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The importance of private gardens and their spatial composition and configuration to urban heat island mitigation

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ABSTRACT

Small Urban Green Infrastructure (UGI; green areas < 2 ha) represents the best opportunity to mitigate Urban Heat Island (UHI) and directly promote microclimate regulation. However, few studies investigate the cooling capacity (CC) of small UGI and how their spatial organization influences its provision. Here, we used an urban cooling model and landscape metrics to understand how UGI in public and private domains influences microclimate regulation in a dense urban region of Rio de Janeiro. Our findings highlight the significant correlation between private UGI and CC, explaining over 80 % of its variation. We found an interaction between UGI composition (i.e. the amount of UGI) and configuration (i.e. spatial distribution of UGI). Nevertheless, UGI configuration exerted the greatest influence with edge density being the most significant landscape metric, suggesting that, with an equivalent green area, patchwork or numerous smaller green areas enhance CC compared to fewer larger ones. This study underscores the pivotal role of private UGI organization in tropical and dense urban context, where public UGI is neglected. We conclude that UGI awareness initiatives must systematically pay attention to spatial configuration of the small UGI, aligning interventions with urban dwellers' needs in order to guarantee microclimate regulation provision.

1. Introduction

Urbanization, with the consequent loss of vegetation cover and creation of built and impermeable spaces, can alter the amount of evapotranspiration, radiative balance and air flow, resulting in increased temperature in urban areas (Oke et al. 2017). This process, known as Urban Heat Islands (UHI), are one of the most well known consequences of the urbanization process and is defined by the presence of higher temperatures in cities compared to rural or vegetated areas (Oke et al. 2017). Sources of anthropogenic heat (e.g. heat release by industry, the burning of fuels by cars and air conditioning) can also reinforce UHI (Alberti 2008; Oke et al. 2017). UHI has a direct impact on the functioning of cities, being associated with increased vector-borne diseases, such as dengue, decreased thermal comfort, increased energy consumption and exposure of vulnerable populations to heat (Duarte et al. 2015; De Azevedo et al. 2018; Kim et al. 2022; Santamouris et al. 2015; Wang and Akbari et al. 2016). One of the most common suggestions to mitigate UHI is encouraging the creation of urban green infrastructures (UGI; *i.e.*, street trees, parks, private gardens; Akbari et al. 2015; Deilami et al. 2018; Grilo et al. 2020; Ziter et al. 2019). This has gained momentum from efforts within institutional spaces, especially with the Nature-based Solution debate concerning climate and biodiversity. UGI can be defined as a strategically planned network of natural and semi-natural areas in cities (see Cohen-Shacham et al. 2016) and can contribute to the microclimate regulation service, in which vegetation can lower the temperature of their surroundings mostly through shading and evapotranspiration (Dobbs et al. 2011; Oke et al. 2017). UGI can also promote other multiple ecosystem services and reduce the environmental and population vulnerability to climate change and urban environmental problems, such as air pollution and flooding (Akbari et al. 2001; Bolund and Hunhammar 1999; Luederitz et al. 2015; Locke and McPhearson 2018).

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Many works focus their analysis on large parks, using coarse spatial scales (Aram et al. 2019; Cao et al. 2010; Derkzen et al. 2015), while few consider and discuss the contribution of different types of UGI for microclimate regulation (Aram et al. 2019; Bowler et al. 2010; Vaz Monteiro et al. 2016). Recent works have highlighted the role of small UGI, such as private gardens, suggesting their effectiveness for microclimate regulation (Shashua-Bar and Hoffman, 2000;Du et al. 2016; Kim et al. 2022; Lee et al., 2023; Ossola et al. 2021;Park et al. 2017; Ziter and Turner 2018), as well as for other ecosystem services (Cameron et al. 2012). Increased attention has been paid to the relationship of landscape patterns and cooling capacity of UGI (Chen et al. 2014, Du et al. 2016; Li et al. 2011; Li et al. 2012; 2013; Zhou et al. 2011). In this regard, composition (i.e., the variety and abundance of a given type of landscape element) and configuration (i.e., the spatial arrangement, position and orientation of landscape elements) have been used to assess the relationship between temperature and spatial heterogeneity of UGI. Both composition and configuration have combined contribution to microclimate regulation, but their relative importance remains controversial, as the cooling capacity (CC) of the UGI is likely to vary among cities subjected to different urbanization processes, ecological context, scale of analysis and how all of these factors interact (Du et al. 2016; Kim et al. 2022; Rajagopal et al. 2023; Zhang et al. 2022; Zhou et al 2017).

Despite the promotion of numerous benefits, UGI cover is declining in some cities (Kabisch and Haase 2013), or is expected to decrease, like private gardens in England (Gaston et al. 2005). In Latin America and the Caribbean, this process will be striking if we consider its high social inequality, informal settlements and lack of maintenance of green areas and poor planning in cities development (Dobbs et al., 2019). Even though it is a challenge to reconcile urbanization with the UGI maintenance and promotion, residential land use already comprises most of the green areas in many cities and possibly represents the best opportunity to increase green infrastructure and promote ecosystem services (Gaston et al. 2005; Lin et al. 2015). Small UGI then might be an important feature of urban landscape as a strategy contributing with social-ecological functions and ecosystem services in dense urban settings (Cameron et al. 2012; Gaston et al. 2005; Ossola et al. 2019b; Ruffato-Ferreira 2016).

Considering the current scenario of accentuation of UHI, climate extreme events (Dereczynski et al. 2013) and loss of UGI cover, it is of great importance to understand how the cover of small UGI, as well as its organization in space, can enhance the mitigation of the UHI. In this study, we investigated the relative contribution of the private and public small UGI to the microclimate regulation, as well as the influence of their composition and spatial configuration of UGI to CC. We used the suburbs of Rio de Janeiro as a model system, one of the hottest regions of the city with private gardens accounting for ~40 % of the total green areas and with the lowest forest cover in the city (Mendonça et al. 2019; Ruffato-Ferreira 2016). In this sense, UGI can stand out as a UHI mitigation strategy, but for that, we need a better understanding of the role of different types of small UGI in providing microclimate regulation to an area with high urbanization and social vulnerability. This makes this area an interesting study case for generating new knowledge about design and urban planning with a social-ecological basis, helping to forge a new urban development framework.

2. Methods

2.1. Study Area

The study was carried out in the urban extent of Rio de Janeiro suburbs. According to the IBGE, the estimated population of Rio in 2021 was ~6.75 million people, making it the second most populous city and the 18th city with the highest population density in Brazil (~5200 inhabitants/km^2; IBGE, 2010). The choice of Rio de Janeiro suburbs as the study area is related to the process of heterogeneous urbanization of Rio de Janeiro and the differentiated political attention to the territorial management of the city, which commonly results in an overvaluation of the wealthier neighborhoods as compared to poorer suburban neighborhoods (Barandier 2016). Rio de Janeiro suburbs, for example, is the most degraded area of the city, having one of the lowest coverage of forest areas, in addition to having the highest coverage of anthropic areas among all the planning areas of the municipality of Rio (Ruffato-Ferreira 2016). The North Zone is also one of the hottest regions of the city. This is driven by geographic factors, such as the presence of the Tijuca massif, blocking the sea breeze to circulate in the region, but also by anthropic factors, as it is an already consolidated urban center with a high proportion of impervious surface (Dereczynski et al. 2013; Lucena et al. 2018).

Importantly, unlike other cities in the world, the concept of suburbs in Rio de Janeiro does not adhere to the common concept of American suburbs (Moreira 2012; Perfeito 2020), where they generally represent areas farther from the urban centers associated with middle-class population. When referring to the suburb of Rio, a specific region of the city is delimited, with specific features, composed mostly of low-income neighborhoods associated with symbolic cultural values linked to the territory and the working-class population (Perfeito 2020; Souza 2010; Santos 2011). In this context, the suburb of Rio is generally understood as the region crossed by the railway lines of the former Central do Brasil, Leopoldina and the extinct auxiliary line Rio D`Ouro (Souza 2010). Considering the current administrative division of the city, the municipality of Rio is divided into 5 planning areas (AP), 33 Administrative Regions (RA) and 160 neighborhoods. In this work, following the theoretical conceptualization of Souza (2010), the suburban region corresponds to the third planning area (AP3) of the administrative division of the city, comprising 80 neighborhoods.

It is also important to define here one of the objects under analysis in this study, the private gardens (hereafter private UGI). In general, they are green spaces present in the private areas of single-family residences and comprise different vegetation types. Cameron et al. (2012) defined private UGI as “areas adjacent to a residential building, whether private or leased”. Ruffato-Ferreira (2016) says that private UGI in Rio de Janeiro have a social function restricted to the family due to their private dimension; however, their contribution may have a more generalized effect in the city. This is the case of their contribution to the provision ecosystem services, especially on Rio de Janeiro suburbs which, unlike the central regions, present an “absolute predominance of residences [...] with large private or collective areas, thus forming a network” (Ruffato-Ferreira 2016) and where most of the green areas are in private areas (Mendonça et al. 2019).

