

Unveiling greenery and visual comfort: Integrating Green View Index and image segmentation in panoramic rural landscapes

 Mohammad Raditia Pradana^{1,2}  —  Muhammad Dimyati^{1,2} —  Jarot Mulyo Semedi¹

¹Department of Geography, Faculty of Mathematics and Natural Sciences, Universitas Indonesia, Depok City, Indonesia.

²Scientific Modeling, Application, Research, and Training for City-centered Innovation and Technology (SMART CITY) Universitas Indonesia, Depok City, Indonesia.

 mohammad.raditia03@ui.ac.id

Abstract

This study explores the intricate relationship between visual comfort (VICO) and greenery distribution - measured by the Green View Index (GVI) - alongside object composition in the rural landscapes of Ciputri Village, Indonesia. Using panoramic imagery and semantic segmentation models, dominant visual elements were identified, categorized, and analyzed for their contributions to landscape perception. The analysis combined linear regression and Random Forest modelling to evaluate the predictors of VICO. While the linear model showed limited explanatory power ($R^2 = 0.37$), the Random Forest model ($R^2 = 0.60$) performed substantially better, highlighting the importance of non-linear relationships. Key findings reveal GVI as a dominant determinant of VICO, underscoring its substantial role in enhancing visual comfort. Specific objects such as trees, mountains, and the sky positively influenced VICO when visually dominant, whereas walls had the opposite effect. Unique patterns were observed for plants and “null” objects, with their contributions varying according to their positional dominance in the visual composition. For instance, plants in primary positions were associated with reduced VICO due to perceived monotony, but they enhanced VICO when secondary or tertiary, reflecting their role as complementary elements that enrich visual diversity. Overall, these results provide a nuanced understanding of the interplay between greenery, object composition, and visual comfort, suggesting that balanced visual diversity and strategic spatial arrangements can moderately shape landscape perception, with direct implications for rural landscape planning in Indonesia.

Keywords

Green View Index, Indonesia, Landscape Perception, Segmentation, Visual Comfort

Received:
23 March 2025

Received in revised form:
7 November 2025

Accepted:
12 November 2025

Highlights for public administration, management and planning:

- Green View Index (GVI) is a critical determinant of visual comfort in rural landscapes.
- Non-linear modelling (Random Forest) outperforms linear regression in predicting visual comfort.
- Strategic spatial arrangements and visual diversity play pivotal roles in enhancing VICO.

1 Introduction

Visual comfort, encompassing psychological relaxation and satisfaction, is influenced by the aes-

thetic and structural characteristics of landscapes. Elements such as color, texture, and composition significantly contribute to the perception of harmony and tranquility (Kaplan & Kaplan 1989; Ul-

rich 1986; Ode et al. 2009). In natural landscapes, visual comfort is enhanced by unaltered elements like mountains or valleys, which evoke feelings of calmness and improve aesthetic satisfaction (Holy-Hasted & Burchell 2022; Setiawan & Amar 2021; van den Berg et al. 2003; Wu et al. 2021).

Recent studies emphasize the spatial dimensions of visual comfort, analyzing how landscape elements and their arrangements influence psychological responses (Sun et al. 2023; Tiara & Gamal 2021; Wu et al. 2020). The Green View Index (GVI), an objective metric, quantifies visible greenery by calculating the ratio of green pixels within an image, effectively bridging subjective perception and measurable spatial characteristics (Jiang et al. 2024; Liu et al. 2023; Sun et al. 2023; Wang et al. 2022; Wu et al. 2020; Zhu et al. 2023). As an advancement, object-based segmentation to keep objectively segmented, applied through deep learning models like ResNet-50, enhances GVI assessments by identifying specific visual elements, such as trees or buildings, within images (Fang et al. 2024; Li et al. 2022; Rui 2023; Sun et al. 2023; Wu et al. 2024; Xu et al. 2024; Yu & Qi 2021; Zhang et al. 2023).

Panoramic photography, offering a 360-degree horizontal view, effectively replicates the human perspective and enables comprehensive spatial analysis of visual comfort and greenery distribution (Curtis et al. 2013; Huang et al. 2022; Labib et al. 2021; Yu & Qi 2021). This approach differs from remote sensing data, which use a bird's-eye perspective to observe patterns from above (Anguelov et al. 2010; Chen et al. 2019; Pradana & Dimiyati 2024; Wu et al. 2020; Xue et al. 2022; Yu & Qi 2021). By integrating panoramic imagery and advanced segmentation techniques, this study explores the relationships among visual comfort, GVI, and the spatial distribution of visual objects in a rural setting. Specifically, it evaluates how these factors interact spatially and influence overall landscape perception (Jin et al. 2023; Lachowycz & Jones 2013; Sun et al. 2023).

The research framework synthesizes these aspects into a cohesive workflow. First, the spatial distribution of greenery is analyzed through GVI calculations derived from panoramic photographs (Labib et al. 2021; Li et al. 2015). Second, visual objects are identified and segmented into dominant categories, enabling the examination of their proportional contribution to landscape composition (Dong et al. 2018; Ferrini et al. 2020; Kameoka et al. 2022; Simpson et al. 2018). Third, the relationship between visual comfort, GVI, and the presence of visual objects is explored through statistical modeling, incorporating both spatial and subjective di-

mensions (Jin et al. 2023; Qi et al. 2023; Qureshi et al. 2010; Sun et al. 2023). This multi-dimensional approach aims to establish a framework for understanding how greenery and visual elements shape human perception.

This study was conducted in Ciputri Village, Cianjur Regency, Indonesia, a rural area of mixed farmland and protected forest near Mount Gede-Pangrango National Park. The site typifies West Java's transitional landscapes between agricultural and natural zones, offering valuable insights for rural landscape planning and conservation where visual quality and ecology intersect. The research integrates objective and subjective analyses using deep learning-based object segmentation and panoramic photography to examine how spatial characteristics influence visual comfort through two objectives:

1. To map and analyze panoramic landscapes that replicate human perspectives objectively using deep learning-based object segmentation techniques.
2. To investigate the relationship between object composition in panoramic photographs (objective domain) and visual comfort (subjective domain) through linear and non-linear statistical methodologies.

2 Methods

2.1 Study area and sampling points

This study was conducted in Ciputri Village, Cianjur Regency, Indonesia, between 106°59'28.99" - 107°4'45.42" E and 6°45'37.42" - 6°47'18.53" S, a rural area with diverse topographies, including parts of Gede-Pangrango National Park, agricultural lands, and hilly terrains (Fig. 1). Its remote location, far from urban centers and inaccessible by vehicles typically used for automated street view data collection (e.g., Google Street View), necessitated manual panoramic photography. This method ensured data availability and captured the unique visual characteristics of the rural landscape, often underrepresented in existing digital databases (Biljecki & Ito 2021; Chen et al. 2019; Huang et al. 2022; Yu & Qi 2021). A total of 75 sampling points were systematically distributed along the primary accessible road network, which runs west to east and follows the main boundaries of the village. This transect-based approach was designed to capture a representative cross-section of the village's visual landscape from a pedestrian perspective. All panoramic images were captured from the side of the road, with the primary barrier to point place-

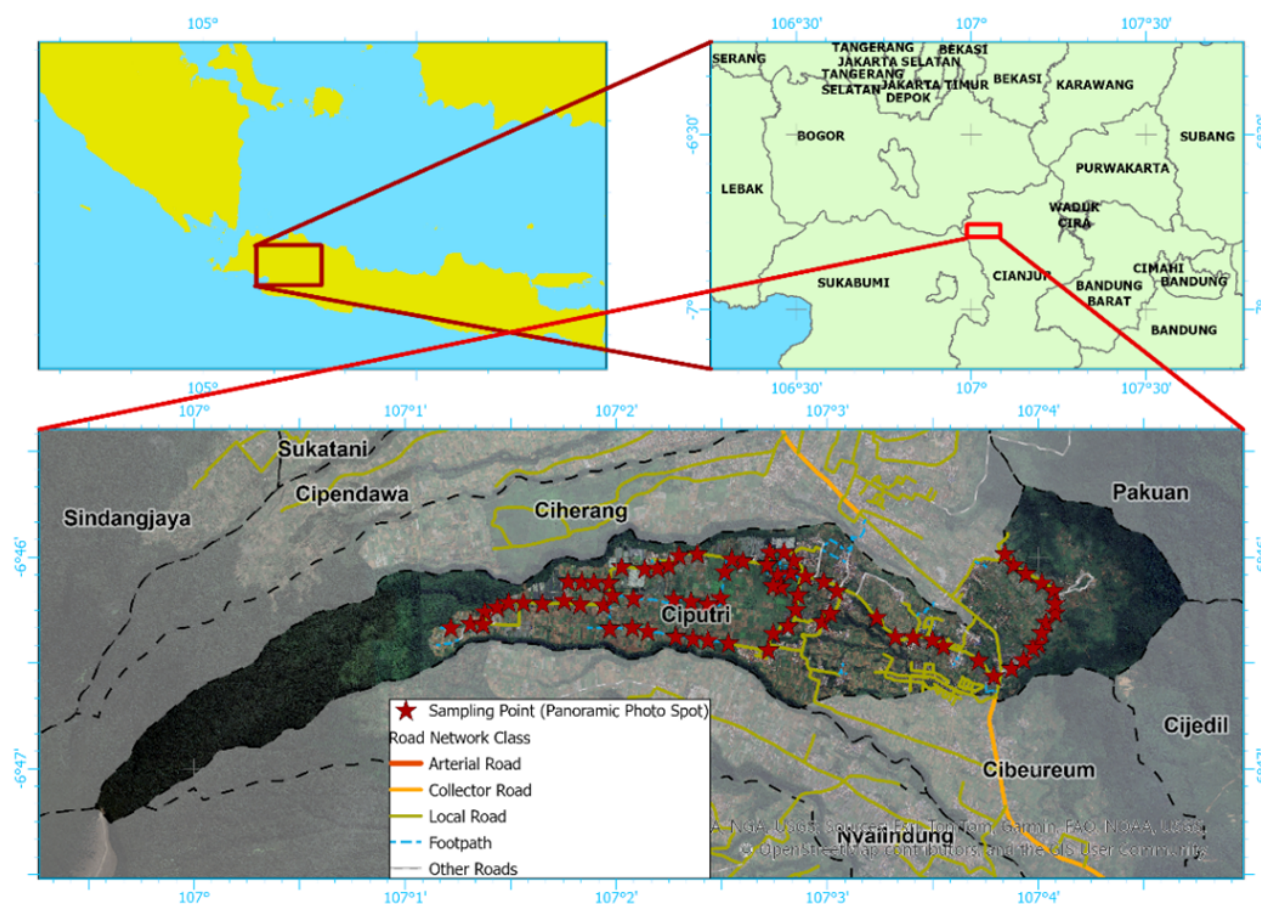


Fig. 1 Study area and sampling point

ment being the lack of safe walking access. Points were placed with a minimum distance of 100 meters between them to avoid spatial autocorrelation and to provide a comprehensive foundation for analyzing greenery, visual objects, and visual comfort.

