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Research into the Influence Mechanisms of Visual-Comfort and Landscape Indicators of Urban Green Spaces

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Abstract: Urban green spaces play a crucial role in providing social services and enhancing residents' mental health. It is essential for sustainable urban planning to explore the relationship between urban green spaces and human perceptions, particularly their visual comfort. However, most current research has analyzed green spaces using two-dimensional indicators (remote sensing), which often overlook human visual perceptions. This study combined two-dimensional and three-dimensional methods to evaluate urban green spaces. Additionally, the study employed machine learning to quantify residents' visual comfort in green-space environments and explored the relationship between green spaces and human visual perceptions. The results indicated that Kitakyushu exhibited a moderate FCV and an extremely low Green View Index (GVI). Yahatanishi-ku was characterized as having the highest visual comfort. Tobata-ku demonstrated the lowest visual comfort. Natural, GVI, openness, enclosure, vegetation diversity, landscape diversity, and NDBI were positively correlated with visual comfort. FCV and ENVI were negatively correlated with visual comfort. Vegetation diversity had the most impact on improving visual comfort. By integrating remote sensing and street-view data, this study introduces a methodology to ensure a more holistic assessment of green spaces. Urban planners could use it to better identify areas with insufficient green space or areas that require improvement in terms of green-space quality. Meanwhile, it could be helpful in providing valuable input for formulating more effective green-space policies and improving overall urban environmental quality. The study provides a scientific foundation for urban planners to improve the planning and construction of healthy and sustainable cities.

Keywords: green spaces; visual comfort; remote sensing; street-view image; machine learning

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1. Introduction

Green spaces in urban environments include parks, gardens, road green spaces, urban forests, and other public areas [1,2]. These spaces, as vital components of the urban ecosystem [3], perform several essential functions, including promoting residents' health [4], enhancing environmental quality [5–7], facilitating daily recreation and leisure [8,9], regulating the climate [10], maintaining biodiversity [11,12], and safeguarding ecological balance [13–15]. However, urbanization has resulted in increased environmental pressures in built-up areas and the expansion of urban land use [16–18]. Consequently, buildings and other rigid structures have increasingly encroached upon green spaces, reducing residents' access to natural environments. They have also been associated with higher rates of psychological stress and mental health issues among urban populations [19–21].

The relationship between urban green spaces and human well-being primarily centers on the impact of the natural environment on overall well-being. As a scarce natural element within urban areas, green spaces play a critical role in enhancing both the physical and

mental health of residents [22]. Green spaces contribute to ecological improvement by purifying water [23], regulating temperature and humidity [24], and sequestering carbon [25], while releasing essential nutrients. Additionally, they serve as vital health-service facilities by providing urban residents with leisure and fitness venues. Therefore, accurately evaluating the quality of urban green spaces and exploring the relationship between urban green spaces and residents' psychological perceptions are critical for improving living environments and promoting mental health recovery.

Currently, research on urban green spaces has expanded to explore their utilization in relation to biodiversity [26], their role in cognitive restoration and overall well-being [27], and their effectiveness in stress relief [28]. Previous studies have demonstrated that green spaces enhance human well-being by improving mental health and fostering positive social relationships [29]. The natural environment significantly contributes to stress recovery by reducing anxiety, depression, and emotional tension while enhancing attention and positive emotions [30,31]. Parks are invaluable for alleviating fatigue, depression, stress, insomnia, and anxiety [32,33]. Additionally, the study by Wolf and Bratton (2006) indicated that even minimal greenery within urban environments can markedly reduce stress. Street trees and green spaces further contribute to stress recovery by providing natural elements that promote relaxation [34].

Some scholars have identified that the structure, biodiversity, naturalness, and other characteristics of green spaces positively influence residents' health, safety, social relationships, and behavior [35]. In particular, the structure of green spaces has been found to enhance mental health [36], public satisfaction [37], and physical activity [38]. Researchers have explored the benefits provided by green-space structure using features such as vegetation coverage [39], connectivity of urban public green spaces [40], and tree canopy coverage [41,42]. The quantity, vegetation coverage, and size of green spaces are linked to improvements in various aspects of human life, especially human health [36]. In addition, the ecological quality of green spaces can be reflected in the visual perception. Additionally, the Green View Index (GVI) has been utilized to assess equity in access to green spaces [43] and is considered an important indicator for measuring the visible amount of accessible green space [44]. The Normalized Difference Vegetation Index (NDVI) has also been associated with physical health benefits [45]. Biodiversity within urban green spaces contributes to human health, safety, and physical activity; factors such as the number of plant species and landscape diversity reflect the biodiversity of green-space systems [22,26]. Some studies have shown that these characteristics positively impact residents' health by reducing stress, enhancing satisfaction, and promoting mental health and physical activity. Visual comfort (VICO) is largely responsible for the overall ecological comfort in the green spaces. Visual landscape has been used in research into the natural environment, the urban environment, and ecological landscapes [46].

With the advent of diverse geospatial big data characterized by wide coverage, high resolution, and renewability, big-data-driven urban analysis has become increasingly crucial for understanding urban landscapes [47–49]. Traditionally, research into urban green-space systems has predominantly focused on two-dimensional indicators derived from remote sensing to represent green-space landscapes [50,51]. However, remote-sensing images provide a bird's-eye view [52], which differs significantly from the ground-level perspective experienced by residents living within green-space environments [53]. As a result, it is challenging to accurately convey how residents perceive urban green-space landscapes solely through remote-sensing imagery. In contrast, street-view images are captured at ground level, offering a perspective similar to how individuals view vegetation in their surroundings [54]. Currently, platforms such as Google Maps, Baidu Maps, Gaode Maps, and Tencent Maps provide extensive data sources for street-view research [55]. Street-view images have emerged as a novel data source for large-scale 3D urban landscape studies [56–58], with applications in psychological perception [59], walkability assessments [60], spatial quality evaluations [61], 3D urban reconstruction [59], and other research areas. For instance, Lu, Wang, Sun, et al. have utilized street-view images to evaluate urban green spaces [62–64].

With the advancement of deep-learning technologies, semantic segmentation has become a powerful tool for efficiently processing large-scale urban data. This technique allows for the partitioning of landscape elements such as sky, streets, and vegetation in street-view images. DeepLabV3+ is a further optimized version of the algorithm developed, in 2018, by Google's technical team. Based on a convolutional neural network system, it can accurately (82.1%) recognize various forms of photos [65]. The ADE20K dataset covers a wide range of scenes and various landscape elements, which can be used to partition 150 landscape elements, including trees, lawns, sky, lake surface, fences, buildings, and sidewalks [66]. By comparing the results from manual extraction with those obtained through semantic segmentation, several scholars have confirmed the effectiveness of this approach [67]. Semantic segmentation is now widely applied in urban design, urban landscape research, and related fields [68].