2.2. Data

The microclimatic regulation provided by the UGI was estimated using the urban cooling model of the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) software. InVEST is a set of spatially explicit models capable of estimating and evaluating the provision of ecosystem services and their impacts on people. The urban cooling model aims to simulate the spatial distribution of the Urban Heat Island considering the land cover and land use of a given location (See Sharp et al. 2020). The model calculates a heat island mitigation index, hereinafter called Cooling Capacity (CC), considering shading, evapotranspiration and albedo, mechanisms by which vegetation reduce the temperature of its surroundings and regulate the radiative balance of the urban spaces (Phelan et al. 2015; Sharp et al. 2020; Zardo et al. 2017). The model utilizes spatialized temperature, land use/land cover (LULC) data and their biophysical characteristics to estimate the effect of land use and land cover on air temperature. *InVEST Urban Cooling Model version 3.9.0* was used to carry out the simulations and all the data inputs are listed in Table 1. The names of data sets and parameters follow the nomenclature provided by the InVEST Urban Cooling Model (see Sharp et al. 2020).

The LULC map (Fig. 1) was produced from the composition and

Table 1
Summary of the data used to run the InVEST Urban Cooling Model with their respective references from which data was retrieved. The names of data sets and parameters follow the nomenclature provided by the InVEST Urban Cooling Model (see Sharp et al. 2020).

Data name	Description	Retrieved from
LULC	Raster map of AP3 Land Use/Land Cover classes for 2016	Amaral et al. 2022; IPP, 2016
ET0	Raster map of mean reference evapotranspiration values for 2015	Muniz Júnior et al. (2020)
Tref	Average air temperature in 2015, in a non-urban reference area where urban heat island effect is not observed	Muniz Júnior et al. (2020)
UHImax	Magnitude of the heat island. It was obtained from the difference between highest average temperature from climatological station record and Tref	Muniz Júnior et al. (2020)
Kc*	Crop coefficient; indicates the evapotranspiration rate for plant organisms	Allen et al. (1998); Grimmond and Oke (1999)
Green Area*	Indicates whether or not a LULC class is considered a green area (1 or 0)	-
Shade*	Proportion of tree vegetation cover (at least 2 meters high)	-
Albedo*	Proportion of solar radiation that is reflected by a surface.	Stewart and Oke (2012)
dcool	Cooling Distance. Distance in meters where IVU greater than 2ha has a cooling effect	Calibration**
r	Air mixing radius in meters	Calibration**
Relative Weight	Shade, evapotranspiration and albedo parameters relative weight values applied while calculating the cooling capacity index.	Calibration**

* Values presented in the biophysical table and corresponding to each LULC class.
** For calibration procedure, see Bosch et al. (2021).

modification of thematic information plans, namely: Original land use map for the municipality of Rio de Janeiro, in ESRI Shapefile format (.shp), from Instituto Pereira Passos (IPP); Limits of the fiscal blocks for the municipality of Rio de Janeiro, in ESRI format, Shapefile (.shp), from Instituto Pereira Passos (IPP); AP3 Intraurban Vegetation Map in ESRI Shapefile (.shp) format, from Amaral et al. (2022); and Territorial boundaries of the municipality of Rio de Janeiro, in ESRI Shapefile (.shp) format, from Instituto Pereira Passos (IPP). A comprehensive and schematic methodology workflow of the study can be found in Fig. 2.

2.3. Methodology

To map and classify the UGI of interest, initially, the classes of interest were identified in the shapefile of the original land use map of Rio de Janeiro. At this stage, the classes of residential, leisure, commercial and industrial use were initially selected. The output layer from this selection was then intersected with the boundary of fiscal blocks in order to define blocks within residential use as private areas. Later, we did the same process to define features outside of these blocks as public areas. Private blocks belonging to commercial and industrial uses were disregarded in the mapping since we are interested in private UGI on residential land. Other types of land use and land cover, such as service areas, military and slums, were outside the scope of this study and were also disregarded from the mapping.

Subsequently, corrections were made to the delimitation of the private area, removing blocks with the wrong classification and correcting the positioning of the limits of residential blocks, which often included sidewalks or part of the street. It is important to note that the common areas of condominiums and housing complexes were also considered as residential blocks, following the understanding of Ruffato-Ferreira (2016) that green areas of these spaces present similar dynamics to the gardens of single-family homes.

The last step was to select the intraurban vegetation and classification as a public UGI or private UGI. For this, the vector layer of land cover and land use of the selected classes was crossed with the vector

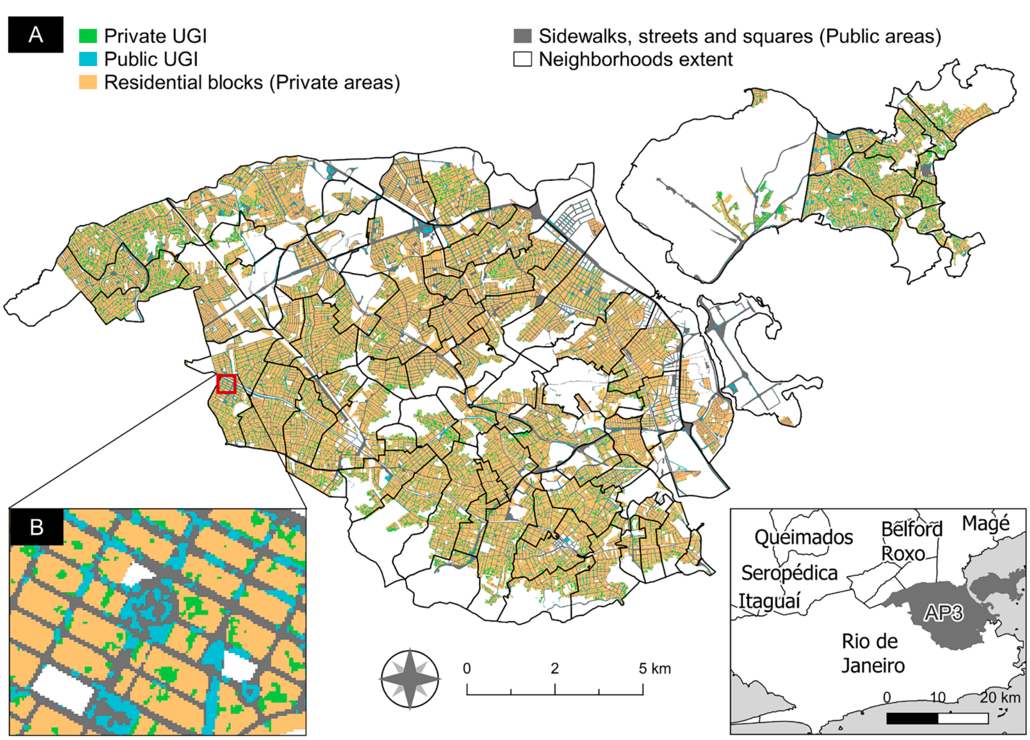

Fig. 1. Land use/land cover map (LULC) showing the delimitation of the neighborhoods in the study area. A) Final LULC used in the model B) Detail of the land use classes. Blank areas are LULC classes out of interest in this work, in this case, representing two schools and one hospital. Green areas represent private Urban Green Infrastructures (UGI) and blue areas represent public UGI. Orange polygons represent residential blocks and dark green lines represent streets, sidewalks and squares.

