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RESEARCH ARTICLE

Urban green inequality and its mismatches with human demand across neighborhoods in New York, Amsterdam, and Beijing

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Abstract
Context Urban green spaces (UGS) are not evenly distributed within cities, and some neighborhoods with high socio-environmental demands require more UGS than others. This raises two challenges: green inequality and demand-based inequity. However, comprehensive assessments of UGS inequality and inequity in cities worldwide are lacking.
Objectives We aim to develop a multi-level approach and supply-demand concept to assess UGS inequality and inequity across neighborhoods in international cities with contrasting geographical and socio-political contexts.
Methods We measured multi-level green accessibility and human demands based on Earth Observation and statistical data. UGS inequality and supply-demand mismatches were assessed by Gini coefficients, spatial cluster analysis, and statistical models.
Results We found that: (1) UGS inequality is primarily reflected by the public park per capita in three cities. New York has larger UGS inequality than Beijing and Amsterdam. (2) Demand-based inequity in terms of low supply and high demand is mainly scattered around the city center in three cities. Tree coverage does not align with environmental pressures (LST/PM2.5) in New York and Beijing. (3) Relations between green supplies and human demands vary by cities and indicators. A shorter distance to the nearest large park is associated with a higher proportion of the elderly and children in New York and Amsterdam.
Conclusions Our findings can inform UGS allocations to improve landscape sustainability in the neighborhoods with low green supply and high human demand, and to prioritize specific green metrics based on demand-oriented equity.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10980-024-01874-4.

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Keywords Green accessibility · Multi-level assessment · Supply-demand relations · Demand-oriented equity · Environmental livability

Introduction

Urban green space (UGS), an indispensable natural element of metropolises, provides environmental and social benefits for urban residents (Triguero-Mas et al. 2015; Veerkamp et al. 2021). The Sustainable Development Goal (SDG) 11.7 has been set to provide universal access to safe, inclusive and accessible, green and public spaces, in particular for women and children, older persons and persons with disabilities by 2030 (UN 2021). However, UGS is unevenly distributed within cities, which is increasingly recognized as an environmental justice issue worldwide (Xiao et al. 2017; Nelson et al. 2021). Common strategies are "just green enough" for every district, such as developing small parks in less green areas (Wolch et al. 2014). Since the potential space for new UGSs is very limited in metropolises (Lin et al. 2022), a better strategy is to optimize the UGS allocation based on the distribution of human demands (Menconi et al. 2021; Liu et al. 2022). To this end, accurately assessing the green supply and its relations to human demand is required for scientifically planning demand-oriented UGS (Lin et al. 2022).

Previous studies have observed the urban green inequality by measuring the total amount (e.g. NDVI, green cover) or accessibility (e.g. distance or travel time to parks) (Wüstemann et al. 2017; Meng et al. 2020; Spotswood et al. 2021). They revealed that the characteristics of UGS matter greatly for its environmental and social benefits. For example, public parks are formal UGS and freely accessible to every inhabitant, and large parks can support more diverse human activities such as jogging or biking than small ones (Shanahan et al. 2015; Hoover and Lim 2021). However, little research assessed UGS inequality in terms of vegetation types, public or private ownership, and park size. In particular, neighborhood-scale inequality was rarely compared among global cities with contrasting geographical, socio-political, and climatic contexts (Fletcher et al. 2021; Veerkamp et al. 2021).

Most studies explored the uneven distribution of UGS without sufficiently considering human demand (Wüstemann et al. 2017; Han et al. 2022), defined as "UGS inequality" in this study. Beyond UGS inequality, recognizing distinct human demands for UGS would reveal mismatches between green supply and human demand (Hunter et al. 2019; Lin et al. 2022), which is defined as "demand-based inequity" (Pham et al. 2012). Pham et al. (2012) illustrated how equity in terms of the urban heat island effect (i.e. demand for cooling) requires different amounts and types of vegetation across blocks. We attempt to evaluate a more comprehensive inequity concerning multiple socio-environmental benefits of UGS, including cooling, air clarification, and the well-being of vulnerable people. As such, green inequality and demand-based inequity are conceptualized as pursuing "Gini perfect equality" and "demand-oriented equity" in this study, respectively.

A growing body of studies started to consider various human demands for UGS in terms of mitigating environmental pressures and supporting human well-being (Luederitz et al. 2015; Baró et al. 2015; Feng et al. 2019). These studies primarily focus on the locations of UGS beneficiaries, without specifically addressing vulnerable groups that could particularly benefit from UGS due to their heightened risk of illness and lifelong impacts. Recent research considered the low-income group and integrated it with environmental pressures and total population to map the overall demand (Fletcher et al. 2021; Lin et al. 2022). Another study considered the elderly and children to examine UGS inequalities, particularly for local parks (Kim et al. 2023). However, those vulnerable groups were often left out of the comprehensive assessment of human demand (Chen et al. 2022; Veerkamp et al. 2021). Moreover, existing demand-based studies have not correlated various UGS metrics with environmental and social demands, respectively, even though the quantity and quality of UGS would support different demands (details can be found in the theoretical basis section).

To fill the gaps in assessing demand-based inequity, this study presented a paradigmatic framework for multi-level analysis of green supply and human demand, implemented at the neighborhood level in New York, Amsterdam, and Beijing by integrating satellite and social data. The specific goals were to (1) quantify multi-level UGS inequality by the Gini coefficient, (2) analyze UGS inequity based on supply-demand mismatches, and (3) explore relationships between green supplies and human demands. Our results can guide demand-oriented UGS allocation to achieve city goals of green equity.

Theoretical basis

Although UGS was initially promoted for food production, modern UGSs are mainly used for leisure, recreation, health, and ecology (van Leeuwen et al. 2011). In this study, we focus on two dimensions of ecosystem services provided by UGSs: (a) environmental benefits, including cooling effects and air purification; (b) socio-economic benefits, encompassing leisure, recreation, character-building, therapy, social interactions, aesthetic value, and market value (Bratman et al. 2019; Hunter et al. 2019; Veerkamp et al. 2021; Lin et al. 2022). Urban residents seek these UGS benefits, and such human demands vary based on environmental pressures and socio-economic vulnerability, as demonstrated in the context of our study cities (Huang et al. 2020; Paulin et al. 2020; Schrammeijer et al., 2022; Wu et al. 2020). Thus, we correlate green supply with human demand at three levels (Fig. 1):

At the first level, the green amount meets the demand for environmental livability (hereafter named 'environmental livability demand'). UGS contributes to the maintenance of a healthy urban environment by adapting to climate change and improving air quality toward a resilient and livable city (Meerow and Newell 2017; Sera et al. 2019). The urban heat island effect is a widely concerning climate issue in cities, caused by hotter built environments than their neighboring rural counterparts (Oke 1982; Hsu et al. 2021). In particular in the future, when the urban heat island effect is likely to intensify due to urbanization and global warming, moderating urban heat and the risk of heat-related illnesses will be of utmost importance (van Leeuwen et al. 2011). UGSs, especially trees, can deliver cooling effects through shade and evapotranspiration (Zhou et al. 2021). Air pollution is another urgent issue in the urban environment, whereas trees can improve air quality by absorbing certain airborne pollutants from the atmosphere at leaf surfaces (Yan et al. 2016). Thus, higher levels of environmental pressures represented by urban heat and air pollution lead to greater environmental livability demand for urban trees.

