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RESEARCH ARTICLE

Mapping urban greenery: The spatial relationship among NDVI, GVI, and greenery perceptions of social media in Rotterdam

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Greenery assessment

Abstract Urban greenery is increasingly recognised for its potential to address urban challenges, necessitating effective methods for its measurement to inform research and guide practical interventions. Conventional greenery measurements primarily rely on indicators derived from remote sensing and street view imagery, whereas emerging social media image data offers novel opportunities to capture greenery from a subjective, user-oriented perspective. However, the characteristics and comparative performance of these greenery measurements remain unclear, and limited attention has been paid to their appropriate application scenarios. Employing Rotterdam as a case study, this research compares three urban greenery measurements: greenery derived from social media, the Green View Index (GVI), and the Normalised Difference Vegetation Index (NDVI), and examines their interrelationships at street and neighbourhood scales. The results indicate that, although these measurements are interrelated and broadly reflect consistent patterns, notable differences exist. Social media greenery aligns closely with NDVI and captures overall greenery conditions, but exhibits greater variability and subjectivity. GVI, while moderately correlated with NDVI, shows higher sensitivity but may underrepresent densely vegetated areas. Spatial analysis reveals coherent structures across measurements, with low clusters in the city centre and high clusters toward the periphery, but further examination shows varying local heterogeneity in measurement relations, with strong coefficients concentrated in selected central areas and fluctuating or negative associations in peripheral and residential or commercial districts. These findings

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highlight the influence of measurement characteristics, biases, and analytical scale selections in urban greenery measurements, and clarify the strengths and limitations of each measurement to guide context-appropriate method selection.
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1. Introduction

Urban greenery, including parks, gardens, street trees, and other green elements, is a crucial component of the urban environment. Amid rapid urbanisation and growing climate and public health pressures (Gong et al., 2012; Lin et al., 2021), urban greenery is increasingly recognised as an essential strategy for addressing these challenges, reflected in global initiatives such as the Sustainable Development Goals (SDGs) and the New Urban Agenda (Andersson, 2021; UN General Assembly, 2015). Urban greenery enhances environmental quality by filtering air pollutants (Chen et al., 2019; Diener and Mudu, 2021), sequestering atmospheric carbon (Nowak and Crane, 2002), mitigating urban heat (Schwaab et al., 2021), and supporting biodiversity (Wong et al., 2023). It also delivers cultural ecosystem services (Grahn and Stigsdotter, 2003; Rahman et al., 2025), promoting residents' health and well-being through instorative, mitigative, and restorative pathways (Hartig et al., 2014; Markevych et al., 2017; Zhang et al., 2022). Accordingly, scholars have called for accurate, multi-dimensional greenery assessment methods that can systematically evaluate these benefits and provide evidence-based support for urban designers and policymakers (Konijnendijk, 2023; Zhang et al., 2024).

Traditionally, urban greenery was assessed through calculations of "green cover ratio", such as vegetation indices and green area per capita (Aikoh et al., 2023). Among them, Normalised Difference Vegetation Index (NDVI) is particularly prevalent and widely employed in environmental and epidemiological research, owing to several advantages (Chen et al., 2022; Gascon et al., 2016). First, NDVI is computed from satellite-based remote sensing spectral reflectance and is easily accessible and straightforward to calculate. Second, it features high-resolution and broad coverage, suitable for multi-scale analyses, especially large-scale greenery assessments (Shahtahmassebi et al., 2021). Third, it provides continuous values, enabling integration into statistical analysis for quantifying various ecosystem services associated with greenery (Ju et al., 2024). However, as a top-down metric, NDVI faces limitations, such as in insufficiently capturing three-dimensional structures of urban greenery (Bai et al., 2024) or detecting small-scale and vertical greenery like understory vegetation beneath canopies and facade greening, leading to potential mismatch with residents' actual perceptions (Larkin and Hystad, 2019). The absence of structural information also presents challenges for policy formulation, as NDVI alone provides insufficient information on the vegetation configurations needed for targeted improvements (Ju et al., 2024), potentially constraining the effectiveness of specific urban policies.

Recently, methods based on street view imagery have emerged as an alternative for evaluating urban greenery. Street view platforms such as Google Street View offer high-resolution panoramic photographs, providing detailed spatial-visual information that better approximates what pedestrians observe in urban environments (Biljecki and Ito, 2021; Wang et al., 2025). By assessing the presence and proportion of greenery in these images, the Green View Index (GVI) quantifies street-level greenery from a pedestrian perspective (Larkin et al., 2021; Zhang et al., 2023). Multiple studies have reported differences between GVI and NDVI, with GVI often more accurately capturing perceived street-level greenery (Larkin and Hystad, 2019; Li et al., 2015a) and better explaining the human impacts or benefits of urban greenery (Helbich et al., 2019; Wang et al., 2019, 2022). Nevertheless, challenges remain in GVI assessment, including low sampling frequencies and discontinuous spatial coverage of street view images, which may affect data availability and timeliness (Biljecki and Ito, 2021). GVI's visual obstruction and distortion due to its collection along vehicular roads and at camera heights above eye level also raise questions about how well it reflects human-perceived greenery (Ki et al., 2023).

In this context, online crowdsourced data, such as social media data, presents a novel means of measuring urban greenery from a subjective perspective (Zhang and Su, 2024). Social media platforms host extensive amounts of geo-tagged user-generated content (e.g., texts, images) that document various aspects of urban environments (Ghermandi and Sinclair, 2019). Social media images, for instance, contain a detailed visual record of physical urban conditions captured by users and offer broad spatial-temporal coverage across cities, making them an increasingly recognised potential data source for urban environmental measurements (Zhang et al., 2026). Importantly, such images reflect users' subjective perspectives and record their attention and interests in cities. Analysis of such content may advance understanding of perceived, individual measures of urban green environments, insights that are particularly meaningful for interpreting greenery's perceptual and well-being impacts (Song et al., 2020b). Existing research has applied social media imagery to investigating greenery-related perceptions (Zhang and Su, 2024), preferences (Wilkins et al., 2022), and experiences (Richards and Friess, 2015). While such data may face constraints related to unstructured formats and sampling biases, evidence demonstrates their validity for landscape perception analyses (Song et al., 2020a; Wilkins et al.,

2022). This emerging data source thus provides a potentially valuable and complementary approach for quantifying urban greenery at the individual level.

Despite the distinct strengths and limitations of urban greenery measurements spanning objective and subjective dimensions, they are often used interchangeably across research and practice, from greenery audits to environmental perception and health outcome studies, with limited attention to their context-specific applicability. This mismatch between measurement choice and research objective may affect both the interpretation of findings and the effectiveness of practical interventions. Existing studies suggest that different greenery measures exhibit both convergence and divergence. For instance, Li et al. (2021) examined the consistency between NDVI and GVI at the urban scale and found that, although the two measures were significantly correlated overall, their relationship displayed marked spatial heterogeneity. Bai et al. (2024) further showed that the association between NDVI and GVI is moderated by specific environmental characteristics. Recent research has further compared the performance of different measurements in assessing green space inequality and explaining health-related outcomes. Luo et al. (2025) compared NDVI, GVI, and park accessibility in assessing inequalities in green space provision for vulnerable groups, and explored the effectiveness and applicability of these indicators across different contexts. Studies by Zhang and Luo (2025) and Wang et al. (2019) further examined the differing potential of NDVI and GVI to support positive health outcomes and derived corresponding planning implications. Overall, systematic evidence on the relative performance, interpretive scope, and appropriate application scenarios of these measurements remains limited.

