

Background climate and socioeconomic conditions constrain global urban–rural contrasts in vegetation amount, subtype, and structure

Rohit Mukherjee

Pacific Northwest National Laboratory <https://orcid.org/0000-0002-8162-3298>

TC Chakraborty

tirthankar.chakraborty@pnnl.gov

Pacific Northwest National Laboratory <https://orcid.org/0000-0003-1338-3525>

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Title: Background climate and socioeconomic conditions constrain global urban–rural contrasts in vegetation amount, subtype, and structure

Authors: Rohit Mukherjee[†], TC Chakraborty^{†*}

Abstract

Urban vegetation provides critical ecosystem services, from microclimate regulation to biodiversity support. However, most large-scale assessments of urban vegetation rely on spectral ‘greenness’ indices that cannot resolve vegetation structure or composition. To address this, we quantify fine-scale structural and compositional vegetation traits, including leaf area index (LAI), tree height, and vegetation subtypes, across 83,102 cities and their rural surroundings by fusing millions of satellite images and satellite-derived products. Fewer than 10%, 24%, and 37% of cities exceed rural LAI, tree height, and tree cover fraction, respectively. These urban–rural contrasts in vegetation characteristics are modulated by background climate, with Arid cities showing weaker structural differences consistent with an ‘oasis effect’. Socioeconomic context, classified by comparing cities in the Global North versus Global South, further shapes these patterns. Our study demonstrates that urban-rural vegetation contrasts emerge from the combined influence of climatic constraints and divergent vegetation management practices globally.

[†] These authors contributed equally to this work.

Corresponding author: TC Chakraborty (tc.chakraborty@pnnl.gov)

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Teaser: Background climate and income modulate urban–rural gaps in local vegetation density, height, and composition.

Introduction

With over half the global population now living in cities (1, 2), urban vegetation is increasingly vital for promoting sustainable and equitable development (3–7). Urban green spaces moderate microclimate through evapotranspirative cooling and shading (8–10), regulate hydrology and stormwater runoff (4), improve air quality by mitigating pollution, support biodiversity (11), and contribute to physical and mental well-being of residents (12). Vegetation can also amplify risks through allergenic pollen, invasive species, wildfire exposure, storm-related hazards, and infrastructure damage (3, 13–16). Given this multifaceted influence on environmental quality and human life, a more nuanced understanding of urban vegetation is crucial.

Despite the importance of urban vegetation, our capacity to characterize it in ways that matter for ecological processes and societal outcomes remains limited at large scales. Most large scale assessments rely on spectral greenness indices like Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) (17–19), which are informative but cannot directly resolve vegetation structure and can be biased due to pixel mixing and differing canopy structures (11, 20–23). Process-based models rarely represent

urban vegetation or resolve subtypes and properties, and when included, it is commonly represented with simplified or uniform plant functional types that ignore key differences (24, 25). However, trees provide more cooling than grass (10, 26), along with various additional ecosystem services that are dependent on structure and function. More broadly, key structural attributes such as canopy height and leaf area index (LAI), largely determine evapotranspirative cooling and shading capacity, aboveground carbon stocks, and habitat heterogeneity, directly shaping ecosystem functioning (10, 26, 27).

Finally, commonly used remote sensing and modeling tools fail to isolate urban specific vegetation signals. Modeling studies estimate first-order urban vegetation impacts on the environment (25, 28), but overlook differences in vegetation structure and function between urban areas and their background climate. Likewise, satellite-derived estimates of critical processes and properties like evapotranspiration and LAI exclude urban areas (28–30). Yet, the urban-rural contrasts in vegetation are important for modulating various urban environmental processes, including local climate signals and energy, economic, and health outcomes (10, 31–33).

To address these gaps, we integrate multiple satellite-derived products and millions of satellite images to globally quantify vegetation in urban areas (for over 83,000 clusters) and their paired surroundings. First, we characterize vegetation amount, composition (trees, grasslands, croplands, shrubland), and structure (LAI and tree height), and test how urban–rural contrasts vary across socioeconomic (Global North versus South) and climatic (Köppen-Geiger (34) climate zones) contexts. This global synthesis resolves how cities differ from their local baselines in both vegetation composition and structural characteristics, revealing patterns jointly shaped by climatic constraints and human management. Together, these global analyses establish a baseline for evaluating urban ecosystem functioning and for improving models and policies that depend on a more accurate representation of urban vegetation.

Results

Urban vegetation cover and its urban-rural contrasts

Urbanization is associated with a near consistent modification of local vegetation cover, with cities typically showing lower vegetation fraction than their surroundings. The area-weighted mean urban vegetation fraction across all cities ($n=83,102$) is $\mu_w=0.38$, substantially lower than the $\mu_w=0.69$ in their surroundings (fig. S1A). This corresponds to an area weighted urban–rural difference (Δ_w) of -0.31 (table S1), with lower urban vegetation observed in 93.6% of all cities (fig. S1B). The local impact of urbanization is even more pronounced in the world's 1,000 largest cities (henceforth, major cities), where μ_w is 0.34 in urban 0.66 in their paired rural background, yielding a slightly wider difference (Fig. 1A–B; table S1). Among these major cities, only 4.3% are greener than their surroundings (Fig. 1B), suggesting that larger cities have disproportionately greater impacts on local vegetation. Nationally, urban vegetation is lower than surroundings in 96.4% of cases. Only four countries show higher urban vegetation (e.g., Mauritania +0.14, Norway +0.06, and Eritrea +0.03), whereas Burkina Faso (-0.5), Colombia (-0.49), and El Salvador (-0.48) display the least urban vegetation compared to their surroundings fig. S2A–B).

These global patterns are modulated by socioeconomic conditions and background climate.

Cities in the Global North are more vegetated ($\mu_w=0.46$ versus 0.31 for all cities, North $n=30,621$, South $n=49,720$ and $\mu_w=0.42$ versus 0.26 for major cities, North $n=419$, South $n=581$; Fig. 1B). However, across all cities, the proportion of cities with higher urban than rural vegetation is similar between regions (5.7% of all Global North cities versus 5.5% of all Global South cities; table S2). Among major cities, this diverges slightly, with 6% of Global North cities showing higher urban vegetation compared to only 1.8% of Global South cities. When considering all cities, the vegetation Δ_w is -0.27 for North cities but -0.35 for the cities in Global South. This gap between major cities within the Global North ($\Delta_w=-0.26$) and Global South ($\Delta_w=-0.38$) is similar.

Background climate more strongly structures these vegetation patterns (Fig. 1D; table S3). Urban vegetation fraction is highest in Continental climates ($\mu_w=0.49$, $n=15,084$), followed by Temperate ($\mu_w=0.40$, $n=44,127$), Tropical ($\mu_w=0.35$, $n=10,406$), and Arid ($\mu_w=0.18$, $n=13,173$). This pattern holds for major cities, where urban vegetation fractions range from 0.45 ($n=141$) in Continental climate to only 0.15 ($n=182$) in Arid. Across cities, Δ_w is smallest in Continental climate (all: -0.26, major: -0.29) and largest in Arid cities (all: -0.33, major: -0.35). Notably, despite these larger mean deficits, the share of cities with higher urban than rural vegetation is greatest in Arid zones (10.13%), followed by Tropical (9.08%), Continental (6.5%), and Temperate (4.32%).

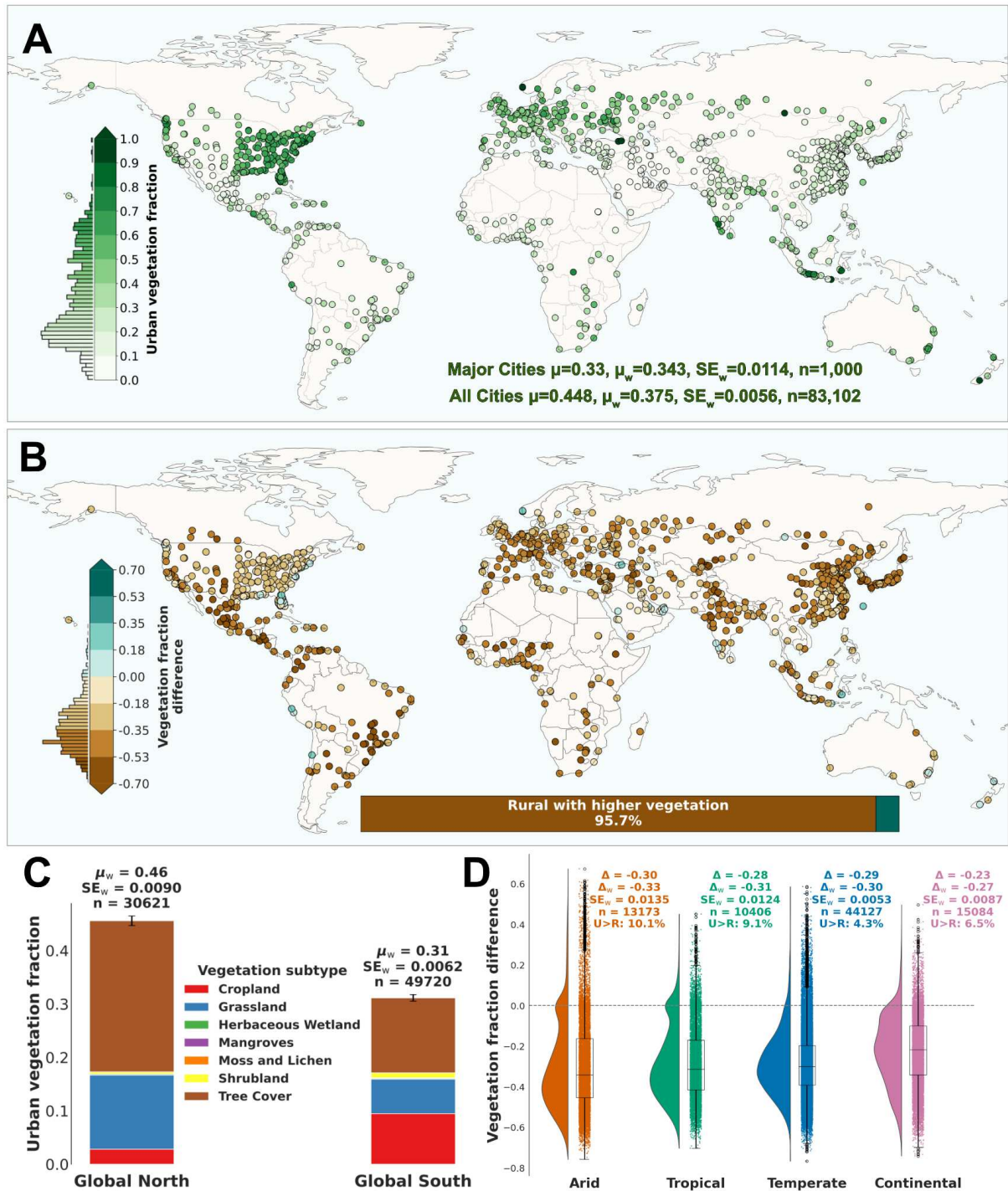


Fig. 1. Global urban vegetation cover and urban-rural differences. (A) Urban vegetation fraction for the world's major cities (top 1,000 by urban area). The weighted mean ($\mu_w=0.34$), the simple mean ($\mu=0.33$), and the weighted SE_w (0.0114) are shown for major cities, along with the stats for all cities ($n=83,102$). (B) Urban-rural vegetation fraction difference (Δ = urban - rural) for major cities; 95.7% have lower urban cover. Brown shading indicates cities where rural areas are greener, while green shading marks those with higher urban vegetation. (C) Global North ($n=30,621$) and South ($n=49,720$) vegetation fractions and their subtypes across all cities. Weighted mean urban vegetation fraction (μ_w), SE_w in the Global North ($\mu_w=0.46$) and Global South ($\mu_w=0.31$). Error bars show SE_w . (D) Distribution of Δ across four major Köppen-Geiger(34) climate zones for all cities, with their Δ , weighted difference (Δ_w), SE_w , number of cities (n), and % of cities with higher urban vegetation ($U>R$): Arid ($\Delta_w=-0.33$, $SE_w=0.0135$, $n=13,173$, $U>R=10.1\%$), Tropical ($\Delta_w=-0.31$, $SE_w=0.0124$, $n=10,406$, $U>R=9.1\%$), Temperate ($\Delta_w=-0.30$, $SE_w=0.0053$, $n=44,217$, $U>R=4.3\%$), and Continental ($\Delta_w=-0.27$, $SE_w=0.0087$, $n=15,084$, $U>R=6.5\%$). Complete statistics in tables S1-3.

Urban vegetation subtypes and their urban-rural contrasts

Urban vegetation composition shows systematic urban–rural reorganization across functional types. The μ_w of tree cover fraction is 0.203, with 37.1% showing higher values than their surroundings (Fig. 2A, fig. S3A, table S1). The urban–rural tree cover gap is slightly more pronounced in major cities, with a similar μ_w (0.213) but a larger difference compared to rural areas, with only 27.2% having higher tree cover (Fig. 2A). Grassland is the next most common subtype ($\mu_w=0.097$ in all cities, 0.076 major), followed by cropland (0.075 all; 0.046 major) and shrubland (0.007 all; 0.005 major; fig. S4A–C, S11). Among non-tree subtypes, grassland shows the highest share of cities (22.8% for all cities and 10.6% for major cities), while only around 9.1% (13%) of all cities and 8.6% (7.3%) of major cities having more shrubland (cropland) than their surroundings (fig. S5A–C, S12). Nationally, Norway (0.53), Sri Lanka (0.53), and Paraguay (0.40) have the highest urban tree cover (μ_w), while Turkmenistan (0.002), Qatar (0.003), and Mongolia (0.003) have the lowest. Regarding tree cover Δ_w values, Moldova (+0.14), Zimbabwe (+0.1), and Ukraine (+0.08) show the largest values, whereas cities of El Salvador (−0.33), Nepal (−0.31), and South Korea (−0.31) have substantially less tree cover than their surroundings. Mongolia's cities contain the highest urban grassland cover ($\mu_w=0.49$), Eritrea's the highest urban cropland cover (0.46), and Namibia's the highest urban shrubland cover (fig. S13).

Vegetation composition differs strongly between the Global North and South (Fig. 2B, table S2). In major cities, the Global North has approximately double the urban tree fraction compared to Global South ($\mu_w=0.28$ versus 0.14 in major cities; Fig. 2B); same for grassland (0.14 versus 0.06). The Global South contains roughly three times the cropland (0.028 versus 0.095) and shrubland (0.004 versus 0.01). The Δ_w mirror these patterns, with slightly larger tree cover differences (−0.068 vs −0.07), similar grassland (−0.08 and −0.08) and shrubland differences (−0.015 versus −0.019), and larger cropland differences in the South (−0.10 vs −0.16). These patterns are consistent across all cities (table S2).

Background climate modulates compositional patterns, especially for tree cover (Fig. 2C, fig. S3C, table S3). Tree cover (μ_w) is highest in Continental climates (0.28 all cities, 0.29 in major cities), followed by Temperate (0.24 all, 0.26 in major), Tropical (0.19 all, 0.18 in major), and lowest in Arid regions (around 0.06 in both). Tropical cities show a tree cover Δ_w of −0.12 across all cities but close to −0.13 in major cities, with only 18.3% (all cities) versus 8.8% (major cities) having higher local tree cover. Arid cities consistently show the smallest tree cover Δ_w (−0.01 all and −0.02 major) and the highest proportion of greater local tree cover in major cities (46.7%). Δ_w for grassland is relatively uniform across climates, with Arid having the greatest Δ_w (−0.10 major cities). Only 4.96% of Continental major cities have higher local grassland versus 27.72% across all Continental cities. Cropland patterns are similar, with Arid cities showing the greatest Δ_w (−0.17) for all cities, but second to Continental for major cities (−0.16 versus −0.14). Tropical cities have the smallest cropland Δ_w (−0.07 all and major). Shrubland remains minimal, with Arid regions containing the highest μ_w (0.02 in all cities and 0.01 in major cities), double that of Tropical cities.

