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Spatial analysis of neighborhood vitality determinants on physical activity: a case study of Chicago

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Abstract Previous research has largely ignored the neighborhood's vitality in creating a relaxing and safe environment for the prevalence of physical activity. Neighborhood vitality is critical for a healthy urban environment, and outdoor safety can only be ensured by reducing crime and repurposing underutilized spaces. A global regression and two local regressions are used to model the cross-sectional, ecological relationships between physical inactivity and multiple environmental variables in Chicago, United States. Multiscale geographically weighted regression showed the best model fit ($R^2 = 0.92$). According to the findings, the factors influencing physical inactivity in Chicago neighborhoods are crime, green space, and vacant properties. Physical inactivity is rising in neighborhoods with a high share of 17 aged and younger and children living in poverty. Besides that, the relationships between neighborhood covariates and physical inactivity are spatially heterogeneous. Our study advocates for multiscale and multidisciplinary policies and institutions to create comfortable outdoor spaces for controlling and reducing physical inactivity prevalence.

Keywords Physical inactivity · Crime · Green space · Neighborhood vitality

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Introduction

An inactive lifestyle is a major public health issue that kills nearly 5 million people worldwide (Buck et al., 2019; Orstad et al., 2020). The costs associated with physical inactivity account for more than 11% of total health care expenditures and are estimated to be $117 billion in 2021 (U.S. America Health Ranking). While more than half of the world's population lives in urban neighborhoods with limited leisure time, understanding physical activity in urban neighborhoods is vital to improving population health (Faka et al., 2019).

There is a long history of research on the impact of neighborhood characteristics on people's healthy behavior. This study is based on the assumption that neighborhood determinants have behavioral consequences. Certain physical and environmental factors enable, facilitate, or inhibit outdoor physical activity (McGinn et al., 2007; Wu et al., 2019). Gehl (2001) classifies outdoor activities of neighborhoods into three categories: necessary, optional, and social. Necessary activities are all the ones that are vital for residents in their socio-cultural context (e.g., going to work, going to school, buying groceries). Optional activities are usually undertaken during free time, for pleasure, and self-initiative, while social activities are the ones that individuals perform in groups. Much research has been conducted to investigate the relationship between neighborhood characteristics and physical and mental well-being. These studies have primarily focused on neighborhood attachment (e.g., Moulay et al., 2018), social cohesiveness (e.g., Kim & Park, 2021), and access to urban facilities (e.g., Feng & Astell-Burt, 2019; Xiao et al., 2022). To the best of our knowledge, the geographical and urban planning aspects of creating a relaxing and safe environment in various neighborhoods ranging from purely residential to mixed commercial residential have not been thoroughly examined.

In this study, "neighborhood vitality" is conceptualized and measured as the extent of a relaxing and safe environment (Jacobs, 1961). While the literature supports the presumption that abandoned urban spaces, outdoor crimes (Kondo et al., 2018), and a lack of green space (Shanahan et al., 2016) contribute to an unsafe and stressful environment, others (Jacobs, 1961; Lynch, 1984; Zeng et al., 2018; Zumelzu & Barrientos-Trinanes, 2019; Mouratidis & Poortinga, 2020) addressed the multifaceted dimensions of neighborhood vitality, such as safety, legibility, diversity of land uses, variety of activities, social interactions, ecological stability, and accessibility.

The vitality of a neighborhood as a result of the quality of the built environment implies health and well-being. Smith and Miller (2013) investigated the socioeconomic environment of neighborhoods as a measure of vitality, whereas Lunecke and Mora (2018) assessed neighborhood vitality based on the accessibility of retail stores, transportation, and local jobs. Maas (1984), on the other hand, defined vitality as people's persistence in an urban space, activities, opportunities, and location. According to Zumelzu and Barrientos-Trinanes (2019), vitality should include the range of experiences required for a healthy lifestyle, including physical activity.

We use identifications from Maas (1984), Rossi et al. (2015), and Zumelzu and Barrientos-Trinanes (2019), where the vitality of the outdoors is heavily reliant on the inhabitants' comfort and their willingness to engage active lifestyle. Safety is the underlying factor in providing comfort and stimulating personal and social activities (Jacobs, 1961). Safety is a social construct (e.g., crime) resulting from neighborhoods' social and physical layouts. Outdoor criminal activity predominates, and urban residents perceive higher local crime rates than suburban residents. People feel less safe, have less trust in others, and harm the community. Besides that, vacant property contributes to urban blight, creating an unsafe environment of conflict, fear, and crime that encourages inactive and sedentary lifestyles (Cheezum et al., 2019; Hohl & Lotfata, 2022; Kondo et al., 2018; Pinto et al., 2022).

In addition, urban green spaces contribute to creating a relaxing environment for individual and social activities (Lopes & Camanho, 2013). They help to develop comfortable areas for personal activities. They can also reduce air pollution in the neighborhood, making it more conducive to residents' outdoor activities, leisure, and social interactions (Rossi et al., 2015), and contributing to its vitality. While the availability of green space is essential for leading an active lifestyle, Luo et al. (2021) found inconsistencies in the relationship between green space and physical activity behavior. The effects of green spaces on health should be evaluated using three indicators: accessibility, availability, and visibility of green spaces, all of which have varying impacts on the level of physical activity. These three are associated with distinct, albeit frequently overlapping, mechanistic pathways that influence health (Nieuwenhuijsen et al., 2017).

