Landscape and Urban Planning 168 (2017) 61–71

Contents lists available at ScienceDirect

Landscape and Urban Planning

journal homepage: www.elsevier.com/locate/landurbplan

Research Paper

Understanding spatial variation of physical inactivity across the continental United States

Kyung Hee Lee[a,*], Robert G. Dvorak[a], Michael A. Schuett[b], Carena J. van Riper[c]

[a] Department of Recreation, Parks and Leisure Services Administration, Central Michigan University, USA
[b] Department of Recreation, Park and Tourism Sciences, Texas A & M University, USA
[c] Department of Natural Resources and Environmental Sciences, University of Illinois at Urbana-Champaign, USA

ARTICLE INFO

Keywords:
Physical inactivity
Geographically weighted regression (GWR) model
Spatial heterogeneity
Regional planning

ABSTRACT

Physical inactivity lies at the heart of the public health crisis in the United States (U.S.). Research on the factors that contribute to inactivity is vast and growing; however, most of this work focuses on individual rather than community-level dynamics such as socio-economics, access to resources, and features of the physical environment. Moreover, few studies have tested spatial relationships between the prevalence of physical inactivity and multiple explanatory variables to identify potential sources of social and environmental justice at the community level of analysis. To address these gaps in previous research, this study drew on an array of secondary data sources to: 1) identify factors that contribute to levels of physical inactivity; 2) examine how these factors affect spatial inequalities; and 3) compare model performance between conventional ordinary least squares regression models and geographically weighted regression (GWR) to predict physical inactivity among U.S. residents. Our findings indicate that multiple variables predict physical inactivity, particularly access to infrastructure, expenditures on recreational activities, and poverty within disenfranchised segments of the population. Given that improvements in our model performance detected non-stationary spatial relationships and reduced the autocorrelation of residual variables, we contend that this technique accounts for greater variation than ordinary least squares regression. Thus, this study provides a comprehensive basis for informing urban and landscape planning decisions across spatial and regional scales.

1. Introduction

1.1. A short background on physical activity

Physical inactivity has been widely recognized as a public health crisis. Particularly in the United States (U.S.), obesity rates are rapidly increasing due to an array of factors such as diet, decreases in leisure-time, and lack of access to healthy foods (Fung & Lo, 2000; Ladabaum, Mannalithara, Myer, & Singh, 2014; Walker, Keane, & Burke, 2010). Intervention programs designed to increase physical activity have been limited to a small number of people who are rarely tracked over space and time (Trost, Owen, Bauman, Sallis, & Brown, 2002; Sugiyama, Leslie, Giles-Corti, & Owen, 2009). This is problematic because most people who start physical activity programs discontinue involvement within the first six months (Stetson et al., 2005), and most interventions do not lead to long-term participation (Lee, Djoussé, Sesso, Wang, & Burning, 2010; Sun, Norman, & While, 2013; Sugiyama et al., 2009; Trost et al., 2002). Moreover, a bulk of research in this area has focused on why individuals (dis)engage in physical activity (Ball et al., 2008; Crespo, Smit, Andersen, Carter-Pokras, & Ainsworth, 2000; Seefeldt, Malina, & Clark, 2002) despite the importance of considering group-level dynamics. That is, multiple levels of social, economic, and environmental determinants should be factored into decisions about landscape and urban planning to identify the reasons why individuals and groups settle into sedentary lifestyles. In response to these knowledge gaps, past research has indicated proximity to green space and access to programs that encourage recreational pursuits are crucial for fostering constructive behavioral outcomes (Norman et al., 2006; Veitch et al., 2014). In this sense, individual use of everyday landscapes is nested within broader contexts and macro-level dynamics that govern healthy lifestyles (Dahmann et. al., 2010; Giles-Corti & Donovan, 2002; Liechty, Genoe, & Marston, 2017; Macintyre, MacIver, & Sooman, 1993).

The architecture and design of landscapes has bearing on levels of physical activity, and in turn, human well-being and quality of life for diverse populations (Wilhelm Stanis, Schneider, Chavez, & Shinew, 2009). In particular, various aspects of the built environment, including

* Corresponding author at: Department of Recreation, Parks, and Leisure Services Administration, Central Michigan University, Finch Fieldhouse 107 Mt. Pleasant, MI 48859, USA.
E-mail addresses: lee8k@cmich.edu, tour.lee@gmail.com (K.H. Lee), dvora1rg@cmich.edu (R.G. Dvorak), mschuett@tamu.edu (M.A. Schuett), cvanripe@illinois.edu (C.J. van Riper).

http://dx.doi.org/10.1016/j.landurbplan.2017.09.020
Received 27 December 2016; Received in revised form 11 July 2017; Accepted 20 September 2017
0169-2046/

degrees of development, transportation networks, and access to food distribution points are associated with health disparities and fitness (Sallis & Glanz, 2009). For instance, previous research has indicated that maintaining sufficiently wide, illuminated and well-designed sidewalks, minimizing traffic and creating pedestrian-friendly spaces will stimulate and redirect use of an environment that is accessible to all members of a community (Berrigan & Troiano, 2002). The National Research Council (2005, p.7) has reinforced this point and noted that human movement patterns are exceedingly complex, particularly in urban contexts, and require consideration of indirect and mediating factors for diverse populations. Despite this complexity, landscape architecture research has tended to focus more on design principles than human behavior. Although helpful, this focus has created a need for sound theoretical frameworks and more complete research designs (Lachowycz & Jones, 2013; Qviström & Vicenzotti, 2016; Silva & Teixeira, 2012; Taylor, 2016; Wylie, 2007). Along with the built environment, the natural world has differential effects on human behavior, health and well-being (Littenberg et al., 2015). A natural amenity scale was developed to measure these effects and test whether people are attracted to areas with varied topography, bodies of water, warmer climates, and low humidity (USDA ERS, 2004). Applications of this scale have laid the groundwork for future research and indicated there are inverse relationships between obesity rates and natural amenities at a national level (Jilcott et al., 2013).

