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Research Paper

Combining spatial clustering and spatial regression models to understand distributional inequities in access to urban green spaces

Bruno Vargas Adorno [a,*], Rafael H.M. Pereira [b], Silvana Amaral [a,c]

[a] Remote Sensing Postgraduate Program (PGSER), Coordination for Education, Research and Outreach (COEPE), Brazil's National Institute for Space Research (INPE), Av. dos Astronautas, 1757, São José dos Campos, São Paulo, 12227010, Brazil
[b] Institute for Applied Economic Research (Ipea), Brasília, Brazil
[c] Earth Observation and Geoinformatics Division, National Institute for Space Research (INPE), São José dos Campos, Brazil

HIGHLIGHTS

- LISA and GWR combined allow classifying levels of access to green spaces.
- Levels of access to green spaces vary considerably by people and urban green spaces.
- Urban peripheries in Goiânia, Brazil, have systematically lower levels of access to public green spaces.
- The lowest levels of access to urban vegetation by elderlies are in the city center of Goiânia, Brazil.

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ABSTRACT

Proximity to urban green spaces offers numerous benefits, sparking increased research and policy interest in equitable access for different population groups. While spatial analyses evaluate access to urban green space, previous studies overlook fine-grained spatial disparities, needed for targeted urban planning. Spatial clustering models (Local Indicators of Spatial Association – LISA) group values significantly higher and lower than the average in the geographic space. In turn, spatial regression (Geographically Wheigted Regression – GWR) reveals the strength and direction of the correlation between variables across space. Here, we investigate whether and how the combination of both types of models helps examine distributional green equity. We show how combining LISA and GWR gives a more nuanced understanding of distributional green equity. We apply this approach to Goiânia, Brazil, with an empirical analysis of access to three categories of green spaces: tree cover, herb-shrub, and public green spaces. Using open-source methods and tools, we examine variations in accessibility for black people, women, and people of different age, literacy, and income groups. We used a new accessibility metric accounting for the size/area of green spaces, walking times and competition for accessing green spaces. The analyses revealed access disparities by population group and green space category identifying specific regions in the city and population groups with consistently limited access to urban green spaces, guiding planners with refined information to prioritize green space interventions where they are most likely needed. This method enables targeted, equitable urban planning that fosters inclusive access to green spaces for diverse communities.

1. Introduction

Having access to urban green spaces is fundamental for city dwellers to benefit from numerous ecosystem services. Urban green spaces are broadly defined as areas with natural surfaces, including vegetation, and public green spaces like parks and squares (Taylor & Hochuli, 2017; WHO, 2016). Among these green spaces, tree cover is efficient in regulating microclimate and reducing air pollution (Drillet et al., 2020; Willis & Petrokofsky, 2017). Herbaceous and shrub areas offer similar benefits and serve as open space for food production on empty lots (Marçal et al., 2021; McPhearson, Kremer, & Hamstead, 2013). Public green spaces, provide diverse vegetation and public amenities like walking and bike trails and playgrounds commonly used by city residents (Taylor & Hochuli, 2017). Urban green spaces also improve public

* Corresponding author.
E-mail addresses: bruno.adorno@inpe.br (B.V. Adorno), rafael.pereira@ipea.gov.br (R.H.M. Pereira), silvana.amaral@inpe.br (S. Amaral).

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health by positively affecting birth outcomes, physical activity, mental health, and cardiovascularand respiratory health (Kondo et al., 2018; WHO, 2016).

The benefits of urban green spaces are particularly important for vulnerable people (Konijnendijk et al., 2023; Rigolon et al., 2021). According to the United Nations' Sustainable Development Goals, governments are expected to provide universal access to safe and inclusive green and public spaces, with particular attention to women and children, older persons and persons with disabilities (IAEG-SDGs, 2017). Nonetheless, advancing policies and techniques to ensure equitable access to green spaces – regardless of gender, age, race, and socioeconomic status – remains a persistent challenge in cities worldwide (Nesbitt et al., 2019; Rigolon et al., 2018; 2024).

The analysis of distributional green equity focuses on the spatial patterns of unjust access to urban vegetation, especially among underserved groups of people (Nesbitt et al., 2018). Although such investigations have grown since the 1990 s (Talen, 1997; Talen & Anselin, 1998), mapping these patters with spatial data remains challenging, mainly in the Global South (Rigolon et al., 2018).

Different studies have explored spatial clustering models to identify neighborhoods with limited accessibility to green spaces. In this literature, accessibility refers to how easily people can reach opportunities by walking or other transportation means (Páez, Scott, & Morency, 2012). Iraegui, Augusto, and Cabral (2020) applied the Local Indicators of Spatial Association (LISA) and identified regions where urban green spaces were largely inaccessible to seniors and children. Zhang (2023), on the other hand, found that neighborhoods with predominantly low housing prices had very limited availability of green spaces.

Other studies have used spatial regression models to investigate the association between access to green space and socioeconomic variables across space. Yang, Yang, and Zhou (2022) applied Geographically Weighted Regression (GWR) to examine spatial variations in green space inequity, observing a negative association between green space access and certain population groups. Their findings revealed that less educated individuals and those living in homes smaller than 50 m^2 experienced significant green inequity in over half the city, whereas inequity in less than 10 % of the city area was found for people under 18 and over 65.

Finally, one study developed spatial clustering and regression models separately to gain a more comprehensive knowledge of the relationship between population characteristics and different types of green spaces like parks, squares, and public facilities (Chen et al., 2020). However, to the best of our knowledge, no study has systematically explored combining the complementary assumptions of both spatial clustering and regression models to create new map results for investigating distributional urban green equity.

To fill this gap, this paper aims to assess how the combination of LISA and GWR methods could provide new understandings for distributional urban green equity. We set out to answer the following questions: (1) where do local demand for and accessibility to urban green spaces exceed or fall below the average? (2) Where do demand for and accessibility to urban green spaces positively and negatively correlate within neighborhoods? (3) Lastly, where are the critical areas for green equity identified in (1) and (2)? We address these questions through LISA and GWR analyses, with an emphasis on combining them to identify distributional equity in access to urban green spaces at varying levels. We examine three categories of urban green spaces and six demographic groups to demonstrate how this methodology aid the understanding of these relationship.

This study offers a key methodological contribution by introducing a typology for assessing varying levels of access to urban green spaces, derived from integrating LISA with GWR results. This typology can be adapted and applied in diverse urban contexts globally where similar data is available. Additionally, our work provides novel insights by mapping differential access to urban green spaces within a major Global South city, addressing an often-overlooked context in the literature.

2. Methods

The method used in this paper is divided into three steps. First, we defined and mapped the variables for this study: access to urban green spaces (i.e., tree cover, herb-shrub, and public green spaces) and share of sociodemographic groups (children, elderly, adult women, black people, literates and income). Next, we conducted LISA and GWR, separately, to explore significant spatial association for each variable and the significant spatial correlation between each greenspace and sociodemographic group. Finally because we wanted to harness the advantages of LISA and GWR complementary results, we combined them to classify varying levels of access to urban green spaces for each analyzed population. An overview of the methodology used in the paper is illustrated in Fig. 1. The study area and each methodological step are detailed next.

2.1. Study area and spatial analysis unit

We investigated the distributional green equity within Goiânia, the capital of Goiás, Brazil, which is home to almost 1.5 million people with a predominantly female adult and elderly population (IBGE, 2023). Goiânia has a high schooling rate for children and teenagers at around 96 %, though 30 % of its residents earn less than one minimum wage per capita. Economic disparities have been present since the city's establishment in the 1930 s when it was envisioned as part of a project to densify Brazil's interior. Goiânia's flat terrain and natural abundance were key factors in its settlement, and today, its climate—characterized by distinct dry and rainy seasons—supports a variety of vegetation, from grasslands and savannas to forests.

