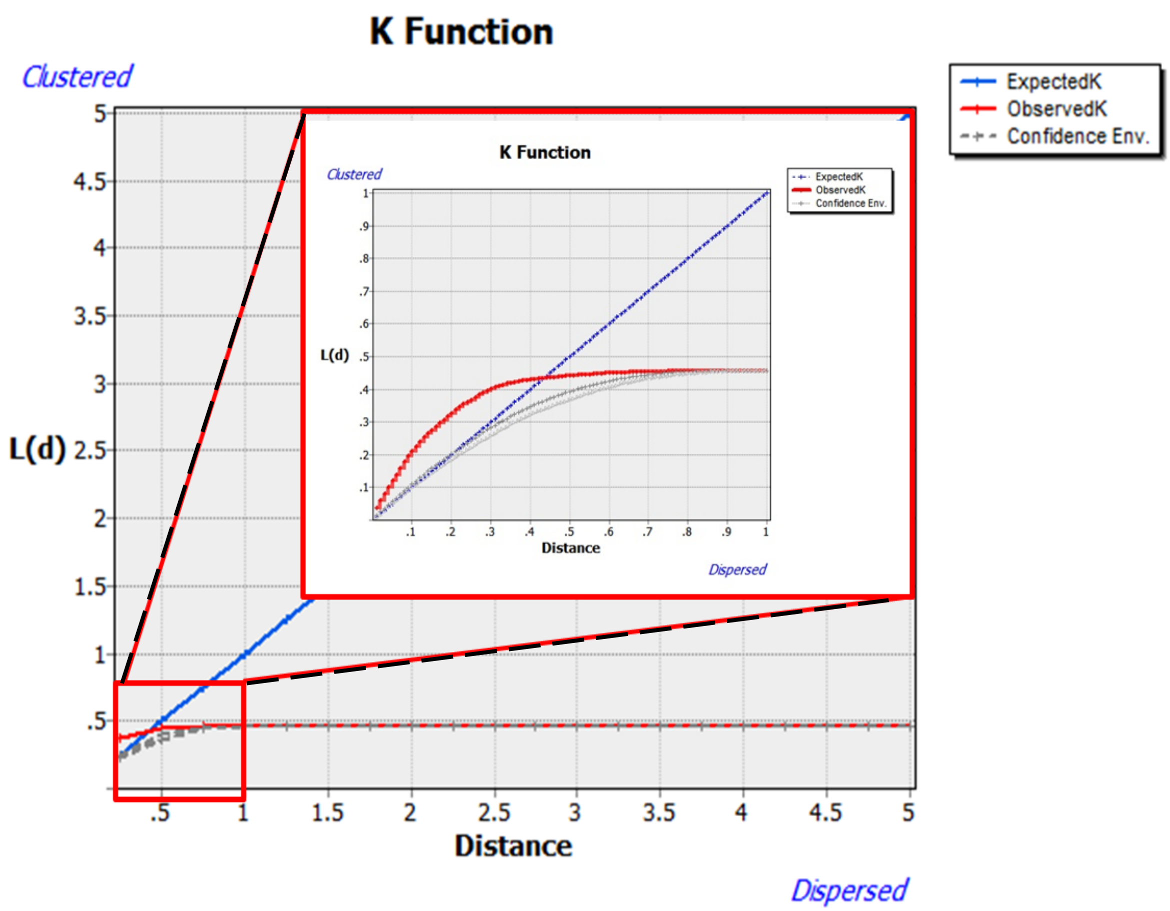

Figure 26. The value of L(d) over a range of distances

Table 13.

The value of L(d) over a range of distances

Distance (mile)	Observed L(d)	Difference (L[d]) (observed – expected)	Minimum L(d) (lower confidence level)	Maximum L(d) (upper confidence level)
0.01	0.04	0.03	0.01	0.02
0.10	0.21	0.11	0.10	0.11
0.13	0.25	0.12	0.13	0.14
0.14	0.27	0.13	0.13	0.15
0.22	0.35	0.13	0.20	0.22
0.23	0.35	0.12	0.21	0.23
0.26	0.38	0.12	0.23	0.25
0.27	0.38	0.11	0.23	0.26
0.30	0.40	0.10	0.25	0.28
0.35	0.41	0.07	0.29	0.32
0.40	0.42	0.03	0.32	0.35
0.42	0.43	0.01	0.33	0.36
0.43	0.44	0.00	0.33	0.37
0.44	0.44	0.00	0.34	0.37
0.45	0.44	-0.01	0.34	0.38
0.50	0.44	-0.06	0.37	0.40
0.60	0.45	-0.15	0.40	0.43
0.70	0.45	-0.25	0.43	0.45
0.80	0.45	-0.34	0.45	0.45
1.00	0.46	-0.54	0.46	0.46

Note: K-function was calculated by 999 Monte Carlo permutation with statistical significance at the level of .05.

Figure 26 and Table 13 show the value of L(d) over a range of distances. All observed L(d) values were greater than the expected L(d) values and than the upper confidence bands between 0.0 and 0.42 miles (radius distance) of the circles centered on each public beach, while all observed L(d) values were less than the expected L(d) values but greater than the upper confidence bands between 0.45 and 0.60 miles of the circles centered on each public beach. These findings indicate evidence of significant clustering between 0.0 and 0.42 miles and significant dispersion between 0.45 and 0.60 miles. The highest degree of clustering appears at the range of distance between 0.14 and 0.22 miles while the highest degree of dispersion appears at a distance of 0.60 miles. These findings indicate that public beaches in the DMA exhibit statistically significant clustering and dispersion at different distances.

O1R4: "How is access to public beaches distributed across the DMA?" This section is divided into two parts. First, the influence of the edge effect was assessed. Second, the two access measures were computed and compared.

The influence of the edge effect. Table 14 shows the results of the two measures of access to public beaches, with and without the additional 59 public beaches outside of the DMA. For the container approach, the number of beaches within 20 miles of each tract centroid is illustrated in increments of 10 beaches. For the minimum distance approach, distance to the nearest public beach is illustrated in increments of one mile. The correlations between the level of access to public beaches with and without the additional 59 public beaches for each of the access measures were both 0.998 (p-value <0.01). These findings indicate that no edge effect exists and the additional 59 public beaches were, therefore, excluded from further analysis.

Level of access to public beaches. The two sets of access results for public beaches in the DMA are displayed in Figure 27 (the container approach) and 28 (the minimum distance approach). According to the container approach, the number of public beaches accessible within a 20-mile journey from each tract centroid ranged from 0 (Grosse Ile township, Wayne County) to 161 (Waterford township, Oakland County), with a mean of 45.1 beaches per census tract. The residents of just over half of the census tracts (n=611, 52.4%) can reach up to 20 beaches within 20 miles (49.6% of the DMA's population); the residents of the other half of the census tracts (n=553, 47.6%) can access more than 20 beaches within 20 miles (50.4% of the DMA's population).

Table 14.

Results of network analysis

	The container approach				The minimum distance approach				
Number of public beaches	Without additional 59 public beaches outside of the DMA (N=178)		With additional 59 public beaches outside of the DMA (N= 237)		Minimum distance (D) to the nearest public beach (mile)	Without additional 59 public beaches outside of the DMA (N= 178)		With additional 59 public beaches outside of the DMA (N= 237)	
	Number of CT (n=1,164)	%	Number of CT (n=1,164)	%		Number of CT (n=1,164)	%	Number of CT (n=1,164)	%
0-10	447	38.4	447	38.4	$0.0 \le D < 1.0$	51	4.3	51	4.3
11-20	164	14.0	163	14.0	$1.0 \le D < 2.0$	60	5.1	60	5.1
21-30	66	5.6	67	5.7	$2.0 \le D < 3.0$	101	8.6	101	8.6
31-40	54	4.6	54	4.6	$3.0 \le D < 4.0$	93	7.9	93	7.9
41-50	35	3.0	34	2.9	$4.0 \le D < 5.0$	118	10.1	118	10.1
51-60	37	3.1	35	3.0	$5.0 \le D < 6.0$	106	9.1	106	9.1
61-70	30	2.5	31	2.6	$6.0 \le D < 7.0$	95	8.1	95	8.1
71-80	37	3.1	36	3.0	$7.0 \le D < 8.0$	92	7.9	92	7.9
81-90	32	2.7	29	2.4	$8.0 \le D < 9.0$	94	8.0	94	8.0
91-100	32	2.7	34	2.9	$9.0 \le D < 10.0$	92	7.9	92	7.9
101-110	33	2.8	28	2.4	$10.0 \le D < 11.0$	66	5.6	66	5.6
111-120	40	3.4	43	3.6	$11.0 \le D < 12.0$	69	5.9	69	5.9
121-130	52	4.4	46	3.9	$12.0 \le D < 13.0$	51	4.3	52	4.4
131-140	34	2.9	35	3.0	$13.0 \le D < 14.0$	20	1.7	22	1.8
141-150	31	2.6	29	2.4	$14.0 \le D < 15.0$	13	1.1	14	1.2
151-160	39	3.3	40	3.4	$15.0 \le D < 16.0$	16	1.3	15	1.2
> 160	1	0.0	13	1.1	$16.0 \le D < 17.0$	10	0.8	10	0.8
					$17.0 \le D < 18.0$	6	0.5	5	0.4
					$18.0 \le D < 19.0$	6	0.5	5	0.4
					$19.0 \le D < 20.0$	2	0.1	1	0.0
					$D \ge 20$	3	0.2	3	0.2

Note. N: total number; CT: census tract

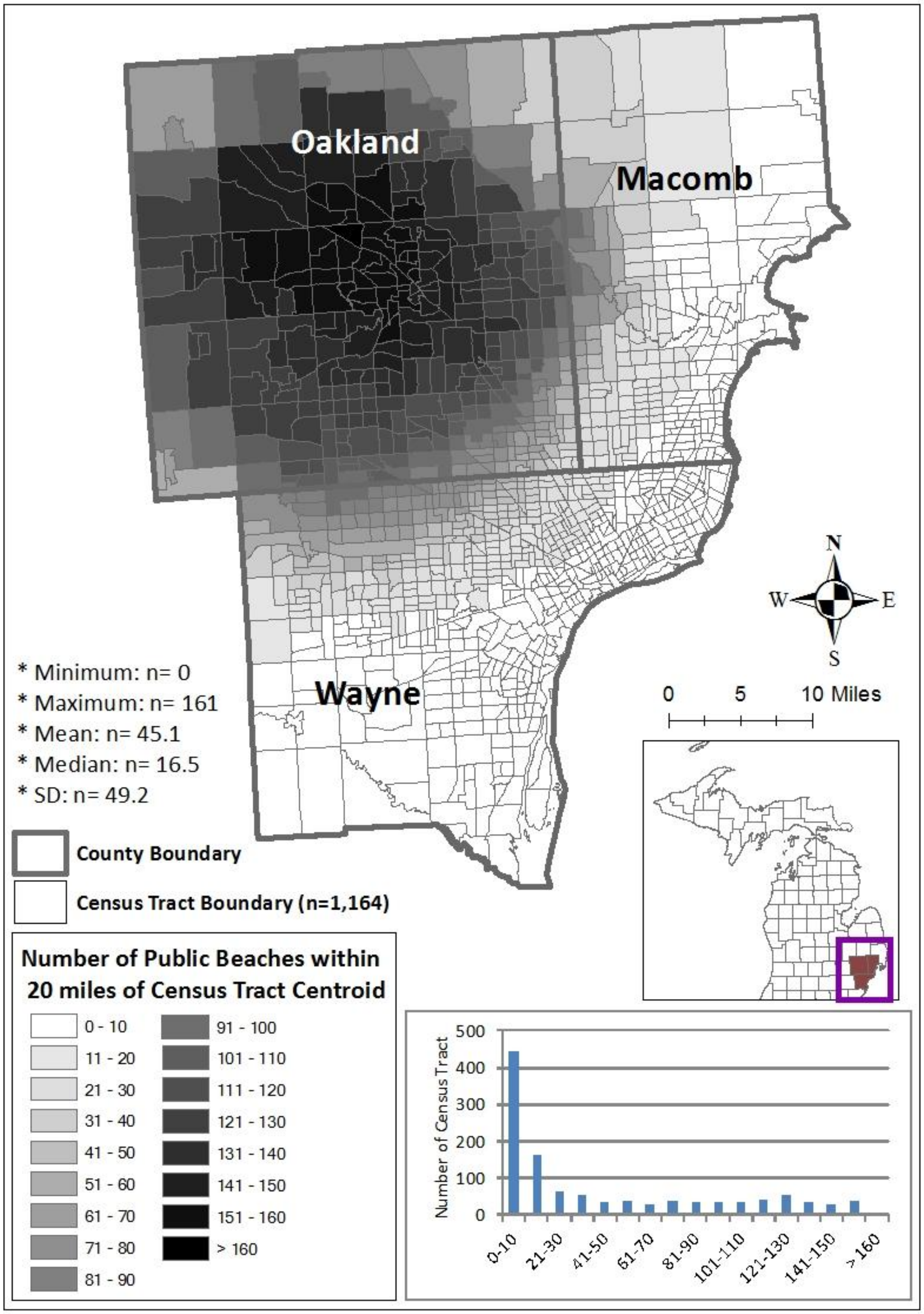

Figure 27. Level of access to public beaches according to the container approach

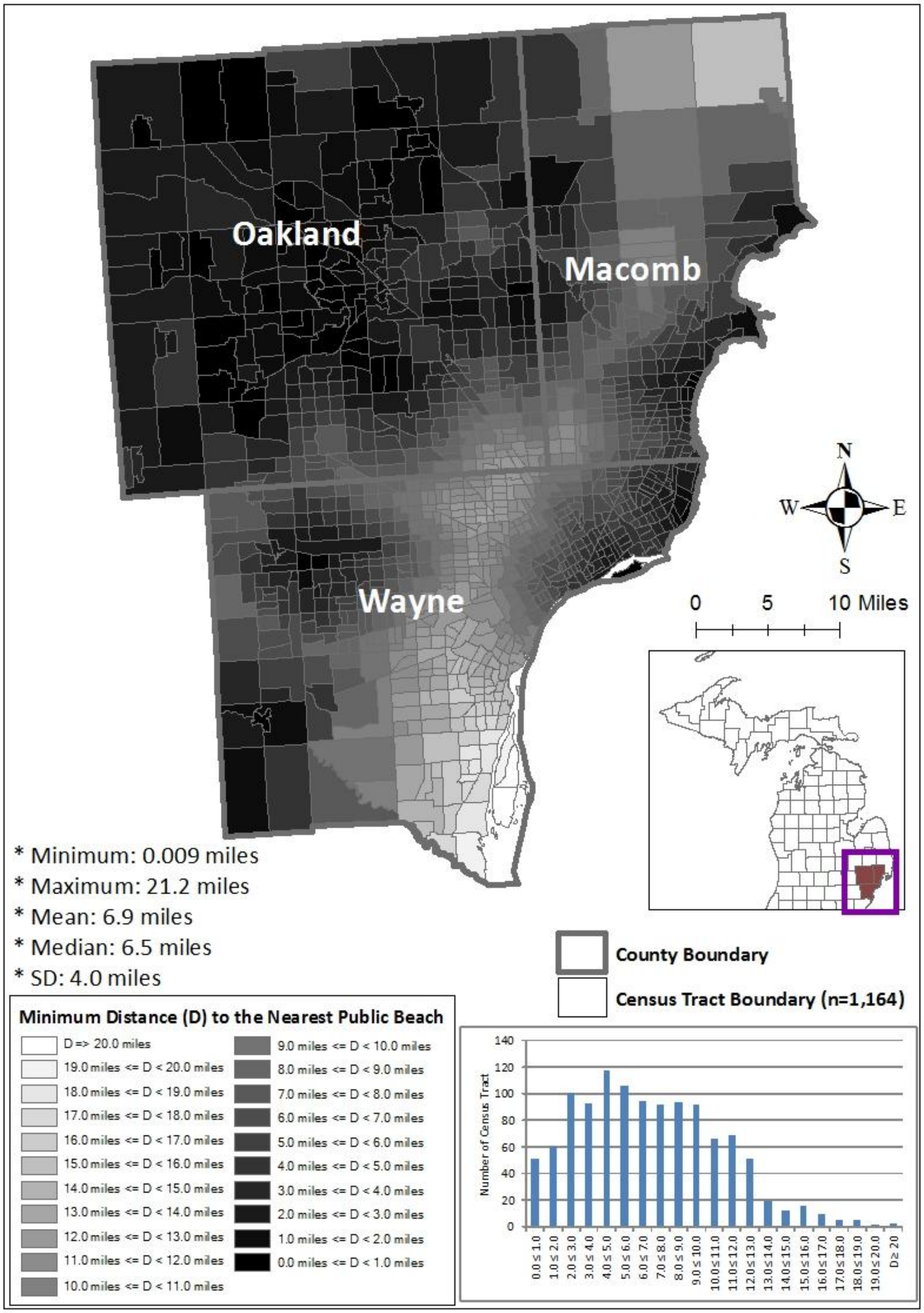

Figure 28. Level of access to public beaches according to the minimum distance approach

According to the minimum distance approach, the minimum distance to the nearest public beach from tract centroids varied from 0.009 miles (Waterford township, Oakland County) to 21.2 miles (Grosse Ile township, Wayne County) (mean: 6.9 miles); 4.3% of the population within all census tracts of the DMA reside within one mile of a public beach, 36.0% within five miles, 77.0% within 10 miles and 99.8% within 20 miles. As shown in Figures 27 and 28, access to public beaches is less prevalent in both Macomb and Wayne counties. In contrast, residents of Oakland County appear to have extremely good access to public beaches.

Objective Two (O2): Exploring the Spatial Patterns of Access to Public Beaches Relative to Residents' Demographic and Socioeconomic Status

The second objective of the study was to explore the spatial patterns of access to public beaches relative to residents' demographic and socioeconomic status. This objective included two research questions; these are discussed below.

O2R1: "Is there spatial autocorrelation associated with the distribution of access to public beaches and residents' demographic and socioeconomic status across the study area?" The spatial patterns of the demographic and socioeconomic variables initially were assessed by testing for spatial autocorrelation using global Moran's I. Table 15 shows the value of global Moran's I for all variables across the 1,164 census tracts in the DMA. All variables exhibited statistically significant and positive global Moran's I statistics. The positive values of the global Moran's I statistic for all variables indicate positive autocorrelation, that is, a tendency toward the spatial clustering of the attribute for each variable in which census tracts exhibiting high (or low) levels of that variable are more likely to be situated next to census tracts with similarly high (or low) levels.

Table 15.

Global Moran's I statistic for spatial autocorrelation of (in)dependent variables

Variable	Moran's I	z-score	p-value
NOPB	0.96	118.1	< 0.01
MINDIST	0.88	107.7	< 0.01
BLACK	0.66	81.9	< 0.01
ASIAN	0.33	41.5	< 0.01
HISPAN	0.36	46.3	< 0.01
POPD	0.41	51.0	< 0.01
MHI	0.53	60.4	< 0.01
MHV	0.54	61.2	< 0.01
AGE18	0.30	37.4	< 0.01
AGE64	0.23	28.9	< 0.01
EDU	0.59	67.3	< 0.01
LAN	0.31	39.3	< 0.01
ECON	0.53	65.8	< 0.01
HO	0.55	67.7	< 0.01
VEHIC	0.48	59.1	< 0.01
WATER	0.20	25.5	< 0.01

Note: NOPB: number of public beaches within 20 miles of tract centroid; MINDIST: minimum distance to the nearest public beach from tract centroid

O2R2: "If there is evidence of spatial autocorrelation, what is its nature and where is it evident?" Although the global Moran's I statistic indicates the existence of spatial autocorrelation, it cannot provide any characterization of the exact nature or distribution of spatial clusters. Therefore, LISA was used to identify the location and significance of spatial clusters in the data set. Figures 29-44 (p. 125-140) illustrate the location and type of spatial clusters for the independent and dependent variables throughout the DMA. Results of the LISA analysis are presented in tabular form in Table 16, indicating the number of census tracts exhibiting each of the five outcomes of LISA analysis (HH, HL, LH, LL, and not statistically significant).

Table 16.

Significant LISA at 5 percent pseudo-significance for (In)dependent variables

Variable	Spatial typology					Total
	HH (%)	HL (%)	LH (%)	LL (%)	Not statistically significant (%)	
NOPB	315 (27.0)	0 (0.0)	0 (0.0)	578 (49.6)	271 (23.2)	1,164
MINDIST	345 (29.6)	0 (0.0)	0 (0.0)	371 (31.8)	448 (38.4)	1,164
BLACK	308 (26.4)	8 (0.6)	40 (3.4)	365 (31.3)	443 (38.0)	1,164
ASIAN	105 (9.0)	9 (0.7)	19 (1.6)	21 (1.8)	1,010 (86.7)	1,164
HISPAN	61 (5.0)	0 (0.0)	10 (0.8)	0 (0.0)	1,093 (93.9)	1,164
POPD	288 (24.7)	6 (0.5)	77 (6.6)	233 (20.0)	560 (48.1)	1,164
MHI	188 (16.1)	21 (1.8)	11 (0.9)	342 (29.3)	602 (51.7)	1,164
MHV	179 (15.3)	21 (1.8)	11 (0.9)	375 (32.2)	578 (49.6)	1,164
AGE18	212 (18.2)	14 (1.2)	21 (1.8)	194 (16.6)	723 (62.1)	1,164
AGE64	154 (13.2)	16 (1.3)	17 (1.4)	166 (14.2)	811 (69.6)	1,164
EDU	222 (19.0)	27 (2.3)	7 (0.6)	384 (32.9)	524 (45.0)	1,164
LAN	130 (11.1)	6 (0.5)	12 (1.0)	168 (14.4)	848 (72.8)	1,164
ECON	259 (22.2)	11 (0.9)	32 (2.7)	282 (24.2)	544 (46.7)	1,164
HO	280 (24.0)	32 (2.7)	7 (0.6)	276 (23.7)	569 (48.8)	1,164
VEHIC	241 (20.7)	12 (1.0)	31 (2.6)	168 (14.4)	712 (61.1)	1,164
WATER	81 (6.9)	2 (0.1)	2 (0.1)	0 (0.0)	1,079 (92.6)	1,164

Note: NOPB: number of public beaches within 20 miles of tract centroid; MINDIST: minimum distance to the nearest public beach from tract centroid; HH: clusters of locations with high values, indicating positive spatial autocorrelation (hot spots); HL: clusters of locations with high values adjacent to locations with low values, indiating negative spaital autocorrelation (spatial outlier); LH: clusters of locations with low values adjacent to locations with high values, indicating negative spatial autocorrelation (spatial outlier); LL: clusters of locations with low values, indicating positive spatial autocorrelation (cold spots)

Number of public beaches (NOPB). Eight hundred ninety-three (76.7%) of the 1,164 census tracts exhibited significant spatial clusters in the LISA analysis. Three hundred fifteen hot spots (labeled HH) were identified. The majority of the hot spots (n=283) are concentrated in Oakland County, in the cities of Auburn Hills, Birmingham, Farmington Hills, Novi, Orchard Lake, Pontiac, Rochester, Southfield, and Wixom and in the townships of Highland, Independence, Lyon, Milford Orion, Waterford, and White Lake. Five hundred seventy-eight cold spots (labeled LL) were identified: in Wayne County (n=446), in the cities of Allen Park, Dearborn, Detroit, Ecorse, Lincoln Park, River Rouge, Riverview, Romulus, Taylor, and Trenton, and in the townships of Grosse Ile, Huron, Sumpter, Van Buren, and Woodhaven; in Macomb County (n=132), in the cities of Fraser, Mt. Clemens, Roseville, and St. Clair Shores and in the townships of Clinton and Harrison. No HL or LH areas were identified. These findings indicate that census tracts exhibit positive spatial association in terms of number of public beaches within 20 miles of each tract centroid, revealing a clustering of census tracts with access to similar numbers of public beaches (Figure 29, p. 125). In other words, census tracts with HH and LL are surrounded by census tracts with similar numbers of public beaches.

Minimum distance to the nearest public beach (MINDIST). Seven hundred twenty-one (61.5%) of the 1,164 census tracts exhibited significant spatial clusters in the LISA analysis. Three hundred forty-five hot spots (HH) were identified. The majority of the hot spots (n=290, 84.0%) are concentrated in Wayne County, in the cities of Dearborn, Detroit, Flat Rock, Lincoln Park, Riverview, Taylor, Trenton, Woodhaven, and Wyandotte and in the townships of Brownstown and Grosse Ile. Three hundred seventy-one cold spots (labeled LL) were identified: in Oakland County (n=194), in the cities of Auburn Hills, Birmingham, Farmington Hills, Ferndale, Hazel Park, Huntington Woods, Novi, Orchard Lake, Pontiac, Rochester Hills, Royal Oak, Southfield, and Wixom, and in the townships of Bloomfield, Brandon, Commerce, Groveland, Highland, Independence, Lyon, Milford, Orion, Oxford, Waterford, West Bloomfield, and White Lake; in Macomb County (n=56), in the cities of Roseville and St. Clair Shores; and, in Wayne County (n=121), in the cities of Grosse Pointe Woods, Livonia, and Westland, and Van Buren Township. No HL or LH areas were identified. These findings indicate that census tracts exhibit positive spatial association in terms of the minimum distance from each tract centroid to the nearest public beach, revealing a clustering of census tracts with similar distances to the nearest public beach (Figure 30, p. 126). In other words, census tracts with HH and LL are surrounded by census tracts with similar distances to the nearest public beach.

Comparing the local patterns of NOPB and MINDIST, the majority of the positive local clusters with regard to NOPB are identified in Oakland County (HH) and Wayne County (LL) while the majority of the positive local clusters with regard to MINDIST are identified in Wayne County (HH) and Oakland County (LL). MINDIST is inversely related to level of access to public beaches. Although hot spots (HH) of NOPB in Oakland County do not completely overlap with cold spots (LL) of MINDIST in Wayne County, local clusters of census tracts in Oakland County represent higher levels of access to public beaches while those in Wayne County represent lower levels of access to public beaches.

Proportion of Black population (BLACK). Seven hundred twenty-one (61.9%) of the 1,164 census tracts exhibited significant spatial clusters in the LISA analysis. Three hundred eight hot spots (HH) were identified. The majority of the hot spots (n=283, 91.8%) are concentrated in the city of Detroit, Wayne County. Three hundred sixty-five cold spots (labeled LL) were identified: in Oakland County (n=131), in the cities of Novi, Rochester Hills, Royal Oak, and Troy and in the townships of Commerce, Independence, and White Lake); in Macomb County (n=121), in the cities of St. Clair Shores, Sterling Heights, and Warren and in the townships of Macomb and Shelby; and, in Wayne County (n=109), in the cities of Livonia, Southgate, Wyandotte, Lincoln Park, Trenton, and Riverview). These census tracts are surrounded by census tracts with a similar proportion of Black population. Although positive spatial autocorrelation is typical between census tracts, census tracts with HL (n=8) and LH clusters (n=40) emerged around Detroit. Census tracts with HL were identified in the cities of

Detroit and Westland and in the townships of Canton and Northville, Wayne County, whereas census tracts with LH were observed in the cities of Detroit in Wayne County, and Hazel Park in Oakland County. These census tracts exhibit negative spatial autocorrelation, thus showing significant spatial heterogeneity. Specifically, census tracts within HL are those with a high proportion of Black population, but are adjacent to census tracts with a low proportion of Black population. The situation appears to be the opposite for census tracts with LH. These findings indicate that census tracts exhibit positive spatial association in terms of proportion of Black population, revealing a clustering of census tracts with similar proportions of Black population. The 48 (4.3%) spatial outliers (HL and LH) do, however, suggest that the ethnic diversity between census tracts is spatially heterogeneous (Figure 31, p. 127).

Proportion of Asian population (ASIAN). One hundred fifty-four (13.2%) of the 1,164 census tracts exhibited significant spatial clusters in the LISA analysis. One hundred five hot spots (HH) were identified. The majority of the hot spots (n=83, 79.0%) are concentrated in Wayne County, in the cities of Dearborn, Melvindale, and Romulus. Twenty-two hot spots also emerged in the city of Pontiac, Oakland County. Twenty-one cold spots (LL) were observed in the city of Detroit, Wayne County. These census tracts are surrounded by census tracts with a similar proportion of Black population. Nine HL areas were observed in Wayne County, in the cities of Ecorse and Detroit and in the townships of Brownstown and Grosse Ile, in Oakland County, in the cities of Madison Heights, Rochester Hills, Oak Park, and Southfield and in Macomb County, in the township of Clinton. Nineteen LH areas were observed in the city of Detroit in Wayne County. These census tracts exhibit negative spatial autocorrelation, thus showing significant spatial heterogeneity. Specifically, census tracts within HL clusters are those with a high proportion of Asian population, but are adjacent to census tracts with a low proportion of Asian population. The situation appears to be the opposite for census tracts with LH. These findings indicate that census tracts exhibit positive spatial association in terms of proportion of Asian population, revealing a clustering of census tracts with similar proportions of Asian population. In addition, there are 28 (2.3%) spatial outliers (HL and LH) that are regarded as negatively associated, thus showing some spatial heterogeneity (Figure 32, p. 128).

