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Multi-Perspective Evaluation of Urban Green Views: Spatial and Street-View Data Integration in Sudirman Central Business District, Indonesia

Abstract: Urban green spaces (UGSs) are critical for enhancing urban livability and sustainability by providing both ecological and human-centered benefits. This study integrates spatial landscape metrics and the street-level visibility of greenery (measured through the green view index [GVI]) in order to evaluate the structural and visual characteristics of UGSs in a dynamic urban area – specifically, the Sudirman Central Business District (SCBD) of Jakarta, Indonesia. The analysis focuses on examining the roles of landscape metrics such as area, perimeter, compactness, shape index, and elongation in influencing the GVI and its spatial variability across different types of urban green spaces (including parks, green corridors, and open spaces). The results indicated that larger and more compact UGSs significantly contributed to higher GVI levels (thus, reflecting better visual greenery), while elongated and fragmented green spaces exhibited greater variability and lower visibility. Non-linear relationships (assessed through random forest regression and SHAP analysis) further revealed the complex interactions between GVI and landscape metrics, thus emphasizing the importance of incorporating advanced statistical approaches. The limitations that are related to data quality, temporal coverage, and spatial heterogeneity are also discussed, thus highlighting opportunities for future research for addressing these challenges through multi-temporal analyses and spatially explicit models. By bridging the gap between the spatial configurations and visual perception of UGSs, this study contributes to sustainable urban-planning strategies that are aimed at optimizing green spaces for ecological functionality and human well-being.

Keywords: green view index, landscape metrics, non-linear analysis, random forest, spatial distribution, street-view, urban green spaces

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1. Introduction

Urban green spaces (UGSs) significantly impact urban environments by providing ecological, social, and psychological benefits [1–3]. Ecologically, UGSs contribute to improving air quality, reducing urban-heat-island effects, and serving as habitats for biodiversity [4–9]. Furthermore, UGSs serve as critical habitats for urban biodiversity, promoting ecological balances amidst rapidly expanding cities [10]. Socially, UGSs enhance public health by reducing stress, fostering social interactions, and mitigating the risks of mental health issues [3, 11–14]. However, the significance of UGSs extends beyond these ecological and social benefits; they also include their roles in shaping urban residents' perceptions and experiences of their built environments [15–17]. The perception of UGSs from a human perspective is equally vital, as the subjective experience of greenery influences comfort and satisfaction with urban spaces [18, 19]; therefore, understanding UGSs through both ecological functionality and human perception is vital for sustainable urban planning [20].

Historically, the evaluations of UGSs have been predominantly based on objective data that has been derived from two-dimensional spatial analyses such as satellite imagery and geographic information systems (GISs) [21–23]. Metrics such as the normalized difference vegetation index (NDVI) [24] are frequently used to quantify vegetation covers, providing bird's-eye views of greenery distribution across vast urban landscapes. In addition, landscape metrics such as area, perimeter, compactness, and the shape index are utilized to describe the spatial geometries and fragmentations of green spaces, shedding light on their potential ecological functions [21, 25, 26]. While these methods are effective in assessing the quantities and spatial arrangements of greenery, they fail to account for the experience of greenery at the human scale. The limitation of these traditional approaches lies in their inability to bridge the gap between the macro-level spatial perspective and the micro-level experiential perspective (where human interactions with green spaces occur) [27–30].

Although traditional metrics provide a robust framework for large-scale assessments, they often overlook the fundamental purpose of UGSs (which is to serve human needs). Urban green spaces must be experienced and valued by the people who live and interact with them daily [31–34]. Evaluating UGSs from the human perspective involves considering how individuals perceive and interact with these spaces [35–38]. Metrics like the green view index (GVI) (the proportion of visible greenery from a pedestrian's perspective) address this gap by providing a lens for evaluating UGSs at the human scale [39]. However, the subjective nature of such evaluations introduces challenges. Human perceptions are inherently influenced by personal preferences, cultural backgrounds, and situational contexts, thus leading to variability and potential biases in the assessments of UGSs. This variability complicates efforts to establish a comprehensive evaluation framework that integrates subjective perceptions with objective measurements.

The integration of subjective and objective perspectives in UGS evaluation bridges the gap between technical accuracy and social relevance [40, 41]. Advances in computational vision and machine learning have enabled hybrid approaches that combine street-view imagery and spatial data [42–44]. Street-view imagery captures greenery from the human perspective, while GIS-based metrics provide insights into spatial geometry and connectivity. Together, these methods allow for a more comprehensive understanding of UGSs that address both ecological functions and human experiences. Techniques such as convolutional neural networks (CNNs) have been employed to quantify greenery visibility, thus complementing landscape metrics like area, compactness, and connectivity [45–48].

Recent studies have demonstrated the potential for combining diverse data sources for UGS evaluation. For instance, Wu et al. [49] integrated street-view imagery and satellite data to assess greenery along urban roads, while other research has quantified visible greenery using panoramic images and artificial intelligence to explore its psychological impacts. Metrics like the GVI have been widely adopted to measure greenery visibility, while GIS-based metrics ensure that the spatial and functional aspects of UGSs are captured [50]. These integrative methods highlight the importance of combining subjective and objective perspectives for a holistic UGS evaluation.

In Jakarta, an open green is legally defined by Governor of Jakarta Regulation No. 9 of 2022 as vegetated areas that serve ecological and social functions and encompass linear green corridors and clustered patches [51]. Not all vegetated spaces qualify as RTHs, as they must meet specific functional and legal criteria. The Kebayoran Baru district (which includes the Sudirman Central Business District [SCBD]) presents diverse RTH geometries such as linear roadside spaces and clustered urban parks. This variety in green space forms makes Kebayoran Baru an ideal case study for evaluating UGSs through integrated spatial and street-view data.

By synthesizing the challenges that were discussed above, this study addresses the need for a comprehensive evaluation framework that integrates both the objective and subjective perspectives of UGSs. The aim of this research is twofold:

1) to analyze the greenery of urban green spaces in the study area, using a multi-perspective approach that combines spatial data and street-view imagery;
2) to evaluate the greenery of the study area based on the characteristics of its landscape forms using advanced landscape metrics.

