

Persistent disparities in urban tree exposure across global demographics

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GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- We assess global disparities in urban tree exposure across demographic groups.
- We reveal a worldwide increase in overall tree exposure, regardless of city characteristics or location.
- We highlight that vulnerable populations consistently experience lower tree exposure than advantaged ones.
- These persistent inequities hinder progress toward Sustainable Development Goal 11.
- Our findings highlight the urgent need to embed environmental justice in future urban greening.

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Urban greenspaces provide various benefits for human well-being. Despite the overall improvement in greenspace exposure in the 21st century, it remains unclear whether the distribution and improvement of greenspaces, particularly urban trees, are equitable across population demographics and regions. Here, we quantified disparities in urban tree exposure across various population groups and age cohorts in 1,057 cities globally over a 15-year period (2000–2015). Our analysis revealed persistent and deepening disparities in tree exposure, with cities identified as the least or most exposed in 2000 largely remaining unchanged until 2015, indicating a lack of progress in equitable greening. Notably, the disparity between regions with higher and lower tree exposure widened from 2.7% to 5.9%, in contrast to the nearly doubling of the global average urban tree exposure during the same timeframe. Sex-based differences in exposure are minimal; however, age-related disparities are significant, with older populations experiencing the most exposure and youths the least. This trend intensified over time, while exacerbating exposure disparities and disadvantaging younger demographics. Our findings illuminate challenges in attaining Sustainable Development Goal 11, particularly the aim of universal access to green and public spaces for women, children, and older persons. These insights underscore the need for nuanced urban greening policies that not only expand green cover but also address persistent disparities and prioritize the needs of socially vulnerable subpopulations.

INTRODUCTION

Cities worldwide have launched ambitious tree-planting initiatives to combat climate crises and build sustainable communities.^{1,2} Consequently, exposure to urban greenspaces has improved globally during the 21st century.³ This improvement is associated with various health benefits including reduced risks of heat exhaustion, stroke, respiratory problems, and cardiovascular diseases; improved mental health status, including reduced stress and anxiety; increased cognitive functioning and attention restoration; and other psychological well-being.^{4,5} Based on individual baseline years or limited numbers of sampled cities, previous studies reveal substantial disparities in greenspace coverage, accessibility, and exposure across population and regions.^{6,7} For instance, urban neighborhoods with lower socioeconomic status often have significantly less tree canopy compared to wealthier districts—a pattern consistently observed in North American cities.^{8,9} On a global scale, cities in the Global South generally offer less greenspace per resident compared to cities in the Global North.^{6,10} Despite these findings, it remains unclear whether these disparities persist over time, particularly given the varying economic status and urbanization levels. Furthermore, it is unknown whether the observed improvements in greenspace exposure mitigated the severe greenspace disparities across different locations and population demographics.

Addressing greenspace disparities and other forms of environmental injustice are among the top priorities in today's policy arenas.^{11,12} The United

Nations (UN) specifies in Sustainable Development Goal (SDG) 11.7 aiming to “provide universal access to safe, inclusive and accessible greenspace, in particular for women and children, older persons and persons with disabilities”.¹³ Socially vulnerable groups, such as women and sensitive age groups, are often at a higher risk of health issues due to environmental injustices. They are more vulnerable to environmental hazards due to factors such as physical conditions (e.g., small body mass to surface area ratios and limited mobility), health status (e.g., predispositions or pre-existing illnesses), and social norms (e.g., living alone and being confined to essential household production).^{14,15} Conversely, these subpopulations often benefit more from greenspace exposure than their male and adult counterparts through pathways that reduce harm (e.g., exposure to extreme heat and air pollution), restore capacities (e.g., decrease in anxiety and depression and improvement in cognitive and attention functioning), and build capacities (e.g., increase in physical activity and enhancement of the immune system).^{16,17} To design inclusive and equitable policies that address greenspace disparities, it is necessary to examine the differential exposure of various population demographics, especially socially vulnerable groups.

Exposure differentials in greenspaces can be represented as absolute or relative disparities, with the former expressed as absolute differences between population subgroups or locations and the latter represented as proportional differences or rank changes.¹⁸ Previous environmental justice studies typically emphasize on quantifying the absolute differences while paying less attentions to relative changes in environmental burdens or amenities.^{6,19} The changes for absolute and relative disparities between two subpopulations could move in opposite directions, as the increase in absolute disparity may not be large enough to allow the increase in relative one.²⁰ As such, focusing on either one would provide an incomplete picture about exposure differentials.²¹ It is unknown whether locations/subpopulations that were historically the least (or most) exposed remain so, nor can the persistence or reversal of relative disparities be inferred based solely on absolute disparities. Understanding both absolute and relative disparities and their differences could provide targeted environmental strategies to improve overall greenspace exposure levels and reduce environmental injustice.^{18,22}

This study examined urban tree exposure disparities in the general population and subgroups across 1,057 global cities (based on urban built-up areas) of varying economic levels and urbanized extents between 2000 and 2015. We focused on urban trees because they are typically more effective at reducing environmental hazards than grass, shrubs, or other forms of greenspace. They are often viewed as essential components of high-quality natural spaces.^{1,23} We consider women, youth (including infants, children, and adolescents), and older persons as the three major subgroups, as they tend to be more vulnerable than their male and adult counterparts, as explicitly emphasized in SDG 11.7.¹³ We utilized and adapted the previously developed human–greenspace demand–supply framework^{6,24} that captures the spatial interaction between greenspaces and populations to quantify urban tree exposure for the general population and specific subpopulations. We

measured absolute or relative disparities in urban tree exposure using the magnitude of difference and the rank-rank comparison method,²¹ and by comparing socially vulnerable groups to their corresponding socially advantaged counterparts.²⁰ We identified a persistent and worsening pattern of urban tree exposure disparities from 2000 to 2015 in the general population. We found that older persons had the highest exposure to urban trees, followed by adults, with youths having the least exposure. Moreover, this age-related disparity intensified over time, exacerbating exposure disparities and disadvantaging younger demographics. Our findings highlight the challenges in attaining SDG 11 to provide universal access to green and public spaces for the general population and subpopulations and highlight the urgency of incorporating environmental justice principles into future urban greening campaigns and environmental policies.

MATERIALS AND METHODS

We combined spatially explicit population, tree canopy, and age and sex structure data with a human–greenspace demand–supply framework to quantify urban tree exposure in 1,057 global cities during 2000–2015. We focused on the 2000–2015 period to ensure the use of consistent and comparable global datasets, enabling reliable cross-regional analysis of urban greenspace dynamics over time. We calculated the absolute and relative disparities in urban tree exposure for the general population and its subgroups. We compared disparities across cities of varying economic levels, cities of different sizes, urban core areas, and newly urbanized areas. Calculations, statistical analyses, and visualization were conducted using Google Earth Engine and R software (version 4.1.1). All the statistical analyses were conducted at a significance level of 5%.

