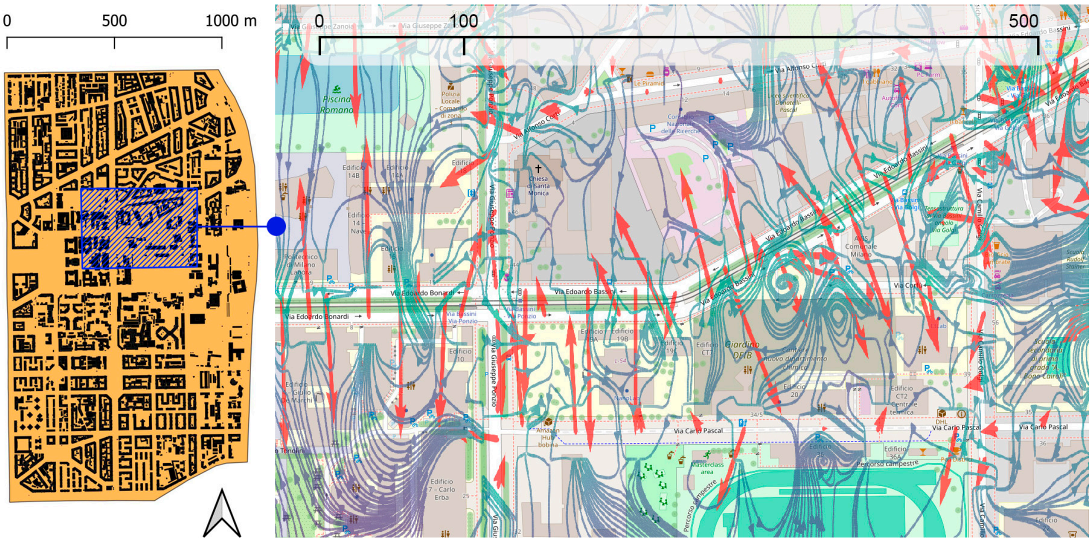

Figure 13. Visual greenery field. On the left is the key map of NIL 22, with the area shown on the right highlighted in blue. This area includes part of the Politecnico, the sports camp, and the main street. On the right, red arrows are the resulting view vectors; blue arrows are the streamlines of a potential green experiential connectivity field. Source: Base map from Open Street Map™; elaboration by the author.

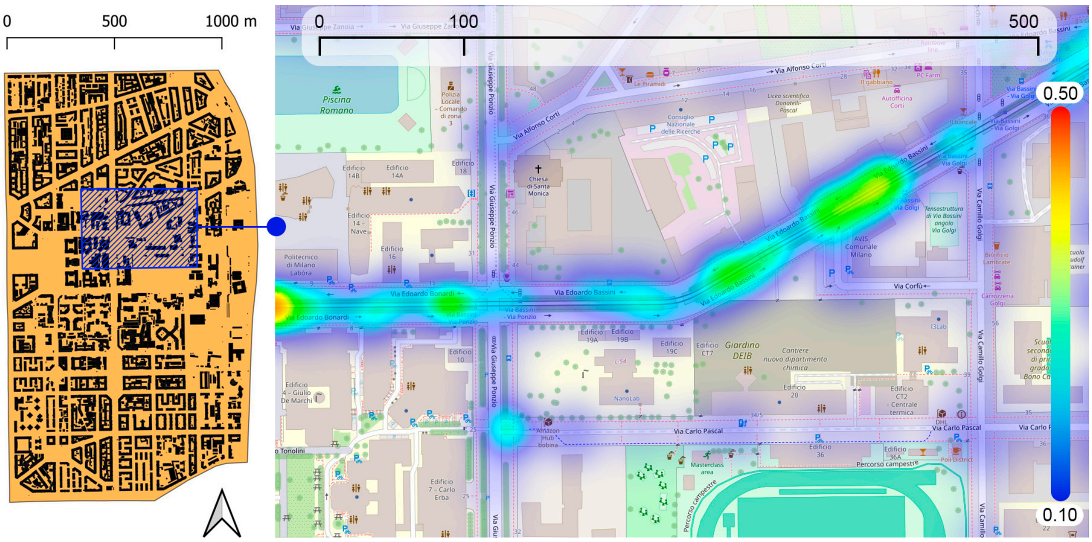

Figure 14. Representation of the GVI heatmap. On the left is the key map of NIL 22, with the area shown on the right highlighted in blue. This area includes part of the Politecnico, the sports camp, and the main street. On the right, this picture highlights that green elements tend to be concentrated along the main streets. Source: Base map from Open Street Map; elaboration by the author.