On the other hand, subjective data derived from social media offer a novel, widely-accessible source for environmental measurement, holding particular value in combining broad spatial coverage with a user-centred perspective, thereby opening up new possibilities for capturing the perceived dimensions of urban greenery (Zhang et al., 2026). However, as an emerging indicator, social media-based measures have not yet been systematically evaluated in large-scale greenery assessments. It thus remains unclear whether they can provide robust and reliable estimates of urban greenery, and to what extent they may complement or substitute for established objective indicators. In addition, the analytical scale is a critical factor shaping greenery measurement outcomes. Although different greenery measurements have been applied at multiple scales (i.e., individual/sampling point, street, and neighbourhood), empirical evidence on cross-scale suitability remains limited. Li et al. (2015b) reported strong correlations between NDVI and GVI at smaller scales that sharply decline with increased analytical scale. Jimenez et al. (2022) and Helbich (2019) showed that, for NDVI, the analysis scale substantially affects estimated greenery, highlighting the importance of aligning scale with the other analytical data. However, consistent and comprehensive conclusions about scale effects across different greenery measurements remain lacking. Therefore, a cross-scale analysis of relationships among greenery measurements not only supports precise descriptions of urban greenery but also provides a methodological foundation for evaluating its multi-dimensional benefits, thereby informing evidence-based interventions.

To address these gaps and advance understanding of urban greenery assessments, this study first quantifies urban greenery using three distinct measurements: NDVI, GVI, and social media image-derived greenery (hereafter, "social media greenery"), and visualises their spatial distribution patterns. Building on this, the study combines multiple spatial analytical methods to systematically examine the relationships among these measurements, with particular attention to spatial heterogeneity and scale effects. In doing so, it seeks to identify areas of convergence and divergence across measurements, and to critically assess their relative strengths, limitations, and context-specific applicability. Compared with conventional comparative studies centred on NDVI and GVI, this paper extends the analytical framework by incorporating social media greenery and by paying greater attention to the distinct dimensions of greenery captured by different measurements, providing an evidence-based foundation for indicator selection and result interpretation in future research and practice. Specifically, using Rotterdam as a case study, this paper addresses three research questions: (1) What spatial patterns of urban greenery do the three measurements reveal, and how are they interrelated? (2) What are the relationships among these measurements, considering the analytical scales and spatial heterogeneity? (3) How can the findings inform the selection and application of greenery measurements in research and practice? The remainder of the paper is organised as follows. Section 2 describes the three measurements, data sources, and analytical methods. Section 3 presents the results and examines the relationships among the measurements. Section 4 discusses the findings and their practical implications. Finally, Section 5 concludes the paper.

2. Materials and methods

2.1. Study area and study design

Rotterdam was selected as the case study to investigate the relationships among three greenery measurements. As the second-largest city in the Netherlands, Rotterdam covers approximately 326 km^2 and had a population exceeding 600,000 in 2022. Located in the province of South Holland, the city has a temperate maritime climate. Rotterdam possesses extensive green space resources and has implemented consistent initiatives over recent decades to enhance and preserve its green infrastructure. These initiatives seek to leverage greenery to address diverse contemporary urban challenges effectively. The recent strategic city plan "Rotterdam goes green: Green agenda 2023—2026 (Rotterdam gaat voor groen: de groenagenda 2023—2026)" highlights the role of green infrastructure and outlines government actions for the next four years. These measures include expanding greenery in residential neighbourhoods, optimising street-level greenery, and transforming existing squares, thereby mitigating climate change impacts, enhancing biodiversity, and promoting healthier, more liveable urban environments. Moreover,

Rotterdam is a major economic centre that hosts one of the world's largest ports. The city uniquely combines modern and traditional styles and accommodates diverse industrial and service sectors. Its varied socioeconomic profile and substantial tourist presence make it well-suited to observing and analysing greenery from multiple perspectives. Accordingly, this study focuses on the city's core urban area, encompassing 80 neighbourhoods.

The research framework comprises five steps (Fig. 1). First, data for the three greenery measurements were collected and calculated. Geo-located photographs uploaded to social media platforms within Rotterdam were analysed to compute the social media greenery. The GVI was then calculated by estimating the proportion of vegetation in street view images. Satellite imagery was utilised to calculate NDVI values at varying buffer distances. All measurements were calculated at the street level and then aggregated to the neighbourhood level. Second, spatial distribution patterns of greenery were analysed using mapping analysis for the three measurements. Third, hotspot analysis was used to identify spatial clusters of high and low greenery values for each measurement, and global correlation analyses were then applied to quantify the overall associations and internal consistency among the three measurements. Fourth, to move beyond global stationarity assumptions, bivariate Local Indicators of Spatial Association (LISA) analyses were used to detect local clusters of spatial consistency and inconsistency between pairwise measurements, and a Geographically Weighted Regression (GWR) model was then employed as a complementary exploratory tool to quantify how the strength and direction of each pairwise relationship vary continuously across space. Finally, the observed relationships and methodological differences were interpreted, and recommendations were provided on appropriate application scenarios and implications for urban planning and design, with attention to the strengths and limitations of each measurement.

2.2. Data sources

The data used in this study were drawn from multiple sources (see Appendix A. for detailed information). Most vector data of spatial features, including neighbourhood and city boundaries, were obtained from the Basisregistratie Grootschalige Topografie (BGT) database via the PDOK platform. Street network data were sourced from OpenStreetMap (OSM) and manually cross-checked against BGT data to ensure consistency. Social media greenery was captured through geo-located images collected from the Flickr platform. For the GVI, Google Street View images were the primary source and were collected through the Google Maps API. NDVI data were provided by the National Institute for Public Health and the Environment (Rijksinstituut voor Volksgezondheid en Milieu, RIVM), representing the mean NDVI for May to August 2022 at a spatial resolution of 10 × 10 m. These values were originally derived from ESA Sentinel-2 Level 2A imagery, with scenes filtered for less than 5% cloud cover. As outlined above, this study examines the relationships between three greenery

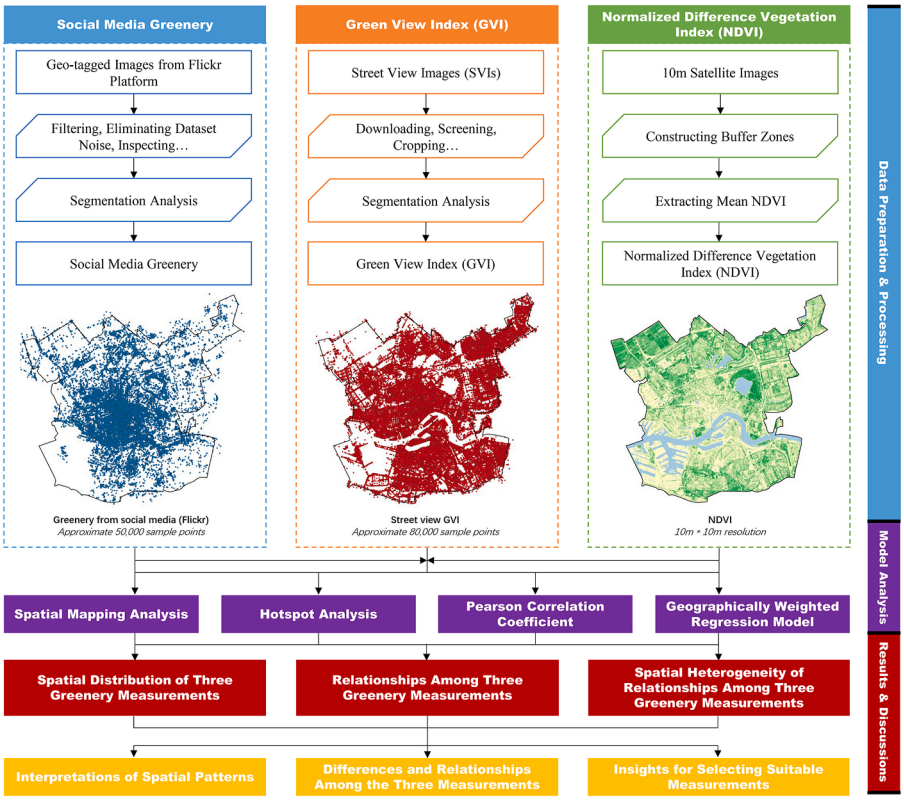


Fig. 1 Research framework.

measurements and their potential to support practical interventions. Given the distinct characteristics of each measurement, the following sections and Appendix A provide detailed descriptions of the methods, results, and interpretations.