This paper investigates the role of neighborhood safety and greenness as indicators of neighborhood vitality in developing and maintaining healthy behaviors, as it provides opportunities for personal leisure-based physical activities, which may improve health (Moulay et al., 2018). Physical inactivity results from the local socio-ecological determinants and is a subject of discourse in urban planning (Macfarlane et al., 2021; Sentell et al., 2020; Sallis et al., 2012). The purpose of this study is to (1) describe the spatial distribution of physical inactivity in Chicago while it ranks among the most physically inactive cities in the United States; (2) identify areas of elevated physical inactivity; (3) describe the environmental determinants associated with physical inactivity; and (4) suggest priority areas for interventions.

Materials and method

Study area

Chicago, Illinois, ranks among the most physically active cities in the United States, with a physical inactivity Score of 62.75 out of 100 (Wallet Hub, 2022). Physical inactivity is a major contributor to the obesity epidemic (Congdon, 2019), and nearly two-thirds of Chicago adults (69%) are overweight or obese (U.S. CDC, 2021a). Overweight and obesity rates in Chicago neighborhoods ranged from 26% in Lincoln Park (a predominantly Caucasian neighborhood) to 45% in Oakland (a predominantly African-American neighborhood) to 52.3% in South Lawndale/Little Village (a predominantly Latino neighborhood) (U.S. Healthy Chicago). Low activity levels increased further during the pandemic as a result of changing perceptions of safety in Chicago neighborhoods plagued by rising crime. In 2020, the crime rate in Chicago was 3926 per 100,000 people. This is 67% higher than the national average and significantly higher than Illinois' average rate of 1985 crimes per 100,000 people (U.S. Chicago Police Department).

Data

We obtained cross-sectional model-based estimates of current physical inactivity among the population for all 796 census tracts in Chicago ("Physical inactivity" variable). The physical inactivity data, along with many other health-related measures, are provided by the Centers for Disease Control and Prevention's PLACES Project and are based on responses to the Behavioral Risk Factor Surveillance System survey (U.S. CDC, 2021b). Physical inactivity is defined as the percentage of respondents who said they did not engage in leisure-time physical activity. Respondents aged 18 years and older who answered "no" to the following question: "Did you participate in any physical activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise during the previous month, other than your regular job?".

Besides, we obtained census tract-level predictor variables from various sources: First, the vacant housing percentage ("Vacant housing" variable) is provided by Chicago Health Atlas (U.S. CHA, 2018). Second, we quantified the Green Space ("Green Space" variable) as the mean of the green space index per census tract using Normalized Difference Vegetation Index (NDVI) data from Landsat 8 NASA Earth Data (Google Earth Engine; Chander et al., 2009). Third, the crime ratio quantified crime ("crime ratio" variable) using data provided by the Chicago Data Portal as the ratio between the number of crimes and the corresponding census tract population (U.S. CDP, 2019). Fourth, the percentage of children per low-income household ("Children in poverty" variable) was provided from City Health Dashboard (U.S. CDH). Lastly, the percentage aged 17 and younger ("aged 17 & younger" variable) per the corresponding census tract population provided by American Community Survey (U.S. ACS, 2018). We obtained census tract polygon geometries as TIGER/Line Shapefiles from the United States Census Bureau in order to conduct mapping and spatial analysis using geographic information systems (GIS). The average tract size is 0.28 square miles with a 0.39 standard deviation. The census tract-level variables were linked to the geometries via their 11-digit FIPS codes.

Spatial statistical analyses

We identified significant predictors of physical inactivity prevalence using a global (i.e., city-wide) ordinary least squares (OLS) regression model. We assessed multicollinearity among predictor variables by computing the variable correlation matrix and ensuring that variance inflation factors (VIF) were below the recommended threshold of 2.5 (Craney & Surles, 2002). Additionally, the variables Gender, Minority, Education, Unemployment, Food Access, Land uses, and Air Pollution (i.e., particulate matter with a diameter < 2.5 µm [$PM_{2.5}$]) are excluded from the model to avoid multicollinearity. As a result, the predictor variables Green Space, Vacant Housing, Crime Ratio, Aged 17 and younger, Children in Poverty were included in our final regression model. We checked for heteroskedasticity by plotting residuals versus fitted values and checked for normality by the histogram of standardized residuals were two of our regression diagnostics. We then examined our OLS model for spatial residual autocorrelation, which violates the OLS assumptions (Anselin, 2001). Using global Moran's *I*, we looked for the presence of residual spatial autocorrelation (Moran, 1950).

We also employed the geographically weighted regression (GWR) model, an extension of the basic

OLS regression that allows for the exploration of local rather than global parameters (Brunsdon et al., 1998). GWR assumes that predictor variable is spatially heterogeneously associated with the response variable and enables monitoring of the spatial variance of regression model outcomes (Fotheringham et al., 2003). GWR models generate a set of local parameter estimates that show how a relationship varies across space. We employ an adaptive kernel function to account for the data's non-uniform spatial distribution. We determined the optimum bandwidth using an adaptive bi-square kernel by iterating the number of nearest neighbors that should be considered for the local regression (Oshan et al., 2019). The optimal bandwidth has the lowest Akaike Information Criterion (AICc) score (Fotheringham et al., 2003). Because the optimal bandwidth may vary across the predictors and is a priori unknown, we employed a multiscale geographically weighted regression (MGWR), whereas each predictor variable has its own bandwidth (Iyanda & Osayomi, 2021). This allows the scale of relationship non-stationarity to vary for each response-to-predictor variable relationship, as described in Eq. (1):

$$Y_i = \beta_0\left(u_i, v_i\right) + \sum_{j=1}^{m} \beta_{bwj}\left(u_i, v_i\right)x_{ij} + \varepsilon. \quad (1)$$

where β_0 is the intercept, x_{ij} represents an independent variable of each observation (u_i, v_i), ε is the error term, and b_{wj} in β_{bwj} indicates the bandwidth used to calibrate the *jth* conditional relationship. A broad bandwidth denotes a stationary process with a weak relationship to obesity prevalence. Technically, the MGWR model calibration is based on an iterative back-fitting procedure; thus, the computational overheads are high when handling a large number of observations (Fotheringham et al., 2017). We adopted the approach of Oshan et al. (2019) to run the GWR and MGWR using Python 3.10.1 (Van Rossum & Drake, 2009).