2.2 Research framework

The research framework integrates data collection, data processing, and data analysis to comprehensively explore the relationships between visual comfort (VICO), greenery distribution, and landscape composition in rural settings (Fig. 2). During the data collection phase, 360-degree panoramic photographs were captured at systematically distributed sampling points to replicate human perspectives of the landscape. These images were stored in a centralized panoramic photo database for subsequent analysis. In addition, subjective evaluations of visual comfort were gathered through a structured Likert-scale questionnaire, where respondents rated psychological relaxation, satisfaction, and visual appeal on a scale of 1

to 6. The score of each photo was determined by mode to reflect the majority opinion, ensuring that the most commonly selected rating represented the overall subjective evaluation. These two primary datasets provided the foundation for objective and subjective analysis.

The data processing phase involved three parallel workflows. First, the Green View Index (GVI) was calculated for each panoramic photograph by determining the ratio of green pixels to total pixels, quantifying visible greenery as an objective metric. Second, semantic segmentation was applied using deep learning models trained by Zhou et al. (2017, 2018, 2019) on the ADE20K dataset to identify and classify visual objects such as trees, buildings, and roads. The segmentation results provided detailed information on the composition of each photo, including the identification of the three dominant object categories. Additional metrics, including Richness (N), Shannon Index, and Simpson Index, were computed to quantify landscape diversity. Third, subjective visual comfort ratings from the questionnaires were averaged for each sample point, resulting in a con-

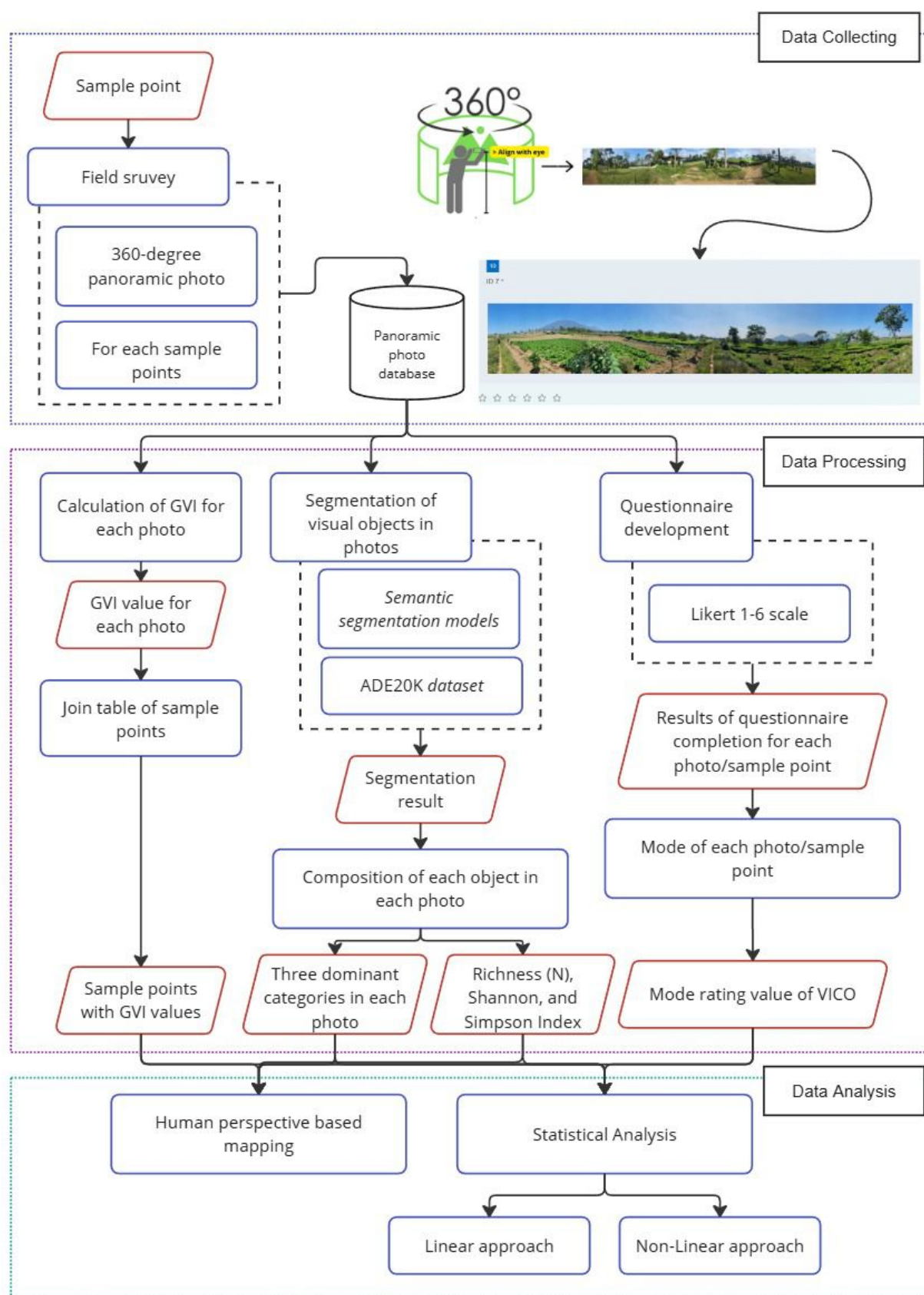


Fig. 2 Research Framework

solidated VICO score that represented perceived comfort for each landscape view.

The data analysis phase combined objective and subjective dimensions to provide a holistic understanding of the landscape. Two approaches were employed: linear and non-linear. The linear approach utilized a Linear Regression model to examine direct relationships between VICO, GVI, object composition, and diversity indices, with model performance evaluated using Root Mean Squared Error (RMSE) and R^2 metrics. The non-linear approach used a Random Forest Regressor to capture complex interactions and non-linear dependencies. Feature importance analysis identified the most significant predictors of VICO, while SHAP (SHapley Additive Explanations) values were calculated to interpret the contributions of individual predictors. SHAP summary and dependence plots visualized the impact of variables such as GVI, object composition, and diversity metrics on VICO. For categorical variables like Dominant Object categories, SHAP values were aggregated and averaged to assess their influence, with results presented in bar charts.

2.3 Data collection and variables

The primary dataset was obtained through manually captured panoramic photographs at 75 systematically distributed sampling points across Ciputri Village, a rural area inaccessible to automated street view data collection like Google Street View. These photographs were used to calculate the GVI, quantifying visible greenery through the ratio of green pixels to total pixels, and to extract visual object compositions via semantic segmentation, identifying dominant elements such as trees, buildings, roads, and sky for landscape analysis. VICO was assessed using a six-point Likert scale questionnaire completed by respondents after observing the photographs, measuring psychological relaxation, satisfaction, and visual appeal. The averaged VICO scores per sampling point served as the dependent variable, linking subjective perceptions with objective metrics. The study variables include GVI (Eq. 1), Richness (N) (Eq. 2), Entropy (Shannon Index) (Eq. 3), Simpson Index (Eq. 4) for plant diversity, Dominant Object (Eq. 5), and mode of VICO for each photo, as detailed in Table 1.

Table 1 Operational definitions and computational formulas for objective landscape metrics and subjective evaluation measures. Variables include greenery quantification (Green View Index), plant community diversity indices (Richness, Shannon Entropy, Simpson), dominant visual object classification, and VICO assessment.