6. Discussion

The results of this study provide information on the visibility of urban greenery in different cardinal directions and its spatial distribution within the examined area. The first key finding is the unequal visibility of greenery, with significant variations between the north and south directions. These findings suggest that directional bias must be considered when assessing the visual perception of urban vegetation, as greenery is not evenly distributed in all orientations. Although urban vegetation is generally placed on the sides of the street, this is not always true, such as at a green roundabout or when a street reaches a park or a square. Previous studies focused on the one-directional view along a path or distributed 360° views, with panoramic approaches losing specific directional information, while non-panoramic studies may fail to capture the broader context of urban greenery [31]. In particular, the vectorial analysis of green intensity across the four cardinal directions highlights the variation in green visibility depending on the viewer's orientation. This consideration suggests that using GVI as a unique value in the analysis can introduce bias in the evaluation of the urban green experience. This study overcomes these limitations by including all cardinal directions, synthesizing global information, and preserving directional data, thus capturing a comprehensive yet directionally detailed analysis of urban green. Geostatistical analyses, particularly Moran's I, revealed that greenery exhibits a spatial clustering tendency, with specific areas showing concentrated peaks. This positive autocorrelation is aligned with the observed heterogeneity in the visual distribution, which confirms that the greenery is not evenly spread. Furthermore, variograms in different azimuth directions reveal that the spatial continuity of greenery can vary significantly, ranging from 404 m to 1076 m depending on the direction, indicating a directional dependence on how greenery is distributed throughout the area.

The most intense vectors occur on tree-lined avenues along roads such as Edoardo Bassini Street, where the effect is amplified by the grass partially covering the tram tracks. This highlights an ambiguity: despite the abundance of greenery, the usability of these green spaces is limited by physical barriers such as tram tracks and roads, which detract from their immersive quality. An exception is Pacini Street, near the Piola metro station, where the section is such that it can offer facilities for sociality. This observation goes beyond the scope of several studies [26,33,34,36,38–42], which measured GVI in different cities but did not address the anisotropic distribution of greenery or its potential barriers to usability. The angular drift from the street axis does not occur facing green roundabouts such as Piola Square, where the presence of greenery is directly observable from radial roads. Analysis of the directional differences in the visibility of greenery further supports the notion of an uneven visual field of greenery. The results of the Friedman test and subsequent post hoc analysis show that specific direction pairs, particularly those involving south-facing views, exhibit the most significant variability. This suggests that individuals' experience of urban greenery is highly dependent on their orientation within the city. The representation of visible green as a vector field shows areas where the opposition of close visual directions generates a sort of turbulence. In contrast, aligned field bands show areas where the vectors' directions are coherent between opposing zones. Changes in the vectors' alignment can suggest incongruency between parts of the neighborhood that are not always mutually connected by crossings and that do not allow for a continuous green immersion experience; a particular case where visual connection corresponds to a possibility of movement through the greenery is constituted by the area of the Politecnico di Milano's rectorate, where it is possible to pass from one perimeter tree-lined avenue to another by walking through the internal campus gardens.

It is worth noting that the sum of vectors following image segmentation implies the existence of two possibilities of zero values: (a) a system at rest, with a lack of green in all directions; (b) a balanced system, with the identical presence of green in all directions. The second possibility is unlikely because the pictures represent an urban environment seen from a street; however, these boundary conditions are considered acceptable, as the research aimed to identify the preferential orientation toward specific directions; thus, obtaining the zeroed vector in the possible presence of 360° of green represents indifference toward any specific direction. Moreover, the vectorial representation is to be considered complementary to the areal one. However, it is important to acknowledge that this vectorial approach, while informative, does not fully capture the complexity of how humans perceive or access greenery in real-world environments. Human perception is influenced by multiple sensory and contextual factors that go beyond the directional quantification of green visibility, and this limitation should be recognized. It is also important to emphasize that this type of analysis is not intended to replace the GVI but to complement it by providing additional information on directional preferences. Relying on an omnidirectional GVI, especially over large areas, risks losing important details about the local distribution of greenery.

A 360° average GVI may not accurately reflect the urban layout at specific observation points. For example, different scenarios, such as a single tree in a built environment versus multiple small plants on facades, can produce similar GVI values despite differing visually. Although the areal GVI derives from directional information, the differences in the directional distribution of greenery are crucial to understanding the perceptual reality of urban spaces, indicating that GVI alone may not capture all the relevant information.

