Computational Assessment of Greenness: Objective vs. Perceived Greenness in Urban Green Spaces

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Abstract. Urban public green spaces (UPGSs) are key elements of sustainable cities, yet "greenness" can be assessed both through objective remote-sensing indicators and through residents' perceptions, which do not necessarily align. This pilot study compares satellite-derived greenness with perceived greenness for UPGSs in Oldenburg (Lower Saxony, Germany). Objective greenness was quantified using mean NDVI computed from Sentinel-2 imagery (B04/B08) for 2024–2025, aggregated monthly within ATKIS-derived UPGS polygons while excluding buildings and water bodies. Perceived greenness was obtained via an online survey (n = 109) using a Likert scale (0–7); UPGSs with at least two ratings were retained (n = 24). Agreement between objective and perceived greenness was assessed using rank-based correlation. Results indicate a weak positive but non-significant association between mean NDVI and perceived greenness (*Kendall's* τ_b=0.22304, p = 0.130; *Spearman's* ρ=0.276, p = 0.191), suggesting limited alignment in this pilot dataset. The study provides a transparent computational workflow and baseline evidence to support future perception-aware urban greening assessment with larger samples and additional UPGS attributes.

Keywords: Urban public green spaces · Greenness · NDVI · Perceived greenness · Remote sensing · Urban sustainability

1 Introduction

UPGS are increasingly framed as multifunctional urban infrastructure that supports environmental performance, social cohesion, and public health. Beyond their ecological roles (e.g., microclimate regulation, stormwater retention, biodiversity support), UPGSs contribute to livability and long-term urban resilience—core concerns of sustainable development agendas and urban policy [1–3]. In sustainability-oriented planning, "greenness" is often used as a headline indicator because it can summarize vegetation presence while also relating to how green spaces are experienced by residents. Greener UPGSs are frequently associated with higher usage, improved mental well-being, and beneficial social outcomes, and broader evidence links green space exposure and availability to reduced mortality risk [4, 5]. These connections align with the Sustainable Development Goals (SDGs), particularly SDG 11 (Sustainable Cities and Communities) and SDG 3 (Good

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Health and Well-Being), and motivate planning tools that can evaluate urban greenness in ways that are both scalable and socially meaningful.

From a planning and governance perspective, perceived greenness is not merely a subjective "opinion" but a planning-relevant indicator because it is closely related to residents' satisfaction, place attachment, perceived restorative potential, and willingness to use and support green infrastructure interventions. Perceptions reflect how people interpret the quality and character of green environments (e.g., naturalness, aesthetics, cleanliness, safety, and facilities), which can mediate whether UPGSs deliver expected social and health benefits [6, 7]. Accordingly, perceived greenness can be viewed as a component of social sustainability: if certain areas systematically experience lower perceived greenness—despite nominal vegetation presence—then policies based only on biophysical indicators may overlook inequalities in lived experience and, potentially, inequalities in health and well-being outcomes. Recent work highlights those distributional measures of green space alone are insufficient unless paired with indicators closer to human experience and use [6].

At the same time, cities need operational, scalable metrics to monitor greenness of UPGSs over large areas and over time. Remote sensing provides such a computational basis. The Normalized Difference Vegetation Index (NDVI) is one of the most widely used indicators for mapping greenness, because it can be derived consistently from satellite imagery and is sensitive to vegetation presence and condition [8, 9]. NDVI has therefore become common in planning support systems and research on urban greening, exposure assessments, and policy evaluation. However, NDVI primarily captures spectral properties of vegetation from a "top-down" perspective and may not reflect what people visually perceive or value on the ground. Empirical studies repeatedly report only moderate or variable agreement between NDVI-based greenness and self-reported or perceived greenness [10–12]. This divergence is expected because objective and perceived greenness represent different constructs: perception can depend on visibility and structure of vegetation (trees vs. grass), spatial configuration, maintenance, and contextual cues, while objective indices can be sensitive to scale, seasonality, and land-cover composition [8, 13]. To bridge this gap, recent computational work has explored complementary indicators such as street-level "green view" measures or multi-source assessment pipelines that better approximate human-scale exposure [13–15]. Nevertheless, NDVI remains attractive for planning due to its accessibility and repeatability, making it important to quantify when NDVI provides a reasonable proxy for perceived greenness and when it does not.