Variable	Description	Formula
Green View Index (GVI)	Quantifies the proportion of visible greenery by analyzing the ratio of green pixels (e.g., trees, grass) to the total pixels in each panoramic photograph (Li et al. 2015).	$GVI = \frac{\sum_{i=1}^n P_{green}}{\sum_{i=1}^n P_{total}} \quad (1)$ where P_{green} = green pixels and P_{total} is the total number of pixels in the image.
Richness (N)	Number of plant community levels (grass, flowers, shrubs, trees) identified through segmentation, representing plant diversity (Hao et al. 2024).	$N = \text{Number of levels of plant categories} \quad (2)$
Entropy (Shannon Index)	Measures plant diversity and distribution across categories, indicating variety within plant communities (Hao et al. 2024).	$Entropy = - \sum_{i=1}^N p_i \ln(p_i) \quad (3)$ where p_i = proportion of the i-th category, N = total number of categories.
Simpson Index	Reflects the degree of equilibrium and dominance within plant communities, balancing diversity and uniformity (Hao et al. 2024).	$Simpson = 1 - \sum_{i=1}^N \left(\frac{p_i}{p} \right)^2 \quad (4)$ where p_i = proportion of category i, $p = \sum_{i=1}^N p_i$ is the cumulative proportion of all categories.
Dominant Object	The visual object (e.g., tree, building, road) covering more than 20% of the total image area, identified through semantic segmentation.	$Dominant\ Object = \max_i(p_i) \quad (5)$ where p_i = Pixels of Obejct i Total Pixels, and $p_i > 20\%$
Visual Comfort (VICO)	Subjective evaluation of psychological relaxation, satisfaction, and visual appeal of landscapes, rated on a six-point Likert scale (Sun et al. 2023).	Mode VICO Score = Score with highest frequency for each photo

2.4 Data analysis

2.4.1 Linear approach

A Linear Regression model was used to assess the relationships between predictors (e.g., GVI, Richness, Entropy, Simpson Index, Dominant Object proportions) and VICO. The dataset was split into 70% training and 30% testing sets, with model performance evaluated using Root Mean Squared Error (RMSE) (Eq. 6) and R^2 (coefficient of determination). Scatter plots of actual vs. predicted values for training, testing, and overall datasets visualized model accuracy.

A correlation matrix with Pearson correlation coefficients (r) was computed to quantify linear associations among variables. The matrix, visualized as a heatmap, highlighted key relationships between predictors and VICO. A residual plot was used to examine prediction errors, plotting residuals (actual - predicted values) against actual VICO scores to check for bias or systematic patterns.

2.4.2 Non-linear approach

To account for complex relationships and interactions between predictors and VICO, a Random Forest Regressor was employed. This ensemble learning model aggregates predictions from multiple decision trees, making it highly effective for capturing non-linear patterns and variable interactions. The dataset was split into 70% training and 30% testing subsets, and the model was trained and evaluated on these splits. Model performance was assessed using Root Mean Squared Error (RMSE) to measure prediction error and R^2 (coefficient of determination) to evaluate the proportion of variance in VICO explained by the predictors. Scatter plots comparing actual versus predicted values were generated for training, testing, and overall datasets to visualize model performance and residual distribution.

To further interpret the model's predictions, SHAP (SHapley Additive ExPlanations) values were computed. SHAP values decompose each prediction into contributions from individual features, providing a clear and interpretable explanation of the model's behavior. The analysis included:

SHAP Dependence Plots: These plots visualized the relationship between specific predictors and their contributions to VICO predictions, revealing trends and identifying critical ranges of variables that influenced visual comfort.

SHAP Summary Plot: A global visualization that ranked predictors by their overall importance

while showing the distribution of their impacts across the dataset.

For categorical variables, such as DominantObject1, DominantObject2, and DominantObject3, SHAP values were aggregated by category and averaged to assess their influence on VICO. This allowed for an in-depth understanding of how specific categories (e.g., types of dominant objects) contributed to VICO. The results were illustrated through bar charts, enabling a clear comparison of the impact of each category.

3 Results

In Ciputri Village, the spatial distribution of visual comfort (VICO) and greenery exhibits clear patterns linked to the rural land mosaic. Central areas near settlements show lower greenery but higher perceived comfort, while outer zones dominated by vegetation exhibit higher GVI and plant diversity. VICO (Fig. 3A) shows higher values in central Ciputri, while GVI (Fig. 3B) is higher in the outer, greener regions. DominantObject1-3 (Fig. 3C-E) indicate trees, earth, and fields dominate peripheral areas, whereas sky and buildings are prevalent centrally. Richness N (Fig. 3F) and Shannon Index (Fig. 3G) highlight greater plant diversity and configuration complexity in the outer zones. Meanwhile, Simpson Index (Fig. 3H) shows better balance between vegetation components in these areas, providing a foundation for analyzing relationships between visual comfort and landscape elements.

3.1 Linear approach result

The linear regression model was employed to examine the relationships between the predictors and VICO (Fig. 4). The model demonstrated moderate performance on the training dataset, achieving an $R^2 = 0.39$ with an RMSE of 1.23, indicating that approximately 39% of the variation in VICO could be explained by the independent variables. However, when applied to the testing dataset, the model exhibited poor generalizability, with an $R^2 = 0.26$ and RMSE of 1.33, suggesting a significant reduction in predictive accuracy. For the entire dataset, the linear regression model exhibited limited explanatory power with an $R^2 = 0.37$ with an RMSE of 1.26, indicating its inability to effectively capture the complex relationships between predictors and VICO. This drop highlights the limited capability of the linear model to capture com-

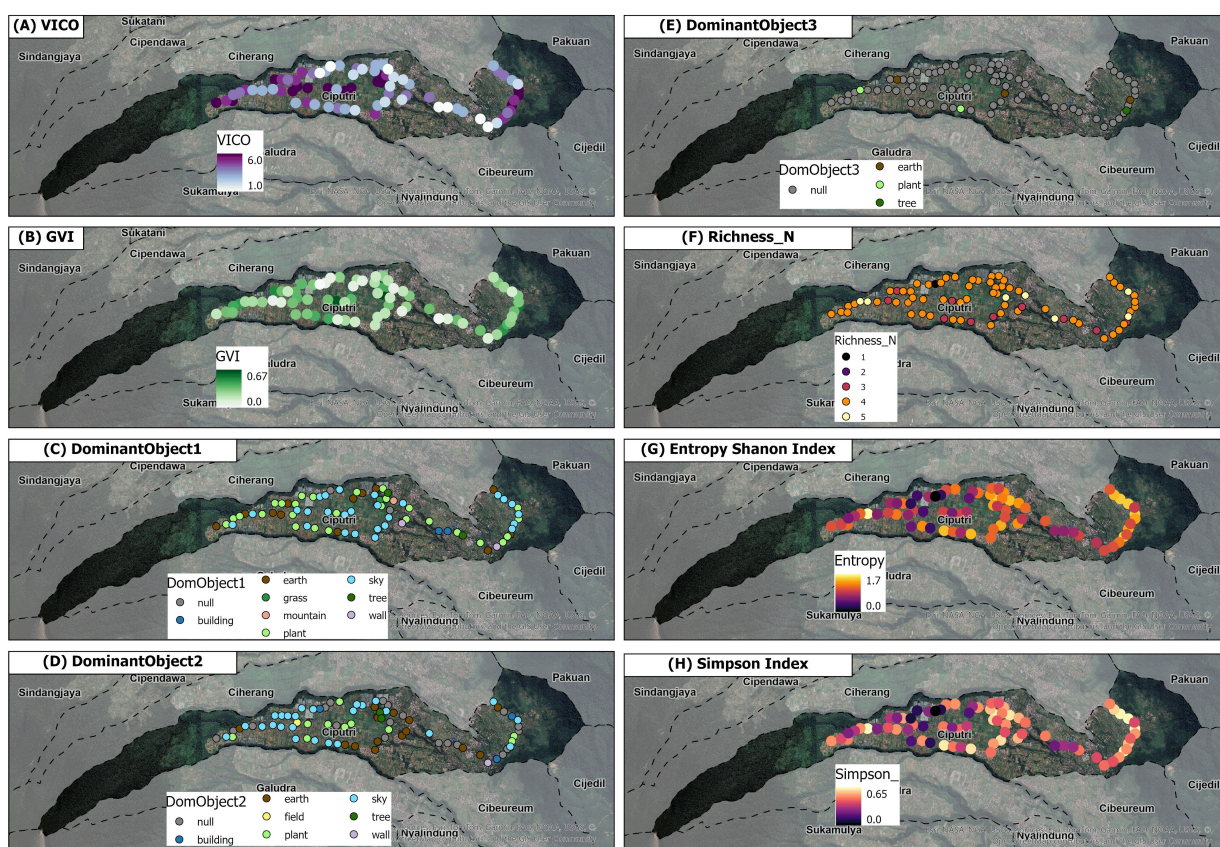


Fig. 3 Spatial distribution of key variables in Ciputri Village: (A) VICO, (B) GVI, (C-E) Dominant objects, (F) Richness_N, (G) Shannon Index, and (H) Simpson Index.

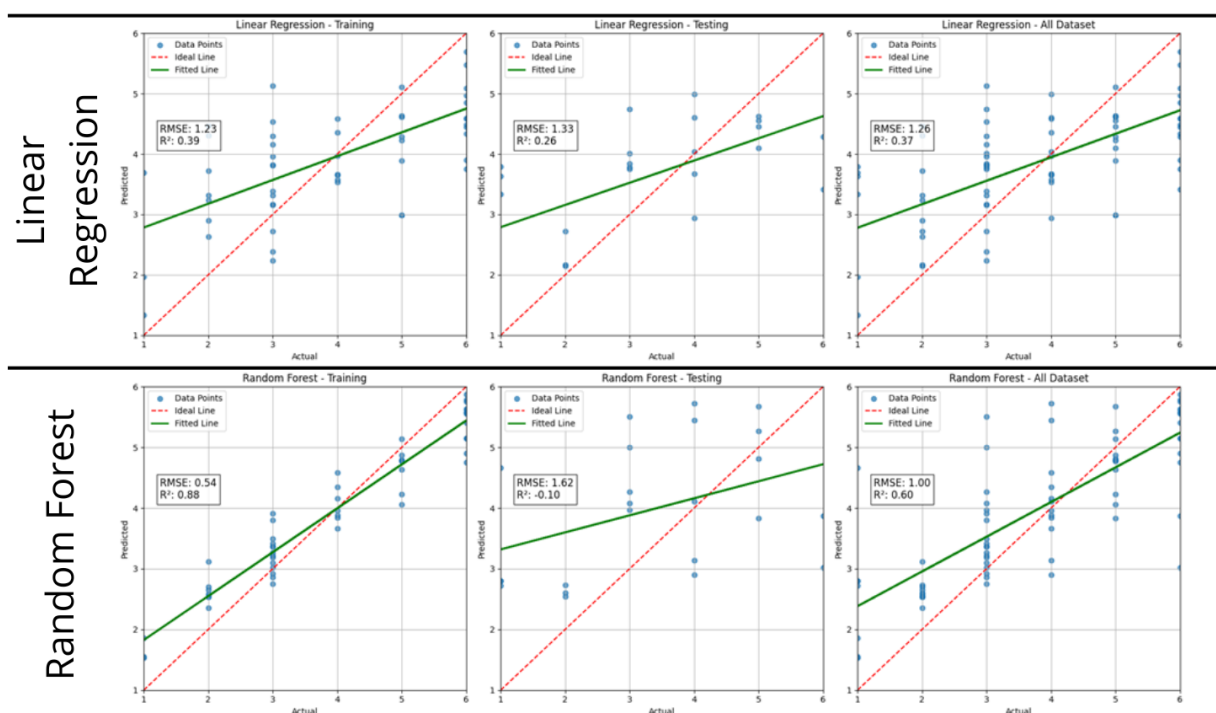


Fig. 4 Linear Regression and Random Forest Result

plex relationships, particularly in out-of-sample predictions.

