Research on landscape quality evaluations of rural roads using computer vision

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Article

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Abstract

Rural roads are important channels connecting residents' lives and production, and their landscape quality affects the appearance of local villages. However, few existing rural studies have investigated rural road landscapes, and there is a lack of a quantitative interpretation system for the visual quality of landscapes. This study aimed to use a set of images to train a semantic segmentation model for rural road landscapes based on computer vision technology, and establish a quantifiable landscape-feature index system. The physical features of a landscape were extracted from panoramic photos of Chunhua Village in Changsha City, Hunan Province, using a semantic image segmentation algorithm, and the relationship between the quantified landscape features and visual perception was explored using multiple linear regression models. It was found that the trained semantic segmentation model of rural-community street-landscape images reached an accuracy of 0.83. The results of the linear regression model showed that the green vision index (GVI), farmland visibility index (FVI), building density index (BDI), and road width index (RWI) had significant effects on visual perception. The GVI and FVI were positively correlated, while the BD and RWI were negatively correlated. In the planning of rural road landscapes, emphasis should be placed on improving the proportion and quality of the natural landscape, and it is necessary to weigh the practicality and appreciation of man-made landscape elements. Finally, this paper provides a research method based on computer vision technology for the study of rural road landscapes, and provides a reference for the quantitative analysis of large-scale rural landscapes.

1. Introduction

Under the background of the development of global digital information technology, the development difference between urban and rural areas is deepening (Gonzalez-Abraham and Radeloff et al., 2007; Liu and Cao et al., 2023). In China, the development of rural areas is also becoming increasingly serious, and the sustainable development of rural areas has been widely discussed (Zhou and Shi, 2022; Lin and Hou, 2023). In recent years, the seriousness of this problem has been the focus of the Chinese government. Since the central government issued instructions to implement a "rural revitalization" strategy, the relationship between people and the land has begun to receive more attention and a certain degree of relaxation (Wang, 2022). The five-year action plan for the improvement of rural human settlements (2021–2025) issued by the State Council of China clearly proposes to accelerate the overall improvement of rural human settlements in China and promote the overall improvement of village appearances (Liu and Gong et al., 2022). Rural landscapes need to be designed and transformed more comprehensively and scientifically.

Rural roads are important basic service facilities for rural production and life, connecting every household of rural residents. They are not only the link between residents, but also the only way to the outside world (Yang and Xu et al., 2019). With the continuous strengthening of rural construction, the status and role of rural roads in the development of rural communities are becoming increasingly prominent (Chai and Wang et al., 2023). At present, in the planning and design process of most rural roads, basic functions such as considering traffic are still the main focus, and their landscape value and ecological value are ignored (Garre and Meeus et al., 2009; Fu and Ren et al., 2022). However, in the face of the environmental improvement needs of vast rural areas and the reality of rural landscapes with different landforms and characteristics, traditional landscape planning methods need to involve conducting field research and collecting data for each project, which is time-consuming and inefficient, and it is difficult to meet the urgent needs of residents for environmental improvement (Suppakittpaisarn and Lu et al., 2022).

Some studies have shown that visual stimulation has a strong impact on people's perception in evaluations of their aesthetic satisfaction with the environmental quality of the landscape (Martinecz and Niitsuma, 2018). In landscape planning, design, and management, the visual quality of the landscape is crucial (Sowinska-Swierkosz and Soszynki, 2019; Diaz and Teixeira et al., 2022). Gradually, research on visual evaluations of landscape aesthetics has matured as more attention has been paid to the visual perception of landscapes (Li and Wang et al., 2022). The main purpose of this research is to enhance the perceived visual value of landscapes by establishing and evaluating the changes caused by mental activity. Evaluations of landscape aesthetics using visual landscape preferences were primarily conducted through photography, questionnaire surveys, and in-person interviews in early studies (Laroche and Domon et al., 2020; Diaz and Teixeira et al., 2022; Suppakittpaisarn and Lu et al., 2022). However, as a result of the limited perspective of traditional photos, they cannot fully convey the aesthetic quality of a landscape, nor can they communicate the three-dimensionality of a landscape (Li and Wang et al., 2022).