Results

Descriptive analyses

Figure 1 depicts the spatial distribution of physical inactivity prevalence in Chicago, Illinois. According to the findings, green space per census tract is high on Chicago's southern and northern sides, while the south and western sides have the highest percentage of vacant housing. Similarly, the crime rate is highest in the south and west. The proportion of people aged 17 and under and children living in poverty is highest in Chicago's western and southern suburbs.

Regression results

The OLS model revealed a positive relationship between green space, vacant housing, crime ratio, aged 17 and younger, and children in poverty. This suggests that tracts with a high proportion of green space, vacant housing, a crime ratio, aged 17 and younger, and children in poverty have a high prevalence of physical inactivity (Table 1). The model fit was adequate overall, with an adjusted R^2 of 0.69. The AICc for the linear model was 1,325.530, and the residual sum of squares (RSS) was 242.062. The Jarque–Bera Statistic confirmed that the OLS residuals have a normal distribution. The spatial analysis of residuals using the Moran's I test revealed that the residuals are spatially autocorrelated ($I = 0.281$, $p = 0.00$).

While describing non-stationary spatial relationships, the GWR mostly confirmed the OLS model's results. The GWR coefficients indicated the presence of spatial variation, as expected. The GWR model fit (AICc = 639.675, RSS = 59.736) had a higher adjusted R^2 of 0.90 than the OLS model, indicating that incorporating spatial structure accounts for previously unexplained variations. Moran's I test ($I = 0.083$, $p = 0.00$) still approves the presence of spatial autocorrelation of GWR residuals. MGWR, like GWR, confirms the OLS result, but its model (AICc = 508.561, RSS = 50.899) with an adjusted R^2 of 0.92 was higher than GWR. Moran's I test ($I = 0.006$, $p = 0.35$) of MGWR turns out to be statistically insignificant confirming a lack of residual spatial autocorrelation congruent with the model assumption.

Table 2 shows the results of the MGWR model. First, the optimal bandwidth ranges from 44 to 178 per census tract, suggesting that the independent variables operate on different scales. It shows that the independent variables "green space," "crime ratio," "vacant housing," and "Children in poverty" operate on a small spatial scale compared to "Aged 17 and

