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Environmental Influences on Leisure-Time Physical Inactivity in the U.S.: An Exploration of Spatial Non-Stationarity

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Abstract: Considerable research has been conducted to advance our understanding of how environmental factors influence people's health behaviors (e.g., leisure-time physical inactivity) at the neighborhood level. However, different environmental factors may operate differently at different geographic locations. This study explores the inconsistent findings regarding the associations between environmental exposures and physical inactivity. To address spatial autocorrelation and explore the impact of spatial non-stationarity on research results which may lead to biased estimators, this study uses spatial regression models to examine the associations between leisure-time physical inactivity and different social and physical environmental factors for all counties in the conterminous U.S. By comparing the results with the conventional ordinary least squares regression and spatial lag model, the geographically weighted regression model adequately addresses the problem of spatial autocorrelation (Moran's I of the residual = 0.0293) and highlights the spatial non-stationarity of the associations. The existence of spatial non-stationarity that leads to biased estimators, which were often ignored in past research, may be another reason for the inconsistent findings in previous studies besides the modifiable areal unit problem and the uncertain geographic context problem. Also, the observed associations between environmental variables and leisure-time physical inactivity are helpful for developing location-based policies and interventions to encourage people to undertake more physical activity.

Keywords: physical activity; spatial regression; spatial autocorrelation; spatial non-stationarity; environmental health; GIS

1. Introduction

For decades, researchers in public health and preventive medicine have examined the effects of environmental exposures on various health problems. There is growing evidence that indicates the association between environmental exposures and health outcomes [1–4]. Concerns about how the environment influences human health have attracted increasing attention with the increasing use of advanced spatial analytical methods and geographic information science (GIS) [5]. In environmental health research, many researchers are interested in physical inactivity [6–8] and its influence on chronic diseases, such as type-II diabetes, obesity, and cardiovascular diseases [9–13]. Physical inactivity includes leisure-time physical inactivity (LTPI) and non-leisure-time physical inactivity (NLTPI) [14]. Previous studies have found that both LTPI and NLTPI are affected by environmental contexts [15–22].

Considerable research has been conducted to advance our understanding of how physical environmental factors [20,23–40] and social environmental factors [19,28,41–46] influence people's physical inactivity. In many of these studies, however, environmental determinants are found to have inconsistent associations with physical inactivity [22,28,31,45–48]. For example, some previous studies have not found any significant association between physical inactivity and weather, which however is one of the perceived factors that influence physical inactivity [22,47,48]. The access to, density of, or proximity to parks have been found to be related to physical inactivity in some studies while unrelated in other studies [20,25,49–53]. Similar inconsistent results were also found in the exposure to recreation facilities [49–52,54,55], street connectivity [20,25,30,50,56–59], and crime-related safety [49,51,55].

Scholars have attributed such inconsistency to the modifiable areal unit problem (MAUP) [60–62] and the uncertain geographic context problem (UGCoP) [63–66]. For example, the correlations found at various spatial scales (e.g., neighborhood, city, county, and state levels) may be different [60]. Furthermore, the different delineations of contextual areas (e.g., census tracts, home buffers, road network buffers) used to derive contextual or exposure measures may also affect the results [67,68]. Nevertheless, even at the same spatial scale and using the same exposure assessment method, environmental factors may operate differently at different geographic locations (a phenomenon known as spatial non-stationarity, which has been largely ignored in previous studies). For instance, street connectivity may be positively correlated with physical inactivity in one city while negatively associated with physical inactivity in another town. To the best of our knowledge, the spatial non-stationarity of environmental effects on physical inactivity and its influence on the consistency of research findings have not been adequately explored in previous studies and thus are worthy of investigation.

To fill the research gap, this paper seeks to explore the inconsistent findings regarding the associations between LTPI and different contextual variables (physical, demographic, and socioeconomic environmental factors) from the perspective of spatial non-stationarity. As an exploratory and ecological study, we examine the spatial variation of environmental effects on LTPI (percentage of population reporting insufficient leisure-time physical activity) at the spatial scale of U.S. counties. Previous studies have examined environmental effects on LTPI at the county level. However, none of these studies has considered the spatial autocorrelation in physical inactivity among neighboring counties as well as the existence of spatial non-stationarity [41,42,69,70]. Although both LTPI and NLTPI have been found to be associated with environmental factors, this study only focuses on environmental effects on LTPI to explore spatial non-stationarity and illustrate its influence on the results. By adopting a cross-sectional approach, the data in this research were collected in 2011. Further, the LTPI from nearby geographic units may have similar values, and spatial dependencies may exist (a phenomenon is known as spatial autocorrelation). To address the problem of spatial autocorrelation and investigate the existence of spatial non-stationarity, this study employs spatial regression models such as the spatial lag model (SLM) and geographically weighted regression (GWR). The result of this study shows that the relationships between contextual variables and LTPI are varied across geographic space at the county level, which indicates the existence of spatial non-stationarity. This study contributes to a better understanding of the environmental influences on LTPI and how these associations vary with geographic locations.

2. Materials and Methods

This research examines the relationships between LTPI and various environmental influences in the 3109 counties of the 48 contiguous states in the U.S. It uses county as the geographic unit and contextual area for all its GIS-based analysis. An SLM and GWR are used to handle spatial autocorrelation and examine the spatial non-stationarity in the associations between LTPI on the one hand and contextual variables on the other. The results are compared with those obtained with an ordinary least squares (OLS) regression.

2.1. Data

2.1.1. Leisure-Time Physical Inactivity Data

The physical inactivity data used in this study were generated by a cooperative project between the Robert Wood Johnson Foundation and the University of Wisconsin Population Health Institute in 2011. It was collected by the Behavioral Risk Factor Surveillance System (BRFSS) of the Centers for Disease Control and Prevention (CDC) through telephone surveys. In this study, LTPI was measured as the percentage of adults aged 20 and over reporting insufficient leisure-time physical activity. Figure 1 visualizes the LTPI data and the spatial pattern of LTPI across the contiguous U.S. Among the 3109 counties of the 48 contiguous states in the U.S., 3108 counties are selected for statistical analysis. One county is excluded because its physical inactivity value is not available. As shown in the figure, lower percentages of LTPI are found in the western and north-eastern states, whereas higher percentages of LTPI are in the south-eastern region. For instance, Colorado and Minnesota have many counties with low levels of LTPI, while West Virginia and Tennessee have many counties with high levels of LTPI.

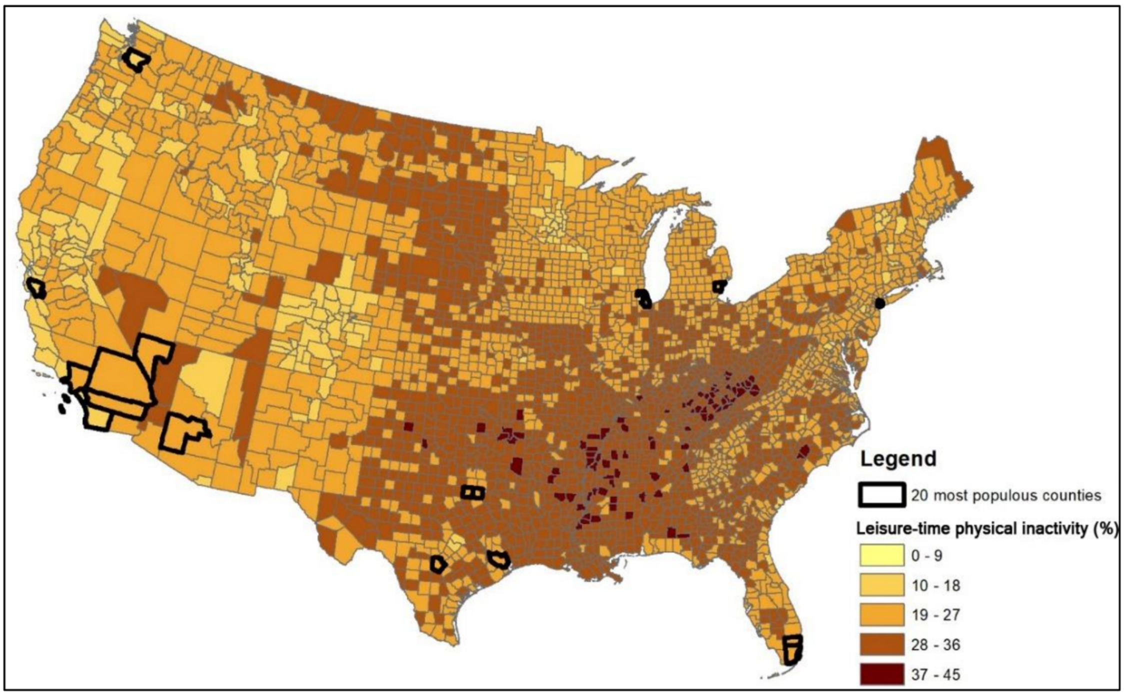

Figure 1. Leisure-time physical inactivity for the contiguous United States at the county level (Indicator: percentage of adults aged 20 and over reporting insufficient leisure-time physical activity).

