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Access for All? Beach Access and Equity in the Detroit Metropolitan Area

Abstract

Beaches are a unique type of recreation setting, offering a variety of water- and land-based opportunities that can meet residents' diverse and complex recreation needs. Providing and improving equitable access to recreation amenities such as beaches have been recognized as essential responsibilities of public leisure agencies. This study assessed the degree of equity inherent in the distribution of public beaches in the Detroit Metropolitan Area; to account for spatial effects, phenomena rarely considered in prior equity analyses, geographically weighted regression was employed. Considerable local variations in the relationships between level of access to public beaches and population density, proportion of elderly population and educational attainment were identified. Such findings can help parks and recreation agencies better understand local patterns of equity, an important first step in facilitating the formulation of more efficient and effective planning and policy approaches.

KEYWORDS: access, Detroit Metropolitan Area, equity, public beaches, geographically weighted regression

1. Introduction

Recreation settings such as parks, playgrounds, trails, and lakes provide a variety of economic, social, recreational and environmental benefits to local residents (Sherer 2006). Access to such settings has also been shown to have a substantial impact on individual and community health and well-being, by fostering active lifestyles that reduce the prevalence of obesity-related diseases such as diabetes and hypertension (Coen and Ross 2006, Frank and Engelke 2001, Krenichyn 2006, Wakefield 2004). Providing and enhancing access to recreation opportunities (ROs) has therefore been recognized as an essential responsibility of public leisure agencies in their quest to improve residents' quality of life and help create more attractive and sustainable residential environments (Aukerman 2011).

However, not all people have adequate access to ROs. Concern continues that those with low socioeconomic status, and racial and ethnic minorities, tend to be disproportionately denied the multiple benefits of access to ROs. Disparities in levels of access to ROs, whether in terms of age, race/ethnicity, income or other socioeconomic or demographic factors, represent an example of environmental injustice (Deng *et al*. 2008; Porter and Tarrant 2001, Tarrant and Cordell 1999, Taylor *et al*. 2007). As noted by Bryne *et al*. (2009), environmental justice can be defined as "a theoretical frame and a civil-right based social movement that seeks to understand how environmental benefits and harms are ethno-racially and socioeconomically differentiated among urban populations" (p. 365) i.e., in the places "where we live, work and play" (attributed to Dana Alston in Agyeman *et al.* 2016, p. 321). Assessing the degree of environmental justice inherent in the distribution of access to ROs is, thus, an essential prerequisite to effective recreation and broader natural resources planning and management, and, ultimately, to the attainment of more attractive, desirable and sustainable communities.

To assess the level of environmental justice associated with distributions of ROs and other locally desirable land uses (LDLUs), previous studies have measured the degree of equity inherent in the distribution of access to them. Numerous equity studies have attempted to determine whether disparities in levels of access occur among different demographic and socioeconomic groups with regard to, e.g., urban parks (Bryne *et al.* 2009, Maroko *et al*. 2009, Moore *et al*. 2008, Nicholls 2001, Omer 2006, Talen 1998), urban trails (Estabrooks *et al*. 2003, Lindsey *et al*. 2001), playgrounds (Smoyer-Tomic *et al*. 2004, Talen and Anselin 1998), golf courses (Deng *et al*. 2008), recreational forests (Tarrant and Cordell 1999), campsites (Porter and Tarrant 2001), libraries (Mladenka and Hill 1977, Park 2012), and health care (Culyer and Wagstaff 1993, Goddard and Smith 2001, Oliver and Mossialos 2004).

Although there have been substantive improvements in the measurement of equity in recent decades, two limitations can still be identified. First, previous RO equity studies have focused on land-based ROs such as parks, urban trails, playgrounds, and golf courses. However, "water is a focal point of outdoor recreation" (Aukermann 2011, p. 2). Major recreational activities such as swimming, sailing, kayaking, canoeing, diving, and fishing take place at water-based sites such as lakes, rivers, oceans, and beaches (Jennings 2007). Beaches are an especially valuable type of setting, offering a variety of water- and land-based ROs that can meet residents' diverse and complex recreational demands (Orams 1999).They can also offer visual interest, wildlife habitat and the economic benefits associated with spending on user fees and at concessions (Dixon *et al*. 2012). If disparities in levels of access to beaches arise with respect to racial/ethnic or socioeconomic status, an environmental injustice can be said to occur. Despite the importance of equitable access to beaches, and though some studies have focused on legal issues in the context of the public trust doctrine, no known empirical study has evaluated whether the level of access to beaches is indeed equitable among different racial/ethnic or socioeconomic groups.

