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Article

Optimization Study of Greening and Ecological Effect in Public Space Based on Big Data Analysis

Liang Wei *

Hefei University of Economics, Hefei 230000, Anhui, China; LIANG_HMILY@163.com

Abstract: People are paying increasing attention to urban environmental quality issues. Future urban competition will not be about speed, height, or scale; instead, concepts such as green, ecological, low-carbon, and sustainable development will be the themes of future urban development. This article analyzes the ecological effects of public green spaces, examines the mechanisms of green space elements, and proposes strategies for creating green public spaces. Taking the public space greening environment of the Pearl River Delta as the research object, this study constructs a public space greening information extraction model based on an improved SRResNet network and a global-local cross-attention mechanism. The model's effectiveness is validated through a dataset, and the optimization effects, ecological effects, and green view rate satisfaction of public space green spaces are analyzed using the SD method and correlation analysis. The results show that the overall accuracy and Kappa coefficient of this model are 93.75% and 0.92, respectively, which are superior to those of the comparison algorithms. The average SD score for public space greening in the Pearl River Delta is 2.47, indicating that the overall ecological effects of public space greening are good, and a green visibility rate of over 29% can significantly improve residents' satisfaction.

Keywords: SRResNet; attention mechanism; SD method; public space greening; ecological effects

1. Introduction

As urbanization accelerates, cities continue to expand in size and population, presenting numerous challenges for urban public spaces [1]. Firstly, the area of urban public spaces has relatively decreased, making it difficult to meet residents' growing needs for leisure, entertainment, and social interaction [2]. Secondly, due to the rapid development of urbanization, urban public spaces are often surrounded by high-rise buildings, creating a “concrete jungle” landscape lacking natural elements and ecological ambiance [3-4]. Additionally, urban public spaces also suffer from issues such as unreasonable planning, single-function design, and poor environmental quality, severely impacting residents' quality of life and the city's sustainable development [5]. Ecological greening, as an important component of urban public spaces, can improve the urban environment, enhance air quality, reduce noise pollution, provide residents with a comfortable and healthy living environment, and enrich urban landscapes, enhance the city's aesthetic appeal, and elevate its image [6-8]. Additionally, ecological greening can promote biodiversity, protect the urban ecological environment, and lay the foundation for the city's sustainable development.

Urban public spaces are important venues for citizens' daily lives, and their environmental quality directly affects citizens' physical and mental health and quality of life [9]. Ecological greening, by introducing green vegetation and natural landscapes, can significantly improve air quality in urban public spaces and reduce air and noise pollution. Empirical analyses by Mata et al. indicate that small-scale ecological greening initiatives can bring about significant positive ecological changes in a short period of time, helping to mitigate the negative impacts of urbanization [10]. Hartig and Kahn Jr. emphasize the importance of integrating natural ecological greening into urban design and infrastructure, noting that natural elements can alleviate ecological stress and improve public health, while also advocating for smart city projects to promote sustainable development [11]. Additionally, Irfeey's research indicates that green plants can regulate urban microclimates, mitigate the urban heat island effect, and create a more comfortable and pleasant living environment for residents [12].

As urbanization accelerates, urban ecological diversity faces severe challenges [13]. Ecological greening design, by introducing diverse plant communities and landscape elements, can enrich the biodiversity of urban public spaces. This not only enhances the stability and resilience of urban ecosystems but also provides residents with a more diverse ecological experience [14-15]. Fahim et al. studied plant species diversity in urban road greening, examining the impact of ecological greening on biodiversity patterns, environmental effects, and diversity indices in urban public spaces, with the aim of providing reference guidelines for urban plant community development and ecological impact improvement [16]. Maclvor et al. integrated green infrastructure into urban planning, noting that understanding evolutionary relationships among plant species can enhance ecosystem functions such as urban cooling, habitat creation, and stormwater management [17]. Additionally, diverse plant communities provide habitats and food sources for wildlife such as birds and insects, promoting the restoration and protection of urban biodiversity [18].

With the development of cities, the conflict between building land and urban green space land has become increasingly acute, and the public has become increasingly concerned about the greening of public spaces. This article first analyzes the ecological effects of public space greening and explores the mechanisms of interaction between the constituent elements of public green spaces, thereby proposing strategies for the creation of public green spaces. Taking the Pearl River Delta as the research object, an information extraction model for public space greening is constructed by combining an improved SRResNet and a global-cross attention mechanism. The effectiveness of the creation strategies and extraction model is validated through analysis, aiming to explore further optimization of public space greening creation strategies.

2. Strategies for Creating Green Public Spaces

Rapid urbanization has led to the deterioration of the ecological environment, affecting people's working and living environments. Therefore, it is necessary to adopt appropriate urban public space greening models under limited land conditions to achieve ecological optimization in various types of urban public spaces. Urban public space greening is developing in a globalized, diversified, and legalized direction, which has a positive impact on the development of urban public space greening construction.

