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Social value-weighted greenspace exposure index: A novel metric integrating cultural ecosystem services for equitable benefits

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ABSTRACT

Well-maintained urban greenspaces (UGSs) can provide benefits for human health and recreation. Existing evaluations often focus solely on greenspace presence, overlooking their attractiveness and the resulting quality as perceived by the citizens. Thereby, we lack comprehensive understanding on whether citizens have equal access to high-quality UGSs that can truly provide health benefits and enhance life satisfaction, obscuring systemic inequalities in environmental justice. Here we sought to address this challenge by taking cultural ecosystem service (CES) and social values of UGSs as a proxy for the perceived UGS quality. Through a four-month survey of 558 citizens in Xiamen, China, we quantified UGS social values and integrated them into the evaluations of UGS use and the inequalities therein between neighborhoods. Our findings indicate that previous metrics may misrepresent actual enjoyment of UGSs (with coverage-based valuation at 10.28% while social value-weighted assessment is 6.49%), typically because neighborhoods may have greenspaces with disparate social values, causing an unbalanced distribution of attractive UGSs. When combined with major inequalities in access to high-quality UGSs, this may cause significant differences in perceived health benefits among citizens (Gini coefficient increases from 0.69 to 0.79). We additionally observed that the three focal drivers of these inequalities—greenspace coverage, local population mobility and UGS social values—vary across neighborhoods, informing targeted policy interventions. We highlight that disparities in UGS social values contribute to major extents to inequalities in health benefits, emphasizing the need to extend greenspace assessments from quantity to quality and ensuring equal access to high-quality greenspaces and their well-being benefits.

Abbreviations: UGS(s), Urban Greenspace(s); CES, Cultural Ecosystem Services; ES, Ecosystem Services; PPGIS, Public Participatory Geographic Information System; SolVES model, Social Values for Ecosystem Services model; DTR, Distance To Roads; DTW, Distance To Waters; DTRA, Distance To Residential Area; AOI, Area Of Interest; ELEV, Elevation; LC, Land Cover; NDVI, Normalized Difference Vegetation Index; MaxEnt, Maximum Entropy; AUC, Area Under the Curve; GE_{sv}, population- and Social Value-weighted Greenspace Exposure; GC, Greenspace Coverage; GE, population-weighted Greenspace Exposure; Gini_GE, the Gini coefficient calculated based on GE; Gini_GE_{sv}, the Gini coefficient calculated based on GE_{sv}; POP_std, the standard deviation of population (by calculating the standard deviation of the population in all grids within one neighborhood); SV_total, the total sum of social value within one neighborhood (indicating the overall UGS social value level); SV_std, the standard deviation of social value within a neighborhood (indicating the internal discrepancy of UGS social value); SV_max, the maximum social value within one neighborhood (indicating the optimal level of UGS social value); VIF, Variance Inflation Factor; VP, Variance Partitioning; RF, Random Forest; SHAP, SHapley Additive exPlanations.

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1. Introduction

Nearly one in four global deaths are linked to the environment (World Health Organization, 2018, 2023). Fundamental components of healthy environments—including clean air, safe drinking water, and climate stability—are increasingly threatened, jeopardizing decades of advancements in global health, particularly within urban contexts. In response to these challenges, urban greenspaces (UGSs) have been strategically implemented as nature-based interventions to mitigate urban health risks and enhance population health outcomes (Pedersen Zari et al., 2022). UGSs are widely acknowledged for delivering multifunctional ecosystem services, including enhancing pollutant removal, regulating microclimate dynamics, protecting biodiversity, mitigating noise pollution, reducing airborne contaminants, and promoting energy efficiency (Goddard et al., 2010; Akpinar et al., 2016; Willis and Petrokofsky, 2017; Browning et al., 2022), collectively supporting the sustainability of urban habitats. Moreover, UGSs also provide cultural ecosystem services, such as recreation, landscape aesthetics, and spiritual experiences (Havinga et al., 2020). These services, through human physical activities, can produce a plethora of benefits spanning physical and mental health (Remme et al., 2021), such as mitigating chronic metabolic diseases (Nieuwenhuijsen, 2018), improving psychological well-being (Lee et al., 2023), and fostering social connections and interactions (Orban et al., 2017).

Building upon extensive groundwork dedicated to quantifying citizens' engagement with UGSs, encompassing metrics such as greenspace coverage (Zhao et al., 2013; Chen et al., 2017; Ju et al., 2022), availability (Xu et al., 2018; Farkas et al., 2022; Xu et al., 2024), accessibility (Fan et al., 2017; Lu et al., 2023; Battiston and Schifanella, 2024), and exposure-related inequalities (Song et al., 2021; Han et al., 2022; Wu et al., 2023; Leng et al., 2023), our study aims to address three interconnected limitations that persist in this field: First, prevailing exposure assessments predominantly operationalize UGSs through broad land-cover classifications (e.g., forests, grasslands, wetlands, parks), overemphasizing spatial abundance while neglecting ecosystem service efficacy and environmental inclusiveness—the latter being explicitly mandated by Sustainable Development Goal 11 (United Nations, 2015). Second, conventional spatial accessibility models fail to incorporate subjective dimensions of UGS engagement, such as spiritual fulfillment and aesthetic preferences, whereas these perceptual factors have been demonstrated as significant predictors of actual usage patterns (Liu et al., 2024). Third, the majority of urban decision-makers overlook the integration of ecosystem service valuations into planning frameworks (Hamel et al., 2021), resulting in institutional barriers beyond spatial accessibility constraints. Collectively, moving beyond these oversights is essential to obscure the extent to which citizens benefit from greenspace-derived values, particularly given established linkages between accessibility inequalities and health disparities (Rutt & Gulsrud, 2016; Chen et al., 2022a,b).

The methodological limitations underscore the need to integrate value-informed exposure metrics, necessitating valuations of cultural ecosystem services (CES) and the corresponding social values—specifically spiritual enrichment, cognitive development, reflection, recreation, and aesthetic experiences (Millennium Ecosystem Assessment, 2005a; Sherrouse et al., 2014). Quantifying CES and social value benefits can effectively delineate the perceived quality of UGSs (Stanley et al., 2022; Benati et al., 2024), offer numerical indicators of their capacity to provide health benefits for humans, and aid decision-making processes in trade-off scenarios (Chen et al., 2020; Dang and Li, 2023).

Compared to other types of more utilitarian ecosystem services (ES) including provisioning, regulating, and supporting services (Millennium Ecosystem Assessment, 2005b), CES are often characterized as "intangible", "subjective" and difficult to quantify in biophysical or monetary terms, thereby hindering their integration within the ES framework (Daniel et al., 2012). To quantify these intangible CES, Public Participatory Geographic Information System (PPGIS) has emerged as a prominent methodological framework in human geography and landscape planning (Brown and Fagerholm, 2015). Critically, PPGIS methodologies offer distinct advantages for capturing perceived greenspace quality by spatially contextualizing citizen evaluations (Kajosaari et al., 2024). These tools overcome methodological constraints inherent in other typical UGS quality measurements. For instance, street view data fail to directly reflect humans' actual interactions with UGS or their perceptual experiences (Wang et al., 2021), while social media-derived datasets exhibit significant representativeness bias due to their highly skewed sampling nature (Brindley et al., 2019). Furthermore, PPGIS facilitates the documentation of place-based quality attributes through geo-referenced participatory surveys and photo elicitation techniques. This capability addresses a critical limitation of aggregate indices (e.g., ParkScore), which prioritize system-level metrics like acreage and facility density at the expense of localized experiential qualities (Rigolon et al., 2018). Complementing these strengths, PPGIS enables predictive extrapolation of quality patterns across broader urban landscapes. This analytical potential is amplified through multidisciplinary integration, as evidenced by the flourishing development of simulation models for ecosystem service value mapping—advancements synergistically combining ecological, geographical, and economic perspectives, such as the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model (Natural Capital Project, 2024) and the Social Values for Ecosystem Services (SolVES) model (Sherrouse et al., 2011). Especially with the emergence of SolVES, the quantification and simulation of CES becomes feasible and more systematic, without requiring dependency on monetary value.

To be specific, SolVES, a GIS-based platform developed by the U.S. Geological Survey's Center in collaboration with Colorado State University, is designed to assess, map, and quantify perceived social values obtained from social survey response data, and facilitate decision-making regarding tradeoffs among diverse ecosystem services. The social values referred to here are the non-market values that the public derives from ES, particularly cultural services for various stakeholder groups (U.S. Geosciences and Environmental Change Science Center, 2018). SolVES has been verified for its effectiveness in incorporating quantification and explicit spatial measurement of social values into ecosystem service assessments across nearly every continent, in various biophysical and social contexts, including forests (Sherrouse et al., 2014), mountains (Zhang et al., 2019), coastal areas (Zhao et al., 2023), riparian zones (Pan et al., 2022), agricultural lands (Petway et al., 2020), and urban ecosystems (Sun et al., 2019).

Building on this foundation, our study examines: (1) How do estimates of greenspace exposure and inequality, considering both presence of social values and its accessibility, differ from those derived from existing greenspace coverage and exposure metrics, (2) Are these inequalities primarily influenced by greenspace coverage, population mobility, social values, or their interactions, and (3) How do these drivers of inequalities vary across different areas, potentially informing decision-makers about tailored UGS management strategies?

Through a four-month PPGIS survey ($n = 558$) in Xiamen, China, we operationalized six types of UGS social values via SolVES model, generating an aggregated social value index as a proxy for UGS quality. Comparative analyses of exposure metrics—including traditional greenspace coverage versus population-weighted greenspace exposure—were conducted at neighborhood scale, with inequality quantified through Gini coefficients. This approach advances understanding of how citizens access and benefit from quality green spaces, directly supporting SDG 11′s mandate for inclusive, accessible urban environments.

2. Methodology

2.1. Overall framework

2.1.1. Descriptions of the framework

The overall framework for deriving estimates of exposure to UGSs and the inequality therein based on perceived social values is delineated into three major steps as follows (see in Fig. 1):

Step 1. Measuring the social values of UGSs based on SolVES: Utilizing the PPGIS concept, an on-site social survey was conducted to investigate citizens' perceptions on social values of UGSs. The survey data and the required environmental variables were jointly put into the SolVES model to estimate social values. Consequently, social values for physically and socially similar greenspaces, where primary survey data are unavailable, could be simulated, resulting a more complete social value map.
Step 2. Evaluating the social value-weighted greenspace exposure and inequality: The simulated social values, considered a proxy for the perceived quality of UGSs, were used as an additional weight in the formula on greenspace exposure. The weights of social value and commonly used population distribution, along with UGS coverage, were integrated to construct a population- and social value-weighted greenspace exposure metric. This metric of perceived exposure to high-value UGSs was calculated at the neighborhood level in this study. Additionally, a social value-weighted Gini coefficient was defined to evaluate the inequality of greenspace exposure from a social value perspective.
Step 3. Interpreting focal drivers of inequality and their differences across neighborhoods: Five measurements within three focal drivers of inequality were identified: the social value of UGS, population distribution, and greenspace coverage. The variance inflation factor was first employed to detect the multicollinearity among variables. By ranking the importance of variables using a random forest (RF) model and applying variance partitioning (VP), we identified the top three factors contributing to social value-weighted greenspace exposure inequality at the city-scale level, along with their individual and interactive effects. To further investigate the differences in drivers' impacts across neighborhoods, we employed the RF model-based SHAP (SHapley Additive exPlanations) method to assess the direction and magnitude of each variable's importance on inequality within each neighborhood, with the potential to either exacerbate or alleviate it. Additionally, hierarchical clustering was used to group neighborhoods with the same dominant drivers. Three major UGS management strategies were proposed, aligned with clusters of drivers on greenspace exposure inequality.

2.1.2. Case study area

This study was executed in Xiamen city as the case study area. Xiamen (24°23′∼24°54′N, 117°53′∼118°26′E) stands as a central city, harbor, and scenic tourist destination along the Southeast coast of China, boasting a land area of 1579 km^2, sea area of 333 km^2, and a total coastline stretching 234 km. The city comprises six administrative regions (Siming, Huli, Jimei, Tongan, Xiangan, Haicang) and 43 subordinate administrative districts (neighborhoods and towns), accommodating approximately 5.16 million population (the seventh Nationwide Census in 2020). The city's landscape features various ecosystems, including mountains in the northwestern region, wetlands along the southeastern coastline, and dispersed lake water systems across the central plain. As of 2021, Xiamen's urban built-up areas boast a green land percentage of 41.5 %, a green coverage percentage of 45.65 %, and a per capita greenspace of 14.84 m^2. The urban built-up greenspace spans 16,830.74 ha, with 5,789 ha allocated to park greenspaces, including comprehensive, special, and community parks. Xiamen's green coverage in built-up areas ranks among the highest in the country, reflecting its commitment to ecological preservation and development. Given its abundant natural resources and current urban planning orientation, Xiamen presents an ideal study area for assessing urban greenspace quality. The map is shown in Fig. 2.

