

Quantifying Visual Quality in Campus Greenways Using Scenic Beauty Estimation and Deep Learning-Based Semantic Segmentation

Jie Gong^{1,a}, Xuefeng Zhao^{1,b,*}, Yifei Zhao^{1,c}, Songhong Yao^{1,d}

¹Shenyang University, Dadong District, Shenyang, China

^a2501715469@qq.com, ^b446489101@qq.com, ^czhaoyifeiz593@gmail.com, ^dyysh0629@qq.com

*Corresponding author

Keywords: Campus greenway; Landscape visual quality; Scenic Beauty Estimation (SBE); Semantic segmentation; Functional zoning

Abstract: This study integrates Scenic Beauty Estimation (SBE) and DeepLabV3+ semantic segmentation to evaluate campus greenway visual quality at Shenyang University. Sixty node images and 130 valid student evaluations were used to link perceived beauty with measurable visual elements. Regression results show that greenway morphology and spatial extension improve SBE values, whereas excessive green visibility, vehicle presence, and spatial closure reduce perceived quality. Teaching-area greenways achieved the highest mean SBE value, while office-area greenways scored lowest. The results support targeted design strategies for strengthening visual corridors, balancing greenery and permeability, and reducing traffic-related visual interference.

1. Introduction

Campus greenways connect teaching, living, and office spaces while supporting movement, recreation, ecological continuity, and psychological restoration [1-5]. In high-density campus environments, these linear spaces are used repeatedly in daily routines, so their visual quality affects orientation, comfort, willingness to stay, and the perceived identity of the campus. However, many campus landscape assessments remain descriptive or focus on isolated elements such as vegetation coverage and road width, which makes it difficult to explain how multiple visual elements jointly affect aesthetic perception.

SBE transforms subjective preference into comparable scores and has been widely used in landscape assessment [6-9]. Greenway preference studies also show that trail characteristics and environmental modeling can explain aesthetic response [10,11]. At the same time, street-view imagery and semantic segmentation make it possible to measure greenery, sky, roads, buildings, and vehicles at pixel level [12-19]. Combining these methods can retain perceptual sensitivity while improving the objectivity and repeatability of evaluation. This study therefore asks three questions: which visual elements significantly affect SBE values, how do their effects differ among teaching, living, and office greenways, and how can the results guide targeted optimization?

2. Materials and Methods

2.1 Study Area and Image Acquisition

The study area covers the teaching, living, and office greenways of Shenyang University. Nodes were photographed at 30 m intervals, including entrances, intersections, midpoints, tree-lined paths, water-edge segments, and building-front interfaces. Images were collected under sunny daytime conditions to reduce the influence of weather and light differences. A total of 60 images were retained for evaluation and analysis (Figure 1). Image-based landscape assessment was adopted because controlled photographs can produce judgments broadly comparable to on-site assessment when viewpoint, sampling, and presentation conditions are standardized [20].

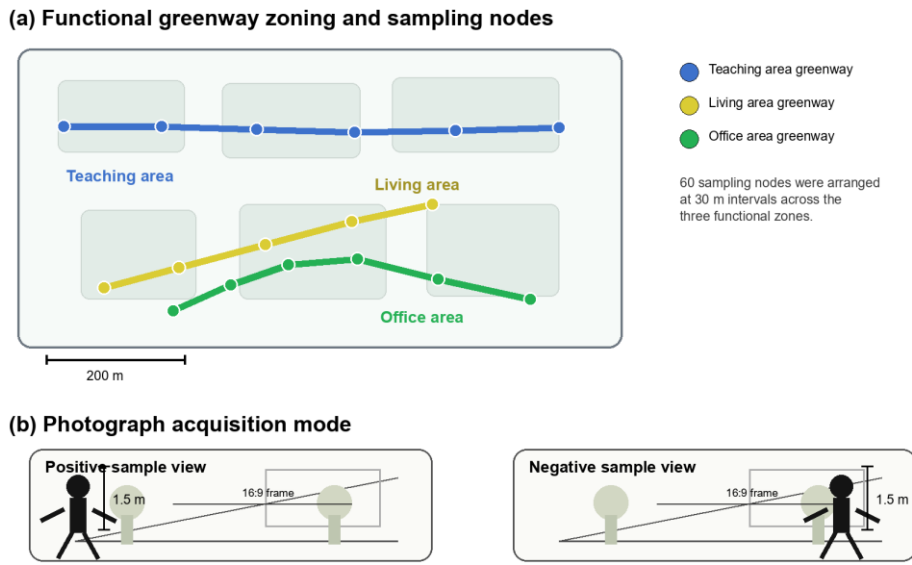


Figure 1. Study area, functional zoning, and photograph acquisition mode.