The correlation matrix provided valuable insights into the linear associations among variables (Fig. 5). GVI displayed the strongest positive correlation with VICO ($r = 0.54$), reinforcing its role as a key determinant of visual comfort. Other predictors, such as DominantObject2 ($r = 0.28$) and DominantObject1 ($r = 0.13$), exhibited weaker correlations, indicating their more limited direct contributions to VICO. Diversity indices, including Simpson Index and Shannon Entropy, showed negligible correlations with VICO ($r < 0.1$), suggesting that their influence may manifest through more complex or indirect mechanisms.

The residual plot for the linear regression model revealed systematic patterns, indicating the presence of non-linear relationships that the linear approach could not adequately capture (Fig. 6). The residuals deviated from zero in a structured manner, particularly at the higher and lower ends of the predicted values, further underscoring the inadequacy

of the linear model in addressing the intricate interactions among variables.

3.2 Non-linear approach result

To address the limitations of the linear approach, a Random Forest Regressor was employed to model the non-linear relationships between predictors and VICO (Fig. 5). The Random Forest model achieved an $R^2 = 0.88$ and an RMSE of 0.54 on the training dataset, demonstrating its ability to account for 88% of the variance in VICO. However, as with many machine learning models, the performance on the testing dataset declined ($R^2 = -0.10$, RMSE = 1.62), indicating overfitting. On the full dataset, the model achieved a moderate performance with $R^2 = 0.60$ and RMSE = 1.00, highlighting its capability to capture non-linear relationships while also emphasizing the need for improved generalization to unseen data. Despite this limitation, the model provided valuable insights into the contributions and interactions of the predictors.

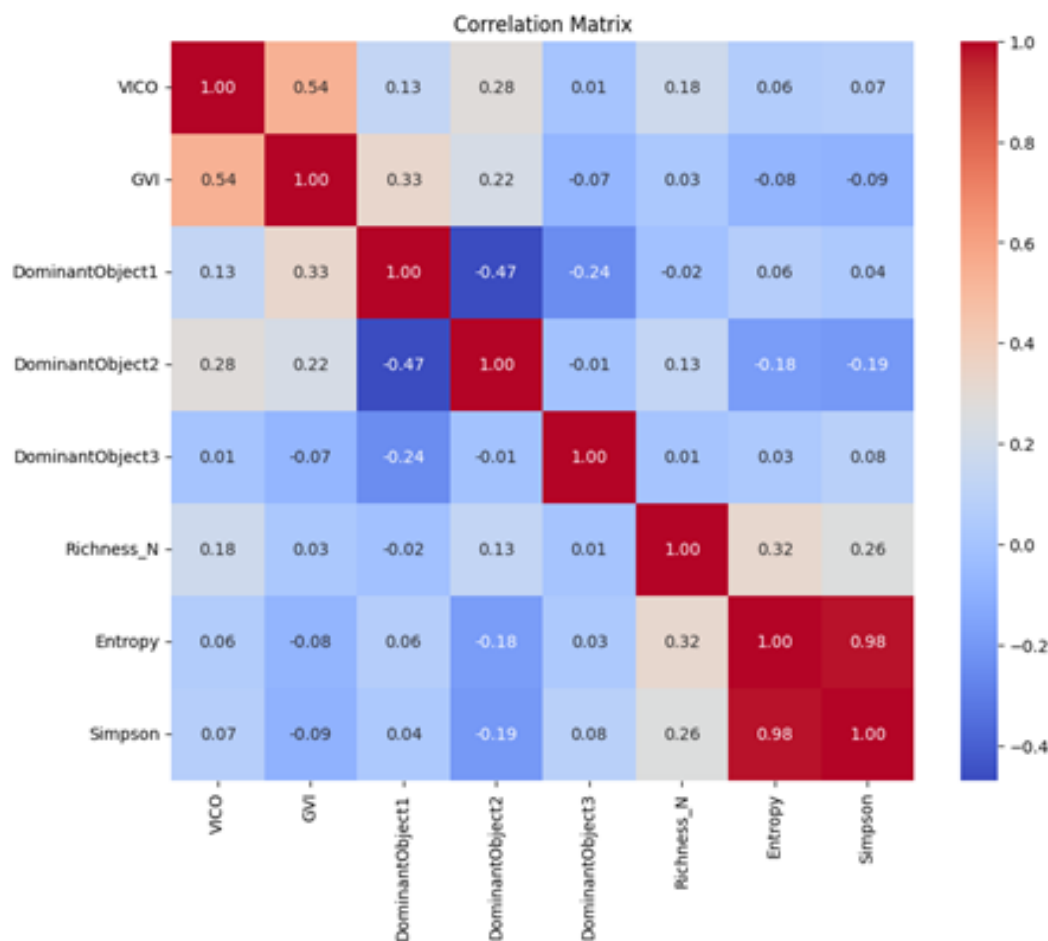


Fig. 5 Correlation Matrix for each variable

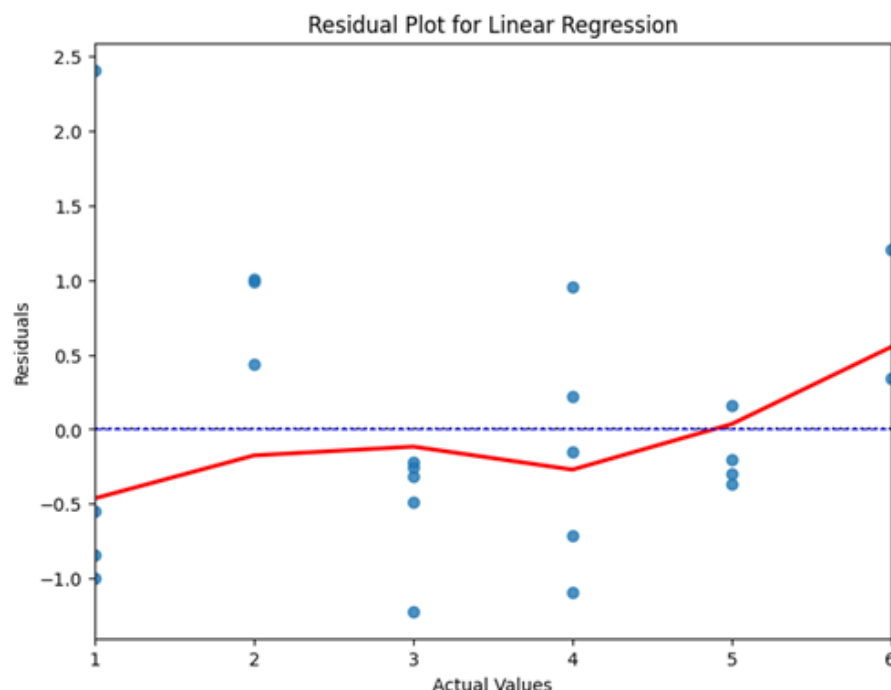


Fig. 6 Residual Plot for Linear Regression

GVI shows the strongest influence, with higher GVI values positively correlating with VICO (Fig. 7). Simpson Index and DominantObject2 also contribute significantly, reflecting the role of vegetation diversity and specific visual object categories. DominantObject1 and Entropy exhibit moderate impacts, highlighting the interplay of dominant object composition and landscape configuration. In contrast, DominantObject3 and Richness_N have minimal influence, suggesting limited variability in these features within the dataset.

Categorical variables, such as Dominant Objects, were analyzed using SHAP values to understand their influence on VICO (Fig. 10). Earth exhibits the highest impact across all three DominantObject variables, with DominantObject3 showing the strongest influence. Sky and Plant also play significant roles, especially in DominantObject1 and DominantObject2, reflecting their importance in visual comfort assessment. Other categories, such as Wall and Mountain, have minimal influence, indicating their limited contribution to the model.

The predictive mapping of VICO using both Linear Regression (LR) (Fig. 8B) and Random Forest (RF) (Fig. 8C) models showcases the spatial distribution of predicted values relative to actual VICO measurements. Both models, as seen in the lower figure, capture general spatial trends in VICO. However, the RF model aligns more closely with the actual VICO distribution, reflecting its higher accu-

racy in capturing non-linear relationships between predictors and VICO. By contrast, the LR model demonstrates less spatial variability, missing certain nuances in the data. This comparison underscores the importance of employing non-linear approaches like RF in scenarios involving complex relationships.