Previous research has examined the spatial distribution of public recreation programs that encourage active living and reduce health problems (see Dahmann, Wolch, Joassart-Marcelli, Reynolds, & Jerrett, 2010). However, fewer studies have examined parks and open spaces as contexts for physical activity (e.g., Kaczynski & Henderson, 2007). This is an important area of inquiry because presence or absence of these settings influence the prevalence of chronic diseases such as obesity across spatial scales. For example, Myers, Slack, Martin, Broyles, and Heymsfield (2015) used spatial cluster analysis to show that physical inactivity was positively associated with obesity prevalence. These authors provided insight into which segments of society accessed open spaces and identified locations most likely to foster healthy lifestyles. Similarly, Black (2014) adopted Geographically Weighted Regression (GWR) rather than traditional aspatial regression to detect locational differences in obesity rates across the U.S. Results revealed a positive correlation between adult obesity and physical inactivity at the county-level and illustrated how the local environment was related to obesity prevalence across spatial scales. Thus, geospatial modeling such as GWR has emerged as a promising method to advance knowledge of the causes and consequences of physical activity in landscape and urban planning. Therefore, this study examined the spatially varying relationships between physical inactivity and both natural and built environments (heretofore referred to as the "physical environment"), as well as socio-economic variables at the county level using geocoded secondary data.

1.2. Application of opportunity theory to understand physical activity

Opportunity theory can be used to guide research focused on the association between health problems such as obesity prevalence and physical activity (Rosenberger, Bergerson, & Kline, 2009; Wells, Ashdown, Davies, Cowett, & Yang, 2007). This conceptual framework postulates, "All things being equal, individuals from different segments of society have the propensity to participate in recreation activities" (Romsa & Hoffman, 1980, p.322). Recreation participation relies on the extent to which recreation resources are accessible and financially available (Hendee, 1969). Although there are a range of psycho-social variables that can be used to understand why people do or do not engage in physical activity, public environments such as parks and related recreation areas are important features of urban settings that stimulate human movement (Koohsari et al., 2015). Residents' proximity to management infrastructure has garnered research attention to document the health benefits of nature and provide implications for land use planning and management agencies (Scott, 2013). Previous research has indicated that racial and ethnic minorities such as African Americans from lower income households and rural environments tend to be less physically active and overweight when recreation amenities are lacking (Gordon-Larsen, Nelson, Page, & Popkin, 2006; Nelson, Gordon-Larsen, Song, & Popkin, 2006; Patterson, Moore, Probst, & Shinogle, 2004). Moreover, in a meta-analysis conducted by Doucouliagos and Hall (2010), multiple socio-economic variables were identified to anticipate barriers that impeded activity engagement. The authors found that income was a particularly strong predictor of physical activity, which could be used to anticipate use of recreation resources.

Opportunity theory has been applied in numerous contexts (e.g., Congdon, 2016; Edwards, Jilcott, Floyd, & Moore, 2011; Scott & Munson, 1994; Sylvester, 2015; Tilley & Sidebottom, 2015; Troy, Nunery, & Grove, 2016). Many of these studies exploring recreation participation have used cross-sectional research designs (Andkjaer & Arvidsen, 2015), thus showing limited generalizability. Differences in the association between socio-economics and recreation participation have yet to be tested on regional or national levels. This gap in previous research calls to question issues of housing, the location of recreation resources and social justice for diverse populations (Dahmann et. al., 2010). If recreation resources are not readily available or affordable, limited opportunity exists to participate (Joassart-Marcelli, 2010). This situation presents a challenge for research to guide planning and management across spatial scales on a national level. A substantive body of previous research on the relationship between physical activity and self-reported wellness has indicated that numerous health-related problems (e.g., stress, obesity) can be influenced by participation, proximity and access to resources (Driver, 1985; Godbey, Graefe, & James, 1992; Kaczynski & Henderson, 2008; Snodgrass & Tinsley, 2010; Godbey, 2009; Rosenberger et al., 2009). Health disparities and perceptions of the neighborhood environment are priorities for funding agencies and those entities focused on promoting health, well-being, and quality of life (Giles-Corti & Donovan, 2002).

1.3. Effects of the physical environment

Previous research has established a broad understanding of how physical activity and related chronic diseases develop across spatial scales using techniques such as multivariate regression analysis. For example, Rosenberger et al. (2009) found a negative relationship between opportunities for recreation and rates of physical inactivity in Oregon. Also using multilevel regression models, Jilcott et al. (2013) demonstrated that natural amenities and the density of recreation facilities were negatively related to obesity rates in the U.S. However, these two previous studies suffered from methodological limitations − namely, variation in the relationships among different physical environments were unaccounted for in their models. Given that physical activity takes place in different activity domains (e.g., household, living environments, and leisure) that are influenced by a variety of determinants (Sugiyama et al., 2009), future research should prioritize consideration of these domains to refine knowledge of the physical attributes that influence engagement.

The effects of physical activity on human health and well-being has been well documented in previous research (Hardman & Stensel, 2009; Kaczynski & Henderson, 2007; Leslie et al., 1999; Stanis et al., 2009). Regional-level assessments of activity engagement have provided particularly valuable insights into the role of physical environments in the provision of opportunities for people to experience open spaces. The location and expanse of infrastructure (e.g., recreation facilities), for example, have been examined to identify availability and access to resources developed to suit individual needs (Roubal, Jovaag, Park, & Gennuso, 2014). Many regional-level planning and management agencies have also considered a host of socio-demographic variables alongside physical conditions. However, surprisingly few studies have tested the spatially varying relationships between the prevalence of physical inactivity and the physical environment across regional scales. Hence, the use of macro-level data in an investigation of human health and well-being will address an important intellectual gap and provide useful information for balancing the provision of recreational services to diverse populations.

1.4. Purpose of the present study

Building on the aforementioned gaps in previous research, this study used geospatial modeling to test the associations between the prevalence of physical inactivity and a range of variables to indicate potential health disparities across the U.S. Specifically, drawing on the tenets of Opportunity Theory, the models developed in this study were tested at the county level to offer a perspective on the role of socio-economic and physical variables on levels of inactivity. The specific study objectives were to: (1) identify the socio-economic and physical factors that contribute to levels of inactivity; (2) examine how these factors affect spatial differences of inactivity; and (3) compare the performance of conventional regression models (i.e., OLS) and spatial regression models (i.e., GWR) in predicting the prevalence of physical inactivity among U.S. residents.

2. Method

2.1. Study area

The study area for this research was the continental U.S., including 3109 counties. The average population size across counties varied substantially. Loving County, TX had the fewest (86) and Los Angeles County, California, had the most residents (9,818,605). On average, counties included 98,641 people. County boundary data for the 2010 Census were downloaded from the Census Bureau website and converted into a Queen neighborhood weighted matrix for cluster mapping and spatial effect estimation. Eight counties were defined as neighbors given that they shared a common boundary. There were no substantive changes in county boundaries performed for this research to uncover the relationship between spatial patterns of physical activity and its associated factors.