2. Methodology

2.1. Study Area

The Sudirman Central Business District (SCBD), which is located in South Jakarta, Indonesia, was chosen as the study area due to its strategic urban significance and the diversity of its UGS configurations (Fig. 1). SCBD is a prominent commercial and residential hub that is characterized by high-density developments interspersed with UGSs that vary in their forms and functions. These green spaces include compact parks, linear green corridors, and fragmented patches that are integrated into the urban fabric; these create a unique spatial variability that is critical for examining the relationship between UGS patterns and their perceived greenery [11, 52].

The variability in the UGS patterns within SCBD reflects the complexity of balancing urban growth with environmental sustainability in one of Jakarta's most dynamic districts. These green spaces provide essential ecological and social functions, including improving urban aesthetics, enhancing air quality, and offering recreational opportunities [53]. By focusing on SCBD, this study explores how the geometric and spatial characteristics of UGSs contribute to urban livability and human perceptions of greenery, thus offering insights into sustainable urban-planning practices.

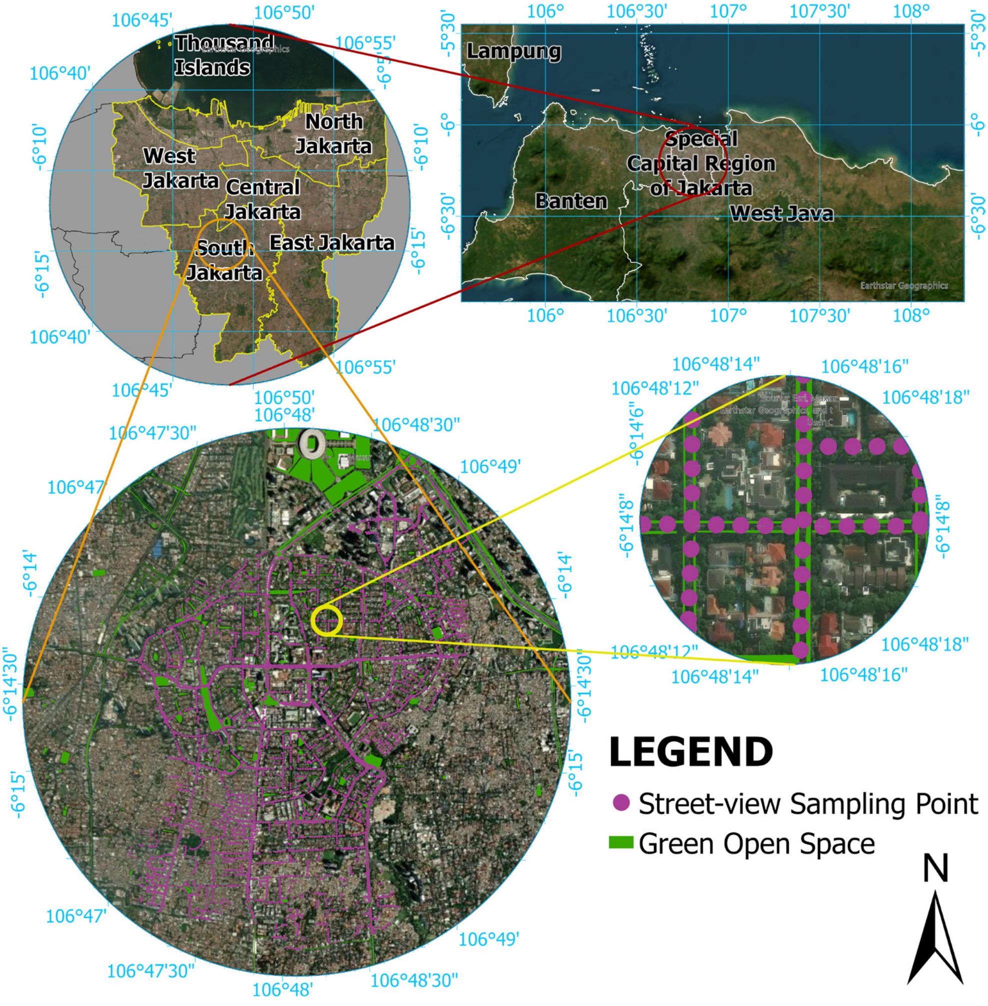

Fig. 1. Sudirman Central Business District (SCBD) as study area in context of Jakarta

2.2. Research Framework

The research framework (Fig. 2) was designed to evaluate urban greenery using a multi-perspective approach that integrated street-view and spatial data in order to provide comprehensive insights into urban green spaces (UGSs). The first step involved data acquisition through the crowdsourced Mapillary database, which provides a collection of street-view images that have been contributed by the public; these images include both panoramic and regular photos [50, 54]. However, the quality and resolution of the imagery vary due to its crowdsourced nature, thus introducing challenges in ensuring uniformity and accuracy. To address this limitation, only available and georeferenced images were selected for further analysis, while any missing data points were excluded from the workflow.

Once the imagery was prepared, the next step involved the quantification of the GVI; this was achieved through deep-learning techniques for semantic segmentation by utilizing the GitHub repository (https://github.com/Spatial-Data-Science-and-GEO-AI-Lab/StreetView-NatureVisibility) by Sánchez and Labib [55]. The segmentation process identified and classified green elements such as trees, grass, and other vegetation in each image by calculating the proportion of green pixels to the total number of pixels. The resulting GVI provided a reliable measure of the greenery that was visible at street level. However, it is crucial to acknowledge that the segmentation's performance depended on the input imagery quality and the robustness of the model's training data.

The spatial-data preparation involved generating vector representations of UGSs from Jakarta's authoritative sources. A 20-meter buffer was applied to these polygons to spatially integrate the street-view data, thus ensuring that the points on the street near the UGSs were overlaid with their respective UGS polygons. The GVI values that were derived from the street-view analyses were zonally averaged within these buffers, thus providing an aggregated measure of greenery per UGS polygon. To further characterize the UGSs, the landscape metrics were calculated; these included area, perimeter, shape index, compactness, and elongation. These metrics enabled the evaluation of the spatial configuration and geometric characteristics of the UGSs.