Proportion of Hispanic population (HISPAN). Only 71 (6.0%) of the 1,164 census tracts exhibited significant spatial clusters in the LISA analysis. Sixty-one hot spots (HH) were identified in Wayne County (n=49), in the cities of Allen Park, Detroit, Ecorse, and Lincoln Park, and in Oakland County (n=12), in the city of Pontiac. These census tracts are surrounded by census tracts with similar proportions of Hispanic population. Ten LH areas emerged in the city of Detroit, Wayne County. These census tracts exhibit negative spatial autocorrelation, thus showing significant spatial heterogeneity. Specifically, census tracts within LH clusters are those with low proportions of Hispanic population, but are adjacent to census tracts with high proportions of Hispanic population. No LL and HL areas were identified. These findings indicate that census tracts exhibit positive spatial association in terms of proportion of Hispanic population, revealing a clustering of census tracts with similar proportions of Hispanic population. In addition, there are 10 (0.8%) spatial outliers (LH) that are regarded as negatively associated, thus showing some spatial heterogeneity (Figure 33, p. 129).

Population density (POPD). Six hundred four (51.8%) of the 1,164 census tracts exhibited significant spatial clusters in the LISA analysis. Two hundred eighty-eight hot spots (HH) were identified. The majority of the hot spots (n=244, 84.7%) are concentrated in Wayne County, in the cities of Dearborn, Dearborn Heights, Detroit, Lincoln Park, and River Rouge. HH areas also emerged in Macomb County (n=26), in the cities of Eastpointe, Roseville, and

Warren, and in Oakland County (n=18), in the cities of Berkley, Ferndale, Hazel Park, and Huntington Woods. Two hundred thirty-three cold spots (LL) were identified. The majority of the cold spots (n=169, 72.5%) are concentrated in Oakland County, in the cities of Auburn Hills, Farmington Hills, Novi, Pontiac, Rochester Hills, and Troy and in the townships of Addison, Bloomfield, Brandon, Commerce, Groveland, Highland, Independence, Lyon, Milford, Oakland, Orion, Oxford, Rose, Springfield, Waterford, West Bloomfield, and White Lake. LL areas also were observed in Wayne County (n=34), in the cities of Flat Rock, Livonia, Rockwood, Trenton, and Woodhaven and in the townships of Brownfield, Grosse Ile, Huron, Sumpter, and Van Buren, and in Macomb County (n=30), in the townships of Armada, Bruce, Chesterfield, Harrison, Lenox, Macomb, Ray, Richmond, Shelby, and Washington. These census tracts are surrounded by census tracts with similar population densities. Six HL areas emerged in Wayne County, in the cities of Northville and Romulus and in the township of Canton. LH areas were identified in Wayne County (n=69), in the cities of Dearborn, Detroit, Ecorse, and Wyandotte; in Oakland County (n=6), in the cities of Ferndale, Oak Park, and Southfield; and, in Macomb County (n=2), in the cities of St. Clair Shores and Warren. These census tracts exhibit negative spatial autocorrelation, thus showing significant spatial heterogeneity. Specifically, census tracts within HL clusters are those with high population densities, but are adjacent to census tracts with low population densities. The situation appears to be the opposite for census tracts with LH. These findings indicate that census tracts exhibit positive spatial association in terms of population density, revealing a clustering of census tracts with similar population densities. In addition, there are 83 (7.1%) spatial outliers (HL and LH), thus showing substantial spatial heterogeneity (Figure 34, p. 130).

Median household income (MHI). Five hundred sixty-two (48.2%) of the 1,164 census tracts exhibited significant spatial clusters in the LISA analysis. One hundred eighty-eight hot spots (HH) were identified. The majority of the hot spots (n=142, 75.5%) are concentrated in Oakland County, in the cities of Farmington Hills, Novi, and Troy and in the townships of Bloomfield, Commerce, Oakland, and West Bloomfield. HH areas also emerged in Macomb County (n=16), in the townships of Chesterfield and Macomb, and in Wayne County (n=30), in the cities of Canton and Livonia. Three hundred forty-two cold spots (LL) were identified. The majority of the cold spots (n=271, 79.2%) are concentrated in the city of Detroit, Wayne County. These census tracts are surrounded by census tracts with residents having similar median household incomes. Twenty-one HL areas also were observed in the city of Detroit. Eleven LH areas emerged in Oakland County (n=7), in the cities of Southfield, Sylvan Lake, and Wixom; in Macomb County (n=1), in the city of Sterling Heights; and, in Wayne County (n=3) in the townships of Canton and Northville. These census tracts exhibit negative spatial autocorrelation, thus showing significant spatial heterogeneity. Specifically, census tracts within HL clusters are those with residents having high median household incomes, but are adjacent to census tracts with residents having low median household incomes. The situation appears to be the opposite for census tracts with LH. These findings indicate that census tracts exhibit positive spatial association in terms of median household income, revealing a clustering of census tracts with similar median household income. In addition, there are 32 (2.7%) spatial outliers, thus showing some spatial heterogeneity (Figure 35, p. 131).

Median housing value (MHV). Five hundred sixty-two (48.2%) of the 1,164 census tracts exhibited significant spatial clusters in the LISA analysis. One hundred eighty-eight hot spots (HH) were identified. The majority of the hot spots (n=142, 75.5%) are concentrated in

Oakland County, in the cities of Farmington Hills, Novi, and Troy and in the townships of Bloomfield, Commerce, Oakland, and West Bloomfield. HH areas also emerged in Macomb County (n=16), in the townships of Chesterfield and Macomb, and, in Wayne County (n=30), in the cities of Canton and Livonia and in the township of Plymouth. Three hundred forty-two cold spots (LL) were identified. The majority of the cold spots (n=271, 79.2%) are concentrated in the city of Detroit, Wayne County. These census tracts are surrounded by census tracts with similar median housing values. Twenty-one HL areas were observed in the city of Detroit. Eleven LH areas emerged in Oakland County (n=7), in the cities of Southfield, Sylvan Lake, and Wixom; in Macomb County (n=1), in the city of Sterling Heights; and, in Wayne County (n=3), in the townships of Canton and Northville. These census tracts exhibit negative spatial autocorrelation, thus showing significant spatial heterogeneity. Specifically, census tracts within HL clusters are those with high median housing values, but are adjacent to census tracts with low median housing values. The situation appears to be the opposite for census tracts with LH. These findings indicate that census tracts exhibit positive spatial association in terms of median housing value, revealing a clustering of census tracts with similar median housing values. In addition, there are 32 (2.7%) spatial outliers (HL and LH), thus showing some spatial heterogeneity (Figure 36, p.132).

Proportion of population under age 18 (AGE18). Four hundred forty-one (37.8%) of the 1,164 census tracts exhibited significant spatial clusters in the LISA analysis. Two hundred twelve hot spots (HH) were identified. The majority of the hot spots (n=156, 73.5%) are concentrated in the city of Detroit, Wayne County. One hundred ninety-four cold spots (LL) were identified in Oakland County (n=69), in the cities of Madison Heights, Royal Oak, and Southfield; in Macomb County (n=69), in the cities of Clinton township, Mt. Clemens, and St.

Clair Shores; and, in Wayne County (n=44), in the cities of Livonia and Southgate. These census tracts are surrounded by census tracts with similar proportions of population under age 18. Only 14 HL areas were observed in Wayne County (n=5), in the township of Grosse Ile, in Oakland County (n=5), in the city of Huntington Woods, and, in Macomb County (n=4), in the township of Clinton. Twenty-one LH areas were identified. The majority of the LH areas (n=19, 90.4%) were concentrated in Wayne County, in the cities of Dearborn, Detroit, and Grosse Pointe Woods. These census tracts exhibit negative spatial autocorrelation, thus showing significant spatial heterogeneity. Specifically, census tracts within HL clusters are those with high proportions of population under age 18, but are adjacent to census tracts with low proportions of population under age 18. The situation appears to be the opposite for census tracts with LH. These findings indicate that census tracts exhibit positive spatial association in terms of proportion of population under age 18, revealing a clustering of census tracts with similar proportions of population under age 18. In addition, there are 35 (3.0%) spatial outliers (HL and LH), thus showing some spatial heterogeneity (Figure 37, p. 133).

Proportion of population over age 64 (AGE64). Three hundred fifty-three (30.3%) of the 1,164 census tracts exhibited significant spatial clusters in the LISA analysis. One hundred fifty-four hot spots (HH) were identified: in Macomb County (n=58), in the cities of St. Clair Shores, Sterling Heights, and Warren and in the township of Clinton; in Oakland County (n=49), in the townships of Bloomfield, Southfield, and West Bloomfield and in the cities of Farmington Hills and Southfield; and, in Wayne County (n=47), in the cities of Livonia and Riverview, and in the township of Grosse Ile. One hundred sixty-six cold spots (LL) were identified. These census tracts are surrounded by census tracts with similar proportions of population over age 64. The majority of the cold spots (n=139, 83.7%) were concentrated in the city of Detroit, Wayne

County. Only 17 LL areas emerged in Oakland County, in the city of Pontiac and in the township of Orion. These census tracts exhibit negative spatial autocorrelation, thus showing significant spatial heterogeneity. Specifically, census tracts within HL clusters are those with high proportions of population over age 64, but are adjacent to census tracts with low proportions of population over age 64. The situation appears to be the opposite for census tracts with LH. These findings indicate that census tracts exhibit positive spatial association in terms of proportion of population over age 64, revealing a clustering of census tracts with similar proportions of population over age 64. In addition, there are 33 (2.7%) spatial outliers (HL and LH), thus showing some spatial heterogeneity (Figure 38, p. 134).

Proportion of population with a four-year university degree or higher (EDU). Six hundred forty (54.9%) of the 1,164 census tracts exhibited significant spatial clusters in the LISA analysis. Two hundred twenty-two hot spots (HH) were identified. The majority of the hot spots (n=182, 81.9%) are concentrated in Oakland County, in the cities of Farmington Hills, Rochester Hills, Royal Oak, Troy, and Novi and in the townships of Bloomfield, Independence, Oakland, Orion, and West Bloomfield. Thirty-nine HH areas were observed in Wayne County, in the cities of Livonia and Plymouth and in the townships of Northville and Plymouth. Three hundred eighty-four cold spots (LL) were identified. The majority of the cold spots (n=322, 83.8%) are concentrated in Wayne County, in the cities of Detroit, Romulus, Taylor, and Westland. Sixty LL areas were observed in Macomb County, in the cities of St. Clair Shores and Warren. These census tracts are surrounded by census tracts with similar proportions of population having a four-year university degree or higher. Twenty-seven HL areas were observed in Wayne County, in the cities of Dearborn and Detroit, and, in Oakland County, in the city of Pontiac. Only 7 LH areas emerged, in Oakland County, in the cities of Farmington Hills and Pontiac, and, in

Macomb County, in the city of Sterling Heights. These census tracts exhibit negative spatial autocorrelation, thus showing significant spatial heterogeneity. Specifically, census tracts within HL clusters are those with high proportions of populations having a four-year university degree or higher, but are adjacent to census tracts with low proportions of population having a four-year university degree or higher. The situation appears to be the opposite for census tracts with LH. These findings indicate that census tracts exhibit positive spatial association in terms of proportion of population having a university degree or higher, revealing a clustering of census tracts with populations having similar educational attainment. In addition, there are 34 (2.9%) spatial outliers (HL and LH), thus showing some spatial heterogeneity (Figure 39, p. 135).

Proportion of population with non-English spoken at home (LAN). Three hundred sixteen (27.1%) of the 1,164 census tracts exhibited significant spatial clusters in the LISA analysis. One hundred thirty hot spots (HH) were identified. The majority of the hot spots are concentrated in Oakland County (n=60), in the cities of Farmington Hills, Rochester Hills, Troy, and West Bloomfield, and in Wayne County (n=51), in the cities of Dearborn and Detroit. One hundred sixty-eight cold spots (LL) were identified. The majority of the cold spots (n=155, 92.2%) are concentrated in the city of Detroit, Oakland County. These census tracts are surrounded by census tracts with similar proportions of population having languages other than English spoken at home. Six HL areas emerged in the city of Detroit, Wayne County. Ten LH areas were observed in Wayne County, in the cities of Dearborn and Detroit. Two LH areas were observed in Oakland County, in the cities of Farmington Hills and Rochester Hills. These census tracts exhibit negative spatial autocorrelation, thus showing significant spatial heterogeneity. Specifically, census tracts within HL clusters are those with high proportions of population having languages other than English spoken at home, but are adjacent to census tracts with low proportions of population having languages other than English spoken at home. The situation appears to be the opposite for census tracts with LH. These findings indicate that census tracts exhibit positive spatial association in terms of proportion of population having languages other than English spoken at home, revealing a clustering of census tracts with similar proportions of population having languages other than English spoken at home. In addition, there are 18 (1.5%) spatial outliers (HL and LH), thus showing some spatial heterogeneity (Figure 40, p. 136).

Proportion of population below the poverty line (ECON). Six hundred twenty (53.2%) of the 1,164 census tracts exhibited significant spatial clusters in the LISA analysis. Two hundred ninety-five hot spots (HH) were identified. The majority of the hot spots (n=285, 96.6%) are concentrated in Wayne County, in the city of Detroit. Two hundred eighty-two cold spots (LL) were identified in Oakland County (n=153), in the cities of Farmington Hills, Novi, Rochester Hills, Royal Oak, and Troy and in the townships of Bloomfield, Commerce, Independence, Oakland, Orion, West Bloomfield, and White Lake; in Macomb County (n=65), in the cities of St. Clair Shores, Sterling Heights, and Warren and in the townships of Chesterfield, Clinton, Shelby, and Macomb; and, in Wayne County (n=64), in the cities of Livonia and Westland and in the townships of Northville and Plymouth. These census tracts are surrounded by census tracts with a similar proportion of population below the poverty line. Only 11 HL areas were observed in Wayne County (n=8), in the townships of Canton, Grosse Ile, and Northville; in Oakland County (n=2), in the city of Madison Heights; and, in Macomb County (n=1), in the township of Harrison. Thirty-two LH areas emerged in the city of Dearborn (n=1) and Detroit (n=31), Wayne County. These census tracts exhibit negative spatial autocorrelation, thus showing significant spatial heterogeneity. Specifically, census tracts within HL clusters are those with high proportions of population below the poverty line, but are adjacent to census tracts with low proportions of population below the poverty line. The situation appears to be the opposite for census tracts with LH. These findings indicate that census tracts exhibit positive spatial association in terms of proportion of population below the poverty line, revealing a clustering of census tracts with similar proportions of population below the poverty line. In addition, there are 43 (3.6%) spatial outliers (HL and LH), thus showing some spatial heterogeneity (Figure 41, p. 137).

Housing occupancy (HO). Five hundred ninety-five (51.1%) of the 1,164 census tracts exhibited statistical significance in the LISA analysis. Two hundred eighty hot spots (HH) were identified in Macomb County (n=105), in the cities of Fraser, St. Clair Shores, Sterling Heights, and Warren and in the townships of Clinton, Shelby, and Macomb; in Oakland County (n=96), in the cities of Farmington Hills, Madison Heights, Rochester Hills, Royal Oak, and Troy and in the townships of Oakland, Orion, and West Bloomfield; and, in Wayne County (n=79), in the cities of Dearborn Heights, Livonia, and Southgate and in the townships of Brownstown, Canton, and Plymouth. Two hundred seventy-six cold spots (LL) were identified. The majority of the cold spots (n=267, 96.7%) are concentrated in the city of Detroit, Wayne County. Only nine LL areas were observed, all in the city of Pontiac, Oakland County, and 32 HL areas emerged in the city of Detroit, Wayne County. These census tracts are surrounded by census tracts with a similar proportion of occupied housing units. Only seven LH areas were observed, in Oakland County (n=3), in the cities of Southfield, Troy, and Wixom; in Macomb County (n=1), in the township of Harrison; and, in Wayne County (n=3), in the township of Northville and in the city of Westland. These census tracts exhibit negative spatial autocorrelation, thus showing significant spatial heterogeneity. Specifically, census tracts within HL clusters are those with high proportions of occupied housing units, but are adjacent to census tracts with low proportions of occupied housing units. The situation appears to be the opposite for census tracts with LH. These findings indicate that census tracts exhibit positive spatial association in terms of proportion of occupied housing units, revealing a clustering of census tracts with similar proportions of occupied housing units. In addition, there are 39 (3.3%) spatial outliers (HL and LH), thus showing some spatial heterogeneity (Figure 42, p. 138).

Proportion of households without a vehicle (VEHIC). Four hundred fifty-two (38.8%) of the 1,164 census tracts exhibited significant spatial clusters in the LISA analysis. Two hundred forty-one hot spots (HH) were identified. The majority of the hot spots (n=238, 98.7%) are concentrated in the city of Detroit, Wayne County. One hundred sixty-eight cold spots (LL) were identified. The majority of the cold spots (n=117, 69.6%) are concentrated in Oakland County, in the cities of Farmington Hills, Rochester Hills, Royal Oak, and Troy and in the townships of Bloomfield, Independence, Oakland, Orion, and West Bloomfield. LL areas emerged in Macomb County (n=28), in the cities of St. Clair Shores and Sterling Heights and in the township of Shelby; and in Wayne County (n=23), in the city of Livonia and in the township of Grosse Ile. These census tracts are surrounded by census tracts with similar proportions of households without a vehicle. Only 12 HL areas were identified, in Oakland County (n=6), in the cities of Farmington Hills, Southfield, Troy, and Wixom; in Macomb County (n=2), in the cities of Roseville and Sterling Heights; and, in Wayne County (n=4), in the cities of Taylor and Westland and in the township of Canton. Only 31 LH areas were observed, all in the city of Detroit, Wayne County. These census tracts are regarded as negative spatial autocorrelation, thus showing significant spatial heterogeneity. Specifically, census tracts within HL clusters are those with high proportions of households without a vehicle, but are adjacent to census tracts with low proportions of households without a vehicle. The situation appears to be the opposite for census tracts with LH. These findings indicate that census tracts exhibit positive spatial association in terms of proportion of non-vehicle ownership, revealing a clustering of census tracts with similar proportions of non-vehicle ownership. In addition, there are 43 (3.6%) spatial outliers (HL and LH), thus showing some spatial heterogeneity (Figure 43, p. 139).

Proportion of water area (WATER). Only 86 (7.3%) of the 1,164 census tracts exhibited statistical significance in the LISA analysis. Eighty-one hot spots (HH) were identified in Oakland County (n=41), in the townships of Commerce, Orion, Waterford, West Bloomfield, and White Lake; in Wayne County (n=23), in the cities of Detroit, Gibraltar, Grosse Pointe, Trenton, and Wyandotte and in the township of Van Buren; and, in Macomb County (n=17), in the city of St. Clair Shores and in the townships of Chesterfield and Harrison. These census tracts are surrounded by census tracts with a similar proportion of water area. Only two HL areas were observed in the city of Detroit (n=2), Wayne County. Only two LH areas emerged, both in Wayne County, in the townships of Brownstown and Grosse Ile. These census tracts exhibit negative spatial autocorrelation, thus showing significant spatial heterogeneity. Specifically, census tracts within HL clusters are those with high proportions of water area, but are adjacent to census tracts with low proportions of water area. The situation appears to be the opposite for census tracts with LH. No LL areas were identified. These findings indicate that census tracts exhibit positive spatial association in terms of proportion of water area, revealing a clustering of census tracts with similar proportions of water area. There are four (0.2%) spatial outliers (HL and LH), thus showing some spatial heterogeneity (Figure 44, p. 140).

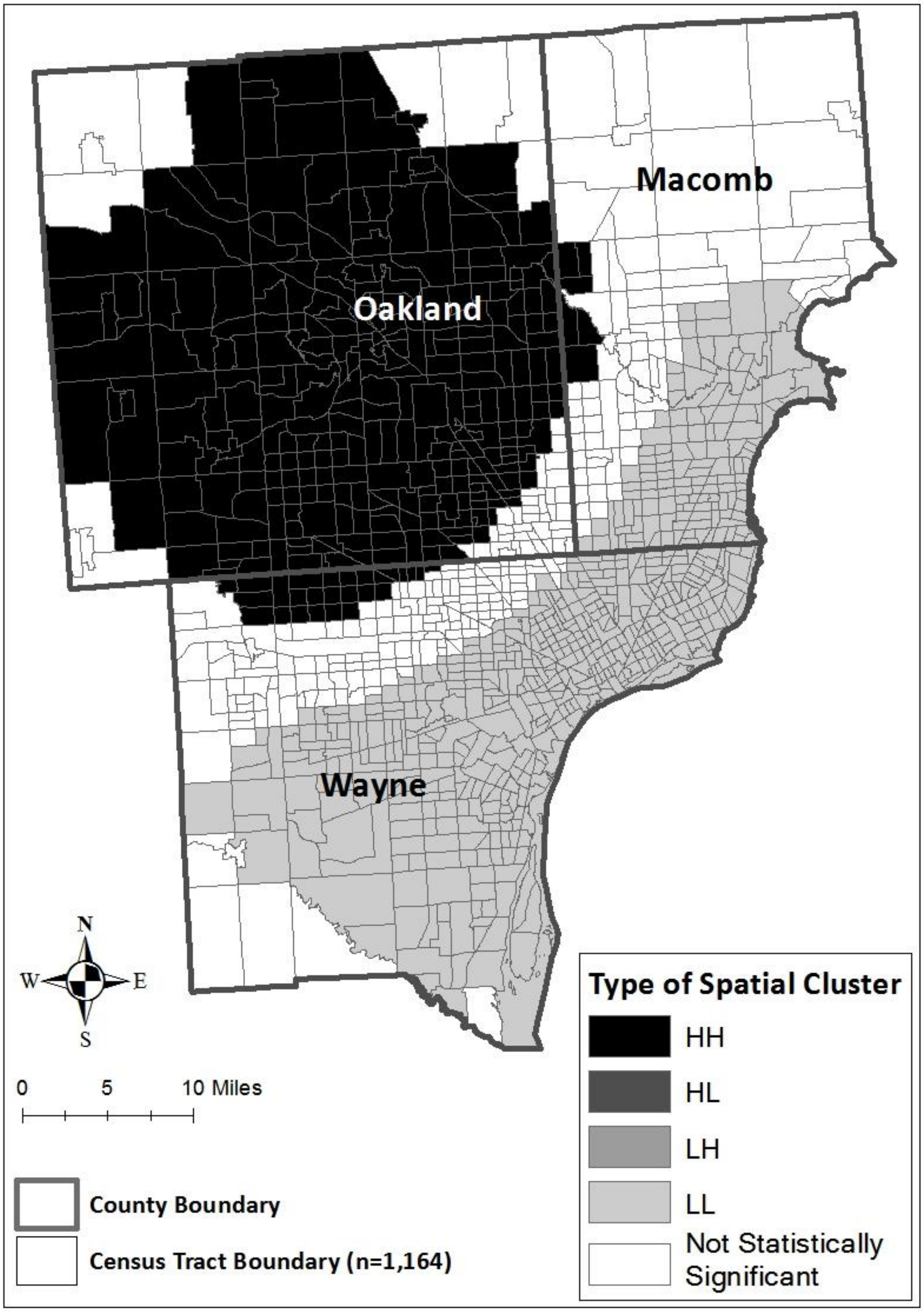

Figure 29. Moran significance map for number of public beaches within 20 miles of tract centroid (HH: high-high; HL: high-low; LH: low-high; LL: low-low)

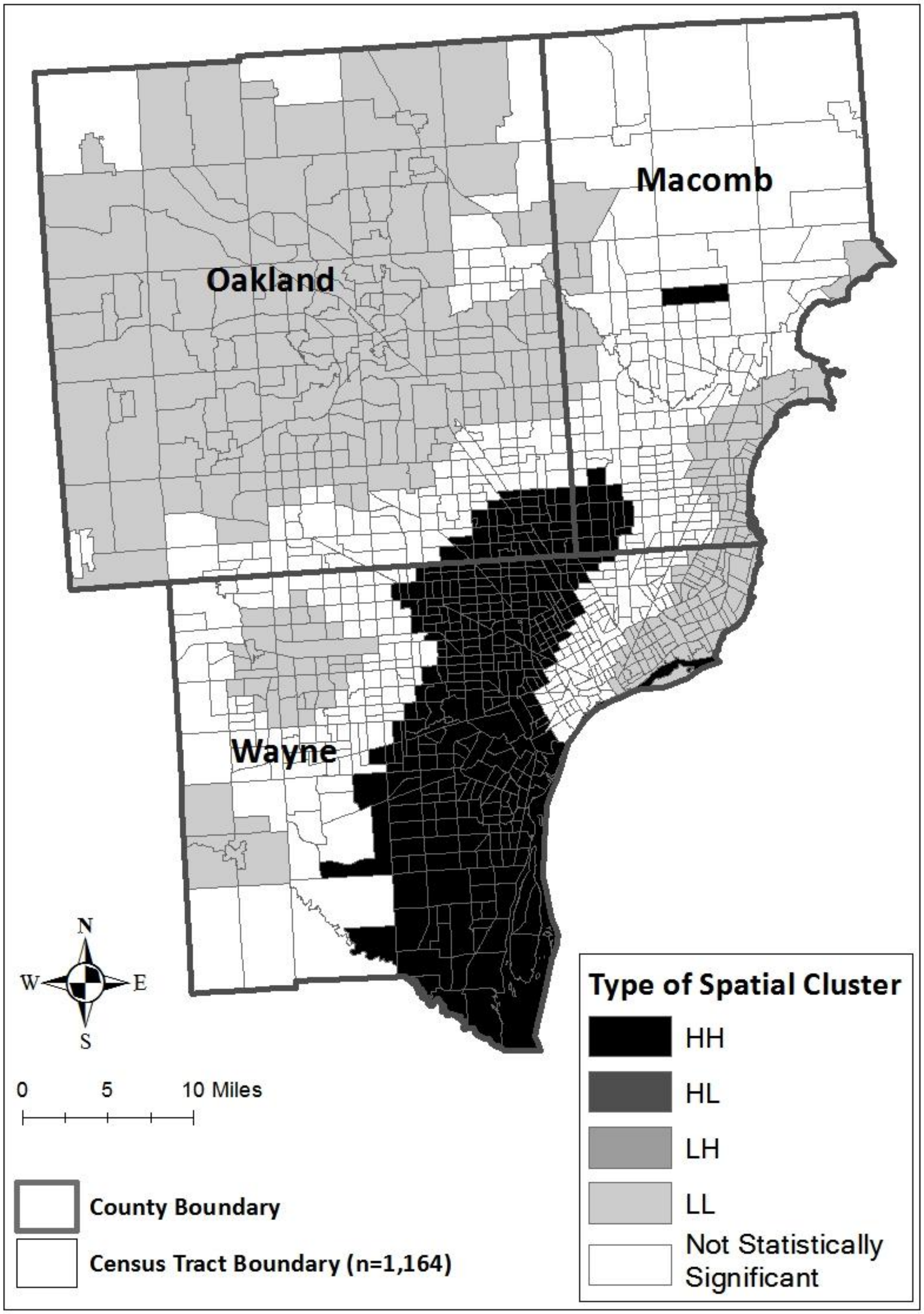

Figure 30. Moran significance map for minimum distance to the nearest public beach from tract centroid (HH: high-high; HL: high-low; LH: low-high; LL: low-low)

