STRATEGIC PLANNING FOR URBAN GREEN SPACE UNDER SUBLINEAR SCALING: EVIDENCE FROM REMOTE-SENSING SCALOGRAMS ACROSS 150 GLOBAL CITIES

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Urban green space is increasingly treated as a core planning asset because it supports heat mitigation, stormwater regulation, biodiversity, and public health. Yet cities also face structural pressures that constrain land available for vegetation as populations and built footprints grow. This article provides a planning-oriented synthesis of evidence on how green space quantity and spatial structure change with city growth, drawing on a globally distributed sample of 150 cities and a published remote-sensing workflow that constructs concentric-circle scalograms around standardized city centers. Green space is derived from Landsat-based NDVI using a city-specific upper-quartile threshold and evaluated with three landscape metrics: green share, mean patch size, and green connectedness. Across cities, reported green share increases with population but follows sublinear scaling (exponent 0.26), indicating declining per-unit green availability as cities become larger. Mean patch size and connectedness also increase with growth, but with patterns that vary by income and climate groupings. At the within-city scale, most cities exhibit statistically significant power-law relationships between scalogram extent and green space metrics, providing cross-scale validation of recurring spatial growth patterns. The findings translate into planning-relevant benchmark targets: if green infrastructure is expected to scale as a universal urban service, strategies must counteract the baseline tendency for green space to grow more slowly than city size.

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INTRODUCTION

Urban green space is widely recognized as an essential planning resource. Vegetated land within and around cities contributes to ecosystem functioning and services that matter for public management: heat mitigation, stormwater regulation, habitat provision, air-quality co-benefits, and mental-health-related outcomes [36, 24, 17]. At the same time, urban development competes with vegetation for land, and the conversion of green areas into impervious surfaces remains a central sustainability challenge in rapidly urbanizing regions [31, 12].

A parallel literature in urban science demonstrates that many urban properties scale with city size in predictable, non-linear ways [5, 3, 35]. For planners and managers, the practical significance of scaling is straightforward: systematic relationships offer baseline expectations against which cities can set targets, benchmark performance, and identify policy levers that shift trajectories. Where scaling is sublinear, the implication is that the quantity of a resource grows more slowly than city size, often yielding declining per-unit availability as cities expand.

This paper evaluates what current global evidence implies about how urban green space scales with city population and spatial extent across a harmonized sample of 150 cities. Rather than claiming a de novo remote-sensing re-estimation, the article develops a management- and planning-focused interpretation of a published, reproducible empirical workflow and uses that evidence to extract operational benchmarks. Its contribution is threefold. First, it treats green space not only as an amenity but as infrastructure-like capacity that must be planned, financed, and protected under growth pressures. Second, it clarifies whether the reported scaling relationships are stable across income and climate contexts, a key issue for policy transfer and benchmarking. Third, it uses within-city scalograms as a diagnostic lens for spatial planning and long-run land management.

Research questions

1. How do green space coverage, fragmentation, and connectedness scale with city population and city area across a global sample?
2. Are these scaling relationships consistent across income and climate classifications relevant to planning capacity and biophysical constraints?
3. What do within-city scalograms reveal about common spatial growth pathways and actionable planning implications?

CONCEPTUAL FRAMING FOR MANAGEMENT AND PLANNING

Green space provision is shaped by interacting constraints that are central to management and planning research: land scarcity, infrastructure investment priorities, institutional capacity, and competing policy objectives. From a strategic planning perspective, three points motivate the empirical analysis and clarify the manuscript's applied contribution.

First, *green space behaves like an infrastructure stock under growth pressure*. If green space scaled linearly with population or spatial extent, per-unit availability would remain roughly stable as cities grow. Sublinear scaling implies that, absent intervention, cities tend to add or preserve green space at rates insufficient to keep per-capita or per-area availability constant [5, 6].

