Accessible Street-level Greenery Assessment in Data-Scarce Environments with GreenviewCOMP

Sri Ramana Saketh Vasanthawada[1], Harish Puppala[2*], Manoj Kumar Arora[3], Pranav RT Peddinti[4], Tata Babu Chukka[5]

[1]Department of Civil Engineering, BML Munjal University, 122413, Kapriwas, India
[2]Centre for Geospatial Technology, SRM University AP, 522502, Guntur, India
[3]Department of Civil Engineering, SRM University AP, 522502, Guntur, India
[4]Centre for Drone Technology, SRM University AP, 522502, Guntur, India
[5]ITE&C Department, Andhra Pradesh Space Applications Centre, 520010, Vijayawada, India

*harish.p@srmap.edu.in

Abstract. Quantifying greenery from an individual's perspective is important due to its role in enhancing emotional well-being and reducing stress. While Google Street View (GSV) imagery has been widely used for street-level greenery assessments, its limited availability in many regions constrains such analysis. To address this gap, we developed GreenviewCOMP, a computationally efficient and user-friendly tool that quantifies greenery using 360° photospheres captured with digital cameras. The tool utilizes a binary thresholding method to classify green vegetation and compute Green View Index (GVI), offering a transparent and lightweight approach suitable for resource-limited contexts. A pilot study at a university campus in Gurugram, India, involved 106 photospheres, demonstrating spatial variations in GVI across the site. Classification accuracy was assessed, resulting in an overall accuracy of 0.97, recall of 0.98, and precision of 0.95. With its GUI, GreenviewCOMP enables novice users to efficiently assess street-level greenery, providing a practical alternative where GSV-based methods or computationally intensive algorithms are not feasible.

Keywords: Street-level greenery, Green View Index, Urban Sustainability

1 Introduction

Urban greenery plays a vital role in shaping the quality of urban life, with well-documented benefits for human health, well-being, and environmental sustainability [1]. The presence of vegetation in cities has been linked to stress reduction, improved emotional health, and enhanced perceptions of livability [2], [3]. Recognizing these benefits, urban planners and policymakers have increasingly developed frameworks and methodologies for reliably quantifying urban greenery at the street-level which is an accurate reflection of a pedestrian perspective [4], [5], [6].

Early influences and the practical application of Green View Index (GVI) came from MIT Senseable City Lab's Treepedia Project which used Google Street View (GSV) to estimate street-level greenery [7]. GVI is defined as a percentage of green pixels to the

S. Mantena (ed.), *Proceedings of the Conference on Social and Sustainable Innovation in Technology & Engineering (SASI-ITE 2025)*, Advances in Intelligent Systems Research 199,
https://doi.org/10.2991/978-94-6463-940-7_5

total pixels in an image. Following this research, multiple studies have been conducted across the world using GSV, and related comprehensive street-level data sources like Baidu Maps in China to demonstrate walkability [8], [9], [10]. However, reliance on GSV introduces a key limitation that the coverage of GSV is not comprehensive across all developing countries. Recent investigation by [11] reveals that 44% of commute routes in small and medium-sized cities in the US do not have adequate GSV coverage. These limitations are likely to be more pronounced in developing regions of the world, where street-level imagery is often sparse or entirely absent [12]. Such unavailability of GSV can introduce geographic bias in the research community and leaves a gap in understanding greenery distribution in regions that are undergoing rapid, uncontrolled, and unplanned urbanization.

Broadly, greenery quantification from imagery has progressed along two broad tracks. One track has an increasing emphasis on pixel and region-based methods which are computationally light weight and interpretable. Literature suggests that appropriate combination of color indices and thresholding techniques report competitive performance for vegetation detection in RGB images [13]. The other track is dominated by deep learning and computationally advanced approaches which achieve high accuracy and are robust to varying environmental conditions [14], [15]. These frameworks usually require annotated datasets, substantial computing power, and fine-tuning of models. Even with pre-trained models, transferring them across domains requires calibration, posing a barrier for planners in resource-limited settings. The complexity of advanced technologies also makes them a black box for non-technical users. As a result, despite their accuracy, these tools remain largely inaccessible to local planners, community groups, and policymakers who could benefit most from greenery assessments

In summary, the literature suggests three practical takeaways to motivate development of a GreenviewCOMP, an accessible, light-weight tool, that leverages custom data

1. GSV is a meaningful tool for street-level greenery assessments but cannot be utilized universally due to coverage gaps.
2. Deep Learning segmentation offers high accuracy, but presents adoption barrier, and is complex to deploy on modest hardware.
3. Existing computational frameworks are complex and inaccessible for non-technical users and stakeholders.