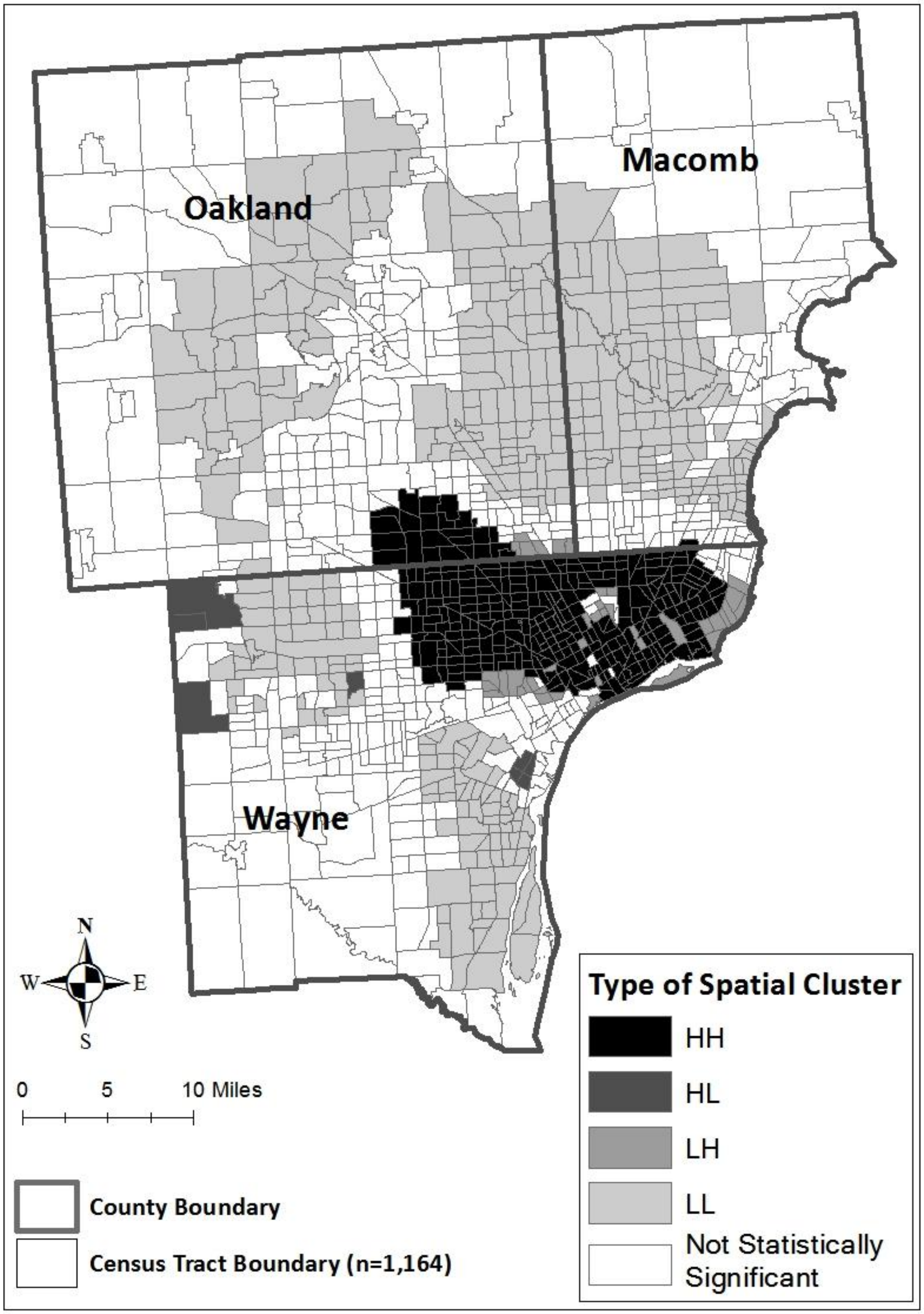

Figure 31. Moran significance map for proportion (%) of population Black by census tract, DMA (2010) (HH: high-high; HL: high-low; LH: low-high; LL: low-low)

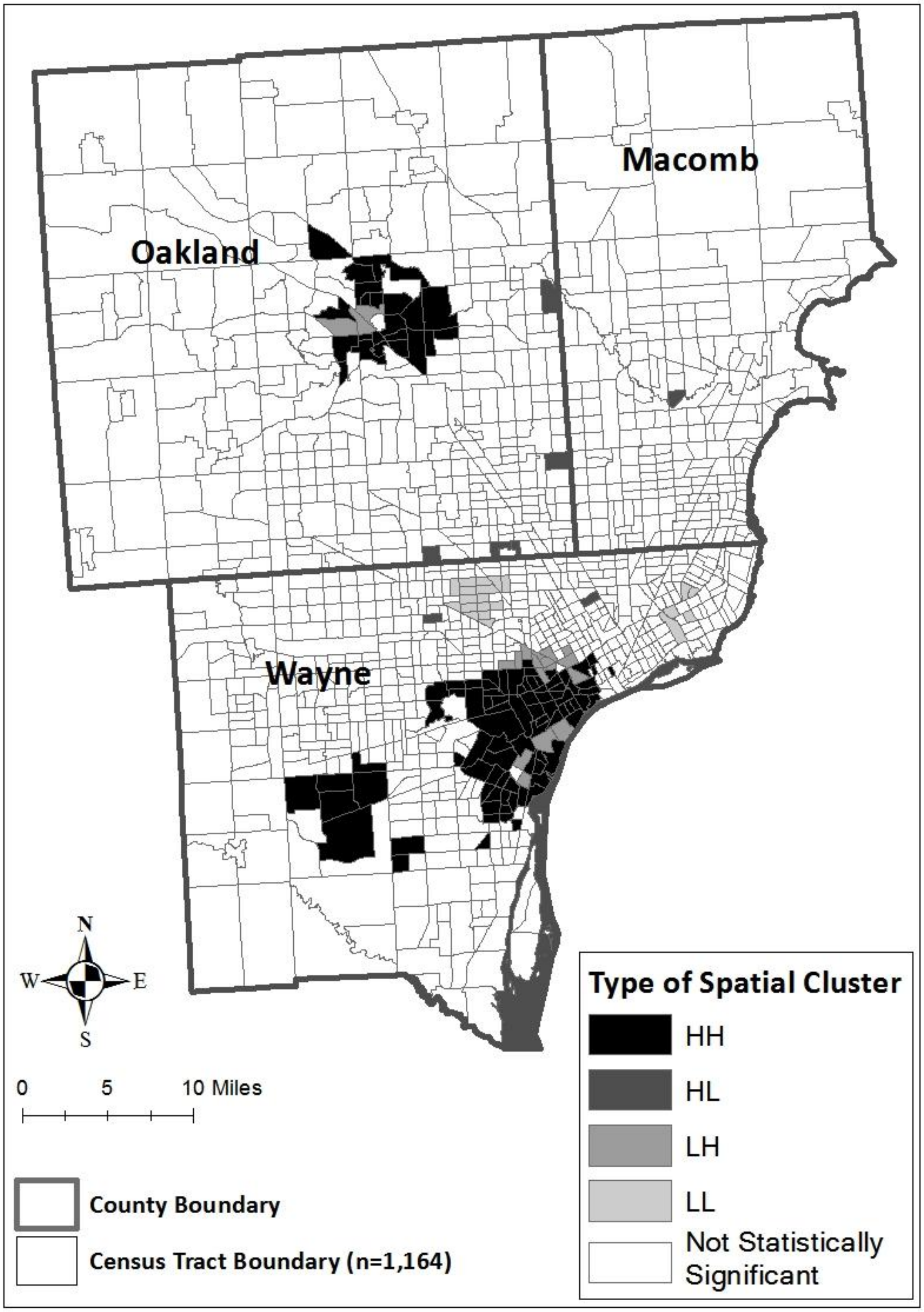

Figure 32. Moran significance map for proportion (%) of population Asian by census tract, DMA (2010) (HH: high-high; HL: high-low; LH: low-high; LL: low-low)

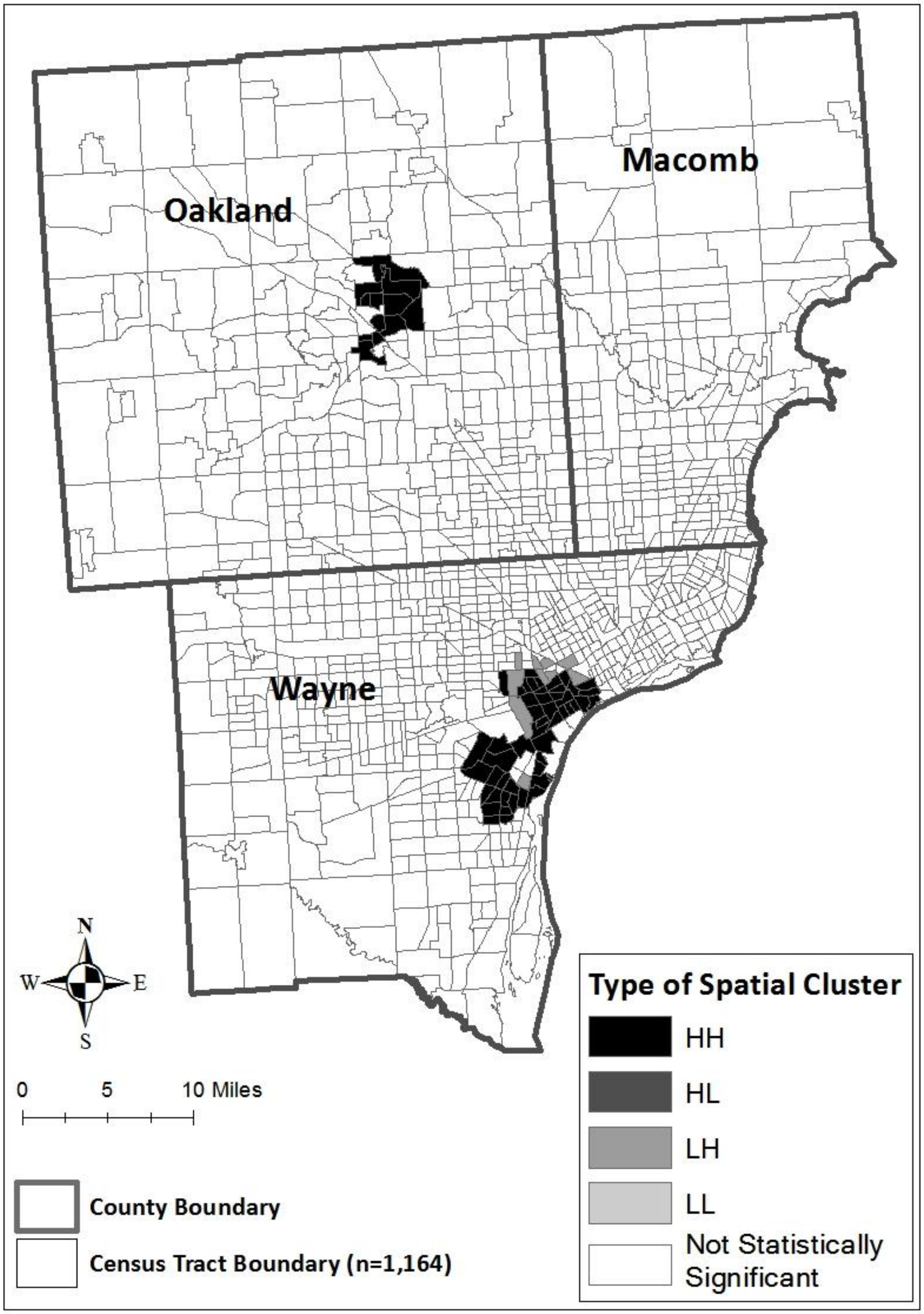

Figure 33. Moran significance map for proportion (%) of population Hispanic by census tract, DMA (2010) (HH: high-high; HL: high-low; LH: low-high; LL: low-low)

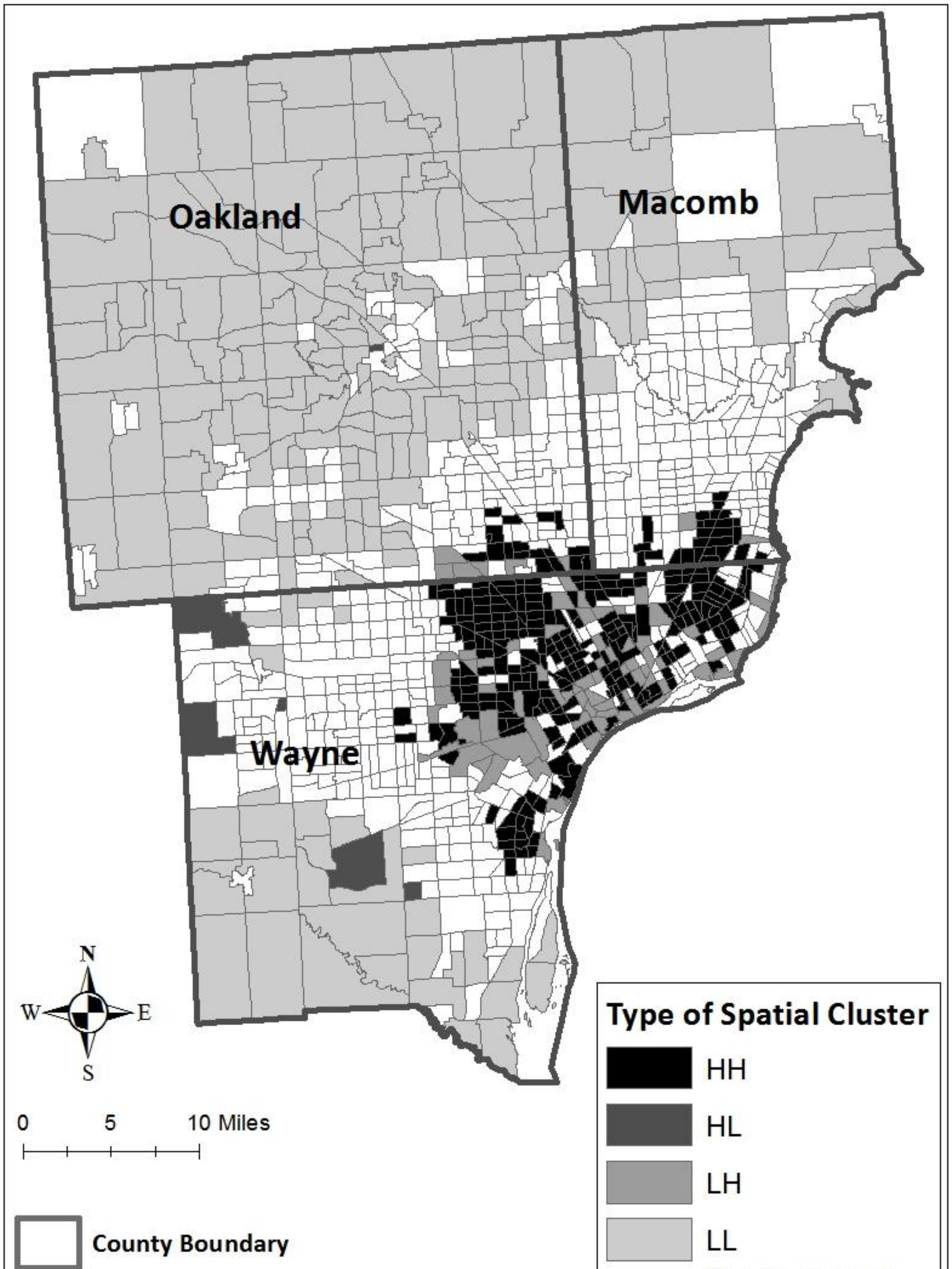

Figure 34. Moran significance map for population per square mile by census tract, DMA (2010) (HH: high-high; HL: high-low; LH: low-high; LL: low-low)

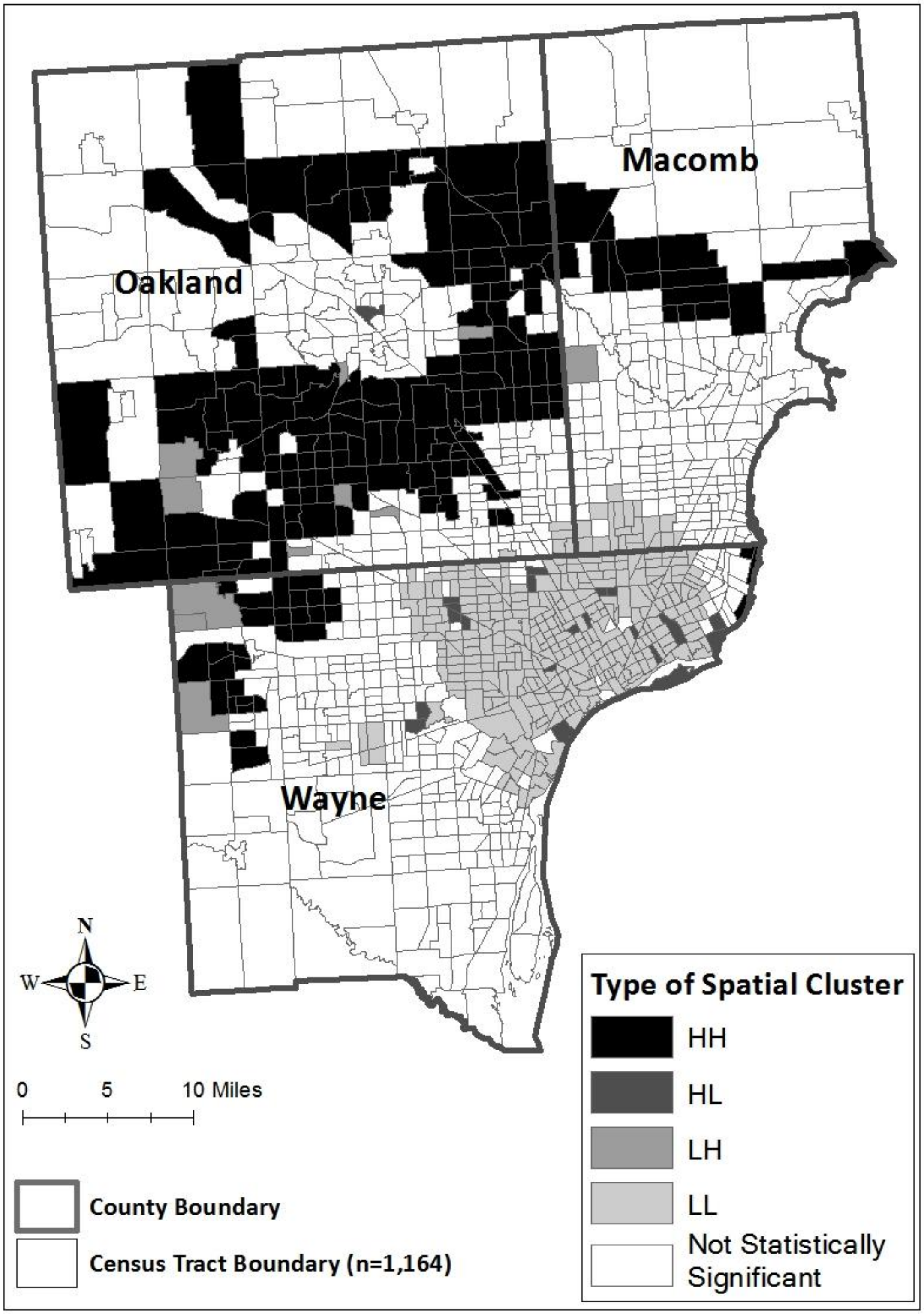

Figure 35. Moran significance map for median household income ($) by census tract, DMA (2010) (HH: high-high; HL: high-low; LH: low-high; LL: low-low)

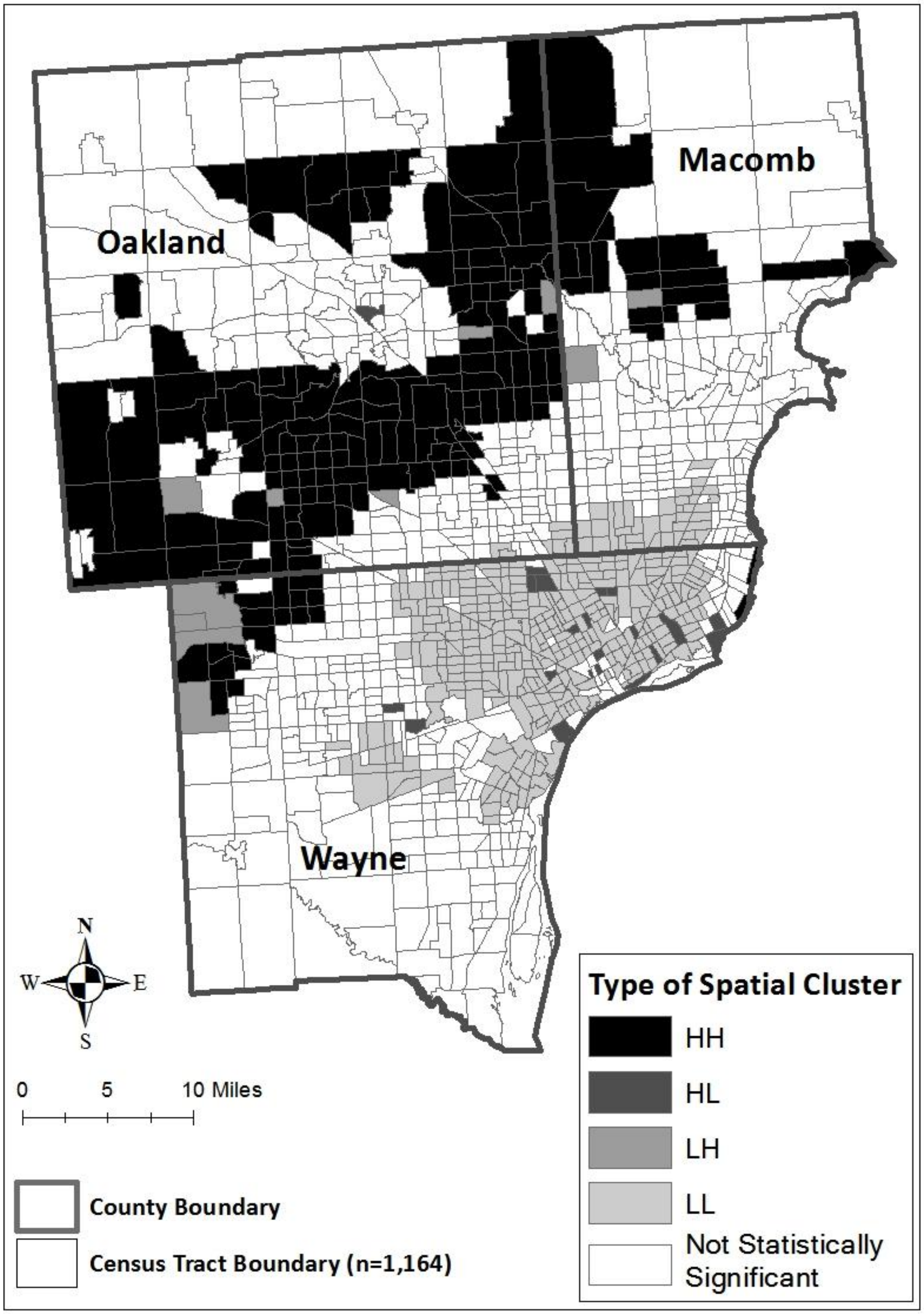

Figure 36. Moran significance map for median housing value ($) by census tract, DMA (2010) (HH: high-high; HL: high-low; LH: low-high; LL: low-low)

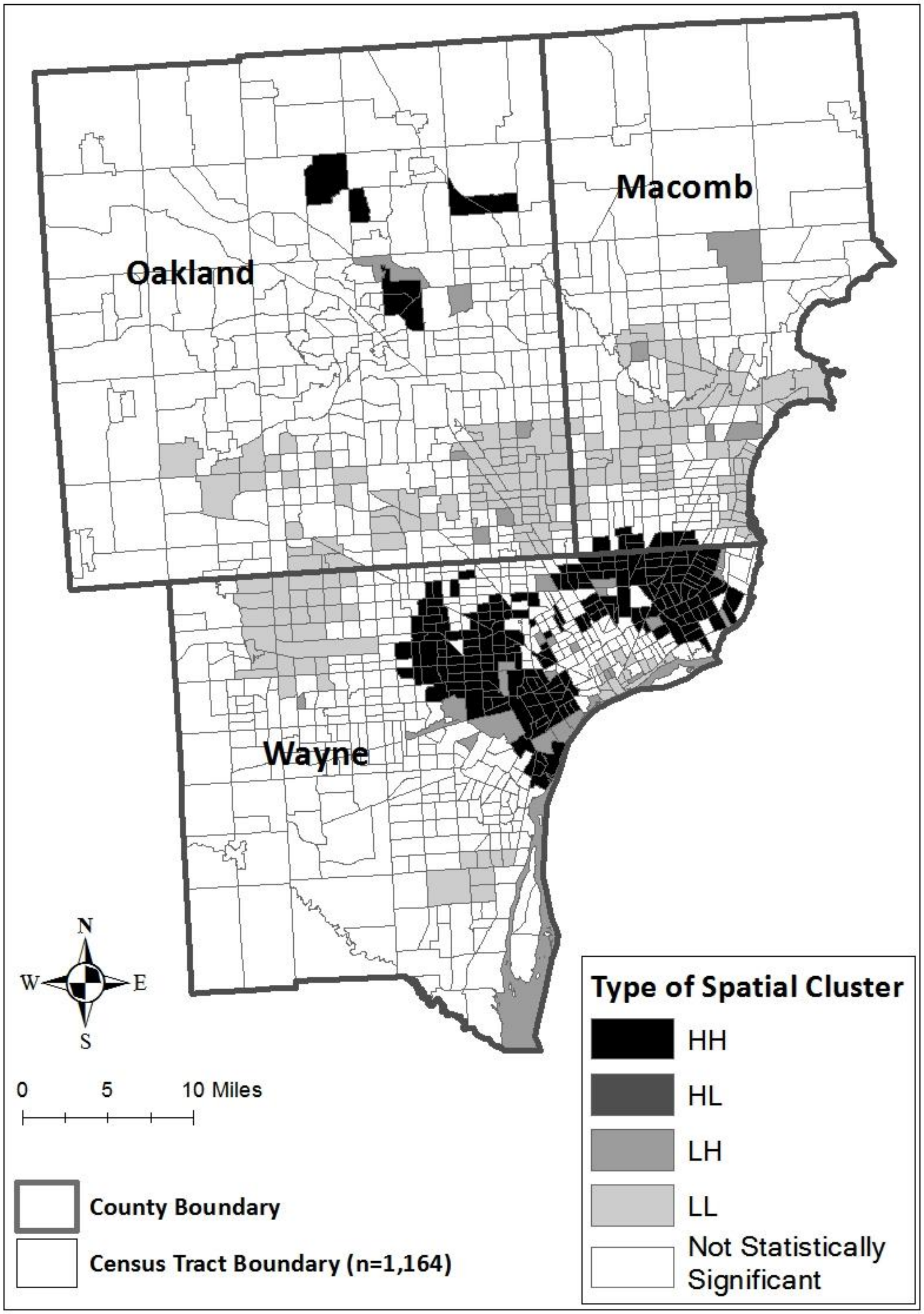

Figure 37. Moran significance map for proportion (%) of population under age 18 by census tract, DMA (2010) (HH: high-high; HL: high-low; LH: low-high; LL: low-low)

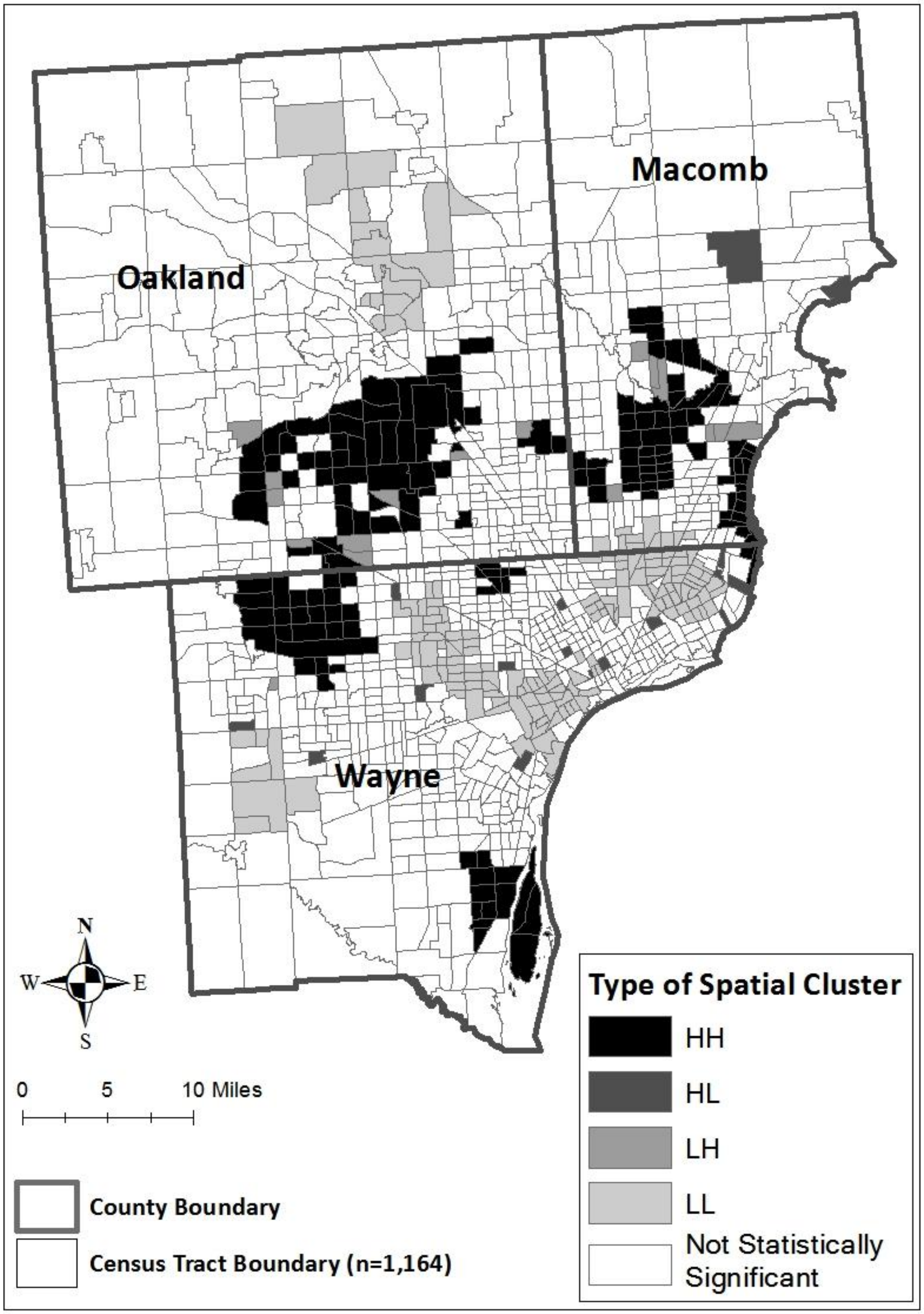

Figure 38. Moran significance map for proportion (%) of population over age 64 by census tract, DMA (2010) (HH: high-high; HL: high-low; LH: low-high; LL: low-low)

