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Spatial is Special: The Need to Consider Spatial Effects in Leisure Research

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Abstract

Though one of the most commonly employed analysis techniques in the leisure literature, multiple regression and in particular the ordinary least squares (OLS) approach are subject to a number of critical assumptions, violation of which threaten the efficiency and validity of OLS findings. This paper demonstrates the utility of an alternative approach, geographically weighted regression (GWR), a local form of linear regression that can be used to model spatially varying relationships and that accounts for the spatial effects of heterogeneity (non-stationarity) and dependence (autocorrelation) in data. The small number of leisure studies that have employed GWR is reviewed, with a focus on the relative performance of the two approaches; GWR is shown to be superior to OLS in every case that the appropriate comparison was conducted. Other areas to which GWR could usefully be applied are suggested, and limitations of GWR are acknowledged.

Key Words

geographically weighted regression, ordinary least squares, spatial effects

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Spatial is Special: The Need to Consider Spatial Effects in Leisure Research

Introduction

Multiple regression is one of the most commonly employed analysis techniques in the leisure literature, offering a powerful method via which to estimate the relationships among variables and to engage in prediction and forecasting. Of the many varieties of multiple regression, the ordinary least squares (OLS) approach is perhaps the most well-known and frequently utilized (Babbie, 1998; Pohlman & Leitner, 2003; Nusair & Hua, 2010). The use of OLS comes with a number of assumptions, however. Of most relevance here, these include that: (i) the data represent a random sample of the population and that the residuals (the differences between observed and predicted values) are statistically independent; (ii) the independent variables are not subject to multicollinearity; and (iii) the expected value of the residuals is always zero and the residuals have constant (homogenous) variance (e.g., Allen, 1997; Sen & Srivastava, 2012; Cohen, Cohen, West, & Aiken, 2013).

In reality, however, in any application of OLS in a spatial context, in which the unit of analysis represents a point or area on the surface of the earth and the independent variables relate to any socioeconomic, demographic or environmental aspect of people or places, these assumptions are likely to be violated (Brunsdon, Fotheringham, & Charlton, 1996). As noted by Longley, Goodchild, Maguire and Rhind, "spatial is special" (2005, p. 5). The two major types of spatial effect are spatial heterogeneity (which is associated with spatial non-stationarity) and spatial dependence (also known as spatial autocorrelation). A variety of social scientists including geographers, economists, criminologists, and environmental planners have all begun to acknowledge the implications of Gilbert and Chakraborty's (2011) observation that, "the analysis of spatial data requires specialized techniques that are different from those used to analyze non-spatial data" (p. 274). This paper similarly demonstrates the utility of an alternative research method that accounts for the spatial effects of spatial heterogeneity and spatial dependence in the leisure realm.

Spatial heterogeneity refers to the uneven distribution of an entity or relationship across a region (Longley et al., 2005). Such a lack of spatial uniformity may result from the lack of homogeneity between spatial units within a study area, or from structural instability in the behavior of a variable across space (Anselin & Getis, 1992). Heterogeneity between spatial units can cause misspecification or measurement errors which result in non-constant error variance (spatial heteroscedasticity in the error term) as well as inefficient estimation of coefficients and invalid t- and F-tests (Anselin, 1988; Porojan, 2001).

Structural instability represents an additional and similarly substantial problem. The global (average) parameter estimates produced by traditional multiple regression techniques assume that the influence of any independent variable is constant across space, meaning that the same average parameter estimate is applied to all observations within the sample (Gilbert & Charkraborty, 2011). This assumption of spatial stationarity is flawed both methodologically, due to the possibility of estimation bias and error, and with respect to interpretation and implications of results, since it suggests that "one-size-fits-all" with respect to planning or management decisions and policy solutions (Fotheringham, Brunsdon, & Charlton, 2002). According to Anselin (1988), methodological violations of basic OLS assumptions (including homoscedasticity, linearity, and independence and normality of residuals) are likely to occur if geographic features are spatially autocorrelated or heterogenous when employing non-spatial (linear) statistical methods such as OLS regression. In the worst case scenario, it is possible that an insignificant coefficient on a variable in a global model can actually be masking the existence of statistically significant positive *and* negative coefficients in a spatially explicit specification (Brunsdon et al., 1996). As noted by Lee and Schuett (2014), "the use of traditional multivariate regression or a single global model can hide key local variations in the relationship between the dependent and explanatory variables" (p. 274).

Spatial dependence represents "the propensity for nearby locations to influence each other and to possess similar attributes" (Goodchild, 1992, p.33), a derivation of Tobler's First Law of Geography, which stated that "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970, p. 236). Application of OLS regression in the presence of spatially dependent observations results in spatially autocorrelated error terms, resulting in inefficient coefficient estimates, underestimation of the error sum of squares, invalid (inflated) t- and F-test statistics, and an increased chance of a Type I error (incorrect rejection of the null hypothesis) (Fotheringham et al., 2002). Estimation results may in addition demonstrate bias if this autocorrelation is due to the omission of one or more variables (Anselin, 1988). Spatial autocorrelation may be positive or negative; positive spatial autocorrelation occurs when similar values consistently occur near one another, resulting in spatial clusters, while negative spatial autocorrelation is demonstrated when dissimilar values consistently occupy adjacent locations (Getis & Ord, 1992). In practice, spatial heterogeneity and spatial dependence are interrelated and they often occur simultaneously (Anselin & Getis, 1992).