2.3. Methods

2.3.1. Social media greenery

Drawing on established studies highlighting the strengths of user-generated images in capturing authentic landscape perceptions (Dunkel et al., 2023; Wilkins et al., 2022), image data from online social media platforms were utilised as the data source. Flickr, a major photo-sharing platform, was selected for its substantial data volume and quality, as well as its broader geospatial coverage compared to other platforms that typically aggregate data by points of interest, making it particularly suitable for large-scale perception analysis. The processing of Flickr data involved three main stages. First, all geo-tagged images taken in Rotterdam between 2010 and 2024, along with their associated metadata, were collected via the Flickr API in December 2024, yielding 80,708 images. Second, to filter and eliminate dataset noise, NIMA, a CNN-based image technical quality classification model (Talebi and Milanfar, 2018), was applied to filter low-quality images that were inadequate for the current analysis. Next, the dataset was manually inspected to retain only outdoor images, resulting in 51,554 qualified images. Third, a pre-trained DeepLab V3+ model based on the ADE20K dataset was employed to perform semantic segmentation on the selected images (see Appendix A for detailed information). This model has demonstrated strong effectiveness and accuracy in urban scene understanding in previous studies (H. Zhang et al., 2023; Zhou et al., 2019; Zhu et al., 2025). The proportion of vegetation pixels in each image was then calculated as an estimate of perceived greenery. These image-level results were subsequently aggregated to the street and neighbourhood scales. This approach enables the assessment and comparison of social media greenery across multiple spatial scales.

2.3.2. Green View Index (GVI) measurement

Following Zhang et al. (2024) and Helbich et al. (2019), the GVI was calculated using Google Street View and the aforementioned deep learning techniques to measure eye-level greenery. First, Rotterdam's street network was segmented at 30-m intervals to establish sampling points, from which approximately 90,000 street view images were retrieved via Python scripts and the Google Street View API in December 2024. Second, consistent with Zhang et al. (2025) and Jeon and Woo (2023), the collected images were cropped according to the human field of view to minimise distortion. Third, the cropped images were semantically segmented using the same pre-trained DeepLab V3+ model based on the ADE20K dataset as that used in the social media greenery analysis. Finally, GVI for each image was calculated as the proportion of vegetation pixels to total pixels. The GVI values for individual street segments were then obtained by averaging the multiple image results for each street. Similarly, neighbourhood-level GVI was subsequently calculated by averaging street-level GVI values within each neighbourhood boundary.

2.3.3. NDVI calculations

NDVI quantifies vegetation density based on satellite imagery, with higher values corresponding to greater vegetation cover. In the research, NDVI was calculated from high-resolution satellite images with a 10 m spatial resolution. Buffers of varying radii (i.e., 10 m, 20 m, 30 m, 40 m, 50 m, 80 m, and 100 m) were generated around Rotterdam streets, and the mean NDVI within each buffer was extracted. Additionally, neighbourhood-level NDVI was calculated using the administrative boundaries of buurten (Dutch for neighbourhoods). Following Teeuwen et al. (2024), only NDVI values greater than 0 were retained for analysis.

2.3.4. Data analysis

Mapping analysis and hotspot analysis. Prior to statistical analyses, mapping and hotspot analysis were applied to explore the spatial distribution and clustering patterns of the three greenery measurements. Initially, the statistical results of the three measurements are presented and analysed, as well as their spatial patterns across two analytical scales. Following Li et al. (2021), greenery levels were classified into five categories for comparison among different measurements: very low (0—5%), low (5%—15%), medium (15%—25%), high (25%—35%), and very high (35%—100%). Spatial hotspot analyses using the Getis-Ord Gi* statistic were then employed to identify statistically significant clusters of high (hotspots) and low (cold-spots) greenery values.

Pearson correlation coefficient. Based on the spatial patterns of the three greenery measurements, the Pearson correlation coefficient (PCC) was used to examine the bivariate linear associations among them. PCC is a standard method for quantifying the strength and direction of a linear relationship between two variables. The calculation formula is as follows:

$$PCC = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2 \sum_{i=1}^{n}(y_i - \overline{y})^2}},$$

where n represents the sample size, x_i and y_i denote individual observations, and $\overline{x}$ and $\overline{y}$ represent the respective mean values. Two rounds of PCC analyses were conducted to identify pairwise correlations among the measurements at the street and neighbourhood scales. PCC values range from −1 to 1, with 1 indicating perfect positive correlation, −1 perfect negative correlation, and 0 no linear correlation.

In addition, the internal consistency across three greenery measurements was evaluated using a standard deviation-based approach. Specifically, z-score standardisation was first applied to ensure comparability of the three measurement results. The standard deviation across the standardised measurements was then computed for each street segment to quantify consistency or divergence among measurements. Lower standard deviations indicate greater internal consistency across social media greenery, GVI, and NDVI, whereas higher values highlight greater discrepancies between measurements.

Spatial correlation analysis. Spatial statistical methods, such as LISA and GWR, have been widely applied to examine the spatial heterogeneity of urban greenery and its links to socioeconomic, built-environment, or health outcomes (Ding et al., 2023; Luo et al., 2025; Zhang et al., 2025). Most of these studies focus on a single greenery indicator, whereas few systematically compare measurements from different sources. To address this gap, this study combines bivariate LISA with GWR to identify local consistency, inconsistency, and continuous spatial variations in the pairwise relationships among NDVI, GVI, and social media greenery. Following the descriptive analysis of the distributions of individual greenery measurements, bivariate LISA analyses were employed to characterise the pairwise local spatial structures among the three greenery measurements and to identify local spatial concordance and discordance. In line with prior studies (Li et al., 2021; Zhang, 2023), Global Moran's *I* was first calculated to assess spatial dependence. Results indicated significant positive spatial autocorrelation of the three greenery measurements, validating the application of spatial modelling techniques (Moran's $I = 0.665$ (NDVI), $p < 0.0001$; Moran's $I = 0.344$ (GVI), $p < 0.0001$; Moran's $I = 0.533$ (social media greenery), $p < 0.0001$). Subsequently, pairwise bivariate LISA analyses were conducted to explore local spatial associations between these greenery measurements. Spatial weights were defined using a fixed distance band of 400 m, with robustness checks using k-nearest neighbours ($k = 6-12$) and distance bands of 300–500 m. Statistical inference was based on 999 random permutations, and Benjamini–Hochberg false discovery rate (FDR) correction ($\alpha = 0.05$) was applied to control for multiple local tests. The bivariate LISA results were classified into High–High (HH), Low–Low (LL), High–Low (HL), Low–High (LH), and non-significant categories, distinguishing areas of spatial concordance (HH/LL) from those of spatial mismatch (HL/LH) among the three greenery measures.

To further examine spatial heterogeneity in the associations between greenery measurements, GWR was employed as a local spatial modelling technique that allows regression coefficients to vary across space, thereby capturing spatially non-stationary relationships that ordinary least squares (OLS) cannot reveal. In this study, three separate bivariate GWR models were specified, one for each pairwise combination of the three greenery measurements, with no additional covariates introduced (see Appendix A for detailed information about the GWR model). The model used a Gaussian kernel with continuous distance decay, and the optimal bandwidth was selected by minimising the corrected Akaike Information Criterion (AICc). All variables were *z*-standardised prior to estimation to ensure comparability of coefficients. The analysis results represent the spatially varying strength and direction of each pairwise relationship, which, together with the LISA clusters, enable a more comprehensive identification of the spatial concordance and divergence between the three greenery measurements. Across both the LISA and GWR analyses, only spatial units with complete observations of all three greenery measurements were retained, yielding a final sample of 62,703 street segments at the street scale and 80 neighbourhoods at the neighbourhood scale.

