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# Internationally Validated Open Access Indicators of Large Public Urban Green Space for Healthy and Sustainable Cities

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## ABSTRACT

Large public urban green spaces (LPUGS) provide multiple health and environmental co-benefits by mitigating urban heat, improving air quality and biodiversity, and promoting physical activity, social interactions, and mental wellbeing. There is a lack of accessible, evidence-informed, and internationally validated LPUGS indicators to assist with benchmarking and monitoring progress toward healthy and sustainable cities globally. This study developed and validated internationally applicable spatial indicators of LPUGS availability and accessibility that are directly relevant to health and sustainability outcomes. For 13 cities across 10 middle- to high-income countries, we identified LPUGS $\geq 1$ ha by fusing OpenStreetMap and satellite-derived Normalized Difference Vegetation Index data, and estimated residents' access within 500 m pedestrian network distance. We conducted a two-step validation process with local collaborators in each city. Our indicator methods identified LPUGS with greater than 80% accuracy for 12 of the 13 cities, and comparisons against official local reference data for four cities further demonstrated validity. While some open data limitations were identified, the indicators address critical gaps in existing methods by enabling standardized and comparable measurement of LPUGS in diverse cities internationally. Our customizable open-source global indicator tools can inform evidence-based green space planning for urban health and sustainability.

## 1 | Introduction

Protecting and promoting health and well-being in the context of climate change is a significant sustainability issue for cities around the world (van Daalen et al. 2024; United Nations 2015). Cities are major contributors to greenhouse gas emissions and face escalating health impacts from climate hazards including heat waves, flooding, deteriorating air quality, and damage

For affiliations, refer to page 13.

to infrastructure from extreme weather (IPCC 2022). However, cities can enhance climate resilience with co-benefits for human health.

Extensive evidence suggests that urban green spaces may mitigate urban heat (Iungman et al. 2023; Massaro et al. 2023), improve air quality (Alpaidze and Salukvadze 2023; Matos et al. 2019), support biodiversity (Gao et al. 2021; Lepczyk et al. 2017), and promote physical activity (Arundel et al. 2017; Koohsari et al. 2015). Thus, urban green spaces have a range of human health benefits (Fernandes et al. 2024; Tate et al. 2024; van Daalen et al. 2024; Hunter et al. 2023; Giles-Corti et al. 2022; Gianfredi et al. 2021; Yang et al. 2021; Houlden et al. 2018). These include reduced all-cause and cardiovascular mortality, lower obesity rates, and decreased type 2 diabetes prevalence and risk of depression (Liu, Chen, et al. 2023; Nguyen et al. 2021; Rojas-Rueda et al. 2019; World Health Organization 2017).

While diverse types of urban greenery are important (Sánchez and Labib 2024; Biljecki et al. 2023), large and accessible green spaces have established health and environmental benefits. Good access and closer proximity to green space are associated with higher physical activity levels and more frequent visits (Bai et al. 2013; Coombes et al. 2010; Kaczynski et al. 2009). Additionally, large green spaces are associated with increased physical activity levels (Costigan et al. 2017; Jansen et al. 2017; Wood et al. 2017). However, beyond an optimal threshold for green space coverage in a neighborhood, there may be detrimental impacts on cognitive health due to reduced availability of other beneficial land uses (Wu et al. 2015). Relative to small spaces, larger green spaces may also have greater cooling effects and better support biodiversity (Xiao et al. 2018; Lepczyk et al. 2017; Jaganmohan et al. 2016).

As cities densify and grow, protecting and expanding public green space is crucial, especially in areas where development pressures have reduced private green space availability (Arundel et al. 2017). Significant geographic inequities exist in access to public green spaces within and between cities internationally (van Daalen et al. 2024; Hunter et al. 2023). Policymakers and practitioners need internationally validated green space indicators to reveal inequities in access, monitor changes in greenery across time, and promote their conservation and expansion. A range of metrics has been used in research and practice to assess the spatial distribution of urban greening and public urban green space access and availability. However, many of these indicator-based methods lack local validation across different cities internationally and/or do not measure green space aspects known to be important for health and climate resilience (Yang et al. 2021), which limits the ability to interpret findings and compare them across cities (Battiston and Schifanella 2024; Browning et al. 2024; UN Habitat 2022). This gap prevents planners and policymakers from benchmarking and monitoring cities' progress toward urgent health and sustainability goals internationally.

Thus, this study developed and validated internationally applicable spatial indicators of large public urban green space (LPUGS) availability and accessibility to support evidence-informed green space planning for health and sustainability. With a focus on worldwide urban measurement, we tested LPUGS indicators for diverse cities internationally, drawing on local collaborator knowledge and data comparisons. We sought to advance the state of the art by developing standardized yet locally adaptable, scientifically validated open-source metrics that are internationally applicable and comparable, directly relevant to health and climate resilience, and able to show neighborhood-level inequities. This facilitates more accurate benchmarking, comparative analyses, and actionable insights for cities worldwide, advancing the capacity to monitor and improve urban health and sustainability.

The indicators were developed for the Global Observatory of Healthy and Sustainable Cities; a collaborative open-data platform for measuring and monitoring urban health and sustainability globally (Global Healthy and Sustainable City-Indicators Collaboration 2022). To ensure consistency and adaptability across diverse urban contexts, the Global Observatory employs an open-source software platform (Global Healthy and Sustainable City Indicators (GHSCI) software) that enables standardized indicator calculation, validation, and reporting undertaken by local city teams for cities worldwide (Higgs et al. 2024). To integrate into this platform, the LPUGS metrics needed to be robust, scalable, and able to be used by researchers, policymakers, and advocates to assess cities anywhere in the world.

## 2 | Literature Review

### 2.1 | Measurement of Urban Green Space

There is no consensus on the most suitable green space metrics for assessing healthy and sustainable cities globally. UN-Habitat's Global Urban Monitoring Framework (UN Habitat 2022) includes green area per capita, but does not consider green space size, public accessibility, or proximity to residences, which all affect user experience, health, and environmental outcomes (Hunter et al. 2023; Kruize et al. 2019). The World Health Organization (2016) identifies availability and accessibility as fundamental considerations for green space spatial metrics. Existing green space indicators specify a range of requirements for size (e.g., 0.5–1 or >1 ha) and distance from dwellings (e.g., 300, 500, 800 m) (Battiston and Schifanella 2024; Konijnendijk 2023; Browning et al. 2022; Long et al. 2022; Nguyen et al. 2021; World Health Organization 2017; van den Bosch et al. 2016). A minimum size of 1 ha has been suggested for optimizing potential public health benefits, and being applicable for global urban green space research (Long et al. 2022; van den Bosch et al. 2016). A systematic review of green space and health studies by Browning et al. (2022) identified a 500 m distance, approximately a five-minute walk, as the most frequently used threshold for measuring walkable access to green space. Relative to Euclidean distance and buffers, which many other indicators have used, distance measured via the pedestrian road network provides more precise estimates of walking through urban environments (Viinikka et al. 2023; Thornton et al. 2011).