Several studies have attempted to use other visual acquisition methods or virtual tools, such as virtual reality (VR), augmented reality (AR), and mixed reality (MR), to restore real scenes before evaluation (Bekele and Pierdicca et al., 2018). VR 360° panoramas provide a greater scene reduction and spatial experience than traditional photos, resolving the limitations of photos as evaluation tools (Bohil and Alicea et al., 2011). Participants wear VR glasses to surround themselves with the panoramas, which creates a more immersive effect than traditional electronic screen displays. At the same time, thanks to the development of artificial intelligence (AI) technology and the upgrading of data collection hardware, it is feasible to use computer technology to assist designers in data acquisition and analyses (LeCun and Bengio et al., 2015; Biljecki and Ito, 2021). Researchers are already exploring the use of computer techniques, such as semantic image segmentation, object detection, and eye-capture techniques, to systematically analyze landscape values in different places (Biljecki and Ito, 2021; Liu and Bober et al., 2021; Wilkins and Van Berkel et al., 2022). For example, researchers have used a large amount of data such as social media images and videos to identify and extract landscape features and user preferences in urban landscapes and streets, and analyze the differences in the data to make landscape planning recommendations (Zhao and Luo et al., 2021; Wilkins and Van Berkel et al., 2022). In addition, recording geographic coordinate information while taking digital photos can now graphically present a wide range of visual landscape-perception data (Poorazizi and Hunter et al., 2015; Biljecki and Ito, 2021). However, at present, the open data sources are mainly located in cities, and there are few databases for rural areas. To apply computer vision technology to the countryside, a set of targeted semantic image segmentation algorithm models must be collected and trained.

Due to the large scales and diverse types of rural landscapes, it is difficult to collect data, so the evaluation criteria of rural landscapes are always a difficult problem (Polednikova and Galia, 2021; Suppakittpaisarn and Lu et al., 2022). In the past, limited by information dissemination and construction efficiency, rural landscape design was often directly assessed by landscape designers and government officials, and the final landscape effect often relied on the personal aesthetics of designers and decision makers, while the real needs of most ordinary people were easily ignored (Rogge and Nevens et al., 2007; Kalivoda and Vojar et al., 2014; Lopez-Martinez, 2017). However, compared to the traditional methods of surveying and evaluating the experts' perceptions of landscapes, a complex model evaluation model based on artificial intelligence and neural networks has an excellent performance in processing large-scale, high-precision, and complex-structure data samples (Huai and Chen et al., 2022; Li and Wang et al., 2022; Wilkins and Van Berkel et al., 2022). It is possible to predict the visual quality of images with similar landscapes using a trained image-processing model (Seresinhe and Preis et al., 2017). The trained model can perform mass quantitative processing on the visual perception of a whole rural landscape image, simulate the results of manual operations, and save labor and time costs (Li and Zhang et al., 2015; Suppakittpaisarn and Lu et al., 2022). Therefore, using computer vision technology to evaluate the visual perception of rural landscapes can make up for the limitations of on-site evaluations and photo evaluations, and it has a wide range of application prospects.

In view of the existing practical needs and the known research methods of rural landscapes, this study is divided into the following four aspects: 1) The computer vision technology and the training that was applied to the semantic image segmentation model in rural areas is discussed. (2) The correlation between physical indicators and the visual perception of rural landscapes was evaluated using a regression model. (3) The town of Chunhua in Hunan Province was used as an example, from a visual perception perspective, to measure the quality of the rural landscape using panoramic images. (4) Rural landscape improvements were proposed to provide a reference for the planning of rural environments.

2. Methodology

2.1 areas under study

The study area was X029 Road in Chunhua Town (Fig. 1). Chunhua Town belongs to Changsha County and is located in the northeast of Changsha City, the capital of Hunan Province. The town covers a total area of 126 square kilometers, the total population is about 49,000 people, and it is a traditional agricultural town. The town's rice-planting area is 10,000 mu; it includes a total of 39 rice-planting cooperatives and large households. The town has a high-standard seed-production area of 0.35 million mu and a vegetable-planting area of 0.5 million mu. The town's transportation location advantages are increasingly prominent, its landscape and pastoral resources are rich, its cultural and historical heritage is thick, and the public support facilities are increasingly perfect. It is close to Liuyang City in terms of its rainfall and water, and the Laodao river flows through most of the territory; the natural conditions are superior. Chunhua Town, as a traditional agricultural production town in Hunan Province, has a huge agricultural foundation and historical heritage. In the scope of this study, a variety of landscape features such as the town, farmland, forest gardens, and rivers were connected. The visual perception evaluation research on the rural landscape of this place is of great significance in the promotion of rural areas in Hunan Province.

2.2 Data collection

2.2.1 Image data collection

In order to restore the real feelings of pedestrians on rural roads, this study used panoramic images for the assessment. When taking panoramic photos, we followed a uniform and fixed shooting standard: the shooting period was concentrated between 10:00 and 16:00 in October, we ensured clear weather, and we tried to avoid negative landscape elements, pedestrians, and vehicles; the panoramic photos were shot with the same camera model, Insta360 ONE RS, with the GPS enabled and connected to the phone to obtain accurate geographic information data. The photos were shot with a fixed-length camera mount perpendicular to the ground, the camera height was set at 1.7 m, and the camera was above the head of the photographer. Panoramic images were taken every 20 meters along the country road. After the photo data acquisition was complete, the Insta360 Studio 2023 software was used to convert the panoramic images into 720° tiled panoramic images. In the end, we collected 379 panoramic images with GPS positioning.

