

Review

Toward a Construct-Based Definition of Urban Green Space: A Literature Review of the Spatial Dimensions of Measurement, Methods, and Exposure

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Abstract: Interdisciplinary research has significantly advanced our understanding, benefits, and measurements of Urban Green Space (UGS). Further, the rapid expansion of research on this topic has resulted in a diverse array of definitions, which can rely on implicit assumptions without a formal definition. This variability highlights the need for a carefully structured framework to refine and combine these definitions. This narrative review examines constructs underlying UGS, particularly focusing on the spatial aspects of how we spatially measure UGS, the measurements of UGS, and how we define exposure; the latter focuses on two methods: viewsheds and image segmentation. Our findings reveal a shift in UGS measurement focus, moving beyond simple quantification of how much green space exists, to incorporate visibility, accessibility, and availability dimensions. Furthermore, advancements in computational tools, including artificial intelligence-driven methods, now enable high-resolution visibility measurements on a city-wide scale, supporting epidemiological research and urban development. These insights aim to guide researchers and practitioners in selecting suitable methodologies and datasets, as well as explicitly defining UGS in their work through a construct-based approach.

Keywords: greenspace; urban; GIS; data collection; health; NDVI; plan view; perspective view; viewshed; green view index



Academic Editor: Alexandru-Ionuț Petrișor

Received: 1 January 2025

Revised: 12 February 2025

Accepted: 24 February 2025

Published: 1 March 2025

Citation: Lee, D.H.; Chamberlain, B.; Park, H.Y. Toward a Construct-Based Definition of Urban Green Space: A Literature Review of the Spatial Dimensions of Measurement, Methods, and Exposure. *Land* **2025**, *14*, 517. <https://doi.org/10.3390/land14030517>

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1. Introduction

Global urbanization continues to rise rapidly [1]. Urbanization can reduce exposure to nature [2] and limit opportunities to experience green spaces, despite evidence that existing Urban Green Spaces (UGS) positively affect residents' well-being [3–11]. Nonetheless, studies also highlight the lack of accessible green spaces across urban districts [12–14]. To better understand the relationship between humans and UGS, researchers developed several ways to measure UGS allocation, accessibility, and visibility. Studies include perspective-view approaches using subjective methods [15,16], as well as more objective approaches such as remote sensing. The latter has facilitated the development of epidemiological and population-level approaches [17,18]. Regardless of the method, urban planners have sought measurement tools to support decision making, including the monitoring and improvement of UGS [19,20].

The literature uses both “green space” and “greenspace”, with variations often reflecting disciplinary perspectives and trends [21]. While we acknowledge these differences,

for consistency, we use “green space” throughout this paper. Using a narrative review process, we strive to synthesize the vast recent scientific literature on UGS by building a UGS construct that clarifies the core elements that constitute UGS—with emphasis on the spatial aspects of UGS. The purpose is to help clarify what UGS measurements are and how they are used, as well as to identify the various scales and constraints of UGS.

To guide our examination of the literature, we pose the following key question: (1) How can we define UGS that considers its wide variety of uses and interpretations? We then ask the following secondary questions: (2) What are the core methods for analyzing UGS, and (3) the key datasets used to measure UGS? Our literature review explores these questions, emphasizing the effects of greenness exposure and the utilization of digitized datasets in geospatial applications for measuring UGS. We develop a framework that presents an overview of the various geospatial and analytical methods employed in the UGS measurements. The framework includes a detailed discussion of the latest techniques for measuring green space and a comprehensive exploration of quantitative methods using GIS-based datasets to analyze UGS. Through this approach, we aim to contribute to a better understanding of UGS measurement and its applications across different fields. In the following subsections, we highlight the significance and importance of UGS, as well as methodological developments and challenges, as these two topics help establish a foundation for our methodological approach.

1.1. Significance of UGS Measurement

UGS typically falls within land use planning as open areas designated for parks and other natural settings [12,22]. However, its definitions and concepts often can vary across different disciplines [23]. For instance, some studies in the health sector define UGS based on administrative criteria, ranging from small gardens of a nursing home to multiple parks of a school district [24,25], while others focus on the overall greenness of geographic context from residential areas [26]. In environmental planning and ecology, the definition of UGS takes on an even broader definition to not only include cities but also regions [27]. Beyond differing definitions of scale, UGS can take on different definitions of function. For instance, UGS can act as a gathering space which may be used to advocate for the inclusion of sociocultural issues [6,28,29]. Consequently, the multifaceted approaches to defining UGS across diverse fields and studies underscore the challenge of establishing a uniform definition, reflecting the complexity and contextual nature of UGS interpretation [12]. Given the diverse interpretations of UGS across different disciplines, the measurement of UGS broadly captures greenery within study areas and often relies on geospatial datasets to assess physical or visual exposure to these spaces [30]. For instance, some studies have measured the physical extent of vegetation in cities such as Munich, Germany [31], Los Angeles, U.S. [32], and Montreal, Canada [33], using these datasets. Other studies have assessed proximity to UGS, such as public parks or semi-natural areas, to explore their association with physical activity [34] and mental health [35]. Despite these efforts, challenges remain, particularly in capturing how residents experience UGSs and the physical or visual interactions that shape urban life [6,8]. To address these limitations, measurements using GIS applications have advanced by improving data collection, processing, and analysis through a variety of means [36].

1.2. Methodological Developments and Challenges in UGS Measurement

These developments have enabled studies employing objective and quantifiable UGS measures, which can be broadly categorized into two groups. The first group focuses on developing original measurements or metrics, while the second group focuses on applications of these measures. Studies in the first group are often based on advanced remote

sensing data [30,37]. Technical advancements have made fine-grained, high-resolution data available, allowing for the use of more complex algorithms [38,39]. Developing original measures and utilizing diverse data have been combined in various interdisciplinary approaches, such as using social media for visibility analysis [40], a GPS accelerometer for nearby park accessibility [41], and machine learning algorithms to identify preferred urban spaces [42]. In particular, various artificial intelligence techniques integrated with image datasets captured by satellites or ground-level devices enable the distinction between green spaces and built areas at the city scale [43–45]. Those approaches lead to further advancement of UGS measuring techniques, such as digitizing individuals' perceived spaces [46–49].

Studies in the second (applied) group aim to better understand the implications of UGS measures on residents [26,50,51]. In these studies, UGS datasets are considered one of the variables, among other factors like socioeconomic status [52], mental health [53], and equity [13]. For instance, in epidemiological studies, they may use UGS datasets [54] or develop specific measurements to provide predictive variables for key health-related objectives [55]. The studies in this group concentrate on identifying what environmental factors affect their participants or how the UGS associates as a mediator [8,56]. Consequently, whether a study has developed a method for measuring UGS or has used the existing datasets, a critical point is that measuring and collecting quantified green space is consistently required in various fields of study.

Given the wide range of uses and methods associated with UGS measurement, there have been theoretical arguments about different kinds of data and related measurement techniques [27]. The literature provides examples of studies that used different source data to measure vegetation (e.g., NDVI derived from Landsat, the US Forest Service Percent Tree Canopy, and the National Land Cover Database). Meanwhile, advancements in technology mean new methods are continuously developed. For example, artificial intelligence-based feature recognition using Google Streetview [42,54] offers a very different approach because it measures green space in perspective view, rather than from above the city. However, this source variability complicates longitudinal studies, as UGS measures may not be consistent between datasets, making it challenging to observe changes over time [56,57] and to conduct quantitative meta-analyses [51]. Additionally, the absence of a specific framework for UGS datasets can make deciphering these data more challenging for planners and policymakers. For instance, the amount of UGS allocated for recreational use differs significantly from UGS displayed for urban aesthetics, yet both are commonly referred to as UGS [58,59]. Based on the findings of this review, the gap between dataset developers and end-users in understanding these distinctions has received little investigation in the context of UGS. To better understand the range of different uses of UGS, it would be helpful to create an organizational schema that assists individuals in identifying the data, methods, and techniques they use and ensures researchers and practitioners are aware of any related limitations.

Accurately measuring UGS, particularly near residential areas, has become increasingly important as these datasets are applied across various disciplines. In epidemiology, for instance, numerous studies have explored the relationship between UGS and population health outcomes [55,60]. While other fields have examined visual impact assessment [61] and the characteristics of urban areas [13,62], health-related research frequently refers to UGS as a *greenness exposure assessment*, emphasizing human interaction with green spaces [8]. This terminology reflects a broader shift in the field towards more human-centered analyses [36,50]. While measuring the perception of greenness remains subjective, the objective UGS measurement continues to provide valuable data for researchers, admin-

istrators, and planners. Such data can serve a wide range of purposes, underscoring its significance beyond mere measurement.

Furthermore, UGS data find application in exploring the potential health-promoting effects of green spaces [51] and ecosystem services provided by green infrastructure to aid urban planning efforts [63]. It demonstrates that understanding how these data are created and used across studies and disciplines can help bridge gaps between the developers of data sources and the users. The variations of UGS measures and definitions across fields further highlight the need for a more universally accepted terminology (or at least a higher-level representation of similar and different definitions). This seeks to clarify these differences and provide a framework to better understand the range of UGS measures and applications.

Lastly, having an organized framework could contribute to achieving Sustainable Development Goals (SDGs) by serving as an indicator of target goals. For example, Goal 11, which emphasizes making cities inclusive, safe, resilient, and sustainable, specifically highlights the importance of increasing public spaces as urban green infrastructure [64]. Achieving this goal necessitates the quantification and analysis of such spaces for equitable access and effective management [64,65]. A structured UGS measurement framework can assist the data users in selecting appropriate measures and understanding the factors that influence datasets.

2. Methods

We conducted a narrative review to explore the range of different measurements and subsequently produced a conceptual framework to represent this variety. A narrative review is advantageous when the topic spans various fields and linked information needs reinterpretation [66,67]. For example, UGS measurements are linked to geography, computer science, urban planning, and epidemiology. Our narrative review integrates findings from research across varied methodologies and theoretical approaches, focusing on the overall implications and improving our theoretical context for how we define UGS. PRISMA is a highly effective review approach, but its focus tends to be on the quantitative assessment of trends, patterns, and knowledge expansion of a particular topic. This model could be useful for UGS. However, a narrative review can be beneficial given the lack of theoretical constructs, the extensive range of methodologies, and the multidisciplinary of the topic [68]. The review process involved multiple iterations and revisions to ensure a thorough screening of articles. Indeed, as we identify in Figure 1, we also followed a structured framework, but it was also important to have the flexibility in our review to explore literature outside a constrained criteria search. Our primary focus was to extract key constructs and measurement approaches from the literature, starting with pre-existing review articles. Figure 1 below outlines our overall process.

