Seeing vertical greenery: Global differences in residents' green exposure and inequality

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Abstract

Achieving the United Nations Sustainable Development Goal (SDG) 11.7.1—"providing universal access to safe, inclusive, accessible, and green public spaces by 2030"—underscores the critical role of urban green space in advancing global sustainability.Although extensive research has examined urban greenery from a traditional planar perspective, green spaces inherently possess vertical structure. Currently, systematic quantitative assessments of urban vertical greenery, residents' actual exposure to vertical green space, and the associated inequalities remain limited. To address these gaps, this study integrates global population data with vegetation height information to construct an exposure-based analytical framework.We quantify spatial patterns of vertical greenery, residents' green exposure, and exposure inequality across global urban areas, and further examine the drivers of inequality. Our findings reveal pronounced spatial disparities in urban greenery worldwide. On average, cities in the Global North exhibit approximately three times greater vertical greenery and nearly four times higher green exposure than cities in the Global South. African urban areas possess only one-sixth of the average vertical greenery and one-seventh of the exposure level observed in North America, while displaying roughly twice the inequality in green exposure, indicating much more uneven access to green resources. We also find that cities with higher average vertical greenery tend to experience lower exposure inequality, suggesting that increasing overall greenery can help promote more equitable access. These results provide new theoretical insights and policy-relevant evidence for advancing sustainable and equitable urban green development, supporting global progress toward sustainable development goals.

1. Introduction

Urban green spaces are fundamental environmental assets of healthy cities and serve as primary venues for outdoor activities. They enhance both physical and mental well-being (Beyer et al., 2014, Sarkar et al., 2018, Vanaken and Danckaerts, 2018, Chen et al., 2024), support urban ecosystems and biodiversity (Aerts et al., 2018, Wolch et al., 2014), and mitigate environmental problems that adversely affect health, such as urban heat islands, air and noise pollution, and pluvial flooding. Alongside economic development, cities have become centers of population and capital concentration and now function as the core hubs of human activity. More than half of the global population currently resides in urban areas—a proportion projected to reach 68% by 2050 (United Nations Department of Economic and Social Affairs, 2019)—characterized by agglomeration, industrialization, and modernization (Fang and Yu, 2017). Despite these advantages, rapid urbanization has also intensified environmental degradation. Urban expansion and population growth place substantial pressure on green spaces through overdevelopment and intensive land use, undermining ecosystem integrity and reducing residents' opportunities to access nature.

As urbanization intensifies and public awareness of environmental protection and sustainable development increases, growing attention has been paid to urban green environments and green development. Constructing green urban environments has become a key goal for advancing urban sustainability, and understanding residents' green exposure and the associated inequalities has emerged as a prerequisite for supporting the development of healthy cities (Yu et al., 2023). However, most existing assessments rely on planar green coverage measures, which fail to capture qualitative and structural differences in vegetation. As a result, significant changes in ecological function can occur while measured green coverage remains unchanged, leading to methodological inconsistencies. At the global scale, robust and accurate assessments of residents' exposure to vertical greenery and its inequality remain largely absent.

To address this gap, we extend the SDG 11.7.1 framework by incorporating vertical greenery metrics that capture the ecological quality and structural characteristics of urban vegetation. This enhancement enables a more comprehensive quantification of global urban greenery, facilitates a nuanced characterization of spatial patterns in residents' green exposure(RGE), and provides a robust basis for evaluating green exposure inequality(GEI). In addition, we develop a multivariate modeling framework that integrates socioeconomic, environmental, and urban form indicators to systematically to identify the drivers of GEI and reveal how these factors collectively shape disparities in access to green-space resources.

The specific work of this study includes the following components: (1) Quantification of global urban vertical greenery. We introduce two indicators — including total vertical greenery (TVG) and average vertical greenery (AVG)—to more comprehensively represent urban greenery and ecological environmental quality. (2) Assessment of RGE and GEI. A population-weighted exposure model is applied to capture the spatial interaction between vertical vegetation and population distribution and to derive per capita green exposure for urban residents. Based on this, we evaluate inequality in green space access using the Gini coefficient. (3) Identification of GEI drivers. Using multisource remote sensing data, we first extract explanatory variables through Pearson and partial correlation analyses.

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We then build a comprehensive set of influencing factors and assess their relative contributions to exposure inequality using ordinary least squares regression, geographically weighted regression, and random forest regression models.

Specifically, this study addresses the following questions: (1) How does the level of urban vertical greenery vary across cities worldwide? (2) Based on a vertical greenery exposure model, how do RGE and GEI vary among urban residents across global cities? (3) What are the main drivers of exposure inequality?

2. Methods

2.1 Research Framework

The overall research framework is illustrated in Figure 1. This study begins by defining the research areathen quantifies the total and average vertical greenery in urban areas to reveal global variations in the distribution of green spaces. Subsequently, a population-weighted green exposure model is employed to calculate the green exposure levels of urban residents worldwide. Inequality indices are then applied to evaluate disparities in green space access among residents, followed by an analysis of global patterns in green exposure and inequality across cities. Finally, a driver analysis of exposure inequality is conducted based on five categories of relevant variables.

