Urban Forestry & Urban Greening 114 (2025) 129169

Contents lists available at ScienceDirect

Urban Forestry & Urban Greening

journal homepage: www.elsevier.com/locate/ufug

Review article

A methodological review of the assessment of urban greenery exposure

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ARTICLE INFO

Keywords:
Greenery exposure
Urban big data
Deep learning
Remote sensing
Digital twin

ABSTRACT

Greenery plays a vital role in urban environments, providing numerous benefits through diverse pathways. Various metrics and methodologies have been proposed to assess multiple dimensions of greenery exposure. For a comprehensive and precise assessment of greenery exposure for different research purposes, it is crucial to identify the most suitable methods and data sources. However, existing reviews primarily address the health outcomes of urban greenery, rather than the methods of assessing greenery exposure. To address this gap, we conducted a review of 312 research articles, focusing on methodologies and technologies for measuring greenery exposure in urban settings. This review categorizes exposure measurement techniques into three categories: proximity-based, mobility-based, and visibility-based, evaluating their strengths, limitations, and synergies. Proximity-based methods generally assess overall greenery level in residential areas or other locations, but they fall short in capturing the actual interactions between humans and greenery. Mobility-based methods track real-time human location and assess greenery exposure based on travel trajectories, but they neglect the specific nature of human-greenery interactions. In contrast, emerging visibility-based methods offer opportunities to measure potential visual interactions between individuals and greenery. We found emerging metrics tend to integrate 3D data, qualitative aspects, and diverse data sources. We advocate for an integrated approach that encompasses both human mobility and potential interactions with greenery across various areas. We also argue that data granularity is balanced against cost, scalability, and ethical constraints. Our comprehensive review offers a framework and categorization to guide studies in designing exposure measurements aligned with their research objectives.

1. Introduction

1.1. Significance of assessing people's exposure to urban greenery

Urban greenery is known to improve mental health (Gianfredi et al., 2021), boost physical activities (Lu, 2019), enhance community cohesion (De Vries et al., 2013; Dzhambov et al., 2018), and contribute to ecological benefits such as air purification (Abhijith et al., 2017) and temperature regulation (Cruz et al., 2021). To effectively monitor and leverage these benefits, it is crucial to measure people's daily exposure to greenery (Markevych et al., 2017).

People's interactions with greenery can be diverse, and each type of interaction may provide distinct benefits. Researchers have summarized these benefits as three major pathways: reducing harm, restoring capacities, and building capacities (Markevych et al., 2017). In the respective of harm reduction, urban greenery mitigates adverse conditions by enhancing microclimate as vegetation absorbs solar radiation, noise, pollutants, and carbon dioxide, thereby improving environmental comfort (Gillner et al., 2015; Zhao et al., 2018). The capacity restoration involves recovery from mental stress through visual or auditory exposure to natural elements, which lowers stress levels and restores directed attention (Ma et al., 2024). Capacity building refers to greenspaces facilitating physical activities and social interactions (Ward et al., 2016). Different pathways entail different types of interactions between people and greenery. For example, physical access to parks or green spaces enables active engagement in various physical activities, such as walking or jogging, which can improve physical health (Hearst et al., 2013; Lu et al., 2018). Visual views of greenery from home or work can enhance mental well-being by reducing stress and promoting relaxation (Bi et al., 2022; Du et al., 2022). Simply living near green spaces might influence air quality and provide a more comfortable microclimate, contributing to general health benefits (Cruz et al., 2021).

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https://doi.org/10.1016/j.ufug.2025.129169
Received 7 April 2025; Received in revised form 6 November 2025; Accepted 6 November 2025
Available online 7 November 2025

1.2. Evolving methods and data sources for measuring greenery exposure

To accurately assess the interactions between individuals and greenery through various pathways, it is essential to evaluate the supply (greenery), demand (people), and the interactions between them (exposure). The most common method for measuring exposure involves using simple buffers around individuals' residential addresses or other locations. It is argued that environmental benefits facilitated by urban greenery, such as noise reduction, temperature moderation, air purification, can be directly gained by nearby greenery without direct physical or visual exposure (Zhang et al., 2022a,b). However, this method provides a very coarse measure of greenery supply around a location. Furthermore, it does not differentiate the interactions, such as physical or visual ones. Some studies illustrated that the proximity between humans and greenery has little direct influence on mental and physical health (Dadvand et al., 2016). Different types of contact between humans and greenery might be an important potential mechanism (L. Zhang et al., 2022a,b). For example, the time spent in green spaces was linked to mental health more than proximity to green spaces (van den Berg et al., 2017). To address these issues, more detailed and sophisticated methods are required.

Traditional studies have often been constrained by technological limitations in assessing greenery exposure at both covering a large scale and capturing fine-grained dimensions (Sadeh et al., 2021). However, advancements in emerging sensing technologies and big data analysis tools have progressively addressed these challenges. Technologies such as GPS tracking and smartphone applications can collect data on individuals' movements and interactions with green spaces, offering insights into actual usage patterns rather than merely availability and potential access (Ladle et al., 2018). Additionally, participatory mapping that incorporates community feedback can provide contextual qualitative data to enhance quantitative analysis (Brown et al., 2018). Advancements in remote sensing, particularly with high-resolution satellite sensors, have improved the granularity of urban greenery mapping using indices such as the Normalized Difference Vegetation Index (NDVI) (B. Chen et al., 2022). Over recent decades, Street View Imagery (SVI) offers a human-centric perspective on greenery exposure and has been widely used to extract the percentage of visible greenery along streets (Li et al., 2015; Lu et al., 2018).

Recent advances in geoinformatics and the growth of 3D city models have also introduced innovative approaches for assessing greenery exposure. For instance, a 3D greening measurement method has been proposed, utilizing multi-dimensional metrics such as volume, area, and diversity, derived from mobile laser scanning (MLS) point clouds (Ferreira et al., 2024; J. Qi et al., 2022; Tang et al., 2023). Furthermore, these technologies facilitate the analysis of urban greenery exposure from various perspectives. For example, deep learning models have been adapted to quantify the proportion of natural views in window-view photographs obtained from 3D photorealistic City Information Models (CIMs) (Li et al., 2022), which can represent the indoor visual exposure of individual buildings.

In addition to emerging data sources, artificial intelligence (AI), particularly computer vision, has demonstrated significant potential for enhancing the analysis of greenery exposure. Recently, there is a rising trend of using advanced computer vision techniques to assess both the quality and quantity of greenery exposure incorporating prevalent urban images or 3D city models (M. Li et al., 2022; Li et al., 2015; Liu, Jiang, Wang, et al., 2023). Furthermore, computer vision is employed to examine the impact of vegetation on individuals' perceptions of urban views, such as aesthetic quality (Southon et al., 2017) and value of property (Xu et al., 2022). Beyond the direct assessment of greenery, computer vision also serves as a tool to generate urban images, offering more detailed information on greenery from low-resolution data, which is easier to acquire. For instance, researchers have utilized Generative Adversarial Networks (GANs) and diffusion models to generate street view images and other urban imagery, as well as 3D city models from 2D satellite images (Toker et al., 2021). Besides computer vision, other AI models such as natural language processing (NLP) and large language models (LLMs) also have the potential to directly or indirectly assess greenery exposure such as analyze people's perception and emotion on green space from user-generate contents from social media platforms (Wei et al., 2023).

1.3. Other related reviews

Most review papers published in international scientific outlets that discuss greenery exposure concentrate on examining its effects on one or several health-related issues (Barnes et al., 2019; Kondo et al., 2018; Luque-García et al., 2023; Twohig-Bennett & Jones, 2018). These issues include mental health (Barnes et al., 2019; Liu, Chen, Cui, et al., 2023; Park et al., 2024), physical health (Liu et al., 2022), cognitive function (Fowler Davis et al., 2024), physical activities (Yen et al., 2021), and others (Ccami-Bernal et al., 2023; Wolf et al., 2020). These reviews always found that different ways of defining and measuring green spaces can produce heterogeneous results of the same health issue. Since greenery may benefit people through multiple pathways regarding diverse outcomes, the measurement of people's exposure to green space must be tailored to concrete study contexts and research questions. However, there is a scarcity of review papers that focus specifically on the methodology and technology used to measure greenery exposure. While numerous studies have highlighted the health benefits associated with exposure to green spaces, few have critically evaluated the various techniques and tools employed to quantify or qualify this exposure. Existing studies have reviewed papers specifically for eye-level urban greenery using SVIs (Lu et al., 2023; Yan, Huang, et al., 2023). Y. Liu (2023) systematically reviewed existing green space representations and metrics for assessing individuals' exposure to green spaces, highlighting the limitations of traditional residence-based paradigms which often overlook individuals' mobility and the uncertainties in exposure along daily activity-travel paths. Notably, their review encompasses literature before 2021. From 2021–2024, advancements in 3D and computer vision technologies have significantly transformed the measurement of greenery and the interactions between people and green spaces.