2.2.2 Data processing

In Photoshop, the tiled panoramic images were converted into 360° autonomous rotating VR images with a human eye angle, and then the photographer in each image was eliminated to minimize interference factors. This is conducive to improving the accuracy of the deep learning algorithm and reducing the participants' sense of abruptness to the image. After the image processing was completed, the initial panoramic image viewing angle was set to position the photographer directly in front of the camera. The field of view (FOV) was 110° and the vertical range was 0°. The subject could adjust the viewing angle independently, with a FOV range between 70° and 110° and a vertical range between − 10° and 25°. Test samples of 50 panoramic images at 150 m intervals were selected as the samples for the questionnaire evaluation, and all the sample photos were tested to ensure that they included all landscape types.

2.3 Image segmentation

In order to identify various landscape elements from rural panoramic photos, we used the convolutional neural network "U-net" to conduct a semantic segmentation of the photo data, because it can be trained with a small amount of data to obtain efficient results with an excellent performance (Kim and Lee et al., 2019; Liu and Cao et al., 2019; Pan and Xu et al., 2020; Mu and Li et al., 2022). It is especially suitable for use in scenes with less data such as rural landscapes (Li and Gao et al., 2022). In this paper, a semantic segmentation model of rural images based on the U-net network results was trained for rural road landscapes. The rural road landscape labels were divided into 10 categories, which were roads, trees, sky, buildings, grass, farmland, communal facilities, landscape ornaments, water, and others. In this process, we used a "resnet50" pre-training weight for feature extraction to increase the accuracy of the prediction. The process of semantic image segmentation was as follows:

(1) The pixels were classified. A total of 50 scenic images in the labelme software were selected to label the 10 types of landscape elements.

(2) The data set was trained by the U-Net segmentation network. After 1000 rounds of training, the accuracy of the model was verified according to Formulas (1) ~ (4). On the basis of reaching the accuracy standard, all images were predicted and the semantic image segmentation results were generated:

$$A_i = \frac{P_{ii}}{P_{ij}}$$

1

$$IoU_i = \frac{P_{ii}}{P_{ij} + P_{ji} - P_{ii}}$$

2

$$PA = \frac{\sum_{i=0}^{k} P_{ii}}{\sum_{i=0}^{k} \sum_{j=0}^{k} P_{ij}}$$

3

$$MIoU = \frac{1}{k+1} \sum_{i=0}^{k} \frac{P_{ii}}{\sum_{j=0}^{k} P_{ij} + \sum_{j=0}^{k} P_{ji} - P_{ii}}$$

4

Here, k indicates the total number of landscape label categories, A_i is the accuracy of the real pixel category i, IoU_i is the intersection ratio of the real pixel class i, P_{ii} is the total number of real pixels when the pixels of class i are predicted as the total number of class i, P_{ij} is the total number of real pixels when the pixels of class i are predicted as the total number of class j, P_{ji} is the total number of real pixels when the pixels of class j are predicted as the total number of class i, PA is the overall pixel accuracy, and $MIoU$ is the average intersection ratio.

2.4 Landscape evaluation index development

The composition elements and form elements of landscapes are important reasons for people's psychological perceptions (Bulut and Yilmaz, 2008; Zhang and Zhao et al., 2019). In previous studies on the aesthetic quality of landscapes from a visual perspective, it was found that plants, water, buildings, roads, and sky have a great impact on landscape aesthetics and aesthetic cognition (Tveit, 2009; Sowinska-Swierkosz and Soszynki, 2019).

Studies have shown that large areas of vegetation and water can have positive effects on people (Bulut and Yilmaz, 2008; Tempesta, 2010). Other studies have shown that the appearance of water movement can have a negative impact on the landscape, and polluted or poorly maintained vegetation in landscapes cannot enhance people's feelings, and may even have a negative effect (Yao and Zhu et al., 2012). The same problem is also reflected in man-made factors; roads and buildings had negative impacts in studies of visual quality (Garre and Meeus et al., 2009; Howley, 2011), but in other landscapes, unique buildings and artifacts had a positive impact on people (Torreggiani and Tassinari, 2012; Hoibo and Hansen et al., 2018). There are many reasons for the different research results, but it is difficult to analyze the problem from the perspective of quantitative research and explore how the physical differences in landscapes affect people's perception.

Based on the previous research on visual landscape quality and the characteristics of rural landscapes, this paper mainly establishes parameters related to rural road landscapes for three aspects: visual space attraction material elements, visual space attraction form elements, and visual space attraction patterns. The green vision index (GVI), farmland visibility index (FVI), natural openness index (NOI), sky visibility index (SVI), building density index (BDI), road width index (RWI), ratio of arbors and shrubs to grass (RTG), landscape ornaments index (LOI), and interference factor index (IFI) were included. The visual perception of a riverfront greenway was quantitatively analyzed using these 9 indicators.