Remote-sensing data provide large-scale, two-dimensional information about urban green-space distribution, such as vegetation cover and green-area size. Street-view images complement this by adding detailed, localized insights from a pedestrian's perspective, capturing the actual experience of green space, combining street-view images with remote-sensing data to ensure a more holistic assessment of green spaces. Meanwhile, by integrating 2D and 3D evaluations, urban planners can better identify areas with insufficient green space or areas that require improvement in terms of green-space quality. This provides valuable input for formulating more effective green-space policies and improving overall urban environmental quality.

Previous studies have separately studied urban green space and people's psychology on streets, but few studies have explored the influence mechanisms between them. In addition, most scholars have evaluated green spaces from a single dimension, such as two dimensions or three dimensions. Therefore, based on remote sensing and street-view images, this study evaluated the spatial distribution of green spaces at the city level using two-dimensional and three-dimensional indicators. Moreover, it quantified the public's visual comfort with green spaces and analyzed the relationship between green-space quality and the public's visual comfort. The study provides a rich theoretical background and experimental evidence for improving the quality of green spaces and human health.

2. Materials and Methods

2.1. Research Framework

This system assessed the spatial distribution of green spaces on an urban scale. Using Kitakyushu city in Japan as a case study, we employed Landsat 8 satellite imagery to calculate two-dimensional indicators such as the Normalized Difference Vegetation Index (NDVI), FCV, landscape diversity, and the Normalized Difference Building Index (NDBI). Street-view images, combined with semantic segmentation, were used to calculate three-dimensional indicators including natural, Green View Index (GVI), openness, and enclosure. Furthermore, in the study, machine learning was used to obtain a human perception of visual comfort. Correlation analysis was then employed to determine the impact of urban green spaces on visual comfort (Figure 1).

2.2. Study Site

In this study, Kitakyushu was selected as the study area. Kitakyushu is located in Fukuoka and has a total area of approximately 491.95 square kilometers. It is bordered by the Kanmon Strait to the east, the Sea of Japan to the west, and Tsuya Bay to the north. The city is characterized by a unique geographical location, being surrounded by the sea on three sides, and features a diverse landscape of mountains and sea (Figure 2). As a typical coastal city, Kitakyushu has been undergoing a transformation towards becoming an environmentally friendly city, with notable increases in green-space coverage and the availability of natural landscapes and green spaces. It comprises seven districts: Kokura Minami, Wakamatsu, Hachiman Nishi, Moji, Kokura Kita, Hachiman Higashi, and Tobata.

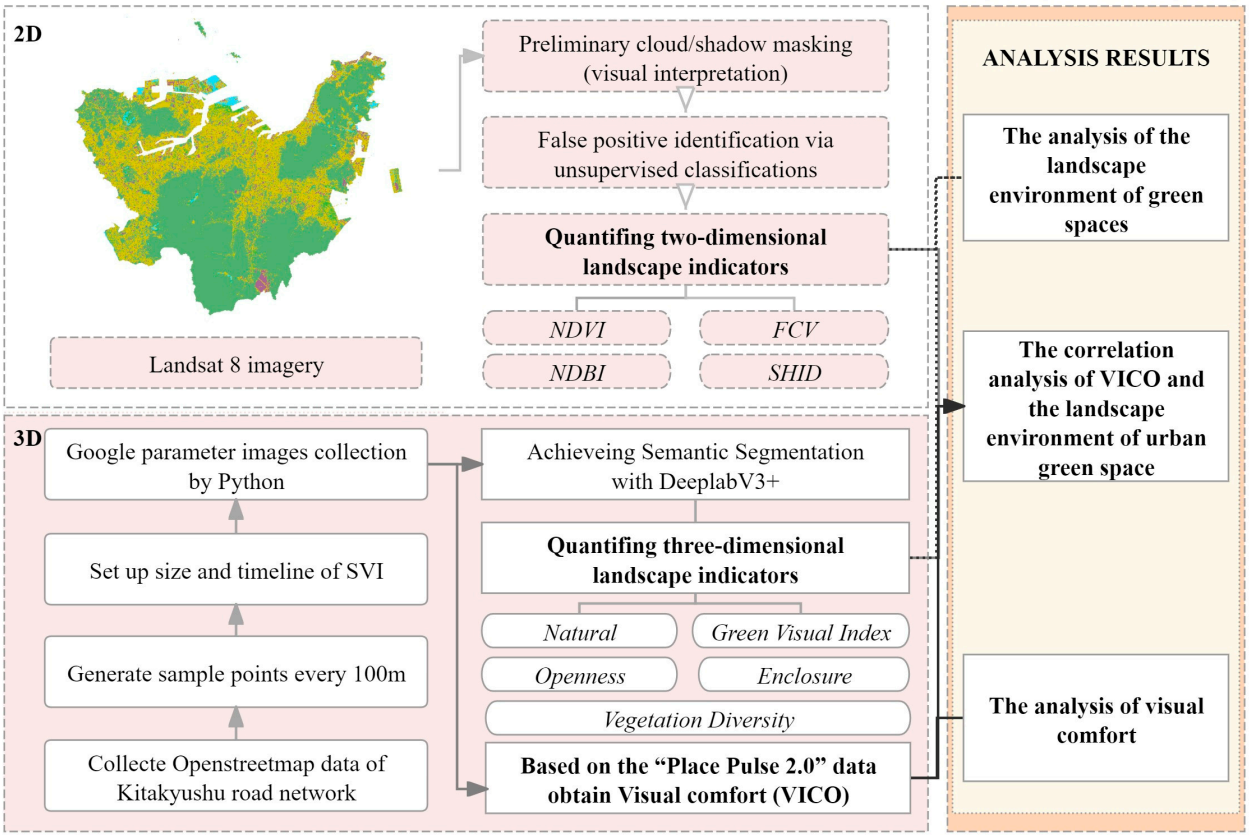


Figure 1. Research framework.