3. Results

3.1. Spatial patterns of NDVI, GVI, and social media greenery

Table 1 reports summary statistics for social media greenery, GVI, and NDVI at the street and neighbourhood scales. The three measurements demonstrate similar data range and distribution patterns, while notable differences also exist. NDVI consistently displays the highest mean values (0.229, 0.210), surpassing social media greenery (0.198, 0.158) and GVI (0.150, 0.142). Social media greenery demonstrates higher standard deviations and coefficients of variation, indicating greater variability. Examining the distribution across five greenery categories (i.e., very low, low, medium, high, very high), NDVI exhibits an approximately symmetric distribution at both scales, with medium-level greenery most prevalent. By contrast, distributions of social media greenery and GVI are skewed towards lower values, with GVI particularly concentrated in the low and medium categories.

Across scales, NDVI shows relatively less variation, while social media greenery and GVI exhibit pronounced scale dependency. The maximum and standard deviation of social media greenery and GVI decrease with increasing analytical scales. For example, at the street scale, GVI and, especially, social media greenery detect streets with higher greenery levels than NDVI does, but at the neighbourhood scale, neither measurement captures the neighbourhoods with the highest NDVI, and the proportion of very high greenery neighbourhoods decreases significantly. Further, GVI distribution becomes more concentrated at higher scales, with marked reductions in both the low- and high-value categories.

Mapping analysis of three measurements at street scale reveals broadly similar trends with lower greenery in central Rotterdam and higher greenery towards peripheral areas, but differences in magnitude and distribution also exist (Fig. 2). GVI shows a concentrated distribution of lower values, with very limited high-greenery streets. Social media greenery spans a broader range, with high greenery values distributed across several central and peripheral green zones. Getis-Ord Gi* hotspot analysis confirms statistically significant clustering patterns of all measurements. Low-value clusters are mainly distributed in the city centre and along both banks of the Nieuwe Maas river. In these areas, some smaller high-value clusters also appear near important green spaces such as Het Park in Nieuwe Werk and Heemraadspark in Nieuwe Westen (detailed information for all neighbourhoods is presented in Appendix A). Major high-value clusters occur in northern, eastern, and southern peripheral areas. Social media greenery and NDVI exhibit broadly similar clustering patterns, whereas GVI identifies fewer significant clusters, likely due to its more concentrated distribution and lower variance. GVI clusters are also relatively discontinuous and more localised, especially in central areas.

Spatial patterns at the neighbourhood scale exhibit notable differences compared to those at the street scale (Fig. 3). Consistent with earlier results, GVI does not identify neighbourhoods with high greenery levels, whereas

Table 1 Statistical results of social media greenery, GVI, and NDVI.

	Min	Mean	Max	SD	CV	<5%	5%–15%	15%–25%	25%–35%	>35%
Street-level social media greenery	0	0.198	0.989	0.142	0.715	12.5%	32.8%	24.4%	15.4%	14.9%
Street-level GVI	0	0.150	0.667	0.097	0.647	13.6%	43.7%	28.5%	10.1%	4.1%
Street-level NDVI	0	0.229	0.606	0.101	0.441	2.1%	19.9%	38.8%	26.8%	12.3%
Neighbourhood-level social media greenery	0	0.158	0.346	0.085	0.542	10.0%	38.8%	36.3%	15.0%	0%
Neighbourhood-level GVI	0.047	0.142	0.245	0.038	0.266	1.3%	58.8%	40.0%	0%	0%
Neighbourhood-level NDVI	0.055	0.210	0.412	0.072	0.341	0%	22.5%	48.8%	26.3%	3%

social media greenery captures more neighbourhoods with very low greenery levels. Hotspot analysis reveals low-value clusters in central neighbourhoods and southwestern port districts, and high-value clusters in northern peripheral neighbourhoods, but patterns also differ at the street scale, notably featuring southwestern rather than western low-value clusters and an absence of southern high-value clusters. In line with prior findings, the high- and low-value clustering patterns of GVI differ from those of the other two measurements.

3.2. Relationships between three measurements

Figure 4 (a) presents the pairwise PCC results among the three measurements at street scale. Additional NDVI metrics based on increasing buffer radii were included to test sensitivity to buffer distance. Results show that all correlations were statistically significant ($p < 0.001$), indicating consistent associations among the measurements (see Appendix A. for detailed results). All NDVI measurements exhibit relatively strong positive correlations with social media greenery ($r = 0.44–0.61$), with the highest coefficient for the 100 m buffer and the lowest for the 10 m buffer. Correlations between GVI and NDVI are slightly lower ($r = 0.46–0.50$) but still significant. The correlation coefficient between social media greenery and GVI is 0.30, indicating some similarities but also clear differences. NDVI metrics are highly correlated with each other ($r = 0.74–0.98$), particularly between adjacent buffer scales, where coefficients generally exceed 0.90, evidencing a strong internal consistency across remote sensing-based greenery measurements.

Figure 4 (b) shows the neighbourhood-scale PCC results. The coefficients exhibit consistently statistically significant high positive values ($r = 0.63–0.97$). Correlations of most measurement pairs are markedly higher than at the street scale, suggesting greater agreement among greenery measurements following spatial aggregation.

Figure 5 shows the spatial distribution of consistency among the three measurements at street and neighbourhood scales. Both results show a similar overall pattern with greater consistency in central and southern areas and differences mainly in peripheral areas. Comparison of the results demonstrates that spatial scale significantly affects

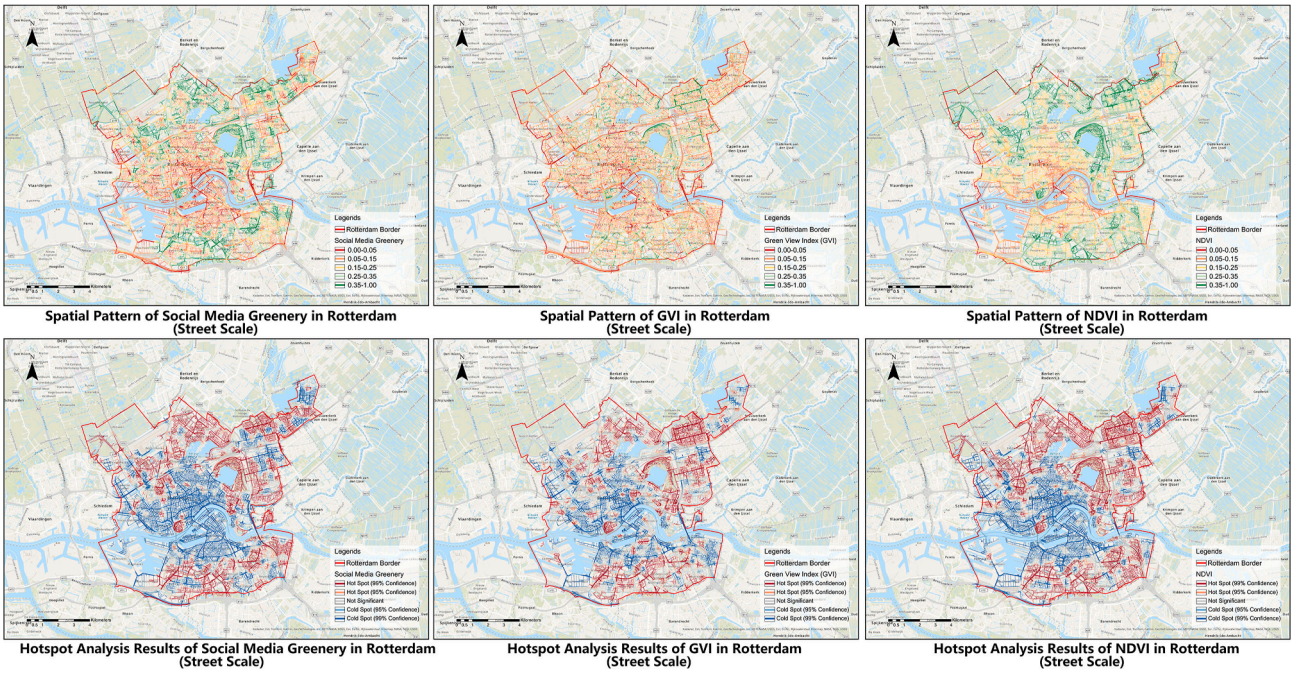


Fig. 2 Spatial patterns of hotspot analyses of the three measurements at the street scale.