1.4. Our review

This paper examines emerging approaches to measuring greenery exposure in urban environments, highlighting their strengths and limitations. We assess the suitability of these advanced techniques and explore the potential for their integration to yield more meaningful assessments. We also identify the research opportunities required to develop a comprehensive framework that integrates the strengths of different techniques. To the extent of our knowledge, this is one of the most comprehensive and wide-ranging reviews on greenery exposure studies focusing on methodology and technology, and adds new insights to the body of knowledge. Fig. 1

2. Methodology

In this study, we followed the established systematic review methods to identify relevant studies (Bowler et al., 2010) (Fig. 2). Our selection of keywords was guided by three primary considerations: firstly, the presence of various types of urban greenery; secondly, the interactions between humans and greenery; and thirdly, focusing on methodology or using the particular approach/metric/data source for the first time.

Various definitions of "greenery exposure" exist in the literature. The 3–30–300 Rule for urban forestry and greenery stipulates that: 1) every individual should have visual access to at least three mature trees from their residence; 2) each neighborhood must achieve minimum 30 % tree canopy cover; and 3) the distance to the nearest green space should not exceed 300 m (Konijnendijk, 2023). Therefore, this study defines "greenery exposure" as comprising: 1) visual access to urban green

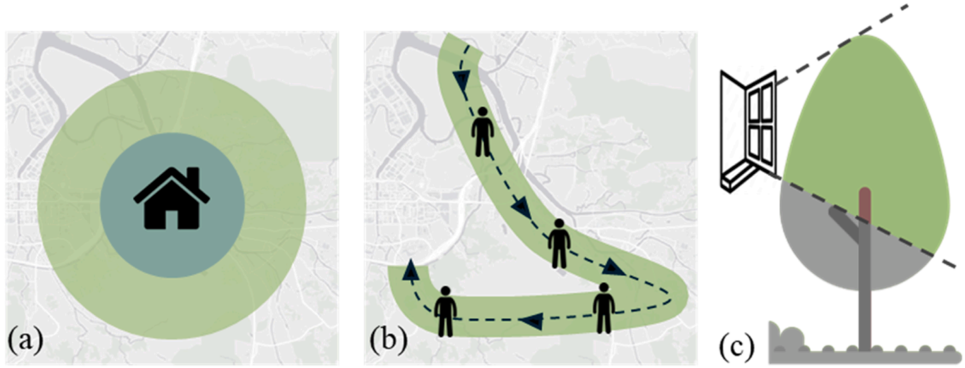

Fig. 1. (a) proximity-based measurements; (b) mobility-based measurements; (c) visibility-based measurements.

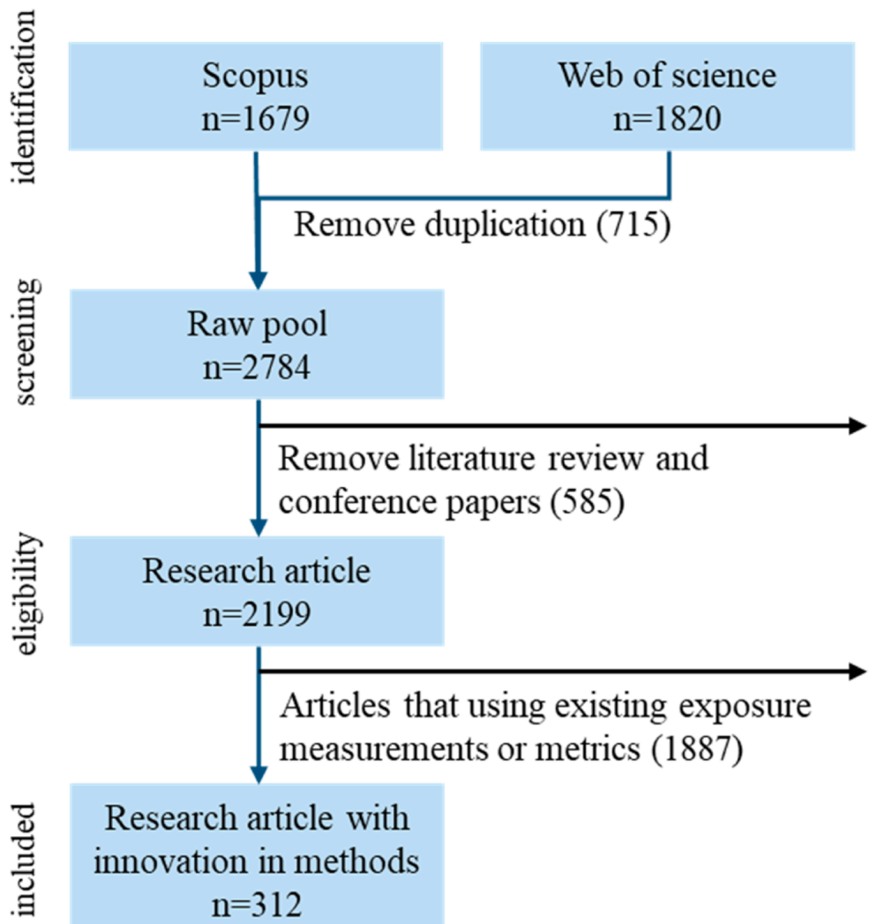

Fig. 2. The flow chart shows the process of literature screening and reviewing.

spaces or vegetation; 2) engagement in activities that involve urban green spaces; 3) physical access through visitation.

In the initial phase of our scoping review, we utilized multiple keywords related to "urban greenery", "exposure", and "methodology" to identify relevant publications by examining the full text of articles in two databases: Scopus, and Web of Science. To encompass the broadest interpretation of "greenery," a publication was included if it contained terms such as "park," "green space," "green infrastructure," "vegetation," "street tree," "shrub," "green belt," "horticulture," "greening" and related words. These keywords were searched across the title, keywords, and abstract. Additionally, the presence of methodology-focused terms such as "assessment," "measure," "approach," "measurement," "index," and "technology", alongside terms indicating human interaction with greenery, such as "exposure," "accessibility," "contact," "live," "work," "exercise," "visit," "visual," and "visibility." was required exists in the title to include only methodology-oriented studies on greenery exposure assessment. The search was restricted to peer-reviewed research articles published between 2000 and 2024. After eliminating duplicates, literature review, and conference papers, the search yielded a collection of 2199 publications, forming a raw literature pool.

In the subsequent phase of the review, the titles and abstracts of the research articles are screened to retain those that meet the following criteria: the study focuses on methodology or has employed one or multiple metrics/data sources to measure greenery, or human-greenery interactions, which not previously documented in earlier greenery-exposure studies. Furthermore, the study must have been conducted within an urban context, excluding rural, forest, or agricultural landscapes. The study should focus on human–greenery interactions (e.g., exposure, accessibility, visibility), excluding those focused solely on ecological or forestry outcomes without human exposure. The selected research is then systematically analyzed to address the research questions of this scoping review.

3. Results

3.1. Research on greenery exposure in the last two decades

A total number of 2199 research articles were identified initially. After the abstract screening, 312 articles that brought innovations in greenery exposure measurement or metrics were retained, while those that employed commonly used metrics as independent variables in environmental behavior and public health studies were excluded. There is a growing trend in the number of publications during both the initial filtration and the final selection stages. Firstly, we categorized selected studies by data sources for exposure assessment (Fig. 3). There is an increasing number of papers across most data sources. Satellite images and questionnaires have traditionally been dominant, but in the past two years, they have been surpassed by SVIs. Questionnaires, as a traditional data source, continue to increase in use because they are often combined with big data sources to provide qualitative information. Social media and mobile phone data experienced a period of growth but have fluctuated over time. SVIs and 3D city models emerged after 2014, with SVIs rising rapidly and 3D city models gradually increasing.

Building on prior classifications (Kwan, 2009), we distinguish three categories of approaches to measuring greenery exposure. First, proximity-based measures (previously referred to as proximity-based) rely on individuals' fixed addresses (e.g., residential or workplace) and the use of surrounding buffers to quantify greenery accessibility or the ratio of greenery to population/buildings. Second, mobility-based measures expand exposure assessment beyond fixed locations by incorporating greenery along individuals' movement paths within a given time frame. Both proximity- and mobility-based measures conceptualize exposure primarily in terms of the relative 2D positioning of individuals and greenery (distance, buffer, accessibility). In contrast, visibility-based measures exclusively capture potential or actual visual interactions between individuals and greenery. This approach emphasizes the role of the 3D built environment in shaping what people can or cannot see, which cannot be accurately represented through 2D proximity or mobility metrics. By explicitly distinguishing visibility-based measures from proximity- and mobility-based ones, we argue that these three represent fundamentally different and complementary ways of operationalizing greenery exposure. (Figure 1). Before 2010, proximity-based approaches dominated related studies. Subsequently, both mobility-based and proximity-based methods advanced in parallel, exhibiting fluctuations starting in 2021 (Fig. 4). Visibility-based methods emerged in 2013 and have steadily increased, reaching a similar level to the other two approaches during the past two years (Fig. 4). Although these three categories show little overlap, visibility- and mobility-based measures not mutually exclusive. In the future, studies that integrate visibility-based and mobility-based approaches are expected to provide a more accurate assessment of greenery exposure.