A variety of enduring questions within the leisure research arena are directly tied to space and place. Indeed, much leisure research is predicated on the unique and special characteristics of places, whether tourism destinations or recreation settings. However, the existence of spatial effects has rarely been acknowledged in this literature, and as this contribution will demonstrate their explicit consideration during analysis is even more uncommon. Lee and Schuett (2014), for example, observed the "lack of research in the recreation and parks field using spatial statistics to figure out spatial disparities in recreation" (p. 214). The purpose of this paper is therefore to demonstrate the utility of an approach that explicitly considers these spatial effects, via the employment of local statistics that are multi-valued. The use of such an approach entails the performance of as many regressions as there are data points (one regression per spatial unit), thereby allowing different values to result at different locations. Allowing for local variation enables the development of better fitting, spatially aware models that highlight rather than mask dissimilarities across the landscape, not only encouraging but actively supporting locally appropriate planning, policy and management decisions. The paper therefore serves as an appeal to leisure researchers to reconsider the traditional use of global OLS regression during the conduct of spatially explicit work.

The next section introduces this approach, known as geographically weighted regression. Then, the limited number of prior applications of this approach in leisure-related research is reviewed. It should be noted that other attempts have been made to develop techniques that can provide localized versions of traditional global multivariate modeling methods. These include: the spatial expansion method; spatially adaptive filtering; and, multilevel, random coefficient, and spatial regression modeling. However, as emphasized by Fotheringham et al. (2002), and as demonstrated in some of the studies reviewed below that have compared multiple techniques, GWR offers the most comprehensive approach via which to address the full range of spatial effects described above. For that reason, it was chosen as the focus of this piece.

Geographically Weighted Regression

Overview

Geographically weighted regression (GWR) is essentially a local form of linear regression that can be used to model spatially varying relationships. As first proposed by Brunsdon et al. in 1996, a GWR model can be expressed as

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

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 a_{ik} is the value of the k_{th} independent variable at point i (Fotheringham et al., 2002). The most critical element of GWR is that it allows the estimation of parameters at a local level (Fotheringham, Charlton, & Brunsdon, 1998). Each coefficient is thus specific to location i and variations between locations are facilitated.

Operationalization

GWR can be conducted in several geographic information system (GIS) and advanced statistical packages such as ArcGIS and GWR or via a programming language such as R (Fotheringham et al., 2002). Application of GWR requires two important specifications on the part of the analyst, that of the weighting matrix and the appropriate bandwidth (Charlton & Fotheringham, 2009b). These two issues are introduced in the following paragraphs; the reader is encouraged to consult the sources cited for a better understanding of how to make and operationalize these choices in practice.

The weighting matrix in GWR represents the spatial structure of the dataset based on Tobler's (1970) First Law. Data points are weighted by their proximity to the regression point, with those closer to that point weighted more heavily than those farther away. The maximum value of the weight of an observed data point occurs when it coincides with the regression point, and decreases as the distance between the two points increases (Fotheringham et al., 2002).

The choice of weighting matrix is between fixed kernel and adaptive kernel. A kernel refers to "a circle of influence or a circular area with a given radius around one particular regression point, and the given radius is called the bandwidth" (Yoo, 2012, p. 27). A fixed kernel (also referred to as the Gaussian kernel function) has a defined bandwidth and assumes that the bandwidth at each regression point is stationary across the study area. It is typically employed when the observed data points are regularly distributed in the study area, and the weighting matrix for the fixed kernel is estimated as follows:

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

where d_{ij} is the Euclidean distance between regression point i and data point j, and b is the bandwidth. A data point's weight is unity at the regression point; as distance from the regression point increases, weights decrease. The weights of all points, however, are non-zero even if they are far from the regression point (Charlton & Fotheringham, 2009b; Fotheringham et al., 2002).

The adaptive kernel is called a bi-square kernel function with adaptive bandwidth and is employed when the observed points are geographically concentrated in the study area (Fotheringham et al., 2002). Generally, the size of the bandwidth increases when the observed data points are widely distributed and decreases when they are clustered (Fotheringham et al., 1998). The weighting matrix for the adaptive kernel is estimated as follows:

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

The weight of the data point is unity at the regression point i and falls to zero if the distance between i and j equals or exceeds the bandwidth (Brunsdon et al., 1996).

Since bandwidth represents a smoothing parameter, choosing this width is a critical issue in GWR because results are sensitive to that choice (Fotheringham et al., 2002). Greater smoothing occurs when a larger bandwidth is employed (Charlton & Fotheringham, 2009b). Choice of the bandwidth is determined by a given distance or a fixed number of nearest neighbors (Brunsdon et al., 1998). Several methods exist to derive the optimal bandwidth, e.g., the one that optimizes the trade-off between goodness-of-fit and degrees of freedom (Fotheringham et al., 2002). These include approaches that involve minimization of the cross-validation (CV) or generalized cross-validation (GCV) criterion (Cleveland, 1979; Craven & Wahba, 1979; Bowman, 1984; Loader, 1999), minimization of the Bayesian Information Criterion (BIC, Weakliem, 1999, also sometimes referred to as the Schwartz Information Criterion or SIC, Schwartz, 1978) or selection of the model with the lowest Akaike Information Criterion (AIC) score (Akaike, 1973; Hurvich, Simonoff, & Tsai, 1998).