Finally, the analysis integrated this data into a multi-layered framework. The relationship between the landscape metrics and the GVI was examined using Pearson correlation and regression models. A non-linear regression approach (specifically, random forest) was employed to evaluate the explanatory power of the landscape metrics on the GVI variability, with a SHAP analysis providing interpretability. The findings contribute to the understanding of how different UGS forms (such as linear or patchy configurations) are related to the greenery that is perceived from street-level views.

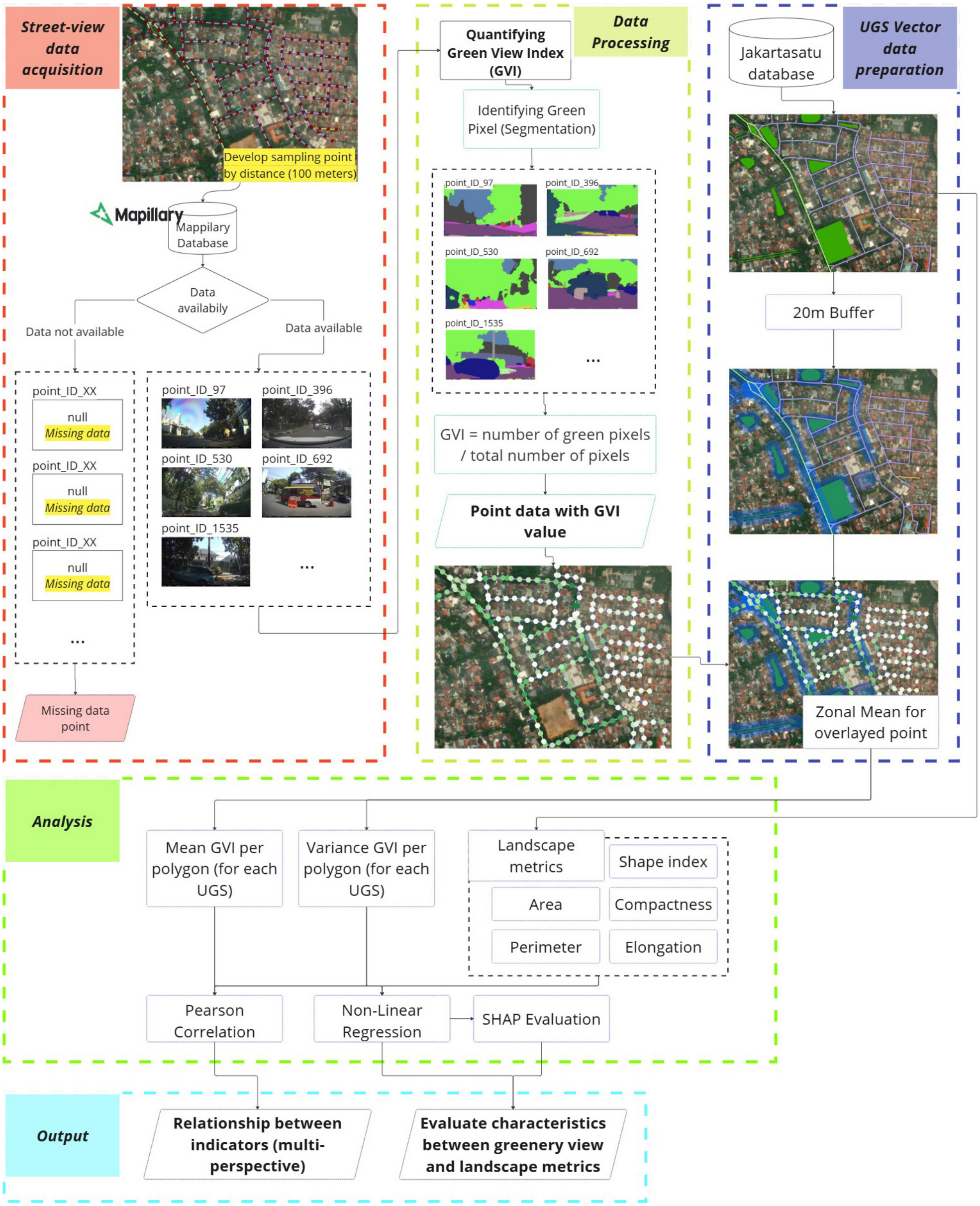

Fig. 2. Research framework

2.3. Data and Variable

Table 1 summarizes the key variables, data sources, and purposes that were used in this study to evaluate the UGSs. Being derived from the street-view data that was processed through the Mapillary crowdsourced database, the GVI measured the presence of green elements from a human perspective on the streets. Landscape metrics such as area, perimeter, shape index, compactness, and elongation were calculated by using spatial data from the Jakarta Spatial Database (JakartaSatu). These metrics served to assess various characteristics of the UGSs: the area evaluated the size and its ecological and recreational contributions; the perimeter reflected the boundary complexity and urban interaction; the shape index measured any irregularity that was linked to ecological efficiency; the compactness determined the spatial optimization; and the elongation identified any stretched forms that were relevant to the connectivity and corridor functionality.

Table 1. Variables and data

Variable	Data	Source	Purpose
GVI	Street-view data	Mapillary crowdsourced database (API)	Measured presence of green elements from human perspective on streets
Landscape metrics – Area	Spatial data of UGS boundaries	Jakarta Spatial Database (JakartaSatu – https://jakartasatu.jakarta.go.id/)	Measured UGS size in order to assess its contribution to urban ecology and recreation
Landscape metrics – Perimeter			Evaluated boundary length, thus indicating shape complexity and urban interaction
Landscape metrics – Shape index			Assessed shape irregularity and linked it to ecological efficiency
Landscape metrics – Compactness			Determined how closely UGS resembled circle, thus optimizing space usage
Landscape metrics – Elongation			Identified stretched shapes, which were useful for understanding connectivity and corridor functions

2.4. Data Analysis

Semantic Segmentation

Semantic segmentation was employed in order to extract the greenery from the street-view images by using a deep-learning model based on the code that was provided by Sánchez et al. (https://github.com/Spatial-Data-Science-and-GEO-AI-Lab/Street-View-NatureVisibility) [55]. The GVI was calculated by using the following equation:

$$GVI = \frac{Number\ of\ green\ pixels}{Total\ number\ of\ pixels} \tag{1}$$

This computation quantified the visible greenery at each sampling point, linking human visual perception to the urban green infrastructure.

