

Article

Effects of River Scale on the Aesthetic Quality of Urban On-Water Sightseeing

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Abstract: On-water sightseeing plays a key role in the tourism of traditional Chinese landscapes. The on-water landscape affects tourism potential and the quality of urban landscapes. Current research on river landscape is mainly based on remote sensing images or on-land approaches, while studies of on-water perspective landscapes at different river scales is lacking. In this paper, with Guilin city rivers taken as an example, we adopt image semantic segmentation technology to evaluate the visual landscape characteristics under different river scales, and subsequently employ automatic linear modeling to screen important factors affecting aesthetic quality. The results reveal the obvious differences between the on-water landscape characteristics of different scale rivers. The on-water landscape quality of large- and small-scale rivers is mainly affected by seven and four factors, respectively. The Karst landform of Guilin is observed to significantly improve the on-water landscape quality of large-scale rivers. By considering the impact mechanism of landscape composition on the aesthetic quality and the different scale rivers, we propose several aesthetic quality improvement strategies based on low-cost methods, including the planting of vegetation and the micro renewal of artificial constructions. This study contributes to the intelligent evaluation of urban on-water landscape and provides reference for on-water route selection and urban planning.

Keywords: visual perception; semantic image segmentation; on-water landscape; river scale; landscape features; Guilin



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1. Introduction

The blue-green system of the urban river channel reflects the characteristics of the natural environment of a city. In the process of urban development, rivers go through the process of “ecological destruction to environmental transformation to waterfront recreation to water tourism” [1]. The production and transportation functions of river transport have gradually been replaced by ecological and recreational purposes. In recent years, many scholars have started to investigate the river landscape quality in terms of macro scale urban river ecological regulation services. Satellite and Unmanned Aerial Vehicle (UAV) remote sensing technology have been employed to extract river basin information for environmental monitoring, landscape pattern changes, visual attribute assessments and river ecosystem health assessments [2–5]. Furthermore, urban river regeneration projects are no longer limited to meeting the urban ecological barrier and providing natural resources on a large scale, but they have also become one of the most important spatial carriers of tourism activities [6]. More attention is focused on improving the cultural service functions of river ecosystems from a humanistic perspective.

The visual environment is considered an important resource, similar to water, soil and mineral resources [7], and the quality of visual environments affects people's aesthetic taste and physical and mental health [8]. With the development of landscape aesthetics dominated by preference and perception, the evaluation of landscape visual aesthetics has

attracted increasing attention and emerged as an important branch of landscape aesthetics. Such evaluations essentially assign a value to the landscape and identify its main evaluation elements in order to predict landscape changes caused by landscape or management activities [9]. Landscape visual evaluation methods, including scenic beauty estimation (SBE) and the analytic hierarchy process (AHP) represented by Likert scale questionnaire scoring with photos, have been widely used by academics [10,11]. The quality of landscape aesthetics will affect the experience of tourists and thus the tourism potential of the region [12]. Visual landscape characteristics can have a strong impact on the quality of landscape aesthetics [13]. The physical characteristics of landscapes can be used to evaluate the corresponding visual perception quality [14]. Previous studies have confirmed that factors related to landscape composition and proportion, such as environmental cleanliness, shoreline shape, visual field width, tree group contour, vegetation coverage, blue visual field index and artificial landscape interference index, have obvious effects on the quality of urban waterfront landscapes [15–18]. Using machine learning to simulate visual perception, research has gradually developed on guided planning and construction based on the relationship between public perception scores and segmentation elements. For example, Cui et al. calculated the green visual rate through image semantic segmentation and superimposed multi-source data to study the fairness of green space distributions [19]. Zhao et al. quantified the visual interface of landscape cities [20] and Wang et al. assessed the quality of street space through street constituent elements [21]. This method realizes the automatic quantification of landscape elements and provides a new concept for the visual perception evaluation of urban river landscape aesthetic quality.

Boating was an important mode of transportation in ancient times, particularly for the literati. In the traditional landscape sightseeing system, on-water sightseeing is often combined with scenic spots in urban areas to form a regional landscape system with regional characteristics. At present, cruises still play an important role in the expectation of landscape tours [22,23]. After COVID-19, on-water tourism has become a hot tourism project across the globe [24]. Many cities in China have rich river networks, and improving the quality of the water sightseeing landscape has become one of the most effective measures to promote the development of water cultural tourism and regional construction in China [25]. In recent years, many cities have also actively developed on-water sightseeing routes [26,27], approaching a peak in water tourism [28]. Compared with the land-based tour mode, in which tourists choose their own tour route and stop freely, on-water tours follow a fixed route and travel speed, providing a relatively independent environment and quiet atmosphere for tourists to immerse in the city facade [29]. Therefore, the selection of the sightseeing route is particularly important. However, the development of existing sightseeing routes is typically based on the macro perspective [30], and visual perception research based on tourists is relatively lacking. In terms of visual perception, the factors affecting the landscape quality of the water perspective are distinct to those of the waterfront perspective [31], and the visual characteristics under different scales have obvious spatial heterogeneity [32]. However, research on the differences between on-water sightseeing landscape aesthetics across multiple scales of urban rivers is currently lacking.

As a famous historical and cultural city in China, Guilin's long-standing urban culture is integrated into the beautiful natural environment. In the Tang Dynasty, Guilin was famous for its beautiful scenery, while during the Song Dynasty, Guilin was famous for its on-water sightseeing. Nowadays, Guilin is a national historical, cultural and key scenic tourist city. The Li River passes through the city, and the urban development has formed a landscape city pattern of "thousands of peaks surrounding the wild and one river embracing the city". Guilin belongs to a Karst landform, and the mountains are the highlight of the urban landscape. On-water touring is key in getting to know the Guilin city style. The implementation of the "two rivers and four lakes" plan has laid a favorable foundation for the restoration of urban on-water sightseeing. However, judging from the current on-water sightseeing section, the tourists' perceptions of the Li River landscape is generally lower than their expectations prior to the tour [33]. How to improve the urban

water landscape construction is thus crucial to enhance the urban landscape quality and image of the city.