2.2. Data and data sources

2.2.1. Dependent variable

Multiple secondary data sources were used for this investigation (Table 1). The primary source of data was the Behavioral Risk Factor Surveillance System (BRFSS), which was coordinated by the Center for Disease Control and Prevention (CDC). The BRFSS is “the largest telephone health survey in the world” with more than 500,000 adults surveyed each year (CDC, 2015; Sharma & Petosa, 2012, p.15). This dataset was selected because it provided county-level data on risk behaviors related to personal activities and preventive health care practices. The response variable used for this research was a county-level indicator of the prevalence of physical activity. The BRFSS developed this age-adjusted indicator of the percentage of individuals older than 20 who were physically inactive (CDC, 2011).

The BRFSS includes data drawn from two samples, the first of which is drawn from landline telephone respondents. Because landline telephones are often shared among people in one residence, household sampling is used whereby interviewers collect information on the number of adults living within a residence and then randomly select a respondent from all eligible adults. The second sample is comprised of cellular telephone respondents that are weighted as single adult households. Disproportionate stratified sampling is used whereby telephone numbers are drawn from two strata (i.e., lists) based on the presumed density of known telephone household numbers. The cellular telephone sample is randomly generated from a sampling frame of confirmed cellular area code and prefix combinations, and respondents are randomly selected with everyone having an equal probability of selection. Most U.S. states complete approximately 20% of their completed interviews with respondents using cell phones. As such, the CDC provides a separate cellular telephone sample for each state according to the total number of target completions for a given year. According to BRFSS (2011), there were 506,467 records for the combined landline and cell phone data set. The response rates for the landline and cell phone surveys are 53.0% and 27.9%, respectively. Detailed information about the BRFSS including sampling design, questionnaires, and survey datasets can be found on CDC web portal (http://www.cdc.gov/brfss/annual_data/annual_data.htm).

Physical activity is a central variable in the BRFSS assessment. The Physical Activity Rotating Core (PARC), as an integral part of the BRFSS since 1984, monitors the percentage of the U.S. adult population meeting physical activity guidelines (CDC, 2011). These guidelines emphasize “the importance of avoiding physical inactivity, because even low amounts of physical activity reduce the risk of premature mortality and the most dramatic difference in mortality risk is found between those who are

Table 1
Dependent and independent variable names, descriptions of data, and sources.

Name	Data description	Source
Dependent Variable		
Physical Inactivity	County level age-adjusted prevalence of physical inactivity	Behavioral Risk Factor Surveillance System, 2011
Independent Variables		
Situational Factors (Macro level)		
Recreation and Fitness Facilities	Recreation & fitness facilities/1000 population	U.S. Census Bureau's County Business Patterns (CBP), 2012
Rural-Urban Continuum Codes	Degree of urbanization	USDA ERS, 2013
Natural Amenities	Natural Amenity Scale	USDA ERS, 2003
Built Amenities	Entertainment/recreation employees	NAICS Code 71, 2014
Socioeconomic Factors (Micro level)		
House Income	Median house income	American Community Survey, 2006–2010
Poverty Rate	Percentage of individuals living in poverty	U.S. Department of Health & Human service, 2009
Occupation	Unemployment rate	American Community Survey, 2006–2010
Expenditures for Recreation Activities	Amount spent on recreation equipment in the past 12 months: $250 +	Consumer Spending, ESRI, 2013
Gender	Percentage of female population	American Community Survey, 2006–2010
Educational attainment	Percentage of individual who obtained bachelor's degree or higher	American Community Survey, 2006–2010
Age	Percentage of young adult population (age 18–29)	American Community Survey, 2006–2010
	Percentage of senior population(age 65 or over)	

physically inactive and those with low levels of activity" (An, Xiang, Yang, & Yan, 2016, p.3). In the BRFSS 2001–2015 surveys used for this research, the operative question asked, "During the past month, other than your regular job, did you participate in any physical activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise?" Thus, self-reported leisure-time physical inactivity was ascertained from response of "no" to this question (An et al., 2016).

2.2.2. Independent variables

A number of situational factors were used for analysis. Natural amenity data were used to measure the effect of the physical environment on inactivity prevalence. These data and rural-urban continuum codes were obtained from the U.S. Department of Agriculture Economic Research Service (USDA ERS) for all counties in the lower 48 states. The natural amenity data consisted of measures of public preferences for conditions encountered in the physical world (USDA ERS, 2016). A county with a natural amenity score above three had high access to natural landscapes, whereas a county with a score lower than three had low access to natural resources. Rural-urban continuum codes were identified by non-metro and metro counties. Metro counties were classified by their population and the degree of adjacency to a metropolitan area (USDA, 2004).

A constructed amenity scale representing cultural and recreational built environments was created by drawing on the percentage of Art, Entertainment, and Recreation Employees data from the North American Industry Classification System (NAICS). One of the key variables, NAICS 71, reflected access to the arts, entertainment and recreational sector based on "live performances, events, and exhibits, as well as places of historic, cultural and educational interest" (U.S. Census Bureau, 2015; Liu, Debbage, & Blackburn, 2006, p. 333). This variable was selected because it has been instrumental in indicating access to the market size of leisure, recreation, and tourism industries (Baade & Matheson, 2004; Humphreys & Ruseski, 2009; Schumann, 2013). Data related to the density of recreation and fitness facilities at the county-level were also used in this research and obtained from the U.S. Census Bureau's County Business Patterns (CBP). This dataset showed the proportion of recreation and fitness facilities such as sports and recreation centers available to segments of 1000 residents in the population (Census, 2015).

In addition to measuring features in the physical environment, socio-economic and demographic data were deemed crucial for informing the planning and management of landscapes that encourage human movement. For this, county-level geocoded poverty rate, median income, younger population (18–29 aged), proportion of female population, educational attainment (bachelor degree or higher), senior population (65 aged or over) were employed. Additionally, an experience-based recreation management model was used to estimate why people took part in activities to benefit their health. This model suggested motivation was a function of two assumptions: (1) effort (e.g., purchasing equipment and licenses, driving to the site) will lead to participation; and (2) participation will lead to psychological benefits (Manfredo, Driver, & Brown, 1983). In this sense, people who intended to purchase equipment were thought to have higher rates of participation in physical activities (Lee & Schuett, 2014). As such, expenditure data for recreation activities were obtained from ESRI's consumer spending database (ESRI, 2014), along with Census data to calculate unemployment rates and median family and household income at the county level.