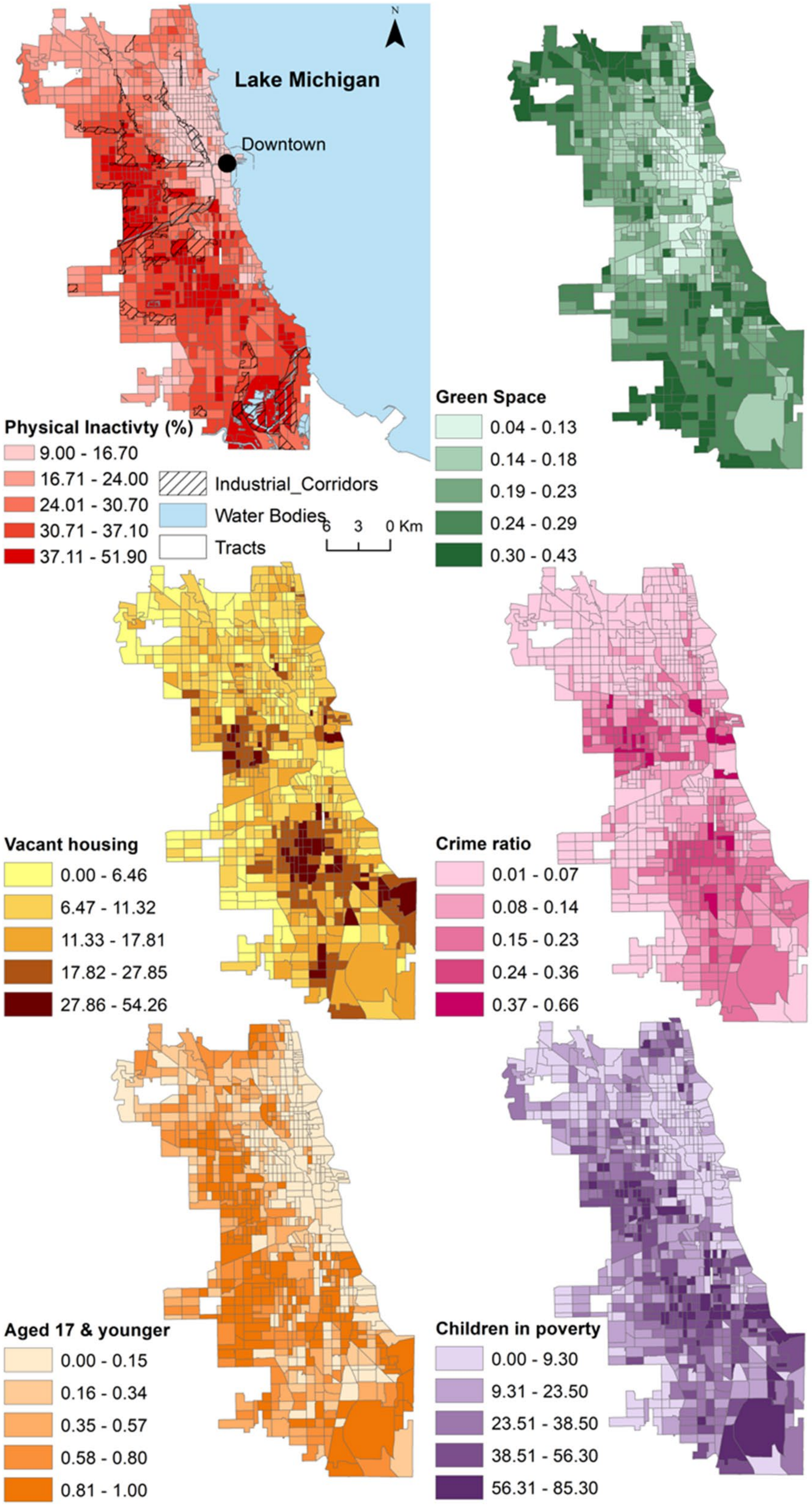


Fig. 1 Spatial Distribution of the variables

Table 1 OLS Results

Variable	Coefficient	Std Error	*t*-Statistic	*p* value	VIF
Intercept	11.70	0.63	18.55	0.00	–
Green space	15.99	2.89	5.52	0.00	1.10
Vacant housing	0.09	0.02	3.44	0.00	1.68
Crime ratio	10.02	2.52	3.97	0.00	1.62
Aged 17 and younger	8.87	0.63	14.02	0.00	1.37
Children in Poverty	0.22	0.01	19.72	0.00	1.62

Table 2 Estimation results of the MGWR

Variable	Mean	St.Dev	Min	Max	Bandwidth
Intercept	0.090	0.480	−0.885	0.763	44
Green Space	−0.011	0.148	−0.414	0.341	48
Crime ratio	0.116	0.107	−0.117	0.524	62
Vacant housing	0.051	0.107	−0.299	0.417	44
Children in poverty	0.276	0.094	0.064	0.763	48
Aged 17 and younger	0.165	0.064	0.031	0.318	138

younger". This is also supported by examining the spatial variability of local parameter values, which revealed that these predictors are primarily local rather than global. The variable measuring criminal activities determine physical inactivity for census tracts on the southern side. The crime ratio covariate indicates that an increase in criminal activity increases the prevalence of physical inactivity. A similar direction of the relationship can be seen for the variable characterizing vacant housing in the south. When analyzing the variables describing the social profile of the neighborhood, the aged 17 and younger predictor should be considered. This covariate is positively correlated with the prevalence of physical inactivity, and it has a significant effect almost everywhere in Chicago. The relationship is highly variable, as shown in Table 2. Physical inactivity and children aged 17 and younger and children from low-income families positively correlate across Chicago (Fig. 2).

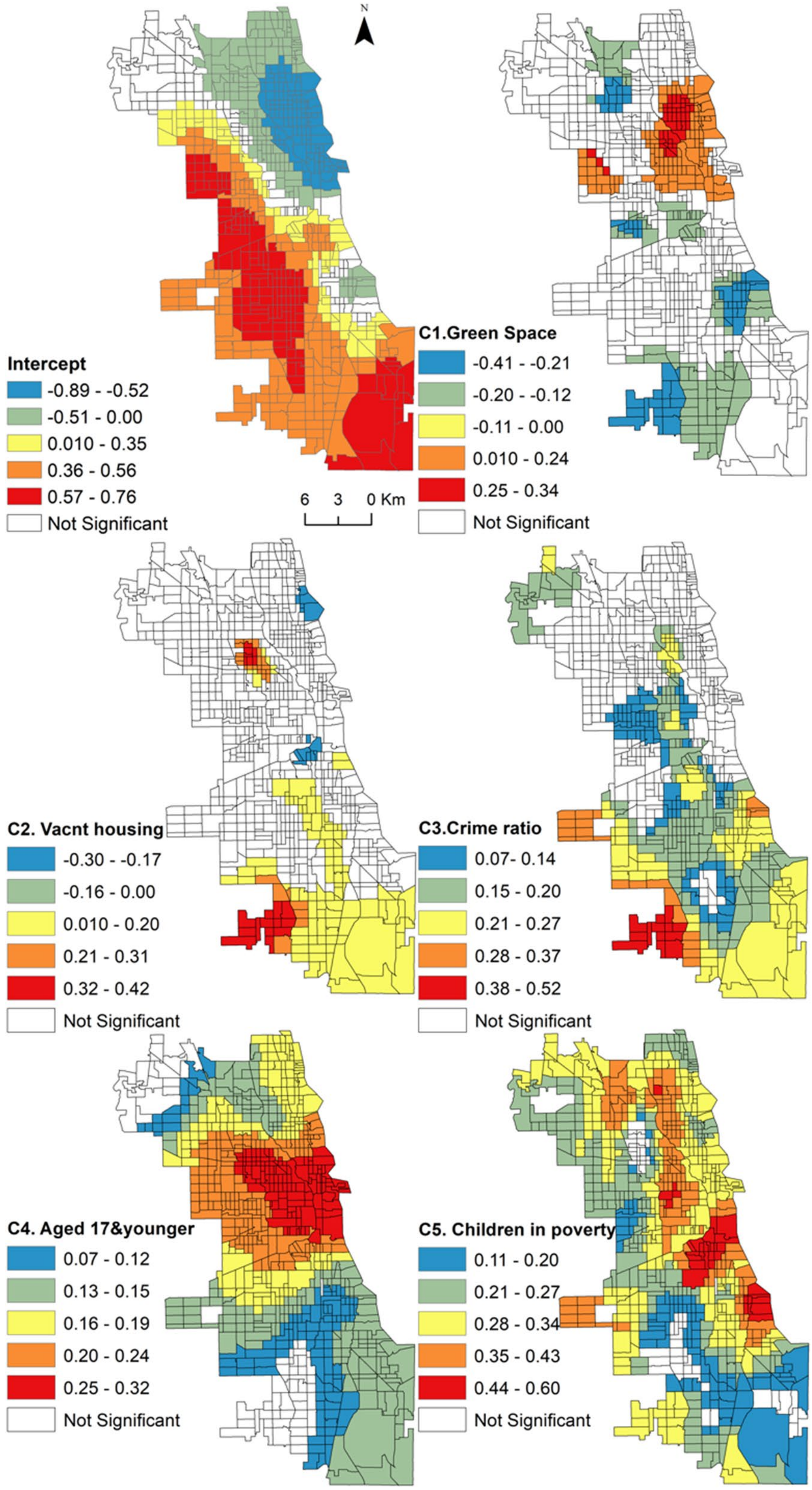
Collinearity may exist in local subsets under the geographically weighted models (Wheeler & Tiefelsdorf, 2005). The variability of local condition numbers for the GWR and MGWR models is depicted in Fig. 3. In particular, for most census tracts, the condition number of the MGWR model is well below the critical value of 8. In contrast, for GWR for the large Chicago area, the condition number equals 8–16. Since all predictor-dependent variable relationships in GWR operate on the same spatial scale, a single optimal bandwidth is determined. As a result, the independent variables are weighted using the same local scheme in the GWR model (Fig. 3).