Therefore, the vectorial representation of urban green visual elements provides information on (i) the prevailing visual direction at a point that maximizes the view of green, (ii) the intensity of green in that direction compared with the surrounding elements, and (iii) the directional coherence between neighboring places. In response to the first research question, the proposed vector-based method quantified the intensity and spatial distribution. This approach allows for a clearer understanding of directional visibility, showing significant differences among the cardinal directions. This directional specificity is essential to represent urban green spaces with more precision, which the traditional GVI, as an omnidirectional measure, fails to capture. Regarding the second research question, vector representation provided information on the directional coherence across the area, highlighting zones of alignment and turbulence across the urban landscape. The alignment of vectors' directions between adjacent areas reflects the congruence of green visibility, which is not easily observable by omnidirectional GVI alone. This allows for a more nuanced interpretation of how greenery is experienced in different parts of the urban fabric.

This type of analysis is tied to panoramic photography conducted along the road axis and, therefore, does not allow for an exact evaluation of perception from different positions, such as that of a pedestrian on the sidewalk. The images were all captured during daylight hours, so assessing how perception varies under special lighting conditions such as dawn or dusk is impossible. Additionally, it was not possible to set different dates to retrieve shots in different seasons. The height of the viewpoint is higher than the average height of a standing person or a driver on the wheel, since it was taken from above the roof of a car; this may distort the human viewpoint. The fineness of viewpoints' discretization along the path can vary the representation, providing more detailed information and, therefore, more localized phenomena. Future work on urban perception would benefit from considering the effects of continuous exposure to greenery compared with punctuated or fragmented ones by adopting such a method to select paths with different qualities and features. Furthermore, future research could focus on integrating different models to quantify urban greenery by combining satellite images with street-level greenery information, such as the GVI and NDVI. This approach should also incorporate the directional aspects highlighted in this study to create a three-dimensional view of the urban environment. Furthermore, recent developments in deep learning processes present an opportunity to handle large-scale geospatial datasets, enabling more refined predictions and analyses, mainly when dealing with detailed urban data.

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Conflicts of Interest: The author declares no conflicts of interest.

Appendix A. Scoping Review

The following appendix details the structured approach used for the literature review. First, the query structures employed for the Scopus, Web of Science, and Dimensions databases are presented. The PRISMA method was used to identify relevant publications. Finally, the identified dataset was validated based on the principle of saturation, ensuring comprehensive coverage of the topic. The search queries were designed to identify peer-reviewed publications related to the Green View Index (GVI) from 2013 to 2023. The Scopus query is focused on the "green view index" and was limited to journal articles and reviews published in English. The Web of Science search followed a similar structure, refining the results by relevance. For dimensions, the term "streetview" was added to narrow the broad scope of the initial results. The SPIDER framework inspired the conceptual query framework [61,62]: S, sample; PI, phenomenon of interest; D, study design; E, evaluation; R, research type. The "publication type" replaced the "research type" section, and the evaluation was subsequently carried out following the PRISMA protocol; the queries were not limited in terms of the design of the study (Figure A1).

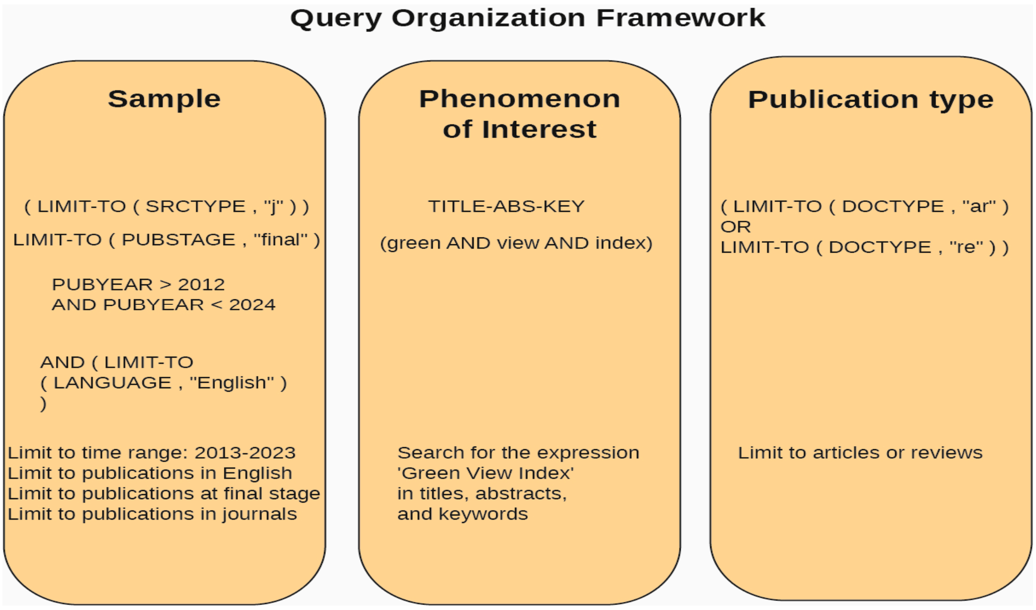

Figure A1. Query organization framework. The three blocks are related to the literature sample, the phenomenon of interest, and the type of publications to be included in the search.