4 Discussion

This study advances the understanding of visual comfort (VICO) by integrating the Green View Index (GVI) with machine learning-based image segmentation, offering a more comprehensive perspective on how greenery, spatial arrangement, and dominant visual objects shape human perception of landscapes. Unlike prior studies that often focused on simple correlations, this research reveals that VICO is influenced not only by the quantity of greenery but also by its spatial organization and interaction with other elements in the environment.

One of the most significant contributions of this study lies in demonstrating the necessity of non-linear approaches in modeling environmental perception. While traditional linear regression provided some insights, it was unable to capture the complex, context-dependent relationships that shape visual comfort. The Random Forest model, supported by SHAP analysis, offered a more

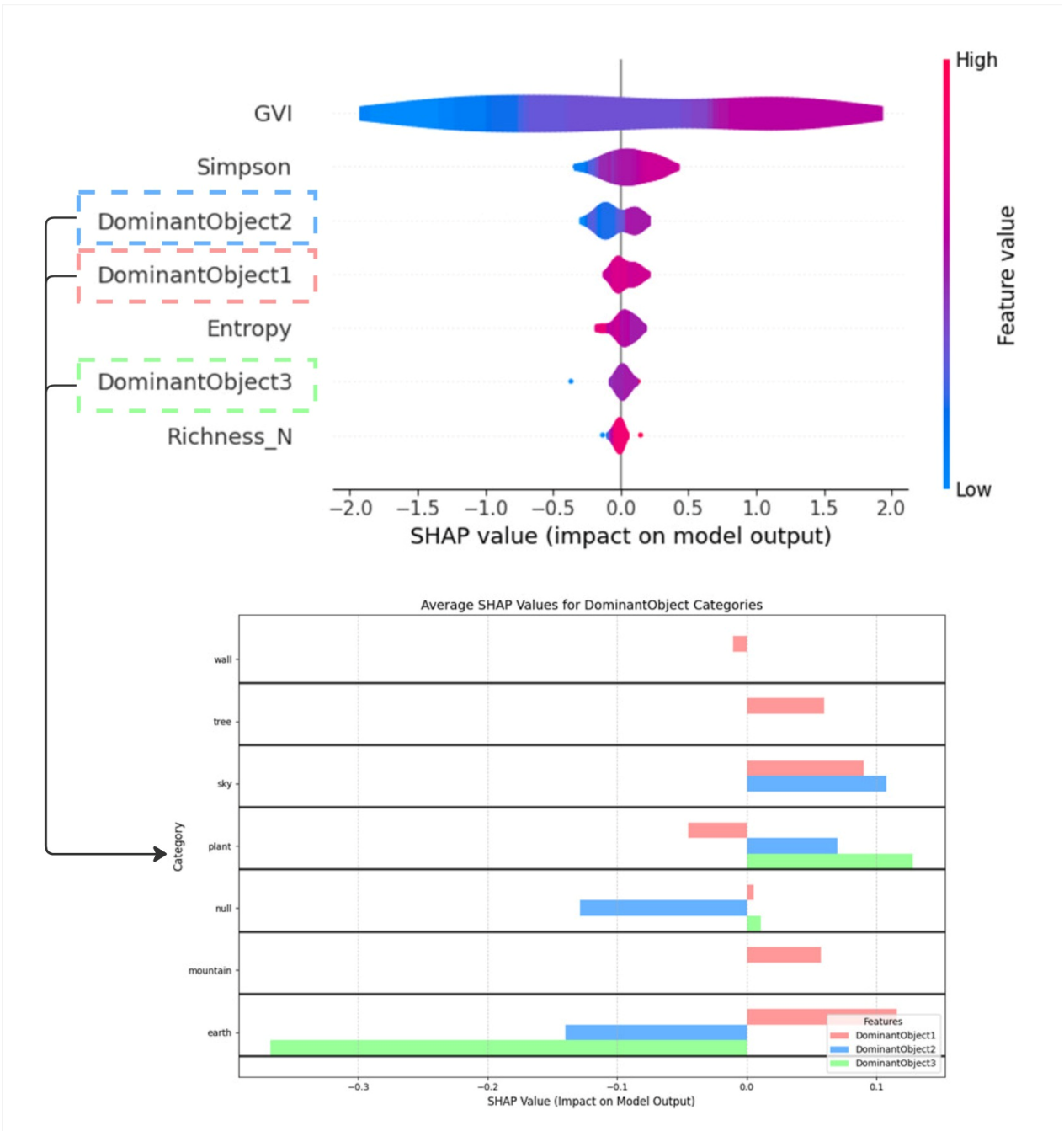


Fig. 7 SHAP Summary Plot and SHAP Values for Dominant Object

accurate and interpretable framework, highlighting how greenery interacts with visual composition in ways that are not immediately apparent through linear models. These findings carry important implications for landscape planning and urban design, emphasizing that enhancing greenery should not be seen as a simple maximization problem but rather as a strategic integration challenge—one that requires careful attention to spatial balance, object diversity, and openness.

4.1 Key drivers of visual comfort

This study confirms that greenery, as measured by the Green View Index (GVI), plays a fundamental role in shaping visual comfort. However, rather than a straightforward linear relationship, the findings reveal a non-linear dynamic in which increasing greenery does not always lead to proportional increases in visual comfort. Beyond a certain threshold, the benefits of additional greenery diminish, and in some cases, excessive vegetation can even

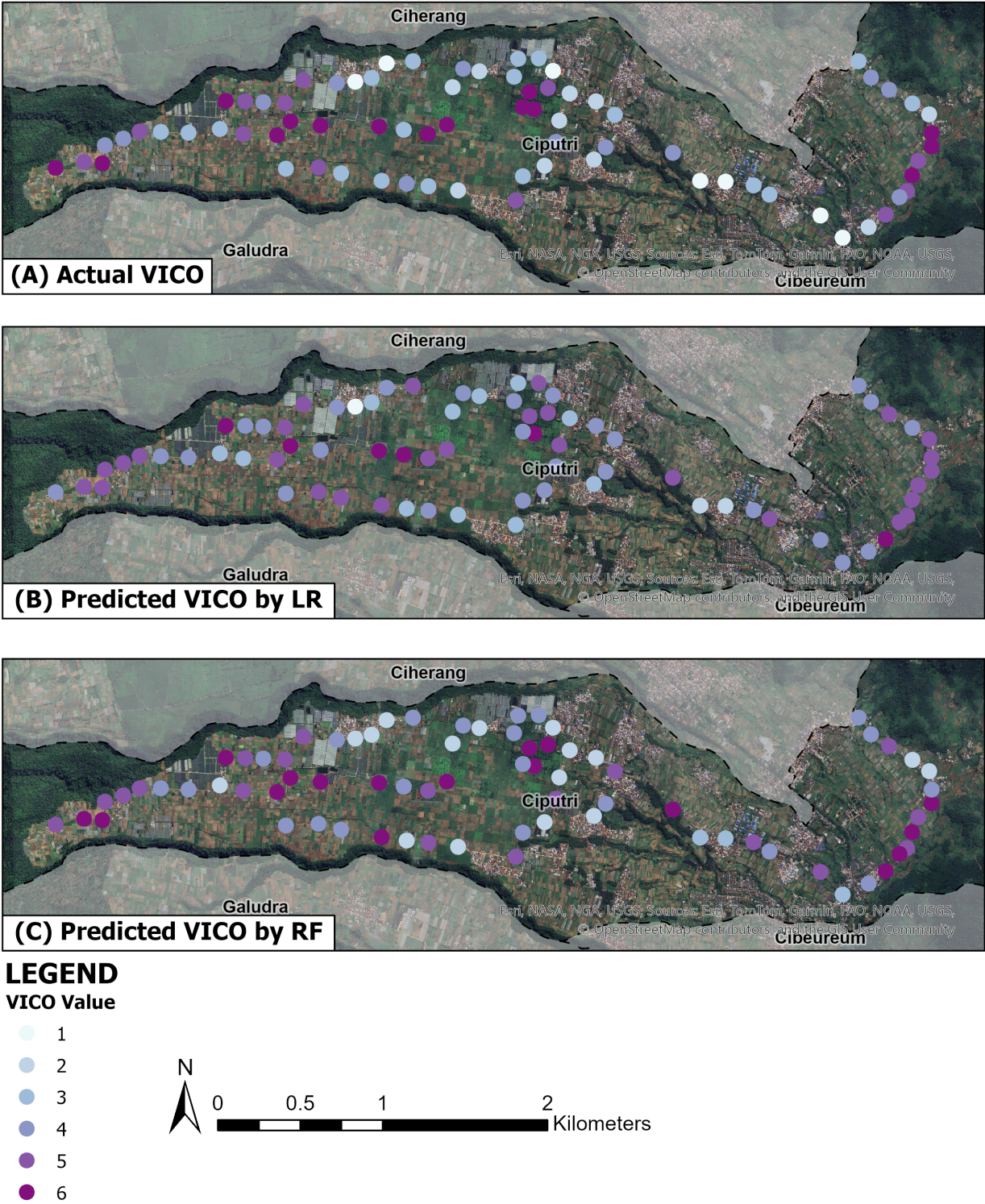


Fig. 8 Prediction Map: (A) Actual VICO, (B) Predicted by Linear Regression, (C) Predicted by Random Forest

reduce VICO due to visual enclosure or monotony. These results highlight the limitations of using GVI as a sole predictor of visual comfort and suggest that spatial arrangement, object diversity, and open-

ness must also be considered when evaluating how landscapes are perceived (Fox et al. 2020; Holy-Hasted & Burchell 2022).