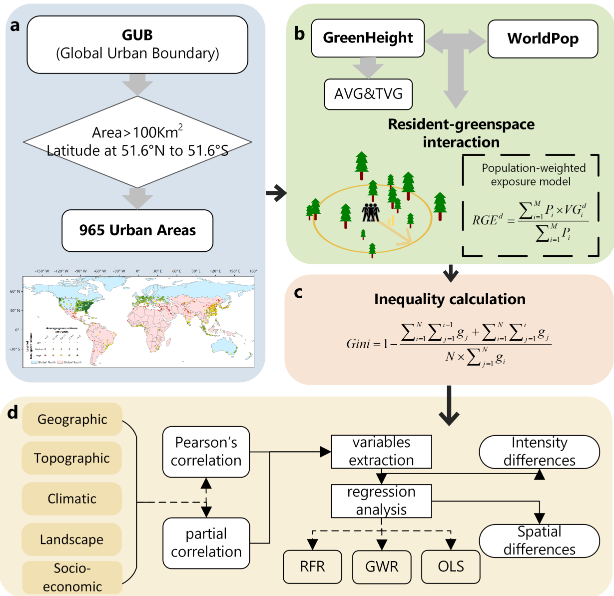

Figure 1. The framework of this study.(a) Selection of 965 global cities. (b) Global urban vertical greenery statistics, combined with population data, modeling the resident-vegetation interaction using a population-weighted green exposure model. (c) Calculation of green exposure inequality. (d) Driver analysis of green exposure inequality.

2.2 Study Area

Unlike traditional urban administrative boundaries, this study focuses on the built-up areas of global cities. We extracted global urban boundary shapefiles based on MODIS data. To ensure sufficient sample size for the inequality indices and adequate coverage of vegetation data, two criteria were applied to select study cities: (1) the geographical area is greater than 100 km², and (2) the city is located between 51.6°N and 51.6°S. A total of 965 urban areas were selected, with 459 cities located in the Global North and 506 in the Global South.

2.3 Green Space and Population

Global vegetation height data with a spatial resolution of 30 meters were obtained from the official Global Ecosystem Dynamics Investigation (GEDI) website (Potapov et al., 2021). By integrating GEDI lidar forest structure measurements with Landsat analysis-ready data time series, vegetation height values were predicted using a machine learning algorithm (regression tree) based on multi-temporal, multi-spectral Landsat data. Due to the constraints of the International Space Station’s orbital inclination, the vegetation height data covers only the region between approximately 51.6°N and 51.6°S. The data is divided into seven regional datasets, provided in 8-bit unsigned GeoTiff format with a pixel size of 0.00025° by 0.00025°.

Population data for 2019 was obtained from WorldPop, based on administrative units and adjusted using official United Nations population estimates. Utilizing the GPWv4 (Gridded Population of the World, version 4) data from the Center for International Earth Science Information Network (CIESIN), detailed census data was integrated with national and sub-national spatial datasets using a random forest-based weighted distribution method. This approach provides spatially consistent gridded population outputs, generating population distribution and demographic maps from 2000 to 2020 worldwide (Stevens et al., 2015). Specifically, the dataset includes population grids for 249 countries, with a grid size of 100 × 100 m. The pixel values represent population counts and offer advantages such as high spatial and temporal resolution compared to global population grids (GPW) (CIESIN, 2018) and high-resolution settlement layers (HRSL) (Tiecke et al., 2017).

2.4 Residents’ Green Exposure and Inequality

RGE reflects the interaction between residents and surrounding green spaces: the more vertical vegetation available around a resident’s living environment, the higher the corresponding level of green exposure. It represents the degree to which individuals can access green space within a defined buffer zone and can therefore indicate, to some extent, the greenery and quality of a city’s environment, its level of sustainable development, and residents’ well-being. In this study, we employ a population-weighted exposure model to quantify RGE, defined as the average vertical greenery accessible to each resident within the surrounding buffer zone. The probability and level of human exposure to green space are computed using Equation (1):

$$RGE^d = \frac{\sum_{i=1}^{M} P_i \times VG_i^d}{\sum_{i=1}^{M} P_i} \tag{1}$$

where RGE^d = population-weighted green exposure level of residents at the urban scale
P_i = population of the ith pixel
VG_i^d = the average vertical greenery around the ith pixel
d = size of the buffer zone vertical greenery around the ith pixel
M = total number of pixels in the urban area

We further employ the Gini coefficient to assess the inequality of residents’ green exposure (Charles et al., 2022). The Gini index is a widely used measure of inequality in the distribution of income or other resources within a region, with values ranging from 0 to 1. A value closer to 1 indicates greater inequality. The Gini index has been applied in many fields, providing valuable insights into the extent, causes, and effects of inequality, and offering key information for policymaking and social development. As shown in Figure 2, the Gini index is calculated using the Lorenz curve, and the formula is as follows:

$$Gini = \frac{S_A}{S_A + S_B} = 1 - \frac{\sum_{i=1}^{N}\sum_{j=1}^{i-1} g_j + \sum_{i=1}^{N}\sum_{j=1}^{i} g_j}{N \times \sum_{j=1}^{N} g_i} \tag{2}$$

where g_j = the green space exposure within the buffer zone around the jth resident
N = total population of the target city

