Habitat International 161 (2025) 103426

Contents lists available at ScienceDirect

Habitat International

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

Assessing the impact of urban amenities on people with disabilities in London: A multiscale geographically weighted regression analysis

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ARTICLE INFO

Keywords:
Points of interest
Vulnerable people
Urban green space
Proximity analysis
Multiscale geographically weighted regression
Environmental justice

ABSTRACT

Disability groups rely on urban infrastructure more than the general urban population. This study examines the spatial distribution of urban amenities in relation to disability groups in London. 17 independent variables were selected from multi-source data and categorized into four groups: green space and amenity, land use, basic service, and transportation network. Employing Ordinary Least Squares (OLS), Geographically Weighted Regression (GWR), and Multiscale Geographically Weighted Regression (MGWR) models, the analysis found no significant correlation between disability density and amenities such as supermarkets, bus stations, and subway stations. However, the results revealed pronounced inequities in green space accessibility and an over-concentration of commercial areas in Inner London. These findings underscore the need for targeted policy interventions to improve access to green spaces, enhance inclusivity in urban planning for individuals with disabilities, and implement data-driven resource allocation strategies to address spatial disparities in urban amenities.

1. Introduction

Social stratification in cities often manifests spatially, resulting in environmental disparities due to the uneven geographic distribution of socio-economic factors such as race, ethnicity, income, and education levels. Scholars have studied these disparities under the theme of 'environmental justice' (Tan & Samsudin, 2017). Environmental justice is defined by the U.S. Environmental Protection Agency as 'the fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies' (2021). Initially focused on industrial pollution, research on environmental justice has since expanded to include the distribution of environmental amenities (Liotta et al., 2020). This study specifically examines distributive justice within environmental justice, which refers to equitable distribution of environmental harms and benefits (Ulibarri et al., 2022). Previous research on environmental justice has primarily focused on individual categories of urban amenities, such as urban green spaces (Fang et al., 2023), transportation (Schweitzer & Valenzuela, 2004), healthcare resources (Song et al., 2020), and supermarkets (Black et al., 2014). While these specialized studies have yielded insightful findings within their respective domains, residents typically interact with a variety of amenities that collectively influence their quality of life and social inclusion.

Urban amenities are defined as desirable packages of goods demanded by urban "consumers," which enhance the attractiveness of a location by offering specific goods and services that influence residential and locational choices (Glaeser et al., 2001; Liu et al., 2025; Nilsson, 2014).These amenities can vary widely, encompassing both natural elements, like parks and green spaces, and built infrastructure, such as community centers and commercial areas. The existing literature highlights the significant environmental and social benefits that different types of urban amenities can provide. For instance, the reductive effects of green spaces on airborne PM concentrations are significant (Diener & Mudu, 2021), and even small green spaces can lower the air temperature of the urban blocks they occupy (Park et al., 2017), contributing to a healthier environment. While built infrastructure, such as community centers and cultural amenities, particularly those dominated by impermeable surfaces like buildings, may not achieve similar environmental outcomes, they are essential for fostering community inclusion (Baldwin & Stafford, 2019) and contributing to a household's sense of belonging (Howie et al., 2010). Moreover, research indicates that urban amenities

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https://doi.org/10.1016/j.habitatint.2025.103426
Received 4 May 2024; Received in revised form 24 April 2025; Accepted 24 April 2025
Available online 30 April 2025

impact physical activity levels (Gordon-Larsen et al., 2006), reduce loneliness (Jamalishahni et al., 2022), alleviate physiological and psychological stress (Beil & Hanes, 2013), enhance self-esteem (Barton et al., 2012), decrease aggression and violence (Kuo & Sullivan, 2001), and improve overall quality of life (Mulligan & Carruthers, 2011). In recent years, the clustering of amenities has become increasingly valued by both residents and local governments, as evidenced by rising real estate prices and the growing emphasis on place-making initiatives by city authorities (Hidalgo et al., 2020; Li et al., 2019).However, Nelson et al. (2021) note that the tangible benefits of urban amenities are often localized. As a result, much of the literature on urban amenities focuses on their spatial distribution and accessibility.

Given the significant impact of urban amenities on general well-being, their availability and accessibility become even more critical for people with disabilities, who may face additional barriers in accessing these benefits. Despite this, disability remains a largely overlooked dimension in urban research. As noted by Levine and Karner (2023) and Lubitow et al. (2017), planning has historically prioritized the needs of affluent, white, able-bodied, and male travelers, thereby marginalizing other groups. Furthermore, issues concerning people with disabilities are frequently framed as matters of regulatory compliance, rather than being recognized as integral to broader discussions of urban equity and justice (Pineda, 2020, p. 169). This persistent oversight may also stem from a reductive view that frames the needs of individuals with disabilities merely as design challenges, rather than as systemic and structural concerns embedded within urban planning paradigms (Terashima & Clark, 2021). Morris (2005) highlights, individuals with disabilities are frequently conceptualised as passive recipients of care rather than active contributors to societal development. This perception relegates them to a marginalized status, where they are exempted from civic responsibilities but simultaneously excluded from meaningful participation in public life. A similar exclusionary dynamic is evident in environmental citizenship theories (Salkeld, 2019). For instance, in Tianjin, people with disabilities face significant spatial disparities and structural inequalities (Qiu et al., 2022), illustrating the broader gap in addressing their planning needs, which remain largely underexplored.

The literature on how urban amenities affect people with disabilities primarily focuses on walkways, public transportation, the quality and accessibility of urban green spaces, as well as the accessibility of hospitals and community centers (Bohorquez et al., 2023). The World Health Organization (WHO) defines disability as 'impairment in a person's body structure or function, or mental functioning' (2001). This study adopts the definition from the Equality Act, which identifies an individual as disabled if they have a significant, long-term impact on their ability to perform ordinary day-to-day activities (2010). Despite often being overlooked, an estimated 1.3 billion people, or 16 % of the world's population, have significant disabilities (WHO, 2022). Disability remains a critical health and social issue, particularly in the context of an aging population (Clarke et al., 2011). As sociologist Nagi (1965) noted, 'disability is the expression of a physical or mental limitation in a social context.' Geographic research on disability began in the early 1970s but initially received limited attention (Hall & Kearns, 2001). From the 1990s, there was an increase in disability research papers, mainly focusing on social justice (Gleeson, 1997; Valentine, 2003), discrimination (Barnes, 1991), ethics and morality (Kitchin, 2002), and inclusion (Hall et al., 2002).

Most environmental equity studies have focused on the United States, the origin of the environmental equity movement, where evidence of inequitable distribution faced by vulnerable populations, including people of color and low-income individuals, has been documented (Byrne, 2007; Chen et al., 2024; Rigolon & Németh, 2021; Wilson et al., 2008). Additionally, evidence regarding environmental equity is mixed; for instance, some research suggests that the uneven spatial distribution of amenities does not significantly correlate with residents' socioeconomic status (Nesbitt et al., 2019). In England and Australia, studies have demonstrated that black and minority ethnic groups, as well as low-income families, respectively, have limited access to green spaces (Comber et al., 2008; Kimpton, 2017). Although there has been extensive research on environmental injustice associated with urban amenities focusing on race, ethnicity, and income, other vulnerable groups, such as people with disabilities, have received relatively little research attention. Specifically, studies on environmental justice for people with disabilities have been almost exclusively limited to the context of green spaces, and even these studies are limited in number (Lasky et al., 2023; Wong et al., 2023). This study aims to address this gap by exploring the relationship between the spatial distribution and accessibility of a comprehensive range of urban amenities and people with disabilities.

Contemporary disability research encompasses a broad range of themes, with researchers often focusing on the subjective experiences of individuals with disabilities in urban environments through questionnaires or interviews (Jespersen et al., 2019; Seeland & Nicolè, 2006; Perry, 2021). However, these studies are predominantly focused on the individual level and fail to capture patterns at spatial scales. Some research highlights the importance of spatial scales in examining urban amenities and influencing urban planning decisions and policies (Hein et al., 2006; Tan & Samsudin, 2017). Although extensive literature has examined the impact of spatial scales on urban residents and individual amenities (Gao et al., 2021; Lin et al., 2021; Nelson et al., 2021), there is a lack of research employing spatial-scale approaches to explore the relationship between comprehensive urban amenities and vulnerable people. Therefore, this study aims to understand the effects of spatial scales on the associations between urban amenities and people with disabilities.