At the second level, access to public parks meets social demands in terms of socio-economic vulnerability represented by low-income households. Public parks, being a predominant type of UGS, often serve

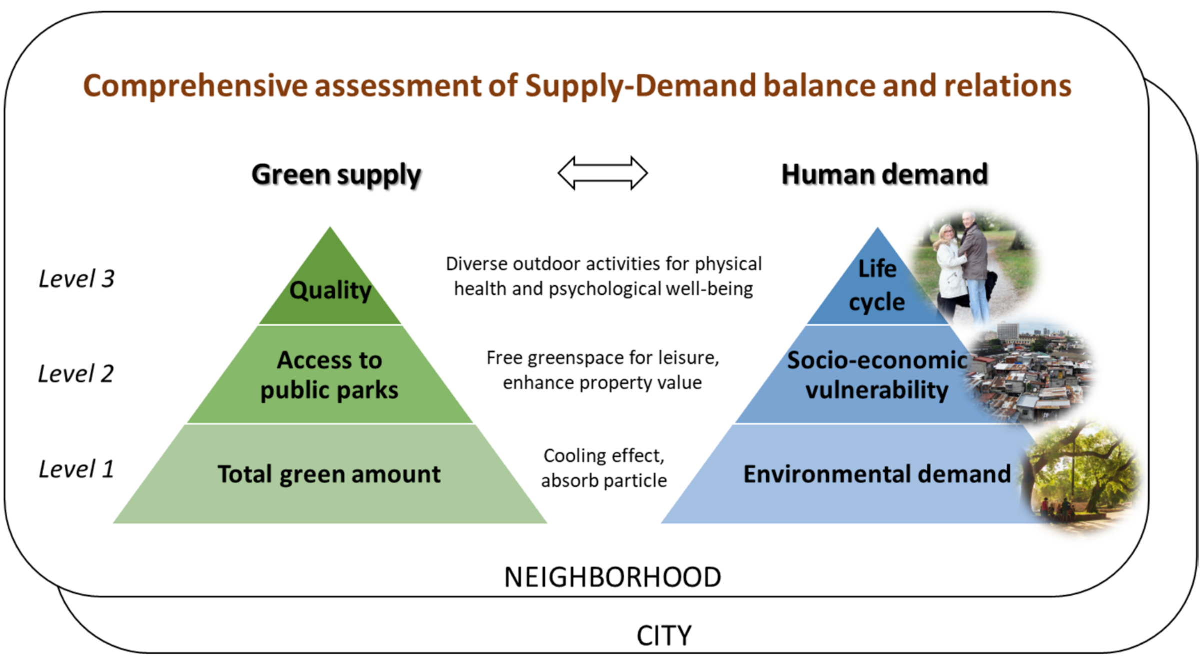

Fig. 1 Conceptual framework of this study

as venues for physical activity accessible to all residents, thereby contributing to enhanced public health (Bedimo-Rung et al. 2005; Schipperijn et al. 2017). Compared to high-income households, low-income households are more dependent on local public parks considering the travel costs to distant UGSs in surrounding rural regions and user fees of private UGSs (Feng et al. 2019; Basu and Nagendra 2021; Lin et al. 2022). Low-income households desire more accessible public parks to improve their livability since their neighborhoods are normally overcrowded with dense buildings, which has been particularly observed in our study cities (Huang et al. 2020). As an attractive urban setting, public parks can enhance the real estate values of low-income communities (Wüstemann et al. 2017). This economic effect may be paradoxical since the resulting gentrification might make it unaffordable for low-income people, but our study cities are developed capital cities and improving the living quality is the first strategy for those relatively low-income neighborhoods (Paulin et al. 2020). Thus, higher numbers of people especially low-income people lead to greater social demand for public parks.

At the third level, distance to a high-quality park meets social demands in terms of life cycle represented by elderly people (aged 65 +) and children (aged 14 −). We chose the size of the park to represent the quality because it is a universal standard for a high-quality park (Kmail and Onyango 2020; Hoover and Lim 2021; Remme et al. 2021). Compared to small parks, large parks can provide more diverse outdoor activities such as jogging and cycling which could reduce the risk for many chronic diseases, and thus enhance the physical health and psychological well-being of urban residents (Wolch et al. 2014; Remme et al. 2021). Such benefits are particularly essential for the elderly and children, since access to parks may increase the longevity of elderly people (Takano et al. 2002), and diverse outdoor activities in large parks can reduce obesity, develop a strong physique, improve attention deficit disorder, build active character, and other life-long impacts on children (Taylor et al. 2001; Wolch et al. 2014; Salthammer et al. 2016). Large parks are usually well managed and include facilities such as high-quality paths and toilets, which are essential to support children's and elderly's outdoor activities (Kemperman and Timmermans 2014). Moreover, senior citizens particularly rely on greenspace within walking distance due to their reduced mobility and cognitive function (Alves et al. 2008), and nearby parks can motivate children to incorporate physical activity into daily life (Sallis et al. 2012). Thus, higher numbers of people especially the elderly and children lead to increased social demand for adjacent large parks.

Given that the above three supply-demand relations are not strictly one-to-one correspondence, the overall balance between green supply and human demand should be assessed by integrating the environmental and social benefits of UGS. According to the above theoretical basis, we define low-income households, elderly people, and children as vulnerable people. Cross-supporting services exist across three supply-demand levels, i.e., the total green amount generally supports social demands, and access to public parks or large parks benefits vulnerable people (Feng et al. 2019; Fletcher et al. 2021). Co-effects also exist between environmental livability and social demands, e.g., elderly people are vulnerable to heat pressure due to a high risk of illness (Hsu et al. 2021). Therefore, high levels of environmental pressure, total population, and vulnerable population would simultaneously lead to increased demand for UGS. Mismatches between green supply and human demand (e.g. low supply-high demand clusters) can be identified from this comprehensive perspective. Such overall mismatches can guide the optimization of urban green allocation toward demand-oriented equity.

Data and methods

Study area

We chose New York, Amsterdam, and Beijing as the study cities for the following reasons. First, they are known as the populous cities on different continents with 2963 inhabitants/km^2 in New York, 3272 in Amsterdam, and 8502 in Beijing in 2015 (Florczyk A. 2019). Second, existing evidence has revealed that urban residents in dense and aging cities usually have scarce and dwindling access to nature and greatly desire public open space (Remme et al. 2021). Third, those developed capital cities have sufficient neighborhood-scale data (e.g. population of age groups) supporting our in-depth supply/demand assessments. Fourth, their municipalities have greatly focused on enhancing and equalizing UGS. The municipality of Amsterdam epitomizes the desire to improve the quality and accessibility of public greenspaces and set the standard of a minimum green provision of 24 m^2 per household (Gemeente Amsterdam 2018). In New York, Million-Trees had aimed to equalize urban forests but failed to "prioritize low-canopy, low-income communities of color" (Garrison 2019). Chinese official UGS planning standards point out that UGS construction should be guided by the ecological civilization strategy and give full play to the multiple functions of UGS in ecology, recreation, landscape, and protection (Ministry of Housing and Urban-Rural Development 2019). Therefore, identifying the UGS inequality and diverse supply-demand mismatches could provide essential information for these official goals.

Our unit of analysis is the neighborhood. We investigated all the neighborhoods within the city boundary that is the metropolitan area of Amsterdam, the borough area in New York, and the area inside the fifth ring road in Beijing. The neighborhoods with less than five people were excluded as outliers.

Urban greenspace measurement and indicator review

Access to UGS has been widely measured by amount, proximity, distance, and quality indices (Wüstemann et al. 2017; Spotswood et al. 2021). We summarized their advantages and disadvantages as shown in Table 1. The amount/proximity metrics are the common measurement that can be obtained from public and timely remote sensing imagery, but they fail to reflect the functional use and quality of UGS (Wüstemann et al. 2017; Schwarz et al. 2018; Yan et al. 2020). The distance metrics can measure geographical accessibility. Many studies have used Geographic Information Systems (GIS) to measure the Euclidean distance or travel times from the centroid of a neighborhood to parks (Giuliani et al. 2021; Wang et al. 2021), but they did not consider the size of UGS. However, small parks are rather frequent and evenly distributed in cities which makes the distance from neighborhoods to parks similarly short. The quality metrics are the highest level of measurement while most existing indicators are subjective or over complicated to be used for multiple cities (Hoover and Lim 2021; Knobel et al. 2021). Trade-offs also exist in different indicators. For example, a study in Baltimore found that although Blacks were more likely than Whites to live within walking distance of a park, Whites had access to more park acres (Boone et al. 2021). Therefore, we combined amount, proximity, distance, and quality to comprehensively measure access to UGS.