### 2.2 | Data Sources

Measuring internationally comparable and consistent indicators requires quality data of global scope. Previous studies have identified public urban green space using pre-processed global land cover datasets (Battiston and Schifanella 2024; Duarte et al. 2023;

Zhao et al. 2023; Long et al. 2022) which are convenient but have varying levels of accuracy. For example, the WorldCover 2021 v200 dataset (Tsendbazar et al. 2022) contains 11 different land cover classes, but there is no land cover class that comprehensively represents LPUGS. Studies comparing WorldCover to other global land cover and national land cover datasets found that each had varying strengths in different contexts (Duarte et al. 2023; Zhao et al. 2023; Liao et al. 2021). Therefore, the suitability of pre-processed global land cover datasets for measurement of LPUGS is uncertain.

Other recent approaches for identifying green space have used street-view imagery (Mahajan 2024; Sánchez and Labib 2024; Biljecki et al. 2023), which can provide hyper-local insights that aerial or satellite imagery may miss (Torkko et al. 2023). However, street view imagery is not reliably available at scale globally (Mahajan 2024), and its peripheral outlook is ill-suited for identifying large green spaces.

Remote sensing data has commonly been used to identify greenery by using spectral indices derived from satellite imagery band arithmetic to extract high-resolution land cover information (Liu, Kwan, et al. 2023). Sentinel-2 Earth observation satellite imagery provides global coverage at 10 m resolution (European Space Agency 2021), from which spectral indices such as the Normalized Difference Vegetation Index (NDVI) can be derived (Huang et al. 2021). NDVI, the most common green space index, is a measure of the physiological health of vegetation cover (Fong et al. 2018). Studies across differing climatic zones and contexts agree upon a standard threshold of NDVI $\geq 0.2$ to distinguish vegetation from non-vegetation (Martinez and Labib 2023; Rakowska et al. 2023; Aryal et al. 2022; Wong et al. 2019; Huang et al. 2017). Satellite indices such as NDVI also provide choice of temporal coverage due to frequent satellite revisit times, enabling calculations of greenery during particular seasons, peak vegetation growth periods, or as an annual average. However, NDVI alone cannot confidently identify LPUGS, as it fails to distinguish aesthetic and functional differences between spaces of the same NDVI value (Martinez and Labib 2023; Donovan et al. 2022). For example, NDVI cannot distinguish between private and public spaces, a key component of our LPUGS indicator.

Fusion of NDVI with supplementary data sources can enable more refined measurement of LPUGS. OpenStreetMap is a collaborative mapping project that uses crowdsourced contributions to create an open access spatially enabled data catalog with global coverage (OpenStreetMap Contributors 2024). Fusing OpenStreetMap with Sentinel-2 derived NDVI can significantly improve estimates of public green space (Teeuwen et al. 2024; Ludwig et al. 2021), as OpenStreetMap data is better able to identify fine-grained urban structures and distinguish public spaces.

As a dynamic data source, OpenStreetMap data quality and completeness varies between different geographical regions (Ludwig and Zipf 2019; Schultz et al. 2017). Perhaps due to these inconsistencies, the validation of OpenStreetMap data in combination with other data sources such as NDVI is relatively unexplored in the green space literature. Previous research has identified a need to further examine the integration of OpenStreetMap data for mapping urban green spaces (Mahajan 2024), and to test the application of these methods in diverse contexts to investigate comparability between cities (Ludwig et al. 2021).

## 3 | Methods

### 3.1 | City Selection

To test their international validity and applicability, we calculated indicators for diverse cities in terms of geographic location, population size, area, climate conditions, and income classification. Cities were selected via convenience sampling, drawing upon the Global Observatory's existing collaborative research network to facilitate validation based on local knowledge (Global Healthy and Sustainable City-Indicators Collaboration 2022). Validators of the findings for each city were researchers or practitioners currently or recently residing in the city and with expertise in urban green space planning, healthy cities, and spatial data science.

The 13 sample cities were in 10 countries spread across five continents: Chennai, India; Porto Alegre, Brazil; Mexico City, Mexico; Austin, Minneapolis, and Los Angeles, USA; Melbourne, Australia; Helsinki, Finland; Munich, Germany; Turin, Italy; Valencia and Vic, Spain; and Belfast, UK. Eleven different climate classifications are represented, including Chennai's tropical climate, Valencia's arid climate, and Helsinki's cold climate (Beck et al. 2018). While most cities were in high-income countries, we included one lower-middle (Chennai) and two upper-middle (Porto Alegre, Mexico City) income country cities. Population estimates for 2025 derived from GHS-POP (Carioli et al. 2023) indicate a wide range of city scales and density, with population estimates of less than 40,000 in Vic to over 18,000,000 in Mexico City. See Table 2 and Supplementary Material for further details on the included cities.

### 3.2 | Data Sourcing and Preparation

Table 1 describes the open data that we used to generate our LPUGS indicators.

Study region boundaries were defined using urban centers sourced from the 2015 Global Human Settlement Urban Centre Database (GHS-UCDB) (Florczyk et al. 2019). In this dataset, urban centers are defined by a combination of specific cut-off values for resident population and built-up surface share representing urban agglomerations that may not conform to political jurisdictions. The GHS-UCDB boundaries were used for Austin, Mexico City, and Turin, whereas coastal cities including Chennai, Los Angeles, Melbourne, Helsinki, Valencia, and Belfast had their GHS-UCDB boundaries clipped to the coastline to exclude the impact of adjacent ocean on land area calculations (see Supplementary Material). Feedback from collaborators in Porto Alegre, Munich, and Minneapolis determined that intersecting the local municipality boundary with the GHS-UCDB boundary provided a more accurate representation. Vic was not present in the GHSC-UCDB, so the local municipality boundary was used.