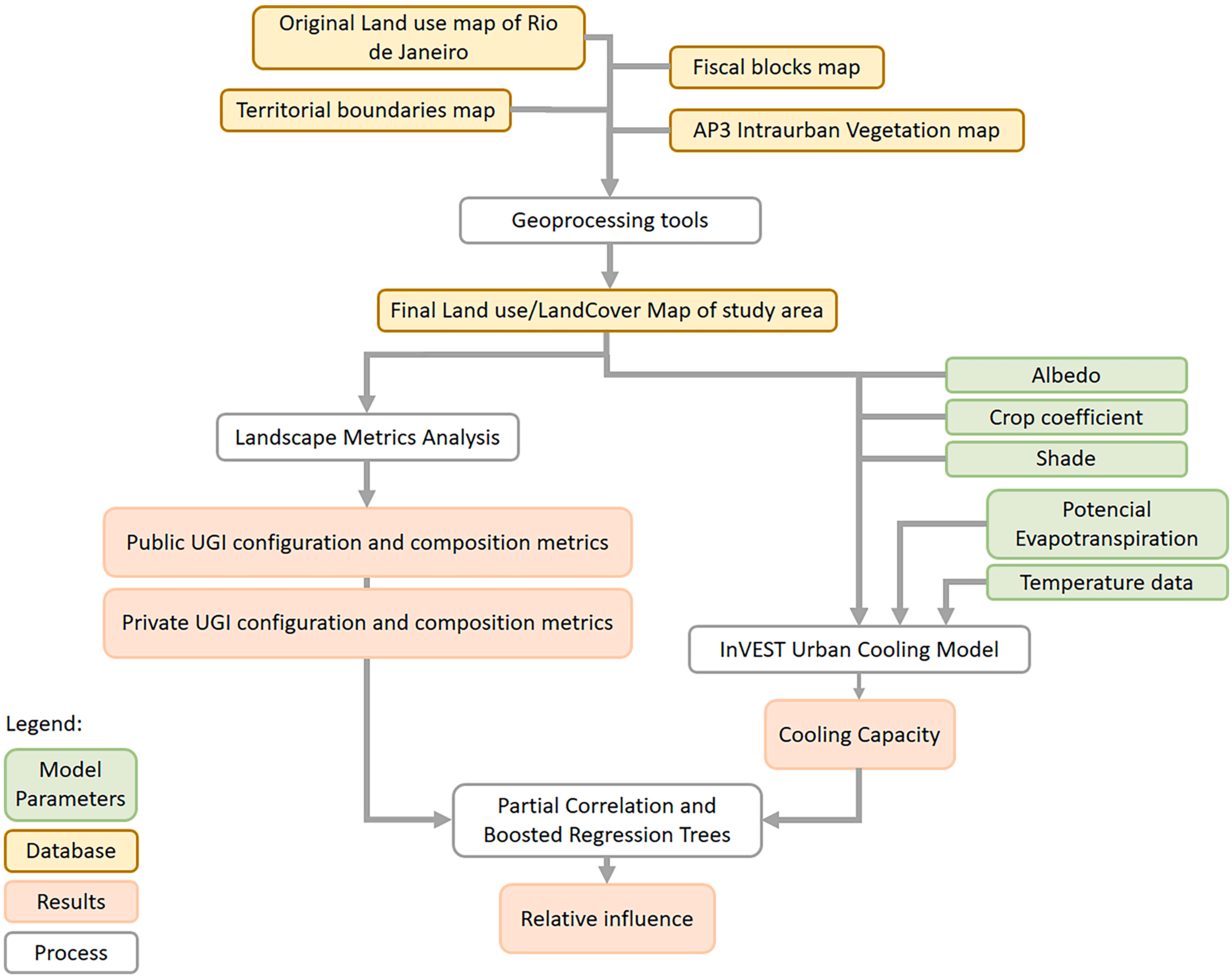

Fig. 2. Methodological workflow to assess the relative influence of configuration and composition metrics of public and private UGI on the cooling capacity in Rio de Janeiro neighborhoods.

map of intraurban vegetation. The map of intra-urban vegetation defines two classes of vegetation: arboreal and shrub-herbaceous, however, the shrub-herbaceous cover corresponds to about 2 % of the total area of AP3, and due to this very low representation, only the arboreal vegetation was considered in the model. After composing and processing the vector masks, the final LULC map was rasterized with a resolution of 5 m. All steps were done using QGIS version 3.16.15.

A temperature raster map was produced from the monthly air temperature averages for the year 2015 using 17 monitoring stations present in AP3 and its surroundings (Table S1). The data used to build the raster were provided by Muniz Júnior et al. (2020) and interpolated following the Inverse Distance Weighted method in QGIS version 3.16.15. The magnitude of the urban heat island (UHImax) was obtained from the difference between the highest and lowest temperature present in the temperature raster map, defined as 3.16 °C. This value is in line with the value between 3 C and 4 C estimated by studies on UHI already developed for the metropolitan region of Rio de Janeiro (Marques-Filho et al. 2009, Meireles et al. 2014). To define the reference temperature (Tref), which consists of the air temperature without the action of the heat island, the lowest air temperature value present in the temperature raster was used, which in this work was 26.41 °C, detected in the vegetation region of the Tijuca massif (Tijuca rainforest).

Regarding the data from the biophysical table (See Table S2), it was necessary to define the values of crop coefficient, shade, albedo and which classes should be considered as green areas. The crop coefficient (Kc) is an index that indicates the actual evapotranspiration rate for plant organisms, based on the reference evapotranspiration (Et0) of the study area. In this work, the coefficients were defined based on the Kc calculated by Allen et al. (1998) and Grimmond and Oke (1999). The albedo and shading values were obtained based on the work of Stewart and Oke (2012).

Potential evapotranspiration (ET0) raster was produced from calculations of the Climatological Water Balance, considering the model proposed by Thornthwaite-Mather. as described in the equations (1), (2) e (3) in Muniz Júnior et al. (2020):

$$ET0 \; = \; FC \times 16 \; \times \left(10 \times \frac{T}{I}\right)^{a} \tag{1}$$

$$a \; = 67.5 \times 10^{-8} \times I^{3} - 7.71 \times 10 - 6 \times I^{2} + 0.01791 \times I + 0.492 \tag{2}$$

Where ET0 = potential evapotranspiration (mm.month-1); T = average air temperature (°C); FC = correction factor in function of the latitude and month, and I = annual thermal index, given by:

$$I = \sum_{i=1}^{12} = (T_i/5)^{1.51} \tag{3}$$

The ET0 data used in the formulation of the map were derived from the monthly air temperature averages of 17 monitoring stations located in the AP3 and nearby. Muniz Júnior et al. (2020) provided the temperature values for the year 2015, the basis for calculating the ET0, as well as the calculation methodology. Once calculated, the evapotranspiration values were interpolated by the Inverse Distance Weighted (IDW) method using QGIS version 3.16.15. The model, however, incorporates the evapotranspiration data as an Evapotranspiration Index (ETi), which is a normalized value of potential evapotranspiration from vegetation calculated for each pixel, as described in equation (4) (See InVEST Urban Cooling Guide):

$$ETi = \frac{Kc \times ET0}{ET0_{max}} \quad (4)$$

The last step was to calibrate the model, by obtaining the weights for shade, evapotranspiration, albedo, cooling distance (dcool), air mixing radius (r) parameters. We followed the calibration process developed by Bosch et al. (2021), in which air temperature simulations are made from iterations of the urban cooling model with different values for each one of these listed parameters. The result of these air temperature simulations is compared to the air temperature data from monitoring stations. The value of the simulation parameters, with results closest to the observed temperatures from the monitoring stations is chosen (See Bosch et al. 2021). To carry out the calibration, LULC, ET0, the biophysical table and the raster map of air temperature from the monitoring stations, described above were used. Calibration was performed using the *invest-ucm-calibration* package in Python 3.0 (Bosch et al. 2021).

To evaluate the spatial organization and describe the structure of the landscape, several landscape metrics can be used. In general, these metrics can be classified into two groups: composition metrics, which measure the variety and abundance of a given type of landscape element, and configuration metrics, which measure the arrangement, position and orientation of landscape elements (McGarigal 2014). In this work, 6 landscape metrics were used to evaluate the spatial organization of the public and private UGI in the suburbs (Table 2), 5 of which are configuration metrics: Mean Area (AREA_MN), patch density (PD), Mean Euclidean distance (ENN_MN), Clumpiness (CLUMP), edge density (ED); and one is a composition metric: tree cover (PLAND). These metrics were chosen because they represent the size, distribution, fragmentation and proportion of UGI coverage. They were also chosen for their common use in the literature, ease of interpretation and the small redundancy between the metrics (Zhou et al. 2011; 2017). To calculate them, the *landscapemetrics* package (Hesselbarth et al. 2019) in R, version 4.0.1 was used.

2.4. Statistical analysis

To test the effect of tree cover and spatial distribution of UGI in the CC, the 80 neighborhoods comprising AP3 were considered as sample units. Initially, a simple correlation between landscape metrics and CC was performed, but a high correlation between tree cover and some of the landscape configuration metrics was attested. Because of this, the relationship between landscape metrics and neighborhood CC was evaluated through a Spearman partial correlation where the effect of tree cover on configuration metrics and the effect of configuration metrics on tree cover was controlled (Zhou et al. 2017).

Subsequently, the Boosted Regression Trees method (BRT; Elith et al. 2008; Friedman et al. 2000) was used to assess the relative influence of public and private UGI in providing the microclimate regulation service, as well as the relative influence of the configuration and composition on CC. As it is a combination of regression tree methods with a boosting technique for improving predictive capacity, the BRT approach brings advantages such as identification of relevant variables, automatically accounting for nonlinearities and and interactions, dealing with different types of explanatory variables, without the need for data transformation or elimination of outliers (Elith et al. 2008).

We fit a BRT model using CC as a response variable and the private and public UGI composition and configuration metrics as explanatory variables. BRT approaches provide multiple benefits, including the ability to include interactions based on the size of the trees employed. They do this by combining a large number of regression trees that are summed in sequence (Elith et al. 2008). It is also possible to generate hypotheses regarding the effects of different combinations of landscape structure metrics because the BRTs account for all potential combinations of explanatory factors. We set the tree complexity (tc) at 10 and calibrated the model to determine the best fit value for the learning rate (lr), bag fraction (bf), and step size parameters. The model's trees' respective contributions, the amount of data to be added at each stage of the regression tree's construction, the number of trees to be added to each step, and the number of nodes in each tree are determined by the parameters *lr, bf*, step size, and *tc* (Elith et al. 2008). The model with the biggest explained deviation and at least 1000 regression trees yields the best calibration result for the lr, bf, and step size parameters. After that, the tc value was calibrated using an iterative BRT method with *tc* values between 1 and 10. Each tc value was the subject of 100 simulations in order to give confidence intervals for the modeling. The R^2 of each of these models and the relative influence of each explanatory variable on the response variable were used to measure the predictive power of the model. The mean and variability of R^2 as well as the relative influence of the factors were then estimated by averaging the 100 values (Pistón et al. 2019). Finally, an ANOVA was used to select the optimal *tc* value. The R^2 was used as the response variable, and the *tc* values were used as the explanatory variables. The optimal *tc* value was defined to be the first *tc* that is not significantly different from the next one. This indicates that model performance has reached a plateau (Pistón et al., 2019). *Tc* optimal value and *gbm.interactions* function were used to evaluate if the interaction between the explanatory variables was observed and modeled. A systematic protocol on the BRT method can be found in Pistón et al. (2019, in Supplementary Material S2). BRT analyzes were performed using the *dismo* package (Hijmans et al. 2017) and *multicomp* (Hothorn et al. 2022) in R, version 4.0.1.