Goiânia has been acknowledged, along with other 33 Brazilian cities, as Tree Cities of the World by the Arbor Day Foundation and the Food and Agriculture Organization of the United Nations (SBAU, 2024). Despite this recognition Ramos et al. (2020), using geoprocessing techniques, found notable disparities in green space per capita across different areas of the city. However, their study did not examine other types of green spaces, nor did it address equity aspects at the citywide level using accessibility metrics or spatial analysis tools.

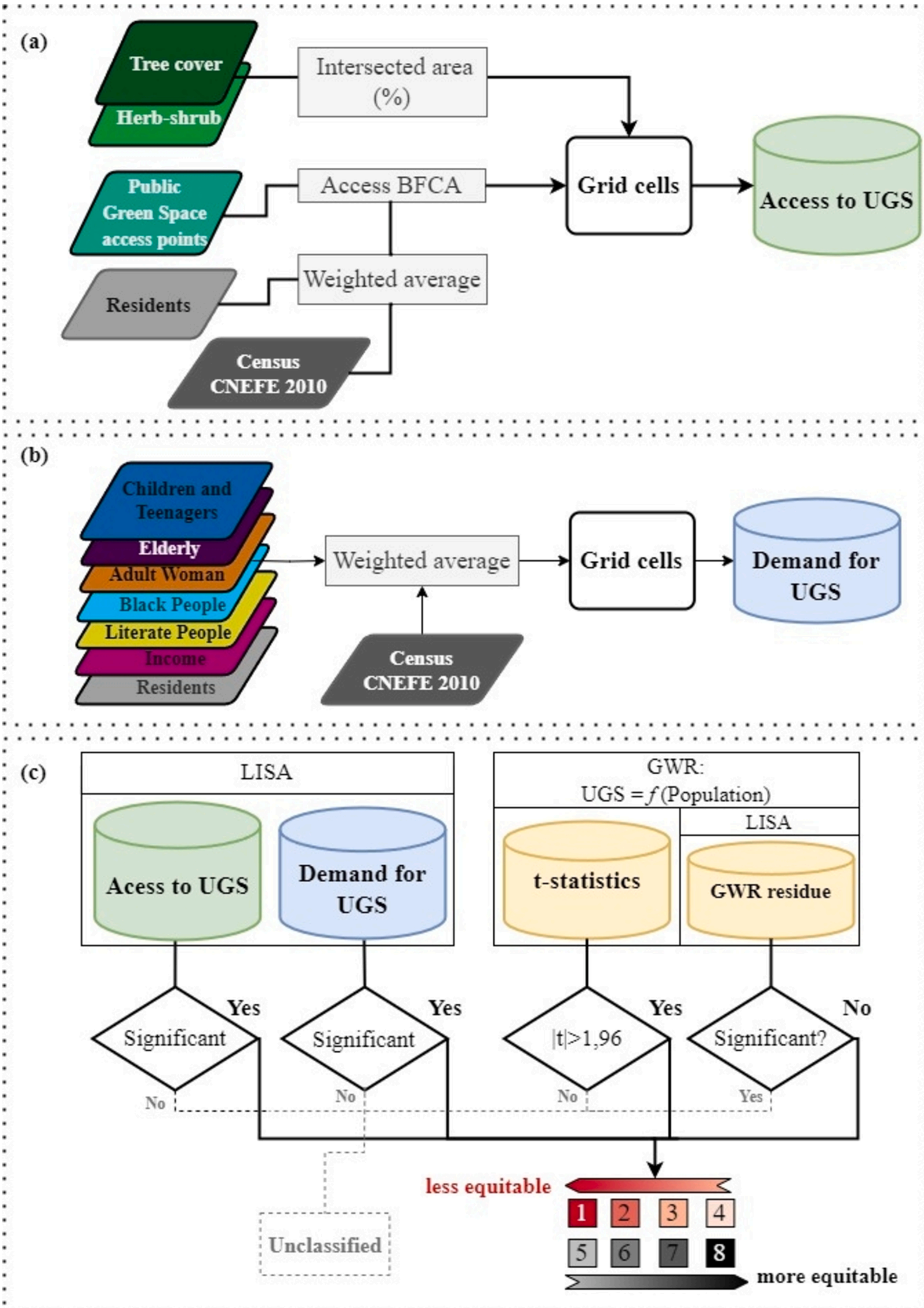
Our analysis intended to analyze the entire urbanized area of the city, considering hexagonal grid cells based on the global H3 index using the resolution 9 (https://h3geo.org/docs/core-library/restable). At this resolution, each cell has approximately a side of 174 m and an area of 0.10 km^2 and does not compromise computational cost. In the city of Goiânia, each hexagon generally covers one to four city blocks. This structure supports a finer-scale analysis of spatial patterns, which is essential for assessing variations in urban green space access. This way we could obtain more nuanced understandings of how combining LISA and GWR methods can favor the analysis of distributional urban green equity.

To represent residents' geolocation (i.e., address point), we extracted centroids from the block-face database of the National Address List for Statistical Purposes (CNEFE) from the 2010 Census, the latest official census survey results published in Brazil by the time we processed the data. Finally, we selected only the cells that were within urban areas in Goiânia, according to the 2020 census tracts (IBGE, 2020), and which contained at least one household (Fig. 2).

2.2. Mapping the access to urban green spaces and population demand

We mapped the access to our three categories of urban green space (i.e. tree cover, herb-shrub and public green space), based on two approaches (see data and method used for each approach in Table 1). In one approach we assumed that the probability of residents accessing local benefits from the types of vegetation increases with its proportion within each spatial unit. Thus, we represented the presence of vegetation in the areas immediately nearby people's residences by calculating the fraction of each hexagonal area covered by each vegetation type.

To measure access to public green space, we used the recently



(caption on next page)

Fig. 1. Flowchart of the method used in this study: (a) we measure access to each type of urban green space (UGS) by (1) integrating the area intersected between each vegetation type and grid cells, and (2) calculating the access to public green spaces using the Balanced Floating Catchment Area Index (BFCA) in each cell. (b) We determine demand for UGS by population group in each cell based on the weighted average of the share of each population group in census tracts that intersect with each cell data. (c) Spatial analyses: we carry out Local Indicator of Spatial Association (LISA) on each variable related to demand and access to urban green spaces; we carry out Geographically Weighted Regression (GWR) to correlate each pair of demand and access to urban green space variables and derive t-statistics, β- coefficient and GWR residuals; finally, we use Boolean algebra to classify each grid cell into eight different levels of access to urban green spaces. Grid cells were not classified if they had no significance for LISA and/or GWR or their GWR residuals had spatial dependency.