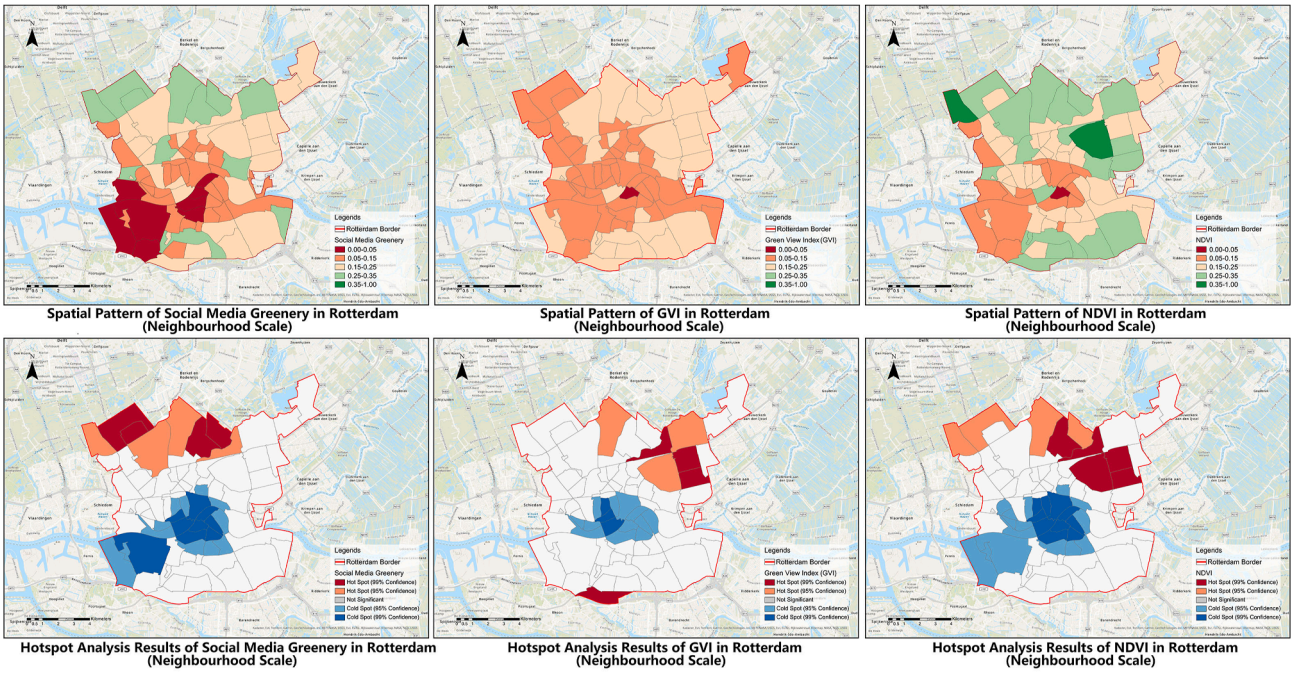


Fig. 3 Spatial patterns of hotspot analyses of the three measurements at the neighbourhood scale.

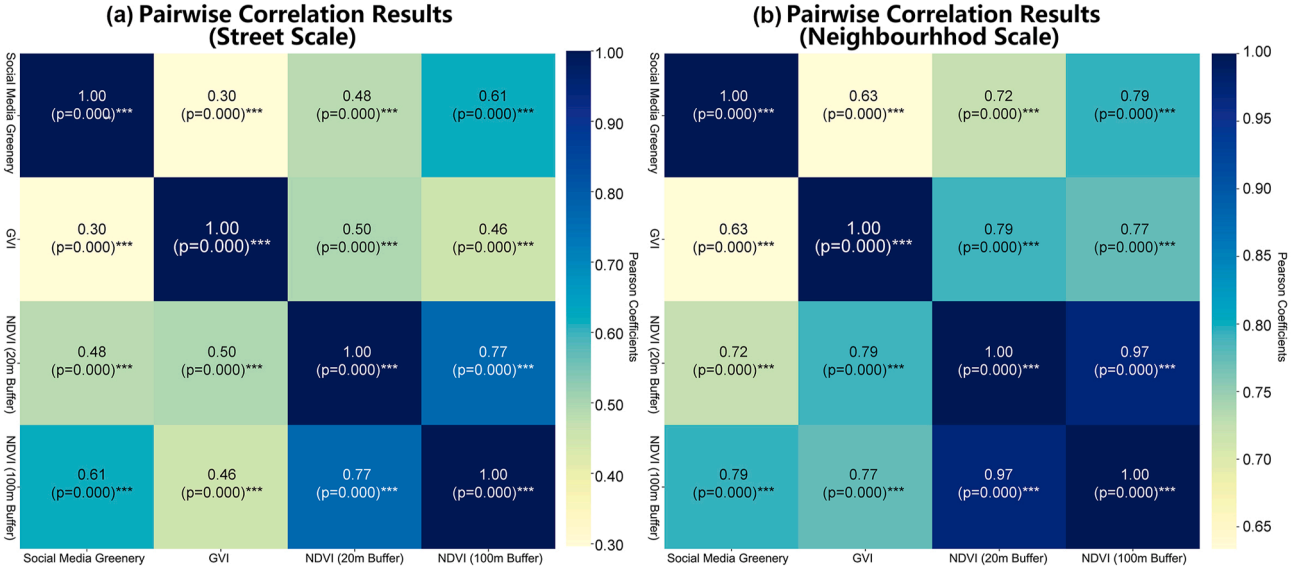


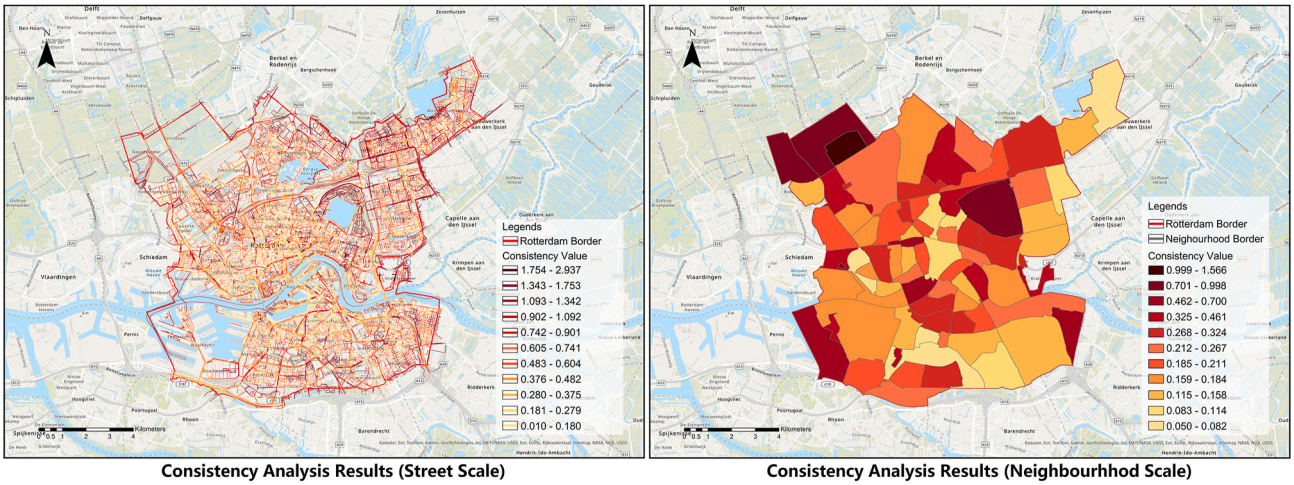
Fig. 4 Results of PCC analysis among various greenery-related measurements.

the observed consistency among greenery measurements, with increasing scales associated with decreased spatial heterogeneity.