Unequal access to urban amenity will contribute to health disparities and hinder the promotion of environmental health equity, leading to exacerbated health challenges for individuals with disabilities who have pre-existing health issues (Pearce et al., 2010). In urban areas, where land resources are often limited, considerable financial, human, and time resources have been allocated to the development and intervention in urban amenity. Therefore, amid rapid urbanization and constrained public spending, understanding the distribution and accessibility of urban amenity becomes crucial. This comprehension is necessary to ensure equitable access to the urban amenity for the entire society, realizing substantial benefits in terms of health, social cohesion, and environmental outcomes.

Guided by the environmental justice hypothesis (Brulle & Pellow, 2006) and prior studies, this research hypothesizes that individuals with disabilities face limited access to urban amenities, including green spaces, land use, basic services, and transportation infrastructure. This disparity is shaped by geographical, economic, and social factors, which collectively create barriers to equitable access. To explore this, the study has three primary objectives:

(1) What spatial patterns exist in the distribution of urban amenities, and how do they relate to disability populations?
(2) Which urban amenities are closely related to individuals with disabilities in London, and what can explain these associations?
(3) How do the impacts of urban amenities on populations with disabilities differ between global and local scales?

2. Methodology

2.1. Study area

London (51°30′26″N, 0°7′39″W) is the United Kingdom's largest city and capital. As of 2023, 15.7 % of its population, or 1.2 million individuals, have disabilities (Office for National Statistics). London includes 4994 Lower Super Output Areas (LSOAs), which are a part of a geographic hierarchy. These LSOAs are demarcated to encompass residential populations ranging typically from 1000 to 3000 individuals and contain 400 to 1200 households (Fig. 1). The Disability Discrimination

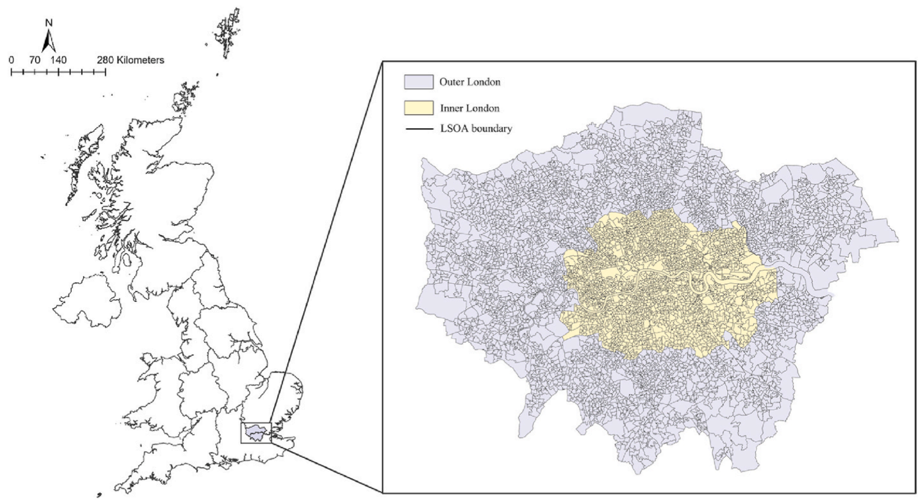

Fig. 1. Study area.

Act 1995, later replaced by the Equality Act, 2010, required accessibility improvements in public buildings. Established in 2000, the Greater London Authority (GLA) oversees strategic planning through the London Plan, which promotes 'Opportunity Areas' to drive growth and improve access to public services and green spaces in underdeveloped regions (GLA, 2004). While these policies aim to promote equitable urban development, critics argue that regeneration projects often unintentionally lead to gentrification, displacing lower-income residents (Lees, 2008).

2.2. Research flow

The workflow of this study is delineated into three primary sections: data sources, variables, and methodology (Fig. 2). Initially, this stage involves compiling a comprehensive dataset from various sources. The Office for National Statistics provides the dependent variable, which is disability information (https://www.ons.gov.uk/). Satellite imagery for evaluating green space quality is acquired through the Google Earth Engine (https://earthengine.google.com/). Detailed land use patterns are sourced from Digimap (https://digimap.edina.ac.uk/). OpenStreetMap (https://overpass-turbo.eu/) supplies Points of Interest (POIs) data, while the London Datastore (https://data.london.gov.uk/dataset) serves as a crucial resource for local urban information. ArcGIS Pro is utilized for the analytical process. Ordinary Least Squares (OLS) regression is used to establish the baseline relationship between variables. Moran's I statistic assesses spatial autocorrelation. Geographically Weighted Regression (GWR) and Multiscale Geographically Weighted Regression (MGWR) are applied to investigate spatial relationship.

2.2.1. Independent variables: urban amenities

Urban amenity in this research refers to specific facilities that enhance the living experience of urban residents (Kelly, 2006). This study encompasses various components, including green space and amenity, land use, basic service, and the transportation network. Like previous studies, this research utilizes POIs data and satellite imagery to identify and measure urban amenities (Zhang et al., 2023).

In this study, data on green space and amenities are divided into three parts: the distribution of officially designated green spaces, the Normalized Difference Vegetation Index (NDVI) representing the quality of green spaces, and the distribution of benches representing amenities in urban green spaces from OpenStreetMap (Fig. 3). The distribution of green spaces utilizes data on designated open spaces from the London Datastore, including Metropolitan Open Land and other public open spaces, which are vital components of London's infrastructure with public value. Based on the differences in light wavelengths absorbed by vegetation and hard surfaces, the satellite-based NDVI is the most widely used objective measure of natural space (Rugel et al., 2017). The NDVI data used in this study were sourced from cloud-free Landsat imagery in 2021 via the Google Earth Engine. Water generally has NDVI values near −1, built-up areas have low values due to minimal near-infrared reflectance, while vegetation shows moderate to high values (Weier & Herring, 2000). NDVI thresholds vary across studies based on research objectives, study area characteristics, and data resolution. For instance, in rural contexts, thresholds are often tailored to account for the characteristics of natural vegetation and agricultural land, with stricter standards for dense vegetation (Rizvi et al., 2009). In this research, thresholds were determined after reviewing relevant literature, conducting preliminary experiments, and aligning with prior urban-focused research (Akbar et al., 2019; Athick et al., 2019). Based on the NDVI values, land cover is categorized into six distinct classes: water (−1.00 to −0.015), built-up areas (0.015–0.14), barren land (0.14–0.18), shrub and grassland (0.18–0.27), sparse vegetation (0.27–0.36), and dense vegetation (0.36–1.00). Due to the focus on green space quality, the distribution of water and built-up areas is not included.

Previous research has demonstrated that land use significantly impacts individuals with disabilities (Botticello et al., 2014). For this study, data on common land use types (residential, commercial, and industrial) were obtained from Digimap. However, these land use areas do not perfectly align with the NDVI-based "built-up" areas. For instance, residential areas may include private parks and parking lots, which might be classified differently in the NDVI system, such as "sparse vegetation" or "barren land." These inconsistencies could result in the underestimation or overestimation of the influence of specific land use types. For instance, residential areas with substantial green features may be misclassified as vegetation-dominant zones, thereby underestimating their association with disability density. This discrepancy was acknowledged during the analysis, and its potential impact has been carefully considered in subsequent interpretations to ensure robust conclusions. The distribution of these land uses exhibits notable spatial variation across the study area. Residential areas predominantly occupy the northern part of the study area, commercial zones are concentrated in the city center, and industrial zones are primarily situated along the river in suburban areas.