Landscape Metrics

The landscape metrics were calculated from the UGS boundaries that were sourced from the Jakarta Spatial Database (JakartaSatu). These metrics include the following:

- area (size of UGS [m^2]), indicating ecological and recreational capacity;
- perimeter (total boundary length [m]), reflecting interaction with urban surroundings;
- shape index, indicating irregularity of shapes:

$$Shape\ Index = \frac{Perimeter}{2\sqrt{\pi \cdot Area}} \tag{2}$$

- compactness, expressing spatial efficiency:

$$Compactness = \frac{4\pi \cdot Area}{Perimeter^2} \tag{3}$$

- elongation, indicating connectivity and corridor functions:

$$Elongation = \frac{Perimeter}{4\sqrt{Area}} \tag{4}$$

Statistical Analysis

The spatial variability of the GVI within each UGS polygon was assessed using variance (σ^2) and was calculated by:

$$\sigma^2 = \frac{\Sigma(x_i - \overline{x})^2}{n} \tag{5}$$

where x_i is each GVI value, $\overline{x}$ is the mean GVI, and n is the number of observations.

A Pearson correlation matrix was constructed in order to evaluate any linear relationships among the GVI, its variance, and the landscape metrics. The correlation coefficients (r) ranged from −1 to 1, thus showing the strengths and directions of the relationships; these were computed using:

$$r = \frac{\Sigma\left(x - \overline{x}\right)\left(y - \overline{y}\right)}{\sqrt{\Sigma\left(x - \overline{x}\right)^2 \cdot \Sigma\left(y - \overline{y}\right)^2}} \tag{6}$$

where x and y are the two variables that are being compared, and $\overline{x}$, $\overline{y}$ are their respective means.

To model the influence of the landscape metrics on the GVI, a random forest regression was performed (with 70% of the data being used as training data, and rest of it as testing data). SHAP (SHapley Additive exPlanations) values were used to interpret the model, thus quantifying each metric's contribution to the GVI prediction. This approach provided a non-linear assessment in order to understand the relationships between the predictors and each dependent variable in a complex modeling framework.

3. Results

3.1. GVI and Variance Distribution

The spatial distribution of the GVI revealed notable heterogeneity across the study area. As illustrated in Figure 3, those areas with dense vegetation along the streets and near the UGSs exhibited higher GVI values (thus, indicating better greenery visibility). Conversely, those areas that were dominated by urban infrastructure displayed lower GVI levels (thus, reflecting limited green coverage). This distribution emphasized the variability of the greenery perception, which was influenced by the spatial arrangements and densities of the vegetation. The polygon-based analysis of the GVI variance (also shown in Figure 3) highlighted the internal heterogeneity within the UGS polygons; those polygons with low variances represented consistent green visibility (which may have corresponded to uniformly vegetated parks or forests), whereas the high-variance polygons indicated fragmented or uneven greenery coverage.

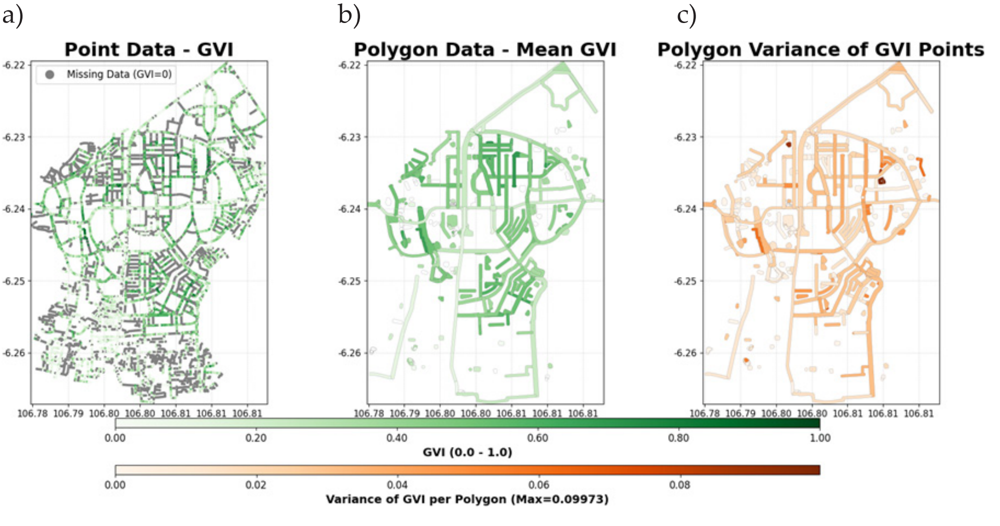

Fig. 3. Distribution of GVI by point (a), mean GVI for each UGS polygon (b), and variance of GVI for each UGS polygon (c)

The distribution of the GVI and the variance across the different UGS types further highlighted their variability and effectiveness in providing greenery visibility. Figures 4 and 5 and Table 2 show boxplots of the mean GVI levels and variances by UGS types. Neighborhood parks and green corridors exhibited higher median GVI values (thus, showcasing their role in enhancing greenery visibility – particularly along the streets); in contrast, the city parks and urban forests showed slightly lower GVI medians due to their compact arrangements and limited visibility from street-level perspectives (even though they displayed consistent greenery). The variance analysis supported this observation, as the green corridors showed higher variability due to their linear structures and fragmented vegetation coverages.