Outputs

Results of GWR are typically presented in tabular form (Yoo, 2012). Unlike OLS results, however, in which solely the global estimate for each variable can be listed, GWR tables include a series of columns showing some combination or all of the minimum and maximum, mean and median, and lower and upper quartile estimates (Gilbert & Charkraborty, 2011). A more powerful ability is to map GWR outputs, e.g., the parameter values or local R^2 for each location or unit of analysis, in a GIS program such as ArcGIS or GeoDa (Charlton & Fotheringham, 2009a). Such maps, which can be produced using points, areas (choropleth) or shaded contours, can provide compelling visual evidence of patterns in the data, allowing variations in parameters to be examined under a “spatial microscope” (Fotheringham et al., 2002). This integration of

GWR results with GIS capabilities thereby also enables the development of new hypotheses based on observed variations in the data (Charlton & Fotheringham, 2009a).

Measures of Performance

GWR performance can be assessed in a variety of manners. The most commonly employed measures include measures common to OLS techniques such as R^2, adjusted R^2 and residuals, as well as the Akaike information criterion and condition number (Charlton & Fotheringham, 2009b). The use of R^2 and/or adjusted R^2 in regression is likely familiar to all readers; in both cases, larger values (up to a maximum of one) indicate that an increasing proportion of the variance in the dependent variable is explained by the independent variables, suggesting a model with a better fit (Cohen et al., 2013). Local R^2, however, is specific to GWR. Values range from 0 to 1, with increasing values indicating that the local regression model better fit the observed values (Fotheringham et al., 2002). An added opportunity, as referenced above, is to map local R^2 values, to identify variations in predictive performance and perhaps gain ideas about variables that might be missing from the regression model (Gilbert & Charkraborty, 2011).

Residuals – the differences between observed and estimated values of the dependent variable – are another measure of performance (Wilcox, 1996). Comparison of standard residuals from OLS and GWR models is one way to assess whether the local regression model (GWR) represents an improvement on the traditional global regression model (OLS). Similarly, the sum of the squared residuals can be compared, with smaller sums indicating closer fit of the model to the observed data (Charlton & Fotheringham, 2009a, 2009b).

Calculation of the Akaike information criterion (AIC) provides another measure of the relative quality of a series of global (e.g., OLS) and local (e.g., GWR) statistical models (Akaike, 1973; Bozdogan, 1987). Models with smaller AIC values are preferable to models with higher values; however, if the difference in the AIC between two models is less than three, they are held to be equivalent in their explanatory power (Fotheringham et al., 2002).

The condition number provides a measure of the degree of local collinearity in the data. This diagnostic is calculated by taking the square root of the largest eigenvalue divided by the smallest eigenvalue (Charlton & Fotheringham, 2009b). In the presence of strong local collinearity, indicated by a condition number in excess of 30, GWR results become unstable; condition numbers below this cut-off indicate a lack of local multicollinearity and therefore that the GWR model performs adequately (Charlton & Fotheringham, 2009a).

Summary of Differences between Local and Global Statistics

To summarize, per Fotheringham et al. (2002), while global statistics such as the parameter estimates associated with OLS regression provide one value or estimate for an entire study area, local statistics such as those derived using GWR are multi-valued, meaning that different values can occur at different places. Thus, while global statistics suggest similarities across space, and are indicative of a search for regularity, local statistics emphasize differences across space and allow for exceptions ('hot-spots') to be highlighted. A variety of diagnostics exist to allow comparison between the relative fit of global and local models. Unlike global statistics, local statistics can be mapped in GIS, providing the powerful ability to identify variations in relationships across space and, thus, actively consider variable, locally appropriate planning, policy and management decisions.

Approach

The search conducted was extensive, incorporating English-language papers from both traditional leisure journals (including those focusing on parks, recreation, tourism and hospitality) and disciplinary venues in which leisure-related research sometimes occurs (e.g., geography, economics). Keywords “geographically weighted regression” or “GWR” were combined with “leisure,” “tourism,” “recreation,” “park,” and “public open space” in Scopus, CAB Abstracts and Google Scholar. Additional citations were sought in the reference sections of this preliminary selection of items. The authors then independently reviewed the articles and created the summaries below. As will be shown, very few applications of GWR appear in the leisure literature. In many of the examples from other fields, the leisure aspect was secondary to some other primary purpose. The inclusion of these items, and overview of their findings and implications, helps build the case for greater application of GWR in leisure research.

Applications to Date

The publications identified have been grouped into four categories, namely those pertaining to: recreation demand; park/recreation access, equity and physical activity; property and room price impacts; and, tourism growth and development. Table 1 summarizes the major characteristics of the studies. It also provides additional methodological notes to those in the text below and lists key performance measures that in every case demonstrate the superiority of GWR over OLS techniques.

Recreation Demand

Recreation demand is one of the most investigated topics within the recreation literature. According to Manning (2011, p. 23), measurement of recreation demand is “The first and most straight forward form of research into the social aspects of outdoor recreation …," though the complexity of some of the econometric techniques commonly applied in the current era belie a portion of this statement. Yet only one study has explicitly considered spatial location within a recreation demand analysis, of national park visitation in Texas (Lee & Schuett, 2014).

The authors employed a large suite of spatial tests and measures to illustrate their findings. First, spatial autocorrelation (clustering) in the dependent variable (the national park visitation ratio) was tested for at the global and local levels; both tests indicated significant clustering in the data. Next, a global OLS model was built using stepwise techniques. Moran's I and the Koenker (BP) statistics were calculated, both of which indicated strong spatial autocorrelation in the OLS residuals, a potential source of flawed statistical inference. Together, these findings demonstrated the desirability of developing a GWR model. When that model was compared with its OLS counterpart, it exhibited improved performance in terms of goodness of fit (R^2) and AIC. Spatial heterogeneity (variations in strength of the coefficient by location) was indicated for all six independent variables. Moran's I indicated a lack of spatial autocorrelation in the GWR residuals, indicating that the model was not mis-specified. Analysis of local R^2 values showed that national park visitation was better explained by the GWR model in 96% of counties, and that more explanatory variables would be required to explain national park visitation in only 4% of counties. Condition numbers indicated a lack of serious local multicollinearity problems in the GWR model. As concluded by the authors, "The GWR was able to account for both spatial autocorrelation and spatial non-stationary processes, thereby providing a better foundation for prediction and explanation than the corresponding OLS model" (Lee & Schuett, 2014, p. 220). The applicability of a spatially explicit approach to recreation and tourism demand is clearly apparent, suggesting the need to fundamentally rethink the methods commonly applied to one of the most prevalent topics in the leisure literature.