Like previous studies, this research also employs POIs data to identify and measure basic services (Chin et al., 2023). Data on hospitals, supermarkets, community centers, and emergency response units such as fire and police stations were sourced from OpenStreetMap, and cultural amenities from the London Datastore, created by the GLA. Given that some individuals with disabilities are more likely to use public transport

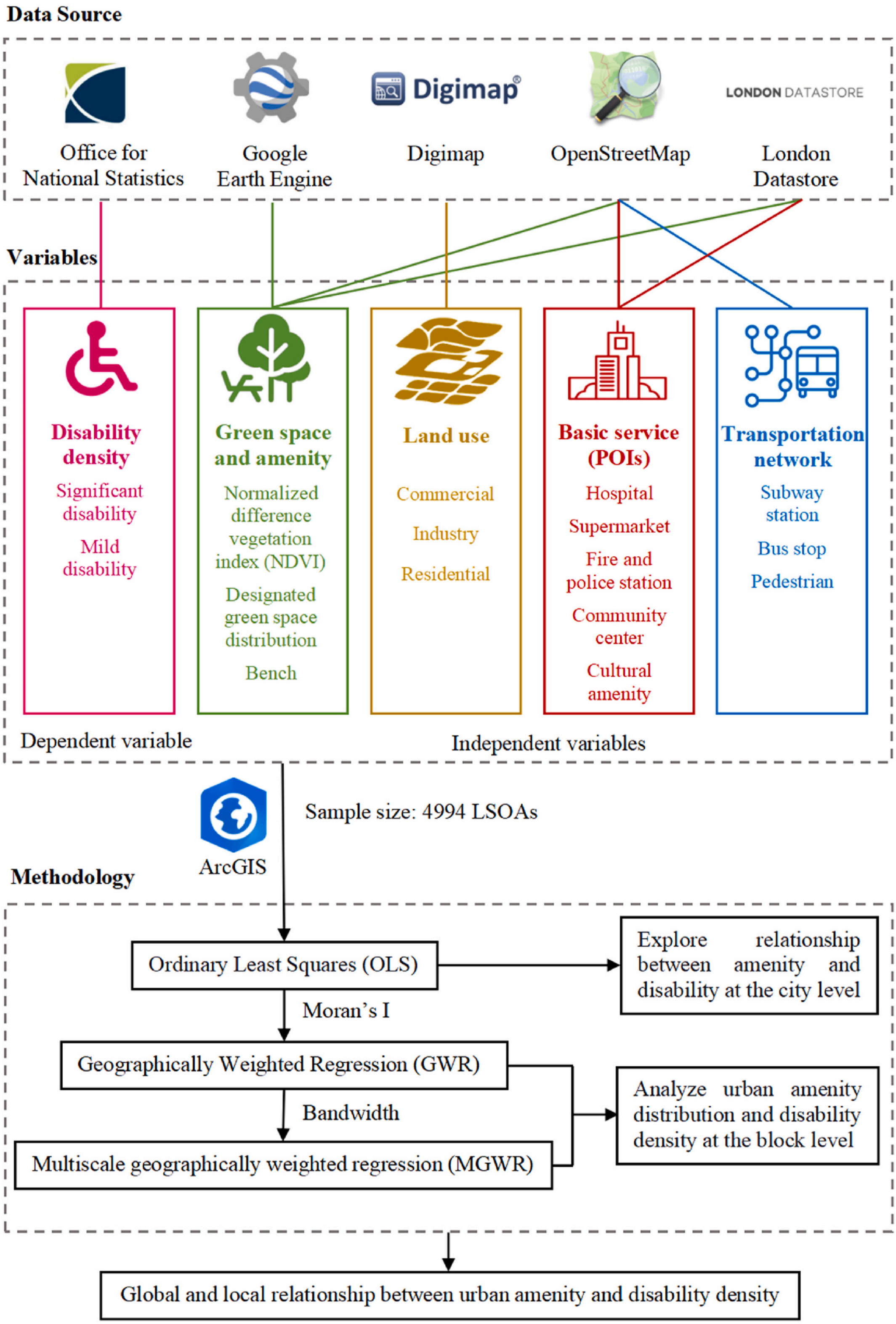

Fig. 2. Research method and framework.

than private vehicles, the transportation network in this study only includes subway stations, bus stops, and pedestrian facilities. Data on these urban amenities were sourced from OpenStreetMap.

The road network distance to the nearest POI within each LSOA is used as a metric in this analysis. This study replaces the commonly utilized Euclidean distance metrics with road network distances. Unlike Euclidean distances, which assume straight-line accessibility, road network distances offer a more realistic representation of actual travel paths by accounting for road layouts. Similar to previous studies, this study's preliminary comparisons indicate that using road network distances improves model performance across various regression methods (So, 2016). For example, models incorporating road network distances

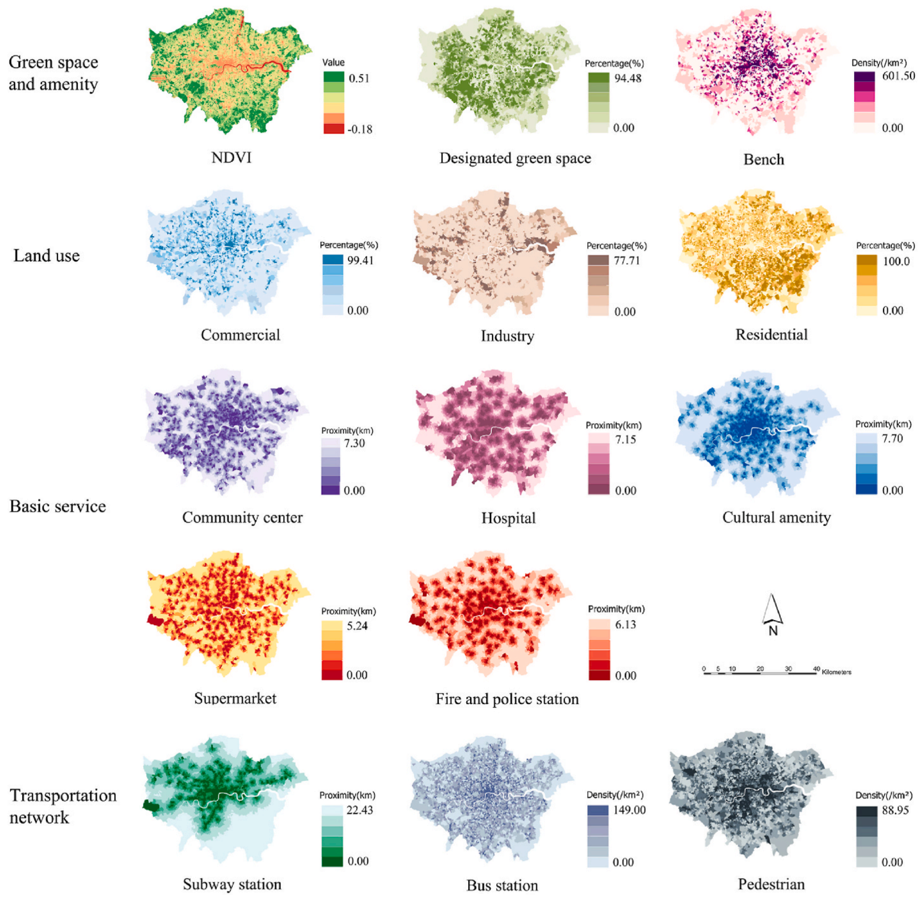

Fig. 3. Distribution map of independent variables: green space and amenity, land use, basic service, and transportation network. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

show higher adjusted R^2 values and lower Akaike informativeness criterion (AICc) scores compared to those using Euclidean distances, particularly in GWR and MGWR. These results suggest that network-based measures more effectively capture the spatial variability in accessibility.