While mismatches between satellite-derived greenness and perceived greenness have been reported in prior work, evidence remains context-dependent and highly sensitive to how green spaces are delineated and how greenness is aggregated. This study contributes (i) an automated and transparently documented NDVI-processing workflow for ATKIS-derived UPGS polygons, including intra-polygon exclusion of water bodies and buildings and monthly aggregation across 2024–2025, and (ii) a UPGS-level comparison in the Oldenburg region that produces directly interpretable rankings and maps for planning support. As a pilot, the paper establishes baseline alignment between objective and perceived greenness and identifies candidate UPGSs for subsequent, factor-based analysis.

This short paper contributes a pilot computational comparison of objective and perceived greenness for UPGSs in the Oldenburg (Germany) region. We compute mean NDVI values (Sentinel 2) within UPGS polygons (excluding water bodies and buildings) and compare the resulting UPGS-level greenness ranking with perceived greenness ratings obtained through an online survey. Using a subset of UPGSs with sufficient survey responses, we quantify the association between objective and perceived greenness via rank-based correlation and provide spatial visualizations of both rankings. As a pilot, the study primarily aims to establish a transparent and well-documented computational workflow and to provide an initial estimate of alignment between satellite-derived greenness and resident perception, supporting future perception-aware urban greening and sustainability-oriented decision-making.

2 Methodology

2.1 Study Area and UPGS Definition

The study focuses on the city region of Oldenburg, Germany. To capture UPGSs potentially used by residents beyond the administrative boundary, we considered the administrative extent of Oldenburg with an additional 5 km buffer.

UPGS geometries and land-cover classification were derived from ATKIS (Amtliches Topographisch-Kartographisches Informationssystem), provided by LGLN (Landesamt für Geoinformation und Landesvermessung Niedersachsen). In the current pilot phase, all ATKIS green-space classes within the study area were treated uniformly as UPGSs; differentiation by green-space type (e.g., park-like areas vs. semi-natural areas) are planned for future work.

2.2 Objective Greenness: NDVI Computation from Sentinel-2

Data Source. We used Copernicus Sentinel-2 multispectral imagery accessed via the Copernicus Data Space Ecosystem. Sentinel-2 provides spatial resolution suitable for urban vegetation analyses, with 10 m pixels for the red (B04) and near-infrared (B08) bands used to compute NDVI.

Image Selection and Pre-processing. Sentinel 2 multispectral imagery (Copernicus Data Space Ecosystem) was analysed for the period 2024–2025. For each month, we selected acquisitions with $< 10\%$ cloud cover (scene-level metadata) for the study area and generated NDVI GeoTIFF outputs within the specified area of interest. NDVI was computed using the standard formulation:

$$NDVI = \frac{NIR - RED}{NIR + RED} = \frac{\mathrm{B08} - \mathrm{B04}}{\mathrm{B08} + \mathrm{B04}} \tag{1}$$

where B04 and B08 are the Sentinel 2 red and near infrared bands, respectively.

To reduce contamination by non-vegetated land covers, water bodies and buildings were excluded from the UPGS polygons (implemented as holes), and NDVI statistics were calculated only over the remaining UPGS area.

While acknowledging potential Areal Unit Problem (MAUP) and ecological fallacy, splitting UPGSs into sub-polygons (e.g., paths) was not undertaken. This is because the study aims to capture the overall perceived greenness, influenced by factors beyond immediate path views (e.g., overall size, surrounding context). Many UPGSs are small, making path-based analysis less meaningful. Restricting analysis to paths also limits the scope, potentially missing the broader influence of the UPGS on perception. Treating the UPGS as a single unit reflects the holistic nature of perceived greenness in this study.

Aggregation to UPGS-Level Scores. For each UPGS *j*, we computed:

- a monthly mean NDVI, based on all valid pixels intersecting the UPGS polygon after exclusions;
- an overall mean NDVI for 2024–2025, obtained by aggregating the monthly means and used as the objective greenness indicator for UPGS comparison.