The review used Google Scholar and Scopus to access a comprehensive range of peer-reviewed literature. While we acknowledge potential redundancy between these databases, we decided that using those ensures broader coverage. As noted in the introduction, users working with UGS datasets typically rely on available geospatial data within their study areas when initiating data collection. This means that studies employing UGS data are abundant, but the data collection process is often guided by practical considerations rather than specific theoretical foundations. Given this, researchers primarily select UGS datasets based on their study objectives and the availability of up-to-date data, rather than adhering to predetermined theoretical criteria. Since this review focuses on methodological applications rather than theoretical evaluations, Scopus provided sufficient coverage without requiring expansion to other databases (e.g., Web of Science or PubMed).

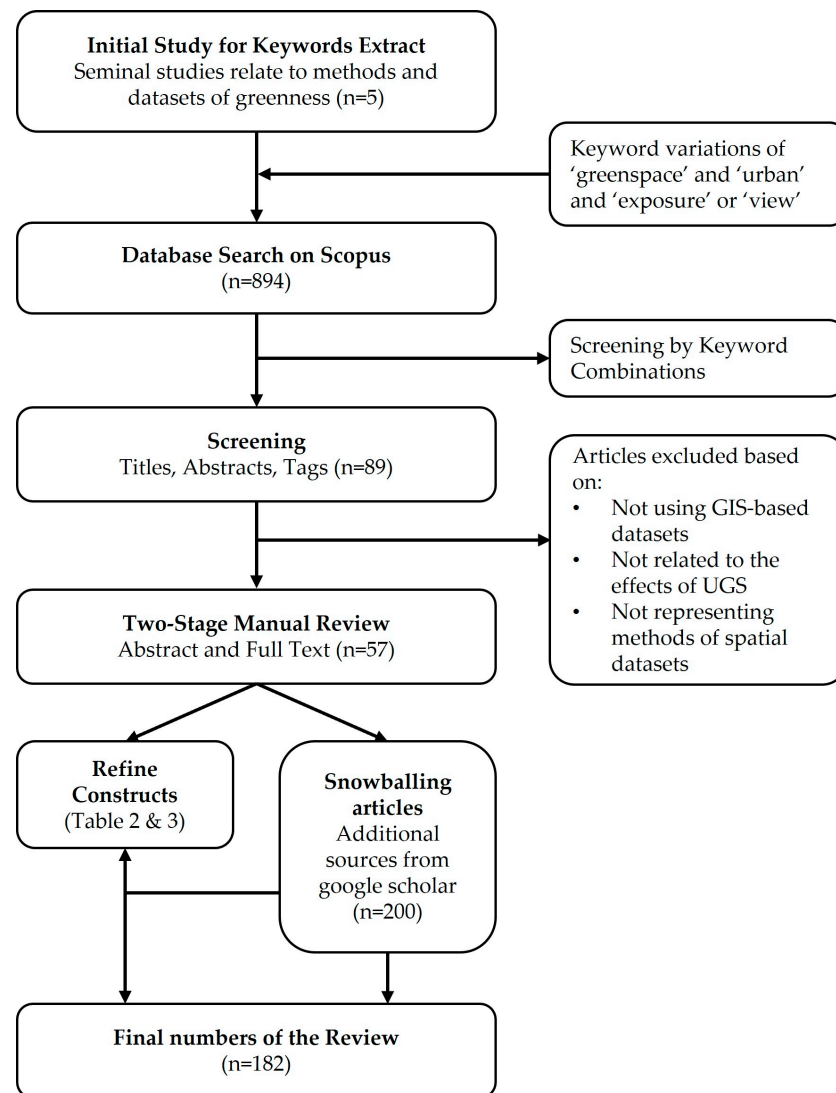


Figure 1. Search approach and the process of the narrative review.

To examine the methods employed in urban areas, initially, we used Google Scholar to search seminal studies (e.g., [8,36,38,56,69]) related to UGS measurements as a literature review. The retrieved literature contains methods for measuring or assessing greenness in certain spatial areas. Through the seminal studies, we extracted search keywords for searching in the Scopus search engine. We iterated through combinations to finalize the list of keyword terms. The following are the search terms: “greenspace” or “green space” or “greenness” or “greenery” or “green infrastructure” and “urban” or “city” or “metropolitan” and “exposure” or “visibility” or “view” or “viewing” or “visual”. We included articles written in English and published in peer-reviewed journals. The keywords search on Scopus retrieved 894 documents. A quick review of these titles (out of 894 documents) resulted in a majority of that seemed to be irrelevant to the purpose of this research. We suspected this was due to the broad range of topics that can be covered under keywords such as “green”, “urban”, and “view”. Additionally, due to the interdisciplinary nature of our research questions and objectives, identifying relevant literature using only specific academic terms may have led to unexpected results. For example, terms such as “green space exposure”, “nature experience”, “perceived natural landscape”, and “green space evaluation” carry distinct definitions but can be applied differently, despite often using similar GIS-based data representing vegetation.

Therefore, we needed to narrow the literature to more directly relevant articles. To accomplish this, results were imported into an Excel file, where we screened the literature by filtering titles, abstracts, manual tags, and automatic tags for the selected keyword combinations (Table 1). We selected studies that met at least one of the three categories of terms. This resulted in 89 articles.

Table 1. Keyword combinations for screening literature.

Green Space-Related Terms	Spatial Context Terms	Measurement-Related Terms
greenspace		exposure
green space	urban	¹ measur-
greenness	city	visibility
greenery	metropolitan	² view-
green infrastructure		visual

“green” was an essential term, inevitably including variations due to its generality. ¹ “measur-” was used to include studies employing independent data collection methods. ² “view-” was used to include studies measuring or collecting data on viewing objects.

The second step of this process was to manually review the 89 articles in a two-stage format: first by examining abstracts for applicability, then by quickly reviewing the full text. We were interested in identifying articles that dealt primarily with measurement along spatial measures (GIS-based approaches) or the effects of greenness exposure (which may have included GIS-based methods). For instance, studies that did not disclose data sources or geoprocessing methods for spatial data were excluded, even if they were conducted in urban areas. Additionally, studies examining psychophysical changes in a small number of participants were excluded despite incorporating spatial datasets. To screen these studies, we primarily focused on their applicability based on the methods section.

After this step, 57 articles remained, which were then subject to a full-text review. In the full-text review, we focused on developing the components of the constructs. The development of the five constructs for UGS measurements and datasets was guided by a structured evaluation of study components.

First, in the data collection section of each study’s methods, we assessed three key aspects: (1) the scale at which UGS data were collected, (2) the representation of the data, and (3) how individuals were exposed to UGS. Next, in the study design section, we examined how UGS data were measured and applied, with a focus on (1) whether a Quantitative or Qualitative approach was used, (2) whether data evaluations were Objective or Subjective, and (3) how exposure was assessed. These considerations formed the Methods construct. Finally, the results sections of the reviewed studies informed two additional constructs: (1) Measures, which capture the expected effects of UGS, and (2) Interactions, which describe the nature of engagement with UGS. The organization of these constructs was based on fragmented yet recurring themes in previous studies, which we systematically compiled in the results section.

To refine the constructs, we employed a snowballing method and iteratively identified additional studies that were not captured in the keyword search. This approach allowed us to trace studies with similar research objectives—primarily investigating the relationship between green space exposure and various influencing factors—while also capturing past datasets that illustrate trends in UGS measurement. This process, conducted via Google Scholar, yielded approximately 200 peer-reviewed journal papers, books, conference papers, reports, and technical webpages, which were reviewed with a focus on research objectives and methodologies. Those articles, identified through the snowballing method, were stored in the Zotero reference management software. We categorized the added references according to their respective constructs and compiled a bibliography.

3. Results

The review process identified approximately 200 articles spanning a broad range of disciplines that contributed toward concepts or applications of UGS. Topics covered in this literature include research on health benefits, ecosystem services, urban planning, and the application of remote sensing techniques. Additionally, a focused review of UGS measurements revealed five dominant constructs that guide the field: **scale, measures, methods, green/blue, and view type**. These constructs emphasize methodological and measurement-oriented approaches, rather than psychophysical or physiological assessments of exposure to UGS.

Through our synthesis of the literature, we found that the five constructs are commonly considered when collecting UGS datasets. While these constructs are not always explicitly introduced in each study's methods, they frequently emerge as limitations or underlying considerations. For instance, can NDVI-derived greenness datasets fully capture a community's direct experiences and intentional interactions with UGS? Or should subjective data collection be incorporated to better assess UGS at the individual level? These recurring limitations, stemming from the choices made in research design, highlight the need for a more standardized framework. We propose that organizing these constructs across studies serves as an initial step toward defining and standardizing UGS measurements.

The five constructs are commonly applied across three key research fields. First, a significant body of literature focuses on the health benefits associated with UGS [26,50]. These studies demonstrate that exposure to green spaces can lead to improved mental health [70,71], reduced stress [72,73], and better physical health outcomes [74,75]. UGS has been comprehensively linked to lower rates of heart disease, obesity, and mortality, highlighting their critical role in public health [23,76]. Additionally, proximity to green spaces is consistently associated with improved mental health and reduced psychological stress among urban residents [23,77]. Second, UGS is studied in the context of assessment of ecosystem services. These studies emphasize the role of UGS in climate regulation through urban heat island mitigation [78], biodiversity conservation [79], and the management of green infrastructure [80]. Third, UGS data are utilized in the realm of urban and environmental planning. Applications include measured visual impact assessments [61], enhancing the aesthetic aspects of urban environments [40], and landscape planning [81]. Recent advancements in computation technology significantly contribute to this discipline through the integration of artificial intelligence [42] by enabling more sophisticated analysis and applications.

To explore deeper into the application of UGS measurements, Table 2 provides an overview of our five key constructs, offering descriptions and subdivisions of the primary characteristics we identified about UGS in the literature. These constructs—scale, measure, methods, green/blue, and view type—are discussed comprehensively in the following subsections, with a focus on their methodological and measurement-oriented approaches.

Table 2. Constructs of Urban Green Space (scale, measures, methods, green/blue, view type).