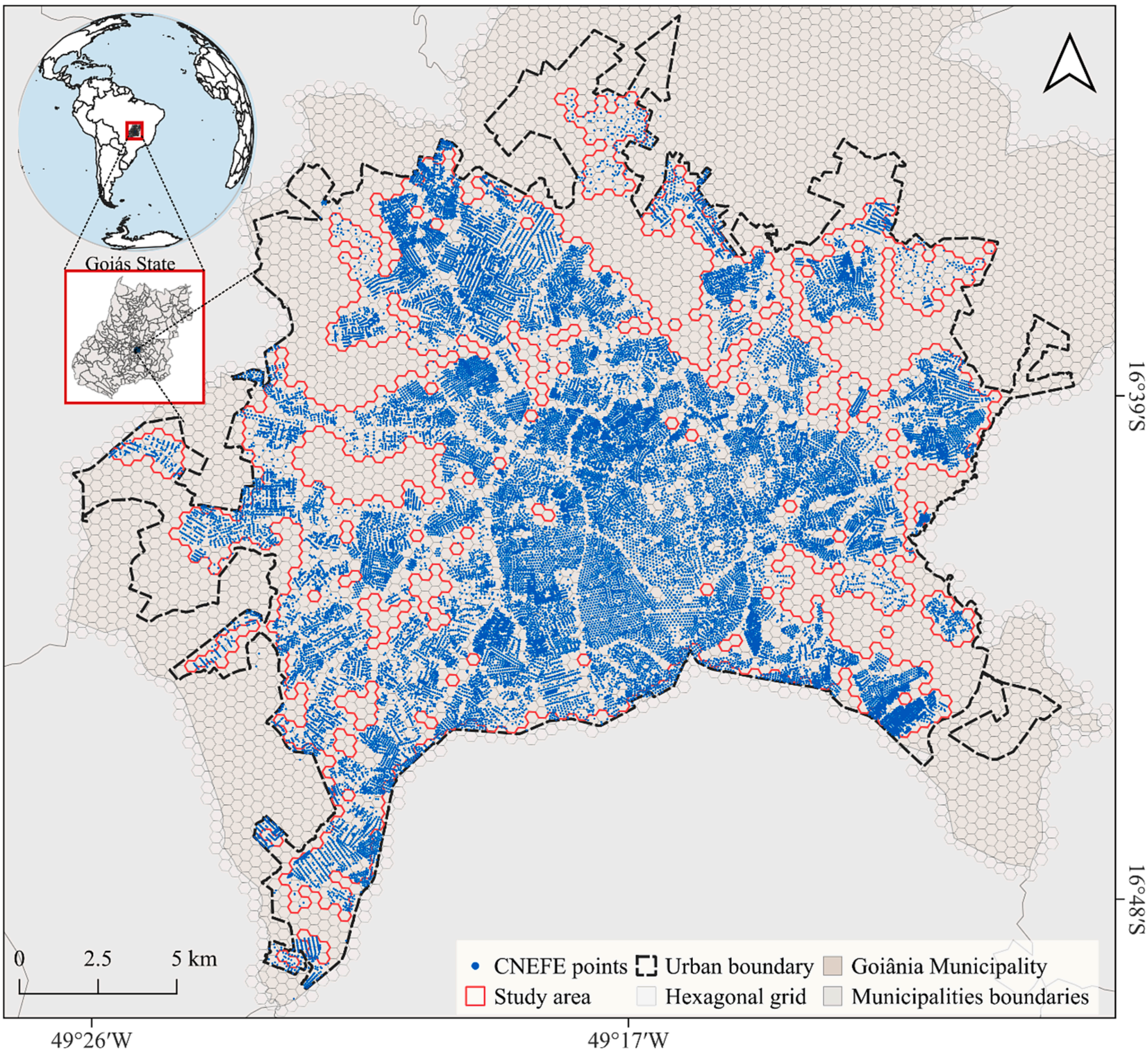


Fig. 2. Study area delimitation: selection of hexagonal cells within urban boundary that contained residences registered in National Address List for Statistical Purposes (CNEFE).

developed Balanced Floating Catchment Area (BFCA) (Paez, Higgins, & Vivona, 2019; Pereira, Braga, et al., 2021). Different from other Floating Catchment Area methods (see Delamater, 2013; Wan, Zou, & Sternberg, 2012), the BFCA avoids generating biased accessibility estimates because it allocates both demand and supply proportionally using a standardized impedance matrix to avoid inflation of potential services supply and demand. In practical terms, these assumptions consider that one person cannot be simultaneously in more than one public green space area, and their willingness to walk to one or another area also consider its congestion probability, dependent on the number of people living within its catchment area.

To run the BFCA, we used the function "travel_time_matrix" from the package {r5r}, version 0.6.0 (Pereira, Saraiva, et al., 2021) and the "floating_catchment_area" function from the {accessibility} package, version 1.4.0 (Pereira & Herszenhut, 2022), both in R Studio software (R version 4.1.1). The BFCA calculation is presented in Equation (1):

$$A_i = \sum_{j=1}^{J} \frac{S_j w_{ij}^{j}}{\sum_{i=1}^{n} P_i w_{ij}^{i}}, \tag{1}$$

in which, A_i is the BFCA indicator at residence address i that represents the sum of accessible opportunities $j (j = 1, \cdots, n)$ per resident (supply–demand ratio). S_j represents the service capacity (supply) at public green space j (public green space area in m^2). The PGS area was attributed to each of their access points to calculate the S_j accessible by residents at the nearest access point. P_i represents the total number of

Table 1
Approach, data, and method used for calculating access to urban green space.

Approach	Data	Method
1) Access to vegetation based on its cover fraction.	• Tree cover and herb-shrub land cover satellite image classification (2 m spatial resolution)(Adorno, Körting, & Amaral, 2023) ;	Calculate the fraction of grid cell covered by each vegetation type as the presence of vegetation nearby people's residence
2) Access to public green space based on Balanced Floating Catchment Area	• geo-objects on urban park and squares, provided by the municipality database (COMDATA, 2016) and Open Street Map.1	Calculate the access points to public green space that can be reached via walking considering walking times (affected by street network distance and terrain elevation), the size/area of green spaces, and the competition in terms of supply and potential demand for these areas.
	• city's street network provided by the Open Street Map.	to represent walkability on streets
	• Access points manually inserted at the intersection of a network and a public green space	To provide accurate geolocation of access points to public green space through street network
	• Digital terrain model (5 m spatial resolution) provided by the Municipal Environment Agency.	to take relief characteristics into account

[1]The data were selected after careful analysis: (1) removing duplicates among the databases, (2) assessing Google Street View pictures taken after 2019, and (3) conducting field visits to specific geolocations lacking street view pictures.

residents (demand) at the address point $i(i = 1,\cdots,n)$, calculated with the dasymetric mapping method described in Equation (2):

$$P_i = \frac{H_{ij}P_j}{\sum_{i=1}^{n} H_{ij}}, \tag{2}$$

in which H_{ij} is the number of households at the address point i in the census tract j, where P_i is located; and P_j, the number of residents in the census tract j. The population aggregated by census tract was obtained from the 2010 population census data, the finest resolution and latest data available by the time of the writing of this paper (IBGE, 2011).

The w_{ij}^{j} and w_{ij}^{i} in Equation (1) are the normalized weights introduced by the BFCA method to correct, respectively, the supply (Equation (3) and demand (Equation (4) levels:

$$w_{ij}^{j} = \frac{w_{ij}}{\sum_{i=1}^{n} w_{ij}}, \tag{3}$$

and

$$w_{ij}^{i} = \frac{w_{ij}}{\sum_{j=1}^{J} w_{ij}}. \tag{4}$$

The w_{ij} weights the willingness residents have to walk to a PGS, considering a distance-decay function, dependent on the travel time between locations i and j. We defined a logistic distance-decay function (Equation (5) to model people's walking behavior:

$$w_{ij} = f(x) = \frac{L}{1 + e^{-k(x-x_0)}}, \tag{5}$$

being $x_0 = 12.5$, $L = 1$, and $k = -0.4$). The chosen parameters reduce w_{ij} from 1 to 0 ($k < 0$) for an increased travel time. Also, 12.5 min was chosen as the travel time when people's willingness to walk reduces by 50 % (x_0), meaning the maximum time spent would be 25 min (circa 1.5 km at 3.6 km/h). The k value was empirically chosen so the decaying function would be smoother up to an 8 to 10 min walk, considered a comfortable walking distance (Filho & Malta, 2010). After a 10 to 12.5 min walk, the decay becomes steeper, tending to zero at 25 min, reported as maximum acceptable travel cost by walking in the international literature (Liu; Kwan; Kan, 2021).

To examine inequities concerning access to urban green space, we also mapped the spatial distribution of key sociodemographic groups: income per capita and the shares of elderly, black people, adult women, children and teenagers, and literate people. Table S1 (*Supplementary Material)* presents a detailed description and justification for choosing each population group. We aggregated the mean share of each group in the hexagons after using the same procedure presented in Equation (2).