Scopus query: TITLE-ABS-KEY (green AND view AND index) AND PUBYEAR > 2012 AND PUBYEAR < 2024 AND (LIMIT-TO (SRCTYPE, "j")) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (PUBSTAGE, "final")) AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "re")).

Web of Science (WOS) query: https://www.webofscience.com/wos/woscc/summary/9e9f03ab-6caa-4646-8a7e-99b127ef7add-af2a77e2/relevance/1 (accessed on 28 October 2023).

Dimensions query: "green view index streetview" in full data; publication year was 2023 or 2022 or 2021 or 2020 or 2019 or 2018 or 2017 or 2016 or 2015 or 2014 or 2013; publication type was article or chapter.

Due to the extensive nature of the results for dimensions, it was necessary to introduce the keyword 'streetview' to obtain a more focused outcome compared with the search queries.

The results of these three databases were merged into a single dataset from which duplicates were removed (Table A1). The saturation principle was followed to validate the dataset, adopting Google Scholar™ as a comparison set. Details of the procedure are provided on the following pages, and the schema is shown in Figure A2. The three publications' dataframes obtained were concatenated, obtaining 1810 items; 47 items have been removed due to missing DOI information; out of the remaining 1763, 447 duplicates were removed. After this filtering, the resulting dataframe contained 1316 items. The process of including datasets to obtain a comprehensive framework could virtually continue without limit; for this reason, it was necessary to establish a threshold of validity for the items collected. The validation of the items was achieved using the saturation principle applied through a comparison of Google Scholar™ (GS) with the final dataset of publications derived from the previous phases. The saturation check used a dataset not initially included to verify the percentage of duplicates that would appear in the original set by merging a new set of items. The comparison was processed under two different conditions: (i) the complete GS dataframe; (ii) the GS dataframe filtered by citations per year (CpY), considering the same threshold that was applied to the original dataframe (CpY = 10). The percentage must be >75% for the complete dataframe and >60% for the filtered dataframe to be valid. The following are the levels overlapping for comparing the DOI in the two datasets:

- Overlapping percentage of whole GS = 83.33% (saturation confirmed);
- Overlapping percentage of filtered GS = 66.66% (saturation confirmed).

This means that including other sources would produce a nearly identical item list to the one initially chosen to represent the state-of-the-art in this field.

Google Scholar™ Query: The search on Google Scholar™ was conducted using Harzing's Publish or Perish tool v. 8.9.4538.8589 2023.07.07.1629 [63] by setting the following parameters:

- Title: green view index;
- Keywords: green view index;
- Years: from 2013 to 2023;
- Maximum results: 200;
- No patents.

Citations per year filtering was used to obtain the most influential publications, and a threshold of 10 citations per year was applied to be included in the screening phase. The resulting subset contained 159 items (1157 were removed).

Title screening: In this phase, the relevant terms were street view, street greenery, Green View Index, view factors, street-level images, and eye-level greenness. Other excluded publications were on satellite images, remote sensing, and crop health assessment. Title screening resulted in 35 items (124 were removed).

Abstract screening: In this phase, publications on transport not explicitly citing the GVI and publications not implying street-eye level images were excluded. Abstract screening resulted in 32 items (3 were removed).

Full text screening: In this phase, a publication was excluded because it was not related to the research questions.

To better describe the framework of the current research, one publication that was not initially included in the original dataframe was added; Table A2 reports on these publications with their motivations. The ultimate set of publications included 32 items.