2.2 SBE Evaluation and Semantic Segmentation

A total of 169 architecture students participated in the online survey. After invalid forms were removed, 130 valid responses were retained. Each participant evaluated 60 photographs using a five-point Likert scale. Raw scores were standardized to reduce individual scoring differences: $Z_{ij} = (R_{ij} - \bar{R}_j) / S_j$, where R_{ij} is the raw score assigned by evaluator j to sample i , $\bar{R}_j$ is the evaluator's mean score, and S_j is the evaluator's score standard deviation. The scenic beauty value was then calculated as $SBE_i = (1/N_i) * \sum_{j=1}^{N_i} Z_{ij}$; the main data types and analytical roles are summarized in Table 1.

DeepLabV3+ was used to obtain pixel-level landscape elements because it can capture multi-scale spatial information and preserve object boundaries in complex outdoor scenes [16-19]. As shown in Figure 2, five image-based indicators were calculated from segmentation results: greenway wideness, green landscape index, sky openness, vehicle occurrence, and spatial closure. These indicators were combined with field-observed variables such as greenway morphology, materials, spatial extension, focused views, vegetation species, vegetation distribution, color richness, and ancillary facilities.

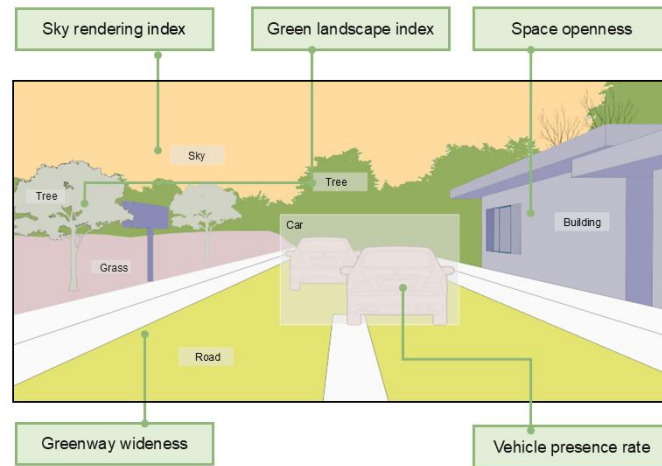


Figure 2. Semantic segmentation indicators used in the study.

Table 1. Data sources and main analytical variables.

Variable group	Operational definition	Analytical role
SBE value	Standardized preference score from 130 valid questionnaires	Dependent variable
Functional zone	Teaching, living, and office greenways	Zonal comparison
Pixel indicators	Road, vegetation, sky, building/wall, and vehicle proportions	Objective visual measures
Site indicators	Form, material, extension, focused view, vegetation richness, and supporting facilities	Regression predictors

3. Results

3.1 SBE Characteristics by Functional Zone

The 60 SBE values ranged from -0.930 to 1.205, indicating clear variation among samples. Most scores were concentrated between -0.5 and 0.5, which suggests that many campus greenway segments were perceived as medium quality rather than extremely positive or negative. Teaching-area greenways had the highest mean SBE value (0.1123), followed by living-area greenways (0.0477), while office-area greenways scored lowest (-0.1601), as summarized in Figure 3 and Table 2.

High-scoring nodes usually contained clear walking sequences, continuous tree-lined corridors, open views, and recognizable spatial rhythm. Low-scoring nodes were often associated with parking edges, weak landscape organization, dense enclosure, or hard building interfaces. The distribution therefore indicates that users respond not only to greenery but also to the organization of the visual field and the degree to which the greenway supports orientation and comfort.