Study extent

We selected our candidate cities (or continuous urban built-up areas) by size, with a geographic area greater than 50 km² based on the 2000 Global Urban Boundary (GUBs) product.²⁵ We define an urban area (based on impervious surface area) as an urban core area in 2000. Assuming that urban land expanded during 2000–2015, we determined newly urbanized areas as the difference in GUBs between 2015 and 2000. We used the 2015 GUBs in our main analysis and conducted separate analyses for the urban core and urban areas. The original 1,161 continuous urban built-up areas in 2000 (with areas greater than 50 km²) expanded and merged, leading to 1057 continuous urban built-up areas in 2015. This is the focus of the study in the main analysis. Based on the 2015 GUBs, we classified all global cities into four groups, including 65 meta-cities (area ≥ 1,000 km²), 84 large cities (area ≥ 500 km²), 557 medium cities (area ≥ 100 km²), and 351 small cities (area < 100 km²). Regarding the geographic distribution, there were 375 in North America, 64 in South America, 221 in Europe, 69 in Africa, 315 in Asia, and 13 in Oceania.

Urban tree canopy data

We used the global 30-m resolution Landsat Vegetation Continuous Fields (VCF) tree cover product (TCC) (Version 4),²⁶ which estimates the percentage of each 30-m pixel covered by woody vegetation taller than 5 m in height. The dataset was derived by rescaling a 250-m MODIS VCF tree cover layer using all bands of Landsat 5 Thematic Mapper (TM) or Landsat 7 Enhanced Thematic Mapper Plus (ETM+).²⁶ The TCC products from 2000, 2005, 2010, and 2015 were used in our study. Although there is evidence that 30-m resolution cannot capture small-sized vegetation patches in urban areas and may underestimate tree cover,²⁷ the continuous percentage TCC estimator in Landsat VCF alleviates this issue.²⁸ To evaluate the performance of the GFCC30TC data in urban areas, we employed the statistical design-based samples and response data from photo-interpretation of high-resolution aerial images in Google Earth. Our assessment revealed that the GFCC30TC data underestimated tree cover by of 3.0% in 2015 and 3.6% in 2000.

Population and sociodemographic data

We used WorldPop datasets to quantify human population distributions. WorldPop datasets provide annual estimates of the population counts residing in each 100-m grid square and their age/gender structures from 2000 to 2020. The dataset was derived using a random forest regression tree-based model and a global database of administrative unit-based census.²⁹ The

WorldPop age/sex structure proportion datasets were organized into male/female and 5-year age classes (plus a < 1-year class). In summary, there were 36 layers for combinations of age and sex groups. We aggregated them to produce the final five years used in our analysis: female, male, youth (0–19 years), adult (20–64 years), and older persons (65 years or above).

Economic data

We collected gross domestic product (GDP) per capita data for each country from the World Bank for 2015. We examine 122 countries with available GDP data, including 40 countries in the Global North and 82 in the Global South. The Global North and South are typically defined based on socioeconomic and political characteristics. We obtained a list of countries in the Global North and South from the UN Development Program.³⁰ We also used the World Bank's economic development categories and classified the countries into three economic categories: High income (41 countries), middle income (62 countries), and low income (19 countries). We statistically compared urban tree exposure and disparities among the different categories.

Population-weighted tree exposure framework

In this study, we adopted a previously developed population-weighted greenspace exposure model^{24,31} in our study. This framework can capture the spatial interactions between trees and people by incorporating spatially explicit tree canopy coverage and population data. The basic assumption of this framework is that a higher population density indicates a higher probability of greenspace visits. Therefore, proportionately higher weights should be assigned to locations with high population densities. The framework is expressed as follows:

$$TE^d = \frac{\sum_{i=1}^N P_i \times TC_i^d}{\sum_{i=1}^N P_i} \quad (1)$$

where P_i indicates the population in grid cell i , TC_i^d represents the fractional tree canopy cover in grid cell i that considers both the focal grid and the surrounding tree environment in nearby neighborhoods with a buffer distance of d (1-km used in this study), N is the total number of cells in a city, and TE^d is the population-weighted tree exposure for a city. We also employed the same framework to calculate the population-weighted tree exposure for specific subpopulations. Specifically, we calculated tree exposure for the general population, including men, women, youths, adults, and older persons. To calculate tree exposure for older persons, we changed P_i from the general population density to the proportion of older persons in grid cell i . To select a buffer distance, a previous study conducted a sensitivity analysis by varying the distance from 500 m to 1,500 m and found negligible differences among greenspace exposure.⁶ Additionally, a 1-km radius is equivalent to a 10–15 min walking distance from home (varying based on age and speed). Previous studies have frequently used it to evaluate physical activity at the neighborhood level.^{32,33} Therefore, d was set to 1-km for this study.

Urban tree exposure differentials

We calculated urban tree exposure differentials using both absolute and relative disparities. The absolute disparity shows the magnitude of the difference between locations, years, and subgroups of the population and is typically calculated by subtracting values for one group from another. Relative disparity displays the relative difference among locations, years, and subgroups of the population and is typically scale-invariant and unitless.²⁰ For this study, we used rank-rank comparisons^{21,34} to represent the relative disparity. We first measured the percentile of cities based on their positions in the distribution of tree exposure, and then ranked cities based on their percentile values. We repeated the process for 2000 and 2015:

$$R_{i,2000} = \text{Rank}(TE_{i,2000}) \quad (2)$$

$$R_{i,2015} = \text{Rank}(TE_{i,2015}) \quad (3)$$

where $TE_{i,\text{year}}$ denotes city i 's percentile values based on its tree exposure value, Rank indicates the function that ranks a city based on the distribution of tree exposure, and $R_{i,\text{year}}$ denotes city i 's ranking based on its percentile