Table 2
Description of landscape metrics (Hesselbarth et al. 2019) used to assess the effect of UGI spatial distribution on the cooling capacity.

Type	Landscape Metrics	Description
Composition	Tree cover (PLAND)	Proportion of tree cover per sampling unit (%)
Configuration	Mean area (AREA_MN)	Average area of UGI per sampling unit (m^2)
	Patch density (PD)	Average number of UGI per hectare per sampling unit (UGI/ha)
	Clumpiness (CLUMP)	Measure of organization of the UGI in relation to the aggregation of fragments. Ranges from -1 (disaggregated) to +1 (aggregated)
	Mean euclidean distance (ENN_MN)	Distance to the nearest neighboring UGI of the same type (m)
	Edge density (ED)	Total perimeter (m) of UGI per hectare per sampling unit (m/ha)

3. Results

3.1. Urban cooling model calibration

Calibration results indicated that the most appropriate values for the characteristics of the study area were 748.98 m and 184.72 m, respectively, for air mixture (r) and cooling distance (dcool) and 0.738, 0.155 and 0.106 as weight for shading, albedo and ETi. These values were used to perform the final air temperature simulation based on the InVEST urban cooling model.

3.2. Landscape metrics variation

All the metrics varied widely, with a different distribution among neighborhoods when considering the two types of UGI (Fig S2, Table

S6). Nevertheless, the overall proportion of tree cover (PLAND) of private UGI are on average 10.8 %, while the PLAND of public UGI corresponds to only 4.98 % (Table 3). This means that private UGI coverage is approximately 2 times greater than public UGI coverage in the suburbs of Rio. In addition to lower coverage, the public UGI presents a larger average distance between UGI units (26 +/- 4,52 m) as compared to private UGI (20 +/- 4,76 m).

Although the CLUMP values for private and public UGI are similar, public UGI has a CLUMP value closer to zero and therefore has a distribution closer to random. A greater private CLUMP value is in line with private UGI organization expectations due to the common positioning of UGI at the back of the lot (i.e backyards), thus allowing greater aggregation of the private UGI. Patch density (PD) and edge density (ED) are measurements related to UGI fragmentation. Our results suggest that private UGI has higher PD and ED than the public UGI. These higher values potentially occur not only because the private UGI has a higher fragmentation, but also because it has a larger AREA_MN and PLAND.

3.3. Cooling capacity throughout neighborhoods in Rio suburbs

InVEST's urban cooling model results in a map of CC values, showing the intensity and spatial variation of CC in the study area (Fig. 3). The neighborhoods in the northeast region stand out for presenting the highest CC values of the suburb, being represented as the only region in blue on the map. The neighborhoods in the south and southwest region of the map also stand out for their intermediate CC, represented in yellow and green, while the rest of the neighborhoods have low and very low CC values. The magnitude effect of CC on temperature variation is in line with what is found both in experimental work and in other computer simulations carried out in different cities for small UGI (see Aram et al. 2019). In this work, the average CC ranged from 0,09 to 0,35, and the effect of CC on decreasing temperature ranged from 0.3 ºC to 1.1 ºC, with an average of 0.6 ºC.

3.4. The relative influence of UGI and the effects of landscape metrics on cooling capacity

For both public and private UGI, AREA_MN, ENN_MN and CLUMP showed a negative correlation with CC (Table 4), while PLAND, PD and ED showed a positive relationship with CC. Private UGI metrics, with the exception of CLUMP, had stronger correlation coefficients with CC than public UGI metrics and all correlation were significant. These results are our first indication that the private UGI are more important to the CC variation of the neighborhoods than the public UGI.

For running our BRT models, we selected the values of the parameters that presented the greatest explained deviation and reached the minimum of 1000 trees (See Table S3). Thus, the values that we used for the calibrated BRT were: $lr = 0.01$, $bf = 0.75$ and step size = 0.50. The $tc = 2$ was chosen based on the statistical comparison of the R^2 of the simulations. This result indicates that there is an interaction between landscape metrics considered in our analysis. In this manner, the tree complexity of the final model was set to 2 (tc=2; See Fig. S1)

BRT analysis was performed in order to assess the relative influence of private and public UGI on CC, as well as understand the relationships and interactions between landscape features. The BRT results (Fig. 4), similarly to the correlation analyses, demonstrate that the relative influence of private UGI on CC is much greater than the relative influence of public UGI. For all analyzed metrics, private UGI has a greater influence on CC than the same metrics when compared to public UGI.

Edge density (ED) was the most influential landscape metric, followed by tree cover (PLAND). About 54 % of the CC variation is explained only by edge density. PLAND, a landscape composition metric, was the second factor with the greatest relative influence, explaining about 28 % of the CC variation. These two metrics are extremely important and combined they have a relative influence of 82 % on the CC. When considering the private UGI typology, ED and PLAND have the highest values of relative influence on CC, contributing approximately 45 % and 26 %, respectively, while the influence of the other metrics is extremely low.

These results indicate that ED and PLAND are the most important landscape metrics for microclimate regulation in the suburbs. In addition to being the two most important metrics, through the BRT analysis, it was possible to determine that there is an interaction between them, indicating a combined effect of ED and PLAND for microclimate regulation in the private UGI (Fig. 5A, see also Table S5) but not for public UGI (Fig. 5B and Table S5). We can see a positive interaction between these variables, demonstrating that the higher the ED and PLAND values, the greater the CC. The highest values were reached when the neighborhoods have around 16 % coverage and around 400 m/ha of edge density.

Table 3
Descriptive statistics referring to landscape metrics analysis of the Urban Green Infrastructure. Mean Area (AREA_MN), Patch Density (PD), Mean Euclidean Distance (ENN_MN), Clumpiness (CLUMP), Edge Density (ED); Tree Cover (PLAND).

LANDSCAPE METRICS	PRIVATE UGI			PUBLIC UGI		
	Mean	±SD	95 % CI	Mean	±SD	95 % CI
AREA_MN	34.4	0.012	[31.18, 36.87]	22.23	0.007	[20.68, 23.84]
PLAND	10.82	4.96	[9.72, 11.9]	4.98	2.12	[4.51, 5.45]
PD	311.34	86.58	[292.07, 330.61]	222.72	58.95	[209.60, 235.84]
ENN_MN	20.52	4.76	[19.5, 21.6]	26.04	4.52	[25.04, 27.05]
CLUMP	0.629	0.049	[0.619, 0.640]	0.58	0.047	[0.57, 0.60]
ED	276.38	103.10	[253.43, 299.32]	148.58	50.11	[137.42, 159.73]

4. Discussion

We simulated the spatial effect of UHI using the InVEST urban cooling model to understand the relative contribution of public and private UGI and the importance of landscape configuration and composition for UHI mitigation. Our analysis indicated that private UGI has a stronger influence on microclimate regulation than public UGI. We also found the importance of landscape characteristics to microclimate regulation. Using a Boosted Regression Tree analysis, we quantified the interaction between spatial configuration and composition, which shows that both play a synergistic role in regulating the microclimate. To our knowledge, this is the one of the first times that the spatial configuration of UGI shows a prominent role in mitigating UHI when compared to the total vegetation cover. This means that considering the same total green area, more numerous small UGI promote stronger cooling capacity as compared to fewer larger ones.

The private UGI played a prominent role in providing microclimate regulation service compared to public UGI. The relevance of private UGI was also found in cities in the USA and Australia (Cameron et al. 2012, Ossola et al. 2021) and is commonly attributed to the high tree cover of private UGI found in the model of western cities (Ossola et al. 2019a). Here we advance on this understanding by showing that the relevance of private UGI in decreasing temperature is not only related to the higher tree cover compared to the public UGI, but also, and mainly, to its spatial configuration, namely a greater edge density. The importance of the spatial configuration of the private UGI was probably due to its small size and the ecological context of the study area. The relevance of certain UGI characteristics for temperature reduction will depend mainly on the balance between evapotranspiration and shading. The edge of green areas provide shade to the surrounding environment. In this way, increased edge density results in more shading around the UGI with positive effects on cooling capacity (Li et al. 2012; Zhou et al. 2011;

