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Journal
Journal of Land Use Science, 20(1)

ISSN
1747-423X

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Publication Date
2025-12-31

DOI
10.1080/1747423x.2025.2514877

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Journal of Land Use Science

ISSN: 1747-423X (Print) 1747-4248 (Online) Journal homepage: www.tandfonline.com/journals/tlus20

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To cite this article: Michelle Stuhlmacher, Amy E. Frazier, Isabella Corya & Wenxin Yang (2025) As cities grow larger, they may also become less green, Journal of Land Use Science, 20:1, 176-196, DOI: 10.1080/1747423X.2025.2514877

To link to this article: https://doi.org/10.1080/1747423X.2025.2514877

JOURNAL OF LAND USE SCIENCE
2025, VOL. 20, NO. 1, 176–196
https://doi.org/10.1080/1747423X.2025.2514877

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As cities grow larger, they may also become less green

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ABSTRACT
There is growing empirical evidence that cities share similar statistical patterns in terms of their social and economic characteristics. Many facets of urban life – ranging from personal income, innovation, crime, amenities, and infrastructure – have been found to follow non-linear, power-law scaling relationships with city size. Using Landsat and other satellite-derived data, we test whether urban green space exhibits scaling relationships on a global selection of 150 cities at global and individual city scales. We find that urban green space follows a pervasive sublinear scaling relationship with city size, both in terms of population and land area. Sublinear scaling indicates that green space declines in per-unit access as cities grow larger, which means that corresponding ecosystem services provided by green spaces will also likely decline. Without interventions to preserve and manage urban green space, future cities may become wealthier and more innovative as they grow, but will be relatively less green.

ARTICLE HISTORY
Received 8 May 2024
Accepted 29 May 2025

KEYWORDS
Urban science; urban scaling; greenspace; landscape metrics; earth observation

1. Introduction

At the beginning of the millennium, humanity crossed a threshold with more people living in urban areas compared to rural areas for the first time in history. Since 2007, the balance has continued to shift, and the global urban population is expected to increase by an additional 2.5 billion over the next 30 years (Mahtta et al., 2022; World Bank Group, 2019). As cities physically expand to accommodate increasing populations, it is often green spaces within and around cities that are converted into impervious surfaces and other built-up land covers (du Pandey & Seto, 2015; Seto et al., 2012). This expansion of the urban built footprint is occurring faster than population growth in some cities (Güneralp et al., 2020; Stuhlmacher, Georgescu, et al., 2022), raising questions about the ecological sustainability, of future cities, in particular the diminishing green space.

Urban green space is any type of urban land covered by vegetation, ranging from formal parks and public street trees to private yards (Stuhlmacher, Kim, et al., 2022; WHO, 2017). Urban green space is critical for maintaining ecosystem functioning, such

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Supplemental data for this article can be accessed online at https://doi.org/10.1080/1747423X.2025.2514877

as reductions in storm water run-off (Kim & Park, 2016), habitat provision (Plummer et al., 2020), mitigation of urban heat island effects (Y. Zhang et al., 2017), and carbon sequestration (Y. Ren et al., 2013). Green space has also been linked to a range of social benefits such as increased physical activity (Tsai et al., 2016), lower levels of noise and air pollution (Sakieh et al., 2017; Shen & Lung, 2017), greater social cohesion (Gehl, 2013), and improved mental health (Ha et al., 2022). As cities continue to grow, the need for these green space benefits, sometimes termed ecosystem services, will only increase (McPhearson et al., 2015). Therefore, it is critical to understand the pace at which green spaces are being added, removed, and otherwise shaped by urbanization.

As the world crossed over to a majority urban population, various general and sustained relationships between urbanization and economic development have been found across different countries and urban systems (Bettencourt et al., 2007). Paramount among them was a classification of power law scaling exponents for the growth of different urban properties with city size. Briefly stated, forces driving efficiency and economies of scale, such as infrastructure networks, have scaling exponents less than one (sublinear); forces driving wealth creation, such as inventions and wages, have exponents greater than one (superlinear); and forces driving individual maintenance, such as total housing or employment, have exponents around one (linear). These relationships have been explored in further studies (Batty, 2008; Bettencourt, 2013; Bettencourt et al., 2010; Kaufmann et al., 2022), largely focused on societal and economic factors, which rely on census data that are captured inconsistently across countries.

Comparatively less research has investigated how ecological characteristics, such as urban green space, scale with city size and whether the scaling relationships indicate sufficient green space preservation for fostering sustainable urban ecosystems. The research focused on urban green space scaling has found a mix of superlinear ($b = 1.18$; Fuller & Gaston, 2009), linear ($b = 1.03$; Kaufmann et al., 2022), and sublinear scaling (b -values ranging from 0.6 to 0.85; Akuraju et al., 2020) – differences that are due, in part, to differences in how green space is defined. Additionally, like much of the urban scaling literature, previous green space scaling research has focused only on western cities (the United States and European Union) limiting the ability to draw universal conclusions – one of the main tenets of urban science (Batty, 2012; West, 2017). Since urban green space can be captured from remotely sensed imagery, there is an opportunity to not only better standardize the comparison of cities in scaling studies but also conduct analyses across a broader range of cities around the world (Burger et al., 2022).

In this work, we integrate multiple remotely sensed data sources to show that the relationships between green space and city size (i.e. population) and city area (i.e. spatial extent) are general and predictable. We present an extensive body of empirical evidence showing that green space, a critical provider of ecosystem services, scales predictably with city size and area, and is consistent across different income classifications and climates. We test for green space scaling relationships at multiple scales because scaling relationships identified from cities around the world may mask green space quality or distribution differences within individual cities. We find general scaling relationship across cities worldwide and for a subset of individual cities. Together, these findings demonstrate that urban green space, unlike wealth and innovation, grows more slowly than the overall population or area of a city – suggesting that future cities will have less green space and corresponding ecosystem services as they grow.