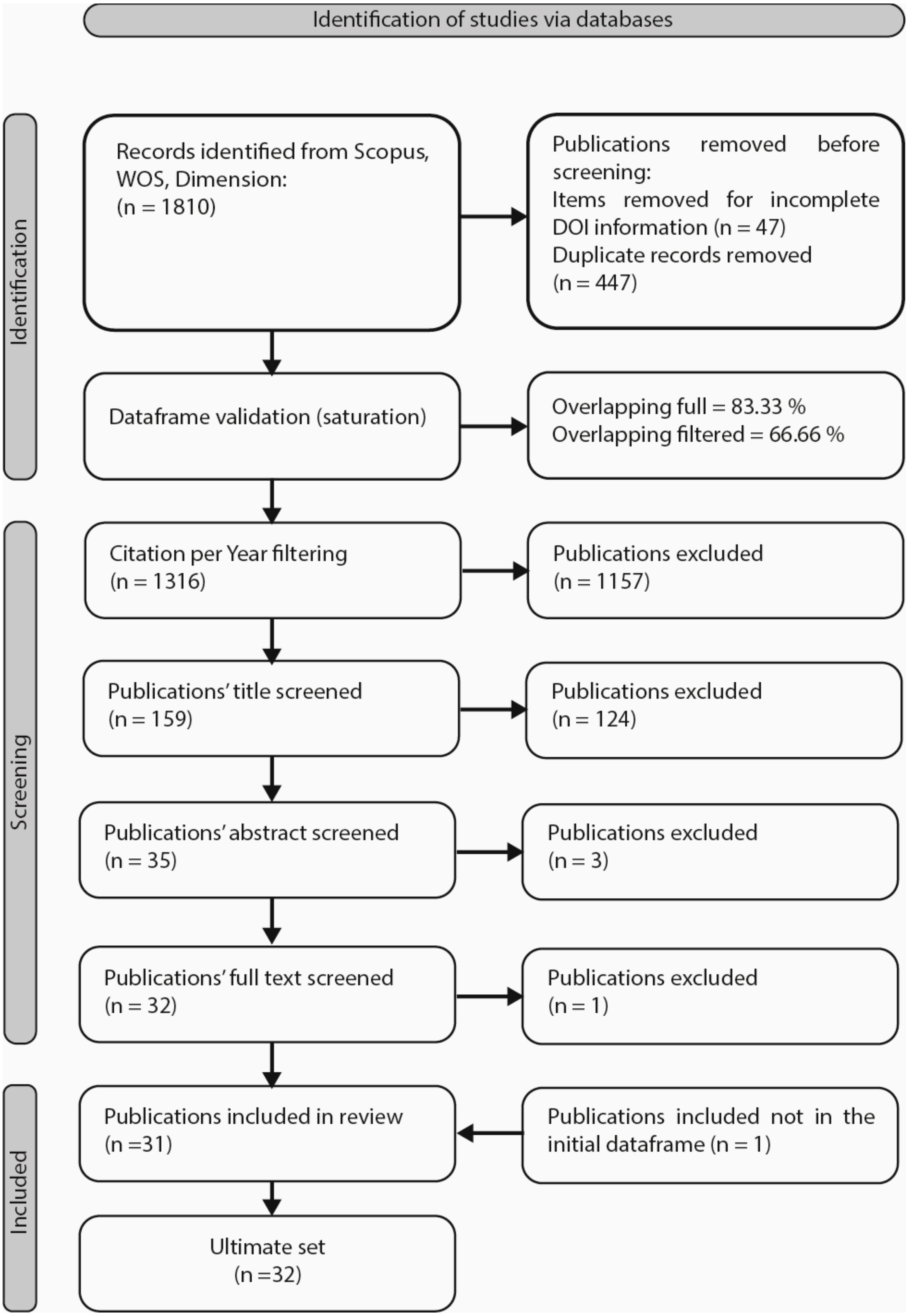

Figure A2. Literature review diagram for the Green View Index. This schema is based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow chart [26]. Retrieved on 2 November 2023, from http://prisma-statement.org.

Table A1. List of publications included after full test evaluation.

Title	Authors	Year	Description
Assessing street-level urban greenery using Google Street View and a modified green view index [26]	Li, Xiaojiang; Zhang, Chuanrong; Li, Weidong; Ricard, Robert; Meng, Qingyan; Zhang, Weixing	2015	Automated calculation of the GVI and its rationalization compared with the previous work in 2009
View-based greenery: A three-dimensional assessment of city buildings' green visibility using Floor Green View Index [33]	Yu, SY; Yu, BL; Song, W; Wu, B; Zhou, JH; Huang, Y; Wu, JP; Zhao, F; Mao, WQ	2016	Three-dimensional evaluation of greenery
How green are the streets? An analysis for central areas of Chinese cities using Tencent Street View [34]	Long, Ying; Liu, Liu	2017	Using conventional methods is generally time-consuming and expensive. To address this issue, the authors developed an automatic method using a street-view service while also borrowing and modifying ideas from existing studies
Green streets—Quantifying and mapping urban trees with street-level images and computer vision [38]	Seiferling, Ian; Naik, Nikhil; Ratti, Carlo; Proulx, Raphäel	2017	Quantifying the amount and distribution of trees in cities
Quantifying street tree regulating ecosystem services using Google Street View [39]	Richards, Daniel R.; Edwards, Peter J.	2017	The study analyses hemispherical photographs extracted from Google Street View to quantify the proportion of green canopy coverage at 50 m intervals across more than 80% of Singapore's road network and estimates the proportion of annual radiation that would be blocked from reaching ground level by the canopy. The study aimed to map the provision of street trees' ecosystem services and prioritize areas for new planting by identifying streets or street sections with low shading
How green are the streets within the sixth ring road of Beijing? An analysis based on Tencent Street View pictures and the Green View Index [35]	Dong, RC; Zhang, YL; Zhao, JZ	2018	This article aimed to quantify the street greenery in the sixth ring road in Beijing, analyze the relations between road parameters and the GVI, and compare the visible greenery of different types of roads
Impacts of street-visible greenery on housing prices: Evidence from a hedonic price model and a massive street view image dataset in Beijing [40]	Zhang, YL; Dong, RC	2018	The authors selected 25 variables that were classified into three categories (location, housing, and neighborhood characteristics) and introduced an index called the horizontal green view index (HGVI) into a hedonic pricing model to measure the value of visual perceptions of street greenery in neighboring residential developments
Mapping sky, tree, and building view factors of street canyons in a high-density urban environment [36]	Gong, Fang-Ying; Zeng, Zhao-Cheng; Zhang, Fan; Li, Xiaojiang; Ng, Edward; Norford, Leslie K.	2018	This study aimed to develop an approach to estimate and map the SVF, TVF, and BVF of street canyons in complex urban living environments, such as high-density urban areas in Hong Kong
The effect of street-level greenery on walking behavior: Evidence from Hong Kong [44]	Lu, Yi; Sarkar, Chinmoy; Xiao, Yang	2018	This study highlighted the impact of eye-level street greenery on the decision to walk and the total walking time for a large urban population of Hong Kong
Using deep learning to examine street view green and blue spaces and their associations with geriatric depression in Beijing, China [28]	Helbich, M; Yao, Y; Liu, Y; Zhang, JB; Liu, PH; Wang, RY	2019	This study was among the first to examine the link between mental disorders (that is, depressive symptoms) and exposure to natural environments at the street level among elderly people in China

