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How well do NDVI and OpenStreetMap data capture people's visual perceptions of urban greenspace?

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HIGHLIGHTS

- We compared NDVI and OpenStreetMap data to people's visual perceptions of greenness.
- NDVI and OpenStreetMap data often diverge from human perceptions of greenness.
- OpenStreetMap captures greenness best in short distance, NDVI best in longer distance.
- Vegetation configuration, variety, and natural elements enhance perceived greenness.
- Vegetated space dominated by built-environment elements may not be perceived as green.

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ABSTRACT

The study of urban greenspaces typically relies on three types of data: people's subjective perceptions collected via *questionnaires*, vegetation indices derived from satellite imagery, such as the *Normalized Difference Vegetation Index* (NDVI), and Land Use or Land Cover maps, such as *OpenStreetMap* (OSM). Data on people's perceptions are essential when researching human activities, yet they scale poorly. NDVI and OSM data, on the other hand, are freely available worldwide, thus valuable for assessing cities at scale or prioritizing locations for interventions. However, it is unclear how effectively NDVI and OSM data capture people's visual perceptions of urban greenspaces. In this work, we collect people's visual perceptions of public spaces in three major European cities through crowdsourcing, quantitatively compare them to NDVI and OSM data, and qualitatively investigate disparities. We found that NDVI moderately correlates with perceived greenness and that not only OSM greenspaces but also pocket parks and play spaces are often considered green. Furthermore, we found that people's perceptions correspond best to OSM data in small radius distances and NDVI data in larger radius distances and that combining NDVI and OSM data can improve identification of places in OSM that are commonly considered green. Our qualitative analysis revealed that configuration and variety of vegetation, and presence of other natural or built-up features, influence people's perceptions of greenspace. With our findings we aim to help researchers and practitioners make more informed decisions when collecting greenspace data for their specific context, ultimately contributing to green urban environments that reflect people's perspectives.

1. Introduction

Urban greenspaces are widely associated with positive effects on human health and well-being. Depending on the discipline, pathway, and context, they are typically examined using one of three types of data sources (Labib et al., 2020; Nieuwenhuijsen et al., 2017; Markevych et al., 2017; Zhang et al., 2021). First, data collected through large-scale *questionnaires* that reflect individual people's perceptions of greenspace, for example of their residential neighborhood, are typical of environmental psychology research (Kruize et al., 2020; Zhang et al., 2021). Second, vegetation indices derived from satellite imagery, such as the *Normalized Difference Vegetation Index* (NDVI), are commonly employed in epidemiological studies to study the abundance of vegetation around people's homes (Larkin and Hystad, 2019; Helbich et al., 2019; Roberts and Helbich, 2021; Dadvand et al., 2015). Finally, Land Use / Land Cover (LULC) maps that describe the land surface in distinct categories, such as *OpenStreetMap* (OSM), are frequently used in city planning or policy assessment to quantify the availability, accessibility,

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or size of formal greenspaces (Larkin and Hystad, 2019; Kabisch and Haase, 2014; Wood et al., 2017; Zhang et al., 2021; Taubenböck et al., 2021).

While environmental perceptions from questionnaires are essential when investigating human activities (Flowers et al., 2016; Fongar et al., 2019), such data scale poorly due to time, costs, geographical coverage, and spatial extent constraints. NDVI and LULC maps such as OSM, on the other hand, are freely available worldwide and routinely updated over time, making them valuable to assess the availability or accessibility of greenspaces at scale, or to prioritize locations for interventions (Larkin and Hystad, 2019; Nieuwenhuijsen et al., 2017; Markevych et al., 2017; Labib et al., 2020). Even though LULC maps often only represent formal greenspaces such as parks and urban forests, informal and small-scale greenspaces or green streets have also been found to benefit people (Luo and Patuano, 2023; Wolch et al., 2014; Rao et al., 2007; Markevych et al., 2017). Furthermore, while both NDVI and LULC maps are essential in greenspace studies, they may not mirror subjective human perceptions (Leslie et al., 2010; Kothencz and Blaschke, 2017; Zhang et al., 2021; Labib et al., 2020; Markevych et al., 2017). Although recent works have attempted to incorporate the human perspective into large-scale greenspace studies using street-level imagery (Rzotkiewicz et al., 2018; Larkin and Hystad, 2019; Biljecki and Ito, 2021; Lu, 2019), to the best of our knowledge, these have primarily employed computer vision techniques such as automated object detection and scene recognition, which do not acknowledge the subjectivity of human perception.

We aim to contribute to a better understanding of how well large-scale open datasets, specifically NDVI and OSM LULC maps, capture people's visual perceptions of urban greenspace. Our goal is to evaluate how well these datasets match with each other, and where they deviate, and to explain such disparities using the spatial features of investigated locations, to inform the design of future greenspace studies.

To that end, we follow a two-step approach. First, we collect large-scale open-source NDVI and OSM data for three major European cities. We apply a crowdsourcing approach to obtain people's visual greenness perceptions of various sorts of public spaces. Second, we assess how well these visual perceptions correspond to or diverge from the information included in NDVI and OSM data. We hypothesize that: (H1) there is a strong positive correlation between NDVI values and perceived greenness, as these are both commonly used to quantify environmental greenness, (H2) perceived greenness is higher for regular-size OSM greenspaces than for pocket parks, play spaces, open public spaces, and streets, as definitions of greenspace are often limited to greenspaces larger than a certain threshold area, whereas pocket parks, play spaces, open public spaces, and streets can also be perceived as (informal) greenspaces, as other studies suggest, and (H3) perceived greenspaces are better reflected in data when they are selected using a combination of OSM categories and NDVI values, rather than simply OSM categories or just NDVI values. To test our hypotheses, we employ statistical analyses, followed by a qualitative thematic analysis to discover which spatial qualities explain differences between NDVI and OSM data and people's visual perceptions.

In the remainder of this paper, we explore greenspace data sources used in related work, detail what data sources we collect and how we analyze them, present and discuss our findings and their implications, and conclude with our key conclusions and future lines of research.

2. Greenspace data sources

In this work, we adapt the definition of greenspace by the WHO Regional Office for Europe (2017) to *"urban space characterized by vegetation of any kind"*, including street trees and roadside vegetation, green roofs and facades, greenspace on private grounds, and parks, playgrounds, or greenways. We narrow our focus to greenspaces that are publicly accessible, thereby allowing people to engage in outdoor activities.

To study greenspaces, researchers use data of varying types and scales, depending on hypotheses and outcomes of interest (Markevych et al., 2017). Examples include measures of availability, accessibility, visibility, and use of greenspace (Labib et al., 2020; Markevych et al., 2017). Large-scale data are essential for informing policy, measuring how well cities adhere to such rules, and studying the epidemiological consequences of greenspace (Markevych et al., 2017; Larkin and Hystad, 2019; Kabisch and Haase, 2014).

Other studies collect data on people's perceptions regarding greenspaces, which are critical when studying people's behavior in greenspaces (Markevych et al., 2017), for instance through questionnaires among residents or interviews with park visitors (Sundevall and Jansson, 2020; Talal and Santelmann, 2021; Kabisch and Haase, 2014). In this work, we focus on people's *visual subjective perceptions*, which we define as perceptions generated by visual stimuli, such as a photo of a place, and further influenced by the individual's experiences, preferences, emotions, and context.

The following sections go over various data sources and collection methods and discuss their differences and similarities that motivate our study.