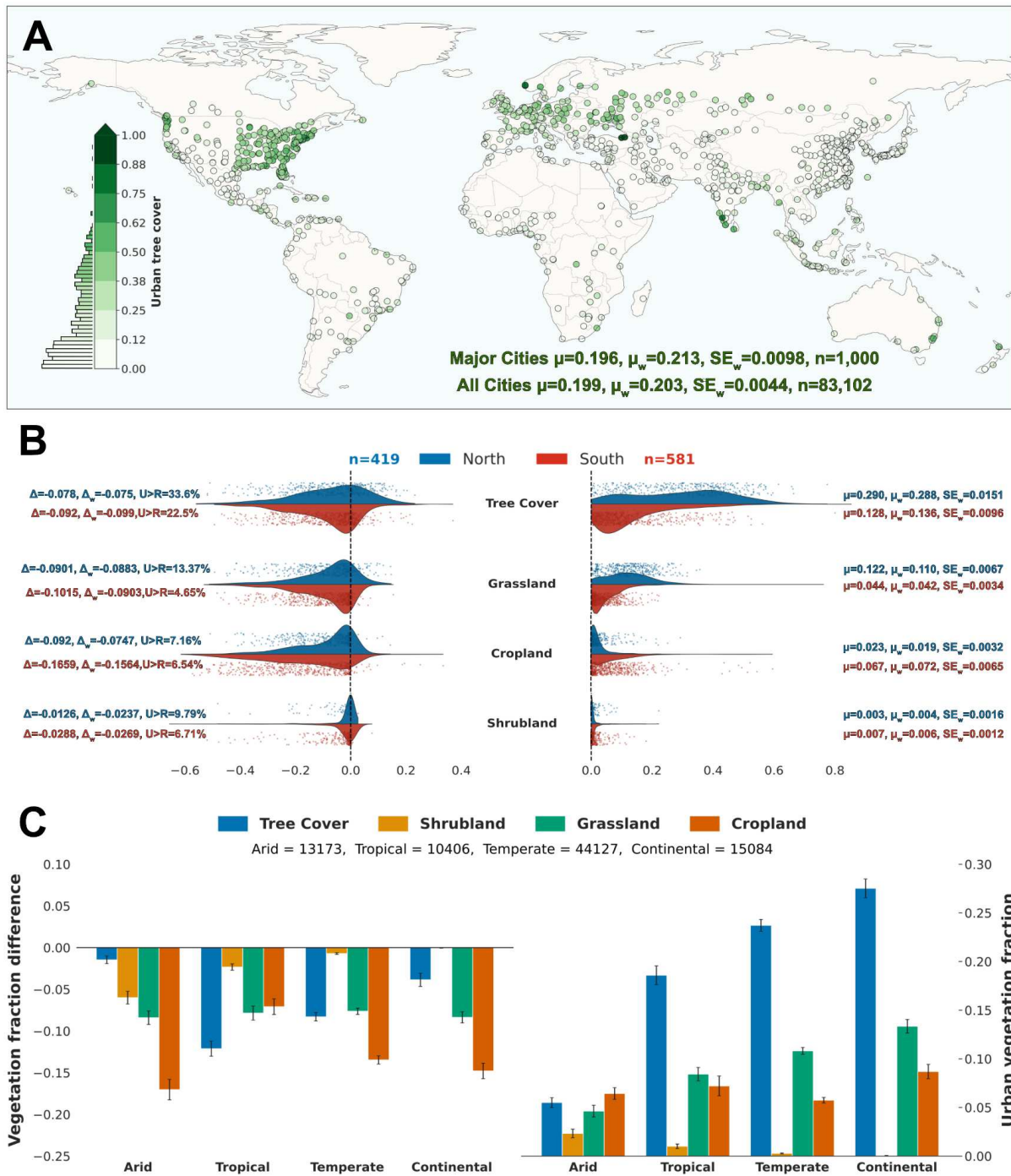


Fig. 2. Urban vegetation subtypes and urban–rural differences. (A) Urban tree cover fraction in major cities (top 1,000 by urban area). The weighted mean ($\mu_w=0.213$), simple mean ($\mu=0.196$), and weighted standard error ($SE_w=0.098$) are shown for major cities, along with the stats for all cities ($n=83,102$). (B) Vegetation subtypes in Global North ($n=419$) and Global South ($n=581$) across major cities. Left, urban–rural vegetation fraction difference (Δ = urban – rural), weighted difference (Δ_w), and % of cities with higher urban vegetation subtype ($U>R$) for each subtype: trees (North $\Delta_w=-0.075$, $U>R=33.6\%$, $\mu_w=0.288$; South $\Delta_w=-0.099$, $U>R=22.5\%$, $\mu_w=0.136$), grass (North $\Delta_w=-0.0883$, $U>R=13.37\%$, $\mu_w=0.110$; South $\Delta_w=-0.0903$, $U>R=4.65\%$, $\mu_w=0.042$), crop (North $\Delta_w=-0.0747$, $U>R=7.16\%$, $\mu_w=0.019$; South $\Delta_w=-0.099$, $U>R=22.5\%$, $\mu_w=0.136$), shrub (North $\Delta_w=-0.0237$, $U>R=9.79\%$, $\mu_w=0.004$; South $\Delta_w=-0.0269$, $U>R=6.71\%$, $\mu_w=0.006$). (C) Urban vegetation patterns across major Köppen-Geiger climate zones and vegetation subtypes across all cities. Left, weighted mean urban–rural differences Δ_w and right, μ_w . Error bars show SE_w . Complete statistics in tables S1-3.

Leaf area index of urban vegetation and their urban-rural contrast

We also demonstrate urban-rural contrasts in vegetation structure using LAI, which measures the one-sided green leaf area per unit ground surface area. For all cities, μ_w for LAI is 0.45 (fig. S6A), lower than the rural baseline (1.21, table S1). Urban LAI exceeds rural values in only 5.6% of cities (fig. S6B). This pattern is pronounced in major cities (μ_w : 0.39 vs 1.18), with only 2.5% having more LAI than their surroundings (Fig. 3A–B). Nationally, Norway ($\mu_w=2.57$) has the highest urban LAI whereas Kuwait (0.01) contains the least. In terms of LAI Δ , only 3 of 169 countries have cities with higher LAI on average with higher Δ_w for Oman (0.05) and the most negative in Luxembourg (-1.73; fig. S2C–B).

Urban LAI is higher in the Global North ($\mu_w=0.56$) than in the Global South (0.36) for all cities (Fig. 3C, table S2). However, the Δ_w is larger in the North (-0.96) than in the South (-0.62), with only 3.45% of the cities having higher LAI in Global North compared to 6.68% of the cities in Global South. In major cities, the pattern holds with Global North ($\mu_w=0.47$) having higher LAI than Global South cities (0.31), similar Δ_w patterns in Global North and South (-0.91 versus -0.67). 3.34% of Global North cities have higher LAI than their rural areas, while only 1.72% of major Global South cities have more.

Climate strongly modulates urban LAI (Fig. 3D, table S3). Mean urban LAI is highest in Temperate ($\mu_w=0.52$) and Continental (0.51) zones, followed by Tropical (0.48) and Arid (0.16) zones. The LAI contrast Δ_w is largest in Temperate zones (-0.88) and smallest in Arid zones (-0.27). Despite lower mean LAI, the share of cities with higher urban than rural LAI is greatest in Arid climates (11.2%), followed by Continental (7.8%), Tropical (4.3%), and Temperate (3.4%) climate zones. Patterns are similar for major cities, where urban LAI is highest in Temperate zones ($\mu_w=0.46$) and lowest in Arid zones (0.15). Within major cities, the LAI Δ_w is smallest in Arid (-0.25) and remains uniform across Temperate (-0.92), Continental (-0.90), and Tropical (-0.83) regions. This pattern of urban LAI exceeding rural is even rarer among these major cities, occurring in only 7.1% of Arid cities and dropping to 2.0% in Temperate, 0.6% in Tropical, and none in Continental zones. In addition to LAI of total vegetation, we evaluated leaf area index separately for trees, grassland, cropland, and shrubland (fig. S7, tables S1-3). The largest contrasts are in tree cover, especially in the Continental cities ($\Delta_w=-1.42$), with only Arid cities showing a positive grassland LAI (+0.03 for all cities).

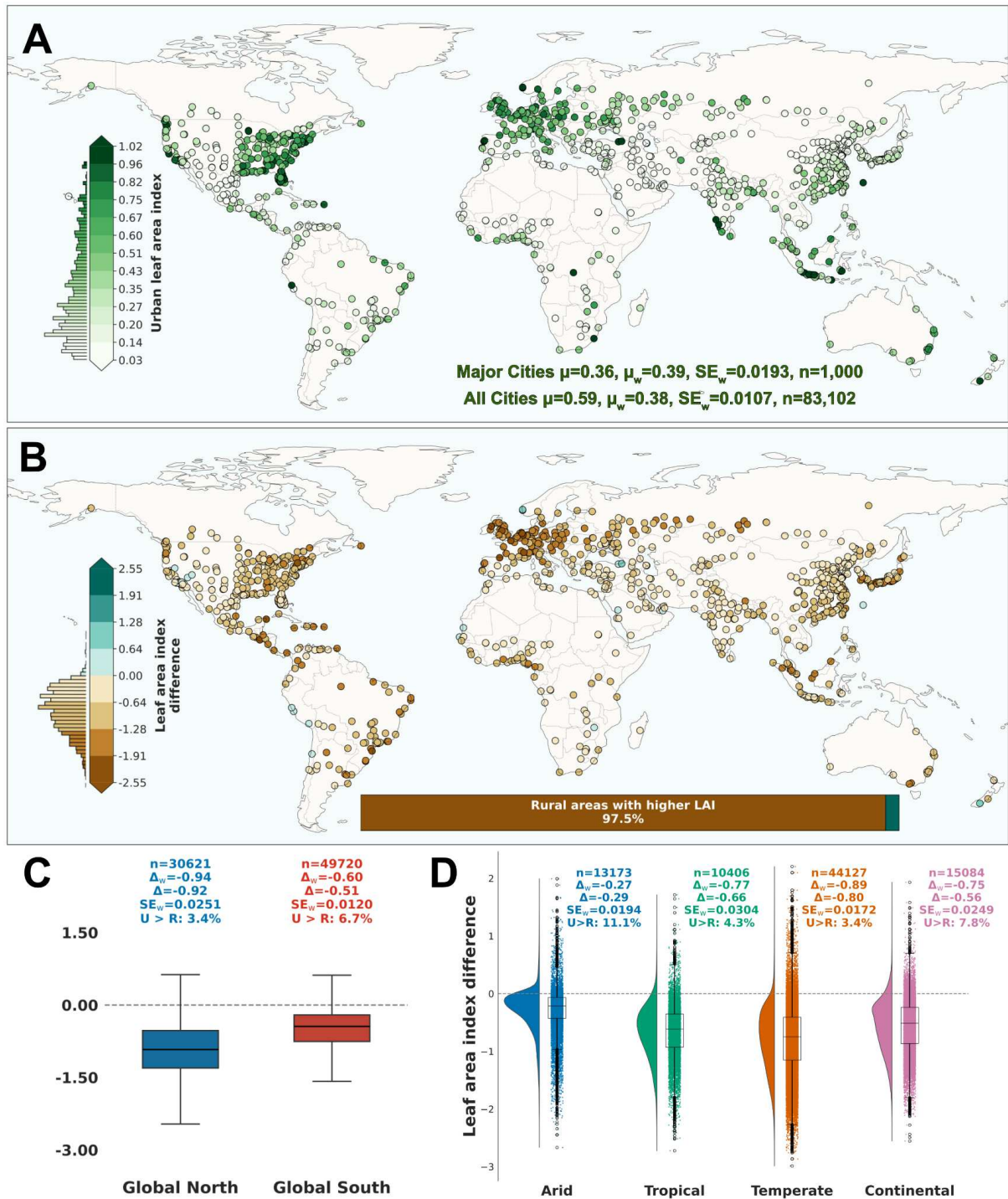


Fig. 3. Urban leaf area index (LAI) and urban-rural difference. (A) Urban LAI patterns for the world's major cities (top 1,000 by urban area). The weighted mean ($\mu_w=0.39$), the simple mean ($\mu=0.36$), and the weighted standard error ($SE_w=0.0193$) are shown for major cities, along with the stats for all cities ($n=83,102$). (B) LAI difference ($\Delta = \text{urban} - \text{rural}$) across major cities; 97.5% have lower urban LAI. Brown shading indicates cities where rural areas are greener, while green shading marks those with higher urban LAI. (C) Global North and Global South LAI Δ , Δ_w , SE_w , number of cities (n), and % of cities with higher urban LAI ($U>R$) across all cities: North ($\Delta_w=-0.94$, $SE_w=0.0251$, $U>R=3.4\%$, $n=30,621$), South ($\Delta_w=-0.51$, $SE_w=0.0120$, $U>R=6.7\%$, $n=49,720$). (D) Distribution of LAI Δ across four major Köppen-Geiger climate zones for all cities, with their Δ , weighted difference (Δ_w), SE_w , n , and $U>R$ %: Arid ($\Delta_w=-0.27$, $SE_w=0.0194$, $n=13,173$, $U>R=11.1\%$), Tropical ($\Delta_w=-0.77$, $SE_w=0.0304$, $n=10,406$, $U>R=4.3\%$), Temperate ($\Delta_w=-0.89$, $SE_w=0.0172$, $n=44,217$, $U>R=3.4\%$), and Continental ($\Delta_w=-0.75$, $SE_w=0.0249$, $n=15,084$, $U>R=7.8\%$). Complete statistics in tables S1-3.

Urban tree height and their urban-rural contrast

Urban vegetation is not only sparse with less canopy density but trees are consistently shorter than their surroundings. Urban trees ($\mu_w=3.66$ meters or m) are shorter than in rural areas (6.34m), with only 23.57% of all cities having taller trees (fig. S8A-B, table S1). This tree height Δ_w is more pronounced among major cities, where the urban (μ_w) was 3.95m vs rural 6.9m, with only 18.5% of these major cities having taller trees (Fig. 4A–B). Nationally, urban trees are taller than their rural counterparts in only 11.2% of countries. The largest urban–rural contrasts are found in Austria (-5.36m), Lithuania (-5.31m), and Switzerland (-5.23m), while Tunisia (+1.01m), Qatar (+0.93m), and Eritrea (+0.75m) had taller local trees (fig. S2E-F).

Urban trees in the cities of the Global North are taller ($\mu_w=3.45$ m) than in the Global South (2.52m), and this difference holds across major cities (3.80m versus 2.94m; Fig. 4C, table S2). Furthermore, the Δ_w is consistently larger in the Global North for both all cities (-2.28m versus -0.83m) and major cities (-3.07m versus -1.09m). However, a much larger share of cities in the Global South (31.1%) have taller urban trees than their surroundings compared to cities in the Global North (10.6%). This pattern holds for major cities as well, where the share is 26.3% in the Global South versus just 7.4% in the Global North. This indicates that while Global North cities typically contain tall trees, their surrounding rural environments support even taller trees (5.73m vs 3.35m), resulting in a greater Δ_w .

Climate is a key driver of urban tree height with high variability across all climate zones (Fig. 4D, table S3). Urban tree height is greatest in Temperate ($\mu_w=3.87$ m) and Continental (3.46m) zones, followed by Tropical (3.22m) and Arid (2.96m) zones. This contrasts with the height Δ_w , which is smallest in Arid climates (-0.20m) while the largest contrasts occur in Continental (-3.24m) and Temperate (-3m) zones. In fact, 50.4% of cities in Arid zones have taller urban trees than their surroundings for all cities, a proportion that drops sharply in Tropical (29.3%), Temperate (18%), and Continental (11.2%) zones. This pattern is consistent but more pronounced for the major cities, where urban trees are tallest in Continental ($\mu_w=4.15$ m) and Temperate (4.14m) zones and shortest in Arid zones (2.99m). Within major cities, the height contrast is again smallest in Arid climate (-0.27m; 52.19% taller) and largest in Continental (-3.79m; 4.96% taller) and Temperate (-3.47m; 10.05% taller).

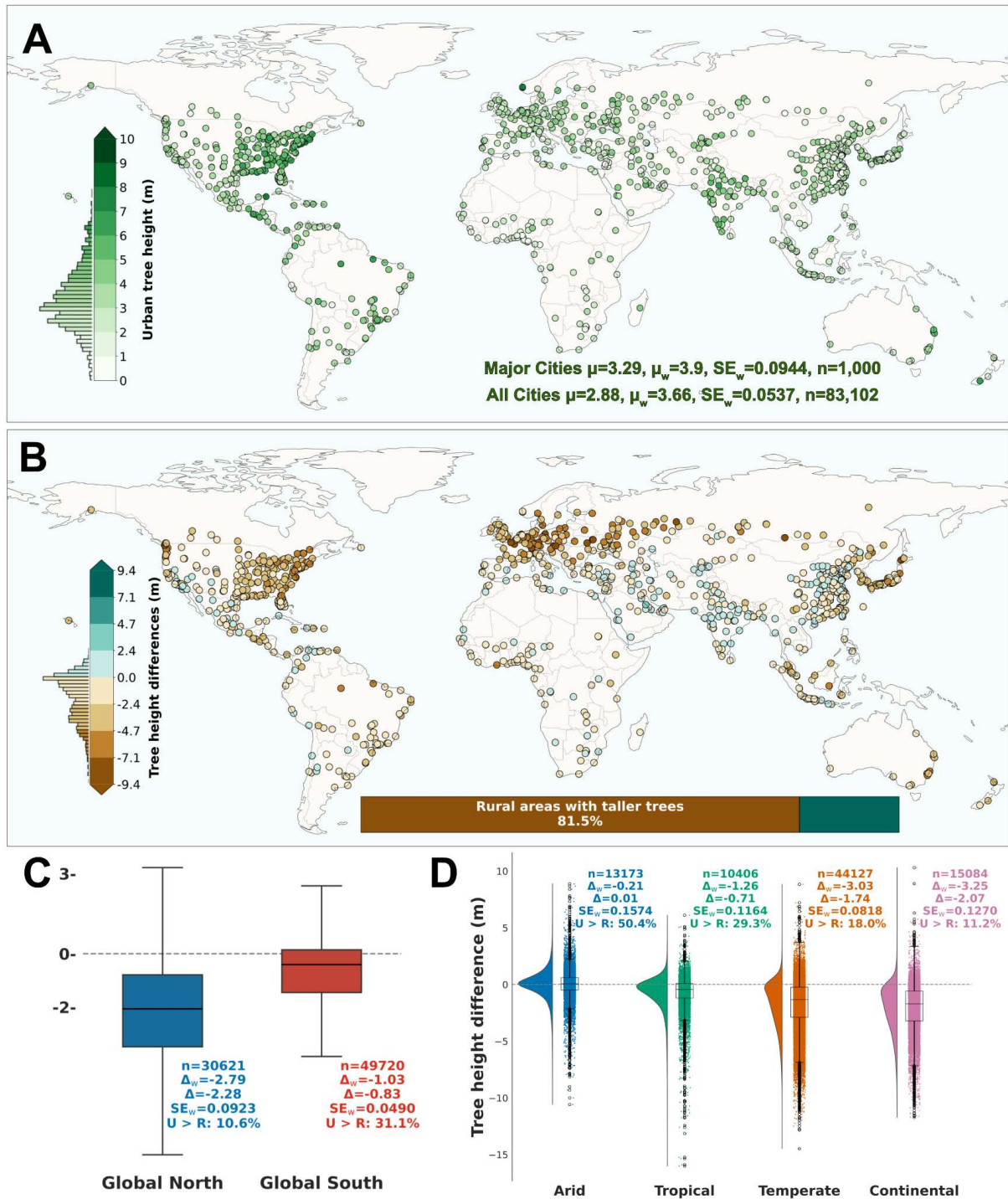


Fig. 4. Urban tree height and urban-rural differences. (A) Urban tree height patterns in meters (m) for the world's major cities (top 1,000 by urban area). The weighted mean ($\mu_w=3.9$ m), the simple mean ($\mu=3.29$ m), and the weighted standard error ($SE_w=0.0944$) are shown for major cities, along with the stats for all cities ($n=83,102$). (B) Tree Height difference (Δ = urban – rural) across major cities; 81.5% have lower urban height. Brown shading indicates cities where rural areas are greener, while green shading marks those with taller trees. (C) Global North and Global South tree height Δ , Δ_w , SE_w , number of cities (n), and % of cities with higher urban tree height ($U > R$) across all cities: North ($\Delta_w=-2.79$ m, $SE_w=0.0923$, $U > R=10.6\%$, $n=30,621$), South ($\Delta_w=-1.03$ m, $SE_w=0.0490$, $U > R=31.1\%$, $n=49,720$). (D) Distribution of tree height Δ across four major Köppen-Geiger climate zones for all cities, with their Δ , weighted difference (Δ_w), SE_w , n , and $U > R\%$: Arid ($\Delta_w=-0.21$ m, $SE_w=0.1574$, $n=13,173$, $U > R=50.4\%$), Tropical ($\Delta_w=-1.26$ m, $SE_w=0.1164$, $n=10,406$, $U > R=29.3\%$), Temperate ($\Delta_w=-3.03$, $SE_w=0.0818$, $n=44,217$, $U > R=18.0\%$), and Continental ($\Delta_w=-3.25$, $SE_w=0.1270$, $n=15,084$, $U > R=11.2\%$). Complete statistics in tables S1-3.