2. Methodology

2.1. Overview

Employing a reproducible big data approach, we constructed a database of 150 world cities (Figure 1). For each city, we identified green spaces using Google Earth Engine (Gorelick et al., 2017) and used landscape metrics to quantify the area and arrangement of green space within a series of concentric circles (also called scalograms). We used traditional and standard major axis (SMA) regressions to determine the statistical significance and robustness of the scaling trends.

2.2. City selection

A random sample of 150 cities around the world was drawn from the Atlas of Urban Expansion (Angel et al., 2012; Figure 1); which, at the time this research began, contained 166 cities with a demarcated center point. The Atlas of Urban Expansion was used because a center point is essential for building the scalograms (see section 2.4). As a first step to determining the final set of 150 cities for analysis, each city and its center point were assessed for its ability to serve as the scalogram origin. Nine cities were removed for a lack of a clear center, along with adjustment to incorrectly placed city centers (in these cases, city centers were moved to the location of the dense urban core, central business district, city hall, or central plazas). The average adjustment was 3.5 km with some city centers (e.g. Lagos, Nigeria; Sydney, Australia) corrected by over 400 km due to errors in the original dataset. The final set of 150 cities was selected via a stratified random sample considering region, city size, population density, climate, and globalization status (Commission & Centre, 2015; Globalization and World Cities Research Network, 2018; Sayre et al., 2020).

Radii Lengths (km)		
4	35	110
6	40	120
8	45	130
10	50	140
12	55	150
14	60	160
16	65	170
18	70	180
20	75	190
22	80	200
24	85	220
26	90	250
28	95	270
30	100	

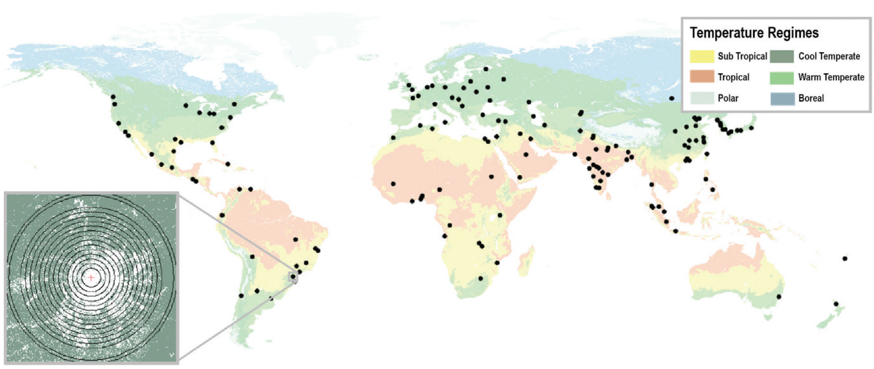

Figure 1. Sample of 150 cities around the world by climate (Sayre et al., 2020). Inset represents Curitiba, Brazil and presents an example scalogram (radii lengths in table to left) over the green space determined from satellite imagery.

Cities around the world define their city/administrative boundaries in a wide variety of ways. Previous global or multi-national scaling research has employed country or region-specific boundaries, but these boundaries are diversely defined and therefore not directly comparable. These urban extents are also primarily defined using social measures (e.g. commuting patterns) and are not ideal for physical or ecological analyses. To correct for these deficiencies, we standardized the definition of urban boundaries using the City Clustering Algorithm (CCA) methodology from Rozenfeld et al. (2008).

The CCA is a data-driven approach that aggregates pixels of built-up land to determine the extent of each urban area (Rozenfeld et al., 2008). We defined built-up pixels using the Global Human Settlement Layers (GHSL) 2015 Built-up Grid (Pesaresi et al., 2015). Drawing from previous urban scaling research, all pixels within a 5 km circular kernel were determined to be part of the same urban area until no connected built-up pixels remained (Oliveira et al., 2014). The boundaries of some small cities could not be captured via this method and were manually drawn. However, since these cities make up only about 6% of the total dataset, and the scalograms do not use the boundaries directly (see below), it was determined that their manual delineation would not contribute considerable differences to the results.

The CCA method ensures that boundaries are determined in a manner that is devoid of arbitrary and artificial political and geographic boundaries (e.g. census tracts or counties). For example, some of the urban agglomerations identified extend across country borders such as McAllen/Reynosa and San Diego/Tijuana on the United States/Mexico border. Therefore, CCA is one of the few methods for defining city boundaries that are physically grounded and directly comparable (Stuhlmacher, Georgescu, et al., 2022). A comparison of the CCA method and Metropolitan Statistical Areas defined by the U.S. Census is available in the Supplemental Information (SI, section 1). CCA boundaries follow the pattern of development in and around a city, often making them more regular in shape than MSA boundaries.

2.3. Data processing

Leveraging Google Earth Engine's cloud computing capabilities (Gorelick et al., 2017), population and green space values were extracted for the 150 city boundaries. Population was derived from the GHSL 2015 Population Grid (Commission & Centre, 2015). The GHSL depicts population density and distribution as the number of people per 250 m pixel. The data are derived from spatial data mining and dasymetric mapping using a large number of data sources including Landsat and fine-scale imagery, census data, and crowd-sourced or volunteered geographic information (Freire et al., 2016). The GHSL population grid is considered the state-of-the-art in terms of open global geospatial population datasets.