2.1. Objective measures of greenspace using spatial data

Among all vegetation indices derived from satellite imagery, the *Normalized Difference Vegetation Index* (NDVI) is the most widely used (Markevych et al., 2017). NDVI is an objective remote sensing index that captures vegetation by calculating the difference between red and near-infrared light reflected by the land surface. NDVI maps are often obtained from Landsat or Sentinel satellite missions. Both of these missions provide open data at regular intervals worldwide, with the European Sentinel-2 mission providing data at a high resolution of 10 m (Labib et al., 2020; Markevych et al., 2017). Alternatives to NDVI include the Green Ratio Vegetation Index (GVRI) (Sripada et al., 2006), Soil-Adjusted Vegetation Index (SAVI) (Huete, 1988), and Enhanced Vegetation Index (EVI) (Huete et al., 2002). Indices such as NDVI are particularly relevant for studying the presence or availability of greenspace, for instance around people's home locations or along the routes they take as captured in GPS tracks (Markevych et al., 2017; Robinson et al., 2018; Spotswood et al., 2021; Roberts and Helbich, 2021).

Land Use / Land Cover (LULC) maps represent the land surface in distinct classes, such as buildings, roads, parks, and forests, allowing to study the size, shape, kind, accessibility, or spatial layout of designated greenspaces (Markevych et al., 2017; Nieuwenhuijsen et al., 2017). LULC maps are commonly utilized for greenspace accessibility studies; they account for a large share of objective studies on greenspace for human activities (Labib et al., 2020). OSM, in particular, is a type of LULC map that is increasingly being used in academic studies as an open-source and global alternative to local commercial or authoritative LULC datasets (Barrington-Leigh and Millard-Ball, 2017) and is an effective alternative to local data in terms of its accuracy and precision (Liao et al., 2021). Alternative LULC maps include, for example, the Urban Atlas in Europe (used by Turunen et al., (2023)) and local data registries (e.g., municipal canopy cover and street tree data used by Baró et al. (2021)).

Geo-located *street-level imagery* is gaining importance for urban analyses, including studies on urban greenery (Biljecki and Ito, 2021; Labib et al., 2020). Examples include measuring the Green View Index in images (Li et al., 2015; Lu, 2019), detecting vegetation objects through computer vision (Song et al., 2022; Chen and Biljecki, 2023), or merging street-level imagery with LULC data (Zhang et al., 2021). Lastly, various studies make use of social media data, such as the frequency of Flickr photos and Tweets posted per location (Hamstead et al., 2018), the contents of Tweets (Roberts, 2017), and the categories of objects detected in Instagram photos (Song et al., 2022).

2.2. Capturing subjective perceptions through interviews, questionnaires, and audits

People's subjective environmental perceptions are typically obtained through interviews or questionnaires (Nieuwenhuijsen et al., 2017; Markevych et al., 2017). Examples include in-situ interviews with park visitors. For instance, Talal and Santelmann (2021) conduct interviews with park visitors to understand their motivations for visiting, experiences, perceptions of accessibility, and suggestions for improvements, and Sundevall and Jansson (2020) conduct walking interviews with greenspace users to learn about their desired use, content, atmosphere, inclusivity, and management of a greenspace.

Questionnaires often employ Likert scales to obtain quantified subjective measurements, for instance asking respondents to rate the perceived quality and amount of greenspace in their surroundings (Zijlema et al., 2018), the perceived amount of greenness and how satisfied people are with its quality, amount, maintenance, and safety (Kruize et al., 2020), or the perceived quantity and usage quality of greenspaces near their homes (Zhang et al., 2021).

Alternatively, researchers conduct audits to measure the quantity and quality of greenspace (Nieuwenhuijsen et al., 2017). A subset of greenspace studies employs street-level imagery to elicit perceptions or to conduct audits, such as assessing the existence of features in greenspaces through street-level imagery (Rzotkiewicz et al., 2018). Other examples include work by Du et al. (2021), who provided park visitors with photos of park scenes to help them recall their visiting experience while answering a questionnaire about their health and well-being, or Van Vliet et al. (2021) who conducted a video-based choice experiment on park attributes such as trees, furniture, cleanliness, facilities, and biodiversity.

Although subjective data prove important when studying use of greenspace (Flowers et al., 2016; Fongar et al., 2019), their collection is typically constrained by time, money, and geographical extent.

2.3. Capturing subjective perceptions through crowdsourcing campaigns

To address these temporal, monetary or geographic limitations, researchers collect people's visual environmental perceptions from many people through *crowdsourcing* campaigns, typically elicited through street-level imagery. Crowdsourcing is a method of recruiting a group of participants to execute a task online, i.e., ex-situ or remotely, whereas street-level imagery allows to remotely mimic at scale what pedestrians may observe (Larkin and Hystad, 2019; Lu, 2019; Markevych et al., 2017). As such, street-level imagery-based crowdsourcing campaigns enable researchers to source perceptions from a vast and diverse number of places and individuals worldwide in a time- and labor-efficient manner (Milias et al., 2023).

Examples include studies that collect perceptions by asking their participants in questionnaires to choose which location they prefer or to rate places on a Likert scale and then inviting them to explain their responses by selecting options from a list or inputting keywords. Examples include asking people to choose the most safe, upper-class, or unique-looking place out of two places presented in imagery (Salesses et al., 2013); or the most happy, beautiful, or quiet place (Quercia et al., 2014); letting participants select the least and most safe or attractive looking place out of four images (Candeia et al., 2017); and by asking people to virtually navigate city streets while rating how safe and attractive they perceive their path in various places (Milias et al., 2023).

2.4. Differences and similarities between subjective and objective greenspace data

Few studies have investigated the extent to which large-scale spatial data and people's perceptions of greenspaces match. These studies suggest, however, that consistency is limited. Leslie et al. (2010) discovered a lack of agreement with overall perceived greenness and a significant but modest correlation only for greenness expanse and not for street greenness, green sports facilities, and green amenities when comparing NDVI maps with people's perceptions of their residential surroundings captured in four greenspace components. Zhang et al. (2021) found no correlation of people's perceived quantity and usage quality of greenspaces near their homes with canopy cover and at best very weak correlation with park area, vegetation cover, and Green View Index. Kothencz and Blaschke (2017) assessed park visitors' ratings of greenness, accessibility, and functions of parks, and found no correlations with NDVI or park area, while they did find a moderate correlation of people's impression of greenness with the percentage of vegetated surface. Hyam (2017) discovered a correlation between the author's rating of perceived naturalness, and natural components in street-view imagery detected through computer vision; And Helbich et al. (2019) found no correlation between NDVI and deep-learning-based metrics of street-view greenness.

Our study aims to add to our understanding of the previously reported (lack of) associations between large-scale greenspace data, such as NDVI and LULC maps, and people's visual perceptions of greenspaces. That is, we do not necessarily presume that these data are comparable, but rather seek to provide evidence on their differences and similarities, as well as in which circumstances substantial differences arise. Three factors distinguish our work. First, we include in our study a diverse range of public spaces that differ in terms of type, geographical setting, and vegetation level. Second, we collect multiple people's perceptions on the same locations. Third, we investigate potential causes of dataset differences by qualitatively analyzing the reasons people give for their assessments and the spatial characteristics of each location to further strengthen our quantitative findings.

3. Methods

We collected and analyzed greenspace data in three European cities: Barcelona, Rotterdam, and Gothenburg. We used Python to collect NDVI data, and LULC data from OSM, and we used a crowdsourcing approach with Google Street View (GSV) imagery to collect people's visual perceptions of greenspaces. We then tested our hypotheses and conducted additional exploratory and sensitivity analyses, and qualitatively investigated what spatial characteristics explain deviations between people's perceptions of greenspace and what is captured in the map data. Fig. 1 shows a summary of our steps and Fig. 2 depicts the data we collected for each location: median NDVI values, OSM categories, and people's visual perceptions of greenness. Links to repositories containing our code and (pseudonymized) data are provided in the data availability statement at the bottom of this article.