2.3. Mapping the levels of access to urban green spaces

A key step in the method used in this paper was the combination of the LISA and GWR results, which carry different but complementary assumptions. LISA provides the local spatial association among one variable's individual location and its surroundings by clustering values significantly higher and lower than the global average (Anselin, 1995). GWR produces local regression models between dependent and independent variables, revealing how the strength and direction of the correlation of these variables vary across space (Brunsdon, Fotheringham, & Charlton, 2014; Fotheringham, Brunsdon, & Charlton, 2002).

We posit that the combination of the results from both methods allows one to determine the main clusters of low access to urban green spaces and classify them into different levels of access to urban green space based on the spatial regression between access to urban green space and its potential demand. For example, while a LISA analysis allows us to determine spatial clusters of areas with low income and low access to green spaces, a GWR analysis could provide additional insight by indicating whether, at the neighborhood level, the lowest access cells are further associated with the lowest incomes, indicating a more severe shortfall of access by a larger population of that particular group. Next, we explain the procedures we carried out to run each method and the suggested typologies created from LISA and GWR combined results.

2.3.1. GWR analysis

Before running the GWR analyses, we performed a linear regression between each pair of dependent (access to urban green spaces) and independent variables (sociodemographic groups), because GWR can omit significant relationships between variables for non-normally distributed residuals (Yu, Peterson, & Reid, 2009). Thus, we transformed the dependent variables with the Box-Cox transformation (Box & Cox, 1964), plotted histograms, and used the two-sided Kolmogorov-Smirnov test to verify the distributions of the residuals before and after transformation (null hypothesis is not rejected for $|p| > 0.05$) (Figs. S1, S2, S3, and Table S2 in *Supplementary Material*). As the transformation tended to normalize the residuals we kept the Box-Cox transformed dependent variables henceforth. Log transformation was also assessed, but did not alter the p-value for residuals dependency in Kolmogorov-Smirnov test.

We conducted GWR analyses in MGWR (1.0), generating eighteen models between each green space and socioeconomic standardized variables, separately, to highlight significant regions where each pair of response and explanatory variables are correlated. The GWR is described in Equation (6):

$$y_i = \beta_0(u_i, v_i) + \beta_z(u_i, v_i)x_{iz} + \varepsilon_i \tag{6}$$

in which y_i is the dependent variable (each urban green space category) at the location i; $\beta_0(u_i, v_i)$, the intercept at the location i; x_{iz} the independent variable z (each population group) at the location i, and ε_i the random error at the location i. The $\beta_z(u_i, v_i)$ coefficient is described in Equation (7):

$$\beta_z(u_i, v_i) = [X^T W(u_i, v_i) X]^{-1} X^T W(u_i, v_i) Y \quad (7)$$

in which Y is the dependent variable vector comprised of a neighborhood denoted by $W(u_i, v_i)$, which represents a weighting matrix for each location i, and X the independent variable vector for the same neighborhood. The $\beta_z(u_i, v_i)$ coefficient t-statistics was estimated to reveal where each GWR model was significant ($|t| > 1{,}96$; $\alpha = 5\ \%$). We chose the kernel bi-square function to represent the neighborhood W, as described in equation (8):

$$W_{ij} = \left[1 - \left(\frac{d_{ij}}{d_{iN}}\right)^2\right]^2, if d_{ij} < d_{iN}, otherwise, W_{ij} = 0, \quad (8)$$

in which W_{ij} is the weight for the j-neighbor of i; d_{ij} the Euclidean distance between i and j centroids; and d_{iN} the adaptive bandwidth, adjusted to the distance between i and its *k-nearest* neighbor. The adaptive bandwidth of 45 neighbors was defined for minimizing the AICc criterium. Moreover, adaptive bandwidth is advantageous to secure that the bandwidth would adjust accordingly to keep the sample sizes for the regression either in border or in central regions.

2.3.2. LISA analysis

LISA analysis was carried out in GEODA (v.1.20.0.8). For the spatial weight matrix, we also fixed the bandwidth to the 45th nearest neighbors as in GWR. We used the inverse distance to the 4th power function in GEODA because it was the most similar to the kernel bi-square available in MGWR. Then, we calculated nine univariate Moran's local indicator (Anselin, 1995) to determine local spatial clusters of access to each category of urban green space and local clusters of each population group. In addition, one LISA analysis for each GWR residuals was carried out to assess their spatial dependency. Close-to-zero indicator expresses no clear association (i.e., randomness) between each analyzed location and its neighbors, positive indicator expresses similarities; and negative, dissimilarities. We carried out a pseudo-significance test to confirm whether associations were significantly different from zero at $\alpha = 5\ \%$ ($|Zi_{-\text{ score}}| > 1.96$).

Finally, by overlapping LISA and GWR results, we classified the study area into different levels of access to urban green space (Fig. 1 c). To inform a reliable classification, we only classified the areas where both LISA and GWR were statistically significant and where the GWR residuals were not spatial dependent. We defined eight levels, ranging from 1 (lowest level) to 8 (highest level).The interpretation for the classes are detailed in Table 2 and completed in Table S3 (*Supplementary material*).

3. Results

3.1. Descriptive results of access to urban green spaces and sociodemographic groups

Fig. 3 presents the urban green spaces data and the spatial distribution in quartiles of each independent and dependent variables used in the analysis. Concerning urban green spaces distribution (Fig. 3a), access to tree cover tends to be more randomly distributed than access to other urban green spaces. However, there are some evident neighborhoods with less than 3 % tree cover in the central, northern, and western regions, and with more than 23 %, in the eastern periphery of the city. Regarding herb-shrub, they cover generally below than 8 % of central neighborhoods and are generally above 18 % or even 33 % in the outskirts. For the public green spaces, we had analyzed 1,782 potential urban green spaces, according to geo-objects from OSM and municipality databases, but only 483 were areas providing both public equipment and vegetation in public areas. These selected public green spaces are concentrated in the center and south regions. The outskirts presented mostly area within conservation units or vacant lots without any usable infrastructure by the population. Thus, only few clusters of higher access to public green space were found towards the outskirts.

Regarding the distribution of sociodemographic groups (Fig. 3b), we found three distinct patterns: (1) the highest concentration of elderlies is in the city core; (2) the highest share of adult women are in smaller clusters between central and peripheral areas and some in northern peripheral areas; (3) compared to other neighborhoods in the city, those located in the outskirts are populated by a higher share of children and teenagers, black people are, individuals with lower education and income.

To give greater focus on the applicability of the proposed method in assessing distinct patterns of variables, in the next sections, we focused on three population groups with clear distinct pattern distribution: elderlies, adult women and children and teenagers. The results for black people, illiterate people and low-income people, whose spatial distribution are quite similar to children and teenagers', are presented in the *Supplementary Material* (Fig. S4, S5, and S6).

3.2. Local clusters of urban green spaces accessibility and potential demand

LISA results highlight the significant regions lacking access to urban green space: in Fig. 4 (a), an hexagon classified with 'L-L' means that both the hexagon and its neighbors have access to urban green spaces lower than the average. We also observed where the results suggest higher demand for urban green spaces demand by each population group. In Fig. 4 (b), every cell and its neighbors classified with 'H-H' have higher demand for urban green spaces than the average.

Larger L-L clusters of access to tree cover and herb-shrub are mainly located in the central-southern area. Concerning the peripheries, herb-shrub is lacking in a few northern and eastern neighborhoods, while tree cover is lacking at some extent in all directions. For public green spaces, the lowest access is towards peripheral zones. The highest clusters of demands for urban green spaces are likely found in central and southern zones, considering the elderlies; between central and peripheral zones, regarding adult women; and in peripheral zones, concerning children and teenagers.