2.3. Analysis procedures and description

2.3.1. Spatial cluster analysis

Spatial cluster analysis was performed to detect the spatial patterns associated with physical inactivity prevalence. Specifically, Moran's I was used to identify the type of cluster pattern that existed across all counties in the contiguous U.S. This indicator was selected because it is a well-established indicator of spatial autocorrelation (Utomo, 2013) and has been used extensively in previous research (Bhattarai, Vetaas, & Grytnes, 2004). The Moran's I value ranged from -1 (meaning robust negative correlation) to 1 (indicating robust positive correlation) and a zero value indicated a random pattern. To analyze these data, a spatial cluster analysis was performed to determine whether physical inactivity patterns were spatially dependent. We tested both Rook and Queen contiguity to define the neighbor relationships. "Queen type and Rook type are two different contiguity definitions coming from the game of chess" (Ibeas, Cordera, dell'Olio, Coppola, & Dominguez, 2012, p.378). We selected Queen contiguity because counties showed spatial interactions within the vertex and edge areas. Next, an aspatial regression modeling technique was used to test the effects of 12 explanatory variables (i.e., socio-economic and physical factors described above) on physical inactivity. Building on previous research (Lachowycz & Jones, 2013), several possible combinations of independent variables were tested to obtain a reliable model and determine the associations between physical inactivity prevalence and related variables using exploratory regression (see Table 1). Several geospatial statistical packages were used, including Geoda 1.6.6 for spatial cluster analysis and Arcmap 10.3 to conduct the GWR analysis and test for locational differences of the association between physical inactivity prevalence and related variables in the U.S.

2.3.2. Ordinary least squares regression

In the OLS regression procedure, an aspatial correlation was estimated for all explanatory variables. Poverty rate, unemployment rate and median incomes were used to measure socio-economic condition. However, median house income (VIF: 11.254) and unemployment rate (VIF: 10.295) were highly correlated and therefore excluded from the final model. Tests for multicollinearity were estimated for all other spatial data. Results from an exploratory regression showed the percentage of urban population and density of population were non-significant predictors of the prevalence of physical inactivity at a 95% confidence level. Furthermore, it was important to consider local multicollinearity (i.e., redundancy among model explanatory variables) before running the spatial regression model. Rural-urban continuum codes, percentage of female population, and percentage of senior population (age 65 or over) were excluded from the variable selection for the final regression model.

2.3.3. Global/local moran's I statistic of physical inactivity

The most commonly used indicator of spatial autocorrelation and degree of spatial dependency was the Moran's I statistics (Lee & Schuett, 2014). The two different levels of Moran's I statistics are considered global measures of spatial autocorrelation that indicate spatial autocorrelation but do not identify the location and type of spatial clusters (Anselin, 1994). The local indicator of spatial autocorrelation (LISA) has been used to identify the location and type of spatial clusters and can be presented as a scatterplot. Generally, the results from both the scatterplot and the significance map are classified into four groups: 1) high–high (HH); 2) high-low (HL); 3) low-high (LH); and 4) low–low (LL). Interpretation of Moran's I Quadrant 1 (HH) and Quadrant 3 (LL) refer to positive spatial autocorrelation while quadrants HL and LH denote negative spatial autocorrelation. Thus, the associations between each county and its neighbors can be detected through Moran's I scatterplots. Quadrant I (HH) shows which regions have variable values and averages of the neighboring variables above the mean (called a "hotspot"). Quadrant II (LH) shows the regions that have variable values below the mean and averages of neighboring values above the mean. Quadrant III (LL) shows the regions that have both variable values and averages of neighboring values below the mean (called a "coldspot"). Quadrant IV (HL) shows the regions that have variable values above the mean and average neighboring values below the mean. Thus, the Moran's I scatterplot shows the relationship between a variable and the average value of its neighbor.

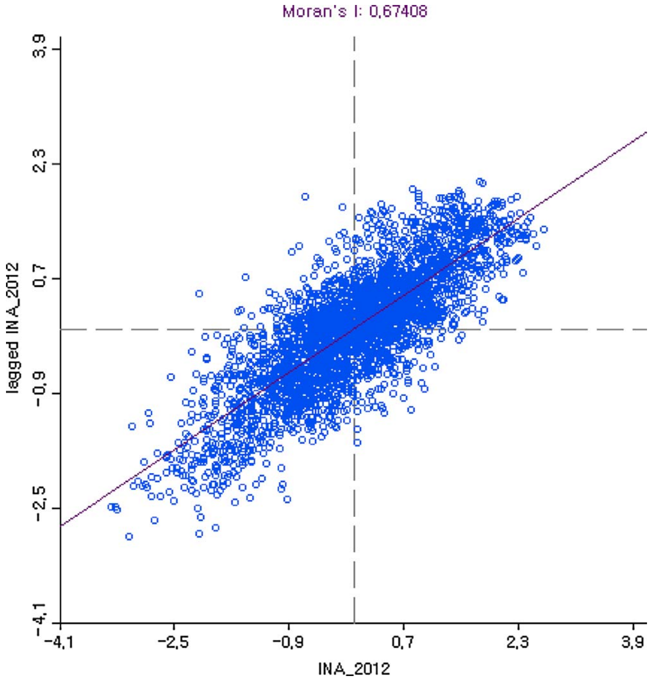

Fig. 1. Moran's I Index.

3. Research results

Results from this research confirmed that the prevalence of physical inactivity in the U.S. was spatially clustered and there was a positive spatial autocorrelation according to the global Moran's I test (I value = 0.674, p-value = 0.00135) (see Fig. 1). The visualization of the local Moran's I test specified where specific cluster patterns emerged (see Fig. 2). Further, results indicated that 590 counties located in Arkansas, Mississippi, Oklahoma, and Tennessee, as well as portions of other states could be considered "hotspots," meaning that one particular county and its adjacent areas showed a higher level of physical inactivity prevalence than the mean values across the country. Conversely, 571 counties located in California, Arizona, Colorado, Oregon, Washington, and Idaho showed lower levels of cluster patterns, indicating that one particular county and its adjacent areas showed a lower level of physical inactivity prevalence than the mean values across the country. The next stage of analysis tested which micro and macro-level variables directly and indirectly influenced these locational variations using aspatial (OLS) and spatial regression models (GWR).