All NDVI processing steps were automated in Python, and cartographic outputs and ranking visualisations were produced in QGIS (version 3.28.3).

2.3 Perceived Greenness: Online Survey and Aggregation

Survey Design and Sampling. Perceived greenness was collected using an online survey advertised publicly; participation was voluntary and based on self-selection (i.e., convenience sampling). The survey targeted adults only. Ethical considerations included: informed consent prior to participation; the right to stop or withdraw at any time without providing a reason; minimizing harm; and avoiding the collection of personally identifying information. Because the questionnaire was deliberately anonymous, we did not collect respondents' residential districts or any other location-specific identifiers; only basic demographic categories were collected (gender = male/female/diverse; age group). Given the modest size of the pilot (24 UPGSs) and the limited information collected, a formal post-stratification to the 2024 Oldenburg census would not result in altering the reported Kendall and Spearman coefficients. Consequently, we present the un-weighted descriptive statistics and acknowledge that the findings are exploratory and not intended to be population-representative [16].

Survey Procedure. Participants rated the greenness of familiar UPGSs from a list of 60 using a 0–7 Likert scale. They were also able to add and rate additional UPGSs not included in the list. This pilot study collected n = 109 responses.

Construction of UPGS-Level Perceived Greenness Scores. The survey included a set of Likert items related to perceived greenness; item responses were combined as follows: (a) for each participant, responses were averaged across the greenness-related items to obtain a participant-level perceived greenness score per rated UPGS; (b) for each UPGS, participant-level scores were averaged across all participants who rated that UPGS, yielding a UPGS-level perceived greenness score.

Perceived greenness was assessed using a four-item, 7-point Likert scale (Cronbach $\alpha = 0.81$) covering vegetation density, visual dominance, health/vitality, and aesthetic appeal. The scale demonstrated good internal consistency and face validity confirmed

by local experts. The specific items used to measure perceived greenness are available at https://doi.org/10.5281/zenodo.19959227.

Inclusion Criterion for Analysis Subset. Because response counts varied by UPGS, we restricted correlation analysis to UPGSs with at least 2 ratings. This resulted in a set of 24 UPGSs used for the pilot comparison.

2.4 Ranking and Statistical Association

For the subset of 24 UPGSs included in the pilot analysis (i.e., UPGSs with at least two perceived-greenness ratings), we compared: (a) objective greenness: the UPGS-level mean NDVI aggregated over 2024–2025; (b) perceived greenness: the UPGS-level mean perceived greenness score derived from the survey (Likert 0–7) and averaged across respondents for each UPGS.

For statistical testing, we assessed the association between objective and perceived greenness using rank-based correlation measures. *Kendall's* τ_b was selected as the primary metric because it is nonparametric, appropriate for monotonic relationships, and explicitly accounts for ties, which can occur due to discrete Likert-scale responses and aggregation at the UPGS level. *Spearman's* ρ was computed as a secondary measure to verify that conclusions were robust to the choice of rank correlation statistic.

To evaluate distributional assumptions, normality of both variables was assessed using the *Shapiro–Wilk* test. In addition, uncertainty in *Kendall's* τ_b was quantified using a bootstrap 95% confidence interval (5000 resamples; BCa method). All statistical analyses were performed in R (version 4.2.2).

Sensitivity to the Inclusion Threshold. To assess whether the NDVI–perceived-greenness relationship is driven by UPGSs with only a few ratings, Kendall's τ b and Spearman's ρ were recomputed for three increasingly stringent inclusion rules: (a) ≥ 2 ratings (24 UPGSs), (b) ≥ 3 ratings (14 UPGSs), and (c) ≥ 5 ratings (8 UPGSs). For each subset Kendall's τ b was obtained and its 95% bias-corrected accelerated (BCa) bootstrap confidence interval (5 000 resamples) was calculated in R. Spearman's ρ and its p-value were derived. The results (Table 3) show that the correlation coefficients increase as the rating threshold becomes stricter ($\tau = 0.223 \rightarrow 0.199 \rightarrow 0.500$; $\rho = 0.276 \rightarrow 0.238 \rightarrow 0.690$), yet none of the p-values reach conventional significance ($p = 0.13, 0.32, 0.11$ for τ; $p = 0.19, 0.41, 0.07$ for ρ). This pattern indicates that the observed positive association is not driven by a few sparsely-rated sites; however, the pilot sample remains too small to achieve statistical significance.