In summary, the majority of existing studies regard urban rivers as a whole to study the landscape quality from the perspective of ecological services and on-land resources. However, research on the landscape aesthetic quality from the unique perspective of on-water sightseeing is relatively lacking, and the differences of the landscape under different river scales is also ignored. Thus, from the perspective of urban on-water sightseeing, this paper performs the following three research activities: (1) taking the Guilin urban river as the research object, we employ image semantic segmentation technology to extract the landscape composition and proportion, and subsequently explore the landscape characteristics of rivers with different scales; (2) the aesthetic quality evaluation under different river scales is compared and analyzed, and it is integrated with the index system based on visual aesthetic quality to determine the importance of impact factors; and (3) we propose several water landscape improvement strategies for rivers of different scales in order to provide reference for water tourism route selection, and urban planning and construction.

2. Materials and Methods

2.1. Research Scope

The study area is located in Guilin City, Guangxi Province, where tourism resources are concentrated, and includes the circular water system formed by the Li River and its tributaries (Xiaodong River and Zizhou River). The total length of the river is 13.6 km, reaching the confluence of the Li River and Xiaodong River in the north, and the upstream dam of Jingpingshan Bridge in the south (Figure 1). The three rivers are adjacent to the ancient city of Guilin and are surrounded by a cluster of tourist attractions. They are connected to the natural scenic area that has a rich cultural and tourism value, and are famous both at home and abroad. Commercial and residential areas are also concentrated around the rivers, and tourists and residents gather in these areas for daily activities.

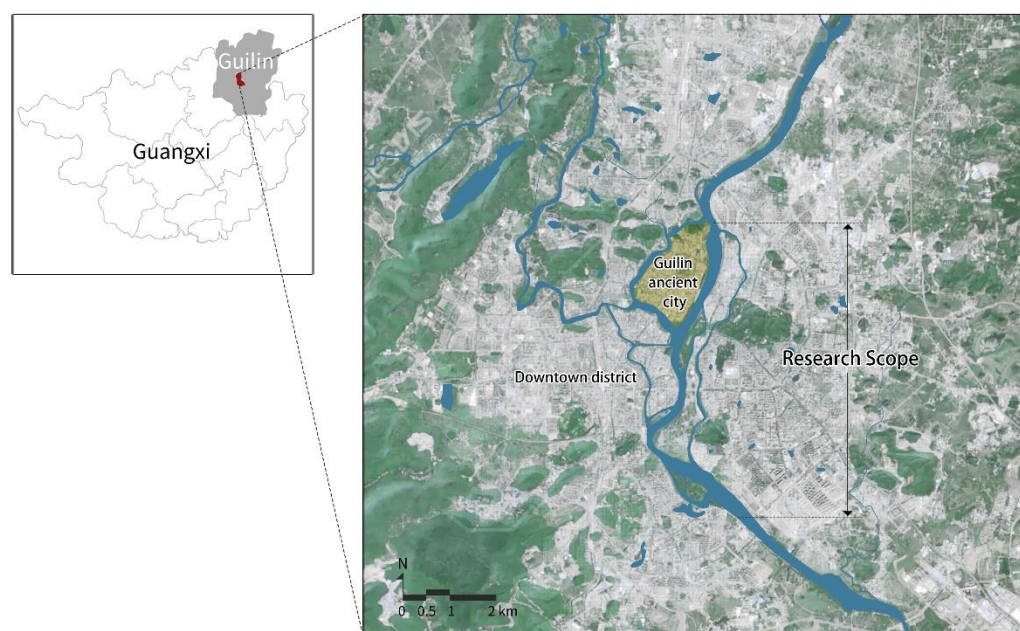


Figure 1. Study area location.

The section from Xiangshan Fisherman's Wharf to Mulong Ancient Ferry surrounding the city on the Li River is known as the "Two Rivers Four Lakes". In addition, the section from the Qixia Bridge to the Longyin Bridge on Xiaodong River has opened up to on-water tour services. Evaluating the visual quality of the on-water landscape in this area is not

only beneficial to the development and construction of the Guilin water system, but also for the cities on both sides of the river.

2.2. Data Acquisition and Processing

2.2.1. Capturing and Preprocessing of Images

In order to ensure the accuracy of the experimental data, a SONY $\alpha 6000$ camera was used to take images on sunny days. The observation height (1.6 m above the water level) of the person taking the images was maintained constantly and the camera was fixed to a tripod for a stable and level perspective. A photo was taken every 100 m and a total of 170 sampling sites were set up along the river, including 95 at Li River, 56 at Xiaodong River and 19 at Zizhou River (Figure 2). The photos were edited in Photoshop (PS) to unify the brightness and contrast, and were classified according to the channel width. The large-scale urban river classification along the Li River included areas with river widths >100 m, and an average channel width of 141.6 m. The small-scale urban river classification along the Xiaodong River and Zizhou River, as well as some narrow sections of the Li River, included areas with river widths <100 m and an average channel width of 44.1 m. After classification, the images were positioned by point elements in ArcGIS 10.2 (Esri).

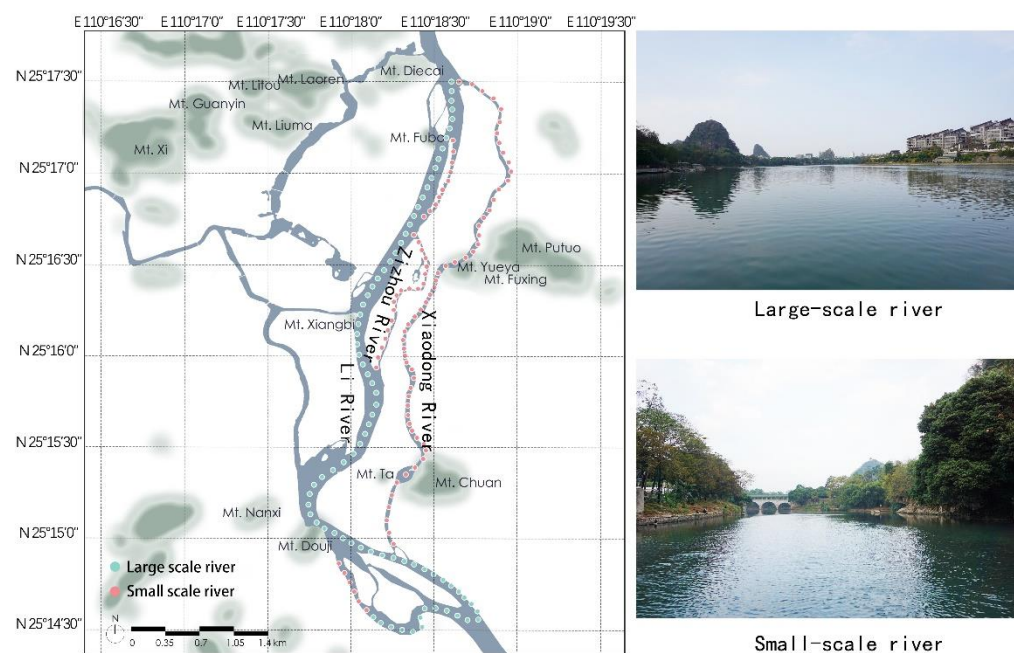


Figure 2. Location of the shooting point.