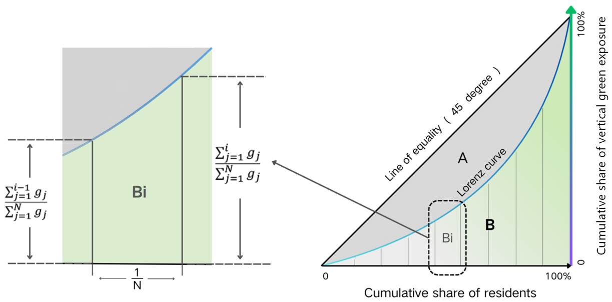

Figure 2. Schematic for evaluating vertical green exposure inequality using the Gini coefficient. The Gini coefficient measures the area between the equal distribution line and the Lorenz curve (area A) relative to the total area under the equal distribution line (areas A + B). The Lorenz curve plots the cumulative share of the vertical green exposure (y-axis) against residents’ cumulative share (x-axis, ranked from lowest to highest green exposure). Bi represents the contribution of the ith resident to the cumulative green exposure and is estimated from the trapezoidal area in the left panel, where gi is the green space exposed to the ith resident, and N is the total number of residents.

2.5 Drivers of Exposure Inequality

In the method developed in this study, the first step involved obtaining the relevant variables, which cover a wide range of driving factors, including geographic variables, topographic variables, climatic variables, socioeconomic variables, and landscape variables. Next, Pearson correlation and partial correlation analyses were conducted to quantify the relationship between the inequality index of the green space exposure and these variables. The significant variables were selected based on a significance level of $p < 0.001$, and correlations were considered relevant if the absolute value of the Pearson correlation coefficient and the partial correlation coefficient exceeded 0.1. Finally, ordinary least squares regression analysis (Zhu et al., 2020) was conducted to assess the relationships between the selected explanatory variables and the inequality index, thus identifying the driving factors behind green exposure inequality. Comparative analysis was performed to evaluate the effects of different factors on the green space exposure inequality. In the full model (Model 6), the variance inflation factor (VIF) was used to measure the multicollinearity among the variables. The results showed that the inflation factors for all of the included variables were less than 4 (Figure 5). Additionally, random forest (RF) regression was used to capture the complex and nonlinear relationships, and combined with the SHapley Additive exPlanations (SHAP) (He et al., 2023) to quantify and interpret global feature contributions to GEI, identifying AVG as the most influential driver. Furthermore, geographically weighted regression was used to account for the spatial non-uniformity of the dependent variables. These methods revealed the occurrence of regional differences in the driving factors of the inequality in green space exposure.

3. Results and Discussion

3.1 Differences in Vertical Greenery across Global Urban Areas

Using regional statistics, we calculated both the total and average vertical greenery across global urban areas and found substantial spatial heterogeneity (Figure 3a). In terms of TVG, cities in the United States generally exhibit high values. At the continental scale, cities with larger TVG are primarily located in eastern North America, central Europe and Southeast Asia, whereas cities in Africa, South America and western Asia show relatively low totals (Figure 3a). Notably, North America has a TVG of 1.2×10^{10} m^3, which is markedly higher than other continents (Figure 3c) and approximately 50 times that of Africa (2.4×10^8 m^3).

For average vertical greenery, U.S. cities also remain among the highest (Figure 3a). However, unlike the pattern observed for total greenery, Asian cities show relatively low average values, likely due to variations in urban area size (Figure 3c). Compared with TVG, the average metric removes the influence of urban extent and therefore better reflects vegetation levels within cities. At the global scale, the AVG of cities in the Southern Hemisphere is noticeably lower than that of the Northern Hemisphere, with values concentrated in the lower range (Figure 3b). Approximately 50% of global cities fall within 0–1 m, and around 30% fall within 1–2.5 m; the remaining high-value cities span a wide range and are predominantly located in the Northern Hemisphere. Across continents, Africa records the lowest average vertical greenery (0.7 m), whereas North America has the highest (4.2 m), roughly six times that of Africa.

These data reveal substantial disparities in the distribution of vertical greenery across different urban regions. Cities in North America and Northern Europe generally perform better, likely benefiting from long-standing investment in and commitment to green infrastructure. For instance, many major U.S. cities (such as New York) have incorporated green spaces as core elements of their urban planning strategies, with parks, green belts, and green walls collectively contributing to higher levels of vertical greenery. In contrast, African cities tend to exhibit lower vertical greenery, partly due to arid climates, limited land resources, and insufficient greening investment. Many African cities (e.g., Cairo, Egypt) face strong pressures from rapid urbanization and population growth, leading to intensive land development and insufficient protection of green space quantity and quality (Du Toit et al., 2018).

In Asia, particularly in West and South Asia, many cities show relatively low average vertical greenery, which is closely linked to the high land demand associated with rapid urbanization. Urban expansion in countries such as India, China, and other developing nations often occurs at the expense of green areas, resulting in high building density and limited vegetated space.