2.1.2. Physical Environmental Factors

As noted by the National Research Council and the Institute of Medicine [71], "the factors in the physical environment that are important to health include harmful substances, such as air pollution or proximity to toxic sites (the focus of classic environmental epidemiology); access to various health-related resources (e.g., healthy or unhealthy foods, recreational resources, medical care); and community design and the 'built environment' (e.g., land use, street connectivity, transportation systems)." Past research has identified various environmental factors that influence people's physical inactivity. These include land-use mix, street length/connectivity, transport facilities, and parks and recreational facilities [27]. High land-use mix and high street length/connectivity within the residential neighborhood have been found to have a negative association with the physical inactivity of both adults and children [20,25,26,30,34,36,39,40,72]. It has been found that the quality or density of sidewalks, the number of bus lines, and walking and biking trails around the home location or within the residential community are also positively correlated with the active travels of adults and children [29,33,38,73,74]. Exposure to green space and recreational facilities in the residential neighborhood has negative associations with physical inactivity [23,24,32,33,35,37,38]. Regarding access to green spaces, some studies, however, indicate that there is no significant association between physical inactivity and green spaces [28,31]. As one of the environmental factors, weather may affect physical inactivity. However, previous studies have not found any significant association between physical inactivity and weather [22,47,48,75].

Among many physical environmental factors, this study focuses on temperature, precipitation, land use, green space, and walkability, which are widely considered as factors that may influence health behaviors. These five physical environmental factors are listed in Table 1. Annual average temperature and precipitation are calculated using the method developed by Schlenker and Roberts [76] based on the 2011 daily temperature, and precipitation data in the U.S. were derived from the U.S. Department of Agriculture's official climatological data. The percentage of tree canopy cover is calculated using the 2011 tree canopy data of the U.S. Forest Service. The percentage of highly developed area for each county is abstracted from the multi-resolution land characteristics consortium. Walkability is calculated by dividing the length of minor roads (km) in a county by the area of the county (km^2). The minor road density is used as a surrogate of walkability, which is consistent with the walkability measurement method introduced by Schlossberg [77]. The road network and street classification data are abstracted from the topologically-integrated geographic encoding and referencing (TIGER) database.

Table 1. List of factors regarding physical environment, demographic characteristic, and socioeconomic status.

Variable		Description	Year	Source
Physical Environment				
Average annual temperature		Annually average daily temperature	2011	US Department of Agriculture (Schlenker & Roberts, 2009)
Average annual precipitation		Annually average daily precipitation		US Department of Agriculture (Schlenker & Roberts, 2009)
Tree canopy		Percentage of tree canopy coverage		US Forest Service
Land cover		Density of highly developed areas with high ratios of residential, business, commercial, and industrial areas		Multi-Resolution Land Characteristics (MRLC) Consortium
Walkability		Minor road density		Topologically Integrated Geographic Encoding and Referencing (TIGER)
Demographic Characteristics				
Age		Median age (years)	2011	American Community Survey (ACS)
Sex		Percentage of residents who are female		
Race	African American	Percentage of residents who are African American		
	Asian	Percentage of residents who are Asian		
	Hispanic and Latino	Percentage of residents who are Hispanic and Latino		

Table 1. *Cont.*

Variable		Description	Year	Source
Socioeconomic Status				
Income		Income per capita (inflation-adjusted dollars)	2011	American Community Survey (ACS)
Employment		Unemployment rate		
Occupation	Management, business, science, and arts	Percentage of residents whose occupation are management, business, science, and arts		
	Natural resources, construction, and maintenance	Percentage of residents whose occupation are natural resources, construction, and maintenance		
	Production, transportation, and material moving	Percentage of residents whose occupation are production, transportation, and material moving		
Self-employed unpaid family workers		Percentage of residents who are self-employed unpaid family workers		
Commuting mode—work at home		Percentage of residents who are work at home		
Commuting mode—walking		Percentage of residents commuting to work by walking		
House ownership		Percentage of housing units that are owner-occupied		
Vehicle ownership		Percentage of families have no vehicles available		

2.1.3. Social Environmental Factors

Besides physical environmental factors, demographic characteristics, and socioeconomic status are also important determinants of physical inactivity. Evidence from many studies shows that young adults and men have lower levels of physical inactivity than older adults and women [41,42,44,46,78]. Regarding ethnicity, studies found that African American women have a higher rate of physical inactivity than white women, and minority groups were also found to have a higher rate of physical inactivity than the white population [41,42,46,78]. Education and income have a negative correlation with physical inactivity, and adults in urban areas have a lower rate of physical inactivity than adults in rural areas [28,41,46,78]. Non-professional workers have a higher rate of physical inactivity than professional workers, whereas marital status shows mixed associations [45,46]. High levels of physical inactivity are also correlated with car ownership, home ownership, and high utilization of active travel (e.g., walking and biking) for commuting [28,43,79].

In this study, county-level demographic and socioeconomic characteristics are used to represent social environmental factors that influence LTPI. By adopting the sociodemographic variables used in previous studies, the factors used in this study include age, gender, race, income, unemployment rate, occupation, travel mode of commute trips, house ownership, and car ownership. They are extracted from the 2011 American Community Survey (ACS) data. ACS five-year estimates data were used because they provide relatively high precision of the estimates based on large sample size when compared to one-year and three-year estimates [80]. These variables are listed in Table 1. The five demographic variables are the median age, the percentage of females, and the percentages of different ethnic groups. The 10 socioeconomic status variables are per capita income, unemployment rate, occupations, commuting mode, house ownership, and vehicle ownership.

2.2. Statistical Analysis

2.2.1. Multicollinearity

To evaluate the multicollinearity among the 20 independent variables, correlations, and variable inflation factors (VIF) are investigated. In a regression model, multicollinearity exists when two or more independent variables have high correlations. Multicollinearity can cause unstable coefficient estimates and thus hinder the precise interpretation of the results. Correlations between all pairs of the independent variable are analyzed using Pearson correlation test (the correlation matrix is not shown). None of the pairs shows strong correlation (correlation coefficient > 0.7 or correlation coefficient < -0.7). For VIF, the common threshold VIF < 10 was used [81,82], and all 20 independent variables are found to have VIF values less than 10. Thus, there is no evidence for multicollinearity among the 20 independent variables, all of which are used for further investigation in this study.

2.2.2. Spatial Regression Models

The presence of spatial autocorrelation in LTPI across counties in the U.S. is examined using the global Moran's I statistic. The first order Queen's contiguity method was applied to define adjacent neighbors since the shapes and sizes of counties and states are irregular [83]. The Moran's I obtained is 0.58, which is greater than the expected value -0.0003 ($p < 0.001$), indicating strong spatial autocorrelation where counties tend to exhibit similar percentages of LTPI as nearby counties. The positive z-score of 119.78 also suggests that similar percentages of county-level LTPI tend to be spatially clustered, which can be observed in Figure 1. However, studies concerning the association between LTPI prevalence and environmental factors have largely ignored how spatial autocorrelation may play an important role in the results, given that environmental factors can have varying effects on LTPI depending on geographic location (a phenomenon known as spatial non-stationarity).

To explore and address the issue of spatial non-stationarity and its effects of the analytical result, spatial regression models (SLM and GWR) are employed in this study to examine the associations between environmental factors and LTPI as a function of geographic location. The results are also compared to those obtained with the OLS. The OLS is a linear regression model, which estimates coefficients by minimizing the sum of squares of the errors of predicted results. The OLS is one of the most widely used methods in LTPI research for investigating the association between environmental factors and LTPI [36,38,39,84]. However, the OLS does not consider any spatial variables or deal with spatial effects (e.g., spatial autocorrelation).

As the global spatial model, spatial lag regression can control the level of spatial autocorrelation by adopting a lag variable for the spatial effect to estimate regression models. The equation of spatial lag regression models [85] is

$$Y = \rho W\left(Y_j\right) + \beta X + \varepsilon \tag{1}$$

where Y is the dependent variable; $\rho W\left(Y_j\right)$ is the weighted dependent variables summed over Queen contiguity neighborhood j; ρ is the coefficient of the spatial lag; β are the coefficients of the independent variables; X are the independent variables; and ε is the random error term.