2.2.2. Evaluation of Aesthetic Quality

The investigation of environmental perception based on vision is the focus of many social studies [34], and visual imaging is the most commonly used research method for this application. Common environmental visual perception is based on subjective feelings, yet they are difficult to interpret. Therefore, the Likert scale, which quantifies subjective will, is used to measure aesthetic quality in this paper.

The Likert scale is typically measured via surveys in social groups, whereby individuals are often more concerned about the average social attitude of the group under investigation, and thus the scores of all respondents should be averaged [35]. When using the Likert scale for mathematical operations, it is necessary to ensure that the set point values are a “sequential approximation of continuous variables” [36], and more points increase the accuracy of the results [37]. We employed a nine-point Likert scale to evaluate the landscape visual quality of images for the public to ensure the accuracy of the data. Higher scores represent a higher quality visual landscape.

The images were randomly divided into four groups. The participants were randomly assigned to four corresponding groups on the “Wenjuanxing” platform to score the visual quality of the assessment point images. The confidence interval of the score was required to be 95%, resulting in 245 valid questionnaires. Table 1 reports the demographic characteristics of the study participants.

Table 1. Participant information statistics.

Entry	Male	Female	All
Number	108	137	245
Percentage	44%	56%	100%
Average age	25.5	29.3	27.6
Age standard deviation	7.8	11.3	9.9

2.3. Research Methods

2.3.1. Physical Feature Extraction Based on Image Semantic Segmentation

The existing open-source data set from Urban Street View lacks the ability to recognize water and revetments required for this research. Thus, the semantic segmentation model needs to be trained. Unity Networking (UNet) is a typical end-to-end semantic segmentation model and is one of the most widely used models in image semantic segmentation [38]. The UNet network structure is very simple and can be split into two components: (i) feature extraction; and (ii) up-sampling, which integrates the global and local information in the image to classify images pixel by pixel. For small sample sizes, UNet segmentation is both accurate and fast [39,40]. In view of the relatively small sample size in this study, the few label categories to be recognized, and the obvious differences among physical features, the structure of UNet neural network is suitable for the semantic segmentation model of the required on-water landscape.

Seven physical feature types were included in this study; water, revetment, plant, building, sky, mountain, and waste. A total of 40 images with obvious landscape characteristics were screened from all images and used as the training set. Accuracy (Acc) and Mean Intersection over Union (MIoU) were used to measure the model segmentation precision (Equations (1) and (2)). Due to their high vegetation coverage in urban areas, mountains show similar landscape vegetation features in the images pixels units. The machine learning approach was easily confused by plants. In image semantic segmentation, mountains were interpreted visually by artificial eyes to obtain the final segmentation results, and the pixel values of various labels were counted. The boundary lines of buildings, bridges, mountains, barges, plants and sky were extracted in Halcon 12.0, their lower edge lines were deleted in Photoshop CC 2018 (PS), and the types of upper edge line pixels were obtained via histograms to calculate the landscape features.

$$MIoU = \frac{1}{k+1} \sum_{i=0}^k \frac{TP}{FN + FP + TP} (100) \quad (1)$$

$$Acc = \frac{TP + TN}{TP + FN + FP + TN} (100) \quad (2)$$

where TP represents the pixels correctly predicted (prediction result = true = positive class); TN represents the pixels correctly predicted (prediction result = true = negative class); FP represents the prediction error, such that (prediction result = positive class) $\neq$ (true = negative class); FN represents the prediction error such that (prediction result = negative class) $\neq$ (true = positive class); k is the category; and $(k+1)$ is the addition of a background class.

2.3.2. Construction of the Index System

The index system established in this paper describes the visual perception of natural landscapes and the visual richness of the landscape of rivers of different scales within the

city. In addition, the aquatic visual landscape feature system is divided into the visual landscape proportion and visual landscape richness. The visual landscape proportion includes the green visual index (GVI), water visual index (WVI), hard revetment visibility (HRV), artificial influence degree (AID), destructive index (DI), visual naturalness (VN) and mountain visual index (MVI). Visual landscape richness includes the number of visible mountains (NVM), horizontal complexity (HC), vertical complexity (VC) and mountain undulation (MU) (Table 2).

Table 2. On-water landscape characteristic system.

Category	Index Item	Instructions	Formula
Visual landscape proportion	Green visual index, GVI	Proportion of plants in the full image	$GVI = P_{g_i} / P_{t_i}$
	Water visual index, WVI	Proportion of water bodies in the full image	$WVI = P_{w_i} / P_{t_i}$
	Hard revetment visibility, HRV	Proportion of revetment in the full image	$HRV = P_{r_i} / P_{t_i}$
	Artificial influence degree, AID	Proportion of buildings and bridges in the full image	$AID = (P_{b_i} + P_{br_i}) / P_{t_i}$
	Destructive index, DI	Proportion of abandoned sites and construction facilities in the full image	$DI = P_{o_i} / P_{t_i}$
	Visual naturalness, VN	Proportion of plants, sky, water, and mountains in the full image	$VN = (P_{g_i} + P_{s_i} + P_{w_i} + P_{m_i}) / P_{t_i}$
	Mountain visual index, MVI	Proportion of mountains in the full image	$MVI = P_{m_i} / P_{t_i}$
Visual landscape richness	Number of visible mountains, NVM	Number of mountains visible in the full image	-
	Horizontal complexity, HC	The skyline length	-
	Vertical complexity, VC	Plant line, building line, mountain line, and shoreline lengths	$VC = L_{g_i} + L_{b_i} + L_{m_i} + L_{r_i}$
	Mountain undulation, MU	Pixel size of the visible upper edge of the mountain	-

Where i is the i th images; P_g , P_w , P_r , P_b , P_{br} , P_s , and P_m denote the number of plant, water, revetment, building, bridge, sky and mountains in the images; P_{t_i} represents the number of pixels in the whole image; L_g , L_b , L_m and L_r represents the number of pixels of the upper edge line length of plants, buildings, mountains and revetment in the image, with the line width of 1 pixel.