3.3. GWR results between three measurements

Figure 6 presents the LISA and GWR results for the three greenery measurements at the street scale, showing spatial association clustering patterns and local regression coefficient strengths for each measurement pair, respectively. Overall, LISA results demonstrate broadly consistent clustering patterns featuring low-low clusters in the centre and high-high clusters in peripheral areas, which suggests a significant degree of spatial consistency among the three measures. In contrast, GWR coefficients reveal nuanced heterogeneities, illustrating varying magnitudes of associations spatially and across measurement pairs.

For the social media greenery and GVI pair, LISA results show more significant clustering in the centre than in the periphery. Notably, scattered high social media-low GVI



Consistency Analysis Results (Street Scale) | Consistency Analysis Results (Neighbourhhod Scale)

Fig. 5 Results of consistency analysis among various greenery-related measurements.

clusters also appear in the centre area, around small green spaces such as Museumpark. Scattered low social media-high GVI clusters are identified, mainly in office and cultural districts. Associations between social media greenery and GVI are less consistent in the periphery, as evidenced by the GWR results, which show substantial fluctuations in association strengths and clear negative correlations emerging in several areas, particularly within residential zones in the northeast and eastern periphery.

In comparison, social media greenery and NDVI show greater concordance in both the city centre and the periphery, where the two measurements yield broadly aligned results. However, a few high social media-low NDVI clusters still emerge around green spaces in the city centre, and areas of mostly low social media-high NDVI are present in the periphery. GWR results similarly show the strongest association strength. Nonetheless, several areas identified as high-high and low-low clusters also show relatively weak coefficients in the GWR, particularly in commercial and residential districts, as well as in certain sections of green spaces, highlighting that the two measurements may still capture aligned but not identical green patterns across the city.

Lastly, the GVI-NDVI pair exhibits more fragmented spatial patterns and local variations, with widespread high GVI-low NDVI outliers scattered throughout the city centre and low GVI-high NDVI outliers appearing across peripheral zones. The GWR analyses indicate mostly positive associations, but the overall coefficients are also lower, with strong associations only in the city centre. Notably, these areas are also where all three measurement pairs exhibit relatively strong positive associations.

At the neighbourhood scale, few significant clustering patterns are identified with LISA analyses, with GWR results also demonstrating varying association strengths of different measurements across neighbourhoods in different areas (see Appendix A). A cross-scale comparison reveals notable differences in spatial heterogeneity patterns.

4. Discussion

4.1. Interpretations of overall statistical and spatial patterns

With increasing recognition of urban greenery's ecological and well-being benefits amid global climate change and urbanisation, accurate and efficient quantification of greenery has become a priority for informing practical interventions. Taking Rotterdam as a case study, this research systematically demonstrated the application of three distinct greenery measurements across two spatial scales and examined their relationships. Although all methods quantify greenery, the findings reveal correlations alongside important differences.

This study proposed a novel social media image-derived urban greenery measurement and found that this approach effectively captures greenery patterns and yields outputs comparable to those of established indices, supporting its potential applicability for greenery assessment. Results also underscore social media greenery's fluctuations and broadest value range, which may be explained by its variability compared to objective indices, highlighting its nature as a more individual-centred measure of greenery (Ghermandi and Sinclair, 2019).

Results show that Rotterdam's mean GVIs are 0.150 (street scale) and 0.142 (neighbourhood scale), which aligns with several studies (Chen et al., 2022; Wang et al., 2022), but are lower than those reported for Singapore (Ye et al., 2019) and Hartford (Li et al., 2015a). Findings reveal that GVI consistently records lower mean values across measurements at both scales, corroborating the findings of Li et al. (2021). As GVI relies on data from vehicular roads, these results may reflect relatively limited visible greenery within Rotterdam's street environments, although methodological characteristics of GVI may also contribute. Rotterdam's GVI shows pronounced clustering variability at the street scale, while at the neighbourhood scale, its variation

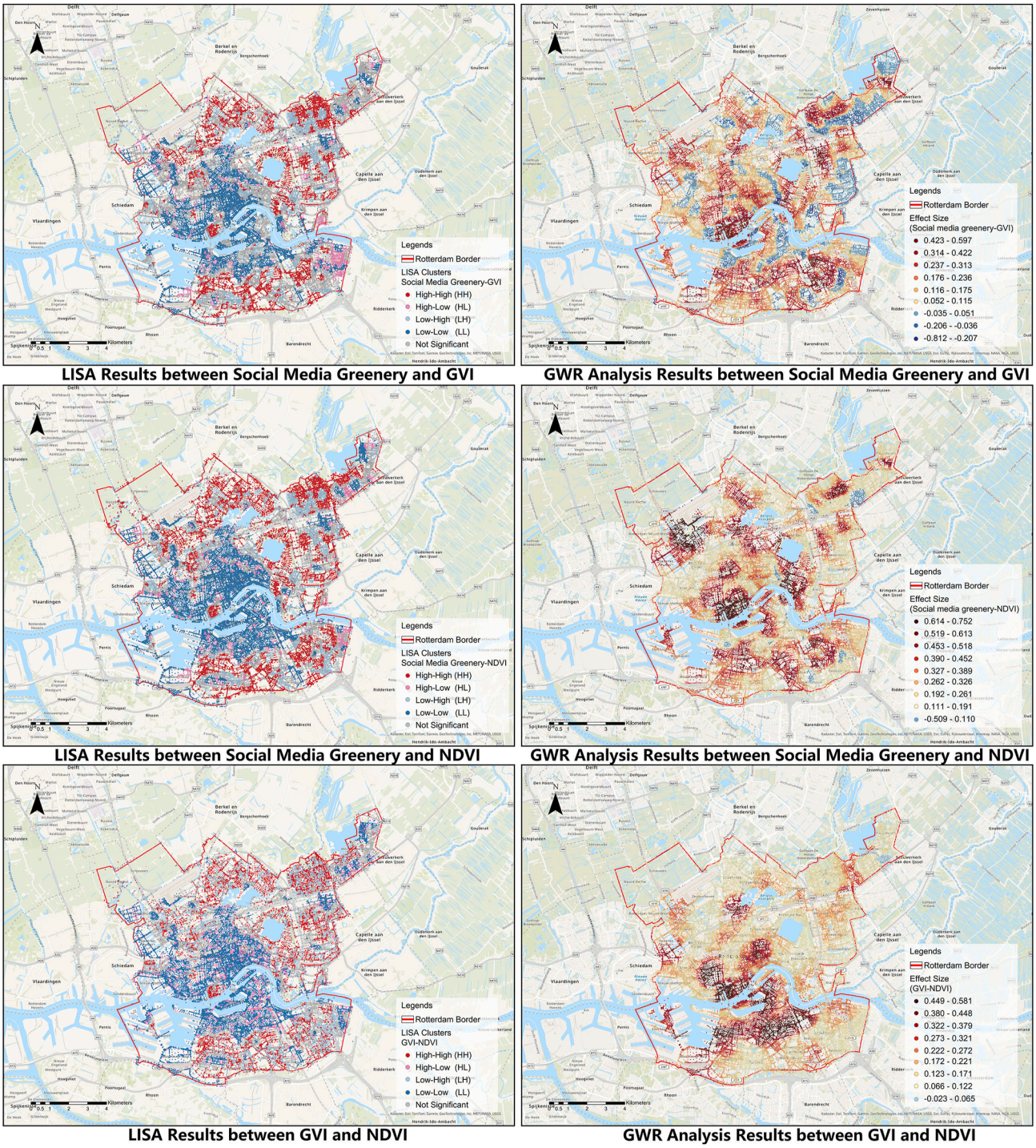


Fig. 6 The key results of the LISA and GWR analyses at the street scale.

decreased substantially. These findings extend the conclusions of Helbich et al. (2019), highlighting the sensitivity of GVI to analytical scale and spatial aggregation.