2.2. Measuring the social values of urban greenspace

2.2.1. Indicators of social values in UGS

Previous work often established their social value indicators according to the definitions in Millennium Ecosystem Assessment (MA) framework (Millennium Ecosystem Assessment, 2005b), combined with pre-survey processes, or consultations with experts and local agencies. For instance, a study conducted in one of the scenic areas of Wuhan city by Chen et al., (2020) adopted 11 indicators, including aesthetic, biodiversity, cultural, economic, future, historic, intrinsic, learning, life-sustaining, recreation, spiritual, and therapeutic values. In comparison, another study in U.S. and Australian marine protected areas by Johnson

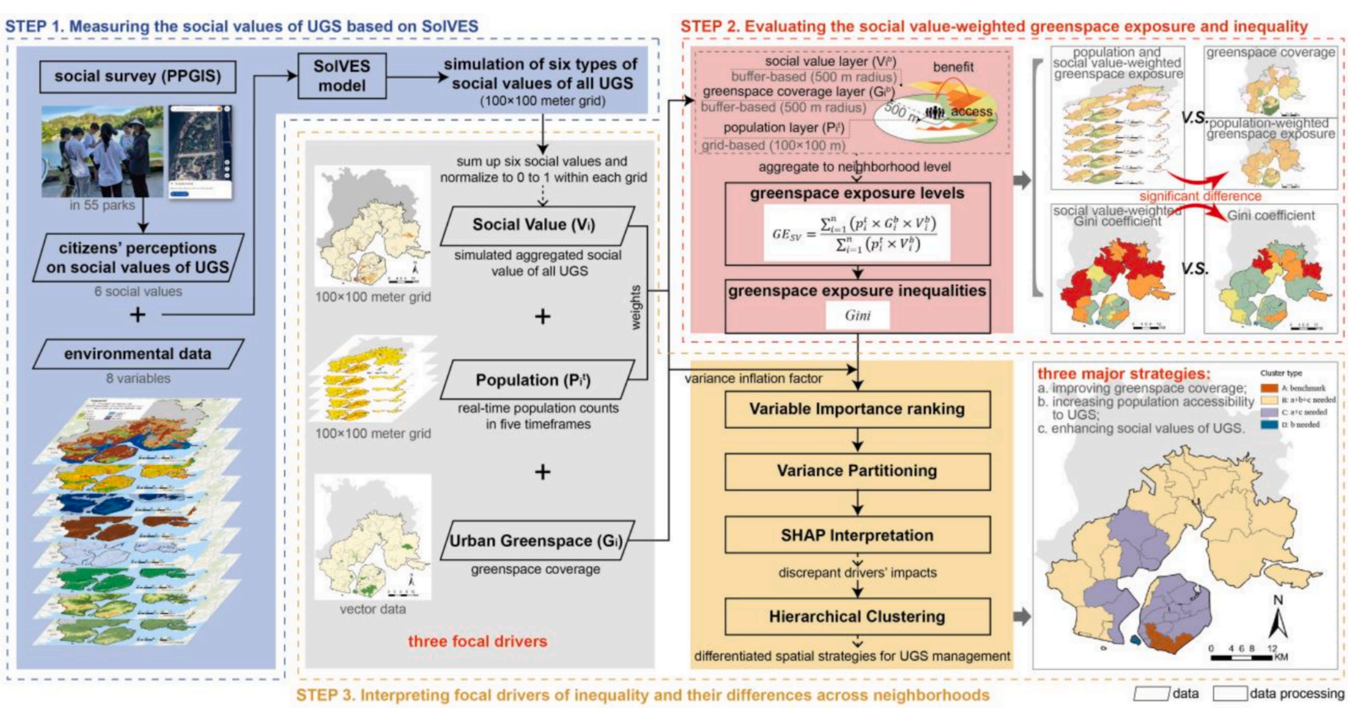

Fig. 1. Research framework.

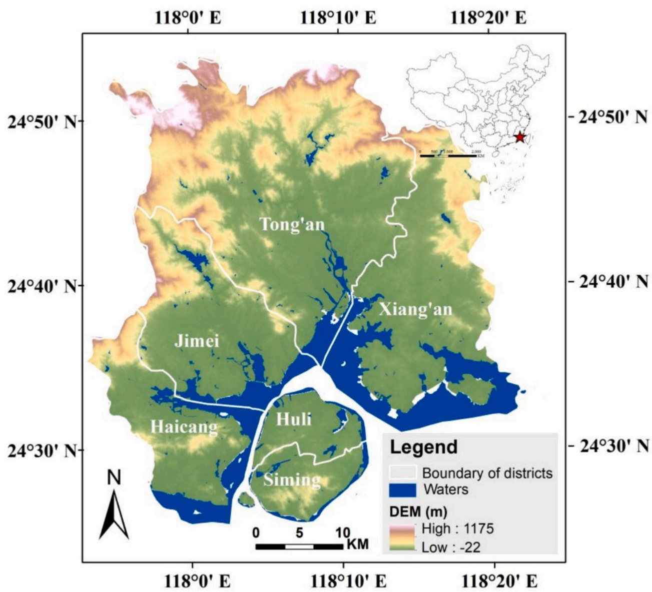

Fig. 2. Study area.

et al. (2019) listed one additional indicator – scientific – to specify the value of "provision of the opportunity for scientific observation or experimentation". Dang and Li's (2023) work in Shenzhen city extracted a more concise classification system, which contains services of aesthetic, cultural heritage, recreational, and spiritual values.

In summarizing past research and to ensure alignment with the study contexts and Chinese language, this study ultimately defined six indicators of UGS social values, as shown in Table 1.

2.2.2. *Social survey on the public's perceived UGS's social values*

We conducted a survey on citizens' perception of the six selected social values in different UGSs. This study focuses on the UGSs within the built-up area in the city to ensure comparability. Fifty-five representative UGSs (Fig. S1) were systematically selected from Xiamen's registry of 220 municipal parks (comprehensive parks: n = 31, 14.1 %; community parks: n = 98, 44.5 %; specialized parks: n = 76, 34.5 %; regional green spaces: n = 15, 6.8 %) to capture potential heterogeneity in cultural ecosystem services and social value patterns across park typologies, sizes, and service radii. Specifically, stratification deliberately adjusted category proportions to optimize CES characterization: (a) comprehensive parks were oversampled (35 % of selections vs. 14.1 % citywide) given their significantly larger size and richer cultural service provision compared to community parks; (b) community parks were proportionally reduced (20 % vs. 44.5 %) to balance service focus while retaining neighborhood-scale representation; (c) specialized parks maintained near-baseline representation (31.6 % vs. 34.5 %), and (d) regional green spaces were slightly increased (13.3 % vs. 6.8 %) to ensure *peri*-urban gradient coverage. Final selection ensured proportional representation across predetermined size-service tiers (1–50 ha/500–3,000 m radius; >50 ha/>3,000 m radius), aligning with China's Standard for planning of urban green space (GB/T 51346–2019, Ministry of Housing and Urban-Rural Development of the People's Republic of China, 2019). The questionnaire-based survey was conducted over four months (from April to July 2023), encompassing high-use holidays (e.g., Labor Day), weekends, weekdays, and various times of the day (including mornings and afternoons), and at least ten respondents were collected for each selected parks. We implemented a dual-channel purposive sampling strategy to recruit information-rich participants capable of providing nuanced assessments of park social values (Andrade, 2021). This approach integrated (a) on-site intercept surveys targeting individuals engaged in characteristic local leisure activities (e.g., tea-drinking on lawns, shade-seeking under trees), with eligibility established through immediate residency verification during initial contact, and (b) community officer-facilitated snowball sampling (Naderifar et al., 2017) referring citizens meeting the ≥ 1 year continuous residency criterion. The synergistic deployment of these channels ensured participants possessed place-based familiarity essential for unbiased spatial evaluations while mitigating self-selection bias inherent in voluntary sampling (Chen et al., 2020).

Table 1
Descriptions of six selected UGS social values in this study.

Social values	Descriptions
Recreation	Provides abundant spaces, facilities and services for daily leisure activities and outdoor entertainment.
Aesthetics	Offers a picturesque environment for aesthetic experiences, characterized by attractive scenery, captivating sights, delightful sounds, etc.
Health Restoration	Integrate health-promoting environmental attributes (e.g., air quality regulation, multifunctional fitness facilities) with inherent biophilic elements (e.g., restorative vegetation landscapes), synergistically facilitating psycho-physiological restoration through enhanced physiological resilience, psychological stress alleviation, and cognitive rejuvenation.
Scientific Education	Offers designated areas for scientific observation or experimentation, facilitating learning about natural environments and promoting the popularization of science.
Cultural Heritage	Preserves architectural landmarks and narratives of natural and human history, serving to conserve historical legacies and foster local cultural identity.
Social Interaction	Provides venues for social interactions, fostering community engagement and enhancing social connections among citizens.

Notes: Preliminary surveys included spiritual values defined as greenspaces' capacity to provide symbolic sanctuaries for meditation, faith practices, and existential solace. However, due to scarce religious attributes in Chinese UGS and recurrent semantic conflation between "spiritual" and "therapeutic" in Chinese terminology as observed, we consolidated spiritually-oriented restoration components into the Health Restoration construct, creating an integrated metric that captures public perceptions of greenspaces' psycho-physiological restoration capacities.

The questionnaire (see in Method S1, Supplementary Materials) comprised three sections, including Part (I) demographic information and individual preferences on visiting UGS; Part (II) perception on six social values of the surveyed park using the Likert scale, and Part (III) social value allocation based on a PPGIS process. For the third section, interviewees were asked how much hypothetical money they would be willing to pay to preserve a given social value and to select the parks on the map that are most representative of the respective social value. Participants could designate multiple parks as social value points on the provided basemap. We excluded responses lacking spatial coordinates, digitized valid points in ArcGIS, and further removed markers positioned over water bodies or outside park boundaries. This procedure yielded 4,605 spatially verified points derived from 558 valid questionnaires (99.64 % validity rate from 560 total surveys). The locations and point densities for each of six social values were determined based on these 4,605 selected points, which were digitized into spatial point data using ArcMap software (Fig. S1). Each point was matched with its corresponding monetary value assigned in Part (III) of the questionnaire. The collected visitor profiles and basic investigated information are presented in Fig. S2.

2.2.3. *Simulation of social values using the SolVES model*

The SolVES model (SolVES 3.0, https://www.usgs.gov/centers/geosciences-and-environmental-change-science-center/science/social-values-ecosystem#overview) provides a systematic framework for evaluating the connections between the social values of UGSs derived from field survey data and environmental variables (Sherrouse and Semmens, 2015). SolVES constructs a predictive model linking social values of surveyed UGSs—derived from Questionnaire Part (II) responses—to environmental variables. This framework enables spatial simulation of social values across non-surveyed greenspaces, generating social value outputs for all UGSs.

The selected environmental variables in this study involved both natural and artificial conditions (see Table 2), and have been widely used in the previous social value researches using SolVES (Johnson et al., 2019; Chen et al., 2020; Dang and Li, 2023). The first three variables comprised Euclidean distances to features, specifically roads (DTR), water bodies (DTW), and residential areas (DTRA). The SolVES model employs Euclidean distance as the metric for calculating distances between environmental variables to ensure data format consistency and algorithm compatibility. Slope, elevation, and hillshade data were derived from a digital elevation model using the surface analyst tool in ArcGIS. These variables were calculated at a spatial resolution of 100 × 100 m based on vector data, which were subsequently converted into raster format as standardized inputs for SolVES. Additionally, land cover types were incorporated to reflect the general environmental background. The mean value of Normalized Difference Vegetation Index (NDVI) in the whole year of 2023 was calculated to represent the vegetation characteristics. The raster layers of land cover and NDVI data were resampled to align with the 100 × 100-meter resolution as consistent inputs of the SolVES model. The maps of geodatabases are shown in Fig. S3.

The model consists of three sub-modules: the Ecosystem Services Social-Values module, the Value Mapping module, and the Value Transfer Mapping module. The first two modules facilitate the evaluation of social values based on a comprehensive collection of questionnaires (Part II), while the latter predicts social values for similar areas without on-site surveys by utilizing models generated from the preceding procedures. Collectively, the SolVES workflow serves three primary functions: (1) generating spatially characterized social value maps represented by a non-monetary 10-point Value Index (VI), (2) developing statistical models that elucidate the relationships between VI and environmental variables, and (3) generating converted social value maps employing a Maximum Entropy (MaxEnt) calculator. The corresponding procedures are described in Method S2 (Supplementary Materials). The model ultimately generated six 100 × 100 m raster maps for each social value. Furthermore, to simplify the calculation of social value-weighted greenspace exposure, a single aggregated social value indicator was defined to represent the overall UGS social value, serving as the social value weight in Eq. (1) in Section 2.3.1. The aggregated social value indicator was calculated by summing up all six values (Table 1) within each 100 × 100 m raster grid and subsequently normalizing the result to the range of 0 to 1.

Table 2
Description of geodatabases for SolVES.