Green space was determined by calculating the Normalized Difference Vegetation Index (NDVI) for a cloud-free composite of summertime Landsat 8 imagery (Tucker, 1979). Summertime imagery from a three-year period aligning with the GHSL population data (2014–2016) was filtered to remove clouds before a median composite was created. Cloud likelihood was detected through a combination of Normalized Difference Snow Index (NDSI), brightness, and temperature (Chander et al., 2009; Foga et al., 2017). Summer was defined as June 21 to September 23 (summer solstice to autumn equinox) for the northern hemisphere and December 22 to March 20 (winter solstice to the spring equinox) for the southern hemisphere. We calculated a 75th percentile threshold (excluding water pixels) for each city to determine the NDVI value at which a pixel should be considered green space. Water pixels were identified with the Global Forest Change dataset's water mask (Hansen et al., 2013) and were excluded to focus on only land-based vegetation; water pixels have low NDVI that would lower the 75th percentile NDVI range. Thresholds, as opposed to a single-cut off value, were used to account for the variety of climates represented in the dataset; we drew on previous research to set the threshold at the 75th percentile (Goldblatt et al., 2018; Stuhlmacher, Kim, et al., 2022). While using NDVI for green space does not allow for differentiating between trees and other types of live vegetation, ecosystem services are provided by all types of green space in urban areas, including grasses (Krishnaswamy et al., 2009).

To account for potential city-to-city differences based on the level of development or vegetation growing conditions, each city was classified by income and climate. Income was classified according to the country-level categories determined by the World Bank because comparable city-level economic data were not available for all 150 cities. The World Bank uses per-capita GNI (Gross National Income) to group countries into four categories: High Income, Upper Middle Income, Lower Middle Income, and Low Income (World Bank Group, 2021). Temperature regime, as opposed to both temperature and moisture groupings, was used as a proxy for climate to reduce the number of climate groupings by half (Sayre et al., 2020).

2.4. Scaling analyses

Scalograms are plots of the scale of analysis versus a metric (Frazier, 2016) and are often used to visualize the response curve of a landscape pattern to progressively changing grain or extent (N. Zhang & Li, 2013). Scalograms can be mathematically modeled using curve fitting or regression techniques to identify general relationships, scale breaks, or inflection points where different mechanisms may be driving spatial patterns (Frazier & Wang, 2013). For each city, we created a series of progressively increasing concentric circles originating from the city center with increasing radii (Figure 1, inset). A concentric ring approach is commonly employed in remote-sensing based scaling studies (Buyantuyev et al., 2010; Ma et al., 2018; Sun et al., 2022) because it is easily replicable, permits construction of a spatially nested urban hierarchy, and can be updated as the city expands without altering the position of inner rings. Consistent with the radii lengths employed in previous urban scalogram research (Ma et al., 2018; Sun et al., 2022), we progressively changed radii lengths, setting smaller radii near the city center, increasing the radius by 2 km until 30 km, then increasing radii by 5 km until 100 km, and finally by 10 km until the end (270 km). Ring addition stopped once the entire city boundary, as delineated through CCA, was encompassed. While the outer rings may capture the outskirts of urban areas, this approach fits with our ecological focus, which includes the contributions of green spaces in the urban outskirts to urban ecosystem functioning (e.g. climate regulation and air quality).

Three landscape metrics measuring the area and arrangement of green space were calculated within each concentric circle (Table 1). These metrics were chosen based on previous research that has found that greater green space, larger green space patches,

Table 1. The area and arrangement variables and the landscape metrics used to define them (Hesselbarth et al., 2019).

Variable	Metric	Definition	Equation
Area	Percentage of Landscape	Percentage covered in green space. Larger values correspond to greater coverage.	$\frac{\sum_{j=1}^{n} a_{ij}}{A} * 100$
Average Patch Area	Mean Patch Size	Average area of green space patches in hectares. Larger values correspond to larger patches, on average.	$\frac{\sum_{j=1}^{n} a_{ij}}{n_i} * \frac{1}{10,000}$
Connectedness	Aggregation Index	The ratio of the actual number of connected green space pixels compared to the maximum possible number of connected pixels. Larger values correspond to greater connectedness.	$\left[\frac{g_{ii}}{\max - g_{ii}}\right] * 100$

WHERE:
$a_{ij} = area\ in\ terms\ of\ number\ of\ cells$,
$A = total\ landscape\ area(m^2)$,
$n_i = number\ of\ patches$,
$g_{ii} = number\ of\ like\ adjacencies\ based\ on\ the\ single\ count\ method$ &
$\max - g_{ii} = classwise\ maximum\ number\ of\ like\ adjacencies$.

and more connected green space contributes to a range of benefits including lower surface urban heat island (Li et al., 2016; Y. Zhang et al., 2017), decreased human mortality (H. Wang & Tassinary, 2019), higher biodiversity (Beninde et al., 2015), and greater habitat provisioning (Shanahan et al., 2011; Stuhlmacher, Andrade, et al., 2020). All metrics were derived from FRAGSTATS (McGarigal et al., 2012) and calculated with queen contiguity (Stuhlmacher et al., 2025) using the 'landscapemetrics' R package (Hesselbarth et al., 2019). Scalograms for each city were created by plotting the metric values against the total area of the concentric circles.

2.5. Statistical analysis

Global scaling. We used SMA regressions to test the type and strength of a power-law relationship between green space and city size/area across the 150 cities. SMA is a least-squares, bivariate, line fitting method that minimizes the sum of the squares of the shortest distance between the data points and the line of best fit (Warton et al., 2006). It is more appropriate for scaling questions than linear regressions because the problem is symmetric – how one variable scales compared to another does not change if the axes are reversed (Ovando-Montejo et al., 2021). SMA was first developed and employed in biological scaling research (i.e. allometry). It has been used to examine the scaling relationships between body size and organism characteristics like brain mass (Warton et al., 2006) and has recently been applied to questions of city scaling as well (Ma et al., 2018; Ovando-Montejo et al., 2021).