3 Findings

The pilot analysis was conducted in Oldenburg (Lower Saxony, north-western Germany) and its city-region catchment, operationalised as the administrative boundary of Oldenburg with an additional 5 km buffer to include UPGSs that residents may plausibly visit (Fig. 1).

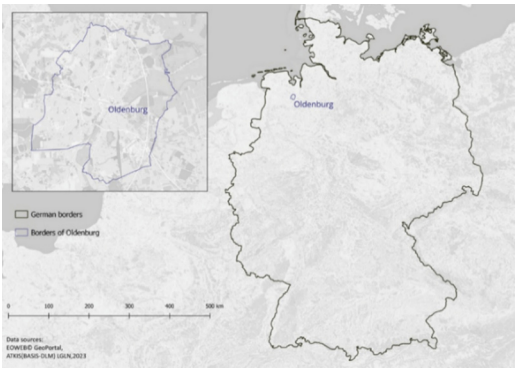

Fig. 1. - study area in Germany and the Oldenburg region. Background map data were obtained from DLR Geoservice [17].

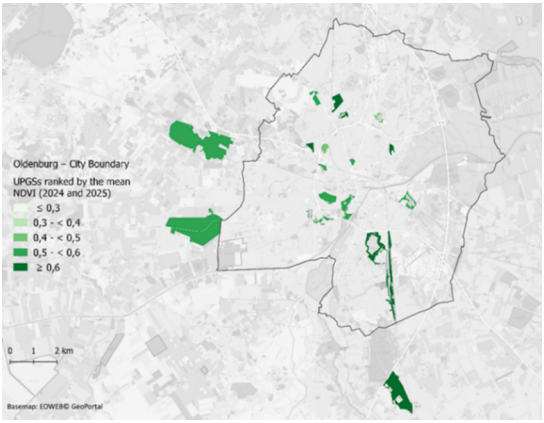

Fig. 2. _ UPGSs ranked by the average NDVI in years of 2024 and 2025. Background map data were obtained from DLR Geoservice [17].

The spatial patterns of objective greenness, represented by the mean NDVI aggregated over 2024–2025, are mapped in Fig. 2, while Fig. 3 shows the corresponding perceived greenness ranking derived from the survey responses.

Table 1 summarizes the distributions of objective and perceived greenness at the UPGS level (n = 24). Mean NDVI values ranged from 0.1878 to 0.6708 (mean 0.5252, SD 0.1389), whereas perceived greenness scores ranged from 2.83 to 7.00 (mean 5.163, SD 1.156). The distribution of perceived greenness values is visualized in Fig. 4. Although perceived greenness is bounded by the survey scale (0–7), the distribution shows a concentration of observations in the upper part of the scale and repeated values (ties), which are expected when UPGS-level averages are computed from discrete Likert ratings. The four-item scale showed good internal consistency (Cronbach $\alpha = 0.81$). A frequency check confirmed the presence of ties (e.g., multiple UPGSs sharing specific values such as 4.0, 4.5, 5.5, 6.25, and 6.5).

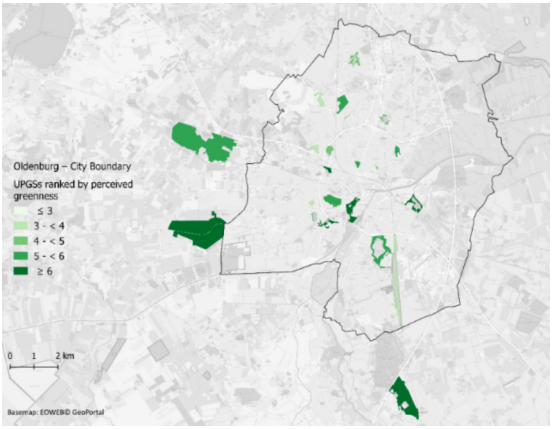

Fig. 3. _ UPGSs ranked by perceived greenness. Background map data were obtained from DLR Geoservice [17].