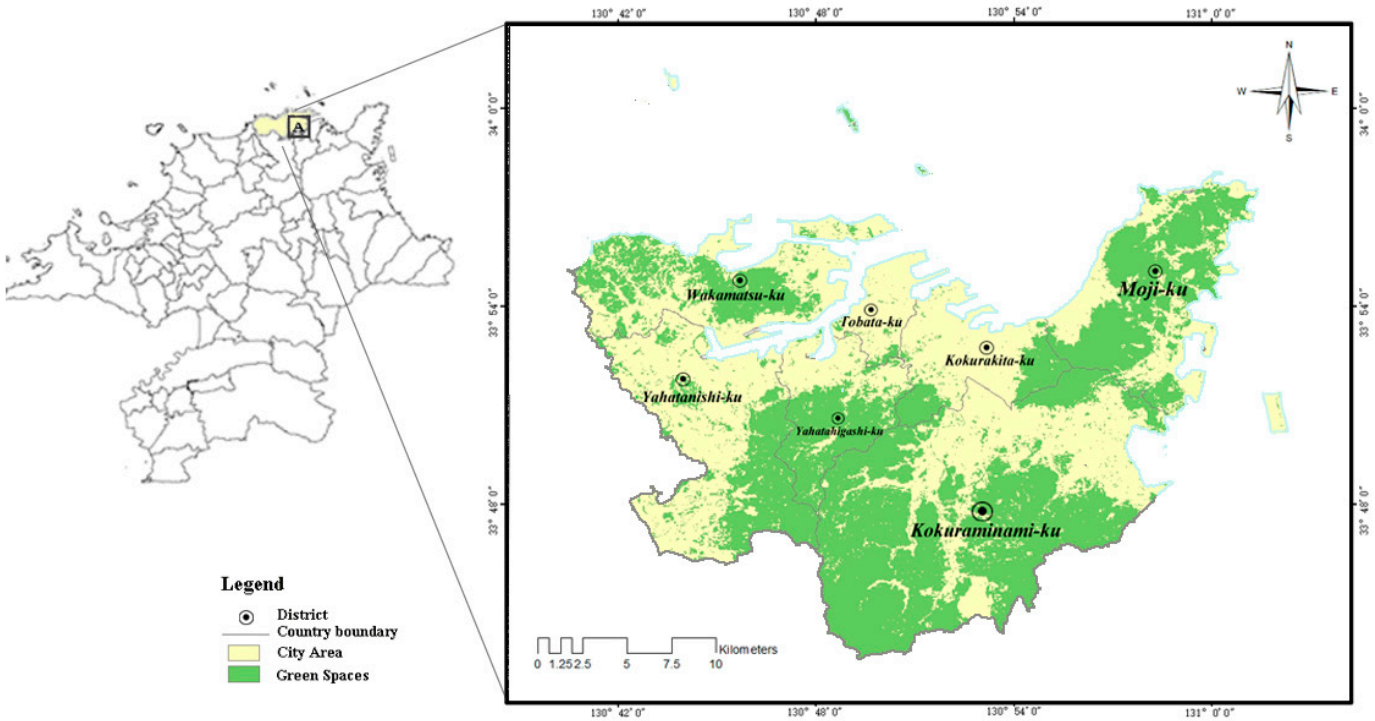


Figure 2. Location of the study site.

Additionally, the Create Fishnet tool in ArcGIS 10.6 was used to construct a grid with a cell size of 500 m × 500 m. A total of 2630 grids were generated within the study area, and subsequent index calculations were conducted on a grid-by-grid basis.

2.3. Quantification of Green Space and Pressure Perception

2.3.1. Quantifying Two-Dimensional Landscape Indicators

Landsat TM satellite images are utilized to detect and analyze various physical features on the Earth's surface [69,70]. In this study, remote-sensing images were employed to derive two-dimensional green spatial indicators for urban areas, including the Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), Vegetation Coverage (FCV), and landscape diversity indicators (SDIH) (Table 1). These indices were calculated using Landsat-8 satellite images acquired in June 2024. These images had a spatial resolution of 30 m × 30 m. Additionally, after conducting preliminary verification and applying unsupervised classification to the remote-sensing images, the land was categorized into five distinct classes: water, forests, land, green spaces, and buildings.

Table 1. The formulas and expressions of 2D and 3D indicators.

Dimension	Landscape Indicators	Formula	Expression
2D	NVDI	$NDVI = \frac{(NIR-Red)}{(NIR+Red)}$	NIR denotes the reflectance in the near-infrared band, Red denotes the reflectance in the red band,
	FCV	$FCV = \frac{NDVI-NDVI_{soil}}{NDVI_{veg}+NDVI_{soil}}$	$NDVI$ is the Normalized Difference Vegetation Index value of a particular pixel. $NDVI_{soil}$ is the NDVI value for bare soil (representing areas with no vegetation, usually close to zero or lower). $NDVI_{veg}$ is the NDVI value for fully vegetated areas.
	NDBI	$NBVI = \frac{(MIR-NIR)}{(MIR+NIR)}$	MIR denotes the reflectance in the mid-infrared band, NIR denotes the reflectance in the near-infrared band.
	Landscape Diversity Indices	$H' = -\sum_{i=1}^{n}(P_i * ln\ P_i)$	P_i is the proportion of class-I landscapes, n is the total number of landscapes.
3D	Natural	$N_i = \frac{\frac{1}{n}\sum_{i=1}^{n} T_n+\frac{1}{n}\sum_{i=1}^{n} G_n+\frac{1}{n}\sum_{i=1}^{n} W1_n+\frac{1}{n}\sum_{i=1}^{n} M1_n+\frac{1}{n}\sum_{i=1}^{n} P1_n}{\frac{1}{n}\sum_{i=1}^{n} B_n+\frac{1}{n}\sum_{i=1}^{n} W2_n+\frac{1}{n}\sum_{i=1}^{n} R_n+\frac{1}{n}\sum_{i=1}^{n} P2_n+\frac{1}{n}\sum_{i=1}^{n} F_n}$ $\{i \in (1,2,\ldots,n)\}$	T_n is the percentage of trees, G_n is the percentage of grass, W_n is the percentage of water, $M1$ is the percentage of mountains, $P1_n$ is the percentage of plants. The molecular addition represents the total number of natural element pixels in each image. B_n is the percentage of building pixels, $W2_n$ is the percentage of wall pixels, R_n is the percentage of road, $P2_n$ is the percentage of pavement, F_n is the percentage of fences. The summation in the denominator represents the total number of artificial element pixels in each image.
	Green Visual Index	$G_i = \frac{1}{n}\sum_{i=1}^{n} T_n + \frac{1}{n}\sum_{i=1}^{n} G_n + \frac{1}{n}\sum_{i=1}^{n} P1_n \{i \in (1,2,\ldots,n)\}$	T_n is the percentage of trees, G_n is the percentage of grass, $P1_n$ is the percentage of plants. The sum indicates the total number of green plant pixels in each image.
	Openness	$O_i = \frac{1}{n}\sum_{i=1}^{n} O_n \{i \in (1,2,\ldots,n)\}$	O_n denotes the proportion of sky pixels. The sum indicates the total number of sky pixels in each image.
	Enclosure	$DIE_i = \frac{\frac{1}{n}\sum_{i=1}^{n} B_n+\frac{1}{n}\sum_{i=1}^{n} T_n+\frac{1}{n}\sum_{i=1}^{n} W2_n}{\frac{1}{n}\sum_{i=1}^{n} P1_n+\frac{1}{n}\sum_{i=1}^{n} F_n+\frac{1}{n}\sum_{i=1}^{n} R_n} \{i \in (1,2,\ldots,n)\}$	B_n is the percentage of building pixels, T_n is the percentage of trees, $W2_n$ is the percentage of wall pixels, $P1_n$ is the percentage of pavement, F_n is the percentage of fences, R_n is the percentage of road.
	Vegetation Diversity	$VD_i = 1 - \left[\left(\frac{T_n}{GVI_n}\right)^2 + \left(\frac{P_n}{GVI_n}\right)^2 + \left(\frac{G_n}{GVI_n}\right)^2\right]$	T_n is the percentage of trees, G_n, is the percentage of grass, $P1_n$, is the percentage of plants, GVI_n, is the green vegetation index for the i-th image.