The volume of literature was compared based on the data sources and types of human-greenery interactions analyzed (Fig. 5). As an emerging data source, most studies on greenery exposure used Street View Images (SVIs) for visibility-based and mobility-based assessments. SVIs were also used for proximity-based assessments to compute aggregate indices for spatial units, such as the Green View Index (GVI) (X. Li et al., 2015). The use of 3D city models enables researchers to measure greenery visibility from specific observation points directly, leading to a predominance of visibility-based assessments, though some studies also include proximity-based and mobility-based assessments. Questionnaires are primarily used to gather data of travel behavior, e.g., via travel log, resulting in their prevalent use in proximity-based and mobility-based assessments. Only a few studies use questionnaires for visibility-based assessments, such as obtaining respondents' scoring on photos taken in the street or from windows (Lin et al., 2022). Social media and mobile phone data offer the advantage of providing real-time locations and geolocated user-generated content, making them popular for mobility-based studies (Y. Chen et al., 2018; Lu et al., 2021). Traditionally, satellite images have been used for top-down greenery measurements in proximity-based assessments. Recently, satellite imagery has been combined with other data sources, such as social media, mobile phone data, and 3D city models, to conduct mobility-based and visibility-based assessments (Yu et al., 2016).

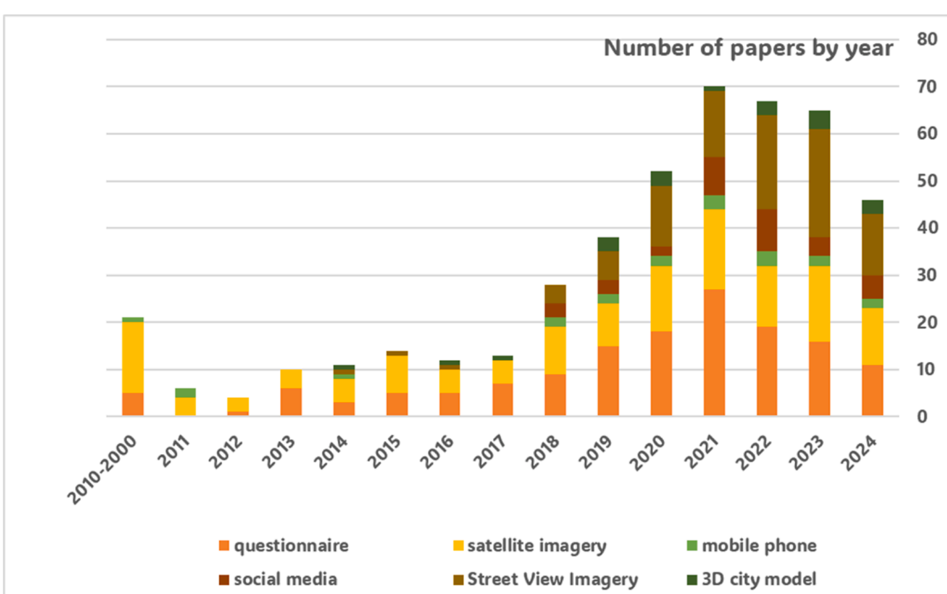

Fig. 3. The temporal evolution of greenery exposure studies by data sources.

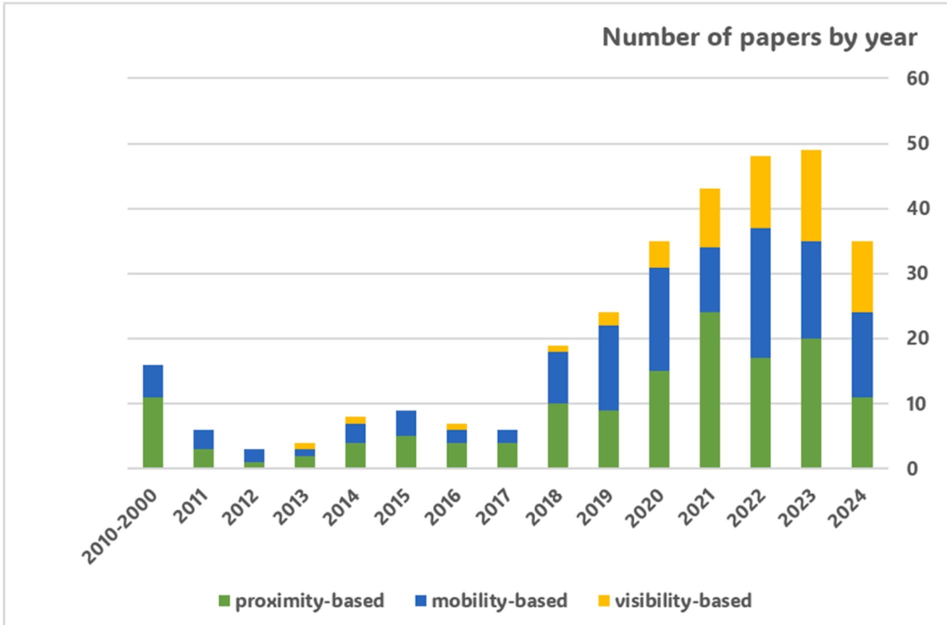

Fig. 4. The temporal evolution of the greenery exposure studies by types of measurements.

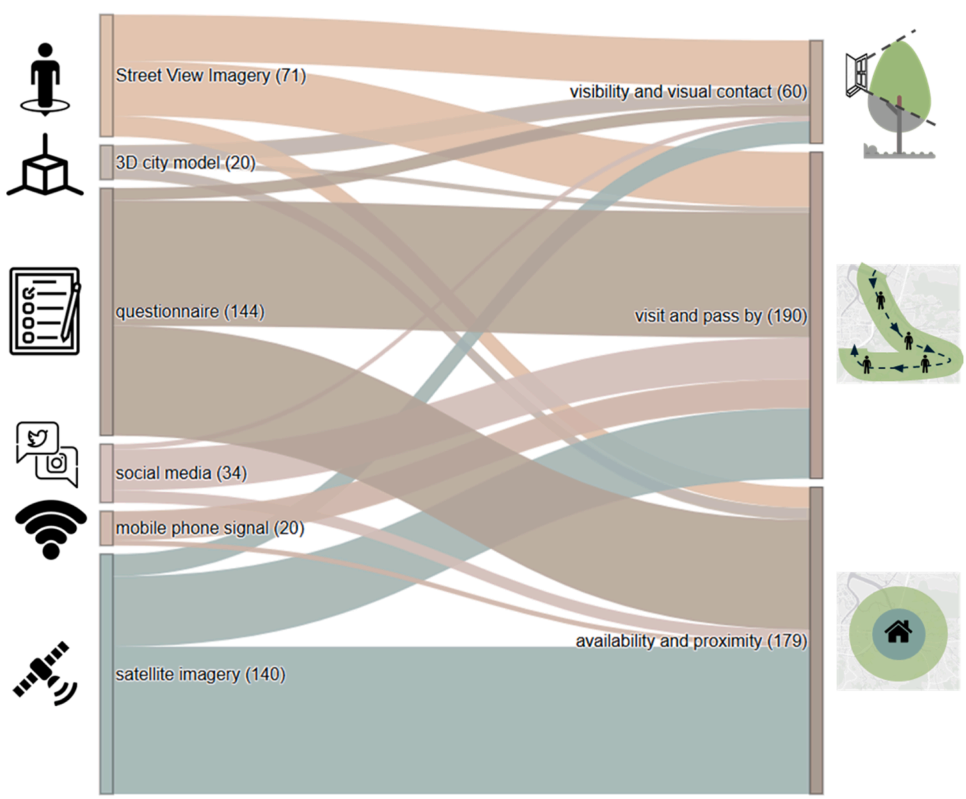

Fig. 5. Sankey diagram depicting the volume of literature based on the relationship between data sources and types of human-greenery interactions. (Note: Some studies utilized multiple primary data sources, resulting in potential multiple counts in this figure.).

3.2. Evolving technologies on greenery exposure measurement

3.2.1. Satellite imagery

Nearly half of the studies utilized satellite data. For decades, satellite imagery has played a crucial role in the large-scale assessment of urban greenery by forestry departments and urban planners (Iverson et al., 1989), and it continues to evolve (Phiri et al., 2020). The advancement of remote sensing technology, particularly the advent of high-resolution satellite systems, has significantly improved the capability to quantify urban greenery with higher spatial precision (Neyns and Canters, 2022; Pristeri et al., 2021). Various indices have been developed to quantify urban greenery and greenery exposure using satellite data, such as the Normalized Difference Vegetation Index (NDVI), which is commonly employed to evaluate vegetation health, density, and coverage in environmental behavior studies and public health research (Rugel et al., 2017; Song et al., 2018). In recent years, satellite imagery has been combined with 3D city models (Donovan et al., 2019; Yu et al., 2016), SVIs (Lu et al., 2019; Tong et al., 2020) to develop more fine-grained and multidimensional metrics for measuring exposure to greenery.