For global green space scaling, the relationship between city size (population/area) and each green space metric (Table 1) is defined:

$$Y = aX^b \tag{1}$$

Where Y is a measure of green space area or arrangement (Table 1), a is the normalization constant, b is the scaling exponent, and X is city size/area. We examined the relationship for two different size variables: 1) city size – the sum of the GHSL Population within the largest circle bounding the urban area and 2) city area – the area of the largest circle bounding the urban area. Our null hypothesis is that b = 1 (i.e. a linear plot); if b does not equal 1 then the scaling has a power-law type relationship (Ma et al., 2018).

A SMA regression assumes that Y and X are linearly related and that the residuals are independent, normally distributed, and have the same variance at all points on the fitted line (Warton et al., 2006). We tested for these assumptions by conducting a rank correlation of the variables and checking the residual plots for a lack of pattern. We also checked residual normality and homoscedasticity using residual plots. A metric we originally planned to use to measure connectedness (contiguity index) was removed because it did not meet these assumptions and replaced with the aggregation index.

City-level scaling

To quantify scaling trends within each city, we fit power-law curves to the city-level scalograms (concentric circle area) for each green space metric. For city-level scaling, we used city area instead of population because area measures are better suited to our focus on ecosystem services, and we were not confident that the gridded population data (250 m grid cells) would generate reliable estimates of population for the smaller concentric rings. Using area versus population did not produce substantive differences for the global scaling (see SI, Section 2).

If a statistically significant trend is present for a city, the slope of the regressions can be compared across cities. Equation 1 also applies to this portion of our analysis, except that X corresponds to the area of each concentric circle in one city following Ma et al. (2018). We fit curves for each metric for all cities with greater than three concentric circles (124 cities) and compared results for cities with statistically significant trends, both overall and by income and climate stratifications. All statistical analyses were completed in R (v4.2.1) using the raster, landscapemetrics, dplyr, rgeos, rgdal, moments, FSA, ggplot2, gridExtra, matlab, and smatr packages (Auguie & Antonov, 2017; Bengtsson et al., 2022; Bivand et al., 2020, 2021; Hesselbarth et al., 2019; Hijmans et al., 2021; Komsta & Novomestky, 2015; Ogle et al., 2020; Warton et al., 2012; Wickham, 2016; Wickham et al., 2021). The code and data for analysis are publicly available and can be accessed at https://github.com/MStuhlmacher/global-green-scaling.

3. Results

3.1. Global green space scaling

As cities increase in size, the area of green space as a percentage of the entire city also increases (Figures 2(a,d)). This relationship exists using both size (Figure 2) and area (SI Figure 2). Note that we refer to population as city size and spatial extent as city area. The overall relationship is statistically significant ($p < 0.001$; SI Tables 1 and 2), and the relationship also holds across income and climatic differences, with countries with higher incomes having slightly higher intercepts compared to lower-income countries. Similar to the scaling of urban infrastructure (e.g. roads, utilities; Bettencourt, 2013), we find that green space area scales sublinearly with population ($b = 0.26$; SI Table 1) and city area ($b = 0.22$; SI Table 2). This sublinear scaling shows that while the absolute green space area increases as cities increase in size, the relative per-unit area of green space actually decreases.

The average area of green space patches increases as cities increase in size (Figure 2(b, e); SI Figure 2). This relationship is also statistically significant ($p < 0.001$) and holds across income and climate (SI Table 2), with only cool temperate cities not showing a significant relationship between average green space patch area and city size. As with total green space area, the scaling of average patch area is sublinear (*b* ranges 0.37–0.59; SI Table 1). Cities in low and lower-middle income countries have slightly steeper regression slopes and lower intercepts compared to cities in higher-income countries, indicating that lower-income cities are characterized by more rapid growth of green space patch area but smaller, initial patch areas.

Green space connectedness also increases with increasing city size, and the relationships are generally significant (SI Tables 1 and 2), but regression slopes vary more across both income and climate compared to total green space area and average patch area (Figure 2(c,f); SI Figure 2). As with green space patch area, the cities in lower-income countries have a steeper slope (i.e. more rapid growth in green space connectedness corresponding to an increase in city size) but a lower intercept (i.e. lower baseline connectedness) compared to cities in higher-income countries (Figure 2(c)). In contrast, the cities in higher-income countries start at a higher level of green space connectedness (i.e. higher intercept), but connectedness grows at a slower rate as the cities get larger. There is a clear ordering of the relationships for connectedness based on the climate classifications, where cities in warmer climates are represented by steeper growth in connectedness with city size, but lower baseline values compared to cities in cooler climates (Figure 2(f)).

For all three green space metrics, cities in high-income countries had weaker relationships (i.e. lower statistical significance and lower R^2 values) between city size and green space area and arrangement. Generally, scaling relationships were strongest for cities in low and lower-middle-income countries (SI Tables 1 and 2). Climatic differences played a small role, cities in tropical climates often had the strongest scaling relationships, while cities in cool temperate climates consistently had the lowest R^2, and relationships that were not statistically significant (SI Tables 1 and 2).

3.2. City-level green space scaling

Overall, 97% of cities exhibited a significant ($p < 0.05$) scaling relationship for green space radiating out from the city center (i.e. measured via scalograms). Approximately 90% of cities also had a good fit ($R^2 > 0.7$ & $p < 0.05$) for the scaling relationship, and 60% had a very strong fit ($R^2 > 0.9$ & $p < 0.05$), indicating consistency and robustness to the city-level power-law relationships (see Frazier et al., 2021). In general, the city-level scaling relationships for cities in higher-income countries were not as robust as those in lower-income countries (Table 2b). The type of climate that had greater significant and robust city-level scaling relationships varied by green space metric (Table 2c).