2.3.3. Identification of Key Control Factors

A regression model was established to explore the relationship between visual landscape features and visual ratings of aesthetic quality. Automatic linear fitting models can be implemented in SPSS 24 (IBM) using different algorithms in order to determine the independent variables with the greatest importance to the dependent variables, discard the independent variables with little or no importance, and select the optimal model [41]. For this work, we selected the step forward model. The score was set as the dependent variable, all landscape features were set as the independent variables, and the confidence degree was set as 95%. Independent variables with a strong influence on the score were selected based on the Akaike information criterion (AIC), and the best model was selected using R^2 as the evaluation standard. Landscape features with a significant influence ($p < 0.05$) in the optimal models were further analyzed to establish their correlation with aesthetic quality.

2.3.4. Comparison of Univariate Differences

The MVI and DI indices were compared in order to further explore the influence of local characteristic landscapes (mountain) and visually destructive elements (abandoned sites and construction facilities) on the scores of rivers at different scales. Images with an indicator ≥ 0.0001 were defined as containing physical elements, while images with an indicator < 0.0001 were defined as not containing physical elements. Box graphs were used to compare different river scales. For MVI and DI values < 0.0001 in each scene are, the proportion of mountains, abandoned sites, and construction facilities in the image is very small, and the scene can be considered to visually lack mountain landscapes and construction facilities.

3. Results

3.1. Image Semantic Segmentation Results

After 100 epochs of UNet neural network training, the MIoU of the model reached 82.50%, and the Acc reached 95.25% (Table 3). It can be seen from the identification results in Figure 3 that the segmentation of various elements in the trained model is consistent with the actual situation, and the boundary lines of water, plants, buildings, sky and other elements are clearly divided, but there are some errors in the segmentation of mountains, which need to be corrected for a small part. The results reveal the high precision of the model, and it can thus be used for image processing.

Table 3. UNet training accuracy.

Epoch	Acc (%)	MIoU (%)
20	90.3885	71.7997
40	92.7365	76.4544
60	94.2221	80.5594
80	94.9267	81.5062
100	95.2519	82.499

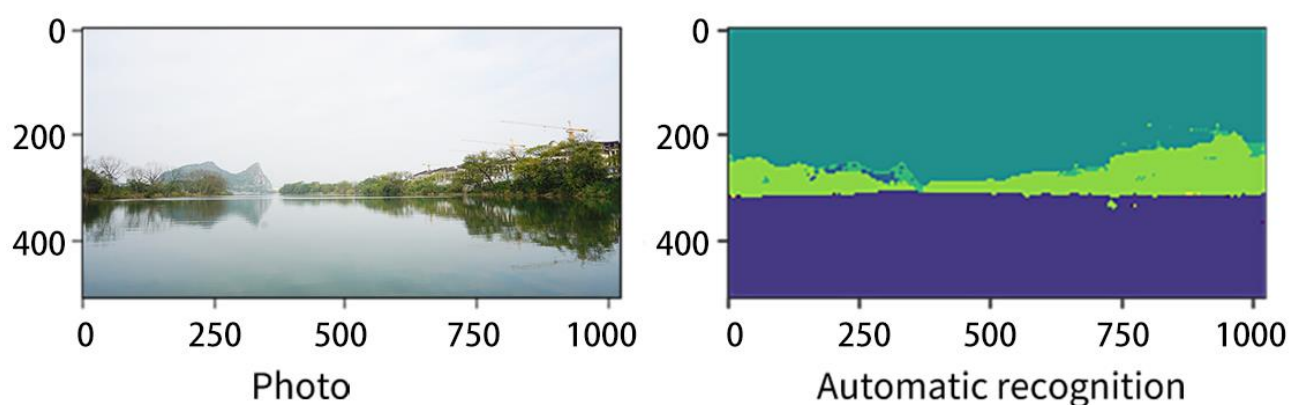


Figure 3. UNet image semantic segmentation.

