

Development of the Global Urban FBR 10-m Grid Dataset (2023)

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Abstract: The spatial distribution and structural characteristics of urban forests are key prerequisites for linking the implementation of SDG 11 (Sustainable Cities and Communities) and SDG 13 (Climate Action). To overcome the limitations of conventional indicators in defining spatial boundaries, enabling intercity comparability, and characterizing intracity equity, this study used 10-m resolution ESRI land-use data (2023) and a 1-km moving window to construct the Forest-to-Built-up Area Ratio (FBR), thereby generating a 2023 FBR dataset for 978 cities worldwide. This indicator focuses on the physical spatial extent of urban built-up areas, eliminates differences in city size by expressing forest land relative to impervious surface, and quantifies spatial heterogeneity at the pixel scale. The dataset is archived in .tif format and consists of 978 files, totaling 53.5 GB (compressed into 3 files, totaling 1.92 GB). This dataset supported the completion of the first author's Master of Science thesis in Resources and Environment.

Keywords: Forest-to-Built-up Area Ratio (FBR); urban built-up area; spatial heterogeneity; global dataset; 10-m resolution; Master of Science thesis

DOI: <https://doi.org/10.3974/geodp.2026.02.02>

Dataset Availability Statement:

The dataset supporting this paper was published and is accessible through the *Digital Journal of Global Change Data Repository* at: <https://doi.org/10.3974/geodb.2025.11.06.V1>.

1 Introduction

The ecosystem services provided by urban forests are substantially greater than those provided by other forms of green infrastructure^[1,2]. Developing urban forests is therefore an important pathway for urban systems to advance SDG 11 (make cities and human settlements inclusive, safe, resilient and sustainable) and SDG 13 (take urgent action to combat climate change and its impacts). However, over the past decade, urban tree cover has declined on every continent except Europe^[3]. Moreover, climate warming has intensified the urban heat

Received: 30-10-2025; **Accepted:** 16-03-2026; **Published:** 25-04-2026

Foundation: National Social Science Foundation of China (25&ZD094)

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Data Citation: [1] Zhao, L. F., Tian, L., Yang, Y., *et al.* Development of the global urban FBR 10-m grid dataset (2023) [J]. *Journal of Global Change Data & Discovery*, 2026, 10(2): 121–127. <https://doi.org/10.3974/geodp.2026.02.02>.

[2] Zhao, L. F., Tian, L., Yang, Y., *et al.* Global urban FBR 10-m grid dataset (2023) [J/DB/OL]. *Digital Journal of Global Change Data Repository*, 2025. <https://doi.org/10.3974/geodb.2025.11.06.V1>.

island effect and significantly reduced the carbon sequestration efficiency of trees^[4]. Urban forests therefore face multiple risks, including area loss and quality degradation. Against this background, scientifically quantifying the spatial distribution and structural characteristics of urban forests is essential for linking the implementation of SDG 11 and SDG 13.

Currently, a variety of indicators and methods are used to quantify the amount of urban forests, mainly including coverage-based indicators and area-based indicators. Coverage-based indicators^[5] (e.g., canopy cover and tree cover) are widely used to assess urban heat island mitigation effects^[6] because they are closely related to climate-regulation indicators such as land surface temperature and thermal comfort. Area-based indicators (e.g., forest cover area and green-space area) provide intuitive quantitative evidence for forest resource monitoring and the assessment of green and sustainable development^[7–9]. These studies have laid an important foundation for understanding the ecological functions of urban forests. However, from the perspective of supporting SDG 11 (Sustainable Cities and Communities) and SDG 13 (Climate Action), existing indicators still have 2 limitations. First, spatial boundaries are defined inconsistently. Most studies use administrative units or natural boundaries as statistical units^[10–12], making it difficult to accurately capture the interaction between forest land and the built environment within the physical urban area, whereas SDG 11 emphasizes the sustainability of “cities and human settlements”, and the core spatial unit of concern should therefore be the urban built-up area in which residents actually conduct their daily activities. Second, comparability and spatial refinement remain insufficient. Absolute indicators such as coverage and area are strongly affected by city size and natural background conditions, making cross-city and cross-regional comparisons difficult. At the same time, traditional indicators usually remain at the level of citywide averages^[7,8] and cannot reveal the spatial heterogeneity of forest distribution or issues of intracity equity, even though these are key dimensions of “inclusiveness” and “safety” in SDG 11.