Indicators	Descriptions	Sources	Years
Distance to roads (DTR)	Distance between the grid centroid and the nearest road in meters	Roads data was derived from Open Street Map (https://www.openstreetmap.org)	2022
Distance to waters (DTW)	Distance between the grid centroid and the nearest waters, like rivers, lakes, reservoirs, ponds, etc. in meters	Data of water bodies was derived from GlobeLand30 (https://www.globeland30.org/)	2020
Distance to residential area (DTRA)	Distance between the grid centroid and the nearest residential area in meters	Data of residential areas was derived from AOI (area of interest) on the Baidu map (https://map.baidu.com)	2020
Slope (SLOPE)	Percent slope	Derived from Geospatial Data Cloud (https://https://www.gscloud.cn/)	2020
Elevation (ELEV)	Digital elevation model (DEM) in meters		
Hillshade (HILLSHADE)	The shade of the mountain, simulating the illuminance of each grid		
Land cover (LC)	8-class categorical land cover data	Derived from GlobeLand30 (https://www.globeland30.org/)	2020
Normalized difference vegetation index (NDVI)	Vegetation Index, ranging from −1 to 1	Derived from Sentinel-2 dataset on Google Earth Engine (https://developers.google.com/earth-engine/datasets/catalog/modis)	2023

The performance and accuracy of the SolVES model was assessed using the Area Under the Curve (AUC) statistics in the model. AUC entails the calculation of the total area under the Receiver-Operating Characteristic plot (ROC), which reflects the performance of the model's results. The MaxEnt model partitions the points from each user-selected social value type into "training" and "testing" datasets at a 3:1 ratio. Subsequently, the computed "training AUC" and "test AUC" values indicate the goodness-of-fit of the model within the study area and the potential predictive utility of the model in extrapolating social values to unobserved areas, respectively. AUC values range from 0 to 1, with higher values indicating better model fitness. As summarized by Sherrouse and Semmens (2015), if AUC $\leq$ 0.5, the model performs at the level of random prediction or worse. Conversely, if AUC $\geq$ 0.7, the model is considered potentially useful to be transferred to similar areas, with values above 0.9 indicating an excellent classification.

2.3. Evaluating the greenspace exposure and inequality based on social value benefits

2.3.1. Real-time population counts and social value-weighted greenspace exposure

The social values, in combination with population counts, were used as weights to create a new greenspace exposure metric, based on which we measured the level of population- and social value-weighted greenspace exposure at the neighborhood level, allowing for comparative analysis. We used the Baidu population heat map data in 2023 to characterize population mobility and assess people's dynamic exposure to greenspace with various social values. Baidu heat map collects individuals' locations and provides a dataset of hourly population counts with a spatial resolution of 200 m. We used the spatial join tool in ArcGIS to align the original population data sampling scale (200 m) with our analysis unit (100 × 100 m). As people's behavior varies over time, we defined five timeframes to characterize population mobility across the following periods: (I) daytime (6 a.m. - 6p.m.), (II) nighttime (6p.m. − next 6 a.m.), (III) weekdays (24 h from Monday to Friday), (IV) weekends (24 h on Saturday and Sunday), and (V) the average whole day (24 h averaged across weekdays and weekends). We computed the total population count of each grid unit within these preset time periods to represent overall population mobility, serving as the population weight for further calculation. A higher cumulative value indicates more people may pass through or consistently stay within a given grid during the specified period, signifying greater population exposure to the grid's environment over time.

The greenspace exposure assessment was firstly based on the factor calculation (i.e., p_i^t, G_i^b, and V_i^b) for each grid cell (100 × 100 m) and its buffer zone, and then aggregated to the neighborhood level by using a weighted sum method for all grids within each neighborhood. Consequently, a neighborhood's greenspace exposure levels can be measured via Eq. (1):

$$GE_{SV} = \frac{\sum_{i=1}^{n} \left(p_i^t \times G_i^b \times V_i^b\right)}{\sum_{i=1}^{n} \left(p_i^t \times V_i^b\right)} \quad (1)$$

where p_i^t refers to the real-time population counts of the i-th grid during a preset timeframe; G_i^b denotes the total fractional greenspace coverage within the i-th grid considering nearby green environments with a buffer radius of 500 m; V_i^b represents the average level of aggregated social value for the corresponding greenspace within the corresponding buffer zone; n signifies the overall number of grids within the administrative region (here, neighborhood), and GE_{SV} is the population-weighted and social value-weighted greenspace exposure level of a neighborhood. A higher value of GE_{SV} indicates a larger greenspace area with higher social values, attracting more people and providing them with its potential benefits through exposure activities.

The extended buffer addresses the limitations of the Baidu-based population dataset, where the population count for each grid reflects the total number of individuals within that pixel, but does not capture their exact locations. Therefore, although we assumed that all individuals are located at the centroid of the grid, we measured the social value-weighted greenspace coverage within an extended buffer. This approach ensures that the ambient greenspace available to any individual within each grid is accounted for. The selected 500-meter buffer is based on commonly used measurement scales in previous studies (Sarkar et al., 2018; Chen et al., 2022a) and aligns with the typical evaluation scale for assessing the service radius of urban park greenspace according to Chinese standards (GB/T 51346–2019, Ministry of Housing and Urban-Rural Development of the People's Republic of China, 2019). Note that, instead of identifying the lands covered by vegetation, this study's calculation of greenspace coverage specifically focuses on urban park green spaces. The boundaries of park green spaces were derived from AOI on the Baidu map, combined with website documents and department data.

To reveal how social value weights impact UGS evaluation outcomes, we additionally calculated greenspace coverage (*GC*) and population-weighted greenspace exposure (*GE*), considering only greenspace abundance or greenspace abundance and population mobility, respectively (formulas can be found in Method S3 (Supplementary Materials).

2.3.2. Gini coefficient measurement and greenspace exposure inequality

The most commonly used metric for inequality evaluation is the Gini coefficient (Gini, 1921), which calculates statistical dispersion to represent the level of inequality and has been validated for use in greenspace exposure inequality research (Song et al., 2021; Chen et al., 2022b; Leng et al., 2023). We calculated the Gini coefficient for each neighborhood via Eq. (2):

$$Gini_{GE_{sv}} = 1 - \frac{\sum_{i=1}^{m}\sum_{k=1}^{i-1} g_k + \sum_{i=1}^{m}\sum_{k=1}^{i} g_k}{m \times \sum_{k=1}^{m} g_k} \tag{2}$$

$$g_k = GC_k \times V_k \tag{3}$$

where g_k refers to the magnitude of social value-weighted greenspace that is exposed to the k-th citizen. GC_k is the magnitude of greenspace coverage that exposed to k-th citizen and V_k is the average social value of the corresponding greenspace that the k-th citizen is enjoying. Then, m is the total number of citizens living within the neighborhood, and $Gini\_GE_{sv}$ represents the inequality of greenspace exposure level considering social value benefits. The Gini value ranges from 0 to 1, where 0 denotes absolute equality and 1 means absolute inequality. An equal exposure means the majority of people in the neighborhood can enjoy most greenspaces with high social values. The calculation was processed using the "*ineq*" package in R (version 0.2–13), and the elaboration of the Gini calculation theory can be found in Method S4 (Supplementary Materials).

Likewise, we additionally computed the *Gini_GE* to unveil the evaluation difference of greenspace exposure inequality before and after considering the social value of greenspace. The *Gini_GE* solely calculates the inequality in the abundance of greenspace coverage enjoyed by people, while the $Gini\_GE_{sv}$ evaluates the inequality in both abundance and the potential social value benefits of greenspace available for people. Furthermore, considering that urban development in Xiamen city initially originated from the main island, specifically Siming and Huli districts, and later expanded beyond the island starting from the early 2000 s, we respectively calculated the average $Gini\_GE_{sv}$ of the main island and outside the island, as a comparison to investigate potential disparities in social value-weighted greenspace exposure inequalities across different urban development periods.

2.4. Interpreting the focal drivers of inequality in social value benefits

2.4.1. Drivers and variance partitioning

In order to identify the drivers of inequality in social value-weighted greenspace exposure (i.e. $Gini\_GE_{sv}$), we used five key measures within three focal drivers derived from the composition of the exposure metric: (a) greenspace coverage (*GC*), representing the physical supply of UGS; (b) aggregation level of population distribution, measured by the standard deviation of population numbers in all grids within a neighborhood (*POP_std*), as this metric captures the degree of population clustering—higher values indicate more uneven distribution with concentration hotspots; and (c) social value levels of greenspace, including three complementary metrics: the overall level (*SV_total*) representing total cultural endowment, internal discrepancy (*SV_std*, measured by the standard deviation of social value) capturing heterogeneity in value distribution, and the optimal level (*SV_max*) indicating peak quality of cultural benefits within the area. These variables were selected to deconstruct the physical, demographic, and quality dimensions inherent to the equality assessment framework, with each metric theorized to distinctly influence equitable distribution patterns.

All variables were calculated at the neighborhood level and standardized to the range of 0 to1. Next, we evaluated the variance inflation factors (VIF) for these five key measures in a multiple linear regression model. Subsequently, we constructed a random forest (RF) model to explore the association between these variables and the Gini coefficient, assessing the relative importance of each variable. The RF model was executed using the '*randomForest*' package (Breiman et al., 2024) in R (version 4.7–1.1), with the importance of variables reported via the increase in node purity after including specific variables and mean square error upon excluding specific variables.

In line with this, we proceeded to select the three most important variables and utilized variance partitioning to quantify the relative variations in the Gini coefficient, which are attributed to the individual effects of focal drivers and their interaction effects. The variance partitioning analysis was performed using the '*vegan*' package (Oksanen et al., 2024) in R (version 2.6–4), and the resulting Venn diagram illustrates both unique and combined effects.

2.4.2. Clustering drivers' impacts on social value-weighted inequality

After gaining a general understanding of how the drivers influence the Gini coefficient at the city-wide level, we examined the variation in impacts of drivers across different neighborhoods, by identifying the dominant driver and the direction and magnitude of its influence in each neighborhood. For this purpose, a second RF model was constructed based on the Gini coefficient and the top three important variables. Utilizing the second RF model, we employed SHAP (SHapley Additive exPlanations) values, a common machine learning interpretation method, to elucidate the impact of each variable on the model's prediction of Gini coefficient at the neighborhood level. SHAP values are highly interpretable and useful in revealing the direction and magnitude of influence exerted by explanatory variables. To accomplish this, we identified the positive and negative influences of each input variable (here, the three drivers) on a sample-wise basis (here, Gini coefficient of each neighborhood), following the approach outlined by Lundberg and Lee (2017).

The resulting distinct impacts of the drivers were further clustered to identify groups of neighborhoods where variables influence greenspace inequality in the same direction and with comparable magnitude. This clustering can inform governments of efficient spatial strategies for managing greenspaces. Three scenarios with specific strategies are hypothesized: (a) if a neighborhood's inequality is mostly due to insufficient greenspace coverage, improving the coverage is recommended; (b) if the inequality arises from population distribution, increasing citizens' availability and accessibility to greenspace is warranted; (c) if the social value of UGS is the primary factor, enhancing social values of UGSs in the neighborhood is necessary. Targeted management strategies can be implemented for neighborhoods within the same cluster. To this end, we employed hierarchical clustering based on SHAP values to classify neighborhoods according to the impacts of drivers. The number of clusters was determined using the Elbow method (Chen et al., 2024). The clustering results were visualized on ArcGIS to illustrate the spatial distribution of neighborhood clusters. Additionally, we computed the mean value of the top three important variables for each cluster type, along with their corresponding mean SHAP value, to determine whether high or low values of these variables exacerbate or mitigate inequality in greenspace exposure within each cluster type.

3. Results

3.1. Social values of urban greenspace and the environmental factors

The SolVES model effectively simulated social values of multiple greenspaces across the large-scale city, which were then visualized on ArcGIS (Fig. S4). Table 3 presents the model's performance, indicating high precision and reliability based on elevated AUC values (all above 0.9). The map of aggregated social values of urban greenspaces in Xiamen city, shown in Fig. 3, highlights hotspots with high social values in Gulangyu Island, the western main island (Huli and Siming districts), the gulf coast region in Jimei district, and the eastern area of Haicang district. These hotspot areas coincide with the typical UGSs in Xiamen city, including highly recognized tourist attractions and important urban park development projects, encompassing Gulangyu Scenic Spot, Xianyue Mountain Park, Huwei Mountain Park, the scenic belt of Zhongshan Park – Wanshi Botanic Garden – Dongping Mountain Park, and Yuanboyuan Park.

Based on the quantitative analysis, a substantial spatial inequality in the distribution of social values across neighborhoods is evident. The average aggregated social value across all 38 neighborhoods is 0.16. The standard deviation of 0.135 exceeds 80 % of the mean value, indicating high absolute variability. Moreover, this disparity becomes more pronounced when comparing the main island districts to the peripheral areas. Neighborhoods within the main island exhibit a notably higher mean social value of 0.27 (standard deviation = 0.12), while those in the periphery have a significantly lower mean value of 0.07 (standard deviation = 0.06). To further quantify the relative disparity, the coefficient of variation (CV) was calculated. The CV for the main island is 44.4 %, compared to 85.7 % for the peripheral neighborhoods. This higher CV in the periphery indicates not only lower average social value but also greater relative inequality among neighborhoods within these areas, clearly demonstrating a dual inequality: both a stark core-periphery divide and intensified internal inequality within less-advantaged regions.