Park/Recreation Access, Equity and Physical Activity

Analyses of the levels of access and equity associated with distributions of parks and other recreation opportunities have appeared in the literature since the late 1990s (e.g., Talen, 1997; Talen & Anselin, 1998; Nicholls, 2001; Nicholls & Shafer, 2001; Wolch, Wilson, & Fehrenback, 2005), gaining additional traction in the last decade with the increasing focus on the relationship between access to places that facilitate physical activity, levels of activity, and individual/community health (e.g., Timpiero, Ball, Salmon, Roberts, & Crawford, 2007; Abercrombie, Sallis, Conway, Frank, Saelens, & Chapman, 2008; Moore, Diez Roux, Evenson, McGinn, & Brines, 2008). Though access and equity are clearly both inherently spatial phenomena, involving relationships between the locations of parks and other recreation opportunities, people's places of residence (or work), and their socioeconomic and demographic characteristics, only two studies of the many dozen that exist have to date incorporated explicit consideration of spatial effects.

In the first of these two exceptions, the results of OLS and GWR models were compared in an assessment of the relationships between the distribution of parks and physical activity sites, and a series of demographic and socioeconomic variables, in New York City (Maroko, Maantay, Sohler, Grady, & Arno, 2009). The six explanatory variables reached statistical significance in eleven of twelve cases across two OLS models. For two of the six variables, however, the coefficients were of the opposing sign. Further, the OLS models both exhibited a low R^2 (and high AIC), whereas the GWR models had much lower AICs. The GWR models indicated spatial non-stationarity in both models, suggesting that disparities in accessibility varied over space. Thus, though the distribution of parks/activity sites throughout the city could not be considered equitable, this inequity was not predicted by the demographic or socioeconomic variables considered at the global level. The authors suggested this finding of “unpatterned inequality” indicated the need for “a number of additional factors, variables, and methods” (p. 1) to be considered in future access studies.

More recently, Kim and Nicholls (2016) demonstrated the utility of GWR in an equity analysis of the distribution of public beaches in the Detroit Metropolitan Area. Thirteen explanatory variables were used to represent residents' need with regard to public beach access. Local regression models based on GWR identified spatially varying relationships between variables, with great improvements in model performance over the corresponding global (OLS) regression models. The OLS models both exhibited a low R^2 (and high AIC_c), whereas the GWR models had much a higherR^2 (and lower AIC_c). In addition to development of an improved approach to the measurement of equity, the findings of studies such as this can help parks and recreation agencies better understand local patterns of (in)equity and could ultimately facilitate the formulation of locally appropriate programming solutions as and where needed.

Studies focusing on relationships between (perceived or actual) levels of access to environments that facilitate leisure-based physical activity, and observed levels of activity or health, have also begun to explicitly account for spatial effects. The four cases identified all emphasized the desirability of a localized approach that recognizes the intrinsic patterning of individual contexts (places) and all highlighted the significant impacts of location on the causal pathway between the environment and individual behaviors/outcomes. In Leeds, UK, the GWR analyses conducted by Edwards, Clarke, Ransley and Cade (2010) showed a non-stationary relationship between all twelve covariates and obesity, “meaning that the same obesogenic stimulus provokes a different response in terms of BMI in some parts of Leeds” (p. 196). The authors characterized these findings as “support[ing] the debate that solutions need to be tailored to the locality for maximum effect (p. 199). More recently, Feuillet et al. (2016) found substantial variations in the intensity of the relationship between characteristics of the built environment and time spent walking for errands and for leisure across the city of Paris. As they concluded, “The effect of the built environment on individual behaviors should be seen at a local scale rather than globally. This has implications in terms of tailoring public health policy to a local scale” (p. 510). For the US, An, Li and Jiang (2017) identified substantial heterogeneity in the environmental determinants of leisure time physical inactivity, observing that “customized policy interventions that address specific and most concerning environmental issue in a local area could be more effective (and cost-effective) than a nationwide universal intervention” (p. 8). Similarly, both spatial clustering in the prevalence of physical inactivity, and spatially varying relationships between activity levels and independent variables, including the density of recreation and fitness facilities, numbers of natural and cultural amenities, and age, were demonstrated in a second analysis of the continental US (Lee, Dvorak, Schuett & van Riper, 2017). The authors highlighted the “precision,” “depth of analysis” and “detailed perspective” facilitated by the use of GWR, with concomitant implications for potential improvements in the targeting of planning and management activities. In every case in which OLS and GWR findings in the above four studies were compared, the latter outperformed the former (as evidenced by the metrics listed in the right-hand column of Table 1).