2.1. Ecological Effects of Public Green Spaces

2.1.1. Ecological Effects of Greening Public Spaces

(1) Increase urban greening rates. With the emergence of slogans such as “Forest City” and “Garden City” aimed at improving urban environments, residents living in cities have begun to aspire to a beautiful urban environment as an ideal way of life. According to data from the United Nations Environment Programme (UNEP), the greening area of a living environment must reach 50 square meters to provide a sense of comfort, but this standard is difficult to achieve in many cities.

(2) Improve the microclimate around buildings. The implementation of vertical greening in urban public spaces reduces radiation, regulates temperature, and slows wind speed, playing a significant role in regulating the urban microclimate. It effectively reduces temperature fluctuations on building facades, helping them maintain a relatively constant temperature.

(3) Sound insulation and noise reduction. In environments with high noise levels, vertical greening on walls acts like sound-absorbing material to block the propagation of sound waves. When noise waves hit the plants, most of the sound waves are reflected by the plant surfaces, thereby reducing the impact of noise.

(4) Reducing light pollution. In urban public spaces, the leaves of plants can effectively reflect light, reducing light radiation and minimizing light pollution in the urban environment. This not only ensures a good living environment for urban residents but also alleviates visual fatigue for drivers, thereby helping to prevent traffic accidents.

2.1.2. Mechanism of Action of Green Space Elements

According to the “Classification Standards for Urban Green Spaces” approved by the Ministry of Housing and Urban-Rural Development, the primary statistical indicators for assessing urban greening levels are green space ratio, per capita green space area, per capita park green space area, and urban-rural green space ratio. However, urban areas are subject to various restrictive conditions, and relying solely on the above indicators for quantification often fails to comprehensively assess the actual green space conditions of a city. This paper conducts case studies on high-density urban areas in selected cities and concludes that green spaces in high-density urban areas are primarily composed of two-dimensional green corridors (linear), green patches (areal), micro-green spaces (point-like), and three-dimensional vertical greening.

Based on the ecological effects of public space greening, its constituent elements primarily include green corridors, green patches, micro-green spaces, and vertical greening. The mechanisms of action for these constituent elements are illustrated in Figure 1. By leveraging these constituent elements, it is possible to establish an effective system structure, patch together a green space network, and create visual greening.

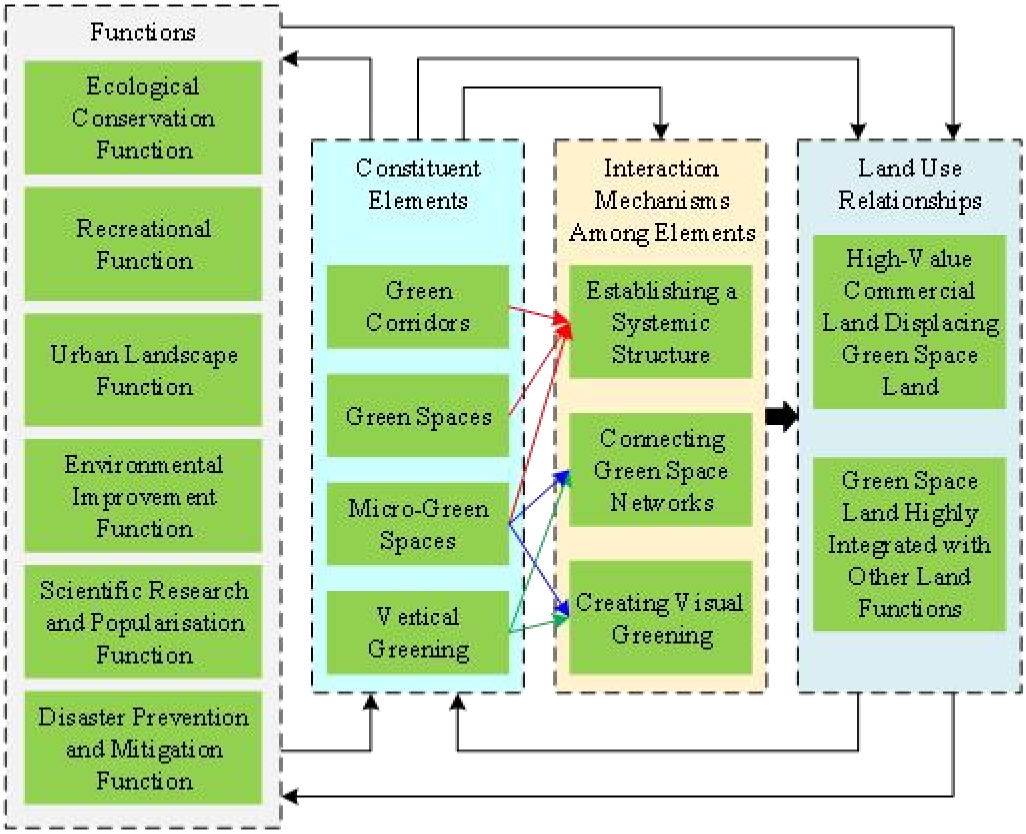

Figure 1. The mechanism of action of green space elements.