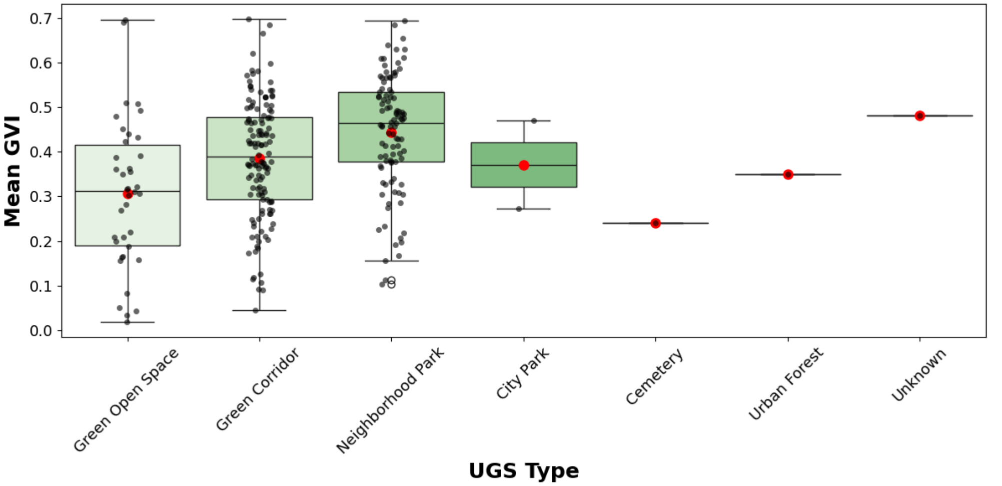

Fig. 4. Boxplot of mean GVI level per polygon of UGSs for each UGS type

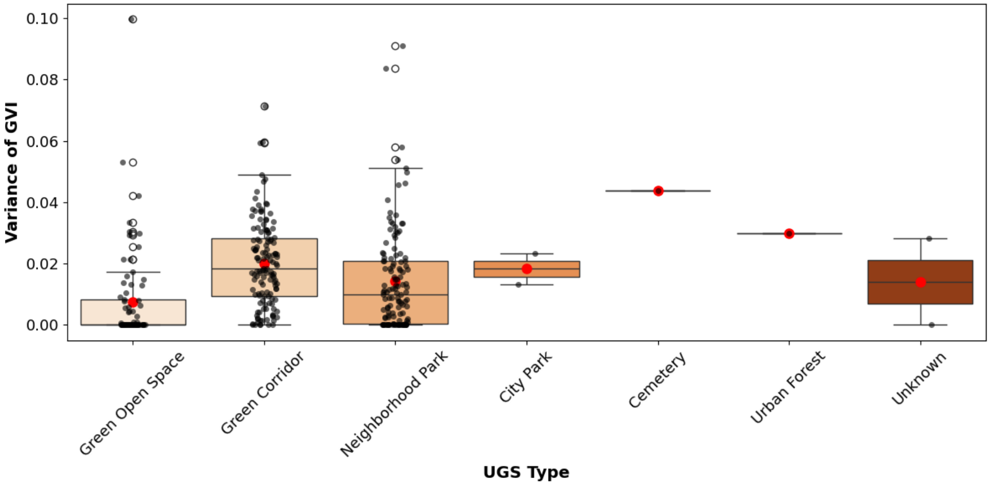

Fig. 5. Boxplot of variance GVI level per polygon of UGSs for each UGS type

Table 2. Mean and variance GVI for each UGS type

UGS Type	GVI						Variance GVI					
	Mean	Median	Q1	Q3	Min	Max	Mean	Median	Q1	Q3	Min	Max
Green Open Space	0.31	0.31	0.19	0.41	0.02	0.69	0.007480	0.000000	0.000000	0.008162	0.000000	0.097338
Green Corridor	0.39	0.39	0.29	0.48	0.05	0.70	0.020047	0.018255	0.009484	0.028133	0.000000	0.071328
Neighborhood Park	0.44	0.47	0.38	0.53	0.10	0.69	0.014334	0.009885	0.000347	0.020943	0.000000	0.091099
City Park	0.37	0.37	0.32	0.42	0.27	0.47	0.018310	0.018310	0.015746	0.020874	0.013812	0.023438
Cemetery	0.24	0.24	0.24	0.24	0.24	0.24	0.043782	0.043782	0.043782	0.043782	0.043782	0.043782
Urban Forest	0.35	0.35	0.35	0.35	0.35	0.35	0.029913	0.029913	0.029913	0.029913	0.029913	0.029913
Unknown	0.48	0.48	0.48	0.48	0.48	0.48	0.014057	0.014057	0.007028	0.021855	0.000000	0.028114