Furthermore, the MaxEnt model delineated response curves illustrate how various social values vary in response to different environmental contexts. Generally, the variables of distance to roads, distance to waters, and distance to residential areas show similar trends across all six social values (see in Fig. S5-S10). For example, social values gradually decrease as the distance to the nearest roads increases from 500 m to 2 km, approaching zero beyond this threshold. This indicates a critical distance of 2 km from the nearest road to be able to benefit from UGS social values, with an optimal distance of 500 m. In terms of distance to residential areas, most social values remain low once the distance exceeds 5 km. However, as shown in Fig. S6 and S8, the response curves for aesthetics value and scientific education value exhibit a slight upward trend, suggesting that citizens may be willing to travel longer distances when seeking these two particular social values.

Additionally, the social value associated with health restoration peaks at slopes approximating 5 % and remains relatively stable below a 20 % gradient. Beyond this threshold, values dramatically decline (Fig. S7), suggesting a public preference for moderate-intensity activities on gently sloped terrain, with optimal conditions occurring at 5 % and diminishing returns beyond 20 %. Furthermore, in most cases, a higher NDVI value is observed for areas with higher social values, indicating that an improved vegetation condition can contribute to the enhancement of social values associated with UGSs. The importance of all environmental variables in affecting each social value are detailed in Table S1.

3.2. Population- and social value-weighted greenspace exposure levels of neighborhoods

The average greenspace coverage (*GC)*, population-weighted greenspace exposure (*GE)*, and population- and social value-weighted greenspace exposure (GE_{SV}) are 10.28 % (0.20 %-100 %), 5.93 % (0.37 %-100 %), and 6.49 % (0.45 %-100 %), respectively. The top three neighborhoods for *GC* are Gulangyu Island (100 %), Huli (46.17 %), and Binhai (42.24 %); for *GE*, Gulangyu Island (100 %), Huli (12.71 %), and Kaiyuan (11.47 %); and for GE_{SV}, Gulangyu Island (100 %), Huli (15.35 %), and Kaiyuan (12.56 %). According to the population distribution (Fig. 4(a)), only a few areas show zero presence of people during the specified timeframe (e.g., the average whole day). Population counts in each grid range from less than 50 to over 500, indicating a significant variation in potential population exposed to surrounding greenspaces.

Examples from Qiaoying, Jimei, and Xinglin neighborhoods in Fig. 4 (b) illustrate how evaluations differ for different metrics. While these neighborhoods have the same level of greenspace coverage (the same size/color of green dots), their levels of greenspace exposure and social value-weighted greenspace exposure differ considerably (different fill colors). The greenspace coverage metric tends to overestimate citizens' enjoyment of UGSs with low social value, which may not attract many visitors (e.g., Qiaoying neighborhood). Conversely, it may underestimate areas with comparable abundance of greenspaces but high social value that draw people and increase exposure (e.g., Xinglin neighborhood).

The spatial distribution of neighborhoods with matching and mismatching values between *GE* and GE_{SV} is also evident in Fig. 4(b). Gulangyu Island, characterized as a scenic park covering the entire area, ranks first in the *GC* index (100 %) as represented by the largest dark green dot. This neighborhood also demonstrates a perfect match between *GE* and GE_{SV}, reflecting that the substantial population distributed on this island is truly embraced by valuable greenspaces with more benefits potentially provided. Other neighborhoods demonstrating a perfect GE-GE_{SV} match (indicated by the dark brown color) are mainly located on the main island, with two additional neighborhoods in the Jimei district and Haicang district, which correspond to hotspots of social value. A mismatching pattern of high *GE* paired with low GE_{SV} is particularly noteworthy, as it pinpoints areas where large populations are highly exposed to abundant greenspace, yet experience limited social value benefits. For instance, Houxi Town exhibits high *GE* but low

Table 3
Performance of the SolVES-based social value model assessment.

	Recreation	Aesthetics	Health Restoration	Scientific Education	Cultural Heritage	Social Interaction
training AUC	0.938	0.943	0.927	0.958	0.930	0.948
test AUC	0.913	0.919	0.909	0.926	0.919	0.915

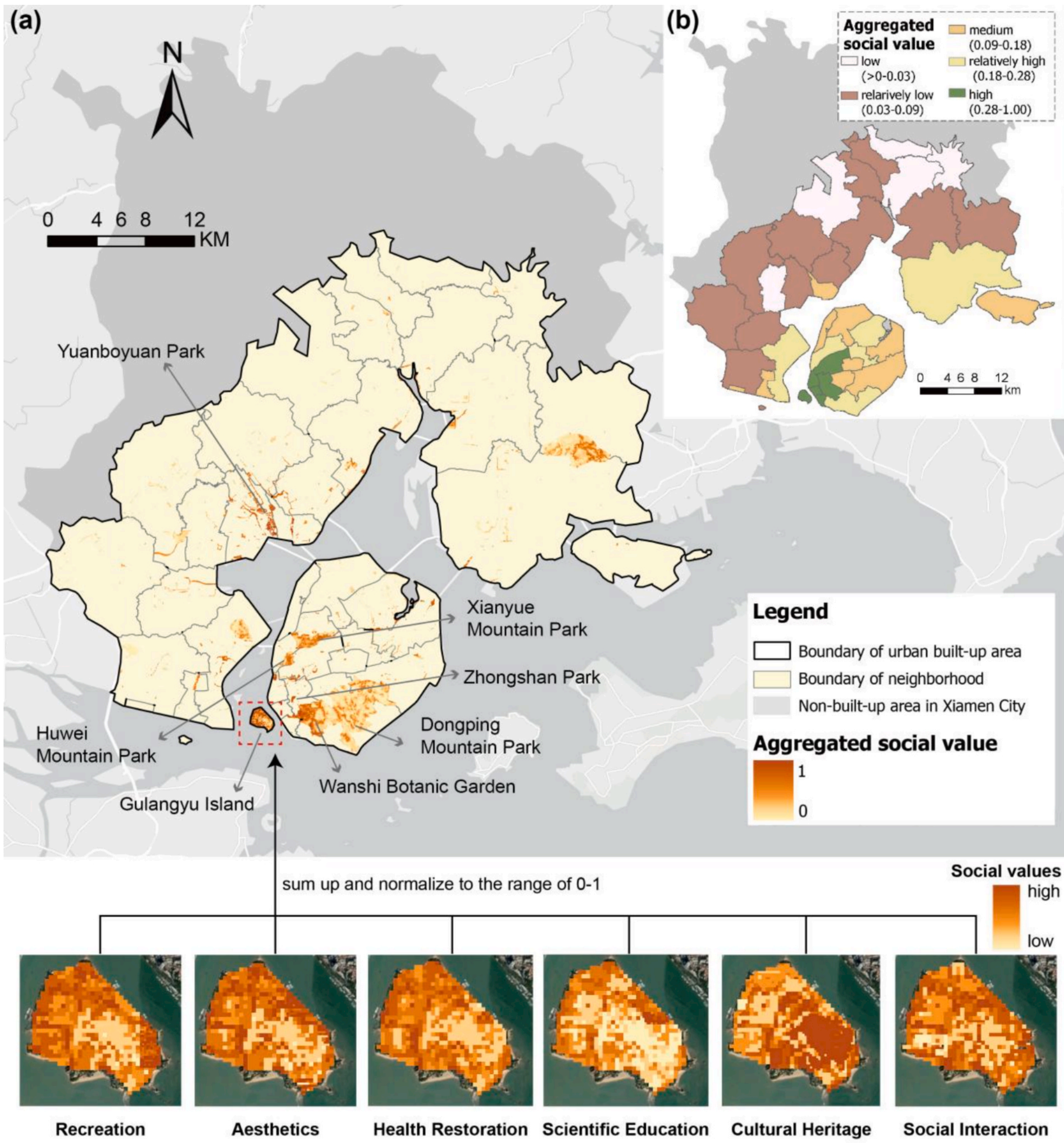

Fig. 3. Social values of urban greenspaces derived from SolVES. (a) The normalized aggregated social value (ranges from 0 to 1) of all urban greenspaces in Xiamen city at the resolution of 100 × 100 m. The bottom panel shows the enlarged view of the six social values of Gulangyu Island. (b) The average aggregated social value across the 38 neighborhoods, classified into five levels using the natural breaks method (Jenks): low (>0–0.03), relatively low (0.03–0.09), medium (0.09–0.18), relatively high (0.18–0.28), and high (0.28–1.00).

GE_{SV}, suggesting a lack of significant social value benefits in its parks. This observation aligns with Houxi Town being a less developed area without high-quality urban park greenspaces. Conversely, Hongtang Town displays high GE_{SV} but low *GE*, likely due to parks along the coastline that possess high social value contributing to its exposure rating.

Next to spatial variation, also temporal variation in exposure to greenspace matter. The GE_{SV} calculated for different timeframes, including daytime (6 a.m.—6p.m.), nighttime (6p.m.—next 6 a.m.), weekdays, and weekends, uncovered considerable differences. Fig. 4(c) demonstrates that certain neighborhoods exhibit higher GE_{SV} levels during nighttime and on weekends compared to daytime and weekdays. These neighborhoods, located near the coastline and offering sunset views or mountain parks, attract individuals seeking specific social values from greenspace, such as aesthetic enjoyment and sporting activities, resulting in elevated exposure levels during evenings and weekends.

3.3. *Inequality of population- and social value-weighted greenspace exposure*

There is a high level of inequality in greenspace exposure in the built-up area of Xiamen city. This is indicated by the high average values of greenspace exposure inequality (*Gini_GE*) and social value-weighted greenspace exposure inequality ($Gini\_GE_{SV}$) of 0.69 and 0.79, respectively. The three neighborhoods with the highest *Gini_GE* values are