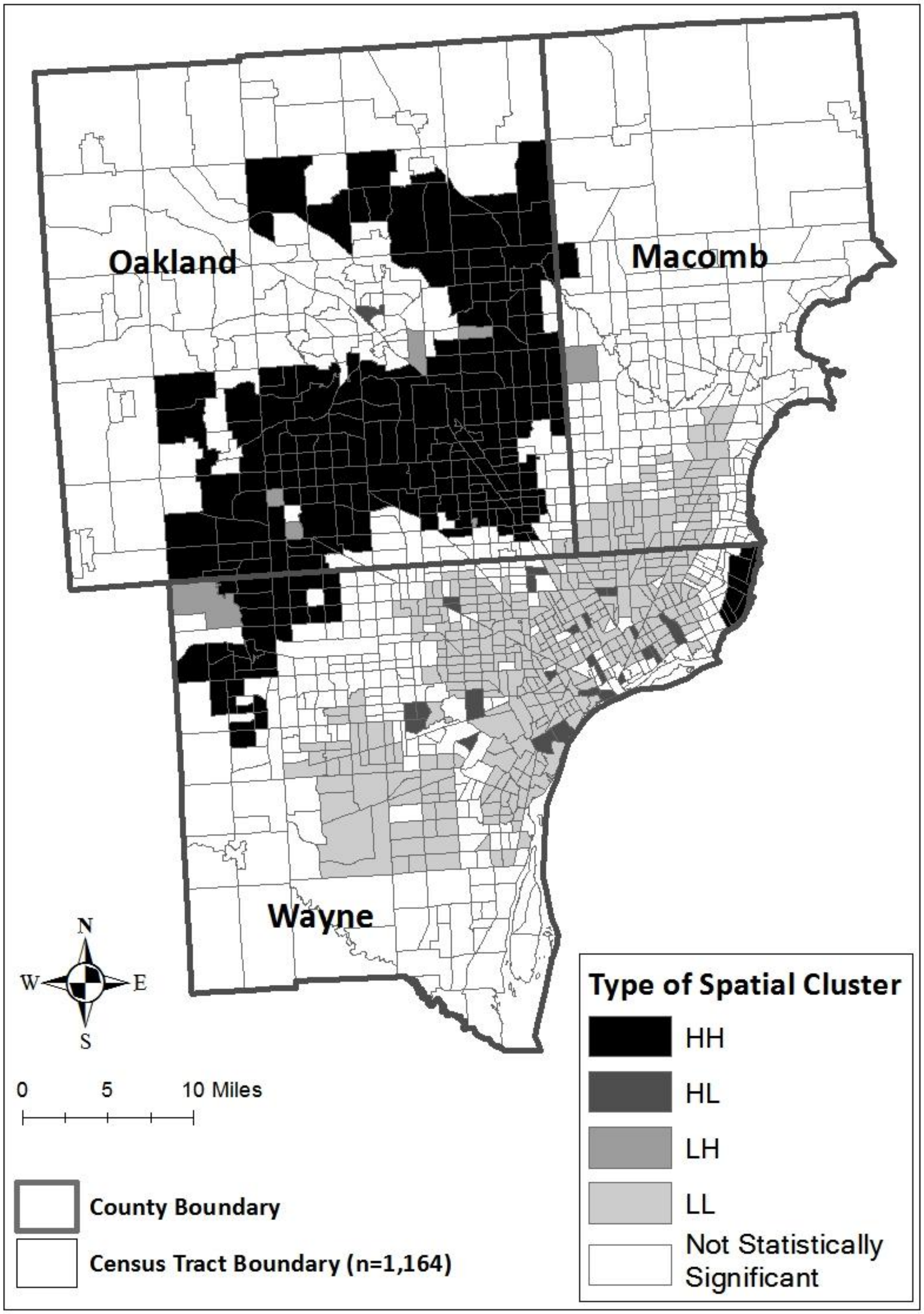

Figure 39. Moran significance map for proportion (%) of population with a four-year university degree or higher by census tract, DMA (2010) (HH: high-high; HL: high-low; LH: low-high; LL: low-low)

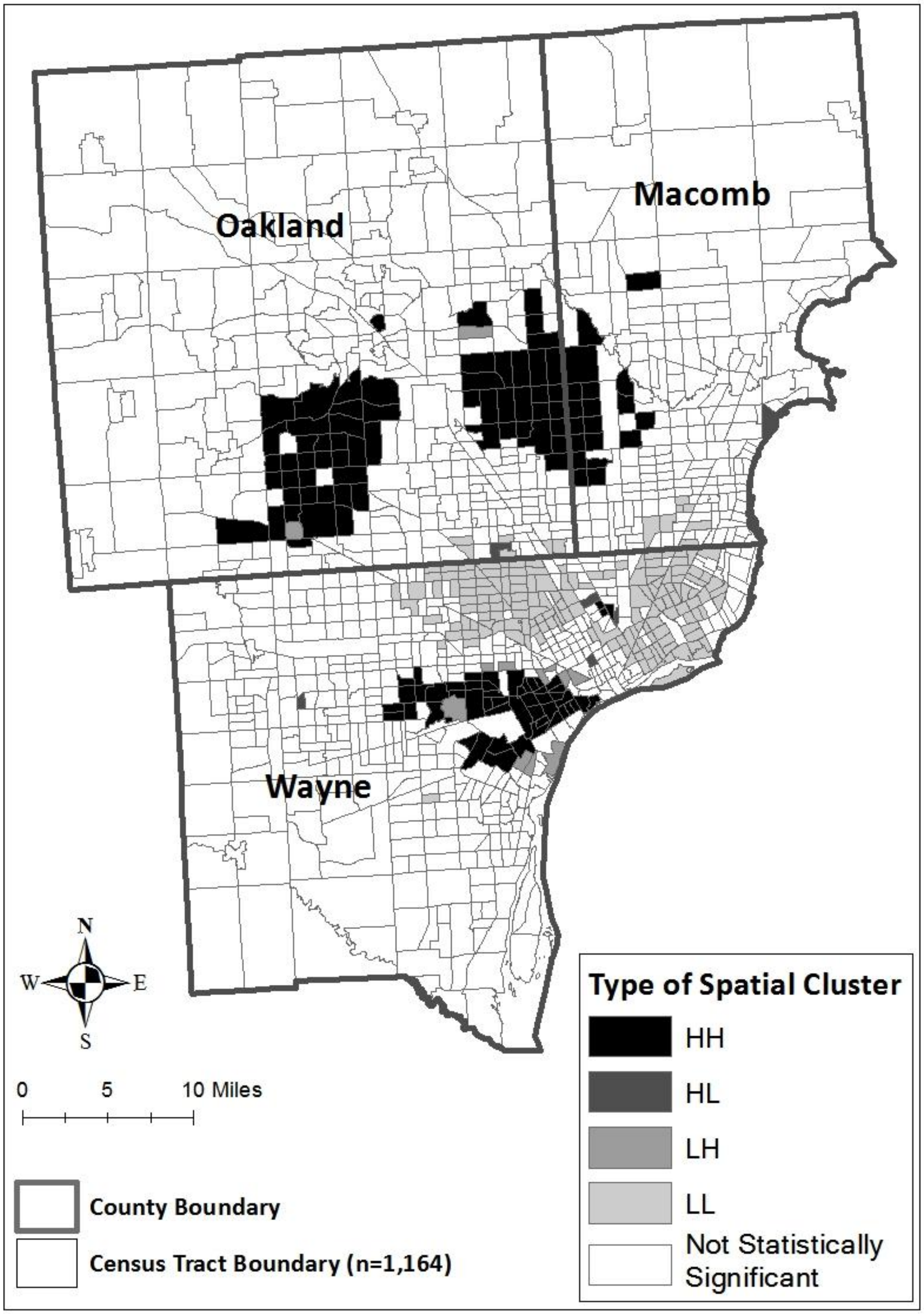

Figure 40. Moran significance map for proportion (%) of population with non-English spoken at home by census tract, DMA (2010) (HH: high-high; HL: high-low; LH: low-high; LL: low-low)

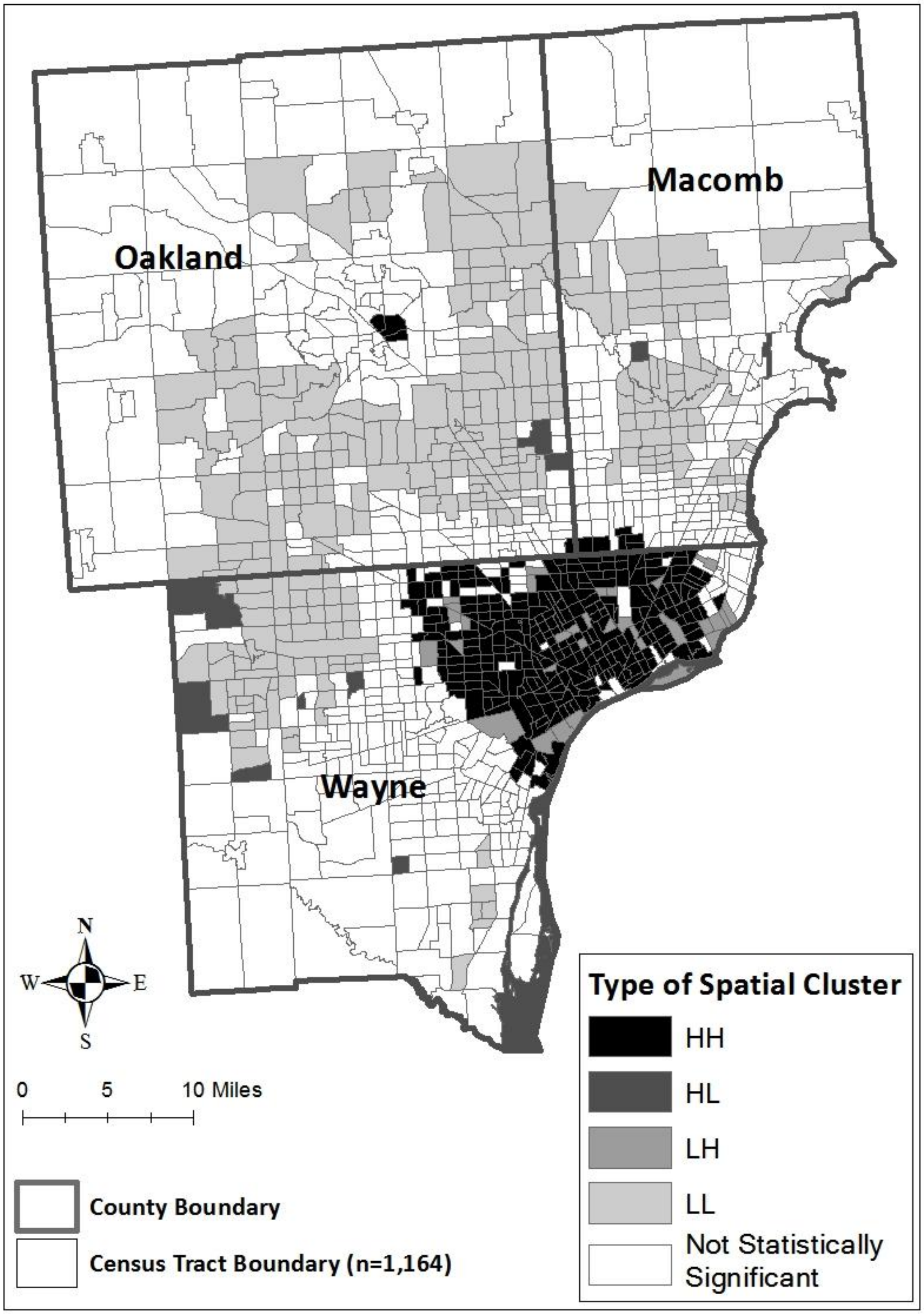

Figure 41. Moran significance map for proportion (%) of population below the poverty line by census tract, DMA (2010) (HH: high-high; HL: high-low; LH: low-high; LL: low-low)

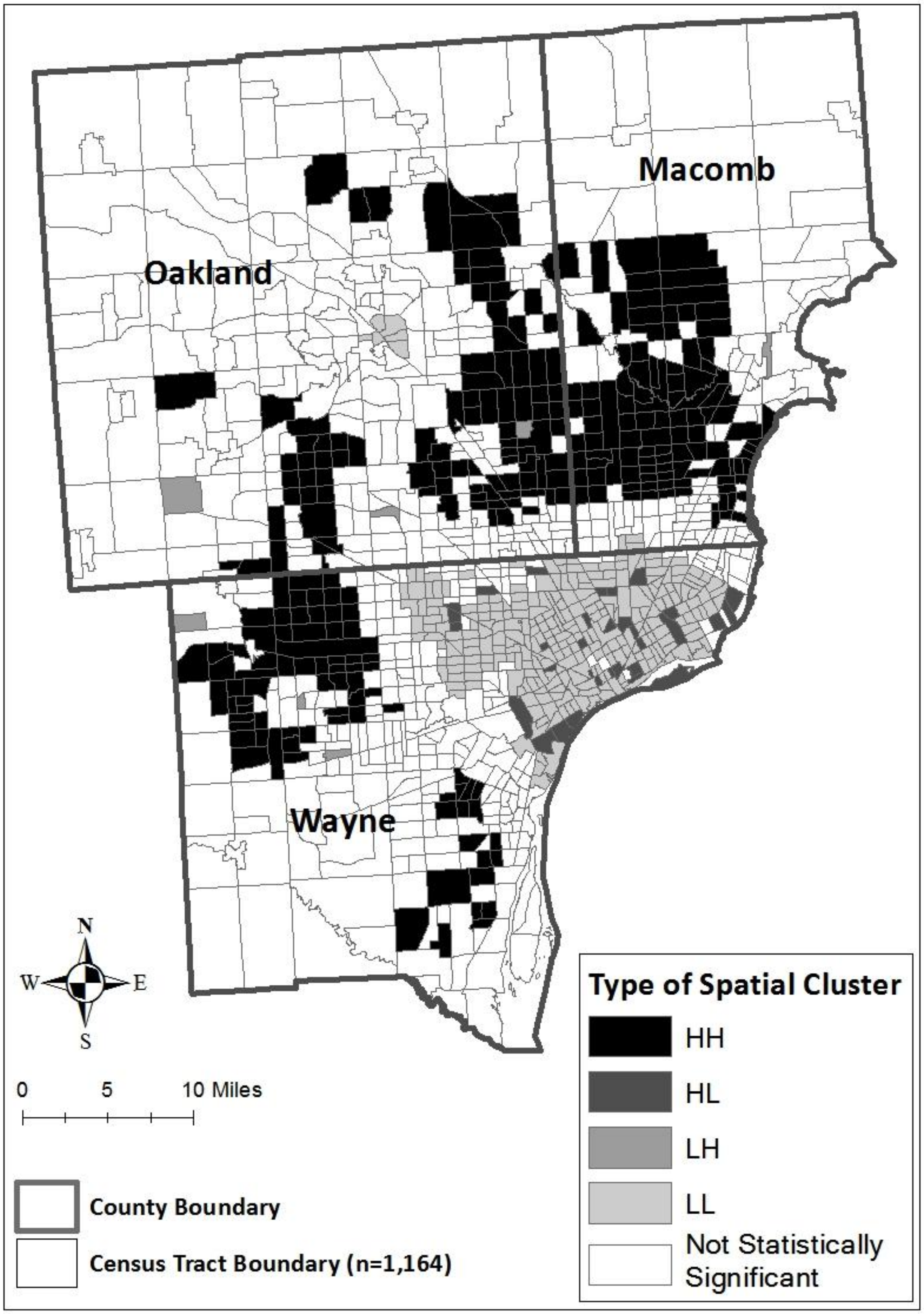

Figure 42. Moran significance map for proportion (%) of occupied housing units by census tract, DMA (2010) (HH: high-high; HL: high-low; LH: low-high; LL: low-low)

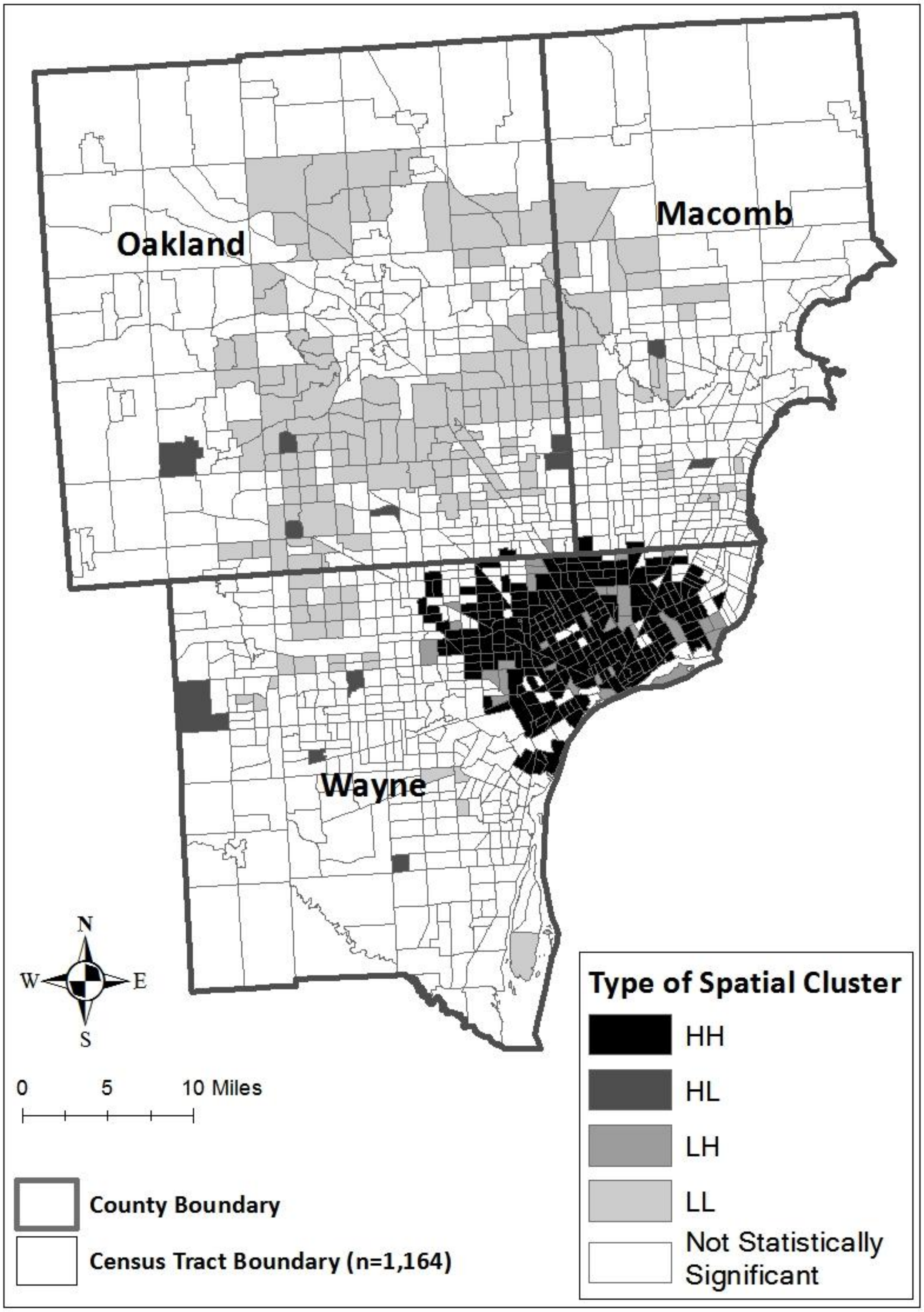

Figure 43. Moran significance map for proportion (%) of households without a vehicle by census tract, DMA (2010) (HH: high-high; HL: high-low; LH: low-high; LL: low-low)

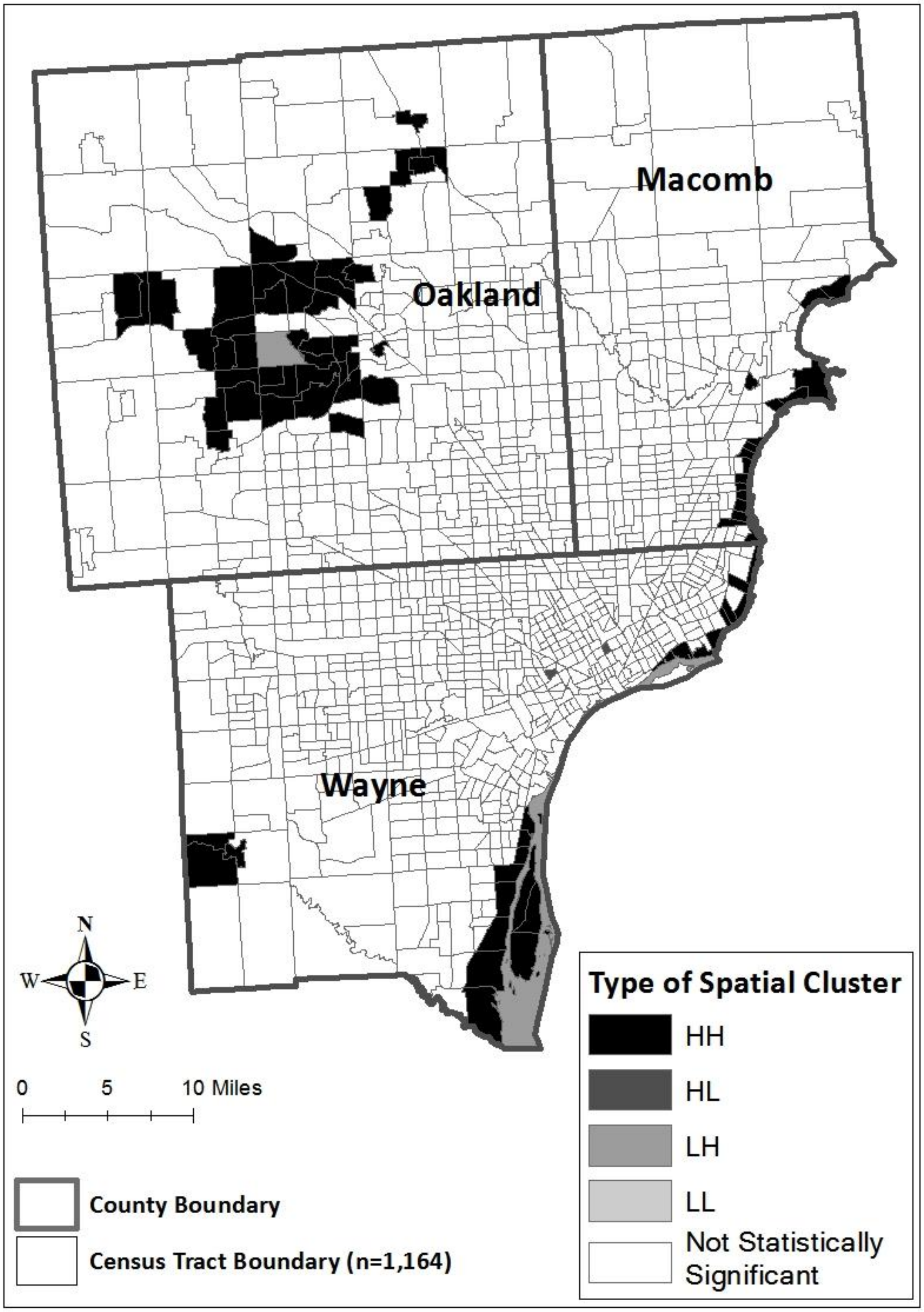

Figure 44. Moran significance map for proportion (%) of water area by census tract, DMA (2010) (HH: high-high; HL: high-low; LH: low-high; LL: low-low)

Objective Three (O3): Demonstrating the Feasibility and Utility of GWR when Measuring the Equity of Access to Public Beaches and Comparing the Results of this Approach with Those of Traditional Multivariate Regression (OLS) Techniques

The third objective of the study was to demonstrate the feasibility and utility of GWR when measuring the equity of access to public beaches and comparing the results of this approach with those of traditional multivariate regression (OLS) techniques. This objective included four research questions; results are discussed below.

O3R1: "What is the relationship between level of access to public beaches in the DMA and residents' demographic and socioeconomic status using OLS?" Two separate OLS regression analyses were performed to examine the effects of residents' demographic and socioeconomic status on the number of public beaches accessible within a 20-mile journey of each tract centroid (Model 1), and the minimum distance to the nearest public beach from each tract centroid (Model 2). As noted by Meleg, Naparus, Fiers, Meleg, Vlaicu, and Moldovan (2014), a VIF value greater than 7.5 suggests redundancy among variables. Because the VIF values associated with MHI were greater than 7.5 (Model 1: 10.25; Model 2: 10.22), MHI was removed from the pool of independent variables. The VIF values for all other variables were smaller than 7.5, indicating the absence of collinearity among the independent variables. As previously noted, WHITE also was excluded due to its extreme negative correlation with BLACK (-0.983, $p < 0.01$). Results of the two regression models are presented in Table 17.

Table 17.

Analysis results of two OLS regression models

Variable	Model 1 (container)						Model 2 (minimum distance)					
	Unstandardized Coefficient		Standardized Coefficent	t	p	VIF	Unstandardized Coefficent		Standardized Coefficent	t	p	VIF
	B	SE	Beta				B	SE	Beta			
Intercept	45.683	25.692		1.77	0.07		3.792	2.39		1.59	0.11	
BLACK	0.190	0.062	0.145	3.06	< 0.01	4.16	0.011	0.006	0.099	1.83	0.06	4.16
ASIAN	0.951	0.435	0.092	2.18	0.02	3.33	0.054	0.041	0.064	1.32	0.18	3.33
HISPAN	0.087	0.213	0.016	0.41	0.68	2.75	0.01	0.020	0.003	0.07	0.94	2.75
POPD	-0.005	0.000	-0.270	-9.54	< 0.01	1.50	0.0002	0.000	0.180	5.55	< 0.01	1.50
MHV	0.000054	0.000	0.091	1.89	0.06	4.28	-0.000005	0.000	-0.098	-1.79	0.07	4.28
AGE18	-0.258	0.320	-0.029	-0.80	0.42	2.40	-0.002	0.030	-0.003	-0.07	0.93	2.40
AGE64	-0.544	0.299	-0.057	-1.81	0.06	1.85	0.065	0.028	0.084	2.32	0.02	1.85
EDU	1.247	0.124	0.471	10.08	< 0.01	4.07	-0.054	0.012	-0.251	-4.70	< 0.01	4.07
LAN	0.038	0.135	0.009	0.28	0.77	2.04	-0.003	0.013	-0.010	-0.27	0.78	2.04
ECON	0.055	0.170	0.018	0.32	0.74	5.92	-0.008	0.016	-0.033	-0.51	0.60	5.92
HO	-0.085	0.248	-0.015	-0.34	0.72	3.57	0.036	0.023	0.079	1.57	0.11	3.57
VEHIC	-0.435	0.186	-0.101	-2.33	0.01	3.50	-0.023	0.017	-0.066	-1.32	0.18	3.50
WATER	-0.364	0.143	-0.063	-2.55	0.01	1.13	-0.046	0.013	-0.097	-3.45	< 0.01	1.13

N = 1,164
R^2 = 0.386, Adjusted R^2 = 0.379
AIC_c = 11,839.75
Joint F-statistic = 55.59 (p-value < 0.01)
Joint Wald statistic = 1,008.19 (p-value < 0.01)
Koenker (BP) statistic = 163.46 (p-value < 0.01)

N = 1,164
R^2 = 0.194, Adjusted R^2 = 0.185
AIC_c = 6,300.11
Joint F-statistic = 45.17 (p-value < 0.01)
Joint Wald Statistic = 365.42 (p-value < 0.01)
Koenker (BP) statistic = 97.63 (p-value < 0.01)

Note: SE: standard error; t: t-value; p: p-value; VIF: variance inflation factor; AIC_c: corrected Akaike's information criterion

According to the results of Model 1 (for the container approach), both the Joint F-statistic and Joint Wald statistic indicated statistical significance for the overall model (Joint F-statistic: 55.59, $p < 0.01$; Joint Wald statistic: 1,008.19, $p < 0.01$). The value of the adjusted R^2 (0.379) showed that the model explains 38% of the variation in the dependent variable, indicating a moderate goodness-of-fit. Six of 13 independent variables (BLACK, ASIAN, POPD, EDU, VEHIC, and WATER) were statistically significant at the 0.05 level. Parameter estimates indicated that BLACK (0.145), ASIAN (0.092), and EDU (0.471) are significantly and positively associated with the number of public beaches accessible within a 20-mile journey of each tract centroid, while POPD (-0.270), VEHIC (-0.101), and WATER (-0.063) are significantly and negatively related to the number of public beaches accessible within a 20-mile journey of each tract centroid. In other words, census tracts with high proportions of Black and Asian populations exhibited significantly higher levels of access to public beaches, while census tracts with high population densities, low levels of educational attainment, and high levels of non-vehicle ownership exhibited significantly lower levels of access to public beaches than for other levels of each characteristic. In addition, census tracts having high proportions of water area also exhibited lower levels of access to public beaches, indicating that water resources are not efficiently distributed or accessible due to lack of public recreational settings such as public beaches. Specifically, the variable BLACK was highly significant ($t = 3.06$, p-value < 0.01), with results indicating a 0.190 increase in number of accessible public beaches when the proportion of Black population increases by 1 percent. The variable ASIAN was highly significant ($t = 2.18$, p-value < 0.05), with results indicating a 0.951 increase in number of accessible public beaches when the proportion of Asian population increases by 1 percent. The variable EDU was highly significant ($t = 10.08$, p-value < 0.01), with results indicating a 1.247 increase in number of accessible public beaches when the proportion of population with a university degree or higher increases by 1 percent. On the other hand, the variable POPD was highly significant ($t = -9.54$, p-value < 0.01), with results indicating a 0.005 decrease in number of accessible public beaches when the population density increases by 1 person per square mile. The variable VEHIC was highly significant ($t = -2.33$, p-value < 0.01), with results indicating a 0.435 decrease in number of accessible public beaches when the proportion of households without a vehicle increases by 1 percent. The variable WATER was highly significant ($t = -2.55$, p-value < 0.01), with results indicating a 0.364 decrease in number of accessible public beaches when the proportion of water area per census tract increases by 1 percent. Educational attainment (EDU) was the most dominant variable. These results suggest that equitable access to public beaches in the DMA exists with respect to proportions of Black and Asian population, but inequitable access to public beaches exists with respect to population density, educational attainment, and vehicle ownership. As seen in Table 17, however, the Koenker (BP) statistic (163.46, $p < 0.01$) indicates statistically significant heteroscedasticity and/or non-stationarity, which refers to spatially varying relationships between variables. Regression models with statistically significant non-stationarity are good candidates for GWR analyses (Fotherinham et al., 2002).