2.3.2. Quantifying Three-Dimensional Landscape Indicators

Firstly, OpenStreetMap was used to obtain the initial road network for Kitakyushu [71]. The basic road network data were refined by removing redundant road segments using ArcGIS 10.6. Then, sampling points were extracted from the road network of Kitakyushu, with

a sampling interval set at 100 m. A total of 61,357 sample points were obtained. Secondly, panoramic images were obtained from Google Maps by Python 3.13.0 and the Google Street View Image API. Meanwhile, the resolution of photos was set to 14,000 × 7000, and the timeline was set for the period between April and October. In total, 39,593 panoramic images were obtained (Figure 3). Finally, the DeepLabV3+ model was used to segment landscape elements in SVI with the ADE20K dataset. Subsequently, the proportions of landscape elements were inputted into Table 1 to obtain five three-dimensional landscape features.

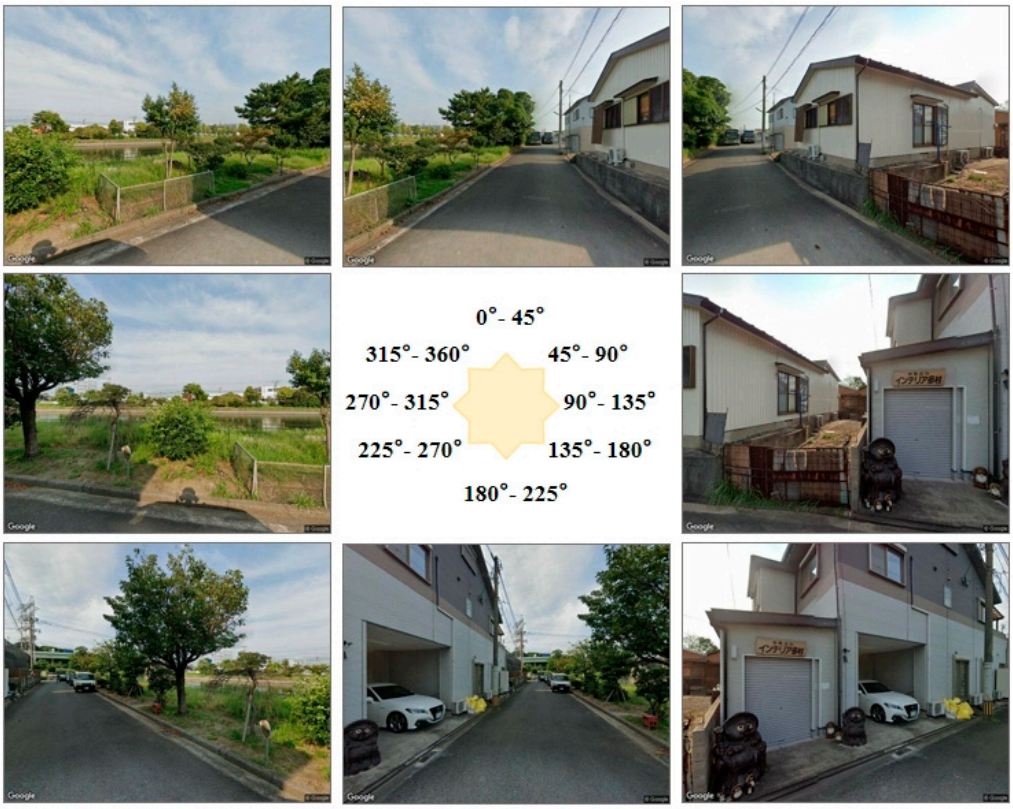


Figure 3. The sample point of a Google Street View image.

2.3.3. Quantification of Visual Comfort

The Aesthetic and Affective Response Model has combined evolutionary aesthetics with affection, emphasizing the initial emotional response of the "like–dislike" continuum for ecological quality [72]. Previous studies of residents' perceptions have been limited to small-scale research due to the small sample size of manual scoring. However, with the development of machine learning, it is now possible to quantify residents' perceptions of the urban environment on a large scale. For example, the machine-learning dataset developed by the Massachusetts Institute of Technology (MIT) can capture six perceptions of residents: wealthy, lively, boring, beautiful, depressing, and safe [73]. This study utilized this training set to assess human visual comfort regarding urban green spaces [74].

3. Results

3.1. The Analysis of Visual Comfort

Based on the Natural Breaks Method [75,76], the study categorized visual comfort scores into seven levels which ranged from low to high, with numbers 1–7 representing the degree of perceived comfort. A higher score indicated that the environment provided a greater sense of comfort to residents. Overall, the level of visual comfort in Kitakyushu city was relatively low. The lowest level, represented by a score of 1, accounted for 40.3%, and was primarily found in areas such as Kokaramiinanii-ku, Yahatahigashi-ku, Tobata-ku, and Kokurakita-ku (Figure 4). Among these, Kokaramiinanii-ku and Yahatahigashi-ku

are areas characterized by mountainous forest environments, where the visual landscape elements are simple; the forests are dense, and these create relatively enclosed spaces. In contrast, Tobata-ku and Kokurakita-ku, urban areas with low building density and narrow streets, led to a poor visual experience for residents in these regions. The highest level, represented by a score of 7, accounted for 3.61% and was mainly distributed in urban areas like Wakamatsu-ku, Yohoranishi-ku, and Moji-ku, which include natural landscapes such as sea views and bodies of water, offering better scenic vistas and a better visual environment.