Discussion

Our global analysis confirms urban–rural vegetation contrasts (35, 36), and shows that urbanization is associated, not only with reduced vegetation amount, but also with systematic shifts in vegetation composition and structure. These patterns are consistent with urban environments acting as a novel ecological filter that constrains attainable vegetation structure, favoring simpler, lower density canopies and, in many regions, reducing tree height, across biomes (37). These nuanced urban-rural contrasts often remain undetected by traditional spectral indices (e.g., NDVI, EVI) (22, 38), when canopy structure and biomass context vary (22, 23). For instance, among major cities, rural NDVI exceeded urban NDVI in 82.3% (and EVI 84.4%) of cases (fig. S9A, S10A), whereas rural LAI was higher in 97.5% of the cases (Fig. 3B), underscoring that reductions in vegetation as a key consequence of urbanization than simply a loss of proxy greenness. This divergence is consistent with evidence that vegetation indices are biased by structure, atmosphere, and shadowing (39), supporting the need for explicit structural metrics when interpreting large scale “greening” signals (22). Recognizing this distinction is critical for assessing ecosystem services, as the cooling benefits provided by dense tree canopies far exceed those offered by lawns (10, 26), at comparable NDVI levels. Furthermore, while spectral indices show marginal differences in the urban–rural greenness contrast between the Global North and South ($\Delta_w = -0.065$ versus -0.077 for NDVI and $\Delta_w = -0.053$ versus -0.051 for EVI), structural metrics reveal a stronger LAI difference in Global North cities ($\Delta_w = -0.94$ versus -0.60). In Arid cities, EVI shows the smallest difference ($\Delta_w = -0.03$), but in terms of vegetation cover, they show the largest difference (-0.33), further illustrating that greenness and vegetation amount/structure can diverge. Our findings underscore the necessity of using structural vegetation metrics instead of spectral indices for a more comprehensive understanding of urban vegetation patterns.

Urban vegetation patterns are strongly modulated by background climate, consistent with climate acting as a dominant environmental filter on attainable vegetation cover and structure. In Arid cities, for instance, an “oasis effect” can occur where intentional greenspace creation can lead to minimal urban–rural structural contrasts (40). While these cities have the lowest vegetation fraction (all cities $\mu_w = 0.19$), their structural contrast is the smallest (LAI $\Delta_w = -0.27$ and tree height -0.21 ; Fig. 3D, 4D). In some cases, this greening can result in urban trees taller than rural ones, as seen in countries like Oman and for 50.4% of all Arid cities. By contrast, cities in Continental and Temperate climate zones have the highest levels of urban vegetation globally ($\mu_w = 0.50$, 0.41 respectively) but exhibit the most pronounced structural losses associated with urbanization (tree height $\Delta_w = -3.25\text{m}$ and -3.03m respectively), with urban trees substantially shorter than in surrounding rural areas. Tropical cities show a distinct pattern, experiencing the highest contrast in tree cover ($\Delta_w = -0.12$) while showing a more balanced tree height contrast ($\Delta_w = -1.26\text{m}$) relative to their surroundings. Lower urban tree height implies reduced vertical niche space and simplified habitat structure, which can translate into avian habitat loss and population declines (27, 41). Such consistent structural filtering represents a selective environment promoting urban phenotypic divergence and eco-evolutionary feedback (42). By incorporating vegetation structure and climate constraints, our analysis resolves climate context of specific greening patterns beyond what spectral indices capture.

Operating within these climatic constraints, socioeconomic context leaves a clear signature on both vegetation composition and structure. Cities in the Global North feature higher

proportions of grassland ($\mu_w=0.14$ versus 0.07) and tree cover (18) (0.28 versus 0.14), consistent with policies and cultural norms reflected in park development, street tree planting, and lawn maintenance, that drive ecological homogenization of urban vegetation across regions (37). In contrast, cities in the Global South contain notably higher cropland cover ($\mu_w=0.095$ vs 0.028), where the urban–rural gap is most pronounced ($\Delta_w=-0.17$ vs -0.10), indicating urban displacement of land traditionally used for food production (43). Although Global North cities are greener in absolute terms (44, 45) ($\mu_w=0.46$ vs 0.31), they also exhibit substantially larger urban–rural contrast in tree cover, canopy density, and tree height, metrics not captured by spectral indices alone. Yet Global North cities are more green than South because they currently exist within greener natural baselines (North rural $\mu_w=0.73$ vs South rural $\mu_w=0.66$ for all cities) leading to a larger contrast with their surroundings.

These geographically distinct urban vegetation patterns are dynamic and evolving, which we confirm using 30 years of data across all cities, leading to increasing global inequities in urban green infrastructure. Between 1990 and 2020, most countries experienced a net loss in both overall urban vegetation (76.4%; Fig. 5A) and urban tree cover (63.2%; fig. S13). This trend appears in NDVI (78.4%) and EVI (76.7%), though note the quantitative differences when using vegetation subclasses (fig. S14). The Global North has undergone sustained urban re-greening and the decline in total greenspace within the Global South may have stabilized or slightly reversed after 2011 (45) (Fig. 5C). Although the overall vegetation appears stable in the Global South, our analysis reveals a decrease in urban tree cover, exposing a divergence between total vegetation and composition, a critical and intensifying inequity within Global South cities (Fig. 5B). Global North and South differences persist even when holding the built-up extents of 1990 and 2020 constant (Fig. 5B). While the Global South cities may appear to be narrowing the gap in total vegetation cover, this increase often reflects cropland expansion, as observed in India (46). This distinction matters because gains in non-tree vegetation can partially offset greenness trends without recovering the structural and functional attributes most tied to canopy mediated cooling and habitat characteristics. In the Global South, vegetation fractions decreased sharply from approximately 0.41 to below 0.30 between 1990 and 2020, illustrated with extremes like Guinea-Bissau ($\Delta=-0.66$). This global divergence between the North and South provides essential temporal context for the importance of vegetation structure and composition when examining urban vegetation characteristics.

While the global scale of this analysis is its key strength and establishes pervasive urban vegetation patterns, it also introduces several constraints. The vegetation metrics used here are derived from multiple satellite products, each with different spatial resolutions and methodological assumptions, which introduces uncertainty into our estimates. LAI retrievals may be less reliable in persistently cloudy (such as Tropical) regions or spectrally complex urban areas, and tree height estimates inherit errors from the raw data product (47) used (see Materials and Methods). In addition, while our paired rural buffers provide a local reference, they do not represent counterfactual pre-urban baselines and may include contributions from peri-urban land use. Finally, the specific drivers of vegetation patterns within individual cities, such as those driven by management practices or historical land use, cannot be identified from this large-scale analysis alone. The global patterns described here are therefore best understood as a broad foundation for more targeted investigation using local datasets and knowledge.

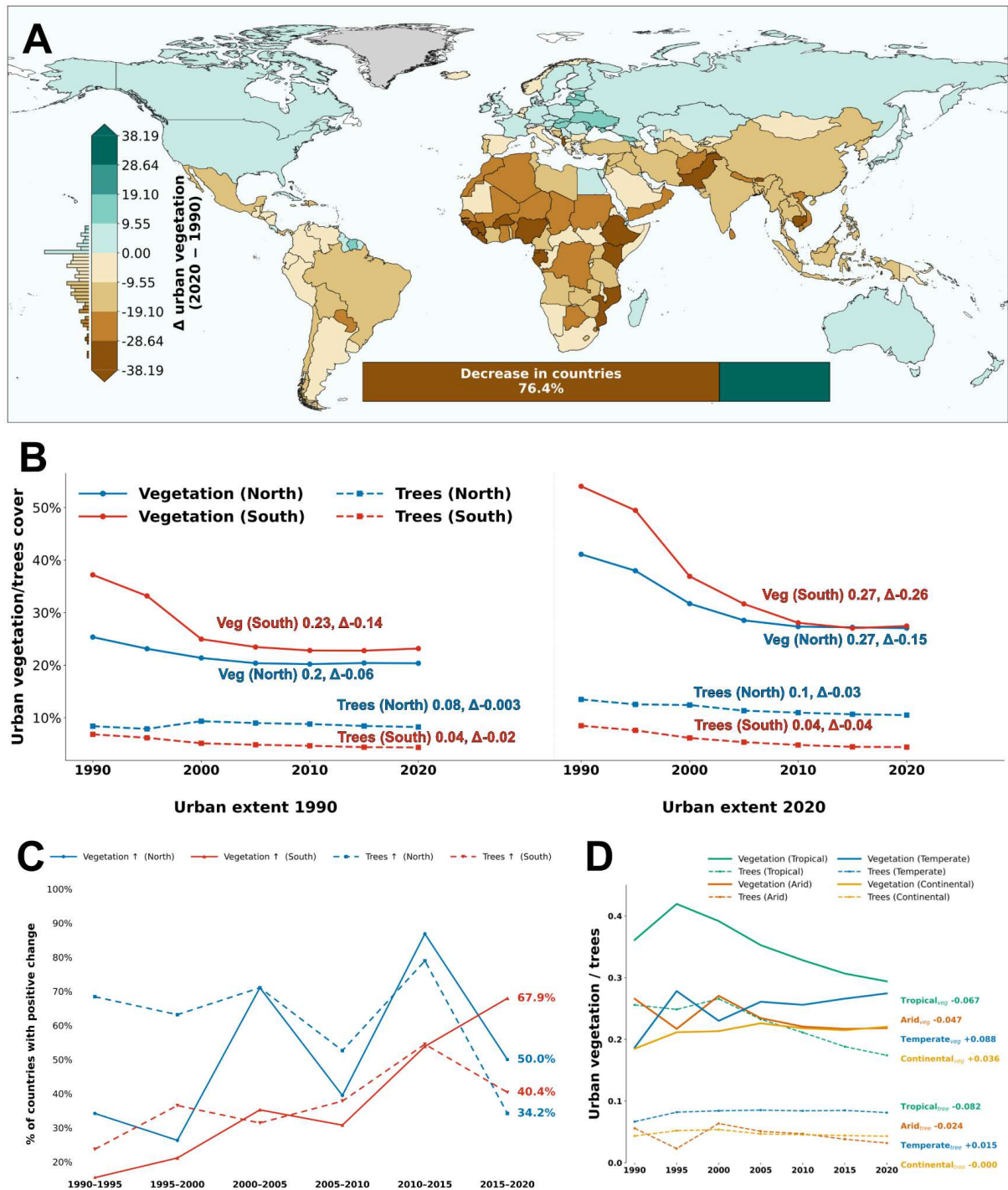


Fig. 5. Long-term changes in urban vegetation and tree cover. (A) Country-level changes in urban vegetation fraction between 1990 and 2020, showing decreases in 76.4% of countries. **(B)** Urban vegetation and tree cover weighted mean fractions (μ_w) and difference (Δ) in the Global North and Global South every 5 years (1990 to 2020) under fixed 1990 extent (left) and under fixed 2020 extent (right). **(C)** Percentage of Global North and Global South countries every 5 years with increase in urban vegetation and tree cover across 1990–2020. **(D)** μ_w and temporal change (Δ_w) of urban vegetation and tree fractions across Köppen-Geiger climate zones: Tropical (vegetation $\Delta_w = -0.067$, trees $\Delta_w = -0.082$), Arid (vegetation $\Delta_w = -0.047$, trees $\Delta_w = -0.024$), Temperate (vegetation $\Delta_w = +0.088$, trees $\Delta_w = +0.015$), and Continental (vegetation $\Delta_w = +0.036$, trees $\Delta_w = 0$).

In summary, urbanization is associated with multifaceted shifts in vegetation amount, composition, and structure, with lower local vegetation fraction alongside reduced leaf area and height. The magnitude and direction of these urban–rural contrasts are jointly modulated

by climatic constraints and socioeconomic context. Furthermore, 30-year temporal dynamics reveal a widening global inequity: while Global North cities exhibit sustained re-greening, an apparent convergence in total vegetation fraction in the Global South masks a persistent divergence in tree cover. By showing that vegetation composition and structural metrics (LAI, height) reveal stronger and more ecologically interpretable contrasts than spectral greenness alone. Our results provide a scalable framework that is directly relevant for evaluating the ecological and societal impacts of urban vegetation and for improving urban representation in process based models that currently rely on simplified vegetation proxies. These results provide a foundation for linking vegetation structure and composition to ecosystem services, biodiversity responses, and the effectiveness of policy interventions, particularly in rapidly urbanizing regions.

Materials and Methods

Study design overview

We quantified how urbanization is associated with vegetation amount, composition, and structure by comparing 83,102 morphologically defined urban clusters to area-matched rural references from their immediate surroundings. This paired design provides a local baseline for environmental assessments while allowing global inference across socioeconomic and climate zones. For each urban–rural pair, we extracted total vegetation cover, major vegetation subtypes (tree, grass, cropland, shrub), leaf area index (LAI) and canopy height, and summarized patterns using city-level contrasts (Δ = urban – rural) and area-weighted statistics. Together, these variables quantify urban vegetation, spanning habitat availability (fractional cover), functional composition (subtypes), and canopy structural characteristics (LAI and height) that support ecosystem functioning and habitat structure.

Delineating urban clusters and their rural surroundings

Morphologically defined urban clusters and their corresponding rural surroundings were delineated using a multi-step approach based on satellite-derived land cover data. The European Space Agency (ESA) Climate Change Initiative Land Cover product for 2018 (CCI-LC 2018) (48) was utilized, specifically its built-up surface class at 300-meter resolution. First, this class was binarized to represent built-up presence (1) or absence (0). Contiguous aggregates of built-up pixels were then identified and vectorized to generate discrete polygons representing potential urban clusters. This initial step produced over 800,000 global clusters for the year 2018. To minimize the inclusion of isolated built-up pixels or misclassifications, we applied a minimum area threshold of 1 km². This filtering step resulted in a final dataset of 83,102 distinct urban clusters globally.

For each urban cluster, we delineated an area-matched rural reference from the immediate surroundings to enable paired comparisons against a local baseline. An iterative buffering algorithm (49) was used, expanding the boundary of each urban cluster outwards in 300 metre increments up to a maximum distance of 10,000 meters. From these generated buffer rings, the one whose area most closely matched the area of the corresponding urban cluster was selected by minimizing the absolute difference in area. Rural buffers exclude the urban polygon itself and provide local environmental context for paired comparisons. This procedure yielded 83,102 urban-rural pairs with comparable spatial extent. This morphology-based delineation captures the physical footprint of urbanization and avoids

inconsistencies in administrative boundaries, which are often defined by historical or political factors (32). All the geospatial extraction and initial processing described here and below were performed on the Google Earth Engine cloud computing platform (50).

Vegetation and subtype cover analysis

Vegetation cover and composition were quantified using the ESA WorldCover 2020 land cover product, derived primarily from 10-meter Sentinel-2 (51) imagery. This global product contains 11 land cover classes, from which vegetation types, including tree cover, shrubland, grassland, cropland, mangroves, herbaceous wetland, and moss and lichen were selected. For each vegetation subtype, binary masks were generated by remapping each class within vegetation as presence (1) or absence (0). We calculated fractional cover within each urban cluster and its paired rural reference zone as the proportion of pixels assigned to that class. These classes were used to define (i) total vegetation (all of the above), and (ii) the four main vegetation subtypes analyzed in the main text (tree cover, grassland, cropland, shrubland) to characterize compositional shifts. Other vegetated classes (e.g. mangroves, herbaceous wetlands, moss/lichen) contributed to total vegetation but were not analyzed as separate subtypes.

Generating leaf area index

Leaf area index (LAI), which measures the one-sided leaf area per unit ground surface area, was derived using a hybrid machine learning and radiative transfer modeling approach (52). Specifically, an enhanced radiative transfer model (53) incorporating soil background and senescent leaf fractions was used to generate training data for a random forest retrieval model, which was then applied to Sentinel-2 imagery to estimate LAI. This hybrid framework explicitly accounts for factors known to confound optical vegetation retrievals, including senescent foliage, mixed soil reflectance, and canopy clumping, thereby improving robustness of LAI estimates relative to algorithms that do not represent these components. Cloud masked Sentinel-2 median composites from 2020 were used to produce a global LAI map at 10-m resolution.

To ensure that LAI represents canopy density conditional on vegetation presence, LAI summaries were computed only over vegetated pixels; non vegetated pixels were excluded rather than treated as LAI = 0. We summarized LAI at two levels. First, we quantified LAI of total vegetation by applying a vegetation mask defined from ESA WorldCover classes and extracting LAI statistics across all vegetated classes within each urban cluster and its paired rural reference zone. Second, to link vegetation composition to structure, we generated subtype specific LAI summaries for the four main subtypes used in the main text, trees, grassland, cropland, and shrubland, by intersecting the LAI map with the corresponding ESA WorldCover subtype masks (fig. S7). Other vegetated classes (for example, mangroves, herbaceous wetlands, moss/lichen) contributed to the total vegetation LAI summaries but were not analyzed as separate subtype specific LAI categories. Subtype specific LAI therefore reflects within class canopy density, while total vegetation.

From the resulting LAI data, we calculated the mean and standard deviation of LAI for each urban cluster and its rural reference zone. For cohort level summaries (Global North/South and climate classes), we additionally computed the simple mean, area weighted mean, standard error, and weighted standard error of LAI across urban–rural pairs. In these cohort

summaries, total vegetation LAI was area weighted using the full urban and rural areas, whereas subtype specific LAI summaries were weighted by the fractional area of each subtype within the corresponding urban or rural zone.

Estimating urban-rural tree height

Tree height was estimated using a 1m resolution Meta canopy height product (47). This global canopy height product was evaluated against alternative sources, including ETH's 10m Sentinel-2 derived product (27), the 30m GLAD dataset based on Landsat imagery (54), and a proxy derived from the differential between 30m GLO (55) and FABDEM (56) (fig. S8c). Canopy height from each product was calculated over urban and their rural surroundings and compared. The Meta canopy height dataset was selected owing to its higher spatial resolution and the ability to better capture fine scale canopy heterogeneity and forest–non forest transitions compared to coarser alternatives (ETH 10-meter, GLAD 30-meter) (57).