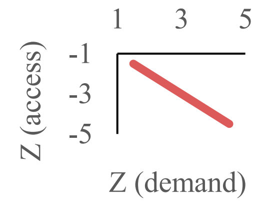
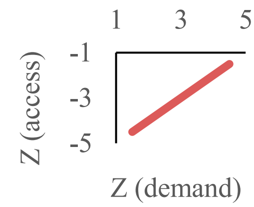
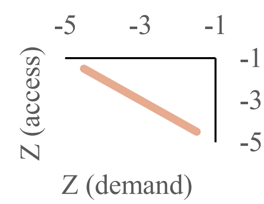
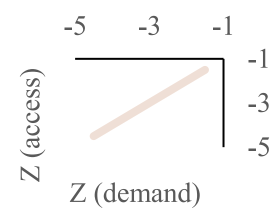
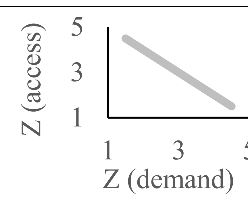
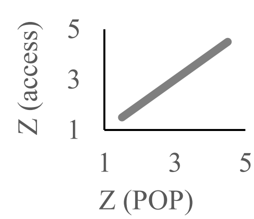
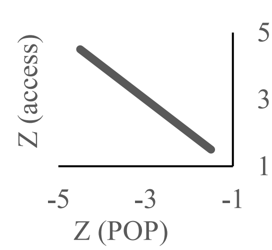
In summary, inequities in access to tree cover and herb-shrub are likely found in the city center, where the highest shares of elderlies live. Most clusters with low access to public green spaces, by contrast, are found towards the outskirts, inhabited by the highest shares of children and teenagers and by few clusters containing relevant share of adult women. Although the LISA helps us determine these spatial clusters of high and low access to green spaces, this method alone does not inform where and whether access and sociodemographic groups are positively or negatively correlated in space. Yet, this additional information can be relevant, as presented in the next section.

3.3. How access to urban green spaces and its potential demand are correlated within neighborhoods

The local correlation between access to each type of urban green space and sociodemographic groups may suggest distributional green inequity mainly in clusters where a significant increase in potential demand is accompanied by significant decrease in access to urban green spaces. This relationship is expected by the GWR negative and significant β-coefficient (|t-statistic| > 1,96). The Fig. 5 highlight these clusters concerning the correlation between the access to each urban green spaces and the shares of adult women, elderlies or children and teenagers.

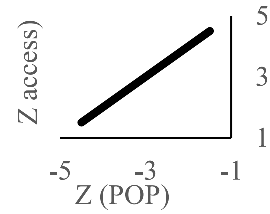
Regarding access to tree cover, the local correlations reveal patchy clusters of inequities (Fig. 5 a, b, and c). However, inequity prevails in peripheral zones for children and teenagers; in smaller clusters and in all directions, for adult women; and in central zones for elderlies. Herb-shrubs (Fig. 5d, e, and f) had a negative correlation mostly with elderlies and in every direction. For children and teenagers and adult women, the negative correlation appeared towards peripheral zones.

Table 2
Levels (L) of access to urban green space by each sociodemographic groups (demand): Children and teenagers, elderly, adult women or black people. The interpretation for the share of literate and income per capita is in Table S3.

L	Interpretation	LISA		GWR	
		access	demand	β	Graph representation
1	Access to urban green spaces is below average, but share of population group (demand) is above average. Furthermore, GWR negative slope indicates the access decreases as potential demand increases within the neighborhood. These two conditions makes level 1 neighborhoods the least equitable concerning access to urban green spaces.	Low	High	−	
2	Access to urban green spaces is below average, but demand is above. However, GWR positive slope indicates that level 2 neighborhoods are more equitable than Level 1 because access increases with demand within the neighborhood.	Low	High	+	
3	Both access to urban green spaces and demand are below average. Because demand is lower in level 3 than in level 2 neighborhoods, relatively fewer people in need might compete for urban green spaces. GWR negative slope indicates the access decreases as demand increases within the neighborhood.	Low	Low	−	
4	Both access to urban green spaces and demand are below average. However, GWR positive slope indicates that level 4 neighborhoods are more equitable than level 3 because access increases with demand within the neighborhood.	Low	Low	+	
5	Both access to urban green spaces and demand are above average. Level 5 neighborhoods are to be more equitable than previous levels because of the greater access. GWR negative slope indicates that the access decreases as the demand increases within the neighborhood.	High	High	−	
6	Both access to urban green spaces and demand are above average. However, GWR positive slope indicates that level 6 neighborhoods are more equitable than level 5 because access increases with demand within the neighborhood.	High	High	+	
7	Access to urban green spaces is above average, but demand is below. Because demand is lower in level 7 than in level 6 neighborhoods, relatively fewer people in need might compete for urban green spaces. GWR negative slope indicates the access decreases as demand increases.	High	Low	−	

(continued on next page)

Table 2 (*continued*)

8	Access to urban green spaces is above average, but demand is below. In addition, GWR positive slope indicates access increases with the demand within the neighborhood. These two conditions make level 8 neighborhoods the most equitable concerning access to urban green spaces.	High	Low	+	

LISA: Local Indicator of Spatial Association; GWR: Geographically Weighted Regression; Z: standard deviation. Levels from 1 to 8 indicate least to most equitable.

The negative correlation between public green spaces and the population (Fig. 5g, h, and i) was significant mainly for children and teenagers, either in central areas and in the outskirts. For adult women and the elderlies those correlation occurred generally in smaller and scattered clusters and in both central and peripherical zones.

The negative correlation between variables in GWR highlighted possible inequitable neighborhoods, not presented by LISA, in which access to urban green space tends to decrease for an increased demand. However, GWR does not inform where the access to urban green spaces is actually lower than average and likely a greater concern to urban planners. For instance, a negative correlation between children and teenagers and public green space (Fig. 5), should be more a concern in peripheral zones, where a higher share of that population lives with lower levels of access to urban green spaces (Fig. 4). Thus, by combining LISA and GWR results, we could highlight such critical regions concerning distributional green equity, as presented next.

3.4. Combined results: Where are the priority areas to improve urban green spaces spatial equity?

We were able to determine eight levels of access to urban green spaces for the cells where GWR residuals were not spatially dependent (see results for GWR residuals in *Supplementary Material*, Fig. S7 and S8). The lower the level of access to urban green space, the greater the distributional green inequities for a particular group (Fig. 6).

Concerning children and teenagers, adult women, and the elderlies, the proportion of the study area classified in different levels of access to tree cover averaged 5,33 % (140 cells), to herb-shrub, 12 % (324 cells), and to public green spaces, 17 % (442) (Fig. 6). Among the classified cells, 62 cells (49 %) were assigned the lowest level of access by elderly people, 24 (15 %) by children and teenagers, and 2 (5 %) by adult women. Regarding classified cells for herb-shrub, there were circa 5 cells (2.4 %) in the study area with lowest access levels for children and teenagers and adult women, and 191 cells (65 %) for elderlies. The lowest levels of access were in central zones for elderlies, but towards periphery, for adult women and children and teenagers.

Concerning the classified cells for public green space, the results point in the opposite directions. Only 2 cells (0,35 %) were classified with the lowest equity levels considering the elderlies. This same class were observed in 68 (44 %) out of 154 classified cells for adult women, and in 166 (44 %) out of 376 classified cells for children and teenagers. For the latter two groups, similar to the vegetation types results, the cells classified as less equitable are generally towards peripheral zones, while for the elderlies towards city center.

4. Discussions

4.1. Methodological contribution

In this study, we proposed a novel approach to examine distributional green equity based on the combination of significant results of spatial clustering and spatial regression methods. While the GWR results alone (Fig. 5) suggested inequity for elderly people to access both tree cover and herb-shrub in central areas and the outskirts, LISA highlighted a high share of elderly with low access mainly in central areas. LISA and GWR combined revealed that the level of access to vegetation types by the elderly people increases towards the outskirts. By knowing where the lowest levels of access are, urban planners can target priority locations to provide more urban green spaces, according to population needs.

Chen et al. (2020) explored green inequity using both GWR and LISA analyses, applied as complementary tools rather than to synthesize a final map result disclosing disparities in green space provision. Using LISA, the authors mapped the uneven distribution of four types of Public Open Spaces (parks, squares, green lands, and public facilities). With GWR, they examined the spatial correlation between population agglomeration and the distance to each type of Public Open Space, identifying significant areas where negative associations occurred. While their study highlights spatial disparities in Public Open Spaces and population agglomeration, it did not propose targeted priority areas for public action, which our approach is able to do by combining LISA and GWR results.