Second, previous RO equity studies have typically employed multivariate linear regression using the ordinary least squares (OLS) method. However, the use of spatial data such as the geographic locations of ROs, measures of access to ROs, and spatially referenced census data in a linear model violates many of the basic assumptions of OLS such as variable independence and homoscedasticity (Gilbert and Chakraborty 2011). Traditional OLS regressions have failed to explore important local variations in the relationships among variables, resulting in inaccurate results including biased parameter estimates and misleading significance tests (Anselin 1988, Yoo 2012, Zhang *et al*. 2009). The purpose of this study was therefore to explore the degree of equity exhibited by the distribution of public beaches in the Detroit Metropolitan Area (DMA) using spatially explicit regression techniques.

2. Literature review

2.1. Equity

Equity, a prevailing concept in the urban service delivery literature, asks questions such as "who benefits and why?" (Talen 1997, p. 521) or "who gets what?"(Crompton and Wicks 1988, p. 288). Nicholls (2001) defined equity as "the fairness or justice of a situation or distribution" (p. 202), while Wicks and Crompton (1986) described equity as "the perceived fairness of resource allocation patterns" (p. 342). However, equity remains an ambiguous concept due to the difficulties of establishing what is "just" or "fair" (Nicholls, 2001). Harvey (1988) characterized this issue as "an ethical problem which cannot be resolved without making important moral decisions" (p. 99).

Although a single definition of equity has not been established and multiple, sometimes competing, interpretations abound, adoption of a definition of equity is a prerequisite to analysis of it (Nicholls 2001). In the US, typologies of equity such as those suggested by Lucy (1981) and Crompton and Wicks (1988) outline four equity models that may be used with regard to the allocation of public services such as recreation amenities. These include equality, compensatory (or need), demand, and market-based approaches.

Insert Figure 1 about here

First, equity can be defined according to two types of equality: input equality and output equality. Input equality refers to equal provision of public services, regardless of geographic area or the socioeconomic characteristics of residents, while output equality is concerned with ensuring that the benefits received by residents as a result of public service provision are equal, even if variations in input are required. Second, compensatory or need-based equity involves providing a given service to those who are deemed to need it most. Based on this premise, disadvantaged residents or the most needy groups or areas are awarded (compensated with) additional services. Third, demand-based equity involves providing resources to those who demonstrate an active interest in a service or facility. Demand can be demonstrated by use, as measured by the rate of participation, or via vociferous advocacy, i.e., active campaigning by or on behalf of a certain area or group. This second demand-based definition could therefore be interpreted to incorporate more recent notions of procedural justice as advanced by, e.g., Agyeman et al. (2016). 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 prevailing price.

2.2. Measuring RO equity and access

Redistributing resources in a compensatory manner is a public sector responsibility (Nicholls 2001, Wicks and Crompton 1986). As a result, the compensatory or need-based model of equity has most commonly been employed to measure the equity of public ROs. Despite some debate regarding identification of who the most disadvantaged or needy groups are, they have typically been defined according to demographic and socioeconomic characteristics such as race/ethnicity and income (Wicks and Crompton 1986). Use of demographic and socioeconomic criteria is justified under 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 RO equity studies have used other variables such as educational attainment (Deng *et al*. 2008, Lindsey *et al*. 2001, Porter and Tarrant 2001, Tarrant and Cordell 1999), age (Nicholls 2001, Smoyer-Tomic *et al*. 2004, Talen 1997, Talen and Anselin 1998), population density (Lindsey *et al*. 2001, Nicholls 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) as proxies for or in addition to race/ethnicity and income. With respect to outdoor recreation and parks, adopting a compensatory or need-based equity model corresponds with 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.

To measure the equity of ROs, previous studies have used non-parametric difference of means tests (Nicholls 2001), linear correlation (Omer 2006; Smoyer-Tomic *et al*. 2004), equity mapping (Talen 1997, 1998, Talen and Anselin 1998), and multivariate linear regression (Deng *et al*. 2008, Porter and Tarrant 2001, Tarrant and Cordell 1999). Among these methods, multivariate linear regression using the OLS method is the most powerful because it considers multiple independent variables simultaneously (Porter and Tarrant 2001).

The OLS method is based on the two basic assumptions of independence and homogeneity (Gilbert and Chakraborty 2011). However, multivariate statistical models that include spatial data may not meet the assumptions of OLS due to spatial effects such as heterogeneity and dependence (Mennis and Jordan 2005). Spatial heterogeneity, also referred to as spatial nonstationarity, refers to the inability of the single coefficient associated with a global regression model to explain varying relationships between variables based on the tendency of geographic places to differ from one another. Rather, the specification of multiple, local, spatially varying relationships is more appropriate (Brunsdon et al. 1996; Fotheringham et al. 2002). Spatial dependence (or autocorrelation) is a function of Tobler's (1970) First Law of Geography, that "everything is related to everything else, but near things are more related than distant things" (p. 236); spatial dependence results in the clustering of similar values among neighboring observations reflecting their physical proximity. When applied to a regression model, ignoring spatial effects can lead to inaccurate estimation results including biased parameter estimates and misleading significance tests.