Compared to the SLM with the spatial lag estimated by weighted values, GWR generates local regression models for each spatial unit (e.g., the county in this study) to deal with spatial autocorrelation. The estimated coefficients of the independent variables thus vary between spatial units and are determined using Gaussian bell curve. The equation for GWR models [86] is

$$y_i = \sum_{k=1}^{L} \beta_k(u_i, v_i) x_{ik} + \varepsilon_i \tag{2}$$

where y_i is the dependent variable at ith observation (e.g., county in this study); $\beta_k(u_i, v_i)$ is the coefficient of the independent variable k at the ith observation, calculated based on Gaussian bell curve function; x_{ik} represents the independent variable k at the ith observation; and ε_i is the random error term. GeoDa and the R software package are used to run the GWR model in this study.

3. Results

3.1. Descriptive Statistics

The characteristics of LTPI and contextual variables are reported in Table 2. The percentage of physically inactive residents ranges from 10% to 45% among different counties. The average percentage of physically inactive residents is 27.15%, with a standard deviation of 5.06%. In terms of physical environmental factors, the counties include areas from tropical (average daily temperature = 24.78 °C) to continental (average daily temperature = −0.09 °C) climate, and from densely forested areas (% tree canopy coverage = 92.25) to deserts (% tree canopy coverage = 0.02). Also, highly developed urban areas (% highly developed area = 48.42) and developed areas with low or medium intensity or rural areas (% highly developed area = 0) are included in these counties. Meanwhile, the socioeconomic status and demographic characteristics of the counties are diverse. For instance, unemployment rates vary from 0% to 18.4%, covering counties without any unemployment problem and counties with significant unemployment problems. Per capita incomes range from $7887 to $61,290, covering impoverished and affluent counties. Population compositions of the counties vary considerably regarding age, gender, and race (e.g., from white to African American-dominated counties; from youngsters to seniors-dominated counties). Vehicle ownership represents the percentage of families who do not own a vehicle. There are some counties in which all families have at least one automobile while there are some in which most of the families do not own any vehicle (78%). The great variation in LTPI, physical environment, socioeconomic status, and demographic characteristics among the counties across the contiguous U.S. provides rich information for a basic understanding of the contexts in different counties.

Table 2. Descriptive statistics of physical and social environmental factors.

Variables	Minimum	Maximum	Mean	Standard Deviation
LTPI	10	45	27.15	5.06
Temperature (°C)	−0.09	24.78	12.78	4.77
Precipitation (inch)	0.00	8.80	2.90	1.28
Tree canopy coverage (%)	0.02	92.25	34.64	25.87
Land cover (%)	0.00	48.42	0.52	2.15
Walkability (km/km^2)	0.09	16.71	2.30	1.61
Commuting mode 1—walking (%)	0.00	31.30	3.23	2.75
Commuting mode 2—work at home (%)	0.00	42.00	4.92	3.50
Occupation 1—management, business, science, and arts (%)	11.10	67.60	30.35	6.44
Occupation 2—natural resources, construction, and maintenance (%)	1.00	52.50	13.28	4.30
Occupation 3—production, transportation, and material moving (%)	1.10	36.70	15.85	5.79
Self-employed unpaid family workers (%)	0.00	11.00	0.31	0.49
Unemployment rate (%)	0.00	18.40	4.80	1.90
Income ($)	7887	61,290	23,044	5460
House ownership (%)	20.10	93.70	73.15	7.69
Vehicle ownership (%)	0.00	78.00	6.30	3.64
Age (year)	21.60	62.20	40.14	4.97
Female (%)	24.20	59.20	50.54	2.78
Race 1—African American (%)	0.00	95.70	1.59	6.39
Race 2—Asian (%)	0.00	34.00	1.00	2.13
Race 3—Hispanic and Latino (%)	0.00	98.00	8.09	13.10

3.2. OLS Regression

As shown by the regression results listed in Table 3, the OLS regression model explain most of the variation ($R^2 = 0.606$) in the dependent variable (county-level LTPI). According to the results, the positively correlated independent variables includes temperature ($p < 0.001$); precipitation ($p < 0.001$); Occupation 1, 2, 3 ($p < 0.001$); self-employed unpaid family workers ($p < 0.001$); vehicle ownership ($p < 0.001$); age ($p < 0.001$); being female ($p < 0.001$); and being African American (Race 1) ($p < 0.001$).

While six other variables are negatively correlated with LTPI—tree canopy coverage ($p < 0.001$); unemployment rate ($p < 0.001$); commuting mode 2 ($p < 0.001$); income ($p < 0.001$); being Asian (Race 2) ($p < 0.01$); and being Hispanic and Latino (Race 3) ($p < 0.001$). As a global regression model, OSL estimates coefficients by globally minimizing the sum of squares of the errors of predicted results. The significant correlations found are universally applied without the consideration of any spatial variables or effects.

Table 3. Summary of OLS and spatial lag models with LTPI as a function of physical environmental factors, socioeconomic status, and demographic characteristics for all U.S. counties.

Variables	OLS (Adjusted R^2 = 0.606; R^2 = 0.608; AIC = 16,063; *F*-Statistic = 239.7 (*df*: 3088); *p*-Value: 0.000; Log Likelihood = −8009.86)		SLM (Nagelkerke Pseudo-R^2: 0.744; LR Test: 1320.8; AIC = 14,745; Rho (Spatial Lag) = 0.607; *p*-Value = 0.000; Log Likelihood = −7349.456)	
	Coefficient (95% Confidence Interval)	*p*	Coefficient (95% Confidence Interval)	*p*
Temperature (β_1)	0.45 (0.42, 0.48)	0.000 **	0.15 (0.12, 0.18)	0.000 **
Precipitation (β_2)	0.76 (0.63, 0.89)	0.000 **	0.26 (0.15, 0.36)	0.000 **
Tree canopy coverage (β_3)	−0.03 (−0.03, −0.02)	0.000 **	−0.02 (−0.02, −0.01)	0.000 **
Land cover (β_4)	0.07 (−0.02, 0.16)	0.128	0.10 (0.03, 0.17)	0.005 *
Walkability(β_5)	0.02 (−0.13, 0.09)	0.736	0.08 (0.0004, 0.17)	0.049
Unemployment rate (β_6)	−0.37 (−0.45, −0.30)	0.000 **	−0.10 (−0.16, −0.04)	0.000 **
Commuting Mode 1 (β_7)	−0.07 (−0.13, −0.02)	0.013	−0.05 (−0.09, −0.005)	0.029
Commuting Mode 2 (β_8)	−0.08 (−0.13, −0.03)	0.000 **	−0.04 (−0.08, −0.01)	0.011
Occupation 1 (β_9)	0.09 (0.05, 0.13)	0.000 **	−0.006 (−0.02, 0.01)	0.445
Occupation 2 (β_{10})	0.19 (0.15, 0.22)	0.000 **	0.13 (0.11, 0.16)	0.000 **
Occupation 3 (β_{11})	0.17 (0.14, 0.20)	0.000 **	0.09 (0.06, 0.11)	0.000 **
Self–employed unpaid family workers (β_{12})	0.41 (0.14, 0.67)	0.002 *	0.19 (−0.01, 0.39)	0.057
Income (β_{13})	−0.0004 (−0.0004, −0.0003)	0.000 **	−0.0002 (−0.0002, −0.0002)	0.000 **
House ownership (β_{14})	0.02 (−0.007, 0.04)	0.178	0.02 (0.003, 0.04)	0.023
Vehicle ownership (β_{15})	0.14 (0.09, 0.19)	0.000 **	0.07 (0.04, 0.11)	0.000 **
Age (β_{16})	0.08 (0.05, 0.11)	0.000 **	0.09 (0.07, 0.12)	0.000 **
Female (β_{17})	0.11 (0.07, 0.16)	0.000 **	0.07 (0.04, 0.11)	0.000 **
Race 1 (β_{18})	0.08 (0.06, 0.10)	0.000 **	0.06 (0.04, 0.07)	0.000 **
Race 2 (β_{19})	−0.12 (−0.20, −0.05)	0.000 **	0.02 (−0.03, 0.06)	0.456
Race 3 (β_{20})	−0.09 (−0.10, −0.08)	0.000 **	−0.04 (−0.05, −0.03)	0.000 **

* Coefficient significant at $p < 0.01$; ** Coefficient significant at $p < 0.001$. AIC: Akaike Information Criterion. LR test: Likelihood rate test. Sample size: $n = 3109$.