2.5 View standard calculation

We recruited 40 graduate students majoring in landscape architecture in universities for evaluation. It was easier for graduate students in colleges and universities to carry out training and practice wearing VR devices. Additionally, studies have shown that the evaluation results of teachers and students in colleges and universities are not significantly different from other groups in the face of common landscape types (Sowinska-Swierkosz and Soszynki, 2019).

We referred to evaluation research on degrees of beauty, which suggested that using a 5-point Likert scale method can effectively evaluate participants' visual perception (Ciftcioglu, 2017; Ciftcioglu, 2019; Fu and Ren et al., 2022). First, the photos were divided into 4 groups, which appeared out of order, and the ratings of 10 subjects were collected from each group. Before the scoring, the subjects first scanned the photos as a whole, and then conducted the experiment after having a good understanding of the overall situation. Then, they looked around each scene for a week and scored them on 5 levels of aesthetic ratings using the Likert scale (a score of 1 indicated the worst level, and a score of 5 indicated the best level) in order to eliminate or reduce the aesthetic differences among different reviewers. Using the formula, the beauty score was standardized, and the beauty value of each scene was obtained by further averaging:

$$R_{xy} = \frac{S_{xy} - min_y}{max_y - min_y}$$

5

Here, S_{xy} is the score of the x participant's question y, min_y is the lowest score of all the scores for the y question, max_y is the highest score of all the scores for the y question, and R_{xy} is the data-standardized value of question y for the x participant.

2.6 Correlation analysis

In the research of planning guidance, a multiple linear regression model can judge the intimate relationship between various variables and then obtain a correlation judgment. According to the selected rural landscape characteristics and visual perception measurement results, SPSS software was used to test the correlation among 10 evaluation indicators, and a multiple linear regression analysis model was built between them and the visual perception scores. In this study, the standardized value of the scenic beauty score was taken as the dependent variable, and the value of each landscape element was taken as the independent variable. In the modeling process, correlation correction factors were gradually proposed through the slice correlation analysis method and the factors with a greater correlation were retained, so as to establish the final scenic beauty model. The degree of influence of various evaluation indicators on the visual perception results and the correlation between different landscape features and visual perception were explored. On this basis, the road landscape feature data of the rural community in Chunhua Town were visualized and expressed in ArcGIS, the spatial distribution characteristics of the rural landscape were analyzed, and future planning suggestions were summarized.

3. Results

3.1 Physical characteristics of rural road landscape in Chunhua Town

Through semantic image segmentation, we obtained the corresponding values of 10 physical characteristics. The semantic image segmentation model under training was effectively divided by the various elements of the rural road landscape, and the results are shown in Fig. 2. The segmentation accuracy met the experimental requirements. The precision of the image's semantic segmentation was higher than the required value (Table 1), and the overall pixel accuracy (PA) was 0.83. The Mean IoU (MIoU) was 0.76 per cent, indicating that this method can be used to accurately batch-process rural road landscape images and is universal.

Table 1 Accuracy of physical feature recognition. IoU - Intersection over union.

Feature	Accuracy	IoU	Feature	Accuracy	IoU
Roads	0.95	0.94	Water	0.96	0.86
Trees	0.86	0.80	Farmland	0.81	0.67
Sky	0.89	0.86	Communal facilities	0.72	0.65
Buildings	0.89	0.75	Landscape ornaments	0.67	0.63
Grass	0.76	0.70	Others	0.74	0.72
Pixel accuracy: 0.83					
Mean IoU: 0.76					

3.2 Assessment of accuracy and importance of predictive models

3.2.1 Model Evaluation

The correlation analysis results for the influencing factors and visual landscape preference scores (Table 2) showed that the correlation coefficient between the influencing factors was low, and there were no strong linear correlations, which also indicates that the set indicators had different impacts on landscape perception. The preference scores results (SR) were strongly correlated with the GVI, FVI, BDI, IFI, and RWI. The GVI and FVI were positively correlated, while the BDI, IFI, and RWI were negatively correlated.

Multiple linear regression was performed on the dependent variables and the independent variables (Table 3). The statistical value of the overall R test was 0.581, and the overall regression equation was significant. Through the residual variance test, a no-difference variance was identified. At the same time, the results of the VIF values in the collinearity statistics were all less than 5, indicating that there was no multicollinearity in the independent variables.