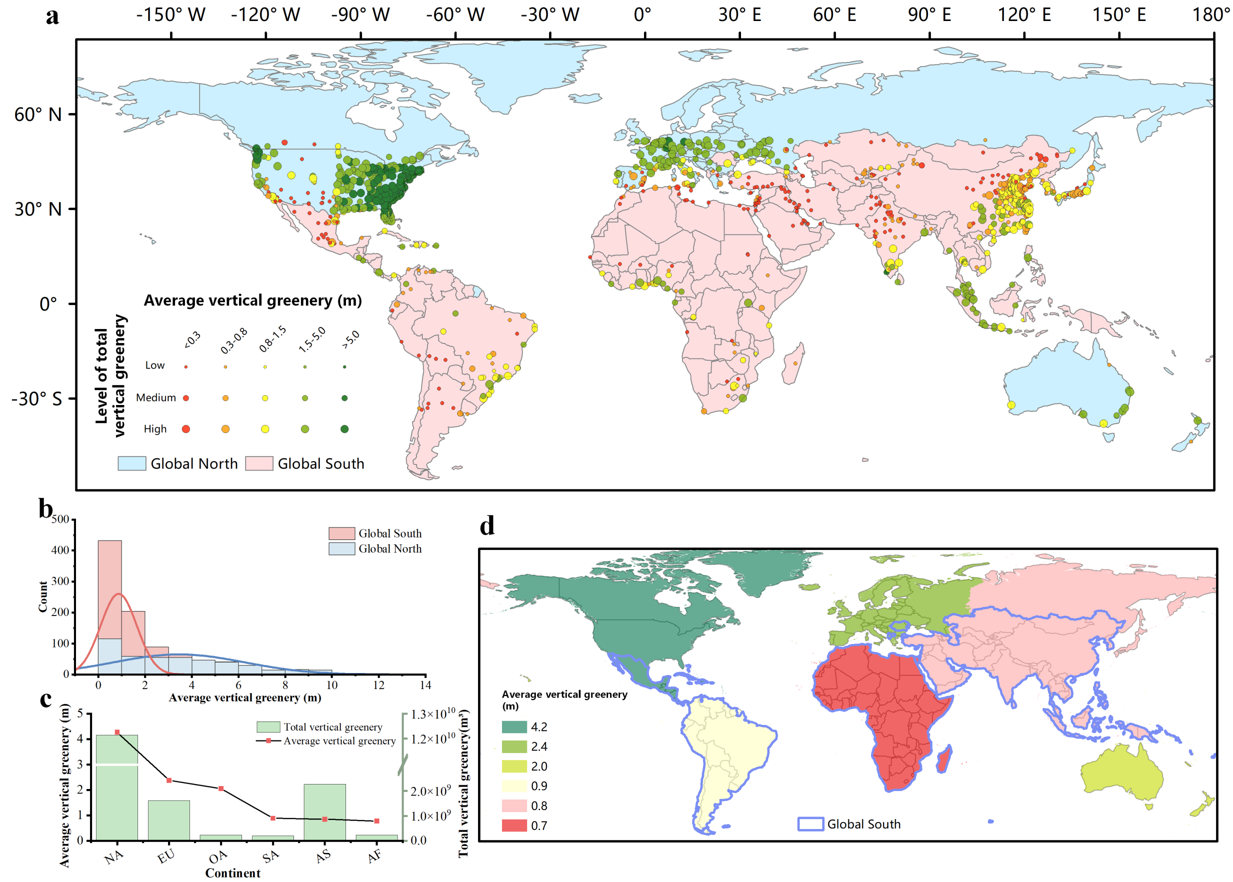

Figure 3. Distribution and statistics of TVG and AVG for 965 global urban areas. (a) Point distribution. Larger bubbles represent higher TVG, while greener colors indicate higher AVG. Light blue (pink) shaded administrative boundaries represent countries in the Global North (South). (b) Histogram of AVG for cities in the Global North and Global South. (c) Regional statistics of TVG and AVG by continent. (d) Map of AVG for cities across continents, showing regional differences.

Meanwhile, environmental management and greening policies in these cities have not fully kept pace with the speed of urbanization, contributing to uneven distribution of green resources. By contrast, some cities in Southeast Asia—such as Singapore and Kuala Lumpur—exhibit higher levels of vertical greenery, a result of sustained governmental investment in sustainable urban planning and green building development (Pomeroy and Director, 2012).

3.2 Global Patterns of Residential Green Exposure and Inequality

Map visualization reveals strong global disparities in urban residents' green space exposure (Figure 4a). The variation in vertical green exposure between cities is substantial, with the highest reaching 12.7 m, and the lowest as low as 0.0001 m. In general, cities with high green exposure are concentrated in the United States and northern Europe, while cities with low exposure are mainly found in northwestern Asia, western South America, and central Africa. In terms of regional differences, cities in the Global North (e.g., the United States, Europe, and Australia) exhibit significantly higher green exposure (3.660 m/capita) compared to cities in the Global South (e.g., China, India, and the Middle East) (0.791 m/capita), a disparity of approximately four times. At the continental level, cities in North America have the highest human green exposure (4.639 m/capita), while African cities have the lowest (0.665 m/capita), approximately 1/7th of that in North America, and around 1/3rd of the levels in European cities (2.303 m/capita) and cities in Australia and Oceania (1.949 m/capita). Cities in Asia (0.792 m/capita) and South America (0.720 m/capita) show slightly better but still suboptimal green exposure compared to Africa (Table 1).