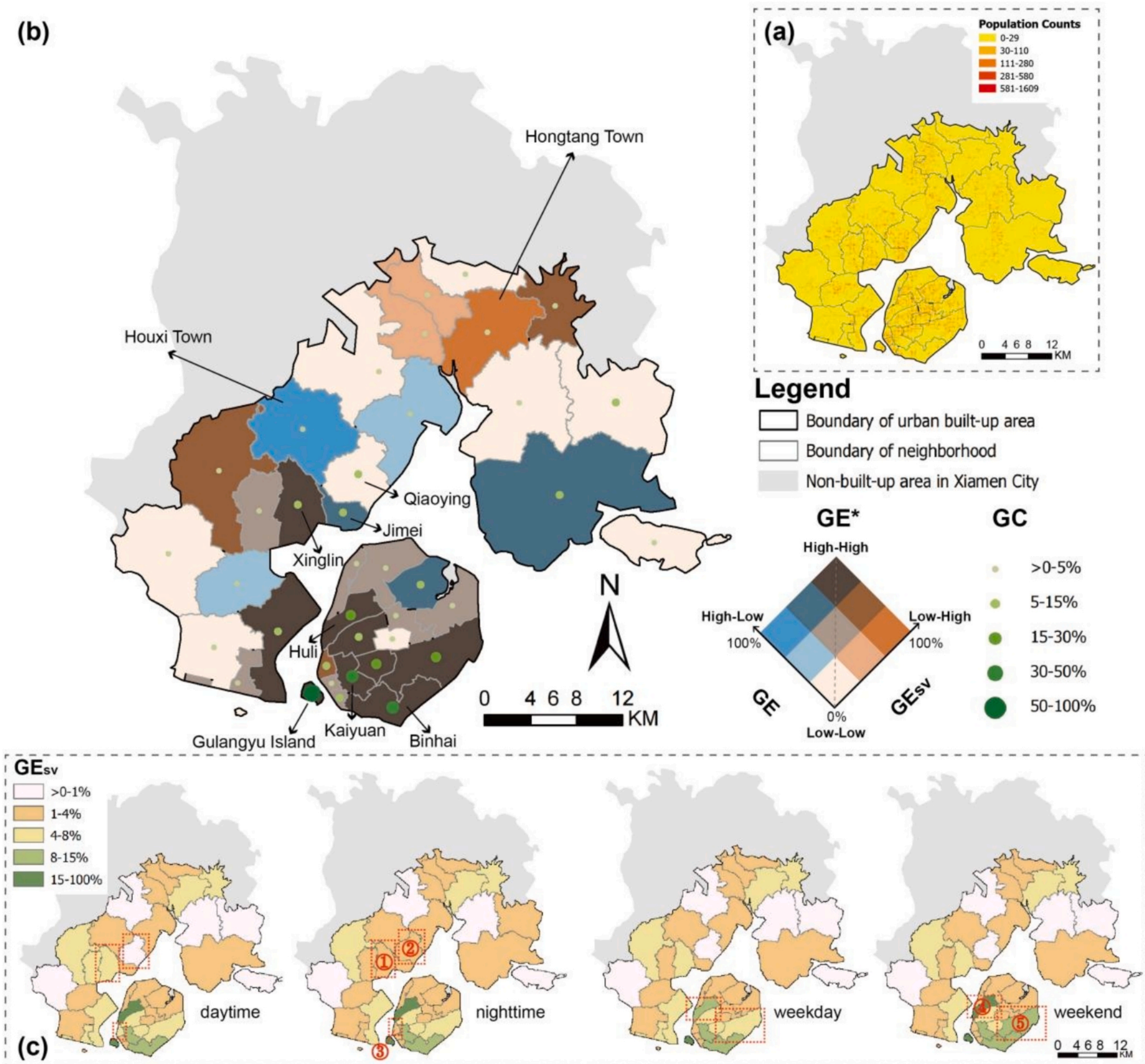

Fig. 4. Spatial-temporal heterogeneity of social value-weighted greenspace exposure. (a) The total population counts of each 100 × 100 m grid during the preset timeframe (the average whole day). (b) Comparison of greenspace coverage, greenspace exposure, and social value-weighted greenspace exposure for 38 neighborhoods. The rating levels (low, medium, and high) for both *GE* and GE_{SV}, were defined using their respective tertiles (i.e., the 33rd and 66th percentiles) to ensure comparability in the relative ranking of neighborhoods for each indicator. The three colored squares along the dashed diagonal line in the legend represent the -matching pattern (i.e., low *GE*-low GE_{SV}, medium *GE*-medium GE_{SV}, and high *GE*-high GE_{SV}), which indicates consistent evaluations across the two metrics. The remaining off-diagonal squares represent mismatching patterns. (c) Social value-weighted exposure levels in four preset timeframes. The red dashed boxes highlight neighborhoods showing significant changes from daytime to nighttime or from weekday to weekend. These neighborhoods contain urban parks with coastal sunset views or mountain parks, including ①Yuanboyuan Park,② Rainbow Beach, ③ Haiwan Park, ④ Xianyue Mountain Park, and ⑤ Dongping Mountain Park. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Neicuo Town (0.94), Xinmin Town (0.90), and Dadeng (0.86), whereas for *Gini_GEsv*, the top-ranking neighborhoods are Xinmin Town (0.97), Maxiang Town (0.96), and Hongtang Town (0.96). The neighborhoods with the lowest inequality in terms of *Gini_GE* are Gulangyu Island (0), Jimei (0.50), and Wuxian Town (0.52), while for *Gini_GEsv*, Gulangyu Island (0), Kaiyuan (0.62), and Jiangtou (0.66) exhibit the lowest inequality levels.

The difference in evaluating greenspace exposure inequality between *Gini_GE* and *Gini_GEsv* is evident in Fig. 5(a). Some neighborhoods with high social value hotspots consistently exhibit low inequality levels, regardless of whether *Gini_GE* or *Gini_GEsv* is utilized (indicated by blue dots and blue fill color). This indicates that in these neighborhoods, a larger greenspace coverage and high social value greenspaces are accessible to a greater number of citizens.

Social value benefits play a critical role in delineating spatial disparities in exposure inequality. For instance, the Wucun Neighborhood, located on the main island, exhibits a high level of inequality according to *Gini_GE* (0.81), but a lower level of inequality based on *Gini_GEsv* (0.77). This indicates that the inequality is somewhat mitigated by the presence of high social value parks that are accessible to a larger

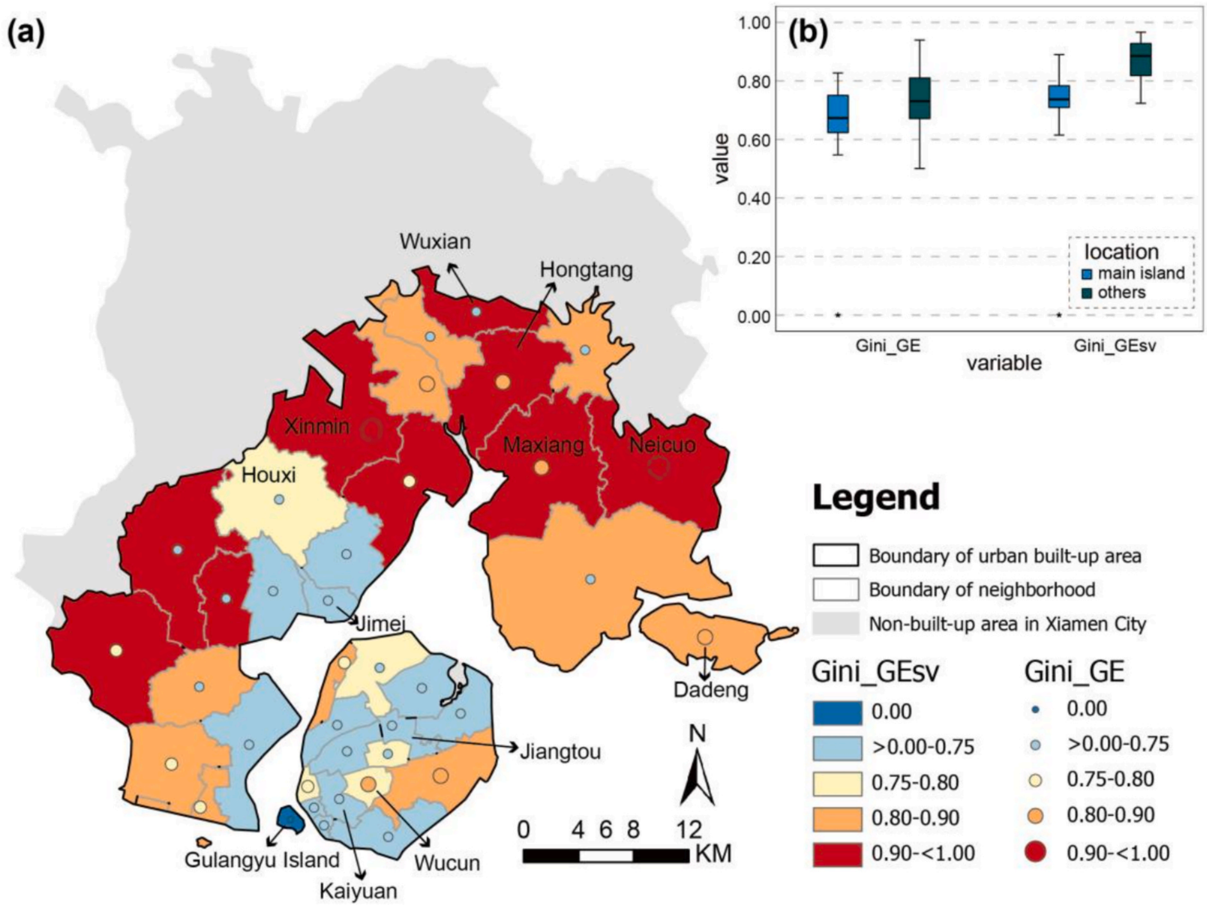

Fig. 5. The Gini-based inequality of greenspace exposure at the neighborhood level. (a) Inequalities of greenspace exposure using Gini coefficient (*Gini_GE*) and social value-weighted Gini coefficient (*Gini_GEsv*), and (b) the comparison of the greenspace exposure inequality on the main island and other areas outside the island.

population. A contrasting situation is observed in Houxi Town, situated in Jimei district, which demonstrates a relatively low level of inequality based on *Gini_GE* (0.65), but a higher level of inequality based on *Gini_GEsv* (0.77). In this case, citizens are exposed to UGSs with disparate social values, which should be considered as a more severe inequality condition.

The main island has lower levels of inequality compared to areas outside the island, as depicted in Fig. 5(b) for both *Gini_GE* and *Gini_GEsv*. This suggests that citizens in more developed neighborhoods on the main island have access to a greater amount of greenspace with higher social values, while experiencing a relatively more equal distribution. This difference in inequality between the main island and other neighborhoods is even more pronounced when considering the social values of greenspace.

3.4. Drivers of social value-weighted greenspace exposure inequality

The top three influential variables explaining the variation in social value-weighted greenspace exposure inequality at the neighborhood level are greenspace coverage (*GC*), aggregation level of population mobility (*POP_std*), and the optimal level of social value (*SV_max*) (Fig. S11). Note that there is no collinearity issue among all five variables according to the VIF detection, as all VIF values are below 4 (Fig. S12). The top three drivers were more important than the overall social value in a neighborhood (*SV_total*) or the internal discrepancy of social value within a neighborhood (*SV_std*).

Greenspace coverage accounts for most of the variation of social value-weighted greenspace exposure inequality among neighborhoods (i.e., 47 % of the variance, Fig. 6). The optimal level of social value contributes 2 % of the variance, while their combined interaction effect contributes 19 %, highlighting the significance of both greenspace quantity (*GC*) and quality (*SV_max*) in inequalities related to greenspace exposure.

3.5. Neighborhood clusters impacted by similar inequality drivers

The different drivers of inequality in benefits from greenspace exposure vary strongly between neighborhoods. This is reflected by various directions and magnitudes of influences, as indicated by the respective SHAP values across neighborhoods (Table S2). Hierarchical clustering, based on the SHAP values, successfully classified all 38 neighborhoods into four distinct clusters, characterized by similar combinations of dominant drivers and the corresponding suggested strategies within their respective clusters (Fig. 7(a)). For each of the cluster A-D, targeted management strategies can address the specific inequality drivers.

In cluster A, greenspace coverage plays a crucial role in reducing exposure inequality, surpassing the influence of population mobility and the maximum social value level of UGS (Fig. 7(c)). This is corroborated by the box plot displayed in Fig. 7(b), which illustrates a considerably higher value of greenspace coverage in cluster A compared to clusters B and C. With limited budgets, no urgent strategies are necessary in these neighborhoods, possibly with the exception of increasing greenspace coverage, allowing governments to prioritize other areas.

Conversely, in cluster B neighborhoods, all three variables exhibit a positive impact on equality in greenspace benefits; lower levels of

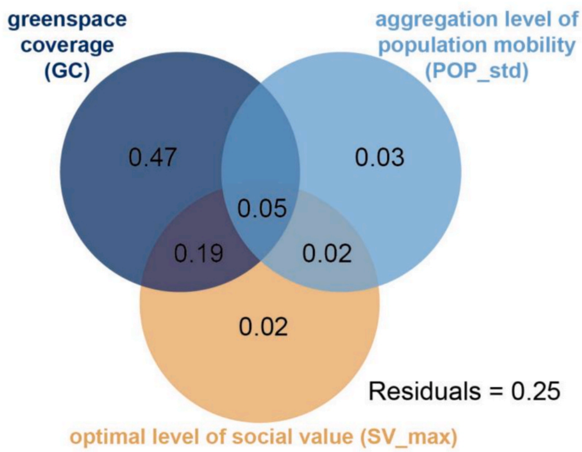

Fig. 6. The Venn diagram based on variation partitioning using the "*vegan*" package in R (version 2.6–4). The values show the contributions of the unique effects of greenspace coverage (*GC*), aggregation level of population mobility (*POP_std*), optimal social value level (*SV_max*), and their pair-wise combined effects. Unexplained residuals account for 25%.

greenspace coverage, a uniform population distribution and limited optimal social value within these neighborhoods all contribute to an increase in the inequality in green exposure. Consequently, all three strategies are required to mitigate the inequality in these neighborhoods.

In cluster C, the population mobility exhibits a relatively high negative impact on the Gini coefficient. This suggests that a concentrated population distribution reduces the inequality of green exposure. We hypothesize that in these neighborhoods, the presence of valuable greenspace attracts peoples' intentional visits, resulting in more equal access to greenspace. However, since greenspaces abundance and social values show no significant negative or positive impacts on the inequality, actions may be implemented based on these two drivers to further optimize the equality of social value-weighted greenspace exposure in these areas.

Cluster D, which consists solely of Gulangyu Island, exhibits high levels of greenspace coverage and optimal social value. High values of greenspace coverage and the maximum social value significantly reduce the Gini coefficient. In contrast, population mobility exhibits a slight positive impact on the Gini coefficient. This can be attributed to the large number of tourists on the small island, resulting in varying distributions across areas with distinct social values. As a consequence, some individuals may be exposed to greenspaces with high social value, while others may not, thus contributing to the observed inequality in greenspace exposure. Strategies to increase population accessibility to greenspaces on the tourist island can be further conducted to enhance the visitors' experiences.

4. Discussion

4.1. Enhancing UGS social values based on insights into their linkages between environmental contexts

Building upon established PPGIS and social value assessment methods, our analysis confirms that UGS hotspots with high social values in Xiamen predominantly coincide with flagship tourism destinations and prioritized municipal park projects (Fig. 3). This spatial alignment suggests congruence between citizens' perceived values and government planning priorities, particularly the strategic development of iconic urban parks through dedicated funding, policy support, and masterplan implementation. Consequently, the enhancement of UGS social values can potentially benefit from a government's focus on key UGS construction projects. This is supported by previous studies, which observed that well-maintained UGSs with governmental coordination and public engagement in green collective initiatives can significantly enhance citizens' sense of safe, beneficial, attachment and belonging (Pineda-Guerrero et al., 2020; Mejia et al., 2024). In contrast, poor-quality nature spaces may limit the capacity for well-being benefits and instead serve as environmental stressors (Berdejo-Espinola et al., 2024). Thus, without considering quality, accurately identifying UGSs that have the potential to benefit humans is challenging, and this oversight may impede the ability to establish a robust connection between the quantification of UGSs and their capacity to promote public health (Song et al., 2021).