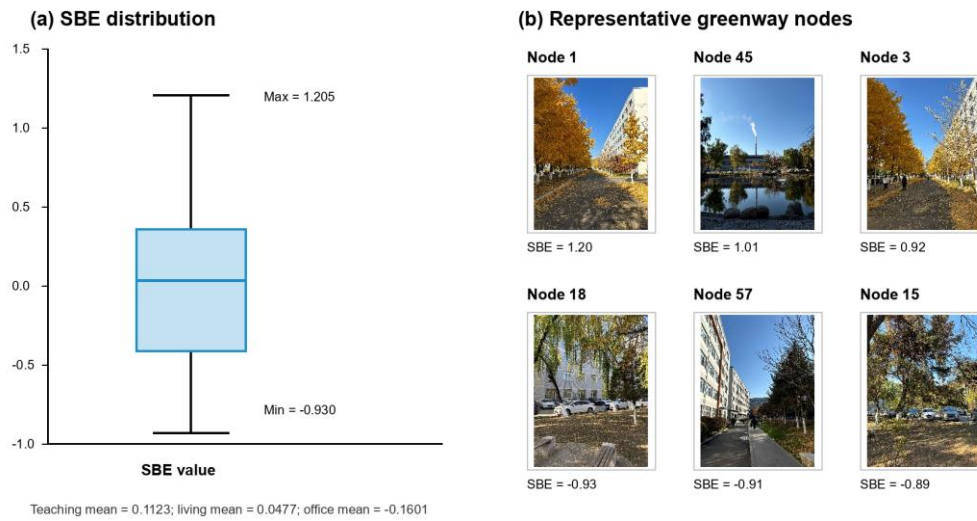


Figure 3. SBE distribution and representative high- and low-scoring greenway nodes.

Table 2. Functional-zone comparison of SBE results.

Functional zone	Mean SBE	Range	Interpretation
Teaching area	0.1123	1.89	Best overall perception, supported by clearer spatial order and visual extension.
Living area	0.0477	1.94	Moderate perception, with high potential for leisure and social use but uneven visual rhythm.
Office area	-0.1601	1.44	Lowest perception, influenced by traffic, parking interfaces, and stronger enclosure.

3.2 Visual Factors and Landscape Elements

Nine additional site indicators and five segmentation indicators were analyzed to explain differences in visual quality (Figures 4 and 5). Greenway morphology and spatial extension showed positive associations with aesthetic perception, indicating that ordered path form and continuous visual corridors improve legibility. In contrast, high vehicle occurrence and strong spatial closure were linked to lower SBE values, especially in office-area greenways where traffic facilities and rigid building fronts are visually prominent.

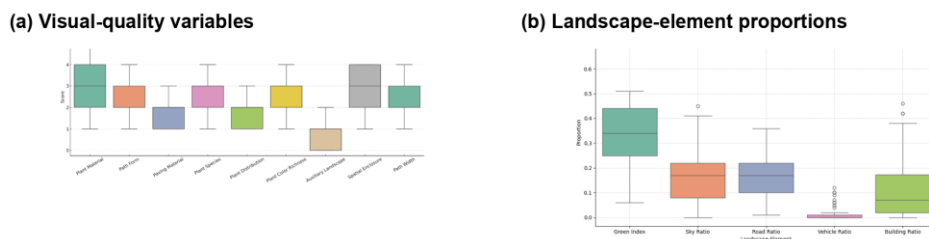


Figure 4. Distribution of visual-quality variables and segmented landscape-element proportions.

The green landscape index showed a negative effect in the regression model. This does not mean

that vegetation is undesirable; instead, it suggests that excessive or poorly organized greenery can reduce permeability, block visual corridors, and increase cognitive load. The result is consistent with the idea that landscape preference depends on balanced complexity, coherence, and visibility rather than on green quantity alone [21-25].