Most studies utilizing satellite imagery as the main data source concentrate on assessing the amount of greenery or the area of green space surrounding locations where people live, work, study, or engage in other activities, without determining whether visual or physical contact occurs (Fig. 5). By integrating smartphone GPS data (Almanza et al., 2012) or 3D building models (Li et al., 2016; Yu et al., 2016), it is now feasible to assess individuals' physical and visual access to greenery.

Compared with other data sources, satellite imagery offers relatively low acquisition costs when using open-access sources, with high spatial scalability and moderate-to-high temporal frequency. Processing demands are modest for basic indices such as NDVI but become more intensive for fine-grained classification. Technical accessibility is moderate, requiring GIS competence but not necessarily advanced expertise.

3.2.2. Eye-level imagery

SVI has been increasingly used in exposure studies since 2018, due to its availability, global coverage, and human-oriented perspective over the past decade (Biljecki & Ito, 2021; Li et al., 2015). It can also bridge some shortcomings of overhead-view greenery assessment. For example, the overhead view of greenery differs from the landscape as it is perceived by humans (Li, 2021). Furthermore, vegetation located beneath tree canopies and within urban vertical greening systems may be neglected in the overhead assessments (Lu et al., 2019). Numerous studies have utilized both eye-level and top-down greenery to evaluate individuals' exposure and compare their associations with human behavior and health issues. Some research concluded that eye-level greenery offers a better assessment compared to top-down methods (Lu et al., 2019), while other findings suggest that eye-level greenery more accurately captures vegetation in urban centers, whereas top-down greenery is more effective in representing vegetation in parks and forests (Labib et al., 2021). For long-term, population-level health outcomes (cohort studies), eye-level images even failed to outperform NDVI (Jimenez et al., 2022a; Yi et al., 2024).

Currently, most urban greenery studies using SVIs aggregately, calculating the average greenery ratio in SVI as the green view index of a spatial unit or the buffer of the residential location of individuals. Therefore, such measures are limited to quantifying greenspace exposure within the immediate residential street network, a scope that fails to account for the totality of an individual's visual experience throughout their daily life. (Liu et al., 2025). Besides, SVIs from map services, such as Google and Baidu, are primarily obtained from vehicle-based cameras on the road, which differs from the perspective of pedestrians (Ito et al., 2024). To conduct disaggregate analysis of greenery views from each SVI, a precise knowledge of the camera's position, such as pedestrians on the street or vehicles on the road, is necessary (Ki et al., 2023). Therefore, some studies have begun to use personal devices to capture street views or utilize crowdsourcing street view platforms (Y. Yang et al., 2021; Zhang et al., 2021), which may provide sufficiently accurate greenery measurements (Biljecki et al., 2023).

SVIs and crowdsourced images provide valuable human-scale perspectives of greenery but involve high processing costs due to computer vision requirements. Their spatial coverage is uneven and temporally inconsistent, depending on platform updates or user contributions. The approach is less technically accessible without advanced machine learning skills.

3.2.3. 3D city model

The application of 3D models in exposure studies remains limited but is experiencing steady growth. A 3D city model is a representation of an urban environment with a three-dimensional geometry of common urban objects and structures, with buildings as the most prominent feature (Biljecki et al., 2015). Such models are typically created using a variety of acquisition techniques, including photogrammetric approach or LiDAR, extrusion from 2D footprints (Arroyo Ohori et al., 2015), and architectural models or drawings (Donkers et al., 2016). However, existing urban 3D modeling predominantly emphasizes buildings and roads, frequently simplifying or excluding vegetation to minimize computational and storage demands (R. Wang et al., 2018). Data acquisition poses significant challenges, as sensors such as LiDAR often fail to capture intricate vegetation details, and seasonal variations hinder the creation of accurate static representations (Balestra et al., 2024; Norton et al., 2022). Furthermore, manually modeling vegetation is both resource-intensive and costly, while legal and privacy considerations may limit the mapping of vegetation in private or protected areas (Wang et al., 2018). However, emerging trends, such as environmental planning, procedural generation tools, and advanced sensors, are driving greater inclusion of vegetation in 3D models (Balestra et al., 2024). Using a 3D city model for greenery exposure measurement involves a comprehensive integration of detailed vegetation data within the urban model to evaluate not only physical accessible but also visible green spaces are from different locations across a city (Li et al., 2023; Yan et al., 2023). The process starts by collecting high-resolution data about the city's existing vegetation and other objects through methods like photogrammetry and laser scanning (Morgenroth and Gómez, 2014). These datasets are then used to generate a 3D city model, which includes detailed representations of city components, such as buildings, streets, and other infrastructure, facilitating an accurate spatial overlay of the existing urban and natural environments (Arroyo Ohori et al., 2018). This integrated model enables the performance of visibility analyses, such as viewshed or line-of-sight assessments, from various vantage points in the city, thereby allowing urban planners and researchers to quantify metrics of greenery exposure, such as the percentage of visible green area and the distance to the nearest green space (Yu et al., 2016).

The evolution of sensing technology, such as advanced LiDAR systems, high-resolution satellite imagery, and drone-based photogrammetry, has significantly contributed to the development of 3D city models at higher levels of detail (Biljecki et al., 2015). These technologies allow for the precise mapping of urban environments, capturing intricate details of buildings, such as the location of windows, and natural elements like vegetation with high accuracy (Bolte et al., 2024). Consequently, these detailed 3D city models can offer precise spatial and non-spatial information regarding both humans and greenery, enabling a nuanced analysis of their interactions to evaluate greenery exposure comprehensively. For instance, researchers attempted to use 3D city models to locate pedestrians' walkways in order to assess eye-level greenery from the perspectives of potential pedestrians (Ki et al., 2023).

3D city models offer precise structural information on urban greenery, though acquisition and processing costs are high. Their spatial scalability is limited to selected cities, with infrequent temporal updates. The method demands advanced 3D GIS and modeling expertise, constraining accessibility.

3.2.4. Data from mobile phone signals and personally equipped GPS devices

Mobile phones and other personally equipped GPS devices offer detailed data for tracking human locations and mobility. Combining with spatial distribution of urban greenery, this data can offer insights into human exposure to urban greenery (Almanza et al., 2012; Guan et al., 2020). There are primarily two ways for utilizing these data in greenery exposure studies. Firstly, GPS and proximity-based services can be employed to track individual movement patterns, allowing them to determine the frequency and duration of personal visits to green spaces or areas with varying levels of greenery (Ladle et al., 2018; Roberts & Helbich, 2021). Secondly, data from mobile signal stations can be used to explore the collective behavior of people in greenery exposure by obtaining the number of people present around each station during specific time periods (Song et al., 2018). Both two ways can help assess accessibility, frequency of use, and the role of urban greenery in daily life (Kim et al., 2023; Xiao et al., 2019). However, ethical considerations, such as privacy and consent, are crucial when using mobile phone data, ensuring that data use is responsible and respects individuals' rights (Fuller et al., 2017).

Mobile signal data enable large-scale and temporally continuous tracking of population exposure, offering strong scalability. However, acquisition is costly and often restricted by privacy regulations and industry partnerships. Technical demands are moderate, requiring data engineering and secure handling protocols.

3.2.5. Social media

Geolocated social media data represents a distinct category of mobile phone data characterized by user-generated content. It was popular in studies on greenery exposure, but their occurrence has declined. Social media serves as a valuable resource in studies on greenery exposure by offering innovative avenues for data collection and participant engagement (Ghermandi and Sinclair, 2019). Researchers can employ geospatial analysis on social media data to study accessibility and usage patterns of green spaces (Ghermandi et al., 2022; Heikinheimo et al., 2020). Additionally, platforms like Instagram and Twitter provide rich datasets through geotagged posts and hashtags, enabling researchers to analyze patterns of green space usage and public sentiment in green space (Grzyb et al., 2021; Plunz et al., 2019; Roberts et al., 2019). While providing diverse data and engagement opportunities, the use of social media inevitably raises ethical concerns about privacy, consent, and biases in data representation (Ghermandi and Sinclair, 2019).

The emerging Natural Language Processing (NLP) technology has boosted the application of social media in evaluating people's exposure to greenery recently. Through analyzing user-generated content, studies obtained insights into public sentiment and interactions with urban greenery from social media (Chen et al., 2018; Heikinheimo et al., 2020; Wei et al., 2024). Through sentiment analysis, NLP can determine whether sentiments of the contents shared on platforms like Twitter or Facebook are positive or negative (Wei et al., 2023). Topic modeling can identify common themes, such as recreational activities or health benefits associated with green spaces (Heikinheimo et al., 2020).

This data source provides highly frequent, real-time observations of greenery exposure but suffers from spatial and demographic biases. Data acquisition is inexpensive, though processing requires expertise in natural language processing and computer vision. Its scalability is moderate, as coverage is concentrated in urban, tech-savvy populations.