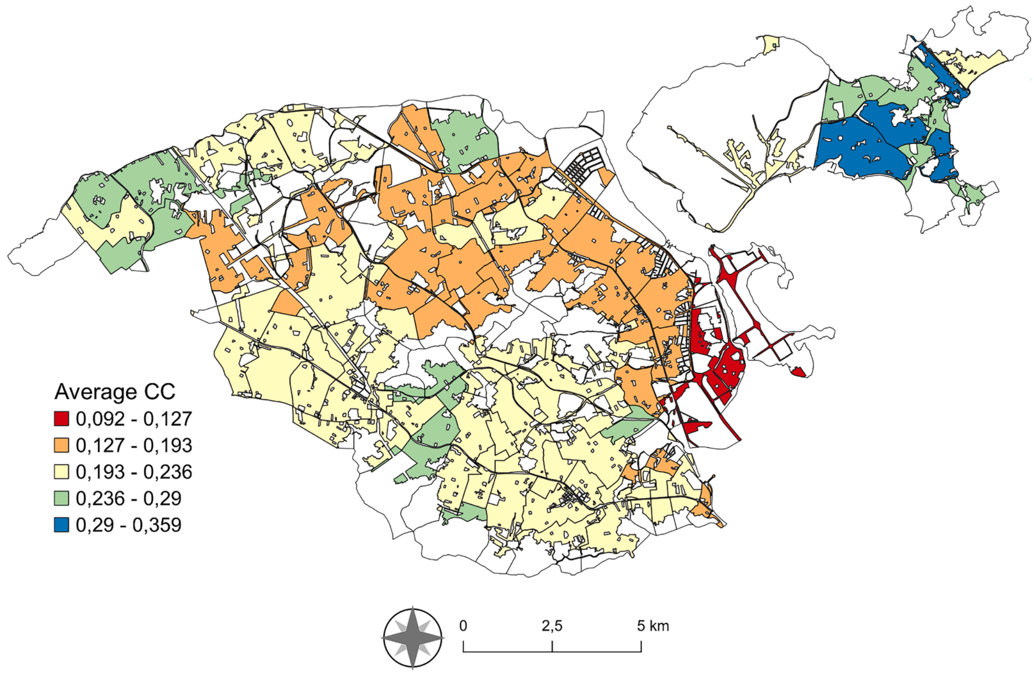

Fig. 3. Average cooling capacity (CC) in the suburban area of Rio de Janeiro obtained from the InVEST urban cooling model. Areas with higher CC are represented in blue and green colors, while areas with lower CC values are represented in orange and red colors.

Table 4
Spearman partial correlation between landscape metrics and cooling capacity (CC). Bold values correspond to significant values. The spearman partial correlation (s) of the configuration metrics was done by controlling the effect of the PLAND, and for the PLAND, the configuration metrics were used as a control. Mean Area (AREA_MN), patch density (PD), Mean Euclidean Distance (ENN_MN), Clumpiness (CLUMP), Edge Density (ED); Tree Cover (PLAND).

UGI TYPE		AREA_MN	PLAND	PD	ENN_MN	CLUMP	ED
PRIVATE	s	**-0,355**	**0,329**	**0,434**	**-0,516**	**-0,356**	**0,521**
	p-value	0,022	0,005	<0,001	<0,001	<0,001	<0,001
PUBLIC	s	-0,210	0,175	0,142	**-0,353**	**-0,372**	**0,265**
	p-value	0,062	0,150	0,211	0,001	<0,001	0,01

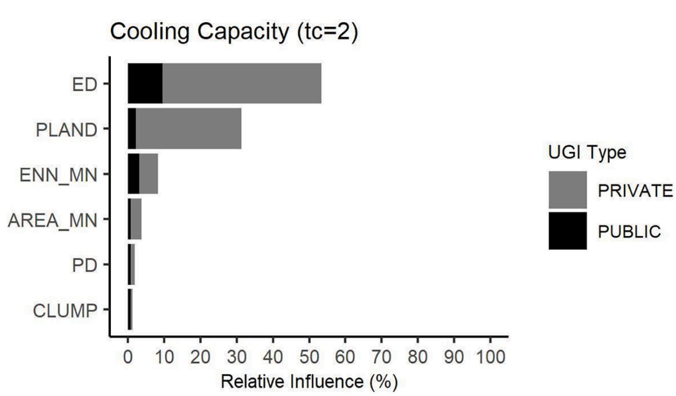

Fig. 4. The relative influence was calculated by averaging 100 simulations for the optimal value of tree complexity (*tc* = 2) using Boosted Regression Trees (BRT). Cooling Capacity (CC) was considered as the response variable and landscape metrics as explanatory variables. The abbreviations correspond to Mean Area (AREA_MN)), patch density (PD), Mean Euclidean Distance (ENN_MN), Clumpiness (CLUMP), Edge Density (ED); Tree cover (PLAND).

2017). In tropical environments, shading is the most important factor for cooling capacity, while the influence of evapotranspiration is reduced (Hwang et al. 2015). This is because high energy exchanges with the surrounding high-temperature environment can reduce plant transpiration rates (Lambers et al. 2008). Thus, when we analyze the role of the small UGI in mitigating the UHI, the weight of shading tends to stand out in relation to evapotranspiration, which results in a larger relative contribution of edge density to the vegetation cooling capacity.

The results found here corroborate the evidence of private UGI's benefit to a dense urban landscape, stressing that some of its services can also extend beyond the property's boundaries. It also supports the importance of considering private UGI as a variable in urban planning and urban environmental studies (Ruffato-Ferreira 2016, Mendonça et al. 2019). Although private UGI are important features for urban landscape and for people's lives, their environmental impact is ambiguous and culturally dependent (Cameron et al. 2012). Intensive resource-demanding garden management practices, for example, can undermine garden contributions to sustaining biodiversity and soil quality (Tresch et al. 2019). Additionally, spatial arrangements that increase cooling capacity might not be the best for promoting other services. For instance, larger green areas, as compared to several small areas, are able to host a larger number of species due to improved environmental conditions, greater availability and diversity of resources and the possibility of establishing larger populations, which reduces the risk of local extinction. This debate, which is known in conservation biology as "single large or several small", often leads to the conclusion that larger land areas should be better for biodiversity conservation (Fahrig et al. 2022). Similarly, large UGIs may be more efficient at reducing the volume and peak flow of storm runoffs (e.g. Liu et al. 2014). This can result in a tradeoff when planning UGIs, with different designs maximizing different ecosystem services. Furthermore, later dynamics after UGI implementation can lead to socioeconomic-spatial

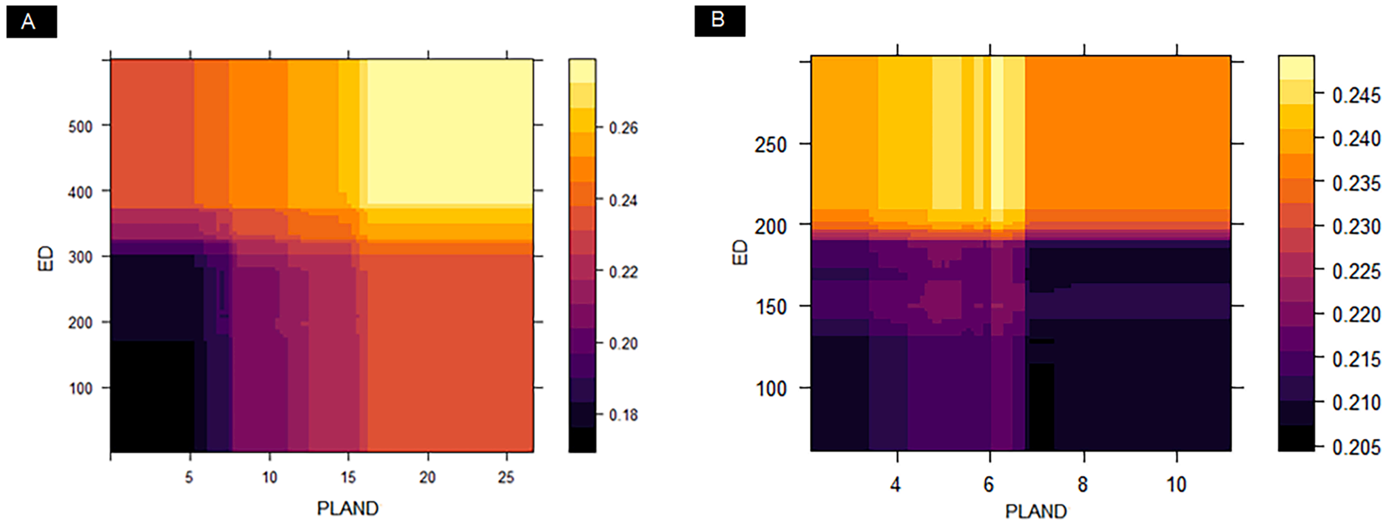

Fig. 5. Partial dependence plot for tree cover (PLAND; %) and edge density (ED; m/ha). A) For private UGI, where these metrics have the greatest relative influence on the cooling capacity (CC). B) Partial dependence plot for the public UGI metrics. Lighter and darker tones represent high and low adjusted values for CC, respectively. For private UGI, an interaction was quantified using the BRT model (Table S5) and it is possible to observe a positive interaction between PLAND and ED, which was not observed for public UGI.

segregation and green gentrification (Pedlowski et al. 2002, Jenerette et al. 2011, Anguelovski et al. 2018). Therefore, it is important to highlight that all environmental policies and strategies need to be built with public participation (Andersson et al. 2006, Ruffato-Ferreira 2016), especially those policies that can strongly change the city landscape. We therefore believe that a clear compromise is needed when planning the UGI implementation for the provision of different urban ecosystem services, considering possible trade-offs and the desired effects.