Prior work has therefore left a clear niche for tools that combine the accessibility of photosphere capture with lightweight, explainable vegetation detection workflows so practitioners in data-scarce environments can generate GVI without relying on GSV or large-scale machine-learning infrastructure. GreenviewCOMP addresses this niche by:

1. Using 360° photospheres captured using digital cameras
2. Applying an interpretable binary thresholding pipeline tuned for speed and usability
3. Packaging the workflow in a GUI targeted at novice users and planning practitioners.

1.1 GreenviewCOMP

GreenviewCOMP is a MATLAB based Graphical User Interface (GUI) tool developed to quantify greenery at street-level. GUI allows the user to perform various operations leading to computation of the GVI at a point of interest. GreenviewCOMP supports several standard image formats jpeg, png, and tiff, with the ability of loading and saving across formats. The first step involves capturing photospheres manually. Photospheres are manually captured, projected in equirectangular format, and geotagged using either built-in camera GPS or a handheld GPS tracker. An overview of data acquisition to computation of GVI is illustrated in Fig. 1.

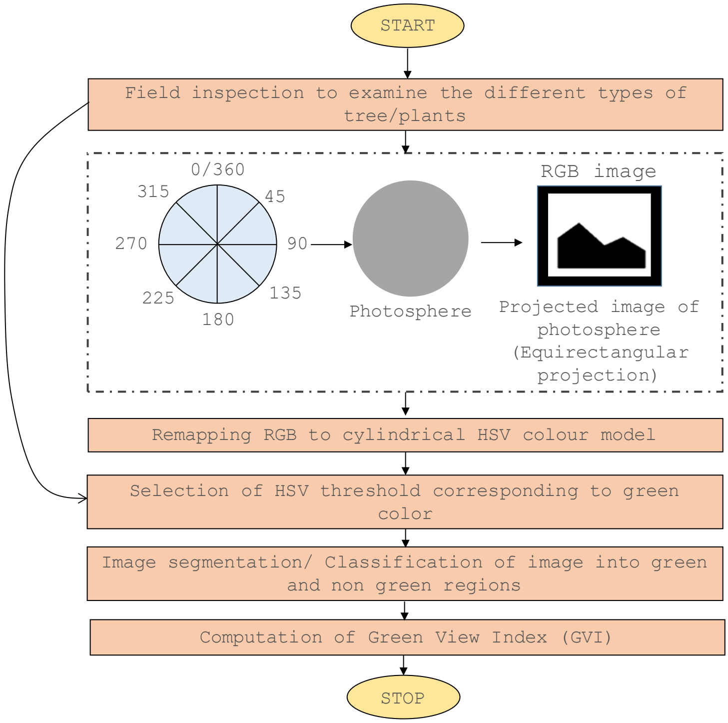
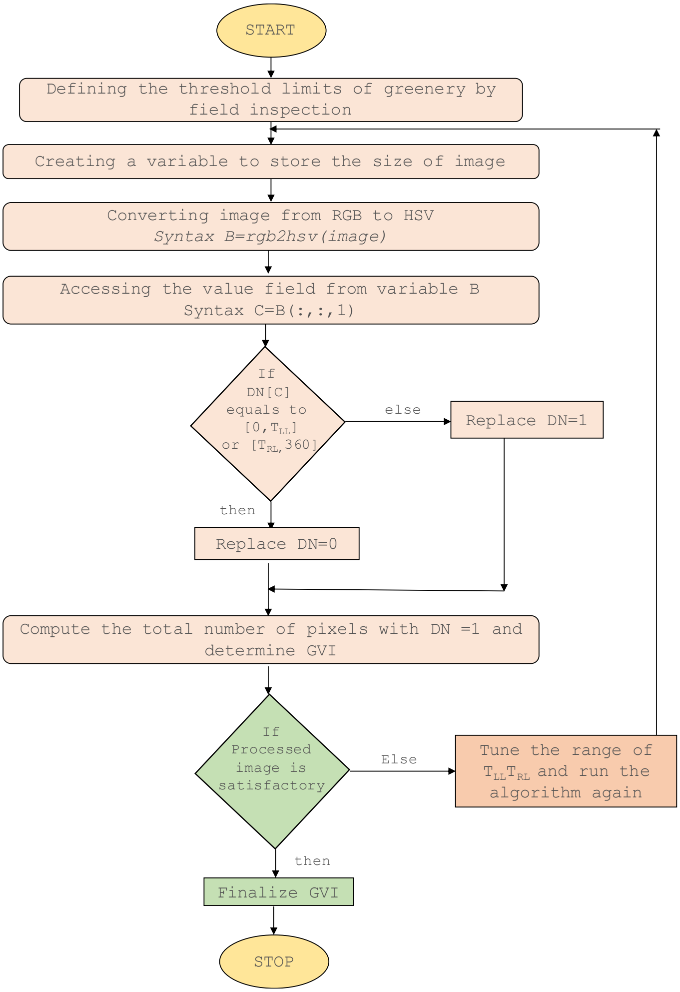