For cities with significant and robust scaling relationships ($R^2 > 0.9$ & $p < 0.05$), scaling exponents (*b*) plotted against city area (Figure 3) show trends similar to the global scaling results presented above. The city-level scaling of green space area is sublinear for all cities, except Guadalajara, Mexico, which has a linear scaling exponent of 1.11. For green space area (Figure 3(a)), the average *b* value is 0.49 (SD = 0.22). The farther *b* is below 1, the slower per-unit green space is increasing moving out from the

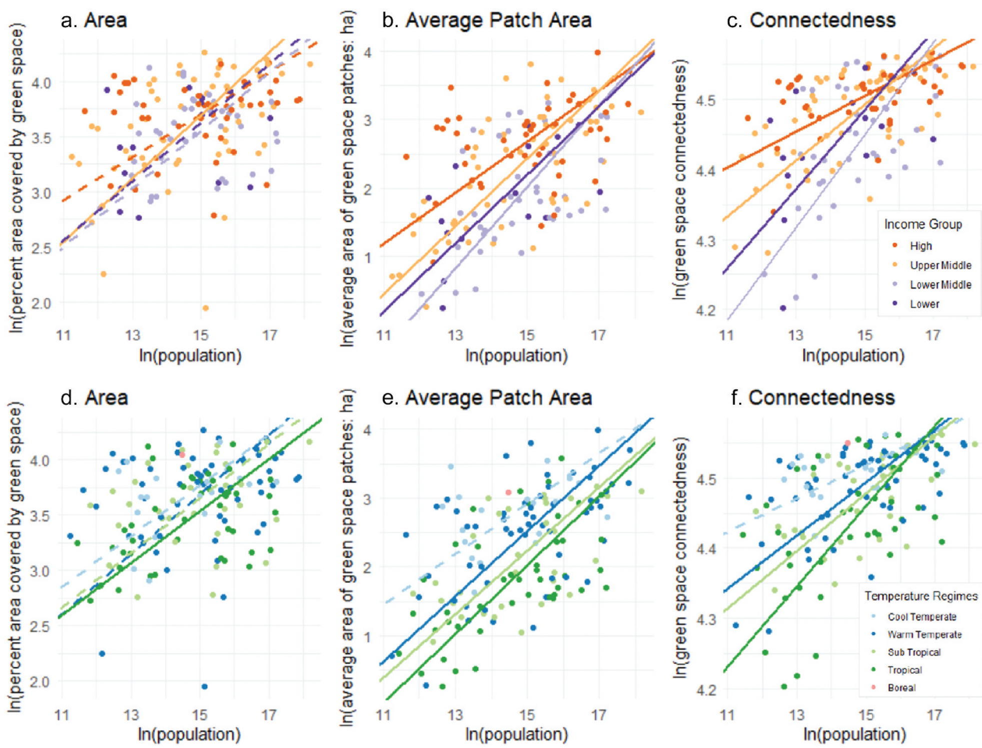

Figure 2. Standard major axis (SMA) regression plots of the scaling relationships between measures of green space area/arrangement and city population. Solid lines represent statistically significant (p<0.05) relationships, dashed lines are not significant. Each point corresponds to a single city. The same cities are represented in both rows. In the top row, the city points are colored by their country's World Bank income classification; the bottom row shows them classified by climate. Note: there is no regression line for boreal climate because there is only one city in this regime.

city center. Lahore, Pakistan ($b = 0.20$), is an example of a city with a small, sublinear exponent. Its scaling curve (Figure 3(e)) depicts higher levels of vegetation at the center of the city but a shallow increase in green space area moving outward from the city center. Our results revealed that very few large cities have high b values, although Chicago, U.S.A., is an exception. Chicago is a large city with a relatively high scaling exponent ($b = 0.68$, Figure 3(d)). Visually, its scaling curve depicts a steeper increase in green space for areas closer to the city center, plateauing below 50% at the outer concentric circles.

Results for city-level average patch area scaling show a slight but perceptible decline in scaling exponents as city area increases (Figure 3(b)). Cities in the highest income countries generally have the lower scaling exponents, but this was not consistent, especially for other income groups. The average b value is 0.57 (SD = 0.21). For this metric, two cities have scaling exponents greater than 1: Culiacán, Mexico ($b = 1.14$) and Córdoba, Argentina ($b = 1.07$). In these two cities, the area of the average green space patch increases moving away from the city center (likely driven by decreases in population density on the edges of the city). For larger cities like Seoul, South Korea ($b = 0.34$, Figure 3(g)) the average green space patch area does not grow considerably moving

Table 2. Percentage of cities with significant and well-fit scaling relationships ($R^2 > 0.90$ & $p < 0.05$) between green space and city area.

	GREEN SPACE METRICS		
	Area	Average Patch Area	Connectedness
A. ALL CITIES (n = 124)	56%	68%	55%
B. BY INCOME:			
High (n = 40)	55%	65%	45%
Upper Middle (n = 43)	56%	67%	56%
Lower Middle (n = 32)	56%	69%	59%
Low (n = 9)	67%	78%	78%
C. BY CLIMATE:			
Cool Temperate (n = 18)	67%	72%	50%
Warm Temperate (n = 45)	56%	62%	47%
Sub Tropical (n = 28)	57%	75%	64%
Tropical (n = 32)	50%	75%	59%

*Boreal not shown as there is only one city in this climate regime (Ulaanbaatar, Mongolia). Ulaanbaatar had robust fits for overall area, average patch area, and connectedness.

away from the city center (likely driven by high population density even at the edges of cities).