3.3. Spatial Regression

Comparing the three models, the results of Akaike information criterion (AIC) show that the two spatial regression models—SLM (AIC = 14,745; *pseudo* R^2 = 0.744) and GWR (AIC =13,415; R^2 = 0.856)—have better explanatory power than the OLS model (AIC = 16,063; R^2 = 0.608) for LTPI. The AIC and R^2 are measures of the relative quality of statistical models for a given dataset: the lower the AIC and the higher the R^2 value, the better fit of the model for the dataset. Furthermore, as to the two spatial regression models, the GWR model, with a lower AIC, works better than SLM. The results from the GWR model are shown in Table 4. The model fits the data well and explains most of the variation in the dependent variable according to the adjusted R^2 of 0.814. Its local R^2 values range from 0.54 to 0.96 as shown in Figure 2. The figure shows that most counties have high R^2 values of 0.68 or above, which indicates that the GWR model predicts LTPI accurately in these counties.

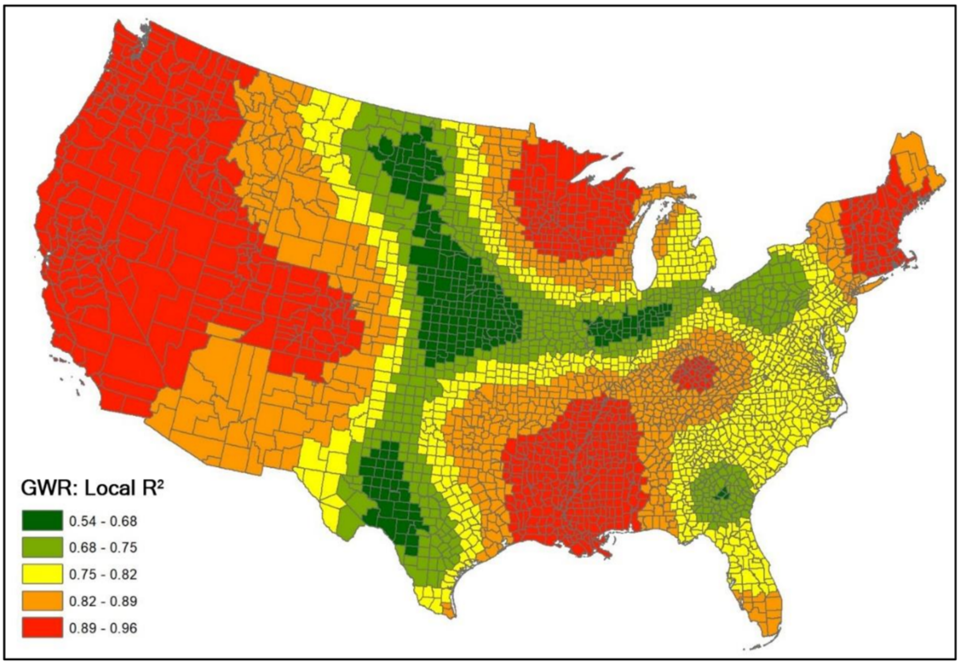

Figure 2. GWR model fit (R^2) by county.

Table 4. Summary of GWR model coefficient estimates with LTPI as a function of physical and social environmental factors for all U.S. counties.

Variables	GWR (Adjusted R^2 = 0.814; R^2 = 0.856; AIC = 13,415)							
	Positive Coefficient Estimates (%)	Significant Positive Coefficient Estimates (%) †	Negative Coefficient Estimates (%)	Significant Negative Coefficient Estimates (%) ††	Minimum Coefficient Estimate	Median Coefficient Estimate	Maximum Coefficient Estimate	Significant Coefficient Estimates (%) †††
β_1	77	72	23	21	−0.4624	0.2880	1.7652	60
β_2	68	33	32	15	−4.6594	0.2492	3.7850	27
β_3	22	25	78	44	−0.2460	−0.0177	0.1481	40
β_4	69	26	31	25	−1.2027	−0.1327	2.7811	26
β_5	34	24	66	40	−3.0601	−0.2528	1.2487	35
β_6	40	31	60	40	−1.1192	−0.0882	0.6460	36
β_7	30	1	70	30	−0.7806	−0.0882	0.1943	21
β_8	23	10	77	39	−0.6463	−0.1092	0.1500	32
β_9	37	28	63	16	−0.2925	−0.0224	0.3016	20
β_{10}	82	42	18	8	−0.2153	0.0938	0.4111	36
β_{11}	82	34	18	13	−0.1519	0.0651	0.3195	30
β_{12}	57	13	43	2	−3.2365	0.1035	2.9226	9
β_{13}	2	0	98	86	−0.0006	−0.0003	0.0001	84
β_{14}	34	16	66	35	−0.2633	−0.0314	0.2317	29
β_{15}	60	35	40	24	−0.6135	0.0376	0.7855	31
β_{16}	81	61	19	21	−0.3432	0.1209	0.3409	53
β_{17}	83	37	17	10	−0.4881	0.0983	0.3467	32
β_{18}	80	67	20	11	−1.2628	0.1312	1.1136	56
β_{19}	24	47	76	39	−1.4387	−0.2622	0.3968	41
β_{20}	16	0	84	55	−0.3264	−0.0617	0.1640	46

† Number of positive significant (|*t*-value| ≥ 2.00) coefficient estimates/Number of positive coefficient estimates. †† Number of negative significant (|*t*-value| ≥ 2.00) coefficient estimates/Number of negative coefficient estimates. ††† Percentage of significant (|*t*-value| ≥ 2.00) coefficient estimates. AIC: Akaike Information Criterion. Sample size n = 3109.

The residuals for both spatial models are visualized and shown in Figures 3 and 4. In these two residual maps, positive residuals (red and yellow in the figures) indicate underestimated LTPI levels, and negative ones (purple and blue in the figures) indicate overestimated LTPI levels. As shown in the two figures, there is no significant spatial autocorrelation in the residual maps of the spatial lag regression model (Moran's I = 0.0957) and the GWR model (Moran's I = 0.0293).

In Table 4, the percentages of positive and negative coefficients, as well as the percentage of significant coefficient estimates, show that relevant environmental factors are mostly inconsistent regarding their associations across all counties. The columns of significant positive coefficient estimates (%) and significant negative coefficient estimates (%) indicate the percentage of the positive and negative coefficient estimates that are statistically significant, while the column of the significant coefficient estimates (%) shows the percentage of significant coefficient estimates among all counties based on the corresponding t-values ($|t\text{-value}| \geq 2.00$). Given the coefficients for two of the variables are significant only in 30–50% of the counties, and that for most of the counties these coefficients are not different from zero (have no effect), we have to interpret the results carefully. For instance, if a coefficient's t-value is not significant, the common advice is that it should not be interpreted it at all because we cannot be sure that the value of the corresponding parameter in the underlying regression model is not really zero. In light of this caveat, we discuss the results of the local regression models as follows.

Based on the t-values, for the self-employed unpaid family workers (β_{12}), only 9% of the counties have significant associations. In addition, precipitation (β_2), land cover (β_4), commuting mode-1 (β_7), occupation-1 (β_9), and house ownership (β_{14}) have low percentages of counties (smaller than 30%) with statistically significant associations. On the contrary, income (β_{13}) has a strong consistent negative association between income and LTPI (i.e., poor people tend to be less active) in 98% (86% of them are statistically significant) of U.S. counties. The temperature (β_1) and race-3 (β_{20}) are also crucial factors, whose coefficients are significant for 60% and 56% of all the counties respectively. All the other variables have fair percentages of significant coefficient estimates. Among them, considering only the significant coefficients, Occupation 2 (β_{10}) show fairly consistent positive associations with LTPI, while being Hispanic and Latino (β_{20}) indicates fairly consistent negative correlations with LTPI. Other variables present inconsistent relationships.

With the relatively inconsistent results concerning the environmental correlates of LTPI, we find evidence of spatial non-stationarity. Tree canopy coverage (β_3) and Race 2 (β_{19}) are chosen as two examples to illustrate the existence of spatial non-stationarity in the relationships between LTPI and environmental factors. Except for the GWR local coefficient for these two variables, the corresponding t-values are also mapped because the t-values help readers to effectively interpret the geographic distribution of the parameter estimates as well as their significance [87]. As shown in Figures 5 and 6, the association between tree canopy coverage (β_3) and LTPI fluctuates from negative (blue in Figure 5) to positive (red in Figure 5), with t-values (40% of them are statistically significant) illustrated in Figure 6. It can be seen that most counties have a significant negative association while some have a significant positive association. All the other counties do not have any significant correlation as indicated by the t-values. Figure 7 illustrates that the association between race-2 (β_{19}) and LTPI also varies from negative (blue in Figure 7; 39% of them are statistically significant) to positive (red in Figure 7; 47% of them are statistically significant) while others do not have any significant association as indicated by the t-values illustrated in Figure 8. It can be seen from these figures that the counties with large positive and negative coefficients are statistically significant (as revealed by the t-values). These variations indicate that the relationships between environmental correlates and LTPI at the county level are spatially non-stationary.