3.2.6. Questionnaire

Questionnaires served as a significant tool in greenery exposure studies for a long time, which is a widely used tool for collecting self-reported data regarding individuals' interactions with urban greenery (Dzhambov et al., 2021; Lin et al., 2022). They can capture a range of individual-level information, including the frequency, duration and motivations of visits to various green environments like parks, gardens, or nature trails (Flowers et al., 2016). Questionnaires are effective for assessing perceived benefits such as improvements in physical health, mental well-being, and stress reduction attributed to time spent in nature (Van Den Berg et al., 2019). They can also be used to identify barriers individuals face in accessing green spaces, such as safety concerns or lack of nearby facilities (Wendel et al., 2012). Additionally, questionnaires offer insights into the quality and features of green spaces that participants find most valuable (Stessens et al., 2020). By gathering demographic and contextual information, researchers can better understand differences in greenery exposure across various populations (Helbich et al., 2020; Wang et al., 2019). Furthermore, questionnaires can also be used in conjunction with other data sources, such as SVIs and GIS, to obtain complimentary subjective and objective data (Stessens et al., 2020; Yang et al., 2021). The advent of mobile phones and the Internet has expanded the dissemination channels for questionnaires, establishing them as a pivotal tool for crowdsourcing data collection in greenery exposure studies (Heikinheimo et al., 2020).

This tradition method is straightforward to implement and highly accessible, with moderate acquisition costs and minimal processing requirements. Its scalability is constrained by sampling limitations, and temporal frequency is typically low due to the resource intensity of repeated surveys. Despite these limits, they remain widely used for self-reported greenery exposure.

3.2.7. Other data sources

In addition to the data sources previously discussed, various tools are available to support the measurement of greenery exposure. Land cover maps, such as OpenStreetMap (OSM) or official maps, serve as significant resources for identifying and quantifying green spaces (Teeuwen et al., 2024). Furthermore, OSM provides contextual information on surrounding facilities and infrastructure, which can influence the quality and accessibility of green spaces (Cimini et al., 2024). As a common and widely used data source for measuring greenery, land cover maps appeared in nearly every study on greenery exposure. However, the innovation in these studies does not stem from the land cover maps themselves but rather from how they are integrated with emerging data sources, such as GPS devices and social media data (Guan et al., 2020; Heikinheimo et al., 2020). Therefore, we do not classify these studies as a separate category but instead group them based on the complementary data sources they are combined with.

Besides, advanced technology such as saliva measurements (Veitch et al., 2022), electroencephalography (EEG) (Lin et al., 2020), and eye-tracking (Li et al., 2020) were utilized to assess human interactions with greenery and their physiological and behavioral outcomes. These innovative tools focus on capturing human responses to green environments; however, they do not provide direct insights into the specific aspects of human interaction with greenery, such as what, where, and how these interactions occur. Therefore, they require integration with complementary data sources to achieve a comprehensive evaluation of exposure so are not included in this review (Table 1).

3.3. Research on greenery exposure according to the type of interactions

3.3.1. Proximity-based exposure

Traditional studies on greenery exposure primarily focus on quantifying vegetation or green space area within the buffer zones surrounding places where individuals live, work, study, or engage in other activities (Giannico et al., 2022; Rugel et al., 2017; Rundle et al., 2011) (Table 2). Initially, researchers evaluated greening within a geographical unit based on the proportion of green space or tree coverage (Lang et al., 2007; Zhu et al., 2003). Subsequently, many scholars began to consider not only the proportion of green areas but also the relative distribution of green spaces and buildings (Gupta et al., 2012; Li et al., 2014). Some studies utilized building characteristics and population data to weight human-centered greenery exposure (Chen et al., 2022; Rugel et al., 2017). Early research mainly relied on satellite imagery to identify green spaces and trees (Gascon et al., 2016; Uto et al., 2008). Over time, the use of street-level images to assess eye-level greenery became more common (Li et al., 2015; J. Yang et al., 2009), alongside employing 3D city models to measure both green and building volumes, with the green-to-building volume ratio serving as an indicator of greenery exposure (Giannico et al., 2022; Lafortezza and Giannico, 2019). However, this approach only reveals the proximity between people's potential locations and vegetation, while neglecting the real interaction of people and urban greenery and failing to provide any insight into how they are using and benefiting from the greenery (Liu, Kwan, Wong, et al., 2023).

3.3.2. Mobility-based exposure

Beyond proximity-based studies, certain research methodologies employ individuals' actual locations to evaluate their exposure to green spaces (Kwan, 2009) (Table 3). These studies can be categorized into

Table 1
The scalability and accessibility of each data source

Data source	Acquisition cost	Processing cost	Spatial scalability	Temporal frequency	Technical accessibility
Satellite images	Low–Medium (many are open-access; very high-res imagery costly)	Low–Medium (basic GIS for NDVI; higher for segmentation)	High (global coverage)	Medium–High (weekly–monthly updates for free sources)	Medium (basic GIS training sufficient; advanced ML for fine detail)
Eye-level images	Low (Google SV free; crowd-sourced images free; but API fees or licensing can add up)	High (computer vision, large storage/processing demand)	Medium (coverage biased to urban, not rural; varies by country)	Low–Medium (commercial SVIs updated irregularly; crowdsourced photos uneven)	Low–Medium (requires ML/CV expertise)
3D city model	High (LiDAR flights expensive; 3D models proprietary in many cities)	Very High (data heavy, need 3D modeling expertise)	Medium (available in selected cities, not global)	Low (updates rare, every few years)	Low (specialized 3D GIS skills required)
Social media	Low (data “free” but API restrictions)	Medium (need NLP + CV for greenery detection; noisy data)	Medium (urban centers only, socio-demographic bias)	High (real-time, continuous posts)	Medium (requires data mining, NLP, CV skills)
Mobile signal	High (requires collaboration with telecoms, costly access)	Medium (spatial aggregation, linkage to greenery maps)	High (near-universal coverage in many countries)	High (continuous, real-time data streams possible)	Medium (requires data engineering + privacy protocols)
Questionnaire	Medium (printing, field staff, incentives, but manageable)	Low (basic stats analysis)	Low–Medium (sample size limits, hard to scale city-wide)	Low (cross-sectional; costly to repeat longitudinally)	High (easy to administer, no special technical skills)

Table 2
The representative approaches of proximity-based measurements.

Study	Greenery exposure measurement	Measurement meaning	Data source	Study area
Zhu et al., (2003)	Vegetation Cover Index (VCI)	Proportion of vegetation cover in an area	Satellite image	Beer Sheva, Israel
Lang et al., (2007)	Weighted Green Index	occurrence and distribution of relevant green structure types weighted by relative importance of these types in the eyes of the citizens	Satellite image / Survey	Phoenix, USA
Gupta et al., (2012)	Urban Neighborhood Green Index (UNGI)	the spatial distribution of UGS in the vicinity of urban built-up	Satellite image	Delhi, India
Li et al., (2014)	Building’s Proximity to Green spaces Index (BPGI)	the green spaces adjacent to a building	LiDAR 3D building models / Satellite image	Székesfehérvár, Hungary
Li et al., (2015); J. Yang et al., (2009)	Green View Index (GVI)	the amount of greenery that people can see on the ground at different locations in a city	Street View Images	Berkeley, USA / New York City, USA
Rugel et al., (2017)	Natural Space Index	potential exposure based on the presence, form, accessibility, and quality of multiple forms of greenspace and bluespace	Satellite based data	Vancouver, Canada
Lafortezza and Giannico, (2019)	Normalized Difference Green-Building Volume (NDGB)	the way people perceive the ecosystem services conveyed by green spaces	LiDAR 3D building models	Bari, Italy
Giannico et al., (2022)	3D Green volume/gray volume and Normalized Difference Green-Gray Volume (NDGG)	the volume of vegetation and its relationship with the volume of buildings	LiDAR 3D building models	Rome, Italy
Chen et al., (2022)	Population-weighted greenery exposure	Population weighted green space coverage	Satellite images	China

Table 3
The representative approaches of mobility-based measurements.