Results for city-level green space connectedness show all cities have sublinear scaling (Figure 3(c)). The b values are lower compared to the other two metrics (ranging from 0.02 to 0.16), indicating that connectedness is growing slower than either total green space area or average green space patch area moving away from dense city centers. As with total green space area and average patch area, small- to medium-sized cities have the highest scaling exponents – see Lubumbashi, Democratic Republic of Congo ($b = 0.12$; Figure 3(h)) – while very large cities have more moderate b values. We found no clear climate trends for city level scaling (SI, Section 3).

4. Discussion

Despite the geographic and economic variability of cities around the globe, urban green spaces appear to follow pervasive scaling relationships with city size and area. These scaling relations characterize the rates at which green space is removed or preserved as the population or area of cities expand. We find that green space scales sublinearly with city size and area across a global selection of cities from different income and climate classifications as well as within individual cities. While sublinear scaling can be interpreted to mean that green space is being 'added' as urban areas grow larger (albeit at a slower rate than linear or super-linear scaling), the reality is that most urban growth happens at the expense of urban green space. Sublinear scaling then means that green space is not being preserved at the same rate as it is being removed in and around cities. Thus, our results suggest that globally there is insufficient development or incorporation of urban green space as urbanization advances and that individual cities rarely maintain green space as they urbanize.

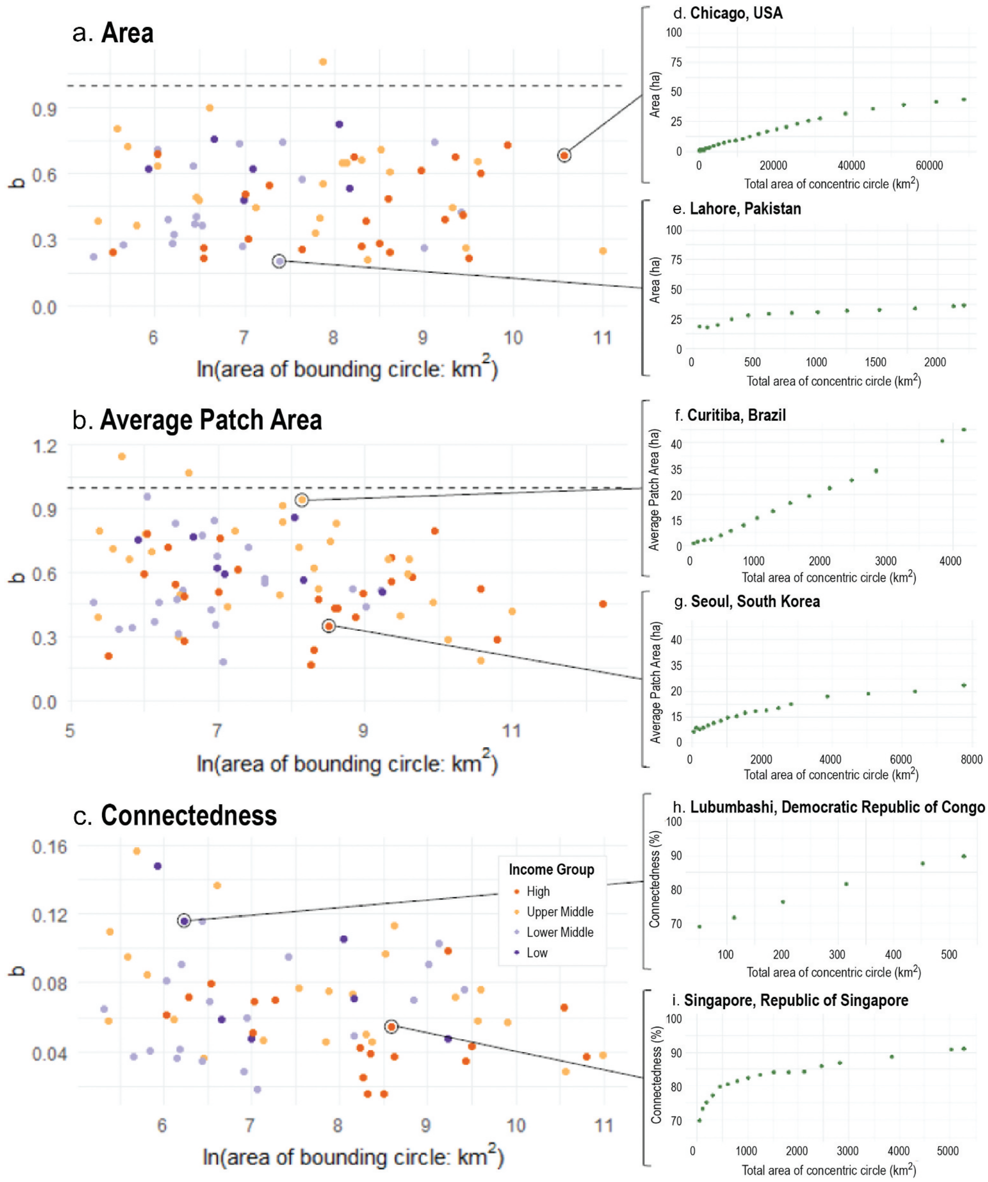

Figure 3. (Left) beta-values (*b*) of within-city scaling plotted in relationship to city area, colored according to country-level income. Plots by climate are presented in the SI. Each point corresponds to a single city with significant and robust scaling ($R^2 > 0.90$ & $p < 0.05$). (right) scalograms of green space for identified city.