To ensure consistency with our land cover definitions, canopy height was summarized only over tree covered pixels by masking the canopy height layer with the 10-m ESA WorldCover 2020 tree cover class, in addition to Meta's internal minimum height filter (≥ 1 m). We then extracted tree height values within each urban cluster and its paired rural reference area and computed simple and tree-area-weighted means, together with weighted and unweighted standard errors, across the 83,102 urban–rural pairs. For weighted summaries, tree height was weighted by the tree covered area within each respective urban or rural area.

Comparison among climate zones, Global North/South cities, and countries

To evaluate how background context structures urban–rural vegetation contrasts, the 83,102 urban clusters were stratified by country (using Natural Earth (58)), socioeconomic status, and climate zone. Socioeconomic status was derived from the 2022 World Bank income classifications (59), categorizing clusters into 'Global North' (high-income countries) and 'Global South' (lower-middle, upper-middle, and low-income countries). Climate classification was conducted using the Köppen-Geiger (34) system, through which clusters were assigned to one of four major categories: Arid (Köppen B types), Continental (D types), Temperate (C types), or Tropical (A types). Clusters that were not classified as one of the income groups (2,761) or climate zones (312) were excluded from the respective comparisons. These stratifications were applied consistently across analyses of vegetation cover and composition, LAI, and tree height.

Temporal analysis of urban vegetation

We quantified long term changes in urban vegetation cover and composition using Landsat-based Global Land Cover (GLC) products at 30m resolution (60). For each target year (1990, 1995, 2000, 2005, 2010, 2015, 2020), we remapped GLC land cover classes to generate binary masks for vegetation and major vegetation subtypes (trees, croplands, shrublands, and grasslands). The subclasses of tree cover included evergreen, deciduous, needle-leaved, mixed, alongside mangroves and orchard croplands. Vegetation fractions were then computed by aggregating 30m vegetation related classes within each 300m built-up pixel, producing a time series of urban vegetation and subtype fractions.

We calculated spectral greenness metrics (NDVI and EVI) from Landsat imagery for 1990 and 2020 at the country level to provide a temporally comparable greenness based reference. To separate vegetation change from changes in the mapped spatial footprint of urbanization, we approximated urban extents for the early and late periods using CCI-LC built-up masks from 1992 and 2018, respectively, and used these as static urban masks for the corresponding analyses (including all urban pixels within each country). Because CCI-LC provides built-up extent for discrete mapping years, we used the closest available years (1992 for the early period and 2018 for the late period) as proxies for 1990 and 2020 urban footprints. For climate zone stratified trends, vegetation fractions were averaged across all urban pixels within each Köppen–Geiger zone. Comparisons of urban vegetation and tree cover between 1990 and 2020, as well as climate zone summaries, were computed at 100-m resolution.

Statistical analysis

All statistical analyses were conducted in Python (NumPy, pandas, SciPy). For each urban–rural pair (city), we computed an urban–rural contrast as $\Delta = \text{urban} - \text{rural}$. For each variable and for each cohort (for example, all cities, major cities, Global North/South, or climate class), we summarized urban and rural values using the mean and standard error, as well as area weighted means (μ_w) with corresponding weighted standard errors (SE_w). We additionally report the mean Δ and the area weighted mean Δ_w .

Within each group, we tested whether the distribution of paired contrasts differed from zero using the Wilcoxon signed-rank test (61), and reported two-sided p-values. To quantify the magnitude and direction of effects independent of sample size, we report effect sizes for paired contrasts using Cohen's d (62) and the rank-biserial correlation (63), together with the percentage of cities where urban values exceed, equal, or fall below rural values ($U > R$, $U = R$, $U < R$).

To compare the magnitude of urban–rural contrasts between Global North and Global South cities, we applied the Mann–Whitney U test (64) to Δ values and reported the U statistic, two-sided p-value, and rank-biserial correlation as summary statistics. Variation in Δ across Köppen climate classes was assessed using one-way ANOVA(65), for which we report the p-value and proportion of variance explained. All tests were two-sided with a significance level of $\alpha = 0.01$. Given the large sample size, we interpret statistical significance alongside effect sizes and directionality metrics (Cohen's d, rank-biserial r, and % $U > R$) to emphasize greenspace magnitude in addition to p-values.

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Supplementary Materials

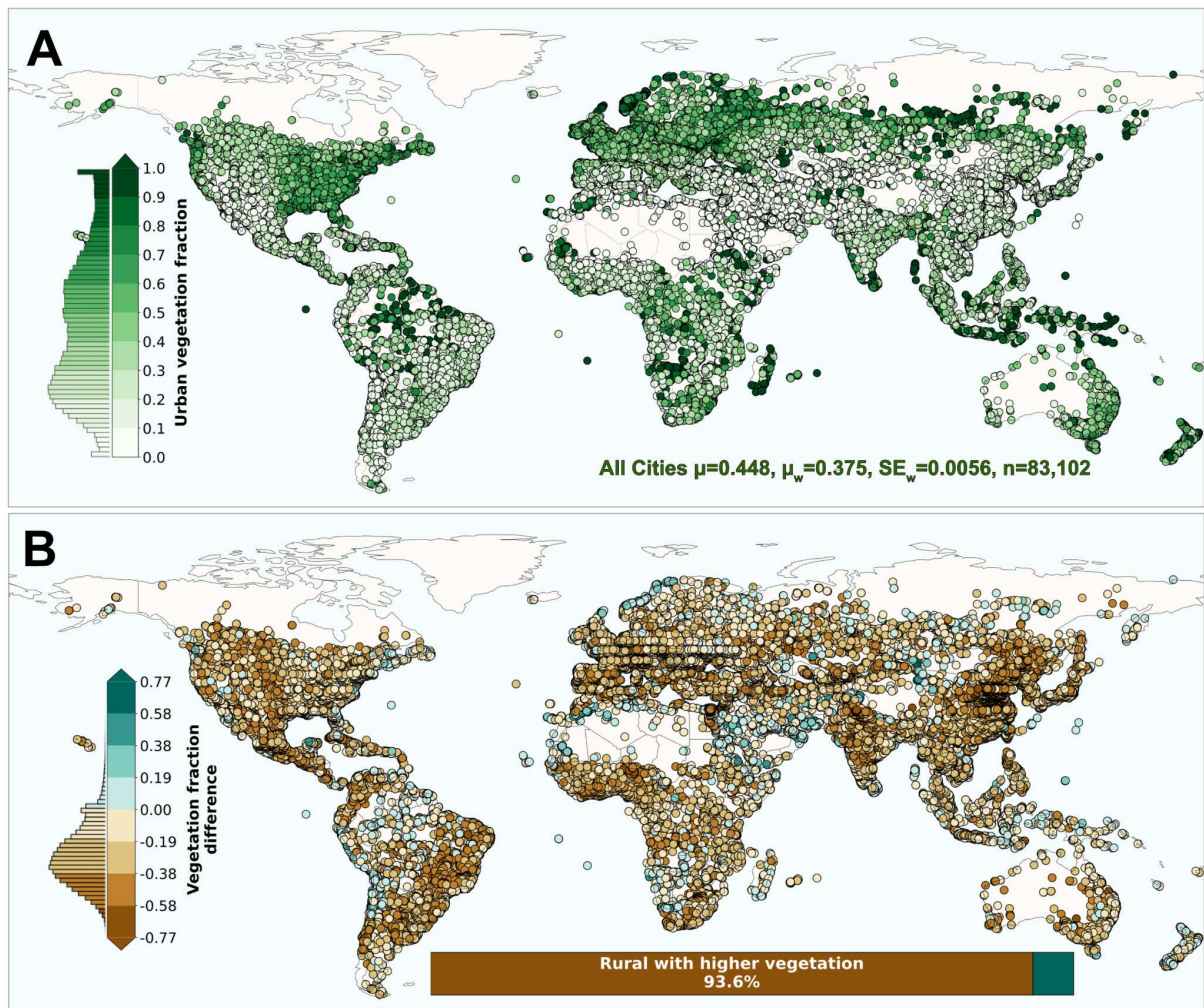


Fig. S1. Global distribution of urban vegetation fraction and urban–rural differences.

(A) Global map of urban vegetation fraction across 83,102 cities. The weighted mean (μ_w) vegetation fraction is 0.37 (simple mean $\mu=0.44$, weighted standard error $SE_w=0.0056$). **(B)** Urban–rural vegetation fraction difference ($\Delta = \text{urban} - \text{rural}$), showing that 93.6% of cities have lower urban vegetation cover. Brown shading indicates cities where rural areas are greener, while green shading marks those with higher urban vegetation. Complete statistics are provided in table S1.

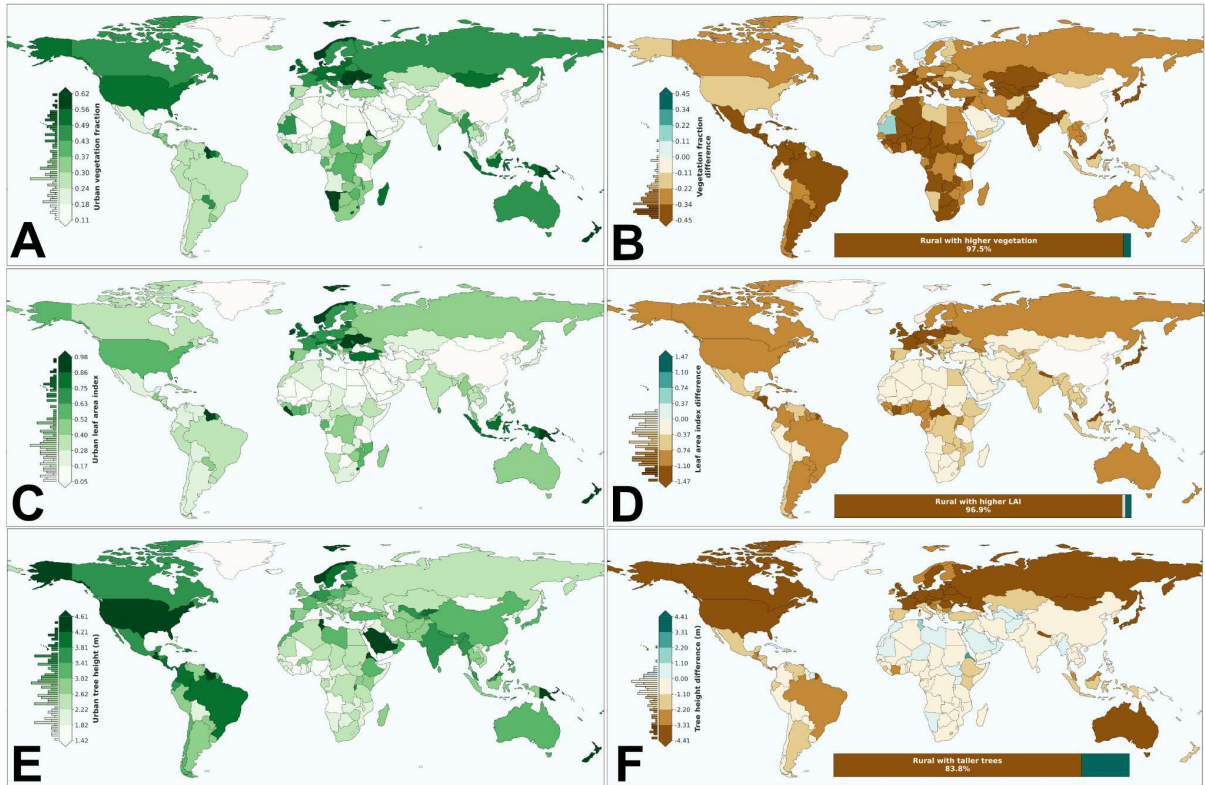


Fig. S2. Country-level urban–rural differences in vegetation amount, density, and structure. A, B, C Global maps showing country-level means of urban vegetation metrics (left) and B, D, F corresponding urban–rural differences (Δ = urban – rural) (right) for (top) total vegetation fraction, (middle) leaf area index (LAI), and (bottom) tree height. 97.6% of countries have lower urban vegetation cover than their rural surroundings (top row), 93.8% have lower LAI (middle row), and 83.4% have shorter trees (bottom row). Brown shading in the right-hand panels denotes countries where their respective weighted values in surrounding rural areas exceed urban values, and green shading denotes urban areas that exceed surrounding rural values.

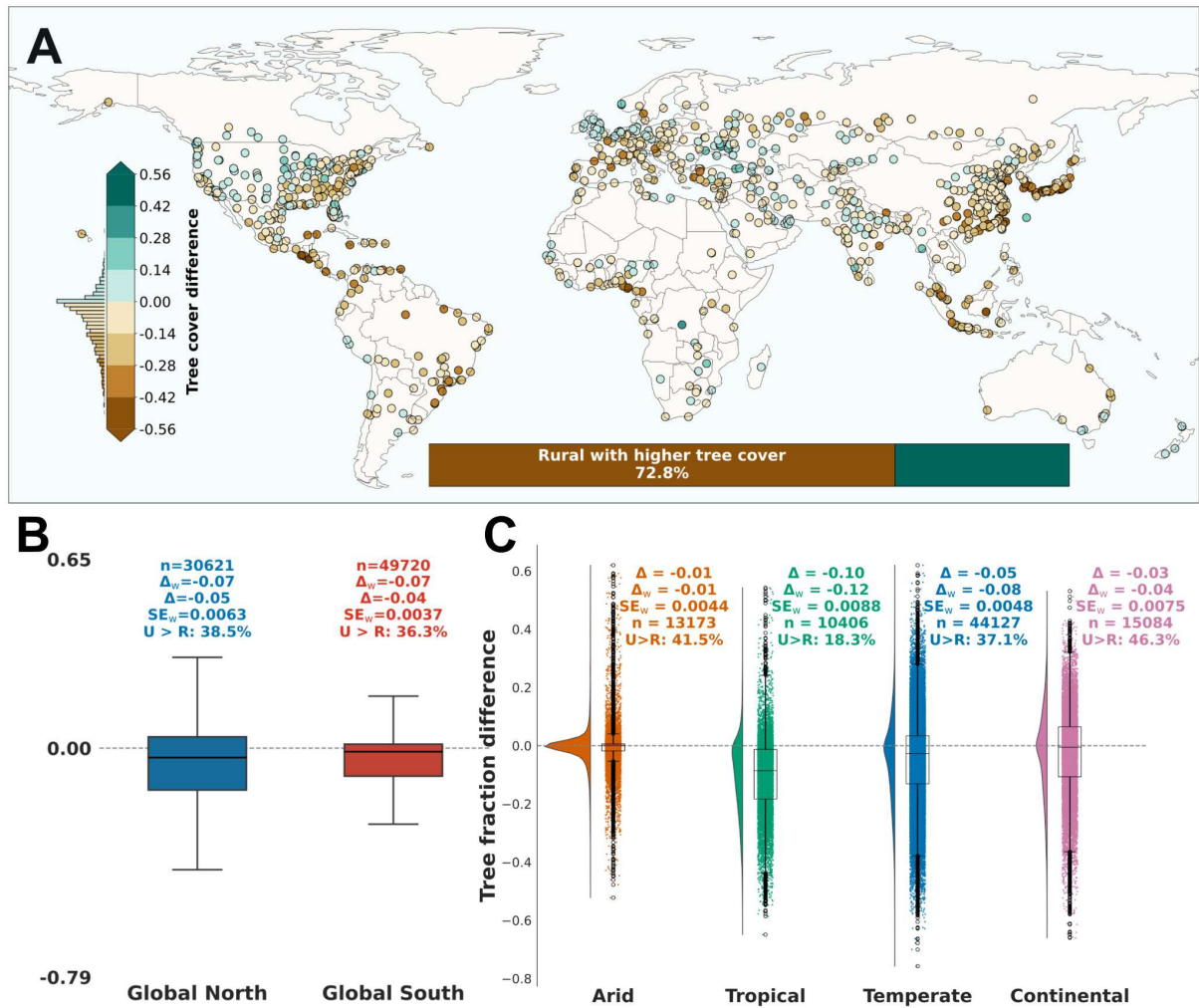


Fig. S3. Global urban–rural differences in tree cover. (A) Global distribution of urban–rural tree-cover differences (Δ = urban – rural) across 83,102 cities; 73% of cities have lower tree cover. Brown shading indicates cities where rural areas contain higher tree cover, while green shading denotes those with higher urban tree cover. (B) Tree cover Δ across Global North ($n=30,621$) and Global South ($n=49,720$) cities. Weighted mean (μ_w) tree-cover differences are -0.07 in both regions. Approximately 38.5% of Global North and 36.3% of Global South cities exhibit higher urban tree cover ($U>R$). (C) Distribution of tree height Δ across four major Köppen-Geiger climate zones for all cities. The smallest difference occurs in Arid cities ($\Delta_w=-0.01$), while Tropical cities show the largest difference ($\Delta_w=-0.12$). Complete statistics are provided in tables S1-3.