Constructs	Characteristics	Description	Citations
Scale	Body/personal scale	The immediate surroundings of an individual (approximately 10 to 100 m)	[36,55,82–84]
	Neighborhood scale	The areas where individuals spend much of their time (up to approximately 500 m)	
	City scale	Used for comparing different administrative jurisdictions	

Table 2. *Cont.*

Constructs	Characteristics	Description	Citations
Measures Effects	Direct effects	The immediate psychological and physiological benefits that individuals experience	[6,85]
	Indirect effects	The broader, long-term benefits of natural environments that contribute to overall well-being	
Measures Interactions	Indirect interactions	Occurring without the need for an individual's physical presence in nature (e.g., video or view through a window)	[6,15,50,86,87]
	Incidental interactions	When individuals are physically present in natural settings, the interaction may be happenstance	
	Intentional interactions	Deliberate experiencing and being with nature (e.g., visiting a park for jogging or a forest for hiking)	
Methods Measuring	Quantitative	The approach measures the amount of UGS (e.g., the proportion of greenness, visible greenness)	[26]
	Qualitative	Using GIS to record individual's preferences (e.g., measuring attractiveness, user's intention to revisit)	[88,89]
Methods Data collection	Objective	Includes evaluative indices, such as the amount of green space (e.g., using aerial or satellite imagery, surveys)	[56,90]
	Subjective	Focuses on personal feelings and perspectives (e.g., attachment, accessibility, and impressions of green amenities)	[6,91]
Methods Exposure	Availability	The distribution ratio or quantity of UGS in the study area(s)	[6,8,36,38]
	Accessibility	Proximity of UGS to the study location(s)	
	Visibility	Viewable and perceptible UGS at spatial location(s) or linear space (e.g., street)	
Green/Blue	Green Only	Vegetation (e.g., using NDVI as a source data)	[23,80]
	Green and Blue	Vegetation and water features (e.g., pond, lake, ocean, river, waterfall)	
View Type	Perspective	Uses a ground-based (or similar) perspective to conduct assessments	[36,92,93]
	Plan	Uses a top-view approach	

3.1. Scale

Spatial scales represent boundaries that are determined through geographical limits or subjects' perceptual spatial boundaries [26,82,94]. There are a variety of different approaches to defining boundaries. For instance, these can include geographical boundaries using a radial buffer of a site, a network buffer from a home location, or administrative boundaries such as postal codes or districts [95,96]. However, these boundaries and scales may not reflect individuals' psychological boundaries, such as places where residents use spaces for daily activities [84]. Studies aligned with this context, measure the extent of exposure to natural environments or visible green spaces in participants' daily routines

through survey responses [15,41,74,97]. Despite various approaches, the relationship between UGS and individuals remains somewhat unclear, as potential discrepancies may exist between geographical and experiential or psychological boundaries (i.e., what a person perceives or feels within a geographical space, or whether they consciously or subconsciously perceive UGS).

Labib et al. [36] provide three different spatial scales ranging from the individual's cognitive domain to the domain affecting the population level: *body/personal scale*, *neighborhood scale*, and *city/district scale*. These spatial scales are pivotal in geographic analysis because they can influence the selection of units for representing the extent to which greenness affects and is a guide for data collection and analysis in studies of green space [83,98]. The study systematically investigated scales used in empirical studies, categorizing them from micro to macro levels [36]. Body/Personal Scale, also called micro-scale, ranges between 10 and 100 m and focuses on an individual's immediate surroundings, making it highly sensitive to environmental changes [82]. Neighborhood scale is defined by the spaces where an individual spends significant time and regularly interacts with the surrounding environment [26,94,99]. This boundary may be nebulous and ever shifting, yet it could reflect a similar socioeconomic population level. Presently, techniques to define these “fuzzy boundaries” in a GIS can better reflect human perceptions [100–102]. Representations at this scale can be either allocentric (e.g., administrative zones) or egocentric (e.g., buffer distances around a home). City/District scale encompasses a broader area, including all potential spaces used by urban dwellers in their daily activities, offering a more extensive overview of UGS utilization [55,103]. For instance, UGS datasets at this scale are paired with similarly scaled datasets on mortality [103], birth weight [104], and childhood obesity [32] to facilitate comparative analyses among cities.

Each spatial scale serves a distinct purpose, influencing how UGS is measured and how outcomes are interpreted. Understanding the implications of these scales is important for selecting appropriate units of analysis and research approaches.

3.2. Measures

UGS measurements in the reviewed literature fall into two themes: the effects of green space and individuals' interactions with the natural environment.

3.2.1. Effects of Green Space

Experimental studies investigate how UGS impacts subjects by distinguishing between the *direct* and *indirect effects* of the natural environment [85]. For instance, studies hypothesize that varying quantities and qualities of UGS exert discernible effects on individuals or residents [90]. These studies posit that different levels of exposure to UGS can lead to varied outcomes, either positive or negative [8].

Direct effects focus on how individuals perceive or use green space, and they are closely tied to the approaches used for measuring these spaces. For instance, studies measuring the direct effects of green spaces focus on designated areas where positive changes can be immediately observed [105]. In contrast, the indirect effects involve assessing the UGS impact on a broader, unspecified population, typically within a buffer zone of distance that may affect nearby residents [95]. Although not all experimental studies explicitly distinguish between the direct and indirect effects of greenness, these two characteristics often influence the location and size of the UGSs to be measured [33,95,106]. Direct effects are often examined in psychological and physiological studies, referring to the immediate benefits that individuals experience when exposed to natural environments. These effects are tangible and observable, often measured through changes in emotional and physical states [107]. For instance, viewing greenness through windows requires measuring only

a limited space of green areas [108,109]. Additionally, walking in a park [110], urban forest [105], street [111], or other natural settings involves measuring the exposure to greenness as participants move through the study area [112]. Such studies focus on whether perceivable greenness brings about psychological restoration or changes participants' mental fatigue by reducing it.

Indirect effects, on the other hand, involve broader, cumulative benefits from perceived natural environments [107]. These effects reflect the present status depending on the measured environments in certain periods, using cross-sectional designs in health-related studies. For instance, Maas et al. (2006) [18] used the total percentage of green space to explore the association between distributed vegetation and perceived general health. Approaches to measuring the indirect effects of existing green space often align with theories of cognitive restoration, measures of general well-being, and mitigating stressors of urbanization [6]. Besides, enhanced accuracy and capacity of UGS data processes have contributed to large-scale epidemiological studies, particularly at the national level [55,113].

3.2.2. Interactions with UGS

Keniger et al. [86] proposed a framework that defines three types of interactions (with the natural element of the environment): indirect, incidental, and intentional types. This framework classifies the extent to which green space is physically present in an individual. While few studies explicitly identify this distinction, the framework provides a structure for understanding how different types of interaction can clarify the relationship between health benefits and the residents in the study area.

Indirect interactions occur without physical presence, such as looking at nature through a window. For example, watching an urban park through the window in the office room or a forest of mountain areas is included in this interaction. Indirect interaction even encompasses green spaces through media so, the studies that examine the laboratory with devices (e.g., television screens, virtual reality) also belong to this type. Indirect interaction also includes viewing green spaces that are inaccessible, such as scenery observed from a building [109] or while in a moving vehicle [92]. Regarding UGS datasets, several studies have focused on sequentially viewing scenery [44] or tracking long-term changes in landscapes [114]. Studies assessing the visibility of UGS to unspecified individuals may implicitly rely on the premise that such interactions take place.

Incidental interactions happen when a person is exposed to green space through an unplanned outcome. For instance, a person's commute may provide a certain degree of green space exposure, despite that person not directly planning the route to engage with the green space. Likewise, a walk from the home to a school may provide incidental interaction [115]. A large body of visibility analyses represent these interactions, whereby they assume effects stem from views of green spaces as the predominate form of exposure. Moreover, studies investigating the benefits of nature using available UGS datasets are likely to account for these incidental interactions. This is because UGS datasets representing availability typically focus on accessible spaces, such as public parks or green spaces located near sidewalks [25].

Intentional interactions require purposeful visiting of green space. The key distinction of these interactions lies in the deliberate intention to experience nature, requiring studies to acknowledge participants' purposeful behavior. This could involve doing an activity within a green space and selecting an activity that maximizes green space exposure, such as gardening, hiking, or picnicking in a park [43]. Research on intentional interactions often necessitates additional user data (e.g., GPS tracking), which can be applied to GIS-based map datasets [87] to explore the relationship between UGS and health benefits.

3.3. Methods

In this section, we explore three different methodological themes identified in the literature. These themes include measurement approaches, methods for data collection, and finally, how researchers are producing exposure assessments. Figure 2 illustrates these three themes (Measure, Data Collection, and Exposure assessment), along with the associated subtopics, which are further explained below.

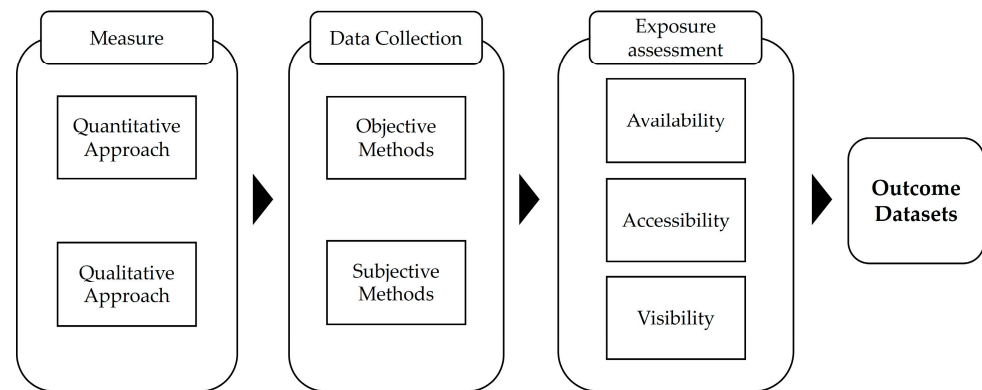


Figure 2. Conceptual diagram of UGS data collection method design. This diagram outlines the internal decision-making processes essential for designing UGS data collection methods. These considerations help researchers anticipate the data's impact on dependent variables within UGS studies.

3.3.1. Quantitative and Qualitative Measures

As with many fundamental research methods, there is often debate over the use of quantitative and qualitative approaches, and UGS studies are no exception. A variety of studies collect UGS data through remote sensing to quantify greenness, typically using these data as variables in statistical analysis (e.g., how much green in each boundary), characterized by their value (density, how green, or how vigorous the growth) and location (boundary). Interestingly, the processes for data collection and the variations of these sources allow for flexibility in how UGS data can be used, both in quantitative and qualitative ways. Quantitative measures primarily focus on the extent of UGS, such as the area occupied by green space, the proportion of tree canopy, and the amount of visibility of greenness along streets [116].

In contrast, qualitative measures emphasize the characteristics that influence UGS performance related to perceived and experienced nature [117]. These assessments mostly involve surveys that evaluate the attractiveness of green spaces using quality audit tools, accessibility [118], or other quality aspects like visual landscape, aesthetic appeal of large gardens, and facility quality for epidemiological studies [119–121]. Despite the predominance of quantitative approaches, the complexities in defining UGS quality may explain the limited empirical research on its health effects [58,89]. Assessing UGS quality can be challenging due to its subjective nature, which is often reliant on individual preferences [122,123]. Due to the limitations of qualitative measures, studies increasingly rely on quantitative data to examine the relationship between residents and green spaces, aiming to provide a more structured understanding of UGS influence.