On the other hand, Yang et al. (2022) mapped urban green space inequity levels in the neighborhood superimposing only GWR results for six vulnerable groups: children, older adults, less-educated individuals, immigrants, residents of homes smaller than 50 m^2, and those in low-rent housing. Although this approach effectively highlighted zones with critical inequity problems in all the groups studied, relying solely on GWR may overlook important distinctions. For instance, it cannot differentiate neighborhoods with reduced green spaces for increasing populations from those with excess green spaces for increasing population, because both situations reflect a negative association between variables. By integrating GWR results with Local Indicators of Spatial Association (LISA), as we propose, it becomes possible to prioritize areas where specific populations face the most significant green space deficits.“

Therefore, integrating GWR and LISA offers a significant advancement in analyzing urban green space inequity by combining their complementary strengths. Together, these methods enable a more comprehensive understanding of inequities. Additionally, the combination enhances the precision of spatial analyses and provides actionable insights for urban planners to prioritize interventions, ensuring more equitable access to green spaces across diverse communities.

4.2. Implications for urban planning

The findings from this paper can be used to raise a few policy implications for Goiânia, but could also be relevant to other mid-size cities with similar patterns of urbanization. Among the three categories of urban green spaces, public green spaces should be a greater concern for children and teenagers living in most peripheral zones, thus guaranteeing the provision of attractive and public playgrounds and sports facilities. This is particularly important when considering families with lowest income are also more concentrated in these areas (Fig. 3 and Supplementary Material Fig S4). In addition to the central versus peripheral aspect of public greenspace provision in Goiânia or other cities in Brazil, studies have reported the lack of maintenance, safety, and quality of these public spaces, when they exist in marginalized areas

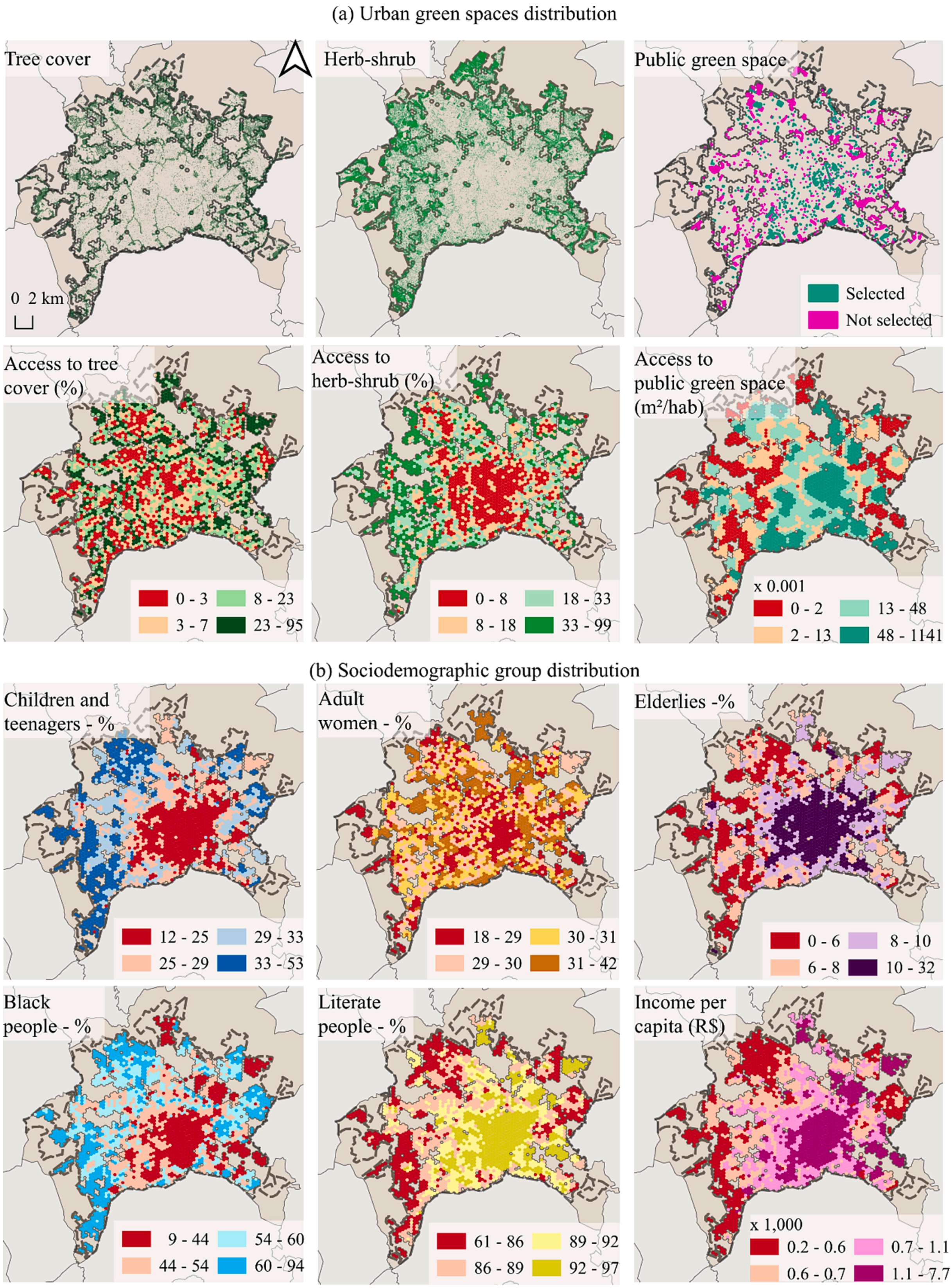


Fig. 3. Spatial distribution of (a) urban green spaces data and access results and (b) the share of (potential demand by) each population group. Access to urban green spaces and population distribution are classified in quartiles.