4.2. Interpretations of differences and relationships of the three measurements

Results show moderately strong correlations between indicators, consistent with existing studies and further confirming that different greenery measurements, calculated from top-down or eye-level approaches, are related but distinct in reflecting urban greenery conditions (Helbich et al., 2019; Larkin and Hystad, 2019; Wang et al., 2019). Notably, the strongest correlations were found consistently between social media greenery and NDVI. Considering social media is commonly viewed as a subjective data source (Wan et al., 2021), this stronger correlation compared to GVI, an established eye-level measurement, is noteworthy. This may be explained by social media's broader coverage:

compared to road network-based GVI, social media data's broader spatial coverage, particularly in pedestrian spaces such as green spaces, more closely approximates the area-based measurement of NDVI (Zhang and Su, 2024), highlighting its potential value in capturing greenery encountered within people's activity spaces. Correlations between social media greenery and GVI are lowest at both scales, further underscoring that they capture different dimensions of urban greenery despite both representing eye-level exposure.

Measurement correlations varied across analytical scales: a notably stronger correlation and consistency between measurements emerged at the neighbourhood scale, suggesting greater alignment with increased spatial aggregation. These results align with Li et al. (2015b), whose buffer-based analysis highlighted that finer-grained spatial units preserve micro-scale variations, whereas larger analytical units tend to smooth local variations and emphasise broader spatial patterns.

Spatial consistencies revealed by LISA and GWR results enable further analysis of the strengths and limitations of different measurements. Overall, results indicate greater agreement among measures in the city centre, which may be explained by better data coverage due to a concentrated population and dense road networks, suggesting potential interchangeability among datasets in central areas. This may also reflect that objective and individual-level green presence are aligned in Rotterdam's highly managed city centre, characterised by modern urban fabric. However, consistently higher concentrations of social media greenery are present in multiple central areas with important green spaces, such as the frequently visited Museum Park and Het Park, which serve as city attractions and receive high visitation and visibility. As photographs inherently reflect individual ways of capturing (and excluding) content within the frame (Song et al., 2020b), social media imagery likely records heightened public awareness of and attention to greenery in these locations beyond what objective conditions alone would suggest. This may be further amplified by the selective nature of social media sharing, whereby visually appealing scenes are more frequently photographed and disseminated (Ghermandi and Sinclair, 2019). This result implies that social media data may identify perceptually significant yet objectively overlooked green spaces that contribute to experiential quality. On the other hand, clusters with lower social media greenery also emerge in eastern central areas dominated by commercial and residential land-use, reflecting a contextual shift. In these areas, the visual prominence of functional urban infrastructure may reduce the share of greenery features in the Flickr image dataset, even where objective green conditions may remain stable. This pattern illustrates that while social media are subject to inherent biases, they may also reflect how people perceive greenery relative to the context, as the study by Teeuwen et al. (2024) highlighted that respondents may judge greenery contextually rather than absolutely. Collectively, findings reveal the distinct lens through which social media data can inform urban greenery research.

Nevertheless, GWR results reveal pronounced fluctuations in the relationships between social media greenery and other measurements in Rotterdam's industrial and residential peripheries. This likely reflects data availability and quality challenges of social media measurement in peripheral areas where image-sharing activities are limited, potentially causing local measurement variability and overrepresentation of data noise and outliers (Ghermandi and Sinclair, 2019). Also, greenery in peripheral zones may be located in less accessible areas or incorporate spontaneous vegetation, receiving less public visitation or attracting less photographic attention (Dunkel et al., 2023; Song et al., 2020b). These findings highlight the limitations of the social media approach, where data availability and quality may be compromised, particularly in less-populated or less-visited areas.

For GVI data, results reveal greater variability along with scattered high-value outliers compared to other measures in Rotterdam's central streets. This may reflect street view images' greater sensitivity to variations of local and street-level green conditions. This is consistent with previous findings that street view images may more effectively capture fine-scale and vertical green elements in the street environment (Larkin and Hystad, 2019). In contrast, more low-value outliers of GVI are found in Rotterdam's western peripheral areas, which feature mainly natural and agricultural landscapes. This may be attributed to discontinuous street view data coverage arising from insufficient road network density in such landscapes. Panoramic distortion in street view imagery, particularly in expansive peripheral areas, may also disproportionately minimise distant greenery and thereby affect GVI accuracy, even though this study applied image cropping to mitigate this effect (Labib et al., 2021). Regarding NDVI, further verification shows that its higher outliers correspond to inaccessible or restricted green spaces, such as private green spaces in southeastern neighbourhoods. These findings align with Labib et al. (2021), highlighting the strengths of NDVI in capturing overall vegetation cover and its relative insensitivity to actual accessibility and visibility conditions.

4.3. Selecting suitable measurements for design and policymaking

The selection of appropriate urban greenery measurements is critical for ensuring reliable findings and guiding effective interventions in research and practice. This study reveals that NDVI, GVI, and social media greenery capture related but different dimensions of urban greenery, each with distinct strengths and limitations. Accordingly, measurement selection should be driven by the research aims and spatial design intentions, as the methodological differences among these measurements shape their suitability for different scenarios.

Consideration of indicator-specific characteristics. The study suggests that NDVI, GVI, and social media greenery are not interchangeable and should be applied according to indicator-specific characteristics or combined as

complementary tools. Social media greenery provides a unique and previously hard-to-access personal perspective, valuable for capturing perceived greenery intertwined with awareness and usage patterns (Donahue et al., 2018; Wan et al., 2021). It can also be integrated with other user-generated content, including textual reviews and place of interest (POI) data, showing potential to generate valuable first-person insights into the human-nature nexus and to offer future methodological avenues (García-Palomares et al., 2015; Niu and Silva, 2023). This can be potentially beneficial, as evidence increasingly demonstrates that public perceptions of urban greenery may differ from actual green conditions (Leslie et al., 2010) and may better explain greenery's human benefits, including physical activity and well-being (Rieves et al., 2024). Therefore, social media emerges as a promising source of subjective information, providing supplementary information on which types of greenery are most perceptible and attractive to the public and thereby supporting inclusive and responsive urban design. However, scrutiny is required in its applications: biases and variations should be acknowledged and better controlled, and data availability should be a prerequisite for delivering credible insight (Bernabeu-Bautista et al., 2021; Jiang et al., 2016; Martin and Schuurman, 2020).