Although there is no universally accepted definition of UGS quality, some studies integrate qualitative measures with evaluations of ecosystem services, such as species richness and land cover diversity [81]. UGS quality assessment often also employs qualitative measures to evaluate landscape aesthetics and mental health impacts. For instance, Swetnam et al. [121] highlighted the integration of perceptual surveys with visual quality indices to capture the aesthetic values of landscapes, recognizing the significance of individual experiences in UGS evaluation. Similarly, Hermes et al. [81] utilized commu-

nity feedback to assess landscape features like naturalness and uniqueness, providing a broader understanding of UGS quality from a public perspective. Bratman et al. [4] discuss the mental health benefits derived from natural settings, emphasizing the necessity of qualitative insights to fully appreciate the therapeutic potential of UGS. These approaches underscore the importance of qualitative measures in capturing the impacts of UGS through quantitative measures on human well-being.

3.3.2. Objective and Subjective Methods

Objective and subjective methods are the foundational approaches in UGS data collection, each diverging significantly during the data collection process. Objective methods strive for unbiased and unintrusive measures of greenness. Quantitative remote sensing data are commonly used in these methods. For instance, the Normalized Difference Vegetation Index (NDVI), Land Use/Land Cover (LULC), and imagery from Google or Baidu Street View are sometimes used as key datasets for objective methods. NDVI is extensively employed to quantify vegetative greenness, measuring areas of vegetative growth that can then be compared across neighborhoods or districts [104,124]. Additionally, NDVI can be coupled with viewshed analyses to represent how much of the vegetation might be visible from the ground level. LULC datasets are a unique product of satellite imagery that has been classified into specific land cover types. A number of these products exist and can provide the classification of the difference between grass, as well as deciduous and coniferous trees (as well as a host of other values). Some data are used to distinguish between urban forests and open parks. This offers a distinct advantage for identifying different kinds of use-cases for green space in urban settings [13,125,126]. However, those datasets need additional analysis to represent more complicated experiences of UGS, such as accessibility or visibility of UGS [127].

Unlike remote sensing (or other imagery captured from aircraft) that captures imagery from above, Street View images provide objective data but from a perspective view. These 360-degree images are increasingly used to measure eye-level urban greenness [128] taken by vehicle-mounted devices, showing what structures or vegetation are visible to individuals on the road. Early methods used Adobe Photoshop to extract green pixels from digital photographs [129] but advances in data handling and algorithmic processing have evolved these methods. Modern approaches use machine learning technology for advanced image segmentation. This technology identifies different types of vegetation, enhancing the scope and accuracy of UGS measurement [44,130].

In contrast, subjective methods prioritize perceived green space, capturing individual experiences and behaviors associated with UGS [131]. These methods explore the qualitative dimensions of urban greenery, emphasizing personal or communal impacts [122]. Common techniques include surveys and interviews [35,132], which explore the green spaces encountered by research participants. For example, Jiang et al. [41] conducted an online survey to assess participants' frequently used routes, measuring the visibility of greenness along these routes as indicators of green space quality.

Subjective assessments often involve direct inquiries into various aspects of green space quality, such as park availability [120], management [122], and visual impression [114]. In research on topics such as visual landscape assessment and when trying to gather empirical data about how people engage with cultural ecosystem services, subjective methods are indispensable. They inherently rely on cognitive paradigms [91,133] that require individuals to assess their use of values and interpret that into some quantitative value or through a story that can later be interpreted by researchers. In many cases, individuals are asked to interpret data using scales (e.g., Likert scales [134]), to evaluate factors like tree cover density [112] or landscape aesthetic potential [135].

3.3.3. Exposure Methods

The measurement of exposure to UGS can use a range of different qualitative and quantitative approaches, as well as incorporate both objective and subjective methods [23,36]. These types of assessments serve as a bridge between how something is measured and how it might be used or experienced [26]. A broad range of studies in urban planning and public health disciplines explore these approaches. Their purpose is typically to link UGS to the quality of the living environment and overall public health [8,56]. One of the seminal studies cited in this review by Labib et al. [36] introduced three different types of exposure methods: *availability*, *accessibility*, and *visibility*.

The availability assessment is most often represented as an amount of greenery. Studies consistently demonstrate that the availability of green space contributes to improved mental health outcomes, reduces heat island effects, and enhances biodiversity [23,76]. The NDVI and LULC datasets are frequently used to objectively measure vegetative cover, providing the amount of greenery and the relationship with general health in the study areas [8,18]. Additionally, the distribution of availability reflects socioeconomic disparities, impacting lower-income neighborhoods with limited green space availability [32]. This inequity suggests that increasing green space availability could be a crucial intervention in reducing health disparities [52].

The accessibility assessment refers to the ease with which urban residents can access (or get to) green spaces. Usually, this refers to a proximity measure. Research indicates that proximity to green space significantly impacts physical activity levels, mental health, and social cohesion [56,124]. For example, proximity to parks and recreational areas has been linked with increased physical activity, which can mitigate chronic diseases, such as obesity and diabetes [27]. By measuring the accessibility of UGS, studies identified mental health benefits [8,23], and encouraging physical activity [73].

Visibility assessments aim to quantify the extent of visible vegetation or greenness. These approaches focus on what is directly visible to individuals in their immediate environment. This assessment fundamentally relies on data collected from an individual's eye-level perspective, often referred to as the perspective or profile view. Unlike the previous two types of assessments, visibility assessments employ a distinct technique [36], which may include viewshed-based analyses or image interpretation methods (e.g., Green View Index).

Data from visibility assessments are utilized for various purposes including the visual impact assessment of landscapes [69], alleviating mental fatigue, and enhancing mood stability [136], as well as evaluating urban landscapes on a large scale [42]. Specifically, GIS-based visibility analysis has been instrumental in assessing changes in suburban landscapes [92,137]. Recently, these analyses have expanded into urban areas, driven by increased computational capacity and the availability of rich datasets [38,136,138]. Moreover, advances in image interpretation techniques over the past decade have also been spurred by the data provided by major technology companies (e.g., Google, Baidu, etc.). For instance, the Green View Index now effectively distinguishes greenness in captured images [128], while machine learning models based on deep neural networks have started to identify preferences in urban landscapes by analyzing street structures [42,44]. Consequently, the scope of visibility assessments is broadening, intersecting with disciplines such as psychology, ecology, and urban planning, thereby enriching the metrics used in urban analysis [38,69].

3.4. Green and Blue

The typical interpretation of UGS focuses on vegetation (green) elements. However, there has been an emergence of research lumping blue features into the same discussion [23]. Where green features encompass a range of elements from grass to forest, blue features incorporate elements such as rivers and the ocean. Thus, when measuring UGS, it is important to identify if both blue and green features are included, and in which way (e.g., do they share the same value).

The distinction between green and blue can be very apparent. For instance, studies using the NDVI often exclude water features to focus on activities that are directly related to health benefits [139], even though blue features can be directly used for health benefits [126]. In contrast, we identified studies that used land use datasets that included water features, as elements like ponds in parks or rivers in waterfront recreation areas. From an ecosystem services perspective, researchers have identified that blue and green features can be used to increase the provision of cultural services [140]. It is well known that water features enhance the aesthetic and recreational value of urban landscapes and contribute significantly to urban biodiversity and microclimate regulation [141,142]. Their presence has been linked to increased property values and improved mental well-being among residents, illustrating the multifaceted benefits of integrating blue spaces in urban planning [143]—benefits that are similar to UGS.

There are multiple other benefits of blue features that make it important for consideration in studies involving nature. For instance, the visibility of water bodies, as discussed by Nutsford et al. [126], is associated with significant mental health benefits, including reduced stress and improved mood stability. This underscores the importance of not only the physical but also the visual access to water features in urban settings. Research by Labib et al. [36] supports this, demonstrating that the eye-level visibility of green and blue spaces significantly influences residents' psychological well-being [23]. The strategic integration of green and blue spaces has been shown to mitigate urban heat island effects and provide essential refuges for urban wildlife, thereby enhancing the sustainability and livability of cities [80]. Studies further highlight the importance of incorporating both green and blue spaces into urban environments to fully capture their benefits for urban residents [30,37]. While water features may sometimes be excluded when assessing the specific impacts of green spaces on individuals, their significance in the broader urban context is increasingly recognized due to their critical roles [36].

3.5. View Type

This construct focuses on representing UGS in two distinct ways: (1) *perspective view* and (2) *plan view* (Table 2). The perspective view (sometimes also referred to as 'profile view') is conducted at ground level, offering a view from the individual's perspective [61,92]. Studies may use the perspective view to represent direct human viewing (and subsequently psychological perspective). Conversely, the plan view typically employs a top-down approach, such as birds-eye or satellite imagery [36]. A key distinction between these techniques lies in the outcomes, which reflect different extents of experiential greenness and assumptions of the way individuals are exposed. They also tend to be based on different data sources. Empirical studies have shown these two views demonstrate weak positive correlations when representing the greenness of a study area [54,93,128]. Therefore, some studies collect data from both perspective and plan view to analyze their effects on residents' perceptions and experiences of UGS [43].

The perspective view differs from the plan view, where the latter is typically driven using geographic information data (e.g., satellite imagery or vector-based representation of urban elements). While datasets derived from plan views have been widely used in various

studies due to their immediate applicability from remotely sensed raw data, the use of perspective-view datasets has also gradually increased in recent decades. It is important to note, that Ekmen and Kocaman [144] argued that remote sensing approaches in urban areas may disproportionately represent studies about UGS, but the subjective interpretations and qualitative methods may not be as well represented—but still carry valuable knowledge. Moreover, Zhu, Zhou, Seto, et al. [57] emphasize the need for collaboration between remote sensing leaders and policy-making to ensure data applicability. Addressing these oversights requires a thorough examination of current measurement techniques and the development of a conceptual framework that fosters mutual understanding between method developers and data users.

Here we emphasize the view types construct as this is frequently discussed in the literature. View types offer a means to represent and discuss how the other constructs are folded together. Table 3 summarizes key methods, data, and outcomes that are associated with these view types. These are further explored in the following subsections.

Table 3. Classification of View Type construct into techniques, geospatial data, and outcomes associated with UGS.