**TABLE 1** | Open data sources used to model LPUGS.

| Data sources | | |
|---|---|---|
| **Custodian** | **Target date** | **References** |
| GHS-UCDB Global Human Settlement Urban Centre Database 2015 | 2015 | (Florczyk et al. 2019) |
| GHS-POP Global Human Settlement Population Grid 2025 | 2025 | (Carioli et al. 2023) |
| OpenStreetMap | up to March 1, 2024 | Geofabrik GmbH and OpenStreetMap Contributors. Data for each city retrieved from https://download.geofabrik.de/. 2024. |
| Harmonized Sentinel-2 MultiSpectral Instrument Level-1C | March 1, 2023—March 1, 2024 | Copernicus Sentinel data [2023–2024]. Retrieved from Google Earth Engine. Available from: https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S2_HARMONIZED |

Using the GHSCI indicator and reporting software (Higgs et al. 2024), urban center boundaries were buffered by 1 km to ensure that peri-urban environments remained accessible. A population grid, pedestrian network, and areas of public open space were then extracted for each city's buffered study region boundary. Gridded 100 m population estimates for 2025 were represented using data from the Global Human Settlement Population Grid (GHS-POP) (Carioli et al. 2023). Pedestrian street networks were derived for each city using OSMnx (Boeing 2017) via the GHSCI software, excluding freeways and paths classified as inaccessible or inappropriate for walking or cycling. The choice of OpenStreetMap tags was a crucial methodological decision as it could significantly impact the results, especially considering the varying environmental and cultural contexts across the cities studied. Therefore, using the GHSCI software, large public open spaces derived from OpenStreetMap data up to the date March 1, 2024 were identified following the method of Higgs et al. (2023) using a series of tagging synonyms and logical relationships validated for use in diverse cities globally (Boeing et al. 2022).

## 3.3 | LPUGS Indicators Calculation

For our LPUGS indicators, we extended the Global Observatory's validated public open space measures derived from OpenStreetMap input data (Boeing et al. 2022) by using Sentinel-2 derived NDVI to filter large public open spaces into a smaller subset of LPUGS. Figure 1 provides a visual summary of the indicator calculation workflow. Based on recommendations from the literature (see Section 2.1), we defined LPUGS as public green areas ≥ 1 ha, and accessibility was evaluated using a 500 m pedestrian network walking distance from dwellings. The established threshold of NDVI ≥ 0.2 was used for identifying greenery, and an annual average was calculated to approximate the lived experience of greenness throughout the year and maintain international comparability of our results, given the inherent seasonal dynamics of greenness across diverse cities internationally (John et al. 2023; Moore et al. 2016).

To generate the LPUGS and NDVI raster for each city, a Jupyter notebook (see Supplementary Material) was developed which generated annual average NDVI for the dates March 1, 2023—March 1, 2024, and then applied filtering of area ≥ 1 ha and NDVI ≥ 0.2 to the areas of public open space generated from the GHSCI software.

QGIS version 3.28 (QGIS Development Team 2024) software was used to generate the statistics. For *LPUGS accessibility*, pedestrian network analysis was performed using the relevant GHSCI software exports (Figure 1). Proxy access entry points were generated along the boundary of each LPUGS with a distance of 30 m between each point (Koohsari et al. 2015). The area and population attributes of each cell of the resultant accessibility grid were used to determine the percentage of total land area within 500 m pedestrian network distance and the percentage of estimated 2025 population with access to LPUGS within 500 m.

For *LPUGS availability*, the NDVI raster and LPUGS polygons were similarly imported into QGIS to calculate the percentage of total land area of the urban center boundary that was NDVI ≥ 0.2 and the percentage of total land area that was LPUGS. A visual summary of the spatial distribution of the indicators for the 13 cities was created using accessible scientific color palettes from Crameri et al. (2020).

## 3.4 | Local Validation Approach

Collaborators provided both quantitative and qualitative validation feedback based on local knowledge of their city. An instructional video (see Supplementary Material) provided details on how to access, navigate, and record validation information. LPUGS availability was validated using the LACO-Wiki Land Cover Validation Platform; an online tool that allows users to perform land cover accuracy assessment in an interactive platform (See et al. 2017; See et al. 2015). Validators could toggle between three basemaps to provide more spatial and seasonal context due to differences in the time of image capture. When checking a sample of green spaces, validators were instructed to assign "correct" if the space included a substantial amount of vegetation or greenery such that it appeared to be a LPUGS. "Incorrect"

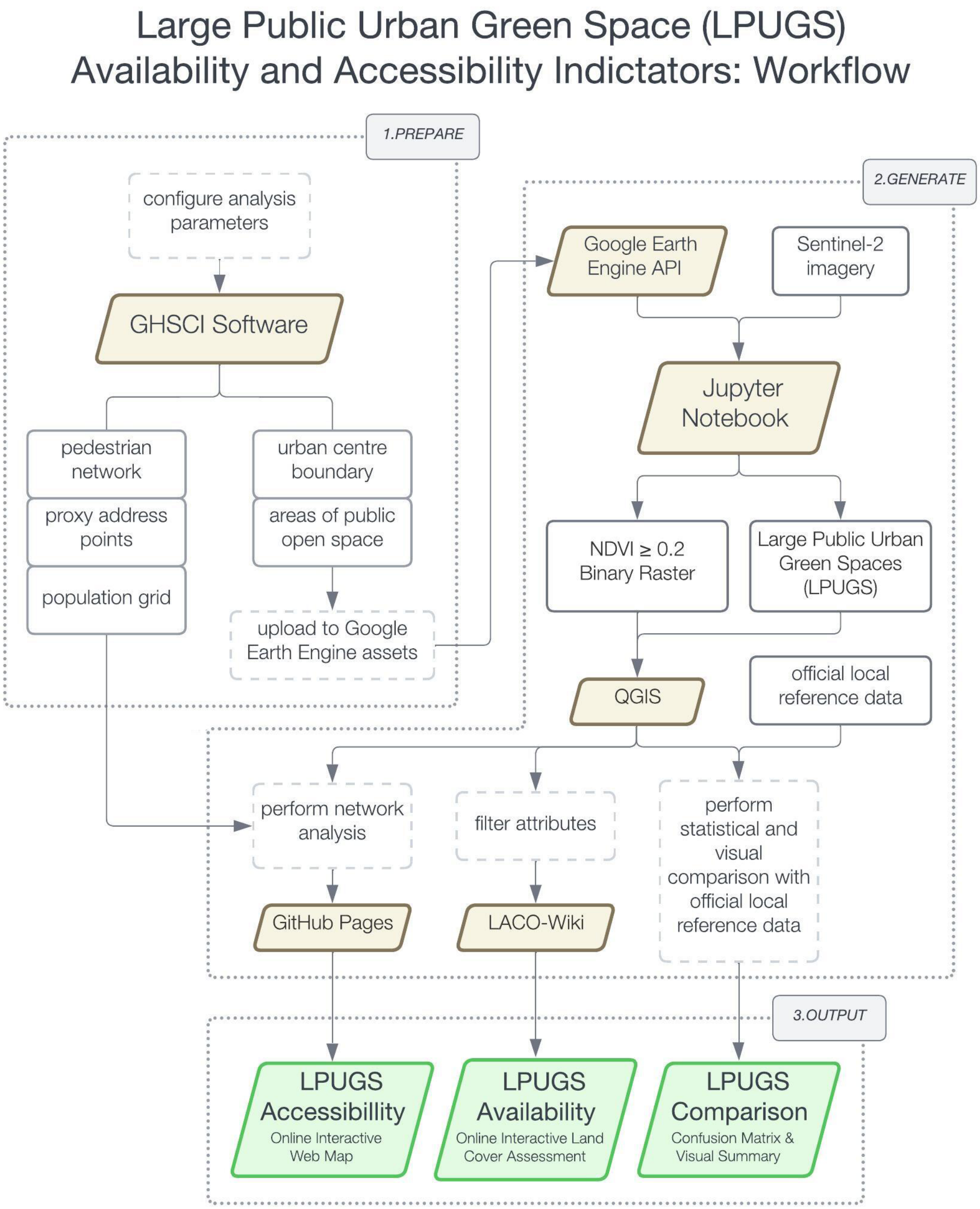


**FIGURE 1** | Technical workflow diagram showing the three stages of "Prepare," "Generate," and "Output" performed for each city.