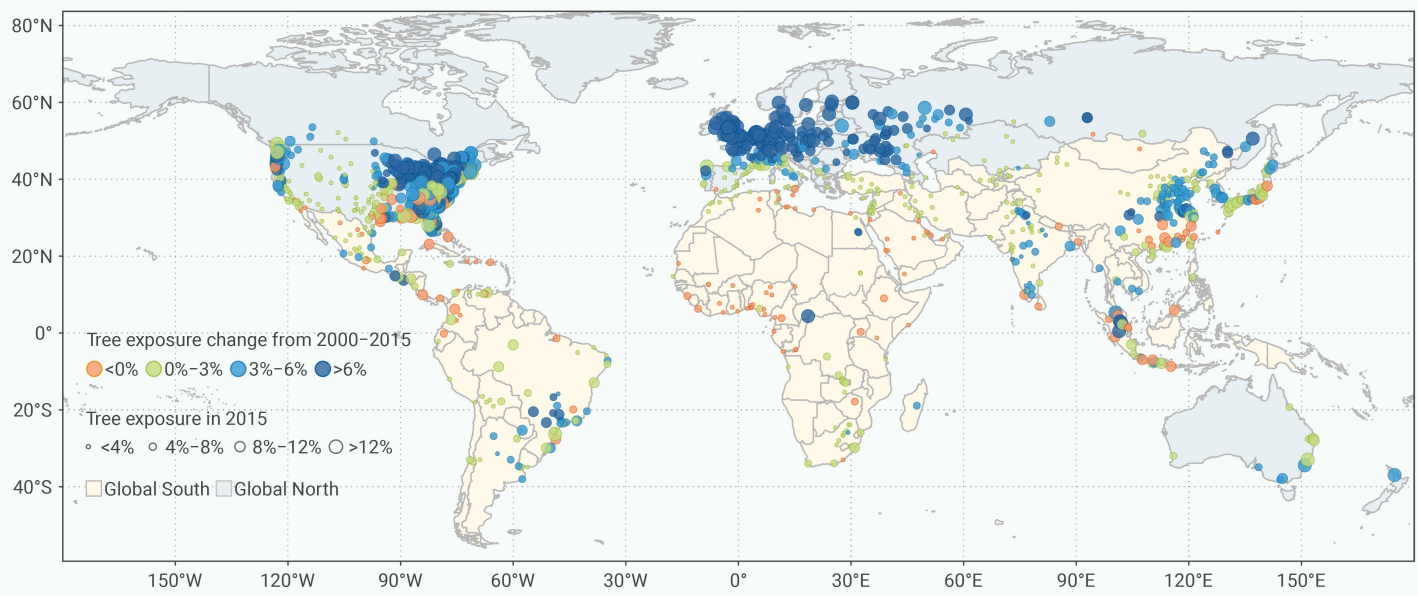


Figure 1. Global distribution of the magnitude change in urban tree exposure between 2000 and 2015 Blue indicates cities where the tree exposure has increased over time, while brown indicates cities where the tree exposure has declined over time. The circle size represents each city's urban tree exposure level in 2015.

value. We then visualized the relative disparity by employing the non-parametric binned scatter plot of the cities' percentile ranks in 2000 and 2015, which plots the mean cities' percentile rank in 2015 within their percentile rank bin in 2000. The process can be expressed as the conditional expectation of cities' rank in 2015 given their corresponding rank p in 2000: $E[R_{i,2015} | R_{i,2000} = p]$. Last, we quantified the relative disparity by calculating rank-rank correlation coefficient between the mean percentile rank of cities in 2015 and their corresponding percentile rank bin in 2000. The rank-rank comparison method has several statistical advantages, such as scale invariance and insensitivity to large differences (or outliers) from the mean.³⁴

For the changes in urban tree exposure differentials across different economic levels, we conducted univariate linear regressions by employing the magnitude change in tree exposure from 2000 to 2015 (absolute change) or percentage rank changes (relative change) as a dependent variable, and GDP per capita as an explanatory variable. In addition, we performed non-parametric Wilcoxon tests to compare pairwise differences in changes in urban tree exposure from 2000 to 2015 for the low-, middle-, and high-income countries. For the disparities among subgroups of the population, we treated males and adult (20–64 years) as socially advantaged groups and, hence, as reference groups to derive our absolute and relative disparities for women, youth, and older persons. For instance, absolute disparity for older persons was calculated by subtracting the three exposure values of older persons from those of adults. Relative disparity was calculated as the ratio of the two groups.¹⁹ We then compared the absolute and relative disparities for different groups of subpopulations across different economic levels, urban sizes, urban core areas, and newly urbanized areas.

RESULTS

Absolute disparities in urban tree exposure

By integrating tree canopy cover (TCC) and population density data (see more details in Methods), we calculated population-weighted TCC exposure (hereafter referred to as "TCC exposure"). It quantifies the average TCC percentage within nearby living environments, with 0% indicating no TCC exposure and 100% indicating total TCC exposure. In the 1057 cities we examined, we found that the average exposure to TCC was 8.4% in 2015, an 80% increase over TCC exposure (4.6%) in 2000. Increased TCC exposure is a worldwide phenomenon, with 938 (88.7%) of the examined cities experiencing an increase in TCC exposure (located above the 1:1 diagonal line) (Figure 2). The cities that experienced TCC exposure gains were mainly clustered in Europe, the United States, Australia, northern China, and southern Brazil. In contrast, a decrease in TCC exposure was observed in cities mainly located in Africa, Central America, and Southeast Asia (Figure 1).

When aggregated at the continental level (Figure 2 & Table 1), cities in Europe experienced the fastest increase (average absolute difference: 7.5%) in TCC exposure from 2000 to 2015, followed by cities in North America and Oceania, with average absolute differences of 3.7% and 2.8%, respectively. In contrast, cities in Asia and South America experienced a moderate absolute increase (around 2.2–2.4%). Meanwhile, African cities witnessed a net loss in TCC exposure, with an average absolute difference of -0.3% from 2000 to 2015. These differences in changes in TCC exposure, combined with the original high/low levels of TCC exposure in global northern and southern cities, exacerbated the disparities between global northern and southern cities, with the average TCC exposure difference increasing from 2.7% in 2000 to 5.9% in 2015. Moreover, the average TCC exposure (4.9%) in Global South cities in 2015 was even lower than that of Global North cities in 2000 (5.7%), indicating that TCC exposure in the former lagged far behind that of the latter. As expected, the absolute change in TCC exposure was closely related to economic level (Figure 2).

When examining individual cities, the disparities and changes in urban tree exposure patterns remained similar. All six cities demonstrated increased TCC exposure (Figure 3). London, England, experienced the fastest growth in TCC exposure among the 6 cities, increasing from 4.61% to 14.14% from 2000 to 2015. The other five cities exhibited a modest increase in TCC exposure. TCC exposure in three Global North cities in 2000 (e.g., New York City, United States; London, England; Sydney, Australia) was higher or of a similar magnitude as that in Global South cities in 2015 (e.g., Shanghai, China; Johannesburg, South Africa, and San Paolo, Brazil). When building a linear regression between the change of tree exposure and Gross domestic product (GDP) per capita, the slope and coefficient of determination were 0.13 and 0.32, respectively, indicating that GDP per capita is a strong predictor of the tree exposure change. We also conducted nonparametric Wilcoxon tests to compare pairwise differences in changes in urban tree exposure among low-, middle-, and high-income countries. Statistical comparisons showed significant differences in tree exposure changes; high-income countries had the highest increase in tree exposure, followed by middle-income countries, with low-income countries having the least increase (Figure S1A). We show the main results for all urban areas; however, when conducting the analyses separately for urban core areas and newly urbanized areas, similar patterns were observed (Figures S2–S3).