Based on the indicator review, we proposed three metrics to assess the multi-level green supply (Fig. 1; Table 2). We selected trees and public parks that can

Table 1 Summary of current indicators of 'access to green space'

Objective	Indicator	Pros	Cons	References
Amount	Open forest cover %; annual maximum NDVI; green area per capita; tree/grass cover	reflect spatial inequality; easy to monitor over time; significantly associated with health	regardless of the distance and inequality within the district	(You 2016; Wüstemann et al. 2017)
Proximity	Green space within the buffer of a neighborhood	combine distance with amount	regardless of population; size of census blocks can vary across countries	(Spotswood et al. 2021)
Distance	Euclidean distance from neighborhood to the nearest green space; average travel times to parks	direct accessibility	regardless of the size of parks; evenly distributed small green	(Wüstemann et al. 2017; Hoover and Lim 2021)
Quality	Tag of parks (functional use); composition (tree/grass); size; facilities	combine land use; distinguish vegetation types; larger parks support jogging/biking	subjective; difficult to quantify	(Hoover and Lim 2021; Remme et al. 2021)
	Tools for green quality	comprehensive assessment	too complicated to measure (e.g. biodiversity)	(Knobel et al. 2021)

Table 2 Overview of data sources and methods of the green supply and demand indicators in Amsterdam/New York/Beijing.

Category	Metrics	Data source	Methodology
Green supply	Tree cover	ESA WorldCover 10 m, 2020	400 m buffer
	Public park per capita	OSM; Census data	400 m buffer
	Distance to the nearest large park	OSM; Block boundary	Euclidean distance from a cell to the nearest large park (> 20 ha); Zonal mean
Human demand	Land surface temperature (LST)	MOD11A2 Terra 8-Day LST 1 km, 2021	Resample; 400 m buffer; Zonal mean
	PM2.5 concentration	Global Annual PM2.5 Grids from MODIS, MISR and SeaWiFS 1 km, 2018	Resample; 400 m buffer; Zonal mean
	Population density	CBS 2021/NHGIS 2020/Jing et al. 2020	Population/Neighborhood size (m^2)
	Income per capita	CBS 2018/NHGIS 2018/Census_district 2020; Rent 2020	Complete missing neighborhoods by Living Atlas maps; Neighborhood_rent / district_rent * income_district for Beijing
	Elderly people & children's density	CBS 2021/Esri 2020/Census_block 2010; Census_district 2020	Neighborhood_rate_2010&district_rate_2020 * population_2020 for Beijing

efficiently provide ecosystem services for urban residents, i.e., trees deliver a higher cooling efficiency by creating shades and evapotranspiration than other vegetation types (Zhou et al. 2021). First, we used a remote sensing product - ESA World Cover at 10 m resolution in 2020 to compute the sum of tree pixels in each neighborhood and get the tree cover. Second, we combined neighborhood-level census data with Open Street Map (OSM) which provides function and ownership information of UGS to compute the public park area per capita. We extracted the public parks under the 'leisure' tag in OSM and compared the obtained maps to the official maps of city parks. A 400 m buffer was used in the calculation of tree cover and public park area per capita for each neighborhood because the UN-Habitat recommends using 400 m as an international walking distance for analyzing the access to public space at a neighborhood level (UN-Habitat 2020). Previous global research has tested the sensitivity of different buffer distances and found a consistent ranking of greenspace exposure (Chen et al. 2022). Third, we combined the distance with quality to measure the highest level of green supply: the distance to the nearest large park. We chose the size of a park to represent quality because larger parks can provide more services (Hoover and Lim 2021). Our threshold for a large park was set as 20 ha based on a widely used standard (Natural England 2010) and previous research for our study cities (Feng et al. 2019). We also analyzed the sensitivity by adjusting the threshold from 15 ha to 25 ha and found no significant impact on the distance to the nearest large park. Euclidean distance tool in ArcGIS pro was used to calculate the distance from each cell to the closest large park excluding the park areas, and the average distance of a neighborhood to the nearest large park was then obtained. Together, we calculated tree cover, public park area per capita, and the distance to the nearest large park (> 20 ha) to measure the multilevel green supply.

Estimating human demands for urban greenspace

The current definitions of human demand for UGS mainly include actual consumption and potential demand. The actual consumptions are based on empirical results, i.e., the sum of actual use or consumption of green services within a certain area over a certain period (Burkhard et al. 2012). The potential demands include the desire to mitigate environmental pressures (Lin et al. 2022), the amount of a service required by society (Luo and Li 2021), and subjective willingness for green services (Fletcher et al. 2021).

In this study, we integrated the metrics of environmental livability and social demand to estimate potential human demand (Table 2). Based on remote sensing products of LST and PM2.5 at 1 km resolution, we used the zonal statistics (mean) to calculate the average LST during summer daytime because heat exposure on summer days is likely to be at a maximum value (Hsu et al. 2021) and annual PM2.5 concentration in each neighborhood (van Donkelaar et al. 2021). Population data of different age groups and income data at the neighborhood level were mainly collected from national and local statistical websites (NHGIS 2020; Statistics 2020; CBS 2021). Since up-to-date statistical data were not available at the neighborhood level for some metrics in New York and China, we used Living Atlas, rent distribution (Lianjia website), and estimated population (Jing et al. 2020) as ancillary data. Specific data and methodology for each demand metric and city are listed in Table 2.

Quantification of inequality/inequity and supply-demand clusters

Although the Gini coefficient is popular in measuring income inequality (Hu and Wang 2005; Xie and Zhou 2014), it has also been used for environmental or social inequality such as water resources, flood drainage, technology, and population (Wu and Xu 2010; Yuan et al. 2017; Zhang et al. 2020). Recent research started to apply the Gini coefficient to UGS (Wüstemann et al. 2017; Feng et al. 2019). As such, we used the Gini coefficient to quantify the distributional "inequality" in green supplies and demands across neighborhoods in each city. The Gini coefficient was calculated as the ratio of the area between the perfect equality line and the Lorenz curve (A) divided by the total area under the perfect equality line (A + B) (Fig. S1). The Gini coefficient ranges between 0 and 1, with 0 representing perfect equality and 1 complete inequality (Wüstemann et al. 2017; Sitthiyot and Holasut 2020). To further explore green "inequity" considering that each neighborhood has different circumstances of demands, we drew the Lorenz lines of green supplies over the ranking of human demands (Fig. 2). Such Lorenz lines could present how UGS disproportionately concentrates on some neighborhoods over others.

We further conducted a cluster analysis to identify overall matches and mismatches between green supply and human demand. Before clustering, metrics of supply and demand were rescaled into values of 0–1 based on min-max normalization within a city. Overall supply and demand in each neighborhood were then calculated by the equally weighted mean of rescaled supply and demand metrics, respectively. Using the overall supply and demand, we applied two algorithms to obtain four clusters: low supply-low demand, low supply-high demand, high supply-low demand, and high supply-high demand (Fig. 6). The first algorithm is that we graded the levels of high and low by the median value of overall supply/demand (Lin et al. 2022). Since we have properly defined these four clusters to guide urban green design, unsupervised algorithms such as k-means were not adopted to segment clusters of similarity. The second algorithm is spatial analysis - bivariate Local Indicators of Spatial Association (LISA), which was applied to map spatial clusters of extremes of green supply and surrounding human demand. Bivariate LISA analysis maps how the value of one variable is surrounded by the values of a second variable and determines the statistical significance for each cluster (Anselin 1995; Tate et al. 2021). In this case, the identified high-high clusters are where high green supply is surrounded by high human demand with significantly positive spatial autocorrelation, and vice versa.