Property and Room Price Impacts

Measurement of the impact of green and blue spaces on surrounding property values and the local property tax base using the hedonic pricing technique has received attention in the parks and recreation, economics, and planning literatures (e.g., Nicholls & Crompton, 2005a, 2005b; Crompton & Nicholls, 2006). Again, however, it is only more recently that spatial effects have been taken into account. The first study to apply GWR to this topic calculated the value of forested landscapes in the Southern Appalachian Highlands, an area popular with tourists, retirees and second home owners (Cho, Kim, Roberts & Jung, 2009). Since GWR was the only approach employed, comparison of GWR performance relative to that of traditional OLS is not possible. Mapping did, however, indicate substantial clustering (spatial autocorrelation), allowing identification of areas where the designation of conservation easements would be the most economically efficient.

Li (2010) examined the influence of neighborhood greenspace on residential property values in Los Angeles County. She compared findings based on a traditional OLS approach with those of two spatial expansion, two spatial regression (lag and error), one GWR and one spatial filtering model. Based on adjusted R^2 and AIC values, the GWR model performed best, producing "the highest model fitness while capturing spatial variations most effectively and leaving its regression residuals free of any significant spatial autocorrelation" (Li, 2010, p. 98). Li also noted the value of the ability to map spatial distributions of variables using GWR, thereby allowing visualization of the causes of spatial variation in distributions.

Property prices are prone to fluctuation not only through space but also over time, a complicating factor recognized by Huang, Wu and Barry (2010). To assess the benefits of accounting for each and then both of these issues, the authors constructed four sets of models in their assessment of the influence of eleven variables, including an undefined measure of green space, on property prices in Calgary, Canada. The four models included a standard OLS regression, a temporally weighted regression (TWR), a GWR, and a geographically and temporally weighted regression (GTWR). Relative to the global OLS model, absolute errors in the three other models were reduced by 3.5% (TWR), 31.5% (GWR) and 46.4% GTWR. Goodness of fit (as measured by R^2) increased from 0.76 (OLS), to 0.78 (TWR), 0.89 (GWR), and 0.93 (GTWR). Improvements made by the GTWR over the TWR and GWR were statistically significant.

Whilst the studies described above focused on the influence of open spaces on prices of residential homes, four studies have applied spatially-explicit hedonic pricing techniques to identify the most significant influences on short-term accommodation rental rates. For hotel room prices in Beijing, China, results of three traditional OLS specifications (linear, log-linear, semi-log) were compared with those using GWR. A substantial increase in R^2 and significant spatial variation within all the independent variables was found. In four of the five cases, parameter estimates in the GWR varied from negative to positive and included zero, conclusive evidence of the limited suitability of an aspatial approach (Zhang, Zhang, Lu, Cheng & Zhang, 2011).

A spatially explicit hedonic pricing technique was also used to determine influences on nightly prices of rural holiday homes in Catalonia, Spain (Hernández, Suárez-Vega & Santana-Jiménez, 2016). Though the significance of variables was for the most part consistent across the four modeling approaches employed (OLS, spatial error, spatial lag, and GWR), the latter three all proved significantly superior to the traditional global OLS approach. In the case of GWR, the adjusted AIC fell from 391.7 to 378.8 and an improvement F-test to assess the extent to which GWR enhanced performance over OLS was significant at the 1% level.

The effect of a sea view on hotel prices was assessed in Halkidiki, Greece (Latinopoulos, 2018). GWR improved upon the performance of OLS for all measures employed, demonstrating that the average 4.85% premium for a room with a sea view actually varied from areas where such a view imbued no premium, to areas where the increase exceeded 11%. For some variables, e.g., distance to the nearest forest, consideration of spatial effects revealed variations in coefficients across the study area that ranged from negative to positive, i.e., factors that positively influenced room rates in some parts of the study area but reduced them in others.

Lastly, Soler and Gemar (2018) made multiple calls for the wider adoption of GWR in hedonic research in their study of hotel prices in Malaga, Spain. Implementation of a GWR model produced a substantial improvement in R^2, and for some variables the range of coefficients included zero, suggesting that "the OLS model can be misleading for some hotels" (p. 133). In practice this suggested the existence of competitive subsystems in the hotel sector "that cannot be detected with the use of OLS alone" (p. 133); for researchers, the authors concluded that "it is essential to include GWR in any hedonic price model" (p. 133).

Tourism Growth and Development

Despite tourism's explicit relationship with and reliance on movement and place, only a handful of studies have applied GWR to tourism topics. Though the earliest example focused on migration patterns among people aged 55 and over in the United States, the inclusion of a battery of amenity factors, including temperature and indexes representing nature-, water-, recreation-, amusement-, tourism- and winter-based activities, has clear implications for shorter term and second home travel patterns (Jensen & Deller, 2007). Comparison of the derived sum of squared residuals and corresponding ANOVA F-statistics showed that the GWR estimates were more efficient than their OLS counterparts in all eight models developed. Among the estimated coefficients, 92 of 240 (38.3%) exhibited significant spatial variation, suggesting that the global parameters derived from the OLS approach masked important spatial differences and adding further support to the use of GWR techniques. The authors concluded that the spatial variation in the amenity measures tested had "distinctly different implications for development in individual localities" (Jensen & Deller, 2007, p. 339). Deller (2010) explored the role of tourism and recreation in changing poverty rates in rural counties in the US using OLS and GWR, characterizing the GWR estimates as "superior" to their OLS equivalents (neither R^2 nor AIC values were reported, however).