Table A1. *Cont.*

Title	Authors	Year	Description
Associations between overhead-view and eye-level urban greenness and cycling behaviors [43]	Lu, Y; Yang, YY; Sun, GB; Gou, ZH	2019	The article's main objective was to examine the association between urban greenness and the odds of cycling for Hong Kong participants, using two ways of measuring urban greenness: overhead-view greenness and eye-level street greenness. The article also aimed to investigate the impacts of the activity-influencing built environment and individual-level covariates on cycling behavior. The findings of the study could help planners and designers build a cycling-friendly city by improving citizens' daily exposure to urban greenness
Using Google Street View to investigate the association between street greenery and physical activity [45]	Lu, Yi	2019	This discusses the association between street greenery and physical activity in a study conducted in Hong Kong. The study used free Google Street View images to assess the quantity and quality of street greenery, and associated them with the recreational physical activity in green outdoor environments of 1390 participants in 24 housing estates in Hong Kong. Multilevel regression models revealed that the quality and quantity of street greenery were positively linked to recreational physical activity
Evaluating street view exposure measures of visible green space for health research [27]	Larkin, A; Hystad, P	2019	This examined how exposure to green space or natural environments can affect physical and mental health outcomes. The study concluded that urban green spaces are associated with multiple physical and mental health benefits, but they are often difficult to measure accurately. The authors used Google Street View (GSV) technology to collect images from Portland, Oregon, and map out the amount of green space in each image, calling it the Green View Index (GVI). They also compared their GVI findings with traditional measures of green space exposure such as the satellite-based normalized difference vegetation index (NDVI), % tree cover, % green space, % street tree buffering, distance to parks, and several neighborhood socioeconomic variables
Perceptions of built environment and health outcomes for older Chinese in Beijing: A big data approach with street view images and deep learning technique [8]	Wang, Ruoyu; Liu, Ye; Lu, Yi; Zhang, Jinbao; Liu, Penghua; Yao, Yao; Grekousis, George	2019	The article discussed the association between the attributes of the built environment and health outcomes for older adults, focusing on perceptions of the built environment. The study used street view images and deep learning techniques to assess perceptions of the built environment for a large-scale study area. The results suggest that perceptions of safety, depression, beauty, wealth, boredom, and liveliness are all associated with the physical and/or mental health outcomes of older adults