2.2. Strategies for Creating Public Green Spaces

2.2.1. Strategies for Improving Greenery in Public Spaces

In the context of accelerated urbanization, people find it difficult to express their affinity for the natural environment, let alone enjoy a healthy lifestyle in an environment with fresh air and the fragrance of flowers. Therefore, when designing public space greening, we must not overlook the planting of greenery. Through such design, we aim to fulfill people's desire for nature to be present in their living spaces, thereby creating a healthy natural green space for them.

(1) Greening forms. The forms of street greening should be reasonably arranged. Greening primarily involves horizontal planting and vertical planting. In public spaces oriented toward health, greening forms mostly adopt horizontal planting, with a small portion of vertical greening. Generally, in resting areas and places with high foot traffic, horizontal planting is often used, followed by vertical planting. This not only provides shade for people but also beautifies the lower interface of the street space, making people feel happy and relaxed when engaging in activities.

(2) Ecological Design. When designing plant arrangements, it is essential to follow the ecological habits of plants. In the space, native plants are primarily used to preserve their natural appearance and processes, satisfying people's recognition of native plants and subtly instilling a sense of security.

Additionally, after understanding the site-specific characteristics of plants, some exotic species can be introduced to enrich the landscape of the space.

(3) Types of greenery. Plant types primarily include evergreen trees, deciduous trees, evergreen shrubs, deciduous shrubs, herbaceous plants, and vine plants. When planting greenery in street spaces, selections should be made after comprehensively analyzing the plant types and their ecological characteristics.

2.2.2. Optimization Strategies for Public Space Elements

(1) Optimization of three-dimensional greening composition. In the early stages of three-dimensional greening, climbing plants were mainly used to create natural landscapes through their natural growth patterns. However, with the continuous development of planting and construction technologies, the forms of three-dimensional greening have become more diverse and rich, with various new forms emerging one after another. Currently, in the design of vertical greening layouts, we are no longer limited to natural-style layouts. We can utilize various new technologies and planting methods to select different types of layouts. Specifically, we can design based on the different functional uses of carriers within public spaces and their surrounding environments.

(2) Color coordination optimization. In public space vertical greening design, color has a stronger visual impact than form. Color is a key element in achieving the desired landscape effect, and appropriate color design can effectively enhance landscape quality. Vertical greening color design is a process of seeking unity in diversity. The colors of vertical greening should harmonize with the surrounding environment, while also considering coordination with the overall environment of the urban public space.

(3) Material texture coordination optimization. In the design of vertical greening in public spaces, the texture and texture of plants and vertical greening carriers should be reasonably coordinated to improve the integration of plant and carrier textures. The design of vertical greening in terms of texture mainly involves two elements: the texture of the plants themselves and the material of the vertical greening carriers.

(4) Coordination based on the growth cycle of plants. The seasonal cycle enables plants to exhibit periodic styles in terms of color and form. Considering that plants produce different landscape effects with seasonal changes, it is necessary to reasonably coordinate plants with different growth cycles during design. Specifically, annual plants can be coordinated with perennial plants, seasonal deciduous plants with evergreen plants, and plants with different flowering periods. This approach ensures the sustained effect of vertical greening landscapes.

3. Extraction Model for Public Space Greening Information

Public space greening, as a new approach to urban greening, plays a crucial role in beautifying the environment and creating a healthy ecological environment. To further analyze the distribution of green space greening information after optimizing public space greening designs, this paper introduces deep learning technology to construct a public space greening information extraction model, providing an intuitive data foundation for optimizing public space greening designs.

3.1. Overview of the Study Area and Data Sources

3.1.1. Selection of Research Areas

The Pearl River Delta is located in the southeastern part of Guangdong Province, adjacent to the mouth of the Pearl River, and across the sea from Southeast Asia. Its advantageous coastal geographical location makes it a gateway for southern China's opening to the outside world, as well as a key region for China's participation in economic globalization. It is one of the most dynamic economic zones in China and the Asia-Pacific region. The Pearl River Delta urban agglomeration, which leads China's reform and development efforts, is one of the “three major urban agglomerations in China,” alongside the Beijing-Tianjin-Hebei urban agglomeration and the Yangtze River Delta urban agglomeration. It is a priority development region at the national level. The broader Pearl River Delta region encompasses nine cities in Guangdong Province (Guangzhou, Shenzhen, Foshan, Dongguan, Zhongshan, Zhuhai, Jiangmen, Zhaoqing, and Huizhou), two special administrative regions (Hong Kong and Macao), and the Shenzhen-Shanwei Special Cooperation Zone.