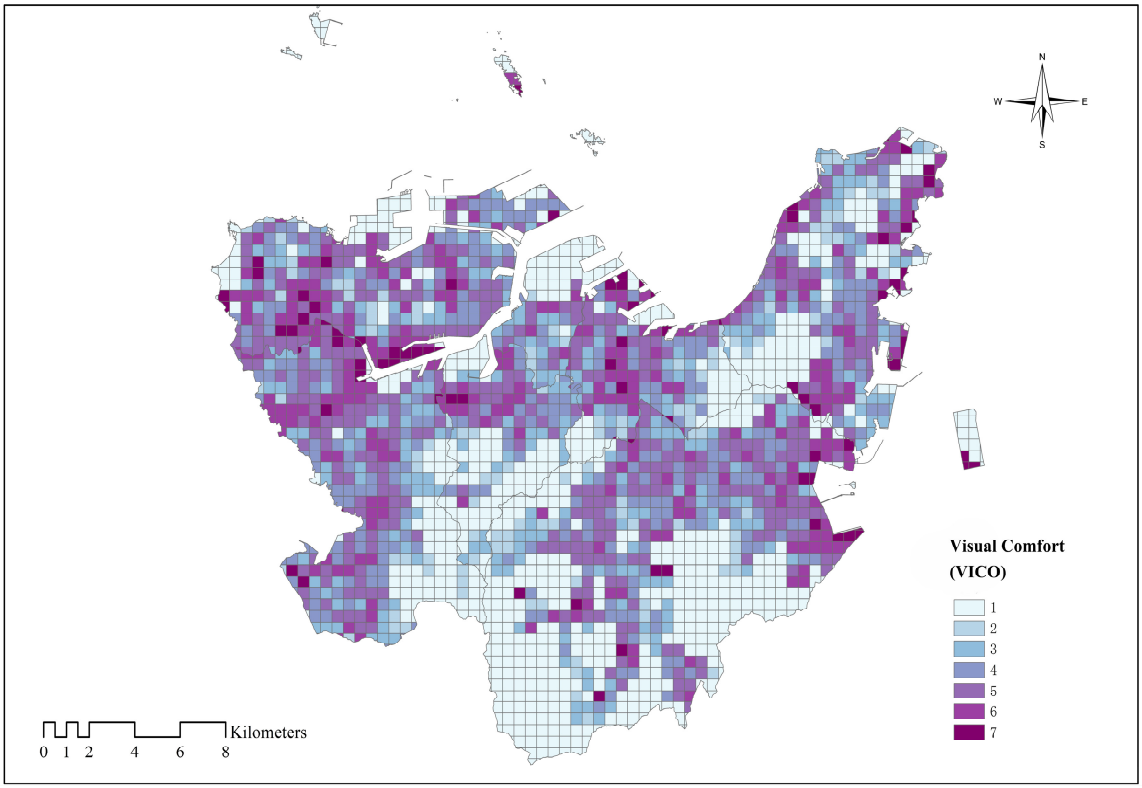


Figure 4. The spatial distribution of visual comfort (VICO).

Analysis of the mean values of visual comfort across the seven administrative districts showed that the overall ranking of visual comfort was as follows: Yahatanishi-ku > Moji-ku > Wakamatsu-ku > Kokurakita-ku > Yahatahigashi-ku > Kokuraminami-ku > Tobata-ku (Table 2). The mean value of visual comfort in Yahatanishi-ku was the highest (12.87). The low score percentage was 25.78%, the lowest among all districts, indicating that the visual comfort in this district was generally better. The high score percentage was 3.10%, slightly higher than in some other districts. In Yahatanishi-ku, there are several natural landscapes, including plains, hills, and mountains. Meanwhile, there are many green spaces like Tagaya-yama and several urban parks. These areas provide residents with opportunities for recreational and outdoor activities that promote physical and mental well-being. The mean value of visual comfort in Tobata-ku was the lowest (7.90). The high score percentage was 0.00%, indicating no areas with high visual comfort. The low score percentage was 48.04%, showing that almost half of the areas in this district have poor visual comfort. Tobata-ku includes residential, commercial, and industrial areas, and its narrow urban streets can create a sense of depression for residents. It should be suggested that there is a need for significant improvements in greenspace planning and landscape design.

Table 2. The result of visual comfort for various districts.

Districts	Overall	Mean Value of Overall	Proportion	Lowest Value	Proportion
Kokuraminami-ku	799	8.76	2.75%	390	48.81%
Wakamatsu-ku	473	10.90	3.59%	189	39.96%
Yahatanishi-ku	419	12.87	3.10%	108	25.78%
Moji-ku	393	11.30	5.09%	137	34.86%
Kokurakita-ku	255	10.83	6.27%	102	40.00%
Yahatahigashi-ku	189	9.06	1.06%	84	44.44%
Tobata-ku	102	7.90	0.00%	49	48.04%

3.2. Analysis of the Landscape Environment of Green Spaces

Table 3 presented the results for the two-dimensional landscape indicators in Kitakyushu.

Table 3. The results of 2D and 3D landscape indicators.

District	Natural	GVI	Openness	Enclosure	Vegetation Diversity	FCV	Landscape Diversity	NDBI	NDVI
Kokuraminami-ku	0.277	0.043	0.279	0.665	0.485	0.646	0.555	−0.622	0.257
Wakamatsu-ku	0.357	0.053	0.320	0.795	0.562	0.335	0.677	−0.411	−0.082
Yahatanishi-ku	0.444	0.065	0.406	1.048	0.711	0.402	0.732	−0.427	−0.078
Moji-ku	0.390	0.059	0.368	0.858	0.647	0.511	0.703	−0.515	0.090
Kokurakita-ku	0.398	0.057	0.334	0.878	0.578	0.284	0.685	−0.374	−0.223
Yahatahigashi-ku	0.369	0.055	0.315	0.795	0.551	0.614	0.634	−0.595	0.203
Tobata-ku	0.322	0.049	0.273	0.740	0.486	0.131	0.817	−0.307	−0.461
Total	0.355	0.053	0.328	0.811	0.573	0.474	0.656	−0.499	0.039

High values of FCV and NDVI were mainly located in areas with dense vegetation coverage. In contrast, high values of landscape diversity and NDBI were observed in highly urbanization areas. There were many landscape elements such as buildings, forests, and water bodies. Conversely, areas with dense vegetation tended to have lower landscape diversity and NDBI. Spatial distribution analysis (Figure 5) showed that the highest values of FCV and NDVI were mainly concentrated in Kokuraminami-ku. The value of FCV was 0.646. It indicated a moderate to high level of vegetation coverage with natural resources such as mountains and forests. Additionally, there were the lowest values of landscape diversity and NDBI in Kokuraminami-ku. This area has a relatively simple landscape structure with lower building density. In contrast, high values of landscape diversity and NDBI were primarily found in Tobata-ku, which had a higher building density (−0.374) and land mainly used for industrial and commercial purposes. This area features a variety of landscape elements. However, Tobata-ku had the lowest values of FCV and NDVI, with the lowest NDVI indicating a larger proportion of non-vegetated areas.