Discussion

The prevalence of physical inactivity varies across Chicago, with higher levels in the city's west and south sides, including Englewood and Little Village communities, which are surrounded by industrial areas and have high Black and Hispanic populations, respectively. While physical inactivity is a widespread problem throughout Chicago, urban crime is a significant predictor of physical inactivity in the city's south and western downtown neighborhoods. Vacant houses contribute to an inactive lifestyle in the south by creating an unsafe urban environment. Additionally, a decrease in green space in the south is linked to an increase in inactive lifestyle; similarly, Richardson et al. (2013) and James et al. (2015) noticed a link between greenness and physical activity. Physical inactivity increased as the greenness of the areas surrounding downtown and to the north increased. In this study, urban green areas include any vegetation in the urban environment, including parks, green open spaces, residential gardens, mangroves, street trees, and green infrastructure (Lindley et al., 2018).

Several scholars (e.g., Basu & Nagendra, 2021) agree that unplanned and unmaintained greenspaces do not contribute to wellness and may even be a source of crime, as found in our study. Some tracts in northwest of downtown have a high concentration of crime and green spaces, creating an unhealthy environment for low-income children and adolescents. People in the southwest side of Chicago, which has

Fig. 2 Spatial distribution of the local parameter estimates based on MGWR



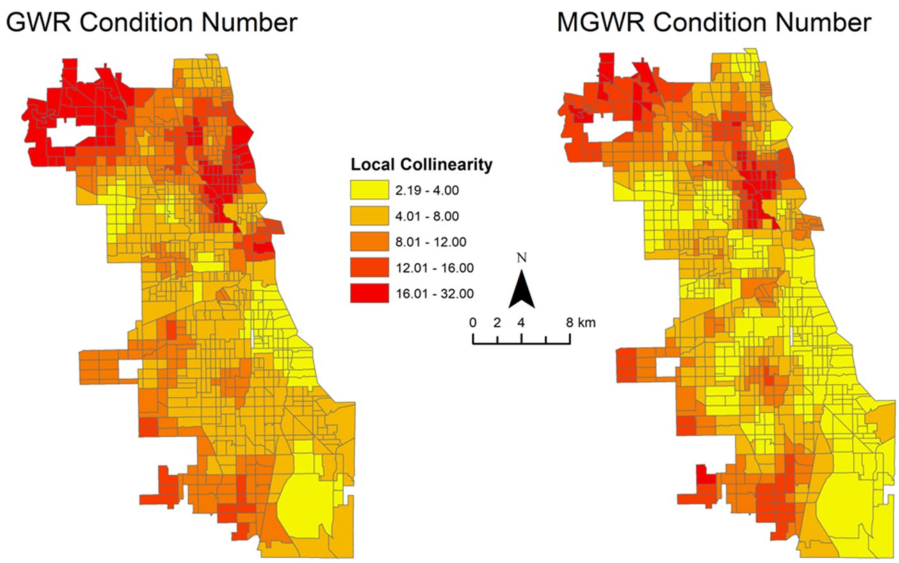


Fig. 3 Evaluation of the collinearity in the GWR (left) and MGWR model (right)

a high percentage of vacant properties, crime, and a lack of green space, are also vulnerable to unhealthy behaviors.

Green, blue, and brown landscapes make up the urban landscape (Egerer et al., 2020). Those landscapes' integration reveals health benefits arising from green space exposure (Krayenhoff et al., 2020), whereas urban expansion makes socio-cultural delivery of green spaces difficult. Boulton et al. (2022) and Luo et al. (2021) specify that green space accessibility, availability, and visibility are three indicators that should be considered together when evaluating the health benefits of green space. Creating a vital neighborhood promotes healthy physical activities identified by urban safety and well-planned green spaces, contributing to neighborhood vitality in various ways, including social cohesion and attachment.

Additionally, encouraging aging in place is centered on developing calm and secure environments in the community to support physical activities (Zhang et al., 2021). Given that cultural traditions are passed down from generation to generation, unhealthy habits may provide the groundwork for long-term health problems. A sedentary lifestyle is brought on by internal, external, societal, and local influences (Lane & Davis, 2022; de Souza et al., 2019; Kohl et al., 2012; Seefeldt et al., 2002). According to our study, children in poverty and adolescent who grow up among adults who lead sedentary lifestyles are more likely to engage in unhealthy behaviors as adults.