A more recent study used a spatial growth regression framework to model regional tourism growth patterns in China between 2002 and 2010 (Yang & Fik, 2014). Recognizing that, "Failure to incorporate the effects of spatial spill-overs and/or spatial heterogeneity in a regional growth model would result in unreliable and potentially misleading coefficient estimates" (p. 145), the authors developed and compared a series of five models: traditional OLS, spatial auto-regressive (SAR), spatial error model (SEM), spatial Durbin model (SDM) and geographically weighted spatial Durbin model (GW-SDM). Significant spatial autocorrelation was found in the predicted OLS residuals, supporting the application of spatially explicit techniques. The SDM specifications outperformed the OLS, SAR and SEM models based on both AIC levels and Wald tests. Since the spatial autocorrelation parameter was significant and positive in both SDM models, the GW-SDM version was developed. This specification identified substantial geographic variations in spatial patterns of tourism growth across the study area. In some cases, though a parameter estimate was insignificant within the global OLS model, it was found to be statistically significant, though sometime positive and sometimes negative, in the GS-SDM specification, clear indication of the propensity for local variations to be masked in global models. In particular, the spatially explicit approach allowed significant spatial spill-over and cross-city competition effects to be identified, allowing a series of important implications for tourism policymakers and marketers to be proposed.

Discussion

As described above, GWR offers a number of advantages over traditional OLS regression, allowing spatial effects such as spatial heterogeneity, non-stationarity and dependence (spatial autocorrelation) to be accounted for. GWR yields error terms (residuals) that are considerably smaller and less spatially dependent than residuals from a corresponding global regression model. GWR also offers the powerful ability to visualize spatial variations in regression diagnostics and model parameters within a study area, allowing exploration of how the direction and significance of statistical relationships between independent and dependent variables vary over space.

Utilization of GWR in leisure research has to date been extremely limited, and the small number of published studies has tended to appear in geography or economics, rather than leisure, journals. Despite their limited number, these studies clearly demonstrate the importance of considering spatial effects. In every case in which the performance of GWR methods was compared to the traditional OLS approach, the former outperformed the latter. In many cases, GWR findings demonstrated not only statistically significant but also extremely meaningful and impactful variations in coefficients at the local level. In some cases these ranged from significantly positive to significantly negative, clear evidence of the extensive masking of delicate nuances in spatial data by global techniques. Identification of these variations suggests the opportunity for locally-based planning, management and development decisions and policy analysis that would not have been evident using a traditional global approach. For example, the finely grained portraits of access and equity possible using GWR might help concentrate the investment of resources into the most underserved areas, while GWR-based analyses of property prices that identify spatial variation in amenity values of green and blue spaces might inform decisions regarding where to prioritize protective measures and how/where to allocate maintenance budgets.

The ability to produce meaningful research, work that not only advances the body of scholarly literature but that also provides useful information to practitioners and can be used to positively influence policy and practice, is critically dependent upon the selection and application of the most appropriate analysis techniques. The overview of GWR provided herein calls into question prior findings that did not take spatial effects into account. In all studies with any spatial context it is clearly time to reconsider the continued use of traditional OLS regression, and the advent of GWR behooves the learning and adoption of this superior approach by both current researchers in and new students to the leisure field.

The studies summarized demonstrate the utility of GWR in studies of recreation demand, park and recreation access and equity, hedonic analyses of the impacts of open spaces on property values, and tourism growth and development. Other areas of leisure research to which it is recommended GWR be applied include but are not limited to the following general topics (any analysis with a spatial dimension and to which OLS has previously been applied would be an appropriate candidate):

- Exploration and analysis of spatial factors influencing the directions and magnitudes of flows of recreationists and tourists between origins and destinations, whether individual sites or cities, counties, countries, etc. (where the dependent variable might be the number of outbound or inbound visitors per geographic unit and independent variables could include economic conditions, climate or weather, and levels of actual or perceived safety and security, as well as the numbers and attractiveness or quality of accommodations and transportation options, events and attractions, etc.). This kind of analysis could be run on annual as well as seasonal or monthly data to identify temporal variations in addition to spatial influence;

- Exploration of the spatial impacts of tourism policy on development and growth patterns, to assess the influence of past policy on historical change and to identify how and where to target future activity. Recognizing the role of tourism policy as an agent of spatial change, Kang, Kim and Nicholls (2014) used spatial statistical techniques such as Moran's I and local indicators of spatial association to relates changes in national tourism policy to spatial patterns of domestic tourism; GWR would be the natural next step to, and would considerably strengthen, such analyses;.
- Exploration of patterns of spatial agglomeration in the lodging sector and the influence of agglomeration on property performance (where the dependent variable might be some measure of hotel performance such occupancy rate or revenue per available room) and independent variables could include levels of spatial agglomeration (e.g., the number of properties within each defined area of a market) and location factors such as proximity to critical transportation and other hubs (e.g., convention centers, major leisure attractions);
- Measurement of the impact of aspects of the built environment on public health, i.e., extension of the work on recreation access to incorporate measures of residents' physical and/or mental health (dependent variables could include any measure of community or

individual physical activity or health, e.g., body mass index) while independent variables might include levels of access to and use of public and private recreation settings (e.g., urban parks, fitness centers, playgrounds, etc.) as well as measure of local walkability, incorporating, e.g., residential and intersection density, land use, sidewalk availability and/or condition, and public transportation availability/distribution.

Limitations of GWR

No one modeling or analysis technique is perfect, and like every other formalism, GWR has its limitations. For example, GWR should be applied to datasets with several hundred features for best results, and is not an appropriate method for small datasets. Though a local approach such as GWR considerably reduces its influence relative to traditional global models, the modifiable areal unit problem (MAUP, Openshaw, 1984) remains a concern. MAUP refers to the influence of scale (or spatial resolution) and zoning (the method of aggregation or grouping of data, e.g., census blocks versus census block groups versus census tracts) on study results. Analysis at the finest, i.e., most spatially disaggregated, scale possible remains the best strategy to address this issue; comparison of results based on different scales and zoning schema demonstrates the sensitivity of specific datasets to the MAUP.