To address the above challenges, this study constructed the urban Forest-to-Built-up Area Ratio (FBR) using ESRI 10-m land-use data. This indicator has 3 main advantages. First, in terms of spatial scope, it focuses precisely on the physical urban entity. City boundaries that this study adopted were extracted from urban built-up areas, thereby excluding interference from suburban areas and non-urban built environments. Second, in terms of comparability, it removes scale effects across cities. By expressing forest land relative to impervious surface, it minimizes the influence of city size and enables cities of different sizes and development stages to be compared on a consistent basis. Third, in terms of scale, it enables fine-grained characterization of spatial heterogeneity, thereby supporting quantitative analysis of the equity and balance of ecological space distribution within cities.

2 Metadata of the Dataset

Information on the dataset name, authors, geographic region, temporal coverage, dataset composition, data publishing and sharing service platform, and sharing policy for the Global urban FBR 10-m grid dataset (2023)^[13] is provided in Table 1.

3 Methods

3.1 Data Sources

The 2018 boundary data for 978 global cities used in this study were sourced from the FROM-GLC group at Tsinghua University^[15], and subsequently from a version processed by CHEN Bin and colleagues at the University of Hong Kong for a specific study^[16]. Based on the 30-m resolution Global Artificial Impervious Area (GAIA) product, the dataset provides global urban boundaries (GUB), which defines the physical spatial extent of cities^[15].

Table 1 Metadata summary of the Global urban FBR 10-m grid dataset (2023)

Item	Description
Dataset full name	Global urban FBR 10-m grid dataset (2023)
Dataset short name	UrbanFBR
Authors	Zhao, L. F., Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, University of Chinese Academy of Sciences, zhaolifeng23@mails.ucas.ac.cn Tian, L., Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, University of Chinese Academy of Sciences, tianli@igsrr.ac.cn Yang, Y., College of Computer Science, Beijing University of Technology, yangyang@emails.bjut.edu.cn Wang, Z. B., Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, University of Chinese Academy of Sciences, wangzb@igsrr.ac.cn
Geographical region	Global
Year	2023
Data format	.tif
Data size	1.92 GB (after compressed)
Data files	FBR grid data for 978 cities
Data computing environment	Python, ArcGIS, QGIS, Google Earth
Data publisher	Global Change Research Data Publishing & Repository, http://www.geodoi.ac.cn
Address	No. 11A, Datun Road, Chaoyang District, Beijing 100101, China
Data sharing policy	(1) <i>Data</i> are openly available and can be free downloaded via the Internet; (2) End users are encouraged to use <i>Data</i> subject to citation; (3) Users, who are by definition also value-added service providers, are welcome to redistribute <i>Data</i> subject to written permission from the GCdataPR Editorial Office and the issuance of a <i>Data</i> redistribution license; and (4) If <i>Data</i> are used to compile new datasets, the “ten percent principal” should be followed such that <i>Data</i> records utilized should not surpass 10% of the new dataset contents, while sources should be clearly noted in suitable places in the new dataset ^[14]
Communication and searchable system	DOI, CSTR, Crossref, DCI, CSCD, CNKI, SciEngine, WDS, GEOSS, PubScholar, CKRSC

On this basis, this study further optimized the boundary data in 3 respects: first, spatial features sharing common boundaries were merged; second, areas where the built-up area boundaries showed obvious deviations from Google Earth high-resolution satellite imagery were corrected; third, misclassified boundary units and built-up area boundary units containing no forest land were removed. The spatial extent data for forest land and impervious surface used in this study were derived from the 2023 ESRI 10-m resolution land-use product¹.