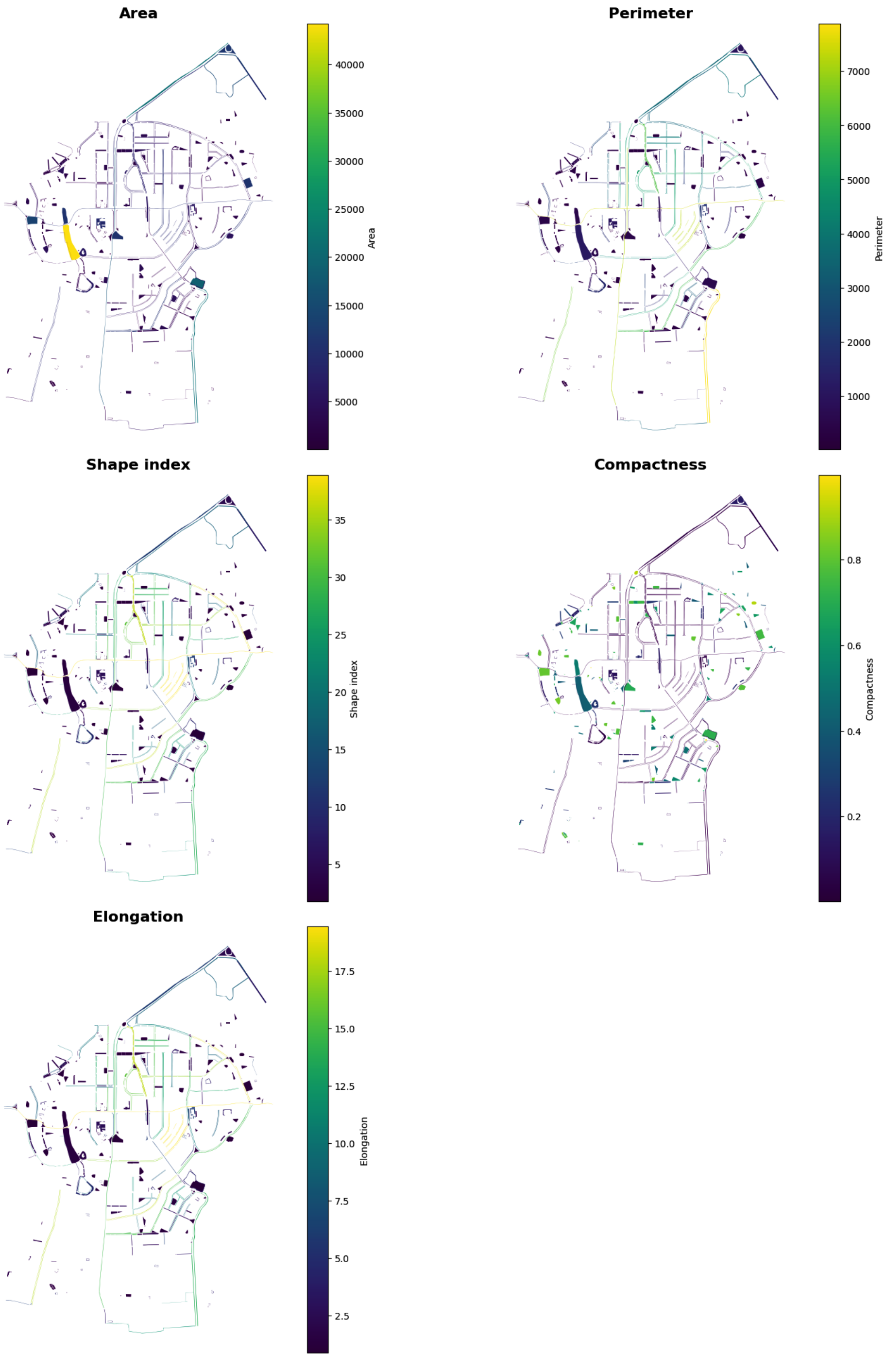

Fig. 6. Landscape metrics map for each UGS

3.2. Landscape Metrics of UGS

The UGS polygons in the study area were characterized using landscape metrics: area, perimeter, shape index, compactness, and elongation. Figure 6 visualizes the spatial distribution of these metrics, thus showcasing the variability in the UGSs' geometries and sizes. The larger UGS polygons demonstrated higher ecological and recreational potentials (as was evidenced by their substantial area and compact shapes), while the smaller and elongated UGSs served as green corridors (thus, enhancing the connectivity but offering limited ecological benefits). Metrics such as the shape index revealed that irregularly shaped UGSs (often influenced by urban boundaries) may face reduced ecological efficiency as compared to compact and well-planned spaces.

The compactness and elongation further revealed the contrasting functionalities of the UGSs. Figure 6 shows that the compact UGSs were more optimized for space usage (thus, indicating efficient green space planning), while the elongated UGSs facilitated connectivity within the urban areas.

3.3. Statistical Relationships and Random Forest Regression

The relationships among the GVI levels, GVI variances, and landscape metrics were examined through a correlation matrix (presented in Figure 7).

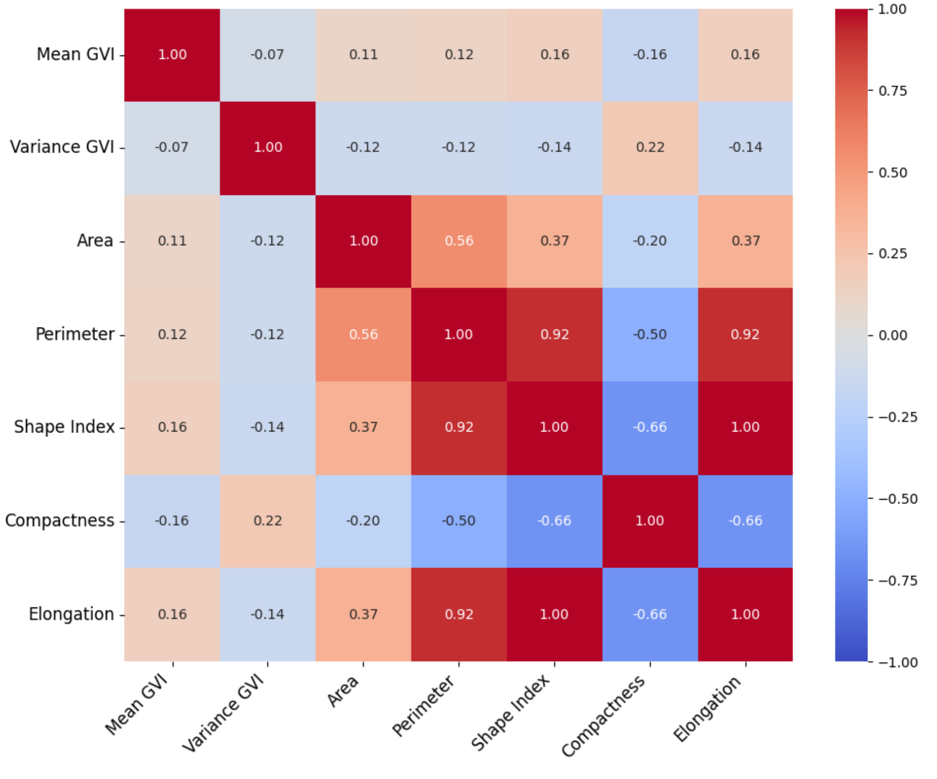

Fig. 7. Correlation matrix between GVI and landscape metrics

The matrix highlights the strong positive correlation between GVI levels and UGS areas (thus, confirming that the larger green spaces contributed significantly to perceived greenery); on the other hand, compactness demonstrated a weak negative correlation with GVI levels (thus, suggesting that the densely packed spaces did not always enhance the visual greenery). This analysis underscored the complexity of greenery perception, which is shaped by multiple geometric and spatial factors.

To further explore these relationships, a random forest regression model was developed (with GVI as the dependent variable and landscape metrics as predictors). As shown in Figure 8, the model achieved strong performance on the training data (R^2 = 0.85, RMSE = 0.06), but its performance on the testing data indicated potential overfitting (R^2 = 0.12, RMSE = 0.13). The SHAP analysis (Fig. 9) provided insights into the feature importance; this revealed that area and perimeter were the most significant predictors of GVI levels, whereas compactness and elongation provided minimal contributions. These findings emphasized the need to consider geometric complexity when assessing greenery visibility.