Table 2
Correlation analysis on influencing factors

Item	SR	GVI	FVI	NOI	SVI	BDI	IFI	RWI	LOI	RTG
SR	1									
GVI	0.606**	1								
FVI	0.422**	0.106	1							
NOI	-0.075	-0.625**	0.454**	1						
SVF	-0.201	-0.733**	0.221	0.965**	1					
BDO	-0.600**	-0.520**	-0.377**	0.063	0.184	1				
IFI	-0.454**	-0.341*	-0.160	0.066	0.139	0.572**	1			
RWI	-0.564**	-0.630**	-0.460**	0.067	0.205	0.407**	0.195	1		
LOI	-0.136	-0.181	-0.133	0.147	0.212	0.108	0.298*	0.177	1	
RTG	0.060	-0.136	-0.092	0.088	0.118	0.122	-0.007	-0.084	-0.063	1
Notes: ** indicates significant at the level of 0.01, * indicates significant at the level of 0.05.										

Table 3
Results of the Pearson correlation analysis.

influencing factors	Pearson Correlation Index	Standard deviation	t	P-value	VIF
GVI	0.532	0.116	4.575	0.000	2.855
FVI	0.295	0.134	2.207	0.032	1.261
SVI	0.358	0.178	2.016	0.050	2.733
IFI	-0.731	0.370	-1.976	0.054	1.172
NOI	-0.030	0.119	− .252	0.802	1.035
BDI	-1.270	0.331	-3.832	0.000	1.238
RWI	-0.697	0.229	-3.041	0.004	1.250
LOI	-0.134	1.284	− .104	0.917	1.059
RTG	0.001	0.001	0.790	0.434	1.051

3.2.2 Impact assessment

We found that the *P*-values of the five influencing factors were less than 0.05 (Table 3). This indicates that there was a strong linear relationship between these individual variables and the score results (GVI, FVI, BD, and RWI), which had a significant impact on the visual perception: (1) The GVI, BDI, and RWI had a very significant impact on the visual perception ($P < 0.01$); the GVI was positively correlated, and the BDI and RWI were negatively correlated. (2) The FVI had a significant effect on visual perception ($P < 0.05$), with a positive correlation. The other influencing factors were not statistically significant.

3.3 Landscape quality of rural roads in Chunhua Town

According to the influence degree of each index, visual perception maps were drawn for the five landscape features that had a significant impact on visual perception, as shown in Fig. 3.

From the scoring results, the scores for rural roads at the north and south ends were low (≥ 0.2), while the scores for the middle section were high (≼ 0.4), which was similar to the GVI distribution in the study area. Chunhua Community and Shitangpu Village at the north and south ends, respectively, are mainly urban residential environments, with many large buildings and a dense layout. Although street trees were installed on both sides of the streets, the planting areas were limited. In the middle of the road in Chunhua Mountain Village, although there are also new residential houses on both sides of the road, a large number of green plants have been planted in the courtyard in front of the houses, and there is a gap between the buildings so that you can look at the distant farmland landscape; therefore, the GVI value was maintained at a high level.

According to the feedback from the experimental personnel, the FVI value greatly affected their visual perception and was one of the important evaluation indicators. According to the distribution of the FVI value, although the study area was a rural area, the overall FVI value was low. Locations with high FVI values show an interval distribution, which is largely influenced by the distribution of buildings, resulting in beautiful views, but no access to either side of the road.

The distribution of the BDI values showed an opposite trend to that of the GVI values. The BDI values in the urban areas on the north and south sides were higher and more continuous, while the BDI values in the middle part were lower. One of the possibilities for this result is that the courtyard in the middle section was better landscaped and mainly residential, and commercial activities were not as intensive there as those in the urban buildings, so the GVI value can be increased in places with more buildings distributed.

The distribution of the RWI values was similar to that of the BDI values. The urban area had a larger area of roads, which is convenient for traffic, while in the farmland area, the demand for roads decreased and the area allocated to farmland increased. The environmental governance situation in the study area was poor, especially at the connection between the urban areas and the rural farmland landscape, where a continuous increase in the IFI values was observed. The main reason for this is that the infrastructure, such as wires and pipelines, was directly exposed and not properly organized, which caused strong interference to the line of sight. On the other hand, the IFI values were low in the urban areas at the northern and southern ends, and it was clear that these disturbance factors can be effectively managed, but they were not implemented in farmland areas.

4. Discussion

4.1 Computer vision technology to achieve mass rural landscape feature recognition

Computer vision technology is becoming more and more mature, and its powerful application ability has been proven in many fields (Leo and Medioni et al., 2017; Li and Guo et al., 2020; Luo and Zhao et al., 2022). However, the existing open-image-data semantic recognition technology has some limitations in the image recognition of rural landscapes, and most research areas use urban open data, resulting in less research on rural areas (Suppakittpaisarn and Lu et al., 2022). This paper draws on a method of landscape feature analysis using a street-view map and U-Net network image processing in street landscape research, and combines semantic image segmentation technology with a deep learning algorithm to train a panoramic image segmentation model for rural landscapes. This method demonstrated an accuracy of 0.83 and an MIoU of 0.76, indicating that it can accurately process street images of rural communities in batches. It is universal. Image segmentation can provide an effective, quantitative image-processing method for designers, planners, decision makers, and experts in other fields studying rural landscapes, and it can provide strong support for riverside landscape planning and the design of human-scale and multi-party research.