According to previous studies, FCV was divided into five levels: 0–10%, 10–30%, 30–50%, 50–70%, and 70–100%. Based on this classification, the FCV in Kitakyushu was analyzed. The overall mean value of FCV was 0.474 in Kitakyushu. This indicated a moderate level of FCV. Kitakyushu offers a substantial number of parks, trails, and recreational areas that promote an active lifestyle. In Tobata-ku and Kokura Kita-ku, the FCV values were 0.131 and 0.284. The result showed that the low FCV (10–30%). Wakamatsu-ku and Yahatanishi-ku had FCV values of 0.335 and 0.402, indicating moderate coverage. In contrast, Moji-ku, Kokura Minami-ku, and Yahatahigashi-ku had FCV values of 0.511, 0.646, and 0.614, respectively, representing a moderate to high level of vegetation coverage.

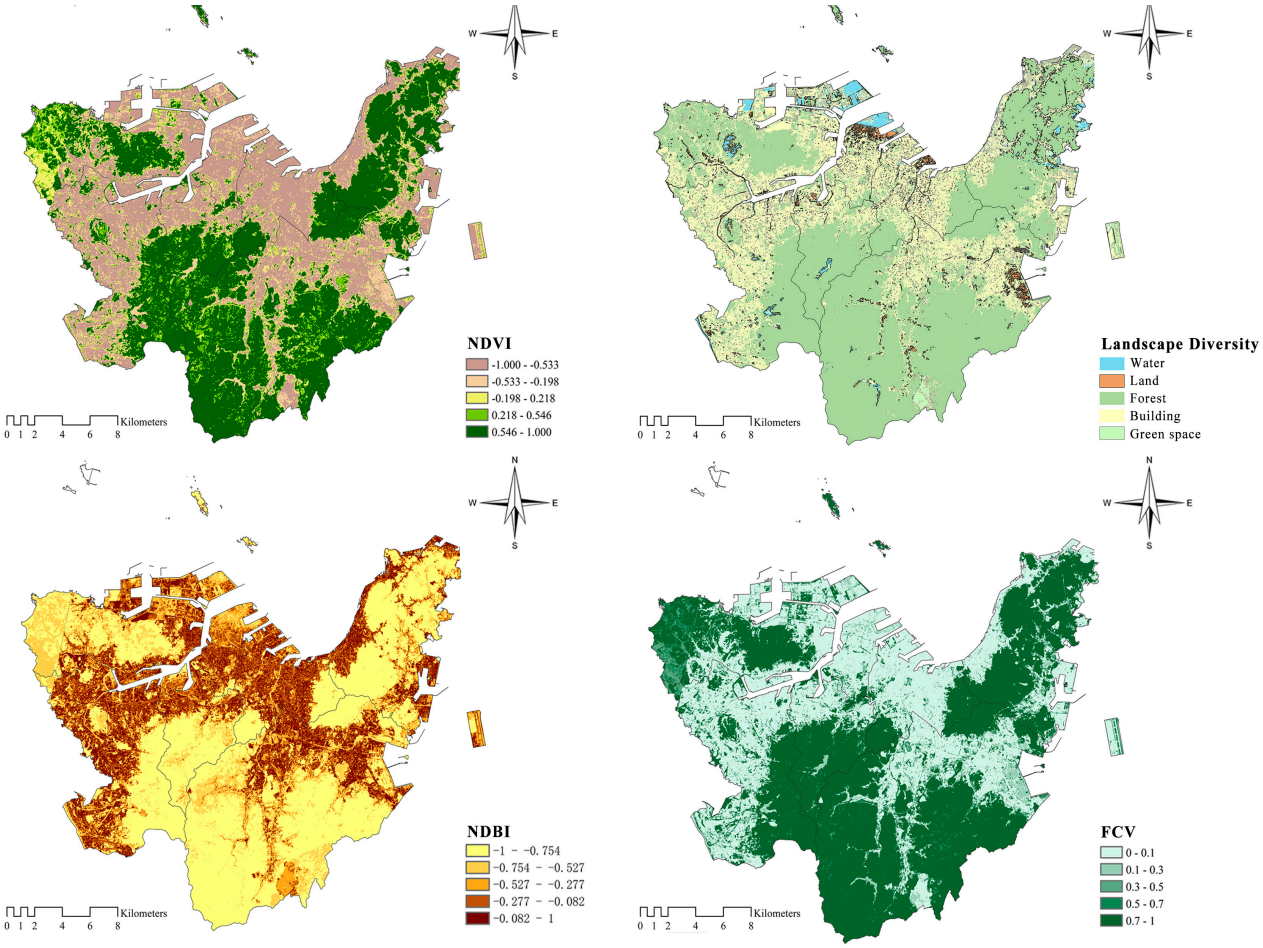


Figure 5. The spatial distribution of 2D landscape indicators.

Table 2 and Figure 6 present the results and spatial distribution of the three-dimensional landscape indicators in Kitakyushu. The highest values for naturalness, GVI, openness, enclosure, and vegetation diversity were mainly located in Yahatanishi-ku. High values for naturalness and vegetation diversity indicated that Yahatanishi-ku had significant natural environment features and natural elements. There was a diverse range of plant species such as street trees, shrubs, and grasses. The highest values for GVI, openness, and enclosure had significant features of the urban green spaces in Yahatanishi-ku. The GVI value of 0.065 indicated a high overall level of green perception from a three-dimensional visual perspective. The openness value of 0.406 suggested that the spatial structure in Yahatanishi-ku was relatively open, with ample open spaces such as parks and green areas. The enclosure value of 1.048 indicated that the vertical interface in Yahatanishi-ku was primarily composed of street trees and forests, creating a notable sense of enclosure.

The lowest values for naturalness, GVI, enclosure, and vegetation diversity were mainly located in Kokuraminami-ku. The lowest values for naturalness and vegetation diversity indicated a high level of urbanization in Kokuraminami-ku. There were fewer noticeable natural environment features and sparse natural landscapes, including fewer plant species such as shrubs and forests. The lowest values for GVI and enclosure signified that the green-space characteristics in Kokuraminami-ku were not prominent. The GVI value of 0.043 indicated a very limited green view, with low visibility of green spaces and vegetation in streets or walking areas. The enclosure value of 0.665 suggested that the streets in Kokuraminami-ku were relatively open, with a more spacious environment. The openness value of 0.273 indicated that Tobata-ku had a more compact spatial layout, with higher density of buildings and other structures, and a lack of open spaces such as parks, plazas, or wide streets.