Models for supply-demand relations

The ordinary least square (OLS) model and spatial Durbin model (SDM) were adopted to analyze the current relationship between human demand and green supply. Since LST and air pollution are inappropriate to explain the distribution of green supply, social demands were set as independent variables and green supplies were dependent variables. To avoid the collinearity between the total population and age groups, we transformed the density of the elderly and children to the percentage of the elderly and children (*EC*). We also performed logarithmic processing on population density (*PD*) and income per capita (*IC*) to reduce estimation errors. The specification of the OLS model is:

$$Y = C + \beta_1 PD + \beta_2 EC + \beta_3 IC + \epsilon$$

where Y is the green supply metric, β is the vector of coefficients, and ϵ is the random error. Since urban trees and parks are normally concentrated in several places (Tian et al. 2014; Haaland and van den Bosch 2015), a neighborhood with large tree cover or park areas is likely to have similarly green neighbors. We demonstrated such spatial autocorrelation in green supplies by Moran's I test. Given that green space in a certain region may also be affected by the population in surrounding regions, we included the spatial lag of the dependent variable (W_Y) and population density (W_{PD}) to yield the SDM (Durbin 1960):

$$Y = C + \rho W_Y + \beta_1 PD + \beta_2 EC + \beta_3 IC + \phi W_{PD} + \epsilon$$

where ρ is the spatial lag parameter of the dependent variable, and W is the spatial weight matrix computed by using the Queen contiguity which defines neighbors by a common boundary (Bivand 2008). The Lagrange Multiplier (LM) test was applied to choose the type of spatial model between the spatial lag model and the spatial error model and whether the spatial model is better than the OLS model (Anselin 1988; Park et al. 2021).

Results

Green inequality within cities

First, Gini coefficients show the inequality in green supplies and human demands across neighborhoods (Table 3). Among green supply metrics, amount metrics, especially the public park per capita, identify larger inequalities than the distance metric. Green inequality is greater in New York and Amsterdam than in Beijing. The Gini coefficients of the public park per capita in New York and Amsterdam are remarkably close to 1 (complete inequality). Inequality in human demand is generally smaller than that in green supply. Among human demand metrics, environmental livability demands are distributed more evenly than social demands, of which Gini coefficients are below 0.1.

Second, Lorenz curves illustrate how green supplies are disproportionately distributed in neighborhoods with uneven human demands (Fig. 2). At the first level (green amount-environmental livability demand), tree cover is more heavily allocated to lower-LST neighborhoods in Beijing (the Lorenz curve is fully located above the Gini perfect equality line) but to higher-PM2.5 neighborhoods in Amsterdam (below the Gini perfect equality line). At the second and third levels (green accessibility-social demands), lower-population-density blocks share more tree cover and lower-income blocks share less public park area per capita in New York. Neighborhoods with more children and elderly people share more distance to the nearest large park in Beijing but share less distance in Amsterdam. Notably, the jagged lines between public park area per capita and income are related to the great inequality in public park area per capita across neighborhoods (Table 3). Overall, Amsterdam performs better than the other cities, according to its close-to-Gini perfect equality lines and uneven green supply but generally follows the ranking of demands.

Demand-based inequity

The spatial inequity in urban green is revealed by comparing distributions of green supply to human demand, as well as integrated supply-demand clusters (Figs. 3, 4, 5 and 6). Overall, high peaks of green supplies are mostly concentrated on the fringe of the

Table 3 Gini coefficients of green supplies and human demands

Category	Metrics	New York	Amsterdam	Beijing
Supply	Tree cover	0.57	0.39	0.21
	Public park per capita	0.96	0.93	0.75
	Distance to the nearest large park	0.39	0.37	0.27
Demand	Population density	0.40	0.42	0.28
	Land surface temperature (LST)	0.04	0.03	0.01
	PM2.5 concentration	0.06	0.09	0.01
	Income per capita	0.38	0.21	0.11
	Elderly people & children's density	0.42	0.44	0.31

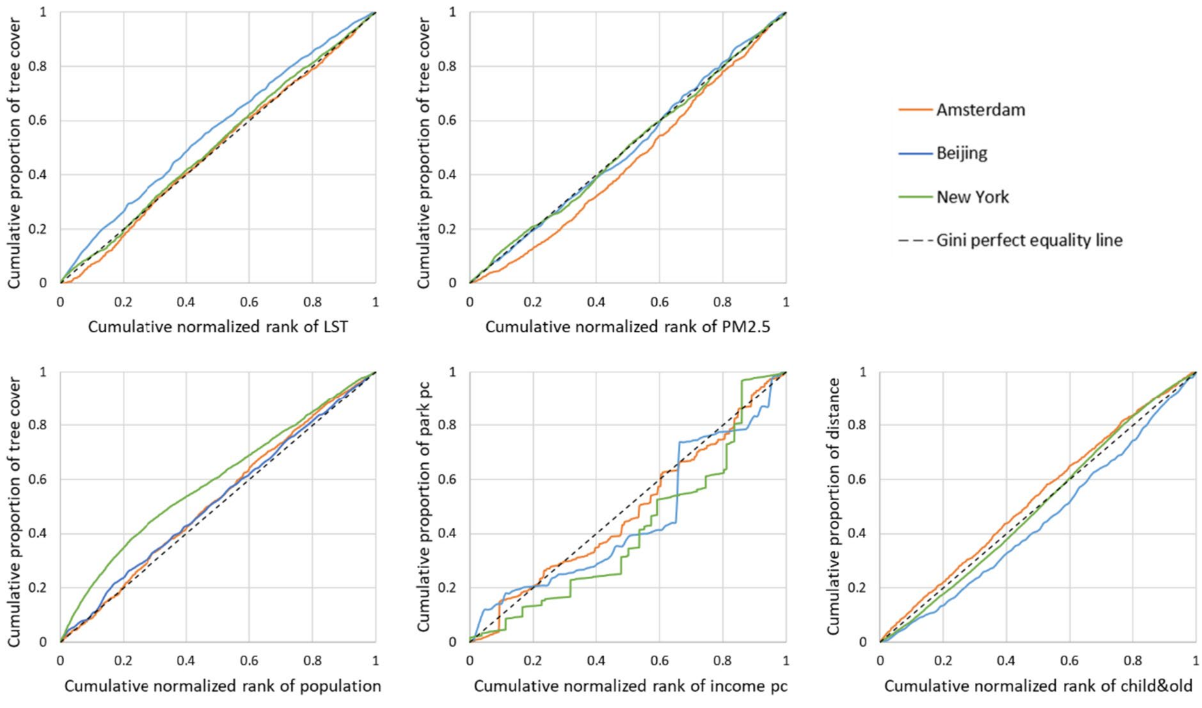

Fig. 2 Lorenz curves for the distribution of urban green supplies over the ranking of human demands across neighborhoods

three cities, while the distribution of high peaks of human demands differs across cities.

In New York, green supplies are concentrated in southwestern and northern parts, but the demands are relatively high in central parts according to the high-density population, the elderly and children (Fig. 3), resulting in overall low supply-high demand clusters in central regions - i.e. Brooklyn district (Fig. 6). The opposite mismatching type (high supply-low demand cluster) is mainly observed in the fringe, especially in the Staten Island reflected as high tree cover but low environmental pressures as well as short distance to large parks but low population density. The LISA map also depicts a large area of high-low clusters in Staten Island representing high supply with surrounding low demand (Fig. 6). Across three supply-demand levels, notable mismatches are observed between tree cover and urban heat and between distance to the nearest large park and elderly/children density.