Relative disparities in urban tree exposure

To examine the relative disparities in TCC exposure, we assigned each city a percentile of the distribution and visualized the TCC exposure percentile rank in 2000 against the average corresponding TCC exposure percentile

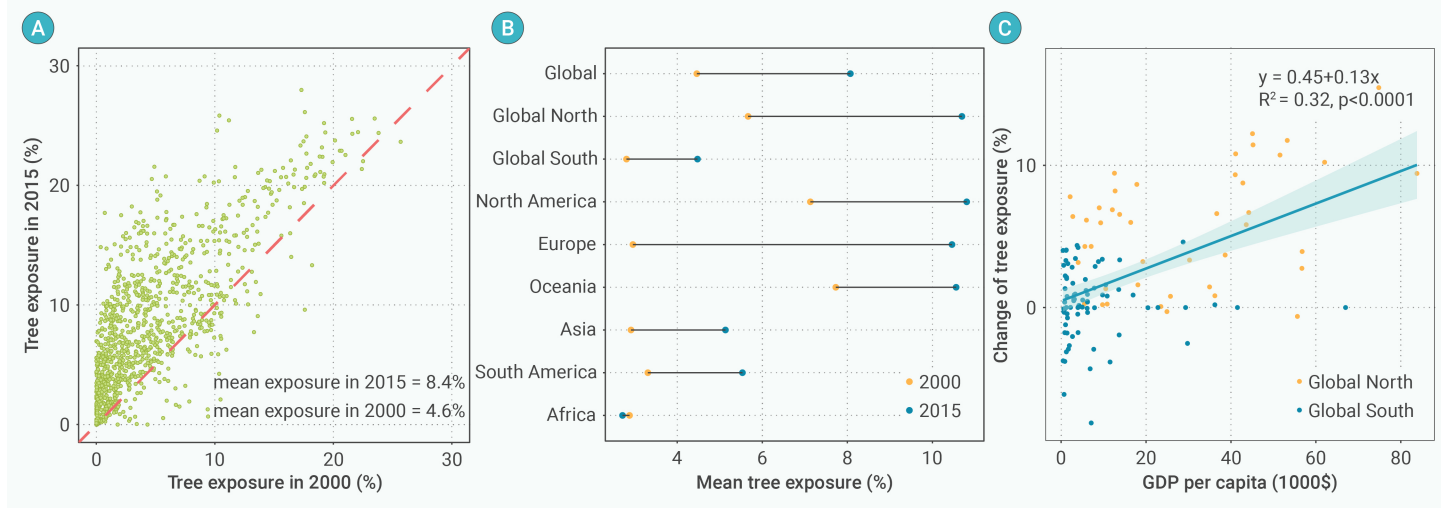


Figure 2. Summary of absolute urban tree exposure disparities in 1,057 global cities between 2000 and 2015 (A) Relationship between urban tree exposure magnitude in 2000 and in 2015. The red line is the 1:1 diagonal line. It indicates no change in magnitude between 2000 and 2015, while the deviations from the line indicate an increase (points above the line) or decrease (points below the line) in urban tree exposure magnitude between years. (B) Magnitude changes of urban tree exposure between 2000 and 2015 across different continents. (C) Univariate linear regression between the magnitude changes of urban tree exposure from 2000–2015 (the y-axis) and the economic development level (GDP per capita in the x-axis). The linear fitting and its 95% confidence interval are represented as the dark blue line and the shallow blue region, respectively. GDP is short for Gross domestic product.

Table 1. Mean and standard deviation of city-level urban tree exposure and its absolute and relative changes between 2000 and 2015. The absolute change is indicated as magnitude change, while the relative change is shown as percentage rank change.

Continent (# of cities)	Urban tree exposure in 2015	Urban tree exposure change between 2000–2015	Percentage rank changes of exposure between 2000–2015
Africa (69)	3.2± 3.7%	−0.3 ± 3.1%	−25.3 ± 23.2%
Asia (315)	5.5± 3.6%	2.4± 2.7%	−3.6 ± 18.8%
Oceania (13)	10.6± 4.4%	2.8± 1.7%	−6.9 ± 11.0%
Europe (221)	10.5± 4.9%	7.5± 4.0%	18.2 ± 20.6%
South America (64)	5.5± 3.0%	2.2± 2.3%	−8.4 ± 19.3%
North America (375)	10.9± 6.6%	3.7± 3.0%	−1.4 ± 14.1%
Global South (425)	4.9± 3.6%	1.8± 2.9%	−8.1 ± 21.3%
Global North (632)	10.8± 5.9%	5.1± 3.8%	5.4 ± 19.0%
Global (1057)	8.4± 5.8%	3.8± 3.8%	—

rank in 2015 (Figure 5). We observed a widespread preservation of percentile rank across the distribution space, with most percentile pairs lying near the 1:1 diagonal line and an estimated rank-rank correlation coefficient of 0.73 (p -value < 0.01). These results indicate that the city's TCC exposure percentile rank in 2000 was similar to its TCC exposure rank in 2015. In other words, on average, the least (or most) TCC exposure cities in 2000 were still the least (or most) in 2015, and vice versa. Despite this general pattern of rank preservation, we also observed a moderate median reversion, with cities below (or above) the median TCC exposure in 2000 experiencing less (or greater) relative TCC exposure in 2015 (Figure 5). Overall, the relative disparities persisted in most cities worldwide from 2000 to 2015.

When examining the geographic distribution of the changes in the TCC exposure percentile rank over time (Figure 4), the primary message remained that the least (or most) TCC exposure cities in 2000 were still the least (or most) in 2015. However, we also observed regional variations in the percentile rank change, with most cities in Europe becoming relatively greener, whereas cities in Africa and Southeast Asia became less green. Looking at the aggregated pattern at the continental level (Figure 5), on average, European cities experienced the largest increase in rank and African cities experienced the largest decrease in rank. The remaining areas showed modest changes in rank. Consequently, there was a modest increase in the average rank of Global North cities and a modest decrease in Global South cities. Similar to the absolute change in TCC exposure (Figure 5), the change

in percentile rank was correlated with GDP per capita, with the slope and coefficient of determination being 0.5 and 0.16, respectively.

Statistical comparisons, based on non-parametric Wilcoxon tests, showed that high-income countries experienced a percentage rank increase and low-income countries witnessed a decrease (Figure S1B). The analyses for all urban areas, urban core areas, and newly urbanized areas displayed similar patterns (Figures S4–S5).

Disparities among women, youth, and older persons

We defined older persons as those aged 65 years or older and youth were defined as people under 20 years. We treated adult (20–64 years) and males as socially advantaged groups and, hence, they served as reference groups to derive absolute and relative disparities for women, youth, and older persons. For the gender difference between 2000 and 2015, both absolute and relative disparities (referencing TCC exposure from women to men) were negligible across cities of different economic levels, cities of varying sizes, and urban cores and urban areas (Figure 6).