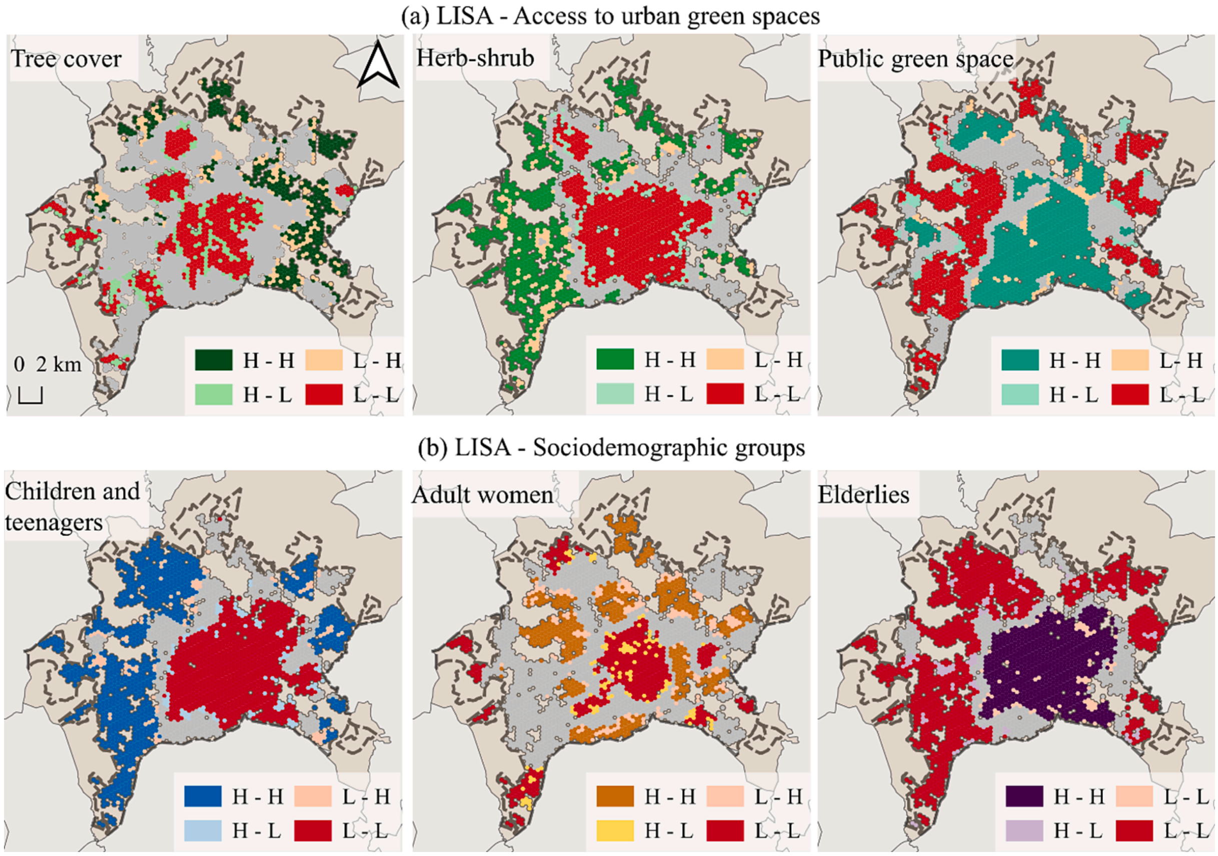


Fig. 4. Local Indicator of Spatial Association for (a) access to urban green spaces and (b) demand by sociodemographic group. H-H: each cell and its neighbors' values are higher than average; L-L: each cell and its neighbors' values are lower than average; H-L: the cell has a value higher than average, but its neighbors, lower; L-H: the cell has a value lower than average, but its neighbors, higher. Grey areas are not significant (LISA $|Zi - \text{score}| < 1.96$ at $\alpha = 0.05$).

(Sakata, 2018; Vieira, 2020). Although not assessed in this study, the condition of and preference for urban green spaces characteristics are also importantly recognized as sub-dimensions of distributional green equity theory and should be considered for urban planning purposes (Nesbitt et al., 2018).

The distributional equity in access to tree cover and herb-shrub was apparently less a concern in the outskirts. Nonetheless, the lacking public green spaces in the periphery reflects that the remaining vegetation are in private areas, vacant lots, or even in conservation units not structured for the public to access. This can be assumed in this study by the areas not selected as public green spaces (Fig. 3a), which are polygons available in Open Street Map and the municipality databases, representing georeferenced green spaces without evidence of public equipment and use. Thus, urban planners should consider that the higher abundance of tree cover and herb-shrub in the periphery in Goiânia can be related to a lower level of urbanization, and not necessarily a deliberate policy effort to conserve that vegetation.

Accordingly, Souza (2019) found that vegetation cover unsettled as public use or destination ended up incorporated into the real estate sector, accentuating urban green inequities in Goiânia. The author investigated laws and decrees on the creation and sale of public areas and evidenced the loss of Municipal Public Areas in Goiânia to other uses that occurred between 1954 and 2016. This phenomenon has intensified over the years, reaching public green space loss of 685,714 m^2 between 2013 and 2016 (eight times the area of a regular park in a privileged area of Goiânia). Even though Goiânia has been recognized for the abundance of green spaces, our study and the findings of Souza (2019) point to the importance of increasing the protection and creation of public spaces and avoiding spaces of segregation in the city.

The results of our study illustrate how the combination of LISA and GWR can help determine which neighborhoods face critically low access to urban green spaces. In this case study, we combined LISA and GWR methods and organized the results by population group. This approach enables urban planners to identify the specific needs of different groups more accurately. Alternatively, urban planners could further map the frequency that every cell is assigned a lowest equity level across all population groups, similar to the idea proposed by Yang et al. (2022). Applying this approach in diverse urban settings could offer green space managers a practical, data-driven framework to guide more equitable green space distribution strategies in cities worldwide.

4.3. Limitations and ways forward

The availability of good quality open data on public green spaces can be considered an important limitation to help scaling the proposed methodology to multiple cities. We found 70 % of misrepresentations of parks and squares destined for public use in Goiânia, according to the municipal databases and OSM. While Google Street View aids the validation process, it can be labor-intensive, based on team size. Additionally, manual insertion of access points for realistic travel time calculations is another issue that demands relevant processing time. Future work should focus on automating access point creation and better organizing OSM labels to facilitate scalable analysis of spatial equity in urban parks and squares.

Another limitation lies in exclusively focusing on walking as mode of transportation for calculating access to public green space. Other means like bikes, cars, or public transportation should provide alternative scenarios of access to public parks and squares. Nevertheless, prioritizing walkability over other transportation means aligns with economic inclusivity, promoting physical health and reducing greenhouse gas

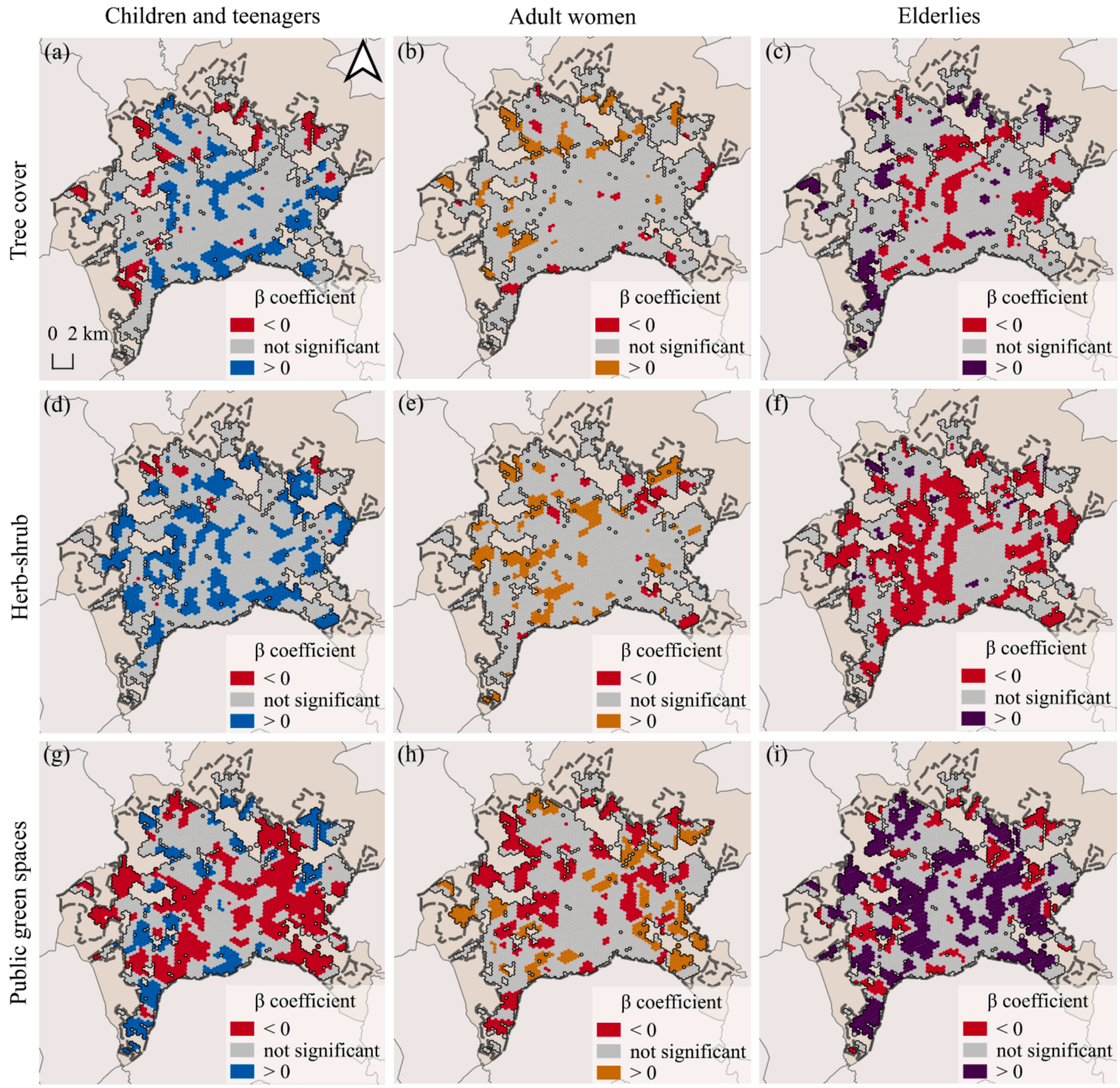


Fig. 5. Geographically Weighted Regression (GWR) β-coefficient between access to each urban green space (tree cover, herb-shrub, and public green space) and each population group (children and teenagers, adult women, and elderly). Grey areas are not significant (|t-statistic| < 1.96 at α = 0.05).