The inequality in green space access among urban residents also exhibits significant variation, with the highest Gini coefficient at 0.99 and the lowest at 0.15. In some cities, the distribution of green space is highly uneven and inequitable, which serves as a warning for certain urban areas. On the whole, cities with higher levels of GEI are concentrated in western Asia, northern Africa, and southern North America, while cities with more equitable green space distribution are mainly found in eastern North America, central Europe, and Southeast Asia (Figure 4b). In terms of north-south differences, cities in the Global North (e.g., the United States, Europe, and Australia) exhibit lower GEI (0.401) than cities in the Global South (e.g., China, India, and the Middle East) (0.512). At the continental level, cities in Africa, Asia, and South America have average inequality indices ranging from 0.53 to 0.60, which are approximately 1.5 times higher than those in North America, Europe, Australia, and Oceania (0.37–0.41) (Table 1). Africa has the highest inequality index, which is attributed to factors such as arid climate, scarce water resources, infertile soils, and highly uneven vegetation distribution, resulting in significant disparities

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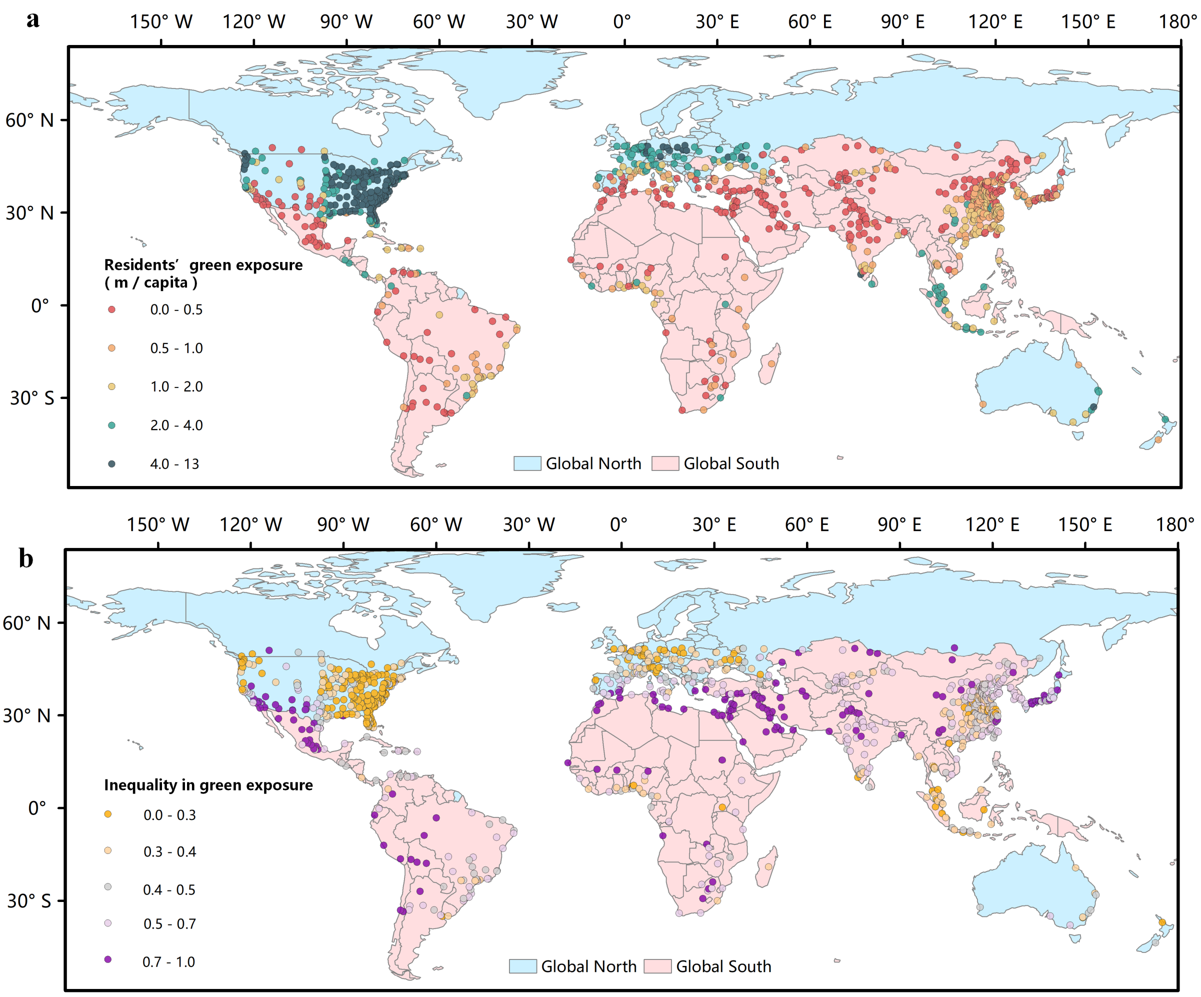

Figure 4. Distribution and Statistics of RGE and GEI for 965 Global Urban Areas. (a) Distribution of RGE. Larger green bubbles represent higher levels of residential green exposure. (b) Distribution of GEI. Larger purple bubbles represent greater disparities in green exposure among residents.

in green space allocation among urban residents.