The use of MGWR aids in better interpreting determinants of physical inactivity prevalence, which vary geographically. Because of GWR's limitations, it is difficult to interpret findings, gain collective insight into physical inactivity promoting processes, and recommend practical policy implementations in physical activity studies (Oshan & Fotheringham, 2018). The GWR model is untrustworthy for investigating the various conditional relationships, while the cause of physical inactivity is complex and multifactorial (Hruby & Hu, 2015). In contrast, the MGWR model estimates each determinant of physical inactivity prevalence using a unique spatial scale (Fotheringham et al., 2022). Socioeconomic determinants, for example, vary at different scales, and using a unique spatial scale improves the estimation of their spatial variation. As a result, geospatial analysis is critical for health officials and regional planners to make informed decisions about reducing health disparities.

There are four limitations of this study. First, the variable capturing physical inactivity is based on survey data, which may introduce response bias. Secondly, this study does not include other determinants of neighborhood vitality, such as legibility and sidewalk/street connectivity, in creating a healthy environment. Third, our study may inform future research by identifying neighborhoods that exhibit elevated physical inactivity levels and their associations with socioeconomic and environmental factors. Still, due to the cross-sectional study design, our ability to identify causal relationships is limited. Fourth, our data is aggregated to census tracts and, therefore, subject to the modifiable areal unit problem (MAUP) (Openshaw &Tayler, 1979).

Conclusion

This study used the MGWR to examine the spatially varying relationships between socio-environmental determinants and physical inactivity prevalence in Chicago, Illinois, USA. Our findings revealed that physical inactivity is rising in neighborhoods with a high share of 17 aged and younger and children living in poverty. Our findings also provide evidence that these relationships vary spatially across Chicago and may operate on different scales. To achieve health equity across neighborhoods, we urge local planning to consider how crime and poorly planned green spaces prevent individuals from engaging with their neighborhoods' social and physical capital. It's also essential to recognize outdoor characteristics that affect a person's propensity to commit a crime.

References

Anselin, L. (2001). *Spatial Econometrics* (p. 310330). Blackwell Publishing Ltd.

Basu, S., & Nagendra, H. (2021). Perceptions of park visitors on access to urban parks and benefits of green spaces. *Urban Forestry & Urban Greening, 57*, 126959.

Boulton, C., Dedekorkut-Howes, A., & Byrne, J. (2022). A 'tug of war' between more parks or better greenspace: The dilemma of meeting 'community expectations' with limited resources. *Cities, 126*(2022), 103665.

Buck, C., et al. (2019). Urban Moveability and physical activity in children: longitudinal results from the IDEFICS and I. Family cohort. *International Journal of Behavioral Nutrition and Physical Activity, 16*(1), 1–13.

Brunsdon, C., Fotheringham, S., & Charlton, M. (1998). Geographically weighted regression. *Journal of the Royal Statistical Society: Series D (The Statistician), 47*(3), 431–443.

Chander, G., Markham, B. L., & Helder, D. L. (2009). Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors. *Remote Sensing of Environment, 113*, 893–903.

Cheezum, R. R., et al. (2019). Using PhotoVoice to understand health determinants of formerly homeless individuals living in permanent housing in Detroit. *Qualitative Health Research, 29*(7), 1043–1055.

Congdon P. (2019). Obesity and Urban Environments. *International Journal of Environmental Research and Public Health, 16*(3), 464.

Craney, T. A., & Surles, J. G. (2002). Model-dependent variance inflation factor cutoff values. *Quality Engineering, 14*(3), 391–403.

de Souza Andrade, A. C., Mingoti, S. A., da Silva Costa, D. A., Xavier, C. C., Proietti, F. A., & Caiaffa, W. T. (2019). Built and social environment by systematic social observation and leisure-time physical activity report among Brazilian Adults: a population-based study. *Journal of Urban Health : Bulletin of the New York Academy of Medicine, 96*(5), 682–691.

Egerer, M., Fouch, N., Anderson, E. C., et al. (2020). Socio-ecological connectivity differs in magnitude and direction across urban landscapes. *Science and Reports, 10*, 4252.

Feng, X., & Astell-Burt, T. (2019). Can green space quantity and quality help prevent postpartum weight gain? A longitudinal study. *Journal of Epidemiology and Community Health, 73*(4), 295–302.

Faka, A., Chalkias, C., Georgousopoulou, E. N., Tripitsidis, A., Pitsavos, C., & Panagiotakos, D. B. (2019). Identifying determinants of obesity in Athens, Greece through global and local statistical models. *Spatial and Spatio-Temporal Epidemiology, 29*, 31–41.

Fotheringham, A. S., Brunsdon, C., & Charlton, M. (2003). *Geographically weighted regression: The analysis of spatially varying relationships*. John Wiley & Sons.

Fotheringham, A. S., Yang, W., & Kang, W. (2017). Multiscale geographically weighted regression (MGWR). *Annals of the American Association of Geographers, 107*(6), 1247–1265.

Fotheringham, A. S., Hanchen, Y., Wolf, L. J., Oshan, T. M., & Li, Z. (2022). On the notion of 'bandwidth' in geographically weighted regression models of spatially varying processes. *International Journal of Geographical Information Science., 36*, 1485–1502.

Gehl, J. (2001). *Life between buildings: Using public space*. The Danish Architectural Press.