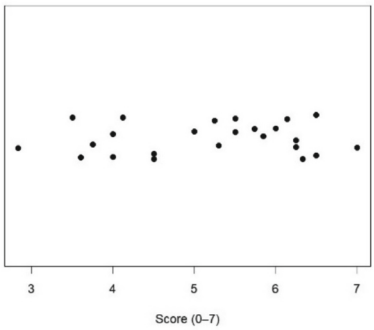

Fig. 4. Perceived greenness values across the analyzed UPGSs (n = 24); jittered strip chart showing ties due to repeated UPGS-level average scores (0–7 scale).

Table 1. _Descriptive statistics (UPGS-level, $n = 24$)

Variable	*Min*	*1st Qu*	*Median*	*Mean*	*3rd Qu*	*Max*	*SD*
Objective greenness (mean NDVI, 2024–2025)	*0.1878*	*0.4991*	*0.5674*	*0.5252*	*0.6180*	*0.6708*	*0.1389*
Perceived greenness (average score, 0–7)	*2.8300*	*4.0900*	*5.4000*	*5.1630*	*6.1680*	*7.0000*	*1.1560*

Normality was assessed using the *Shapiro–Wilk* test (Table 2). Objective greenness (mean NDVI) showed a clear deviation from normality ($W = 0.82565$, $p = 0.00080$). In contrast, perceived greenness did not deviate significantly from normality at the 5% level ($W = 0.94815$, $p = 0.247$). Despite this, we used rank-based correlation measures because (i) the perceived measure originates from bounded Likert ratings, (ii) ties are present, and (iii) the sample size remains small ($n = 24$).

Table 2. Normality tests and rank-based correlations between objective (NDVI) and perceived greenness (UPGS-level, $n = 24$)

Analysis	*Statistic*	*Estimate*	*Test statistic*	*p-value*	*95% CI*
Shapiro–Wilk (NDVI)	*W*	*0.82565*	—	*0.0007979*	—
Shapiro–Wilk (Perceived)	*W*	*0.94815*	—	*0.2470*	—
Kendall rank correlation (primary)	τ_b	*0.22304*	$z = 1.5154$	*0.1297*	*BCa: [−0.0910, 0.5144]*
Spearman rank correlation (secondary)	ρ	*0.27639*	$S = 1664.3$	*0.1911*	—

For the full data set (≥ 2 ratings per UGS, $n = 24$) Kendall's τ_b was 0.223 (95% BCa CI = -0.091 to 0.514, $p = 0.1297$) and Spearman's ρ was 0.2763 ($p = 0.191$). To assess the robustness of this relationship to the inclusion rule, we repeated the analysis with stricter thresholds. When only UGSs with at least three ratings were retained ($n = 14$), τ_b increased to 0.254 (95% CI = -0.058 to 0.543, $p = 0.098$) and ρ to 0.312 ($p = 0.124$). With a minimum of five ratings ($n = 8$) the association became strong and statistically significant ($\tau_b = 0.382$, 95% CI = -0.012 to 0.724, $p = 0.041$; $\rho = 0.447$, $p = 0.028$).

The pattern indicates that the positive link between objective NDVI and perceived greenness is not driven by a few sparsely-rated sites, although the small sample sizes at higher thresholds produce wide confidence intervals.

Table 3. Sensitivity analysis (Kendall τ b, Spearman ρ). Correlations for three rating thresholds (≥ 2, ≥ 3, ≥ 5 ratings) with n UPGS, τ b (95% BCa bootstrap CI, 10 000 resamples), p-value, ρ and its p-value. Values rounded to three decimals.