2.2.2. Dependent variable: disability density

Data representing disability, originally sourced from the Office for National Statistics, was released in January 2023. This data comes from the census concerning disability, which is conducted every 10 years and provides a comprehensive demographic overview of all individuals and

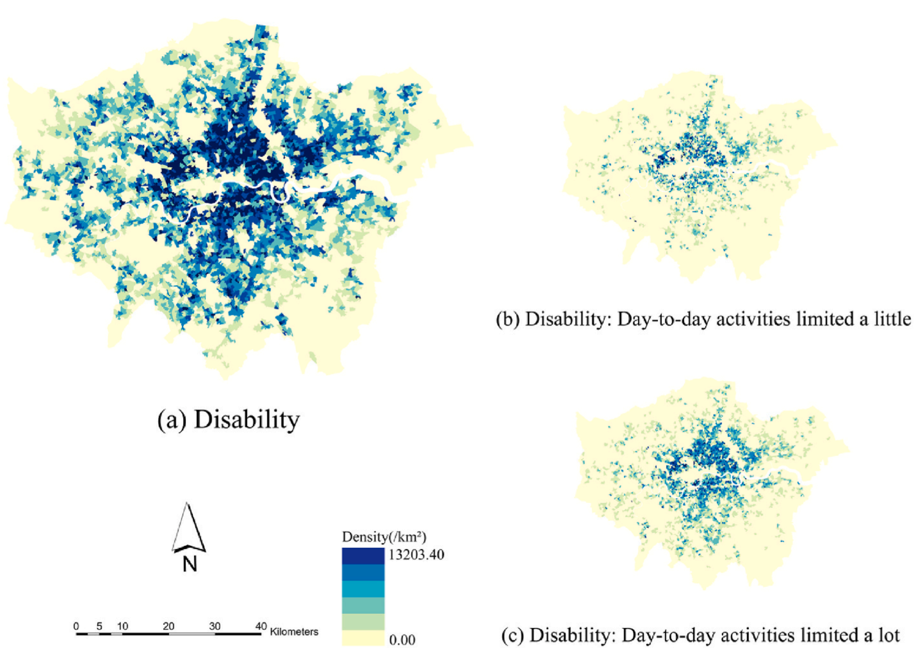

Fig. 4. Dependent variable disability distribution map: Sum of mild and significant disability.

households in England and Wales (Office for National Statistics, 2022). Census data has often been used in UK research to analyze spatial population patterns, including demographic trends in health and well-being as well as spatial patterns of population turnover (Bailey & Livingston, 2008; Doran et al., 2003). The census employs a disability classification framework that aligns with the Equality Act of 2010. According to this framework, individuals who report conditions that 'limited their day-to-day activities a little' or 'a lot' are classified as disabled (Fig. 4). Conversely, those without long-term physical or mental health conditions or whose conditions do not limit their daily activities are classified as non-disabled. The disability data is geolocated to small geographic units known as LSOAs, allowing for detailed spatial analysis of disability across different regions. Disability density is calculated as the ratio of the total number of disabled individuals, defined as day-to-day activities being either 'limited a little' or 'limited a lot', to the total area of each LSOA. This ratio serves as the dependent variable in the analysis.

Table 1 provides detailed information about the chosen variables. Table 2 provides a detailed sample extraction of the data used in the study for a specific LSOA, identified as E01002724. This sample extraction serves as a representative example of how various metrics were compiled and analyzed across different LSOAs in the study area.

2.3. Ordinary least squares

The OLS model is a traditional statistical method that quantitatively evaluates the global relationship between the dependent and independent variables. The model ignores spatial heterogeneity in the relationships between variables, assuming a spatially constant functional structure (Mansour et al., 2021). The OLS model can be interpreted as the following formula (Eq. (1)):

$$y = \beta_0 + \sum\nolimits_{i=1}^{p} \beta_i x_i + \varepsilon \quad (1)$$

where y is the dependent variable (disability); β0 represents the intercept term; β_i is the estimated coefficients; x_i represents the array of independent variables (distribution of urban amenity), and ε is the error term.

2.4. Geographically weighted regression

Since OLS ignores spatial heterogeneity, Brunsdon, Fotheringham, and Charlton introduced GWR to employ a multiple regression model that accommodates different relationships at various points in space (1996). It is recognized that the impact of urban amenities on disability prevalence may exhibit spatial variation across London. The GWR approach facilitates the examination of geographical variation in the relationships between the dependent and independent variables (Brunsdon et al., 1996). By fitting a local regression equation to each LSOA, the GWR model enables the exploration of how these relationships shift from one location to another. The mathematical expression of the GWR model is as follows (Eq. (2)):

$$y_i = \beta_{0i}(u_i, v_i) + \sum\nolimits_{n=1}^{k} \beta_{ni}(u_i, v_i) x_{ni} + \varepsilon_i \quad (2)$$

where y_i represents the density of disability; (u_i, v_i) are the coordinate locations of LSOA i; $\beta_{0i}(u_i, v_i)$ denote the local intercept, and $\beta_{ni}(u_i, v_i)$ denote the coefficient of variable n for LSOA i, x_{ni} indicates the values of the i-th independent variable (urban amenity), and ε_i is a random error term.

2.5. Multiscale geographically weighted regression

While standard GWR assumes a uniform bandwidth across all predictor variables, this simplification may be inappropriate in contexts where different predictors influence the dependent variable at varying

Table 1
Variables explanation.

Category	Variable	Definition	Data source	Year
	Dependent variable			
	Disability density	The ratio of disability to the total area of each LSOA (per km^2)	Office for National Statistics	2021
	Independent variables			
Green space and amenity	Barren land	The proportion of barren land in each LSOA (%)	Google Earth Engine	2021
	Shrub and grassland	The proportion of shrub and grassland in each LSOA (%)	Google Earth Engine	2021
	Sparse vegetation	The proportion of sparse vegetation in each LSOA (%)	Google Earth Engine	2021
	Dense vegetation	The proportion of dense vegetation in each LSOA (%)	Google Earth Engine	2021
	Designated green space distribution	The proportion of Metropolitan Open Land (strategic open land within the urban area) and other public open spaces (any other designated open spaces with public value) in each LSOA (%)	London Datastore	2022
	Bench density	The number of benches per LSOA (per km^2)	OpenStreetMap	2023
Land use	Commercial	The proportion of commercial area in each LSOA (%)	Digimap	2023
	Industry	The proportion of industry area in each LSOA (%)	Digimap	2023
	Residential	The proportion of residential area in each LSOA (%)	Digimap	2023
Basic service	Proximity to community centre	Road network distance to nearest community center from LSOA (km)	OpenStreetMap	2023
	Proximity to hospital	Road network distance to the nearest hospital from LSOA (km)	OpenStreetMap	2023
	Proximity to cultural amenity	Road network distance to the nearest amenity (museum, theatre, gallery, art centre, or cinema) from LSOA (km)	London Datastore	2022
	Proximity to supermarket	Road network distance to the nearest supermarket from LSOA (km)	OpenStreetMap	2023

(*continued on next page*)

Table 1 (*continued*)

Category	Variable	Definition	Data source	Year
	Proximity to fire and police station	Road network distance to the nearest fire station or police station from LSOA (km)	OpenStreetMap	2023
Transportation network	Proximity to subway station	Road network distance to the nearest subway station from LSOA (km)	OpenStreetMap	2023
	Bus stop density	The number of bus stops per LSOA (per km^2)	OpenStreetMap	2023
	Pedestrian density	Length of pedestrian (km) in each LSOA (per km^2)	OpenStreetMap	2023

Table 2
Data for LSOA E01002724.