4.1. Green space scales like infrastructure

In most cases, green space metrics scale sublinearly with city size and area, with exponents typically less than 0.5. These results hold globally across a set of 150 world cities (Figure 2) and within individual cities (Figure 3). Based on Bettencourt et al. (2007) findings, we find that urban green space exhibits the economies of scale that characterize infrastructure (sublinear) rather than the increasing returns (superlinear) that characterize wealth creation and innovation. While economies of scale are beneficial for forms of infrastructure – only an 85% increase in the road network is needed for doubling the population (Bettencourt & West, 2010; Bettencourt et al., 2007) – they are likely not ideal for green space. The question of whether it is sustainable for green space to scale akin to physical infrastructure has not been addressed empirically, but research on green space and urban heat mitigation suggests that sublinearly scaling may not be sufficient for localized cooling because green space only provides cooling for a short distance (Y. Zhang et al., 2017). If cities are to rely on nature-based solutions for climate and other environmental concerns (Kabisch et al., 2016), green space will likely need to scale with city growth as a resource, with an exponent of 1 or greater. The scaling exponents we identified are very small, suggesting that green space is added to cities at rates similar to cemeteries (b = 0.27) and airports (b = 0.40; Kaufmann et al., 2022), which is even lower than other forms of critical physical infrastructure, like electrical cables and roads that typically have exponents around 0.75–0.9 (Bettencourt et al., 2007).

The multi-city sublinear scaling of green space suggests that less per-unit or per-capita green space is available as the population and/or area of a city expands, even as urban population densities decline (Güneralp et al., 2020; Stuhlmacher, Georgescu, et al., 2022). Kaufmann et al. (2022) found that the number of parks scales with an exponent of 1.03 in US cities. Increasing the number of parks alone, however, may not be sufficient for sustaining many of the ecological functions of green space, particularly when these parks are small, contain minimal vegetation (i.e. pocket parks), or are focused on human-centered designs (Nordh & Østby, 2013) rather than ecosystem functioning. Large, well-connected areas of green space are needed to support biodiversity and contribute to greater provisioning of some ecosystem services such as increased biomass and carbon sequestration and reduced water and nutrient runoff (Beninde et al., 2015; Grafius et al., 2018). Cities have traditionally relied on surrounding areas to provide these services, but with continued expansion and the accompanying environmental degradation (Q. Ren et al., 2022), outlying regions may soon no longer be able to provide the same level of ecosystem services, such as cooler ambient air temperatures (Georgescu et al., 2014). Protecting and maintaining green space in and around urban agglomerations is a valuable investment in nature-based solution for adapting to and mitigating climate change (Kabisch et al., 2016).

Compared to the existing socially focused body of scaling research, which relies on inconsistent definitions of cities across countries, the approach used here standardizes city boundaries based on physical and structural characteristics from satellite imagery. This standardization permits a more direct comparison between countries and better captures ecological relationships in cities and their supporting regions. However, this methodology likely results in different scaling values than would be expected with socially defined city boundaries (Bettencourt, 2013) but these differences would not alter the overall findings that green space scales sub-linearly for most cities worldwide. Additionally, recent research using a broader sample of world cities (Burger et al., 2022) found that many cities do not follow the previously identified general scaling relationships (e.g. Bettencourt et al., 2007). Considering the very low scaling exponents of green space we identified, more proactive and ecosystem centered approaches are needed to ensure sufficient green spaces are protected both within cities and around the outer boundaries before urban expansion occurs.

4.2. The inverse connection between wealth and green space

Many studies have shown that within cities, green space is not distributed equally, and wealthier areas of cities have more green space (Jenerette et al., 2011; Nesbitt et al., 2019; Quinton et al., 2022; H.-L. Zhang et al., 2022). From a global perspective, however, we find that while cities in wealthier countries started with higher green space indicators (i.e. higher regression intercepts), green space area, average patch area, and connectedness increased at lower rates compared to cities in lower-income countries (Figure 2, SI Figure 2). This difference could be due to wealthier and more developed cities replacing green space with development at a faster rate both in the city interior and at the outskirts. Lower rates of green space incorporation by wealthier cities does not discount prior research on the local distribution of greenery and wealth, but it does demonstrate that intra-city relationships between wealth and green space do necessarily not extend to the global scale.

Growing cities are linked with a host of positive social and economic outcomes including increasing wealth, innovation, and quality of life (Bettencourt et al., 2007; Leon, 2008). Our results show, however, that the amount and connectedness of urban green space declines relative to urban population and area growth, along with the likely decline of any ecosystem services provided by these areas. Without efforts to preserve it, city sprawl and infill will continue to remove existing green space. Thus, cities of the future may be wealthier and more innovative but relatively less green.

4.3. What individual cities can tell us about sustainable urban futures

The current rates of sublinear green space scaling have negative implications for the sustainability and equity of future urban ecosystems. Larger and more connected green space patches often yield greater ecosystem services (Aragon et al., 2019; Clinton et al., 2018; Kim & Park, 2016; Sakieh et al., 2017). Shrinking urban green space and a more fractured spatial relationship between green space patches decreases the availability of green space to provide nature-based solutions for the plants, animals, and humans that rely on them. Moreover, sublinear growth of urban green space could exacerbate green space inequality. Green space is already not distributed equally within cities (Nesbitt et al., 2019; Stuhlmacher & Kim, 2024) but if green space area declines as urban areas grow, this puts an increased premium on the remaining green space. While we are not able to assess access directly with this research (see section 4.4 on limitations and opportunities for future research), an overall increase in per-capita or per-area green space may also contribute to decreased green space access and equity.