3.1. Variable selection and analysis to determine factors that contribute to inactivity

In response to the first study objective to identify the factors that contributed to levels of physical inactivity, we examined and selected the following independent variables using an exploratory regression: 1) natural amenities; 2) constructed amenities; 3) recreation-related spending; 4) poverty rate, 5) density of recreation and fitness facilities, 6) educational attainment, and 7) proportion of young adults. Analysis of the generalized form for the final OLS model indicated that a high density of recreation and fitness facilities, expenditures on recreation activity, natural amenities, built amenities, education attainment, and proportion of young adults in the population negatively influenced the

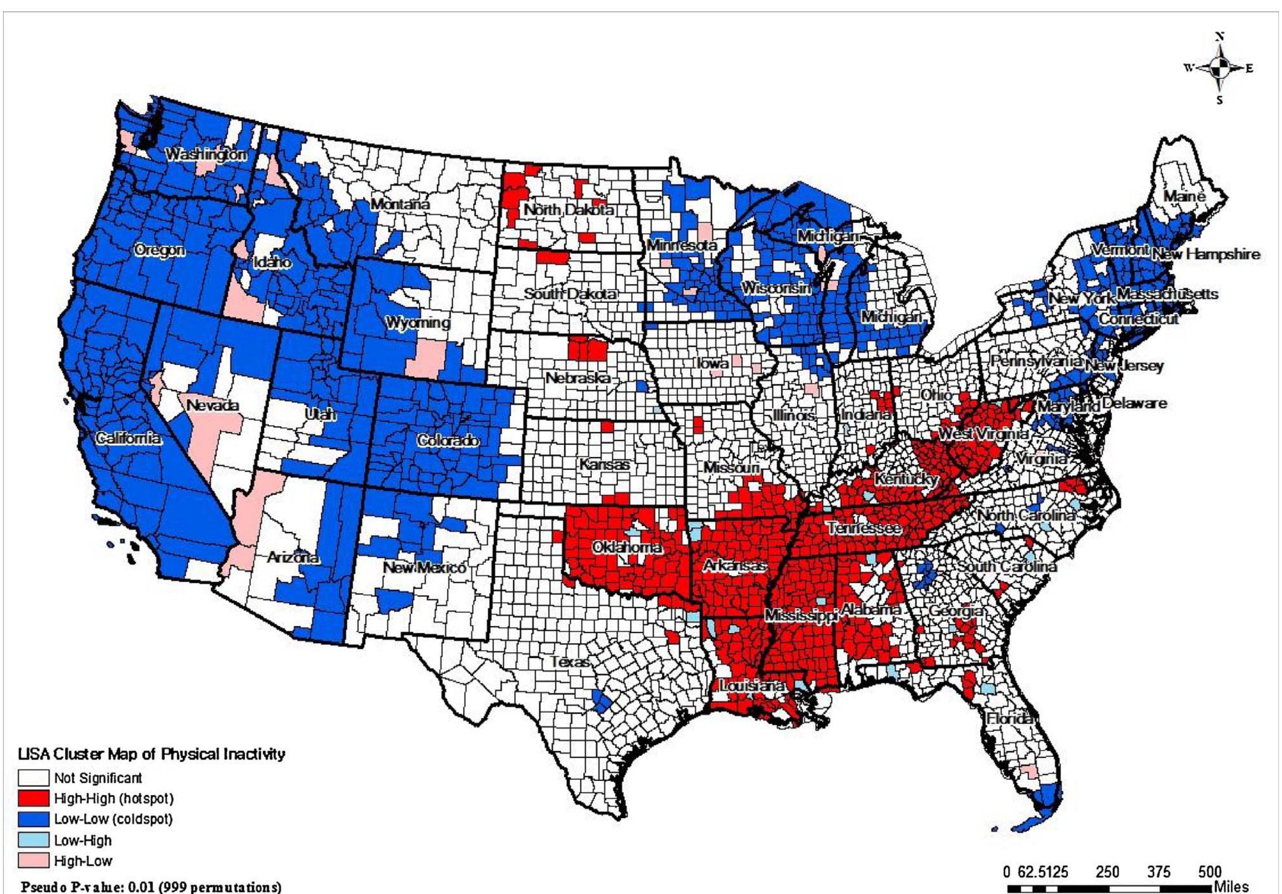

Fig. 2. Local Moran's I cluster map of the physical inactivity prevalence.

Table 2
Ordinary least squares regression results.

Variable	Coefficient	SE	t-value	Robust SE	Robust t-value	VIF
Intercept	33.26	0.40	84.15*	0.411	80.98*	
Expenditure for recreation activities	−1.28*	0.10	−12.74*	0.106	−12.12*	1.49
Density of recreation and fitness facility	−2.80*	0.71	−3.94*	0.000	0.78*	2.51
Poverty rate	0.30*	0.01	20.93*	0.019	16.05*	1.76
Natural amenities	−0.54*	0.03	−17.43*	0.033	−16.45*	1.16
Constructed amenities	−0.00*	0.00	−7.57*	0.115	−3.09*	1.31
Educational attainment	−0.19*	0.01	−15.59*	0.013	−14.31*	2.50
Age (18 − 29)	−0.15*	0.02	−8.25*	0.0179	−8.17*	1.43

Note. Prob (> chi-squared), (2) degrees of freedom: 0.001*.
Jarque-Bera Statistic**: 11.45.
Koenker (BP) Statistic*: 99.28.

prevalence of physical inactivity, while higher poverty rates positively affected the prevalence of physical inactivity (See Table 2).

We examined the OLS residuals using spatial cluster analysis. Given the z-score of 31.46, there was less than a 1% likelihood that this clustered pattern could be the result of random chance (I = 0.179, p value = 0.000). Therefore, our results demonstrated that an OLS model could provide a biased prediction. Also, the results from a Breusch–Pagan test (99.28, p < 0.01) indicated that this study's regression models had statistically significant non-stationarity meaning that spatial regression should be employed to reflect more accurate associations (Fotherinham et al., 2002).

3.1.1. Spatial regression (GWR) analysis

Spatial regression GWR analysis was used as a local spatial statistical technique to detect spatial heterogeneity (i.e., spatial non-stationarity in spatial data). The GWR assumed that relationships between variables may have differed from location to location, and generated a separate local regression coefficient for each county in the study area. Each local regression coefficient was calibrated using a different weighting of observations (Fotheringham, Brunsdon, & Charlton, 2002).