Variable	Value
Area	0.263 km^2
Disability density	905.899 per km^2
Barren land percentage	4.915 %
Shrub and grassland percentage	6.108 %
Sparse vegetation percentage	0.429 %
Dense vegetation percentage	0.000 %
Green space percentage	4.409 %
Bench density	91.351 per km^2
Commercial percentage	22.283 %
Industry percentage	0.000 %
Residential percentage	1.469 %
Proximity to community centre	0.357 km
Proximity to hospital	1.188 km
Proximity to cultural amenity	0.100 km
Proximity to supermarket	0.908 km
Proximity to fire and police station	0.613 km
Proximity to subway station	0.207 km
Bus stop density	34.259 per km^2
Pedestrian density	12.696 per km^2

spatial scales. In this study, urban amenities such as bus stop density, green space quality, and proximity to hospitals likely exhibit distinct spatial relationships with disability density, reflecting varying scales of influence. For instance, the impact of green space quality might operate at a broader spatial scale compared to the localized influence of bus stop density. GWR's uniform bandwidth approach cannot adequately capture these nuances, as it averages the optimal scale of relationship non-stationarity for all predictors, potentially misrepresenting the dynamics of the spatial relationships. To address this limitation, a MGWR model, proposed by Fotheringham et al. (2017), is adopted in this study. MGWR assigns a unique bandwidth to each predictor variable, enabling a more precise examination of the spatial variability in predictor-to-target relationships at different scales. This flexibility makes MGWR more suitable for understanding the varying spatial relationships of urban amenities with disability density in London. The mathematical expression of the MGWR model is as follows (Eq. (3)):

$$y_i = \beta_0(u_i, v_i) + \sum_{j=1}^{m} \beta_j(u_i, v_i) x_{ij} + \varepsilon_i$$

where y_i represents the dependent variable (disability density); x_{ij} is the values of the i-th independent variable (urban amenity); $\beta_j(u_i, v_i)$ are the local regression coefficients for the j-th explanatory variable (urban amenity) at location i.

3. Result

3.1. OLS result

Table 3 presents the results of the OLS model for disability density. The combination of positive and negative coefficients shows that the urban amenity variables have varied relationships with disability density in both magnitude and direction. P-values of less than 0.050 are considered statistically significant. Shrub and grassland percentage, sparse vegetation percentage, dense vegetation percentage, and green space percentage exhibited significant negative correlations with disability density, indicating that both high-quality green spaces and officially designated green spaces in London are negatively correlated with disability density. All three land use types demonstrated significant correlations with disability density, though potential inconsistencies between functional land-use areas and NDVI classifications were considered during the analysis to ensure robust interpretations. Both industrial and commercial area densities exhibited a significant negative correlation with disability density. This indicates that areas with higher concentrations of industrial and commercial activities tend to have lower disability density. In other words, regions characterized by substantial industrial and commercial development are associated with fewer individuals with disabilities living in those areas. In contrast, residential area density was positively correlated with disability density, indicating that higher residential densities were associated with higher disability density. The distances to all basic service community centers, hospitals, cultural amenities, fire and police stations were significantly negatively correlated with disability density, suggesting that areas further from these amenities had lower disability density. This implies that regions with fewer amenities or where amenities are more dispersed are less likely to have higher disability density. Among transportation indicators, only pedestrian density showed a significant positive correlation with disability density, suggesting that areas with higher pedestrian density had higher disability density. However, bus stops and subway stations did not show significant correlations with disability density, suggesting that the density or proximity of public transportation infrastructure does not have a strong relationship with the spatial distribution of individuals with disabilities.

Overall, the results indicate that green space, land use types, and accessibility to basic services play significant roles in shaping the spatial

Table 3
Coefficient estimates of OLS model (N = 4994).

Variable	Coefficient	Robust standard error	Probability
Intercept	2517.441	101.455	0.000[a]
Barren land percentage	1.030	1.649	0.532
Shrub and grassland percentage	−8.291	0.914	0.000[a]
Sparse vegetation percentage	−21.736	1.170	0.000[a]
Dense vegetation percentage	−14.901	1.260	0.000[a]
Green space percentage	−5.920	0.663	0.000[a]
Bench density	−0.711	0.747	0.341
Commercial percentage	−14.509	2.356	0.000[a]
Industry percentage	−23.279	1.295	0.000[a]
Residential percentage	1.390	0.342	0.000[a]
Proximity to community centre	−168.227	12.652	0.000[a]
Proximity to hospital	−33.257	9.306	0.000[a]
Proximity to cultural amenity	−56.639	7.834	0.000[a]
Proximity to supermarket	−10.135	15.130	0.503
Proximity to fire and police station	−31.785	10.360	0.002[a]
Proximity to subway station	−1.938	3.071	0.528
Bus stop density	0.382	1.203	0.751
Pedestrian density	13.652	2.113	0.000[a]

Adjusted R^2 = 0.473, AICc = 79727.285.
Note.
[a] $p < 0.05$.

distribution of disability density, whereas the transportation network does not exhibit a strong relationship with disability density.

3.2. Moran's index

To verify the necessity of GWR, Moran's I was calculated for the residuals of the OLS model. The analysis yielded a Moran's I of 0.179, indicating a low to moderate positive spatial autocorrelation within the residuals. This suggests that the residuals are not randomly distributed but exhibit some degree of spatial clustering. The z-score of 57.279 and a p-value of 0.000 strongly reject the null hypothesis of no spatial autocorrelation. To further examine the spatial structure of the OLS residuals, a Local Moran's I cluster map was generated (Fig. 5). The results show that High-High and Low-High clusters are concentrated in Central London, while Low-Low and High-Low clusters are mainly found in Outer London. High-High clusters indicate areas where high residuals are surrounded by other high residuals, suggesting potential model overestimation. Conversely, Low-Low clusters suggest model underestimation in areas with low residuals. High-Low and Low-High clusters represent spatial outliers, where residual patterns differ significantly from their neighbors. OLS assumes that residuals (the differences between observed and predicted values) are independent and identically distributed. However, the presence of spatial clustering in the residuals violates this assumption, potentially leading to misleading inferences. Therefore, a spatially adaptive modeling approach, such as GWR, is necessary to account for spatial heterogeneity and capture local variations in the relationship between disability density and explanatory variables.

3.3. Model comparison and visualization

Adjusted R^2 of the OLS model is only 0.473, which means that it fails to explain 52.70 % of the variation in disability density throughout London, suggesting that other unaccounted factors may be affecting the results. To explore the spatial differences in the relationships between urban amenities and disability density, GWR and MGWR employ the same variables as the OLS model. The GWR model shows a better fit compared to the OLS model, as evidenced by its adjusted R^2 of 0.614 and a lower AICc value of 9778.037. Besides, the MGWR model shows the best performance of the evaluated models, achieving the highest adjusted R^2 value of 0.629 and the lowest AICc value of 9538.062. A lower AICc indicates that the MGWR model offers a better fit to the data while mitigating overfitting by penalizing unnecessary complexity. The higher adjusted R^2 reflects that the MGWR model explains a greater proportion of the variation in disability density, accounting for the number of predictors. MGWR outperformed GWR by assigning unique bandwidths to each explanatory variable, which enables the model to capture spatial heterogeneity at varying scales. This approach ensures that local variations in the relationships are modeled more accurately, preventing overfitting or oversmoothing that may arise from using a single bandwidth in GWR.As shown in Table 4, there are differences between the results from GWR and the MGWR. The intercept range in the GWR model is wide, ranging from −1.3 to 1.42, while the intercept range observed in the MGWR model is of −0.803 to 0.549. In the MGWR model, proximity to community centre demonstrates the greatest standard deviation, followed by proximity to subway station, which indicates significant spatial variation in the effect of accessibility to these amenities. Such variability underscores the uneven distribution of these amenities across different areas. Conversely, dense vegetation percentage displays the lowest standard deviations, meaning an almost uniform effect across locations and suggesting a more equitable distribution. Excluding barren land percentage, all other green space metrics have negative mean values, representing an inverse relationship between green spaces and disability density.

Fig. 6 visualizes and compares the results of the GWR model and the MGWR model. It can be observed that the spatial distribution trends of GWR and MGWR are broadly similar, but differences do exist. MGWR shows a smoother transition in the spatial distribution of coefficients, suggesting a more stable spatial pattern. In contrast, GWR exhibits more pronounced spatial variability with sharper transitions between areas. This variability can be attributed to GWR's use of a single bandwidth for all independent variables (Bandwidth = 7018.610). A small bandwidth can cause the model to overly respond to local variations in the data, which sometimes leads to overfitting or capturing noise. However, MGWR assigns different bandwidths to each independent variable, thus making them more reliable than those obtained from GWR (Fotheringham et al., 2017). The intercept, which represents the predicted value of the dependent variable when all independent variables are zero, reflects the relationships between different locations and disability density in this analysis. Inner London shows a significant positive correlation with the intercept, suggesting a higher disability density relative to the suburbs, where a negative correlation is observed.