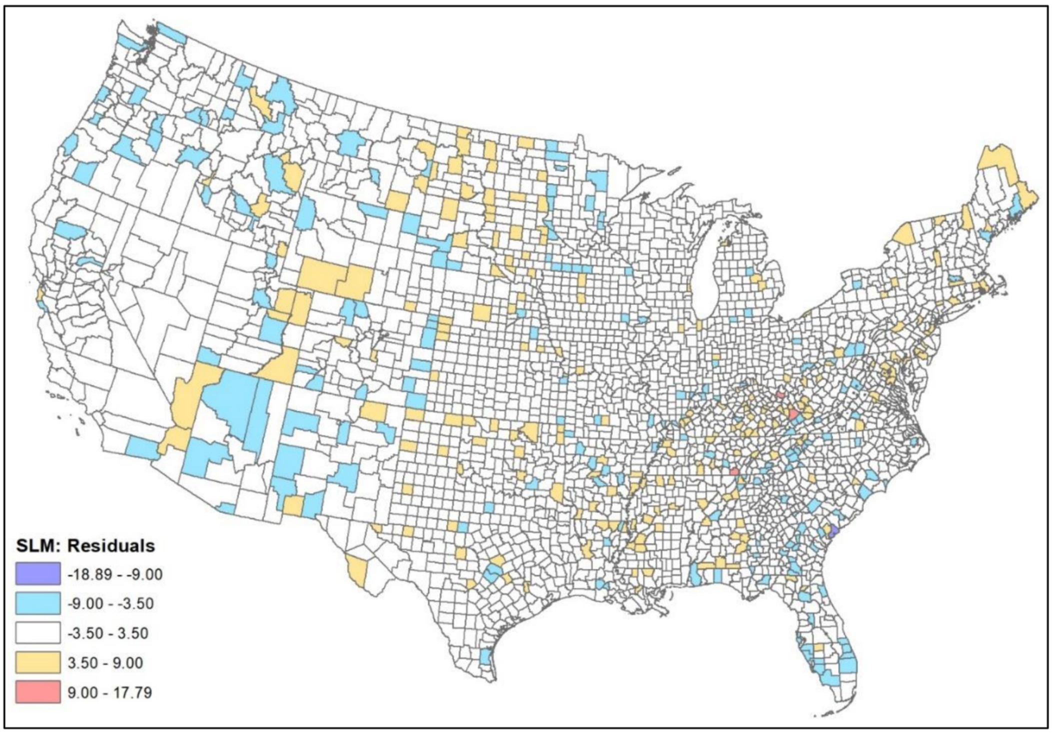

Figure 3. Residuals of LTPI at the county level for SLM.

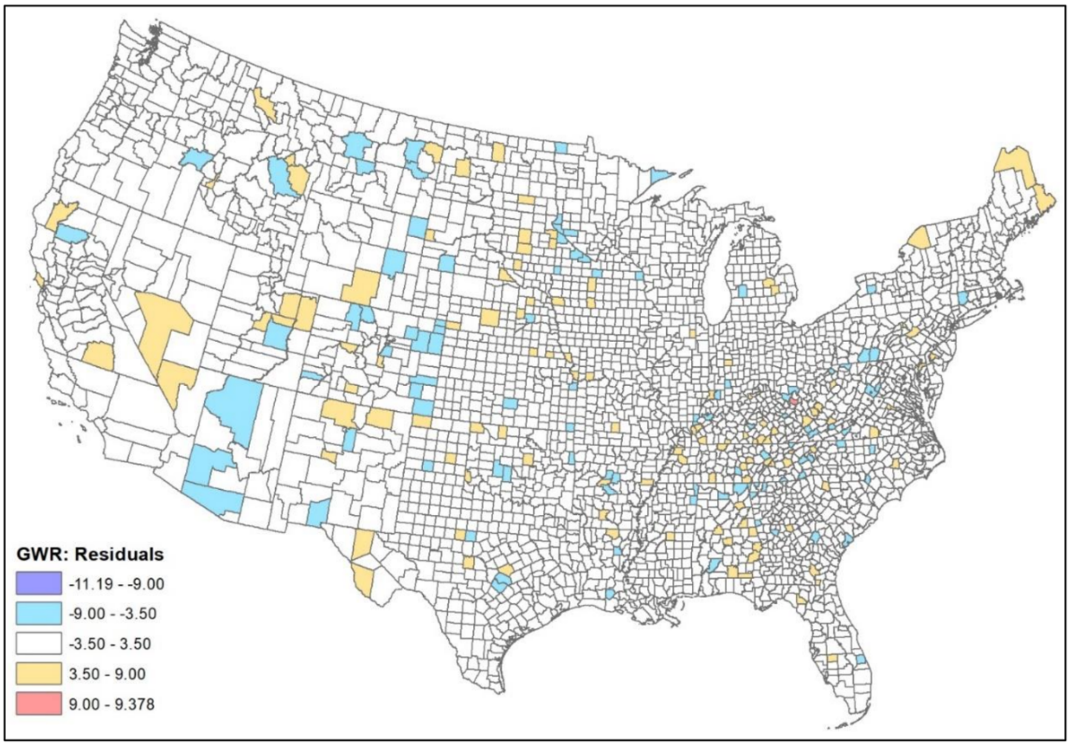

Figure 4. Residuals of LTPI at the county level for GWR.

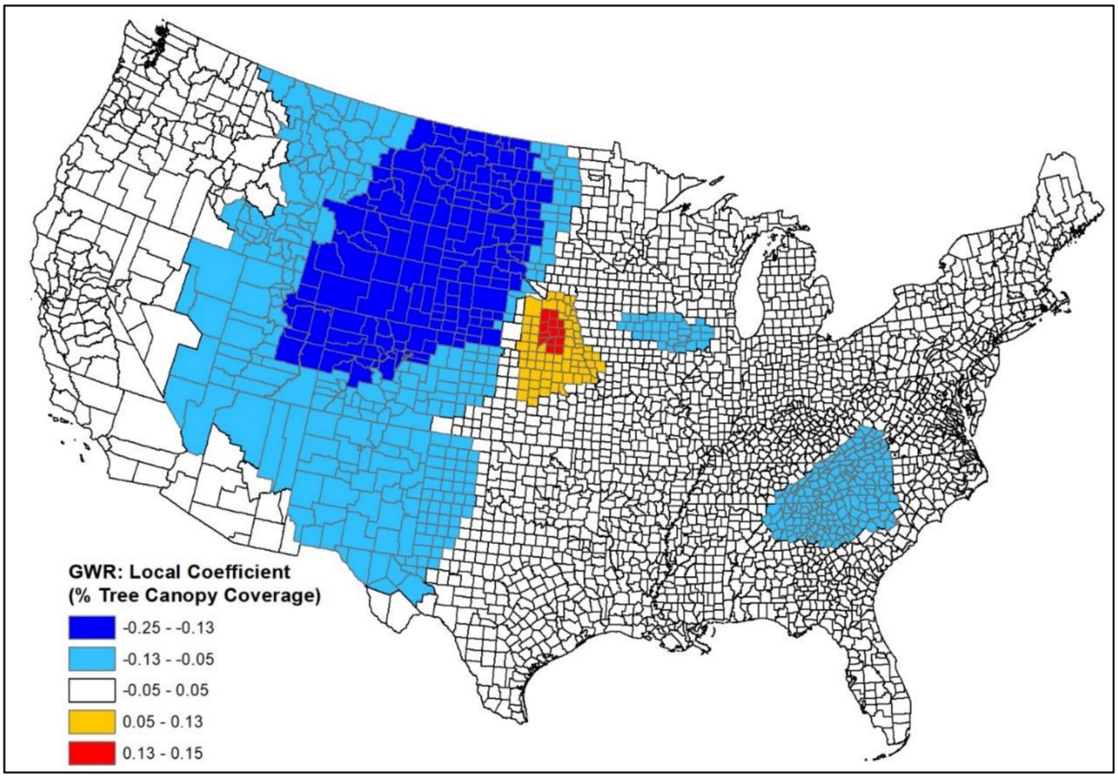

Figure 5. GWR local coefficient between LTPI prevalence and tree canopy coverage at the county level.