The predictive modeling comparison further reinforces this argument. The linear regression model, while capturing basic trends, exhibited low explanatory power ($R^2 = 0.37$), indicating that visual comfort is shaped by interactions beyond simple linear dependencies. In contrast, the Random Forest model significantly improved prediction accuracy ($R^2 = 0.60$), validating the necessity of non-linear approaches when assessing environmental perception. Moreover, SHAP analysis provided deeper insights, revealing that beyond greenery, dominant objects such as sky and earth play a crucial role in moderating the effects of greenery on visual perception. These findings suggest that planners should design landscapes that optimize openness while integrating greenery in a structured and context-sensitive manner.

These insights underscore the need to move beyond a simplistic approach of increasing green coverage. Instead, planners should consider how greenery is distributed and how it interacts with built and natural elements. The findings advocate for a balanced distribution of green spaces, ensuring that vegetation enhances rather than overwhelms visual composition. This shift from a purely quantitative approach to one that integrates qualitative spatial characteristics is essential for optimizing visual comfort and creating visually engaging environments in rural settings.

4.2 The role of greenery and object composition

While the presence of greenery is a key driver of visual comfort, this study highlights that the composition of visual elements is just as crucial. Through semantic segmentation, the analysis revealed how different dominant objects—such as trees, mountains, sky, and built structures—shape the perception of landscapes. Trees, mountains, and sky consistently enhanced VICO, reinforcing their role in providing psychological relaxation and aesthetic satisfaction (Hu et al. 2024; Zhang & Zeng 2024). Conversely, walls and artificial structures were found to decrease VICO, suggesting that built environments that lack integration with natural elements can diminish perceived comfort.

One particularly interesting finding concerns the role of plants in visual perception. While plants are generally associated with greenery and positive visual experiences, their impact on VICO varied depending on their dominance within a scene. When plants were the primary visual element (DominantObject1), they tended to reduce VICO, likely due to the monotony of uniform agricultural fields,

which lack the structural diversity that makes landscapes visually engaging. However, when plants appeared as secondary or tertiary elements (DominantObject2 or DominantObject3), they contributed positively to VICO, suggesting that they play a complementary role in breaking up visual monotony and enhancing landscape diversity.

It suggests that while greenery is important, it must be carefully integrated with other visual elements to create balanced and aesthetically pleasing environments. A well green natural view should not only provide a high percentage of greenery but also incorporate visual diversity, including structured tree placement, open sky exposure, and elements that enhance contrast and variation. This aligns with previous studies showing that people prefer environments that offer a mix of greenery, open space, and structured visual elements rather than monotonous green coverage (Antrop & Van Eetvelde 2000; Belmahdi & Djemili 2022; Keshtkaran 2019; Ode et al. 2008, 2010).

4.3 Anomalies and spatial patterns in VICO-GVI

Although GVI and VICO were generally correlated (Fig. 9), this study uncovered notable anomalies where greenery coverage did not align with visual comfort. These findings provide valuable insights into the limitations of using GVI as a standalone metric and highlight the need for a more holistic approach to evaluating landscape perception.

In high-GVI but low-VICO areas (Fig. 10B), excessive, unstructured greenery often reduced visual comfort. Overgrown vegetation, dense tree coverage, or monotonous landscapes lacking diversity were found to diminish the aesthetic appeal of the scene, reinforcing the idea that not all greenery contributes equally to perceived comfort (Kaplan & Kaplan 1989; Ulrich 1986). These findings align with prior research suggesting that chaotic, uncontrolled vegetation can create a sense of enclosure or even reduce accessibility, leading to lower comfort levels (Jennings & Bamkole 2019).

Conversely, low-GVI but high-VICO areas demonstrated that structured openness can enhance visual comfort even in the absence of extensive greenery. Landscapes featuring well-maintained paths, scenic vistas, or natural openness (such as mountain views or water bodies) compensated for lower greenery levels, indicating that spatial arrangement and visual engagement are just as important as green coverage itself.

The spatial clustering analysis reinforces these findings (Fig. 10):

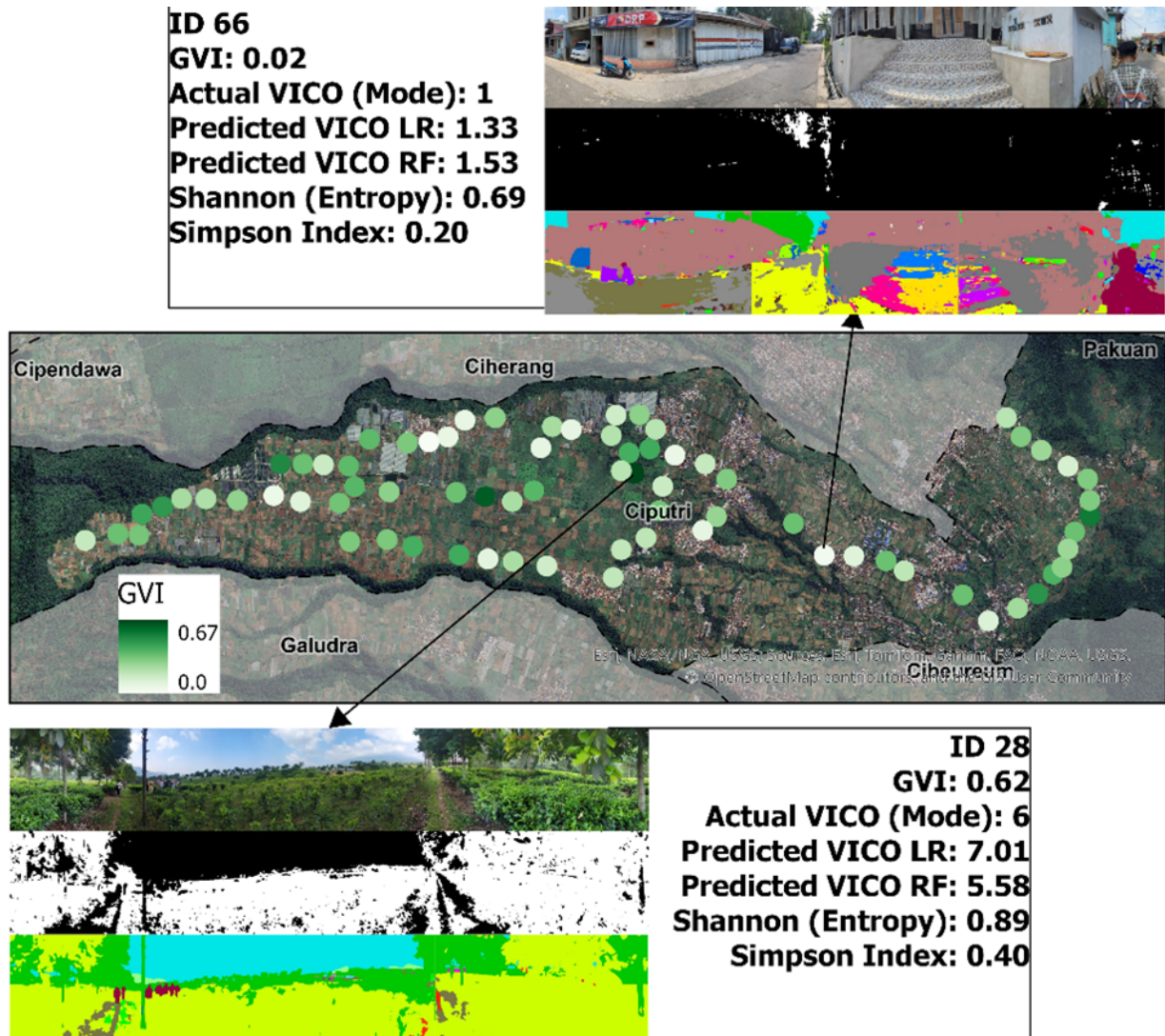


Fig. 9 Example of VICO and GVI for two cases (High VICO-High GVI and Low VICO-Low GVI)

High-GVI, high-VICO areas (H-H) exhibited well-balanced landscapes that integrate greenery with structured visual arrangements, enhancing both aesthetics and psychological comfort (Fig. 10A). Low-GVI, high-VICO areas (L-H) demonstrated that open space aesthetics and scenic visual elements can create a comfortable environment even with minimal greenery (Fig. 10C) (Huang et al. 2022; Jin et al. 2023). High-GVI, low-VICO areas (H-L) revealed that excessive, chaotic vegetation can reduce visual appeal, reinforcing the need for thoughtful greenery placement rather than indiscriminate vegetation expansion (Fig. 10D) (Tong et al. 2020). These findings provide clear guidance for planning strategies Ciputri Village and similar Indonesian contexts. Rather than focusing solely on increas-

ing green spaces, planners should prioritize spatial balance, visual diversity, and integration between natural and built elements (Sun et al. 2023; Zhang & Zeng 2024). In densely vegetated but less comfortable areas (H-L), selective clearing or creating scenic paths can reduce enclosure, while in central zones with limited greenery (L-H), adding trees or vegetated buffers can enhance comfort without losing openness. Overall, balancing greenery and openness supports visually engaging, ecologically resilient rural landscapes and informs broader strategies for tourism, scenic route design, and spatial planning across Southeast Asia.