Fig. 1. Framework for GreenviewCOMP

1.1.1 Processing workflow

Fig.2 presents the algorithm of GreenviewCOMP. This tool is based on simple thresholding where the user defines the range of HSV corresponding to green shade. The processing pipeline utilizes the HSV color model over the RGB model due to its ability for separation of chromatic attributes for thresholding. Considering the seasonal and geographical variations, a standard green range from the HSV model has not been prescribed. It is recommended to conduct a field examination before defining a threshold range. Subsequently, the threshold range of HSV related to green colour is chosen as a filter, and the fraction of greenery is determined. Based on the proposed algorithm (Fig. 2), the pixel values in the threshold range are converted into a binary format. Here GVI is defined as in Eq 1. The GVI values range between 0 – 100% and based on the user's satisfaction, the threshold range can be fine-tuned.

$$Green\ View\ Index = \frac{Count\ of\ green\ pixels}{Count\ of\ all\ pixels} \times 100 \qquad (1)$$



T_{LL} is the lower limit of the threshold and T_{RL} is the upper limit of the threshold level

Fig. 2. Algorithm for the computation of GVI

1.1.2 Components and functions of GUI

The main GUI of the GreenviewCOMP contains four panels, i.e. Command panel, Display and export panel, Metadata panel, and Operational panel. The GUI displayed by default after executing the developed tool is shown on Fig.3. This section elaborates the functionalities of each panel.

Command panel

Load image (A1): Browse and load compatible images

Image directory (A2): Verify loaded images

Display and Export panel

Image (B1): Display original 360° photosphere.

Thresholding (B2): Shows the processed image with applied threshold; displays color histogram.

Processed image (B3): Displays HSV-converted image.

Brightness Slider (B4, B6): Adjust image brightness.

Save image (B5, B7): Save processed images.

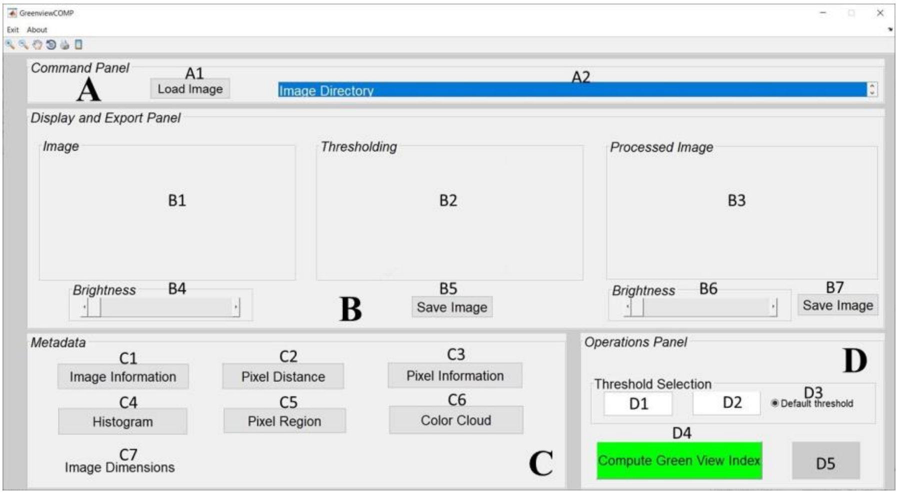


Fig. 3. GreenviewCOMP user interface

Metadata panel

Image Information (C1): Shows basic image attributes and metadata.