3.1. Three case-study cities

We selected three case-study cities in Europe: Gothenburg (Sweden), Rotterdam (The Netherlands), and Barcelona (Spain). OSM data in Europe is found to be relatively complete (Zhou et al., 2022). The selected cities are all major cities in their respective countries, with Gothenburg and Rotterdam having comparable populations of approx. 583,000 (in 2021) and approx. 592,000 (in 2022), respectively, while Barcelona has a substantially larger population of over 1,640,000 (in 2022) (Ajuntament de Barcelona, 2022; CBS, 2022; Statistikmyndigheten, 2021). All three cities have an important harbor. By selecting case-study cities from Northern, Western, and Southern European regions (UN, 2019), different vegetation zones (Roy et al., 2012), and diverse coverage of green land (Zhou et al., 2022), we account for varying environmental qualities. Barcelona is situated between a seaside with beaches and a forested mountain range inland, with a variety of parks, including historic parks such as the *Montjuïc* hill and architect Antoni Gaudí's *Park Güell*, complemented by trees distributed along its streets. Gothenburg is strategically placed at a river outlet into the sea, and it has several greenspaces within its borders, including parks such as the

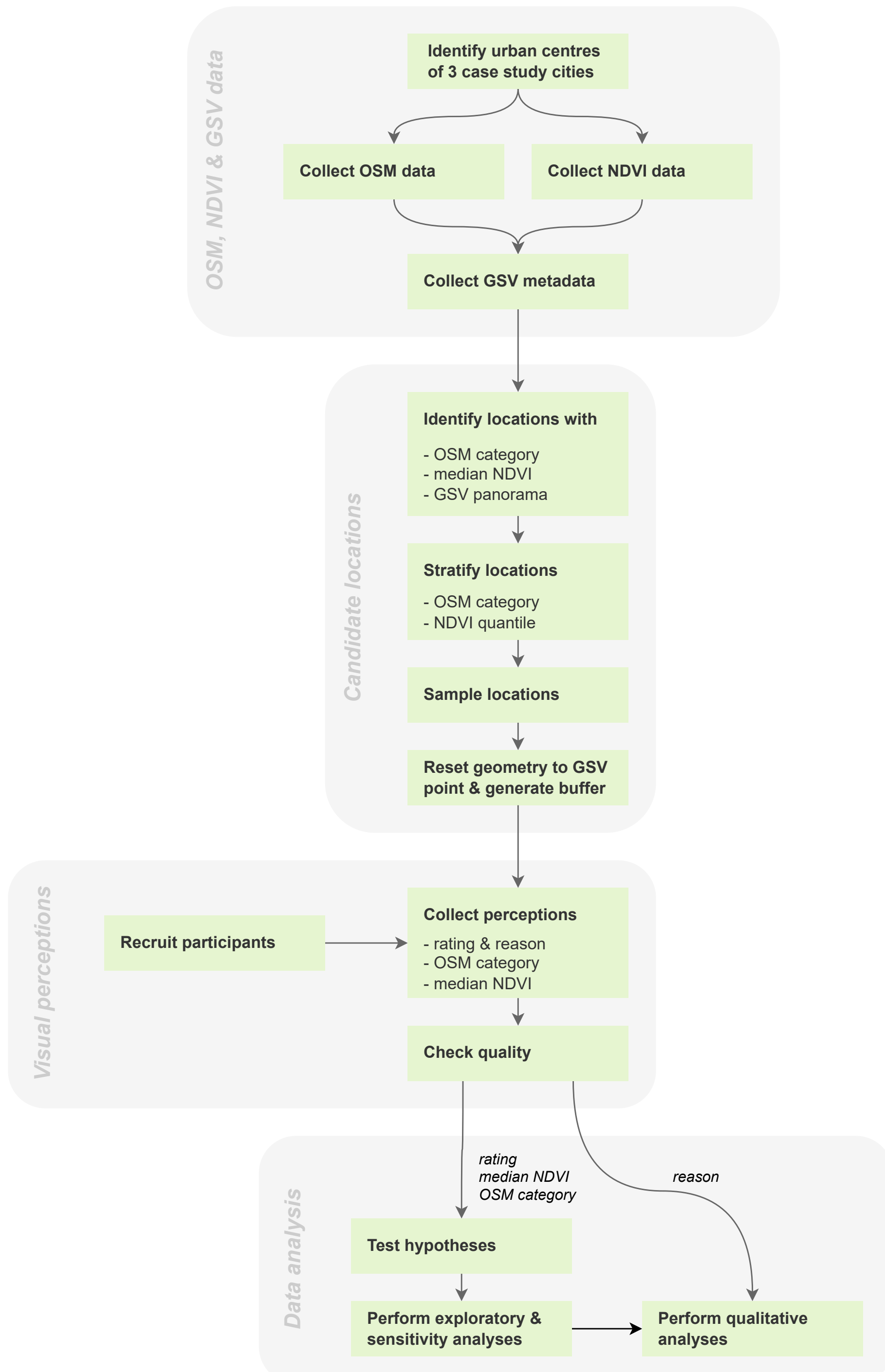


Fig. 1. Overview of methodological steps.

centrally located *Kungsparken*, nature reserves such as *Änggårdsbergen*, and other types of greenspaces. Rotterdam is distinguished by modern morphology and architecture resulting from the city's reconstruction following significant bombing during World War II. It has several well-known parks such as the *Kralingse Bos* forest and lake, and *The Park* located on the *Meuse* riverside. Both Rotterdam and Gothenburg have temperate maritime climates, while Barcelona has a warmer Mediterranean climate.

3.2. *Collecting OSM, NDVI, and GSV data*

As candidate locations for analysis, we identified urban public spaces with relevant OSM categories, NDVI values, and GSV imagery available. We scoped to public spaces located within walking distance from the urban centers of these case-study cities, based on the European Commission's Human Settlement Layer models and guidelines (Schiavina et al., 2022; Waddell and Ulfarsson, 2003).

OSM data: We collected public space and pedestrian street network data from OSM using the *Overpass API* and the *Osmnx* library (Boeing, 2017). We collected a variety of public spaces, represented as polygons: vegetated spaces, typically referred to as greenspace; and other spaces that may — depending on their character — be perceived as such according to the WHO definition (WHO Regional Office for Europe, 2017). We excluded spaces that are inaccessible via the pedestrian street