A potential target for maintaining urban ecosystem functioning is growing urban green space linearly with city size (i.e. b-values near 1). In the subset of 150 cities we examined, three had scaling exponents greater than 1. These cities – Guadalajara and Culiacán, Mexico; and Córdoba, Argentina – are a range of sizes (their populations are estimated between 889,000 and 3.5 million people). They are located adjacent to large, protected areas and other conserved lands. Physically, large tracts of protected lands adjacent to cities may act as a natural urban growth boundary, which increases the amount of green space that is included within the concentric footprint as the city grows. Ecologically, protecting natural areas along the periphery of cities may help achieve area-based conservation targets – such as the 30 × 30 aim of the Convention on Biological Diversity's Post-2020 Global Biodiversity Framework (UN 2021) – as well as ensure that growing urban populations have access to ecosystem services. Area-based protection is particularly salient for small to mid-sized cities because continued population expansion may threaten surrounding green spaces, leading to the observed decline in scaling exponents as cities grow larger (Figure 3).

Cities like Curitiba, Brazil demonstrate that intentional green space planning may improve scaling outcomes. Curitiba is a mid-sized city and its nearly linear scaling for average patch area ($b = 0.94$; Figure 3(f)) may be attributable to policy and design efforts to incorporate urban green space (Macedo & Haddad, 2016). Similarly, Chicago, U.S.A., exhibited the highest scaling exponent for green space area ($b = 0.68$, Figure 3(d)) of the large cities we analyzed, and this quality may be attributed to the city's long-standing attention to green space planning and park design (Chicago Park District, 2021; Trust for Public Lands, 2022). Green space scaling exponents can help identify individual cities, particularly large ones, that can serve as exemplars for mid-sized cities as they plan for sustainable urban growth. How policies, climate, or other conditions in these exemplar cases have affected green space scaling is an important avenue for future research to further leverage these findings (Stuhlmacher, Turner, et al., 2020; C. Wang et al., 2018).

Intentional green space planning does not always correspond to linear green space scaling. Cities like Seoul, South Korea ($b = 0.34$, Figure 3(g)) and Singapore, Republic of Singapore ($b = 0.05$; Figure 3(i)) are recognized for their green space investments (Landscape Architecture Foundation, 2011; Tan et al., 2013) but generated relatively low b values. Both cities have high population density and are adjacent to large water bodies, which may be impacting their ability to grow green space, particularly in outer rings. In coastal cities like Singapore, green and blue infrastructure provide overlapping but also unique ecosystem services. An examination of the scaling of blue infrastructure independently as well as the combination of blue and green infrastructure is an area of future research to tease out the contributions and scaling of various nature-based solutions to socio-environmental issues such as climate change.

4.4. Limitations and opportunities for future research

This research uses a form of space-for-time substitution to examine the potential future trajectories of smaller cities by looking at the characteristics of larger cities. This type of approach is widely used in urban scaling research (D'Acci, 2024) and can assist in identifying general trends and simple mathematical 'laws' that can contribute to a unified theory of urban living to understand how city growth affects society and the environment (Bettencourt & West, 2010). However, space-for-time substitution, while useful for generating hypotheses, does have limitations (Pickett, 1989). Namely, for our urban application, it assumes that the 150 cities in our sample are sufficiently similar to be meaningfully compared. This may not be the case; urban green spaces are intertwined with governance, climatic conditions, and topographical constraints. While we used a large and diverse sample size to help to alleviate bias introduced by this heterogeneity, future research could test the viability of space-for-time substitution by employing a longitudinal approach. Validating scaling relationships through a set of longitudinal cases could help evaluate how green space changes within a single city as it grows, as these cases could hold constant more – but not all – of the factors influencing green space scaling in urban environments.

Second, a limitation of this and other scaling research is the inability to capture within city heterogeneity in quality (Lobo et al., 2024). For example, if housing scales linearly in a city, that suggests that new housing units are added for each new resident but does not give a sense of the affordability or characteristics of the housing (Sarkar, 2019). A city could have linear scaling but still experience housing shortages or surpluses if the housing is in poor condition or unaffordable to the average resident. Similar concerns apply to green space measured from NDVI. We know that the green space evaluated in this research is in the upper quartile of greenness (one measure of quality) but not what type of green space it is, whether the green space is well maintained or even publicly accessible. An area of future research to address this limitation is the examination of how green space scales when defined by a variety of measures such as park area, tree canopy coverage, or other NDVI thresholds. Whether or not these green space variables scale similarly to each other will help to build a more wholistic understanding of urban green space scaling and how it may be shaped by green space type or accessibility.

5. Conclusion

Green space scales predictably with city size and area and is consistent globally with different income and climate classifications. Additionally, green space is not scaling with city growth because the amount of green space per-person or per area declines as cities grow larger. Based on scaling exponents computed for 150 cities around the world, we find that green space scales sublinearly (similar to infrastructure) rather than linearly as a human need (like housing) or superlinearly (like wealth). Contrary to studies showing wealthier cities have more green space, we find that for cities in wealthier countries, green space area and connectedness increase at lower rates than cities in low-income countries. Looking to the future, small to mid-sized cities in lower-income countries may provide the greatest return on investment in terms of protecting and enhancing urban green space due to their higher scaling exponents. Investments to protect or create green space, regardless of where they take place, must be done so in partnership with local communities to mitigate unintended negative consequences (Curran & Hamilton, 2012; Curran et al., 2023).

Author contributions

MS: Conceptualization, Methodology, Data Curation, Formal Analysis, Visualization, Writing – Original Draft, Writing – Review & Editing
AF: Conceptualization, Methodology, Writing – Original Draft, Writing – Review & Editing
IC: Data Curation, Formal Analysis, Visualization
WY: Validation, Writing – Review & Editing

Acknowledgments

AEF and WY acknowledge support from National Science Foundation grant 2416164.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by the U.S. National Science Foundation [2416164].

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