By examining the inequality results, we identify the city with the highest level of GEI (0.99) as Khartoum, the capital of Sudan. In contrast, the most equitable case (0.15) is Moore County, located in North Carolina, United States. Khartoum lies along the northern margin of the Sahara Desert and is characterized by an arid desert climate with extremely low precipitation, which limits vegetation growth and leads to sparse green cover. Desertification further constrains vegetation distribution across the region. As a result, most residents experience negligible green exposure, with values close to 0 m/capita, while only a small proportion of residents are exposed to 0–0.1 m/capita of green space. This highly uneven distribution of vegetation resources leads to pronounced disparities in residents’ green exposure. In contrast, Moore County is located in the inland eastern region of North Carolina and benefits from moderate precipitation, abundant sunlight, and a mild climate, conditions favorable for vegetation growth. In addition, local governments and communities place strong emphasis on ecological conservation and green space planning through measures such as forest protection, grassland restoration, and tree planting. Consequently, vegetation is relatively abundant and evenly distributed. Most residents experience green exposure levels ranging between 4 and 13 m/capita , while only a small proportion have lower exposure around 1 m/capita, resulting in a comparatively equitable distribution of green resources.

Region (# of cities)	RGE (m/capita)	GEI
Global North (459)	3.660±0.137	0.401±0.008
Global South (506)	0.791±0.036	0.512±0.008
North America (291)	4.639±0.182	0.378±0.011
Europe (129)	2.303±0.138	0.403±0.012
Australia/Oceania (12)	1.949±0.343	0.412±0.033
Asia (410)	0.792±0.035	0.534±0.008
South America (60)	0.720±0.074	0.565±0.021
Africa (63)	0.665±0.077	0.604±0.025
Global (965)	2.156±0.081	0.474±0.006

Table 1. Statistics on RGE and GEI by region.

The generally higher levels of green exposure inequality observed in the Global South reflect systemic deficiencies in the spatial allocation of green space and in urban governance. This is not only driven by the scarcity of green resources but is

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also closely linked to rapid urbanization, unregulated urban expansion, policy lags, and intensified land-use competition. Moreover, in large cities with limited resources, green segregation further exacerbates social disparities in green exposure (Gould and Lewis, 2012). High-income groups often reside in gated communities with better landscaping and abundant greenery, whereas low-income populations are concentrated in densely built-up areas with scarce green space.

Existing studies assessing urban green exposure have largely relied on green coverage data, where urban greenery is represented as a planar surface without accounting for its vertical structure (Chen et al., 2022). Our comparison indicates that such planar assessments tend to underestimate global disparities in green exposure. Using planar data, cities in the Global North exhibit only about twice the level of green exposure observed in the Global South, whereas the differences revealed in this study reach approximately fourfold, highlighting a substantially stronger imbalance in global urban green development.

Moreover, inequality in urban green exposure derived from the three-dimensional assessment (mean GEI: 0.47) is consistently higher than that estimated using planar approaches (0.35). Planar assessments therefore tend to mask disparities in residents' access to green resources, giving the impression of a more equitable distribution than actually exists. By incorporating the vertical dimension of vegetation through a green volume–based exposure metric, our approach provides a more realistic representation of how green resources are distributed among urban residents and more effectively reveals inequalities in access to urban greenery.

Both the overall level of green exposure and the associated inequality index highlight the combined effects of green space provision, urbanization pressures, and socio-economic structures in shaping global patterns of urban green exposure. Particular attention should be paid to regions where low exposure coincides with high inequality—such as Africa, South Asia, West Asia, and Central America—as these areas may face heightened environmental and public-health risks. This underscores an urgent need for more targeted and context-specific strategies to support green transitions in cities worldwide.

3.3 Drivers of Inequality in Green Exposure

To further understand the factors influencing the inequality in human exposure to green space, we selected and investigated the drivers using five categories, namely, geography, topography, landscape, climate, and socioeconomics, and used various analytical methods to assess their effects and regional variations. Correlation analysis revealed the occurrence of significant associations between the GEI and multiple determinants (Table 2): (1) the geographic parameter, LNG; (2) the topographic characteristic, slope; (3) socioeconomic indicators, including PD and ANLI; (4) climatic variables, including TEMP, VPD, and GHI; and (5) the landscape metric, AVG, which represents the mean height of green space per unit area. Specifically, the landscape (R2 = 45.4%) and climate (R2 = 41.8%) variables explain the largest proportions of the variations in the urban GEI, identifying them as the primary drivers (Table 3). To address potential multicollinearity among explanatory variables, we calculated VIFs. The results showed that the inflation factors for all of the included variables were less than 4 (Figure 5).