GWR extended the traditional multiple linear regression model by allowing local parameters to be estimated as follows:

$$y_i = \beta_{i0} + \beta_{i1} \times {}_{1i} + \beta_{i2} \times {}_{2i} + \ldots\ldots + \beta_{in} x_{ni} + \varepsilon_i$$

β_{i0} was the intercept, and β_n measured the association between the explanatory variables and the set of i county's age-adjusted physical inactivity. εi was the error related to county i. Local coefficients (β_i) varied according to location ($_i$) instead of one global coefficient for each variable. The GWR model exposed statistically local variations that were masked by one global estimation such as OLS model. The GWR equation can be written as follows:

$$\begin{aligned}\%PhysicalInactivity_i = \beta_{0i} + \sum_1 \beta_{1i} Naturalamenity_i + \sum_2 \beta_{2i} Poverty_i \\ + \sum_3 \beta_{3i} Constructedamenity_i \\ + \sum_4 \beta_{4i} Expenditureforrecreationactivities_i \\ + \sum_5 \beta_{5i} Densityofrecreationandfitnessfacility_i \\ + \sum_6 \beta_{6i} Educationattainment_i + \sum_7 \beta_{7i} Age18 \\ - 29population_i + e_i\end{aligned}$$

The adaptive kernel function was employed to select the appropriate bandwidth of local relationships. It was deemed appropriate when distribution varied across a spatial scale (i.e., geospatial units were heterogeneous and/or events were clustered). Adaptive kernel width was determined through the minimization of the Akaike Information Criterion (AIC).

3.1.2. Condition number and local coefficient estimates

A condition number was referenced to evaluate local collinearity (Hu, 2009). Results from the GWR showed that the study area had a condition number less than 30 (from 16.253 to 29.992). Given that the condition numbers were not larger than 30, results were considered reliable and local multicollinearity was not a problem.

The strength and direction of the relationships were indicated by the local regression coefficients. In GWR, instead of one single coefficient being generated for each variable, coefficients were able to vary according to each location. This spatial difference in coefficients revealed interesting patterns which otherwise would have been concealed. Thus, the visualization of locally calibrated coefficients discovered the impact of various factors across the entire U.S. Given that the local coefficients varied in space, non-stationarity was identified (See Fig. 3a).

3.2. Predictors of physical activity

The second study objective examined how five factors affected spatial differences in physical activity. This range of variables included the natural and built amenity scales, poverty rate, density of recreation and fitness facilities, and expenditures for recreation activities. First, as illustrated in Fig. 3c, the global natural amenity scale was a significant predictor of physical inactivity (global coefficient: −0.535; See Table 2) and both positive and negative associations were found as indicated by the GWR. Specifically, the local coefficient raged from −0.229 to 0.4187. Negative values were found in New Mexico, Louisiana, Arizona, and Texas whereas positive values were predominantly located in Missouri, Iowa, eastern part of Kansas, and Minnesota. Furthermore, the central part of the country showed a spatial pattern of increasing coefficient values from the north to the south. The findings may be due to an underlying relationship between these factors and location and access to public land. The distribution of negative values coincided with abundant federal and municipal public lands (e.g., national parks, forests, preserves, refuges), whereas areas with positive values represented rural landscapes with fewer natural amenities, or smaller distributions of natural landscapes relative to population densities. Overall, this parameter showed reasonable distributions at a significance level of 5%.

Second, a significant positive relationship was found in the relationship between physical inactivity prevalence and poverty rate (global coefficient: 0.298). This result indicated that poor economic situations positively affected the prevalence of physical inactivity across the country. As shown in Fig. 3d, the local coefficient for poverty rate ranged from 0.001 to 0.3601. The variability in local coefficients demonstrated that the relationships were not stationary at the county level. In other words, counties in the eastern region of the U.S. showed higher levels of local coefficients for poverty, especially hotspots. These findings demonstrated that social and economic conditions of the community were significantly related to residents' lifestyle. That is, "because of low incomes, minorities are seen as having constraints on