This study focuses on the core cities of the Pearl River Delta urban agglomeration, including Guangzhou, Shenzhen, Foshan, Dongguan, Zhongshan, Zhuhai, Jiangmen, Zhaoqing, and Huizhou, totaling nine cities. As the core economic hub of southeastern China, the Pearl River Delta urban agglomeration exhibits robust economic growth and significant urbanization trends. In terms of topography, the Pearl River Delta Urban Agglomeration features significant elevation variations, with plains primarily distributed in the central region, mainly located south of Guangzhou City, east of Jiangmen City, north of Zhongshan City, and west of Dongguan City. The surrounding areas are characterized by hills, mountains, and islands.

3.1.2. Data Sources and Platforms

The medium-resolution remote sensing imagery used in this study was obtained from the Geospatial Data Cloud website. The data selected for this study consists of imagery from the Gaofen-1 satellite covering the Pearl River Delta urban area from May 1, 2018, to December 30, 2024. Through the fusion of multispectral and panchromatic imagery, multispectral imagery data with a resolution of 1.5 meters was obtained, which was used for object-oriented information extraction and land cover status analysis. Elevation data covers the entire globe, encompassing all countries and regions worldwide, and is available for free download from the website. The vertical error of the elevation data is less than 15 meters, and no-data values may appear in major water body areas. All vector data used in this study were downloaded from the Harvard University China Historical GIS (GHGIS) database. The CHGIS project aims to establish a database of basic geographic information systems for China's historical period. This database is based on GIS technology, which maps historical geographic information to modern spatial locations. It expresses the spatial distribution of this basic geographic information and its changes over time, while providing users with the simplest data query, retrieval, data mapping, and user data connection functions.

The software used in this study includes the ENVI remote sensing image processing platform, the eCognition Developer image processing system, the Fragstats landscape index calculation software, the ArcGIS geographic information desktop processing system, Matlab, and the SPSS statistical analysis software.

3.2. Construction of a Greening Information Extraction Model

3.2.1. Improving the SRResNet Structure

In research on image information extraction based on deep learning, deeper network structure models can achieve higher-quality extraction results. However, as the number of model layers increases, the model becomes increasingly unable to converge effectively, often failing to achieve the desired results. Deep Residual Networks (ResNet) incorporate residual learning modules into convolutional neural networks, effectively addressing the issues of accuracy degradation and gradient vanishing in deep networks. This allows for a significant increase in the number of network layers while maintaining accuracy. Deep Residual Networks define the mapping relationship learned at each layer as:

$$H(x) = F(x) + x \tag{1}$$

In the equation, x represents the original input image, $H(x)$ represents its expected predicted value, and $F(x)$ represents the residual function. In other words, the original input is added at the end of each layer, and as the number of layers increases, $F(x)$ tends toward 0 or a relatively small value.

In this case, even as the number of layers increases, the training error is kept within a small range, preventing the model from diverging during training.

The SRResNet deep learning model is a network structure for image information extraction based on SRCNN, incorporating a residual learning network structure. The SRResNet model takes low-resolution images as input and outputs reconstructed high-resolution images. The main body of the model consists of six residual modules, each containing three convolutional layers, three BN layers, and one PreLU activation function, with three sub-pixel convolutional layers used to increase the feature map size. In addition to the main deep residual modules and sub-pixel convolution modules for enlargement, a convolutional layer is added at the beginning and end of the entire model for data adjustment and enhancement. The BN layer is a crucial component in deep learning, significantly increasing training speed and preventing overfitting.

3.2.2. Global-Local Cross Attention

Although SRResNet can quickly capture global features, its limitation lies in its inability to fully capture local details, neglecting the subtle differences in local regions that are critical for classification. Especially in the task of extracting green space information in public spaces, the absence of these local details severely limits the representational ability of global features, and relying solely on global features for extracting green space information in public spaces significantly reduces classification performance. To address this issue, this paper innovatively proposes a Global-Local Cross-Attention Module (GLCAM). The core mechanism of this module lies in calculating the interactive information between coarse-grained global features and fine-grained local features, and utilizing this interactive information to enhance the expressive capability of global features. Through this approach, global features not only retain the overall structural information of the image but also integrate the subtle differences and detailed features of local regions, thereby enhancing the representational capability of coarse-grained global features.