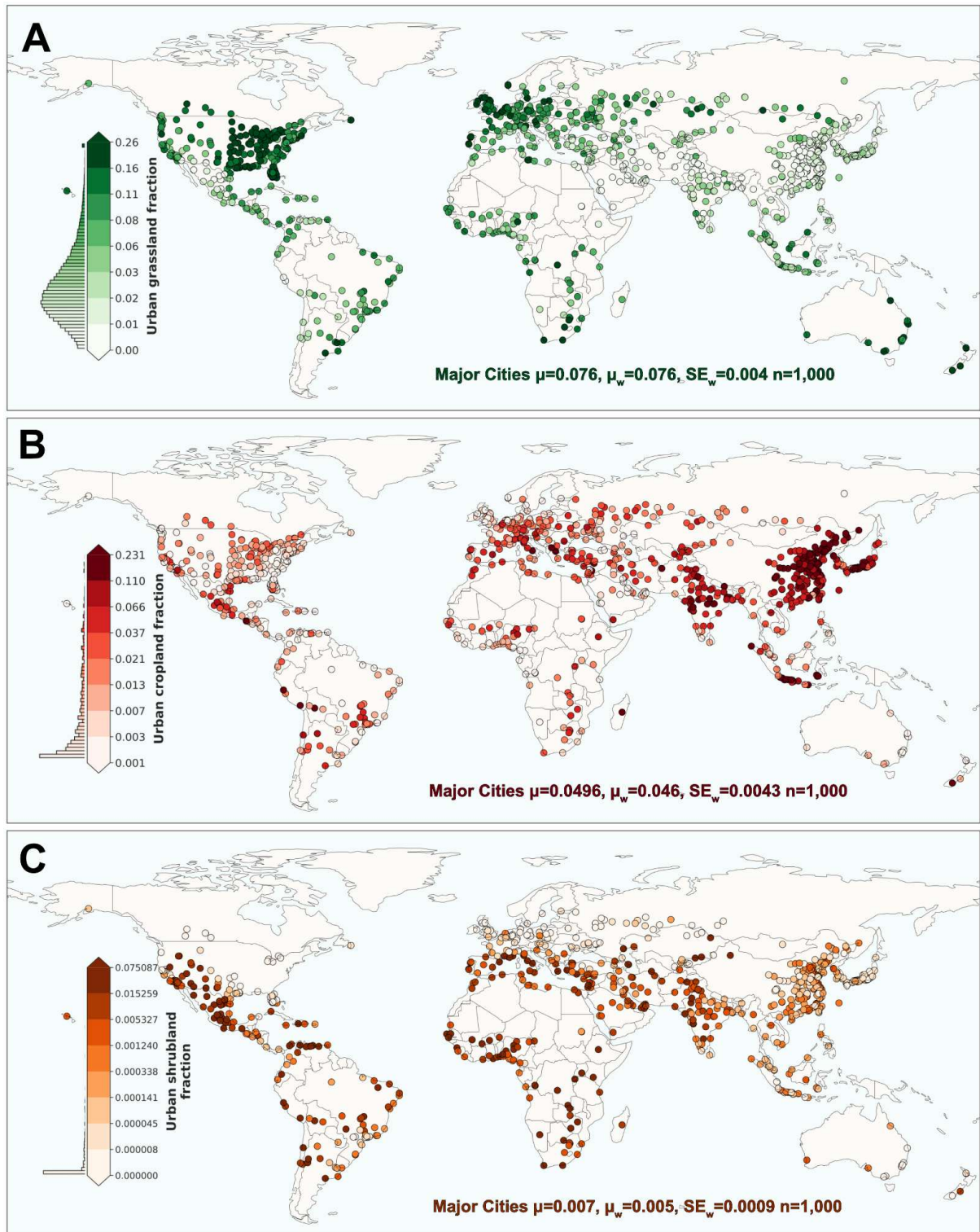


Fig. S4. Global distribution of urban grassland, cropland, and shrubland fractions. (A) Urban grassland fraction across major cities (top 1,000 by urban area). Weighted mean (μ_w) grassland fraction is 0.076 and $SE_w=0.0027$. Simple means (μ) are also provided. (B) Urban cropland fraction across major cities ($\mu_w=0.046$, $SE_w=0.0043$). (C) Urban shrubland fraction across major cities ($\mu_w=0.0407$, $SE_w=0.0008$). Complete statistics are available in table S1.

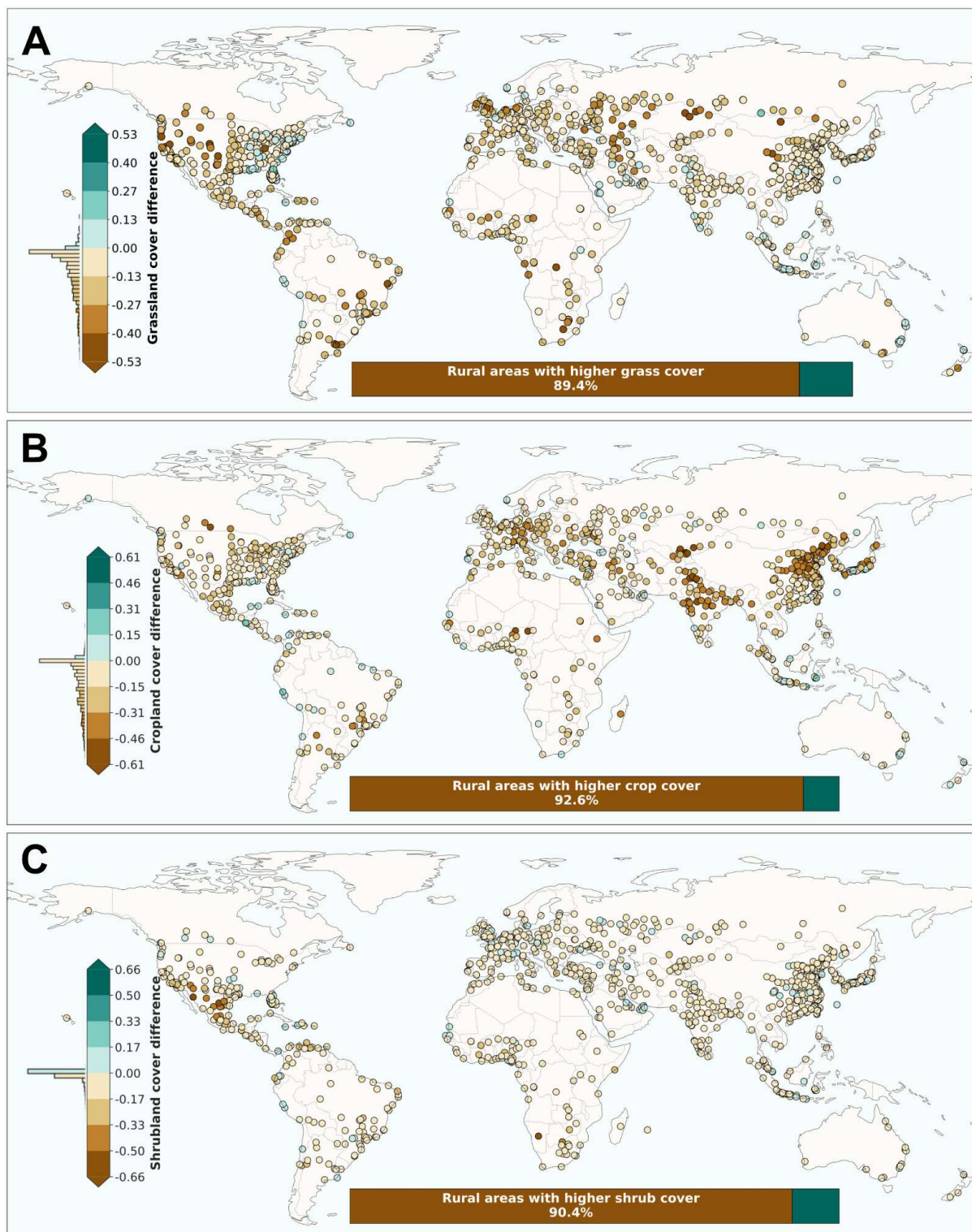


Fig. S5. Global urban–rural differences in grassland, cropland, and shrubland cover. (A) Urban–rural grassland cover difference (Δ = urban – rural) across major cities (top 1,000 by urban area). Rural areas have higher grass cover in 89.4% of cities. (B) Cropland cover Δ showing that 92.6% of cities have lower cropland cover within their urban boundaries. (C) Shrubland cover Δ , with 90.4% of cities exhibiting lower urban shrubland cover compared to their surroundings. Brown shading indicates cities where rural areas have higher vegetation subtype cover, and green shading denotes higher urban cover. Complete statistics are available in table S1.

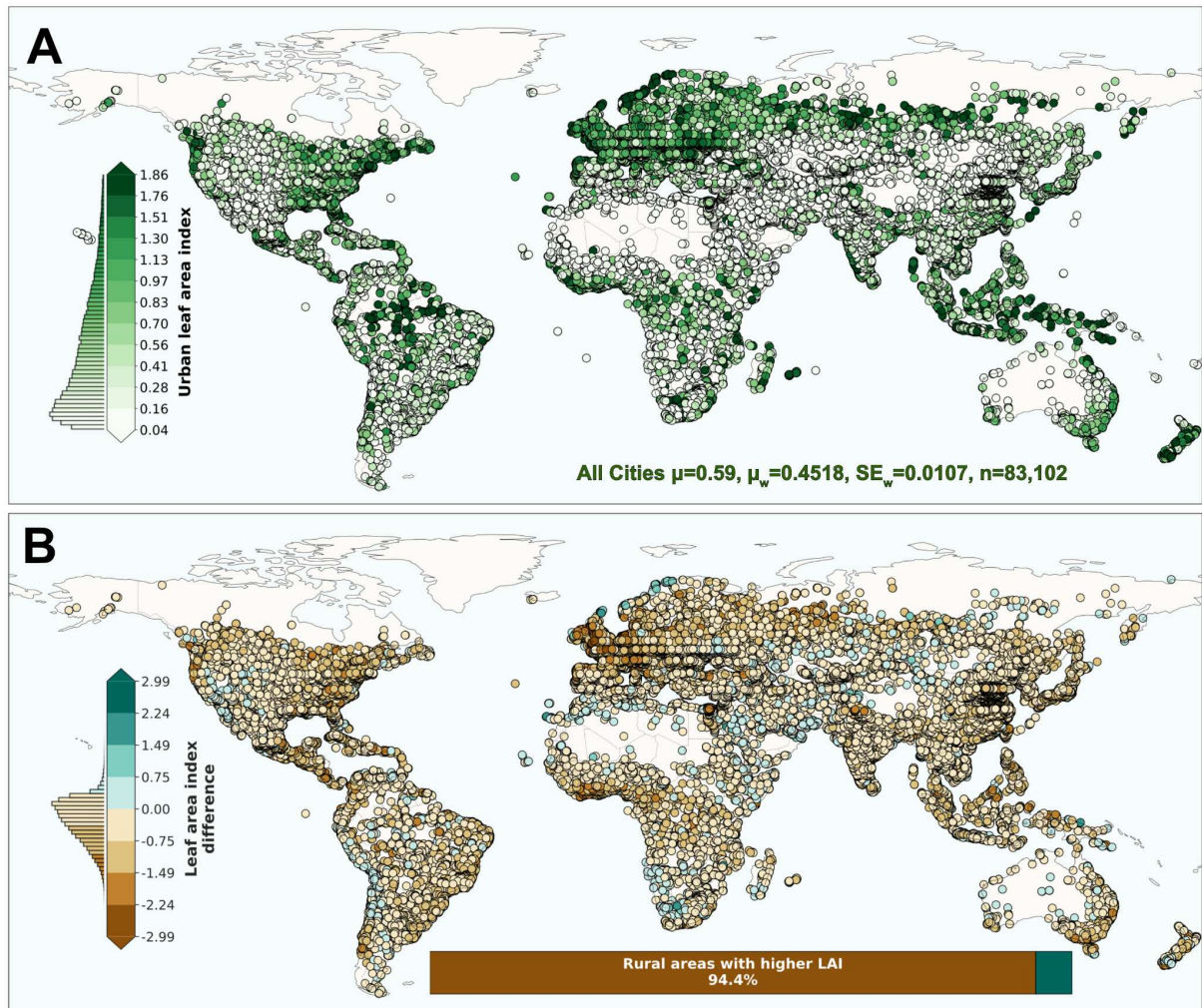


Fig. S6. Global distribution of urban leaf area index (LAI) and urban-rural differences. (A) Urban LAI across 83,102 cities. The weighted mean (μ_w) LAI is 0.4518 (simple mean $\mu=0.59$, weighted standard error $SE_w=0.0107$). **(B)** Urban-rural LAI differences ($\Delta = \text{urban} - \text{rural}$), showing that 94.4% of cities have lower urban LAI relative to their immediate rural surroundings. Brown shading marks cities where rural areas exhibit higher LAI, whereas green shading denotes higher urban canopy density. Complete statistics are provided in table S1.

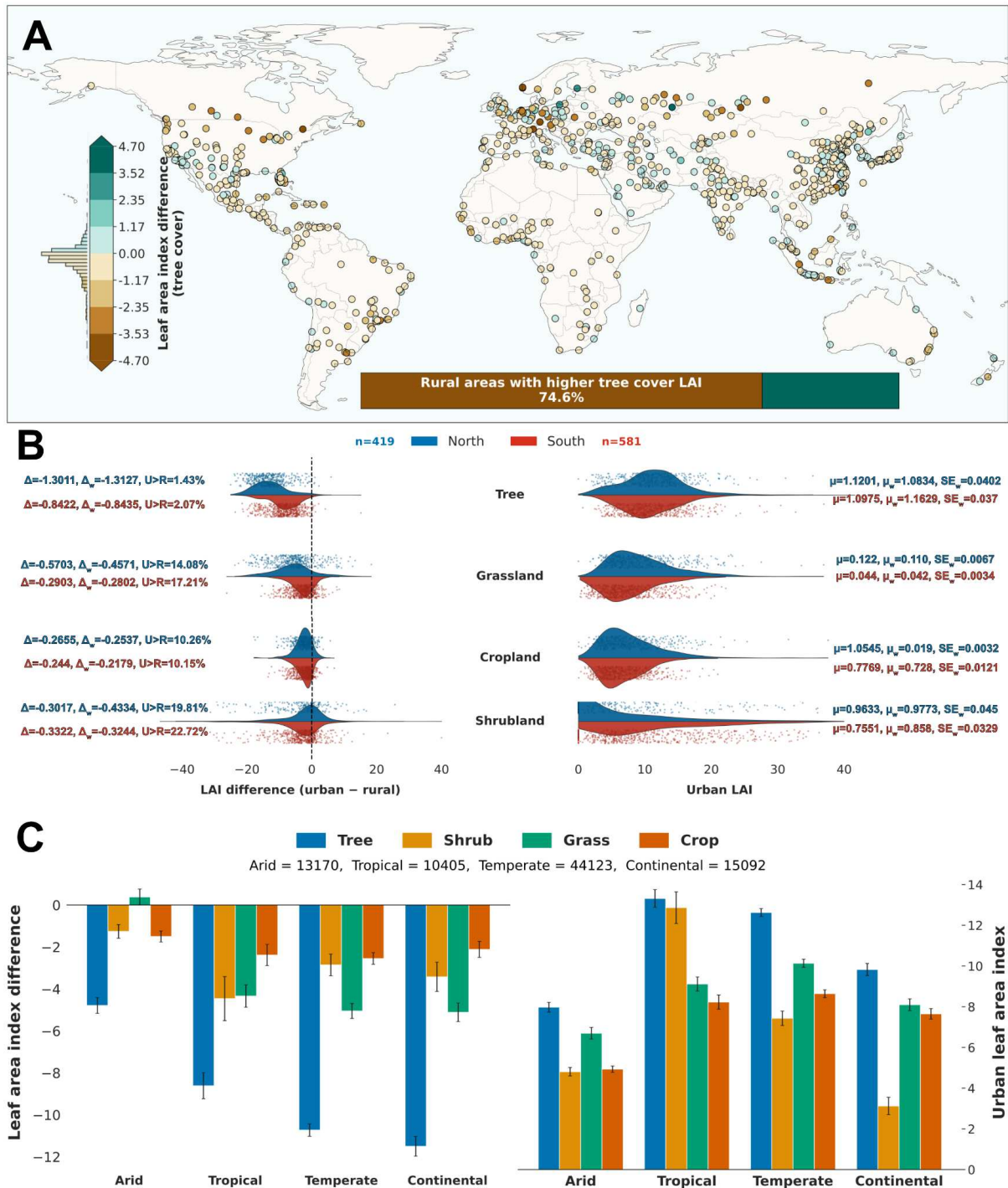


Fig. S7. Leaf area index (LAI) of vegetation subtypes and global urban-rural differences. (A) Urban-rural LAI differences for tree cover ($\Delta = \text{urban} - \text{rural}$) across the world's major cities (1,000 largest). Brown shading indicates cities where surrounding rural areas have higher tree LAI and green shadings indicate cities with higher urban tree LAI. Overall, 74.6% of major cities exhibit lower urban tree LAI. **(B)** LAI patterns for vegetation subtypes: tree, cropland, grassland and shrubland, in Global North ($n=419$) and Global South ($n=581$) across major cities. Left, urban-rural LAI difference ($\Delta = \text{urban} - \text{rural}$), weighted difference (Δ_w), and % of cities with higher urban LAI ($U > R$) for each subtype. Right, urban LAI (μ , μ_w , SE_w) for each vegetation subtype. **(C)** Urban LAI patterns across major Köppen-Geiger climate zones and vegetation subtypes across all cities. Left, area-weighted mean urban-rural differences (Δ_w) in LAI for tree, shrub, grass and crop cover across Arid ($n=13,170$), Tropical ($n=10,405$), Temperate ($n=44,123$) and Continental ($n=15,092$) climates. Right, area-weighted mean urban LAI (μ_w) by subtype and climate zone. Error bars denote weighted standard errors (SE_w). Complete statistics are provided in tables S1–3.

Fig. S8. Urban tree height and comparison across datasets. (A) Global map of mean urban tree height (μ)

across 83,102 cities. Weighted mean tree height (μ_w) is 3.66 m (simple mean $\mu=2.88$ m, weighted standard error $SE_w=0.0537$). **(B)** Urban–rural tree height differences (Δ = urban – rural), showing that 76.2% of cities have shorter urban trees. Brown shading indicates cities where rural trees are taller, while green marks those with taller urban trees. Complete statistics are given in table 1. **(C)** Comparison of urban and rural canopy height estimates across four global canopy height products: GLAD(54), Meta(47), ETH(27), and GLOFAB(55, 56), demonstrating consistent patterns of shorter urban canopy height compared to their immediate surroundings across datasets.