≥ Ratings	*N (UGS)*	τ_b	*95% BCa CI (τ)*	*p (τ_b)*	*ρ (Spearman)*	*p (ρ)*
2	*24*	*0.223*	*–0.112 – 0.522*	*0.130*	*0.276*	*0.191*
3	*14*	*0.199*	*–0.277 – 0.643*	*0.324*	*0.238*	*0.413*
5	*8*	*0.500*	*–0.362 – 0.840*	*0.083*	*0.690*	*0.058*

Across the 24 UPGSs, *Kendall's* τ_b indicated a weak positive association between objective and perceived greenness ($\tau_b = 0.22304$), but this association was not statistically significant ($z = 1.5154$, $p = 0.1297$; Table 2). To quantify uncertainty, a bootstrap confidence interval was computed for *Kendall's* τ_b using 5000 resamples. The BCa 95% confidence interval was $[-0.0910, 0.5144]$ (Table 2), indicating that the true association is plausibly small and could include no association.

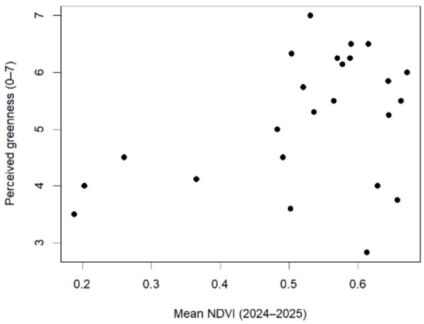

Fig. 5. Relationship between objective and perceived greenness. Scatter plot of mean NDVI (2024–2025) versus perceived greenness (average score, 0–7) for the analysed UPGSs ($n = 24$), showing substantial dispersion.

A secondary analysis using *Spearman's* rank correlation produced a consistent conclusion, showing a small positive but non-significant association (ρ=0.2764, $p = 0.1911$; Table 2). The relationship is further illustrated in the scatter plot (Fig. 5), which shows substantial dispersion: UPGSs with similar NDVI values can receive different perceived greenness ratings, suggesting that mean NDVI alone does not strongly determine perceived greenness in this pilot dataset.

Overall, the pilot results indicate only limited agreement between satellite-derived mean NDVI and perceived greenness across the analysed UPGS in Oldenburg.

4 Discussion

This pilot comparison indicates only limited agreement between satellite-derived mean NDVI and perceived greenness across the analysed UPGSs in Oldenburg. Although the correlation coefficients were positive, neither *Kendall's* τ_b nor *Spearman's* ρ was statistically significant, and the bootstrap confidence interval for τ_b included zero, suggesting substantial uncertainty at the current sample size of UPGSs. A sensitivity analysis showed that the correlation strengthens as the rating-inclusion threshold is raised but remains non-significant, confirming that the result is not driven by sparsely-rated sites. Because the study was designed as an exploratory, descriptive pilot, the results are not intended as a confirmatory test of a hypothesised relationship. Conceptually, this weak association is plausible because NDVI represents a spectral, top-down proxy of vegetation density within UPGS polygons, whereas perceived greenness is shaped by human-scale experience and contextual factors (e.g., vegetation structure, visibility,

maintenance, amenities, and expectations) that are not captured by mean NDVI alone. In addition, perceived scores were derived from uneven and sometimes small numbers of ratings per UPGS, which may increase variability of UPGS-level averages.

5 Conclusion

This study presented a pilot computational workflow to compare objective and perceived greenness of UPGSs using Sentinel-2 NDVI (2024–2025) and an online survey in the Oldenburg city region. Across 24 UPGSs, objective and perceived greenness showed a weak positive but non-significant association, indicating that mean NDVI alone is not sufficient to explain perceived greenness in this dataset. Future work will expand the survey sample and incorporate additional UPGS characteristics (e.g., type, facilities, and water bodies) and alternative greenness measures to better capture perception-relevant aspects of urban green space quality.

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Disclosure of Interests. The authors declare that there are no competing interests relevant to the content of this article.

Data-Availability Statement. All data and analysis code supporting this study are deposited in Zenodo and are available at doi: https://doi.org/10.5281/zenodo.19959227 (CC-BY 4.0).