Pixel Distance (C2): Enables an interactive line on the image to measure the distance between pixels. Since the measurement is uncalibrated, it provides a relative understanding for planning purposes.

Pixel Information (C3): Displays coordinates and pixel values.
Histogram (C4): Plots thresholded image histogram.
Pixel region (C5): Zooms into selected regions for RGB analysis.
Colour Cloud (C6): Displays full RGB color gamut.
Image Dimensions (C7): Returns the image dimensions.

Operations panel
Threshold limits (D1, D2): Prescribe green color thresholds.
Default threshold (D3): Use pre-defined threshold ranges.
Calculate Green View Index (D4): Computes greenery percentage and displays GVI.

2 Pilot Study

A pilot study was conducted in BML Munjal University, Haryana. A digital database of the campus was created using a digital camera with built-in GPS, while the campus area and road network were digitized in QGIS, an open-source geospatial software. 360^{o} Photospheres at 106 locations are captured manually. This results in nearly 20 points for each kilometre of road network. The sampling strategy was chosen to ensure representative coverage of the study area while optimizing resources and minimizing bias. The spatial distribution of the identified points is shown in Fig.4. For easy identification, a unique number is assigned to each sample point.

Fig. 4. Sampling points in the study area

Once captured, the images are loaded into GreenviewCOMP using the command key (A1). For example, the transformed image of a sampling point (e.g. point 35) is processed into GreenviewCOMP to compute the GVI as shown in Fig.5. The percentage of green pixels in an image is calculated for all the sampling points, and the variation of GVI across the study area can be observed in Fig. 6.

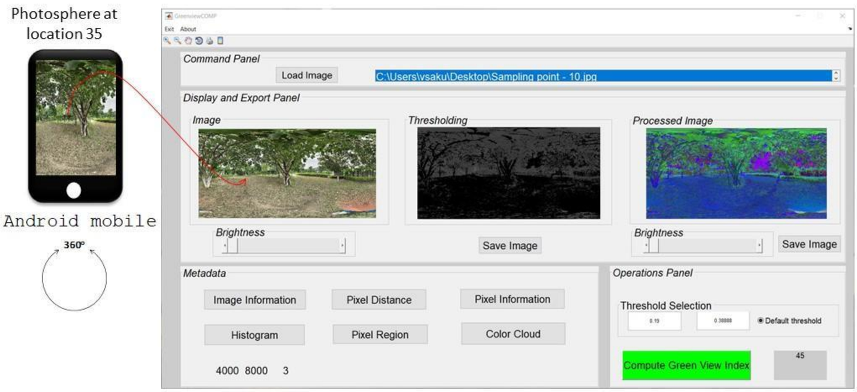


Fig. 5. GUI computation of sampling point 35 using GreenviewCOMP

Table 1. Excerpt of GVI values at sampling points

Unique ID of sampling point	Latitude	Longitude	GVI [%]
1	28.2461°N	76.8116°E	40.6
2	28.2466°N	76.8154°E	29.0
3	28.2462°N	76.8117°E	28.9
4	28.2462°N	76.8119°E	27.5
5	28.2462°N	76.8125°E	33.6
6	28.2462°N	76.8127°E	40.6
7	28.2462°N	76.8130°E	29.6
8	28.2463°N	76.8133°E	49.5
9	28.2462°N	76.8137°E	22.5
10	28.2463°N	76.8139°E	17.2

Table 1 presents the GVI values for a subset of sample points and Fig. 6(a) and Fig.6(b) provides an overview of GVI variation in the study area and overall GVI variation.