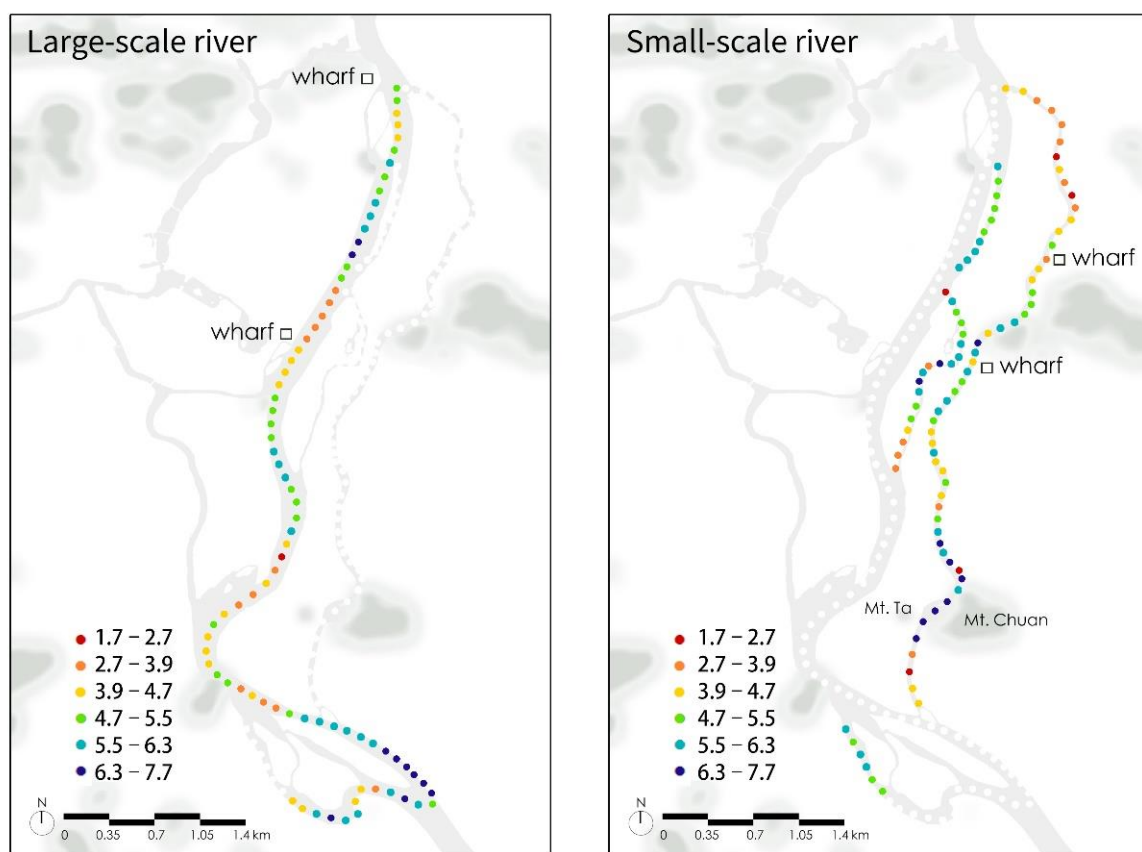
3.2. Public Preference Survey Results

Table 4 reveals the average on-water landscape aesthetic quality scores for large- and small-scale rivers to be at the medium level (5.02 and 5.03, respectively). Moreover, the standard deviation (STD) values for large- and small-scale rivers are 1.05 and 1.22, respectively, indicating that the water landscape scores of different scenes in the group varies significantly. The water landscape quality differences in small-scale rivers are greater than those in large-scale rivers.

Table 4. Statistics of landscape characteristics at different river scales.

Type	Score	GVI	WVI	HRV	AID	DI	VN	MVI	NVM	HC	VC	MU
Large scale	AVG	5.01772	0.07157	0.42304	0.00937	0.02812	0.00171	0.96041	0.01996	1.54430	25,035.35568	8235.785
	STD	1.05439	0.03178	0.04344	0.00950	0.04258	0.00536	0.04496	0.03309	1.20679	6743.56479	7426.490
Small scale	AVG	5.03077	0.23105	0.37113	0.03679	0.04729	0.00736	0.90794	0.00547	0.27473	6887.28600	1664.286
	STD	1.21990	0.11120	0.03975	0.02758	0.07222	0.02659	0.07745	0.02203	0.66777	5131.49900	4542.005

Figure 4 depicts the overall distribution of the on-water landscape quality scores. The score variations for large-scale rivers are generally minimal, and the continuity is high. There are two sections within the research scope of large-scale rivers with high overall scores. The first section is on the main river in the south of the research scope, and the second section is between the two wharfs on the Li River where an upstream line has been set up, but the score near the south wharf is low. For small-scale rivers, the landscape diversity with an interval of 100 m between adjacent scenes is strong, and the scores exhibit large changes. The score between the two wharfs that have opened the upstream water line is at a medium level, which is necessary to improve the landscape quality; in the south, there is a continuous point with high landscape quality between the two mountains; the points with low scores are mainly in the form of abrupt changes in small-scale rivers.

**Figure 4.** Aesthetic quality score of numerous scenes of rivers with different scales.

Following this, 20 images were randomly selected from 170 images, and the aesthetic quality score of each image was divided into two groups for *t*-tests. The results of the two groups of 20 images were not significantly different ($p \geq 0.05$), and thus the influence of gender on the landscape quality score was not considered.

3.3. River Landscape Characteristics under Different Scales

All the landscape characteristics of rivers were observed to differ significantly at different scales, with the exception of VN (Table 4). The average values (AVG) of GVI, HRV, AID and DI in small-scale rivers were significantly higher than those of large-scale rivers, indicating that vegetation, revetments, buildings and bridges, abandoned sites and construction facilities accounted for a high proportion of visible water landscapes in small-scale rivers. The STD values of large- and small-scale river landscape features were high, indicating large differences in the landscape features of rivers of the same scale. The AVG of WVI, MVI, NVM, HC, VC and MU of large-scale rivers were significantly higher than those of small-scale rivers. This reveals that compared with small-scale rivers, large-scale rivers have the characteristics of visible water and mountains account for a higher proportion, the number of mountains is larger, the degree of skyline and mountain fluctuations is more obvious, and the landscape is richer. The high STD of MVI, NVM, HC, VC and MU indicates large changes in these landscape features under different scenes of the same scale. Moreover, the low STD of WVI indicates minimal differences in the blue field index across different scenes of the same scale.

3.4. Main Control Factors Affecting On-Water Landscape Quality

The best models were selected using automatic linear modeling. The adjusted R^2 of the optimal model for large- and small-scale rivers is 71.4% and 62.9%, respectively. The regression model between the aquatic landscape feature system and the score at both scales (Figure 5) is highly accurate, and the selection of the main control factors is convincing.

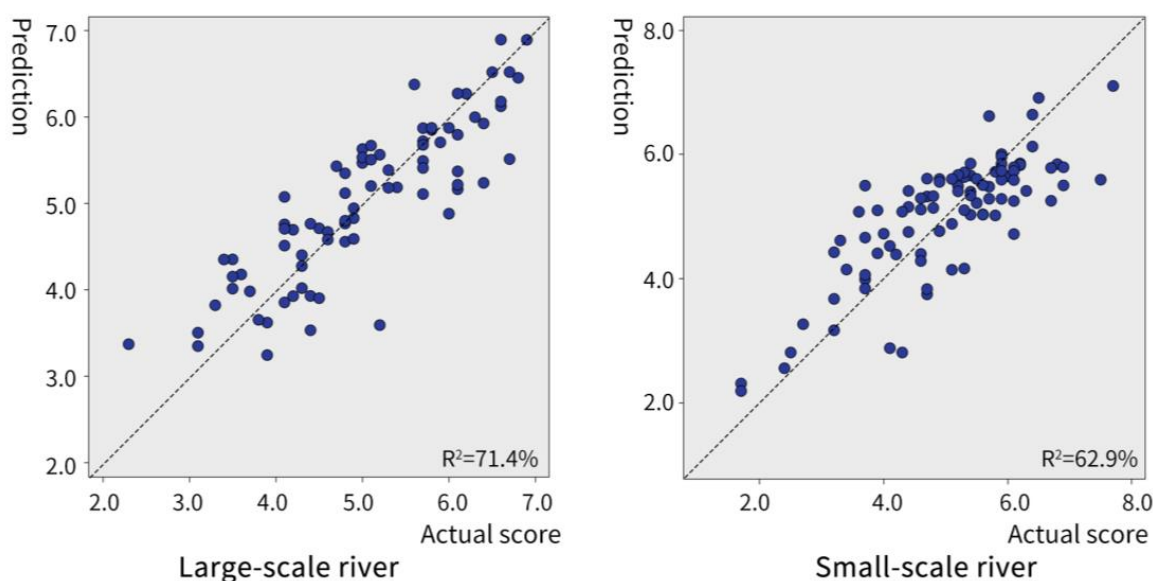


Figure 5. Distribution of the model-predicted values.