For older persons (Figure 6), the absolute disparities in TCC exposure (defined as the differences between older persons and adults) improved from 2000 to 2015, regardless of economic level, city size, or urbanization stage. However, there were some variations in the disparity changes from 2000 to 2015. The largest improvements were observed in large- (0.88%), medium- (0.87%), low-income (0.77%), and middle-income (0.68%) areas, whereas the

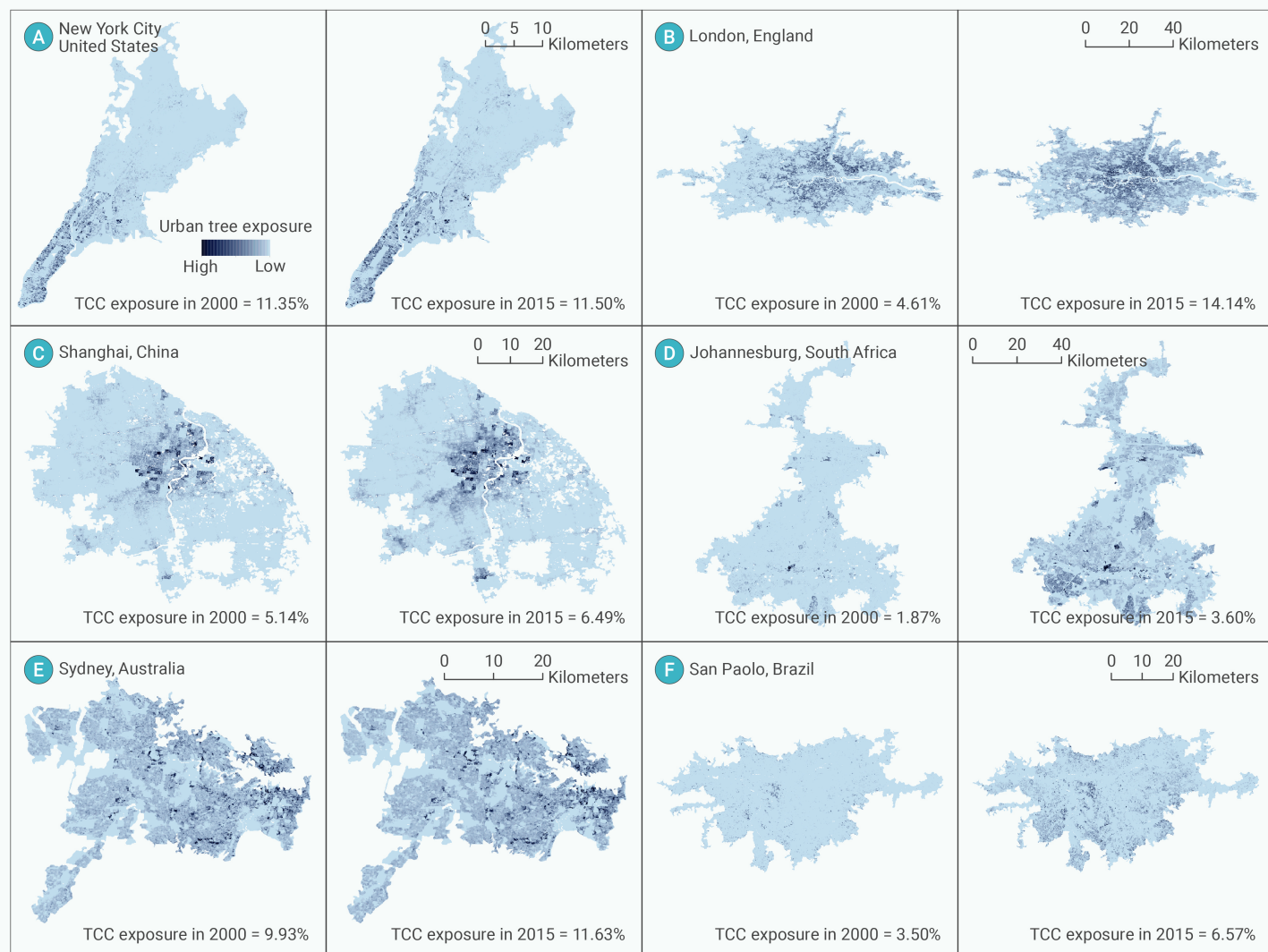


Figure 3. City-level comparison of urban tree exposure between 2000 and 2015 for six metropolitan cities (A) New York City, United States; (B) London, England; (C) Shanghai, China; (D) Johannesburg, South Africa; (E) Sydney, Australia; and (F) San Paolo, Brazil. The light green indicates less tree exposure and dark green indicates more tree exposure. City-level urban tree exposure is specified inside each panel. The demonstrated cities were selected to be representative and covered diverse contexts, with 3 in Global North, 3 in Global South, and 1 in each continent. Note that the city boundary is based on the continuous urban built-up areas from the 2015 global urban boundary product, and therefore may not be coincident with the administrative boundary for each city. For instance, New York City mainly consists of Manhattan, the Bronx, and the adjacent urban areas, and does not include Brooklyn, the Queens, and Staten Island that are separated by the East River.

improvements in mega-cities (0.25%) and high-income areas (0.24%) were relatively modest. The relative disparities in TCC exposure (ratio of older people to adults) displayed similar patterns. In contrast, the disparities for the youth (referencing TCC exposure for youth to adults) worsened from 2000 to 2015, with the exception of megacities, where the absolute disparity increased by 0.23%. The changes in absolute disparities were -0.19% for low-income areas, -0.39% for middle-income areas, -0.14% for medium cities, and -0.25% for small cities, while the rest showed negligible changes during 2000-2015. The relative disparities for youth showed a pattern similar to the absolute disparities. Overall, older persons had greater TCC exposure than adults, and the advantages increased over time. Youths showed less TCC exposure than adults, and the disadvantages increased over time.

DISCUSSION

Our study investigated disparities in urban tree canopy cover (TCC) exposure across the general population as well as specific age- and sex-based subpopulations in 1,057 cities globally with varying economic statuses and degrees of urbanization from 2000 to 2015. We examined disparities in urban tree exposure across different demographic groups—a dimension that has been largely overlooked at the global scale. In particular, we focused on vulnerable populations such as the elderly, children, and women. Our findings contribute directly to Sustainable Development Goal 11—Sustainable Cities

and Communities—by providing globally comparable evidence on disparities in access to urban greenspace. In particular, we address the SDG target of ensuring universal access to safe, inclusive and accessible green and public spaces, especially for women, children, and older persons.