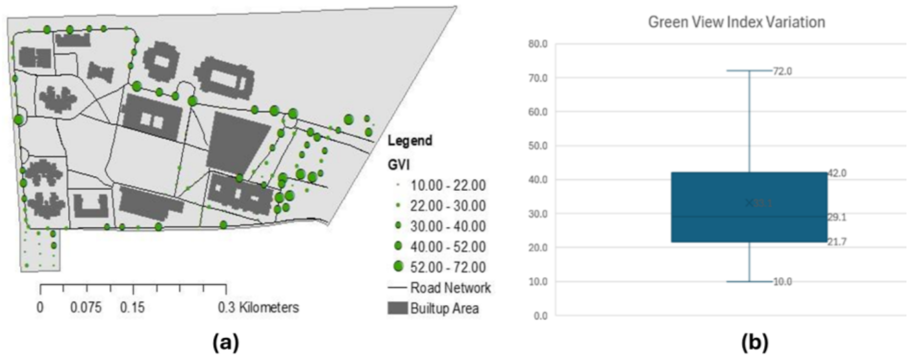


Fig. 6. GVI (%) at the sampling points and its distribution (a) spatial variation (b) statistical variation

The box-and-whisker plot (Fig. 6) illustrates the variation in the GVI across the study area. The median GVI is 29.1, while the mean value is 33.1. The distribution shows a slight right skew, as the upper whisker is longer than the lower whisker and the mean exceed the median. This suggests that while most sampling points have moderate greenery levels, a few locations exhibit significantly higher GVI values. Overall, the plot highlights substantial variability in street-level greenery across the study area, providing insight into areas of dense versus sparse vegetation.

3 Accuracy Assessment

Confusion matrix is developed to determine the accuracy of the developed tool. This matrix, also known as the error matrix, helps quantify the classification accuracy [16]. It is a popular technique while addressing the accuracy assessment of a classified image [17]. Various performance metrics, such as overall accuracy, recall, and precision, are evaluated using the standard relations shown in Eq.2, Eq.3, and Eq.4, respectively. Overall accuracy measures the fraction of correct estimations; recall determines how good the classifier is in determining the positive events; precision defines how good the classifier is in assigning positive events to the positive class.

$$Overall\ Accuracy\ (A) = \frac{TP + TN}{TP + TN + FP + FN} = 0.97 \tag{2}$$

$$Recall\ (R) = \frac{TP}{TP + FN} = 0.98 \tag{3}$$

$$Precision = \frac{TP}{TP + FP} = 0.95 \tag{4}$$

Where TP is the True positive; FP is False positive; FN is False negative, and TN is True negative. Discrete points (n=121) have been generated on the captured image. The ground truth values, and the estimated values are used to develop a confusion matrix, as shown in Table 2. Also, Table 2 is used to compute accuracy, recall, and precision, which are 0.97, 0.98, and 0.95, respectively.

Table 2. Confusion matrix of the classified image (sampling point 35)

		Truth		
Predicted		Green	Non-green	Total
	Green	59 (TP)	2 (FP)	61
	Non-green	1 (FN)	59 (TN)	60
	Total	60	61	121