3.2 Methods

The pixel-level Forest-to-Built-up Area Ratio (FBR) was calculated for each pixel using a moving window based on the ESRI land-use data at a spatial resolution of 10 m by 10 m. The moving window was defined as a square centered on the target pixel with a side length of approximately 2 km; that is, the perpendicular distance from the central pixel to each of the four window edges was about 1 km. This 1-km threshold was set with reference to the typical service radius of the “15-minute living circle” in urban studies, with the aim of capturing the proportional relationship between forest land and the built environment within residents’ daily activity range.

$$FBR_{i,j} = \frac{1 + Pixels_{Trees}^{i,j}}{1 + Pixels_{BuiltArea}^{i,j}} \quad (1)$$

Where $Pixels_{Trees}^{i,j} \in [0, 40401]$ is the number of pixels classified as trees within the moving window corresponding to pixel i in city j ; $Pixels_{BuiltArea}^{i,j} \in [0, 40401]$ is the number of

¹ Esri Land Cover Explorer. <https://livingatlas.arcgis.com/landcover/>.

pixels classified as built area within the moving window corresponding to pixel i in city j . $FBR_{i,j} \in (0, 40402]$ denotes the FBR for pixel i in city j . A smaller $FBR_{i,j}$ indicates less forest land and more built-up surface within the 1-km range of pixel i in city j ; a larger $FBR_{i,j}$ indicates more forest land within the 1-km range of pixel i in city j ; $FBR_{i,j}=40402$ indicates that the 1-km range around pixel i is entirely covered by forest land.

4 Data Results

4.1 Dataset Composition

The dataset contains FBR grid data for 978 cities. Each file is named after the principal administrative division to which the corresponding city belongs. The dataset is archived in .tif format and consists of 978 files, totaling 53.5 GB (compressed into 3 files, 1.92 GB).

4.2 Data Results Analysis

The FBR values within the urban built-up areas of 978 cities worldwide show significant spatial heterogeneity and regional clustering. Overall, high-FBR areas (≥ 0.13) are mainly concentrated in the mid- to high-latitude regions of the Northern Hemisphere and in some humid tropical regions, whereas low-FBR areas (0.00–0.05) are widely distributed across arid and semi-arid regions of the mid- and low-latitudes and in some densely populated areas undergoing rapid urbanization. This pattern indicates that the trade-off between forest retention and construction intensity within cities is strongly constrained by the broader geographical context.

At the global scale, FBR exhibits distinctly different spatial patterns across continents and subregions. First, North America shows a pronounced east-west differentiation. Urban agglomerations in the eastern and southeastern United States generally exhibit high FBR values (≥ 0.26), corresponding closely to the favorable hydrothermal conditions of this region; By contrast, cities in the central and western United States and in Mexico generally have low FBR values because of arid climatic constraints. Europe displays clear latitudinal zonality, with urban FBR increasing from south to north across the continent. Cities on the Scandinavian Peninsula, in Eastern Europe, and in the Russian Federation largely fall within the highest value range (≥ 0.26), reflecting low building density and abundant urban green space against the background of high-latitude coniferous and broadleaf forest zones. By contrast, cities along the Mediterranean coast of Southern Europe have relatively low FBR values, mostly between 0.02 and 0.12. Asia, in turn, shows a complex and strongly polarized pattern. Under the combined influence of population density and urbanization processes, urban clusters in South Asia (e.g., India) are almost entirely dominated by low FBR values (0.00–0.05), highlighting the extreme compression of forest space by high-intensity impervious surface expansion. By contrast, East Asia, especially China, shows a pattern of higher values in the south and lower values in the north. Cities in Southern China and Japan, influenced by the subtropical monsoon climate and mountain-water urban morphology, have significantly higher FBR values than cities in North China and the northwestern inland region. In South America, Africa, and Oceania, cities along the South American coast and in Southern Brazil exhibit relatively high FBR values; African cities generally have low FBR values, especially in North Africa and parts of sub-Saharan Africa, reflecting an arid climatic conditions and unplanned urban sprawl; and cities along the eastern and southern coasts of Australia and in New Zealand generally have high FBR levels.