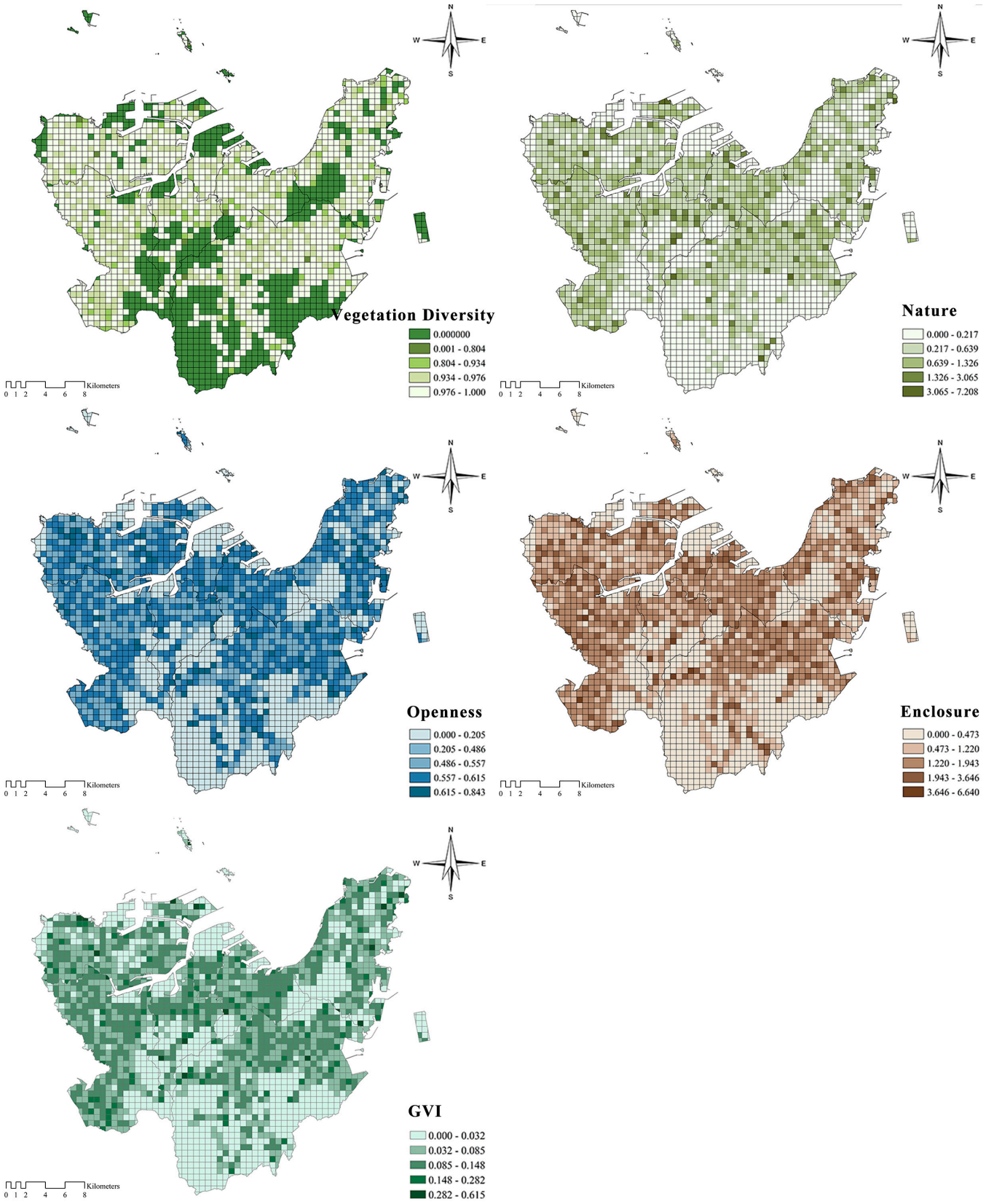


Figure 6. The spatial distribution of 3D landscape indicators.

Japanese scholars have divided GVI into five levels: 0–5%, 5–15%, 15–25%, 25–35%, and above 35%. Based on this classification standard, the GVI in Kitakyushu city was

analyzed. The overall mean GVI for Kitakyushu city was 0.053, indicating very poor green perception from a three-dimensional perspective. Kokuraminami-ku and Tobata-ku had GVI values of 0.043 and 0.049, respectively, reflecting extremely low green visibility in these areas. Wakamatsu-ku and Yahatanishi-ku, among other regions, had GVI values in the 5–15% range, indicating relatively low green visibility. Overall, the GVI in Kitakyushu was low, suggesting a need to improve the level of greenery visible from residents' perspectives.

3.3. The Correlation Analysis

The nine landscape indicators and visual comfort were analyzed by correlation analysis (Figure 7). This showed that naturalness, GVI, openness, enclosure, vegetation diversity, landscape diversity, and NDBI were positively correlated with visual comfort. FCV and ENVI were negatively correlated with visual comfort. Vegetation diversity had the most significant impact on improving visual comfort. The correlation coefficient of vegetation diversity was 0.836. This suggested that more vegetation was closely linked to higher visual comfort. The correlation coefficient of naturalness was 0.492. It indicated a medium positive correlation with visual comfort. The results showed that the higher natural elements, the more visual comfort was perceived by the public. The correlation coefficient of GVI was 0.602. It was strongly positively correlated with visual comfort. The results showed that the higher GVI, the more visual comfort was perceived by the public. The correlation coefficient of openness was 0.820, which indicated a very strong positive correlation with visual comfort, meaning that larger open spaces are strongly associated with visual comfort. The correlation coefficient of enclosure was 0.692. It indicated a strong positive correlation with visual comfort and a preference for green spaces. The correlation coefficient of landscape diversity was 0.655. It indicated a strong positive correlation with visual comfort. The result showed that more landscape elements could enhance visual comfort. The correlation coefficient of NDBI was 0.320, which indicated a weak positive correlation with visual comfort. It suggested that higher building density areas have a slight positive relationship with visual comfort. Meanwhile, the correlation coefficient of FCV was −0.290. This showed that an increase in FCV slightly decreases visual comfort. The correlation coefficient of ENVI was −0.400. This moderate negative correlation indicates that the vegetation coverage negatively affected visual comfort.