Given the explicitly spatial nature of need-based equity analyses, which directly relate the distributions of amenities such as ROs to the characteristics of surrounding residents, recreational equity ideally should be examined using specialized research methods that identify and account for spatial effects. Such techniques have been used to assess environmental inequities in the distributions of locally unwanted land uses and their outcomes, e.g., toxic air releases (Gilbert and Charkraborty 2011, Mennis and Jordan 2005) and air pollution (Jephcote and Chen 2012), and, in one case, the locally desirable land use of urban parks (Maroko et al. 2009). For this reason, as further described in the Method section, spatially explicit techniques that account for the special nature of spatial data were employed in this study, representing only the second known attempt to apply this technique in a recreation context.

Assessment of needs-based equity first requires measurement of access, i.e., the establishment of which places have access is a precursor to identification of who enjoys access. Zhang et al. (2011) identified four different approaches to measuring access: (1) container, which defines accessibility according to the presence of ROs within a geographic unit, e.g., the number or total area of ROs within a census tract; (2) minimum distance, meaning the minimum distance someone must travel to reach the nearest RO, which is inversely related to accessibility; (3) travel cost, which defines accessibility according to the average or total distance between each residential unit and all ROs; and (4) spatial interaction, based on a gravity model in which ROs are weighted by their attractiveness and the friction of distance. This study adopted the minimum distance approach.

2.3. Public beach access

Public beach access 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). In the US, the importance of public beach access has received much attention since 1972 when the *Coastal Zone Management Act* (CZMA) was passed. Brower and Dreyfoos (1979) described private property ownership as an inhibitor to tourists' and local residents' rights to access beaches. Lam (1991) illustrated past and present policies on public access in Hawaii, while Pirkle (1994) examined the history and current status of public access in Texas. Pogue and Lee (1999) introduced various tools and processes (e.g., acquisition, planning, regulations, technical assistance, and public outreach) for improving the provision of public beach access, while Thompson and Dalton (2010) demonstrated the utility of a boat-based offset survey method to measure public beach access along the northern part of Narragansett Bay, Rhode Island. In South Carolina, Oh *et al*. (2009) assessed tourists' preferences for public beach access using a stated preference choice method; more recently, Dixon *et al*. (2012) compared the economic values coastal residents and tourists assign to public beach access using the travel cost and contingent valuation methods. The analyses presented here are therefore novel in their emphasis on measurement of public beach access and equity using geographic information systems and geographically weighted regression.

3. Method

3.1. Study area: Detroit Metropolitan Area (DMA), Michigan

The Detroit Metropolitan Area (DMA) is located in southeast Michigan and includes three counties (Oakland, Wayne, and Macomb). According to the U.S. Bureau of the Census (2010), the DMA is the 12^{th} largest metropolitan area in the US, with a population of 3,863,924 and an area of 1,958.96 square miles (3,463.2 km^2). The DMA was selected as the study area for two reasons. First, the DMA contains a high density of public beaches; 178 (14.5%) of the

1,224 public beaches in Michigan are concentrated in the DMA (Michigan Department of Environmental Quality [MDEQ], 2013). Second, the DMA is a demographically diverse area with the highest population density in Michigan (2,792.5 inhabitants per square mile). As of the 2010 Census, the racial composition of the DMA included: White (70.1%), African American (22.8%), Asian (3.3%), Native American (0.3%), and Pacific Islander (0.02%). Ethnic composition was 6.2% Hispanic.

3.2. Unit of analysis, variables, and data acquisition

Defining the unit of analysis is critical in any spatial study. In this study, the census tract (CT) was utilized. A CT is 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). The DMA includes 1,164 CTs. Figure 2 illustrates the distribution of public beaches (n = 178) and the CT boundaries within the study area.

Insert Figure 2 about here

The dependent variable in this study was the level of access to public beaches, defined as the shortest road network distance from each CT centroid to the nearest public beach. This access measure reflects the minimum distance approach, recognizing that many ROs are mainly used by nearby residents and that the nearest RO typically represents the easiest opportunity for frequent or everyday use. Several previous recreation equity studies have employed the minimum distance approach (e.g., Byrne *et al*. 2009, Lotfi and Koohsari 2009, Smoyer-Tomic *et al*. 2004, Talen 1998, Talen and Anselin 1998).

The study adopted a need-based definition of equity. Selection of independent variables was limited to those available for CTs. They included: (1) population density; (2) age (young (under 18) and older (over 64)); (3) race/ethnicity (Black and Asian (to represent race) and Hispanic (ethnicity)); (4) housing value; (5) educational attainment; (6) language spoken at home; (7) vehicle ownership; (8) housing occupancy; and (9) economic status relative to the poverty line. Disadvantaged residents or the most needy groups were hypothesized to be those residing in more densely populated areas, the young and elderly, non-Whites and Hispanics, those living in lower value housing, those having lower educational attainment, those without English spoken at home, those without a vehicle, and those residing in areas with lower proportions of occupied housing and higher poverty rates. Based on the need-based approach adopted, an equitable distribution would therefore be demonstrated when the disadvantaged received better than average access to public beaches (i.e., a lower travel distance), whereas inequity would be demonstrated when the disadvantaged received significantly lower levels of access than the less needy (i.e., higher travel distance). The independent variables and their operational definitions are summarized in Table 1.