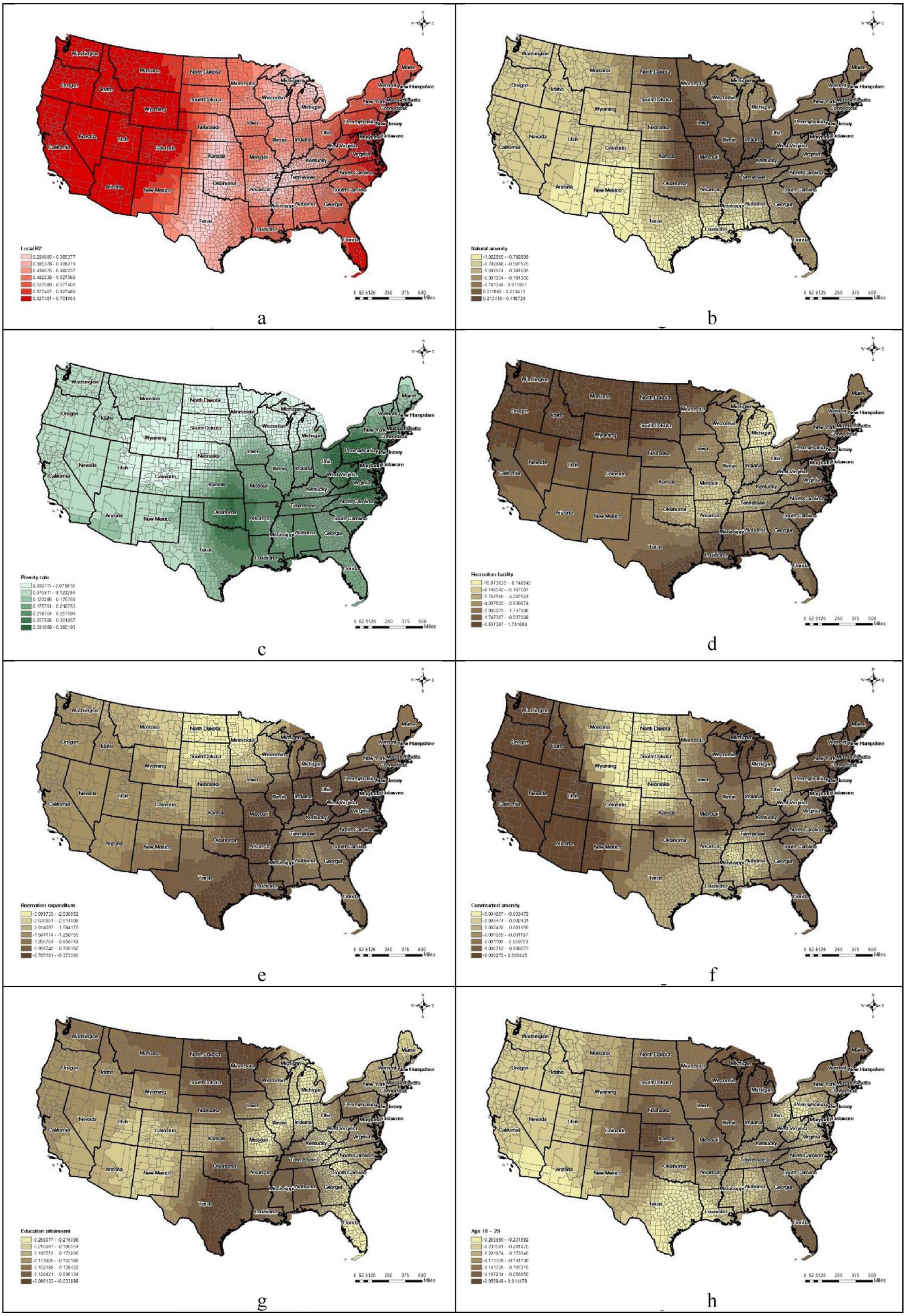

Fig. 3. Mapping the results of the GWR model (Spatial variations in the relationship).

their availability to afford the cost of participation, or of transportation to recreation sites" (West, 1989, p.11).

Third, the global estimate of the density of recreation and fitness facilities and all spatial estimates were negative (global coefficient: −2.797). The local coefficient ranged from −10.873 to 1.752, and the variation of these coefficients demonstrated that the relationship between physical inactivity prevalence and density of recreation and fitness facilities was nonstationary. Dark green colored counties where

Table 3
Comparison between ordinary least squares and geographically weighted regression results.

	OLS	GWR			
		Mean	Minimum	Maximum	SD
Intercept	33.265*	32.539	27.066	38.932	2.502
Expenditure for recreation activity	−1.283*	−1.109	−3.099	−0.373	0.580
Density of recreation and fitness facility	−2.797*	−2.616	−10.873	1.752	2.221
Poverty rate	0.298*	0.189	0.0001	0.3601	0.084
Natural Amenity	−0.535*	−0.229	−1.023	0.4187	0.3736
Constructed amenity	−0.001*	−0.001	−0.005	0.0004	0.00104
Educational attainment (bachelor degree or higher)	−0.186*	−0.161	−0.258	−0.034	0.0437
Young adult (age 18–29)	−0.146*	−0.156	−0.264	0.0145	0.0563
Local R^2		0.513	0.285	0.702	0.0942
R^2	0.549	0.727			
Adjusted R^2	0.548	0.718			
AIC	16858.483	15435.23			
Moran's I of Standard residual	0.431	0.179			
Koenker Statistics	99.289*	Neighbors: 816			
Jarque-Bera Statistics	11.457*	Bandwidth methods: AICc Kennel type: Adaptive			

* $p < 0.001$.

there was an increased density of recreation and fitness facilities, predicted lower physical inactivity prevalence. The urbanized coldspot areas of physical inactivity were heavily influenced by the density of recreation facilities, especially given that this pattern emerged in states such as Michigan, Missouri and Arkansas (See Fig. 3e).

Fourth, negative associations were found for expenditures for recreation activities greater than $250 and physical inactivity as indicated by the GWR. The estimated value for the global model was −2.321. The visualization of local coefficients indicated the influence of this variable in the model varied significantly across states, with a strong prevalence in the north central part of the country. The local coefficient for expenditures ranged from −0.373-3.099 in southern states such as Texas, Louisiana, Mississippi, and Arkansas to −3.099 in northern states such as North Dakota, South Dakota, and Minnesota (See Fig. 3f). Among the people who consumed $250 or more for recreation activities in the past 12 months, residents in the northern U.S. were more likely to show intensive spatial patterns of physical inactivity than residents in the southern U.S. Hotspot areas of physical inactivity were not influenced as much by recreation spending than other regions.

Fifth, the global estimate of cultural and recreational amenities was negative, as were all other spatial estimates (global coefficient: −0.001). The weakest relationship was found for cultural and recreational amenities. The local coefficient ranged from −0.0002 to 0.004 and the mean value was −0.001. Fig. 3g illustrates that coefficient values below −0.001 were located in the southern states such as Mississippi, Alabama, and Arkansas as well as central states such as Wyoming, Colorado, Nebraska, Montana, South Dakota, and North Dakota. Coefficients larger than the mean were concentrated in western states such as California, Nevada and Utah.

Sixth, the global estimate of educational attainment (percentage of individuals who obtain a bachelor's degree or higher) was negatively associated with physical inactivity (global coefficient: −0.186). The local coefficient ranged from −0.034 in the central states such as North Dakota, South Dakota, Minnesota, and Texas, to −0.264 in the western and eastern states such as Utah, Arizona, Florida, and South Carolina. The mean value was −0.161 (See Fig. 3h). Although there were difference in the strength of the relationships across counties, all counties showed negative associations with physical inactivity. These results align with previous research suggesting people with high levels of education are more likely to participate in physical activity (Trost et al., 2002).

Finally, negative associations were found for percentage of young adult population (age 18–29) and physical inactivity. The estimated value for the global model was −0.146. The visualization of the local coefficients discovered that the influence of this variable in the model varied significantly across states, with a strong prevalence in the south western part of the country. The local coefficient for expenditures ranged from −0.0145 in the north central part of country such as Michigan, Wisconsin, Colorado, and Kansas to −0.264 in the south western states such as Texas, Arizona, Utah, and California (See Fig. 3a). This result supported previous research findings that suggests people become less active over time (Mazzeo et al., 1998; Cushman, Gidlow, & Hopkins, 2014). Furthermore, GWR identified geographical variation based on local coefficients.

3.3. Comparison of modeling results

In response to the third study objective, the R^2, adjusted R^2, and AIC values were used to assess model performance. If the difference between the two AIC values was more than three, the model with the lower AIC was considered better (Fotheringham et al., 2002). The value of the Koenker (BP) statistic also was employed to assess model stationarity. The GWR model performed better in exploring the relationships between the prevalence of physical inactivity and explanatory variables than the OLS model. We found the AIC value decreased in the GWR model, in that the OLS model included an AIC value of 16858.483 and in the GWR model, the AIC value converged at 15435.23. The reduction in the AIC from the OLS model indicated that the GWR model performed better (Fotheringham et al., 2002).