Based on the 10-m resolution spatial FBR data, the standard deviation of log-transformed FBR ($SD_{\ln(FBR)}$) was calculated for each of the 978 cities to measure intracity spatial heterogeneity. This indicator essentially reflects the degree of imbalance in the interactive distribution of green ecological space and built-up space within cities.

Overall, the spatial pattern of $SD_ln(FBR)$ across the 978 cities worldwide is broadly consistent with that of FBR. Areas of high heterogeneity ($SD_ln(FBR) \geq 0.36$) are concentrated in specific economies or geographic locations, whereas areas of low heterogeneity ($SD_ln(FBR) \leq 0.05$) occur as large contiguous zones in some developing countries and arid climate regions. This pattern indicates substantial differences among cities worldwide in the equity and balance of intra-urban greening.

By comparing the spatial distributions across continents and countries, together with Figure 1, several typical patterns of intracity landscape heterogeneity can be identified. The first is the “low-total-amount, low-heterogeneity” homogeneous ecologically deficient zone represented by South Asia and the Middle East. Most cities on the Indian subcontinent and in the arid regions of the Middle East and North Africa fall within the lowest FBR range (0.00–0.05) in Figure 1 and also exhibit very low standard deviations (≤ 0.05) in Figure 2. This double-low pattern means that these cities not only lack forest land overall, but also display a highly homogeneous scarcity of forest across the entire urban built-up area. The second is the “high-total-amount, high-heterogeneity” spatial polarization zone represented by parts of North America, Latin America, and Southern Chinese cities. Cities in the eastern half of the United States, the southeastern coast, the coastal urban clusters of South America (e.g., Brazil), and southern and southeastern coastal China generally exhibit high absolute FBR values (≥ 0.26) in Figure 1, indicating strong forest endowments; However, these cities

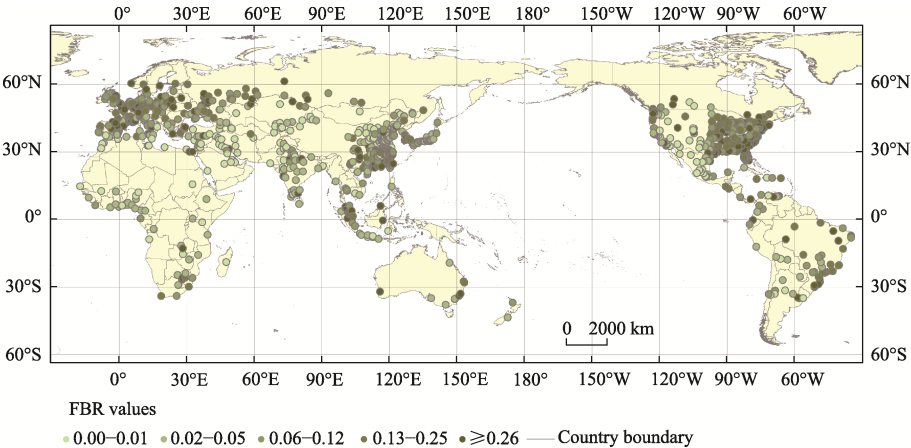


Figure 1 Spatial distribution map of FBR within the urban built-up areas of 978 cities worldwide