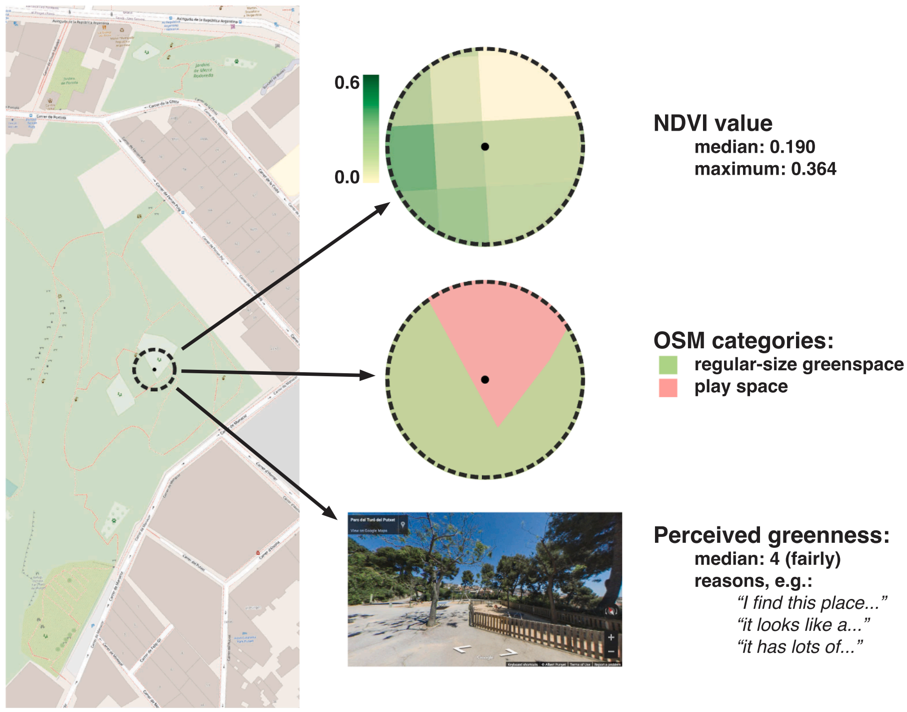


Fig. 2. Collected data per sampled location: NDVI values and OSM categories within radius distance, perceived greenness, and reasons. Example in Parc del Turó del Putxet, Barcelona.

network or that are smaller than 200 square meters (i.e., the size of a typical tennis court). For vegetated spaces, we merged overlapping or adjacent spaces into one, such as shrubbery adjacent to a forest, and differentiated between different sizes. As a result, we obtained OSM polygons of *five OSM categories*: *regular-size greenspaces* (specifically parks, nature reserves, forests, woods, scrubs, shrubbery, heath, meadows, grass(lands) village greenery, and fells, at least 0.5 ha in size (Teeuwen, Psyllidis, & Bozzon, 2023; Ambiente Italia, 2003)); *pocket-size greenspaces* (same categories, up to 0.5 ha in size (Wood et al., 2017; Labib et al., 2020; Peschardt et al., 2014)); *public open spaces* (specifically squares, pedestrian areas, marketplaces, and common grounds); *play spaces* (specifically playgrounds and public schoolyards); and *streets* accessible to pedestrians (i.e., for walking as defined by Boeing (2017)).

NDVI data: We used Google's *Earth Engine* API to collect high-resolution satellite vegetation indices from the Copernicus Sentinel-2 mission (Markevych et al., 2017; Labib et al., 2020). We used all imagery between May and September 2021, i.e., the growing season for vegetation in Europe (Roberts and Helbich, 2021), and calculated the average NDVI value per raster cell. We then calculated the average NDVI value per OSM polygon, while ignoring values less than 0 (i.e., water) (Markevych et al., 2017).

GSV metadata: Using Google's *Street View Static* API, we looked for the nearest GSV imagery for up to 10 random points within each OSM polygon, with a maximum search radius of 15 m (Amiri and Crain, 2019). When we found an image captured from 2018 to 2022 in May to September (i.e., the vegetation growing season (Roberts and Helbich, 2021; Turunen et al., 2023)), we stored its metadata. We considered imagery sourced by Google, and 360-degree panoramas uploaded by GSV users, as particularly in green urban areas that are inaccessible by car, user-contributed imagery is a widespread alternative to imagery sourced by Google.

Identifying candidate locations: Our candidate locations are OSM polygons of various categories for which we have both an NDVI value and GSV imagery available. We then took a random sample of 140 candidate locations per case-study city, while ensuring equal spread between both OSM categories (i.e., sampling equal numbers of regular-size greenspaces, pocket-size greenspaces, public open spaces, etc.) and NDVI-value quarters. We manually checked if their associated GSV imagery is suitable for collecting visual perceptions: we excluded images captured indoors or underground, during night-time or events, of poor image quality, taken from bird's or frog's view perspective, or when sight to the location they were sampled for was obstructed (e.g., by a wall). We replaced these locations with another randomly sampled candidate from the same OSM category, NDVI quartile, and city, until all sampled locations passed the check.

Finally, we reset the geometry of these sampled locations to the point from which the GSV image was taken. We recalculated the median NDVI and determined which OSM place categories were located within 15 m buffer zone around this point (Amiri and Crain, 2019). By doing so, we ensured that people's perceptions, NDVI values, and OSM categories all referred to the same location. We also investigated buffers of 25, 29, 43 and 100 m to define a location's immediate surroundings to assess the sensitivity of our results to the radius distance chosen. In related studies, 25 m were found to be relevant for capturing greenery visible from a location (Kuo et al., 2018); 29 and 43 m for observing events in urban environments (Amiri and Crain, 2019); and 100 m for representing the individual human scale in greenspace health research (Labib et al., 2020).

3.3. Collecting people's visual perceptions

We then collected people's visual perceptions of the sampled locations through a questionnaire on Prolific: an online crowdsourcing platform designed for academic research (Peer et al., 2017). We recruited participants who currently live in Europe and are proficient in the English language. We ensured diversity in age and gender and paid participants minimum wage in the Netherlands, the country of the authors' affiliation. Participants provided informed consent to participate and could only submit a single questionnaire.

Crowdsourcing task: Our questionnaire, implemented using the *Qualtrics* platform, took about fifteen minutes to complete. On average,

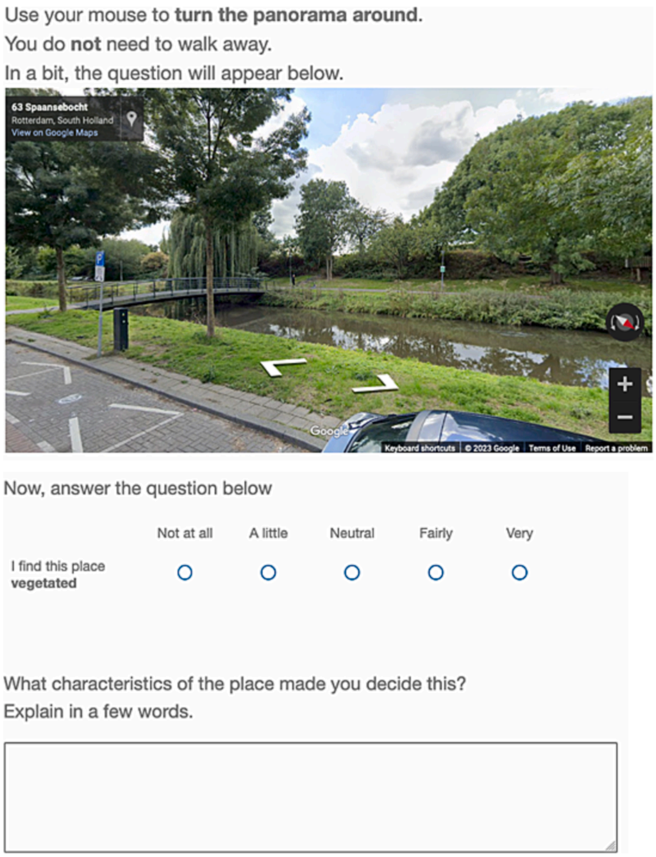


Fig. 3. Impression of crowdsourcing interface.

we expected each location to be rated by five people. We formulated our questions based on related questionnaires used in environmental health research (Kruize et al., 2020; Zijlema et al., 2018), while keeping them simple and straightforward for crowdsourcing (Salesses et al., 2013; Quercia et al., 2014; Milias et al., 2023; Candeia et al., 2017). Fig. 3 depicts an impression of the interface. First, we introduced the topic and asked participants to provide some demographics. Second, for each participant, we randomly sampled five locations from the same case-study city. For each location, we showed them the panoramic GSV image and instructed them to pan around for at least 10 s. We then collect participants' visual perceptions of greenness by asking them to indicate *to what extent they find the place vegetated* (on a 5-point Likert scale: not at all (1) to very (5)); and *what characteristics of the location* motivated their choice (in open text). We included quality checks consisting of a reCAPTCHA bot test and an attention check and collected the number of panning clicks participants made. Finally, we asked participants some more demographics and asked how clear they found the crowd-sourcing tasks.