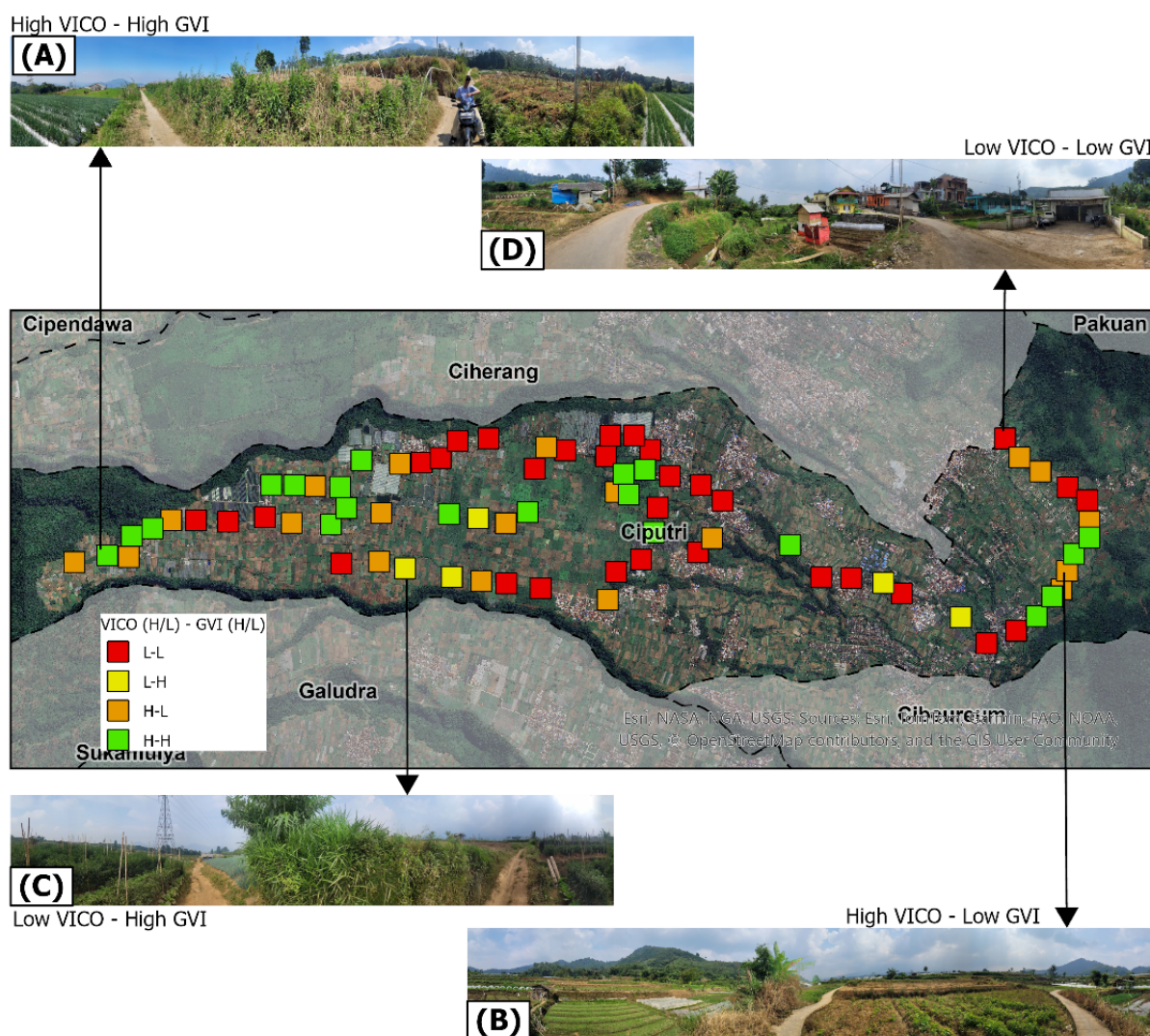


Fig. 10 Distribution of VICO-GVI: (A) H-H, (B) H-L, (C) L-H, and (D) L-L

5 Conclusions

This study concludes that VICO in rural landscapes is primarily influenced by greenery distribution, quantified through the GVI, and the composition of dominant visual objects. The findings establish GVI as a key predictor of VICO, with strong positive relationships underscoring the importance of greenery in enhancing visual perception. Additionally, specific object categories, such as trees, mountains, and sky, were found to significantly increase VICO when dominant in visual composition, while walls and primary positions of plants reduced it, likely due to perceived monotony or artificial arrangements. The application of Random Forest modeling demonstrated superior performance over linear regression, effectively capturing non-

linear and complex relationships among predictors. This highlights the importance of employing advanced computational methods for more accurate predictions in environmental studies. Unique patterns in the contributions of plant and "null" objects further revealed the role of diversity and spatial arrangements in shaping visual comfort, emphasizing the importance of visual variety. These insights advance the understanding of the interplay between greenery, object composition, and human perception, contributing to landscape research and offering a methodological foundation for future studies. The integration of semantic segmentation and machine learning models showcases the potential of combining computational and spatial analyses for more nuanced environmental assessments and design strategies.

For rural planning practice in Indonesian contexts such as Ciputri Village, these findings highlight the need to move beyond quantitative greenery metrics toward integrated approaches that account for visual composition, spatial arrangement, and cultural preferences. Future research should further explore how structural and cultural factors mediate the influence of greenery and visual elements on human perception, extending this framework across diverse environmental and cultural settings to achieve a more holistic understanding of the cognitive and aesthetic dimensions of landscape experience.

Acknowledgement

The author extends heartfelt gratitude to the Department of Geography, Universitas Indonesia, for organizing and facilitating the fieldwork activities that were instrumental in collecting the data for this research. The support and resources provided by the department were invaluable in ensuring the successful completion of this study. The authors reported no potential conflicts of interest.

References

- Anguelov D, Dulong C, Filip D, Frueh C, Lafon S, Lyon R, Ogale A, Vincent L, Weaver J, (2010), Google Street View: Capturing the World at Street Level. *Computer*, 43, (6):32–38. ISSN 0018-9162. doi: 10.1109/mc.2010.170.
- Antrop M, Van Eetvelde V, (2000), Holistic aspects of suburban landscapes: visual image interpretation and landscape metrics. *Landscape and Urban Planning*, 50, (1–3):43–58. ISSN 0169-2046. doi: 10.1016/s0169-2046(00)00079-7.
- Belmahdi HS, Djemili A, (2022), Urban landscape structure anatomy: Structure patterns and typology identification in the space-time of Setif City, Algeria. *Frontiers of Architectural Research*, 11, (3):421–439. ISSN 2095-2635. doi: 10.1016/j.foar.2021.12.004.
- Biljecki F, Ito K, (2021), Street view imagery in urban analytics and GIS: A review. *Landscape and Urban Planning*, 215: 104217. ISSN 0169-2046. doi: 10.1016/j.landurbplan.2021.104217.
- Chen X, Meng Q, Hu D, Zhang L, Yang J, (2019), Evaluating Greenery around Streets Using Baidu Panoramic Street View Images and the Panoramic Green View Index. *Forests*, 10, (12):1109. ISSN 1999-4907. doi: 10.3390/f10121109.
- Curtis JW, Curtis A, Mapes J, Szell AB, Cinderich A, (2013), Using google street view for systematic observation of the built environment: analysis of spatio-temporal instability of imagery dates. *International Journal of Health Geographics*, 12, (1):53. ISSN 1476-072X. doi: 10.1186/1476-072x-12-53.
- Dong R, Zhang Y, Zhao J, (2018), 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. *International Journal of Environmental Research and Public Health*, 15, (7):1367. ISSN 1660-4601. doi: 10.3390/ijerph15071367.
- Fang YN, Tian J, Namaiti A, Zhang S, Zeng J, Zhu X, (2024), Visual aesthetic quality assessment of the streetscape from the perspective of landscape-perception coupling. *Environmental Impact Assessment Review*, 106:107535. ISSN 0195-9255. doi: 10.1016/j.eiar.2024.107535.
- Ferrini F, Fini A, Mori J, Gori A, (2020), Role of Vegetation as a Mitigating Factor in the Urban Context. *Sustainability*, 12, (10):4247. ISSN 2071-1050. doi: 10.3390/su12104247.
- Fox EW, Ver Hoef JM, Olsen AR, (2020), Comparing spatial regression to random forests for large environmental data sets. *PLOS ONE*, 15, (3):e0229509. ISSN 1932-6203. doi: 10.1371/journal.pone.0229509.
- Hao N, Li X, Han D, Nie W, (2024), Quantifying the Impact of Street Greening during Full-Leaf Seasons on Emotional Perception: Guidelines for Resident Well-Being. *Forests*, 15, (1): 119. ISSN 1999-4907. doi: 10.3390/f15010119.
- Holy-Hasted W, Burchell B, (2022), Does public space have to be green to improve well-being? An analysis of public space across Greater London and its association to subjective well-being. *Cities*, 125:103569. ISSN 0264-2751. doi: 10.1016/j.cities.2022.103569.
- Hu Y, Wu Y, Tiantian Z, Sun G, (2024), Capturing urban green view with mobile crowd sensing. *Ecological Informatics*, 81: 102640. ISSN 1574-9541. doi: 10.1016/j.ecoinf.2024.102640.
- Huang D, Jiang B, Yuan L, (2022), Analyzing the effects of nature exposure on perceived satisfaction with running routes: An activity path-based measure approach. *Urban Forestry & Urban Greening*, 68:127480. ISSN 1618-8667. doi: 10.1016/j.ufug.2022.127480.
- Jennings V, Bamkole O, (2019), The Relationship between Social Cohesion and Urban Green Space: An Avenue for Health Promotion. *International Journal of Environmental Research and Public Health*, 16, (3):452. ISSN 1660-4601. doi: 10.3390/ijerph16030452.
- Jiang Y, Liu D, Ren L, Grekousis G, Lu Y, (2024), Tree abundance, species richness, or species mix? Exploring the relationship between features of urban street trees and pedestrian volume in Jinan, China. *Urban Forestry & Urban Greening*, 95: 128294. ISSN 1618-8667. doi: 10.1016/j.ufug.2024.128294.
- Jin B, Geng J, Ke S, Pan H, (2023), Analysis of spatial variation of street landscape greening and influencing factors: an example from Fuzhou city, China. *Scientific Reports*, 13, (1). ISSN 2045-2322. doi: 10.1038/s41598-023-49308-6.
- Kameoka T, Uchida A, Sasaki Y, Ise T, (2022), Assessing streetscape greenery with deep neural network using Google Street View. *Breeding Science*, 72, (1):107–114. ISSN 1347-3735. doi: 10.1270/jsbbs.21073.
- Kaplan R, Kaplan S, (1989), *The experience of nature: A psychological perspective*. Cambridge university press.
- Keshtkaran R, (2019), Urban landscape: A review of key concepts and main purposes. *International Journal of Development and Sustainability*, 8, (2):141–168.
- Labib S, Huck JJ, Lindley S, (2021), Modelling and mapping eye-level greenness visibility exposure using multi-source data at high spatial resolutions. *Science of The Total Environment*, 755:143050. ISSN 0048-9697. doi: 10.1016/j.scitotenv.2020.143050.