In Amsterdam, green supplies are low in the city center, where high peaks of demands in LST, population density, and elderly/children density are located (Fig. 4), resulting in the overall low supply-high demand cluster scattering around the central area (Fig. 6). The opposite mismatching type (high supply-low demand cluster) is mainly observed in the fringe, especially in southwestern areas reflected as high tree cover but low LST as well as short distance to large parks but low population density. The LISA map presents a large area of low-low clusters in the northeast representing a spatial match with low supply and surrounding low demand (Fig. 6). Across three supply-demand levels, the notable mismatches are similar to those in New York. Interestingly, the demand for improving air quality increases from the city center to the edge, which generally matches the corresponding green supply (tree cover) pattern.

In Beijing, overall low supply-high demand clusters cover a large area in both the north and south (Fig. 6), which are reflected at different supply-demand levels (Fig. 5). The low-high mismatches in the north are mainly reflected as low public park per capita but high population density, while mismatches in the south are mainly reflected as low tree coverage but high environmental pressures. Matches occur in the southeastern part where the large public park area per capita meets the high demand of low-income neighborhoods. The LISA clusters are mostly

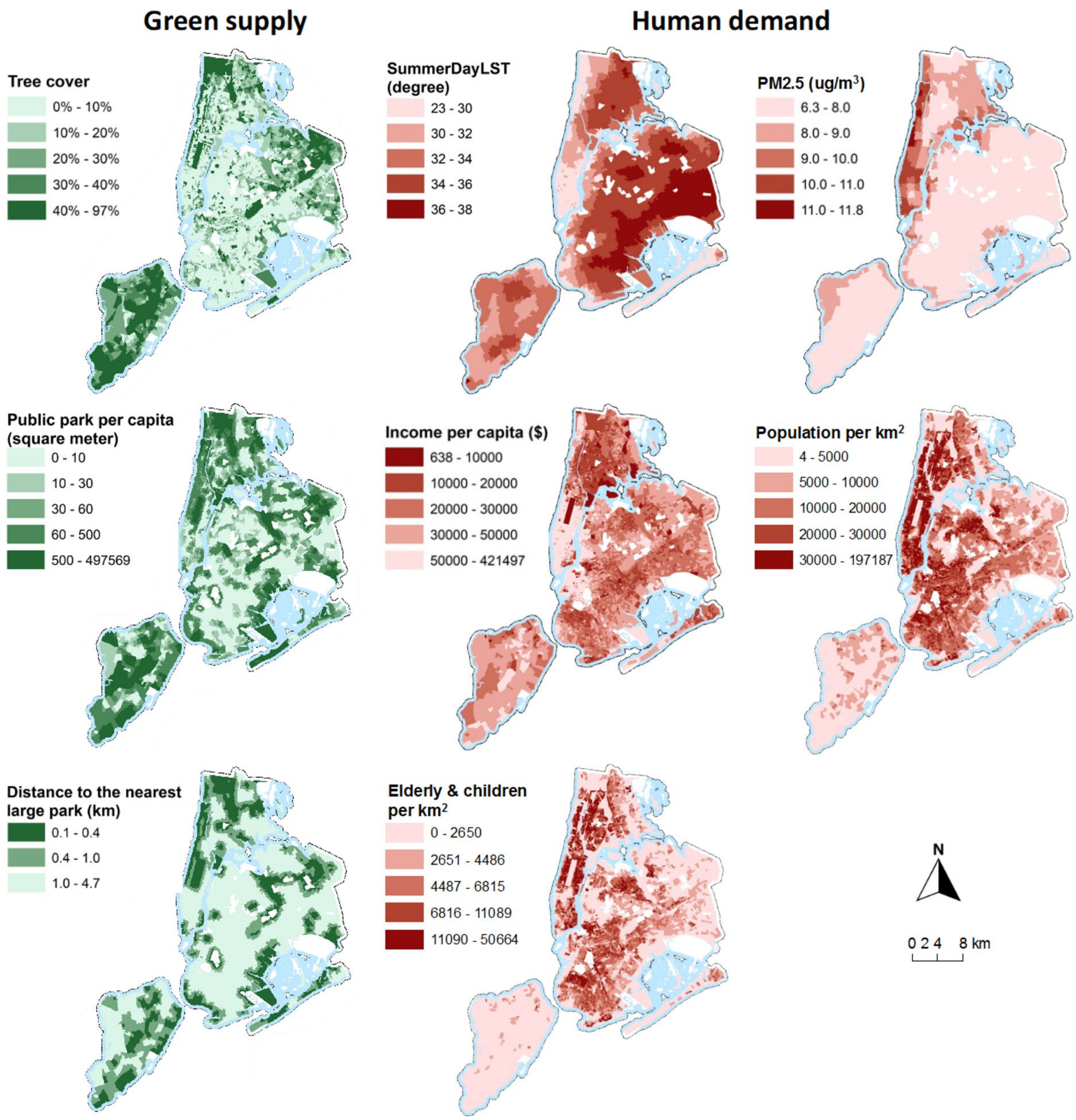

Fig. 3 Spatial distributions of green supply metrics and demand metrics across urban block groups in New York

not significant indicating weak spatial autocorrelation between green supply and human demand (Fig. 6).

Relations between green supply and human demand

In addition to supply-demand maps, OLS and SDM models further unraveled diverse associations between green supply and social demand in cities (Table 4). Our models are quite robust since OLS and SDM estimates are generally similar. Overall, Amsterdam performs well since most social demands are positively associated with green supplies ($p < 0.05$), while most associations in Beijing and New York are negative ($p < 0.05$) or insignificant. Specifically, higher population density is related to less tree cover in New York and Beijing ($p < 0.05$). Neighborhoods