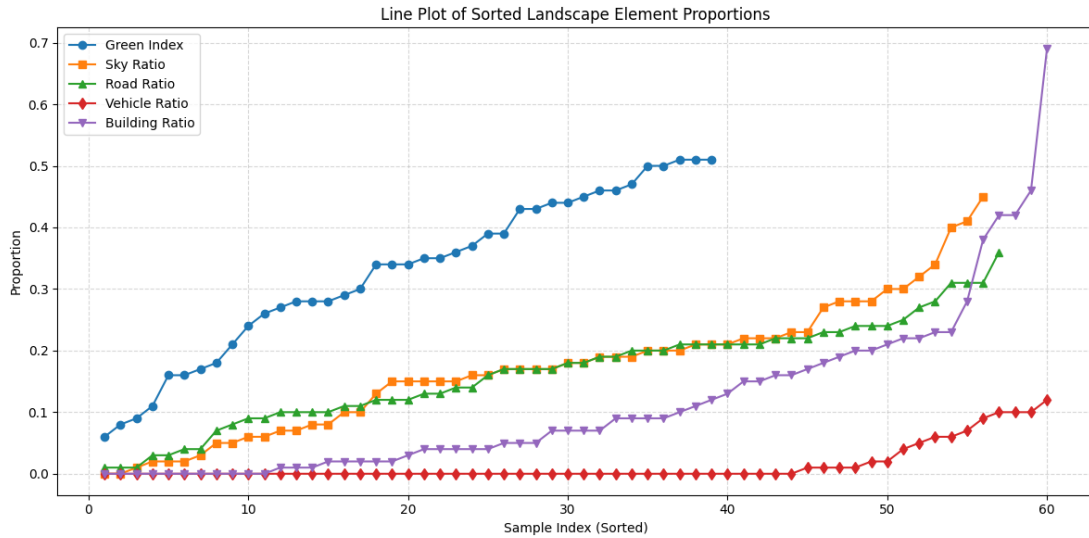


Figure 5. Sorted landscape-element proportions across samples.

3.3 Regression Model

Using SBE as the dependent variable, a multiple linear regression model was constructed with significant visual factors. The significant coefficients are summarized in Table 3, and the final model can be summarized as $SBE = 0.571 + 0.120X_1 + 0.131X_2 - 0.088X_3 - 0.207X_4 - 0.252X_5$, where X_1 is greenway form, X_2 is spatial extension, X_3 is green landscape index, X_4 is vehicle occurrence, and X_5 is spatial closure. The standardized residual range (-1.739 to 2.319) and collinearity diagnostics indicated acceptable model applicability (Figure 6, Table 4).

Table 3. Significant factors influencing campus greenway visual quality.

Factor	Standardized effect	p value	Implication
Greenway morphology	+0.247	0.018	Clear form improves legibility and spatial order.
Spatial extension	+0.287	0.015	Continuous corridors strengthen depth and orientation.
Green landscape index	-0.244	0.046	Dense greenery can reduce permeability if poorly organized.
Vehicle occurrence	-0.493	<0.001	Traffic elements disrupt safety perception and leisure quality.
Spatial closure	-0.698	<0.001	Over-enclosure creates pressure and weakens comfort.

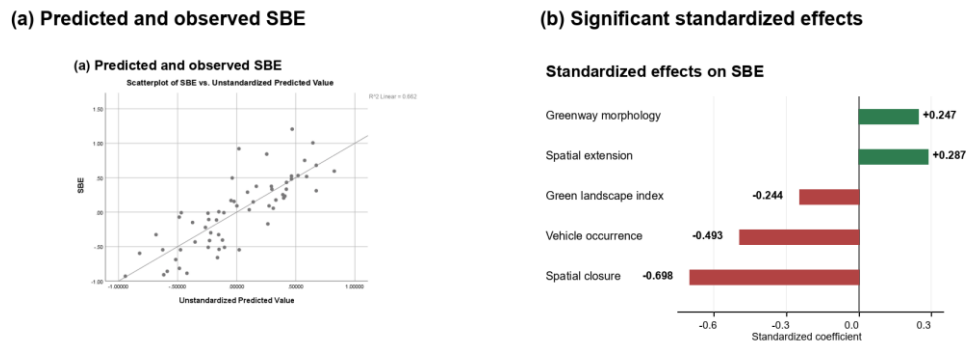


Figure 6. Regression fit and significant visual factors.

Model reliability was further checked through residual statistics and collinearity diagnostics. The predicted values were centered around zero, the residual mean was close to zero, and standardized residuals remained within an acceptable interval. These results indicate that the regression model captured the main direction of visual-quality change without being dominated by a few extreme samples. Because the model combines field-observed factors and segmentation indicators, it is especially useful for comparing which design problems should be addressed first in different campus zones.

Table 4. Compact diagnostics for the regression model.

Diagnostic item	Minimum	Maximum	Mean	Interpretation
Predicted value	-0.981	0.886	0.000	Predicted SBE values were balanced around the sample mean.
Residual	-0.552	0.736	0.000	No strong systematic deviation was observed.
Standardized residual	-1.739	2.319	0.000	Residuals remained within an acceptable range.
Collinearity	VIF < 10	Most < 2	-	No severe multicollinearity affected interpretation.