3.4. Data analysis

After collecting all necessary data (see Fig. 2), we could assess how well NDVI and OSM capture people's visual perceptions of greenspaces.

Quantitative (statistical) analysis: First, we filtered out participants or visual perceptions that did not meet our quality standards (e.g., through bot detection and an attention check, and checking if participants panned around in the panorama). We then calculated descriptive statistics based on the NDVI value, OSM category, and perceived vegetation level of each location, and aggregated ratings into a median value per location for further analysis. To compare perceived vegetation levels to the binary OSM data categories (i.e., something either is tagged as a greenspace, or not), we also converted perceived vegetation levels into binary values, by defining *perceived greenspaces* as locations with a median perceived vegetation level of 4 (fairly) to 5 (very) vegetated (Zijlema et al., 2018). We statistically tested our hypotheses and conducted several exploratory analyses. Table 1 summarizes our hypotheses (H1-3) and the non-parametric methods we used to test them. First, we tested for correlations between visual perceptions (on a 5-point Likert scale) and NDVI data using Spearman's ρ (H1). Second, we compared the perceived greenness distributions (on a 5-point Likert scale) of various OSM categories using the Mann-Whitney U and Kruskal-Wallis tests (H2.1); and calculated the percentage of OSM regular-size greenspaces that are perceived as greenspaces (in binary values) (H2.2). Third, we implemented three algorithms to select greenspaces from the different data sources and compared them on how well they captured perceptions of greenspace using McNemar's test. We also performed sensitivity analyses to identify how our results change when we increase the buffer zone radius from which we identify the median NDVI value and the presence of OSM greenspaces. Given that we performed 8 different significance tests (i.e., 1 for H1, 5 for H2, and 2 for H3), we applied a Bonferroni correction to our significance threshold of $\frac{0.05}{8} = 0.006$. We used the same cutoff for exploratory analyses.

Qualitative analysis: To understand potential causes of differences between visual perceptions and map data, we conducted a reflexive thematic analysis (Clarke and Braun, 2013). Based on our quantitative findings, we identified the places for which perceptions notably deviated from NDVI and OSM map data and analyzed the spatial characteristics of these places that participants mentioned as reasons. We used *Atlas TI* to conduct our thematic analysis, employing inductive coding and iterative identification of themes.

4. Results

4.1. Descriptive statistics

This section describes the number of perceptions we collected, the number of places we included in our analysis, and the number of people who participated in our study.

Between March and May 2023, 423 Prolific participants, living in 21 different European countries, completed our crowdsourcing task. Of these people, 409 passed our quality checks and were therefore included in our study. A majority found the tasks clear (100 %), panned the panoramas around as requested (93 %), did *not* move away to adjacent places (71 %) and were *not* familiar with the places presented (95 %). Participant genders vary (49 % female, 49 % male, and 2 % non-binary, third gender, or prefer to self-describe or not to say), as well as ages (12 % age 18–24, 19 % 25–34, 20 % 35–44, 20 % 45–54, 18 % 55–64, and

Table 1
Overview of hypotheses and statistical methods.

	Hypothesis	Method
H1	There is a strong positive correlation between NDVI and perceived greenness.	Spearman's Rho
H2.1	Perceived greenness is higher for OSM regular-size greenspaces than for pocket parks, play spaces, open public spaces, and streets.	Mann–Whitney U & Kruskal-Wallis
H2.2	Pocket parks, play spaces, open public spaces, and streets can be perceived as greenspaces.	Descriptive statistics (percentages)
H3	Perceived greenspaces are better captured in data when selecting them based on a combination of OSM categories and NDVI values, opposed to only OSM categories, or only NDVI values.	Descriptive statistics (true positives and negatives) & McNemar's test

10 % 65 years or older). Most participants are city dwellers (61 %). When testing differences in perceptions among pairs of demographic groups using the Mann-Whitney *U* test, we did not find any statistically significant differences.

From these 409 participants, we obtained a total of 1956 perceptions on greenness, after filtering out data in case of technical issues (e.g., the panorama did not load in time) or in case the participant did not interact at all with the panorama (i.e., made no clicks to pan the panorama around or zoom in).

Out of 420 places, 413 received valid perceptions from our participants. On average, each place was rated on greenness by 5 people. Table 2 shows descriptive statistics on the places, their NDVI values and OSM categories, and associated perceptions per city. People perceived 180 of the places (44 %) as green.

4.2. Quantitative analyses

4.2.1. H1: Perceived greenness in relation to NDVI values

Hypothesis and outcome: We hypothesized to find a strong positive correlation between NDVI and perceived greenness. Using Spearman's ρ, we tested the correlation between how green places are perceived to be, and their NDVI values, and found a statistically significant correlation of moderate strength (ρ: 0.459, p-value < 0.006), thus not supporting our hypothesis.

Exploratory analyses: No apparent NDVI value threshold that differentiates greenspaces from other spaces could be identified. When comparing correlations between cities, we found that correlation is much weaker in Barcelona (ρ: 0.269, p-value < 0.006) than in Rotterdam (ρ: 0.540, p-value < 0.006) and Gothenburg (ρ: 0.570, p-value $<$ 0.006) Furthermore, we did not find stronger correlations when using the maximum NDVI value in a place's proximity, as opposed to the median (i.e., ρ: 0.47, p-value < 0.006).

Sensitivity analyses: To analyze how sensitive our correlation results are to the radius distance used to calculate a place's NDVI value, we found that by increasing the radius distance to 25, 29, and 43 m, correlation strengths increase from 0.459 to 0.556, 0.585 and 0.600 (all p-value < 0.006), while decreasing again for larger distances. Furthermore, from 25 up to 100 m, the differences in correlations among case-study cities largely disappeared.

4.2.2. H2: Perceived greenness in relation to OSM categories

Hypothesis and outcome H2.1: We hypothesized (H2.1) that perceived greenness is higher for OSM regular-size greenspaces than for pocket-size greenspaces, play spaces, open public spaces, and streets. Using the Kruskal-Wallis test, we found significant difference in perceived greenness occurs between OSM categories (H: 107, p-value < 0.006). Using a one-tailed Mann-Whitney *U* test, with the alternative hypothesis that regular-size greenspaces are perceived *more green* than others, we found that regular-size greenspaces (median perceived greenness: 4.0, n: 112) are indeed perceived greener than: pocket-size greenspaces (median: 4.0, U: 5878, n:86, p-value < 0.006); open public spaces (median: 2.0, U: 9723, n: 102, p-value < 0.006); and streets (median:3.0, U: 8741, n: 107, p-value < 0.006); while no significant difference was found with play spaces (median: 4.0, n: 78); showing that OSM regular-size greenspaces are only perceived greener than pocket-size greenspaces, open public spaces, and streets.