could be selected if there was little or no presence of vegetation. We aimed to validate a 10% random sample of the total number of LPUGS in each city. This was adjusted to a minimum of 30 spaces for Chennai, Porto Alegre, Turin, Valencia, Vic, and Belfast, to ensure that these cities with relatively small LPUGS datasets had an adequate validation sample. The sample was capped at 120 spaces for Melbourne and Los Angeles, which had larger datasets of over 2000 LPUGS, to ensure feasibility of the validation task.

For LPUGS accessibility, an interactive online web map was provided to each collaborator (see Supplementary Material). A live spreadsheet was used to capture written feedback on: (1) whether the urban boundary was an accurate spatial representation for each city; (2) the spatial distribution of the LPUGS outputs, including omission (LPUGS not identified that should have been) and commission errors (areas wrongly identified as LPUGS); and (3) whether the percentage population within 500 m of LPUGS appeared accurate (see Supplementary Material). Where validation queries were raised by collaborators, we investigated the reasons behind potential inaccuracies in our LPUGS indicator measurement, including by conducting sensitivity analyses.

## 3.5 | Official Local Reference Data Comparison Approach

Additional validation was performed for Porto Alegre, Minneapolis, Melbourne, and Belfast, through comparison of our LPUGS

| Confusion Matrix | | *Gold Standard Reference* | | |
|---|---|---|---|---|
| | | + | - | ∑ |
| | + | TP | FP | TP + FP |
| *Classifier* | - | FN | TN | FN + TN |
| | ∑ | TP + FN | FP + TN | N |

**FIGURE 2** | Confusion matrix with four components of true positive (TP), true negative (TN), false positive (FP), and false negative (FN).

outputs with official local reference data sources. Although collaborators provided official local reference data for Helsinki, Los Angeles, Austin, and Mexico City, these were excluded from this second phase of validation, as the spatial extent of the reference data did not fully enclose that of their respective LPUGS outputs, making direct comparison difficult.

To achieve consistency with the criteria of our LPUGS, the official local reference data (see Supplementary Material) were filtered to only include polygons ≥ 1 ha. No additional filtering was necessary for Belfast and Minneapolis, but Melbourne's and Porto Alegre's datasets were filtered to only include publicly accessible areas.

Following the workflow diagram (Figure 1), the relevant data were imported into QGIS and projected to the same coordinate reference system. A 500 m buffer around the urban center boundary was created, and both datasets were clipped to this buffer to ensure each had the exact same spatial extent. Following Foody (2023), our statistical validation method involved creating a confusion matrix (see Figure 2) comparing our LPUGS outputs with the reference dataset for each city.

For clarity of communication when comparing green space, we expressed all the results as a percentage of the total urban center boundary, where $N = 100\%$. Using a spatial intersection computation, true positive areas were where both datasets agreed that an area was indeed green space. Calculated with a spatial difference computation, false positive areas were where our dataset identified LPUGS where the reference data did not, and inversely, false negatives were where our dataset did not include areas that the reference data identified as green space. True negatives were the areas that both datasets agreed was not green space, calculated by subtracting the spatial union from the total urban center boundary area. The sum ($\sum$) row and column ensure that the total areas of both datasets are equal. From the confusion matrix, the overall "accuracy" or ratio of correctly allocated cases was calculated using Equation (1) (Foody 2023).

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} = \frac{\text{TP} + \text{TN}}{\text{N}} \tag{1}$$

The confusion matrix and accuracy metric provide statistical comparison between two datasets; however, a corresponding visual summary was also created to contextualize the spatial agreements and disagreements. Where discrepancies were found between our LPUGS results and the official local reference data, we examined the data more closely to find the reasons behind these differences.

## 4 | Results

### 4.1 | LPUGS Indicators

LPUGS indicator results are listed in Table 2. In terms of LPUGS availability, findings for the total amount of green land cover (annual average NDVI ≥ 0.2) varied widely from 28.78% in Los Angeles to 74.20% in Vic. Within this range, 5 of the 13 cities had greater than half of their land area identified as greenery: Porto Alegre, Austin, Minneapolis, Munich, and Vic. While all in the Americas or Europe, these cities were diverse in terms of climate zones, urban area, and population size.

Vic and Munich had the highest total land area identified as LPUGS, at 14.00% and 13.99%, respectively. For the remaining 11 cities, LPUGS made up less than 10% of their total land area. Greater green cover (land area with annual average NDVI ≥ 0.2) did not always indicate higher availability of LPUGS. For example, among the North American cities, Austin had greater green land cover (66.28%); however, Minneapolis had more LPUGS, at 9.38% compared to Austin's 5.82%. Further, while Chennai had 43.32% green cover, only a very small portion of the city (0.32%) was identified as LPUGS.

In terms of LPUGS accessibility, Chennai had the lowest percentage of the total urban center area within a 500 m pedestrian network distance of LPUGS (accessibility grid, see Figure 3) at 3.88%, and the greatest coverage was in Melbourne at 60.36%. The percentage of the population with access to LPUGS within 500 m varied widely across the 13 cities. Vic, the smallest city in our sample, had the highest population percentage with access at 79.93%, followed closely by Melbourne with 79.63%. Among the other European continent cities, results ranged between 73.76% of the population in Munich and 50.13% in Belfast. Among the US cities, 73.94% of the population of Minneapolis had nearby access to LPUGS, compared to 45.88% in Austin and 29.66% in Los Angeles. Porto Alegre had 45.49% of the population living within 500 m of LPUGS. The two lowest scoring cities for population access to LPUGS were middle income country cities: Mexico City (16.24%) and Chennai (7.82%).

Figure 3 shows the spatial distribution of LPUGS availability and the accessibility grid for each city. Helsinki, Munich, Melbourne, Minneapolis, and Los Angeles appear to have relatively well-distributed access to LPUGS, but the maps also show areas without nearby access. All other cities appear to have significant spatial inequities in access to LPUGS, with clusters of accessibility contrasted with large areas without nearby access.