Category	Variable	Correlation	Partial correlation
Geographic	LAT	0.159***	0.030
	LNG	0.187***	0.272***
Topographic	ELEV	0.352***	-0.008
	Slope	0.199***	0.975***
Socio-economic	**PD**	0.192***	0.103**
	ANLI	0.411***	0.118**
	TNLI	0.088*	0.095*
	SHDI	0.364***	0.026
	BC	0.375***	0.003
Climatic	PRE	0.375***	0.005
	TEMP	0.208***	0.214***
	VPD	0.529***	0.168***
	GHI	0.501***	0.246***
Landscape	**AVG**	0.674***	0.209***
	TVG	0.261***	0.077**

Note: *** p-value < 0.0001, ** p-value < 0.001, and * p-value < 0.01.

Table 2. Correlation coefficients between the explanatory variables and the inequality index of the greenspace exposure.The partial correlation coefficient was derived by controlling for all of the other variables. From top to bottom, the considered variables include the latitude (LAT), longitude (LNG), elevation (ELEV), slope, population density (PD; number of people per 10,000 square meters), average nighttime light index (ANLI), total nighttime light index (TNLI), subnational human development index (SHDI), building coverage (BC), precipitation (PRE), temperature (TEMP), vapor pressure deficit (VPD), global horizontal irradiation (GHI), average vertical greenery (AVG), and total vertical greenery (TVG).

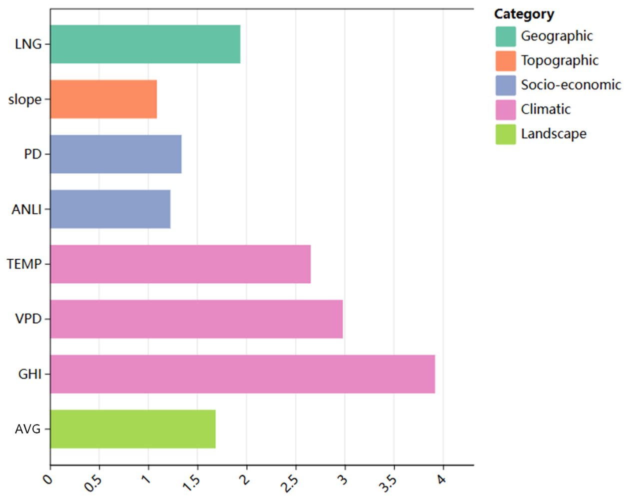

Figure 5. Bar chart of the variance inflation factors for the eight variables in the multiple linear regression model.

In addition, we combined the random forest and SHAP to determine the relative importance of explanatory variables. According to the variable importance ranking derived from the SHAP model (Figure 6c), AVG remained the most influential factor. Redder colors indicate higher AVG values, which cor-