We observed that increased exposure to urban trees is a global trend, with most cities in our study showing increasing TCC exposure. Nevertheless, disparities in TCC exposure not only persist, but also appear to widen over time, as indicated by consistent percentile rankings and an expanding gap in TCC exposure between cities. Without intervention, these disparities are likely to be exacerbated. Our research confirms significant urban tree inequities, supporting previous work that is limited to fewer cities,^{9,35} and emphasizes that a greener planet does not inherently ensure fairness.³⁶ The greater increase in TCC exposure in cities in the Global North can be attributed to greater investments in urban greening, more sophisticated urban planning, and greater public awareness and involvement in developed countries.³⁷⁻³⁹ Conversely, many cities in the Global South may face significant challenges in expanding urban tree coverage. These challenges include resource constraints—such as limited funding, technical capacity, or institutional support; informal urban growth, where rapid and often unplanned expansion outpaces formal planning and greening efforts; and high population density, which limits the availability of land for tree planting and the development of green infrastructure.^{40,41}

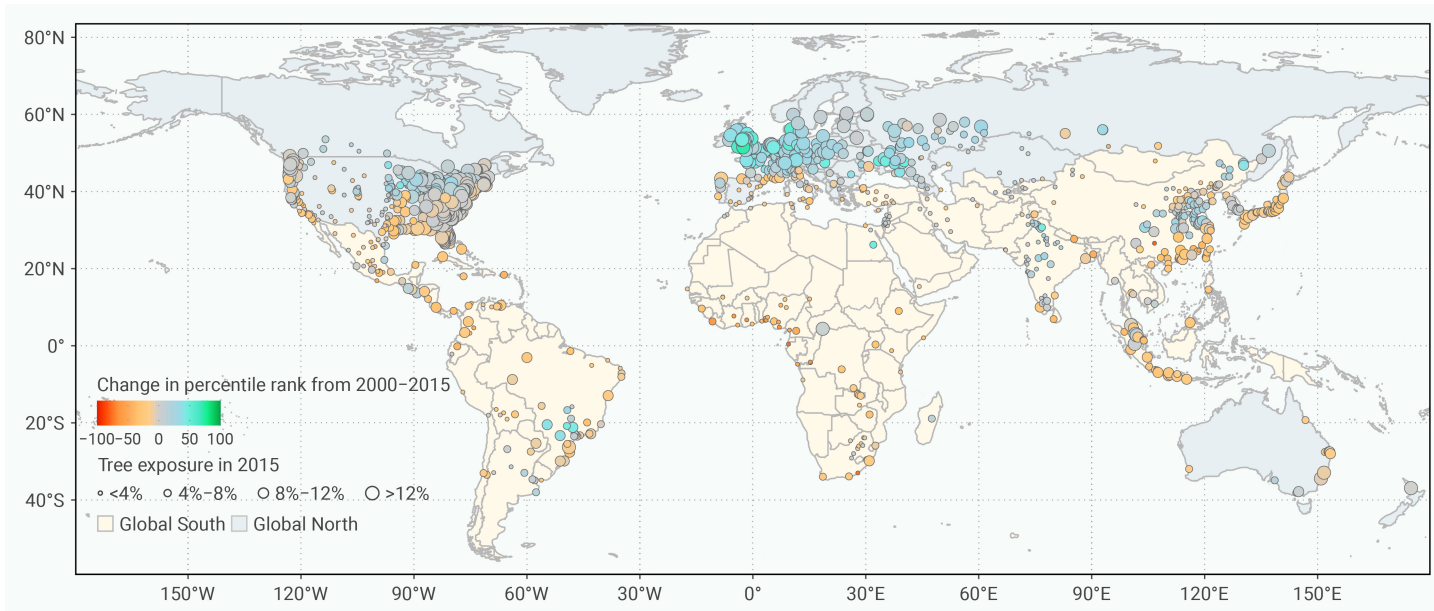


Figure 4. Global distribution of the rank change in urban tree exposure between 2000 and 2015 Green indicates cities where the rank has increased, while brown indicates cities where the rank has declined over time. The circle size represents each city's urban tree exposure level in 2015.

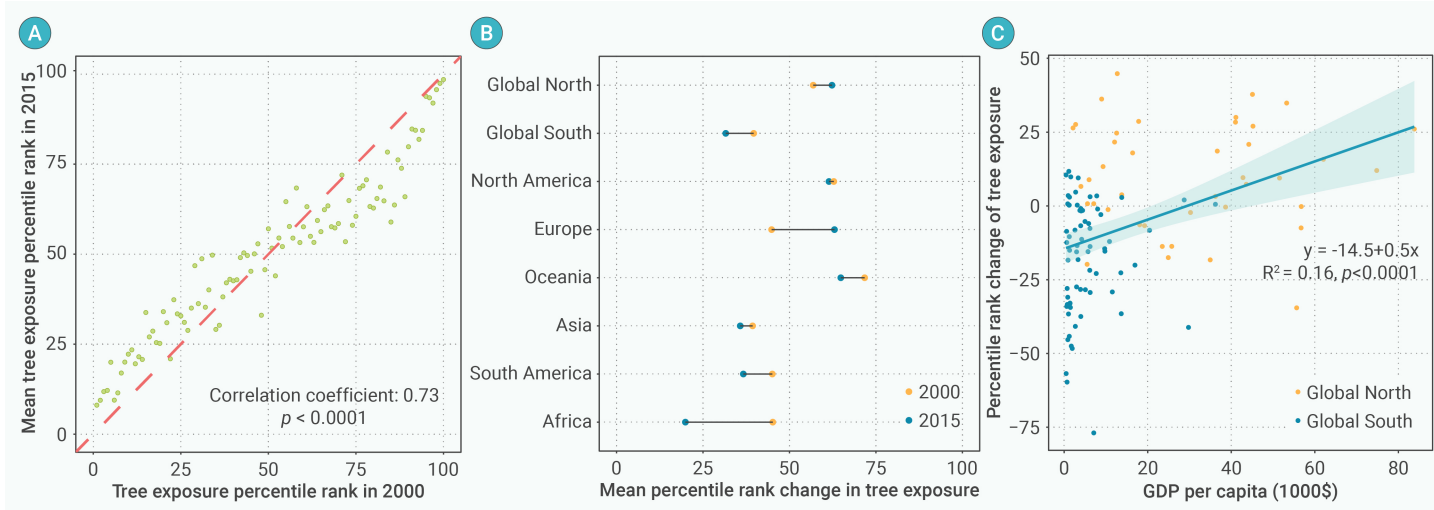


Figure 5. Summary of relative urban tree exposure disparities in 1,057 global cities between 2000 and 2015 (A) Relationship between urban tree exposure rank in 2000 and rank in 2015. The red line is the 1:1 diagonal line. The line indicates no change in rank between 2000 and 2015, while the deviations from the line indicate an increase (points above the line) or decrease (points below the line) in relative urban tree exposure between years. (B) Percentile rank changes of urban tree exposure between 2000 and 2015 across different continents. (C) Univariate linear regression between percentile rank changes of urban tree exposure from 2000–2015 (the y-axis) and the economic development level (GDP per capita in the x-axis). The linear fitting and its 95% confidence interval are represented as the dark blue line and the shallow blue region, respectively. GDP is short for Gross domestic product.