### 4.2 | Validation Results

Twelve of the 13 cities had LACO-Wiki results above 80% (Table 2), suggesting that our methodology identified LPUGS with sufficient accuracy for a diverse range of cities. Indeed, collaborators from Chennai, Helsinki, and Vic indicated that 100% of their LPUGS sample was correctly identified. The lowest result was 61.70% in Mexico City.

Collaborators' written feedback also indicated consensus that the results were accurate based on local knowledge. In terms of

**TABLE 2** | LPUGS indicator results, and LACO-Wiki validation results, with city area and population characteristics for further contextualization.

| Region, country, city | City characteristics: Urban center boundary area (km$^2$) (Florczyk et al. 2019) | City characteristics: 2025 population estimate (Carioli et al. 2023) | LPUGS indicator results – Availability: % of total land area that is annual average NDVI ≥ 0.2 | LPUGS indicator results – Availability: % of total land area that is LPUGS | LPUGS indicator results – Accessibility: % of total land area within 500 m pedestrian network distance of LPUGS | LPUGS indicator results – Accessibility: % of population with access to LPUGS within 500 m pedestrian network distance | LACO-Wiki validation results: Total number of LPUGS | LACO-Wiki validation results: Sample size | LACO-Wiki validation results: % correct responses |
|---|---|---|---|---|---|---|---|---|---|
| Asia | | | | | | | | | |
| India | | | | | | | | | |
| Chennai | 909 | 11,268,605 | 43.32 | 0.32 | 3.88 | 7.82 | 77 | 30 | 100 |
| South America | | | | | | | | | |
| Brazil | | | | | | | | | |
| Porto Alegre | 242 | 1,417,495 | 60.86 | 4.56 | 29.79 | 45.49 | 215 | 30 | 96.67 |
| North America | | | | | | | | | |
| Mexico | | | | | | | | | |
| Mexico City | 2312 | 18,322,420 | 31.51 | 1.75 | 12.38 | 16.24 | 472 | 47 | 61.70 |
| USA | | | | | | | | | |
| Austin | 604 | 1,553,406 | 66.28 | 5.82 | 33.34 | 45.88 | 458 | 46 | 84.78 |
| Los Angeles | 5534 | 14,967,143 | 28.78 | 3.87 | 21.15 | 29.66 | 2129 | 120 | 95.00 |
| Minneapolis | 291 | 713,911 | 54.27 | 9.38 | 50.94 | 73.94 | 425 | 43 | 95.35 |
| Australasia | | | | | | | | | |
| Australia | | | | | | | | | |
| Melbourne | 1638 | 4,440,107 | 47.91 | 8.65 | 60.36 | 79.63 | 2438 | 120 | 98.33 |
| Europe | | | | | | | | | |
| Finland | | | | | | | | | |
| Helsinki | 305 | 932,836 | 39.38 | 9.44 | 51.99 | 71.81 | 592 | 59 | 100 |
| Germany | | | | | | | | | |
| Munich | 271 | 1,657,042 | 65.18 | 13.99 | 58.44 | 73.76 | 449 | 45 | 91.11 |

(Continues)

**TABLE 2** | (Continued)

| Region, country, city | City characteristics | | LPUGS indicator results | | | | LACO-Wiki validation results | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | Availability | | Accessibility | | | | |
| | Urban center boundary area (km$^2$) (Florczyk et al. 2019) | 2025 population estimate (Carioli et al. 2023) | % of total land area that is annual average NDVI ≥ 0.2 | % of total land area that is LPUGS | % of total land area within 500 m pedestrian network distance of LPUGS | % of population with access to LPUGS within 500 m pedestrian network distance | Total number of LPUGS | Sample size | % correct responses |
| Italy | | | | | | | | | |
| Turin | 207 | 1,245,485 | 46.72 | 9.10 | 36.60 | 67.13 | 283 | 30 | 83.33 |
| Spain | | | | | | | | | |
| Valencia | 308 | 1,508,205 | 42.96 | 2.68 | 24.21 | 53.99 | 134 | 30 | 83.33 |
| Vic | 31 | 38,104 | 74.20 | 14.00 | 25.80 | 79.93 | 52 | 30 | 100 |
| UK | | | | | | | | | |
| Belfast | 160 | 485,512 | 43.78 | 5.15 | 35.73 | 50.13 | 115 | 30 | 96.67 |

omission errors, most feedback concerned the completeness of OpenStreetMap-derived parcel geometry. Feedback from Turin, Los Angeles, Melbourne, and Valencia included detailed comments on particular parks, nature reserves, and green open spaces that were not present in the indicator outputs, which collaborators believed should be included. In particular, validation comments for both Munich and Helsinki questioned the exclusion of cemeteries in our criteria for LPUGS. In Helsinki, it was also noted that many urban forested woods and wetlands are open to the public for recreational use but were not included in our outputs when not annotated in OpenStreetMap using tags that would indicate public access. Similarly, Mexico City's most significant LPUGS, the Bosque de Chapultepec, was reported to be missing from the outputs. Upon investigation, it was found that an OpenStreetMap user had modified the tagging for this green space, changing it from "leisure = park" to "natural = wood." The tag "natural = wood" alone does not imply public access. Therefore, areas tagged exclusively as "natural = wood" were not captured as they did not meet the default criteria for identifying public open space in the GHSCI software.

Sensitivity analysis to examine the effect of including the "natural = wood" tag when identifying public space in the GHSCI software identified three additional LPUGS in Mexico City and 17 in Helsinki. With these additional LPUGS, the percentage of the population with access to LPUGS within 500 m increased only slightly from 71.81% to 72.45% in Helsinki, and from 16.24% to 16.38% in Mexico City. Thus, while not configuring the "natural = wood" tag to imply public access may have risked omission errors in some geographical contexts, the effect on accessibility indicator results appeared to be minor.

Commission errors mostly related to public versus private accessibility status. LACO-Wiki results for Mexico City included some green spaces within gated communities, which are only accessible to residents of those communities rather than the general public. Similarly, it was reported that some of the LPUGS identified in Los Angeles had admission fees. Collaborators also reported inconsistencies in public access to some recreational and sports facilities in Austin, Belfast, and Vic. Results for Munich included green areas beside high-speed autobahns, which are infrequently visited by people and therefore perhaps should not be considered public.

For the LPUGS accessibility indicator, with the exception of Austin, all local collaborators confirmed reasonable accuracy of the results. Feedback for Austin noted that the population percentage with access (45.88%) differed from the 70% stated in a City of Austin's Parks and Recreation report (Parks and Recreation Open Data Asset Owners 2020). The discrepancy may be explained by the fact that this latter calculation of population access used less strict distance criteria, so it was not directly comparable to our results.