First, different linear transformations are performed on the global feature $\tilde{Z}_L \in \mathbb{R}^{(n+1)\times d}$ and the local feature $Z_{L'} \in \mathbb{R}^{(N_{fine}+1)\times d}$ at the fine-grained level. yielding the query $Q_1 \in \mathbb{R}^{(n+1)\times d_k}$, the key $K_1 \in \mathbb{R}^{(N_{fine}+1)\times d_k}$, and the value $V_1 \in \mathbb{R}^{(N_{fine}+1)\times d_k}$. That is:

$$Q_1 = \tilde{Z}_L W_{Q_1}, K_1 = Z_L' W_{K_1}, V_1 = Z_L' W_{V_1} \tag{2}$$

Among these, $W_{Q_1} \in \mathbb{R}^{d\times d_k}$, $W_{K_1} \in \mathbb{R}^{d\times d_k}$, and $W_{V_1} \in \mathbb{R}^{d\times d_k}$ are all learnable weight matrices, where $d = H \times d_k$ and H denotes the number of attention heads. The output $head_i \in \mathbb{R}^{(n+1)\times d}$ under the ith head is calculated as follows:

$$head_i = soft\max\left(\frac{Q_i K_i^T}{\sqrt{d_k}} + E_{pos}^1\right) V_i \tag{3}$$

where $E_{pos}^1 \in \mathbb{R}^{(n+1)\times(N_{fine}+1)}$ is the relative positional embedding that can preserve the positional information of features.The outputs under multiple heads are combined before the final linear transformation to obtain the fused global feature Z_L, i.e.,:

$$Z_L = \tilde{Z}_L + Concat\left(head_1, \cdots, head_H\right) W^O \tag{4}$$

where $W^O \in \mathbb{R}^{d\times d}$ denotes the learnable weight matrix.

3.2.3. Greening Information Extraction Models

In this study, a CAMRNet model for urban green space information extraction is proposed, which chooses to use the SRResNet model as the backbone architecture of the network, i.e., an encoder-decoder structure combining deep and shallow semantic information in order to realize a smooth transformation from image to segmentation mask.In order to enhance the feature extraction capability of the network, the idea of global-local cross-attention mechanism is also introduced.The network structure of CAMRNet is shown in Fig. 2, which can be divided into three parts, i.e., the encoder, the hopping connectivity module incorporating the global-local cross-attention mechanism, and the decoder.

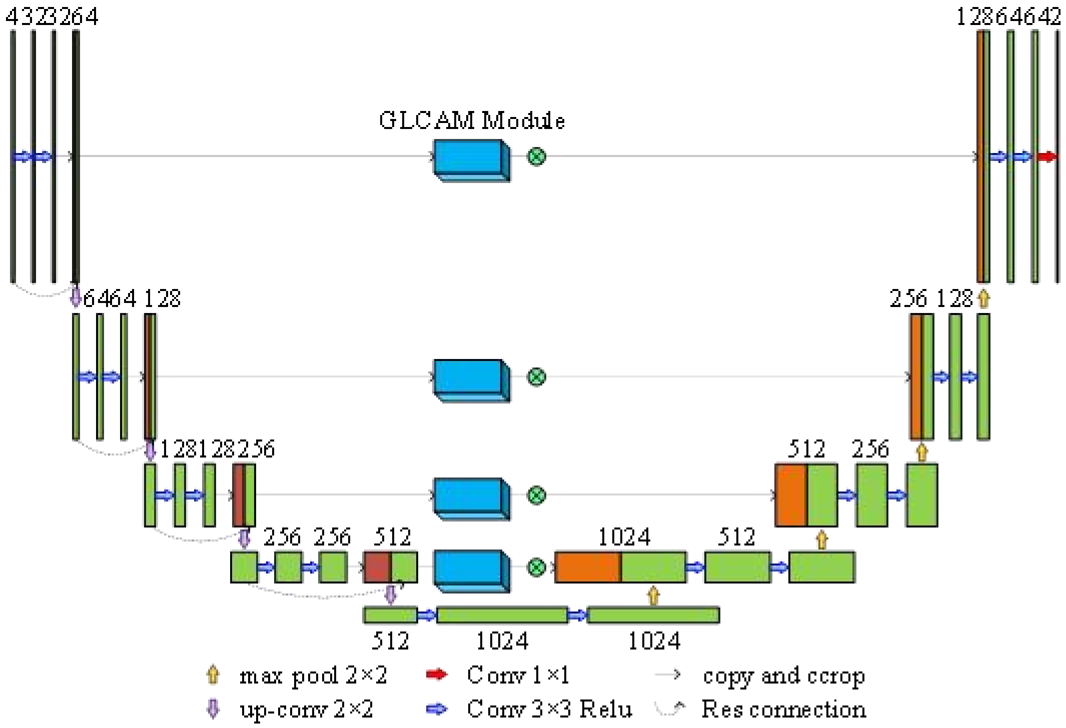

Figure 2. Greening information extraction model.