The explanatory power of the OLS model for explaining the relationship between physical inactivity prevalence and its associated factors determined by variable selection procedures remained comparatively good ($R^2 = 0.549$). This value increased when the GWR was applied ($R^2 = 0.727$; See Table 3). More than 21% of U.S. counties showed a higher R^2 than with the OLS.

The local R^2 varied over the study area with a minimum of 28.5% to a maximum of 70.2% of variability. Light white colored counties in Tennessee, Texas, Oklahoma, Kansas, and Wisconsin indicated that the model predicted physical inactivity prevalence poorly in those regions. However, the GWR explained more than 40% of the variability in the U.S. Results thus demonstrated that the OLS could not clarify non-stationary association across all U.S counties. Furthermore, the OLS model could not effectively control spatial dependence of regression residuals and spatial autocorrelation in the dataset from the methodological perspective.

The GWR identified spatially varying relationships by identifying a local model for each county in the study area, while the OLS had less success detecting local variations. In this sense, GWR was a more suitable spatial modeling technique compared to OLS for predictive mapping of physical inactivity prevalence in the U.S.

4. Discussion of research results

This study advanced understanding of the relationships between physical inactivity and both socio-economic and physical conditions at the county level to provide insight into the factors driving the public health crisis in the U.S. Drawing on the tenets of opportunity theory (Hendee, 1969) to address the causes and consequences of social and environmental justice, this research showed that the provision of resources available to mitigate physical inactivity across a national spatial scale depended on a complex array of conditions. Specifically, a range of amenities was related to the spatial distribution of physical inactivity modeled using multivariate regression analysis. Findings from this research revealed the prevalence of physical inactivity in the U.S. was regionally clustered and the density of infrastructure and investments in this infrastructure had strong relationships to physical inactivity distribution patterns. Also, indicators of cultural and recreational amenities provided helpful insights into the importance of context (Liechty et al., 2017) and capacity of places for encouraging physical activity of local residents (Michimi, Ellis-Griffith, Nagy, & Peterson, 2013).

To address several methodological limitations highlighted in past research, this study identified clustered areas of infrastructure through a local spatial cluster analysis (See Fig. 3h). Given the diversity and prevalence of hotspots of physical inactivity, as well as the uneven distribution of recreation and fitness facilities, this study identified locations that warrant policy attention and may harbor injustice. This information will enable planners and managers to make spatially-explicit decisions about the provision of opportunities for physical activity to improve quality of life and human well-being in an equitable manner. Moreover, this research moved beyond aspatial regression techniques (e.g., OLS model) and individual-level data for predicting health-related issues (Edwards et al., 2011) to account for diverse associations that existed at the county level in the U.S. More specifically, given the directions and strength of relationships across the study area (Lee & Schuett, 2014; Shi, Zhang, You, Shan, & Zhang, 2006), this study showcased GWR as a promising tool to refine understanding of the spatial relationships associated with physical activity and its explanatory variables (Gao & Li, 2011).

The GWR tools used in this research offer multiple benefits for regional level planning and management. For example, this study's use of GWR identified particular locations that would be amenable to promoting physical activity and considering the use of different strategies in these areas. This information will allow decision-makers to tailor policies to particular communities that may be unnecessarily consuming financial resources, more amenable to interventions, or those at a deficit for relevant resources. However, even though GWR can be used to generate useful information, it is not without limitations. For example, this study used the bi-square kernel function (i.e., kernel with adaptive bandwidth), because it allowed for use of variable bandwidth (Fotheringham et al., 2002). The bi-square kernel function was used when the observed data points were not regularly spaced but clustered in the study area. The size of the bandwidth increased when the observed data points were widely spaced and decreased when the observed data points were clustered. Because of this inconsistency, observed data at the county level were estimated based on proximate counties as defined by the kernel type. Also, counties located on the edges of the continental U.S. (e.g., coastal regions) did not have the 360° influence of those counties in the nation's interior (Hipp & Chalise, 2014).

5. Implications for planning and management

Several management implications from this research should be considered to more effectively integrate policies across government agencies, non-profit organizations, and commercial enterprises focused on landscape and urban planning. First, this study provided information about the extent to which residents had access to safe, high-quality resources that mitigate public health disparities at the community level. Multiple decision-making authorities such as public health organizations can ensure a more equitable distribution of benefits for communities where there is a dearth of resources and/or limited access to health facilities. Agencies can use this information to question whether the provision of opportunities and resources are congruent with their goals and objectives (Ussery et al., 2016). Moreover, the precision and depth of analysis performed for this research can be referenced to gain a detailed perspective − on a county-by-county basis − of where pertinent issues exist and/or are emerging across an entire country. In this sense, results will help to identify places where physical activity levels can be raised to ensure an array of people in the U.S. live healthier and more fulfilling lives (Kaczynski & Henderson, 2007).

Results presented in this study provided spatially relevant information about areas across the U.S. that require immediate attention. For example, physical activity was negatively affected by poverty status in the U.S, indicating that economic growth and development would likely spur physical activity, and in turn, help to combat public health challenges such as obesity. In line with past research (e.g., Jilcott et al., 2013) natural amenities may address some of these problems in places like rural communities; however, locations with high amenities were not always positively associated with physical activity. The variable and sometimes opposing relationships that emerged across different counties within the same region can be accounted for in future research using GWR analysis. The more refined statistical technique can use important factors such as amenities for understanding the spatial disparities of physical inactivity, while not discounting other possible explanations that may be working in concert to explain clustering in specific locations. Future research may consider using techniques such as participatory GIS to provide additional insights on physical activity at a local level of analysis (De Valck et al., 2016; van Riper & Kyle, 2014). While our study results provide a realistic interpretation of spatial distributions, additional variables or data sources could result in different conclusions. Future research should test these relationships with variables that focus on other types of pertinent information, (e.g., average medical expenditures at the county-level, recreation facility type) that may have regional significance. Engaging individuals throughout the planning process would yield helpful place-based knowledge that could be coupled with regional and national-level information to determine how best to combat physical inactivity across spatial scales. Moreover, exploratory analysis including assessments of population loss may be employed to take into consideration the impacts of local economies (Michimi & Berentsen, 2008). Population loss in urban areas is particularly problematic because it affects a city's fiscal situation, and hence the delivery of recreation service. (Joassart-Marcelli, 2010). This and other relevant information could be used as a roadmap to enhance understanding of social and environmental justice, specifically the role of access to infrastructure, availability of recreation resources and amenities that can alleviate public health problems.

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