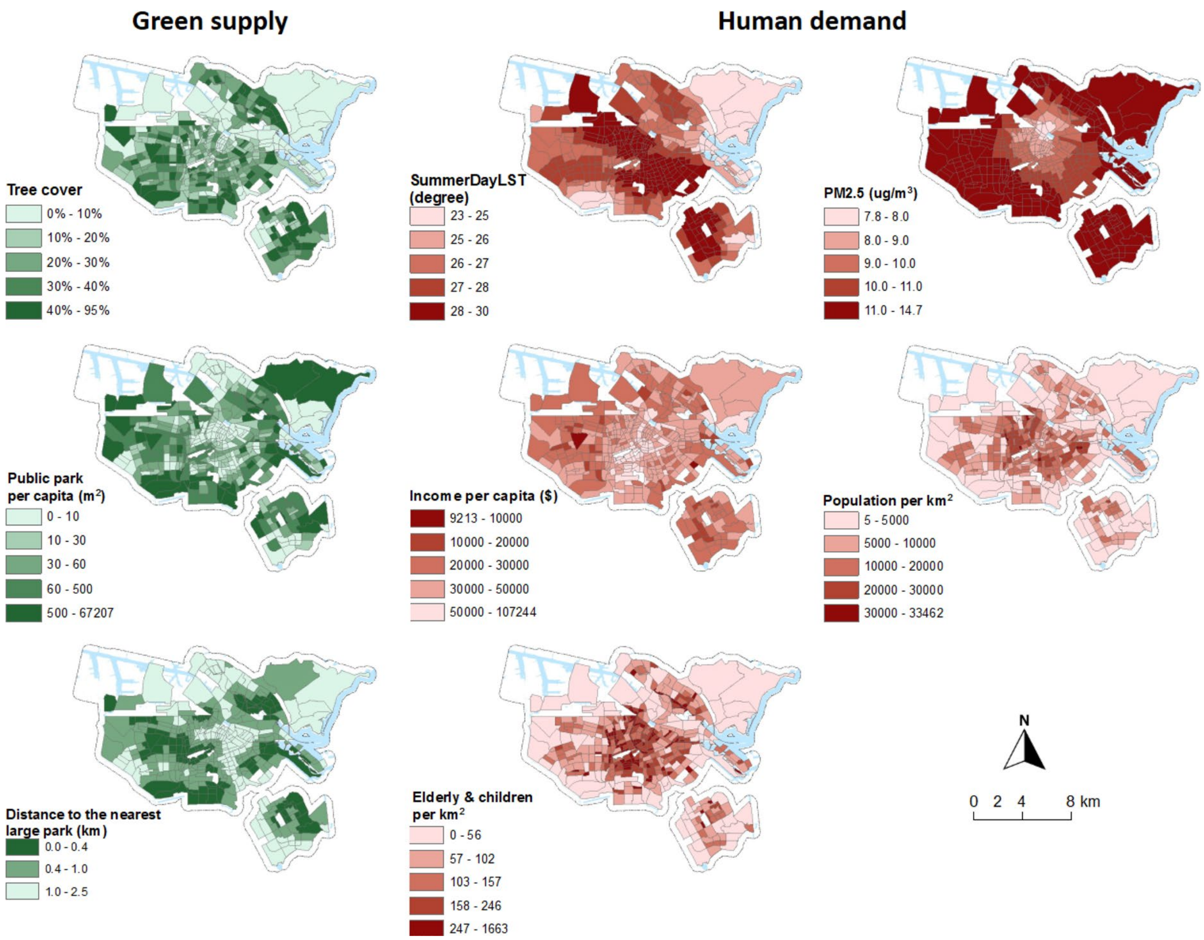

Fig. 4 Spatial distributions of the green supply metrics and demand metrics across urban neighborhoods in Amsterdam

with a higher proportion of the elderly and children tend to have a shorter distance to the nearest large park representing easier access to high-quality parks in New York and Amsterdam ($p<0.01$). Notably, income per capita is not significantly connected with green supplies, except for the negative connections with distance to the nearest large park in New York ($p<0.01$) which means that higher social demands of low-income neighborhoods tend to have less supply of high-quality parks.

When we look at spatial lag factors in SDM, most spatial lag effects of dependent variables (lag.Y) are significantly positive, suggesting that green supply in a neighborhood is significantly related to green supplies in its bordering neighborhoods. Population density also has spillover effects (lag.Population density) on tree cover and public park area per capita, which means that more green supplies in a certain neighborhood are associated with higher population density in bordering neighborhoods.

Discussion

Gini perfect equality or demand-oriented equity

Urban green inequality in study cities has been observed in previous research in terms of green coverage and urban park accessibility, which is consistent with our findings (Feng et al. 2019; Paulin et al. 2020; Pipitone and Jović 2021). We integrated tree cover, park accessibility, and green quality to assess multi-level UGS inequality. In contrast to a previous finding that UGS inequality is mainly reflected by

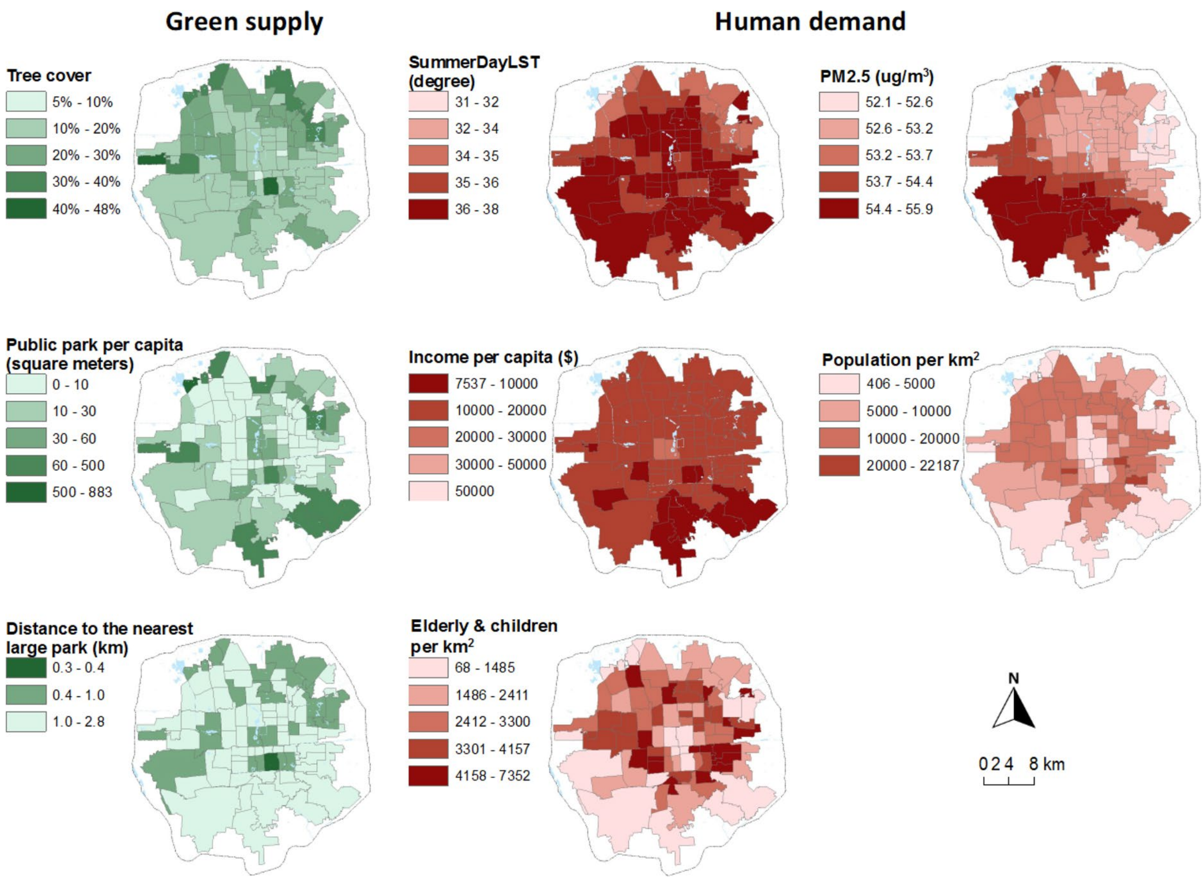

Fig. 5 Spatial distributions of the green supply metrics and demand metrics across urban neighborhoods in Beijing

coverage instead of distance in Germany (Wüstemann et al. 2017), our results show comparable inequalities in tree coverage and distance (Table 3). In addition to distinct cities, varying measurements of distance can be another reason: the previous study used the common distance metric – distance to any nearest UGS, while small and informal UGSs are rather frequent but have fewer benefits than large parks. To address such shortages, we considered green quality (i.e. park size) and obtained an improved distance metric – distance to the nearest large park (> 20 ha), which identified meaningful inequalities in three cities. The measurement strategy of green accessibility can therefore have a significant impact on the findings and makes it difficult to compare our findings to others.

City performance varies by the objective of environmental justice – "Gini perfect equality" or "demand-oriented equity". According to the concept of perfect equality implied in the Gini coefficient, Beijing performs the best among study cities as its Gini coefficients of green supplies are the smallest indicating the most evenly distributed UGS (Table 3). However, when we involve the demand to get the concept of equity, Amsterdam has the best performance since UGS distribution follows the ranking of human demands (Fig. 2). For instance, neighborhoods with higher PM2.5 pressures share more trees and those with more elderly people and children share more nearby large parks in Amsterdam (Fig. 2). Those findings suggest that evenly distributed UGS is not necessarily concurrent with demand-oriented equity and vice versa – highlighting the necessity to concern demand variation towards environmental justice (Chen and Huang 2021).