4. Discussion

The results demonstrate that campus greenway visual quality is shaped by visual organization rather than by a single landscape component. Greenway form and spatial extension represent the ability of the space to provide orientation, rhythm, and coherent movement. When these qualities are strong, users can read the path sequence more easily and experience the corridor as open, continuous, and comfortable. This explains why teaching-area greenways, which often have clearer sequences and stronger visual extension, achieved the highest SBE scores.

Negative factors reveal the opposite mechanism. Vehicle occurrence interrupts pedestrian continuity and adds visual and psychological pressure. Spatial closure, especially when created by dense building interfaces or walls, weakens openness and reduces the perceived leisure value of greenways. The negative coefficient of green landscape index further shows that high visible greenery must be carefully interpreted. Planting that blocks sightlines or lacks hierarchy may reduce rather than improve visual quality, whereas layered and permeable planting can support comfort and ecological atmosphere.

These findings also show why functional zoning matters. Teaching areas carry frequent movement and short stays, so legibility and guidance should be prioritized. Living areas need a balance of shade, social space, seasonal atmosphere, and permeability. Office areas require the strongest intervention because traffic exposure and hard interfaces jointly depress SBE values. The regression model should therefore be used as a diagnostic tool for design priorities rather than as a universal prediction formula.

5. Optimization Strategies

Table 5. Zone-specific optimization strategies.

Zone	Main issue	Design response
Teaching areas	High-frequency movement needs clear orientation.	Maintain axial views, rhythmic tree sequences, small pause nodes, and clear entrances.
Living areas	Leisure and transition require balance.	Combine shade, seating, seasonal planting, and permeable sightlines instead of only increasing vegetation density.
Office areas	Traffic and hard edges reduce SBE values.	Screen parking, soften building interfaces, separate pedestrian and vehicle flows, and open partial view corridors.

The zone-specific responses are summarized in Table 5. For teaching areas, design should reinforce visual order and wayfinding. Continuous tree rows, low shrubs that do not block views, and small rest spaces near classroom buildings can support both movement and short breaks. For living areas, the priority is to create a more sociable and restorative atmosphere by combining seating, shade, seasonal color, and semi-open edges. For office areas, the most urgent task is to reduce vehicle dominance and visual enclosure through planting buffers, pedestrian-priority surfaces, and softer building-front landscapes.

Across all zones, the goal is not to maximize a single variable, but to coordinate vegetation, path form, building edges, and traffic management. A visually successful campus greenway should offer recognizable sequence, moderate complexity, safe walking conditions, and enough openness for users to feel oriented and comfortable. The combined SBE-segmentation approach can support rapid comparison among renewal alternatives before detailed design is prepared, especially when pedestrian comfort, restoration, and built-environment behavior are considered together [26-28].

6. Limitations and Conclusion

This study has several limitations. The evaluation group consisted mainly of architecture students, and photographs were collected in one season under controlled weather conditions. Future research should include more user groups, seasons, and campus types, and should test whether the model can be generalized to other institutional landscapes. More refined segmentation categories and eye-tracking data could also improve the interpretation of attention and preference.

In conclusion, integrating SBE with DeepLabV3+ semantic segmentation links subjective visual perception with measurable landscape composition. The study identifies clear functional-zone differences and shows that greenway morphology and spatial extension improve campus greenway beauty, whereas excessive green visibility, vehicle occurrence, and spatial closure reduce it. The framework provides an efficient evidence-based method for campus greenway assessment and

offers targeted strategies for improving teaching, living, and office-area landscapes.