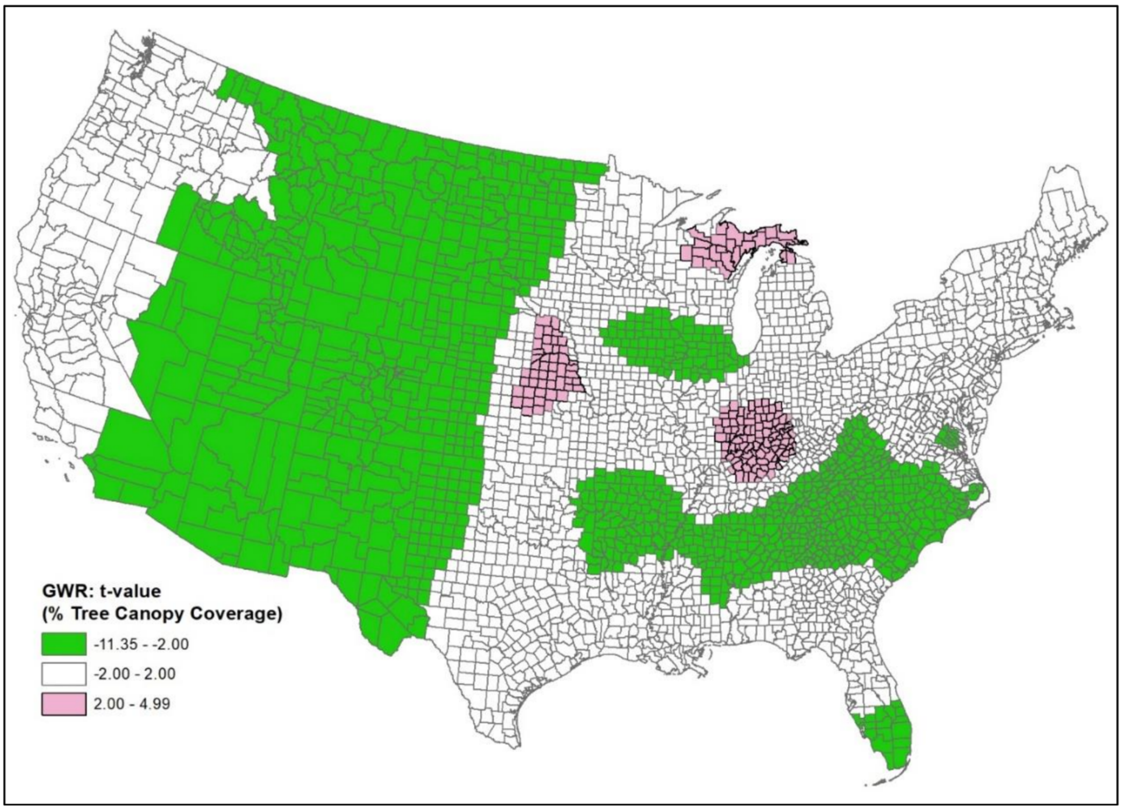

Figure 6. GWR *t*-value of tree canopy coverage at the county level.

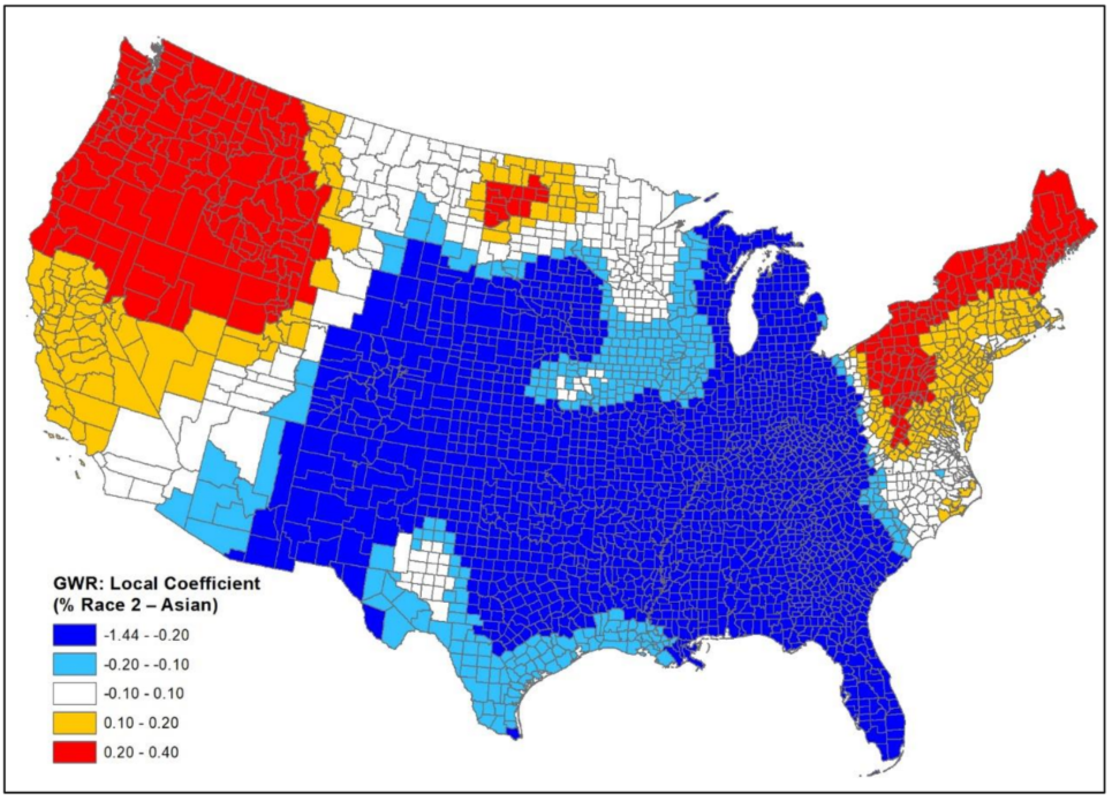

Figure 7. GWR local coefficient between LTPI prevalence and the percentage of residents who are Asian.

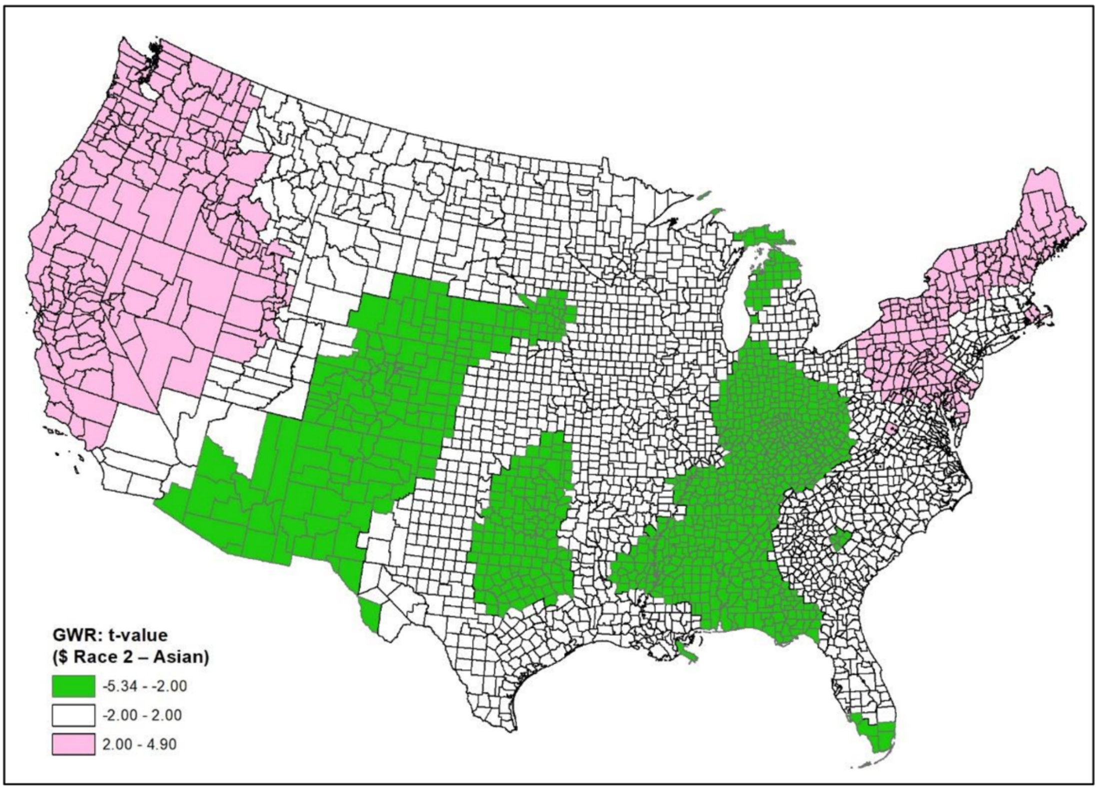

Figure 8. GWR *t*-value of the percentage of residents who are Asian.