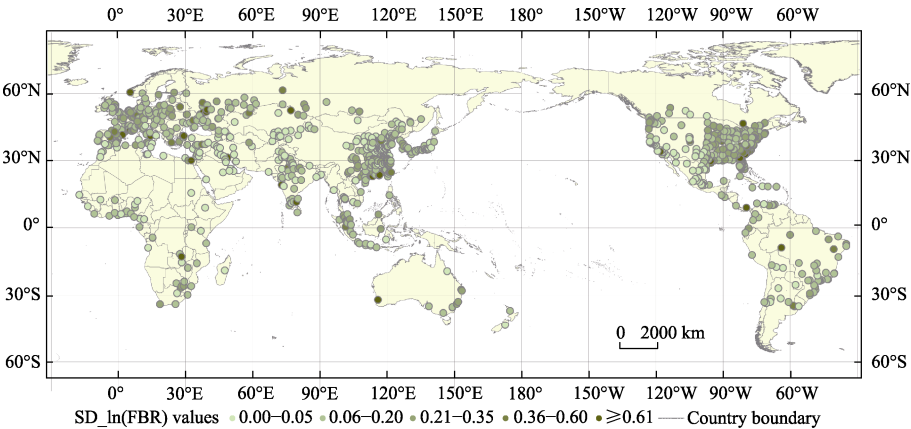


Figure 2 Spatial distribution map of FBR spatial heterogeneity within the urban built-up areas of 978 cities worldwide

also show very high spatial heterogeneity (≥ 0.36) in Figure 2. This coupled pattern clearly reveals issues of spatial justice within cities. In addition, there are “medium-low-total amount, high-heterogeneity” zones represented by East Asia and Northern Chinese cities, as well as “high-total-amount, medium-low-heterogeneity” zones represented by high-latitude Europe and some cities in Oceania.

5 Discussion and Conclusions

This study constructed the global urban FBR. Based on 10-m resolution land-use data and a 1-km moving window, this indicator offers 2 improvements. First, it shifts from representing absolute quantities to characterizing relative relationships. FBR focuses on the proportional structure between forest land and built-up surface, and more accurately reflects the interaction and trade-off between ecological space and built-up space in the urban human-land system. Second, it shifts from citywide averages to the fine pixel scale, enabling the simultaneous characterization of forest extent and spatial heterogeneity, and providing data support for urban typology and pattern analysis. The results show that the global distribution of urban forest land is dominated by “high-total-amount, high-heterogeneity” spatial polarization zones and “low-total-amount, low-heterogeneity” homogeneous ecologically deficient zones.

Although this dataset was designed and processed with great care, it still has several limitations. First, in terms of temporal consistency, the core dependent variable of the dataset is based on land use data for 2023, whereas the reference year of the urban boundary data is 2018, resulting in a temporal mismatch. It should be noted that this version of the urban boundary data was the latest publicly available and most widely used version worldwide at the time of dataset development^[17–20], and it was adopted in this study to maintain comparability and consistency with mainstream research. Second, This dataset is subject to error propagation arising from the accuracy of the 2023 ESRI 10-m resolution land-use product. At the time of dataset development, the ESRI 10-m land-use product was the highest-resolution globally covered dataset available for large-scale land-use research. To demonstrate the reliability of this product, this study randomly placed 100 validation sample points within the spatial extent of forest land and 100 within the spatial extent of impervious surface for each of the 978 global city boundaries. The accuracy assessment results show that the overall classification accuracy exceeded 85%, and most misclassified samples were located along the edges of the corresponding land-cover classes, a phenomenon mainly constrained by spatial resolution. This dataset supported the completion of the first author’s thesis for a degree of Master of Science in Resources and Environment.

Author Contributions

Zhao, L. F. contributed to the overall design, data collection and processing, data visualization, manuscript writing, and formatting; Tian, L. contributed to the overall design, data collection, content review, and revision; Yang, Y. contributed to data collection and processing; Wang, Z. B. contributed to the overall design.

Acknowledgements

The authors would like to express their sincerest gratitude to Professor Liu, C. and Associate Professor Shi, R. X. We thank them for their valuable academic guidance throughout the revision of this dataset. The constructive suggestions provided by the two experts at key stages, including the optimization of the dataset calculation and classification methods, validation of the scientific rigor of the dataset, and refinement of the scientific questions,

played a crucial role in improving the quality and rigor of this study. The authors are deeply grateful for their insight and generous assistance.

Conflicts of Interest

The authors declare no conflicts of interest.

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