View Type	Technique	Methods	Geodata for Analysis	Outcome Data Description	Citations
Perspective View	Viewshed	Viewshed	TIN model, LULC	Landscape composition	[114]
			DEM, NDVI	Visibility maps of greenery	[25]
		Visual Magnitude	LiDAR-derived surface height model	Mapping the perceivable greenness on the urban trails	[145]
			DTM, DSM, LULC	Measuring visibility of transmission lines (visual impact assessment of green area)	[61]
			DEM, Wildlife Tree Patches	Visibility analysis for scenic areas of forest	[146]
		Vertical Visibility Index	DEM, LULC	Conversion of green space visibility to an ordinal score	[126,147]
		Visual Exposure	DSM, Tree Canopy data, Geographical Boundary of city	Mapping eye-level greenness visibility exposure	[136]
				Mapping green visual exposure to individuals	[106]
	GVI	GVI	SVIs, Coordinated map of image locations	The ratio of the total green area in street view images	[45,93,128]
		GVI with AI		Interpretation of vegetation ratio in SVI images	[44]

Table 3. Cont.

View Type	Technique	Methods	Geodata for Analysis	Outcome Data Description	Citations
Plan View	Multi-Spectral Remote Sensing	NDVI measurement	CIR photography from satellite or uncrewed aerial vehicles.	The ratio of total vegetation area in each study area	[77,115,148]
		LULC measurement	The Anderson land cover classification system, Decision Tree Algorithms (e.g., LANDSAT, NLCD, and LGN)	Measuring the ratio of parks and the forests or the percent of green space (trees, shrub, and grass-herbs)	[18,32,96,148]
				Measuring the proportional abundance of vegetative cover (i.e., forest, shrubland, and herbaceous)	[53]
		Tree canopy measurement	Photo interpretation of multi-spectral imagery and other ground and ancillary information	Calculating the average or percentage of tree canopy cover within the defined administrative boundaries	[17,55,149]
	Other	GPS tracking of users	Location (e.g., GPS device or smartphone)	Measuring the activity spaces where exposure to green space occurs	[87,150]

Definitions: AI: Artificial Intelligence; CIR: Color Infrared; DEM: Digital Elevation Model; DSM: Digital Surface Model; DTM: Digital Terrain Model; GVI: Green View Index; LGN: Land Use Database of the Netherlands; LULC: Land Use Land Cover; NLCD: The US Geological Survey National Land Cover Database; SVI: Street View Image; TIN: Triangulated Irregular Network.

3.5.1. Perspective View

The perspective view approach involves various methods typically derived from variations of a GIS-based viewshed algorithm [38,92,106,136,147], but includes a fundamentally distinct approach called the *Green View Index* (discussed at the end of this section). Viewshed approaches are usually based on geospatial datasets, such as NDVI, LULC, and Tree Canopy Cover datasets together with topography data (and other visual constraints). These analyses identify the amount of green space that might be visible from a given location or route. The second technique, known as the Green View Index, quantifies visibility by analyzing large collections of geo-tagged photographs. This process identifies the amount of green within a photograph. The various techniques are highlighted in bold italic text in the following paragraphs.

Viewshed analysis is a key technique used to determine the visibility of objects or areas from specific viewpoints [151,152]. An early concept was developed by Tandy [153] as a line-of-sight (what can be seen from a place) known as an “isovist” [154]. With the advent of topography data (e.g., Digital Elevation Model or Triangulated Irregular Network) and GIS-based computer applications viewsheds have become popular. They have been used to identify historic sites [155], estimate the visual impact of landscapes [61], and evaluate the conservation of scenic views [156]. These have been studied in a range of different disciplines (i.e., archaeology, natural resources, urban planning, and computational) due to the ease of tool access through GIS applications [38]. Viewshed analysis is an umbrella term for several specific kinds of implementations (e.g., viewshed, isovist, voxel, visualscape, etc.). There are also advanced versions, including VIEWIT [157], Visual Magnitude [92],

and the Viewshed Greenness Visibility Index [136]. These developments highlight the adaptability and expanding scope of viewshed analysis.

Viewshed analysis quantifies areas as visible or invisible and is commonly used to assess viewing landscapes at designated points. Previously, calculating visibility for numerous viewpoints on a large scale, such as metropolitan regions, posed computational challenges. However, advancements in processing power now enable the handling of visibility calculations for millions of viewpoints [136,158]. For example, during the early period when GIS applications began including viewshed modeling as one of their functions, Palmer [114] employed a viewshed to analyze changes in landscape composition across a township, employing 56 viewpoints with a 30 m resolution DEM. More recent studies have expanded this approach to city scales. For example, Nutsford et al. [126] utilized 46 viewpoints with a 5 m resolution over four distance ranges (i.e., below 300 m, 300 m to 3 km, 3–6 km, and 6–15 km). Additionally, Laszkiewicz and Sikorska [25] assessed the visibility of greenness along children’s school commute routes by analyzing data at 10-m intervals across 73,376 points in an urban area. These studies illustrate that the visibility of specific features or greenness can be quantified across entire cities. Furthermore, the visibility data can be integrated with other urban datasets, such as health or socioeconomic data, to explore complex environmental and social relationships within urban contexts.

The viewshed analysis delineates areas visible from selected points on a map [151,159]. By overlaying vegetation or tree canopy data onto the viewshed results, one can approximate the extent of visible greenness from the points. Visible greenness data from the viewshed differs from NDVI measurements, which are conducted through a plan view and show the existing green space on the ground. However, some studies have noted that existing green space on the ground and visible greenness derived from image analysis do not correlate as the measurement area radius increases [93,128]. Although measuring visible greenness through images utilizes a different approach, there are common reasons why the visibility of greenness and actual greenness might differ, particularly in terms of perceivable green space. For example, private gardens or small parks nestled between buildings may not be visible to pedestrians unless they move to see those spaces, yet the data from the plan view include those as existing green space [136]. Furthermore, urban structures such as highway overpasses, high-rise buildings, and other physical barriers often obstruct views of green spaces. Thus, often, some communities have proximity to large green spaces but are neither accessible nor visible.

The viewshed analysis has evolved over the years to include other variations, which include *visual magnitude*, *vertical visibility index*, and *visual exposure*. These enhanced approaches shift away from the binary representation of viewshed analysis (to see or not to see) to account for a more continuous representation of visibility [92]. One development in this field is the introduction of visual magnitude which computes the portion of visible area within an observer’s sight, factoring in topographical elements including slope, angle, and observer-relative distance [152,157]. Visual magnitude quantifies the extent of visible areas within an observer’s view, with values ranging from 0 (not visible) to 1 (fully visible). A related analysis, “Cumulative Viewsheds” incorporates the frequency with which areas are seen from different viewpoints. One of the earliest implementations of this work was produced in the program “VIEWIT” [157,160]. Numerous other methodologies have been applied to represent a more human-centric visibility measurement, such as fuzzy analysis [161], vertical visual angles [152], and route-based visual magnitude [92].

Many studies from the literature focus on visual magnitude methods to assess the visual dominance of specific objects within landscapes. Wilson et al. [145] utilized visual magnitude to analyze the visual characteristics of urban trails, with a focus on aspects such as visual openness and perceived greenness from the observer’s eye level while

walking. Other studies, including those by Chamberlain et al. [146] and Palmer [61], used visual magnitude to quantify the visibility of undesirable objects, such as logging areas and transmission towers. These studies not only measured the extent to which the negative visual impacts of these objects could be mitigated but also provided a quantitative assessment of visibility based on observer location, including Key Observation Points and route-based viewpoints. Although these studies do not directly focus on UGSs, they offer important examples of how visibility measurements can be applied to minimize negative visual impacts on landscapes.

We also identified another approach called the vertical visibility index as one of the viewshed extension methods. This approach calculates visibility by assessing vertical angles and distances from each observer point, effectively representing the visibility of greenness from a vertical perspective [147]. In validating this method within an urban context, a significant positive correlation was found between Vertical Visibility Index scores and the visibility verified through Google Street View imagery. This method was employed to measure residents' exposure to green and blue spaces, which was associated with psychological distress and other socioeconomic factors [126]. The study integrated elevation models with land cover data to assess the visibility of green and blue spaces across four distance spectrums. Notably, this research measured the visibility of green space in an urban setting and explored the relationship between viewing natural landscapes and the mental health of participants.

Visual exposure and visual magnitude share similarities in their measure, but visual exposure also attempts to account for the density of green visible. This can require a higher resolution of data to process or supplemental data to determine how to quantify density. In our review, only a few previous works applied visual exposure to quantify visible UGS. Here, we identify two recent studies based on the technique and developed innovation models: (1) the Viewshed Greenness Visibility Index and (2) green visual exposure. The Viewshed Greenness Visibility Index was developed by Labib et al. [136]. This technique reduces computational complexity through the filtering process and increases the accuracy of the green space visibility through the necessary parameters (i.e., distance decay of visibility). The Viewshed Greenness Visibility Index used digital terrain models and LULC to identify UGS, calculating approximately 86 million observation points in a metropolitan area in the UK. The second technique developed by Cimburova and Blumentrath [106], incorporates existing viewshed extensions such as visual magnitude [92], solid angles [162], and the distance decay function [136]. Their approach is based on the reverse-viewshed that the number of visual objects (e.g., street trees) is fewer than the number of potential observation points. For example, while trees can be seen from numerous locations, the actual number of trees or tree groups in an urban environment is less than the number of observation points. This approach reduced the time for calculations so, they could analyze the visibility of urban trees in Oslo, Norway. These studies demonstrate that visual exposure, assessed through viewshed-based visibility analysis, is a feasible method for utilizing high-resolution datasets at the city scale.

An alternative to viewshed-based analyses is the green view index. Measures the proportion of greenness in an image or photograph taken at a specific location. This method has gained widespread use as a variable representing green space visibility, especially with the accessibility of street view images provided by platforms like Google, Baidu, and OpenStreetMap. Initially developed by Aoki et al. [163], the Green View Index involved manually counting vegetation pixels in images, which later became automated with digital tools like Adobe Photoshop [129]. As computer programs evolved, Green View Index calculations could be scaled to entire cities, making it a valuable variable in epidemiological studies. Green View Index, constructed from a perspective view of images, effectively represents

the visibility of green spaces from the observer's viewpoint. Its prominence has grown due to the abundance of street view data and advancements in automated processing.

In recent years, artificial intelligence has further enhanced the accuracy of street-view image interpretation. For example, Zhang and Hu [44] used artificial intelligence to improve the Green View Index by distinguishing street trees and ground vegetation through semantic segmentation—a computer vision technique that categorizes groups of pixels. Notably, their study calculated the Green View Index for the entire city of Osaka, Japan, using a large dataset of street view images and artificial intelligence models trained with the Cityscapes Dataset [164] and Objects Contextual Representation model for pixel classification [165]. Like other Green View Index studies, this research integrated the index into GIS-based maps, creating two types: one showing greenness at image locations and another depicting the average Green View Index for road segments.