Insert Table 1 about here

Geographic data such as CT boundaries and the street network were acquired from the Michigan GIS data library (http://www.mcgi.state.mi.us/mgdl/). Public beach locations were collected from MDEQ (http://www.deq.state.mi.us/beach/). Census data were obtained from the 2010 Census summary file 1 (SF1) and file 3 (SF3) of the U.S. Bureau of the Census.

3.4. Data analysis

Network analysis was employed to measure the level of access to public beaches by calculating the shortest road network distance from each CT centroid to the nearest public beach. Then, geographically weighted regression (GWR) was used to explore relationships between level of beach access and residents' demographic and socioeconomic status. GWR is a regression technique that allows exploration of spatial heterogeneity at the local level. GWR estimates regression coefficients locally by fitting a regression equation to every feature in a dataset, by modifying the traditional OLS equation for each observation's location 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 i^{th} point in the study area, y_i is the vector of the estimated parameter at point i, $a_{io}(u_i, v_i)$ is the intercept parameter at point i, $a_{ik}(u_i, v_i)$ is the local regression coefficient for the k^{th} independent variable at point i, and x_{ik} is the value of the k^{th} independent variable at point i (Fotheringham *et al*. 2002). While conventional OLS regression generates a single equation to represent the global relationship between variables, GWR calibrates the regression equation differently for each observation (Mennis and Jordan 2005).

Using GWR, each regression coefficient is calculated using spatially dependent weights. In other words, observed data points closer to the regression points are more heavily weighted than those located farther away. Two methods – the bi-square function and the Gaussian function – have typically been used when determining the weight. The bi-square function is typically utilized in cases such as this one, when the observed data points are not regularly distributed in the study area (Fotheringham et al., 2002). The weight (w_{ij}) for the bi-square function is calculated as follows:

$$w_{ij} = [1 - (d_{ij} / b^2)] \text{ when } d_{ij} \leq b, w_{ij} = 0 \text{ when } d_{ij} > b$$

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 i, the weight of the data point is unity and falls to zero when the distance between i and j equals the bandwidth. Generally, the optimal bandwidth can be determined either by selecting the bandwidth that minimizes a cross-validation (CV) score or the one that minimizes the Akaike Information Criterion (AIC). The AIC method is more commonly employed than the CV method (Zhang *et al.* 2011), and was used here. AIC is a measure of the relative quality of a statistical model; AIC_c is a corrected AIC for finite sample sizes (Bozdogan 1987). It can be estimated as follows:

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

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 spatial variability of the parameters was tested using the rho values (equivalent to *p* values) generated by the Monte Carlo significance test attributed to Hope (1968). Lastly, choropleth mapping was used to visualize statistical diagnostics (e.g., local parameter estimates and local R^2). Data analysis was conducted using ArcGIS (version 10.0), the ArcGIS Network Analyst extension, and GWR (version 4.0).

4. Results

4.1. Level of access to public beaches

Level of access to public beaches in the DMA is displayed and summarized in Figure 3 and Table 2. The minimum distance to the nearest public beach from each CT centroid 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 of the DMA resides within 1 mile of a public beach, 36.0% within 5 miles, 77.0% within 10 miles and 99.8% within 20 miles. Access to public beaches is less prevalent in both Macomb and Wayne Counties. In contrast, residents of Oakland County have extremely good access to public beaches.

Insert Figure 3 and Table 2 about here

4.2. GWR model results

Results of the GWR model are presented in Table 3. The range of local adjusted R^2 was from a minimum of 0.27 (Rochester Hills, Oakland County) to a maximum of 0.92 (River Rouge, Wayne County), with a mean of 0.70 (Figure 7). The model had the best explanatory power (>80.0%) in Dearborn, Dearborn Heights, Detroit, Lincoln Park, Romulus, and Westland and in Brownstown, Huron, and Sumpter townships (Wayne County); in Royal Oak, Southfield, and Troy (Oakland County); and, in Sterling Heights and Warren (Macomb County). However, the model had very low explanatory power in Rochester Hills and in Groveland, Highland, Holly, Rose, Springfield, and White Lake townships (Oakland County), indicating that level of access to public beaches in these areas is not explained adequately by the independent variables included. These findings indicate that the explanatory power of the local model is not stationary, i.e., that the degree of model performance is spatially heterogeneous across the study area, and suggest the need to consider the inclusion of additional explanatory variables that might further improve model performance. The local condition index ranged from a minimum of 8.6 to a maximum of 24.4, indicating the absence of local collinearity among the independent variables.