Our findings have direct application to urban management and planning, shedding light on the opportunity to regenerate and transform the quality of life of the inhabitants of an already consolidated urban space, such as the suburbs of Rio de Janeiro, through the systematic promotion of different types of Nature-based Solutions. The low proportion of green cover on public spaces shows the necessity to increase the public UGI and to requalify common urban spaces (Mendonça et al. 2019), even knowing that most of the political efforts for urban management are already directed to public areas (Ossola et al. 2018). However, considering the important role that private UGI has for microclimatic regulation and its direct impact on its beneficiaries (Ziter et al. 2019), we also emphasize the importance of creating effective instruments to encourage the promotion of ecosystem services beyond the street, by adopting Nature-based Solutions throughout the private-social-public domain (Ossola et al. 2018). Incentive measures, like tax incentives and benefits, may be an effective short-term instrument for maintaining and increasing small private UGI in cities, like tree cover in backyards and green roofs (Ruffato-Ferreira 2016, Liberalesso et al. 2020). The cooling capacity maps, as the one produced in this work, could be used as an initial step to define priority neighborhoods or regions for UGI implementation and requalification targeting UHI mitigation.

It should be borne in mind that the simplicity of the air mixing equation used by the urban cooling InVEST model, as well as the simplification of "park effects" are a limiting factor. The model considers only a linear relationship of temperature variation in relation to tree cover (Sharp et al. 2020, Bosch et al. 2020), as opposed to the non-linear relationship already seen in other works that explore the relationship between temperature and tree cover empirically (Wu et al. 2019, Ziter et al. 2019, Wang et al. 2020, Ossola et al. 2021). Another aspect to be considered is the temporal and seasonal variation of the UHI. The metropolitan region of Rio de Janeiro demonstrates a change in the strength of the UHI throughout the year, as well as a daily variation. Opposite to what was found for other cities, where the UHI is nocturnal, in Rio de Janeiro the UHI is mainly diurnal (Marques-Filho et al. 2009, Meireles et al. 2014). In this work, we only considered the average annual temperature, which allows a first step on understanding the UGI role on microclimate regulation. Future works should incorporate the non-linear relationships of composition and configuration of the UGI with temperature, either through using other models, remote sensing or empirical studies, and assess seasonal variation of microclimatic regulation, as the importance of private UGI can be even higher during the summer or during heat waves. Lastly, it would be interesting that future studies on small UGI evaluate the cooling capacity in the entire city of Rio de Janeiro or even in the metropolitan region. For this, it is necessary to carry out a complete and up-to-date mapping of the intra-urban vegetation cover and a better spatial distribution of climatological stations for the region, which is still missing.

5. Conclusion

Using Rio de Janeiro's suburbs as a model, we have assessed the importance of UGI in the private and public realm and evaluate the relative contribution of composition and configuration of UGI to microclimate regulation. Results reveal that (1) private UGI cover is two times higher than public UGI in the region; (2) private UGI has a greater correlation and the greater relative contribution to the provision of microclimate regulation; (3) both composition and configuration of small UGI are important and have a combined effect, with tree cover and edgy density being the most important metrics; (4) Although the combined effect, configuration, specifically edge density, has the greater relative importance to microclimate regulation. Our findings advance the discussion on the importance of landscape patterns in providing microclimate regulation, demonstrating that for small UGIs, their spatial distribution may be more important for microclimate regulation than their cover. These findings can help forge new policies for dense urban areas where the role of the public and private domains can undergo a requalification, using private UGI along with public UGI as a tool in urban design to mitigate the UHI effects and systematically considering UGI configuration to maximize temperature reduction.

CRediT authorship contribution statement

Carson Silveira: Writing – review & editing, Writing – original draft, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **André Tavares Corrêa Dias:** Conceptualization, Writing – review & editing, Supervision. **Felipe Gonçalves Amaral:** Writing – review & editing, Data curation. **Givanildo de Gois:** Writing – review & editing, Data curation. **Nuria Pistón:** 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.

Data availability

Data will be made available on request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.scs.2024.105589.

References

Akbari, H., Pomerantz, M., & Taha, H. (2001). Cool surfaces and shade trees to reduce energy use and improve air quality in urban areas. *Solar Energy, Urban Environment, 70*(3), 295–310. https://doi.org/10.1016/S0038-092X(00)00089-X

Akbari, H., Constantinos, C., Kolokotsa, D., Muscio, A., Pisello, A. L., Rossi, F., Santamouris, M., Synnef, A., Wong, N. H., & Zinzi, M. (2015). Local climate change and urban heat island mitigation techniques – the state of the art. *Journal of Civil Engineering and Management, 22*(1), 1–16. https://doi.org/10.3846/13923730.2015.1111934

Alberti, M. (2008). *Advances in urban ecology*. Boston, MA: Springer US. https://doi.org/10.1007/978-0-387-75510-6

Allen, R., Pereira, L., Raes, D., & Smith, M. (1998). Crop Evapotranspiration - guidelines for computing crop water requirements" chapter. *FAO irrigation and drainage paper 56*. FAO - Food and AgrUHIlture Organization of the United Nations. Rome https://www.fao.org/3/x0490e/x0490e0b.htm#tabulated%20kc%20values.

Amaral, F. G.; Araujo, P. L. C. Bastos, R. M. C.; Cruz, L. M.; Cruz, C. B. M. 2022. "O Verde Intraurbano Da Àrea De Planejamento 3 Carioca: Mapeamento e Padrões Espaciais Com Apoio Das Geotecnologias" Chapter. In: Souza, Elizabeth Maria Feitosa da Rocha de. (Org.). Geoinformação E Análise Espacial: Métodos Aplicados a Áreas Antropizadas. Appris 1 (1) p. 246-269.

Andersson, E. (2006). Urban landscapes and sustainable cities. *Ecology and Society, 11*(1), 34 [online] URL: http://www.ecologyandsociety.org/vol11/iss1/art34/.

Anguelovski, I., Connolly, J., & Brand, A. L. (2018). From landscapes of utopia to the margins of green urban life: For whom is the new green city? *City, 22*(3), 417–436. https://doi.org/10.1080/13604813.2018.1473126

Aram, F., García, E. H., Solgi, E., & Mansournia, S. (2019). Urban green space cooling effect in cities. *Heliyon, 5*(4), e01339. https://doi.org/10.1016/j.heliyon.2019.e01339

Barandier, H. (2016). Negligência urbanística e projeto urbano na Cidade do Rio de Janeiro. *Cadernos do Desenvolvimento Fluminense, 11*, 25–40. https://doi.org/10.12957/cdf.2016.35871

Bolund, P., & Hunhammar, S. (1999). Ecosystem services in urban areas. *Ecological Economics, 29*(2), 293–301. https://doi.org/10.1016/S0921-8009(99)00013-0

Bosch, M., Locatelli, M., Hamel, P., Jaligot, R., Chenal, J., and Joost, S. 2020. "Evaluating urban greening scenarios for urban heat mitigation: A spatially-explicit approach". https://doi.org/10.1101/2020.11.09.373779.

Bosch, M., Locatelli, M., Hamel, P., Jaligot, R., Chenal, J., & Joost, S. (2021). A spatially explicit approach to simulate urban heat mitigation with InVEST (v3.8.0). *Geoscientific Model Development, 14*(6), 3521–3537. https://doi.org/10.5194/gmd-14-3521-2021

Bowler, D. E., Buyung-Ali, L., Knight, T. M., & Pullin, A. S. (2010). Urban greening to cool towns and cities: A systematic review of the empirical evidence. *Landscape and Urban Planning, 97*(3), 147–155. https://doi.org/10.1016/j.landurbplan.2010.05.006

Cameron, R. W. F., Blanuša, T., Taylor, J. E., Salisbury, A., Halstead, A. J., Henricot, B., & Thompson, K. (2012). The domestic garden – its contribution to urban green infrastructure". *Urban Forestry & Urban Greening, 11*(2), 129–137. https://doi.org/10.1016/j.ufug.2012.01.002

Cao, X., Onishi, A., Chen, J., & Imura, H. (2010). Quantifying the cool island intensity of urban parks using ASTER and IKONOS data. *Landscape and Urban Planning, 96*(4), 224–231. https://doi.org/10.1016/j.landurbplan.2010.03.008

Chen, A., Yao, L., Sun, R., & Chen, L (2014). How many metrics are required to identify the effects of the landscape pattern on land surface temperature? *Ecological Indicators, 45*, 424–433. https://doi.org/10.1016/j.ecolind.2014.05.002

Cohen-Shacham, E., Walters, G., Janzen, C., & Maginnis, S. (2016). *Nature-based Solutions to address global societal challenges*. Gland, Switzerland: IUCN. https://doi.org/10.2305/IUCN.CH.2016.13.en. xiii + 97pp.

De Azevedo, T. S., Bourke, B. P., Piovezan, R., & Sallum, M. A. M. (2018). The influence of urban heat islands and socioeconomic factors on the spatial distribution of *Aedes aegypti* larval habitats". *Geospatial Health, 13*(1). https://doi.org/10.4081/gh.2018.623

Deilami, K., Kamruzzaman, Md., & Liu, Y. (2018). Urban heat island effect: A systematic review of spatio-temporal factors, data, methods, and mitigation measures. *International Journal of Applied Earth Observation and Geoinformation, 67*, 30–42. https://doi.org/10.1016/j.jag.2017.12.009

Dereczynski, C., Silva, W. L., & Marengo, J. (2013). Detection and projections of climate change in Rio de Janeiro, Brazil. *American Journal of Climate Change, 02*(01), 25–33. https://doi.org/10.4236/ajcc.2013.21003

Derkzen, M. L., van Teeffelen, A. J. A, & Verburg, P. H. (2015). REVIEW: Quantifying urban ecosystem services based on high-resolution data of urban green space: an assessment for rotterdam, the Netherlands. Edited by Sarah Diamond *Journal of Applied Ecology, 52*(4), 1020–1032. https://doi.org/10.1111/1365-2664.12469.