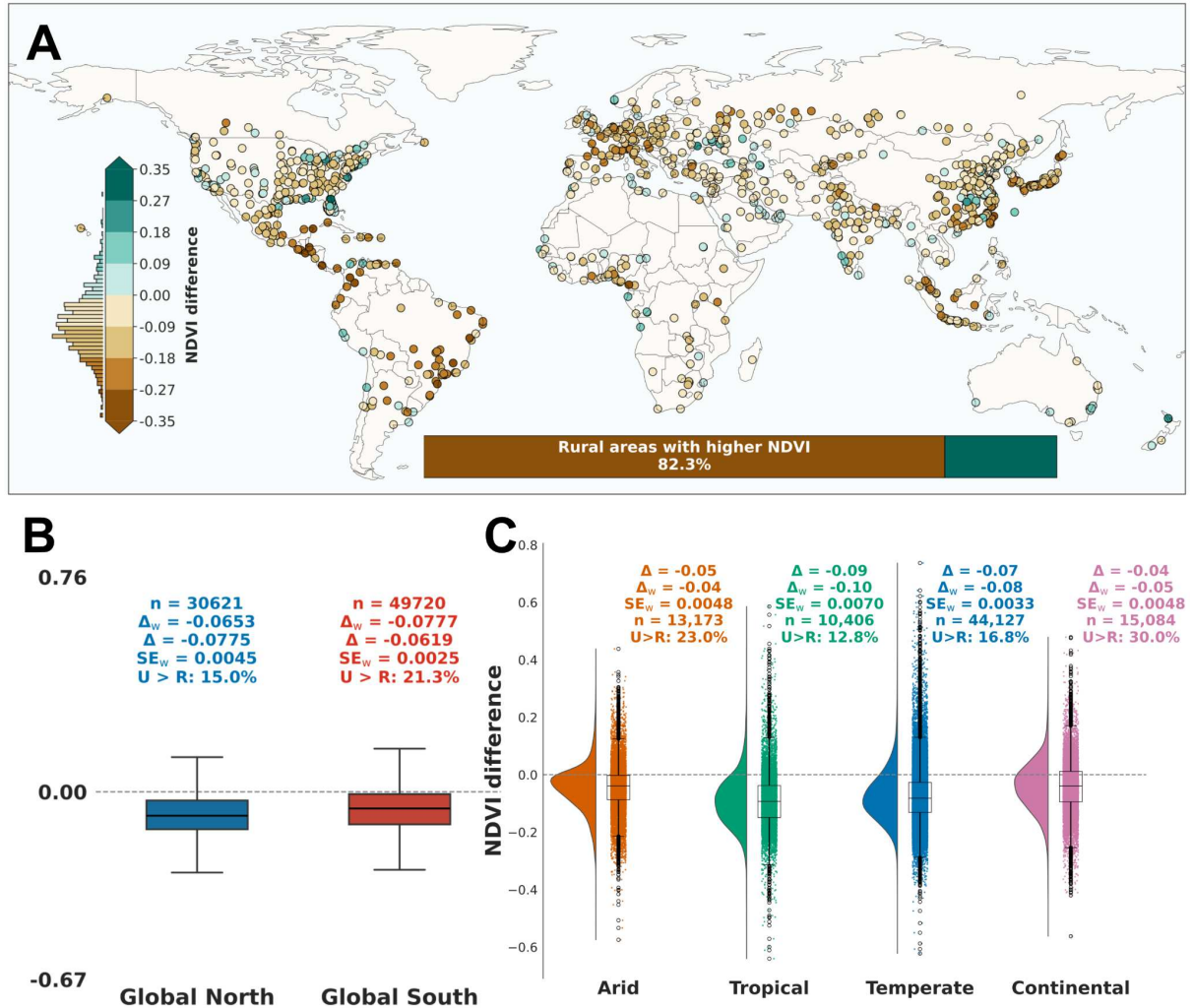


Fig. S9. Global urban–rural differences in NDVI. **(A)** Global distribution of urban–rural NDVI differences (Δ = urban – rural) across major cities (top 1,000 by urban area); 82.3% lower urban NDVI. Brown shading indicates rural areas with higher NDVI, while green shading denotes higher urban greenness. **(B)** NDVI Δ for Global North ($n=30,621$) and Global South ($n=49,720$) cities. Weighted mean NDVI differences (Δ_w) are -0.0653 in the Global North and -0.0777 in the Global South, with 15% and 21.3% of cities, respectively, exhibiting higher urban NDVI. **(C)** Distribution of NDVI across four Köppen-Geiger climate zones. NDVI Δ_w are smallest in Arid cities (-0.04) with 23% of cities having higher NDVI ($U>R$) than surrounding rural areas.

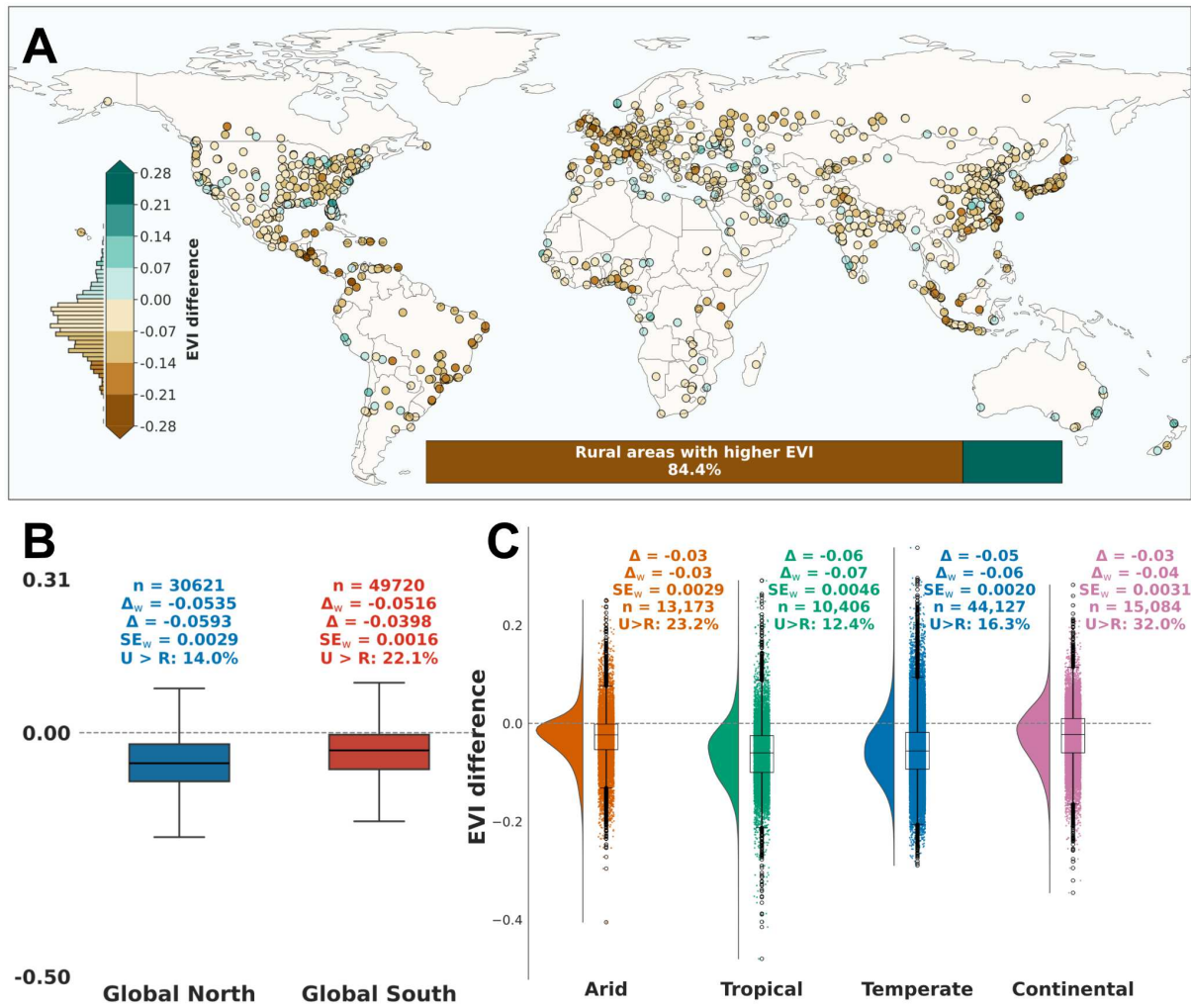


Fig. S10. Global urban-rural differences in EVI. (A) Global distribution of urban-rural EVI differences (Δ = urban - rural) across major cities (top 1,000 by urban area); 84.4% of cities with lower EVI. Brown shading indicates rural areas with higher EVI, while green shading denotes higher urban greenness. (B) EVI Δ for Global North ($n=30,621$) and Global South ($n=49,720$) cities. Weighted mean EVI differences (Δ_w) are -0.054 in the Global North and -0.052 in the Global South, with 14% and 22.1% of cities, respectively, exhibiting higher urban EVI. (C) Distribution of EVI across four Köppen-Geiger climate zones. The smallest difference occurs in Arid cities ($\Delta_w=-0.03$) with 23.2% of cities having higher EVI ($U>R$) than surrounding rural areas.

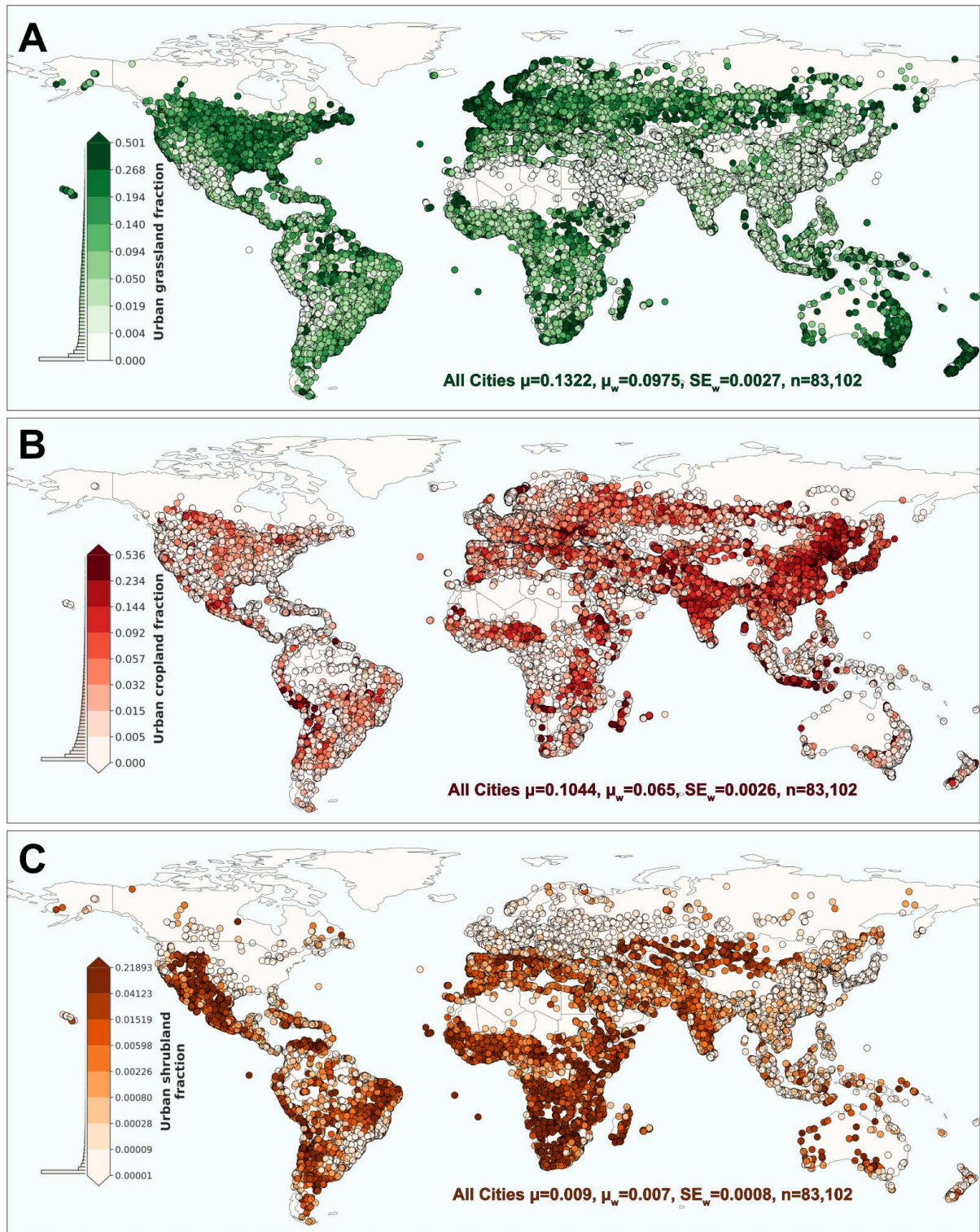


Fig. S11. Global distribution of urban grassland, cropland, and shrubland cover. (A) Urban grassland covers 83,102 cities with a weighted mean (μ_w) of 0.097 (simple mean $\mu=0.13$, and weighted standard error $SE_w=0.0027$). (B) Urban cropland fraction ($\mu_w=0.065$, $\mu=0.1044$, $SE_w=0.0026$). (C) Urban shrubland fraction ($\mu_w=0.007$, $\mu=0.009$, $SE_w=0.0008$). Complete statistics are available in table S1.

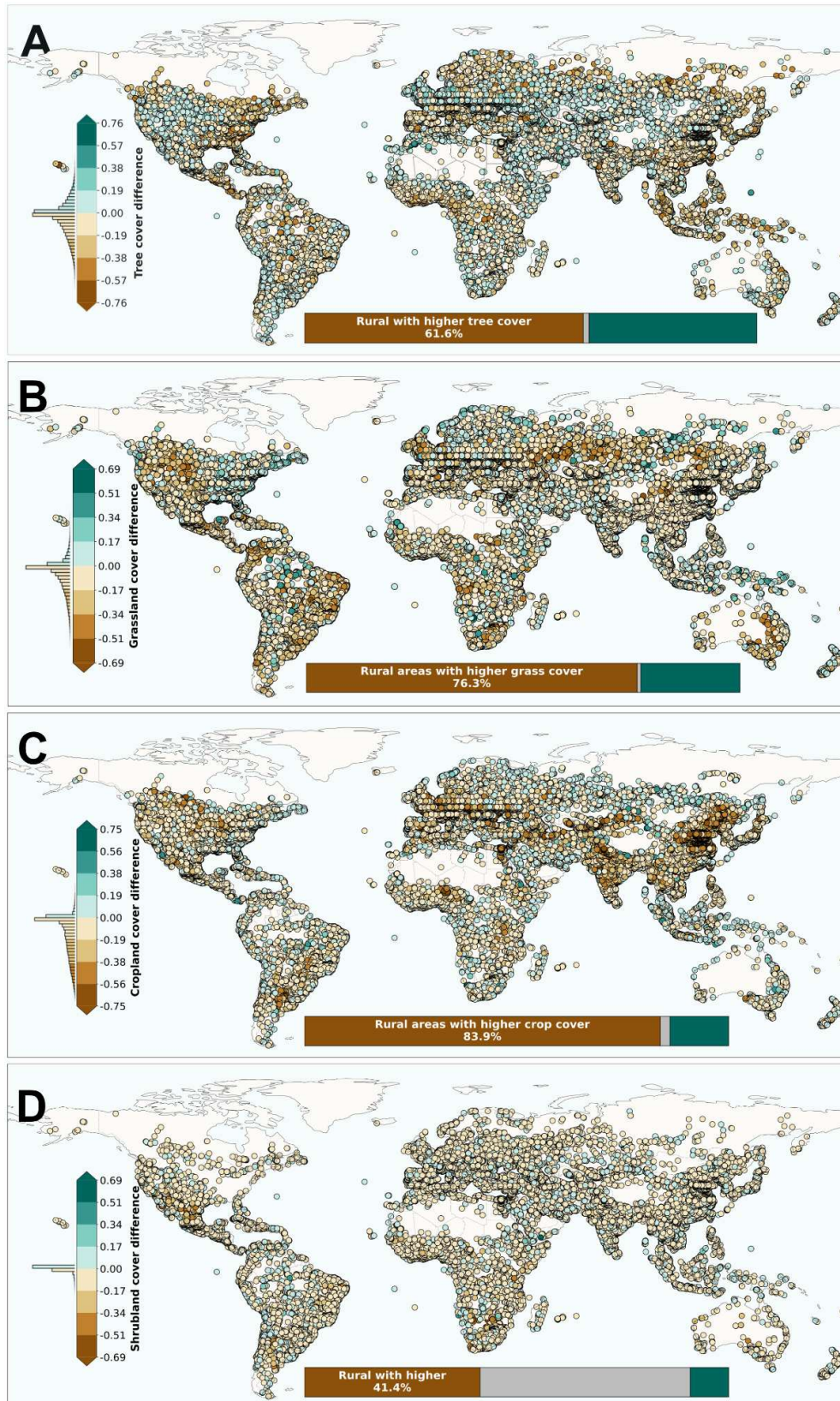


Fig. S12. Global urban–rural differences in grassland, cropland, and shrubland cover. Global maps showing urban–rural vegetation cover differences (Δ = urban – rural). **(A)** Rural areas have higher tree cover than 61.6% of cities. **(B)** Higher grassland cover in 77.1% of cities. **(C)** Higher cropland cover in 83.9% of cities. **(D)** Higher shrubland cover in 82% of cities. Across all vegetation subtypes, brown shading indicates cities where rural areas are greener, while green shading denotes higher urban cover. Complete statistics are provided in table S1.

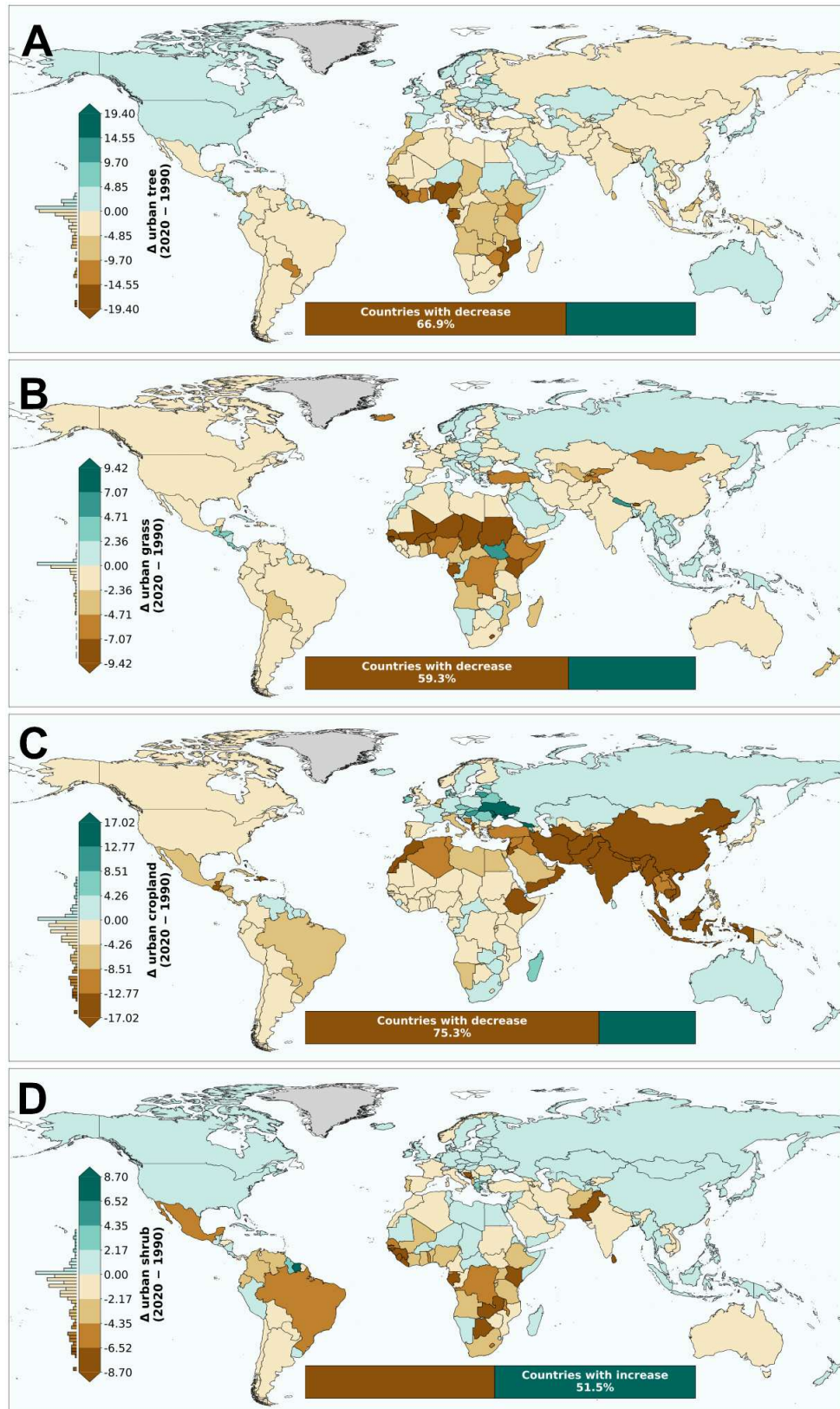


Fig. S13. Country-level change in vegetation subtypes across three decades. Country-level changes in urban vegetation composition over three decades (2020–1990). **(A)** Urban trees decreased in 66.9% of the countries. **(B)** Urban grassland cover decreased in 59.3% of countries. **(C)** Urban cropland cover declined in 75.3% of countries. **(D)** Urban shrubland cover increased in 51.5% of countries. Brown shading indicates a decrease and green shading an increase in urban vegetation in 2020 relative to 1990 levels.