Insert Table 3 and Figure 4 about here

Based on rho values, three of the twelve independent variables (POPD, 0.01; AGE64, 0.02; EDU, 0.01) showed evidence of spatial variation in the parameter estimate values at the 0.05 level. The ranges of the local coefficients for these variables were -1.29 to 1.40 (mean: 0.14, POPD), -1.01 to 2.85 (mean: 0.12, AGE64), and -3.25 to 2.73 (mean: -0.02, EDU), respectively. The inclusion of zero in these ranges indicates that traditional OLS would have produced misleading findings for these variables, i.e., that the relationships between minimum distance to the nearest public beach and population density, proportion of elderly population and educational attainment are heterogenous across the study area. None of the other independent variables reached statistical significance, suggesting no distinct (in)equity patterns with respect to those factors.

4.3. Local coefficient estimates

The spatial distribution of local R^2 and local coefficients for those independent variables that reached statistical significance in the GWR model are mapped in Figures 4-7. Lighter colors indicate negative values, suggesting equitable access to public beaches with regard to population density and age over 64 and inequitable access to public beaches with regard to education level (i.e., as minimum distance to the nearest beach increases, population density and proportion age over 64 decrease, suggesting that these two 'needier' portions of the population have better access, whereas as distance increases, the proportion of the population with a four-year university degree or higher decreases, suggesting those with lower levels of education attainment have less access). Darker colors indicate positive values, suggesting equitable access to public beaches with regard to education level and inequitable access with regard to population density and age over 64. Table 4 summarizes these maps while Table 5 lists the neighborhoods with inequitable access to public beaches and their residents' demographic and socioeconomic status.

Insert Tables 4 and 5 about here

POPD. Figure 5 and Table 3 show that there are both positive (n=771, 66.2%) and negative (n=393, 33.7%) correlations across the study area. The range of the local coefficients for POPD was from -1.29 (Warren, Macomb County) to 1.40 (Shelby township, Oakland County), with a mean of 0.14. Strong positive correlations (local coefficient >1.04 [2 standard deviations above the mean]), indicating inequitable access to public beaches with regard to population density, and strong negative correlations (local coefficient<-0.76 [2 standard deviations below the mean]), indicating equitable access, were indicated as listed in Table 5.

Insert Figure 5 about here

AGE64. Figure 6 and Table 3 show that there are both positive (n=628, 53.9%) and negative (n=536, 46.0%) correlations across the study area. The range of the local coefficients for AGE64 was from -1.01 (Detroit, Wayne County) to 2.85 (Canton, Wayne County), with a mean of 0.12. Strong positive correlations (local coefficient > 1.06), indicating inequitable access to public beaches with regard to elderly population, and strong negative correlations (local coefficient < -0.82), indicating equitable access, were observed (Table 5).

Insert Figure 6 about here

EDU. Figure 7 and Table 3 show that there are both positive (n=536, 46.0%) and negative (n=628, 53.9%) correlations across the study area. The range of the local coefficients for EDU was from -3.25 (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 regard to educational attainment, and strong negative correlations (local coefficient < -1.86), indicating inequitable access, were (Table 5).

Insert Figure 7 about here

5. Discussion and implications

This study explored the degree of equity inherent in public beach access in the DMA using GWR. It is one of only a few equity analyses to employ GWR, and the first to measure the equity of access to public beaches, thereby offering significant practical and methodological implications for recreation planners and managers. More broadly, for anyone concerned about the role of access to everyday amenities in the attainment of more just and sustainable communities (per, e.g., Agyeman et al. 2016), the study is a reminder of the importance of the distributions of ROs and related natural resource-based settings.

The GWR model specified enabled the exploration of spatially varying relationships between level of access to public beaches and residents' demographic and socioeconomic status, rather than assuming a single (global) association between each independent variable and level of access. The spatial heterogeneity demonstrated implies that local variations do indeed exist in the relationships between level of access to public beaches and certain demographic and socioeconomic characteristics (specifically with respect to population density, age and education level), emphasizing intricate patterns of (in)equity that cannot be identified using traditional OLS techniques. This finding complements those of Maroko *et al*. (2009) with respect to urban parks in New York City, the only prior study to apply GWR to RO equity. Their study indicated significant local variations between level of access and all of the racial/ethnic, socioeconomic and demographic characteristics they tested (black, Hispanic, below poverty line, education level, English proficiency, and population density).

Despite significant local variations between the access levels and population density, proportion of elderly population and educational attainment, the mean values of the GWR coefficients for these variables indicate that on average residents living in more densely populated areas, the elderly, and those with lower levels of educational attainment, are significantly less likely to be able to access a public beach, suggesting the inequitable distribution of access to public beaches with respect to these segments of the DMA population (Table 3). These findings are consistent with those of Estabrooks *et al*. (2003), that inequitable access to urban trails is associated with residents' educational attainment, but inconsistent with

Nicholls (2001)'s finding that equitable access to urban parks is associated with proportion of elderly population and population density. According to Hasse and Milne (2005), each community has its own unique atmosphere and regional characteristics, and this variation between study areas is thus to be expected. The findings of this study not only support that argument but also emphasize the importance of highlighting variations within individual communities due to spatial heterogeneity at the local level.