Second, *spatial configuration affects service delivery*. Larger patches and higher connectedness often support stronger ecosystem functioning than highly fragmented vegetation [4, 20]. Planning instruments that protect contiguous corridors, limit fragmentation, or consolidate green networks may therefore matter as much as total green coverage.

Third, *institutional and biophysical context influences baselines*. Differences in income classification proxy fiscal and administrative capacity; climate regimes shape growing conditions and baseline vegetation. Management relevance follows: realistic performance targets may require benchmarking within comparable peer sets, while still recognizing cross-cutting structural pressures.

DATA AND METHODS

City sample and center points

This planning analysis draws on a global sample of 150 cities from the Atlas of Urban Expansion, selected via stratified random sampling to represent variation in region, city size, density, climate, and globalization status [1]. A curated center point for each city serves as the origin for scalograms. Consistent with the published workflow, cities lacking a clear center were excluded, and a limited number of center points were manually corrected only when the initial point did not align with the principal dense urban core or an equivalent central place [32].

Standardized urban boundaries

To ensure physically comparable urban extents across countries, the analysis follows the published City Clustering Algorithm (CCA) delineation, which aggregates built-up pixels using the Global Human Settlement Layer (GHSL) 2015 built-up grid and a 5 km kernel to form contiguous urban agglomerations [29, 26, 32]. This approach reduces dependence on administratively defined boundaries that vary across national statistical systems and yields a common baseline for cross-city benchmarking.

Population and green space data

Population counts are derived from the GHSL 2015 population grid (250 m resolution), which provides globally consistent estimates of population distribution [9, 14]. Green space is identified from summertime Landsat 8 imagery by calculating NDVI on a cloud-free median composite aligned to 2014–2016. Summer is defined as June 21 to September 23 in the northern hemisphere and December 22 to March 20 in the southern hemisphere [33, 8, 13, 32]. To accommodate climatic heterogeneity, each city uses a 75th percentile NDVI threshold (excluding water pixels), thereby classifying the upper quartile of vegetation greenness within the city context [15, 32]. This relative threshold should be interpreted as a harmonized indicator of comparative greenness within each urban system, not as a direct substitute for an absolute park or canopy inventory. Water pixels are excluded using a global water mask [18].

Scalograms and concentric-circle construction

For each city, progressively increasing concentric circles are constructed around the curated city center. Radii increase by 2 km until 30 km, then by 5 km until 100 km, and finally by 10 km until 270 km; circle expansion stops once the outer circle encompasses the full CCA-defined urban extent [22, 32]. Scalograms are formed

Table 1: Green space metrics used in the scaling and scalogram analyses.

Construct	Metric	Planning interpretation
Coverage	Green share (percentage of landscape)	Higher values indicate greater green coverage, relevant to citywide ecosystem service potential.
Fragmentation / patch structure	Mean patch size (hectares)	Higher values indicate larger green patches on average, often associated with stronger ecological functioning.
Connectivity	Aggregation index	Higher values indicate greater spatial connectedness of green pixels, relevant to corridor and network planning.

by plotting metric values against the total area of each circle [16]. Using the same radial logic across all cities allows within-city trajectories to be compared as standardized spatial benchmarks rather than as city-specific cartographic narratives.

Outcome variables

Three landscape metrics quantify green space area and arrangement within each circle. All metrics are derived using FRAGSTATS-style definitions and computed with queen contiguity via open-source tooling [23, 19, 32].

Statistical analysis

Scaling relationships are tested with standard major axis (SMA) regression on log-transformed variables, consistent with urban scaling practice where the relationship is treated symmetrically [34, 25, 32]. Global scaling evaluates relationships between (i) city population and each green metric and (ii) city area and each green metric. Stratified estimates compare scaling patterns across World Bank income groupings and climate temperature regimes [37, 30]. Within-city scaling evaluates power-law relationships between circle area (extent) and each metric for cities with sufficient concentric circles [22, 32]. Because the article synthesizes a published empirical workflow for planning interpretation, the emphasis is on the direction, magnitude, and consistency of reported coefficients across these complementary comparisons.