The widening gap in urban tree exposure poses a major challenge for sustainable development, reflecting a form of environmental injustice with cascading implications for social, climate, and health equity.^{6,42} Urban trees and greenspaces are increasingly recognized as critical contributors to multiple SDGs,⁴³ as highlighted in recent Intergovernmental Panel on Climate Change (IPCC) assessments. assessments—such as equitable tree planting programs or integrated heat mitigation strategies—to narrow exposure gaps and advance more just, inclusive, and climate-resilient urban futures.

Our analysis also sheds light on disparities in urban tree exposure among socially vulnerable subpopulations. We found that older persons had the highest exposure to urban trees, followed by adults, with youths having the least exposure. Moreover, this disparity increased between 2000 and 2015. A general increase in TCC exposure does not guarantee improved access for all subpopulations, which is influenced by various factors, including the spatial density and distribution of subpopulations, the proximity of people to tree coverage, and societal age demographics.^{44,45} Our work goes beyond prior studies that concentrated on the exposure of the general population to

greenspaces³⁶ by highlighting the need to target nature-based solutions to alleviate environmental injustice and social vulnerability. We argue that future planting initiatives should be more towards equity-centered to prioritizing tree planting in high-density residential areas with large populations of specific age groups, particularly in rapidly growing or hotter communities. This includes incorporating demographic data into urban greening plans to better align green infrastructure investments with the needs of age-specific populations; and designing age-inclusive green spaces near schools, elderly care centers, and residential zones where targeted age groups are concentrated. In addition, community engagement strategies, such as actively involving residents—especially from marginalized or underrepresented communities—in the planning, design, and stewardship of green infrastructure to ensure local relevance and long-term support, are crucial for the success of planting initiatives and the goal of addressing disparities.⁴⁶

Urban trees and greenspaces are increasingly being recognized as essential urban infrastructure that are critical for sustainable communities and human well-being, mainly through the pathways of providing ecosystem

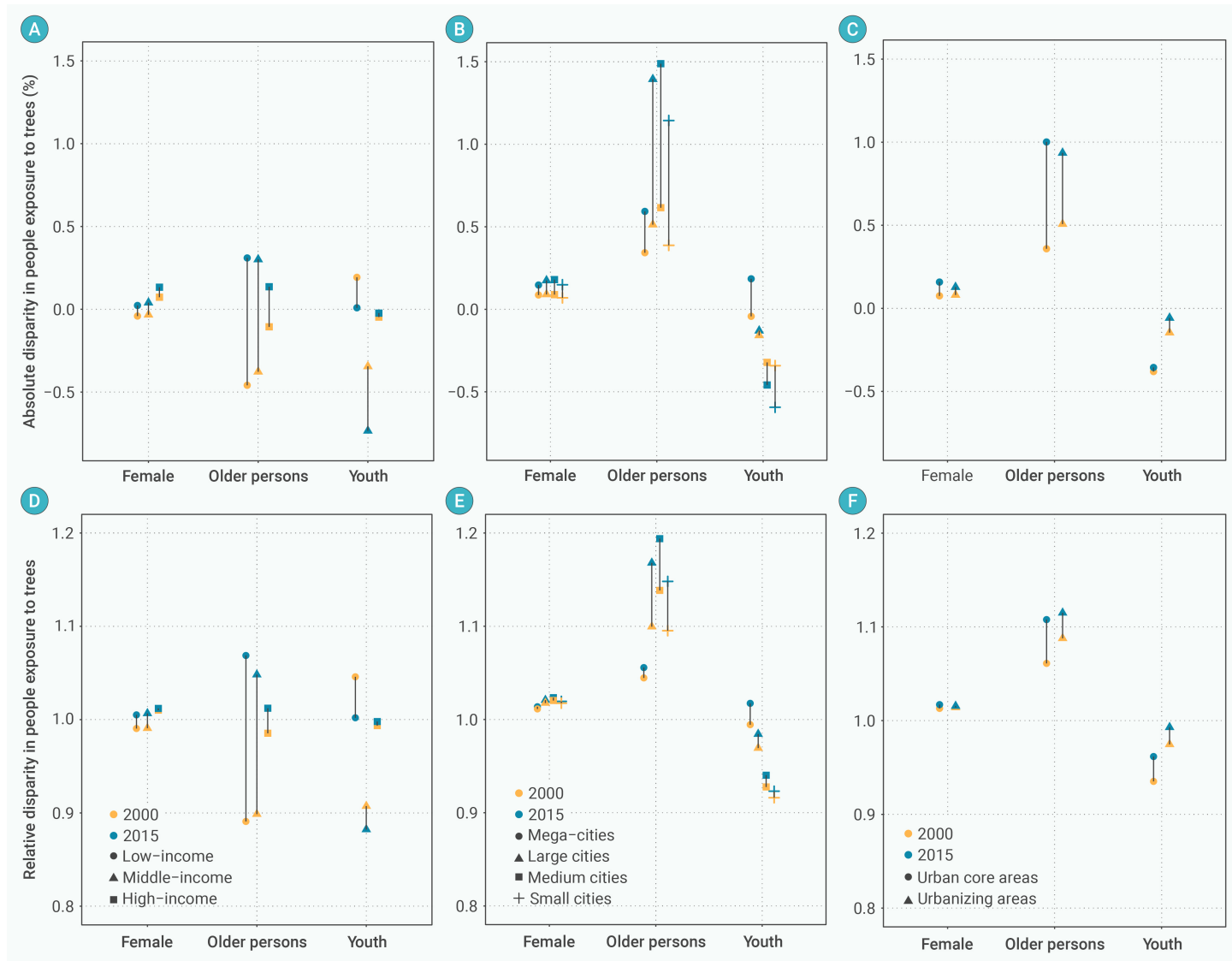


Figure 6. Absolute and relative disparities in urban tree exposure for women, youth, and older persons by referencing their male and adult counterparts for 2000 and 2015 The absolute (or relative) disparity was calculated as the difference (or ratio) between socially disadvantaged groups and their more advantaged counterparts. (A) Absolute urban tree exposure disparities for low-, middle-, and high-income areas. (B) Absolute urban tree exposure disparities for different city sizes. (C) Absolute urban tree exposure disparities for urban core and newly urbanizing areas. (D) Relative urban tree exposure disparities for low-income, middle-income, and high-income areas. (E) Relative urban tree exposure disparities for different city sizes. (F) Relative urban tree exposure disparities for urban core and newly urbanizing areas.