Moreover, the spatial significance is visually represented in Fig. 6, showing that while the significant areas identified by GWR and MGWR are largely consistent, MGWR detects a slightly broader extent of significant regions. This is due to MGWR's use of adaptive bandwidths for each variable, which enables a more nuanced analysis of spatial heterogeneity and captures significant areas that may not be identified by GWR. Notably, proximity to fire and police stations exhibits minimal significant areas, suggesting that this variable has a relatively weak or

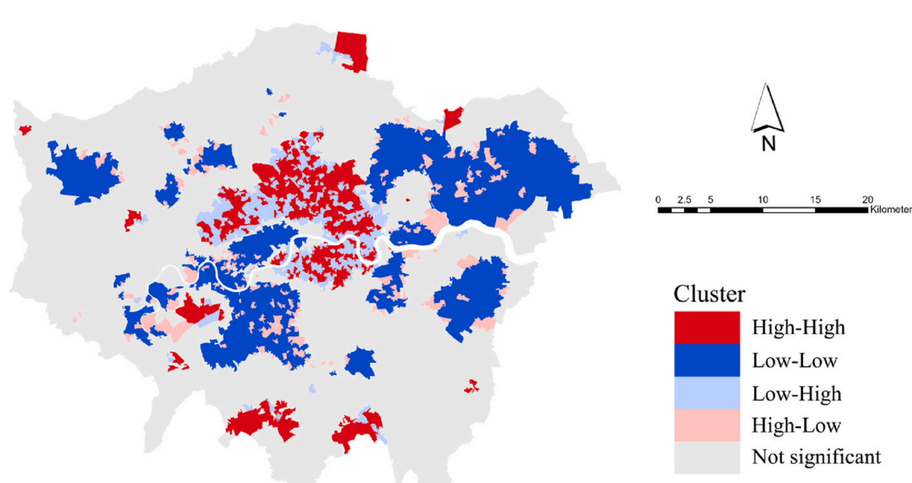

Fig. 5. Local Moran's I cluster map.

Table 4
GWR coefficient estimations results (N = 4944).

Variable	GWR				MGWR			
	Min.	Max.	Mean	STD	Min.	Max.	Mean	STD
Intercept	−1.3	1.42	−0.028	0.35	−0.803	0.549	0.029	0.287
Barren land percentage	−0.33	0.58	0.036	0.126	−0.138	0.4346	0.038	0.096
Shrub and grassland percentage	−0.39	0.65	−0.059	0.134	−0.258	0.234	−0.08	0.084
Sparse vegetation percentage	−0.7	0.37	−0.275	0.125	−0.489	−0.121	−0.302	0.078
Dense vegetation percentage	−0.38	0.274	−0.117	0.1	−0.169	−0.076	−0.144	0.023
Designated green space percentage	−0.46	0.247	−0.084	0.102	−0.159	0.017	−0.097	0.032
Bench density	−0.71	0.154	−0.088	0.107	−0.817	0.102	−0.076	0.092
Commercial percentage	−0.33	0.62	−0.085	0.092	−0.312	0.194	−0.089	0.076
Industry percentage	−0.306	0.55	−0.15	0.064	−0.217	−0.067	−0.166	0.031
Residential percentage	−0.066	0.41	0.096	0.09	−0.099	0.425	0.108	0.095
Proximity to community centre	−0.75	0.14	−0.187	0.21	−0.585	0.138	−0.166	0.172
Proximity to hospital	−0.52	0.17	−0.059	0.1	−0.101	0.019	−0.052	0.031
Proximity to cultural amenity	−0.57	0.87	−0.03	0.18	−0.100	0.186	0.026	0.063
Proximity to supermarket	−0.214	0.235	0.029	0.073	−0.248	0.052	−0.039	0.061
Proximity to fire and police station	−0.28	0.227	−0.0051	0.078	−0.070	0.073	−0.009	0.036
Proximity to subway station	−0.37	1.67	0.061	0.313	−0.065	0.358	0.160	0.124
Bus stop densi	−0.27	0.256	−0.0089	0.059	−0.200	0.093	−0.014	0.048
Pedestrian density	−0.083	0.56	0.16	0.114	−0.332	0.410	0.159	0.111

GWR: Adjusted $R^2 = 0.614$, AICc = 9778.037.
MGWR: Adjusted $R^2 = 0.629$, AICc = 9538.062.

inconsistent spatial relationship with disability density across the study area. The concentration of significant areas for multiple variables in Inner London indicates that these factors exert a stronger influence on disability density in this region, highlighting the increased sensitivity of disability distribution to urban environmental conditions in Inner London.As shown in MGWR, all green space and amenity indicators have a wide area with negative coefficients. Besides, there is only a negative correlation between dense vegetation, sparse vegetation and disability density. Sparse vegetation and designated green space exhibit a decreasing negative effect on disability density from the city centre to the suburbs. The data reveal a significant inequity in the distribution of green spaces, particularly in Inner London.

Commercial and industrial areas exhibit a decreasing negative correlation with disability density from the city centre to the suburbs. There is only a negative correlation between industry and disability density. In contrast, the relationship between residential area density and disability density is reversed, showing a positive correlation in the city centre and a negative correlation in the suburbs.

The decreasing coefficient of proximity to community centers from the suburbs to the city centre suggests that individuals with disabilities have easier access to community centers in the city centre compared to those in the suburbs. Proximity to hospitals exhibits a strong negative correlation in the western central areas and a positive correlation in the eastern areas. The relationship between proximity to cultural amenities and fire and police stations with disability density is similar: in the northern part of the study area, there is a negative correlation, while in the southern part, there is a positive correlation. The relationship between pedestrian density and disability density is marked by some irregular negative correlations scattered throughout, reflecting complex spatial patterns.

4. Discussion

4.1. Global level factors

This research explores the relationship between urban amenities and disability density at a spatial scale, providing empirical evidence of environmental injustice in London. The findings of this study are consistent with current research suggesting that environmental injustice exists in London (Higgins et al., 2014). Nicoletti et al. (2023) found that in most of the cities studied, disadvantaged communities face lower accessibility to urban amenities, highlighting existing inequalities. Previous research on disabilities and urban amenities has primarily focused on how urban infrastructure influences the behavioral preferences of disabled individuals. For example, Sze and Christensen (2017) demonstrated that urban infrastructure plays a critical role in ensuring equal opportunities for disabled individuals to participate in community activities. Studies have often centered on the impact of specific amenities, rather than a comprehensive range of urban amenities, on disabled individuals. For instance, Perry et al. (2021) found that the accessibility of park environments, including the location and number of amenities, significantly affects park usage among disabled individuals. Similarly, Schreuer et al. (2019) observed that the implementation of accessible design increases public transportation usage among disabled people. Despite these findings, no environmental justice research to date has specifically examined the spatial relationship between disability and urban amenities. Traditionally, studies on environmental inequality have focused on variables such as race, ethnicity, and income. However, our study shifts the focus to the socioeconomic disadvantages faced by disabled individuals—a vulnerable group that is often overlooked. This oversight can be attributed, in part, to a longstanding perception of disability issues as primarily legal or design-related challenges rather than as central to urban equity. By addressing this gap in the literature, our research reveals significant disparities in the distribution of amenities such as green spaces, supermarkets, and commercial areas, which disproportionately disadvantage disabled people in London.

By comparing OLS, GWR, and MGWR models, we observed an increase in R^2 after accounting for spatial heterogeneity, confirming that spatial distribution significantly impacts study outcomes. The Moran's I index revealed spatial autocorrelation in the distribution of disabilities, leading to the use of standard GWR. However, because a single bandwidth is applied across all variables, this approach results in model overfitting and underfitting, causing highly localized variation patterns in coefficient estimates. To address this restriction, MGWR was undertaken to allow the scale of the relationship between disability density and each urban amenity variable to vary, enabling the analysis of local (spatially non-stationary) and global (stationary) relationships between them. This could facilitate a deeper understanding of the relationship between urban amenities and disability distribution. Additionally, this study analyzes a substantial sample of 4994 LSOAs, a relatively high number compared to many GWR studies that only analyze a few hundred samples.