In the encoder part, the building blocks of each layer in the original ResNet model are replaced with improved convolutional residual modules in order to eliminate the phenomena of gradient vanishing and explosion, which are prevalent in deep neural networks, and to make the forward and backward propagation of information smoother.Each layer of the encoder contains a maximum pooling layer after it, in addition to the residual structure proposed in this paper.The size of the convolution kernel in the convolutional layer is 3×3, followed by a BN layer and a ReLU, and the role of the max-pooling layer is to downsample the feature maps output from each layer to half of the original size.After the original image passes through the building blocks of each encoder, the number of channels for the input features will become twice the original number and the size of the feature map will be halved.The feature map passes through each layer in the encoder in turn, completing the extraction of deep features in the image.

The structure of the decoder part is similar to that of the encoder, but the residual structure is not used, while the maximum pooling layer is replaced with an upsampling layer for feature reconstruction to generate segmented images.Here, the choice is made to utilize bilinear interpolation for up-sampling, which ultimately restores the feature map to the same size as the original image resolution.In each decoder building block, the upsampling rate is set to 3 in order to ensure that the output feature map has the same size as the output of the encoder.

In the jump connection part, in order to better utilize the information of multi-resolution feature maps, the jump connection structure of the SRResNet network is improved to include the global-local cross-attention mechanism, which strengthens the useful greenfield features and suppresses the ineffective background features in the channel dimensions, and thus improves the computational efficiency of the network model.And then, the output of this part is connected with the output of the previous layer of the decoder and fed into the decoder of the current layer.The final features input to the decoder part via the attention mechanism in the jump connection are expressed as Eq:

$$D_i = F_{conv}(F_{up}D_{i+1}) + \lambda_{weight}E_i \tag{5}$$

where D_i is the hidden feature at the i th layer of the decoder part, D_{i+1} is the hidden feature at a lower level of D_i , F_{up} stands for the up-sampling operation, and F_{conv} represents the convolution operation.This method of increasing the resolution of convolutional features provides finer features for segmentation at the edges and avoids the checkerboard effect.

4. Extraction and Analysis of Greening Information in Public Space

China's urbanization process has been accelerating after the 21st century, and with it comes environmental degradation.Resource shortages and various urban problems have arisen one after another.Urban land tension, traffic congestion, high population density, the urban heat island effect is increasing, and the environmental carrying capacity has reached an unprecedented load.Faced with various challenges, various urban planning trends and movements have emerged. In China, with the development of the economy, people pay more and more attention to the ecological environment, and the green movement is developing vigorously.

4.1. Verification of the Effectiveness of Green Space Information Extraction

4.1.1. Comparison with Other Networks

The training environment in this study uses Python programming language, and the GPU is NVIDIA RTX 3090Ti-8GB. The deep learning framework is PyTorch. the SRResNet model is trained with fixed random seeds to ensure the reproducibility of the experiments, and the main parameters are the learning rate, batch size, and the number of rounds.Among the training parameters, the initial learning rate is set to 10^{-5}, the learning rate decrease factor is 0.1, the batch size is set to 5, and a total of 50 rounds of training are performed.In order to avoid model overfitting, the experiment adds an early termination operation, i.e., training is stopped after 20 rounds if the accuracy is not improved.

In this paper, five metrics are selected to evaluate the accuracy of the model: overall accuracy, mean intersection and merger ratio (mIoU), frequency weight intersection and merger ratio (FWIoU), number of parameters, and average number of frames.The overall accuracy represents the ratio of all correctly categorized pixels to the total pixels, the IoU is obtained by calculating the ratio of the intersection area and the concatenation area of the real and predicted regions, the mIoU is the result of summing and averaging the intersection and concatenation ratios of each category, and the FWIoU is set up with weights based on the frequency of each category, which is multiplied by the IoU of each category and summed up.The number of parameters (Para) is a measure of the volume of the model, the smaller its value represents the lighter the model, and the average number of frames (AFN) is an indicator for evaluating the speed of the model, which specifically means the number of images per second of inference, and the larger the value represents the faster the model is extracted.

The dataset used in this study is not only the self-constructed dataset in the previous section, but also the LoveDA dataset is chosen as a comparison.In order to verify the effectiveness of SRResNet chosen as the backbone network in this paper, PSPNet, HRNet, Deeplabv3 and ResNet are chosen as comparisons.The test set is input into the trained model for testing, and the test results of different networks in the self-built dataset and LoveDA dataset are obtained as shown in Table 1 and Table 2, respectively.