Study	Mobility Measurement	Mobility data	Greenery measurement	Data source	Study area
Almanza et al., (2012)	Time and location of participants	Data from portable GPS	NDVI	Satellite imagery	Chino, USA
Ladle et al., (2018)	The location history data from 280 university students	Smart phone GPS data	Land use data	Land cover map	The City of Calgary, Canada
Song et al., (2018)	Hourly human distribution map	Mobile phone data (Tencent)	Normalized Difference Greenness Index (NDGI)	Satellite imagery	Thirty Chinese cities
Chen et al., (2018)	time-spatial distribution of urban park users	Social media real-time Tencent user density (RTUD) data	Park boundary	Land cover map	Shenzhen, China
Guan et al., (2020)	park visit and residential locations of visitors	mobile signaling data	Park boundary	Land cover map	Tokyo, Japna
Heikinheimo et al., (2020)	Geolocated posts about park use	Social media data and mobile phone data	Park boundary	Land cover map	Helsinki, Finland
Zhang et al., (2021)	Wearable GPS	Real time location from GPS	Images taken by a wearable camera	Wearable camera	Beijing, China
Ghermandi et al., (2022)	Number of geolocated social media photos	Geolocated social media photos	Element in geolocated social media photos	Social media	Haifa, Isreal
Liu et al. (2023)	GPS-equipped mobile phones	7-day GPS trajectories	NDVI	Satellite imagery	Hong Kong, China

two groups. The first involves measuring the aggregate number of people present in various areas during specific time intervals such as the pedestrian volume of streets (Liu, Wang, Grekousis, et al., 2023; Yin et al., 2015). These areas may consist of spatial units with varying levels of greenery, such as streets, or may directly be greenspaces like parks (Chen et al., 2018; Guan et al., 2020; Heikinheimo et al., 2020). Traditional studies typically obtain the number of pedestrians or visitors by manually counting in the field. Recently, studies automatically estimated number of people through social media, SVIs, video surveillance to calculates the people-weighted greenery exposure (Chen et al., 2018; Yin et al., 2015).

The second method focuses on assessments of individual real-time trajectories or locations (Almanza et al., 2012; Liu et al., 2023). The most common approach involves using questionnaires to gather travel logs of respondents (Pliakas et al., 2014). In recent years, some studies utilize geolocated social media images to pinpoint individuals' locations and recognize how they use green space (Ghermandi et al., 2022), though this approach may face challenges regarding insufficient spatiotemporal resolution, recall biases, and limitations in understanding the actual activities of individuals. Some of these studies assess green space exposure within relevant spatial contexts at specific moments (Xiao et al., 2019), and the other evaluates the spatiotemporally weighted accumulation of exposure throughout an individual's activity-travel trajectories (Liu et al., 2023). Besides, studies used wearable cameras equipped with GPS to capture images along participants' daily routes and analyze the proportion of greenery in these images (Liu et al., 2023; Zhang et al., 2021).

3.3.3. Visibility-based exposure

While mobility-based methods focus on the dynamic location of people therefore can evaluate the real-time proximity between individuals and greenery, how a human and greenery interacted remains unclear. Two major types of interactions between humans and greenery exist, which are visual and physical contact to greenery (Cox et al., 2017). Proximity-based and mobility-based exposure can be considered as physical contact (or physical proximity) to urban greenery.

Compared with physical contact, the assessment of visual accessibility or direct visibility is more complex due to the influence of three-dimensional factors. 3D city models are particularly effective for various visibility analyses, such as determining the line of sight between two points within urban environments and estimating the volume of sight (Biljecki et al., 2015). Initially, manually constructed virtual models were utilized to assess the visibility of green spaces from different buildings (Yasumoto et al., 2011). Some research also employs 3D city models to obtain viewsheds and integrates these with greenery detected from satellite images (Meng et al., 2020; Yu et al., 2016) or SVIs (Qi et al., 2024) to measure greenery visibility. With advances in photo-realistic 3D models, studies can directly derive greenery distribution from 3D city models and assess greenery views for buildings (Li et al., 2022) and pedestrians (Ki et al., 2023; Tang et al., 2023). Additionally, some studies have developed indices based on 3D city models to evaluate the visual exposure to greenery (Bolte et al., 2024; Xia et al., 2024). Besides 3D city model, studies also employ urban greenery maps and high-resolution digital surface models to evaluate greenery visibility (Cimburova & Blumentrath, 2022). SVI also has the potential to assess the visual accessibility of greenery, but it should be transformed from a vehicle's perspective to a pedestrian's perspective using deep learning methods (Ito et al., 2024) (Table 4).

4. Discussion

4.1. Trend in automatic greenery exposure assessment

4.1.1. From 2D to 3D measurement

In greenery exposure studies, the large-scale representation of urban greenery has traditionally relied on 2D indicators, such as the Normalized Difference Vegetation Index (NDVI), which are derived from satellite imagery (De La Iglesia Martinez and Labib, 2023).

However, 2D indicators alone are insufficient for the detailed measurement of urban greenery, and benefits related to 3D greenery volume, including carbon stock estimation, heat mitigation, and air pollutant removal. Meanwhile, the increasing vertical expansion of urbanization especially in high density areas has led to morphological heterogeneity in the urban landscape. This development has resulted in diverse spatial patterns of urban infrastructure and urban greenery, influencing the interaction of urban residents and urban greenery. Research has delved into the link between the visibility of nature and mental health benefits, including the relief of stress and fatigue (Du et al., 2022), reduction of anxiety and depression (Bi et al., 2022), enhanced positive emotions (Lin et al., 2022), and increase residential satisfaction (Kley & Dovbischuk, 2024). Recently, SVIs have emerged as an omnipresent data source for assessing urban greenery visibility. However, SVIs are captured by vehicles traveling along the center of roads, which may not accurately represent views from other locations, such as pedestrians on the

Table 4
The representative approaches of visibility-based measures.

Study	Greenery exposure measure	Measurement meaning	Data sources	Study area
Yasumoto et al., (2011)	Access to the view of green spaces	The visibility of green space from different buildings	virtual city model developed manually	Kyoto, Japan
Yu et al., (2016)	Total Floor Green View Index (TFGVI)	the area of visible urban vegetation on a particular floor of a city building	LiDAR 3D building models / Satellite image	Shanghai, China
Meng et al., (2020)	Floor-level exposure opportunity index	the amount of vegetation people perceived on a particular floor of a city building	LiDAR data and aerial imagery	Székesfehérvár, Hungary
Lin et al., (2022)	Greenery ratio in window view content	the ratio of pixels for Greenery in a window's view	Manual taken photos in questionnaire	Taibei, China
Li et al., (2022)	Window View Indices (WVIs) of Green	the ratio of pixels for Greenery in a window's view	3D photogrammetric city model	Hong Kong, China
Cimburova & Blumentrath, (2022)	visual exposure to urban greenery	viewshed-based method for modelling visual exposure to urban greenery	GRASS GIS	Oslo, Norway
Ki et al., (2023)	human-centric virtual street view greenery	the ratio of pixels for Greenery in pedestrians' view from sidewalk	3D photogrammetric city model	New York City, USA
Tang et al., (2023)	Green View Index	the ratio of pixels for Greenery in pedestrians' view from sidewalk	Mobile laser scanning (MLS) point cloud data	Fuzhou, China
Xia et al., (2024)	Greenspace Composite Index framework	3D greenery exposure levels in communities considering the range of residents' activities	LiDAR data based 3d model	Nanjing, China
Qi et al., (2024)	Building Green View Index	visible green space from a building	Street view images and urban construction data	Shenyang, China
Bolte et al., (2024)	The green window view index	The proportion of visible vegetation area in a field of view when looking out of a specific window	airborne LiDAR data	Bonn, Germany

sidewalk or residents near windows (Ito et al., 2024).

Recent advancements in technologies such as Light Detection and Ranging (LiDAR), photogrammetry, high-resolution aerial remote sensing, and 3D Geographic Information Systems (GIS) have significantly enhanced the precision and comprehensiveness of 3D city model, which may it feasible to measure comprehensive 3D characteristics of urban greenery. These 3D city models provide opportunities to extract 3D indicators of greenery consider elements like green volume, vegetation types, shade and microclimate effects, and offer a more detailed understanding of the features of greenery in a given space (Giannico et al., 2022; Spano et al., 2023). Meanwhile, incorporating 3D measurements allows researchers to accurately assess people's daily exposure to urban greenery. Traditional 2D greenery measurement methods primarily focus on the horizontal distribution of green spaces using GIS mapping and fixed buffer zones, which often overlook vertical elements and provide a static, oversimplified view. 3D city model offers opportunities considering factors like different locations people occupied, e.g., window view, street view. Hence, it provides a more accurate, detailed, and human-centric view of urban greenery, capturing the intricated dynamics of human and green space interactions. They support the integration with other technological tools, such as simulation models and environmental sensors to support the planning, designing, and managing green infrastructure (Jia and Wu, 2020).

4.1.2. Automatically greenery measurement: from quantitative to qualitative

Another trend in greenery exposure studies is that the automatic assessment of urban greenery has evolved from a sole focus on quantifying the level of greenery to a more comprehensive approach that includes both quantitative and qualitative assessments. Quantitative assessment of urban greenery involved using metrics such as number of trees around housing of people, the percentage of green area within a certain radius, which are easy to automatically be obtained from urban big data using advanced computer vision technology (Seiferling et al., 2017). Qualitative assessment of greenery exposure encompasses various non-quantifiable aspects of urban greenery, such as aesthetics, maintenance, safety, and amenities (Stessens et al., 2020). Qualitative evaluation of green spaces is crucial for understanding their subtle values and impacts beyond what quantitative measures can capture (Li and Wang, 2021). User engagement and accessibility are significantly influenced by qualitative factors (Palliwoda and Priess, 2021; Tan et al., 2019). Furthermore, urban greenery's health benefits, including mental restoration and stress relief, are enhanced by features like vegetation type, shade, and noise reduction, while also reflecting ecological values and social-cultural significance that strengthen community identity and cohesion (De Vries et al., 2013).