Note: TP-True positive; FP-False positive; FN- False-negative; TN-True negative

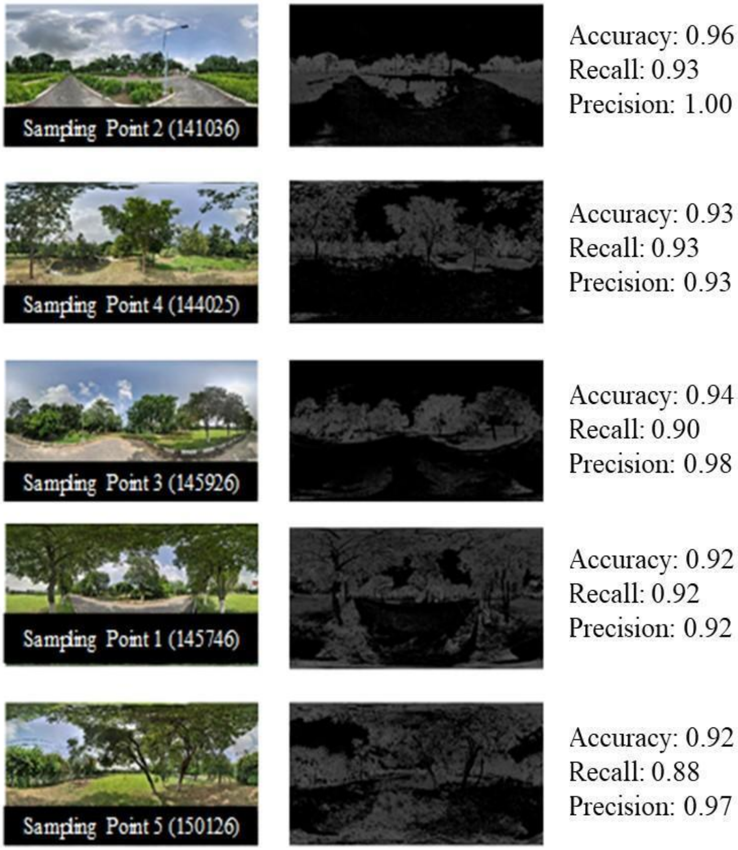


Fig 7. Accuracy assessments of sampling points

Equivalent accuracy assessments have been performed for five more images, and the analysis is presented in Fig 7.

4 Discussion

The pilot study demonstrates the utility of GreenviewCOMP as a practical approach for quantifying street-level greenery using manually captured pictures. The results show that the tool can generate GVI for a given location with fine-tuning the threshold values. Unlike computationally intensive methods such as LiDAR or deep learning-based segmentation, GreenviewCOMP is designed for ease of use while still delivering reliable outputs, making it accessible to planners, and researchers with limited technical expertise. At the same time, the study highlights important limitations and provides avenue for future research. The inability to distinguish vegetation from non-vegetative green objects such as painted walls and signage introduces potential bias, particularly in dense urban areas where the tool would experience complex conditions. This would lead to overestimation of greenery, which should be accounted for while reporting the GVI. Another limitation is that the study was conducted on a university campus, which may not be representative of complexity of urban areas. Future efforts therefore should be to test the tool in diverse dense urban environments and mixed-use areas to evaluate the scalability. Despite the limitations, the findings suggest that GreenviewCOMP can complement existing tools to evaluate urban greenery. While satellite or aerial imagery captures vegetation cover at a broader scale, street measures like GVI provide critical insights and opens opportunities and integrating tools into planning and design contributing to liveable spaces.

5 Conclusion

This study introduces GreenviewCOMP, a user-oriented tool for estimating street-level greenery through digital imagery and applied in a pilot setting to evaluate its performance. The primary contribution lies in offering a method that balances accessibility and effectiveness. The tool demonstrates potential for integration into urban planning workflows, and environmental modelling programs. A key limiting factor is the ability to differentiate between vegetation and other green colored objects. While this constrains generalizability of the tool, it provides avenues for future research and development. Future research could incorporate a light-weight artificial intelligence (AI) based classification model to improve vegetation detection and scalability to varying urban contexts. In conclusion, GreenviewCOMP contributes to ongoing efforts to provide accessible street-level greenery assessments that are practical and adaptable. By addressing the current limitations and extending the scope, the tool has potential to support communities in advancing greenery and more sustainable environments.

References

[1] A. Bressane, M. B. Silva, A. P. G. Goulart, and L. C. de C. Medeiros, "Understanding How Green Space Naturalness Impacts Public Well-Being: Prospects for Designing Healthier Cities," *Int. J. Environ. Res. Public. Health*, vol. 21, no. 5, p. 585, May 2024, doi: 10.3390/ijerph21050585.

[2] J. Parker and G. D. Simpson, "Public Green Infrastructure Contributes to City Livability: A Systematic Quantitative Review," *Land*, vol. 7, no. 4, p. 161, Dec. 2018, doi: 10.3390/land7040161.

[3] A. Zumelzu and M. G. Herrmann-Lunecke, "Mental Well-Being and the Influence of Place: Conceptual Approaches for the Built Environment for Planning Healthy and Walkable Cities," *Sustainability*, vol. 13, no. 11, p. 6395, Jan. 2021, doi: 10.3390/su13116395.