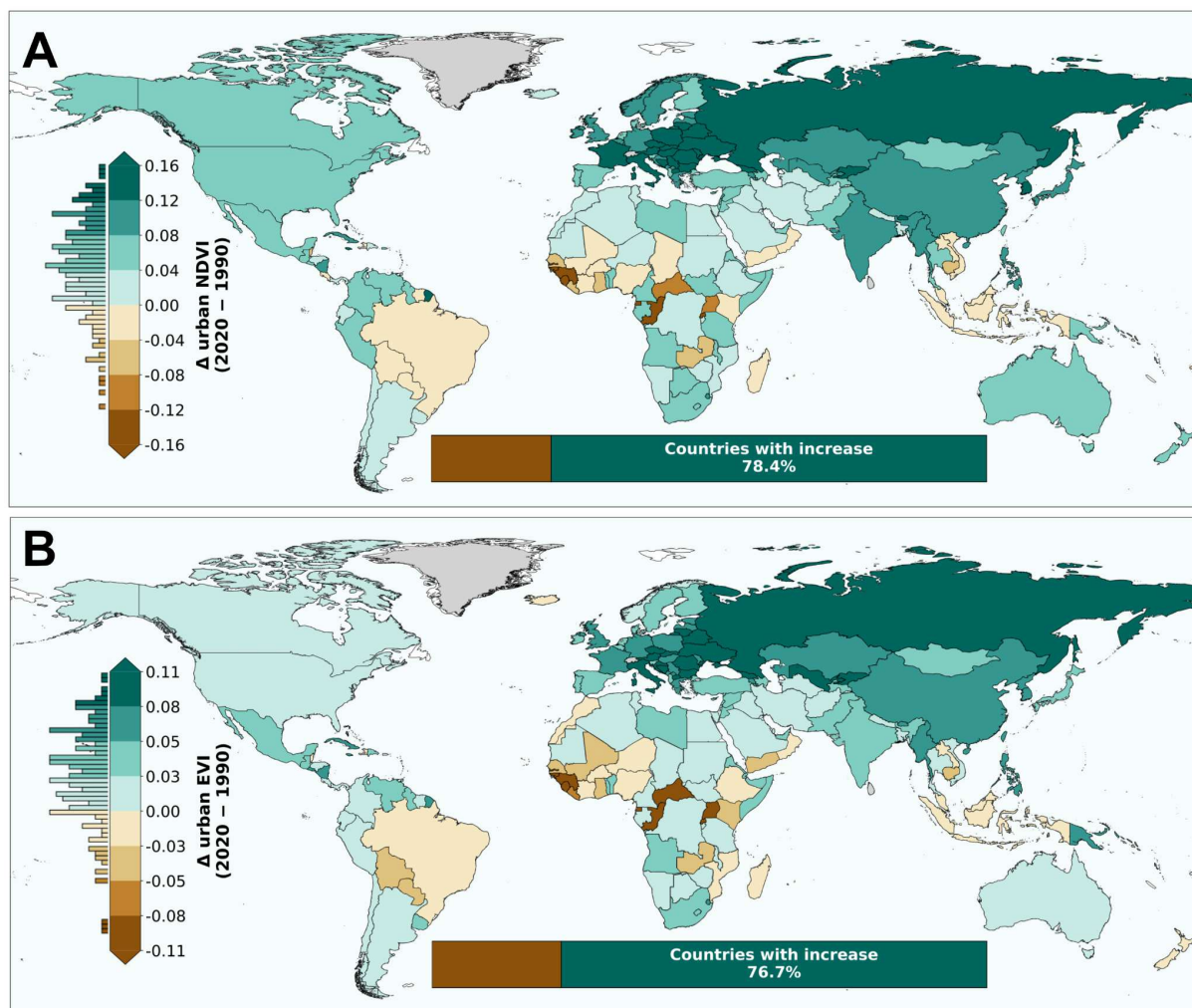


Fig. S14. Long-term changes in urban NDVI and EVI. a, Country-level change in urban NDVI (Δ = 2020 – 1990). b, Δ in EVI. Positive values denote greening; negative values denote browning. The share of countries with greening is indicated on each panel (NDVI: 78.4%; EVI: 76.7%). Gray areas indicate insufficient data.

Table S1. Summary of global urban and urban–rural differences in vegetation cover, structure, and density. Summary statistics for all cities ($n=83,102$) and major cities (1,000 largest) showing mean (μ) and weighted mean (μ_w) vegetation cover, structure, and density within urban and surrounding rural areas. Variables include total vegetation fraction, fractional cover by subtype (tree, grassland, cropland, shrubland), leaf area index (LAI, total and by vegetation subtype), and tree height. For each variable, Δ and Δ_w represent unweighted and weighted urban–rural differences (urban – rural), with negative values indicating lower urban vegetation or structure. Cohen’s d quantifies the weighted effect size between the urban and rural vegetation, and “% U>R” gives the percentage of cities where the urban value exceeds the rural value. All tests are significant ($p<0.01$).

Variable	Cohort	Urban μ	Urban SE	Urban μ_w	Urban SE _w	Rural μ	Rural SE	Rural μ_w	Rural SE _w	Δ	Δ_w	Cohen’s d	Rank-biserial r	% U>R	% U==R	% R>U
Vegetation	Major cities	0.3298	0.0059	0.3433	0.0114	0.6658	0.0054	0.6597	0.0101	-0.336	-0.3164	-2.0551	-0.9855	4.3	0	95.7
Vegetation	All cities	0.4479	0.0008	0.3754	0.0056	0.7237	0.0007	0.6881	0.0044	-0.2758	-0.3127	-1.5985	-0.9608	6.33	0.11	93.56
Tree cover	Major cities	0.1958	0.0052	0.2133	0.0098	0.2778	0.0063	0.2991	0.0117	-0.082	-0.0858	-0.6371	-0.6516	27.2	0	72.8
Tree cover	All cities	0.1987	0.0006	0.2034	0.0044	0.243	0.0007	0.2719	0.0049	-0.0443	-0.0885	-0.3271	-0.3538	37.09	1.28	61.63
Grassland	Major cities	0.0763	0.0024	0.0763	0.0041	0.1663	0.0045	0.1577	0.008	-0.09	-0.0813	-0.8292	-0.8882	10.6	0	89.4
Grassland	All cities	0.1325	0.0005	0.0976	0.0027	0.1979	0.0006	0.1783	0.0038	-0.0654	-0.0807	-0.5601	-0.6477	22.83	0.88	76.29
Cropland	Major cities	0.0496	0.0023	0.0461	0.0043	0.1818	0.0055	0.1595	0.0096	-0.1322	-0.1135	-0.9302	-0.9415	7.3	0.1	92.6
Cropland	All cities	0.1044	0.0005	0.065	0.0026	0.2563	0.0008	0.2041	0.0048	-0.152	-0.139	-0.8851	-0.8744	13.85	2.28	83.87
Shrubland	Major cities	0.0061	0.0006	0.0052	0.001	0.0279	0.0026	0.0303	0.005	-0.0218	-0.025	-0.3228	-0.8942	8.3	15.5	76.2
Shrubland	All cities	0.0094	0.0002	0.0071	0.0009	0.0195	0.0002	0.0241	0.0018	-0.0101	-0.017	-0.2403	-0.7271	9.06	49.56	41.39
LAI	Major cities	0.369	0.01	0.3932	0.0193	1.1577	0.0204	1.182	0.037	-0.7887	-0.7888	-1.5618	-0.9845	2.5	0.1	97.4
LAI	All cities	0.5931	0.0018	0.4518	0.0107	1.2497	0.0026	1.2105	0.0165	-0.6566	-0.7587	-1.2596	-0.9567	5.62	0.15	94.23
LAI (Tree)	Major cities	1.1099	0.015	1.1256	0.0281	2.1363	0.0216	2.2038	0.0392	-1.0273	-1.0782	-1.944	-0.9944	1.7	0.1	98.2
LAI (Tree)	All cities	1.2347	0.0024	1.1536	0.0144	2.002	0.0029	2.109	0.018	-0.7673	-0.9554	-1.3538	-0.9608	6.12	1.69	92.19
LAI (Grass)	Major cities	0.8459	0.0145	0.9198	0.0277	1.2478	0.0237	1.2872	0.0423	-0.4019	-0.3674	-0.7996	-0.7987	15.7	0.1	84.2
LAI (Grass)	All cities	0.9543	0.0023	0.9109	0.014	1.3494	0.003	1.3167	0.0192	-0.3951	-0.4059	-0.7596	-0.8063	16.37	1.27	82.36
LAI (Crop)	Major cities	0.714	0.0123	0.7147	0.0215	0.9694	0.0154	0.9526	0.0267	-0.2553	-0.238	-0.9836	-0.9086	10	0.3	89.7
LAI (Crop)	All cities	0.8796	0.0021	0.7808	0.0126	1.0607	0.0023	1.01	0.0136	-0.1809	-0.2293	-0.4104	-0.5827	25.58	2.84	71.58
LAI (Shrub)	Major cities	0.8676	0.0277	0.9244	0.0537	1.1903	0.0313	1.304	0.06	-0.3226	-0.3796	-0.4335	-0.6245	21.2	16.6	62.2
LAI (Shrub)	All cities	0.399	0.0027	0.7133	0.0236	0.6528	0.0034	1.0006	0.0253	-0.2538	-0.2874	-0.3117	-0.602	12.46	51.23	36.31
Tree height	Major cities	3.2888	0.0393	3.9511	0.0944	5.1711	0.0865	6.9087	0.1898	-1.8823	-2.9576	-0.9099	-0.8266	18.5	0	81.5
Tree height	All cities	2.9373	0.0059	3.6639	0.0537	4.3392	0.0097	6.3442	0.0906	-1.4018	-2.6804	-0.7081	-0.7256	23.57	0.24	76.2

Table S2. Summary of global urban and urban–rural differences in vegetation cover, structure, and density by socioeconomic condition. Summary statistics comparing vegetation cover, structure, and density between the Global North ($n=30,621$) and Global South ($n=49,720$), shown separately for all cities ($n=83,102$) and major cities (1,000 largest). Variables include total vegetation fraction, fractional cover by subtype (tree, grassland, cropland, shrubland), leaf area index (LAI, total and by vegetation subtype), and tree height. For each variable, Δ and Δ_w represent unweighted and area-weighted urban–rural differences (urban – rural), with negative values indicating lower urban vegetation or canopy structure in cities. “% U > R” gives the percentage of cities with higher urban values, while the rank-biserial r indicates the non-parametric effect size of unweighted urban–rural differences in Global North and Global South cities. Rows with * indicate non-significant p -values.

Variable	Region	Cohort	Urban μ	Urban SE	Urban μ_w	Urban SE _w	Rural μ	Rural SE	Rural μ_w	Rural SE _w	Δ	Δ_w	U>R	U<R	U==R	n	Rank-biserial r
Vegetation	Global North	All cities	0.5155	0.0011	0.4558	0.009	0.7817	0.0009	0.7316	0.0079	-0.2662	-0.2758	5.75	94.18	0.07	30621	-0.0991
Vegetation	Global South	All cities	0.4058	0.0012	0.3114	0.0062	0.6962	0.0009	0.6618	0.0049	-0.2904	-0.3503	5.59	94.3	0.11	49720	
Vegetation	Global North	Major cities	0.4413	0.0089	0.4257	0.0173	0.7163	0.0086	0.6893	0.0169	-0.275	-0.2637	6.68	93.32	0	419	-0.4199
Vegetation	Global South	Major cities	0.2503	0.0059	0.2593	0.0116	0.638	0.0062	0.6357	0.011	-0.3877	-0.3764	1.89	98.11	0	581	
Tree cover	Global North	All cities	0.2741	0.001	0.283	0.0078	0.3275	0.0012	0.3511	0.009	-0.0535	-0.0681	38.47	61.19	0.34	30621	0.0468
Tree cover	Global South	All cities	0.1507	0.0007	0.1404	0.0042	0.1892	0.0009	0.2111	0.005	-0.0385	-0.0707	36.33	61.84	1.83	49720	
Tree cover	Global North*	Major cities	0.2902	0.0079	0.2887	0.0151	0.389	0.0095	0.3635	0.0178	-0.0788	-0.0749	33.65	66.35	0	419	-0.0634
Tree cover	Global South*	Major cities	0.1284	0.0052	0.1363	0.0096	0.2151	0.0073	0.235	0.0134	-0.0867	-0.0987	22.55	77.45	0	581	
Shrubland	Global North	All cities	0.0038	0.0001	0.0039	0.0008	0.0094	0.0003	0.0182	0.003	-0.0056	-0.0144	5.54	25.05	69.41	30621	-0.2138
Shrubland	Global South	All cities	0.0127	0.0003	0.0095	0.0012	0.0257	0.0004	0.0289	0.0022	-0.013	-0.0193	10.91	50.84	38.25	49720	
Shrubland	Global North	Major cities	0.0038	0.0008	0.0041	0.0016	0.0164	0.0031	0.0278	0.0081	-0.0126	-0.0237	9.79	57.28	32.94	419	-0.4877
Shrubland	Global South	Major cities	0.0077	0.0008	0.0063	0.0012	0.0366	0.0039	0.0333	0.0062	-0.0288	-0.0269	6.71	89.85	3.44	581	
Cropland	Global North	All cities	0.0464	0.0004	0.0281	0.0022	0.1833	0.0011	0.1328	0.0067	-0.1368	-0.1047	12.94	85.13	1.93	30621	-0.0994
Cropland	Global South	All cities	0.1431	0.0007	0.0948	0.0035	0.3106	0.0011	0.2653	0.0059	-0.1677	-0.1705	13.35	84.36	2.29	49720	
Cropland	Global North	Major cities	0.0232	0.0018	0.0199	0.0032	0.1152	0.0061	0.0948	0.0098	-0.092	-0.0747	7.16	92.84	0	419	-0.2945
Cropland	Global South	Major cities	0.0676	0.0033	0.0726	0.0065	0.2335	0.0079	0.2289	0.0133	-0.1659	-0.1564	6.54	93.29	0.17	581	
Grassland	Global North	All cities	0.1909	0.0007	0.1407	0.0047	0.2609	0.0009	0.2281	0.0065	-0.07	-0.0874	26.09	73.6	0.31	30621	0.0248
Grassland	Global South	All cities	0.0987	0.0006	0.0661	0.0029	0.1692	0.0008	0.154	0.0044	-0.0706	-0.0879	17.94	81.23	0.83	49720	
Grassland	Global North*	Major cities	0.1239	0.004	0.1127	0.0069	0.214	0.0068	0.2011	0.0121	-0.0901	-0.0883	13.37	86.63	0	419	-0.0474
Grassland	Global South*	Major cities	0.0457	0.0023	0.0432	0.0034	0.1472	0.0059	0.1335	0.0102	-0.1015	-0.0903	4.65	95.35	0	581	
LAI	Global North	All cities	0.7412	0.003	0.5569	0.0184	1.6578	0.0043	1.5149	0.0315	-0.9166	-0.958	3.45	96.45	0.1	30621	0.4584
LAI	Global South	All cities	0.4932	0.0022	0.3619	0.0116	0.9988	0.0028	0.9787	0.0154	-0.5056	-0.6168	6.68	93.17	0.15	49720	
LAI	Global North	Major cities	0.4948	0.015	0.4666	0.0243	1.4781	0.033	1.3811	0.0603	-0.9833	-0.9145	3.34	96.42	0.24	419	0.3704
LAI	Global South	Major cities	0.2756	0.0117	0.3146	0.0268	0.9396	0.0218	0.9859	0.0392	-0.664	-0.6713	1.72	98.28	0	581	
LAI (Shrub)	Global North	All cities	0.2593	0.0037	0.4682	0.0366	0.4206	0.005	0.7599	0.0451	-0.1613	-0.2916	8.43	20.85	70.72	30621	-0.1725
LAI (Shrub)	Global South	All cities	0.4684	0.0036	0.8936	0.028	0.7767	0.0045	1.1762	0.0281	-0.3083	-0.2826	14.54	45.35	40.12	49720	
LAI (Shrub)	Global North	Major cities	0.5715	0.0406	0.5778	0.0702	0.8732	0.0494	1.0112	0.0942	-0.3017	-0.4334	19.81	45.58	34.61	419	-0.1575
LAI (Shrub)	Global South	Major cities	1.0676	0.0354	1.2706	0.0676	1.3998	0.0381	1.595	0.0685	-0.3322	-0.3244	22.72	72.98	4.3	581	
LAI (Tree)	Global North	All cities	1.3701	0.0036	1.1823	0.0249	2.379	0.0042	2.4013	0.0303	-1.0089	-1.219	3.61	95.81	0.58	30621	0.416
LAI (Tree)	Global South	All cities	1.1378	0.003	1.121	0.0165	1.762	0.0036	1.8803	0.0191	-0.6243	-0.7592	7.51	90.21	2.28	49720	
LAI (Tree)	Global North	Major cities	1.1201	0.0231	1.0834	0.0402	2.4212	0.0329	2.3961	0.0603	-1.3011	-1.3127	1.43	98.33	0.24	419	0.5306
LAI (Tree)	Global South	Major cities	1.0975	0.0192	1.1629	0.037	1.9397	0.0252	2.0064	0.0447	-0.8422	-0.8435	2.07	97.93	0	581	
LAI (Grass)	Global North	All cities	1.1883	0.0038	1.0425	0.0264	1.804	0.0054	1.6128	0.0395	-0.6157	-0.5703	9.31	90.18	0.51	30621	0.4073
LAI (Grass)	Global South	All cities	0.8072	0.0027	0.8059	0.0145	1.0673	0.0031	1.0864	0.0172	-0.2601	-0.2805	20.68	77.61	1.71	49720	
LAI (Grass)	Global North	Major cities	0.9633	0.0245	0.9773	0.045	1.5336	0.0421	1.4344	0.0737	-0.5703	-0.4571	14.08	85.68	0.24	419	0.3631
LAI (Grass)	Global South	Major cities	0.7551	0.0167	0.858	0.0329	1.0455	0.0247	1.1383	0.044	-0.2903	-0.2802	17.21	82.79	0	581	
LAI (Crop)	Global North	All cities	1.0545	0.0042	0.847	0.0261	1.2633	0.0043	1.1053	0.0275	-0.2088	-0.2582	25.88	71.45	2.66	30621	0.0702
LAI (Crop)	Global South	All cities	0.7769	0.0022	0.728	0.0121	0.9412	0.0025	0.935	0.0135	-0.1644	-0.2071	25.29	72.08	2.63	49720	
LAI (Crop)	Global North*	Major cities	0.7742	0.0222	0.7053	0.0344	1.0397	0.0257	0.9591	0.0433	-0.2655	-0.2537	10.26	89.26	0.48	419	0.0535
LAI (Crop)	Global South*	Major cities	0.6691	0.0137	0.7223	0.0263	0.9131	0.0184	0.9403	0.0315	-0.244	-0.2179	10.15	89.67	0.17	581	
Tree height	Global North	All cities	3.4522	0.0104	3.6984	0.0699	5.7329	0.0165	6.4651	0.1238	-2.2807	-2.7667	10.57	88.97	0.45	30621	0.4605
Tree height	Global South	All cities	2.5208	0.0069	2.8152	0.0391	3.3545	0.0102	3.8112	0.0611	-0.8337	-0.9961	31.06	66.49	2.45	49720	
Tree height	Global North	Major cities	3.7768	0.0622	3.8483	0.1142	6.8496	0.1276	6.9374	0.2492	-3.0728	-3.0891	7.4	92.6	0	419	0.5621
Tree height	Global South	Major cities	2.9531	0.0461	3.0807	0.081	4.0531	0.0912	4.2936	0.1648	-1.1	-1.2129	26.33	73.67	0	581	