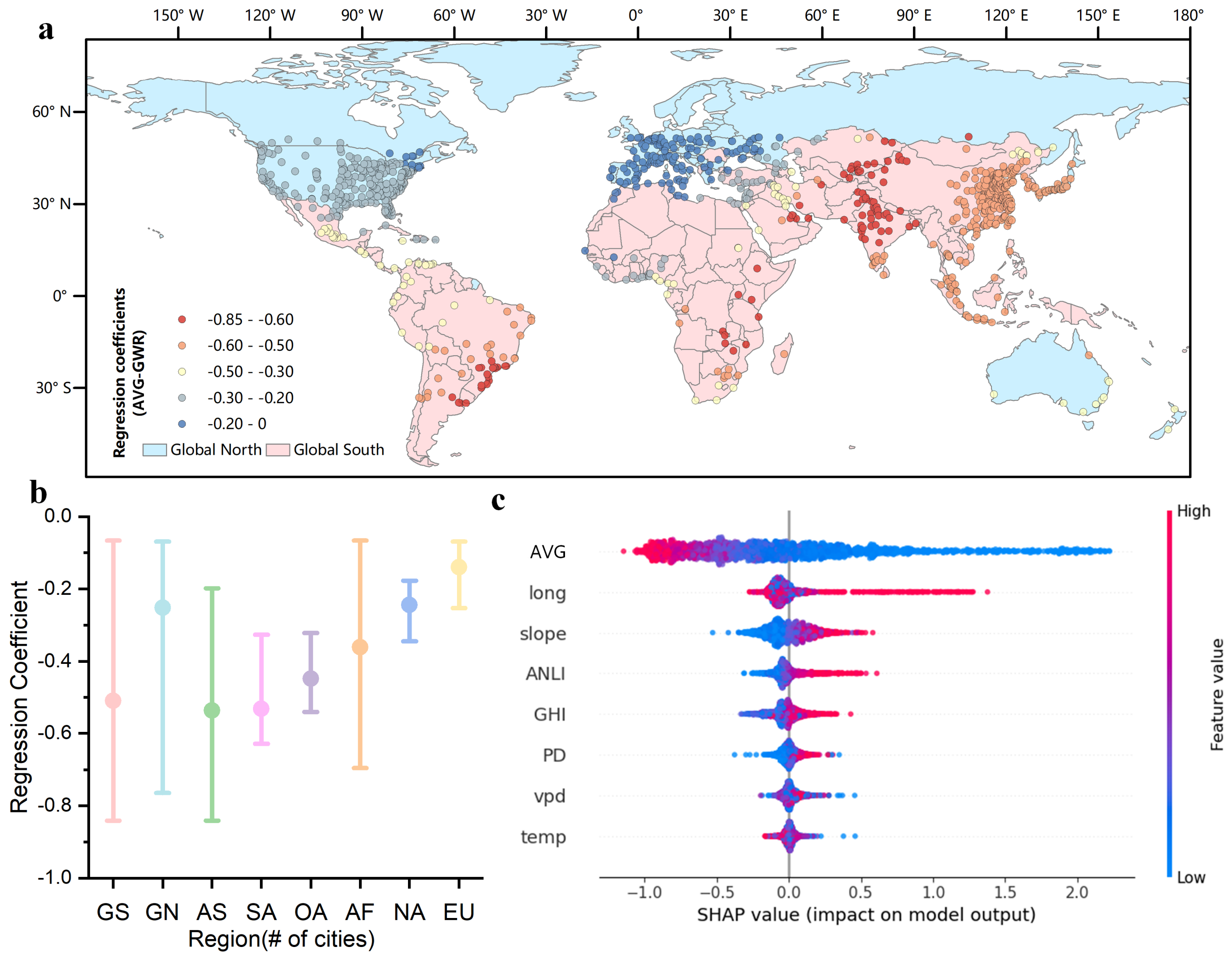

Figure 6. Distribution of regression coefficients between the GEI and the explanatory variable AVG. (a) Spatial distribution of regression coefficients for 965 cities worldwide. (b) Interval plot showing the average regression coefficients of the AVG for cities in the Global North and Global South, as well as various continents. Abbreviations: GS, Global South; GN, Global North; AS, Asia; SA, South America; OA, Australia/Oceania; AF, Africa; NA, North America; and EU, Europe. (c) Summary plot of feature importance ranking and positive and negative influence in SHAP.

Category	Covariate intercept	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Geographic	LNG	0.004***					0.003***
Topographic	slope		0.208***				0.241***
Socio-economic	PD			0.010***			0.005***
	ANLI			0.050***			0.024***
Climatic	TEMP				0.048***		0.105***
	VPD				1.707***		1.291***
	GHI				0.795***		0.941***
Landscape	AVG					0.307***	0.294***
Adjusted R^2		5.8%	12.9%	34.1%	41.8%	45.4%	67.9%

Note: *** p-value $<$ 0.0001, ** p-value $<$ 0.001, and * p-value $<$ 0.05.

Table 3. Summary of ordinary least squares regression results for multiple models.

respond to smaller and consistently negative Shapley values, implying a stronger negative contribution (underestimation) to the GEI. Conversely, bluer colors represent lower AVG values, where the Shapley values gradually increase from negative to positive, indicating a shift from negative (underestimation) to positive (overestimation) contributions to the inequality index. In contrast, LNG, slope, ANLI, and PD exhibit the opposite trend: higher variable values are associated with larger Shapley values, suggesting an increasing positive contribution to GEI.

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Geographically weighted regression analysis further revealed that the AVG consistently exhibited a negative regression coefficient with the green exposure inequality, and its effect varied spatially. Higher AVG typically reflects greater total greenery and more widespread spatial distribution. In this case, residents, regardless of socioeconomic status, tend to have access to more green space resources, thereby reducing disparities in green space accessibility. The strongest negative effect occurred in South Asia and southeastern South America, whereas the effect was weakest in central North America and Europe (Figure 6a). Statistical comparisons revealed that cities in the Global South exhibited significantly higher absolute regression values (0.51) than those in the Global North (0.25). Furthermore, cities in Asia, South America, and Australia/Oceania exhibited a stronger correlation between the AVG and GEI (Figure 6b), suggesting that increasing the vertical greenery in these regions could effectively reduce the exposure inequality, making this a key policy target.

4. Conclusion

Overall, our study finds significant variations in both the amount of greenery and the level of residential exposure to vertical green space across global cities. This finding provides important insights for prioritizing green management and planning and has far-reaching implications for achieving the global sustainable development goals.

First, this research helps identify hotspots for vulnerable green spaces worldwide, particularly in regions with limited and unevenly distributed green space, such as Africa. The average vertical greenery in Africa is only about one-sixth that of North America, with exposure levels approximately one-seventh. The green exposure inequality index in Africa is roughly twice that of North America, indicating more uneven access to green space resources. These findings offer strategic directions for policymakers and planners to improve green space provision in these areas.

Second, by constructing a population-weighted residential green exposure index, this study reveals the supply-demand relationship between vertical green space and urban populations. Compared to traditional two-dimensional green coverage, the inclusion of vertical greenery allows for a more accurate reflection of differences in green space quality, providing a new perspective on understanding residents' actual green exposure levels and their inequality.

Third, our research shows that the supply of green space is a key driver in explaining urban green exposure inequality, with a stronger impact in regions such as Eastern South America and Southern Asia. This suggests that these areas should prioritize increasing the quantity of green space. Policymakers, urban planners, and landscape designers must collaborate to ensure sustainable and equitable urban green development by increasing the supply of green space in appropriate locations.

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