Furthermore, the response curves (Fig. S5-S10) clearly illustrate the correlations between social values and environmental contexts. To enhance natural landscapes and improve travel convenience, governments are encouraged to develop parks in close proximity to water bodies, roads, and residential areas. Furthermore, the incorporation of slope design should be considered to increase the health restoration value. The refined interpretation of these curves provides valuable insights into the environmental variables influencing social values in urban parks. This serves as a fundamental basis for efforts to eliminate social value-weighted inequality in greenspace exposure. Besides, enhancing the social values of UGSs also requires publicity and promotional campaigns (Wan and Shen, 2015), as well as community engagement (Mullenbach et al., 2019), to strengthen the intensity of citizens' perceptions.

4.2. Social value benefit and its impact on greenspace exposure and the inequality

This study emphasizes the notable disparities in evaluating greenspace exposure levels and inequalities when considering greenspace coverage (*GC*), population-weighted greenspace exposure (*GE*), and population- and social value-weighted greenspace exposure (*GEsv*). Examples in Fig. 4(b) highlight the limitations of the commonly used greenspace coverage metric—focusing solely on UGS spatial abundance and failing to account for population distribution (i.e., actual exposure based on usage rate) and social values (i.e., UGS quality perceived by citizens) associated with UGSs (Song et al., 2021). Besides, the notable disparities in UGS exposure levels when using *GE* and GE_{SV} further highlight the necessity of incorporating the social value benefits of UGSs into exposure assessments..Furthermore, by integrating dynamic mobility data, subtle temporal variations in greenspace exposure levels (Fig. 4) yield insightful conclusions about city characteristics and human activity preferences, emphasizing the importance of integrating dynamic population mobility data into greenspace exposure evaluations.

In terms of equality, previous studies have characterized equal exposure as a scenario where the majority of the population has access to most greenspaces (Song et al., 2021; Wu et al., 2023; Leng et al., 2023). We expand upon this definition to encompass the quality of greenspaces—equal exposure signifies that the majority of individuals can enjoy most greenspaces with high social values.

Overall, our findings indicate pronounced greenspace exposure inequality across Xiamen (*Gini_GE* = 0.69). This disparity is potentially amplified by the uneven distribution of social value benefits, evidenced by a substantially higher social value-weighted greenspace exposure inequality (*Gini_GEsv*) of 0.79. Critically, the modulating effects of social value benefits on Gini-based inequality exhibit neighborhood-scale heterogeneity, with observed outcomes ranging from mitigation to exacerbation (Fig. 5).

Collectively, our analysis shows that the equality of greenspace exposure should be viewed as a function of both UGS abundance and their perceived quality, as represented by their social values. This demonstrates that the link between nature exposure and life satisfaction is conditioned by the quality, type, and manageability of nature. Notably, studies across global contexts reinforce this duality: research in Global North cities often emphasizes the health and well-being benefits

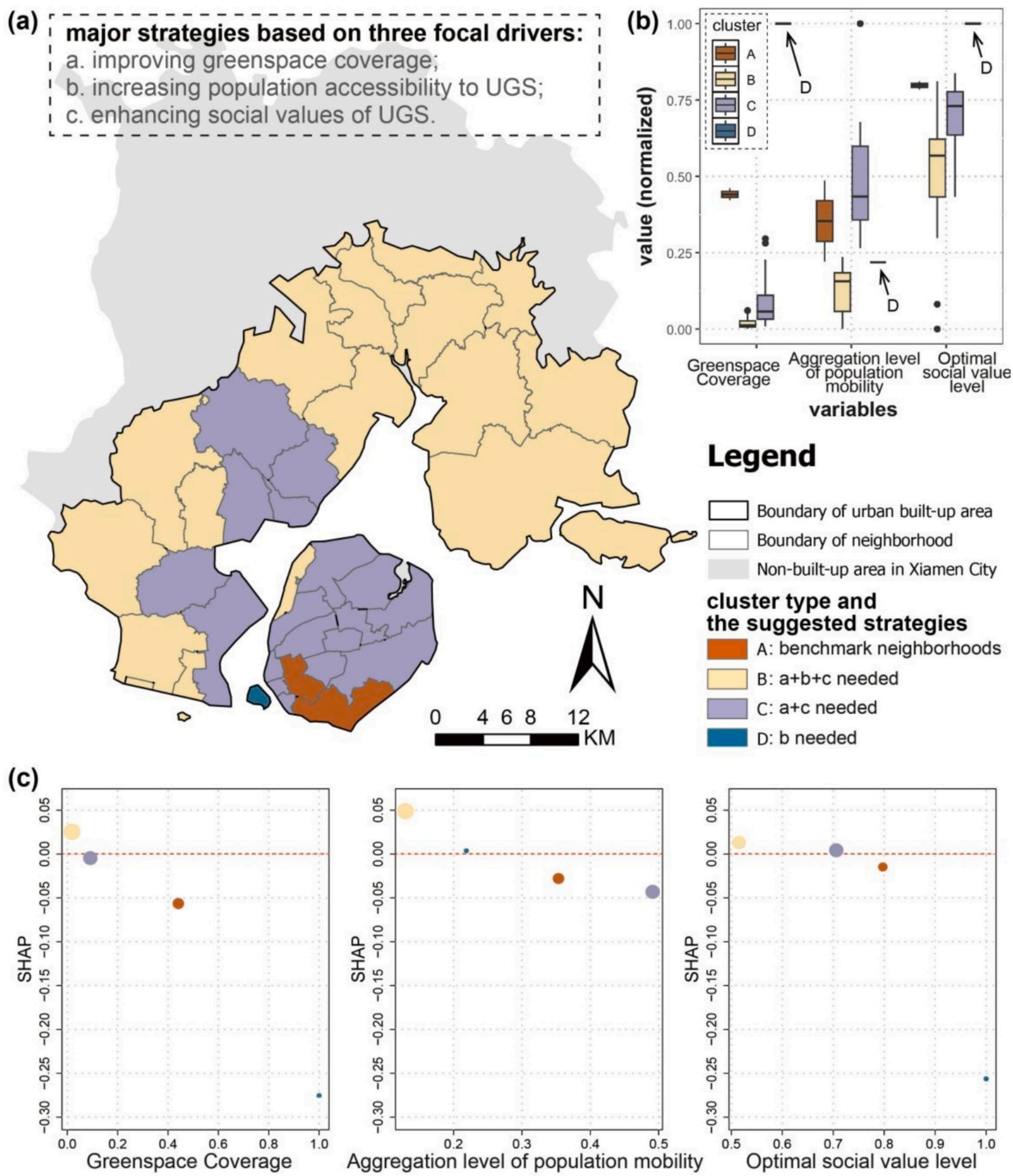

Fig. 7. Spatial visualization of the clusters and their discrepant influential patterns of inequality, with the targeted UGS management strategies. (a) The 38 neighborhoods are clustered into four clusters, based on their distinct combinations of drivers of inequality as determined by the SHAP value. Each cluster corresponds to targeted management strategies/drivers to reduce inequality in social value benefits of UGS exposure within this group of neighborhoods. (b) The box plot illustrates the mean value, as well as the 25th and 75th percentiles, of three focal drivers for each cluster. Note that the values of the variables were normalized to a range of 0–1 for comparison. (c) The diagram shows the different directions and magnitude of variables' impacts on the SHAP value for each neighborhood cluster. The X-axis represents the mean values of greenspace coverage, aggregation level of population mobility (measured as the standard deviation of population numbers in all grids within a neighborhood), and optimal level of social value (maximum social value of greenspace within the area) for each cluster, and the Y-axis represents the corresponding mean SHAP values. The size of the dots denotes the magnitude of the Gini coefficient for each cluster (A: 0.67; B: 0.90; C: 0.76; D: 0). Positive SHAP values above 0 (red dashed line) indicate a positive impact of the variable on the Gini index (increasing Gini and exacerbating inequality), while negative SHAP values below 0 indicate a negative impact (decreasing Gini and reducing inequality). To interpret the figure integrally, note that a dot located farther above the red dashed line in (c) indicates a stronger driving force exacerbating inequality, necessitating the implementation of the corresponding targeted strategy outlined in (a) to mitigate this effect. This need is often corroborated by a low value of that same variable in the box plot (b). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

linked to high-perceived-quality UGSs rich in CES (Hegetschweiler et al., 2017; Nesbitt et al., 2019), while evidence from Latin America reveals that poorly maintained greenspaces may exacerbate safety concerns such as crime (Berdejo-Espinola et al., 2024). Moreover, significant disparities in green resource distribution and equality persist between developed and less-developed regions (Chen et al., 2022b; Han et al., 2022). Integrating CES and social values into exposure equality frameworks is therefore essential to meaningfully assess and address geographical inequality worldwide. Decision-makers should particularly concern with the areas where populations are unequally exposed to UGSs with distinct social values, implying that some individuals may be surrounded by poor-quality greenspace.

4.3. Implementing differentiated strategies to eliminate the inequality

Multiple analytical methods confirmed that greenspace coverage, local population mobility, and the maximum social value of UGS are the three primary drivers of inequality in social value-weighted greenspace exposure. Among the social value-related variables, the metric of *SV_max* demonstrated predominance, indicating that UGSs with maximum social value can significantly impact the inequality of greenspace exposure in a given area (Fig. S11). The Venn diagram based on variance partitioning (Fig. 6) highlights the combined effect of greenspace coverage and maximum social value on the provision of greenspace, demonstrating that both quantity and quality are integral to the observed inequality (Zhang et al., 2021).

Beyond assessing aggregate variable impacts, identifying neighborhood-specific dominant drivers through SHAP value analysis is critical. Based on the clustering of neighborhoods by their dominant drivers, we propose contextually tailored interventions:

For clusters where greenspace coverage (*GC*) is the primary constraint, we recommend utilizing underutilized urban spaces—including vacated lands from urban redevelopment, marginal lands, and abandoned areas—for creating pocket parks and micro-greenspaces (Peschardt et al., 2012). In a high-cost city like Xiamen, where housing prices rank among the nation's highest, the prevalence of residential compounds offers a unique opportunity: club green spaces within these compounds can serve as a crucial supplementary resource to public UGS, effectively enhancing coverage without necessitating new public land acquisition (Xiao et al., 2016; Shan et al., 2024).

For clusters where accessibility issues dominate (indicated by *POP_std*), infrastructure improvements should be prioritized. Enhancing urban road networks, bus routes, and station layouts within the "15-min community living circle" framework directly addresses mobility barriers (Wu and Kim, 2021). Xiamen's well-developed Bus Rapid Transit (BRT) system and its iconic Mountains-to-Sea Trail (Wang et al., 2023) provide a strategic foundation. Interventions could focus on better integrating these systems, for instance, by creating first-and-last-mile connections from BRT stations to neighborhood greenspaces or by strategically extending the trail network to improve pedestrian and cyclist access to high-value UGS. Additionally, multi-scalar urban design interventions—from hierarchical green network planning to street-space reclamation—can reduce physical barriers to access, particularly in high-density areas where expansion is constrained (Zhou and Gan, 2025).

For clusters where social value provision (particularly *SV_max*) is the main driver, quality-enhanced interventions are most appropriate. Rather than expanding territory, resources should focus on maximizing the social value of existing UGS through targeted enhancements. This includes designing urban furniture to accommodate diverse needs (e.g., dog walking, children's play, socializing, resting) and vulnerable groups (elderly, migrant children, individuals with disabilities) (Wolch et al., 2011; Gómez et al., 2018; van den Berg et al., 2019). Implementing a phased quality improvement plan, prioritizing disadvantaged neighborhoods (urban villages, public rental housing, aged communities) (Xiao et al., 2017), and establishing an evaluation system integrating both objective and subjective indicators are essential for ensuring effectiveness and equity. Strengthening neighborhood ties and place attachment through UGS design can create a virtuous cycle of use and satisfaction, further enhancing mental health benefits (Li et al., 2025).

In the context of high-density urban planning in most Chinese cities, blind expansion or creation of new greenspaces is often impractical. Instead, improving accessibility to existing greenspaces and enhancing their social values—particularly by maximizing the social value of key urban park projects—represents a more feasible and promising approach (Benati et al., 2024; Liang et al., 2024). These targeted strategies, informed by our driver analysis, enable efficient governmental response through uniform management within clusters and differentiated strategies across clusters.

4.4. Limitations and future research

Despite the insights generated, this study has several limitations. First, practical constraints in recruiting respondents limited demographic balance, disproportionately sampling 20–39 year-olds with tertiary education. While ensuring data validity, this reduces assessment representativeness (Gobster et al., 2007). Future implementations should prioritize stratified sampling of various subgroups.