According to the results of Model 2 (for the minimum distance approach), both the Joint F-statistic and Joint Wald statistic indicated statistical significance for the overall model (Joint F-statistic: 45.17, $p < 0.01$; Joint Wald statistic: 365.42, $p < 0.01$). The value of the adjusted R^2 (0.185) suggested a lower level of model performance than that of Model 1. Four of 13 independent variables (POPD, AGE64, EDU, and WATER) were statistically significant at the 0.05 level. Parameter estimates indicated that POPD (0.180) and AGE64 (0.084) were significantly and positively associated with the minimum distance to the nearest public beach, while EDU (-0.257) and WATER (-0.097) are significantly and negatively related to the minimum distance to the nearest public beach. As low distance values correspond to high accessibility, census tracts having high proportions of water areas exhibited significantly higher levels of access to public beaches than for other levels of each characteristic while census tracts having high population densities, more elderly populations, and lower levels of educational attainment area exhibited significantly lower levels of access to public beaches than for other levels of each characteristic. Specifically, the variable POPD was highly significant ($t = 5.55$, p-value < 0.01), with results indicating a 0.0002 miles increase in minimum distance to the nearest public beach when the population density increases by 1 person per square mile. The variable AGE64 was highly significant ($t = 2.32$, p-value < 0.05), with results indicating a 0.065 miles increase in minimum distance to the nearest public beach when the proportion of elderly population increases by 1 percent. The variable EDU was highly significant ($t = -4.70$, p-value < 0.01), with results indicating a 0.054 miles decrease in minimum distance to the nearest public beach when the proportion of population with a 4-year university degree or higher increases by 1 percent. The variable WATER was highly significant ($t = -3.45$, p-value < 0.01), with results indicating a 0.046 miles decrease in minimum distance to the nearest public beach when the proportion of water area per census tract increases by 1 percent. Educational attainment was again the most dominant variable. These results suggest that inequitable access to public beaches in the DMA exists with respect to population density, proportion of elderly population, and educational attainment. As seen in Table 17, the Koenker (BP) statistic (97.63, $p < 0.01$) also indicates that Model 2 exhibits spatial non-stationarity, which refers to spatially varying relationships between variables.

O3R2: "What is the relationship between level of access to public beaches in the DMA and residents' demographic and socioeconomic status using GWR?"

Although the two OLS regression analyses examined the global effects of residents' demographic and socioeconomic statuses on public beach access, they cannot explore spatial variations in the regression coefficients and goodness-of-fit within the study area. Two GWR models, therefore, were developed to identify local variations using the same dependent and independent variables as employed in the global OLS models. A local condition index of 30 was used as a threshold value to detect the existence of local collinearity (Wheeler, 2007). Results of the two GWR models are presented in Table 18.

According to the results of GWR Model 1 (for the container approach), while the global value of adjusted R-square was 0.379, the local adjusted R^2 varied over the study area from a minimum of 0.02 to a maximum of 0.92 (mean: 0.69) for the local Model 1. The local condition index is between 9.7 (minimum) and 24.8 (maximum), indicating the absence of local collinearity among the independent variables. Compared to the OLS coefficients for BLACK (0.145), ASIAN (0.092), POPD (-0.270), EDU (0.471), VEHIC (-0.101), and WATER (-0.063) variables, the ranges of the local coefficients for these variables were -126.40 to 67.72 with a mean of -1.98 (BLACK), -21.79 to 27.46 with a mean of -1.39 (ASIAN), -18.55 to 26.81 with a mean of -1.36 (POPD), -8.09 to 58.92 with a mean of 4.87 (EDU), -25.34 to 19.55 with a mean of -1.12 (VEHIC), and -372.85 to 156.97 with a mean of -3.76 (WATER). This variability in the local coefficients suggests that the relationships between the number of public beaches accessible within a 20-mile journey from each tract centroid and residents' demographic and socioeconomic statuses are not stationary. In other words, the relationships among variables vary over space.

According to the results of GWR Model 2 (for the minimum distance approach), while the global value of R^2 was 0.185, there were large variations in the performance of the model across the study area, ranging from a minimum of 0.27 to a maximum of 0.92 (mean: 0.70). The local condition index ranges from a minimum of 8.6 to a maximum of 24.4, indicating the absence of local collinearity among the independent variables. Compared to the OLS coefficients for POPD (0.180), AGE64 (0.084), EDU (-0.257), and WATER (-0.097) variables, the ranges of the local coefficients for these variables were -1.29 to 1.40 with a mean of 0.14 (POPD), -1.01 to 2.85 with a mean of 0.12 (AGE64), -3.25 to 2.73 with a mean of -0.02 (EDU), and -19.06 to 19.69 with a mean of -1.09 (WATER). This variability in the local coefficients suggests that the relationships between the minimum distance to the nearest public beach and residents' demographic and socioeconomic statuses are not stationary. In other words, the relationships among variables vary over space.

Table 18.

Analysis results of two GWR models

Variable	Model 1 (container)					Model 2 (minimum distance)				
	OLS Coefficient	GWR Coefficients			Range	OLS Coefficient	GWR Coefficients			Range
	Beta	Minimum	Mean	Maximum		Beta	Minimum	Mean	Maximum	
Intercept		-36.64	41.68	151.21	187.85		1.29	6.90	16.13	14.84
BLACK	0.145	-126.40	-1.98	67.72	194.12	0.099	-5.55	0.31	7.77	13.32
ASIAN	0.092	-21.79	-1.39	27.46	49.25	0.064	-2.81	0.09	4.71	7.52
HISPAN	0.016	-104.82	-2.30	205.51	310.33	0.003	-7.54	0.17	8.64	16.18
POPD	-0.270	-18.55	-1.36	26.81	63.91	0.180	-1.29	0.14	1.40	2.69
MHV	0.091	-21.24	0.90	29.69	50.93	-0.098	-4.10	-0.17	2.84	6.94
AGE18	-0.029	-15.71	-1.33	8.53	24.24	-0.003	-1.57	0.04	4.58	6.15
AGE64	-0.057	-11.18	0.07	12.14	23.32	0.084	-1.01	0.12	2.85	3.86
EDU	0.471	-8.09	4.87	58.92	67.01	-0.251	-3.25	-0.02	2.73	5.98
LAN	0.009	-21.43	0.93	19.28	40.71	-0.010	-1.66	-0.09	4.30	5.96
ECON	0.018	-20.37	1.07	47.97	68.34	-0.033	-2.51	0.02	4.15	6.66
HO	-0.015	-29.58	-0.57	13.80	43.38	0.079	-1.61	0.21	4.89	6.50
VEHIC	-0.101	-25.34	-1.12	19.55	44.89	-0.066	-1.85	0.05	2.20	4.05
WATER	-0.063	-372.85	-3.76	156.97	529.82	-0.097	-19.06	-1.09	19.69	38.75
Adjusted R^2	0.379	0.02	0.69	0.92	0.90	0.185	0.27	0.70	0.92	0.65
Condition Index		9.7	14.6	24.8	15.1		8.6	16.3	24.4	15.8
N = 1,164 AIC_c (OLS) = 11,839.75 AIC_c (GWR) = 8679.89 Neighbors = 147						N = 1,164 AIC_c (OLS) = 6,300.11 AIC_c (GWR) = 4,085.73 Neighbors = 147				

Note: Beta: standardized OLS coefficient; AIC_c: corrected Akaike's information criterion

O3R3: "How does the spatial relationship between level of access to public beaches and residents' demographic and socioeconomic status vary across the study area (using GWR)?"

Although Table 18 suggests the existence of spatial variations in the local coefficients and goodness-of-fit of the GWR models, it does not show how the relationships between level of access to public beaches and residents' demographic and socioeconomic status vary across the study area. The local coefficients and local R^2 for the two GWR models, therefore, were mapped. Figures 45-54 (p. 156-169) illustrate the spatial distributions of local coefficients and local R^2 for those independent variables that were statistically significant variables in the OLS models. For all local coefficient maps (Model 1: BLACK, ASIAN, POPD, EDU, VEHIC, and WATER; Model 2: POPD, AGE64, EDU, and WATER), lighter colors indicate negative values whereas darker colors indicate positive values. These maps also are summarized in Table 19, indicating the number of census tracts exhibiting each of the four classes by the value of local coefficient (LC > 0 [census tract in which the value of the local coefficient is greater than 0], LC < 0 [census tract in which the value of the local coefficient is less than 0], LC > GC [census tract in which the value of the local coefficient is greater than the value of the global coefficient], and LC < GC [census tract in which the value of the local coefficient is less than the value of the global coefficient]), and the value of local R^2 (0.00-0.25 [census tract in which the value of local R^2 is between 0.00 and 0.25], 0.26-0.50, 0.51-0.75, and 0.76-1.00.

Table 19.

Classification of census tracts by values of local coefficient and local R^2

	Variable	Number of census tracts (N = 1,164)			
		LC > 0 (%)	LC < 0 (%)	LC > GC (%)	LC < GC (%)
Model 1	BLACK	523 (44.9%)	641(55.0%)	492 (42.2%)	672 (57.7%)
	ASIAN	678 (58.2%)	486 (41.7%)	411 (35.3%)	488 (41.9%)
	POPD	446 (38.3%)	718 (61.6%)	447 (38.4%)	717 (61.5%)
	EDU	749 (64.3%)	415 (35.6%)	598 (51.3%)	566 (46.6%)
	VEHIC	480 (41.2%)	684 (58.7%)	630 (54.1%)	534 (45.8%)
	WATER	544 (46.7%)	620 (53.2%)	455 (39.0%)	455 (39.0%)
	R^2	Adjusted R^2 (OLS): 0.379		GWR > OLS (%)	GWR < OLS (%)
		Adjusted R^2 (GWR): 0.690		1,120 (96.2)	44 (3.7)
Model 2	POPD	771 (66.2%)	393 (33.7%)	770 (66.1%)	394 (33.8%)
	AGE64	628 (53.9%)	536 (46.0%)	550 (47.2%)	614 (52.7%)
	EDU	536 (46.0%)	628 (53.9%)	566 (48.6%)	598 (51.3%)
	WATER	283 (24.2%)	881 (75.6%)	303 (26.3%)	861(73.9%)
	R^2	Adjusted R^2 (OLS): 0.185		GWR > OLS (%)	GWR < OLS (%)
		Adjusted R^2 (GWR): 0.700		1,164 (100)	0 (0.0)

Note: LC: local coefficient by GWR; GC: global coefficient by OLS; LC > GC: census tract in which the value of the local coefficient is greather than the value of the global coefficient; LC < GC: census tract in which the value of the local coefficient is less than the value of the global coefficient; 0.00-0.25: census tract in which the value of local R^2 is between 0.00 and 0.25; 0.26-0.50: census tract in which the value of local R^2 is between 0.26 and 0.50; 0.51-0.75: census tract in which the value of local R^2 is between 0.51 and 0.75; 0.76-1.00: census tract in which the value of local R^2 is between 0.76 and 1.00

BLACK (Model 1). The map of local coefficients for GWR Model 1 for BLACK is shown in Figure 45. According to Table 18, the OLS coefficient for BLACK is 0.145 ($p < 0.05$), indicating equitable access to public beaches with regard to Black population across the study area. However, Figure 45 (p. 156) and Table 19 show that both positive (n=523, 44.9%) and negative (n=641, 55.0%) correlations are spatially distributed in the study area. The local coefficients for BLACK ranged from -126.39 (city of Sterling Heights, Macomb County) to 67.72 (Bruce Township, Macomb County), with a mean of -1.98. Strong positive correlations (local coefficient > 31.7 [2 standard deviations above the mean]), indicating equitable access to public beaches with respect to Black population, were observed in the cities of Troy and Rochester Hills and in the townships of Addision and Oakland, Oakland County, and in the townships of Bruce and Washington, Macomb County. Strong negative correlations (local coefficient < -35.66 [2 standard deviations below the mean]), indicating inequitable access to public beaches with respect to Black population, were identified in the city of Sterling Heights and in the townships of Shelby and Washington, Macomb County. Four hundred ninety-two (42.2%) of the 1,164 census tracts had local coefficients greater than the OLS coefficient, while 672 (57.7%) of the 1,164 census tracts had local coefficients lower than the OLS coefficient. This variability in the model parameters suggests that the relationship between number of public beaches accessible within a 20-mile journey and proportion (%) of Black population is not stationary within the study area at the census tract level.

ASIAN (Model 1). The map of local coefficients for the GWR Model 1 for ASIAN is shown in Figure 46. According to Table 18, the OLS coefficient for ASIAN is 0.092 ($p < 0.05$), indicating equitable access to public beaches with regard to Asian population across the study area. However, Figure 46 (p. 157) and Table 19 show that both positive (n=678, 58.2%) and negative (n=486, 41.7%) correlations occur across the study area. The local coefficients for ASIAN ranged from -21.79 (Plymouth Township, Wayne County) to 27.46 (city of Farmington Hills, Oakland County), with a mean of -1.39. Strong positive correlations (local coefficient > 10.55), indicating equitable access to public beaches with respect to Asian population, were observed in the cities of Farmington Hills and Novi and in the townships of Lyon and Milford, Oakland County, and in the city of Sterling Heights, Macomb County. Strong negative correlations (local coefficient < -13.33), indicating inequitable access to public beaches with respect to Asian population, emerged in the city of Troy, Oakland County, and in the townships of Canton and Plymouth, Wayne County. Four hundred eleven (35.3%) of the 1,164 census tracts had local coefficients greater than the OLS coefficient while 488 (41.9%) of the 1,164 census tracts had local coefficients lower than the OLS coefficient. This variability in the model parameters suggests that the relationship between number of public beaches accessible within a 20-mile journey and proportion (%) of Asian population is not stationary within the study area at the census tract level.

POPD (Model 1). The map of local coefficients for the GWR Model 1 for POPD is shown in Figure 47. According to Table 18, the OLS coefficient for POPD is -0.270 ($p < 0.05$), indicating inequitable access to public beaches with regard to population density across the study area. However, Figure 47 (p. 158) and Table 19 show that both positive (n=446, 38.3%) and negative (n=718, 61.6%) correlations occur across the study area. The local coefficients for POPD ranged from -18.55 (Shelby Township, Macomb County) to 26.81 (Groveland Township, Oakland County), with a mean of -1.36. Strong positive correlations (local coefficient > 9.12), indicating equitable access to public beaches with respect to population density, were observed in the townships of Brandon, Groveland, Holly, Independence, Oxford, Rose, and Springfield, Oakland County. Strong negative correlations (local coefficient < -11.84), indicating inequitable access to public beaches with respect to population density, emerged in the city of Troy, Rochester, and South Lyon, Oakland County; in the city of Livonia, Wayne County; and in the townships of Macomb, Ray, Shelby, and Washington, Macomb County. Four hundred forty-seven (38.4%) of the 1,164 census tracts had local coefficients greater than the OLS coefficient while 717 (61.5%) of the 1,164 census tracts had local coefficients lower than the OLS coefficient. This variability in the model parameters suggests that the relationship between number of public beaches accessible within a 20-mile journey and population per square mile is not stationary within the study area at the census tract level.

EDU (Model 1). The map of local coefficients for the GWR Model 1 for EDU is shown in Figure 48. According to Table 18, the OLS coefficient for EDU is 1.247 ($p < 0.01$), indicating inequitable access to public beaches with regard to education attainment across the study area. However, Figure 48 (p. 159) and Table 19 show that both positive (n=749, 64.3%) and negative (n=415, 35.6%) correlations occur across the study area. The local coefficients for EDU ranged from -8.09 (city of Pontiac, Oakland County) to 58.92 (Washington Township, Macomb County), with a mean of 4.87. Strong positive correlations (local coefficient > 15.95), indicating inequitable access to public beaches with respect to educational attainment, were observed in the cities of Rochester and Rochester Hills and in the townships of Addision and Oakland, Oakland County, and in the townships of Armada, Bruce, Richmond, Shelby, and Washington, Macomb County. Strong negative correlations (local coefficient < -6.21), indicating equitable access to public beaches with respect to educational attainment, emerged in the cities of Auburn Hills and Southfield and in the townships of Bloomfield, Commerce, Highland, Milford, Waterford, White Lake, and West Bloomfield, Oakland County; in the cities of Roseville and Warren, Macomb County; and in the cities of Detroit and Dearborn Heights, Wayne County. Five hundred ninety-eight (51.3%) of the 1,164 census tracts had local coefficients greater than the OLS coefficient while 566 (46.6%) of the 1,164 census tracts had local coefficients lower than the OLS coefficient. This variability in the model parameters suggests that the relationship between number of public beaches accessible within a 20-mile journey and proportion (%) of population having a four-year university degree or higher is not stationary within the study area at the census tract level.

VEHIC (Model 1). The map of local coefficients for the GWR Model 1 for VEHIC is shown in Figure 49 (p. 160). According to Table 18, the OLS coefficient for VEHIC is -0.101 ($p < 0.05$), indicating inequitable access to public beaches with regard to vehicle ownership across the study area. However, Figure 49 and Table 19 show that both positive (n=480, 41.2%) and negative (n=684, 58.7%) correlations occur across the study area. The local coefficients for VEHIC ranged from -29.34 (Brandon Township, Oakland County) to 19.55 (city of Rochester, Oakland County), with a mean of 1.12. Strong positive correlations (local coefficient > 8.86), indicating equitable access to public beaches with regard to vehicle ownership, were observed in the city of Rochester Hill and in the township of Oakland, Oakland County, and in the townships of Armada, Lenox, Macomb, Ray, and Richmond, Macomb County. Strong negative correlations (local coefficient < -11.1), indicating inequitable access to public beaches with regard to vehicle ownership, emerged in the cities of Novi and Troy and in the townships of Brandon, Groveland, Independence, Oxford, Oakland County; in the townships of Northville and Plymouth, Wayne County; and in the city of Sterling Heights, Macomb County. Six hundred thirty (54.1%) of the 1,164 census tracts had local coefficients greater than the OLS coefficient while 534 (45.8%) of the 1,164 census tracts had local coefficients lower than the OLS coefficient. This variability in the model parameters suggests that the relationship between number of public beaches accessible within a 20-mile journey and proportion (%) of households without a vehicle is not stationary within the study area at the census tract level.

R^2 (Model 1). Figure 50 (p. 161) shows the spatial distribution of local R^2 by census tract. The global value of R^2 was 0.379, but the local value of R^2 varied over the study area from 0.02 (Harrison township, Macomb County) to 0.92 (city of Sterling Heights, Macomb County), with a mean of 0.690. As seen in Table 19, the majority of the census tracts (n=1,120, 96.2%)

had local R^2 values greater than the global value of R^2 while only 44 (3.7%) of the 1,164 census tracts had local R^2 values lower than the global value of R^2. The local model had the best explanatory power in the cities of Madison Heights, Rochester Hills, Royal Oak, and Troy and in the townships of Addison, Lyon, Milford, Oakland, Orion, and Oxford, Oakland County; in the cities of Sterling Heights and Warren and in the townships of Armanda, Bruce, Macomb, Ray, Richmond, Shelby, and Washington, Macomb County; and in the cities of Dearborn, Detroit, Livonia, and Westland and in the townships of Redford and Northville, Wayne County (in excess of 80%). However, the local model had very low explanatory power in the township of Harrison, Macomb County, and in the city of Romulus and in the townships of Huron and Sumpter, Wayne County (as low as 20%), indicating that level of access to public beaches in these areas is not explained adequately by the set of explanatory variables with the local R^2 falling below the global value of 0.379 (OLS Model 1) and the local mean value of 0.690 (GWR Model 1). These findings indicate that the explanatory power of the local model is not stationary, indicating that the degree of model performance is spatially heterogeneous across the study area.

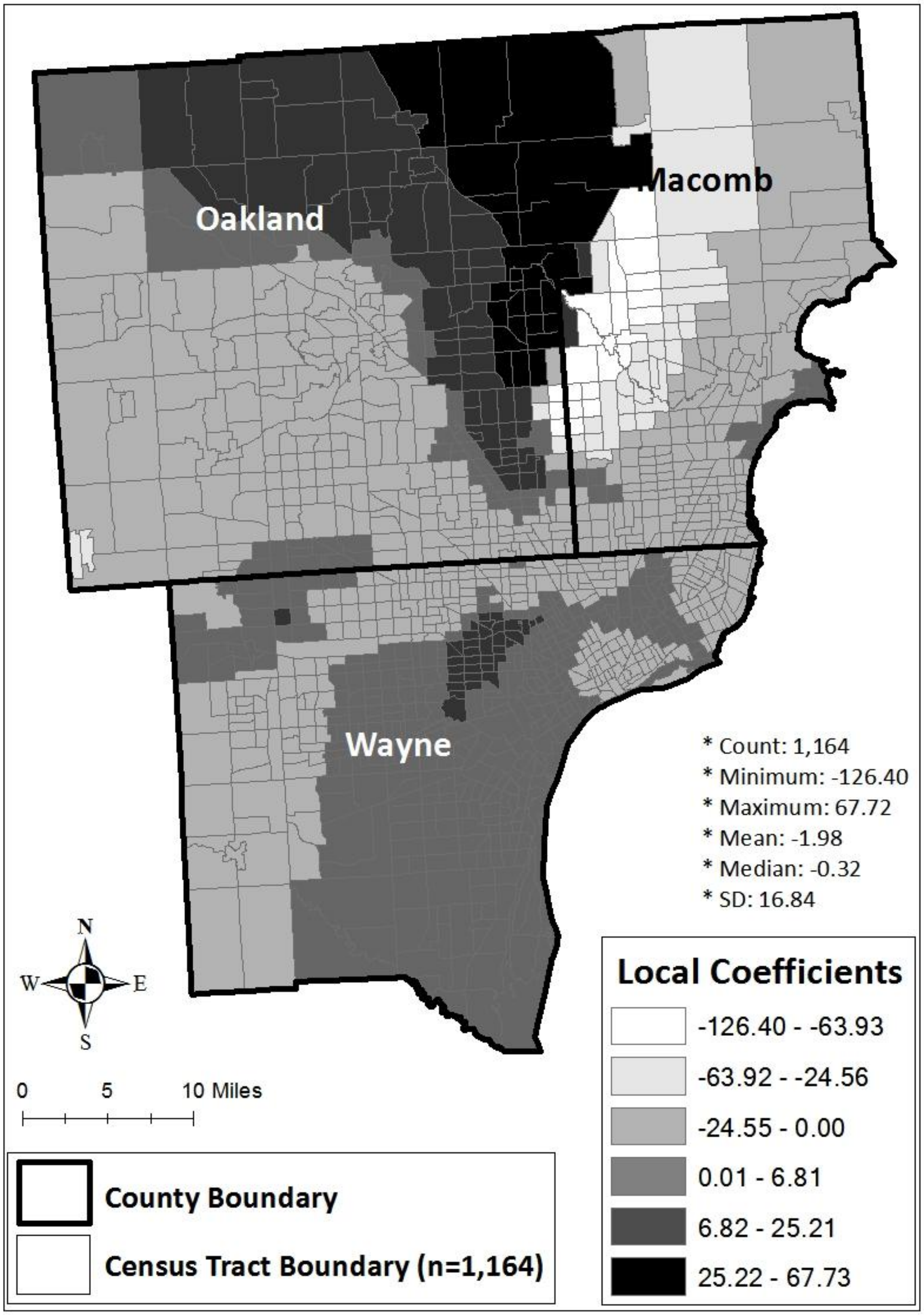

Figure 45. Spatial distribution of local parameter estimates for proportion (%) of Black population by census tract, DMA (Model 1)

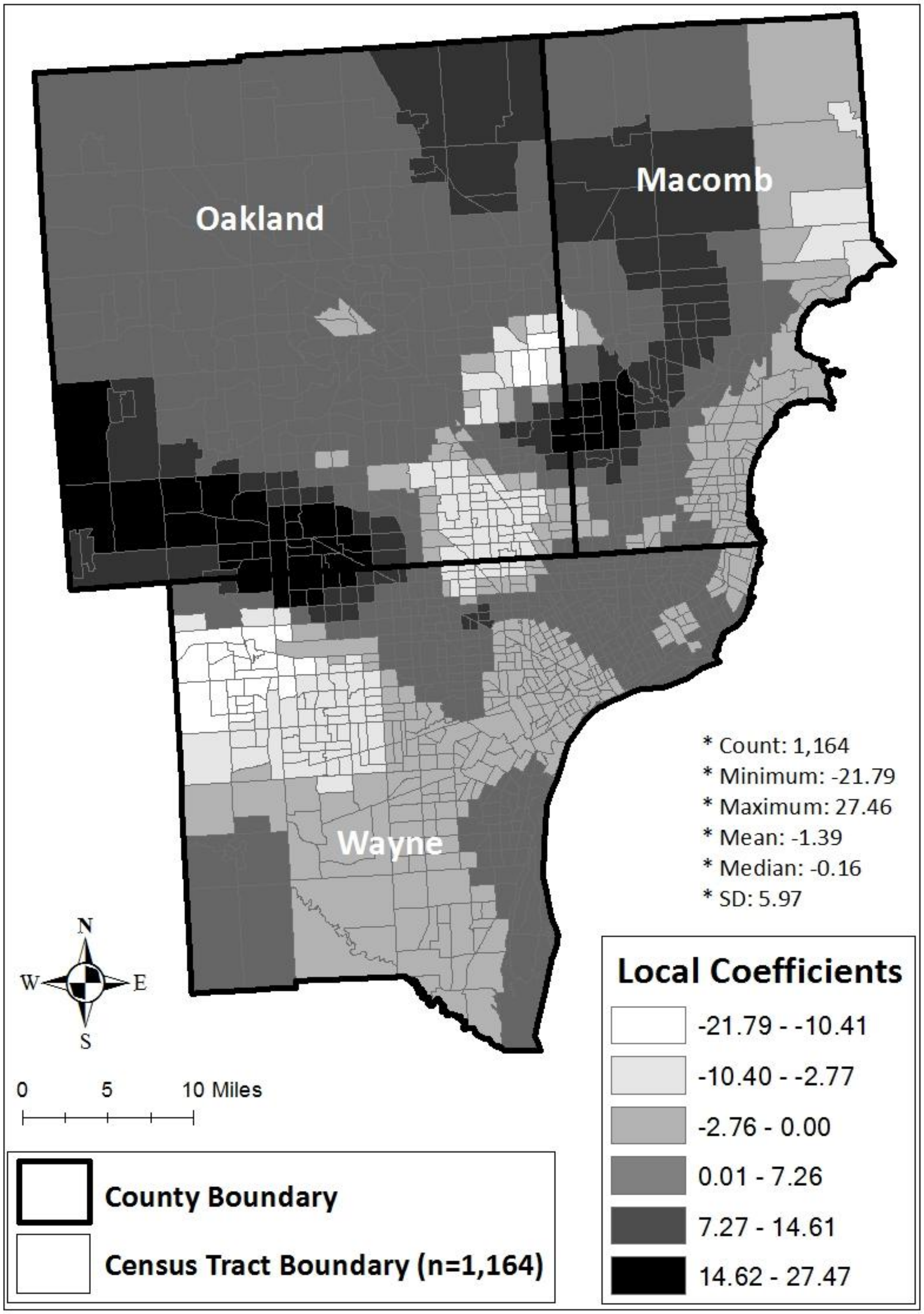

Figure 46. Spatial distribution of local parameter estimates for proportion (%) of Asian population by census tract, DMA (Model 1)