Findings also suggest several practical and methodological implications for recreation policy that could be used to inform initiatives that might improve access to water or beach-based recreation resources in the DMA. For instance, the study identified where inequitable access to public beaches exists with regard to specific demographic and socioeconomic variables. Previous equity studies in the urban service delivery literature have typically addressed "who gets what" in the context of environmental justice (Talen, 1998, p. 22). Using GWR, however, this study extended the focus from “who gets what” to “who gets what, where, and to what extent (how significantly),” allowing identification of specific neighborhoods where inequitable access to public beaches is provided with regard to particular demographic and socioeconomic minorities in the DMA. As noted by Gilbert and Chakraborty (2011), land-use planning and zoning decisions that contribute to environmental (in)equities are typically regulated at local levels of government. Local statistical methods such as GWR, that highlight rather than mask local variations, provide highly specific results that can help local parks and recreation agencies allocate limited budgets more equitably by pinpointing the most needy groups and areas, thereby encouraging the formulation of the most locally relevant and appropriate policy solutions. Whereas application of traditional, global regression techniques would simply have highlighted the presence or absence of equity across the entire DMA, use of

GWR enabled identification of specific cities and townships in which inequity occurs and for which subsets of the population (Table 5), representing an important addition to the urban planners analytical toolkit. The findings generated here could be combined with other observations, e.g., access levels to other types of water- and land-based ROs, into an index of recreation opportunity which could be used to more finely prioritize appropriate interventions such as those outlined below. This approach echoes the call made by Maantay (2013), “to replace the subjective approach by providing decision-makers with a more quantitative, evidence-based foundation for determining priority areas” (p. 10).

Since beaches are fixed in space and dependent on the existence of geographic features such as rivers and lakes, creating new beaches is not feasible (with the exception of the creation of temporary beach settings such as occurs along the banks of the Seine in Paris each summer). A more realistic option is to identify coastline already in the public realm where new access points might be established, or private or not-for-profit owners who might be willing to grant permanent or seasonal easements. Alternatively, public leisure agencies and community organizations could build strategic public-private partnerships to locate water features such as swimming pools or spray parks in neighborhoods that suffer from poor accessibility to beaches (though before expensive capital projects are embarked upon, residents' attitudes regarding the desirability of water-based recreation activities and facilities should first be assessed, i.e., their recreation preferences should be firmly established). Moreover, public leisure agencies should investigate partnerships with public transportation services, e.g., local and regional bus systems, to encourage free or reduced-cost access to public beaches for underserved groups.

Attractive visual, i.e., map-based, illustrations of the outcomes of accessibility and equity analyses may also contribute to greater awareness on the part of local stakeholders, and, ultimately, to more inclusive and successful community recreation planning, by increasing residents' levels of access to and interaction with information. 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). Maps can also be a useful tool for improving users' perceptions of public authorities' accountability and openness, increasing interaction and understanding between leisure agencies and their constituents, decreasing perceptual gaps, and leading to more informed and satisfied community members.

Public leisure agencies have a responsibility not only to share information, but also to be proactive in negotiations between diverse stakeholders with potentially different perspectives with respect to the application of that information in planning and management decisions. Thus, though visual representation of, e.g., distributions of access and equity, using maps can provide insightful data, it is ineffective without active explanation and understanding of their meaning and without full integration of reactions to them into truly participatory decision-making processes. Traditionally, public meetings have been used as the standard tool for sharing information and soliciting input in public RO planning and management processes (Hilderbrand 1997). However, drawbacks such as the geographic separation between potential participants and venues, other participant mobility issues, scheduling and financial constraints, and limited numbers and durations of input sessions have stymied their productivity (Ball 2002). Participatory GIS (PGIS) via the web offers opportunities to overcome such limitations. As noted by Kingston *et al.* (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 PGIS also offers citizens and neighborhood organizations instant access to data and data processing tools at potentially any time and place

(Sieber 2006), and even those without private access to the Internet or a mobile device may utilize public venues such as local libraries. Web PGIS thus creates opportunities for more people to participate in the public debate regarding complex resource planning and management issues than the traditionally inflexible town-hall meeting schedule (Kingston *et al*. 2000). Furthermore, web-based PGIS offers interactivity between users and information during the decision-making process, since users can retrieve and query complex information via the web (Luchette and Crawford 2008). More importantly, with adequate training, users can conduct analyses and obtain instant results (Jankowski and Nyerges 2001). PGIS therefore offers an example of the notion of citizen or street science that has emerged over the last decade, and that allows public participation not only in the development of solutions, but also in the framing and analysis of those problems that purportedly need to be solved (Agyerman *et al*., 2016), offering the opportunity to move towards Walker's ideal of justice as participation and procedure.