- Lachowycz K, Jones AP, (2013), Towards a better understanding of the relationship between greenspace and health: Development of a theoretical framework. *Landscape and Urban Planning*, 118:62–69. ISSN 0169-2046. doi: 10.1016/j.landurbplan.2012.10.012.
- Li X, Zhang C, Li W, Kuzovkina YA, Weiner D, (2015), Who lives in greener neighborhoods? The distribution of street greenery and its association with residents' socioeconomic conditions in Hartford, Connecticut, USA. *Urban Forestry & Urban Greening*, 14, (4):751–759. ISSN 1618-8667. doi: 10.1016/j.ufug.2015.07.006.
- Li Y, Peng L, Wu C, Zhang J, (2022), Street View Imagery (SVI) in the Built Environment: A Theoretical and Systematic Review. *Buildings*, 12, (8):1167. ISSN 2075-5309. doi: 10.3390/buildings12081167.
- Liu Y, Pan X, Liu Q, Li G, (2023), Establishing a Reliable Assessment of the Green View Index Based on Image Classification Techniques, Estimation, and a Hypothesis Testing Route. *Land*, 12, (5):1030. ISSN 2073-445X. doi: 10.3390/land12051030.
- Ode Å, Tveit MS, Fry G, (2008), Capturing Landscape Visual Character Using Indicators: Touching Base with Landscape Aesthetic Theory. *Landscape Research*, 33, (1):89–117. ISSN 1469-9710. doi: 10.1080/01426390701773854.
- Ode Å, Fry G, Tveit MS, Messenger P, Miller D, (2009), Indicators of perceived naturalness as drivers of landscape preference. *Journal of Environmental Management*, 90, (1):375–383. ISSN 0301-4797. doi: 10.1016/j.jenvman.2007.10.013.
- Ode Å, Hagerhall CM, Sang N, (2010), Analysing Visual Landscape Complexity: Theory and Application. *Landscape Research*, 35, (1):111–131. ISSN 1469-9710. doi: 10.1080/01426390903414935.
- Pradana MR, Dimiyati M, (2024), Tracking Urban Sprawl: A Systematic Review and Bibliometric Analysis of Spatio-Temporal Patterns Using Remote Sensing and GIS. *European Journal of Geography*, 15, (3):190–203. ISSN 1792-1341. doi: 10.48088/ejg.m.pra.15.3.190.203.
- Qi Z, Duan J, Su H, Fan Z, Lan W, (2023), Using crowdsourcing images to assess visual quality of urban landscapes: A case study of Xiamen Island. *Ecological Indicators*, 154:110793. ISSN 1470-160X. doi: 10.1016/j.ecolind.2023.110793.
- Qureshi S, Breuste JH, Lindley SJ, (2010), Green Space Functionality Along an Urban Gradient in Karachi, Pakistan: A Socio-Ecological Study. *Human Ecology*, 38, (2):283–294. ISSN 1572-9915. doi: 10.1007/s10745-010-9303-9.
- Rui J, (2023), Measuring streetscape perceptions from driveways and sidewalks to inform pedestrian-oriented street renewal in Düsseldorf. *Cities*, 141:104472. ISSN 0264-2751. doi: 10.1016/j.cities.2023.104472.
- Setiawan W, Amar, (2021), Spatial Perception towards Social Conflicts and the Built Environment in Indonesia. *International Review for Spatial Planning and Sustainable Development*, 9, (2):134–150. ISSN 2187-3666. doi: 10.14246/irspdc.9.2_134.
- Simpson J, Freeth M, Simpson KJ, Thwaites K, (2018), Visual engagement with urban street edges: insights using mobile eye-tracking. *Journal of Urbanism: International Research on Placemaking and Urban Sustainability*, 12, (3):259–278. ISSN 1754-9183. doi: 10.1080/17549175.2018.1552884.
- Sun D, Ji X, Gao W, Zhou F, Yu Y, Meng Y, Yang M, Lin J, Lyu M, (2023), The Relation between Green Visual Index and Visual Comfort in Qingdao Coastal Streets. *Buildings*, 13, (2):457. ISSN 2075-5309. doi: 10.3390/buildings13020457.
- Tiara S, Gamal A, (2021), The Correlation Between Spatial Configuration and User Satisfaction: A Case Study of an Activity-based vs a Conventional Office. *International Journal on Advanced Science, Engineering and Information Technology*, 11, (2):648–655. ISSN 2088-5334. doi: 10.18517/ijaseit.11.2.12643.
- Tong M, She J, Tan J, Li M, Ge R, Gao Y, (2020), Evaluating Street Greenery by Multiple Indicators Using Street-Level Imagery and Satellite Images: A Case Study in Nanjing, China. *Forests*, 11, (12):1347. ISSN 1999-4907. doi: 10.3390/f11121347.
- Ulrich RS, (1986), Human responses to vegetation and landscapes. *Landscape and Urban Planning*, 13:29–44. ISSN 0169-2046. doi: 10.1016/0169-2046(86)90005-8.
- van den Berg AE, Koole SL, van der Wulp NY, (2003), Environmental preference and restoration: (How) are they related? *Journal of Environmental Psychology*, 23, (2):135–146. ISSN 0272-4944. doi: 10.1016/s0272-4944(02)00111-1.
- Wang J, Liu W, Gou A, (2022), Numerical characteristics and spatial distribution of panoramic Street Green View index based on SegNet semantic segmentation in Savannah. *Urban Forestry & Urban Greening*, 69:127488. ISSN 1618-8667. doi: 10.1016/j.ufug.2022.127488.
- Wu J, Wang B, Ta N, Zhou K, Chai Y, (2020), Does street greenery always promote active travel? Evidence from Beijing. *Urban Forestry & Urban Greening*, 56:126886. ISSN 1618-8667. doi: 10.1016/j.ufug.2020.126886.
- Wu L, Dong Q, Luo S, Jiang W, Hao M, Chen Q, (2021), Effects of Spatial Elements of Urban Landscape Forests on the Restoration Potential and Preference of Adolescents. *Land*, 10, (12):1349. ISSN 2073-445X. doi: 10.3390/land10121349.
- Wu Z, Xu K, Li Y, Zhao X, Qian Y, (2024), Application of an Integrated Model for Analyzing Street Greenery through Image Semantic Segmentation and Accessibility: A Case Study of Nanjing City. *Forests*, 15, (3):561. ISSN 1999-4907. doi: 10.3390/f15030561.
- Xu H, Lu H, Liu S, (2024), Online Street View-Based Approach for Sky View Factor Estimation: A Case Study of Nanjing, China. *Applied Sciences*, 14, (5):2133. ISSN 2076-3417. doi: 10.3390/app14052133.
- Xue C, Jin C, Zhou L, Li G, (2022), Exploring the distribution of city street greenery from eye-level: an application of Baidu Map panoramic images data. *Geografisk Tidsskrift-Danish Journal of Geography*, 122, (1):73–86. doi: 10.1080/00167223.2021.2019073.
- Yu X, Qi W, (2021), Measuring vegetation greenery in park using iPhone panoramic image and a new green vegetation extraction index. *Urban Forestry & Urban Greening*, 65:127310. ISSN 1618-8667. doi: 10.1016/j.ufug.2021.127310.
- Zhang L, Wang L, Wu J, Li P, Dong J, Wang T, (2023), Decoding urban green spaces: Deep learning and google street view measure greening structures. *Urban Forestry & Urban Greening*, 87:128028. ISSN 1618-8667. doi: 10.1016/j.ufug.2023.128028.
- Zhang W, Zeng H, (2024), Spatial differentiation characteristics and influencing factors of the green view index in urban areas based on street view images: A case study of Futian District, Shenzhen, China. *Urban Forestry & Urban Greening*, 93:128219. ISSN 1618-8667. doi: 10.1016/j.ufug.2024.128219.

- Zhou B, Zhao H, Puig X, Fidler S, Barriuso A, Torralba A, (2017), Scene Parsing through ADE20K Dataset. In: *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. IEEE, pp. 5122–5130. doi: 10.1109/cvpr.2017.544.
- Zhou B, Lapedriza A, Khosla A, Oliva A, Torralba A, (2018), Places: A 10 Million Image Database for Scene Recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 40, (6):1452–1464. ISSN 1939-3539. doi: 10.1109/tpami.2017.2723009.
- Zhou B, Zhao H, Puig X, Xiao T, Fidler S, Barriuso A, Torralba A, (2019), Semantic Understanding of Scenes Through the ADE20K Dataset. *International Journal of Computer Vision*, 127, (3):302–321. ISSN 1573-1405. doi: 10.1007/s11263-018-1140-0.
- Zhu H, Nan X, Yang F, Bao Z, (2023), Utilizing the green view index to improve the urban street greenery index system: A statistical study using road patterns and vegetation structures as entry points. *Landscape and Urban Planning*, 237:104780. ISSN 0169-2046. doi: 10.1016/j.landurbplan.2023.104780.