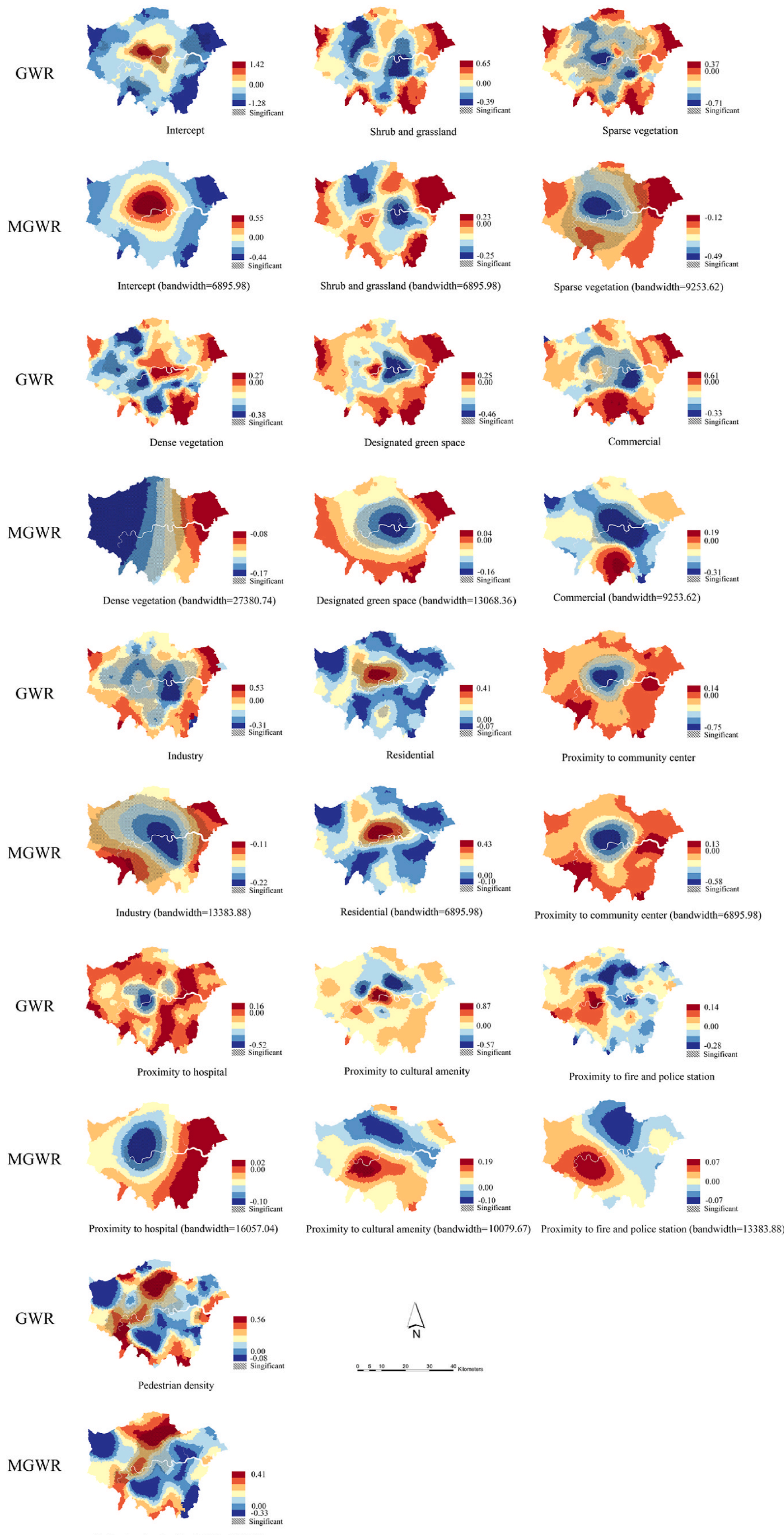

Fig. 6. Comparison of spatial distributions of coefficients from the GWR and MGWR models (distance unit: meters).

4.2. Local level factors

Among all indicators, the distribution of green spaces is the most inequitable for individuals with disabilities, highlighting an environmental justice concern. NDVI provides a sophisticated metric that quantifies the density and health of vegetation. The use of NDVI refines the evaluation of green space quality beyond traditional methods that merely categorize areas based on the presence or absence of greenery. Within the range of green space and amenity indicators, barren land, defined by an almost complete lack of greenery, shows no significant correlation with disability density. In contrast, other green space and amenity metrics, encompassing both low and high-quality green spaces, exhibit a significant negative relationship with disability density, emphasizing the unequal allocation of green spaces. This concurs with Rigolon, Browning, Lee, and Shin's (2018) findings that areas with higher populations of individuals with disabilities typically have insufficient green spaces. Xu et al. (2018) found that green space distribution becomes more inequitable when moving outward from urban core areas to rural regions. In contrast, inequities in green spaces are particularly evident in Inner London, where the area and quality of green spaces (sparse and dense vegetation, and designated green spaces) demonstrate a significant negative correlation with disability density. Zhang and Chen (2024) also identified this disparity, reporting that over 80 % of LSOAs in Inner London have below-average accessibility to UGSs. This study also found that while suburban areas contain significantly larger green spaces compared to urban areas, the distribution of people with disabilities in Inner London appears to be more sensitive to urban environmental conditions. This heightened sensitivity is likely due to higher population density and the concentration of amenities in the area. Although there are many parks in the city center, they are primarily small parks. This is due to high land values in inner London, particularly within the City of London and surrounding areas, which have historically been financial hubs with significant land dedicated to commercial and mixed-use developments (Chen et al., 2025). As a result, there is limited non-profit green spaces and a predominance of built environments. The observed negative correlation between green space and disability density may be attributed to the socioeconomic disadvantages faced by individuals with disabilities. Green spaces often positively influence neighboring property values (Trojanek et al., 2018; Bockarjova et al., 2020). Since individuals with disabilities are more likely to experience income poverty, insecure employment, and high living costs (Dermott, Main, Bramley, & Bailey, 2018; Kavanagh et al., 2016), they are often restricted to more affordable areas that not only lack high-quality green spaces but also suffer from inadequate accessibility features, such as poorly maintained pathways and a shortage of ramps. This dual disadvantage of insufficient and inaccessible green spaces reflects a systemic environmental injustice that prioritizes commercial profitability over the health and well-being of marginalized communities. Current policies, such as those outlined in the London Environment Strategy, aim for more than half of London to be green by 2050 (Greater London Authority, 2018). However, these policies do not specify requirements for the equitable distribution of green spaces, potentially exacerbating existing inequalities.

Regarding land use, both industrial and commercial areas exhibit a significant negative correlation with the density of disabled people, whereas residential areas show a positive correlation. The observed negative correlation between the industrial area and disability density indicates that zones with more industrial activity tend to support fewer residents and, consequently, have a lower density of individuals with disabilities. However, the negative association with commercial areas in Inner London indicates that commercial facilities are not evenly distributed according to the needs of individuals with disabilities but are instead concentrated in the city center with fewer disabled populations. This distribution likely poses challenges for individuals with disabilities, causing inconvenience in their daily activities.

Within the scope of basic services, the OLS model reveals that only the correlation between proximity to supermarkets and disability density is insignificant. The distance to other facilities shows a negative correlation with disability density, indicating that the overall distribution of basic services is relatively equitable. Unlike other amenities that may be more concentrated in specific areas, supermarkets tend to be more evenly distributed across urban and suburban environments. This even distribution reduces the likelihood of significant spatial disparities in access to supermarkets for individuals with disabilities, thereby may leading to a lack of strong correlation with disability density. Similar findings on the even spatial distribution of supermarkets have been reported in Montreal (Apparicio et al., 2007). Additionally, the GWR and MGWR models indicate that proximity to community centers and hospitals exhibits a negative correlation with disability density, particularly in central London. This area, being more urbanized and historically centered, naturally has a higher concentration of public facilities. For cultural amenities, as well as fire and police stations, areas with higher disability density in North London are generally located closer to these facilities, indicating better service coverage. In contrast, South London shows a positive correlation where areas with higher disability density are farther from these facilities, suggesting a disparity in service accessibility. This inequitable distribution reflects a broader environmental justice issue, where access to critical services for vulnerable populations is not evenly distributed across the city.