Ultimately, however, decisions must be made by people rather than information systems like GIS. Despite the visualization and analytical advantages of web-based PGIS as described above, it lacks the capability to incorporate decision makers' preferences (Simao, Densham, & Haklay, 2009). Thus, advanced spatial decision support systems that can consider diverse stakeholders' perspectives and viewpoints are ultimately required. Capacitated methods have long been recognized as useful tools for allocating limited resources more efficiently in the location-allocation literature (Aikens 1985, Jacobsen 1983, Murray and Gerrard 1997, Rahman and Smith 2000, Zhou and Liu 2003). But, as noted above, identifying optimal locations for new recreational facilities is a complicated issue involving diverse stakeholders with varying perspectives, and 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 while minimizing conflicts between stakeholders (Feick and Hall, 2002). The benefits of spatial multi-criteria decision analysis (SMCDA), which involves the methodological integration of GIS and multi-criteria decision analysis via "a process that combines and transforms geographical data (input) into a resultant decision (output)" (Malczewski 1999, p. 90), have been emphasized for implementing a participatory approach (Feick and Hall 2002, Phua and Minowa 2005).

6. Limitations and Future Studies

Despite significant implications for practice and methods, several limitations of this study should be acknowledged, the first batch of which are issues of measurement. First, when measuring the level of access to public beaches, this study employed a relatively simple distance-based metric that assumed users choose to visit their nearest beach; as described in 2.2, there are other methods of measuring access, each of which might have produced different outcomes in terms of distributions of access and (in)equity. Ideally, future studies should compare the results of multiple of these measures and identify areas of (dis)agreement with respect to results. Further, this measure did not consider important objective and subjective factors such as beach width/length, allowable activities, environmental quality, and perceived or actual levels of crowding and safety, all of which might affect residents’ beach choice, i.e., influence a user to visit an amenity at a farther distance rather than simply choosing the nearest one. Similarly, a resident might consciously choose to visit a more distant amenity to increase their variety of experiences, or do so unknowingly out of lack of awareness of the nearer opportunity. Future studies should integrate these variables to provide more comprehensive assessments of overall accessibility.

Second, this study used the centroid of a CT to measure the distance of residents within that tract. However, the centroid approach can produce aggregation error that leads to biased measurement results (Smoyer-Tomic *et al*. 2004); in future studies, aggregation error could be reduced by employing minimally aggregated spatial units such as census blocks. Consideration of alternative census units also raises the issue of the modifiable areal unit problem, that the choice of a different unit of analysis such as census blocks or block groups might have produced different results than those found for census tracts. However, the use of smaller units would even further limit the number and variety of socioeconomic variables available for inclusion in the analyses since these depend upon those variables collected in the census.

The study also assumed that residents have access to a reliable and affordable means of transportation. Future studies should employ multiple travel distances and incorporate public transportation routes when measuring the level of access to public beaches, to accommodate variations in the availability of, access to and preferences for different modes of mobility. In addition, the study focused on a single RO type (public beaches) and geographic location (DMA); given the explicit purpose of GWR to highlight local variations, its findings are not generalizable. Analysis of other types of ROs (land- and water-based) in other areas is desirable. The focus of the study was on hypothetical access rather than actual use or, of even more interest, outcomes such as improved health. A valuable next step would therefore be to conduct assessments of levels of use and to correlate those with physical and mental health indicators. Combination of the findings presented here with additional metrics as mentioned above, and the use of resulting outcomes to pinpoint needy areas and ultimately prioritize resource allocation, would mirror the index approach advocated by Maantay (2013). An approach such as this would also better capture the multiple additional dimensions of greenspace highlighted by Walker, who notes how this “is not an entirely uncontested and unproblematic “good thing” that contributes equally to wellbeing for all” (2009 p. 621).

Lastly, while the findings of this study do demonstrate the utility of GWR as an exploratory spatial regression technique and illustrate how statistical relationships between beach access and demographic and socioeconomic status vary across the DMA, they do not address the underlying causes of these variations, i.e., the focus here was on outcome rather than process. As noted by Fotheringham et al. (1998), "there are spatial variations in people’s tastes or attitudes or there are different administrative, political, or other contextual issues that produce different responses to the same stimuli across space” (p. 1906); as such, additional quantitative or qualitative investigations should be conducted to explore the variety of social, political, economic, and historical factors that might help explain the inequities identified in terms of e.g., settlement patterns and population growth and redistribution, roadway construction, land use change, etc.