services (e.g., heat reduction, air pollutant removal, and water purification) and promoting healthy lifestyles (e.g., increase physical activities, and enhance social cohesion).^{16,47,48} Consequently, cities worldwide have launched ambitious tree-planting campaigns to increase tree coverage and exposure.¹ These efforts are evident across policy levels, from the global commitment of SDG 11.7, which pledges universal access to greenspace for urban residents,¹³ to the Great Green Wall for Cities Initiative, which calls for planting 500,000 ha of new urban forests across 90 cities in 30 African and Asian countries by 2030,⁴⁹ to local endeavors such as the One Million-Mu Plain Afforestation Project in Beijing, China, which aims to add more than 50 million trees within the city administrative boundary.⁵⁰ Importantly, unlike Global North cities that have relatively stable city boundaries and constructed city layouts, many Global South cities are still undergoing a process of rapid urbanization and urban renewal. It is projected that 90% of increased urban population between 2018 and 2050 will take place in Asia and Africa.⁵¹ The rapid urbanization presents an emerging opportunity for Global South cities to carry out greening initiatives to increase greenspace coverage and alter city layout to enhance greenspace exposure while reducing exposure disparities, but the challenges for these cities lie in how to design and manage greening initiatives to tackle multiple social and environmental objectives, especially taking into account the needs of vulnerable subpopulations.

Despite many urban greening initiatives strive to increase greenspace coverage and exposure, there is a growing concern that they do not adequately address environmental justice.⁵² Current urban greening initiatives often prioritize sustainability goals such as increasing overall tree canopy cover while paying less attention to addressing structural inequities.^{53,54} This is largely due to a lack of integration of distributional, procedural, and recognition justice in urban greening efforts, resulting in minimal engagement or representation from marginalized populations in the planning and execution of these initiatives.^{52,55} Distributional justice focuses on the final outcomes and spatial patterns of tree resources — essentially, who gets access to what, and where. In contrast, procedural inequity addresses the decision-making processes that result in these uneven distributions, often perpetuating or deepening existing disparities. Recognition justice adds a critical ethical and political dimension by calling for the acknowledgment and respect of diverse identities, cultures, and lived experiences. It emphasizes the importance of ensuring that marginalized groups are properly recognized and valued within both social and environmental contexts.^{56,57} If environmental justice is not explicitly considered, tree-planting programs may inadvertently widen environmental disparities by favoring more affluent communities.⁵⁸ Considering that a significant portion of urban trees are public assets and urban greening is typically led by government

entities with citizen involvement, it is crucial that these policies undergo rigorous equity scrutiny.⁵⁹ Our study highlights the need to assess the equity impacts of urban greening movements to ensure that future environmental policies incorporate environmental justice principles.

Although extensive, this study also had a few limitations. First, our findings should be interpreted in the context of the limitations of the data at hand. We used the 30-m resolution tree canopy data. Our independent assessment revealed that the dataset tended to underestimate tree canopy cover in urban areas (See the details in the Supplementary Information). This may be attributed to the limited capability of 30-m resolution data to detect fine-scale tree patches in heterogeneous urban environments where trees may be interspersed with built-up structures.⁶⁰ This limitation may lead to conservative estimates of urban tree exposure, especially in densely built areas with street trees or small green patches not fully captured at this resolution. While our results likely reflect lower-bound estimates of tree cover, the comparative and temporal patterns identified remain robust and meaningful for evaluating global disparities in urban tree exposure. Despite that the 30-m resolution tree canopy data are frequently employed for urban tree studies,^{3,28,52} future studies using higher-resolution datasets (e.g., Sentinel-2 or aerial imagery) could help refine these estimates and provide more valuable insights. Second, our analysis was constrained to the period from 2000 to 2015 owing to the availability of consistent global tree canopy cover data. While the most recent data exists,⁵¹ combining different datasets could lead to inconsistent findings. Future studies that consider longer temporal changes, both historical observations and future projections, may help reveal nuanced urban greening policies for effectively addressing environmental injustice. Third, we employed the static population dataset in the tree exposure studies. Despite that the practice is commonly employed in the environmental field (e.g., air pollution exposure, greenspace exposure),^{6,18} it overlooked the population dynamics that might modify urban residents' exposure to environmental amenities and harms.⁶¹ Incorporating population dynamics, with aid of the spatiotemporal big data and mobility data, could improve the environmental exposure estimates. Fourth, we focused on women, youth, and older persons without considering the urban tree exposure disparities for persons with disabilities, a group explicitly highlighted in SDG 11.7, among other vulnerable demographics. Income level, race/ethnicity, and other markers of social disadvantage (e.g., education, disability, housing status) are also critical factors that influence both access to environmental amenities and exposure to urban environmental burdens. The current study was constrained by the availability of globally harmonized sociodemographic datasets. A more thorough vulnerability assessment should consider a wider array of socioeconomic and demographic attributes individually and collectively, and examine how the attributes affect (in) ability of people or communities to reshape the comparative risks for vulnerable subpopulations and thus inform equitable strategies for environmental planning.⁵² Lastly, our analysis relies on previously developed population and tree canopy data, each subject to distinct sources of uncertainty. Understanding and quantifying these uncertainties is crucial for enhancing the reliability and interpretability of our findings. Future research could benefit from employing statistical techniques—such as Monte Carlo simulations or sensitivity analyses—to estimate, propagate, and integrate these uncertainties into exposure assessments.

Despite these limitations, our study provides a valuable global perspective on disparities in urban tree exposure, contributing to the broader discourse on SDG 11.7. By highlighting these disparities, we aim to inform more nuanced and equitable urban greening initiatives strategies that not only enhance access to urban greenery but also address the intertwined challenge of mitigating environmental injustices.

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AUTHOR CONTRIBUTIONS

J.L., M.C., and B.H. contributed to concept and design of the study. J.L. and Q.W. contributed to the data cleaning. J.L. contributed to the data analyses and drafted the manuscript. J.L. M.C., and B.H. participated in interpretation of the data. All authors contributed to the manuscript and approved the final version.

DECLARATION OF INTERESTS

Huadong Guo and Min Chen are Editorial Board members of The Innovation Geoscience and was blinded from reviewing or making final decisions on the manuscript. Peer review was handled independently of this member and their research group. The other authors declare no conflicts of interest.

DATA AND CODE AVAILABILITY

We obtained the global urban boundaries (GUBs) from the Star Cloud Data Service Platform (<https://data-starcloud.pcl.ac.cn/>), the Gross domestic product (GDP) per capita from the World Bank (<https://www.worldbank.org/en/home>), the population and age/sex structure proportion datasets are derived from the WorldPop (<https://www.worldpop.org/>), and the tree canopy cover data from the Google Earth Engine Platform (<https://earthengine.google.com/>). The code that support the findings of this study is available from the corresponding author upon reasonable request.

SUPPLEMENTAL INFORMATION

It can be found online at <https://doi.org/10.59717/j.xinn-geo.2026.100186>