Hohl, A., & Lotfata, A. (2022). A geographical analysis of socioeconomic and environmental drivers of physical inactivity in post pandemic cities: The case study of Chicago, IL,, USA. *Urban Science., 6*(2), 28. https://doi.org/10.3390/urbansci6020028

Hruby, A., & Hu, F. B. (2015). The epidemiology of obesity: A big picture. *PharmacoEconomics, 33*(7), 673–689.

Iyanda, A. E., & Osayomi, T. (2021). Is there a relationship between economic indicators and road fatalities in Texas? A multiscale geographically weighted regression analysis. *GeoJournal, 86*, 2787–2807.

Jacobs, J. (1961). *The death and life of great American Cities*. Vintage Books.

James, P., Banay, R. F., Hart, J. E., & Laden, F. (2015). A review of the health benefits of greenness. *Current Epidemiology Reports, 2*(2), 131–142.

Krayenhoff, E. S., Jiang, T., Christen, A., Martilli, A., Oke, T. R., Bailey, B. N., Nazarian, N., Voogt, J. A., Giometto, M. G., Stastny, A., & Crawford, B. R. (2020). A multi-layer urban canopy meteorological model with trees (BEP-Tree): Street tree impacts on pedestrian-level climate. *Urban Climate, 32*, 100590.

Kim, J., & Park, M. J. (2021). Multilevel effect of neighborhood social cohesion and characteristics on suicidal ideation among Korean older adults. *Community Mental Health Journal, 57*(3), 522–528.

Kohl, H. W., Craig, C. L., Lambert, E. V., Inoue, S., Alkandari, J. R., Leetongin, G., Kahlmeier, S., & Lancet Physical Activity Series Working Group (2012). The pandemic of physical inactivity: global action for public health. Lancet (London, England), *380*(9838), 294–305.

Kondo, M. C., Morrison, C., Jacoby, S. F., Elliott, L., Poche, A., Theall, K. P., & Branas, C. C. (2018). Blight abatement of vacant land and crime in New Orleans. *Public Health Reports, 133*(6), 650–657.

Lane, J. M., & Davis, B. A. (2022). Food, physical activity, and health deserts in Alabama: the spatial link between healthy eating, exercise, and socioeconomic factors. *GeoJournal*. https://doi.org/10.1007/s10708-021-10568-2

Lopes, M. N., & Camanho, A. S. (2013). Public green space use and consequences on urban vitality: An assessment of European cities. *Social Indicators Research, 113*(3), 751–767.

Luo, M., Li, H., Pan, X., Fei, T., Dai, S., Qiu, G., Zou, Y., Vos, H., Luo, J., & Jia, P. (2021). Neighbourhood speed limit and childhood obesity. *Obesity Reviews : an Official Journal of the International Association for the Study of Obesity, 22*(Suppl 1), e13052.

Lunecke, M. G. H., & Mora, R. (2018). The layered city: Pedestrian networks in downtown Santiago and their impact on urban vitality. *Journal of Urban Design, 23*(3), 336–353.

Lindley, S., Pauleit, S., Yeshitela, K., Cilliers, S., & Shackleton, C. (2018). Rethinking urban green infrastructure and ecosystem services from the perspective of sub-Saharan African cities. *Landscape and Urban Planning*, *180*, 328-338, ISSN 0169-2046 (2018)

Lynch, K. (1984). *Good City Form; MIT Press: Cambridge*. MA.

Maas, P. R. (1984). *Towards a theory of urban vitality*. Vancouver, BC, Canada: University of British Columbia.

Macfarlane, G. S., Boyd, N., Taylor, J. E., & Watkins, K. (2021). Modeling the impacts of park access on health outcomes: A utility-based accessibility approach. *Environment and Planning b: Urban Analytics and City Science, 48*(8), 2289–2306.

McGinn, A. P., Evenson, K. R., Herring, A. H., Huston, S. L., & Rodriguez, D. A. (2007). Exploring associations between physical activity and perceived and objective measures of the built environment. *Journal of Urban Health : Bulletin of the New York Academy of Medicine, 84*(2), 162–184.

Mouratidis, K., & Poortinga, W. (2020). Built environment, urban vitality and social cohesion: Do vibrant neighborhoods foster strong communities? *Landscape and Urban Planning, 204*, 103951.

Moran, P. A. (1950). Notes on continuous stochastic phenomena. *Biometrika, 37*(1/2), 17–23.

Moulay, A., Ujang, N., Maulan, S., & Ismail, S. (2018). Understanding the process of parks' attachment: Interrelation between place attachment, behavioural tendencies, and the use of public place. *City, Culture and Society, 14*(2018), 28–36.

Nieuwenhuijsen, M. J., Khreis, H., Triguero-Mas, M., Gascon, M., & Dadvand, P. (2017). Fifty shades of green: Pathway to healthy urban living. *Epidemiology (cambridge, Mass), 28*(1), 63–71.

Oshan, T. M., Li, Z., Kang, W., Wolf, L. J., & Fotheringham, A. S. (2019). mgwr: A Python implementation of multiscale geographically weighted regression for investigating process spatial heterogeneity and scale. *ISPRS International Journal of Geo-Information, 8*(6), 269.

Oshan, T. M., & Fotheringham, A. S. (2018). A comparison of spatially varying regression coefficient estimates using geographically weighted and spatial-filter-based techniques. *Geographical Analysis, 50*(1), 53–75.

Openshaw, S., & Taylor, P. J. (1979). A million or so correlation coefficients: three experiments on the modifiable areal unit problem. In N. Wrigley & R. J. Bennett (Eds.), *Statistical applications in the spatial sciences* (Vol. 21, pp. 127–144). Pion: London.