RESULTS

Global scaling across 150 cities

Across the global sample, green coverage increases with city population, but the relationship is sublinear. The reported scaling exponent for green share relative to population is 0.26, and relative to city area is 0.22 [32]. Taken together, these estimates indicate that larger cities tend to be greener in total amount, yet become less green in per-unit availability as they grow. The agreement in sign across population-based and land-area-based comparisons strengthens confidence that the result reflects a broad scaling tendency rather than a single-model artifact.

Mean patch size also increases with city size and exhibits sublinear scaling, with reported exponent ranges on the order of 0.37 to 0.59 depending on stratification [32]. This indicates that larger cities tend to contain larger green patches on average, but patch growth still lags behind the growth of city size. Read together with green share, the pattern suggests that total vegetated area and patch consolidation can rise simultaneously while still failing to preserve constant per-unit provision.

Green connectedness increases with city size as well, although slopes vary more across income and climate contexts than for green coverage and patch size [32]. Income patterns indicate higher baseline green indicators in higher-income contexts (higher intercepts), coupled with slower rates of increase as cities become larger, while lower-income contexts tend to show steeper growth in patch size and connectedness from lower baselines [32]. Climate stratifications show ordering consistent with biophysical constraints: warmer climates tend to exhibit faster growth in connectedness with city size but lower baseline connectedness than cooler climates [32]. The convergence of these subgroup patterns with the pooled estimates supports the interpretation that the main result is structurally robust even though local magnitudes vary.

Within-city scaling from scalograms

Within-city scalograms show that scaling patterns are not only visible across cities but also widely present within cities as extent expands outward from the center. For the set of cities with adequate scalogram depth, approximately 97% exhibit statistically significant within-city scaling relationships for green metrics, about 90% show good fit (reported as $R^2 > 0.7$ with statistical significance), and about 60% show very strong fit ($R^2 > 0.9$ with statistical significance) [32]. These fit frequencies provide an internal validation check: a compact power-law description often captures how green structure changes as the analyzed urban extent grows.

For cities with statistically significant and robust within-city fits, the mean within-city scaling exponent for green area is reported as 0.49 (SD 0.22), with substantial heterogeneity across individual cases [32]. Illustrative examples include Lahore (exponent 0.20), indicating shallow growth in green coverage with increasing extent, and Chicago (exponent 0.68), indicating relatively stronger growth compared to other large cities [32]. For mean patch size, the average within-city exponent is reported as 0.57 (SD 0.21) [32]. For connectedness, within-city scaling exponents are smaller (reported between 0.02 and 0.16), suggesting that connectedness grows more slowly than coverage or patch size as extent increases [32]. The coexistence of strong average regularities and meaningful city-level dispersion makes the scalogram framework especially useful for benchmarking, diagnosis, and targeted intervention.

DISCUSSION: IMPLICATIONS FOR MANAGEMENT AND PLANNING

Green space behaves like infrastructure under growth

The central empirical message is that green space tends to increase with city size, yet does so sublinearly, producing declining per-unit availability as cities become larger [32]. For management and planning, the value of this result lies less in causal attribution than in baseline benchmarking: it resembles the scaling logic of physical infrastructure, where economies of scale reduce required expansion relative to population growth [5, 7]. The difference is normative and operational: economies of scale may be efficient for roads or cables, but may be insufficient for green infrastructure if policy objectives emphasize distributed ecosystem services (e.g., localized cooling) that depend on spatial presence and not only total area [21, 39].

Table 2: Share of cities with statistically significant and robust within-city scaling relationships ($R^2 > 0.90$ and $p < 0.05$) between green metrics and city area (scalograms).