The VN, GVI, HC, MU, VC, HRV and NVM are observed to exert a significant influence on the scores of large-scale rivers (Figure 6a). VN is the most important, followed by GVI. Factors with $p < 0.05$, namely, VN, GVI, HC and MU. VN, GVI and MU are positively correlated with the score, while HC is negatively correlated with the score (Figure 7a). DI, VN, MVI and GVI have significant effects in small-scale rivers (Figure 6b), with DI as the most important, followed by VN. p values for all four factors are <0.05 . DI is negatively correlated with the score, while the remaining exhibit positive correlations (Figure 7b). It can be seen from Figure 7 that under different river scales, the natural degree of the scene and the proportion of plants have a positive impact on the quality of visual aesthetics. The mountains also have a positive impact on the aesthetic quality. For large-scale rivers, the

impact of mountain undulation is strong, and for small-scale rivers, the impact of mountain proportion is strong.

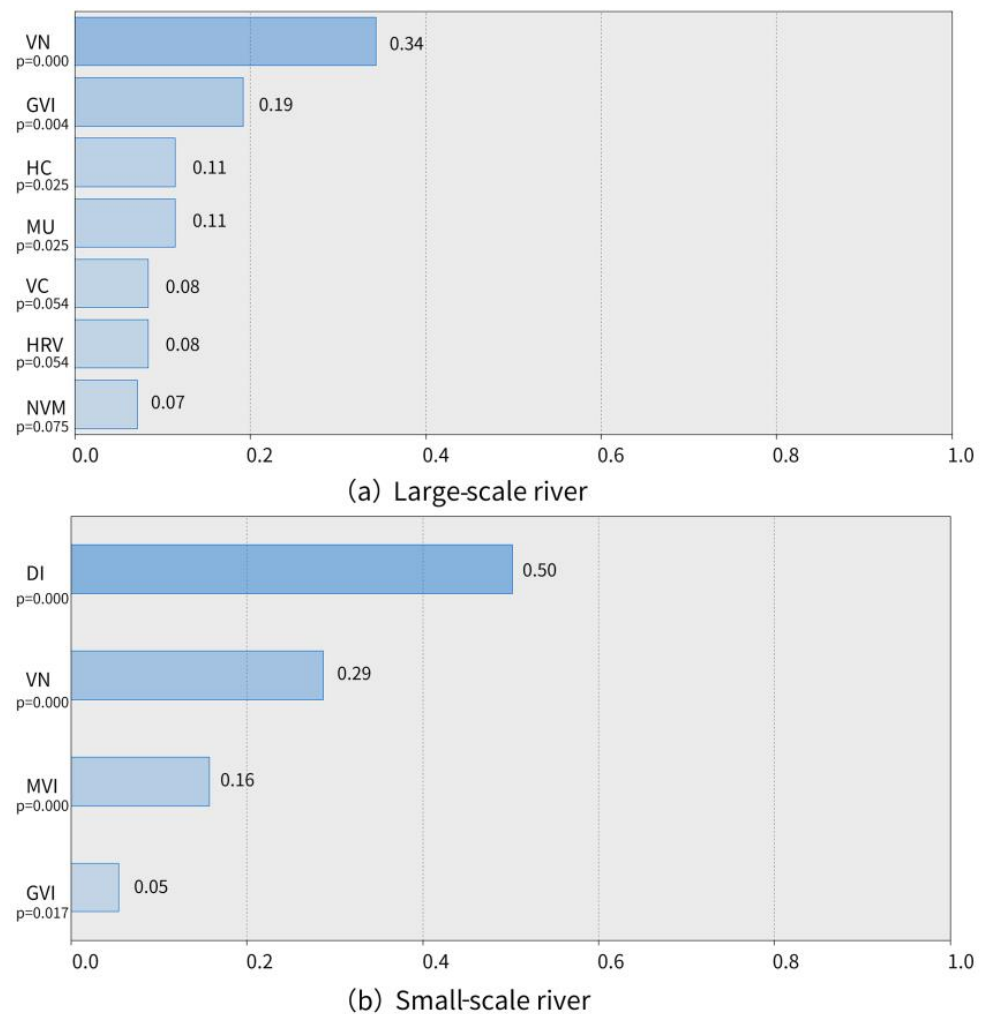


Figure 6. Importance of landscape characteristics on landscape quality at different river scales.

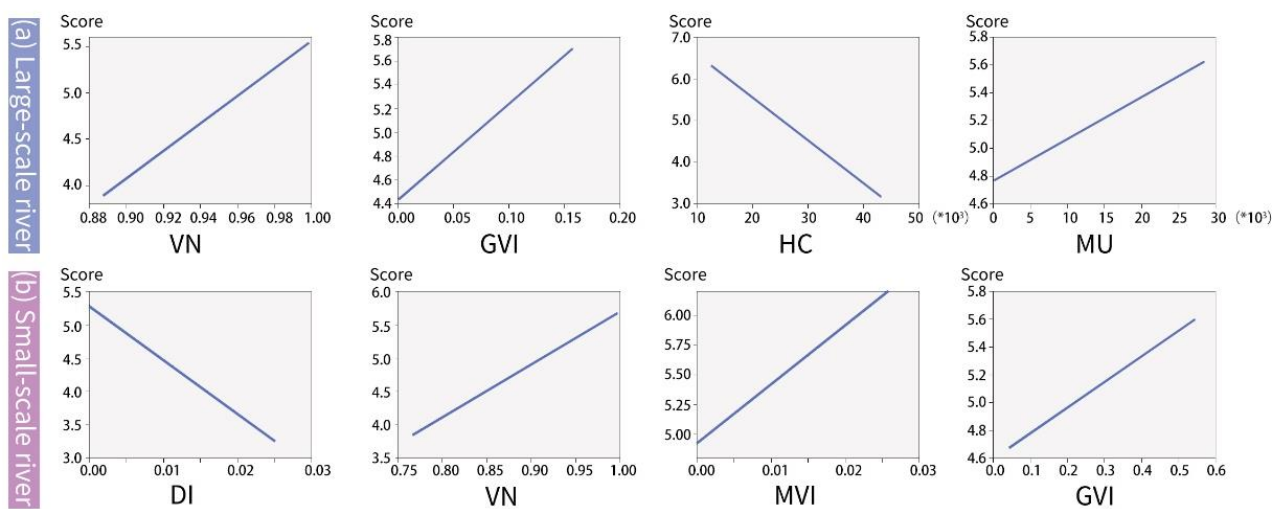


Figure 7. Correlation between each influence factor and score.