## 4.3 | Official Local Reference Data Comparison Results

Table 3 shows the confusion matrices comparing the LPUGS outputs with official local reference data for Porto Alegre, Minneapolis, Melbourne, and Belfast. Consistent with the local validation

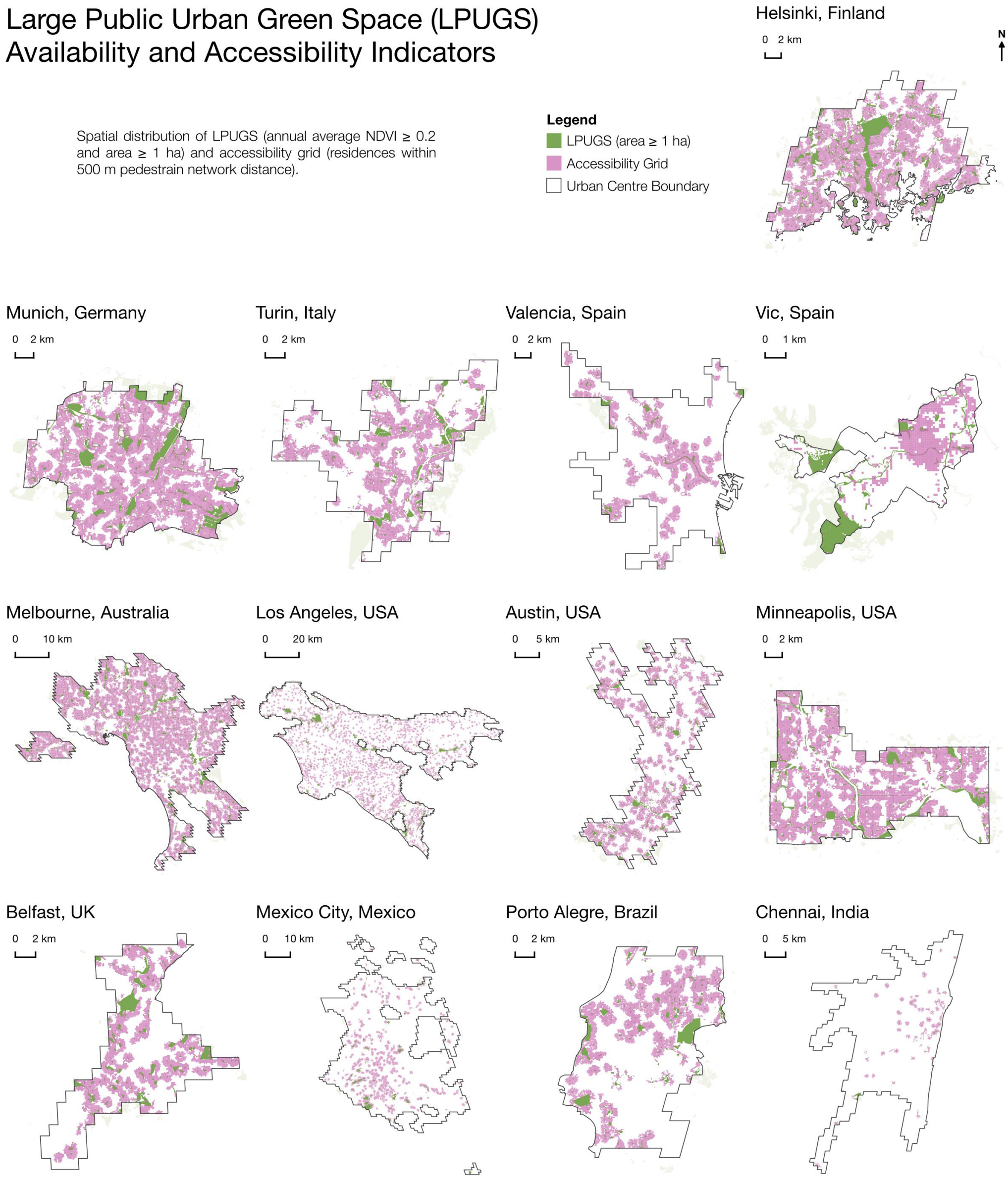


**FIGURE 3** | Visual summary of LPUGS availability and accessibility indicator results for each city.

findings, high accuracy metrics of greater than 90% were found for the four cities. This provided further evidence that our selected indicator parameters and methods were acceptably valid. For all four cities, the false negative areas were less than 8% of the urban center boundary area, whereas false positives were less of a concern at less than 4%. The visual summary in Figure 4 highlights where some green spaces in the official local reference data were not matched in our LPUGS results.

False negatives in Melbourne largely consisted of land cover types (i.e., golf courses, cemeteries and racecourses) that were included in the reference data but explicitly excluded from our identification of publicly accessible spaces. The Minneapolis reference data also included golf courses. Belfast and Porto Alegre had the highest accuracy metrics at 93.93% and 93.78% respectively. This may be because their official local reference data were updated more recently than the other two sample cities' data. Belfast's reference data also defined green space size and specified public access in a way that most closely aligned with our criteria for LPUGS.

## 5 | Discussion

### 5.1 | Validated LPUGS Indicators for Diverse International Cities

Urban green spaces are crucial for promoting health and mitigating adverse impacts of climate change in cities (United Nations Environment Programme 2024; van Daalen et al. 2024). Large green spaces offer significant economic benefits by reducing healthcare and environmental costs (Tefera et al. 2024). Relative to smaller spaces, our indicators' focus on large green spaces (area ≥ 1 ha) ensures established benefits related to increased physical activity, cooling, and biodiversity are captured (Xiao et al. 2018; Lepczyk et al. 2017; Jaganmohan et al. 2016; Bai et al. 2013). Research-derived indicators of LPUGS can inform decisions on

**TABLE 3** | Confusion matrices and accuracy metrics for Porto Alegre, Minneapolis, Melbourne, and Belfast.

| **Porto Alegre** | | *Official Local Reference Data* | | | **Minneapolis** | | *Official Local Reference Data* | | |
|---|---|---|---|---|---|---|---|---|---|
| | | + | - | ∑ | | | + | - | ∑ |
| | + | 2.68 | 3.59 | 6.28 | | + | 9.00 | 2.65 | 11.65 |
| *LPUGS* | - | 2.62 | 91.10 | 93.72 | *LPUGS* | - | 5.70 | 82.65 | 88.35 |
| | ∑ | 5.31 | 94.69 | 100 | | ∑ | 14.70 | 85.30 | 100 |
| | | Accuracy | | 93.78% | | | Accuracy | | 91.64% |
| **Melbourne** | | *Official Local Reference Data* | | | **Belfast** | | *Official Local Reference Data* | | |
| | | + | - | ∑ | | | + | - | ∑ |
| | + | 8.17 | 2.31 | 10.48 | | + | 7.51 | 1.80 | 9.31 |
| *LPUGS* | - | 7.23 | 82.29 | 89.52 | *LPUGS* | - | 4.27 | 86.42 | 90.69 |
| | ∑ | 15.40 | 84.60 | 100 | | ∑ | 11.79 | 88.21 | 100 |
| | | Accuracy | | 90.46% | | | Accuracy | | 93.93% |

where to prioritize the expansion or creation of new green spaces and/or preservation of existing ones amid rapid urban growth and development pressures (Hunter et al. 2023).