3.5.2. Plan View

The plan view is a top-down approach that aims to calculate UGS from above, typically with less focus on measuring how people view green space as in the perspective view. For several decades, green space data derived from satellite or aerial imagery have been considered effective for research and planning, particularly due to their broad coverage at city and regional scales [8,51]. These data represent the distribution of vegetation to derive a UGS exposure. In this subsection, we identify four different approaches to assessing UGS from the plan view, including remote sensing approaches such as NDVI, LULC, Tree Canopy, and another variation that combines existing data (remote sensing or vector-based data) but focuses on exposure by directly tracking individual movement. As in the previous section, each of these techniques is highlighted in bold italic font.

The Normalized Difference Vegetation Index (NDVI) is one of the most commonly and frequently used metrics for measuring UGS [8,77,148,166]. NDVI is calculated by determining the ratio of red and near-infrared bands using multispectral imagery captured by multispectral cameras [167]. Although recent studies have employed various approaches to measuring UGS through multispectral imagery—such as the Enhanced Vegetation Index, which is more responsive to tree canopy structure [166], and the Soil Adjusted Vegetation Index, which can suppress soil pixels [139]—NDVI remains a consistently used method due to its popularity [23,51]. Since many other indices are derived from NDVI, this review focuses on the application of NDVI and current trends in its usage.

The resulting geospatial data are, generally, published in raster format, which are ortho-mapping products classified into plan view datasets. Most studies we found collect the proportion of greenness or vegetation areas from satellite imagery, such as Landsat 5 [77,93,148], WorldView-2 [90], and Sentinel-2 [136]. NDVI effectively distinguishes areas covered with healthy vegetation from non-vegetated areas, such as concrete or bare land, because the calculation is designed to be sensitive to chlorophyll content. As a result, studies using NDVI should consider seasonal effects, ensuring that imagery captured during the growing season is used to measure UGS accurately. Additionally, selecting cloud-free imagery [115] and excluding areas with rivers or reservoirs, due to the presence of aquatic plants that also contain chlorophyll [139], are critical factors in accurately gauging greenness, which directly affects residents.

In recent studies, imagery captured via uncrewed aerial vehicles has emerged as a promising alternative to satellite imagery. Several studies have validated that NDVI derived from satellite imagery corresponds well with NDVI from uncrewed aerial vehicle imagery equipped with multispectral sensors [168,169]. Moreover, Uncrewed Aerial Vehicles can overcome limitations inherent in satellite-based approaches. For instance, satellites can only capture a region when their orbit passes directly overhead, whereas

uncrewed aerial vehicles offer greater temporal flexibility, as long as they can fly over the area [170]. Additionally, uncrewed aerial vehicle imagery provides high spatial resolution and is relatively low-cost compared to traditional aerial photography captured by airplanes, making it a viable alternative to current satellite image capture methods. Lastly, uncrewed aerial vehicle-based remote sensing is particularly suitable for smaller scales, such as city management, a point increasingly emphasized in studies focused on measuring urban environments [169,171].

Land Use and Land Cover (LULC) data are extensively utilized to quantify and characterize specific aspects of the built environment [8]. Numerous studies focusing on UGS use these datasets to identify areas such as parks [32], urban forests [125,148], or non-agricultural vegetated areas [18,172]. Additionally, LULC data within urban contexts are employed to analyze ecosystem services, sustainability, and urban sprawl, enabling the creation of comprehensive models [5,27,173]. A key distinction between LULC data and the NDVI lies in their creation: LULC data are derived from classification systems (e.g., The Anderson land cover classification system) and processes [174], while NDVI is calculated using an algebraic formula [175].

LULC datasets are widely utilized as geospatial maps [176]. Land use data represent functions of land, such as recreational areas or residential zones, whereas Land Cover datasets depict the land's physical attributes, including water bodies, forests, and wetlands. For instance, in the United States, the National Land Cover Database provides detailed land cover information, while the Major Land Uses dataset from the Economic Research Service captures socioeconomic changes and landscape alterations driven by human activity [177]. Similarly, datasets like the Urban Atlas from the European Union's space program [178] and the National Land Use Database from the Netherlands (LGN) offer multiple layers of information under the combined category of Land Use and Land Cover [18,179].

Although both LULC and NDVI data utilize a plan view to represent UGS, they serve distinct yet complementary purposes in analysis. LULC data categorizes land use and cover types, while NDVI provides insights into vegetation health and density. Their combined use offers a more comprehensive understanding of green spaces. For instance, Dennis et al. [117] quantified various types of green spaces using LULC data, while NDVI was employed as a quality metric for assessing vegetation health. Similarly, Yin [148] used NDVI to measure overall greenness and LULC data to estimate tree canopy coverage, providing detailed insights into the extent and types of green spaces across different buffer zones. Consequently, researchers and planners must have a clear understanding of how to effectively use LULC data in UGS measurement, along with a well-defined process for classifying vegetation types, to ensure accurate and relevant analysis.

Tree Canopy Cover (TCC) refers to the area covered by trees when viewed from a plan view and is increasingly used in various UGS measurements. These data provide information on the proportion of tree canopy that urban residents can visually perceive [106] and is used to assess the overall quality of UGS, as it contributes to the ecosystem services of urban areas [180]. Although often a byproduct of LULC data analysis—such as data derived from the classification of high-resolution satellite imagery, for example, Foliage Projection Cover from SPOT 5 [180], Tree Canopy Cover from Landsat [77], and City of Trees from Copernicus Sentinel [117]—Tree Canopy Cover is considered to have unique characteristics in UGS measurements, unlike NDVI and LULC.

We reviewed studies that applied Tree Canopy Cover data as a factor in UGS measurement. In epidemiological studies, Tree Canopy Cover represents the percentage of tree canopy coverage in different neighborhoods and is used to evaluate vegetation quality through complex models, such as green infrastructure calculations [117], assessments of street tree influence on health perceptions [17], and air pollution reduction measurements

using the U.S. EPA Environmental Benefits Mapping and Analysis Program model [149]. These studies indicate that Tree Canopy Cover data are often used to provide a more precise representation of greenery that directly impacts urban residents through managed vegetation. Conversely, other studies have used Tree Canopy Cover data as a variable to account for household characteristics [180,181] and city-level health outcomes [55]. For example, in Lowry's [181] study, the influence of built environment and socioeconomic factors on neighborhood tree canopy was analyzed using high-resolution (1-m resolution) data from aerial color-infrared digital imagery, such as from the National Agriculture Imagery Program.

Tree Canopy Cover data in UGS measurements is frequently integrated into green infrastructure assessments due to its specific resource-related characteristics [182]. In urban contexts, trees require ongoing management and resources to thrive. Additionally, as an infrastructure element that provides direct benefits, tree canopy can represent shaded areas or rest spaces in impervious, developed areas. For instance, several studies have used Tree Canopy Cover data to explore the relationship between sun exposure and skin health [183]. Therefore, as this dataset increasingly improves in accuracy, it becomes a critical indicator of environmental quality in residential areas, directly offering benefits tied to investments in natural resources.

One downfall of plan view techniques is their assumption of how individuals are exposed to UGS. Some work has overcome this limitation by employing GPS tracking of UGS. This allows for precise analysis of individuals' movements about green spaces [87,99,150]. Recent studies have shown that combining GPS tracking with GIS data improves the measurement of environmental exposures by capturing daily mobility patterns and providing a more comprehensive analysis of interactions with urban environments [99]. These datasets typically include information on the frequency of visits to green spaces and the duration of time spent there, providing a practical understanding of user behavior and engagement with UGS. Chaix et al. [99] claimed that GPS data allows for an assessment of environmental exposure, moving beyond static residential data to include detailed daily mobility patterns. Further, Marquet et al. [87] found that increased greenness within GPS-defined activity spaces positively correlates with higher physical activity levels, emphasizing the health benefits of regular exposure to green spaces. Additionally, Zhou et al. [150] further highlighted that GPS data can capture both the frequency and duration of visits to green spaces, offering a deeper understanding of how environmental perceptions, such as park safety and beauty, influence park usage.

Future research directions suggest various integrations of GPS data into GIS systems to not only map patterns of users but also contextualize environmental and health-related data. In the review by Chaix et al. [99], they advocate for more studies that explore how these datasets can be used to assess long-term health impacts. On the other hand, in the experimental study by Marquet et al. [87], they propose linking GPS data with health interventions and urban planning strategies to create more sustainable and walkable cities. Similarly, Zhou et al. [150] call for integrating temporal variations in GPS-tracked park usage with perceptions of safety and beauty to inform the development of UGSs. Consequently, the reviewed studies emphasize the need to store data consistently using GPS devices and to integrate such datasets with other geospatial datasets to better analyze relationships between these datasets.

4. Discussion

4.1. Defining Urban Green Space: Challenges and Approaches in Current Research

Defining UGS through a set of uniform criteria remains a challenging task. Most studies reviewed in this study treat UGS as a variable, collecting the datasets depending on

their study areas that are typically urbanized with high populations [35,55,71,77,104,113]. Complexity arises from the diverse functions and perceptions of UGS, making it difficult to establish standardized definitions [12,184]. For example, when grouping UGS by function, if all vegetation areas measured by the NDVI are classified as UGS, questions emerge about whether private lands or inaccessible urban forests should be included.

Beyond these function-based classifications, a wide range of disciplinary perspectives could further enhance a construct-based definition of UGS. For instance, ecosystem services approaches evaluate UGS based on the benefits it provides, such as mitigating urban heat islands, improving air quality, supporting biodiversity, and others. Economic valuation methods, such as hedonic pricing and contingent valuation methods, assess UGS by quantifying its financial impacts, including how green spaces influence property values, consumer preferences, and cost-benefit trade-offs in urban planning. Civil and environmental engineering may take an infrastructure perspective and focus on aspects like stormwater management and noise mitigation. Psychological and perceptual frameworks expand the definition of subjective experiences and interactions. While some of these approaches align with the construct-based framework presented in this paper, our approach could be expanded further, reinforcing the idea that UGS is best defined through constructs rather than a singular, fixed definition [12].

While these perspectives offer valuable insights, they are often structured around pre-defined benefits or functional roles of UGS rather than explicitly addressing the variability in how UGS is or could be defined and measured. For example, the Ecosystem Services framework assesses UGS based on its ecological and social contributions which could be measured and assessed in a variety of ways. Similarly, the Green Infrastructure framework integrates UGS into broader sustainability and planning strategies, which typically focus more on outcomes or effects. In contrast, our construct-based framework provides a systematic classification scheme that does not assume a predefined set of functions of purpose but instead enables researchers to define UGS explicitly through scales, methods, measures, and exposure types relevant to their specific study contexts. This adaptability allows for greater comparability across studies or policies by helping to define how an outcome or benefit might be explicit. Therefore, the construct-based approach can address implicit assumptions in UGS-related research.