In the self-constructed dataset, the models with the highest overall accuracy, mIoU, and FWIoU are all SRResNet networks, which are ahead of the other four networks by different margins.The model with the lowest number of parameters and the highest average frame rate is still SRResNet. compared to the original ResNet network, SRResNet improves the overall accuracy, mIoU, and FWIoU by 0.61%, 1.31%, and 0.63%, respectively, and reduces the number of parameters by 76.84%, and improves the average frame rate by 2.93 times.The highest overall accuracy on the LoveDA dataset is Deeplabv3 (90.27%), which is 0.03% higher than the model in this paper. mIoU, FWIoU, and the model with the highest average frame rate are all SRResNet, with the same number of parameters.Compared to the original ResNet network, there is an improvement of 0.23%, 0.74%, 0.36% on the overall accuracy, mIoU, FWIoU, and 2.78 times on the average frame rate, respectively.With high overall accuracy and low mIoU and FWIoU, the model is relatively worse at extracting urban green space and relatively better at extracting non-urban green space.In the LoveDA dataset, although the overall accuracy of Deeplabv3 is slightly higher than that of SRResNet, SRResNet is better at extracting urban green spaces because SRResNet's mIoU and FWIoU are higher than Deeplabv3.The test results of both datasets show that SRResNet ensures the extraction accuracy while significantly reducing the number of parameters, providing an improved idea and method for the urban green space extraction task to improve the accuracy and speed.

Table 1. Test results of the self-made dataset.

Model	Precision/%	mIoU/%	FWIoU/%	Para/M	AFN/fps
PSPNet	94.37	77.85	88.93	46.72	58.98
HRNet	94.78	80.12	90.58	9.65	80.13
Deeplabv3	95.69	83.34	92.69	54.76	46.52

ResNet	95.81	83.76	92.64	30.14	33.06
SRResNet	**96.42**	**85.07**	**93.27**	**6.98**	**96.94**

Table 2. Test results of the LoveDA dataset.

Model	Precision/%	mIoU/%	FWIoU/%	Para/M	AFN/fps
PSPNet	90.12	73.42	81.89	46.72	46.12
HRNet	90.05	73.67	81.97	9.65	74.83
Deeplabv3	**90.27**	74.05	82.53	54.76	38.95
ResNet	90.01	74.64	82.69	30.14	30.42
SRResNet	90.24	**75.38**	**83.05**	**6.98**	**84.51**

4.1.2. Extraction Effects of Different Models

In order to further illustrate the reliability and accuracy of the CAMRNet model designed in this paper, the maximum likelihood method (LR), the minimum distance method (MD), the object-oriented method (Obj), the support vector machine method (SVM), and the decision tree (DT) classification method are selected for the comparative experiments of the experimental region based on the self-constructed dataset of this paper.The overall accuracy and Kappa coefficient are selected as the evaluation indexes, and the comparison of the extraction results of different methods is obtained as shown in Fig. 3.

As can be seen from the figure, the maximum likelihood method can extract the green space information, but it is easy to recognize it as construction land, and there are more misclassification and omission phenomena, and the classification accuracy and Kappa coefficient are only 71.24% and 0.62, respectively, which are the lowest accuracy, the largest error, and the most serious misclassification and omission phenomena among the methods used in the experiment.Compared with the maximum likelihood method, the minimum distance method significantly reduces the misidentification phenomenon in the construction land, with an accuracy of 75.38%, which is 4.14% higher than the maximum likelihood method, and the Kappa coefficient is also improved, but it is easy to incorrectly identify the swamp as an artificial wetland, and part of the fine river water bodies are not recognized.The extraction accuracy of object-oriented method is 84.41%, which is significantly improved compared with maximum likelihood method and minimum distance method, the extraction accuracy is greatly improved, and it can extract most of the water bodies, and the misclassification phenomenon of artificial wetland is reduced, and the classification accuracy of greenland information is better, and there exists a small amount of misclassification and omission phenomenon, but marshes are easy to confuse and difficult to differentiate from water bodies.The accuracy and Kappa coefficient of green space information classification result of support vector machine are 86.17% and 0.82 respectively, and its classification accuracy is close to that of object-oriented method.The classification result accuracy of decision tree classification method reaches 89.52%, the overall classification accuracy improves 18.28 percentage points compared with maximum likelihood method, and the Kappa coefficient improves 0.23 compared with maximum likelihood method, while the overall accuracy and Kappa coefficient of this paper's method are 93.75% and 0.92, respectively, and compared with the other five algorithms, the green space information extraction result of this paper's model is obviouslybetter, with the highest overall classification accuracy and Kappa coefficient.

Therefore, this paper introduces deep learning technology into the extraction of green space information in public space, which can provide data support for the optimization of green space in public space, so as to formulate the optimization strategy of green space in public space that is more in line with the actual situation in the region.