There may be situations in which only some of the variables within are model are likely to vary spatially, in which case employment of a GWR would generate inefficient estimations and incorrect conclusions about the influence of the variables under consideration. In this case, mixed GWR (MGWR) allows for the simultaneous existence of spatially stationary and non-stationary effects. Helbich, Brunauer, Vaz and Nijkamp (2013) explored the use of MGWR with respect to hedonic house price models in Austria.

Another limitation of GWR relates to local multicollinearity and spatial autocorrelation among coefficients (Wheeler & Tiefelsdorf, 2005). Even if GWR models are better able to capture spatial dependence patterns in the dataset than OLS models, they cannot control for all of it (Griffith, 2008). In addition, the GWR method tends to generate extreme local coefficients and may overstate spatial heterogeneity (Farber & Paetz, 2007). Future studies should investigate specific diagnostic tools, or remedial methods, for addressing these methodological issues.

Conclusion

The purpose of this paper was to stress the importance of the consideration of spatial effects in leisure research. Further, it has demonstrated the utility of GWR as a method via which to assess and address these effects, thereby refining our understanding of important spatial relationships among and between dependent and independent variables in a variety of contexts. The paper is reflective of similar calls that have previously been made in a diversity of other fields, e.g., from fisheries (Windle, Rose, Devillers & Fortin, 2010) to prenatal care (Shoff, Yang & Matthews, 2012). As these and the papers reviewed above emphasize, GWR facilitates far more spatially aware and nuanced analysis, resulting in more targeted and tailored implications to be drawn and hence more meaningful recommendations to be developed.

GWR is in fact but one of a number of relatively new spatially-aware data collection, analysis and modeling techniques from which leisure researchers could immensely benefit; other emerging approaches beginning to gain traction in the field include global positioning systems (Hallo, Beeco, Goetcheus, McGee, McGehee, & Norman, 2012; Grinberer, Shoval, & McKercher, 2014), the use of georeferenced photographs (Girardin, Dal Fiore, Ratti, & Blat, 2008) and agent-based modeling (Nicholls, Amelung, & Student, 2016). We hope this piece generates additional interest in, and more explicit attention to, the special nature of spatially-bound studies.

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Table 1. Summary of Leisure-Related Studies Employing Geographically Weighted Regression

Author(s) (Year) Journal	**Topic**	**Study Site**	**Notes on Method**	**Key Findings and Performance**
Jensen & Deller (2007). *The Review of Regional Studies*	Role of amenities in migration patterns of older people	Counties in the USA	Compared OLS and GWR. Used Monte Carlo tests to confirm GWR findings.	Comparison of derived sum of sq corresponding ANOVA F-statisti estimates more efficient in all 8 n coefficients exhibited significant
Cho et al. (2009). *Ecological Economics*	Influence of forest-patch size and density on residential property prices	Southern Appalachian Highlands, GA/NC/SC/ TN/VA/WV, USA	Traditional OLS results not reported. Used the adaptive bi-square weight function. Used CV approach to select bandwidth. Tested residuals for SA using LM test. Used Monte Carlo tests to confirm GWR findings.	Amenity value of mean patch size during the study period. Conserva patches of greatest amenity value north of Atlanta. Conservation of patches of greatest amenity value Knoxville, Roanoke and Greensb
Maroko et al. (2009). *International J. of Health Geographies*	Park/physical activity site access and equity	New York City, NY, USA	Compared OLS and GWR. Used the adaptive kernel method. Used Monte Carlo tests to confirm GWR findings.	OLS models had R^2 (AIC) of 0.11 GWR models had AICs of 2014 a indicated spatial non-stationarity suggesting that disparities in acce space. Though distribution of par equitable, not globally predicted l
Deller (2010). *Annals of Tourism Research*	Influence of tourism and recreation on poverty rates in rural areas	Counties in the USA	Compared OLS and GWR. Used the adaptive kernel method. Used Monte Carlo tests to confirm GWR findings.	GWR estimates "superior" to OL tourism and recreation activities t poverty rate. Minimal spatial vari control (social and economic) var variation within two of the six me tourism (ski, commercial recreati
Edwards et al. (2010). *J. of Epidemiology and Community Health*	Relationships between childhood obesity and 12 obesogenic variables	Census wards in Leeds, UK	Traditional OLS results not reported. Local relationship identified as non-stationary if interquartile range of local parameter estimate greater than twice the global standard error.	All 12 of the covariates included relationship with obesity.