4.2 Application in rural road landscape management and planning

The multiple regression analysis of influencing factors revealed that the GVI and FVI had the greatest positive impact on visual perception (Fig. 3). In previous studies, it has been shown that the proportion of green vision, the sky openness, and the plant, shrub, and grass collocation have a significant effect on the perception of landscapes. On this basis, this paper finds that the unique rice field landscape in rural areas can more effectively stimulate a positive evaluation, but sky openness does not effectively affect the evaluation result, which may be related to the surrounding objects. In urban environments, the landscape is mainly negatively evaluated because the view is blocked by tall buildings; in rural environments, there are no tall buildings (Li and Ren et al., 2020; Chung and Lin et al., 2022), but enclosed spaces of trees instead, which do not cause the same effect (Seresinhe and Preis et al., 2017; Marcelo and Constance et al., 2022). Conversely, a larger area of green vision also resulted in a more positive evaluation. Trees have a greater landscaping function in rural environments than other physical features. When a person is walking or looking horizontally, trees have the strongest visual appeal and have a big impact on the score. In addition, there was no significant impact of plant abundance on the evaluation, which indicates that people are more expected to enjoy simple and direct natural landscapes in rural areas, rather than rich plant designs such as those used in urban spaces. This is because, on one hand, it is not convenient to achieve in open areas, and on the other hand, it will destroy the beauty of the natural rural environment.

Artificial objects have a negative effect on visual quality (Garre and Meeus et al., 2009; Howley, 2011; Li and Wang et al., 2022) This study also confirmed that hard landscape features such as roads, buildings, and supporting facilities were negatively correlated with the aesthetic landscape evaluation results. However, there was a surprising finding that the landscape service facilities did not improve the scores of rural landscapes as envisaged, but showed some negative effects. This may be because, under the policy guidance of trying to improve the quality of rural landscapes, decision makers and designers often lack a scientific basis and blindly copy without consideration, which is also one of the problems that this study aims to solve.

In the end, what kind of rural construction do people want and like? The answer may be found in the design of tourist attractions. Whether it is a natural landscape or a historical and cultural landscape, the successful construction of scenic spots often integrates service facilities into the environment so that tourists can naturally accept the beauty of the environment. However, in the research area of this study, the construction of landscape sketches often appears in the environment abruptly and without reason, which is not only time-consuming and laborious, but also fails to achieve the purpose of enhancing people's favorability. In addition, studies on eye tracking have found that human visual observations are more focused on the visual center of a picture (Dupont and Ooms et al., 2016; Seresinhe and Preis et al., 2017). Therefore, a building has a greater visual impact than a road, and no matter how the perspective is changed, the building's own volume cannot be ignored. In this study, the north and south ends were urban communities with street buildings primarily engaged in commercial activities, and the scores were generally low. However, in the middle part of the study area, there were also some densely arranged buildings with a higher score than the former areas. This phenomenon may have been due to the fact that the latter area contained more residential buildings with smaller volumes and courtyard plants as decoration and shelter, which can alleviate the impact of the building itself on people and provide references for subsequent design work.

4.3 Limitations and prospects of this study

At present, this study still has some limitations, which are mainly reflected in the following aspects. Although the research method has been verified to be feasible, deep learning has its own limitations. If there is a lack of big data, training, or other prerequisite measures, this type of research may not be possible, especially in vast rural areas due to their characteristics such as population loss and industrial decline. In these areas, large numbers of open databases are not available to use like for urban environments. This requires research institutions to establish long-term, large-scale data collection work. Computer vision technology is very powerful, but there is still a lot of potential waiting for us to develop. As a practitioner in the landscape industry, on one hand, it is necessary to promptly understand the development of new technologies. On the other hand, we should actively cooperate across disciplines, constantly improve our professional capabilities, and contribute to the development of the industry.

In the collection of visual perception score data, considering that the experiment required a certain learning cost and adaptation time, graduate students were preferentially recruited as the scoring basis for the data in this study. There may be some deviation between this and an evaluation by rural residents. Future studies can expand the size and diversity of the samples, analyze the visual perception similarities and differences of different groups, and eliminate the visual perception errors of minority groups.

5. Conclusions

Through research on the visual aesthetic quality of rural road landscapes, this study used artificial intelligence to build a prediction model and extract landscape feature panoramas to achieve a quantitative evaluation of the visual aesthetic quality of street landscapes in rural areas. This will significantly improve the efficiency of rural landscape planning and design. In addition, the high-quality development of rural areas is an inevitable trend in the future, and how to better serve rural areas with landscape design, following the trend of the times, is a focus that our landscape designers should think about.