In this study, we used a novel methodology that integrates OpenStreetMap data with Sentinel-2 satellite imagery to assess LPUGS availability and accessibility as key determinants of healthy, sustainable, and climate-resilient cities. Specific criteria of annual average NDVI $\geq 0.2$, area $\geq 1$ ha, and accessibility within 500 m pedestrian network distance were defined based on previous literature. Our study provides evidence that these parameters are appropriate for a diverse range of cities and enable sufficiently accurate measurement of LPUGS. By measuring the indicators in a consistent way using open data and open-source software, and validating them through a multi-stage process, we confirmed their broad applicability and comparability internationally. Previous research has calculated green space indicators using various parameters and open data sources (Battiston and Schifanella 2024; Teeuwen et al. 2024; van den Bosch et al. 2016; Wüstemann et al. 2016). In particular, a previous study by Ludwig et al. (2021) prompted our research into methods of mapping green space using OpenStreetMap data supplemented with remote sensing. The international validation by collaborators with local expertise is a key contribution of our study that builds upon past methodologies. Statistical comparisons and visual audits against official local reference data provided additional validation insights.

The indicators developed in this study provide a globally applicable and comparable method for measuring LPUGS accessibility and availability in a way that is directly relevant to health and sustainability. When mapped, they demonstrate spatial inequities within and between cities, highlighting priority areas for targeted green space interventions. The results for all 13 cities analyzed highlight the need to enhance equity of access to LPUGS, especially in lower-income countries.

Our methodology can support local researchers, policymakers, and advocates around the world to calculate standardized LPUGS indicators for their cities, using open or custom data. In line with the Global Observatory of Healthy and Sustainable Cities' open science mission, we will integrate the LPUGS indicator workflow into the GHSCI software (Higgs et al. 2024; Global Healthy and Sustainable City-Indicators Collaboration 2022). Making the calculation and reporting of LPUGS indicators available via this open-source software will facilitate their use in cities globally as part of the 1000 Cities Challenge, and enhance local advocacy toward healthy, sustainable, and climate-resilient city planning.

### 5.2 | Strengths and Limitations of Open Data

Our method for identifying public spaces from OpenStreetMap data has previously been validated for 25 cities internationally (Higgs et al. 2023; Boeing et al. 2022; Liu et al. 2022), but has some potential limitations. OpenStreetMap data provides an alternative or complement to official data, which can have restrictions in terms of data quality, recency, appropriateness for green space studies, and comparability between and within cities, regions, and countries. However, the dynamic, crowdsourced nature of OpenStreetMap data creates challenges when used as the primary data source for identifying public spaces, especially in diverse contexts internationally. For example, areas only tagged with "natural = wood" were excluded in our analysis if they lacked additional tags indicating these were publicly accessible areas. While including the "natural = wood" tag would be appropriate for capturing the full variety of LPUGS in Helsinki and Mexico City, in the other cities analyzed this tag might have risked increasing false positives. In addition, our validated criteria for identifying public space excluded golf courses, cemeteries, and racecourses to reduce the risk of false positives where these spaces are not reliably accessible to the public. Cemeteries may provide walking routes in some cases, but they are not designed

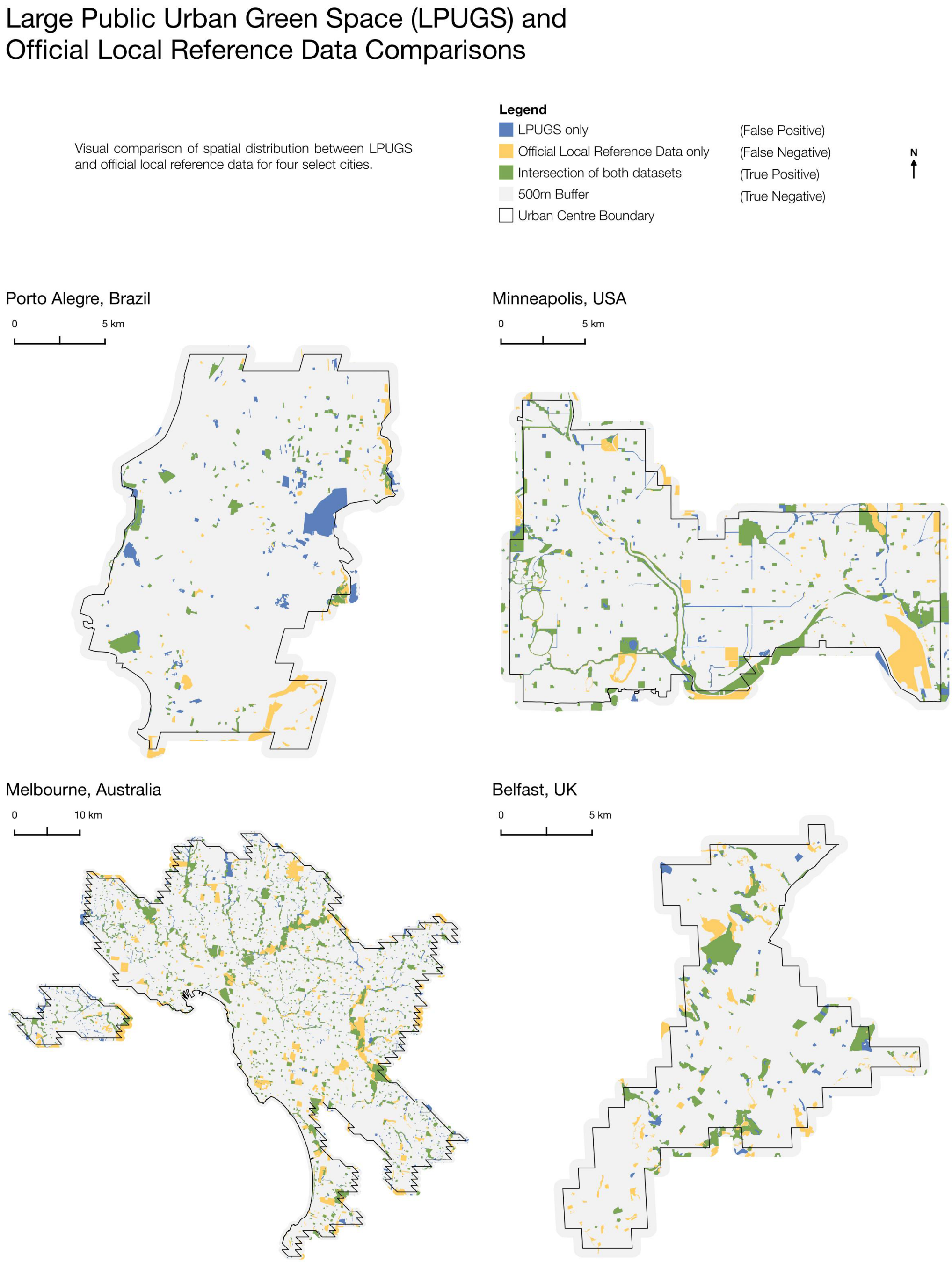


**FIGURE 4** | Visual summary of large public urban green space (LPUGS) and official local reference data comparisons, showing areas of agreement between the two datasets.