Second, greenspace exposure assessment incorporates dual methodological constraints. The fixed spatial parameters (500 m buffer; 100 $\times$ 100 m resolution) may introduce aggregation uncertainties, as buffer size variations significantly influence exposure outcomes (Chen et al., 2022a). Concurrently, Baidu Heatmap data exclude non-user groups (e.g., elderly, children), creating digital divide biases (Song et al., 2022). These limitations necessitate cautious interpretation of exposure patterns.

Third, cultural ecosystem services' intangible nature required interviewer-mediated collection, inherently constraining large-scale generalization (Millennium Ecosystem Assessment, 2005c).

Fourth, methodological simplifications include using single-metric inequality assessment (Gini coefficient). Comparative validation with alternative indices (Theil, Atkinson; Wu et al., 2023) would strengthen culturally-sensitive equality diagnostics by revealing metric-dependent distribution patterns.

Notwithstanding these limitations, the framework's successful implementation supports transferability to global municipalities with comparable semantic contexts. Future work should: (a) analyze spatial parameter sensitivity across scales, (b) integrate heatmaps with ground surveys targeting vulnerable populations, (c) implement multi-metric inequality validation, and (d) develop lexical gap analyses for cross-cultural surveys alongside crowdsourced PPGIS for demographic expansion.

5. Conclusions

Our findings reveal substantial differences in evaluations of greenspace exposure levels when the weight of social value is factored in, as a proxy for the perceived quality of greenspace. Traditional greenspace coverage tends to underestimate exposure levels in areas with limited UGSs but high social value, while overestimating exposure in areas with ample green coverage but poor social values. Citizens may have access to greenspace yet miss out on the potential health benefits associated with high-quality greenspace. Incorporating social value considerations has significant implications for Gini-based inequality assessments of greenspace exposure. The inequality-inclusive metric enables pinpointing areas where individuals are unevenly enjoying greenspaces with different UGS amounts and disparate social values, highlighting inequalities in social value benefits experienced by the public. These insights underscore that UGS provision is the product of the interplay between both quantity and quality. Only by accounting for both dimensions can we achieve a more nuanced understanding of citizens' actual enjoyment of UGSs and recognize the subtle and often-overlooked inequalities in health benefits that stem from disparities in greenspace quality.

Our analyses provide a critical framework for decision-makers to prioritize interventions in areas facing more pronounced inequalities, addressing deficiencies in both quantity, accessibility and perceived quality of UGSs. Given that the importance of available greenspace, population mobility and UGS social values in determining inequalities between neighborhoods, a customized, strategic combination of these factors in UGS planning is needed. In areas constrained by limited natural endowments or a dearth of available land, enhancing the quality of existing greenspace offers a more pragmatic and impactful alternative. Such measures can mitigate greenspace privileges and promote environmental justice from the perspective of UGS social values, ultimately promoting citizens' enjoyment of UGSs and universal access to public health benefits derived from urban greenspace.

CRediT authorship contribution statement

Jingyi Wang: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Ruichuang Zheng:** Methodology, Investigation, Formal analysis, Data curation. **Sanwit Iabchoon:** Writing – review & editing, Data curation. **Peter M. van Bodegom:** Conceptualization, Writing – review & editing. **Joeri Morpurgo:** Writing – review & editing. **Roy P. Remme:** Writing – review & editing. **Mingming Hu:** Writing – review & editing. **Arnold Tukker:** Writing – review & editing. **Wei-Shan Chen:** Writing – review & editing. **Yunfeng Huang:** Supervision, Investigation. **Zhen Wang:** Data curation. **Chunming Li:** Writing – review & editing, Supervision, Funding acquisition. **Shenghui Cui:** Writing – review & editing, Supervision, Funding acquisition, 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.ecolind.2025.114300.

Data availability

Data will be made available on request.

References

Akpinar, A., Barbosa-Leiker, C., Brooks, K., 2016. Does green space matter? Exploring relationships between green space type and health indicators. Urban For. Urban Green. 20, 407–418. https://doi.org/10.1016/j.ufug.2016.10.013.

Andrade, C., 2021. The inconvenient truth about convenience and purposive samples. Indian J. Psychol. Med. 43, 86–88. https://doi.org/10.1177/0253717620977000.

Battiston, A., Schifanella, R., 2024. On the need for a multi-dimensional framework to measure accessibility to urban green. Npj Urban Sustain. 4, 10. https://doi.org/10.1038/s42949-024-00147-y.

Benati, G., Calcagni, F., Matellozzo, F., Ghermandi, A., Langemeyer, J., 2024. Unequal access to cultural ecosystem services of green spaces within the city of Rome - a spatial social media-based analysis. Ecosyst. Serv. 66, 101594. https://doi.org/10.1016/j.ecoser.2023.101594.

Berdejo-Espinola, V., Fuller, R.A., Zahnow, R., 2024. Well-being from nature exposure depends on socio-environmental contexts in Paraguay. Nat. Cities 1, 335–345. https://doi.org/10.1038/s44284-024-00058-0.

Breiman, L., Cutler, A., Liaw, A., Wiener, M., 2024. randomForest: Breiman and Cutlers Random Forests for Classification and Regression. https://cran.r-project.org/web/packages/randomForest/index.html. (accessed 15 July 2024).

Brindley, P., Cameron, R.W., Ersoy, E., Jorgensen, A., Maheswaran, R., 2019. Is more always better? Exploring field survey and social media indicators of quality of urban greenspace, in relation to health. Urban For. Urban Green. 39, 45–54. https://doi.org/10.1016/j.ufug.2019.01.015.

Brown, G., Fagerholm, N., 2015. Empirical PPGIS/PGIS mapping of ecosystem services: a review and evaluation. Ecosyst. Serv. 13, 119–133. https://doi.org/10.1016/j.ecoser.2014.10.007.

Browning, M.H.E.M., Rigolon, A., Mcanirlin, O., Yoon, H.V., 2022. Where greenspace matters most: a systematic review of urbanicity, greenspace, and physical health. Landscape Urban Plan. 217, 104233. https://doi.org/10.1016/j.landurbplan.2021.104233.

Chen, B., Nie, Z., Chen, Z., Xu, B., 2017. Quantitative estimation of 21st-century urban greenspace changes in chinese populous cities. Sci. Total Environ. 609, 956–965. https://doi.org/10.1016/j.scitotenv.2017.07.238.

Chen, B., Tu, Y., Wu, S., Song, Y., Jin, Y., Webster, C., Xu, B., Gong, P., 2022a. Beyond green environments: Multi-scale difference in human exposure to greenspace in China. Environ. Int. 166, 107348. https://doi.org/10.1016/j.envint.2022.107348.

Chen, B., Wu, S.B.A., Song, Y.M., Webster, C., Xu, B., Gong, P., 2022b. Contrasting inequality in human exposure to greenspace between cities of Global North and Global south. Nat. Commun. 13, 4636. https://doi.org/10.1038/s41467-022-32258-4.

Chen, S., He, P., Yu, B., Wei, D., Chen, Y., 2024. The challenge of noise pollution in high-density urban areas: Relationship between 2D/3D urban morphology and noise perception. Build. Environ. 253, 111313. https://doi.org/10.1016/j.buildenv.2024.111313.

Chen, Y., Ke, X., Min, M., Cheng, P., 2020. Disparity in Perceptions of Social Values for Ecosystem Services of Urban Green Space: a Case Study in the East Lake Scenic Area. Wuhan. Front Public Health. 8, 370. https://doi.org/10.3389/fpubh.2020.00370.

Dang, H., Li, J., 2023. Supply-demand relationship and spatial flow of urban cultural ecosystem services: the case of Shenzhen. China. J Clean Prod. 423, 138765. https://doi.org/10.1016/j.jclepro.2023.138765.

Daniel, T.C., Muhar, A., Arnberger, A., et al., 2012. Contributions of cultural services to the ecosystem services agenda. P Natl Acad Sci USA 109 (23), 8812–8819. https://doi.org/10.1073/pnas.1114773109.

Fan, P.L., Xu, L.H., Yue, W.Z., Chen, J.Q., 2017. Accessibility of public urban green space in an urban periphery: the case of Shanghai. Landscape Urban Plan. 165, 177–192. https://doi.org/10.1016/j.landurbplan.2016.11.007.

Farkas, J.Z., Kovács, Z., Csomós, G., 2022. The availability of green spaces for different socio-economic groups in cities: a case study of Budapest. Hungary. J Maps. 18 (1), 97–105. https://doi.org/10.1080/17445647.2022.2079433.

Gini, C., 1921. Measurement of inequality of incomes. Econ. J. 31 (121), 124–125. https://doi.org/10.2307/2223319.

Gobster, P.H., Nassauer, J.I., Daniel, T.C., Fry, G., 2007. The shared landscape: what does aesthetics have to do with ecology? Landsc. Ecol. 22, 959–972. https://doi.org/10.1007/s10980-007-9110-x.

Goddard, M.A., Dougill, A.J., Benton, T.G., 2010. Scaling up from gardens: biodiversity conservation in urban environments. Trends Ecol. Evol. 25 (2), 90–98. https://doi.org/10.1016/j.tree.2009.07.016.

Gómez, E., Baur, J.W.R., Malega, R., 2018. Dog park users: an examination of perceived social capital and perceived neighborhood social cohesion. J. Urban Aff. 40, 349–369. https://doi.org/10.1080/07352166.2017.1343634.

Hamel, P., Guerry, A.D., Polasky, S., et al., 2021. Mapping the Benefits of Nature in Cities with the InVEST Software. Npj Urban Sustain. 1 (1). https://doi.org/10.1038/s42949-021-00027-9.

Han, Y., He, J., Liu, D., Zhao, H., Huang, J., 2022. Inequality in urban green provision: a comparative study of large cities throughout the world. Sustain. Cities Soc. 89, 104229. https://doi.org/10.1016/j.scs.2022.104229.

Havinga, I., Bogaart, P.W., Hein, L., Tuia, D., 2020. Defining and spatially modelling cultural ecosystem services using crowdsourced data. Ecosyst. Serv. 43, 101091. https://doi.org/10.1016/j.ecoser.2020.101091.

Hegetschweiler, K.T., de Vries, S., Arnberger, A., Bell, S., Brennan, M., Siter, N., Olafsson, A.S., Voigt, A., Hunziker, M., 2017. Linking demand and supply factors in identifying cultural ecosystem services of urban green infrastructures: a review of European studies. Urban For. Urban Green. 21, 48–59. https://doi.org/10.1016/j.ufug.2016.11.002.

Johnson, D.N., van Riper, Chu, M., Winkler-Schor, S., 2019. Comparing the social values of ecosystem services in US and Australian marine protected areas. Ecosyst. Serv. 37, 100919. https://doi.org/10.1016/j.ecoser.2019.100919.

Ju, Y., Dronova, I., Delclos-Alio, X., 2022. A 10 m resolution urban green space map for major Latin American cities from Sentinel-2 remote sensing images and OpenStreetMap. Sci. Data 9 (1), 586. https://doi.org/10.1038/s41597-022-01701-y.

Kajosaari, A., Hasanzadeh, K., Fagerholm, N., Nummi, P., Kuusisto-Hjort, P., Kyttä, M., 2024. Predicting context-sensitive urban green space quality to support urban green infrastructure planning. Landscape Urban Plan. 242, 104952. https://doi.org/10.1016/j.landurbplan.2023.104952.

Lee, K.O., Mai, K.M., Park, S., 2023. Green space accessibility helps buffer declined mental health during the COVID-19 pandemic: evidence from big data in the United Kingdom. Nat. Ment. Health 1 (2), 124–134. https://doi.org/10.1038/s44220-023-00018-y.