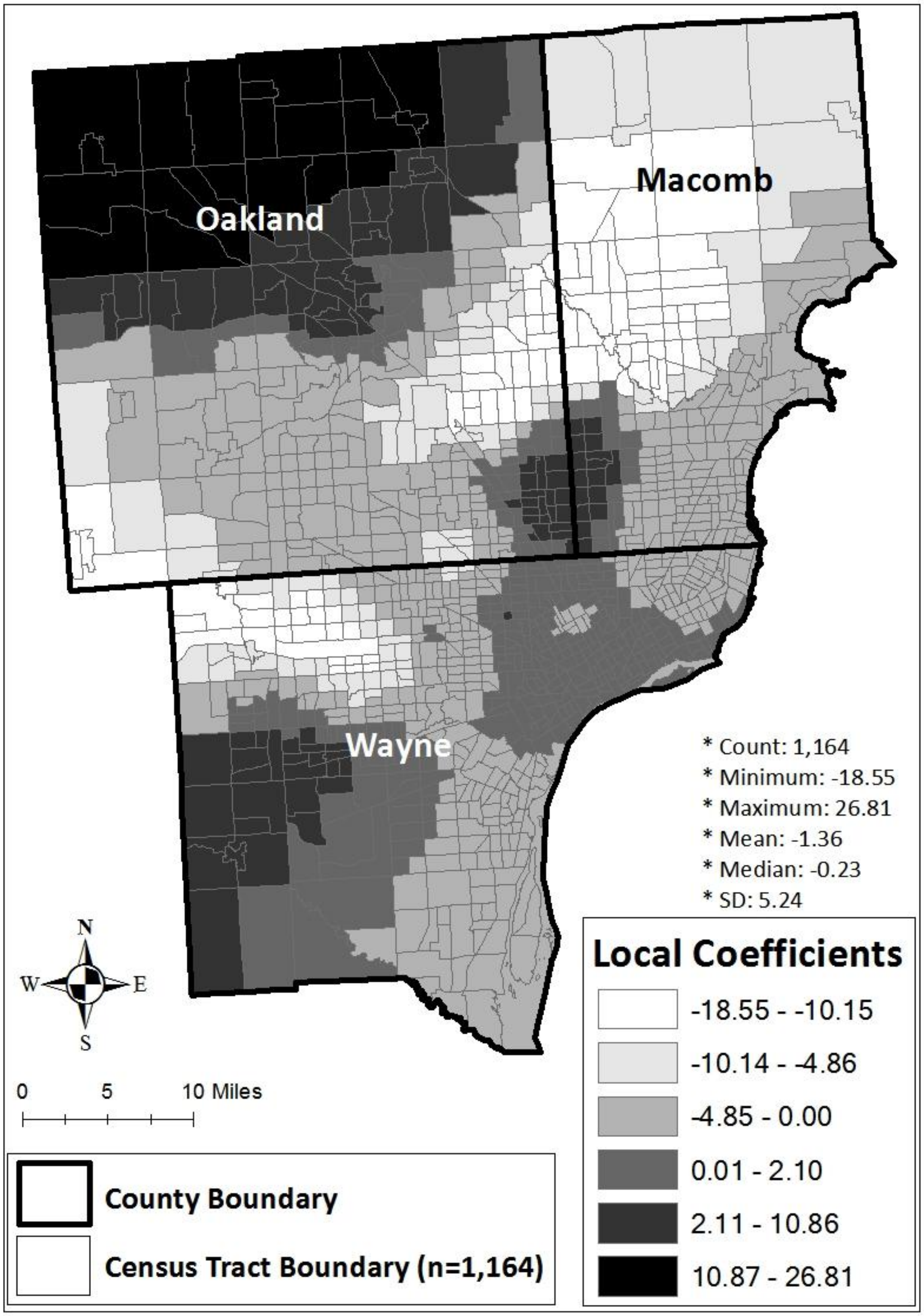

Figure 47. Spatial distribution of local parameter estimates for population per square mile by census tract, DMA (Model 1)

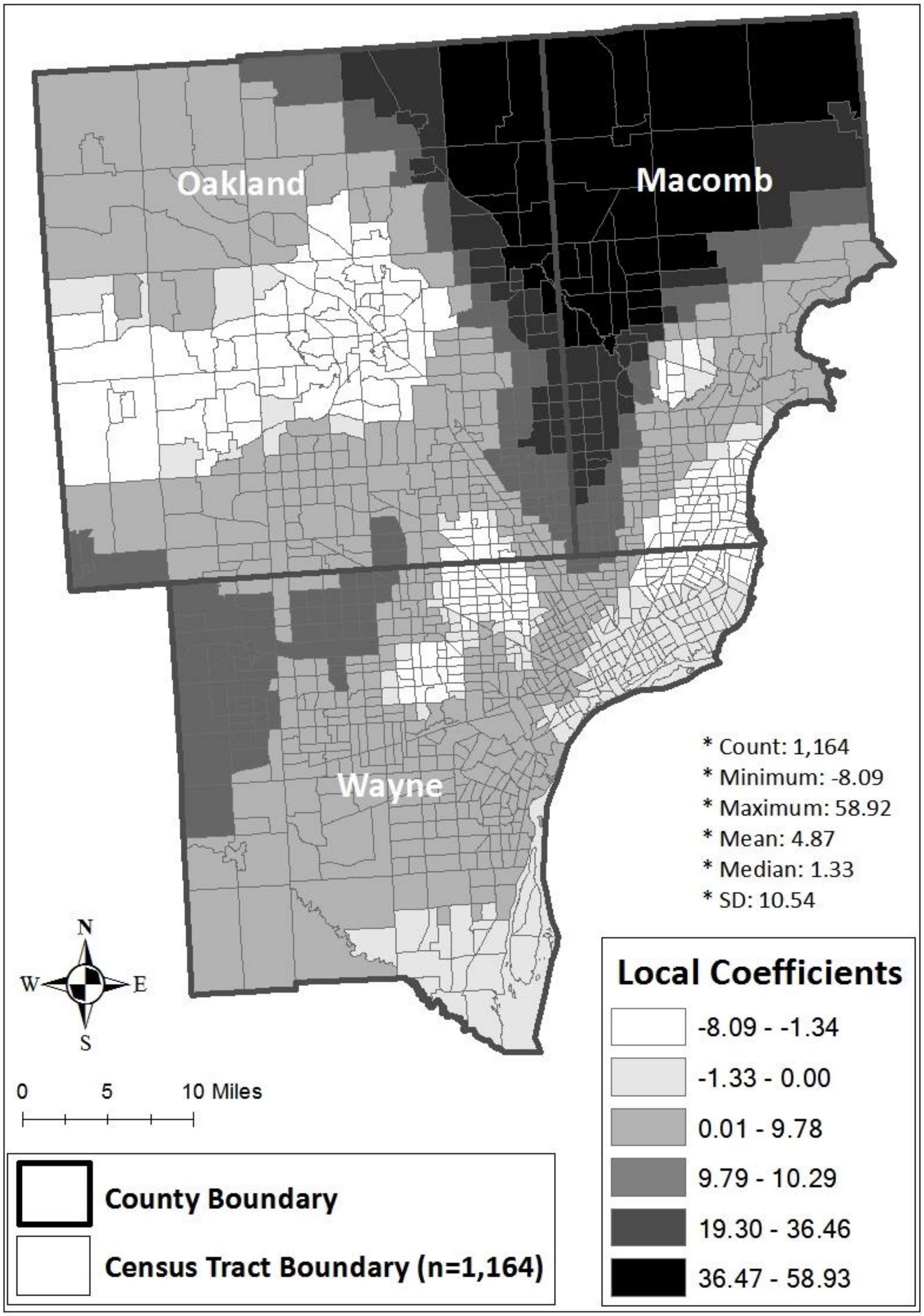

Figure 48. Spatial distribution of local parameter estimates for population with a four-year university degree or higher by census tract, DMA (Model 1)

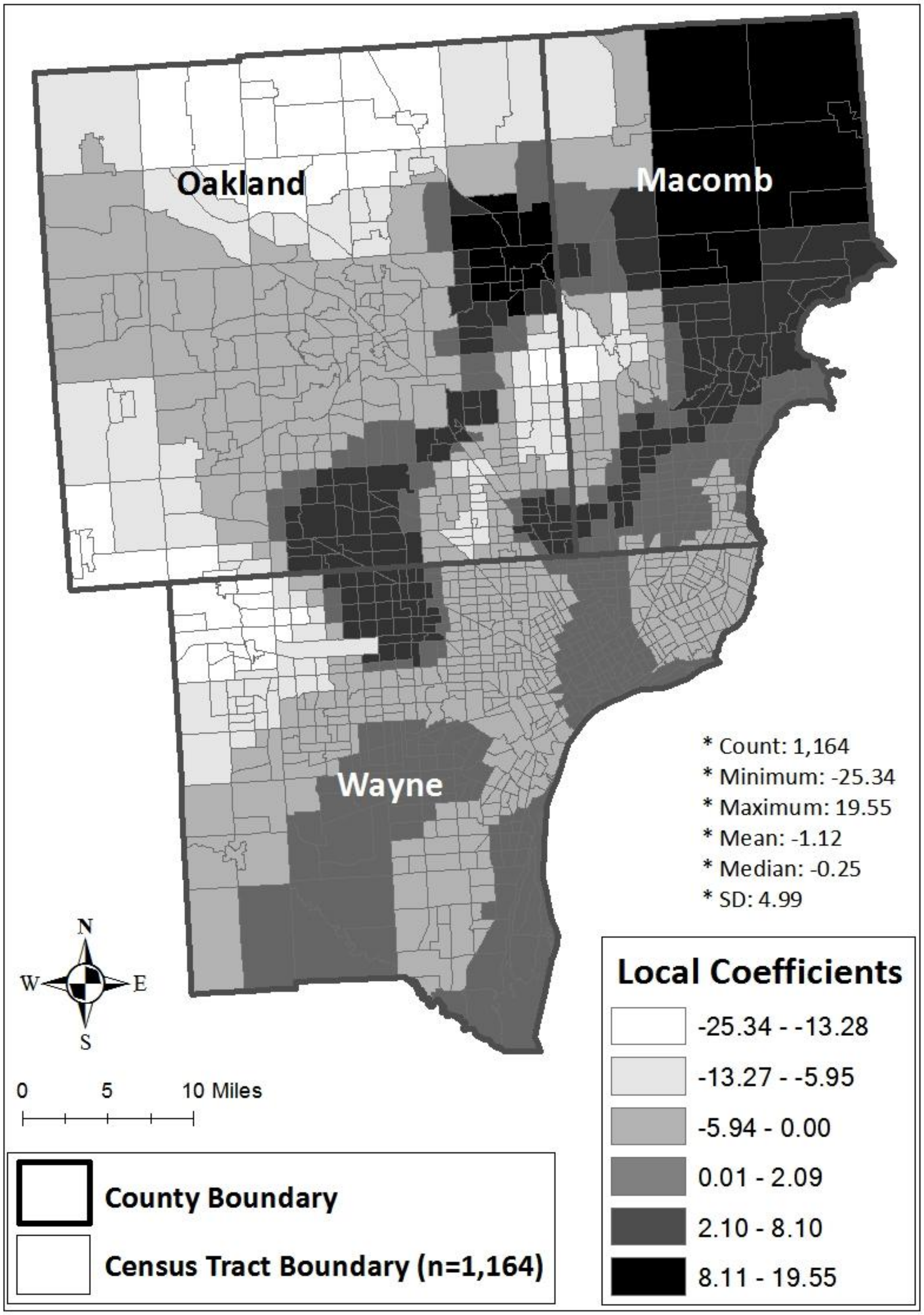

Figure 49. Spatial distribution of local parameter estimates for proportion (%) of households without a vehicle by census tract, DMA (Model 1)

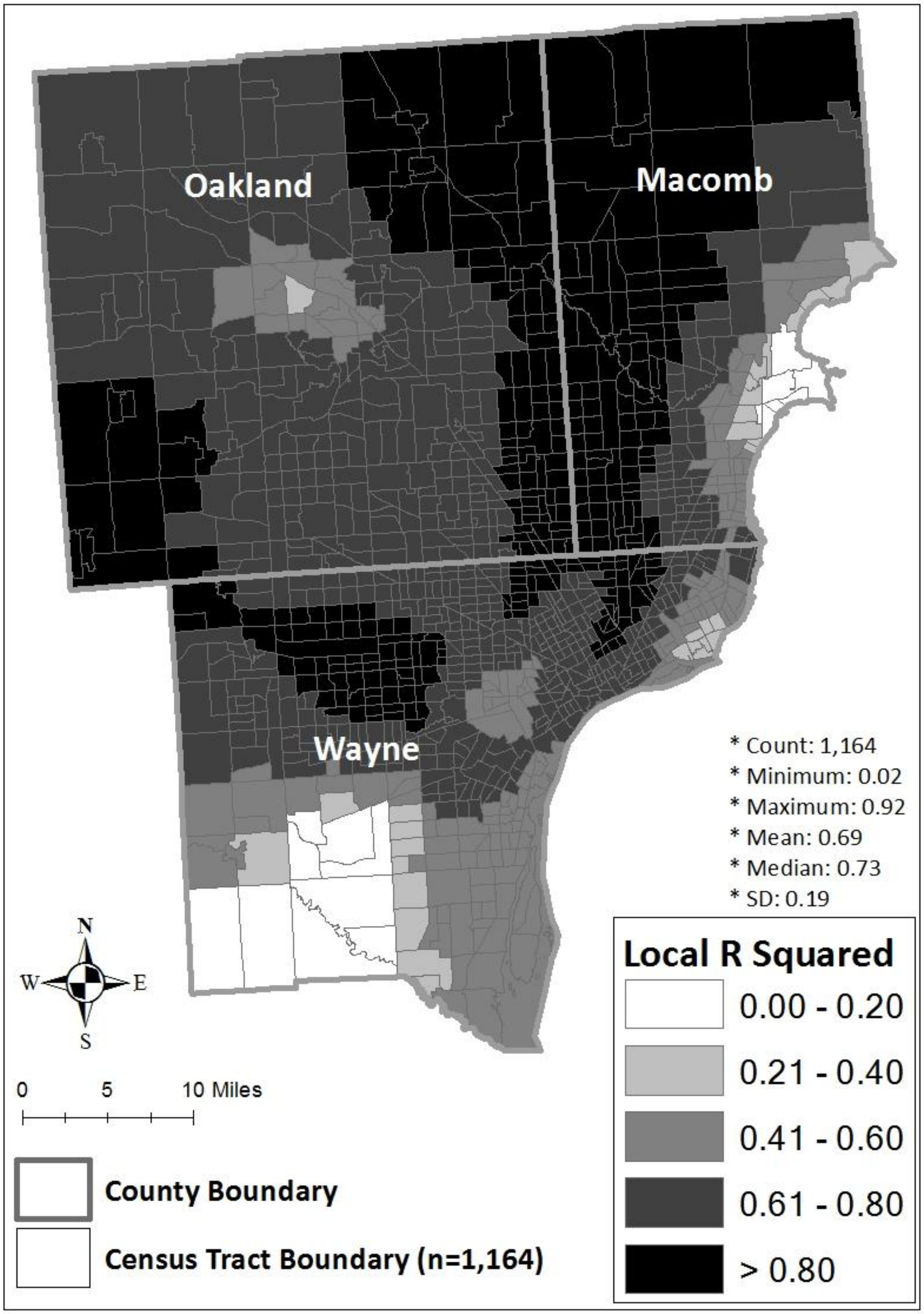

Figure 50. Spatial distribution of local R^2s by census tract, DMA (Model 1)

POPD (Model 2). The map of local coefficients for the GWR Model 2 for POPD is shown in Figure 51 (p. 166). According to Table 18, the OLS coefficient for POPD is 0.180 ($p < 0.05$), indicating inequitable access to public beaches with regard to population density across the study area. However, Figure 51 and Table 19 show that both positive (n=771, 66.2%) and negative (n=393, 33.7%) correlations occur across the study area. The local coefficients for POPD ranged from -1.29 (city of Warren, Macomb County) to 1.40 (Shelby Township, Oakland County), with a mean of 0.14. Strong positive correlations (local coefficient > 1.04), indicating inequitable access to public beaches with respect to population density, were observed in the cities of Rochester Hills and Troy and in the townships of Bloomfield and Oakland, Oakland County, and in the townships of Shelby and Washington, Macomb County. Strong negative correlations (local coefficient < -0.76), indicating equitable access to public beaches with respect to population density, emerged in the townships of Groveland, Holly, Independence, Rose, Springfield, and Waterford, Oakland County; in the cities of Roseville and Warren, Macomb County; and in the city of Livonia and in the township of Northville, Wayne County. Seven hundred seventy (66.1%) of the 1,164 census tracts had local coefficients greater than the OLS coefficient while 394 (33.8%) of the 1,164 census tracts had local coefficients lower than the OLS coefficient. This variability in the model parameters suggests that the relationship between the minimum distance to the nearest public beach and population density is not stationary within the study area at the census tract level.

AGE64 (Model 2). The map of local coefficients for the GWR Model 2 for AGE64 is shown in Figure 52 (p. 167). According to Table 18, the OLS coefficient for AGE64 is 0.084 ($p < 0.05$), indicating inequitable access to public beaches with respect to elderly population across the study area. However, Figure 52 and Table 19 show that both positive (n=628, 53.9%) and negative (n=536, 46.0%) correlations occur across the study area. The local coefficients for AGE64 ranged from -1.01 (city of Detroit, Wayne County) to 2.85 (Canton Township, Wayne County), with a mean of 0.12. Strong positive correlations (local coefficient > 1.06), indicating equitable access to public beaches with regard to elderly populations, were observed in the cities of Royal Oak and Troy and in the townships of Brandon and Independence, Oakland County. Strong negative correlations (local coefficient < -0.82), indicating inequitable access to public beaches with regard to elderly populations, emerged in the townships of Armada, Bruce, Ray, and Washington and in the city of Warren, Macomb County; in the cities of Ferndale and Rochester Hills and in the townships of Addision and Oakland, Oakland County; and in the cities of Detroit and Livonia, Wayne County. Five hundred fifty (67.5%) of the 1,164 census tracts had local coefficients greater than the OLS coefficient while 614 (52.7%) of the 1,164 census tracts had local coefficients lower than the OLS coefficient. This variability in the model parameters suggests that the relationship between the minimum distance to the nearest public beach and proportion (%) of population over age 64 is not stationary within the study area at the census tract level.

EDU (Model 2). The map of local coefficients from the GWR Model 2 for EDU is shown in Figure 53 (p. 168). According to Table 18, the OLS coefficient for EDU is -0.257 ($p < 0.05$), indicating inequitable access to public beaches with regard to education attainment across the study area. However, Figure 53 and Table 19 show that both positive (n=536, 46.0%) and negative (n=628, 53.9%) correlations occur across the study area. The local coefficients for EDU ranged from -3.25 (city of Detroit, Wayne County) to 2.73 (Clinton Township, Macomb County), with a mean of -0.02. Strong positive correlations (local coefficient > 1.82), indicating equitable access to public beaches with respect to education attainment, were observed in the cities of

Fraser, Sterling Heights, and Warren and in the townships of Chesterfield, Clinton, Harrison, and Macomb, Macomb County; and in the cities of Dearborn Heights, Detroit, Flat Rock, Garden City, Riverview, Trenton, Westland, and Woodhaven and in the townships of Brownstown, Grosse Ile, and Huron, Wayne County. Strong negative correlations (local coefficient < -1.86), indicating inequitable access to public beaches with respect to educational attainment, emerged in the cities of Detroit and Romulus and in the townships of Sumpter and VanBuren, Wayne County, in the cities of Eastpointe, Sterling Heights, and Warren and in the townships of Armada, Bruce, Ray, Richmond, Shelby, and Washington, Macomb County. Five hundred sixty-six (48.6%) of the 1,164 census tracts had local coefficients greater than the OLS coefficient while 598 (51.3%) of the 1,164 census tracts had local coefficients lower than the OLS coefficient. This variability in the model parameters suggests that the relationship between the minimum distance to the nearest public beach and proportion (%) of population having a four-year university degree or higher is not stationary within the study area at the census tract level.

R^2* *(Model 2). Figure 54 (p. 169) shows the spatial distribution of local R^2 by census tract. The global value of R^2 was 0.185, but the local value of R^2 varied over the study area from 0.27 (city of Rochester Hills, Oakland County) to 0.92 (city of River Rouge, Wayne County), with a mean of 0.70. As seen in Table 19, all census tracts (n=1,164, 100.0%) had local R^2 values greater than the global value of R^2. The local model had the best explanatory power in the cities of Dearborn, Dearborn Heights, Detroit, Lincoln Park, Romulus, and Westland and in the townships of Brownstown, Huron, and Sumpter, Wayne County; in the cities of Royal Oak, Southfield, and Troy, Oakland County; and in the cities of Sterling Heights and Warren, Macomb County (in excess of 80%). However, the local model had very low explanatory power in the city of Rochester Hills and in the townships of Groveland, Highland, Holly, Rose, Springfield, and White Lake, Oakland County (as low as 40%), indicating that level of access to public beaches in these areas is not explained adequately by set of explanatory variables, with the local R^2 falling below the local mean value of 0.70 (GWR Model 2). These findings indicate that the explanatory power of the local model is not stationary, indicating that the degree of model performance is spatially heterogeneous across the study area.

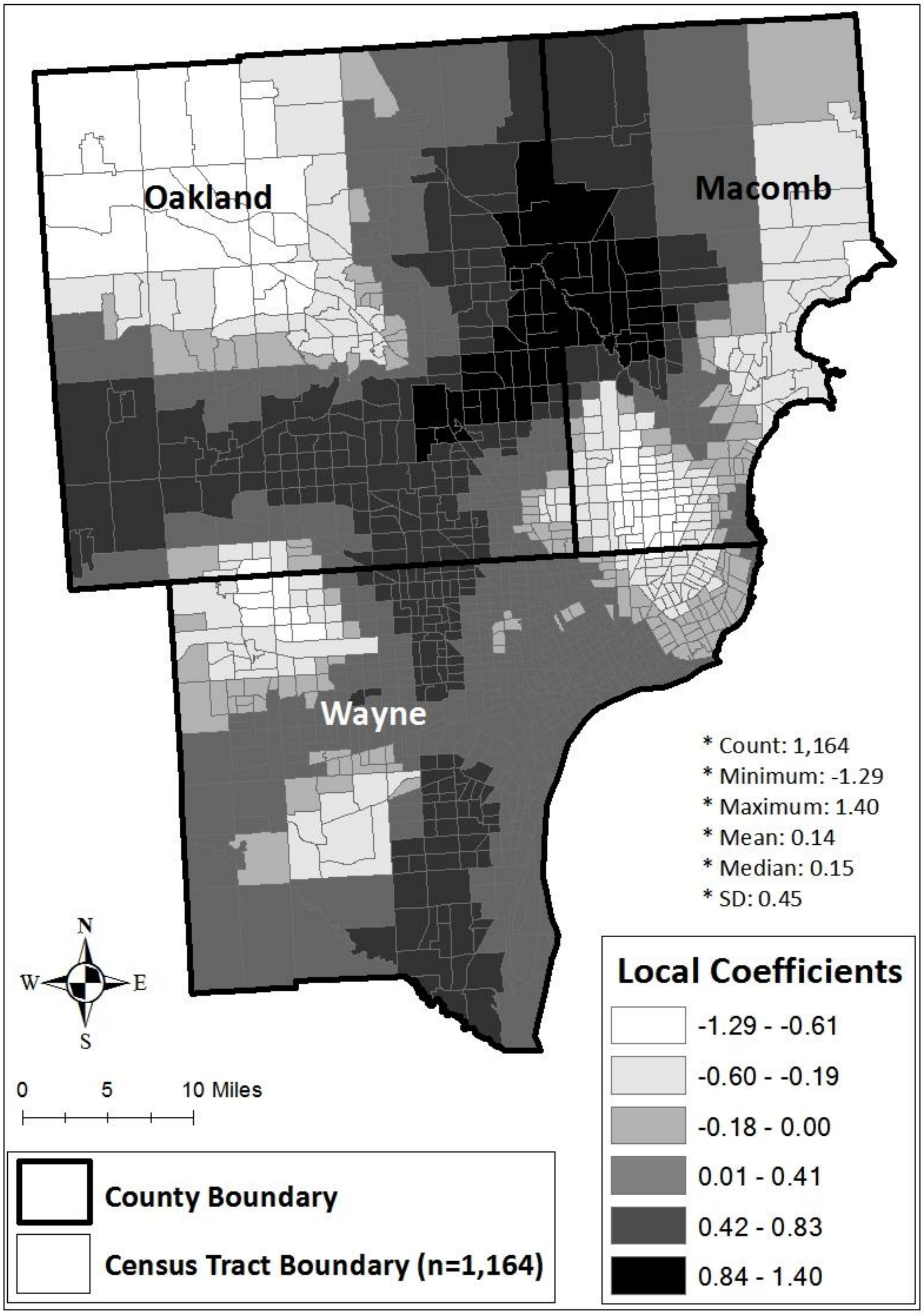

Figure 51. Spatial distribution of local parameter estimates for population per square mile by census tract, DMA (Model 2)

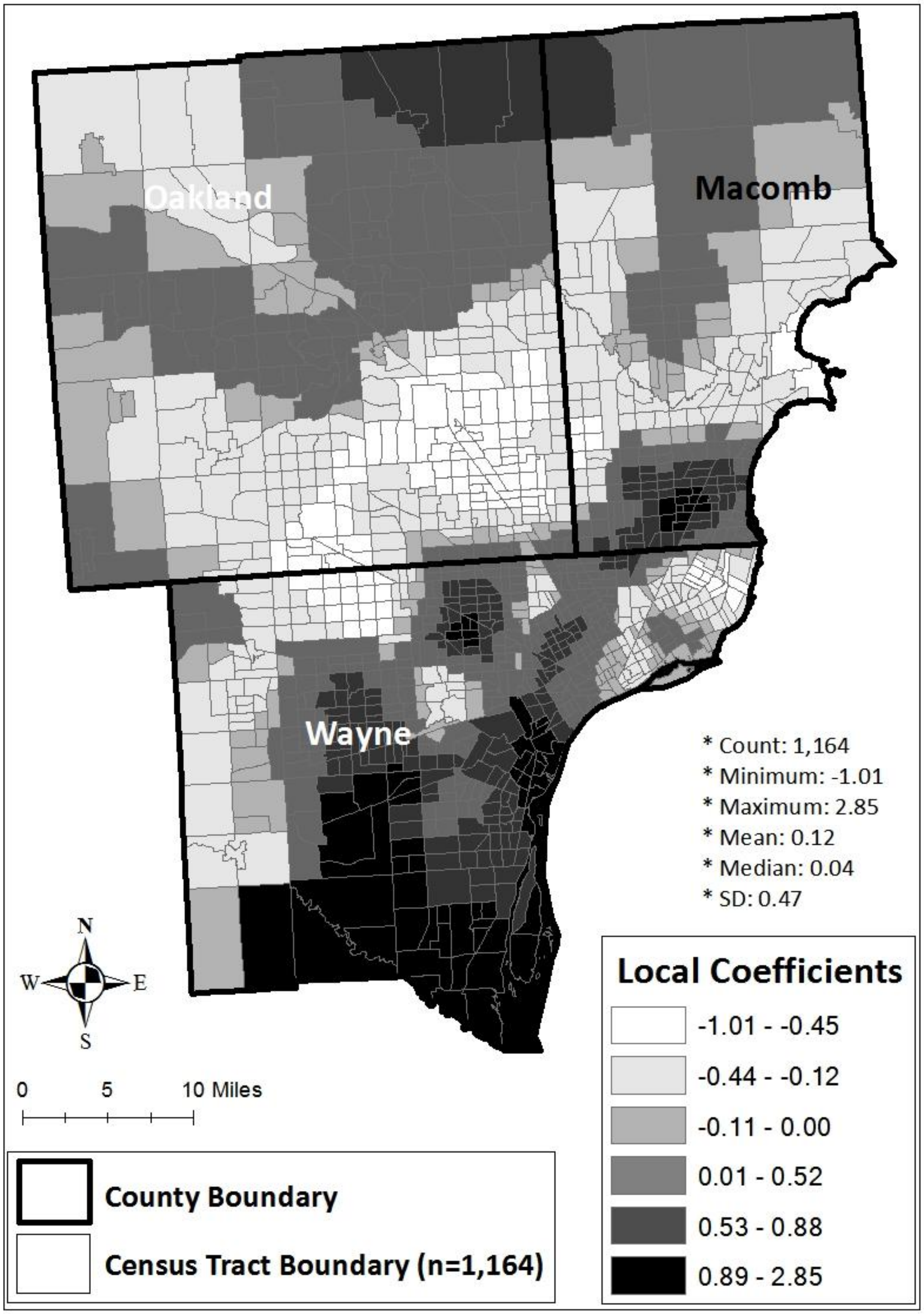

Figure 52. Spatial distribution of local parameter estimates for proportion (%) of population over age 64 by census tract, DMA (Model 2)