Group	Area (coverage)	Average patch area	Connectedness
All cities (n = 124)	56%	68%	55%
High income (n = 40)	55%	65%	45%
Upper middle income (n = 43)	56%	67%	56%
Lower middle income (n = 32)	56%	69%	59%
Low income (n = 9)	67%	78%	78%
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%

Notes: Percentages reflect the subset of cities with more than three concentric circles and meeting robustness criteria for within-city scaling. Boreal climate is omitted due to a single city in that category.

Planning performance targets and policy levers

The findings support several actionable planning strategies:

- **Set explicit green-infrastructure scaling targets.** If green space is treated as a core urban service, planning frameworks can benchmark performance against a linear expectation and use observed sublinear exponents as a risk indicator for future per-unit declines.
- **Protect contiguous green networks as the city grows.** Because connectedness grows slowly within cities (small within-city exponents), corridor protection and anti-fragmentation measures become central tools for sustaining service delivery under densification.
- **Act early in rapidly growing cities.** City-level evidence suggests that small to mid-sized cities, particularly in lower-income contexts, may experience growth trajectories where green systems can still be shaped before path-dependent land conversion locks in long-run scarcity [32].
- **Align green space expansion with community outcomes.** Green investments can generate unintended consequences such as environmental gentrification; planning and public management should pair green infrastructure strategies with safeguards and participation mechanisms [10, 38].

Equity and accessibility considerations

Remotely sensed greenness captures vegetation presence but does not directly measure public access, safety, maintenance, or distribution across neighborhoods. Management and planning research should treat sublinear scaling as an equity warning signal: as per-unit green availability declines, competition over remaining green amenities may intensify, potentially amplifying unequal outcomes even where total greenness rises [28, 38]. Integrating administrative park layers, canopy data, and accessibility proxies (e.g., travel-time catchments) can translate ecological scaling evidence into more directly policy-actionable equity metrics.

Limitations

Three constraints are central for interpretation. First, this article is a planning-oriented synthesis of a published empirical workflow; it should therefore be read as an interpretive benchmark study rather than as an independent reprocessing of raw satellite scenes, and longitudinal validation would further strengthen causal inference about urban trajectories [27, 11]. Second, NDVI thresholds do not distinguish public parks from private vegetation and cannot fully capture quality; the relative 75th-percentile threshold improves cross-context comparability but does not eliminate the need for alternative definitions of green space (parks, canopy, multiple NDVI thresholds) as robustness checks [32]. Third, gridded population at 250 m is appropriate for city totals but is less reliable for fine-grained intra-urban accounting in very small rings, motivating complementary data and methods for accessibility analysis [14, 32].

CONCLUSION

Using a standardized global sample of 150 cities and a reproducible remote-sensing scalogram approach, this article consolidates evidence that urban green space increases with city growth but does so sublinearly. Green coverage scales with a reported exponent of 0.26 relative to population and 0.22 relative to city area, implying that larger cities are typically greener in total amount yet less green in per-unit availability. Mean patch size and connectedness also increase with growth, and within-city scalograms reveal that power-law relationships are widespread and often robust. By combining pooled, stratified, and within-city evidence, the manuscript offers a clearer benchmark for planning evaluation than any single comparison taken in isolation.

For the *Journal of Management and Planning Research*, the core implication is managerial: green infrastructure requires explicit performance targets and governance instruments capable of counteracting baseline scarcity dynamics. Without proactive planning to preserve, connect, and expand green networks, continued urban growth is likely to yield cities that are economically larger yet relatively less green as a practical matter of service provision. The paper's contribution is thus to translate an established remote-sensing evidence base into a form that is directly usable for strategic planning, benchmarking, and policy design.

DATA AND TRANSPARENCY STATEMENT

This manuscript is a planning-focused interpretive synthesis built from openly available satellite and global settlement datasets and from the reproducible workflow reported in the primary empirical study cited throughout. It does not claim a separate reprocessing of raw imagery; rather, it transparently translates that published empirical base into management- and planning-oriented benchmarks and implications.

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