People often believe that transportation investments and operations have historically inflicted environmental harm on poor and minority communities (Schweitzer & Valenzuela, 2004). However, in this study, the absence of significant correlations between disability density and the distribution of bus and subway stations, coupled with the observed positive correlation between pedestrian density and disability density, indicates that the distribution and accessibility of major transportation services do not disproportionately disadvantage the disabled population. Public transportation in London faces challenges related to accessibility, such as issues with wheelchair access, which are particularly difficult to resolve within an older transit network (Ferrari et al., 2014). Currently, over half of tube stations lack step-free access. Additionally, subway stations are unevenly distributed, with a higher concentration in northern London and none in the southeastern region. This uneven distribution can limit accessibility in the south, where transferring between services is often required. For individuals with disabilities, such transfers can be considerably more challenging than for those without disabilities. Previous research indicates that individuals with disabilities in London generally prefer not to use public transport due to accessibility barriers, yet those residing in Inner London are significantly more likely to rely on public transport or walking compared to individuals in Outer London (Schmöcker et al., 2008). This difference can likely be attributed to the higher density of public transport services and reduced reliance on private vehicles in the city center. Nevertheless, this reliance on public transport may reflect a lack of viable alternatives rather than a genuine preference, given the uneven distribution of step-free access and other critical accessibility features across the network. The limitations in public transport coverage and physical accessibility barriers may contribute to the lack of a distinct preference among individuals with disabilities for residing near public transportation, which could explain the absence of a significant correlation between the distribution of bus and subway stations and disability density.

4.3. Practical implications and future study

This study contributes to the literature on urban environmental justice by illuminating the complex relationship between urban amenities and disability density. It aids in achieving the goal of just and healthy cities by providing a strategic framework for resource allocation that promotes equity and enhances livability, particularly by addressing disparities in access to green spaces and essential urban facilities.

Our research provides valuable practical implications for government agencies involved in urban amenity planning in London, as well as for broader applications in landscape planning, public policy, and funding allocation.

Firstly, disparities in access to green spaces, particularly in Inner London, underscore the need for targeted interventions to enhance accessibility and quality. While the Supplementary Planning Guidance on Accessible London (2014) promotes general accessibility, our findings suggest the necessity of more localized measures. Policymakers should focus on improving the quality of existing green spaces and increasing the proportion of high-quality green areas, especially in Inner London. However, urban planning must consider the potential risk of green gentrification, which could displace low-income residents and deprive them of the ecosystem services and benefits provided by urban nature (Hochstenbach, 2017). The phenomenon of green gentrification, where property values increase near new or renovated green spaces, has been observed in many prominent cities, often resulting in the displacement of vulnerable populations. This underscores the need for strategies to prevent such unintended consequences. For instance, urban planners should take into account the spatial distribution and characteristics of UGS. Research suggests that prioritizing smaller, active green spaces is less likely to trigger significant gentrification effects (Kim & Wu, 2022; Wolch et al., 2014).

Secondly, given the persistent environmental injustices faced by individuals with disabilities, urban planning and policy should be more inclusive of their needs. People with disabilities have historically been marginalized and remain less visible than other vulnerable groups (Pineda, 2008). To ensure inclusivity, urban development plans should incorporate accessibility and inclusivity metrics, adopt participatory approaches in policy formulation and implementation, and enforce accessibility standards in both public and private development projects. Policies should prioritize the principles of Universal Design and Access, as well as align with the United Nations Convention on the Rights of Persons with Disabilities (CRPD, 2006).

Finally, a data-driven approach to resource allocation is essential in addressing spatial disparities in urban amenities. For example, the MGWR results reveal an inequity in the distribution of community centers and hospitals in Outer London, highlighting the need to increase the number of these critical facilities in outer LSOAs. Considering the growing population of individuals with disabilities, who are among the most in need of the convenience and social welfare provided by urban amenities, it is imperative to center disability issues in discussions of environmental justice.

While inequity in facility distribution is an inevitability, future research should aim to incorporate several factors for a more comprehensive and precise understanding of these disparities: (1) the range of services provided by amenities, detailing both the breadth and depth of services available; (2) disparities in amenity distribution should be analyzed in relation to residents' needs and preferences, as variations may not always stem from inequitable processes but could instead reflect community-specific demands. For instance, if the spatial distribution of amenities aligns with the preferences of the majority within a community, it may not necessarily indicate inequity; and (3) building upon this study, conducting more detailed local quantitative or qualitative analyses focused on facilities and regions that experience severe inequities. For instance, surveys could provide valuable insights into individuals' experiences, offering a deeper understanding of the underlying factors contributing to these disparities and informing the development of targeted policy interventions. By integrating these factors, future studies can deepen the discourse on environmental justice and inform the creation of urban spaces that are equitable and supportive of all community members.

4.4. Limitations

Despite the unique findings from this study, some limitations need to be acknowledged. Firstly, due to the reliance on objective data, the index employed in this study may not comprehensively represent the subjective aspects of urban amenities that could influence residents' preferences. Secondly, there is an inconsistency in the temporal resolution of the data used. The dependent variable, disability density, is based on the 2021 Census data provided by the Office for National Statistics, which is collected every ten years. In contrast, the independent variables are sourced from different years: data from OpenStreetMap and Digimap are from 2023, while cultural amenities and designated green space distribution data from the London Datastore are from 2022. This discrepancy may introduce biases, as changes in the urban environment during this period could affect the observed relationships, potentially compromising the accuracy of the findings. Moreover, while London's diverse and complex urban landscape provides a valuable case study for examining issues of environmental equity and accessibility, these findings might not directly apply to other cities. Researching the determinants of environmental equity is inherently complex, with cities constantly changing, resulting in variations in living conditions between cities (Galea & Vlahov, 2005).

5. Conclusion

Over the past two decades, achieving an equitable spatial distribution of urban amenities has emerged as a critical focus of academic research (Dadashpoor et al., 2016). This study, using London as a case study, highlights persistent disparities in the distribution of urban amenities. By integrating multi-source data and employing a comparative analysis of OLS, GWR, and MGWR models, this research provides nuanced insights into these disparities. The findings reveal that OLS results alone do not adequately capture spatial distribution due to spatial heterogeneity. While GWR improves upon OLS by accounting for local variations, it uses a uniform bandwidth across the study area. In contrast, MGWR offers a more refined analysis by accommodating varying spatial scales. This approach reveals that the relationship between urban amenities and access for individuals with disabilities varies across different spatial contexts. Specifically, the study finds that, despite their uneven spatial distribution, the availability of basic services and transportation does not exhibit a significant negative correlation with disability density at the city level. However, significant inequalities are evident in the distribution of green spaces and commercial areas, reinforcing the hypothesis that individuals with disabilities face limited access to certain urban amenities. The findings emphasize that the inequitable distribution of green spaces, particularly in Inner London, requires targeted policy interventions. Policies should prioritize enhancing green space quality and accessibility, particularly in high-density urban areas where high land values constrain the availability of non-profit green spaces. Additionally, the negative correlation between commercial areas and disability density indicates that commercial facilities are disproportionately concentrated in city centers, potentially creating accessibility challenges for those living in outer London. This research contributes to the broader discourse on environmental justice by shifting the focus from traditional variables such as race and income to the socioeconomic challenges faced by disabled individuals. It advocates for urban planning strategies that address these disparities and promote a more equitable distribution of urban amenities. Policymakers should consider these findings to ensure a more even distribution of urban amenities, fostering an inclusive urban environment that meets the needs of all residents, including those with disabilities.

CRediT authorship contribution statement

Jiaxi Yang: Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mingze Chen:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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