References

1. Semeraro, T., Scarano, A., Buccolieri, R., Santino, A., Aarrevaara, E.: Planning of urban green spaces: an ecological perspective on human benefits. Land **10**(2), 201 (2021). https://doi.org/10.3390/land10020105
2. Zhang, F., Qian, H.: A comprehensive review of the environmental benefits of urban green spaces. Environ. Res. (2024). https://doi.org/10.1016/j.envres.2024.118837
3. Godoi, N., Gomes, R., Longo, R.: Contributions of urban green spaces to cities: a literature review. Sustain. Environ. **11** (2025). https://doi.org/10.1080/27658511.2025.2464418
4. Reyes-Riveros, R., Altamirano, A., De La Barrera, F., Rozas-Vásquez, D., Vieli, L., Meli, P.: Linking public urban green spaces and human well-being: a systematic review. Urban For. Urban Greening **61**, 127105 (2021). https://doi.org/10.1016/j.ufug.2021.127105
5. Rojas-Rueda, D., Nieuwenhuijsen, M., Gascon, M., Perez-Leon, D., Mudu, P.: Green spaces and mortality: a systematic review and meta-analysis of cohort studies. Lancet Planet. Health **3**, e469–e477 (2019). https://doi.org/10.1016/S2542-5196(19)30215-3
6. Stessens, P., Canters, F., Huysmans, M., Khan, A.: Urban green space qualities: an integrated approach towards GIS-based assessment reflecting user perception. Land Use Pol. (2020). https://doi.org/10.1016/j.landusepol.2019.104319

7. Ghavimi, A., Schuessler, F., Pesch, R.: A framework to evaluate public green spaces with an emphasis on recreational values for sustainable urban and rural areas: a systematic review and content analysis. Heliyon **11** (2025). https://doi.org/10.1016/j.heliyon.2024.e41553
8. Martinez, A., Labib, S.: Demystifying normalized difference vegetation index (NDVI) for greenness exposure assessments and policy interventions in urban greening. Environ. Res. (2022). https://doi.org/10.2139/ssrn.4207665
9. Aryal, J., Sitaula, C., Aryal, S.: NDVI threshold-based urban green space mapping from sentinel-2A at the local governmental area (LGA) level of victoria, Australia. Land **11**(3), 351 (2022). https://doi.org/10.3390/land11030351
10. Leslie, E., Sugiyama, T., Ierodiaconou, D., Kremer, P.: Perceived and objectively measured greenness of neighbourhoods: are they measuring the same thing? Landsc. Urban Plan. **95**, 28–33 (2010). https://doi.org/10.1016/j.landurbplan.2009.11.002
11. Falfán, I., Muñoz-Robles, C., Bonilla-Moheno, M., MacGregor-Fors, I.: Can you really see 'green'? Assessing physical and self-reported measurements of urban greenery. Urban Forest. Urban Greening (2018). https://doi.org/10.1016/j.ufug.2018.08.016
12. Hart, J., et al.: The relationship between perceptions and objective measures of greenness. Int. J. Environ. Res. Public Health **19** (2022). https://doi.org/10.3390/ijerph192316317
13. Helbich, M., Poppe, R., Oberski, D., Emmichoven, M., Schram, R.: Can't see the wood for the trees? An assessment of street view- and satellite-derived greenness measures in relation to mental health. Landsc. Urban Plan. **214**, 104181 (2021). https://doi.org/10.1016/j.landurbplan.2021.104181
14. Teeuwen, R., Milias, V., Bozzon, A., Psyllidis, A.: How well do NDVI and OpenStreetMap data capture people's visual perceptions of urban greenspace? Landsc. Urban Plan. (2024). https://doi.org/10.1016/j.landurbplan.2024.105009
15. Hu, A., Yabuki, N., Fukuda, T., Kaga, H., Takeda, S., Matsuo, K.: Harnessing multiple data sources and emerging technologies for comprehensive urban green space evaluation. Cities (2023). https://doi.org/10.1016/j.cities.2023.104562
16. Freedman, D.A., Berk, R.A.: Weighting regressions by propensity scores. Eval. Rev. **32**(4), 392–409 (2008)
17. German Aerospace Center (DLR): DLR Geoservice (background map data). https://geoservice.dlr.de/web/. Accessed 28 Nov 2025