We further investigate four selected coefficient estimates—tree canopy coverage (β_3), walkability (β_5), income (β_{13}), and race-2 (β_{19})—of the GWR model for the 20 most populous U.S. counties (see Table 5). Most big cities are located in these 20 counties (bold polygons in Figure 1), which LTPI researchers may be interested in. The shaded coefficients in the table are statistically significant ($|t\text{-value}| \geq 2.00$). The R^2 values of the 20 local models are high, ranging from 0.702 to 0.962. Income (β_{13}) consistently shows a significant negative association with LTPI in the 20 counties. Note that the coefficients and 95% CI for income (β_{13}) are close to zero because it has large values (ranging from 7887 to 61,290). Tree canopy coverage (β_3) consistently shows a significant negative association with LTPI in 9 out of the 20 counties, while the other half of the counties do not have significant coefficients. Also, the walkability (β_5) and Race 2 (β_{19}) have mixed associations. As further demonstrated in Table 6, in the 20 most populous U.S. counties, no significant correlation is found for Commuting Mode 1 (β_7) and Occupation 1 (β_9). Also, different from the results of all counties, only temperature (β_1), walkability (β_5), unemployment rate (β_6), age (β_{16}), and Race 2 (β_{19}) have inconsistent associations with LTPI while all the other contextual factors indicate relatively consistent associations.

Table 5. Summary of 4 selected coefficient estimates of GWR model for the 20 most populous US counties

County	State	β_3	95 CI	β_5	95 CI	β_{13}	95 CI	β_{19}	95 CI	Local R^2
Santa Clara	CA	0.0027	(−0.06, 0.06)	−0.3870	(−1.00, 0.23)	−0.0002 *	(−0.00, −0.00)	0.1741 *	(0.03, 0.32)	0.955
King	WA	−0.0210	(−0.06, 0.02)	0.4379	(−0.51, 1.38)	−0.0005 *	(−0.00, −0.00)	0.3608 *	(0.01, 0.71)	0.946
Los Angeles	CA	−0.0358	(−0.07, −0.00)	−0.4353 *	(−0.84, −0.03)	−0.0003 *	(−0.00, −0.00)	0.1165 *	(0.01, 0.22)	0.919
Orange	CA	−0.0382 *	(−0.06, −0.01)	−0.3063	(−0.66, 0.05)	−0.0003 *	(−0.00, −0.00)	0.0535	(−0.04, 0.15)	0.910
San Bernardino	CA	−0.0464 *	(−0.07, −0.02)	−0.3292	(−0.68, 0.02)	−0.0003 *	(−0.00, −0.00)	0.0594	(−0.04, 0.16)	0.906
Clark	NV	−0.0625 *	(−0.09, −0.03)	−0.3423 *	(−0.67, −0.01)	−0.0003 *	(−0.00, −0.00)	0.0698	(−0.03, 0.17)	0.902
San Diego	CA	−0.0372 *	(−0.05, −0.02)	−0.1495	(−0.45, 0.15)	−0.0003 *	(−0.00, −0.00)	−0.0264	(−0.11, 0.06)	0.898
Riverside	CA	−0.0403 *	(−0.06, −0.02)	−0.1768	(−0.48, 0.13)	−0.0003 *	(−0.00, −0.00)	−0.0162	(−0.10, 0.07)	0.898
Maricopa	AZ	−0.0407 *	(−0.06, −0.02)	0.0292	(−0.24, 0.30)	−0.0003 *	(−0.00, −0.00)	−0.1413 *	(−0.23, −0.05)	0.874
Harris	TX	−0.0048	(−0.02, 0.02)	−0.3865	(−1.11, 0.34)	−0.0002 *	(−0.00, −0.00)	−0.1942	(−0.45, 0.06)	0.857
Queens	NY	−0.0230	(−0.05, 0.01)	0.2636 *	(0.03, 0.50)	−0.0002 *	(−0.00, −0.00)	0.1138	(−0.05, 0.27)	0.856
New York	NY	−0.0221	(−0.05, 0.01)	0.2583 *	(0.01, 0.50)	−0.0002 *	(−0.00, −0.00)	0.1110	(−0.05, 0.27)	0.854
Kings	NY	−0.0222	(−0.05, 0.01)	0.2565 *	(0.02, 0.49)	−0.0002 *	(−0.00, −0.00)	0.1132	(−0.05, 0.27)	0.851
Dallas	TX	−0.0057	(−0.03, 0.02)	−0.4800	(−1.31, 0.35)	−0.0002 *	(−0.00, −0.00)	−0.3829 *	(−0.70, −0.07)	0.850
Miami-Dade	FL	−0.0201 *	(−0.03, −0.01)	−0.5922 *	(−0.78, −0.40)	−0.0004 *	(−0.00, −0.00)	−0.2133 *	(−0.40, −0.03)	0.840
Broward	FL	−0.0213 *	(−0.03, −0.01)	−0.6060 *	(−0.83, −0.39)	−0.0004 *	(−0.00, −0.00)	−0.2160 *	(−0.42, −0.01)	0.835
Tarrant	TX	−0.0057	(−0.03, 0.02)	−0.5548	(−1.35, 0.24)	−0.0002 *	(−0.00, −0.00)	−0.3952 *	(−0.70, −0.09)	0.834
Cook	IL	−0.0327 *	(−0.06, −0.01)	0.0424	(−0.36, 0.44)	−0.0003 *	(−0.00, −0.00)	−0.2707	(−0.61, 0.06)	0.798
Wayne	MI	−0.0021	(−0.02, 0.02)	0.0073	(−0.34, 0.35)	−0.0004 *	(−0.00, −0.00)	−0.2406	(−0.68, 0.20)	0.751
Bexar	TX	−0.0164	(−0.05, 0.02)	−0.6656	(−1.62, 0.29)	−0.0002 *	(−0.00, −0.00)	−0.2040	(−0.45, 0.04)	0.699

95 CI: 95% confidence interval. * Significant coefficient estimates (| t-value | $\geq$ 2.00).

Table 6. Summary of percentages of positive and negative coefficient estimates of GWR model for the 20 most populous US counties.

	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	β_{10}	β_{11}	β_{12}	β_{13}	β_{14}	β_{15}	β_{16}	β_{17}	β_{18}	β_{19}	β_{20}
Positive Coefficient Estimates (%)	65	60	5	80	35	15	45	0	50	100	95	65	0	70	85	90	85	85	45	10
Significant Positive Coefficient Estimates (%) †	69	25	0	13	43	33	0	0	0	45	47	38	0	14	35	50	35	82	33	0
Negative Coefficient Estimates (%)	35	40	95	20	65	85	55	100	50	0	5	35	100	30	15	10	15	15	55	90
Significant Negative Coefficient Estimates (%) ††	14	0	47	0	31	41	0	70	0	0	0	0	100	0	0	100	0	0	45	72
Significant Coefficient Estimates (%) †††	50	15	45	10	35	40	0	70	0	45	45	25	100	10	30	55	30	70	40	65

† Number of positive significant (| t-value | $\geq$ 2.00) coefficient estimates/Number of positive coefficient estimates. †† Number of negative significant (| t-value | $\geq$ 2.00) coefficient estimates/Number of negative coefficient estimates. ††† Percentage of significant (| t-value | $\geq$ 2.00) coefficient estimates.

4. Discussion and Conclusions

This study examined the effects of various contextual factors on LTPI at the county level in the contiguous U.S. The associations between these factors and LTPI were investigated using a non-spatial regression model (OSL) and two spatial regression models (SLM and GWR). By comparing the results of these three models, we found the existence of spatial autocorrelation and non-stationarity, which could lead to biased estimators but were mostly ignored in previous studies. While utilizing spatial regression models to address spatial autocorrelation, the inconsistent associations found between environmental factors and LTPI highlights the existence of spatial non-stationarity, which is another source of uncertainty for environmental health studies besides the MAUP and the UGCoP. The existence of spatial non-stationarity can partly explain the inconsistent findings in previous research conducted at different geographic locations. Also, the observed associations between environmental variables and LTPI are helpful for developing policies and interventions to create environmental settings that diminish LTPI at the county level.