Taking the rural road landscape of Chunhua Town, Changsha City, Hunan Province, as an example, it was found that the GVI, FVI, BDI, IFI, and RWI had a significant impact on the results of the aesthetic quality evaluation, for which the GVI and FVI were positively correlated while the BDI, IFI, and RWI were negatively correlated. The aesthetic quality of the visual perception in the study area was lower in the north and south, and higher in the middle. This result was due to differences in the layout of the towns and the spatial distribution of farmland. From an analysis of the results, the GVI was found to be an important index affecting aesthetic quality, indicating that people prefer to see natural landscapes in rural areas. In design work, the layout should be reasonably planned so that some distance between artificial objects such as buildings is left to allow the natural scenery to be enjoyed, and rural environments should be deeply investigated so that artificial objects can be better integrated into the environment, rather than separated from the environment.

Finally, with rural roads being important transportation channels enabling residents to travel, live, and work, how to balance the relationship between their practical value and landscape value is an issue that designers need to focus on. Landscape designers should try their best to improve the aesthetic quality of rural landscapes on the basis of fully satisfying practicability so that rural residents can also enjoy the same high-quality landscape living environment as urban residents, and so that residents' life happiness and satisfaction can be improved.

Declarations

Ethics approval and consent to participate

The study protocol was reviewed and approved by the Hunan Agricultural University research ethics committee (2023/106) and conformed to the ethical standards for medical research involving human subjects, as laid out in the 1964 Declaration of Helsinki and its later amendments. Participants provided written informed consent prior to taking part in the study.

Author Contributions

Conceptualization, Z.S. and X.T.; methodology, Z.S.; software, Z.S.; validation, X.T., X.H., and K.W.; formal analysis, Z.S.; investigation, X.T.; resources, Z.S.; data curation, Z.S.; writing—original draft preparation, Z.S.; writing—review and editing, X.T.; visualization, X.H.; supervision, X.T.; project administration, K.W.; funding acquisition, X.H. All authors have read and agreed to the published version of the manuscript.

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Availability of data and material

The authors confirm that the data supporting the findings of this study are available within the article (its supplementary materials).

Competing interests

The authors declare no conflicts of interest.

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Figures

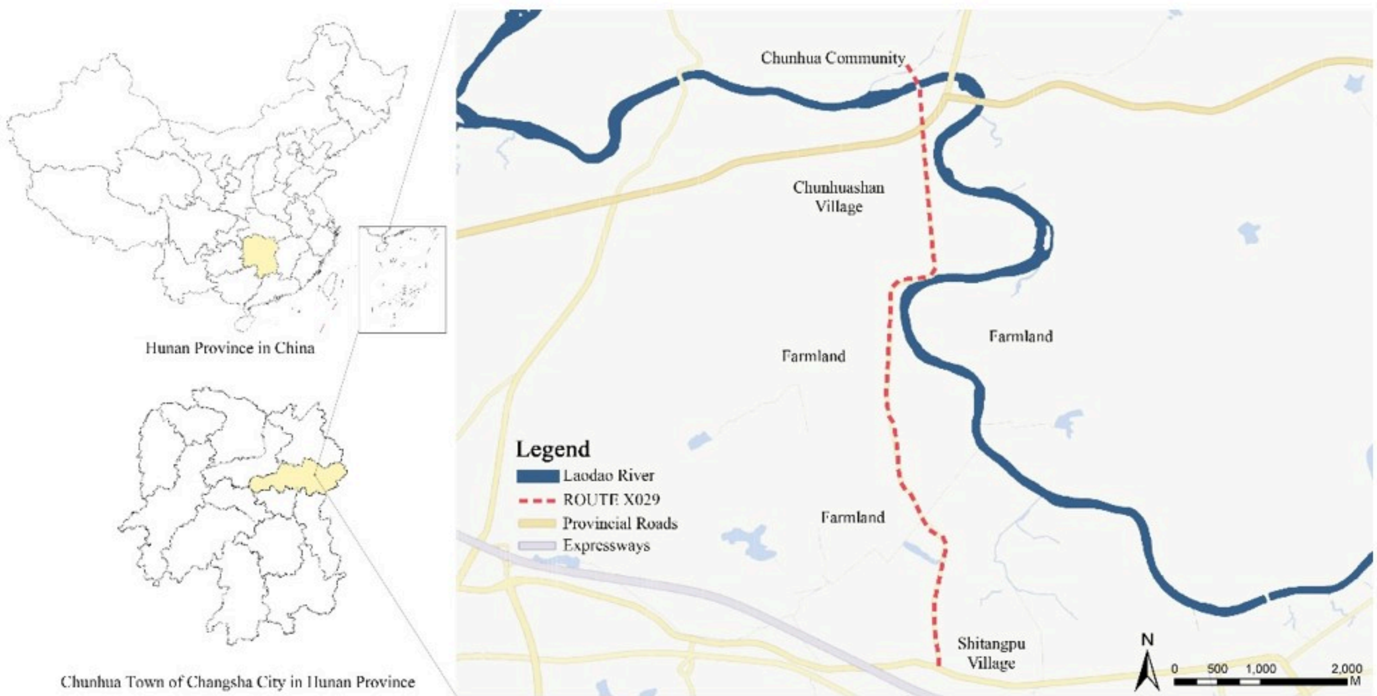

Figure 1

Map of the study area.