Dobbs, C., Escobedo, F. J., & Zipperer, W. C. (2011). A framework for developing urban forest ecosystem services and goods indicators. *Landscape and Urban Planning, 99*(3), 196–206. https://doi.org/10.1016/j.landurbplan.2010.11.004

Dobbs, C., Escobedo, F. J., Clerici, N., et al. (2019). Urban ecosystem Services in Latin America: mismatch between global concepts and regional realities? *Urban Ecosyst, 22*, 173–187. https://doi.org/10.1007/s11252-018-0805-3

Du, S., Xiong, Z., Wang, Y., & Guo, L. (2016). Quantifying the multilevel effects of landscape composition and configuration on land surface temperature. *Remote Sensing of Environment, 178*, 84–92. https://doi.org/10.1016/j.rse.2016.02.063

Duarte, D. H. S., Shinzato, P., Gusson, C. S., & Alves, C. A. (2015). The impact of vegetation on urban microclimate to counterbalance built density in a subtropical changing climate. *Urban Climate, 14*, 224–239. https://doi.org/10.1016/j.uclim.2015.09.006

Elith, J., Leathwick, J. R., & Hastie, T. (2008). A working guide to boosted regression trees. *Journal of Animal Ecology, 77*(4), 802–813. https://doi.org/10.1111/j.1365-2656.2008.01390.x

Fahrig, L., Watling, J. I., Arnillas, C. A., Arroyo-Rodríguez, V., Jörger-Hickfang, T., Müller, J., Pereira, H. M., Riva, F., Rösch, V., Seibold, S., Tscharntke, T., & May, F. (2022). Resolving the SLOSS dilemma for biodiversity conservation: a research agenda. *Biological reviews of the Cambridge Philosophical Society, 97*(1), 99–114. https://doi.org/10.1111/brv.12792

Friedman, J., Hastie, T., & Tibshirani, R. (2000). Additive logistic regression: A statistical view of boosting. *The Annals of Statistics, 28*, 337–407. https://doi.org/10.1214/aos/1016218223

Gaston, K. J., Warren, P. H., Thompson, K., & Smith, R. M. (2005). Urban domestic gardens (IV): The extent of the resource and its associated features. *Biodiversity & Conservation, 14*(14), 3327–3349. https://doi.org/10.1007/s10531-004-9513-9

Grilo, F., Pinho, P., Aleixo, C., Catita, C., Silva, P., Lopes, N., Freitas, C., Santos-Reis, M., McPhearson, T., & Branquinho, C. (2020). Using green to cool the grey: Modeling the cooling effect of green spaces with a high spatial resolution. *Science of The Total Environment, 724*, Article 138182. https://doi.org/10.1016/j.scitotenv.2020.138182

Grimmond, C. S., & Oke, T. R. (1999). *Evapotranspiration rates in urban areas* (pp. 235–249). IAHS-AISH Publication.

Hesselbarth, M. H. K., Sciaini, M., With, K. A., Wiegand, K., & Nowosad, J. (2019). Landscapemetrics: An open-source r tool to calculate landscape metrics. *Ecography, 42*(10), 1648–1657. https://doi.org/10.1111/ecog.04617

Hijmans, R. J., Phillips, S., Leathwick, J., & Elith, J. 2017. dismo: Species Distribution Modeling. R package version 1.1-4.

Hothorn, T., Bretz, F., Westfall, P., Heiberger, R.M., Schuetzenmeister, A., and Scheibe, S. 2022. "Multcomp: Simultaneous inference in general parametric models". https://CRAN.R-project.org/package=multcomp.

Hwang, Y. H., Lum, Q. J. G., & Chan, Y. K. D. (2015). Micro-scale thermal performance of tropical urban parks in Singapore. *Building and Environment, 94*, 467–476. https://doi.org/10.1016/j.buildenv.2015.10.003

Instituto Brasileiro De Geografia E Estatística - IBGE. (2010). *IBGE-Cidades: População estimada*. Rio de Janeiro: IBGE. https://cidades.ibge.gov.br/brasil/rj/rio-de-janeiro/panorama.

Instituto Municipal de Urbanismo Pereira Passos - IPP (2016). Cidade do Rio de Janeiro - Uso do Solo 2016. DATARIO. https://www.data.rio/datasets/PCRJ::uso-do-solo-2016/about.

Jenerette, G. D., Sharon, L. H., Stefanov, W. L., & Martin, C. A. (2011). Ecosystem services and urban heat riskscape moderation: Water, green spaces, and social inequality in Phoenix, USA''. *Ecological Applications, 21*(7), 2637–2651. https://doi.org/10.1890/10-1493.1

Kabisch, N., & Haase, D. (2013). Green spaces of european cities revisited for 1990–2006. *Landscape and Urban Planning, 110*, 113–122. https://doi.org/10.1016/j.landurbplan.2012.10.017

Kim, Y., Yu, S., Li, D., Gatson, S. N., & Brown, R. D. (2022). Linking landscape spatial heterogeneity to urban heat island and outdoor human thermal comfort in Tokyo: Application of the outdoor thermal comfort index. *Sustainable Cities and Society*, (87), Article 104262. https://doi.org/10.1016/j.scs.2022.104262

Lambers, H., Chapin, F. S., & Pons, T. L. (2008). *Plant physiological ecology*. New York, NY: Springer New York. https://doi.org/10.1007/978-0-387-78341-3

Lee, H., Lim, H., & Park, S. (2023). Quantitative assessment of green coverage changes under the human-biometeorological perspective: A simulation case study in Jeju, Republic of Korea. *Sustainable Cities and Society*, (97), Article 104734. https://doi.org/10.1016/j.scs.2023.104734

Li, J., Song, C., Cao, L., Zhu, F., Meng, X., & Wu, J. (2011). Impacts of landscape structure on surface urban heat Islands: A case study of Shanghai, China. *Remote Sensing of Environment, 115*(12), 3249–3263. https://doi.org/10.1016/j.rse.2011.07.008

Li, X., Zhou, W., Ouyang, Z., Xu, W., & Zheng, H. (2012). Spatial pattern of greenspace affects land surface temperature: Evidence from the heavily urbanized Beijing metropolitan area, China. *Landscape Ecology, 27*. https://doi.org/10.1007/s10980-012-9731-6

Li, X., Zhou, W., & Ouyang, Z. (2013). Relationship between land surface temperature and spatial pattern of greenspace: What are the effects of spatial resolution? *Landscape and Urban Planning, 114*, 1–8. https://doi.org/10.1016/j.landurbplan.2013.02.005

Liberalesso, T., Cruz, C. O., Silva, C. M., & Manso, M. (2020). Green infrastructure and public policies: An International review of green roofs and green walls incentives. *Land Use Policy, 96*, Article 104693. https://doi.org/10.1016/j.landusepol.2020.104693

Lin, B., Meyers, J., & Barnett, G. (2015). Understanding the potential loss and inequities of green space distribution with urban densification. *Urban Forestry & Urban Greening, 14*(4), 952–958. https://doi.org/10.1016/j.ufug.2015.09.003

Liu, W., Chen, W., & Peng, C. (2014). Assessing the effectiveness of green infrastructures on urban flooding reduction: A community scale study. *Ecological Modelling, 291*, 6–14. https://doi.org/10.1016/j.ecolmodel.2014.07.012. ISSN 0304-3800.

Locke, D. H., & McPhearson, T. (2018). Urban areas do provide ecosystem services. *Frontiers in Ecology and the Environment, 16*(4), 203–205. https://doi.org/10.1002/fee.1796

Lucena, A., Farias, L.P., and Miranda, V.F.V.V. 2018. "Os Espaços De Calor Da Região Metropolitana Da Cidade Do Rio De Janeiro" Chapter. In: Júnior, Antonio Carlos Oscar, e Núbia Beray Armond. A climatologia geográfica no Rio de Janeiro: reflexões, metodologias e técnicas para uma agenda de pesquisa. 1ª edição. Curitiba, PR: Appris Editora.

Luederitz, C., Brink, E., Gralla, F., Hermelingmeier, V., Meyer, M., Niven, L., Panzer, L., et al. (2015). A review of urban ecosystem services: six key challenges for future research. *Ecosystem Services, 14*, 98–112. https://doi.org/10.1016/j.ecoser.2015.05.001

Marques-Filho, E., Karam, H., Miranda, A., & Franca, J. R (2009). Rio de Janeiro's tropical urban climate. *Newsletter of the International Association of Urban Climate (IAUC)* (p. 32).