Table A1. *Cont.*

Title	Authors	Year	Description
Measuring daily accessed street greenery: A human-scale approach for informing better urban planning practices [5]	Ye, Yu; Richards, Daniel; Lu, Yi; Song, Xiaoping; Zhuang, Yu; Zeng, Wei; Zhong, Teng	2019	This was a research article on a measurement approach for quantifying urban residents' daily exposure to eye-level street greenery by integrating high-resolution measurements of both greenery and accessibility. The proposed approach used Google Street View (GSV) images and street networks collected from Open Street Map (OSM) and combined them with machine learning algorithms to accurately measure visible greenery. The integration of greenery and accessibility helps to measure greenery from a human-centered perspective, and it provides a tool for urban planners to prioritize planning interventions
A review of urban physical environment sensing using street view images in public health studies [49]	Kang, Yuhao; Zhang, Fan; Gao, Song; Lin, Hui; Liu, Yu	2020	This article reviewed urban physical environment sensing using street view images in public health studies. The article systematically reviewed the use of street view images to detect urban environments in public health studies, describing the characteristics of street view images and summarizing the challenges of quantifying urban environments in terms of data and methodology. The manuscript included a discussion of future research directions that would benefit public health research and practices in urban environment research
Examining the spatial distribution and temporal change of the green view index in New York City using Google Street View images and deep learning [41]	Li, XJ	2021	This study mapped the spatial distribution of and temporal changes in street tree canopies using ground-based images in New York City
The distribution of greenspace quantity and quality and their association with neighbourhood socioeconomic conditions in Guangzhou, China: A new approach using deep learning method and street view images [42]	Wang, RY; Feng, ZQ; Pearce, J; Yao, Y; Li, XJ; Liu, Y	2021	This study developed a new machine learning method to assess the quality of green space based on street view images collected from Guangzhou, China. It also examined whether disparities in greenspace exposure are linked to the neighborhood's socioeconomic status (SES)
Street view images in urban analytics and GIS: A review [31]	Biljecki, Filip; Ito, Koichi	2021	This provided a comprehensive systematic review of the state of the art of how street-level images are currently used in studies about the built environment. The article outlined how street-level images are now an entrenched component of urban analytics and GIScience; most of the research relies on data from Google Street View, which are used across many domains with numerous applications
Using Google Street View images to capture micro built environment characteristics in drug places, compared with street robbery [7]	Zhou, Hanlin; Liu, Lin; Lan, Minxuan; Zhu, Weili; Song, Guangwen; Jing, Fengrui; Zhong, Yanran; Su, Zihan; Gu, Xin	2021	The authors calculated safety scores, extracted physical elements, and built logistic regression models to examine the impact of the micro-built environment's variables on drug activities. The results suggested that less place management and higher accessibility increase the risk of drug activities. The study also suggested that these street-view variables may generally apply to other types of crime research in the micro-built environment

Table A1. *Cont.*

Title	Authors	Year	Description
Can't see the wood for the trees? An assessment of street view- and satellite-derived greenness measures in relation to mental health [51]	Helbich, Marco; Poppe, Ronald; Oberski, Daniel; van Emmichoven, Maarten Zeylmans; Schram, Raoul	2021	The article examined the association between urban greenness and mental health using different greenness metrics, including remotely sensed and street view measurements. The results indicated that different methods of measuring greenness may capture different aspects of greenery in urban environments. However, these differences in the exposure metrics did not translate into significant associations with mental health outcomes
Modelling and mapping eye-level greenness visibility exposure using multisource data at high spatial resolutions [32]	Labib, SM; Huck, JJ; Lindley, S	2021	This article introduced a methodology for modeling and mapping eye-level greenness visibility and exposure at high spatial resolutions. The methodology used multisource spatial data and applied viewshed analysis with a distance decay model. The aim was to capture eye-level greenness visibility and exposure at observers' locations on the ground. The article compared top-down greenness exposure metrics with eye-level greenness exposure metrics
Assessing bikeability with street view images and computer vision [29]	Ito, Koichi; Biljecki, Filip	2021	This discussed the use of street view images (SVI) and computer vision (CV) to evaluate bikeability, which was defined as the extent to which cycling is facilitated in urban areas. An exhaustive index of bikeability composed of 34 indicators was developed and applied in Singapore and Tokyo to evaluate the usefulness of these technologies. The results suggested that SVI and CV are adequate for evaluating bikeability, present a contribution to transportation and analytics, and are scalable enough to widely assess the appeal of cycling
Analyzing the effects of Green View Index of neighborhood streets on walking time using Google Street View and deep learning [47]	Ki, D; Lee, S	2021	This discussed the effects of greenery on walking time and the importance of examining the relationship between urban greenery and walking behavior from multiple angles. It utilized Google Street View (GSV) and deep learning to calculate the Green View Index (GVI) by semantic segmentation, referring to greenness from the visual perspective of pedestrians. The GVI was found to be more closely associated with walking time than traditional greenery variables from an overhead perspective, such as park areas and the normalized difference vegetation index (NDVI)
Relative importance of quantitative and qualitative aspects of urban green spaces in promoting health [50]	Zhang, LQ; Tan, PY; Richards, D	2021	This research examined the relative importance of quantitative and qualitative aspects of urban green spaces (UGS) in the promotion of health. The study examined relationships between multiple UGS provision indicators and mental and general health outcomes in Singapore
Urban neighbourhood environment assessment based on street view image processing: A review of research trends [52]	He, Nan; Li, Guanghao	2021	The selected articles were classified into 5 broad categories and 15 subcategories of research directions, with research methods including reviews, experimental-based research, simulations, experiments + simulations, and surveys/audits. The review elaborated on the themes and content trends in the use of street views in the study of urban neighborhood environments