NDVI, derived from remote sensing, offers advantages in wide, continuous coverage and greater adaptability across different analytical scales compared to others, thereby better supporting analyses of long-term dynamics as well as multi-scale and cross-regional comparisons (Hu and Zeng, 2025). By contrast, GVI and social media greenery may have limitations for modelling future greenery changes due to their reliance on existing observational data, whereas NDVI is better suited for predictive scenario analyses. These features, along with its relative independence from typology and accessibility variations, make it well-suited for city-scale assessments of land cover, ecological structure, and climate adaptation (Ai et al., 2023; Chen et al., 2026;Wang et al., 2025), but potentially less effective for assessing experiences. GVI, in turn, is more suitable for capturing street greenery, which may differ considerably from top-down greenery measures. At the street scale, GVI exhibited greater sensitivity to local variations and small-scale green hotspots than NDVI or social media, demonstrating its value for street-level measurements. This makes GVI particularly suitable for capturing pedestrians' direct experience of streets, squares, and everyday public spaces, potentially informing route planning and street/public spaces design (Ki and Lee, 2021; Wang et al., 2021; Zhang et al., 2024). Nevertheless, potential coverage issues and distortion constraints should be acknowledged. Such complementarity is particularly relevant for the implementation of the Rotterdam Green Agenda, which aims not only to increase the total amount of greenery but also to promote climate adaptation, public space quality, and neighbourhood livability. Specifically, NDVI informs city-wide ecological and climate-adaptation interventions, GVI supports the design of streets and everyday public spaces, and social media greenery helps identify places that already resonate with the public. Rather than competing, the three measurements thus play distinct yet complementary roles in implementing the Agenda's multi-faceted objectives into evidence-based strategies.

Consideration of local contextual and environmental conditions. The applicability of greenery measurements is shaped by local spatial and environmental contexts, which have direct implications for how each measurement should be deployed across different urban settings. This study reveals greater measurement agreement in the city centre and highlights potential limitations of social media data in peripheral and less-populated areas. Areas with extensive greenery also display consistently high agreement across measurements, though GVI tends to underrepresent greenery within large green spaces, potentially due to coverage issues. The measurements also differ in their sensitivity to forms and scales of greenery. Accordingly, from a practical view, this research recommends integrating the measurements, as they capture related but distinct dimensions of urban greenery from ecological, visual, and perceptual standpoints. Combined application may thus offer valuable multi-dimensional perspectives to support more comprehensive assessments and better targeted spatial interventions. Importantly, these measurements are complementary rather than mutually exclusive. For instance, when assessing the heat-mitigation benefits of urban greenery, all three measurements may provide valuable perspectives: NDVI for objectively estimating cooling potential, GVI and social media greenery for understanding perceived heat reduction and public heat experiences. This context-sensitive feature is particularly relevant for the local interventions, such as the Rotterdam Green Agenda, which spans interventions from neighbourhood greenery to the renewal of squares, streets, and public spaces. In active inner-city settings, GVI and social media greenery can jointly inform the design of streets and public spaces by capturing both eye-level exposure and perceived use, whereas NDVI offers a more reliable assessment for peripheral districts and for district-to city-scale planning of ecological structure and climate adaptation.

Consideration of analytical spatial scale. Previous studies have often combined neighbourhood-level greenery indicators with street- or individual-level data without explicitly addressing the scale mismatch. This study demonstrates that aggregating street-level data into neighbourhood-level units substantially alters analytical outcomes. At the street scale, GVI, NDVI, and social media greenery exhibit significant spatial heterogeneity. However, as the scale increases from street to neighbourhood, local heterogeneities are smoothed out, and differences among measurements become less pronounced, yielding higher correlations at larger scales. This phenomenon highlights the significant implications of the Modifiable Areal Unit Problem (MAUP) for these three measurements, an issue widely recognised in ecology, human geography, and urban studies (Jelinski and Wu, 1996; Nouri et al., 2017; Wong, 2004). This scale-dependency is not merely a methodological concern but directly influences the types of patterns and relationships that can be detected, and therefore the planning questions they can meaningfully inform. In particular, this research indicates that GVI captures local conditions but is notably sensitive to scale, potentially producing substantially different results when aggregated. The present findings reaffirm the need for

future research to align analytical scales with research objectives carefully, utilising strategies such as multi-scale parallel analyses, optimised aggregation techniques, and spatial statistical modelling to mitigate information loss and enhance the robustness and relevance of results (Briz-Redón et al., 2019; Kwan, 2018; Wu, 2004). Aligning analytical scale with planning objectives is particularly pertinent for the Rotterdam Green Agenda and related practices. Larger-scale analyses support city-wide goal setting and implementation evaluation related to overall green supply and climate adaptation, while street-scale analyses inform the identification and prioritisation of concrete spatial interventions along streets, squares, and everyday living spaces.

4.4. Limitations

Despite the insights gained, several limitations merit attention in future research. Firstly, temporal and spatial inconsistencies exist across the analysed datasets. Specifically, NDVI is derived from satellite imagery at a 10 m $\times$ 10 m spatial resolution for May to August 2022, while the GVI uses street view imagery captured after 2020, and social media images span the past 15 years to ensure data coverage. Although efforts are made to ensure temporal alignment during the analysis, and vegetation change may be minimal in densely urbanised settings such as Rotterdam, the potential impact of temporal mismatches warrants further consideration. Secondly, differences in photographic angles introduce uncertainty into greenery estimates derived from eye-level measurements, such as social media greenery and GVI. Generally, street view images are captured on streets, so the exact location of the capture point can influence results, particularly on wide streets with multiple lanes. By contrast, social media greenery depends on user-uploaded photos, whose capture locations and angles vary according to individual preferences, potentially resulting in overestimating greenery. Thirdly, significant spatial disparities in data availability exist, especially for social media images. This spatial imbalance impedes the accurate assessment of overall greenery, yet it offers valuable insights into its potential applications.

Future research should address these limitations in several ways. Firstly, expanding the geographic scope of case studies would allow stronger tests of the consistency among these greenery measurements and broaden the generalisability of findings. Given Rotterdam's relatively high population density and level of urban greenery, it is necessary to assess the methodological applicability within cities of differing contexts, employing standardised data collection protocols (e.g., consistent timing and photographic angles). Secondly, as methodological diversity and data sources evolve, such as the widespread city-wide point cloud data, the feasibility of employing these emerging measurements as alternatives or complements to NDVI merits investigation. Future work could integrate such methods and measurements to provide more comprehensive assessments of urban greenery. Lastly, while this study discussed methodological differences and their potential applications, future studies could explicitly link these greenery measurements to tangible outcomes, such as public health or environmental improvements, to empirically evaluate each measurement's practical implications and suitability.

5. Conclusions

Urban greenery is increasingly recognised for its potential to address contemporary urban challenges, requiring accurate and efficient assessment methods to inform research and guide practical interventions. Using Rotterdam as the case study, this research systematically applies and compares three distinct urban greenery measurements: social media greenery, the Green View Index (GVI), and the Normalised Difference Vegetation Index (NDVI). Mapping and hotspot analyses reveal a broadly similar spatial distribution of greenery, with lower levels in the city centre and higher levels in peripheral areas. GVI demonstrates sensitivity to spatial scale and a reduced capacity in detecting areas of high greenery, whereas social media greenery exhibits significant variability and reflects unique perceptual representations of urban greenery. Correlation analysis identifies statistically significant positive associations among all three measurements at both street and neighbourhood scales, with stronger correlations at the neighbourhood scale. Spatial consistency analysis reveals substantial heterogeneity among measurements at the street scale, whereas neighbourhood-scale analyses show more homogeneous patterns. This scale-dependent variation underscores the critical influence of analytical scale on greenery assessment results. Finer-grained spatial units retain detailed micro-scale variability, whereas larger units tend to average local differences and emphasise broader patterns. LISA results show broadly coherent spatial structures shared by all three measures, with low—low clusters concentrated in the centre and high—high clusters in peripheral zones, alongside pair-specific outliers. GWR analyses expose pronounced local heterogeneity, with strong positive coefficients confined to selected central areas and fluctuating or negative relationships in residential, commercial, and mixed-use districts. Together, these findings show that while greenery measures align in broad spatial patterns, their local relationships diverge, reflecting distinct facets of urban greenery. Practically, the results support the selection of measures tailored to specific contexts and tasks, facilitating targeted spatial interventions that advance the Sustainable Development Goals and the development of healthy cities.

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foar.2026.05.007.

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