Our study contributes to the scientific understanding of urban environmental justice, by highlighting the concept of demand-oriented equity. We

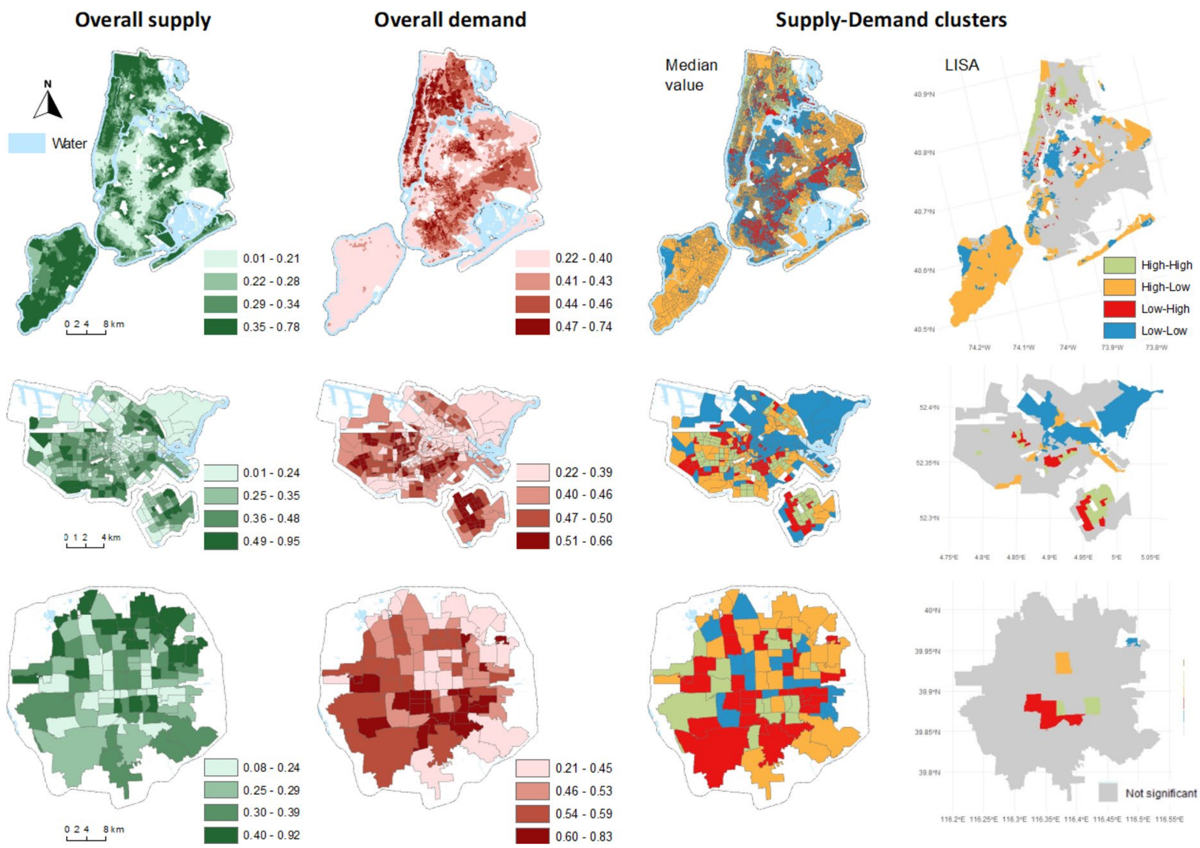

Fig. 6 Spatial distributions of overall supply, overall demand, and two types (columns) of supply-demand clusters (classified by the median value and LISA, respectively) in New York, Amsterdam, and Beijing (from top to bottom)

should reflect on whether the Gini perfect equality or demand-oriented equity is the ideal goal for environmental justice. On the one hand, Gini perfect equality represents evenly distributed UGS across neighborhoods, which is the definition of environmental justice in most previous research (Wolch et al. 2014; Xiao et al. 2017). On the other hand, as UGS is serving people, UGS should be more allocated to neighborhoods with higher demand. This UGS inequality is consistent with the demand variation which can be regarded as demand-oriented equity. Nevertheless, demand-oriented equity has difficulty determining how much UGS should be prioritized in high-demand neighborhoods. Moreover, the distribution of human demands changes over time, and thus investigating how to achieve demand-oriented equity based on circular statistics is warranted (Li et al. 2022).

Supply-demand mismatches: calling for UGS allocation optimization

In addition to measurements of inequality and inequity, we presented spatial patterns of supply-demand mismatches, which are generally consistent with previous studies. Specifically, in New York, we found mismatches between tree cover and environmental pressures, and a recent study in US cities also revealed that tree planting is not prioritized by urban heat distribution (Zhou et al. 2021). In Amsterdam, previous research detected an increasing gradient of tree coverage from the center to the edge but an opposite gradient of population density and cooling demands (Paulin et al. 2020; Schrammeijer et al. 2022), which are also shown in our maps (Fig. 4). In Beijing, an earlier study observed a mismatch between the spatial distribution of urban parks and population in 2017, particularly for elderly residents (Feng et al. 2019), and

Table 4 The ordinary least square (OLS) model and spatial Durbin model (SDM) between green supply (dependent variables) and social demand (independent variables) in study cities

	New York		Amsterdam		Beijing	
	Dependent variable: Tree cover %					
	OLS	SDM	OLS	SDM	OLS	SDM
Constant	0.387***	0.178***	0.619**	0.210	0.375	− 0.064
Population Density	− 0.053***	− 0.040***	0.014**	0.002	− 0.015	− 0.024**
Elderly and Children %	0.383***	0.225***	0.378***	0.298***	− 0.515**	− 0.430**
Income per capita	0.016***	0.001	− 0.048**	− 0.024	0.012	− 0.01
Lag.Population density		0.019***		0.015*		0.072***
Lag.Y		0.683***		0.530***		0.222
Observations	6235	6235	448	448	89	89
Adjusted R^2	0.13		0.025		0.093	
	Dependent variable: Public park area per capita					
	OLS	SDM	OLS	SDM	OLS	SDM
Constant	3.309***	1.713***	1.009*	0.855	0.071*	0.023
Population Density	− 0.305***	− 0.479***	− 0.060***	− 0.090***	− 0.009***	− 0.010***
Elderly and Children %	− 0.623***	− 0.353**	1.885***	1.712***	− 0.033*	− 0.029
Income per capita	− 0.008	− 0.007	− 0.047	− 0.060	0.002	0.001
Lag.Population density		0.329***		0.062***		0.008***
Lag.Y		0.209***		0.138**		− 0.095
Observations	6235	6235	448	448	89	89
Adjusted R^2	0.10		0.338		0.474	
	Dependent variable: Distance to the nearest large park					
	OLS	SDM	OLS	SDM	OLS	SDM
Constant	3.326***	0.181***	1.255*	0.704***	0.106	0.935
Population Density	0.045***	0.010***	− 0.082***	− 0.013	0.381***	0.406***
Elderly and Children %	− 1.060***	− 0.091***	− 1.470***	− 0.550***	− 0.132	0.116
Income per capita	− 0.189***	− 0.014***	0.027	− 0.039	− 0.223	− 0.138
Lag.Population density		− 0.011***		− 0.015		− 0.276
Lag.Y		0.996***		0.961***		0.408***
Observations	6235	6235	448	448	89	89
Adjusted R^2	0.017		0.045		0.165	

*$p<0.1$; **$p<0.05$; ***$p<0.01$

our study found a similar mismatch for the year 2020 and more specific mismatch between distance to the nearest large park and vulnerable population (Fig. 5). Compared to existing findings, our results reflected more dimensions and spatial detail of up-to-date mismatches between green supplies and human demands.