The landscape quality of large-scale rivers impacts the main control factors, and with the exception of VN and GVI, all factors have a similar effect. The large-scale river comprehensive effect on the on-water landscape impact factor is stronger. The seven key controlling factors contain all four visual richness indices, two of which are significant ($p < 0.05$). This shows that visual richness and overall undulation rhythm have a stronger impact on large-scale river on-water landscapes compared to other visual richness indices.

There are four key factors influencing the water landscape quality of small-scale rivers, and the influence of each factor differs significantly. This indicates that the strong factors are dominant to the landscape quality. The four main controlling factors are all landscape vision proportion indicators, revealing the large impact of the proportion of different elements in small-scale rivers on the score, and individuals focus strong attention to the performance of landscape details.

3.5. Univariate Comparison of Influencing Factors

By comparing the average MVI values of the scenes with mountains under the two scales from Figure 8, it can be seen that the MVI values of the small and medium-sized rivers are slightly higher than those of the large-scale rivers, while the scene without mountains scores the small and medium-sized rivers significantly higher than the large-scale rivers. The existence of mountains has a significant positive impact on the landscape quality of large rivers, yet no significant impact on small rivers is observed. It can be seen that the Karst mountain landscape with local characteristics in Guilin has a better viewing effect in the large-scale river scene with relatively wide vision.

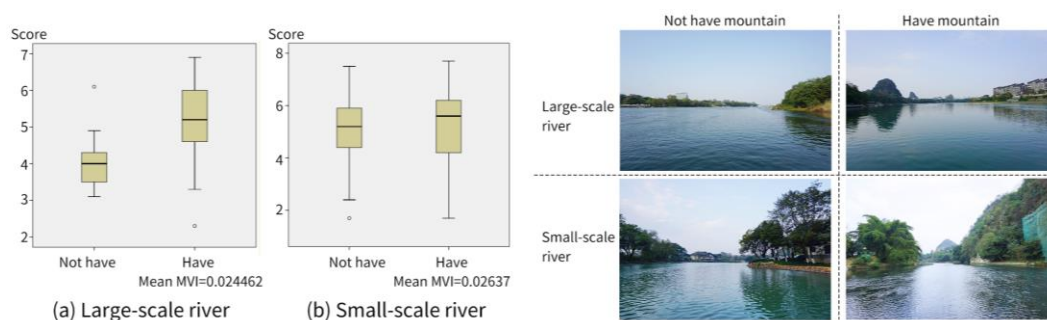


Figure 8. Aesthetic quality of the presence of mountains under different river scales.

It can be seen from Figure 9 that the presence of abandoned sites and construction facilities has a significantly negative effect on the on-water landscape quality of small-scale rivers. However, there is little difference between the scores with and without it in large-scale rivers, and its influence on large-scale rivers is not obvious. In different river scales with abandoned sites and construction facilities, the scores of small-scale rivers are significantly lower than those of large-scale rivers.

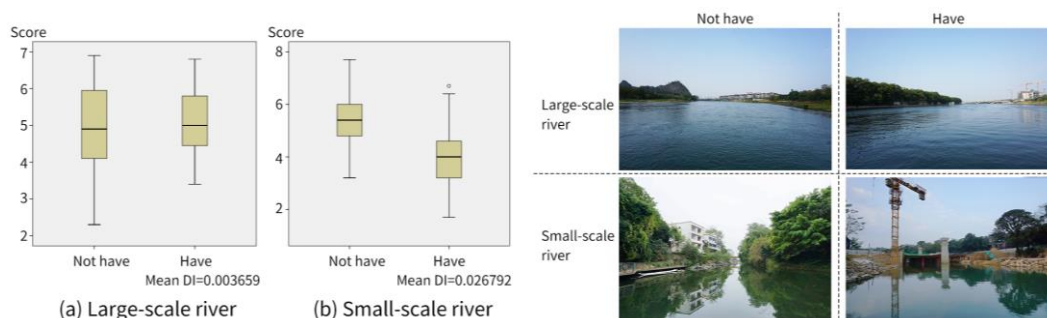


Figure 9. Aesthetic quality of the presence of abandoned sites and construction facilities under different river scales.

4. Discussion

4.1. Influence Mechanism of Landscape Composition on Aesthetic Quality

The negative correlation between HC and score in large-scale rivers is attributed to towering cranes in construction facilities; construction facilities damage the visual quality of landscapes [31]. In addition, artificial skylines cause vertical rises and disrupt the continuous landscape expected by visitors. The positive correlation between MU and the score is related to the tourists' expectations of the natural landscape. People are more likely to enjoy the urban landscape like a painting [42]. Although mountain undulations increase the HC value, they have a weak effect on the skyline relative to artificial facilities. The minimal fluctuation of mountains is consistent with the "Guilin Mountain and River Landscape" expected by visitors, and thus high MU values enhance the landscape quality scores.

VN, MVI and GVI values in rivers of different scales are positively correlated with the score and with people's preferences for natural landscapes. Green plants are conducive to mood relief and relaxation, and increase the sense of pleasure [43,44]. VN has an important influence on the score, and its degree of influence is higher than that of GVI in small rivers. Compared with the preference for green landscapes in urban parks [45] and waterfront environments [46], attention to the overall natural degree of the environment increases during on-water sightseeing. Moreover, the effect of plants is weaker during on-water tours than with park and riverside environments. However, the effect of harmony among plants, sky, mountains and water is stronger.