Hypothesis and outcome H2.2: We further hypothesized (H2.2) that also pocket-size greenspaces, play spaces, open public spaces, and streets can be perceived as greenspaces, as some literature suggests. We considered a place to be perceived as greenspace when it was rated on median 4 (fairly) or 5 (very) vegetated. We found that 70 % of all OSM regular-size greenspaces are perceived as greenspaces. Furthermore, 47 % of pocket-size greenspaces, 11 % of open public spaces, 36 % of play spaces, and 23 % of streets (all excluding those that also lie within direct proximity of a regular-size greenspace) are perceived as greenspaces. Thus, we can confirm that not only regular-size greenspaces, but also pocket-size greenspaces are perceived as green more often than 40 % of times (i.e., if greenness ratings were distributed equally over our 5-point scale, 2/5 or 40 % would be considered green).

Sensitivity analyses: When we gradually increased the radius distance which we use to define if a place lies in proximity to an OSM greenspace, we observed that results for H2.1 remain rather stable up to 43 m. Yet for H2.2, we observed that percentages decline: with a radius of 15 m, 70 % of places located near OSM greenspace are indeed perceived by people as green; while with 25, 29, and 43 m, the percentages declined to 67 %, 66 %, and 63 %, respectively.

4.2.3. H3: Perceived greenness in relation to both NDVI values and OSM categories

Hypothesis and outcome: We hypothesized that if perceived greenspaces are selected using a *combination* of OSM categories and NDVI values, they are better recorded in data than when only OSM categories or only NDVI values are used. To test our hypothesis, we implemented three greenspace selection algorithms based on our findings in H1 and H2: 1) OSM-based, selecting all locations near OSM regular-size greenspaces; 2) NDVI-based, selecting places with an NDVI value larger than the median NDVI value of all sampled locations in the same city; and 3) combination-based, selecting locations near OSM regular-size greenspaces, and pocket-size greenspaces and play spaces with an NDVI larger than the median. We compared their results to the crowdsourced perceptions of greenspace. In 67.8 % of cases, the OSM-based algorithm correctly captured perceptions of greenspace, compared to 65.6 % for the NDVI-based algorithm, and 71.8 % for the combination-based algorithm. McNemar's one-tailed test revealed that the combination-based algorithm performed significantly better than the NDVI-based algorithm (n: 401, p-value < 0.006), while no significant difference was found with the OSM-based algorithm.

Sensitivity analyses: When we repeated our analysis with NDVI values and OSM categories within larger radius distances, we discovered that the percentages of the OSM-based and combination-based algorithms gradually decreased with distance, while they increased for the NDVI-based algorithm, which is consistent with the findings in H1 and H2 (see Table 3). Regardless of radius distance, the combination-based algorithm outperformed the OSM-based algorithm, while at a 43-meter radius distance, the NDVI-based algorithm achieved the highest score of 72.3 %. Using McNemar's test, we observed the NDVI-based algorithm outperforms the OSM-based algorithm significantly (n: 412, p-value < 0.006), while the difference with the combination-based algorithm was not statistically significant.

Table 2
Descriptive statistics of places and associated perceptions per case-study city.

case city	places n	NDVI [0–1] med.	min	max	OSM category [%] reg.-size greensp.	poc.-size greensp.	open space	play space	street	perceptions n
Barcelona	139	0.139	0.017	0.379	30.9 %	20.1 %	31.7 %	20.1 %	28.1 %	647
Rotterdam	137	0.188	0.023	0.539	26.3 %	21.9 %	21.9 %	19.7 %	27.0 %	645
Gothenburg	137	0.140	0.019	0.492	24.1 %	20.4 %	20.4 %	16.8 %	22.6 %	664
Total	**413**	**0.151**	**0.017**	**0.539**	**27.1 %**	**20.8 %**	**24.7 %**	**18.9 %**	**25.9 %**	**1956**

Table 3
Quantitative results per radius distance. Per row, highest scores are emphasized in bold.

		radius distance [m]			
		15	25	29	43
H1	correlation perception & NDVI	0.459	0.556	0.585	**0.600**
H2.2	percentage OSM greenspaces perceived as such	**69.6 %**	66.9 %	66.4 %	62.9 %
H3	correctness OSM-based algorithm	**67.8 %**	67.0 %	66.8 %	65.3 %
	correctness NDVI-based algorithm	65.6 %	69.7 %	70.8 %	**72.3 %**
	correctness combination-based algorithm	**71.8 %**	70.2 %	70.0 %	68.2 %

4.3. Qualitative analyses

The following paragraphs present qualitative findings following up on testing hypotheses H1 and H2. Exemplary quotes denoted as *Q-i* are included in the supplementary material, as is exemplary street-level imagery.

4.3.1. Deviations between perceived greenness and NDVI values (following H1)

To understand deviations between perceived greenness and NDVI values, we explored *why people regard places green, while NDVI values are low, and vice versa.* We selected places for analysis based on our quantitative results, using a 43-meter radius distance, i.e., where correlations were strongest.

Regarding places that do have a high surrounding NDVI value but are not deemed green (n = 6, see Table A1 and Fig. A1 in supplementary material), we identified that these are typically characterized by the place being in between *two distinctive sides*, resulting in mixed opinions among participants (*Q-1*). Specifically, these places are characterized by greenness on one side, with grass, trees, and occasionally other vegetation or natural features. However, the other side is generally dominated by built-up elements (e.g., buildings, concrete, and infrastructure) or, when there is some vegetation present (e.g., trees, grass, greenery, or private gardens, sometimes located further away or combined with other natural features), it remains too little or too barren (Q-2, Q-3). Less often, we observed that greenery may be present, but is *physically inaccessible*, for instance due to height difference (*Q-4*).

Regarding places that are perceived by people as green but have a low NDVI value (n = 10, see Table A2 and Fig. A2 in supplementary material), first, we identified that vegetation is often *present and varying* in type, but only on a low level (e.g., only grass, other ground-covering greenery, or low-level bushes), still young (e.g., tiny trees), or scattered around in small bits (e.g., stand-alone trees, some vegetation in every garden) (*Q-5*). We also observed that vegetation may be lush, but only on a limited area, in private gardens, or located further-on (*Q-5*). Second, participants also mentioned *other natural features*: riverfronts, sand or small tiles on the ground, wooden fences, or a seemingly good local climate (e.g., shaded, clean air) (*Q-6*, *Q-7*). Third, we observed spaces are characterized by a *lack of features*, for example: distant from traffic, secluded, or quiet (*Q-8*). We do note, however, that some participants still characterized places dominated by built-up elements as *"green for an urban environment"* (*Q-10*), in which cases the judgment seemed *contextual* rather than absolute (*Q-9*). Lastly, mentions of *attractiveness* were more prevalent among places perceived as green, than *vice versa* (*Q-11*).

4.3.2. Deviations between perceived greenness and OSM categories (following H2)

Subsequently, we explored *why people regard places green, while OSM does not tag them as such, and vice versa.* Again, we selected our cases based on quantitative results, now using the 15-meter radius distance at which OSM performed best.

As to places tagged by OSM as greenspaces, but not perceived as such by people (n = 12, see Table A3 and Fig. A3 in supplementary material), we identified two main reasons. First, despite being tagged in OSM as green and seemingly *equipped* for use by people, e.g., with benches or an elevated pedestrian walkway, some places were not perceived by people as green (*Q-12*). People state vegetation is too low, young (e.g., tiny trees), scattered, dry, constrained, located too far away, or only on one side, or the space is too open and empty (*Q-13*, *Q-14*, *Q-15*, *Q-16*). In these cases, the vegetation was *overruled by built-up structures*: major roads or tramways, high building blocks, concrete and other paved areas, and associated sense of a bad local climate (*Q-17*, *Q-18*, *Q-19*). Second, again, we observed that some places are characterized by *two distinct sides*: major apartment buildings on one side, versus a natural rock landscape with vegetation on the other; concrete and constructions works, versus a carefully designed green-looking space; and a major road, versus an extensive vegetated area. These differences sometimes caused *disagreement* among people, depending on what attracted their attention the most (*Q-20* versus *Q-21*).