McGarigal, K. (2014). Landscape pattern metrics" Chapter. *Wiley StatsRef: Statistics Reference Online*. John Wiley & Sons, Ltd. https://doi.org/10.1002/9781118445112.stat07723

Meireles, V. H. P., França, J. R. A., & Peres, L. F. (2014). A study of the phenomenon of urban heat Island in Rio De Janeiro metropolitan region. *Anuário do Instituto de Geociências - UFRJ, 37*(2), 180. https://doi.org/10.11137/2014_2_180_194

Mendonça, B. R. E., Tângari, V. R., & Vasconcellos, V. (2019). Espaços livres e arborização: uma análise do subúrbio ferroviário do Rio de Janeiro. *Paisagem e Ambiente, 30*(44), Article e161067. https://doi.org/10.11606/issn.2359-5361.paam.2019.161067

Moreira, R. (2012). O rapto do subúrbio. Resenha de O rapto ideológico da categoria subúrbio, de Nelson da Nóbrega Fernandes. Rio de Janeiro: Editora ApUHIri/Faperj, 2011. *GEOgraphia, 14*(27), 157–164. https://doi.org/10.22409/GEOgraphia2012.v14i27.a13639

Muniz Júnior, J. G. R., Oliveira-Júnior, J. F. D, De Gois, G., Sobral, B. S, Teodoro, P. E., Silva Junior, C. A. D., Correia Filho, W. L. F., & Santiago, D. D. B. (2020). Climatological water balance in the municipality of Rio de Janeiro. *Revista Brasileira de Geografia Física, 13*(5), 2388. https://doi.org/10.26848/rbgf.v13.5.p2388-2401

Oke, T. R., Mills, G., Christen, A., & Voogt, J. A. (2017). Urban heat island." chapter. *Urban Climates* (pp. 197–237). Cambridge: Cambridge University Press. https://doi.org/10.1017/9781139016476.008

Ossola, A., Jenerette, G. D., McGrath, A., Chow, W., Hughes, L., & Leishman, M. R. (2021). Small vegetated patches greatly reduce urban surface temperature during a summer Heatwave in Adelaide, Australia. *Landscape and Urban Planning, 209*, Article 104046. https://doi.org/10.1016/j.landurbplan.2021.104046

Ossola, A., Locke, D., Lin, B., & Minor, E (2019a). Greening in style: urban form, architecture and the structure of front and backyard vegetation. *Landscape and Urban Planning, 185*, 141–157. https://doi.org/10.1016/j.landurbplan.2019.02.014

Ossola, A., Locke, D., Lin, B., & Minor, E. (2019b). Yards increase forest connectivity in urban landscapes. *Landscape Ecol, 34*, 2935–2948. https://doi.org/10.1007/s10980-019-00923-7

Ossola, A., Schifman, L., Herrmann, D. L., Garmestani, A. S, Schwarz, K., & Hopton, M. E. (2018). The provision of urban ecosystem services throughout the private-social-public domain: A conceptual framework. *Cities and The Environment, 11*(1), 1–15.

Park, J., Kim, JH, Lee, D. K, Park, C. Y, & Jeong, S. G (2017). The influence of small green space type and structure at the street level on urban heat island mitigation. *Urban Forestry & Urban Greening, 21*, 203–212. https://doi.org/10.1016/j.ufug.2016.12.005

Pedlowski, M. A., Silva, V. A. C. D., Adell, J. J. C. A., & Heynen, M. C. (2002). Urban forest and environmental inequality in Campos Dos Goytacazes, Rio de Janeiro, Brazil. *Urban Ecosystems, 6*(1), 9–20. https://doi.org/10.1023/A:1025910528583

Perfeito, L. (2020). Onde fica o subúrbio carioca? Limites territoriais suburbanos no Rio de Janeiro do século XIX ao XXI. *junho*. https://doi.org/10.5821/siiu.9790

Phelan, P. E., Kaloush, K., Miner, M., Golden, J., Phelan, B., Silva, H., & Taylor, R. A. (2015). Urban heat island: Mechanisms, implications, and possible remedies. *Annual Review of Environment and Resources, 40*(1), 285–307. https://doi.org/10.1146/annurev-environ-102014-021155

Pistón, N., de Bello, F., Dias, A. T. C., Götzenberger, L., Rosado, B. H. P., de Mattos, E. A., Salguero-Gómez, R., & Carmona, C. P. (2019). Multidimensional ecological analyses demonstrate how interactions between functional traits shape fitness and life history strategies. *Journal of Ecology, 107*(5), 2317–2328. https://doi.org/10.1111/1365-2745.13190

Rajagopal, P., Priya, R . S., & Senthil, R. (2023). A review of recent developments in the impact of environmental measures on urban heat island. *Sustainable Cities and Society*, (88), Article 104279. https://doi.org/10.1016/j.scs.2022.104279

Ruffato-Ferreira, V. J. (2016). *Uma Nova Variável no Planejamento para o Desenvolvimento Urbano Sustentável: Áreas Verdes em Quintais no Subúrbio da Cidade do Rio de Janeiro*. Doutorado, Rio de Janeiro: UFRJ/COPPE Programa de Planejamento Energético. http://www.ppe.ufrj.br/images/publica%C3%A7%C3%B5es/doutorado/Vera_Jane_Ruffato_Pereira_Ferreira.pdf.

Santamouris, M., Cartalis, C., Synnefa, A., & Kolokotsa, D. (2015). On the impact of urban heat island and global warming on the power demand and electricity consumption of buildings—a review". *Energy and Buildings, Renewable Energy Sources and Healthy Buildings, 98*, 119–124. https://doi.org/10.1016/j.enbuild.2014.09.052

Santos, L. (2011). Os subúrbios do Rio de Janeiro no iní-cio do século XX. *Mneme - Revista de Humanidades, 12*(30). https://periodicos.ufrn.br/mneme/article/view/1265.

Sharp, R., Douglass, J., & Wolny, S. (2020). InVEST 3.9.0 User's Guide. *The Natural Capital Project*. Stanford University, University of Minnesota, The Nature Conservancy, and World Wildlife Fund. http://releases.naturalcapitalproject.org/invest-userguide/latest/index.html.

Shashua-Bar, L., & Hoffman, M. E. (2000). Vegetation as a climatic component in the design of an urban street. *Energy and Buildings, 31*(3), 221–235. https://doi.org/10.1016/S0378-7788(99)00018-3

Souza, R. R. 2010. "As representações subalternas dos homens suburbanos" Chapter. In: Oliveira, M. P.; Fernandes, N. Da N. (Eds.). "150 anos de subúrbio carioca". Primeira ed. Rio de Janeiro: Lamparina - Faperj - EdUFF. p. 219–233.

Stewart, I. D., & Oke, T. R. (2012). Local climate zones for urban temperature studies. *Bulletin of the American Meteorological Society, 93*(12), 1879–1900. https://doi.org/10.1175/BAMS-D-11-00019.1

Tresch, S., Frey, D., Bayon, RC. L., Mader, P., Stehle, B., Fliessbach, A., & Moretti, M. (2019). Direct and indirect effects of urban gardening on aboveground and belowground diversity influencing soil multifunctionality. *Sci Rep, 9*, 9769. https://doi.org/10.1038/s41598-019-46024-y

Vaz Monteiro, M., Doick, K. J., Handley, P., & Peace, A. (2016). The impact of greenspace size on the extent of local nocturnal air temperature cooling in London. *Urban Forestry & Urban Greening, 16*, 160–169. https://doi.org/10.1016/j.ufug.2016.02.008

Wang, Y., & Akbari, H. (2016). The Effects of street tree planting on urban heat island mitigation in montreal. *Sustainable Cities and Society, 27*, 122–128. https://doi.org/10.1016/j.scs.2016.04.013

Wang, J., Zhou, W., Jiao, M., Zheng, Z., Ren, T., & Zhang, Q. (2020). Significant effects of ecological context on urban trees' cooling efficiency. *ISPRS Journal of Photogrammetry and Remote Sensing, 159*, 78–89. https://doi.org/10.1016/j.isprsjprs.2019.11.001

Wu, Z., Dou, P., & Chen, L. (2019). Comparative and combinative cooling effects of different spatial arrangements of buildings and trees on microclimate. *Sustainable Cities and Society, 51*. https://doi.org/10.1016/j.scs.2019.101711

Zardo, L., Geneletti, D., Pérez-Soba, M., & Van Eupen, M. (2017). Estimating the cooling capacity of green infrastructures to support urban planning. *Ecosystem Services, 26*, 225–235. https://doi.org/10.1016/j.ecoser.2017.06.016

Zhang, H., Zhao, Xi, Kang, M., & Han, J. (2022). Contrasting changes in fine-scale land use structure and summertime thermal environment in downtown Shanghai. *Sustainable Cities and Society*, (83), Article 103965. https://doi.org/10.1016/j.scs.2022.103965

Zhou, W., Huang, G., & Cadenasso, M. L. (2011). Does spatial configuration matter? understanding the effects of land cover pattern on land surface temperature in urban landscapes. *Landscape and Urban Planning, 102*(1), 54–63. https://doi.org/10.1016/j.landurbplan.2011.03.009

Zhou, W., Wang, J., & Cadenasso, M. L. (2017). Effects of the spatial configuration of trees on urban heat mitigation: A comparative study. *Remote Sensing of Environment, 195*, 1–12. https://doi.org/10.1016/j.rse.2017.03.043

Ziter, C. D., Pedersen, E. J., Kucharik, C. J., & Turner, M. G. (2019). Scale-dependent interactions between tree canopy cover and impervious surfaces reduce daytime urban heat during summer. *Proceedings of the National Academy of Sciences, 116*(15), 7575–7580. https://doi.org/10.1073/pnas.1817561116

Ziter, C. D., & Turner, M. G. (2018). Current and historical land use influence soil-based ecosystem services in an urban landscape. *Ecological Applications, 28*(3), 643–654. https://doi.org/10.1002/eap.1689