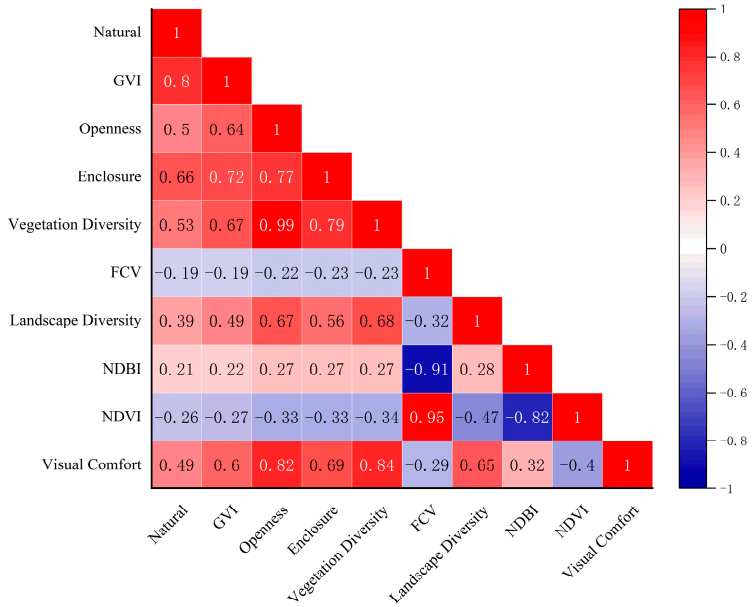


Figure 7. The correlation analysis of the visual comfort and landscape indicators.

4. Discussion

4.1. Factors Influencing Visual Comfort in Urban Green Spaces

Research indicates a significant correlation between the distribution of urban green spaces and visual comfort. Urban areas exhibiting high levels of visual comfort are mainly situated around natural environments such as mountains, rivers, and water. These natural elements offer significant advantages in terms of green-space provision and visual accessibility [77]. Gascon et al. (2015) demonstrated that natural environments, particularly those characterized by blue and green spaces, are associated with enhanced visual comfort [78]. Natural landscapes contribute to the reduction in visual fatigue and psychological stress, thereby being helpful in improving residents' emotional well-being and overall visual experience [62,79]. A rich vegetation diversity and varied landscape structures can significantly enhance visual attractiveness and increase human visual comfort. Green spaces offer open space that mitigates feelings of enclosure and oppression, thereby enhancing overall visual comfort [80]. A high coverage of green spaces had been shown to improve visual comfort by providing natural landscapes. Natural elements such as trees, flowers, and lawns play a crucial role in alleviating visual fatigue and discomfort [81,82] and can reduce the sense of oppression by building density. Furthermore, when green-space coverage reaches 20%, it not only provides essential ecological functions but also has a notable cooling effect that enhances human visual comfort [83]. In Kitakyushu, there are many mountains and urban forests. These natural environments offered shade and contribute to lower temperatures, thus mitigating the risk of heat-related illnesses among urban inhabitants [84]. The high visibility of green environments in Kitakyushu presents some green elements, such as diverse tree and plant forms, which increase visual diversity and attractiveness. These landscapes are often perceived as having psychologically restorative benefits [85]. Additionally, Kitakyushu exhibits relatively high enclosure, primarily due to the partial obstruction of views by buildings or other hard landscapes. It is considered to enhance residents' sense of security and comfort. Green spaces also provided social and leisure facilities that foster interaction and social cohesion among residents [86].

4.2. Potential Applications and Contributions

In this study, we explored the potential of different data sources as tools for quantifying urban green spaces. We constructed a landscape-indicator evaluation system from both two-dimensional and three-dimensional perspectives. We applied this system to provide a more accurate and detailed analysis of urban green spaces in Kitakyushu. Remote-sensing data provide comprehensive green coverage information from regional to urban scales [87,88]. High-resolution satellite imagery can accurately measure green coverage, landscape diversity, vegetation indices, and building density [70]. Street view images capture detailed street-level green-space characteristics, including tree density, vegetation diversity, and the condition of greenery [64]. These images offer the features of green space from a pedestrian's perspective [87] and provide crucial data for overall urban green-space planning. By integrating remote-sensing data with street-view imagery, researchers can obtain more precise data on green spaces. This combination enhances both the spatial resolution and the level of detail, providing a more accurate representation of the actual conditions of urban green spaces [47]. It can also help urban planners to identify areas needing increased greenery to enhance the health benefits of urban green spaces, providing a scientific basis for the planning and construction of healthy cities.

4.3. Limitations

This study examined the impact of green-space landscape indicators on visual comfort. We employed a multidimensional evaluation framework incorporating both two-dimensional and three-dimensional perspectives. Although some impact factors were considered, there were still some limitations in this study.

Visual comfort and psychological restoration were considered mediators through which green spaces influence residents' mental health. The natural landscapes enhanced

psychological well-being by improving visual comfort. In the future, this mechanism could be further validated by incorporating additional psychological variables, such as stress levels and emotional states [89]. For a more comprehensive assessment of green spaces' benefits on visual comfort, future research could integrate diverse data sources, including physiological measurements (e.g., heart rate, cortisol levels), behavioral data (e.g., walking frequency), psychological assessments (e.g., stress scores), and subjective perception data [90].

Individual responses to green spaces may vary based on factors such as age, gender, cultural background, health status, and personal preferences [91]. This study acknowledges that these individual differences were not fully explored. Additionally, the distribution and quality of green spaces are often linked to socioeconomic factors, such as income levels, education, and community resource allocation [92,93]. For instance, higher-income neighborhoods may have more and better-maintained green spaces, potentially enhancing the health benefits of these areas. Conversely, lower-income neighborhoods may experience diminished green-space quality and availability, which could attenuate the health benefits. Environmental factors such as air quality, noise levels, and temperature also play a role in modulating the health effects of green spaces. Future research should explore how these factors influence the relationship between green spaces and visual comfort.

5. Conclusions

Kitakyushu was selected as a study site in this study. By combining two-dimensional (remote sensing) and three-dimensional (street-view image) landscape indicators, the study provided a multi-dimensional landscape indicator evaluation system. Meanwhile, it quantified the visual comfort of urban green spaces in Kitakyushu. Finally, the study explored the impact of landscape indicators in the urban green space on residents' visual comfort.

The results showed that there was moderate FCV and low GVI in Kitakyushu. Natural elements, landscape diversity, and openness were positively correlated with visual comfort, while building density and enclosure were negatively correlated with visual comfort. Vegetation diversity was found to have the most significant impact on improving visual comfort. Moreover, the study highlighted significant regional differences, with Yahatanishi-ku showing the highest visual comfort, while Tobata-ku had the lowest.

The study combined remote-sensing, street-view-image, and machine-learning techniques to achieve a comprehensive analysis. It aimed to understand the relationship between natural environments and human perception. The study covered a large spatial area, making the results more generalizable and applicable. Additionally, it offers theoretical support for academic research and practical decision-making in urban planning and ecological management. The study provides scientific foundations for improving green-space quality in urban planning and enables a more comprehensive and effective approach to managing and enhancing urban green spaces.

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