Traditionally, qualitative studies were carried out through field studies or questionnaires which were limited to sample sizes (Yang et al., 2021; Zhang et al., 2022a,b). Recently, advancements in AI and computer technology have introduced new changes to these methods (Liu, 2023). As a large-scale metric of greenery, NDVI also provides people with both quantitative and qualitative information on greenery (De La Iglesia Martinez and Labib, 2023). NDVI provides a measure of vegetation health overtime (Ji and Peters, 2003). By comparing NDVI values over different time periods, researchers can monitor changes in vegetation conditions over time (Kinyanjui, 2011). However, NDVI does not differentiate between different types of vegetation or species, limiting its ability to assess species-specific health or stress (De La Iglesia Martinez and Labib, 2023).

With the advantage of both easy to be acquired and high-resolution, Street view images recently also become an effective tool for evaluating the quality of greenery and greenery exposure (Ma et al., 2024; Tong et al., 2020). Street view images provide a detailed view of trees from the ground level, allowing researchers to assess tree species, vegetation structure, leaf index and health (Liu, et al., 2023). Also, street view images were used to grade people's perceptions on greenery such as aesthetic levels (Xu et al., 2022). This information can be calculated into aggregate index such as tree species mix and proportion of a specific species of trees to assess the impact of greenery quality on people's walking behavior (Jiang et al., 2024).

3D models generated through LiDAR and photogrammetry can offer detailed information about vegetation structure (Hancock et al., 2017). LiDAR generates high-resolution 3D models of vegetation, allowing researchers to analyze the structure of urban forests, including species, health conditions, leaf index (Kamoske et al., 2019). Photogrammetry can also generate 3D models but with color information, which can be beneficial for distinguishing different species or vegetation types based on color and texture (Tuominen et al., 2018). The use of 3D city models for qualitative assessing urban greenery and exposure to greenery is still underexplored, but it holds promise for the near future.

It should be noted that street view imagery is characterized as a 2.5D data between 2D and 3D (Taneja et al., 2013). While it conveys the impression of depth and a 3D environment, it fundamentally lacks explicit volumetric geometry (Armagan et al., 2017). These ground-level panoramic images offer immersive visual cues such as perspective and parallax, yet they remain surface-based projections anchored to specific camera viewpoints (Ito et al., 2024). In contrast, urban models derived from LiDAR or airborne photogrammetry explicitly encode spatial geometry through point clouds or textured meshes with precise x–y–z values, enabling comprehensive analytical capabilities, such as volumetric measurement (Casalegno et al., 2017), and occlusion-accurate visibility analysis (Li et al., 2022), that street-view images cannot support.

4.1.3. Adoption of AI in greenery exposure assessment

The significance of AI in measuring exposure to greenery has been increasingly recognized. The application of advanced computer vision techniques has greatly enhanced the capacity to extract information from images, including satellite imagery, street view photographs, social media images, manual taking images, and even images extracted from 3D city models (Li et al., 2022; Li et al., 2015; Y. Zhang et al., 2022a,b). Meanwhile, natural language processing (NLP) has also been employed to assess human exposure to greenery by analyzing user-generated content from social media, questionnaires, and interviews, thereby capturing more subjective evaluations of greenery and its perceived impact (Chen et al., 2018; Heikinheimo et al., 2020; Wei et al., 2024). Beyond the direct assessment of greenery, computer vision also serves as a tool to generate urban images, offering more detailed information on greenery from low-resolution data, which is easier to acquire. For example, researchers have employed Generative Adversarial Networks (GANs) and diffusion models to generate street view images (Toker et al., 2021) as well as transformed vehicle-view SVIs to a pedestrian perspective, more closely reflecting what pedestrians observe on the road (Ito et al., 2024). These AI-generated images can subsequently be used to evaluate eye-level greenery exposure.

The role of AI in exposure studies has evolved from objective measurement (Li et al., 2015) to inductive reasoning (Suppakittpaisarn et al., 2022) and, more recently, toward emerging applications of deductive generation (Ito et al., 2024). Objective measurement primarily involves estimating the quantity or quality of greenery from urban images (Li et al., 2015). Inductive reasoning involves drawing inferences from analysis rather than relying only on number or volume. This includes subjective perception on greenery such as interpreting people's comments on social media and review platforms, or scoring imagery to evaluate green quality (Havinga et al., 2021; Wang et al., 2023), and also objective analysis such as assessing the health condition of vegetation (Windrim et al., 2020) and how tree canopy functions on heat stress (Liu et al., 2024, 2024). Nonetheless, inductive reasoning AI, which draws conclusions from specific data observations, may face challenges in contexts with limited or unstructured data unless extensive datasets support it. Conversely, deductive generative AI leverages established scientific theories and principles, making it well-suited for environments defined by comprehensive regulations and standards (H. Xu et al., 2024). More recently, researchers have begun to explore generative approaches. Current demonstrated applications are relatively narrow, such as transforming greenery views across different perspectives (Ito et al., 2024; Toker et al., 2021). Beyond these, there is growing interest in potential applications such as predicting human behavior or simulating vegetation growth and microclimates. However, these remain exploratory rather than established.

A prevalent challenge across AI applications is the scarcity of high-quality datasets specifically curated for urban greenery. Furthermore, the application of AI in greenery studies is hindered by biases stemming from various data sources. For instance, SVIs used to extract greenery data are captured at different times across different locations. Additionally, other sources, such as mobile phone signal data and social media data, contribute to biases related to the demographic distribution of users. Early discussions suggest that generative AI might help mitigate such biases, although empirical validation remains limited (Mehrabi et al., 2022; Zhang et al., 2018). To facilitate this, there is a critical need for developing standardized, transparent measurement frameworks to ensure coherence and reproducibility in future research.

4.1.4. Multi-modal data integration

Another trend in greenery exposure evaluation is the integration of multi-modal data, combining diverse datasets and capturing the complex ways in which people interact with greenery (Weng et al., 2024). Studies employed satellite imagery for vegetation mapping, GPS-based mobility and wearable sensor data for dynamic exposure assessments, SVIs for evaluating greenery visibility, and social media or survey data to capture perceptions and emotional interactions, bringing human-centered insights, incorporating multiple aspects such as mobility, visibility, accessibility, and behavioral patterns over time (Chen et al., 2018; Guan et al., 2020; Yu et al., 2016). The key is to synthesize these diverse data points to create a richer understanding of when, where, and how people encounter greenery in their environments (Weng et al., 2024).

Data integration techniques such as spatial-temporal overlays, machine learning algorithms, and composite indices enable combining such varied datasets into meaningful metrics (Hashemi and Karimi, 2020). For example, wearable GPS data can be aligned with satellite-derived vegetation data to track individual exposure (Liu et al., 2023). Social media data, such as geotagged photos or text posts, can be used alongside objective measures to assess qualitative experiences and seasonal trends in greenery exposure (Guan et al., 2020). By combining these sources, we can analyze patterns of exposure across different demographic groups and geographic regions, identify disparities in access to green spaces, and investigate dynamic changes in exposure (Liu et al., 2023).

Besides, multi-modal data integration also enables multi-sensory exposure assessment, capturing auditory and olfactory dimensions of greenery experiences. For instance, acoustic data can reveal the presence of natural sounds such as birdsong or rustling leaves (Stobbe et al., 2022), while environmental sensors can capture odor-related compounds that shape olfactory experiences (He et al., 2022). By linking these non-visual sensory pathways with visual and mobility datasets (Korpilo et al., 2023), researchers can develop a more comprehensive understanding of how green environments influence human perception, comfort, and well-being across multiple senses.

However, key challenges persist, such as addressing data fragmentation caused by varying resolutions or timeframes, protecting user privacy when integrating human mobility and greenery data, and minimizing bias, as some data sources (e.g., social media or app data) may not represent all population groups (Senaratne et al., 2017).

4.2. From proximity-based exposure to mobility-based and visibility-based exposure

Researchers have classified human-nature interactions into three distinct types: intentional, incidental, and indirect (Keniger et al., 2013). ‘Intentional interactions’ refer to deliberate visits to natural spaces such as parks or gardens. ‘Incidental interactions’ occur when individuals encounter nature elements while engaged in other activities. ‘Indirect interactions’ involve viewing nature without being physically present within it. Studies found that in urban areas, indirect interactions dominate as the primary mode of human engagement with nature (Cox et al., 2017). Proximity-based measures indicate the potential for human-greenery interaction, relating to a concept of ’capacity building’—such as providing opportunities for physical activity or social engagement (Markevych et al., 2017). However, mere proximity does not confirm that these interactions actually occur. With the increasing availability of urban data sources in the era of big data and advances in AI, studies on greenery exposure are evolving towards more detailed and comprehensive measurements. Mobility-based methods focus on capturing individual movements, addressing methodological issues associated with proximity-based data, such as the Uncertain Geographic Context Problem (UGCoP) (Kwan, 2012). This type of measurement captures both ‘intentional interaction’ and ‘incident interaction’ combining with data delineating greenery, which can offer insights to both “reducing harms” and “restoring capacities” (Markevych et al., 2017). By considering human mobility, these methods allow for the assessment of real time distance between human and greenery by determining where and how much time individuals spend on their daily activities, rather than assuming exposure within a static place buffer (Kwan, 2009). Furthermore, by accounting for individual activity spaces and movement patterns, mobility-based measurements provide personalized insights into greenery exposure, enabling tailored health recommendations and interventions (Zhang et al., 2021). This approach is particularly valuable for examining short-term exposure impacts, such as stress reduction from brief park visits (Kabisch et al., 2021), as well as the long-term benefits from consistent interaction with green environments over years or decades (De Keijzer et al., 2016).