Places that are not tagged as greenspaces of regular size in OSM, but still are perceived as green by people, outnumbered all other qualitative cases: 102 places. We identified two main themes (see Table A4 and Fig. A4 in supplementary material). First, *presence and number* of trees, other greenery such as bushes, shrubs, and smaller plants, and to a lesser extent grass played a major role, while people also mentioned variation in vegetation, flowers, and fields (*Q-22, Q-23, Q-24*). We also observed vegetation *configuration* was explicitly or implicitly referred to (*Q-25*): vegetation on different heights (e.g., grass fields, tree canopies, and vegetated walls) (*Q26*); and places that are spacious or have vegetation all around and far extending (*Q-27*). Second, we see again that people judged urban greenspace contextually rather than absolutely: they are green *"for an urban setting"* (*Q-28*). These included residential neighborhoods with lots of private greenspace and natural buildings materials (*Q-29*); and regular or dense road-side vegetation (*Q-30*). Also, *other qualities* were associated with greenness: water, shade and fresh air, and quietness, attractiveness, and safety (*Q31*, *Q-32*, *Q-33*). Yet we do note that the conflict between built-up and greenspace remained, with people motivating their greenness by the lack or presence of built-up elements, such as buildings, traffic, concrete, and parking lots (*Q-34*, *Q-35*, *Q-36*, *Q-37*).

Table 4 summarizes the outcomes of our hypothesis tests and exploratory, sensitivity, and thematic analyses.

5. Discussion

5.1. Interpretation of results

Our findings suggest that NDVI and OSM data capture how green people find places to be rather well, yet significant discrepancies remain. Fig. 4 shows exemplary locations where perceptions of greenspace deviate from NDVI and OSM map data.

We found no evidence for a strong correlation between how green places are perceived and the NDVI values in their immediate vicinity. However, we did discover a significant moderate correlation. Our findings of a significant correlation contrast with those of Kothencz and Blaschke (2017) and Leslie et al. (2010), who found no significant correlation of NDVI values with park visitor's perceptions of greenspace, or with people's perceptions of their home environment. What distinguished our method from Leslie et al. (2010) is that we collected data for

Table 4
Summary of quantitative and qualitative findings.

H1	**Perceived greenness in relation to NDVI**	
	hypothesis test	No evidence for a strong correlation with median NDVI.
	exploratory analysis	Significant moderate correlation instead, weak correlation for Barcelona, while moderate for Rotterdam and Gothenburg, and moderate but less strong correlation with maximum NDVI.
	sensitivity analysis	NDVI within 43 m radius distance yields strongest correlation.
	qualitative analysis	Places perceived not-green, but with high NDVI: have two distinctive sides; or the greenspace is physically inaccessible. Places perceived green, but with low NDVI: have varying vegetation; other natural features nearby; absent built-up features; are rated in context.
H2	**Perceived greenness in relation to OSM**	
	hypothesis tests	Regular-size greenspaces are perceived as greener than pocket-size greenspace, open public spaces, and streets, but not greener than play spaces. Pocket-size greenspaces are oftentimes perceived as greenspaces.
	sensitivity analysis	OSM within 15 m radius distance yields best outcomes.
	qualitative analysis	Places perceived not-green, but in OSM: are still equipped for people; have dominant built-up features; or two distinctive sides. Places perceived green, but not in OSM: have large amount and good configuration of vegetation; are rated in context; have other natural and soft features.
H3	**Perceived greenness in relation to NDVI and OSM**	
	hypothesis test	Algorithm combining OSM and NDVI data yields better results than NDVI-based algorithm, but no significant difference with OSM-based algorithm.
	sensitivity analysis	Combination- and OSM-based algorithm perform best with 15 m radius distance, while NDVI-based algorithm with 43 m radius distance scores highest overall.

one single point in place, rather than an entire residential neighborhood, and unlike Kothencz and Blaschke (2017), we collected data for a broader range of public spaces, potentially with a wider range of NDVI values.

When we investigated the influence of radius distances, we discovered that the strongest correlation was 0.600 when using median NDVI values within a 43-meter radius distance. We saw the greatest change in correlation strength with increasing radius distance in Barcelona, rising from 0.269 to 0.577, implying that perceptions of places in Barcelona are based on greenery located further away: One could hypothesize that Barcelona's public spaces are more spacious or have more mature trees that can be seen from a distance, as opposed to grasslands or small vegetation that is more evenly distributed in space.

We found evidence to support our hypothesis that OSM regular-size greenspaces are perceived significantly greener than pocket-size greenspaces, streets, and public open spaces, while OSM seems to use open space tags almost exclusively for places where vegetation is not dominant. We also discovered that nearly half of OSM pocket-size greenspaces are perceived as green, adding to the body of evidence that pocket-size greenspaces are important for green cities as well (Wood et al., 2017; Labib et al., 2020; Peschardt et al., 2014). Surprisingly, no significant difference in greenness perception was found between OSM regular-size greenspaces and play spaces. We discovered that many play spaces are unanimously perceived by people as green, even though OSM does not provide any indication of the presence of greenery. Furthermore, examples of greenery that are unexpectedly missing from OSM include forests and groves located on the outskirts of cities that are not represented in OSM. Other deviations were not due to a lack of greenery in OSM data, but rather to how we filtered our greenspaces. That is, we selected greenspaces of significant size based on a minimum size of 0.5 ha of adjacent green land (Ambiente Italia, 2003). Some greenspaces, however, are mapped in such granularity in OSM — for example, every individual patch of grass separated from others by narrow footpaths — that our algorithm filtered them out.

We also observed that some places in OSM are labeled as green but are not perceived as such. When we look at these places in OSM, we see that half of them are tagged as *parks*. The term park is explicitly included in the WHO definition of greenspace that we used (WHO Regional Office for Europe, 2017a), and many other definitions of greenspace in the literature (Taylor and Hochuli, 2017), and participants often seemed to regard parks equivalent to greenspaces. According to OSM, a park is *"an area of open space for recreational use, usually designed and in semi-natural state with grassy areas, trees and bushes"* (OpenStreetMap, 2023). As this definition and our findings suggest, OSM parks are typically but not always vegetated.

We demonstrated that combining OSM categories and NDVI values can help to better select perceived greenspaces from these data in many cases, providing an answer to the question raised by Liao et al. (2021) whether combining multiple datasets improves performance. Surprisingly, we observed that the NDVI-based selection algorithm outperformed all others at a 43-meter distance. Qualitative results suggested refining these algorithms with information on other spatial characteristics from OSM has great potential, such as proximity to water or presence of greenery in all directions; proximity to traffic infrastructure or high-rise buildings; and presence of private gardens. Other qualities, such as vegetation variety, quietness, attractiveness, and safety, may be more difficult to capture in large-scale data, but are studied in related work (Milias et al., 2023; Candeia et al., 2017; Salesses et al., 2013; Quercia et al., 2014).

Our qualitative findings indicated that people seem to judge the greenness of a place contextually rather than absolutely. Specifically, people stated, for example, that *"for an urban setting, more trees than I would have expected"* (Q-28), suggesting that people have different expectations of greenspaces within cities opposed to outside of them. Furthermore, they stated *"considering it's in the middle of a man made square it seems quite green"* (Q-9), indicating that within the constraints of the type or function of a given urban space (e.g., a crossroads or a major road), people sometimes simply considered a place as green as can be.