Here, we discuss two example studies to illustrate how the construct approach can be implemented (Table 4). For example, Wolch et al. [32] assessed the impact of adjacent parks in a residential area. Their spatial analysis focused on neighborhood scales in communities in Southern California, U.S. The relevant categories under measures include direct effects and intentional interactions. Regarding methods, the study analyzed distance to parks within 500 to 1000 m radii buffers to compare obesity rates among communities. The study employed a quantitative approach to measure UGS areas and objective data collection of the built environment. Moreover, the dominant exposure to green space was classified as accessibility of UGS from participants' residential areas. The study included ponds in its park distribution dataset, reflecting the inclusion of water bodies (blue-space) as part of UGS. Lastly, a plan View dataset was used to capture UGS (refer to Table 2 for detailed definitions of these categories).

Table 4. Example of defining UGS and the datasets by constructs.

Citations		Wolch et al., 2011 [32]	Maas et al., 2006 [18]
Scales		Neighborhood	City
Measures	Type of effects	Direct effects (park visiting for activities)	Indirect effects (contribution of natural environments)
	Types of interactions	Intentional interactions	Incidental interactions (no specific activities)
Methods	Measuring approaches	Quantitative (park area within 500 m)	Quantitative (green spaces; 3 km radius)
	Data type	Objective (built environments)	Objective
	Dominant exposures	Accessibility	Availability
Includes water bodies		Yes (several parks with ponds)	N/A
View Types		Plan View	Plan View

Although this classification framework is derived from numerous studies that have conducted UGS measurements, it may not encompass all measurement types (as hinted in the second paragraph of this section). Nevertheless, establishing such a structured system is essential as it facilitates meta-analyses of similar experimental studies conducted both presently and in the future [51]. Furthermore, this framework can serve planners and policymakers, aiding in the formulation of policies to introduce or preserve UGS. In practice, several studies evaluating urban policies using UGS datasets primarily rely on per capita UGS extent [185,186], while more recent research has assessed available parks and accessible water features to examine spatial inequality [187]. A key challenge identified in these studies is the absence of consistent monitoring using standardized UGS datasets. Since the framework is designed to classify dataset characteristics, it can clarify assumptions by explicitly defining UGS for these policies, as well as research.

4.2. Exposure Methods and View Type

This review identifies key characteristics of constructs classified under “Methods” that are closely related to UGS datasets: quantitative, objective, and the three types of exposure—availability, accessibility, and visibility. Although qualitative approaches or subjective methods can also utilize UGS datasets and represent specific exposure assessments, they were not directly considered within the scope of this literature review for two reasons. First, subjective methodologies for collecting individual-level data are highly diverse. For example, the criteria for measuring objectives range from post-experience feelings [105] to regular social interactions of UGS [184]. These methods often illustrate the datasets with GIS-based mapping but do not primarily focus on the GIS-based analysis or techniques. Second, such approaches are predominantly explored in fields outside this review’s scope, such as anthropology, sociology, and psychology. Although we included qualitative approaches as a construct of UGS measurements, their application remains limited within the context of this review. Therefore, this discussion focuses on the relationship between UGS datasets and constructs linked to quantitative approaches, objective methods, and exposure assessments, which are further categorized by view type.

While many studies have explored specific aspects of these components, such as comparisons of measurement techniques in Quantitative Approaches, determining buffer

radii for Objective Methods [95], or examining the roles and impacts of Exposure assessments [51], few studies have integrated these constructs into a cohesive framework connecting them to UGS datasets.

Throughout our review of the literature, we found that UGS measurements and datasets categorized by View Type are significantly associated with Exposure assessments, which precede the generation of outcome datasets (Figure 2). This is because exposure assessments are an empirical step in understanding how individuals interact with green spaces. They capture both the extent of green spaces that are perceived or experienced and the datasets used to analyze those perceptions. Specifically, exposure assessments examine factors such as green space availability, accessibility, and visibility, all of which contribute to understanding the physical and visual interactions between individuals and UGS. By analyzing how datasets represent these dimensions of perception, we can establish connections between positional considerations of view types and green space exposure assessments. The following sections provide examples illustrating how different techniques or calculated datasets are positioned within UGS datasets (Figure 3).

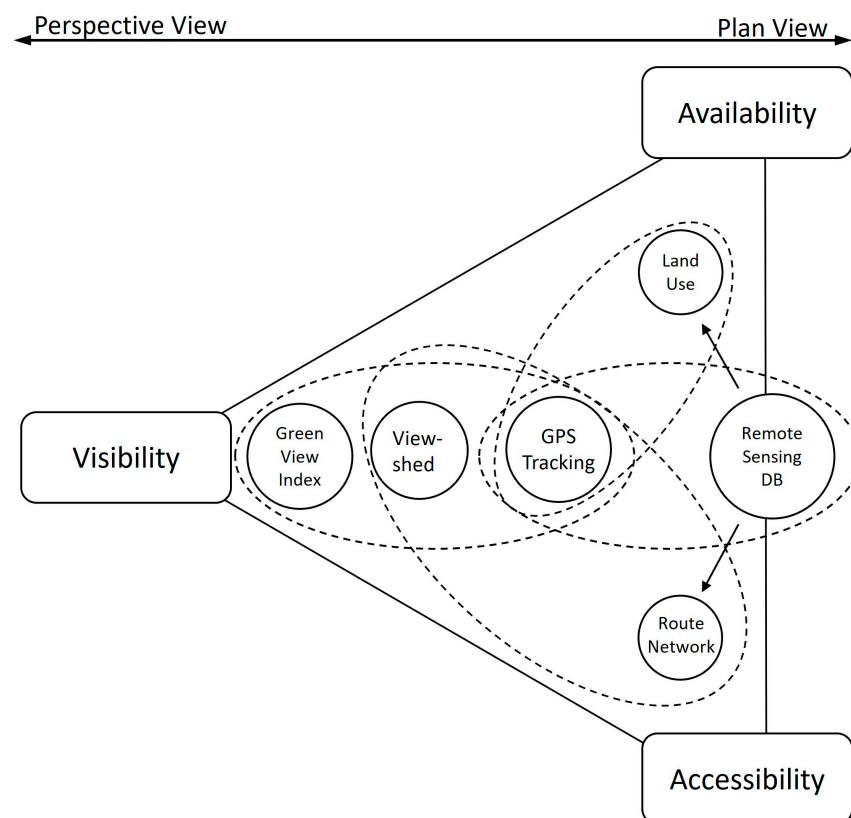


Figure 3. Integration of UGS measurement constructs across View Types and exposure categories (dashed lines represent hybrid techniques integrating UGS datasets).

4.2.1. Datasets by Multi-Spectral Remote Sensing

NDVI, a representative dataset of Remote Sensing DBs, plays a central role in exposure assessments. As a product of multi-spectral remote sensing categorized under Plan View, NDVI datasets provide a comprehensive representation of green spaces that are Available, Accessible, and Visible. Due to this broad applicability, NDVI is widely used. However, without additional analysis, such as user investigation or viewshed analysis, NDVI alone might not explain how green spaces interact with individuals, yet researchers could assume that the space could provide some benefits [8]. Consequently, the use of NDVI as a standalone metric in empirical research has been declining. Instead, Land Use datasets

have emerged as a more suitable alternative and are increasingly utilized due to the connotative usage of space.

To refine analyses for specific participants, GPS devices can be integrated to identify which spaces are available and accessible [87]. GPS devices are particularly valuable as they provide insights into interactions with UGS, assuming the participants' occurring activities and inquiring appreciation of experiences [99]. Furthermore, frequently visited locations in urban areas (e.g., schools, malls, or high-density residential zones) could offer valuable data to explore the long-term benefits of UGS. For instance, the impact of UGS can be investigated by repetitively visiting areas. Therefore, combining UGS facility maps with user-specific information is a recommended approach to examine UGS's lasting effects.

4.2.2. Datasets by Viewshed

Green space datasets derived from viewshed-based techniques and the Green View Index are closely aligned with Visibility in exposure assessments, as they rely on individuals' visual perception of green spaces. These datasets are categorized under Perspective View and are primarily used to measure visibility at the numerous observation points, enabled by advanced calculation capabilities [38,106,136]. Depending on the designated location within a city, viewshed-based datasets could also capture green spaces that are not only Visible but also Available or Accessible. For instance, if a visually adjacent green space is a park or garden, it likely provides both availability and accessibility for users. Such research topics explore the impact of varying visibility levels in urban areas where UGS availability and accessibility remain equal [36].

Additionally, integrating GPS devices can add contextual depth by identifying whether participants are positioned in locations that meet availability and accessibility criteria [41]. For example, by tracking personal and daily travels with GPS, investigating the different visibility of the individuals who live in a place having similar availability and accessibility of UGS. This research design could be applied to many residents living in high-density or urban apartment complexes. This integration allows for more sophisticated assessments of visually perceived green spaces and enhances the understanding of how visibility interacts with other dimensions of UGS exposure.

Particularly, viewshed-based UGS measurements can extend beyond Visibility to address Availability and Accessibility. This is because the analysis fundamentally relies on map data representing vegetation to measure visible green spaces. In urban environments, viewing green spaces plays a critical role in fostering awareness of seasonal changes and appreciating the aesthetic qualities of urban landscapes. Consequently, studies can be designed to account for the dynamic sequence of changes in nature while incorporating aesthetic evaluations. Thus, integrating visibility analysis could become essential when collecting datasets related to UGS Availability and Accessibility.

4.2.3. Consideration of Location and Position

Incorporating the observer's location and position into the relationship between exposure methods and View Type supports more integrative research approaches. These approaches, often referred to as hybrid techniques (as discussed in the previous two sections), can be further refined by focusing on the details of observing locations. A few studies reviewed here demonstrate such techniques by considering both the observer's location and positional aspects, along with individual movements [39]. For instance, individuals may perceive varying amounts of green space depending on whether they are walking, cycling, or driving [41,138,188]. Accounting for these conditions could help identify differing perceptions within the same urban environment.

Although this approach is challenging to implement on a population level, especially in epidemiological investigations, it could be feasible through controlled experiments with smaller sample groups, such as individuals with similar daily routines or occupational patterns [41,97,130]. Expanding this idea further, urban areas also differ in terms of zoning, geography, and land use policies. For example, researchers could identify optimized observation points tailored to the geographic characteristics of urban spaces [138]. In such cases, the context of location becomes a primary factor for applying diverse techniques effectively.

Most studies utilizing UGS measurements and datasets calculate green space exposure based on designated locations (e.g., the centroid points of census tracts or intersections within a road network). However, if observation points are chosen with specific purposes in mind, research can move beyond randomized exposure calculations and uncover the significance of these locations. For instance, green space exposure can be quantified along specific routes (e.g., commutes, recreational paths) [189] or exposure near participants' residences can be analyzed by identifying frequently used pathways [41]. These integrative approaches often involve multiple constructs working together to provide a more comprehensive understanding of UGS exposure.