Table S3. Summary of global urban and urban–rural differences in vegetation cover, structure, and density by climate zone. Summary statistics comparing vegetation cover, structure, and density across four Köppen–Geiger climate groups (Arid, Tropical, Temperate, Continental), for all cities ($n=83,102$) and major cities (1,000 largest). Variables include total vegetation fraction, vegetation subtypes (tree, grassland, cropland, shrubland), leaf area index (LAI; total and by subtype), and tree height. For variables, μ and μ_w denote unweighted and area-weighted means for urban and rural areas; Δ and Δ_w are the corresponding urban–rural differences (urban – rural), where negative values indicate lower urban vegetation cover or structure. “% U > R” is the percentage of cities with higher urban values, Cohen’s d and rank-biserial r quantify parametric and non-parametric effect sizes of Δ_w , and ANOVA η^2 reports the proportion of variance in Δ_w explained by climate zone. Rows with * indicate non-significant p -values.

Variable	Climate	Cohort	Urban μ	Urban SE	Urban μ w	Urban SEw	Rural μ	Rural SE	Rural μ w	Rural SEw	Δ	Δ w	Cohen's d	Rank-biserial r	n	% U-R	% U-R	% U-R	% U-R	ANOVA F	ANOVA p
Vegetation	Arid	All cities	0.2473	0.0018	0.1899	0.0105	0.5429	0.0021	0.5243	0.0151	-0.2957	-0.3296	-0.13566	-0.9165	13173	10.13	89.22	0.65	542.6958	0.0193	
Vegetation	Tropical	All cities	0.4172	0.0024	0.3597	0.0144	0.7006	0.0016	0.6792	0.0096	-0.2834	-0.3139	-1.5881	-0.9583	10406	9.08	90.92	0	542.6958	0.0193	
Vegetation	Temperate	All cities	0.4676	0.001	0.4068	0.007	0.7538	0.0008	0.7177	0.005	-0.2861	-0.3038	-1.8714	-0.9776	44127	4.33	95.67	0	542.6958	0.0193	
Vegetation	Continental	All cities	0.5863	0.0019	0.4989	0.0118	0.8126	0.0011	0.7822	0.0068	-0.2264	-0.2722	-1.3578	-0.9564	15084	6.52	93.48	0	542.6958	0.0193	
Vegetation	Arid	Major cities	0.1527	0.007	0.1587	0.0136	0.5179	0.017	0.5152	0.0339	-0.3652	-0.3565	-1.9022	-0.9786	182	6.04	93.96	0	6.8148	0.0201	
Vegetation	Tropical	Major cities	0.3045	0.0124	0.3444	0.0259	0.674	0.0091	0.6568	0.0169	-0.3995	-0.3399	-2.2448	-0.9686	170	2.94	97.06	0	6.8148	0.0201	
Vegetation	Temperate	Major cities	0.376	0.0083	0.3857	0.015	0.6906	0.0062	0.6916	0.0106	-0.3176	-0.3061	-2.0345	-0.9848	507	4.93	95.07	0	6.8148	0.0201	
Vegetation	Continental	Major cities	0.4256	0.0129	0.4486	0.0249	0.7514	0.0085	0.7469	0.0159	-0.3258	-0.2993	-2.5109	-0.9996	141	0.71	99.29	0	6.8148	0.0201	
Tree Cover	Arid	All cities	0.0464	0.0008	0.055	0.005	0.0525	0.0007	0.0687	0.0058	-0.0061	-0.0143	-0.0882	-0.187	13173	41.55	52.17	6.3	1201.7142	0.0417	
Tree Cover	Tropical	All cities	0.2044	0.0017	0.1859	0.0096	0.3091	0.0021	0.3083	0.0124	-0.1047	-0.1203	-0.8053	-0.79	10406	18.33	81.39	0.29	1201.7142	0.0417	
Tree Cover	Temperate	All cities	0.2235	0.0008	0.2372	0.0061	0.2716	0.001	0.317	0.0065	-0.0481	-0.0813	-0.3365	-0.3558	44127	37.11	62.67	0.22	1201.7142	0.0417	
Tree Cover	Continental	All cities	0.2545	0.0015	0.2752	0.0096	0.2795	0.0018	0.3114	0.0107	-0.025	-0.038	-0.173	-0.1478	15084	46.32	53.29	0.38	1201.7142	0.0417	
Tree Cover	Arid*	Major cities	0.0461	0.0036	0.0641	0.0086	0.0568	0.0049	0.0857	0.0143	-0.0107	-0.0217	-0.2135	-0.1891	182	46.7	53.3	0	38.2387	0.1033	
Tree Cover	Tropical	Major cities	0.1691	0.0066	0.1812	0.0149	0.3087	0.0128	0.308	0.0235	-0.1395	-0.1272	-1.1004	-0.9185	170	8.82	91.18	0	38.2387	0.1033	
Tree Cover	Temperate	Major cities	0.2371	0.0076	0.2382	0.0142	0.3036	0.0084	0.3038	0.0147	-0.0965	-0.1059	-0.6958	-0.6893	507	23.87	76.13	0	38.2387	0.1033	
Tree Cover	Continental	Major cities	0.2743	0.0126	0.2937	0.0231	0.3287	0.0157	0.3404	0.0288	-0.0545	-0.0473	-0.4716	-0.49	141	35.46	64.54	0	38.2387	0.1033	
Cropland	Arid	All cities	0.1084	0.0011	0.0644	0.006	0.3116	0.0023	0.2411	0.0147	-0.2032	-0.1712	-0.9885	-0.9005	13173	11.02	84.24	4.74	1413.4315	0.0487	
Cropland	Tropical	All cities	0.0817	0.0017	0.0721	0.0102	0.1512	0.002	0.1445	0.0119	-0.0695	-0.0703	-0.5035	-0.6948	10406	21.08	74.67	4.27	1413.4315	0.0487	
Cropland	Temperate	All cities	0.0916	0.0006	0.0574	0.0028	0.256	0.001	0.1982	0.006	-0.1644	-0.1356	-1.0226	-0.9288	44127	10.89	88.16	0.96	1413.4315	0.0487	
Cropland	Continental	All cities	0.1551	0.0014	0.0869	0.0073	0.2858	0.0021	0.241	0.0121	-0.1307	-0.1456	-0.7768	-0.7882	15084	19.65	78.09	2.27	1413.4315	0.0487	
Cropland	Arid	Major cities	0.0518	0.0046	0.0424	0.008	0.2277	0.0146	0.1831	0.0275	-0.1759	-0.1409	-1.066	-0.953	182	7.69	92.31	0	16.6906	0.0479	
Cropland	Tropical	Major cities	0.0649	0.0068	0.0775	0.0192	0.1529	0.0084	0.1402	0.0206	-0.0978	-0.0705	-0.6058	-0.9011	170	11.18	88.82	0	16.6906	0.0479	
Cropland	Temperate	Major cities	0.0469	0.0026	0.0401	0.0042	0.1742	0.007	0.146	0.0114	-0.1273	-0.1096	-0.9729	-0.9475	507	6.71	93.29	0	16.6906	0.0479	
Cropland	Continental	Major cities	0.0499	0.0054	0.0402	0.0097	0.2096	0.0159	0.2033	0.0306	-0.1597	-0.163	-1.1291	-0.9949	141	3.55	95.74	1.42	16.6906	0.0479	
Grassland	Arid	All cities	0.0582	0.0011	0.0463	0.006	0.1136	0.0015	0.1287	0.0106	-0.0555	-0.0826	-0.5075	-0.7318	13173	18.99	76.01	5.03	95.909	0.0035	
Grassland	Tropical	All cities	0.1065	0.0014	0.0842	0.0069	0.1877	0.0018	0.1633	0.0098	-0.0811	-0.0775	-0.6104	-0.7262	10406	18.48	81.31	0.21	95.909	0.0035	
Grassland	Temperate	All cities	0.1473	0.0006	0.1082	0.0036	0.2124	0.0008	0.1867	0.005	-0.0651	-0.075	-0.5811	-0.643	44127	23.26	76.67	0.07	95.909	0.0035	
Grassland	Continental	All cities	0.1711	0.0012	0.1334	0.007	0.2354	0.0014	0.2188	0.0081	-0.0643	-0.0813	-0.522	-0.5761	15084	27.72	72.2	0.08	95.909	0.0035	
Grassland	Arid	Major cities	0.0361	0.0033	0.0357	0.0057	0.1444	0.0122	0.1366	0.0218	-0.1083	-0.1011	-0.8332	-0.9371	182	10.44	89.56	0	4.4447	0.0132	
Grassland	Tropical	Major cities	0.0665	0.0038	0.0722	0.0079	0.1591	0.0084	0.1402	0.0206	-0.0978	-0.0705	-0.6058	-0.9011	170	10.59	89.41	0	4.4447	0.0132	
Grassland	Temperate	Major cities	0.0862	0.0026	0.0641	0.0056	0.1667	0.0063	0.1638	0.0118	-0.0785	-0.0796	-0.7322	-0.9475	507	12.23	87.77	0	4.4447	0.0132	
Grassland	Continental	Major cities	0.0992	0.0085	0.1133	0.0147	0.2028	0.0115	0.1953	0.0196	-0.1035	-0.0824	-0.9823	-0.9505	141	4.96	95.04	0	4.4447	0.0132	
Shrubland	Arid	All cities	0.0326	0.0008	0.0233	0.0044	0.062	0.0021	0.0081	0.0091	-0.0294	-0.0589	-0.3652	-0.7119	13173	14.54	65.71	19.83	1681.6811	0.0574	
Shrubland	Tropical	All cities	0.017	0.0006	0.0101	0.0023	0.0376	0.0008	0.0331	0.0049	-0.0206	-0.0229	-0.4023	-0.7676	10406	14.18	68.25	17.82	1681.6811	0.0574	
Shrubland	Temperate	All cities	0.0036	0.0001	0.0028	0.0005	0.0089	0.0002	0.0097	0.0012	-0.0053	-0.007	-0.2169	-0.7417	44127	7.78	35.87	56.48	1681.6811	0.0574	
Shrubland	Continental	All cities	0.0004	0.0001	0.0003	0.0003	0.0008	0.0001	0.0007	0.0003	-0.0003	-0.0004	-0.0669	-0.6596	15084	4.25	17.48	78.43	1681.6811	0.0574	
Shrubland	Arid	Major cities	0.0177	0.0024	0.0158	0.0045	0.0833	0.0114	0.1002	0.0221	-0.0857	-0.0892	-0.514	-0.8584	182	10.99	86.81	3.85	42.1177	0.1126	
Shrubland	Tropical	Major cities	0.0089	0.0014	0.0084	0.0021	0.0397	0.0059	0.0268	0.0084	-0.0308	-0.0226	-0.4523	-0.8648	170	5.29	94.71	0	42.1177	0.1126	
Shrubland	Temperate	Major cities	0.0027	0.0004	0.0023	0.0006	0.0116	0.0016	0.0108	0.0029	-0.009	-0.0085	-0.31	-0.9051	507	8.08	71.01	24.85	42.1177	0.1126	
Shrubland	Continental	Major cities	0.0003	0.0001	0.0002	0.0002	0.0007	0.0002	0.0005	0.0003	-0.0004	-0.0003	-0.2885	-0.8789	141	8.51	58.87	45.39	42.1177	0.1126	
LA1	Arid	All cities	0.2051	0.0022	0.1782	0.0139	0.4824	0.0037	0.4491	0.0215	-0.2874	-0.2654	-0.7742	-0.8563	13173	11.44	88.3929	0.4631	3981.0164	0.1261	
LA1	Tropical	All cities	0.5891	0.0058	0.4758	0.03	1.252	0.0067	1.2542	0.0378	-0.6629	-0.7673	-1.7421	-0.975	10406	4.334	95.4257	0.2402	3981.0164	0.1261	
LA1	Temperate	All cities	0.6629	0.0024	0.5184	0.0149	1.4628	0.0034	1.4259	0.0214	-0.7999	-0.8912	-1.4972	-0.9748	44127	3.4378	96.5577	0.0045	3981.0164	0.1261	
LA1	Continental	All cities	0.7268	0.0046	0.5106	0.0244	1.2908	0.0052	1.2498	0.0312	-0.5641	-0.7464	-1.2429	-0.9433	15084	7.803	92.197	0	3981.0164	0.1261	
LA1	Arid	Major cities	0.137	0.011	0.1851	0.0256	0.4106	0.0211	0.436	0.0409	-0.2736	-0.2504	-1.0627	-0.9319	182	6.5934	93.4066	0	103.1455	0.237	
LA1	Tropical	Major cities	0.3802	0.0203	0.4454	0.0402	1.274	0.0364	1.2778	0.0637	-0.8938	-0.8327	-2.0717	-0.9997	170	0.5882	99.4118	0	103.1455	0.237	
LA1	Temperate	Major cities	0.4498	0.0157	0.4543	0.0294	1.3685	0.0272	1.3997	0.0463	-0.9186	-0.9471	-1.8598	-0.986	507	2.1696	97.8204	0	103.1455	0.237	
LA1	Continental	Major cities	0.363	0.0175	0.3746	0.0322	1.2398	0.0482	1.2782	0.0833	-0.8769	-0.9054	-2.0504	-1	141	0	100	0	103.1455	0.237	
LA1 (Tree)	Arid	All cities	0.7576	0.0052	0.834	0.0333	1.131	0.0064	1.3076	0.0392	-0.3734	-0.4808	-0.6859	-0.7714	13173	16.78	75.22	8	3169.5091	0.103	
LA1 (Tree)	Tropical	All cities	1.3769	0.0076	1.3303	0.0433	2.0753	0.0074	2.192	0.0441	-0.6984	-0.8584	-1.3655	-0.9672	10406	5.72	93.75	0.53	3169.5091	0.103	
LA1 (Tree)	Temperate	All cities	1.3521	0.0029	1.2582	0.0179	2.2346	0.0034	2.3449	0.0208	-0.8825	-1.0761	-1.6277	-0.9828	44127	3.78	95.92	0.31	3169.5091	0.103	
LA1 (Tree)	Continental	All cities	1.2102	0.0054	0.981	0.0297	2.0401	0.0063	2.1301	0.0368	-0.8299	-1.1268	-1.5653	-0.9795	15084	3.92	95.6	0.48	3169.5091	0.103	
LA1 (Tree)	Arid	Major cities	0.8364	0.0036	0.8946	0.0611	1.4164	0.0364	1.4434	0.0666	-0.58	-0.5482	-1.4696	-0.9809	182	5.49	94.51	0	82.1576	0.1984	
LA1 (Tree)	Tropical	Major cities	1.287	0.0374	1.3338	0.0733	2.2399	0.0433	2.2929	0.0818	-0.9629	-0.9693	-2.3425	-0.9999	170	0.59	99.41	0	82.1576	0.1984	
LA1 (Tree)	Temperate	Major cities	1.2199	0.0197	1.2055	0.0358	2.3557	0.0266	2.4323	0.0445	-1.1358	-1.2291	-2.2993	-0.9985	507	0.99	99.01	0	82.1576	0.1984	
LA1 (Tree)	Continental	Major cities	0.843	0.0269	0.8367	0.0462	2.1597	0.0551	2.2612	0.0928	-1.3168	-1.4254	-2.3709	-0.9838	141	0.71	99.29	0	82.1576		