The presence of mountains in small-scale rivers does not significantly increase the landscape water quality scores. The Karst landscape with local characteristics in Guilin exhibits a stronger viewing effect in large-scale river scenes with good sight effect. This can be attributed to the similarity between the on-water space scale and street space scale. Different proportions of the vertical element height and river width on both sides will generate distinct feelings in tourists. The higher the ratio of height to width, the stronger the sense of space closure and pressure [47]. On urban rivers, people prefer open spaces, and towering mountains increase the sense of pressure in small-scale rivers. In addition, the visual difference between mountain and plant landscapes is small in the near view, while the effect of the mountain form is well when the mountain is in the distance [48]. When visiting small spaces, we pay more attention to landscape details [49]. In small-scale rivers, due to the occlusion of plants and urban buildings on both sides of the river and the limitations of the space itself, the ability to view mountains from a distance is limited, and thus their effect on on-water landscape quality is limited.

Abandoned sites and construction facilities are known to have a destructive effect on visual quality. Their presence has a significant impact on the on-water landscape quality of small-scale rivers, but not large-scale rivers. This is because landscape satisfaction is highly correlated with the visual attractiveness of elements [50]. The average DI scores for large-scale rivers are lower than those for small-scale rivers. Destructive elements make up a very small visual proportion in the large-scale river on-water sightseeing, therefore they play only a minor role in damaging the landscape quality. For small-scale rivers, although abandoned sites and building facilities account for a small proportion in the water scene, destructive elements are rare and more noticeable in the water environment. Thus, they exert a strong impact on the landscape.

4.2. Improvement Strategies of On-Water Landscape Quality of Rivers at Different Scales

For the development and landscape improvement of urban rivers, the basic functions of ecological value must be met. The quality of landscape water must meet the fourth-class standard of surface water quality [51] in order to have a clean surface and ensure the continuity and stability of the urban blue-green system. Based on this, through the development of on-water tourism activities, the cultural service function of urban rivers will be further developed to increase the aesthetic, entertainment, cultural, artistic value, scientific and educational values. When improving the visual quality of urban on-water sightseeing,

we should excavate natural landscapes (such as mountains) with local characteristics to improve the quality of public tourism and the regional characteristics of the landscape. Based on the research results of this paper, we put forward targeted planning and design schemes based on low-cost methods such as planting vegetation, artificial constructions and the micro regeneration for rivers of different scales.

In the on-water landscape reconstruction of large-scale rivers, the coordination of the landscape and the fluctuation and transition of landscape edge lines under large-scale scenes are emphasized. In particular, attention should be paid to the proportion of artificial elements, and the degree of visual naturalization and the ornamental nature of plants should be improved. This can include, for example, planting Guangxi native arbor species with tall trees, bright flowers or autumn leaves on the waterfront side, such as kapok (*Bombax ceiba* L.), flame tree (*Delonix regia* (Boj.) Raf.), maple (*Acer* spp.) and China fir (*Cunninghamia lanceolata* (Lamb.) Hook.). Such an approach not only shelters urban buildings, but also enhances the visual attraction of plants and reduces the impact of urban construction on the natural landscape. The existing municipal bridges on the tour route have been slightly renovated by trifoliate plants such as bougainvillea (*Bougainvillea glabra* Choisy) to soften the visual effect of the bridge. Moreover, the continuity of the landscape should be strengthened by controlling the overall visual ups and downs of the landscape. This can include reducing the visibility of super high-rise and retreating high-rise buildings, leaving a buffer space between the city and river, and reducing the water skyline view. Medium and high-rise buildings should not be built around the mountain to protect its visual integrity. In addition, reduce the impact of construction facilities on the quality of water landscape by reducing riverside construction projects in the peak on-water tourism season.

In the reconstruction of small-scale rivers, the main task is to improve the proportion of the visual components and the quality of the visible elements. It is also important to ensure the cleanliness of the landscape and reduce the visibility of destructive elements. When taking a boat trip, an environment with more natural features can appeal to people, yet a scenic value does negate the value of human influence [52]. When developing the visual ratio of natural landscapes, we should pay attention to enhancing the visual effect of artificial elements, for example, improving the material and color of building facades. White, gray and brown are commonly used in Guangxi traditional folk houses [53] and are the main colors of riverside building facades, while bamboo and imitation bamboo materials are used for micro renewal. To reduce the sense of visual violation, existing flat roof buildings will be renewed by adding the second slope roof on the top of the flat roof, imitating traditional roof forms such as overhanging gable roofs or round ridge roofs. Small-scale river revetments should be treated as near-natural, for example stacked with block stones or stone paving to soften the visual transition between vertical and horizontal interfaces. With the aim of not having an impact on sailing, appropriate amounts of aquatic plants should be planted at the water edge to increase the proportion of green plants and improve the sense of hierarchy and richness.

In addition, government departments should formulate corresponding public policies to guide the selection of on-water routes from the urban planning and development level and the improvement of water landscapes from the design level. This will aid in the improvement and development of water landscapes in other cities.

5. Conclusions

In this paper, image semantic segmentation technology was used to segment the on-water image, and it showed that the on-water landscape characteristics of different river scales exhibited obvious variations. The automatic linear model is used to establish the relationship between the public's evaluation of the visual aesthetic quality of the on-water sightseeing landscape and the landscape feature system at different river scales. For large-scale river on-water sightseeing, the landscape quality was mainly influenced by environmental naturalness, the visual proportion of vegetation, and visual landscape

richness. The Guilin characteristic Karst landform greatly improved the visual satisfaction of the public during large-scale river on-water tours. For small-scale rivers, the landscape quality was generally influenced by the proportion of destructive elements, environmental naturalness, mountain visibility and vegetation visual proportion.

At this stage, this research has the following shortcomings: (1) the limitations of photo perspective. This study was carried out from a perspective parallel to the river, without looking at the river bank. In subsequent research, the on-water landscape research will be carried out in four directions: front and back, left and right; (2) in this research, landscape features were extracted from the physical composition features of the image. In subsequent research, we could continue to deeply explore on other visual influencing factors, such as color in similar landscape features.

The development and landscape improvement of on-water sightseeing routes not only enhances the ecological value of urban rivers, but also improves the corresponding cultural service function. The continuity of the natural landscape and the changes of the elements of landscape composition are key to improving the on-water landscape of large-scale rivers. For small-scale rivers, the cleanliness of the landscape, the enhancement of the natural element proportion, and the improvement of the landscape quality of artificial elements are crucial factors to improve the on-water landscape of small-scale rivers.

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