Similar to most studies on supply-demand mismatches (Luo and Li 2021; Lin et al. 2022), we identified mismatches as low supply-high demand and high supply-low demand clusters. Beyond that, we distinguished multi-level mismatches that can separate the deficit for environmental livability demands and social demands. For example, Fig. 6 presents a large area of low supply-high demand mismatches in Beijing, and Fig. 5 further reveals that such mismatches are mainly caused by low park accessibility-high social demand in the North but by low tree cover-high environmental livability demand in the South. Accordingly, UGS development in Beijing should focus on developing public parks in the North and planting trees in the South, rather than making undifferentiated plans.

Relationships between green supplies and human demands vary by city and metric (Table 4). Overall, the distribution of green supplies meets the distribution of social demands in Amsterdam with positive relationships, while they are not positively related in New York and Beijing. Our models indicate that higher-demand neighborhoods with greater population density tend to have lower green supplies with less tree cover and longer distances to the nearest large park in New York and Beijing. Such mismatches can be explained by that high population density is usually related to high built-up density (Li et al. 2019) and are consistent with the previous studies (Feng et al. 2019; Chen and Huang 2021). Beyond the consistent findings, our spatial lag factors imply that green supply in a certain neighborhood tends to meet the demand of population density in its bordering neighborhoods. Moreover, existing studies have shown that low-income people have less access to green space than other people in our study cities (Wolch et al. 2014; Hughey et al. 2016; de Vries et al. 2020; Wu et al. 2020). Our models unravel more specific mechanisms that the low-income communities tend to have shorter distances to the nearest large park in New York and Amsterdam but have no significant association with tree cover or public park area per capita. In addition, our spatial models reveal that green supplies in a neighborhood are significantly influenced by green supplies in its bordering neighborhoods, which can be explained by that the distribution of parks is primarily determined by geographical locations and the development history (Tian et al. 2014; Haaland and van den Bosch 2015).

Our results on supply-demand mismatches at the neighborhood level can help guide local green planning toward meeting diverse human demands (Liu et al. 2020; Menconi et al. 2021). The low supply-high demand clusters we identified should be the focus of future urban greening projects. Negative relationships between green supply and human demand would cause a series of inequity issues, particularly warranting intervention. As such, our results provide concrete green advice for study cities: Green plans in New York (e.g. Million-Trees NYC) can plant more trees in the blocks with high population density, and expand the public parks around the low-income blocks. The municipality of Amsterdam should particularly develop large public parks around low-income neighborhoods to more efficiently achieve its target of increasing the public park area per capita and UGS quality. With the largest supply-demand mismatches, Beijing officials are supposed to make extra efforts to allocate more trees and new public parks to neighborhoods with higher levels of temperature, PM2.5, and vulnerable people. How to better meet human demand with limited UGS is an important challenge for environmental equity and sustainable development in these capital cities.

Uncertainties and limitations

Uncertainties exist in the data source which might influence the results. Given that our study involves a comparative analysis of three international cities, it is imperative to adopt globally remote sensing products with uniform definitions and methodology for estimating tree cover, LST, and PM2.5 concentration. However, the LST and PM2.5 datasets at 1 km resolution are relatively coarse to capture neighborhood-level environments and can omit localized or fine-grain patterns, which might result in underestimated inequalities across neighborhoods. Due to this limitation, we did not involve LST and PM2.5 concentration in the statistical models but only depicted spatial patterns. The user's accuracy of the tree cover in the World Cover 2020 product is around 80%, also affecting the precise assessment of the distribution of green spaces (Tsendbazar et al. 2021). Therefore, we recommend the use of globally consistent products based on high-resolution data for future investigations into urban green spaces and environments in international cities. For instance, further research can produce high-resolution LST products from Landsat 8 and Sentinel-2 imagery to obtain more accurate LST at the neighborhood level.

Furthermore, the statistical data we gathered to assess social demands exhibit variations among cities regarding which data are publicly available, at what administrative resolution, and how up-to-date the datasets are. For instance, while Amsterdam and New York provide neighborhood-level income data for the year 2018, Beijing only offers district-level income information, which was then downscaled using rent distribution for every neighborhood. These disparities in data sources may influence the absolute value of demands, but we mainly look at the ranking of demands where the influence is diminished. Our regression models between green supply and social demand were built for each city, and thus the regression coefficients are comparable between cities.

Our study design and methodology also have some limitations. First, different divisions of neighborhoods and income concepts between cities can lead to differences in the Gini coefficient we used to measure inequality. Second, we directly compared green supply with human demand without converting them into the same evaluation system, i.e., ecosystem services (Lin et al. 2022; Liu et al. 2020). Environmental services provided by UGS can be calculated by cooling rates and PM2.5 removal amount per day of trees, woodland, shrubs, and grass, and then linked to environmental livability demands (Lin et al. 2022). Third, our assessment of 'human demand' is not sufficient. We assessed the potential demands without considering the actual use of parks. Given park space in low-income communities may be perceived as unsafe for children (Wolch et al. 2014). Although previous research in the Global North has revealed that UGS could decrease the number of total crimes and gun assaults by relieving stress, studies in the Global South found tree cover associated with higher sexual crimes (Hunter et al. 2019; Venter et al. 2022). Further research is needed to explore causal mechanisms behind crime-green space associations and complement the demand assessment in terms of safety. We also used environmental pressures such as LST to represent the demand but did not concern the various heat tolerance of residents. Future research can improve the assessment of human demands for UGS through more indicators and surveys, such as conducting surveys and interviews on human preferences. Fourth, we established a singular set of regression coefficients to obtain a general relationship between green supply and human demand within each city, disregarding spatially varying relationships. Although spatially varying relationships can be analyzed by models such as the Geographically Weighted Regression (GWR), it requires a unified distance or range used for spatial correlation which is difficult to set due to varying neighborhood size and density in three international cities. Nevertheless, we recommend future research to apply GWR on a large scale, creating a map of the green supply-demand relation.

Conclusions

Using a unique green supply-human demand concept at the neighborhood level, we proposed "demand-oriented equity" as a sustainable goal of urban green justice, rather than the common "Gini perfect equality". This study has measured multi-level green inequality and analyzed supply-demand mismatches based on spatial clusters and models.

Overall, the public park per capita reflects the largest inequality in green supplies, and the mismatching neighborhoods with low supply and high demand are mainly scattered around urban centers. Among study cities, New York is the city with the greatest inequality in green supplies, and mismatches between tree cover and population density and between the access to public parks and low-income households are remarkable. In Beijing, the green supplies are more evenly distributed compared to other cities, but the distribution of green supplies does not match that of environmental livability demands and social demands, particularly of the elderly and children. Amsterdam performs well in demand-oriented equity with green supplies generally consistent with the demand distribution, while the green supply around low-income communities can be enhanced.

Our findings can guide urban greening projects by pinpointing areas with low supply and high demand, facilitating the development of neighborhood-specific strategies for landscape sustainability. A key contribution of this study lies in creating a pyramid of green supply indicators corresponding to human demand indicators. This framework is applicable across diverse cities and analysis scales. Future research can improve the assessment of human demand and debate how to achieve demand-oriented equity of urban green in cities, ultimately fostering urban sustainability.

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Author contributions Yunyu Tian: Conceptualization, Methodology, Software, Investigation, Visualization, Writing. Eveline van Leeuwen: Conceptualization, Writing—Review and Editing, Supervision. Nandin-erdene Tsendbazar: Conceptualization, Methodology, Writing—Review and Editing, Supervision. Chuanbao Jing: Data resources. Martin Herold: Conceptualization, Methodology, Writing—Review and Editing, Supervision.

Declarations

Competing interests 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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