References

- [1] LITTLE, C. E. 1995. *Greenways for America*, JHU Press.
- [2] JONGMAN, R. H., KULVIK, M. & KRISTIANSEN, I. 2004. European ecological networks and greenways. *Landscape and Urban Planning*, 68, 305-319.
- [3] ANDERSON, C. E., ZIMMERMAN, A., LEWIS, S., MARMION, J. & GUSTAT, J. 2019. Cyclist and pedestrian behavior on an urban greenway. *International Journal of Environmental Research and Public Health*, 16, 201.
- [4] DOBER, R. P. 2000. *Campus Landscape: Functions, Forms, Features*, John Wiley & Sons.
- [5] GABR, M., ELKADI, H. & TRILLO, C. 2019. Recognizing greenway network for quantifying student experience on campus-based universities. *Proceedings of the Fabos Conference on Landscape and Greenway Planning*.
- [6] ZUBE, E. H., PITT, D. G. & ANDERSON, T. W. 1974. Perception and measurement of scenic resources. *Landscape Research*, 1, 10-11.
- [7] BROWN, T. C. & DANIEL, T. C. 1986. Predicting scenic beauty of timber stands. *Forest Science*, 32, 471-487.
- [8] XU, X., DONG, R., LI, Z., JIANG, Y. & GENOVESE, P. V. 2024. Visual experience evaluation by integrating SBE-SD and eye movement analysis. *Heritage Science*, 12, 281.
- [9] ZHANG, X., XIONG, X., CHI, M., YANG, S. & LIU, L. 2024. Visual quality assessment and landscape elements of rural greenways. *Ecological Indicators*, 160, 111844.
- [10] LEE, J., LEE, H.-S., JEONG, D., SHAFER, C. S. & CHON, J. 2019. User perception and preference of greenway trail characteristics. *Sustainability*, 11, 4438.
- [11] LI, X., WANG, X., JIANG, X., HAN, J., WANG, Z., WU, D., LIN, Q., LI, L., ZHANG, S. & DONG, Y. 2022. Prediction of riverside greenway aesthetic quality using environmental modeling. *Journal of Cleaner Production*, 367, 133066.
- [12] HAO, X. & LONG, Y. 2017. Street greenery: A new indicator for evaluating walkability. *Shanghai Urban Planning Review*, 1, 32-36.
- [13] YU, Y., ZHANG, X. & ZENG, W. 2019. Human-scale quality on streets based on street-view images and urban analytical tools. *Urban Planning International*, 34, 18-27.
- [14] HU, X., ZOU, X. & FAN, H. 2023. Landscape influencing factors of waterfront greenways based on scenic beauty estimation. *Frontiers in Earth Science*, 11, 1211775.
- [15] QI, Z., DUAN, J., SU, H., FAN, Z. & LAN, W. 2023. Using crowdsourcing images to assess visual quality of urban landscapes. *Ecological Indicators*, 154, 110793.
- [16] GARCIA-GARCIA, A., ORTS-ESCOLANO, S., OPREA, S., VILLENA-MARTINEZ, V. & GARCIA-RODRIGUEZ, J. 2017. A review on deep learning techniques applied to semantic segmentation. *arXiv:1704.06857*.
- [17] LONG, J., SHELHAMER, E. & DARRELL, T. 2015. Fully convolutional networks for semantic segmentation. *Proceedings of CVPR*, 3431-3440.
- [18] RONNEBERGER, O., FISCHER, P. & BROX, T. 2015. U-net: Convolutional networks for biomedical image segmentation. *MICCAI*, 234-241.
- [19] JIANG, J. & DAI, K. 2021. Landscape image segmentation and beauty evaluation based on convolution neural network. *IEEE TOCS*, 1020-1023.
- [20] DUPONT, L., ANTROP, M. & VAN EETVELDE, V. 2015. Landscape expertise and visual perception of landscape photographs. *Landscape and Urban Planning*, 141, 68-77.
- [21] BUHYOFF, G. J., WELLMAN, J. D., HARVEY, H. & FRASER, R. 1978. Landscape architects' interpretations of people's landscape preferences. *Journal of Environmental Management*, 6(3), 255-262.
- [22] EDENSOR, T. 2010. Walking in rhythms: Place, regulation, style and the flow of experience. *Visual Studies*, 25, 69-79.
- [23] QIN, X., GAO, L. & SHEN, Y. 2016. Road landscape enclosure scale and sequence characteristics. *Journal of Testing and Evaluation*, 44, 734-743.
- [24] LIU, M. & NIJHUIS, S. 2020. Mapping landscape spaces. *Environmental Impact Assessment Review*, 82, 106376.
- [25] NIE, W., JIA, J., WANG, M., SUN, J. & LI, G. 2022. Panoramic green view index and pleasure level based on EEG experiment. *Landscape Architecture Frontiers*, 10, 36-51.
- [26] GEHL, J. 2011. *Life Between Buildings: Using Public Space*. Washington, DC: Island Press.
- [27] ULRICH, R. S. 1979. Visual landscapes and psychological well-being. *Landscape Research*, 4, 17-23.
- [28] BAI, Y., BAI, Y., WANG, R., YANG, T., SONG, X. & BAI, B. 2023. Built environment and cycling behaviour around urban greenways. *Land*, 12, 619.