Orstad, S. L., Szuhany, K., Tamura, K., Thorpe, L. E., & Jay, M. (2020). Park proximity and use for physical activity among urban residents: Associations with mental health. *International Journal of Environmental Research and Public Health, 17*(13), 4885.

Pinto, B., Ferreira, F., Spahr, R. W., Sunderman, M. A., & Pereira, L. F. (2022). Analyzing causes of urban blight using cognitive mapping and DEMATEL. Annals of operations research, 1–28. Advance online publication.

Rossi, F., Anderini, E., Castellani, B., Nicolini, A., & Morini, E. (2015). Integrated improvement of occupants' comfort in urban areas during outdoor events. *Building and Environment, 93*, 285–292.

Richardson, E. A., Pearce, J., Mitchell, R., & Kingham, S. (2013). Role of physical activity in the relationship between urban green space and health. *Public Health, 127*(4), 318–324.

Sallis, J. F., Floyd, M. F., Rodríguez, D. A., & Saelens, B. E. (2012). Role of built environments in physical activity, obesity, and cardiovascular disease. *Circulation, 125*(5), 729–737.

Seefeldt, V., Malina, R. M., & Clark, M. A. (2002). Factors affecting levels of physical activity in adults. *Sports Medicine, 32*(3), 143–168.

Shanahan, D. F., Franco, L., Lin, B. B., Gaston, K. J., & Fuller, R. A. (2016). The benefits of natural environments for physical activity. *Sports Medicine (auckland, N.z.), 46*(7), 989–995.

Smith, R., & Miller, K. (2013). Eco-city mapping using GIS: Introducing a planning method for assessing and improving neighborhood vitality. *Progress in Community Health Partnerships: Research, Education, and Action, 7*(1), 95–106.

Sentell, T., Vamos, S., & Okan, O. (2020). Interdisciplinary perspectives on health literacy research around the world: more important than ever in a time of COVID-19. *International Journal of Environmental Research and Public Health, 17*, 3010.

U.S. Census Bureau. American Community Survey (ACS), 2014–2018 (5-Year) Socioeconomic Data. 2018. Available online: https://data.census.gov/cedsci/deeplinks?url=https%3A%2F%2Ffactfinder.census.gov%2F (accessed on 25 December 2021).

U.S. Centers for Disease Control and Prevention (CDC) (2021a). Social Determinants of Health. Available online: https://www.cdc.gov/socialdeterminants/about.html (accessed on 15 December 2021a).

U.S. Centers for Disease Control and Prevention (CDC) (2021b). PLACES Project. Local Data for Better Health. Available online: https://www.cdc.gov/places (accessed on 15 December 2021b).

U.S. Healthy Chicago. Available online: https://www.chicago.gov/city/en/depts/cdph/provdrs/healthychicago.html (accessed on 15 December 2021c).

U.S. Chicago Police Department. Available online: https://www.chicago.gov/city/en/depts/cpd.html (accessed on 15 December 2021d).

U.S. Chicago Health Atlas (CHA) Available from: https://chicagohealthatlas.org/. (accessed December 10, 2021e).

U.S. Chicago Data Portal (CDP), Crime, Available from: https://data.cityofchicago.org/resource/x2n5-8w5q.json. (Accessed December 2021f).

U.S. Chicago Health Dashborad (CHD), Children in poverty, Available from: https://www.cityhealthdashboard.com/?gclid=Cj0KCQjwpImTBhCmARIsAKr58czLuodi8c9nFQou8ZnYfj6JQrn-ksdmx7Rq3hWIx94yk8waGQlMg2QaAq5nEALw_wcB . (Accessed on 15 December 2021g).

U.S. American Community Survey (ACS). Available from: https://www.census.gov/geographies/mappingfiles/time-series/geo/tiger-line-file.html (Access 1 January 2022).

U.S. America Health Ranking, Available from: https://www.americashealthrankings.org/. (Accessed 10January 2022).

Van Rossum, G., & Drake, F. L. (2009). *Python 3 Reference Manual*. Scotts Valley, CA: CreateSpace.

WalletHub (2022). 2022's Best & Worst Cities for an Active Lifestyle. Available from: https://wallethub.com/edu/best-and-worst-cities-for-an-active-lifestyle/8817. (accessed December 5, 2021).

Wheeler, D., & Tiefelsdorf, M. (2005). Multicollinearity and correlation among local regression coefficients I, geographically weighted regression. *Journal of Geographical Systems, 7*(2), 161–187.

Wu, Z. J., Song, Y., Wang, H. L., Zhang, F., Li, F. H., & Wang, Z. Y. (2019). Influence of the built environment of Nanjing's Urban Community on the leisure physical activity of the elderly: An empirical study. *BMC Public Health, 19*(1), 1459.

Xiao, Y., Miao, S., Zhang, Y., Xie, B., & Wu, W. (2022). Exploring the associations between neighborhood greenness and level of physical activity of older adults in shanghai. *Journal of Transport & Health, 24*, 101312.

Zhang, F., Loo, B. P. Y., & Wang, B. (2021). Aging in place: From the neighborhood environment, sense of community, to life satisfaction. *Annals of the American Association of Geographers., 112*, 1484–1499.

Zeng, C., Song, Y., He, Q., & Shen, F. (2018). Spatially explicit assessment on urban vitality: Case studies in Chicago and Wuhan. *Sustainable Cities and Society, 40*, 296–306.

Zumelzu, A., & Barrientos-Trinanes, M. (2019). Analysis of the effects of urban form on neighborhood vitality: Five cases in Valdivia, Southern Chile. *Journal of Housing and the Built Environment, 34*(3), 897–925.

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