Huang et al. Barry (2010). *International J. of Geographical Information Science*	Influence of 11 variables (including green space) on residential property values	Calgary, Canada	Compared OLS with TWR, GWR and GTWR models. Used CV approach to select bandwidth.	ANOVA indicated significant ter stationarity, RSS and MS improv models. Relative to OLS model, a by 3.5% (TWR), 31.5% (GWR) a Goodness of fit: OLS, 0.76; TWR GTWR, 0.93. AIC: OLS, -5595.6 8693.9; GTWR, -8850.4.
Li (2010). Chapter 4 of PhD Dissertation	Influence of neighborhood greenspace on residential property values	Los Angeles County, USA	Compared OLS with two spatial expansion (SE1, SE2), two spatial regression (lag and error), one GWR and one spatial filtering (SF) model. Selected bandwidth using adaptive kernel function.	Adjusted R^2 and AIC: OLS, 0.65, SE2, 0.72, 652.7; lag, N/A, 418.8 GWR, 0.77, 363.0; SF, N/A, 793.
Zhang et al. (2011). *International J. of Hospitality Management*	Determinants of hotel room prices	Beijing, China	Compared OLS with GWR. Used Moran's I to test for SA in the DV and residuals. Used Monte Carlo tests to confirm GWR findings.	Adjusted R^2: OLS linear, 0.49; O semilog, 0.53; GWR, 0.84 (range indicated significant positive SA, GWR. Significant spatial variatio IVs; in four of five cases, parame zero.
Lee & Schuett (2014). *Applied Geography*	Spatial variations in relationships between recreation demand and socioeconomic/ demographic factors	Counties in TX, USA	Compared OLS and GWR. Used global Moran's I and LISA to test for global and local SA in DV. Selected bandwidth using adaptive kernel function. Used Moran's I and Koenker (BP) statistic to test for SA in OLS and GWR residuals. Calculated local R-squared value and condition number.	Global and local SA tests indicate (clustering) in DV. Moran's I and indicated strong SA in the OLS m OLS, 0.73; GWR, 0.75. AIC: OL Significant spatial variation indic Moran's I indicated lack of spatia GWR residuals. Visitation better model in 96% of counties. Condit lack of serious local multicolline GWR model. Family structure an important influences on national
Yang & Fik (2014). *Annals of Tourism Research*	Spatial patterns of regional tourism growth rates	Prefectural-level cities in mainland China	Compared OLS with SAR, SEM, SDM and GW-SDM. Used nearest neighbor weighting matrix. Used CV approach to select bandwidth.	Significant SA found in predicted specification outperformed other levels and Wald test for both depe OLS, 1218.0 and 649.6; SAR, 11 1147.6 and 613.3; SDM, 1133.0 a

				autocorrelation parameter signific SDM models. GW-SDM identifie variations in spatial patterns of to
Feuillet et al. (2016). *Journal of Transport & Health*	Built environmental correlates of walking for errands and for leisure	Paris, France	Conducted global and local (semiparametric geographically weighted) Poisson regressions. Determined kernel size of the spatial weighting scheme by minimizing corrected AIC.	Spatial heterogeneity of relations and the built environment occurre area (odds ratios ranged from 1.0 errands and from 1.07 to 1.35 for
Hernández et al. (2016). *Tourism Management*	Determinants of price per night of rural holiday homes	Catalonia, Spain	Compared OLS, spatial error, spatial lag and GWR. Selected bandwidth using adaptive kernel function.	Adjusted R^2 and AIC: OLS 0.21, 363.4; spatial lag 0.25, 365.8; GV improvement of GWR over OLS
Kim & Nicholls (2016). *J. of Leisure Research*	Public beach access and equity	Detroit Metropolitan Area, MI, USA	Compared OLS and GWR. Used the adaptive bi-square weight function. Used Moran's I to test for SA in the regression residuals.	Adjusted R^2 and AIC: OLS (mode OLS (model 2), 0.18, 6,300.11; C 8,679.89; GWR (model 2), 0.70, identified important local variatio non-stationarity. Global Moran's model 1), 0.61 (OLS model 2), 0. (GWR model 2). GWR models in reducing SA in the residuals.
An et al. (2017). *International J. of Environmental Research and Public Health*	Geographical variations in environmental determinants of leisure time physical inactivity	Counties in the USA	Compared OLS and GWR using two key sets of independent variables (overall Environmental Quality Index (EQI) and five individual EQI subdomains). Used Moran's I to test for SA in the residuals.	R^2: increased from 0.58 (OLS) to overall EQI as key independent v 0.58 (OLS) to 0.86 (GWR) using Moran's I of the residuals: reduce 0.090, 0.093) (OLS) to -0.0003 (9 (GWR) for overall EQI; reduced 0.088, 0.090) (OLS) to 0.0002 (9 (GWR) for five EQI subdomains.
Lee et al. (2017). *Landscape and Urban Planning*	Situational and socioeconomic determinants of physical inactivity	Counties in the USA	Compared OLS and GWR. Selected bandwidth using adaptive kernel function. Used Moran's I to test for SA.	R^2 increased from 0.55 (OLS) to (increased from 0.55 (OLS) to 0.7 from 16,858.5 (OLS) to 15,435.2

Latinopoulos (2018). *Tourism Management*	Effect of sea view on hotel prices	Halkidiki, Greece	Compared OLS and GWR. Selected bandwidth using adaptive kernel function. Used Moran's I to test for SA.	R^2 increased from 0.78 (OLS) to (increased from 0.77 (OLS) to 0.8 from 195.0 (OLS) to 49.7 (GWR) (OLS) to 0.06 (GWR). F-test of i over OLS significant at 1%.
Soler & Gemar (2018). *J. of Destination Marketing and Management*	Determinants of hotel room prices	Malaga, Spain	Compared OLS and GWR. Selected bandwidth using adaptive kernel function.	Adjusted R^2 increased from 0.64 (

AIC = Aikaike information criterion, ANOVA = analysis of variance, CI = confidence interval, CV = cross-validation, DV GTWR = geographically and temporally weighted regression, GWR = geographically weighted regression, GW-SDM = ge spatial Durbin model, IV = independent variable, J. = Journal, LISA = local indicator of spatial association, LM = Lagrang mean square, OLS = ordinary least squares, RSS = residual sum of squares, SA = spatial autocorrelation, SAR = spatial au spatial Durbin model; SEM = spatial error model, SES = socio-economic status, TWR = temporally weighted regression.