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Table 1. Dependent and independent variables

Variable	Operational definition	Abbreviation	Inequity
Level of access to public beaches (DV)	Shortest road network distance from CT to the nearest public beach (in miles)	DISTPB	-
Population density (IV)	Population per square mile	POPD	Decrease
Age (IV)	(1) Proportion (%) of population under age 18 (2) Proportion (%) of population over age 64	(1) AGE18 (2) AGE64	Decrease Decrease
Race/ethnicity (IV)	(1) Proportion (%) of Black population (race) (2) Proportion (%) of Asian population (race) (3) Proportion (%) of Hispanic population (ethnicity)	(1) BLACK (2) ASIAN (3) HISPAN	Decrease Decrease Decrease
Housing value (IV)	Median housing value ($)	MHV	Increase
Income (IV)	Median household income ($)	MHI	Increase
Education (IV)	Proportion (%) of population with a four-year university degree or higher	EDU	Increase
Language (IV)	Proportion (%) of population with non-English spoken at home	LAN	Decrease
Vehicle ownership (IV)	Proportion (%) of households without a vehicle	VEHIC	Decrease
Housing occupancy (IV)	Proportion (%) of occupied housing units	HO	Increase
Economic status (IV)	Proportion (%) of population below the poverty line	ECON	Decrease

Note: DV (dependent variable), IV (independent variable), * need-based inequity with respect to each indepen
indicated by increase/decrease in that variable as level of access increases (i.e., shortest distance declines)

Table 2. Results of network analysis

Minimum distance (D) to the nearest public beach (mile)	Number of CT (n=1,164)	%	Cumulative %
0.0 ≤ D < 1.0	51	4.3	4.3
1.0 ≤ D <2.0	60	5.1	9.4
2.0 ≤ D < 3.0	101	8.6	18.0
3.0 ≤ D < 4.0	93	7.9	25.9
4.0 ≤ D < 5.0	118	10.1	36.0
5.0 ≤ D < 6.0	106	9.1	45.1
6.0 ≤ D < 7.0	95	8.1	53.2
7.0 ≤ D < 8.0	92	7.9	61.1
8.0 ≤ D < 9.0	94	8.0	69.1
9.0 ≤ D <10.0	92	7.9	77.0
10.0 ≤ D < 11.0	66	5.6	82.6
11.0 ≤ D < 12.0	69	5.9	88.5
12.0 ≤ D < 13.0	51	4.3	92.8
13.0 ≤ D < 14.0	20	1.7	94.5
14.0 ≤ D < 15.0	13	1.1	95.6
15.0 ≤ D < 16.0	16	1.3	96.9
16.0 ≤ D < 17.0	10	0.8	97.7
17.0 ≤ D < 18.0	6	0.5	98.2
18.0 ≤ D < 19.0	6	0.5	98.7
19.0 ≤ D < 20.0	2	0.1	98.8
D ≥ 20	3	0.2	99.0

Note. CT: census tract; D: minimum distance to the nearest public beach from CT centroid

Table 3. Results of GWR model

Variable	GWR coefficients (β)			Rho (spatial variability)	Range	Equity (ineq when value
	Minimum	Mean	Maximum			
Intercept	1.29	6.90	16.13	0.58	14.84	
BLACK	-5.55	0.31	7.77	0.45	13.32	Negativ
ASIAN	-2.81	0.09	4.71	0.53	7.52	Negativ
HISPAN	-7.54	0.17	8.64	0.12	16.18	Negativ
POPD	-1.29	0.14	1.40	0.01	2.69	Negativ
MHV	-4.10	-0.17	2.84	0.20	6.94	Positive
AGE18	-1.57	0.04	4.58	0.08	6.15	Negativ
AGE64	-1.01	0.12	2.85	0.02	3.86	Negativ
EDU	-3.25	-0.02	2.73	0.01	5.98	Positive
LAN	-1.66	-0.09	4.30	0.57	5.96	Negativ
ECON	-2.51	0.02	4.15	0.39	6.66	Negativ
HO	-1.61	0.21	4.89	0.32	6.50	Negativ
VEHIC	-1.85	0.05	2.20	0.15	4.05	Negativ
Adjusted R^2	0.27	0.70	0.92		0.65	
Condition Index	8.6	16.3	24.4		15.8	
n=1,164; AIC_c (GWR) = 4,085.73; neighbors = 147						

Note. Rho: Rho value per Monte Carlo analysis; β(Beta): regression coefficient; VIF: variance inflation facto Akaike's informaiton criterion

Table 4. Classification of census tracts by values of local coefficient

Variable	Number of CT (n=1,164)			
	LC > 0 (%)	Indicates	LC < 0 (%)	Indicates
POPD	771 (66.2%)	Inequity	393 (33.7%)	Equity
AGE64	628 (53.9%)	Inequity	536 (46.0%)	Equity
EDU	536 (46.0%)	Equity	628 (53.9%)	Inequity

Note. CT: census tract; LC: local coefficient by GWR

Table 5. Neighborhoods with inequitable access to public beaches by demographic and socioeconomic status

Variable	Inequitable neighborhood	
	City (County)	Township (County)
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), Washington (M)

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

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