[4] D. Yin and T. Hirata, "Comprehensive Comparative Analysis and Innovative Exploration of Green View Index Calculation Methods," *Land*, vol. 14, no. 2, p. 289, Feb. 2025, doi: 10.3390/land14020289.

[5] X. Li, C. Zhang, W. Li, R. Ricard, Q. Meng, and W. Zhang, "Assessing street-level urban greenery using Google Street View and a modified green view index," *Urban For. Urban Green.*, vol. 14, no. 3, pp. 675–685, Jan. 2015, doi: 10.1016/j.ufug.2015.06.006.

[6] S. Yu *et al.*, "View-based greenery: A three-dimensional assessment of city buildings' green visibility using Floor Green View Index," *Landsc. Urban Plan.*, vol. 152, pp. 13–26, Aug. 2016, doi: 10.1016/j.landurbplan.2016.04.004.

[7] X. Li, C. Zhang, W. Li, R. Ricard, Q. Meng, and W. Zhang, "Assessing street-level urban greenery using Google Street View and a modified green view index," *Urban For. Urban Green.*, vol. 14, no. 3, pp. 675–685, 2015, doi: 10.1016/j.ufug.2015.06.006.

[8] Y. Kumakoshi, S. Y. Chan, H. Koizumi, X. Li, and Y. Yoshimura, "Standardized Green View Index and Quantification of Different Metrics of Urban Green Vegetation," *Sustainability*, vol. 12, no. 18, p. 7434, Jan. 2020, doi: 10.3390/su12187434.

[9] J. Zhang and A. Hu, "Analyzing green view index and green view index best path using Google street view and deep learning," *J. Comput. Des. Eng.*, vol. 9, no. 5, pp. 2010–2023, Oct. 2022, doi: 10.1093/jcde/qwac102.

[10] R. Dong, Y. Zhang, and J. Zhao, "How Green Are the Streets Within the Sixth Ring Road of Beijing? An Analysis Based on Tencent Street View Pictures and the Green View Index," *Int. J. Environ. Res. Public. Health*, vol. 15, no. 7, p. 1367, July 2018, doi: 10.3390/ijerph15071367.

[11] J. Kim and K. M. Jang, "An examination of the spatial coverage and temporal variability of Google Street View (GSV) images in small- and medium-sized cities: A people-based approach," *Comput. Environ. Urban Syst.*, vol. 102, p. 101956, June 2023, doi: 10.1016/j.compenvurbsys.2023.101956.

[12] F. Umar *et al.*, "On the potential of Google Street View for environmental waste quantification in urban Africa: An assessment of bias in spatial coverage," *Sustain. Environ.*, vol. 9, no. 1, p. 2251799, Dec. 2023, doi: 10.1080/27658511.2023.2251799.

[13] M. Hassanein, Z. Lari, and N. El-Sheimy, "A New Vegetation Segmentation Approach for Cropped Fields Based on Threshold Detection from Hue Histograms," *Sensors*, vol. 18, no. 4, p. 1253, Apr. 2018, doi: 10.3390/s18041253.

[14] L. Zhang, L. Wang, J. Wu, P. Li, J. Dong, and T. Wang, "Decoding urban green spaces: Deep learning and google street view measure greening structures," *Urban For. Urban Green.*, vol. 87, p. 128028, Sept. 2023, doi: 10.1016/j.ufug.2023.128028.

[15] M. Helbich, Y. Yao, Y. Liu, J. Zhang, P. Liu, and R. Wang, "Using deep learning to examine street view green and blue spaces and their associations with geriatric depression in Beijing, China," *Environ. Int.*, vol. 126, pp. 107–117, May 2019, doi: 10.1016/j.envint.2019.02.013.

[16] O. Okwuashi *et al.*, "GIS Cellular Automata Using Artificial Neural Network for Land Use Change Simulation of Lagos, Nigeria," 2012, Accessed: Sept. 14, 2025. [Online]. Available: http://irepo.futminna.edu.ng:8080/jspui/handle/123456789/17559

[17] R. G. Congalton, "A review of assessing the accuracy of classifications of remotely sensed data," *Remote Sens. Environ.*, vol. 37, no. 1, pp. 35–46, July 1991, doi: 10.1016/0034-4257(91)90048-B.