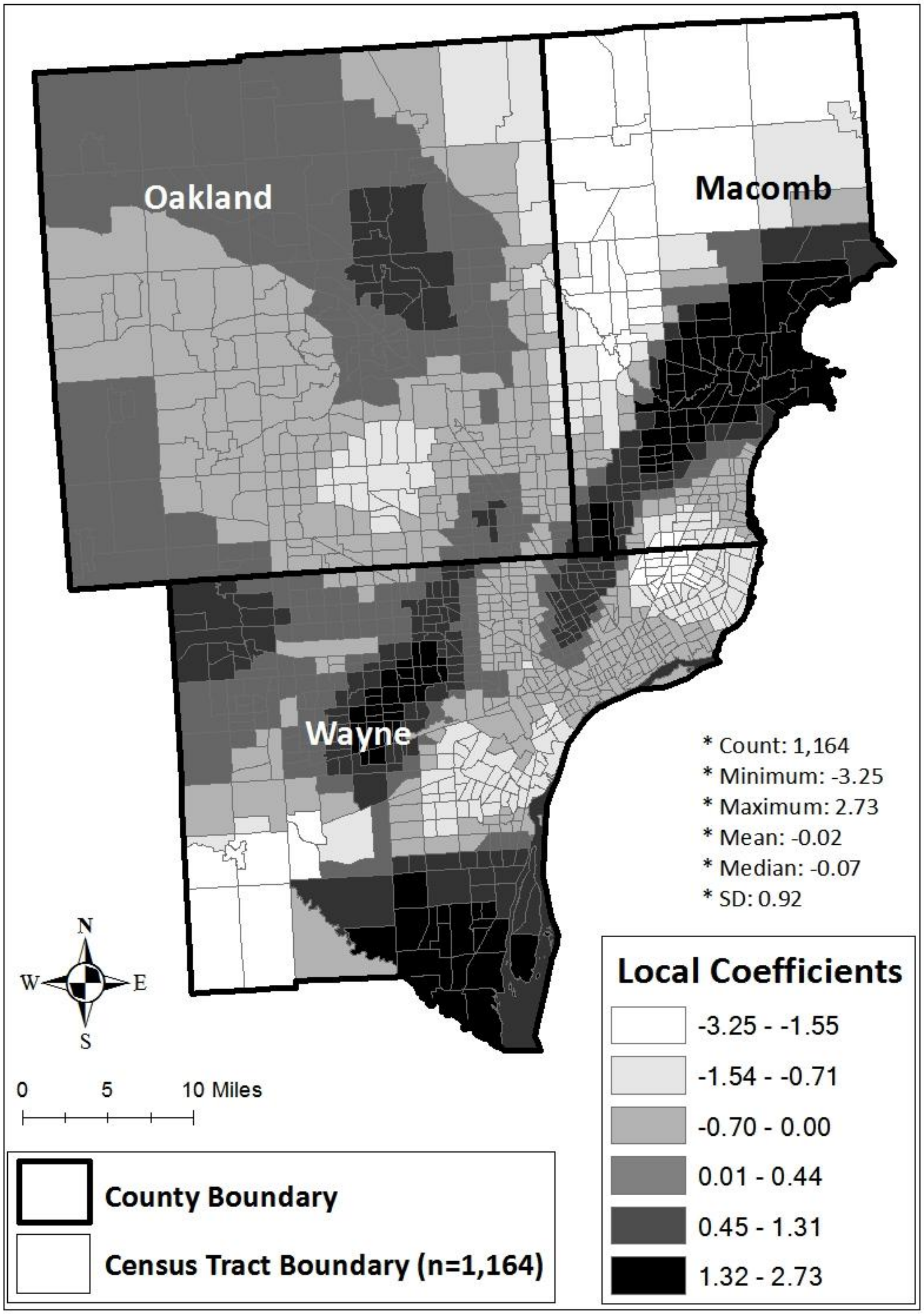

Figure 53. Spatial distribution of local parameter estimates for population with a four-year university degree or higher by census tract, DMA (Model 2)

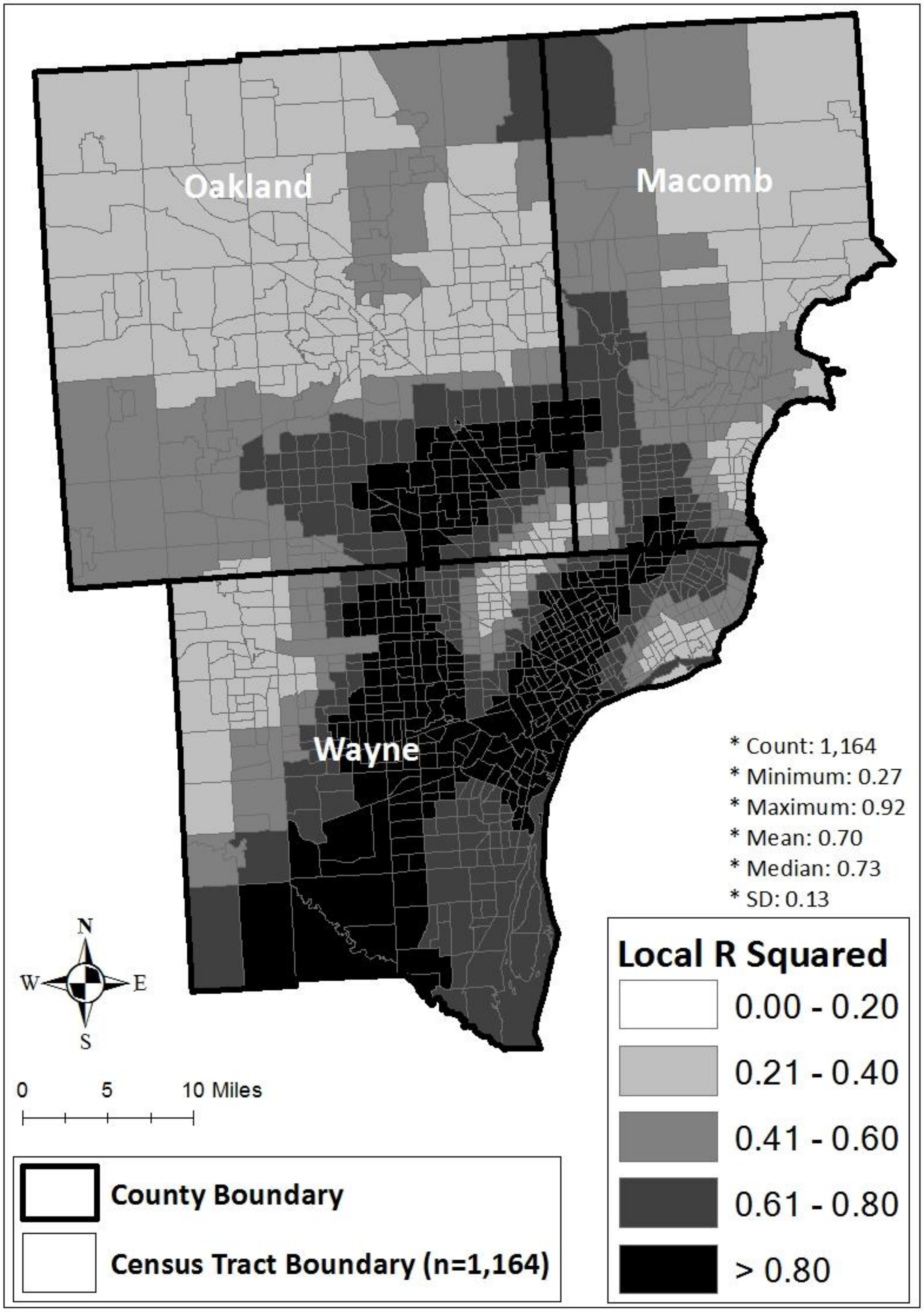

Figure 54. Spatial distribution of local R^2s by census tract, DMA (Model 2)

O3R4: "How well does the GWR approach perform in terms of model diagnostics compared to the traditional OLS approach?" This section is divided into three parts: (1) comparison of spatial autocorrelation of residuals between OLS and GWR; (2) comparison of model performance between OLS and GWR; and (3) verification of improvement in model fit of GWR over OLS.

Comparison of spatial autocorrelations of residuals between OLS and GWR. Because statistically significant spatial clustering of high and/or low residuals indicates an absence of key explanatory variables, which effectively could capture the inherent spatial structure in the dependent variable (Gao & Li, 2011), global Moran's I of residuals from each of the OLS and GWR models were computed to compare the degree of spatial autocorrelation between them (Table 20).

Table 20.

Comparison of spatial autocorrelations of residuals between OLS and GWR

	Model 1		Model 2	
	OLS	GWR	OLS	GWR
Moran's I (residual)	0.36	0.10	0.61	0.15
z-score	63.87	18.5	105.83	26.34
p-value	< 0.01	< 0.01	< 0.01	< 0.01

As seen in Table 20, although significant positive spatial autocorrelation is found for both OLS models, as characterized by Moran's I statistic (Model 1: 0.36; Model 2: 0.61) and p-value (Model 1: $p < 0.05$; Model 2: $p < 0.05$), and both GWR models, as characterized by Moran's I statistic (Model 1: 0.10; Model 2: 0.15) and p-value (Model 1: $p < 0.05$; Model 2: $p < 0.05$), the global Moran's I statistics of residuals from the GWR models are much lower than those for the OLS models. These findings show that GWR models can improve model fit by reducing the spatial autocorrelation in the residuals.

Comparison of model performance between OLS and GWR. The purpose of comparing the GWR and OLS models was to identify whether GWR models exhibit better model performance than the corresponding OLS models. The comparison was performed by comparing the R^2 and the AIC_c values for both GWR and OLS models. According to Gilbert and Chakraborty (2011), a model with a lower AIC_c and higher R^2 value is preferable to a model with a higher AIC_c and lower R^2 value. In other words, if the adjusted R^2 value of the GWR is higher and the AIC_c value of the GWR is at least three points lower than those of the OLS, the GWR model is considered to improve singificantly upon its corresponding OLS model. The values of adjusted R^2 and AIC_c from both OLS and GWR models are shown in Table 21.

Table 21.

Comparison of model performance between OLS and GWR models

Model	OLS/GWR	Adjusted R^2	AIC_c
Model 1	OLS	0.379	11,839.75
	GWR	0.693	8,679.89
Model 2	OLS	0.185	6,300.11
	GWR	0.702	4,085.73

For Model 1, the adjusted R^2 dramatically increased from 0.379 for the global OLS model to 0.693 for the local GWR model. AIC_c considerably decreased from 11,839.75 for the global regression model to 8,679.89 for the local GWR model. For Model 2, the adjusted R^2 value dramatically increased from 0.185 for the global OLS model to 0.702 for the local GWR model. AIC_c considerably decreased from 6,300.11 for the global regression model to 4,085.73 for the local GWR model. These findings indicate that GWR models provide better goodness-of-fit than OLS models when assessing the spatial distribution of access to public beaches in the DMA.

Verification of improvement in model fit of GWR over OLS. To verify the improvement in model fit of GWR over OLS, the null hypothesis that the GWR model represents no improvement over a global model was tested by conducting analysis of variance (ANOVA) (Table 22). According to Model 1, the sum of squares (SS) value for residuals dramatically decreased from 1,736,219.80 for the OLS model to 71,325.18 for the GWR model. In terms of Model 2, the SS value for residuals also decreased, from 15,016.30 in the OLS model to 1,377.64 in the GWR model. All F-statistics (model 1: 69.77; model 2: 29.59) were statistically significant at the 0.05 level. Therefore, the null hypothesis can be rejected based upon the ANOVA results, indicating that the GWR technique offers significant improvement over the OLS model.

Table 22.

ANOVA test for improvement in model fit of GWR over OLS

Model	Source	SS	DF	MS	F	p-value
Model 1	Global residuals	1,736,219.80	1,150.00			
	GWR improvement	1,664,894.61	288.270	5,775.46		
	GWR residuals	71,325.18	861.73	82.77	69.77	< 0.01
Model 2	Global residuals	15,016.30	1,150.00			
	GWR improvement	13,638.66	288.27	47.31		
	GWR residuals	1,377.64	861.73	1.59	29.59	< 0.01

Note: SS: sum of squares; DF: degrees of freedom; MS: residual mean square; F: F-statistic

CHAPTER 5

DISCUSSION AND CONCLUSIONS

This chapter is divided into three parts: (1) a summary of the study and discussion of key findings; (2) implications for and contributions to practice and methods; and (3) limitations and recommendations for future research.

Summary of the Study and Discussion of Key Findings

The purpose of this study was to demonstrate the utility of spatial statistical techniques for assessing the degree of equity inherent in the distribution of access to beach-based recreation opportunities within the framework of environmental justice. In this section, the results of this location-specific study are summarized and key findings with reference to the three research objectives discussed.

Objective One: Assessing the Spatial Distribution of Public Beaches and Determining Levels of Access to Public Beaches in the DMA

The first objective of the study was to (1) assess the spatial distribution of public beaches and (2) determine levels of access to public beaches in the DMA. GIS-based spatial centrographic analyses, in combination with point pattern analyses and network analysis, were used to assess the spatial distribution of public beaches and to measure levels of access to them. The results indicated substantial regional disparities in access to public beaches resulting from spatial clustering of public beaches in the DMA. Specifically, Oakland County has much better access than Wayne and Macomb Counties.

Public beaches in the DMA were geographically concentrated in Oakland County (Figure 25, p. 101). This finding may be explained partially by the physical geography of the study area (i.e., the existence of lakes and rivers); 3,342 (74.1%) of the 4,507 lakes and 168

(94.3%) of the 178 public beaches in the DMA are concentrated in Oakland County. However, the physical geography of the study area does not explain why relatively few public beaches are located alongside the river in Wayne County. This may be related to the different types of land use alongside the Detroit River, one of the busiest waterways in the world and an important transportation route connecting Lakes Michigan, Huron, and Superior to the St. Lawrence Seaway and Erie Canal (Hartig, Zarull, Ciborowski, Gannon, Wilke, Norwood, & Vincent, 2009). The Detroit River became notoriously polluted and toxic due to rapid industrialization at the turn of the 20th century and the construction of industrial-related land uses such as factories, piers/docks, commercial buildings, and warehouses located adjacent to the river. According to Smoyer-Tomic et al. (2004), the quality of LDLUs is a major factor that attracts visitors. Despite vast restoration efforts such as the Detroit River Remedial Action Plan in recent years, negative perceptions of the water quality of the Detroit River might be related to the lack of public beaches. This study highlights the need to consider the quality of LDLUs when measuring the level of access to them. Physical characteristics of the shoreline of the Detroit River may also be related to the lack of public beaches. Generally, beach development is based on the physical characteristics of the shoreline such as gentle gradient, clean water, and shallow water level. However, the physical characteristics of the shoreline of the Detroit River are not amenable due to its depth and steep gradient. In addition, privatization of waterfront areas may be another more fundamental reason for lack of public beaches.

Another key finding of this study is the regional disparity in access to public beaches. Specifically, residents in Oakland County have much better access than residents in Wayne and Macomb Counties (Figures 27 and 28, p. 106-107). This finding may also be explained by the nature of the study area, as discussed above, thereby supporting Talen's (1997) argument that level of access to LDLUs is associated with their distribution.

Based on the network analyses conducted, different accessibility measures indicate different spatial patterns of accessibility (Figures 27-30, p. 106-107 and 125-126). There is substantial regional differential between levels of access according to the minimum distance and container approaches. Such different spatial patterns of accessibility may be due to the different definitions of accessibility employed by these two approaches. Specifically, the minimum distance approach defines the level of access to public beaches as the network distance from the tract centroid to the nearest public beach, whereas the container approach defines the level of access to public beaches as the number of public beaches within 20 miles of the tract centroid. The container approach map (Figure 27, p. 106) shows that census tracts with the highest levels of access to public beaches are observed in Oakland County while the minimum distance approach map (Figure 28, p. 107) shows that census tracts with the highest levels of access to public beaches are located throughout the study area. This finding is consistent with those reported by previous studies (Smoyer-Tomic et al., 2004; Talen & Anselin, 1998; Zhang et al., 2011), and suggests that utilizing two or more access measures can provide a better sense of the range of actual levels of access and is therefore preferable to employing any one approach. Further, employing more than one access approach recognizes the potential for variations in residents' perceptions about beach accessibility.

As shown in Figure 27 (p. 106), access in this study appears to be based heavily on availability, which is one of the geographic dimensions of access (Penchansky & Thomas, 1981). Although the availability of LDLUs commonly has been measured as the number of LDLUs or the total area of LDLUs within a geographic unit, such as a census tract, zip code, or local neighborhood unit, such traditional container-based measures cannot consider spatial externalities and edge effects, which have been recognized as methodological issues that can lead to create biased access outcomes. This study included a more accurate access measure by dealing with spatial externalities and edge effects using GIS-based network analysis.

Objective Two: Exploring the Spatial Patterns of Access to Public Beaches Relative to Residents' Demographic and Socioeconomic Status

The second objective of the study was to explore the spatial patterns of access to public beaches relative to residents' demographic and socioeconomic statuses using spatial autocorrelation analyses. The results indicated that the distributions of access to public beaches and residents' racial/ethnic and socioeconomic variables were spatially autocorrelated at the global and local levels. In particular, the majority of the hot spots for level of access to public beaches (number of public beaches within 20 miles of the tract centroid), housing value, income, age (proportion of population over age 64), educational attainment, housing occupancy, and water area were identified in Oakland County, whereas the hot spots for level of access to public beaches (shortest road network distance from tract centroid to the nearest public beach), race/ethnicity (proportions of Black, Asian, and Hispanic populations), population density, age (proportion of population under age 18), economic status, language spoken at home, and non-vehicle ownership were concentrated in Wayne County. From an equity perspective, these findings indicate racial segregation and a spatial mismatch between level of access to public beaches and residents' socioeconomic statuses across the study area.

As shown in Table 15 (p. 109), one key finding was the existence of positive spatial autocorrelation for all variables (including levels of access to public beaches and residents' racial/ethnic and socioeconomic statuses), indicating a tendency toward the spatial clustering of the attribute for each variable in which census tracts exhibiting high (or low) levels of that variable were more likely to be situated next to census tracts with similarly high (or low) levels. This finding supports previous equity studies of LDLUs that show that the spatial clustering of people exhibiting similar demographic and socioeconomic variables is almost inevitable for two reasons. First, human populations generally live in spatial clusters rather than according to random distributions (Deng et al., 2008; Smoyer-Tomic et al., 2004; Talen & Anselin, 1998). Second, many people prefer to live with others similar to themselves (Kalmijn, 1998).

Anselin (1988) stated that an occurrence of spatial autocorrelation may be explained by several reasons. The first cause of spatial autocorrelation may be measurement errors when data are collected at aggregated levels. As noted by Anselin (1988), "if there is a disjunction between the underlying process of the data collected and areal unit used, this may cause the observed characteristics to spill over across different areal units, possibly causing spatial dependence and spatial autocorrelation" (p. 64). The second cause of spatial autocorrelation is related to the way phenomena are geographically organized. As noted by Anselin (1988, p. 64),

> spatial dependence is related to human behavior and human geography. The locations and distances are important factors influencing spatial interaction, and they may lead to interdependencies of human behavior in space. For this reason, an observation of any given space is influenced by what happens in other places. This will likely cause some levels of spatial dependence.

The existence of spatial autocorrelation in this study is more appropriately explained by the first reason because, as stated in Chapter 3, the aggregation error produced by employing the census tract as the unit of analysis may cause spatial dependence and spatial autocorrelation. As noted by Smoyer-Tomic et al. (2004), "aggregation error can be reduced by integrating finer resolution data that better indicate the spatial distribution of individuals living within highly aggregated units" (p. 289).

Although census tracts represent the smallest territorial unit for which population data are available in many counties in the US (Estabrooks et al., 2003), census tracts are subdivided into block groups and blocks. The findings of this study suggest that the choice of a finer areal unit might have altered results due to the MAUP. Several authors, such as Cressie (1993) and Griffith and Layne (1999), indicated that measuring the degree of spatial autocorrelation tends to increase the percentage of variance explained for the dependent variable in the predictive model by compensating for unknown variables missing from a model.

Another finding of this study is that substantial racial segregation between Blacks and non-Blacks exists across the DMA. According to Card and Rothstein (2007), racial segregation is defined as the separation of humans into racial groups in daily life. In other words, it is the spatial separation of activities such as eating in restaurants, drinking from a water fountain, using urban parks, attending school, and others. As shown in Figure 31 (p. 127), hot spots of Black population are concentrated within the city of Detroit, whereas cold spots exist in the Detroit suburbs. Detroit's history is characterized by racial conflict, represented by racial riots in 1943 and 1967 (Fine, 1989). In addition, hot spots of Asian population are concentrated in Wayne County, in the cities of Dearborn, Melvindale, and Romulus, and, in Oakland County, in the city of Pontiac, whereas hot spots of Hispanic population are concentrated in Wayne County, in the cities of Allen Park, Detroit, Ecorse, and Lincoln Park, and, in Oakland County, in the city of Pontiac. Previous studies have regarded Black, Asian, and Hispanic populations as minority groups in urban areas (Lindsey et al., 2001; Maroko et al., 2009). The findings of this study, at least in terms of the Black, Asian, and Hispanic populations in the DMA, support Deng's (2008) statement that "minority groups often live in concentrated communities" (p. 222). According to Nathan (1987), the numbers, proportions, and concentrations of the urban poor increased as the population of central cities declined between 1970 and 1980. In that period, the population of Detroit fell by 20%, but the Black population increased from 43.6% to over 60% of the total population (Wilson, 1992). The concentration of the Black population in the city of Detroit could be due to industrial decline, uneven development, and racial discrimination. As noted by Wilson (1992, p. 203),

> massive losses of industrial jobs impacted most heavily on blacks in Detroit. Residential segregation trapped blacks, particularly low-income blacks, within the central city. Economic growth in the peripheral suburban areas, continual decline in the central city, and the concentration of blacks in the central city, left blacks spatially separated from areas of job growth. Direct and institutional discrimination further reduced job opportunities for blacks.

As Gilbert and Charkraborty (2011) explained, neighborhoods with minority groups often exhibit lower household incomes, lower housing values, higher population density, lower levels of educational attainment, and lower vehicle ownership. The LISA maps of population density (Figure 34, p. 130), household income (Figure 35, p. 131), housing values (Figure 36, p. 132), educational attainment (Figure 39, p. 135), population below the poverty line (Figure 41, p. 137), and vehicle ownership (Figure 43, p. 139) provide empirical evidence to confirm Gilbert and Charkrabory's (2011) statement.

Another finding of this study is the spatial mismatch between level of access to public beaches and residents' socioeconomic status. This finding is consistent with the results of previous studies that populations with low-socioeconomic-status minorities tend to be disproportionately denied the multiple benefits of access to LDLUs. According to Wicks and Crompton (1986), levels of access to LDLUs should be superior for groups with high-social needs (e.g., non-White, those earning low incomes, youth and the elderly, those residing in more densely populated areas, those having low educational attainment, those with non-English spoken at home, and those without a vehicle) because groups having low social need (e.g., White, those earning high incomes, those residing in less densely populated areas, those having high educational attainment, and those with a vehicle) have more options available to them for accessing alternative recreational opportunities that, for example, require car travel or registration fees. However, this study shows that neighborhoods with high social needs (except Black population) had limited access to public beaches while neighborhoods with low social needs had much higher levels of access to public beaches.

The spatial mismatch between level of access to public beaches and residents' socioeconomic status may be explained by several theoretical models: market-based equity (Lucy, 1981; Crompton & Wicks, 1988), deprivation amplification (MacIntyre, 2000), and marginality (Park, 1928). First, as discussed in Chapter 2, the model of market-based equity assumes that an inequity in goods and services distribution occurs if minority groups cannot pay the necessary market price (Deng et al., 2008). As shown in Table 4 (p. 61), the median housing value (MHV) of Oakland County ($177,600) is greater than the MHVs of Wayne County ($97,100) and Macomb County ($134,700). Not only do the residents of Oakland County exhibit higher levels of purchasing power (e.g., higher incomes and housing values), but they are able to use that purchasing power to acquire properties in more attractive areas close to desirable amenities. Authors such as Nicholls and Crompton (2005a, 2005b, 2005c, 2007) have demonstrated the premiums associated with properties adjacent to or nearby a variety of land-and water-based recreation opportunities. Second, the spatial mismatch between level of access to public beaches and residents' socioeconomic status in the DMA also may be discussed in relation to MacIntyre's (2000) model of "deprivation amplification," which refers to a pattern of diminished opportunities related to the features of the local environment. As noted by Taylor et al. (2007, p. 55),

> deprivation amplification indicates that in places where people have limited resources (e.g., money, private transportation), there are fewer safe, open green spaces where people can walk, jog, or take their children to play; children's playgrounds are less attractive; and there are more perceived threats (e.g., litter, graffiti, youth gangs, assaults) in these environments.

The median household income (MHI) of Oakland County ($65,636) is substantially greater than the MHIs of Wayne County ($41,504) and Macomb County ($53,628) (Table 4, p. 61). Therefore, the theory of deprivation amplification could help to explain the variations in levels of access to public beaches in the DMA. Third, the spatial mismatch between level of access to public beaches and residents' socioeconomic status in the DMA may also be explained by the theory of "marginality," which attempts to explain socio-cultural, political, and economic constraints, whereby disadvantaged groups have difficulties gaining access to resources (Park, 1928). As noted by West (1989), "because of lower incomes, minorities are seen as having constraints on their ability to afford the cost of participation, or of transportation to recreation sites" (p. 11). This study provides strong empirical evidence to support the theory of "marginality."

Objective Three: Demonstrating the Feasibility and Utility of GWR when Measuring the Equity of Access to Public Beaches and Comparing the Results of This Approach with Those of Traditional Multivariate Regression (OLS) Techniques

The third objective of the study was to (1) investigate the spatial relationships between levels of access to public beaches and residents' racial/ethnic and socioeconomic statuses using both OLS and GWR models and (2) compare the statistical diagnostics from the OLS and GWR models. Two separate OLS regression analyses were performed to examine the effects of residents' demographic and socioeconomic statuses on the number of public beaches accessible within a 20-mile journey of each tract centroid (Model 1) and the minimum distance to the nearest public beach from each tract centroid (Model 2). OLS Model 1 indicated that equitable access to public beaches in the DMA exists with respect to proportions of Black and Asian, but inequitable access to public beaches in the DMA exists with respect to population density, educational attainment, and vehicle ownership. OLS Model 2 showed that inequitable access to public beaches in the DMA exists with respect to population density, proportion of elderly population, and educational attainment.