5.2. Implications for research and practice

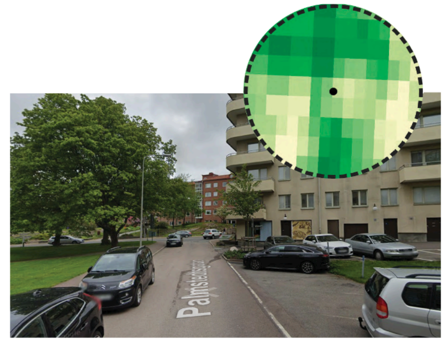
According to our findings, NDVI maps are only moderately associated with how green people perceive places to be. For optimum results, perception data should only be exchanged for NDVI maps while keeping this limitation in mind, ideally utilizing median NDVI values within 43 m. When using OSM data, similar limitations arise, but we suggest using a short radius distance of 15 m instead.

Our results further suggest that incorporating NDVI data into OSM-based analyses produces more accurate results. In the case informal and small-scale greenspaces are of interest, NDVI values may help to filter out those parks that are not perceived green, or to identify pocket parks and play spaces that are often perceived as green.

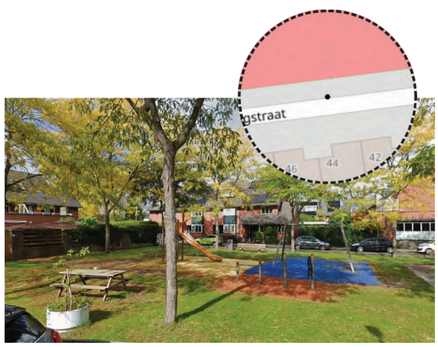
Our qualitative findings suggest that when identifying locations for greenspace interventions, urban planners could consider prioritizing greenspaces that appear in large-scale data but are not perceived as such, e.g., where built-up features are too dominant.

Our findings could also serve as guidance when aiming to make cities *"just green enough"*: greenspace strategies that limit adverse effects of interventions to make neighborhoods healthier and more attractive,

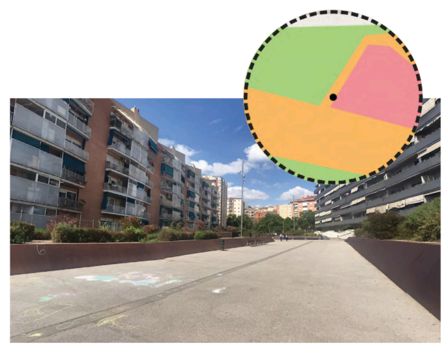
A. **Perceived on median very green (5/5) by 6 participants who rated it, but with a low median NDVI of 0.076 (Barcelona).**



B. **Unanimously perceived a little green (2/5) by 3 participants who rated it, but with a high median NDVI of 0.296 (Gothenburg).**



C. **Perceived green by 6 out of 7 partici pants who rated it, but surround ings not tagged in OSM as green- space, tagged as play space (colored pink) instead (Rotterdam).**



D. **Not perceived green by any of the 5 participants who rated it, but surroundings tagged in OSM as regular size greenspace (colored green, specifically, a park), as well as open public space (orange) and play space (pink) (Barcelona).**

Fig. 4. Exemplary locations where perceptions deviate from NDVI or OSM data.

such as increased property values, so-called green gentrification, and displacement of the residents in whose interests these interventions were originally designed (Curran & Hamilton, 2012; Wolch et al., 2014). Potential solutions are green interventions that are small-scale, in scattered locations, and evenly distributed rather than concentrated projects in one focal place that may kick-start gentrification (Wolch et al., 2014). Our qualitative findings regarding what it is that makes a location be perceived as green, while not formally tagged or depicted as such in data registries, may inspire such interventions. Examples include selecting varying vegetation extending in multiple directions; combining vegetation with other natural features such as water fronts or pervious surfaces; greening roadsides or traffic squares that may be perceived as green within their specific urban context; and limiting concrete or hiding built-up structures from view by tree canopies and hedges.

5.3. Limitations and future work

Several remaining limitations in this study could be addressed in future research. First, we collected only visual perceptions using street-level imagery, which should be interpreted as a proxy for perceptions in real urban environments (Salesses et al., 2013). Nonetheless, street-level imagery is becoming more important in urban analyses and is a promising source for efficient urban environment auditing (Biljecki and Ito, 2021; Rzotkiewicz et al., 2018). Second, the participants of our study cannot be considered a representative sample of the general population or of the case-study cities. We did, however, recruit European participants, balanced in age and gender, and found no significant differences in greenness perceptions among different groups. Third, regarding our questionnaire implementation, due to random chance, not all locations were rated as often as others. Furthermore, participants' perceptions may be influenced by the locations they have previously seen, or the places they are familiar with (Mehta, 2008), although we expect the effect of familiarity bias to be small given that less than 5 % of participants reported knowing some places from personal experience. Fourth, we limited our study to three European cities, but our method can be applied to any city in the world. We did notice some differences between Barcelona, and Rotterdam and Gothenburg. Future work could research how our findings hold across continents, climates, and cultures (Markevych et al., 2017; Catterall, 2009; Zhou et al., 2022), for LULC maps other than OSM, and for case study cities dominated by hills and viewpoints. Fifth, NDVI values are subject to change over time (Helbich et al., 2019), and the lushness of vegetation in street-level imagery is only a snapshot in time. While we used NDVI data and street-level imagery from similar years and months, we cannot rule out the effects of temporal changes. Sixth, we only analyzed places that were at least 200 square meters in size, which means that places smaller than approximately the size of a tennis court were not studied. Finally, future work could assess how people's visual perceptions are captured in other quantitative data, such as the Green View Index or computer-detected objects in street-level imagery; or to develop refined algorithms to select potential perceived greenspaces by combining NDVI and LULC maps, potentially using viewsheds and incorporating other spatial characteristics.

6. Conclusion

In this study we looked at how well NDVI and LULC data captured people's visual perceptions of urban greenspaces. While NDVI and LULC data are widely used in greenspace studies and planning, insight into their representation of visual perceptions has remained lacking to date.

We crowdsourced perceptions of public spaces in three European cities and quantitatively compared them to NDVI and to LULC data sourced from OSM, and qualitative explored reasons for deviations. Although we discovered an overall match between NDVI and OSM data and people's perceptions of greenness, notable deviations remain. NDVI values moderately correlate with perceived greenness, and OSM greenspaces are perceived to be greener than other types of public spaces except for play spaces, while pocket-size greenspaces are frequently perceived to be green as well. Selecting perceived greenspaces based on both OSM and NDVI yields better results in many cases. Furthermore, built-up elements may overpower the presence of vegetation, while a space may still be considered green given its urban context. Not only the amount of vegetation but also its configuration and variety influence people's perceptions of greenness, as do other natural features and perceptual qualities.

Our findings can help researchers and practitioners to make more informed decisions when collecting data for greenspace studies and planning. Future work could improve greenspace data collection by including more qualities that influence greenspace perception or test the transferability of our findings to other geographical contexts around the world.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Repositories containing our code and (pseudonymized) data are available at https://doi.org/10.4121/558f6150-a3e9-4960-82b2-cd2115c070d4 and https://doi.org/10.4121/5c3ad699-5ed4-4e91-8435-fb537e01f325, respectively.

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Appendix A. Supplementary data

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