emissions (Ngo, Frank, & Bigazzi, 2018). Ensuring access to public green spaces and urban services within walking distance aligns with the UN's sustainable development goals of promoting more inclusive and low-carbon cities (IAEG-SDGs, 2017).

We should also mention that other outputs of GWR models, namely, the *β-coefficients* and the *local* R^2 values were not analyzed in this paper. We only attempted to highlight significant areas where both access to urban green spaces and population characteristics were correlated according to *β-coefficient* direction and significance. However, we acknowledge that including these indicators in future analyses may add robustness or bring more nuances to the results.

On the theoretical side, urban green equity presupposes the analysis of several dimensions (Low, 2013; Nesbitt et al., 2018). In tis study we only looked at the distributional aspect, more specifically, how access to urban green spaces is distributed in the urban space and across socio-demographic groups. Previous investigations on the quality of public squares and parks in Goiânia highlighted the differences in the maintenance of public equipment and infrastructure investment in the city's neighborhoods (Sakata, 2018; Vieira, 2020). Thus, integrating the distributional aspect analyzed in this study to other green equity dimensions could be pursued in future analyses conducted by both urban planning researches and practitioners.

Despite the shortcomings mentioned above, the method developed in this research can importantly contribute to advance the distributional green equity agenda by providing a means to identify spaces with very low levels of green equity. In addition, as the method rely on open software and widely recognized spatial data analyses it can be replicated in any other city provided with urban green spaces and population data.

5. Conclusions

The proposed method classified an urbanized areas into eight levels of access to urban green space, aimed at identifying priority areas for providing urban green spaces that could reduce distributional green inequities. These classifications varied significantly based on the type of green space and demographic characteristics. The lowest equity levels,

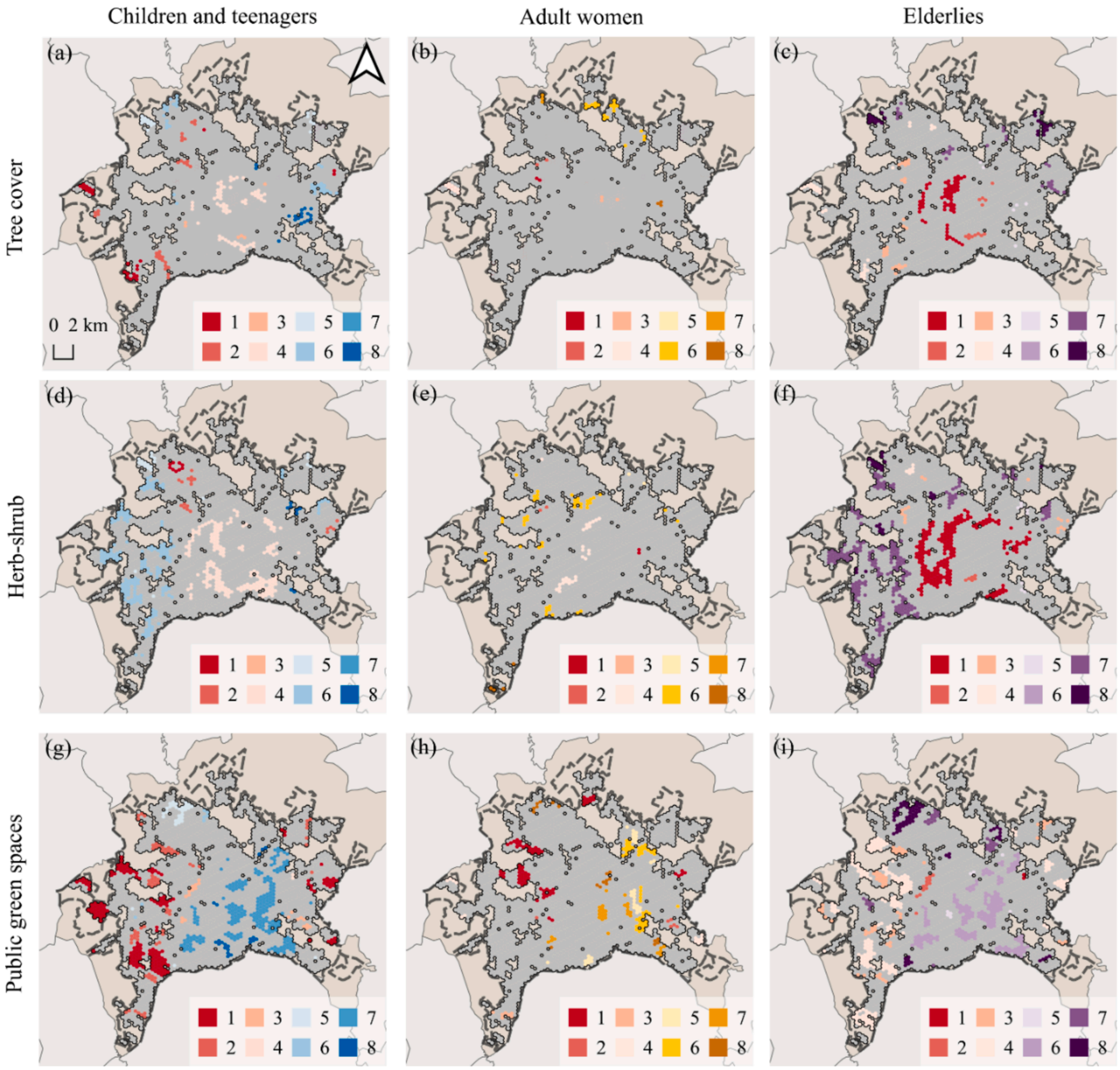


Fig. 6. Levels of green equity between each population group (children and teenager, adult women, and elderlies) and tree cover (a, b, and c), herb-shrub (d, e, and f) or Public green spaces (g, h, and i).

indicating areas of highest priority, were characterized by neighborhoods not only lacking urban green spaces in comparison to more affluent areas but also showing a trend of even lower provision for the most vulnerable populations. Conversely, the highest equity level, denoting the lowest priority, was associated with neighborhoods having a low concentration of vulnerable populations, high access to urban green spaces, and a trend of even higher provision of green spaces in closer proximity to these vulnerable groups.

In summary, we demonstrated how LISA and GWR spatial analyses combined provided nuanced spatial disparities that could enhance targeted prioritization of areas for urban green spaces provision. While LISA and GWR have assisted discussions on this topic in previous studies, their combined results in a synthetic map, as performed in this study, provided novel understandings that would not been possible simply using each of these methods alone.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Chat GPT/OpenAI in order to improve language and readability. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

CRediT authorship contribution statement

Bruno Vargas Adorno: Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Rafael H. M. Pereira:** Writing – review & editing, Conceptualization. **Silvana Amaral:** Writing – review & editing, Supervision, 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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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2025.105297.

Data availability

Data will be made available on request.

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