The visibility-based method emphasizes occurred or potential visual contracts between individuals and greenery, which belongs to ‘indirect interaction’. The visual perception of greenery serves as a primary pathway for “restoring capacities”, such as attention restoration and stress recovery (Markevych et al., 2017). The primary distinction between visibility-based methods and the other two types of methods (proximity- and mobility-based) is that the former focuses on the nuanced human visual contact with greenery, whereas the latter two merely considers the availability of greenery in an area or a location (Zhang et al., 2022a,b). For visual contacts, individuals residing on higher floors in the same building can have vastly different visual access to greenery compared to those living on lower floors (Li et al., 2022, 2023). Even within the same room, the view of greenery can vary significantly for individuals standing near the windows compared to those positioned further away or near other windows (Bolte et al., 2024). Therefore, a person’s location and posture also play a critical role; individuals in the same spot who are standing, sitting, lying down, or of different heights may experience different views of greenery. For example, individuals with mobility limitations living on upper floors of a high-rise building might have difficulty physically accessing nearby greenery but can still enjoy a visual connection to greenery (Rosso et al., 2011).

However, most visibility-based measures are resource-intensive and constrained in spatial coverage and temporal resolution, making them less practical for health research compared with location- or mobility-based approaches. To fully realize the accuracy of visibility-based exposure, detailed information is required not only on the precise location and form of greenery and the surrounding built environment (e.g., window placement), but also on individuals’ exact locations and the duration of their presence there (Li et al., 2023). For long-term, population-level health outcomes such as those examined in cohort studies, proximity-based measures often perform as well as or better than visibility-based ones (Jimenez et al., 2022b; Yi et al., 2024), potentially due to its greater temporal consistency, broader effective exposure area, and lower susceptibility to measurement. Furthermore, studies employing visibility-based measures often present a simplified view of human-greenery encounters, which prioritizes visual stimuli to the detriment of other sensory channels of greenery like sound (Bates et al., 2020) and smell (He et al., 2022), resulting in a 'visual bias' in health outcomes.

4.3. Ethical considerations in greenery exposure measures

While methodological advances in mobility- and visibility-based approaches have substantially enriched our capacity to quantify greenery exposure, they also raise profound ethical challenges. These methods generate highly granular data that can inadvertently expose sensitive aspects of individuals' daily lives, including residential locations, commuting routines, and social activities. The risks become even more acute when such exposure metrics are linked to health outcomes, as this combination heightens the potential for re-identification and misuse.

First, concerns about geoprivacy are paramount. Studies increasingly rely on personal location data, including home, work, and daily itineraries, that may be reverse-identified even after anonymization (Farzanehfar et al., 2021). The risk of inferring sensitive personal information and recommend safeguards such as pseudonymization and geographical methods is across all stages of research (pre-collection, processing, analysis, sharing) (Ribeiro et al., 2022). In recent urban health studies, for instance, smartphones have been used to collect minute-by-minute GPS traces that were then matched with street-view imagery classified by deep learning to quantify greenery exposure (Yi et al., 2025). Similarly, studies integrating wearable cameras and physiological sensors to capture participants' stress responses in different urban contexts have underscored the challenge of handling visual data that may inadvertently include bystanders or private environments without consent (Z. Zhang et al., 2021).

Beyond privacy, issues of informed consent and autonomy warrant critical attention. Participants may not fully grasp the extent to which their spatial traces or imagery reveal lifestyle patterns or vulnerabilities (Zhang et al., 2023). The complexity increases in studies using opportunistic or passively collected data, such as mobile phone records or large-scale street-view images, where consent is often indirect, opaque, or absent (Meyer et al., 2022). In such cases, individuals whose data or images are analyzed may not even be aware of their participation, raising fundamental concerns about autonomy and fairness (Zhang et al., 2023).

To address these challenges, researchers should adopt robust governance frameworks that go beyond legal compliance (Kelly et al., 2013). Recommended practices include minimizing the collection of sensitive variables, implementing privacy-preserving techniques such as aggregation or differential privacy, securing storage and access controls, and ensuring that consent procedures are transparent and comprehensible (Ribeiro et al., 2022). Ethical oversight should be iterative rather than static, adapting to evolving data practices, and community stakeholders should be engaged in decisions around data use. Epidemiological studies involving georeferenced personal data demand proactive ethical reflection to ensure that scientific benefits clearly outweigh the risks to participants (Ribeiro et al., 2022).

4.4. Future directions for greenery exposure assessment

The measurement of greenery exposure is becoming increasingly fine-grained and efficient. To achieve more precise exposure assessments, it is possible to evaluate the real-time, real-distance, and real-type interactions between greenery and humans. This requires accurate measurement of both individual's location and greenery drawing on emerging big data sources such as SVIs, 3D city models, social media data. Another direction involves utilizing limited available data to maximize the measurement of greenery exposure. AI, mainly computer vision (CV) and natural language processing (NLP), would play a crucial role in extracting information, reasoning problems, and generating data for more accurate and comprehensive measurements. Recent emerging LLMs have the potential to synthesize heterogeneous data sources—such as satellite imagery, SVIs, IoT sensors, and social media—to create holistic models of greenery exposure, enhancing decision-making through improved data analysis, participatory engagement, predictive modeling, and policy automation (Malekzadeh et al., 2025). Furthermore, future work may look beyond greenery measures to incorporate behavioural and psychological factors in exposure research. Even within identical green spaces, differences in behaviour, psychological status, and cultural background may result in vastly disparate "effective doses" of exposure for individuals (Sella et al., 2023). How to incorporate factors related to these behavioural and psychological contexts may represent another potential aspect requiring attention in fine-grained greenery exposure studies.

The results of these fine-grained and comprehensive measures would further inform studies in public health, environmental behavior, and transportation. These outcomes would guide planners and decision-makers regarding which types or features of nature provide the greatest benefits and how nature interventions compare to other measures that could enhance well-being, potentially at lower cost or with more lasting impact. Finally, a viable direction are comparative and quality assessment studies of measuring urban greenery. There has been some research initiated on this topic, e.g. studies comparing the performance of different data sources (Helbich et al., 2021; Huang et al., 2025), and studies on examining the reliability and coverage of particular data sources such as SVI (Biljecki et al., 2023; Fan et al., 2025). However, further work is needed to critically grasp the capability of each approach and the integrity of the derived measurements.

4.5. Limitation

This review has several limitations. First, a complete inter-rater reliability process was not conducted. The initial search, screening, and data extraction were performed by the first author, and the second and third authors independently checked the screened results for consistency with the predefined inclusion and exclusion criteria. Although a formal inter-rater reliability assessment was not carried out, this quality control procedure helped reduce subjectivity and enhance the rigor of the review. Second, the scope of this review was limited to methodological aspects of greenery exposure assessment. While this focus allowed us to provide a detailed synthesis of methodological advances, it did not extend to evaluating health outcomes, which may limit the applicability of findings for public health implications.

5. Conclusion

Urban greenery is a crucial element of urban environments, offering numerous benefits through various pathways. Traditional proximity-based methods inadequately capture the actual interaction between humans and greenery. Mobility-based methods focus on real-time human location data and potential human-greenery physical contact. Emerging visibility-based methods further provide opportunities to measure potential visual interactions between humans and greenery. Emerging data sources and technology enable developing metrics that account for both human mobility and potential contact with greenery, while traditional methods still held an advantage in scalability and accessibility. Current systematic reviews on greenery exposure primarily focus on the health outcomes of urban greenery and have largely ignored emerging visibility-based studies. To address this gap, we reviewed 312 studies using the particular approach/metric/data source for the first time to assess human exposure to urban greenery. We categorized these studies by the data sources used to measure greenery and human presence, and further classified them based on the aspects of details captured in human-greenery interactions as proximity-based, mobility-based, and visibility-based assessments. Our review offers the most comprehensive analysis of methodologies available for measuring human exposure to urban greenery. Our conceptual framework and categorization may guide a wide range of greenery exposure studies to design their exposure measurements according to the level of detail required for their research objectives.

CRediT authorship contribution statement

LU Yi: Writing – review & editing, Supervision, Funding acquisition. **Dongwei Liu:** Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Filip Biljecki:** Writing – review & editing.

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.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ufug.2025.129169.

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