Figure 2

Comparison of an image before and after semantic segmentation. a) The original image. b) The image after U-Net semantic image segmentation.

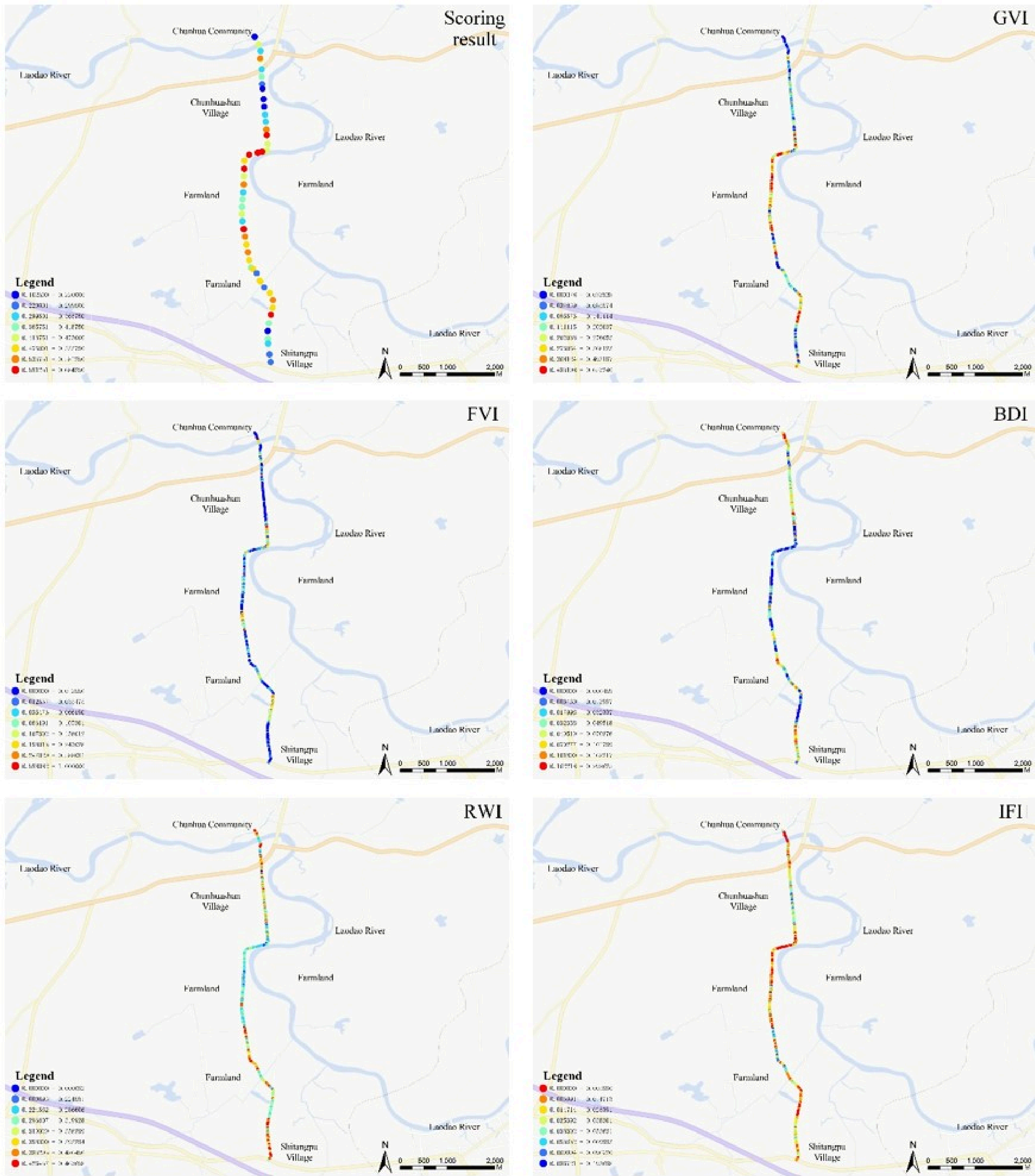

Figure 3

Scoring results and visual perception map of 5 features with significant impact