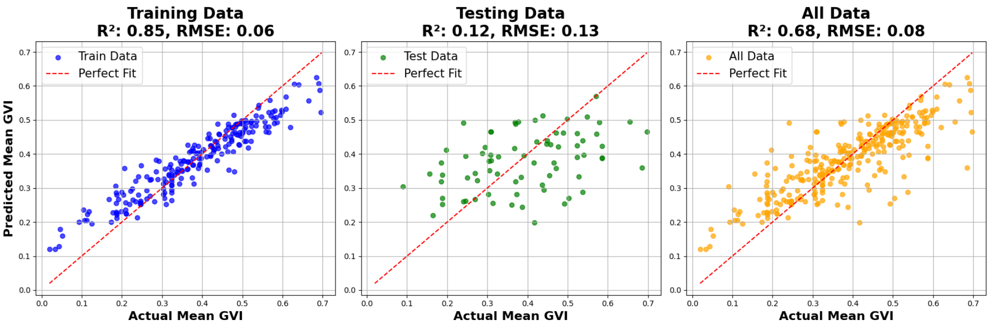

Fig. 8. Actual vs. predicted values from random forest regression for GVI and landscape metrics

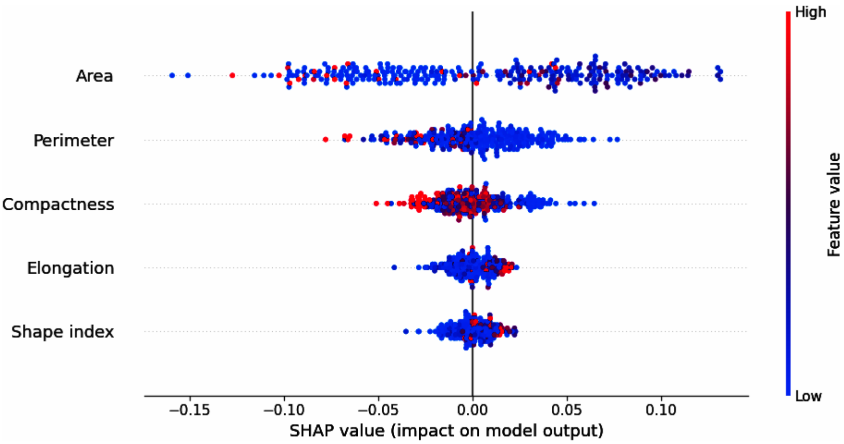

Fig. 9. SHAP value based on random forest regression model

4. Discussion

4.1. Role of Landscape Metrics in UGS Structure

Landscape metrics play a critical role in quantifying the structural characteristics of UGSs by measuring attributes such as area, perimeter, shape index, compactness, and elongation. These metrics help capture the spatial configurations and complexities of UGSs, which are key indicators for assessing the ecological and functional contributions to the urban environment and human well-being [56]. For example, the area of a UGS determines the scale of its green infrastructure and its capacity to provide ecological services, while the perimeter highlights the degree of urban interaction at the boundaries of the green spaces. Additionally, metrics like shape index and compactness reveal irregularities in a UGS's geometry and its efficiency in utilizing urban space [25].

The spatial analysis that was conducted in this study demonstrated considerable variability in the landscape metrics across different UGS types. As shown in the landscape metrics maps (Fig. 6), larger UGS areas such as urban parks tended to exhibit higher compactness and lower elongation values (thus, reflecting their spatial efficiency and continuity); conversely, the smaller UGS types (like green corridors) were often elongated (thus, emphasizing their connectivity function within the urban fabric). Such variability underscores the role of landscape metrics in understanding the structural heterogeneity of a UGS and its implications for both ecological functionality and human access [25, 26].

4.2. Linking GVI and Landscape Metrics

As a measure of greenery visibility from a human perspective, the green view index (GVI) is inherently influenced by the structural attributes of UGSs that are captured through landscape metrics. The findings indicated a moderate to weak correlation between GVI and specific landscape metrics such as area and shape index (as is shown in the correlation matrix – Fig. 7). Larger UGS areas tended to exhibit higher GVI values due to their substantial green coverage, whereas fragmented or elongated UGSs often produced lower GVI scores (thus, reflecting their limited visual accessibility from street-view perspectives).

The boxplot analysis further highlighted the variations in the mean GVI levels and the variances across the different UGS types (Figs. 4, 5). The neighborhood parks, which were characterized by larger compact structures, consistently showed higher mean GVI values (thus, indicating their significant visual greenery contribution); conversely, the green corridors displayed greater variability in their GVI levels (thus, suggesting inconsistent greenery perceptions along the elongated and narrow spaces) [26, 57]. This linkage between GVI levels and landscape metrics provides critical insights into optimizing UGS configurations for enhancing visual greenery and maximize its aesthetic and psychological benefits in urban environments.

4.3. Significance of Non-Linear Relationships in UGS Evaluation

The integration of non-linear models such as random forest regression revealed any complex relationships between the GVI levels and the landscape metrics that the linear models may have overlooked. As demonstrated in the model performance (Fig. 8), the non-linear approach successfully captured subtle interactions and non-monotonic patterns among the variables, achieving an R^2 score of 0.68 for the combined data set. This highlighted the importance of considering non-linear dynamics when evaluating UGS characteristics and their influence on greenery visibility.

The SHAP analysis (Fig. 9) further identified the relative importance of each landscape metric in predicting the GVI levels. Metrics such as area and compactness exhibited stronger positive impacts on GVI levels, while elongated shapes contributed negatively (thus, reflecting their fragmented greenery visibility). These results emphasized that traditional linear models may have underestimated the multi-faceted relationships between the UGS structures and the human-perceived greenery.