to offer the breadth of recreational opportunities of LPUGS. However, in prioritizing the true identification of LPUGS, relevant spaces may have been missed in some cities. On the other hand, some commission errors related to public versus private accessibility status were identified in the validation sample for Mexico City, which may explain its relatively low LACO-Wiki validation percentage result compared to the other cities in this study. Future enhancement of the GHSCI software could enable customization of the inclusion of specific OpenStreetMap tags for defining public green space. For example, cemeteries could be included, where required.

There were also potential issues with mis-tagging by OpenStreetMap users. In the case of Mexico City, a recent tagging change resulted in one of the largest and socially relevant LPUGS being unidentifiable as a public space, according to our criteria. Validation of indicator results can help inform necessary tagging changes to a particular city or area, to more accurately capture LPUGS data. Importantly, users of our methods could choose to supplement the use of OpenStreetMap data with their own data on public areas where available or make direct contributions to OpenStreetMap for their study region with benefits for their own analysis and the broader community.

## 5.3 | NDVI Parameters

Collaborator feedback confirmed that the use of NDVI was suitable for identifying green spaces. The NDVI threshold of $\geq 0.2$ for identifying levels of greenness is an established threshold well documented in the literature (Martinez and Labib 2023; Rakowska et al. 2023; Aryal et al. 2022; Wong et al. 2019; Huang et al. 2017). However, one possible limitation relates to capturing green spaces that contain a high percentage of blue space, as demonstrated in the visible omission of Pig's Eye Regional Park in Minneapolis's southeast (Figure 4). As in this example, where the majority of a space was covered by water bodies rather than vegetation, these areas were excluded in our methodology as they did not meet the NDVI threshold criteria. Evidence exists that green spaces that incorporate water bodies may also be valuable for health and climate (Hunter et al. 2023; Wang et al. 2022).

Annual average NDVI was used as a default setting for our global indicator, to account for seasonality differences in vegetation across the year and capture the general lived experience of greenness. Using parameters that target specific seasons or times of the year would contradict the international comparability of our indicator. However, to measure particular time periods of interest (e.g., peak vegetation growth periods), users could adapt our open-source tools by adjusting date ranges of satellite image capture.

## 5.4 | Official Local Reference Data Comparison Insights

There was a lack of official local reference data directly comparable to our identified LPUGS for many cities. For the four cities with relevant reference data, we found inconsistencies in the categorization of various land cover types. In general, our stricter criteria for defining public access appeared to result in false negatives or underestimation of the amount of LPUGS relative to the local reference data. Careful consideration must be given to the quality and scope of official data, rather than assuming it is "gold standard."

Furthermore, official datasets were often limited to municipality boundaries, which present challenges when analyzing entire city regions. OpenStreetMap has advantages in terms of data for harmonized spatial regions, even in high-income countries where high-quality local data was available. Gaps and inconsistencies in local data between cities highlight the value of indicators derived from globally available open data such as OpenStreetMap, which makes international comparisons more feasible. However, where high-quality official government data are available, our indicator methods could be amended to use these data inputs.

## 5.5 | Future Research

Our LPUGS indicators capture only certain aspects of green space relevant to health (Hunter et al. 2023). Green space size is likely non-linearly associated with cognitive health (Wu et al. 2015), so further research is needed to determine the optimal size of green spaces in relation to various health outcomes. Furthermore, the identification of green spaces containing blue space could be enhanced by supplementing NDVI measures with other remote sensing spectral indices that capture hybrid land cover types (Wu et al. 2020). Additional metrics could complement LPUGS indicators, providing a more comprehensive review of urban greening needs. These include population demand for and use of green space (Battiston and Schifanella 2024; Xue et al. 2023); greenery visibility using street-view imagery (Sánchez and Labib 2024; Biljecki et al. 2023; Konijnendijk 2023); residents' perceptions of green space (Bai et al. 2013); and various green space quality aspects such as vegetation type, amenities, and usage patterns (Heikinheimo et al. 2020; Chen et al. 2018). Although not all measurable using globally available open data, future research could focus on developing and testing such indicators for international application to better capture green space complexities across differing contexts (Battiston and Schifanella 2024).

While our study included diverse cities across five continents, the absence of any cities in Africa and low-income countries in general was a limitation of the study and a possible source of bias, with implications for the generalizability of our findings. Integration of the indicators into the open-source GHSCI software will provide future opportunities to validate the indicators for a wider range of cities, including those in low-income countries, and explore ways in which users interact with the software and apply the indicator outputs in research and practice. Software enhancements to enable streamlined customization of data inputs would enhance flexibility for defining LPUGS across different geographical regions based on local context. The open-source nature of our tools allows for modification to various applications as needed.

# 6 | Conclusion

This study demonstrates the international validity of a methodology for calculating LPUGS availability and accessibility indicators using open-source software and data. Through validation by international collaborators and comparisons with official local reference data, we demonstrated the strengths of our open data fusion methodology for application to cities globally, especially those lacking official green space data. We also identified key limitations, particularly related to the use of OpenStreetMap data. We found that a key risk is underestimating the amount of LPUGS due to incomplete or inaccurate OpenStreetMap data. This underscores the value of citizen science initiatives in improving OpenStreetMap data and expanding the data commons.

Our study addressed critical gaps in existing indicator methods by providing robust, standardized, and comparable LPUGS metrics that are applicable to cities internationally and directly relevant to health and climate resilience. We present validated evidence for use of the default parameters of annual average NDVI $\geq 0.2$ and accessibility distance of 500 m walking distance to LPUGS of area $\geq 1$ ha. Yet, these default parameters can be adjusted by users of our open-source tools as necessary for application in diverse climatic or cultural contexts, as well as substitution or supplementation with existing high-quality official data where available. These indicators can guide local policy interventions and planning efforts to promote LPUGS availability and accessibility, offering multiple health and environmental benefits.

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### Data Availability Statement

All research data, code and validation material are available at https://doi.org/10.25439/rmt.26870314.

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