Leng, S., Sun, R., Yang, X., Chen, L., 2023. Global inequalities in population exposure to urban greenspaces increased amidst tree and nontree vegetation cover expansion. Commun. Earth Environ. 4 (1), 464. https://doi.org/10.1038/s43247-023-01141-5.
Li, Q., Wu, R., Zhu, P., 2025. Quality or quantity of urban greenery: which matters more to mental health? evidence from housing prices in the Pearl River Delta. Landscape Urban Plan. 263, 105438. https://doi.org/10.1016/j.landurbplan.2025.105438.
Liang, H., Yan, Q., Yan, Y., 2024. Evaluating green space provision development in Shanghai (2012–2021): a focus on accessibility and service efficiency. Sustain. Cities Soc. 103, 105269. https://doi.org/10.1016/j.scs.2024.105269.
Liu, D., Kwan, M.-P., Yang, Z., Kan, Z., 2024. Comparing Subjective and Objective Greenspace Accessibility: Implications for Real Greenspace Usage among adults. Urban For. Urban Green. 96, 128335. https://doi.org/10.1016/j.ufug.2024.128335.
Lu, W., Jiang, W., Qiao, D., Liu, Q., Chen, G., Huang, Q., Xu, C., 2023. Embracing green spaces: Exploring spatiotemporal changes in urban green space accessibility and its equity in Guangzhou, China for sustainable urban greening. Environ Sustain Ind. 19, 100290. https://doi.org/10.1016/j.indic.2023.100290.
Lundberg, S.M., Lee, S.-I., 2017. A unified approach to interpreting model predictions. In: Proceedings of the 31st International Conference on Neural Information Processing Systems. Presented at the NIPS'17. Curran Associates Inc., Red Hook, NY, USA, pp. 4768–4777.
Mejia, D.M.B., Chilton, J., Rutherford, P., 2024. Collective urban green revitalisation: crime control an sustainable behaviours in lower-income neighbourhoods. World Dev. 177, 106534. https://doi.org/10.1016/j.worlddev.2024.106534.
Millennium Ecosystem Assessment, 2005a. Ecosystems and Human Well-being: Current State & Trends Assessment. Island Press, Washington, DC.
Millennium Ecosystem Assessment, 2005b. Ecosystems and Human Well-being: a Framework for Assessment. Island Press, Washington, DC.
Millennium Ecosystem Assessment, 2005c. Ecosystems and Human Well-being: Synthesis. Island Press, Washington, DC.
Ministry of Housing and Urban-Rural Development of the People's Republic of China, 2019. Standard for Planning of Urban Green Space. https://www.chinesestandard.net/PDF/English.aspx/GBT51346-2019. (accessed 15 July 2024).
Mullenbach, L.E., Baker, B.L., Benfield, J., Hickerson, B., Mowen, A.J., 2019. Assessing the Relationship between Community Engagement and Perceived Ownership of an Urban Park in Philadelphia. J. Leis. Res. 50 (3), 201–219. https://doi.org/10.1080/00222216.2019.1581719.
Naderifar, M., Goli, H., Ghaljaie, F., 2017. Snowball sampling: a purposeful method of sampling in qualitative research. Strides Dev Med Educ. 14 (3), e67670.
Natural Capital Project, 2024. InVEST 3.14.2. Stanford University, University of Minnesota, Chinese Academy of Sciences, The Nature Conservancy, World Wildlife Fund, Stockholm Resilience Centre and the Royal Swedish Academy of Sciences. https://naturalcapitalproject.stanford.edu/software/invest. (accessed 15 July 2024).
Nesbitt, L., Meitner, M.J., Girling, C., Sheppard, S.R.J., Lu, Y., 2019. Who has access to urban vegetation? A spatial analysis of distributional green equity in 10 US cities. Landscape Urban Plan. 181, 51–79. https://doi.org/10.1016/j.landurbplan.2018.08.007.
Nieuwenhuijsen, M.J., 2018. Influence of urban and transport planning and the city environment on cardiovascular disease. Nat. Rev. Cardiol. 15, 432–438. https://doi.org/10.1038/s41569-018-0003-2.
Oksanen, J., Simpson, G. L., Blanchet, F. G., et al., 2024. Vegan: Community Ecology Package. https://CRAN.R-project.org/package=vegan. (accessed 15 July 2024).
Orban, E., Sutcliffe, R., Dragano, N., Joeckel, K.-H., Moebus, S., 2017. Residential Surrounding Greenness, Self-rated Health and Interrelations with Aspects of Neighborhood Environment and Social Relations. J. Urban Health 94 (2), 158–169. https://doi.org/10.1007/s11524-016-0112-3.
Pan, J., Ma, Y., Cai, S., Chen, Y., Chen, Y., 2022. Distribution patterns of lake-wetland cultural ecosystem services in highland. Environ. Dev. 44, 100754. https://doi.org/10.1016/j.envdev.2022.100754.
Pedersen Zari, M., MacKinnon, M., Varshney, K., Bakshi, N., 2022. Regenerative living Cities and the Urban Climate–Biodiversity–Wellbeing Nexus. Nat. Clim. Chang. 12 (7), 601–604. https://doi.org/10.1038/s41558-022-01390-w.
Peschardt, K.K., Schipperijn, J., Stigsdotter, U.K., 2012. Use of Small Public Urban Green Spaces (SPUGS). Urban For. Urban Green. 11, 235–244. https://doi.org/10.1016/j.ufug.2012.04.002.
Petway, J.R., Lin, Y.-P., Wunderlich, R.F., 2020. A Place-based Approach to Agricultural Nonmaterial Intangible Cultural Ecosystem Service Values. Sustainability 12 (2), 699. https://doi.org/10.3390/su12020699.
Pineda-Guerrero, A., Escobedo, F.J., Carriazo, F., 2020. Governance, nature's contributions to people, and investing in conservation influence the valuation of urban green areas. Land 10, 14. https://doi.org/10.3390/land10010014.
Remme, R.P., et al., 2021. An ecosystem service perspective on urban nature, physical activity, and health. PNAS 118, e2018472118. https://doi.org/10.1073/pnas.2018472118.
Rigolon, A., Browning, M., Jennings, V., 2018. Inequities in the quality of urban park systems: an environmental justice investigation of cities in the United States. Landscape Urban Plan. 178, 156–169. https://doi.org/10.1016/j.landurbplan.2018.05.026.
Rutt, R.L., Gulsrud, N.M., 2016. Green justice in the city: a new agenda for urban green space research in Europe. Urban For. Urban Green. 19, 123–127. https://doi.org/10.1016/j.ufug.2016.07.004.
Sarkar, C., Webster, C., Gallacher, J., 2018. Residential greenness and prevalence of major depressive disorders: a cross-sectional, observational, associational study of 94 879 adult UK Biobank participants. Lancet Planet. Health 2 (4), e162–e173. https://doi.org/10.1016/S2542-5196(18)30051-2.
Shan, L., Fan, Z., He, S., 2024. Towards a better understanding of capitalization of urban greening: Examining the interactive relationship between public and club green space accessibility. Urban For. Urban Green. 96, 128359. https://doi.org/10.1016/j.ufug.2024.128359.
Sherrouse, B.C., Clement, J.M., Semmens, D.J., 2011. A GIS application for assessing, mapping, and quantifying the social values of ecosystem services. Appl. Geogr. 31 (2), 748–760. https://doi.org/10.1016/j.apgeog.2010.08.002.
Sherrouse, B.C., Semmens, D.J., Clement, J.M., 2014. An application of Social Values for Ecosystem Services (SolVES) to three national forests in Colorado and Wyoming. Ecol. Ind. 36, 68–79. https://doi.org/10.1016/j.ecolind.2013.07.008.
Sherrouse, B. C., Semmens, D. J., 2015. Social Values for Ecosystem Services, version 3.0 (SolVES 3.0): documentation and user manual. https://doi.org/10.3133/ofr20151008. (accessed 15 July 2024).
Song, Y.M., Chen, B., Ho, H.C., et al., 2021. Observed inequality in urban greenspace exposure in China. Environ. Int. 156, 106778. https://doi.org/10.1016/j.envint.2021.106778.
Song, Y., Lyu, Y., Qian, S., Zhang, X., Lin, H., Wang, S., 2022. Identifying urban candidate brownfield sites using multi-source data: the case of Changchun City. China. Land Use Policy. 117, 106084. https://doi.org/10.1016/j.landusepol.2022.106084.
Stanley, C., Hecht, R., Cakir, S., Brzoska, P., 2022. Approach to user group-specific assessment of urban green spaces for a more equitable supply exemplified by the elderly population. One Ecosyst. 7. https://doi.org/10.3897/oneeco.7.e83325.
Sun, F., Xiang, J., Tao, Y., Tong, C., Che, Y., 2019. Mapping the social values for ecosystem services in urban green spaces: Integrating a visitor-employed photography method into SolVES. Urban For. Urban Green. 38, 105–113. https://doi.org/10.1016/j.ufug.2018.11.012.
United Nations, 2015. GOAL 11: Sustainable cities and communities. https://www.unep.org/topics/sustainable-development-goals/why-do-sustainable-development-goals-matter/goal-11 (accessed 15 July 2024).
U.S. Geosciences and Environmental Change Science Center, 2018. Social Values for Ecosystem Services (SolVES). https://www.usgs.gov/centers/geosciences-and-environmental-change-science-center/science/social-values-ecosystem. (accessed 15 July 2024).
van den Berg, M.M., van Poppel, M., van Kamp, I., Ruijsbroek, A., Triguero-Mas, M., Gidlow, C., Nieuwenhuijsen, M.J., Gražulevičiene, R., van Mechelen, W., Kruize, H., Maas, J., 2019. Do Physical activity, Social Cohesion, and Loneliness Mediate the Association between Time Spent visiting Green Space and Mental Health? Environ. Behav. 51, 144–166. https://doi.org/10.1177/0013916517738563.
Wan, C., Shen, G.Q., 2015. Encouraging the use of Urban Green Space: the Mediating Role of Attitude, Perceived Usefulness and Perceived Behavioural Control. Habitat Int. 50, 130–139. https://doi.org/10.1016/j.habitatint.2015.08.010.
Wang, P., Wang, K., Li, K., Feng, S., 2023. An evaluation model for the recreational carrying capacity of urban aerial trails. Tour. Manag. Perspect. 48, 101152. https://doi.org/10.1016/j.tmp.2023.101152.
Wang, R., Feng, Z., Pearce, J., Yao, Y., Li, X., Liu, Y., 2021. The distribution of greenspace quantity and quality and their association with neighbourhood socioeconomic conditions in Guangzhou, China: a new approach using deep learning method and street view images. Sustain. Cities Soc. 66, 102664. https://doi.org/10.1016/j.scs.2020.102664.
Willis, K.J., Petrokofsky, G., 2017. The natural capital of city trees. Science 356 (6336), 374–376. https://doi.org/10.1126/science.aam9724.
Wolch, J., Jerrett, M., Reynolds, K., McConnell, R., Chang, R., Dahmann, N., Brady, K., Gilliland, F., Su, J.G., Berhane, K., 2011. Childhood obesity and proximity to urban parks and recreational resources: a longitudinal cohort study. Health Place 17, 207–214. https://doi.org/10.1016/j.healthplace.2010.10.001.
World Health Organization, 2018. Preventing disease through healthy environments. https://www.who.int/news-room/facts-in-pictures/detail/preventing-disease-through-healthy-environments (accessed 15 July 2024).
World Health Organization, 2023. Climate change. https://www.who.int/news-room/fact-sheets/detail/climate-change-and-health (accessed 15 July 2024).
Wu, L., Kim, S.K., 2021. Exploring the equality of accessing urban green spaces: a comparative study of 341 chinese cities. Ecol. Ind. 121, 107080. https://doi.org/10.1016/j.ecolind.2020.107080.
Wu, S., Chen, B., Webster, C., Xu, B., Gong, P., 2023. Improved human greenspace exposure equality during 21st century urbanization. Nat. Commun. 14, 6460. https://doi.org/10.1038/s41467-023-41620-z.
Xiao, Y., Li, Z., Webster, C., 2016. Estimating the mediating effect of privately-supplied green space on the relationship between urban public green space and property value: evidence from Shanghai. China. Land Use Policy. 54, 439–447. https://doi.org/10.1016/j.landusepol.2016.03.001.
Xiao, Y., Lu, Y., Guo, Y., Yuan, Y., 2017. Estimating the willingness to pay for green space services in Shanghai: Implications for social equity in urban China. Urban For. Urban Green. 26, 95–103. https://doi.org/10.1016/j.ufug.2017.06.007.
Xu, C., Haase, D., Pauleit, S., 2018. The impact of different urban dynamics on green space availability: a multiple scenario modeling approach for the region of Munich. Germany. Ecol Indic. 93, 1–12. https://doi.org/10.1016/j.ecolind.2018.04.058.
Xu, C., Huang, Q., Su, M., Gu, Z., Haase, D., 2024. The inequity of urban green space availability between urban villages and residential quarters: an empirical study in Shenzhen. China. J Clean Prod. 448, 141704. https://doi.org/10.1016/j.jclepro.2024.141704.
Zhang, H., Gao, Y., Hua, Y., Zhang, Y., Liu, K., 2019. Assessing and mapping recreationists' perceived social values for ecosystem services in the Qinling Mountains. China. Ecosyst Serv. 39, 101006. https://doi.org/10.1016/j.ecoser.2019.101006.
Zhang, L., Tan, P.Y., Richards, D., 2021. Relative importance of quantitative and qualitative aspects of urban green spaces in promoting health. Landscape Urban Plan. 213, 104131. https://doi.org/10.1016/j.landurbplan.2021.104131.

Zhao, J., Chen, S., Jiang, B., Ren, Y., Wang, H., Vause, J., Yu, H., 2013. Temporal trend of green space coverage in China and its relationship with urbanization over the last two decades. Sci. Total Environ. 442, 455–465. https://doi.org/10.1016/j.scitotenv.2012.10.014.

Zhao, Q., Chen, Y., Gone, K.P., Wells, E., Margeson, K., Sherren, K., 2023. Modelling cultural ecosystem services in agricultural dykelands and tidal wetlands to inform coastal infrastructure decisions: a social media data approach. Mar. Policy 150, 105533. https://doi.org/10.1016/j.marpol.2023.105533.

Zhou, S., Gan, Y., 2025. The green space availability paradox in high-density cities: Evidence from Shenzhen. China. Cities. 167, 106340. https://doi.org/10.1016/j.cities.2025.106340.