Table A1. *Cont.*

Title	Authors	Year	Description
Quantifying the shape of urban street trees and evaluating its influence on their aesthetic functions based on mobile lidar data [37]	Hu, T.; Wei, D.; Su, Y.; Wang, X.; Zhang, J.; Sun, X.; Liu, Y.; Guo, Q.	2022	The proposed method for assessing the esthetic functions of street trees quantified the shape of greenness, inspired by the skyline's esthetics. The authors used LIDAR data and panoramic images to extract the canopy line, identifying peaks and gaps, and six indexes to describe the fluctuations and continuities of street canopy lines. They analyzed the abundance and spatial distribution of these indexes alongside esthetic survey responses, finding significant correlations with human perception. Compared with indexes of the amount of greenness, these shape indexes have a stronger influence on the esthetic beauty of street trees, differing from previous studies focused solely on ecological services
Investigating pedestrian-level greenery in urban forms in a high-density city for urban planning [22]	Hua, J.; Cai, M.; Shi, Y.; Ren, C.; Xie, J.; Chung, L.C.H.; Lu, Y.; Chen, L.; Yu, Z.; Webster, C.	2022	The authors developed the Green View Factor (GVF) to measure pedestrian-level street greenery in Hong Kong using Google Street View (GSV) images. The study revealed significant variability in greenery across different urban forms, with older, high-density areas showing less greenery, often correlating with lower incomes. The GVF was strongly correlated with satellite-derived vegetation metrics (NDVI), though this varied by urban form. The findings suggested that the combination of multiple methods of assessing greenery is essential for a comprehensive understanding of the distribution of greenery in urban settings and can guide equitable urban planning strategies for high-density cities
Exploring the associations between neighborhood greenness and level of physical activity of older adults in Shanghai [46]	Xiao, Y.; Miao, S.; Zhang, Y.; Xie, B.; Wu, W.	2022	Green space was shown to be effective in encouraging people to undertake physical activity, while for older people, health conditions and socioeconomic characteristics were stronger influences on the amount of physical activity performed
Analyzing the effects of nature exposure on perceived satisfaction with running routes: An activity path-based measure approach	Huang, D.; Jiang, B.; Yuan, L.	2022	This discussed the positive association between running satisfaction and nature exposure, including eye-level greenness, top-down greenness, and blue space density. The study utilized an activity path-based measure approach using Public Participation GIS (PPGIS) to investigate these associations
Do emotional perceptions of visible greeneries rely on the largeness of green space? A verification in Nanchang, China [48]	Huang, S.; Zhu, J.; Zhai, K.; Wang, Y.; Wei, H.; Xu, Z.; Gu, X.	2022	This discussed a study that investigated the effect of the size of green spaces on the emotional perceptions of visitors in Nanchang City, China. The study used machine learning and sentiment analysis to analyze panoramic photos and visitors' facial expressions in green spaces. The results suggested that increasing the Panoramic Green View Index (PGVI) in green spaces can lead to more positive emotions in visitors

Table A2. Publications included in the final set of literature.

Reference	Motivation
Yang, J., Zhao, L., Mcbride, J., & Gong, P. (2009). Can you see green? Assessing the visibility of urban forests in cities. Landscape and Urban Planning, 91(2), 97–104. https://doi.org/10.1016/j.landurbplan.2008.12.004 [24]	This article is the origin of the GVI research.

Appendix B. Materials and Tools

The analyses were conducted using various systems, including drafting custom codes and scripts developed by the author. All GIS processing was performed using shapefiles provided by the geoportal of the Milan Municipality, employing QGIS 3.30.3-'s Hertogenbosch software. Image processing was performed using Python in the Google Colab^{TM} environment; specifically, the Google Streetview 1.2.9 and GluonCV 0.10.5 libraries were used. For the validation of the results of segmentation, the opencv-python 4.8.1.78 library was adopted. The semantic dataset used for the image segmentation model was the ADE20K dataset [56] developed by MIT. The Magpylib 4.4.0 library [64] and the Matplotlib 3.8.1 streamplot function were used to represent the vector field. Mapping representation was accomplished using the folium 0.14 library with Open Street Map base layers. Regarding statistical calculations, the Moran's I calculation was performed using the esda 2.5.1 library, and the Shapiro–Wilk tests were conducted using the Scipy 1.11.3 library.

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