Moreover, studies employing hybrid techniques to quantify UGS or analyze its datasets are on the rise. However, it is critical to disclose the precise attributes and limitations of the datasets used. This transparency is essential for facilitating longitudinal studies and accurately tracking changes over time. This is particularly important because research findings comparing the quantity of UGS are often utilized to identify opportunities for improving urban environments in specific locations. Practitioners rely on such results and datasets to effectively implement urban planning strategies and zoning regulations [30,37,130]. Therefore, as hybrid techniques grow increasingly complex, providing clear context regarding study areas and dataset attributes becomes essential to ensure the reliability and applicability of research findings.

4.3. Developing a Framework: Plan View and Perspective View in UGS Measurements

In reviewing UGS measurements, numerous academic studies have adopted diverse methodologies, focusing on precisely capturing the extent or characteristics of UGS through novel techniques [13,77,93,188]. For instance, recent studies measuring UGS typically utilize imagery datasets with varying resolutions, such as a 30-m resolution [77] compared to a 1-m resolution [13]. Additionally, the studies consistently utilize multiple measurements for collecting the datasets, ranging from availability to visibility of UGS [93,188]. While the application of novel techniques is essential for enhancing measurement precision, the fragmented nature of these methodologies can create confusion for planners and other data users in practical applications [8,38].

This confusion arises because each technique often targets specific aspects of UGS, requiring users to select appropriate datasets or measurements based on their specific goals. For example, if an urban designer wants to enhance the visual exposure of UGS in a district and evaluate the subsequent effects of increased visibility, they can refer to datasets or measurement techniques categorized under the Perspective View. This highlights the importance of organizing UGS measurements into structured frameworks, such as Plan View and Perspective View, to help users effectively navigate and apply appropriate techniques.

To promote the practical use of UGS measurements, it is crucial to determine which measurements best reflect the needs of the community and the characteristics of UGS that need to be implemented. As for the end-users, we concentrate on the simplification of diverse measurement approaches to identify the characteristics. Consequently, we provide a classification framework for UGS measurements based on View Types of the

representing greenery, intended for use by urban designers, planners, and stakeholders (see Table 3 for detailed measurements and Figure 4 for the overview of the classification). The classification of UGS measurements accommodates a variety of geospatial datasets, each suited to different research purposes (Figure 4). In the urban context, both Plan View and Perspective View classifications are compatible with existing and newly developed UGS datasets, as they attempt to encompass measurable aspects of UGS that can be perceived and assessed through remote sensing.

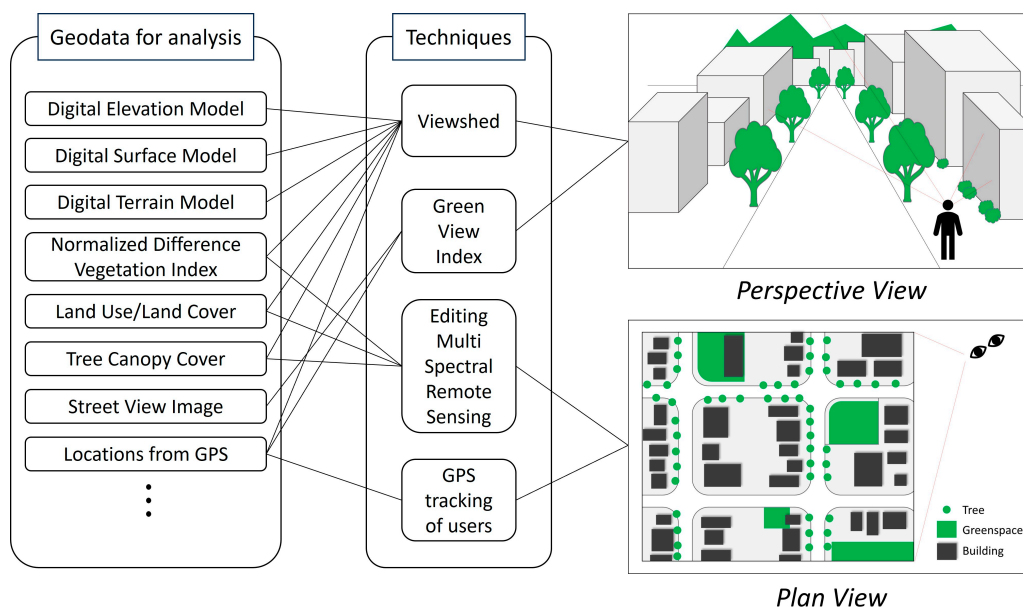


Figure 4. Classification of UGS datasets by GIS-based analysis and techniques.

For example, consider a scenario where a vast patch of natural areas (e.g., urban forests without trails or public accessibility) might not promote physical activity due to limited accessibility, making it unavailable to the public. In such cases, focusing on the perspective view—which aligns measurements with pedestrian pathways and ground-level interactions—would be more appropriate [25,74]. Conversely, data collected through the GPS tracking of users, which reflects individuals’ engagement with greenness through the extensive movement patterns, can be classified under plan view as it pertains to the broader spatial distribution and accessibility of UGS [99]. However, if these data are joined with some type of viewshed analysis, then it could serve to also function as a perspective view [106,136]. Therefore, it is essential to treat the plan view and perspective view as distinct classifications within a single study to capture the multifaceted constructs of UGS in Table 2. This dual classification ensures that measurements are tailored to the specific perspectives from which users interact with green space. This classification framework offers several benefits:

1. **Consistency in data management:** By categorizing measurements into Plan View and Perspective View, the framework promotes consistency in data collection and management across different studies. This consistency facilitates meta-analyses and comparative research, enhancing the robustness of findings related to UGS and health outcomes [51].
2. **Practical application for policymakers and planners:** The framework serves as a practical roadmap for city planners and policymakers, aiding in the formulation of policies related to the introduction or preservation of UGSs. Measurement data organized within this framework can be utilized to demonstrate how specific types of UGS initiatives impact residents, thereby supporting informed policy decisions [15,190].

3. Enhanced understanding of UGS impacts: By distinguishing between aerial and ground-level perspectives, the framework allows for a more nuanced understanding of how UGS influences various aspects of urban life, such as physical activity, mental well-being, and environmental quality [112,136].
4. Support for health-related studies: The framework underscores the necessity for health-related studies examining UGS to define which health-related factors correspond to specific constructs. Within this framework, appropriate measurements and datasets can be selected to foster mutual understanding between researchers and end-users, supporting long-term, consistent series of studies that provide improved causal inferences between UGS and health outcomes [23,56].

4.4. Future Direction of UGS Measurements

The future direction of UGS measurements is expected to involve the development of new devices and the integration of novel methods through interdisciplinary approaches. While existing measurements have primarily focused on quantifying the accurate amount of vegetation, future advancements will aim to incorporate quality evaluations and subjective assessments. A variety of emerging devices and methods will likely be applied to better capture the value of UGS and the extent of human interactions with these spaces [8,54,182].

Novel technologies, such as virtual reality, are being utilized to evaluate the experiential aspects of UGS, replacing traditional visual experiences to assess the indirect impacts of greenery [46,47]. Several studies have attempted to identify individual perceptions within virtual environments, focusing on the attention-restorative effects of UGS [48,49]. Additionally, the urban digital twin approach, which replicates urban environments in virtual spaces, could offer a method for exploring the influence of UGS by collecting data on both existing and perceivable green spaces [191]. These advancements in data collection and analysis could further refine the construct-based classification. For instance, scale considerations could be expanded to account for virtual representations of UGS.

Advancements in algorithms, particularly Convolutional Neural Networks (which are commonly classified under artificial intelligence), have been developed to improve the accuracy of visually perceived UGS by identifying street trees through perspective view imagery [44]. In line with that advancement, those deep learning algorithms can evaluate and predict aesthetic factors through street view images by using training sets of participants involved [42].

Advanced recording devices are also providing new data sources. Smaller camera devices mounted on individuals are now capturing street view images in areas previously inaccessible to car-mounted cameras [192], but they can also capture imagery of user interactions (e.g., hiking, walking, cycling) where these data were not available previously. Likewise, Uncrewed Aerial Vehicles can be used to capture hyperspectral images, such as near-infrared imagery, to calculate vegetation indices. The regularity of these data collection techniques could expand the construct to consider how time and seasonality influence the definition.

UGS measurement methods are becoming increasingly diverse, allowing for improved accuracy alongside technological advancements [8,38,42]. As data collection methods continue to diversify, the importance of organizing and categorizing these data will also grow. The proposed classification in this study offers a structured approach that enhances the practical and interdisciplinary application of UGS measurements. By using this classification, measured datasets can become more meaningful and adaptable across various fields, supporting a more comprehensive understanding of UGSs.

5. Conclusions

This review offers a thorough examination of a diverse range of methodologies and datasets used to measure UGS. These have been formalized into a framework for their classification and application. The framework is grounded on a construct-based definition of Urban Green Space into five different elements: scale, measures, methods, green/blue spaces, and view type. In addition to the construct approach, the review provides an overview of the evolution of UGS measurements from basic approaches in quantifying green spaces to more integrative and experiential techniques meant to quantify visibility, accessibility, and availability. These techniques underscore the critical role of exposure assessments in bridging both the physical and perceptual aspects of UGS.

This review also emphasizes the potential of hybrid techniques that combine quantitative and qualitative approaches, such as integrating GPS data with visibility analyses or applying multi-scale methods to capture user-specific interactions with UGS. These integrative methods address gaps in understanding how green spaces impact diverse populations and urban environments.

While UGS research continues to advance and play a role in policy, variability in dataset attributes, differences in geographic contexts, and the lack of consistent definitions across studies can limit generalizability and comparability. To address these limitations, transparency in dataset characteristics and methodological choices is essential. Practitioners and policymakers require reliable, clearly communicated data to inform urban planning strategies and enhance UGS accessibility and usability.

Finally, this review points to future directions, including the refinement of UGS measurement frameworks, the development of longitudinal data to assess green space changes, and the application of novel tools such as artificial intelligence-driven semantic segmentation technologies. By advancing these methodologies and addressing current challenges, UGS research can continue to provide meaningful insights for urban development and improve the quality of life for urban residents.

Author Contributions: Conceptualization, D.H.L. and B.C.; methodology, D.H.L. and B.C.; data curation, H.Y.P.; writing—original draft preparation, D.H.L.; writing—review and editing, D.H.L., B.C. and H.Y.P.; visualization, H.Y.P.; supervision, B.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the Utah Agricultural Experiment Station, Utah State University, and approved as journal paper number #9859.

Acknowledgments: We gratefully acknowledge the Visual Resource Stewardship Conference for providing valuable critiques during the oral presentation of an earlier version of this research.

Conflicts of Interest: The authors declare no conflicts of interest.

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