As indicated by the result of the Moran's *I* statistic, LTPI is spatially autocorrelated, which has rarely been considered in previous studies [13,21,41,70,88]. The lagged variable (Rho = 0.607) of SLM indicates the effect of the dependent variable in the neighbors on the dependent variable in the focal area. Neglecting the problems of spatial autocorrelation may lead to biased estimators and inaccurate results. Therefore, the spatial regression models, such as the SLM and GWR models, should be used in environmental health research. In this study, the spatial regression models perform better than the conventional OLS model based on the values of AIC and Log likelihood listed in Tables 3 and 4. As indicated in Figures 3 and 4, the low values of Moran's *I* (SLM: 0.0957; GWR: 0.0293) in the residual maps suggest that the two spatial regression models handled the spatial autocorrelation in LTPI across different counties well and there is no systematic error in the models. The results also indicate that the performance of the GWR is better than the SLM in several ways. The Moran's *I* of the SLM (0.0957) is larger than the Moran's *I* of the GWR (0.0293), indicating that the GWR model may provide better predictions than the spatial lag model. Note that the Akaike information criterion (AIC) of the GWR model is 13,415, which is lower than the one of SLM (AIC = 14,745). These results corroborate the findings in previous research that GWR outperformed the spatial lag model in its explanatory power and predictive accuracy [89].

In addition, variations in the associations between environmental factors and LTPI across counties indicate the existence of spatial non-stationarity in such relationships, which has largely been ignored in previous research [13,70]. Different from conventional OLS and SLM regression models, the coefficient estimates of the environmental factors in the GWR show inconsistent results as indicated in Table 4. The results of the GWR model with *t*-values could help to investigate the various effects of environmental factors at different geographic locations. That is, one contextual factor can have statistically positive or negative coefficients ($|t\text{-value}| \geq 2.00$) or no correlation ($|t\text{-value}| < 2.00$) depending on geographic location, which can be justified by the results from the local models. For instance, tree canopy coverage (β_3) is significantly positively associated with LTPI for about 6% of the counties and negatively associated with LTPI for another 34% of the counties, while there is no significant association in the rest of the counties (60%). Figures 5 and 6 visually reveal that its associations with LTPI fluctuate from negative (blue colored polygons) to positive (red colored polygons) and the corresponding *t*-value of each county. As shown in the figures, most of the western counties in states like Idaho, Nevada, Arizona, Utah, and Colorado have significantly negative coefficients, which means the percentage of tree canopy coverage is negatively associated with LTPI. In other words, the higher the percentage of tree canopy coverage, the lower the LTPI level. It is highly possible that these counties are mostly located in the semiarid and desert area with a lack of trees and green spaces, and thus tree canopy coverage may work more than expected to decrease LTPI. This finding also supports the empirical evidence of negative associations between tree canopy and LTPI in previous research [90–92]. On the other hand, tree canopy coverage (β_3) in 6% of the counties has a positive association, and in 60% of the counties, it is not associated with LTPI, which does not correspond to the expected association. This finding may be interpreted in different perspectives considering the complicated interactions of LTPI with other environmental factors. Another example is Race 2 (β_{19}), which is positively associated with LTPI in 11% of the counties while negatively associated with LTPI in 30% of the counties, and there is no significant association found in the other 59% of the counties. The distribution of the coefficients between Race 2 and LTPI as well as the *t*-values are illustrated in Figures 7 and 8. It can be seen from the figures that there is a general pattern that in the western and northeastern counties, there are significantly positive relationships, while the relationship is significant and negative in the central and southern counties. These mixed results indicate that the relationships between environmental factors and LTPI at the county level are spatially non-stationary. Due to spatial non-stationarity, the direction of the association between environmental factors and LTPI varies by geographic location, which cannot be explained by classical 'global' models. Thus, the research findings at one location may not be generalized and applied globally. From the perspective of health policy, an effective policy that helps to decrease LTPI and promotes public health in one county may not be effective in another place due to spatial non-stationarity.

Different from the inconsistent associations found across all U.S. counties, some environmental factors show consistent associations with LTPI in the 20 most populous counties if not considering the non-significant estimates. For instance, tree canopy coverage (β_3) has both positive and negative associations with LTPI as discussed above across all counties in the U.S., while it is only found to have significant negative coefficient estimates (see Table 5). Without surprise, the most populous counties usually are densely developed areas, and higher tree canopy coverage provides residents with more physical-activity-friendly spaces (e.g., parks) and therefore helps to decrease LTPI. In addition, as illustrated in Table 6, considering only the statistically significant estimates, contextual factors—such as Commuting 2 (β_8), Occupation 2 (β_{10}), and Occupation 3 (β_{11})—are all found to have consistent associations with LTPI in the 20 most populous counties while they are inconsistent across all counties in the U.S. (see Table 4). That means, due to the differences between rural and urban areas, there is a likelihood that environmental covariates can have consistent associations with LTPI in big cities despite the fact that they are inconsistently associated with LTPI across all counties in the U.S. Another interesting finding is the significant positive associations between walkability (β_5) and LTPI in the northeastern counties (e.g., Queens, New York, and Kings), while walkability is negatively associated with LTPI in western and southeastern U.S. counties (e.g., Los Angeles, Clark, Miami-Dade, and Broward), and there is no significant relationships between them for all the other counties. It may be because of potential differences in culture and social structure among different areas of the U.S. Nonetheless, the reasons for the contrary associations are not clear, and further investigation is needed.

Consistent with expectations but in contrast to most previous studies, the findings of this study indicate the existence of spatial non-stationarity in environmental health studies. Thus, it is possible and not surprising that two similar studies concerning the effects of the same environmental factor on LTPI would observe inverse associations if they are conducted in different regions of the country. This is perhaps one of the reasons why research findings were often inconsistent concerning the effects of environmental factors on health behaviors and outcomes, given that past studies on the same issue (e.g., LTPI) were often conducted in different geographic locations (e.g., [93,94]). The assessment of spatial non-stationarity and the varying environmental effects on LTPI as a function of geographic location may help us investigate and better understand how space plays a role in the prevalence of LTPI across space [95].

This study found the location-based relationships between LTPI and different environmental, socio-economic, and demographic variables. These variables will be helpful for developing location-based policies and intervention measures that aim at decreasing LTPI and promoting health. For instance, communities in high-temperature and high-precipitation areas should provide more indoor physical activity facilities instead of outdoor facilities. Intervention policies that target social groups with higher levels of LTPI (e.g., women and African Americans) should be developed to encourage them to increase their physical activity levels. Also, in light of the negative association between tree canopy coverage and LTPI in urban areas, constructing more green spaces or parks in densely developed areas will be helpful for encouraging more physical activity. Other possible policies include promoting the use of active transport (e.g., walking), more flexible work schedules, and provision of more indoor physical activity facilities in densely developed areas.

This research has several limitations that need to be addressed in future studies. First, although 20 contextual factors are selected for the analysis, other contextual factors may also influence LTPI. Therefore, more contextual variables need to be considered and explored in future studies. For instance, more physical environmental variables can be included in the model, such as road network connectivity, the quality and density of sidewalks, the number of bus lines, and the length of walking and biking trails. Furthermore, this study used tree canopy coverage as a proxy for assessing the overall accessibility of green spaces in a county to its residents: the more green space a country has, the easier its residents can access parks and green spaces. However, future studies should consider measuring accessibility to green space more directly and including it to the models. Second, as an exploration of spatial non-stationarity, this study did not consider NLTPI, which has also shown to be associated with specific environmental factors. Further analysis of NLTPI is needed to understand the effects of environmental factors on physical inactivity comprehensively. Third, this is a cross-sectional study that used LTPI and environmental data only for the year 2011. Longitudinal analysis based on multi-year data may provide further insights into the effects of many environmental factors on people's physical inactivity. Lastly, this study explored the inconsistent associations between LTPI and environmental factors at the county level to illustrate the existence of spatial non-stationarity and its influence on the results, which is underexplored. Spatial non-stationarity and its influence on the results may be different at various spatial scales. Thus, further investigation on how geographic scale may affect spatial non-stationarity is needed. Explorations of the effects of the MAUP (e.g., scale effects) and the UGCoP on the inconsistent results are outside the scope of this paper. Future study needs to thoroughly investigate all these three sources of contextual uncertainty through experiments conducted at different spatial scales with varying methods of measurement in environmental health studies (e.g., [96–98]).

This study highlights the existence of spatial non-stationarity and the importance of spatial regression model in environmental health studies. It provides useful insights into the environmental influences on health behaviors, such as LTPI. Since spatial autocorrelation and spatial non-stationarity are often present in public health data, they should be addressed seriously to generate reliable results. LTPI is and will continue to be one of the most critical public health concerns in the U.S., the knowledge generated from this study will assist community health professionals, city planners, and government decision-makers in diminishing LTPI and mitigating the rise of inactivity-related chronic disease.

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