4.4. Limitations and Future Research Directions

While this study offers valuable insights into the relationships between GVI and landscape metrics, several limitations remained:

- First, the reliance on crowdsourced street-view data introduced variabilities in the data's quality, coverage, and resolution. Images that are collected from platforms such as Mapillary may lack uniformity, such as different types of images (like panoramic and normal photos) (Fig. 10) – particularly, in areas with limited public participation; this can lead to spatial gaps in GVI measurements.
- Second, another limitation was the static nature of the analysis, which did not account for temporal changes in the vegetation. Seasonal variations in greenery such as deciduous foliage changes significantly influence GVI levels and UGS visibility. Integrating multi-temporal data sets would allow for a dynamic evaluation of a UGS's performance over time and help assess the long-term impacts of urban-greening policies.
- Third, while non-linear models offer improved accuracy, spatial heterogeneity and autocorrelation remain underexplored. Future studies should integrate spatially explicit models like geographically weighted regression (GWR) to identify localized variations and spatial clusters in GVI levels and landscape metrics [33, 58].
- Finally, expanding the study to include diverse urban contexts beyond SCBD would improve the generalizability of the findings and account for socio-environmental differences in a UGS's structure and perception.

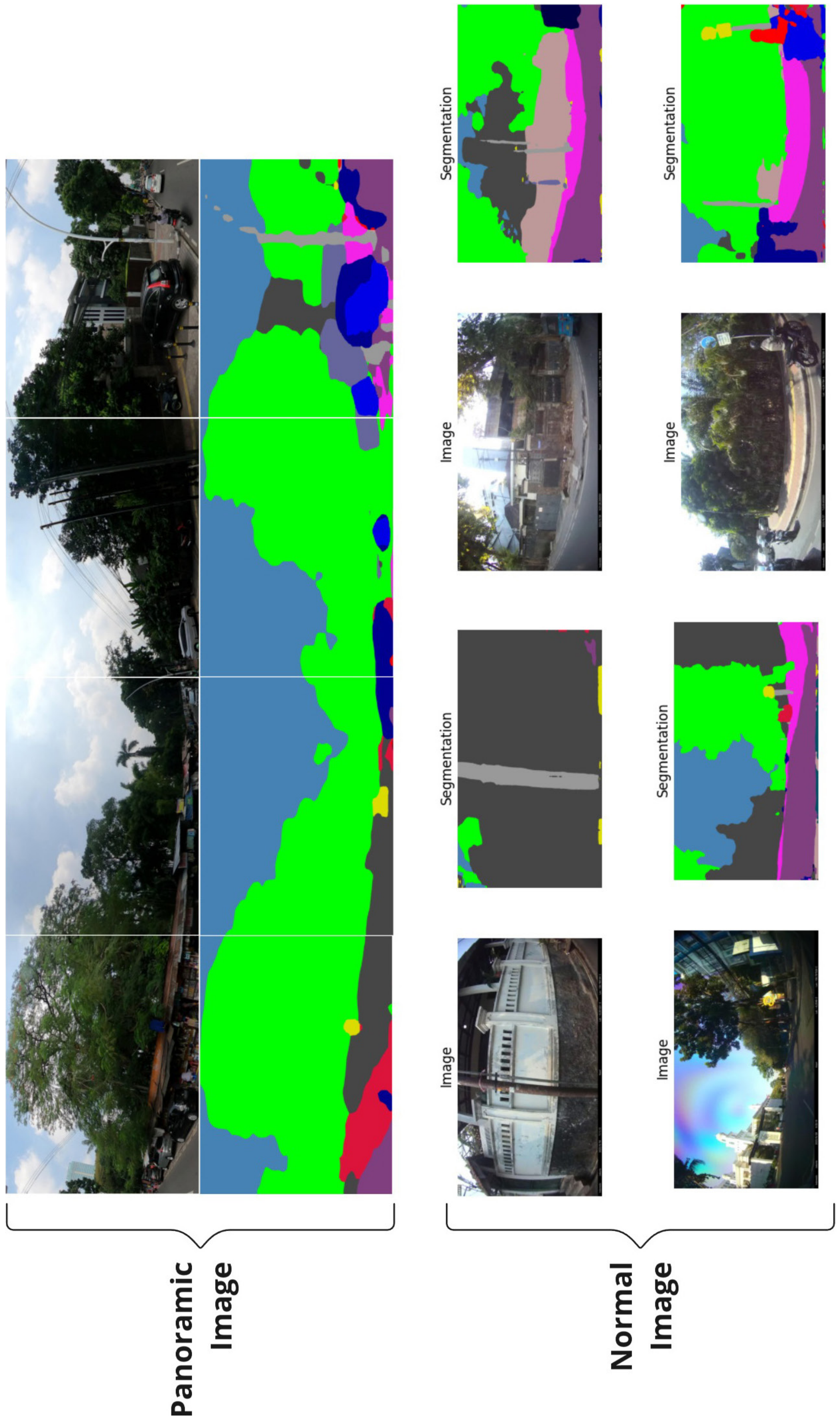

Fig. 10. Different views of panoramic and normal images

5. Conclusion

This study presents a comprehensive evaluation of UGSs by integrating street-level GVI data with spatial landscape metrics in order to analyze greenery visibility and UGS structural characteristics. The results demonstrated that GVI is influenced by multiple landscape attributes, including area, perimeter, compactness, and elongation; larger and more-compact UGSs show higher greenery visibility, while elongated and fragmented shapes exhibit greater visual variability. The non-linear random forest regression and SHAP analyses effectively captured the complex relationships between GVI levels and the landscape metrics, thus revealing nuanced patterns beyond linear associations. The boxplot analysis of the GVI levels and their variance across the UGS types further highlighted significant differences in greenery visibility among categories such as parks, green corridors, and open spaces. While the study provides valuable insights into the role of a UGS's structure in enhancing urban greenery perception, limitations remain regarding data availability, temporal coverage, and the homogeneity of street-view imagery. Future research should address these limitations by incorporating temporal analyses, higher-quality data sources, and expanded urban contexts in order to develop more-robust frameworks for sustainable UGS planning and design.

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CRediT Author Contribution

M. R. P.: conceptualization, data curation, formal analysis, methodology, investigation, visualization, writing – original draft, writing – review & editing.

A. W.: supervision, validation, writing – review & editing.

J. M. S.: conceptualization, methodology, supervision, project administration.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests nor personal relationships that could have appeared to influence the work that is reported in this paper.

Data Availability

The data that supports the findings of this study is available upon reasonable request from the corresponding author.

Use of Generative AI and AI-Assisted Technologies

Generative AI and AI-assisted technologies were utilized in this research to troubleshoot coding issues, check for typographical errors, and ensure clarity in the writing of the manuscript.

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