The same dependent and independent variables from the global OLS models also were entered into two GWR models to explore spatial variations between levels of access to public beaches and residents' racial/ethnic and socioeconomic statuses. The two GWR models explored spatially varying relationships between variables, with great improvements in model performance (as measured by R^2, $AIC_{c,}$ and Moran's I statistics of standardized residuals) over their corresponding OLS models. Table 17 (p. 142) indicates that the results of the OLS models explained only 37.9% (Model 1) and 18.5% (Model 2) of the variation in public beach access. These results are generally consistent with those of previous equity studies of LDLUs (Deng et al., 2008 [R^2: 0.28]; Maroko et al., 2009 [R^2: 0.23]; Porter & Tarrant, 2001 [R^2: 0.18]; Tarrant & Cordell, 1999 [R^2: 0.27]). However, those relatively low levels of explanatory power imply that the OLS models may not be properly specified. This may be explained by two reasons. First, there may be some missing determinants of level of access to public beaches that could improve model performance, such as median contract rent, proportion of white collar workers, average family size, and proportion of unemployed. Second, local variations exist in the relationships between level of access to public beaches and residents' demographic and socioeconomic status that can reduce the explanatory power of the global model. Several authors such as Bailey and Gatrell (1995), Brunsdon et al. (1996), Fotheringham et al. (2002), and O'Sullivan and Unwin (2003) indicated that local variations between variables can reduce the explanatory power of models when employing traditional multivariate techniques. Table 18 (p. 148) indicates that the GWR models provide more desirable statistical results, including higher R^2, lower standardized residuals, and lower AIC_c than the global OLS models. Specifically, the adjusted R^2 dramatically increased from 0.379 (Model 1) and 0.185 (Model 2) for the global OLS models to 0.693 (Model 1) and 0.702 (Model 2) for the local GWR models, whereas the AIC_c considerably decreased from 11,839.75 (Model 1) and 6,300.11 (Model 2) for the global OLS models to 8,679.89 (Model 1) and 4,085.73 (Model 2) for the local GWR models. These results are consistent with those of previous environmental equity studies of locally unwanted land uses (Gebreab & Diez Roux, 2012; Gilbert & Charkraborty, 2011; Mennis & Jordan, 2005) and LDLUs (Maroko et al., 2009). Those findings not only indicate the need for researchers to realize the usefulness of GWR, but also suggest the need for additional data collection at the individual level, e.g., via a resident survey or qualitative methods, to identify missing explanatory variables that might improve model performance.

Another finding of this study is that the GWR models identified spatially varying relationships between level of access to public beaches and residents' demographic and socioeconomic statuses at a local level (Figures 45-54, p. 156-169). While this study demonstrates the utility of GWR as an exploratory tool and illustrates how statistical relationships between level of access to public beaches and residents' demographic and socioeconomic statuses vary across the DMA, the findings represent a starting point for future quantitative or qualitative investigations into the various social, political, economic, and historical factors associated with the inequities of access to recreation opportunities observed in specific areas. The study suggests that a more detailed analysis of the interrelationships between residents' political attitudes, land use, industrial development, road networks, and the demographic and socioeconomic settlement patterns of each racial or ethnic group should be conducted to understand why the analytical results for each variable differ across the DMA.

Another finding of this study is that the GWR models provided more accurate parameter estimates than the OLS models by exploring important local variations between the variables. As shown in Table 17 (p. 142), OLS Model 1 indicated that equitable access to public beaches in the DMA exists with respect to proportions of Black and Asian populations. These findings, however, were unexpected and are inconsistent with those of previous studies (Abercrombie et al., 2008; Deng et al., 2008; Gilbert & Chakraborty, 2011; Moore et al., 2008; Talen, 1997), and may be due to local variations between the variables that are caused by spatial dependence and spatial heterogeneity. As shown in Figure 45 (p. 156), GWR Model 1 explored important local variations between the number of public beaches accessible within a 20-mile journey and the proportion (%) of Black population across the study area. Specifically, equitable access to public beaches with respect to Black population was observed in the cities of Troy and Rochester Hills, in the townships of Addison and Oakland in Oakland County, and in the townships of Bruce and Washington in Macomb County, whereas inequitable access to public beaches with respect to Black population was observed in the city of Sterling Heights and in the townships of Shelby and Washington, Macomb County. Figure 46 (p. 157) indicates that GWR Model 1 also explored important local variations between the number of public beaches accessible within a 20-mile journey and proportion (%) of Asian population across the study area. Specifically, equitable access to public beaches with respect to Asian population was observed in the cities of Farmington Hills and Novi, and in the townships of Lyon and Milford, in Oakland County, as well as in the city of Sterling Heights, Macomb County, whereas inequitable access to public beaches with respect to Asian population emerged in the townships of Canton and Plymouth, Wayne County. According to Fotheringham et al. (2002), ignoring local variations between variables gives rise to inaccurate results, such as biased parameter estimates and misleading significance tests. In this study, OLS Model 1 failed to explore important local variations between variables. As a result, the global coefficients of BLACK (0.190) and ASIAN (0.951) were obtained through a linear combination of the independent variables without any consideration of spatial effects. However, as shown in Table 18 (p. 148), the mean GWR coefficients of BLACK (-1.98) and ASIAN (-1.39) for NOPB (number of public beaches within 20 miles of tract centroid) indicated inequitable access to public beaches by exploring local variations between the variables. These results are consistent with those of previous studies (Deng et al., 2008 [OLS]; Gilbert & Chakaraborty, 2011 [GWR]; Lindsey et al., 2001 [OLS]; Moore et al., 2008 [OLS]), and clearly demonstrate the utility and feasibility of GWR when measuring the degree of equity inherent in the distribution of access to public beaches.

The two OLS models showed that inequitable access to public beaches in the DMA exists with respect to population density (Model 1 and Model 2), proportion of elderly population (Model 2), educational attainment (Model 1 and Model 2), and vehicle ownership (Model 2) (Table 17, p. 142). These findings are consistent with previous literature showing that inequitable access to LDLUs is associated with residents' educational attainment (Estabrooks et al., 2003; Porter & Tarrant, 2001) and vehicle ownership (Lindsey et al., 2001). Although the elderly population (Nicholls, 2001; Nicholls & Shafer, 2001) and groups residing in more densely populated areas (Lindsey et al., 2001; Maroko et al., 2009; Nicholls, 2001; Nicholls & Shafer, 2001) have been considered as 'needy' groups who should be compensated with better access to LDLUs, there was no empirical evidence to support inequitable access to LDLUs associated with those variables in the DMA. Study areas are each unique and these variations in findings highlight these differences.

Traditionally, race and ethnicity have been recognized as the dominant variables accounting for inequitable access to LDLUs (Abercrombie et al., 2008; Deng et al., 2008; Gilbert & Chakraborty, 2011; Moore et al., 2008; Talen, 1997). In this study, however, the most dominant variable related to inequitable access to public beaches was educational attainment. Several authors such as Gilliland et al. (2006), Maroko et al., (2009), and Smoyer-Tomic et al. (2004) excluded the effects of racial/ethnic variables but suggested the importance of other socioeconomic variables (e.g., educational attainment, age, vehicle ownership, population density, language, dwelling structure, family composition, and occupation) in accounting for inequitable access to LDLUs. This finding provides strong empirical evidence that regional disparities in level of access to LDLUs can be more influenced by residents' socioeconomic status than by their race and ethnicity. It is important to recognize the interrelationship between variables when applying multiple exploratory variables due to multicollinearity, the statistical phenomenon in which two or more exploratory variables in a multiple regression model are highly correlated, meaning they reflect the same information and, hence, introduce redundancy (Wichers, 1975).

Although previous equity studies have regarded those without a vehicle and those residing in more densely populated areas as needy groups (Lindsey et al., 2001; Nicholls, 2001; Nicholls & Shafer, 2001; Maroko et al., 2009), only few empirical studies have assessed the impacts of those variables inherent in the distributions of land-based recreational settings such as urban parks and trails. In this study, public beaches are inequitably distributed with regard to non-vehicle ownership and population density. The findings of this study also can provide strong empirical evidence that inequitable distributions of access to public beaches can be associated with non-vehicle ownership and population density across the study area.

Implications

Previous equity studies of LDLUs have focused on land-based LDLUs such as parks, urban trails, playgrounds, and golf courses. According to Hall and Harkonen (2006), water is an important element of outdoor recreation. As noted by Aukerman (2011), "people show a strong urge for water-oriented recreation" (p. 2). A number of major recreational activities such as swimming, sailing, kayaking, canoeing, diving, and fishing take place at water bodies such as lakes, beaches, and rivers (Prideaux & Cooper, 2009). Public beaches are a unique type of LDLU that offer a variety of water- and land-based recreation opportunities that can meet residents' diverse and complex recreational demands (Aukerman et al., 2004; Orams, 1999). If disparities in levels of access to public beaches arise with respect to racial/ethnic or socioeconomic status, an inequity can be said to occur. Although there has been some discussion regarding the regional disparities in levels of access to beaches (Dyer, 1972; Kohoe, 1995; Mongeau, 2001; Negris, 1986; Poirier, 1996), these studies have focused on legal issues in the context of the public trust doctrine, and no empirical study has evaluated whether the level of access to public beaches is indeed equitable among different racial/ethnic or socioeconomic groups. This study therefore suggests several practical and methodological implications for community recreation planning and management.

Practical Implications

The findings of this study have several practical implications for recreation policy and can be used to inform initiatives that improve the status of access to water and beach-based recreation resources in the DMA.

Table 23.

Neighborhoods with inequitable access to public beaches according to their residents' racial/ethnic and socioeconomic statuses

	Variable	Inequitable Neighborhood	
		City (County)	Township (County)
Model 1	BLACK	Sterling Heights (M)	Shelby (M), Washington (M)
	ASIAN	Troy (O)	Canton (W), Plymouth (W)
	POPD	Livonia (W), Rochester (O), South Lyon (O), Troy (O)	Macomb (M), Ray (M), Shelby (M), Washington (M)
	EDU	Rochester (O), Rochester Hills (O)	Addison (O), Armada (M), Bruce (M), Oakland (O),
	VEHIC	Novi (O), Sterling Heights (M), Troy (O)	Brandon (O), Groveland (O), Independence (O), Plymouth (W),
Model 2	POPD	Rochester Hills (O), Troy (O)	Bloomfield (O), Shelby (M), Washington (M)
	AGE64	Detroit (W), Ferndale (O), Livonia (W), Warren (M)	Addison (O), Armada (M), Bruce (M), Oakland (O),
	EDU	Detroit (W), Eastpointe (M), Romulus (W), Sterling Heights (M), Warren (M)	Armada (M), Bruce (M), Ray (M), Richmond (M), Shelby (M), Wahsington (M)

Note: O: Oakland County; M: Macomb County; W: Wayne County

First, this study identified where inequitable access to public beaches exists with regard to specific demographic and socioeconomic variables. Table 23 summarizes the neighborhoods with inequitable access to public beaches and their residents' racial/ethnic and socioeconomic statuses. The results can guide state and local leisure agencies to support public service delivery through the allocation of resources in areas where racial/ethnic minorities currently are facing inequity issues. This information also can assist local advocacy groups, organizations, and minority populations in their attempts to provide or gain equitable access to recreation opportunities.

Second, public leisure agencies and managers should attempt to ensure equitable allocation of public resources that does not unfairly benefit specific groups over other groups. When measuring the equity of public resources, identifying who is receiving the benefits (costs) of public resources is very important. As noted by Tarrant and Cordell (1999), "when inequities do arise, either the cost of resource utilization should be borne proportionately by all those who benefit or individuals who bear the costs should be fairly compensated" (p. 32).

Third, GWR can be particularly useful due to its capacity to provide information about regional differences in the relationships between level of access to public beaches and residents' racial/ethnic and socioeconomic statuses. This knowledge can assist policy formation by highlighting the unique issues faced by a city or region. Because land-use planning and zoning decisions that contribute to inequities typically are regulated at local levels of government (Gilbert & Chakraborty, 2011), local statistical methods such as GWR can be expected to provide valuable insights that facilitate the formulation of locally appropriate policy solutions.

Fourth, the mapping of spatial distributions of level of access to public beaches (Figures 27-28, p. 106-107) could contribute to the development of a regional water and land recreation opportunity spectrum (WALROS). WALROS is a zoning system or framework that identifies a spectrum of water- and land-based recreation opportunities on a continuum ranging from "primitive" to "urban" (Aukerman, 2011). As a specialized recreation opportunity spectrum that is based on the concept of recreation opportunity, WALROS can provide planners and managers with a framework and procedures for making better decisions to conserve a spectrum of high-quality and diverse water- and land-based recreation opportunities by incorporating a variety of physical, social, and managerial attributes (Aukerman, 2011). Access is a critical physical attribute in the context of WALROS planning. The spatial patterns of access to public beaches, as portrayed in this study, could be used as input into WALROS planning.

Fifth, the visual maps created by GIS could be useful tools for improving users' perceptions of public authorities' accountability and openness. These maps can contribute to increased interaction and understanding between public leisure agencies and users that may be likely to decrease the perceptual gaps between them, thereby leading to more satisfied users.

Sixth, because disadvantaged groups need more options to be available to them for accessing alternative recreational opportunities (Wick & Crompton, 1986), locating new recreational facilities (community swimming pools or indoor water-parks) closer to them may be one of the solutions to meet residents' water-based recreational demands. To accomplish this, public leisure agencies and community organizations should build strategic public-private partnerships to locate community swimming pools or indoor water-parks in neighborhoods that suffer from poor accessibility to recreation opportunities in the DMA. According to Lee and Lim (2009), providing financial assistance to private developers, giving tax abatements, providing site-related assistance such as site location identification and clean-up, enhancing public security/community policing, and offering public infrastructure (e.g., parking spaces or transit service) are examples of strategies used in developing promote public-private partnerships. These strategies potentially may improve spatial equity for water-based recreation opportunities in deprived neighborhoods. However, residents' attitudes about the construction of water-based recreational facilities might be different. Therefore, strategic public-private partnerships to locate water-based recreational facilities should be based on residents' attitudes about and demand for the construction of these facilities.

Seventh, perhaps more realistically than the recommendation above, public leisure agencies should provide public transportation services to enhance access to public beaches for minority populations in Wayne and Macomb Counties. This study measured level of access to public beaches assuming residents' reliable and affordable means of transportation when they visit public beaches. In reality, however, the proportion of households without a vehicle is high in Wayne County and access to public beaches is extremely low (Figure 23, p. 95). The spatial mismatch between access to public beaches and to private transportation could directly inform local community policy makers in developing innovative and effective public recreation planning strategies to improve beach access and use. While the acquisition of new beach access points is unlikely, because they are dependent not only on economic resources but on the physical geography of a place (i.e., the existence of public bodies of water and of vacant land adjacent to them from which to provide access), parks and recreation agencies could partner with local transportation authorities to provide free or low-cost passes to beach access sites. Thus, measuring levels of access to recreation opportunities is a useful precursor to community evaluation and planning interventions when considered in combination with access to other public and private resources.

Eighth, public leisure agencies should understand the role of information in community recreation planning. As noted by Yang et al. (2012), "access to information is a prerequisite in order to create positive attention and attitudes that directly trigger enhanced action" (p. 854). The findings of this study can provide essential information for promoting localized recreation policy and planning decisions, such as locating new urban parks or community swimming pools in neighborhoods with inequitable access to public beaches. Public leisure agencies not only have a responsibility to share their information, but also to negotiate between diverse stakeholders who have their own perspectives in the decision-making process. Accordingly, appropriate systems or tools should be developed for easy access to map displays and visualizations of local accessibility and equity patterns to promote participatory decision making. For example, specific information regarding beach accessibility may be displayed via web-based GIS. In particular, geospatial technologies via the Internet and mobile devices such as smart phones can contribute to a spatial decision supporting system (SDSS) for efficient community recreation planning and management.

Ninth, although beyond the scope of this study in terms of any detailed discussion, the methodological principles developed can be applied to a range of other urban services and facilities to which good access typically is considered desirable. These might include health clinics, libraries, supermarkets, and schools.

Tenth, the findings of this study are of utility to public leisure agencies and managers as well as any other groups interested in broadening the spectrum of beach-based recreation opportunities available to local residents. The findings of this study also suggest segments of the areas and population that should be given higher priority in making future resource allocation decisions.

Eleventh, residents' physical activities require access to recreation opportunities. The findings of this study suggest that minorities and those having low socioeconomic status are especially likely not to engage in physical activities. So, investigating the relationship between level of access to public beaches and health would be an important avenue of future research.

Lastly, maintaining the quality of public beaches is essential for enhancing public beach access. According to Smoyer-Tomic et al. (2004), the quality of LDLUs is a major factor in determining the degree of equity. Thus, it is recommended that beach managers initiate educational programs or campaigns to encourage residents to help maintain the quality of public beaches. These efforts could contribute to promoting active public involvement, an essential part of the participatory approach with regard to water-based recreation planning and management.

Methodological Implications

To measure the degree of equity inherent in the distribution of access to public beaches, this study employed rigorous spatial analysis and statistical techniques that have rarely been discussed in the recreation, park, and tourism literature, thereby leading to several methodological implications and suggestions for future equity research in the outdoor recreation, park, and tourism area.

First, spatial statistical techniques in this study offer public leisure agencies opportunities to improve their methods of measuring the equity of LDLUs. The GWR approach described here constitutes an advance over the use of traditional OLS methods to measure the equity of LDLUs. Specifically, the GWR approach dealt with spatial effects, such as spatial dependence and spatial heterogeneity that can lead to biased estimation results, thereby providing more accurate estimation results with better model performance compared to the traditional OLS approach. Thus, the GWR approach can offer public leisure agencies a tool for the more efficient and effective planning and management of recreation opportunities subject to successful implementation of what is a relatively complex method.

Second, GWR also can be used as an exploratory tool to identify an appropriate spatial extent (size) of the study area. Identifying the spatial extent of a study area is important because it can be related to details of the information created by spatial data analysis. The findings of this study (Figures 53 and 54, p. 168-169) identify where the local equity model has higher exploratory power. Mapping the spatial distribution of the local R^2 provided information to identify an appropriate spatial extent of the study area when measuring the equity of public beach-based recreation opportunity in the DMA.

Third, measuring the equity of any recreation opportunity is a complex task. It involves a sequence of activities that assess the spatial distribution of LDLUs and ends with investigating the spatial relationships among variables. Thus, all processes should be conducted in exploratory and confirmatory manners. However, previous studies have focused on investigating the spatial relationships among variables using only confirmatory research methods. To measure the equity of recreation opportunity, this study provides a comprehensive methodological framework by incorporating exploratory and confirmatory spatial statistical techniques. Such a framework can provide important methodological guidance for conducting equity research in parks and outdoor recreation.

Fourth, researchers should employ multiple access measures when measuring the equity of LDLUs to provide a better sense of the range of actual levels of access to LDLUs. The findings of this study showed that different accessibility measures (e.g., container approach and minimum distance approach) not only indicate different spatial patterns of accessibility, but also lead to different equity outcomes. Thus, utilizing multiple access measures has important methodological implications for future equity research.

Fifth, although it was previously recommended to utilize multiple access measures, identifying the most appropriate access measure is another methodological issue. As seen in Figure 25 (p. 101), public beaches in the DMA were geographically concentrated in Oakland County, indicating that the container approach is more appropriate when measuring the level of access to public beaches in Oakland County. On the other hand, the minimum distance approach is more appropriate when measuring the level of access to public beaches in Macomb or Wayne County. However, it is difficult to answer which access measure is more appropriate because residents' perceived access might differ according to regional heterogeneity. Thus, identifying the most appropriate access measure should be based on residents' perceived access, which might be ascertained via resident surveys.

Sixth, researchers should employ multiple distance indicators to provide portrayals of levels of access rather than any one distance indicator. Distance is a critical element when measuring level of access to LDLUs. Although walking-distance proximity to LDLUs can facilitate their use as well as elevate levels of participation in recreational activities, residents often travel beyond their local neighborhood to use certain types of LDLUs such as beaches (Haas, 2009; Houghton, 1988; McCormack, Giles-Corti, Bulsara, & Pikora, 2006). It is therefore recommended to employ a vehicle-based distance threshold when measuring the level of access to certain types of LDLUs. However, previous studies have measured access using only walking travel distance (typically less than 2 miles). As shown in Figure 27 (p. 106), this study considered residents' increased travel distance to access public beaches by employing a 20-mile distance threshold, which would help ascertain levels of vehicle-based mobility. However, each community has its own regional characteristics (Hasse & Milne, 2005); thus, residents' travel distance for beach-based activities may differ due to the heterogeneous nature of local factors.

Seventh, researchers should develop advanced research methods for allocating limited resources more efficiently and equitably. Capacitated models have been recognized as useful tools for allocating limited resources more efficiently in the location-allocation literature (Aikens, 1985; Jacobsen, 1983; Murrary & Gerrard, 1997; Rahman & Smith, 2000; Zhou & Liu, 2003). However, identifying optimal locations for alternative recreational facilities such as community parks is a controversial local issue associated with diverse local stakeholders who have different perspectives. Therefore, such research is best implemented via a participatory approach that involves large numbers of stakeholders in the decision-making process to encourage the reaching of local consensus regarding community issues while minimizing conflicts between stakeholders (Feick & Hall, 2001). Spatial multi-criteria decision analysis (SMCDA) has been emphasized for implementing a participatory approach (Feick & Hall, 2001; Malczewski, 1999; Phua & Minowa, 2005). SMCDA involves the methodological integration of GIS and multi-criteria decision analysis. As noted by Malczewski (1999), SMCDA is "a process that combines and transforms geographical data (input) into a resultant decision (output)" (p. 90). Thus, it is recommended that future studies utilize SMCDA, in combination with location-allocation models, for allocating limited resources more efficiently and equitably by minimizing conflicts between stakeholders in water-based recreation planning.

Lastly, researchers should develop advanced research methods to promote the participatory decision-making approach for outdoor recreation, parks, and tourism. Although spatial statistical techniques provide insightful local information, they are useless if diverse stakeholders do not share the information. Traditionally, public meetings have been used as a tool for sharing information in community-based resource planning and management processes (Hilderbrand, 1997). However, some difficulties (e.g., the geographic separation of participants, scheduling and financial constraints in attending meetings, and the limited duration of meetings) have negatively affected productive decision making that incorporates public participation (Barndt, 1998; Ball, 2002). Such limitations of public meetings offer opportunities to integrate participatory GIS (PGIS) via the web. As noted by Kingston, Carver, Evans, and Turton (2000), web-based PGIS can overcome "at least two obstacles in the traditional public meeting or public hearing, such as the dominant vocal few and the inflexibility of meeting time" (p. 111). Web-based PGIS also offers citizens and neighborhood organizations instant access to data and data-processing tools anywhere at any time (Sieber, 2006). This creates more opportunities for more people to participate in the public debate regarding complex resource planning and management than the traditionally inflexible town-hall meeting schedule (Kingston et al., 2000; Talen, 2000). Furthermore, web-based PGIS offers interactivity between users during the decision making process. Users can efficiently retrieve and query complex information right on the web page (Luchette & Crawford, 2008). More importantly, users can conduct analyses and get instant results (Jankowski & Nyerges, 2001). However, decisions are made by people and not information or information systems like GIS. Despite some advantages of web-based PGIS in decision making processes, web-based PGIS lacks capabilities for incorporating the decision makers' preferences into the GIS-based decision making process (Simao, Densham, & Haklay, 2009). In addition, there are other difficulties. First, GIS user interfaces are sometimes too complex for non-experts (Talen, 2000). Second, GIS functions and operations focus on quantitative methods whereas the integration, analysis, and representation of local knowledge often benefits from qualitative approaches (Ball, 2002). Third, GIS lacks the high level of interactively required to efficiently support collaborative and participative processes (Jankowski & Nyerges, 2001). These weaknesses still make it difficult for web-based PGIS to be applied as a demographic or participatory decision making tool in our society.

Limitations and Recommendations for Future Research

Despite promising implications for practice and methods, several limitations of this study should be acknowledged. First, while measuring the level of access to public beaches, this study ignores other objective and subjective factors, such as facility size, perceived or actual levels of safety, willingness or ability to walk or drive, environmental quality, perceived or actual levels of crowding, noise levels, and the presence of commercial development, all of which can influence residents' choice of recreational destination (Oh et al., 2009). Future studies should incorporate one or more of these variables into their analyses to provide more comprehensive assessments of overall accessibility.

Second, the results of this study are limited by geographic location and facility type of public beaches in the DMA. Thus, the results may not be generalizable because every area has its own unique population characteristics, recreation opportunities, street networks, and other elements of regional heterogeneity. Analyses of other geographic regions and types of recreational opportunities would shed additional light on the utility and applicability of the tested approach. In particular, consideration of substitutable opportunities would be useful, such as public swimming pools, in this case. Future studies should employ the same spatial statistical techniques to explore spatial effects when measuring the accessibility to and equity of other types of recreational facilities such as urban parks, golf courses, and playgrounds in different geographic settings.

Third, this study does not consider the modifiable areal unit problem (MAUP). The choice of a different scale (census block or census block group) might have produced different results than those found at the scale of the census tract. Future studies should, therefore, employ different scales as well as compare different access measures and distances.

Fourth, this study does not consider regional disparities with regard to vehicle ownership; rather, it assumed that residents have access to a reliable and affordable means of transportation when measuring the level of access to public beaches. In reality, however, the proportions of households without a vehicle are spatially heterogeneous. Future studies should employ multiple travel distances and incorporate public transportation routes when measuring the level of access to public beaches.

Fifth, this study used 20 miles as the distance threshold that residents are willing to travel for beach-based recreation activities, as used in a case study of East Bay, California (Haas, 2009). However, residents' perceived geographical access to public beaches might differ according to regional heterogeneity. Therefore, future studies should identify residents' perceived geographical access to public beaches by using a resident survey.

Sixth, this study assumed that populations are evenly distributed throughout census tracts and all areas in the census tract have the same demographic and socioeconomic characteristics. However, populations, in reality, live in spatial clusters. Therefore, future studies should consider regional heterogeneity with regard to the clustered pattern of population distribution and their different demographic and socioeconomic characteristics by measuring spatial autocorrelation of residents' demographic and socioeconomic statuses at global and local levels.

Seventh, this study used the centroid of a census tract to measure the distances between residents and public beaches. However, the centroid approach can produce aggregation error that leads to biased measurement results (Smoyer-Tomic et al., 2004). Therefore, in future studies, aggregation error should be reduced by minimally aggregating spatial units.

Eighth, the access measures in this study do not consider spatial cognition or spatial destination choice set issues, which have been recognized as serious methodological problems in prior access research. Although citizens could theoretically access all LDLUs in their local environment, destination choice with regard to LDLUs such as urban parks is, in reality, based on a more compact choice set due to individuals' limited spatial knowledge and information processing capacity (Fotheringham & Curtis, 1999; Zhang et al., 2011). A typical individual can make a maximum of seven pair-wise comparisons among all alternatives (Miller, 1956; Saaty & Ozdemir, 2003; Zhang et al., 2011). Hence, future studies should include a more realistic beach access measure by incorporating this psychological upper limit of individual information processing.

Ninth, the equity measures in this study do not consider procedural equity. Because environmental justice has been defined as the procedure or process used to ensure fair distribution (Zimmerman, 1999), process equity analysis could be critical for more comprehensive environmental justice research. Therefore, future research should incorporate historical analyses that examine the series of actions leading to an inequitable outcome. A process equity analysis would add depth to the current study's findings and would help to explain the origin of the significant disparities found in the DMA.

Tenth, although water area is utilized as an additional independent variable to account for variations in the prevalence of water bodies such as lakes and rivers, proportions of water area for certain census tracts located alongside the Detroit River and Lake St. Clair are overestimated. Thus, future studies should estimate more accurate proportions of water areas for census tracts that are located nearby the Detroit River and Lake St. Clair by including only the water areas of the shorelines of the Detroit River and Lake St. Clair using a straightforward buffering technique.

Eleventh, this study does not consider the methodological issues of local multicollinearity and spatial autocorrelation among coefficients. According to Wheeler and Tiefelsdorf (2005), multicollinearity among local estimates in the model is one of the pitfalls of GWR. In addition, the GWR method tends to generate extreme local coefficients and may overstate spatial heterogeneity (Farber & Paez, 2007). Thus, future studies should propose diagnostic tools, or remedial or alternative methods, for addressing these methodological issues in GWR.

Twelfth, although the issues of multicollinearity have been criticized as the pitfalls of GWR, which can affect estimation results (Griffith, 2008; Wheeler & Tiefelsdorf, 2005), specific diagnostic tools and a remedial method for collinearity in GWR also have been proposed (Barcena, Menendez, Palacios, & Tusell, 2014; Paez, Farber, & Wheeler, 2011; Wheeler, 2007). Future GWR studies should integrate diagnostic tools and remedial methods to address this limitation.

Lastly, although the GWR models explored spatially varying relationships between levels of access to public beaches and residents’ racial/ethnic and socioeconomic statuses, this study could not identify the optimal areas for allocating limited resources more equitably. Public leisure agencies need to identify optimal locations for alternative recreational facilities, such as community parks, for neighborhoods with inequitable access to public beaches, according to residents' racial/ethnic and socioeconomic statuses. According to Yaffee (1994), multiple-use resources, including recreational facilities, are important elements of local communities. As noted by Tarrant and Cordell (1999), "sustainability is concerned with the optimal allocation and use of natural resources to meet the long-term needs of an increasingly diverse public" (p. 31). Identifying the optimal locations for recreational facilities is a complex spatial multi-criteria decision problem that should take into consideration not only the geographical features of the resource attributes but also other criteria, as identified by diverse stakeholders. It also can become a controversial local issue with major impacts on the natural environment, land use and activity patterns, and the economy of the host community. Thus, it is recommended that future studies utilize location-allocation models, in combination with spatial multi-criteria decision analysis, as tools for identifying optimal locations for community parks or other recreational facilities. In addition, the results should be shared to encourage participatory decision-making through the methodological integration of web-based public participation GIS.

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