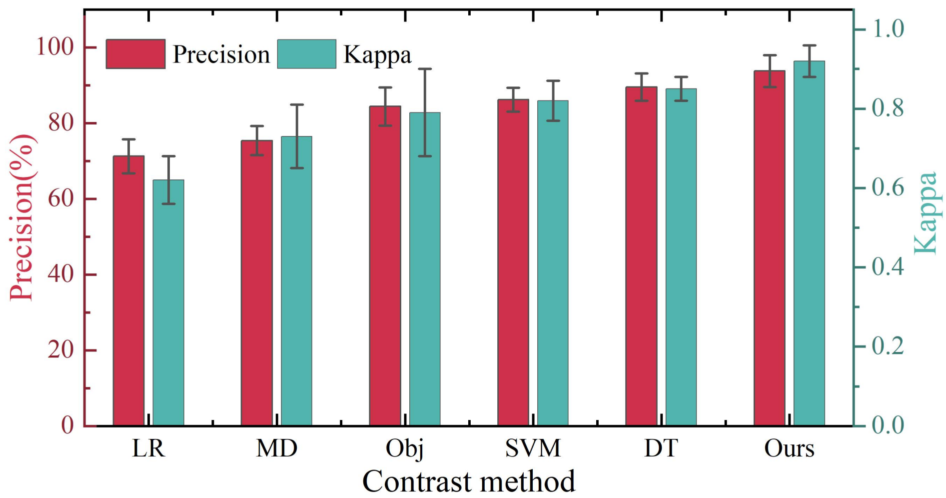

Figure 3. The extraction results of different methods.

4.2. Optimization Effect of Green Space in Public Space

4.2.1. Greening the SD Evaluation Curve

In the research process of public space greening, in order to further enhance the objective accuracy of the research results, the data obtained from the research are usually analyzed by questionnaire survey method and semantic analysis method combined with mathematical statistics.The questionnaire survey method is that in the early stage, after the researchers have a clear understanding of the characteristics of the research object in general, the corresponding questionnaire content is designed and distributed to the respondents for measurement.Finally, the researchers collect and summarize the questionnaires and analyze the data to finally get the users' evaluation of the spatial environment.

In order to come up with a more accurate design optimization strategy for greening suitability of public space in the Pearl River Delta, it is necessary to go further and conduct specific evaluation and analysis as well as more detailed investigation of each area, therefore, the SD method is chosen for the analysis.Before the evaluation of SD method, the investigator needs to extensively collect a large number of adjective pairs describing the characteristics of the pictures.At present, the number of adjective pairs used in SD method evaluation is not specified, and the sample size varies from study to study, but there are certain principles for their selection.When selecting adjective pairs, try to choose familiar words and word pairs with obvious positive and negative semantics.

Based on the summary of existing related studies, this study identifies 12 pairs of descriptive adjectives, whose evaluation factors are sense of scale, leisure facilities, functionality, building materials, cultural expression, memorability, paving treatment, water features, green plants, sense of light, sense of color, and interestingness, which are denoted as L1~L12, respectively.These 12 pairs of descriptive adjectives are mainly centered on the scale, leisure facilities, distribution, color culture, architectural detailing, and the distribution of leisure facilities, color culture, and architectural detailing in public space environments.distribution, color culture, architectural detailing, surrounding landscape, and other aspects of the public space environment, and set up a 5-level evaluation mechanism for the respondents, and assigned scores of -4, -2, 0, 2, and 4 to each level, in order to represent the different levels of perception of the space by the respondents.

The data obtained this time were mainly obtained through the Questionnaire Star questionnaire, and the questionnaire was released through the network, and finally 121 valid questionnaires were obtained.Excel software was used to organize and count the questionnaire data on the greening of public spaces in the Pearl River Delta, and to calculate the comprehensive average of the evaluation factors of the greening of public spaces in the Pearl River Delta.The specific results are shown in Figure 4.

The basic situation of greening of public space in the Pearl River Delta can be visualized through the comprehensive evaluation SD scores. The scores of the 12 evaluation factors are all greater than 0, and the overall mean is 2.47, indicating that the evaluation of greening of public space in the Pearl River Delta at this stage comprehensively belongs to the range between average and better.Among them, the score of paving treatment (L7) is low (1.81) compared with other factors, indicating that the overall paving treatment in the greening process of public space is relatively lacking or the landscape is poor, and the design needs to be strengthened.Light sense (L10) has the highest score (3.19), indicating that the greening strategy for public spaces in the Pearl River Delta can effectively distribute light and create a good ecological effect.In addition, the scores of sense of spatial scale (L1), spatial functionality (L3), and greening plants (L9) are higher than 0 but lower than the other factors, which also indicates that the greening of public spaces in the PRD needs to be strengthened in these three areas.

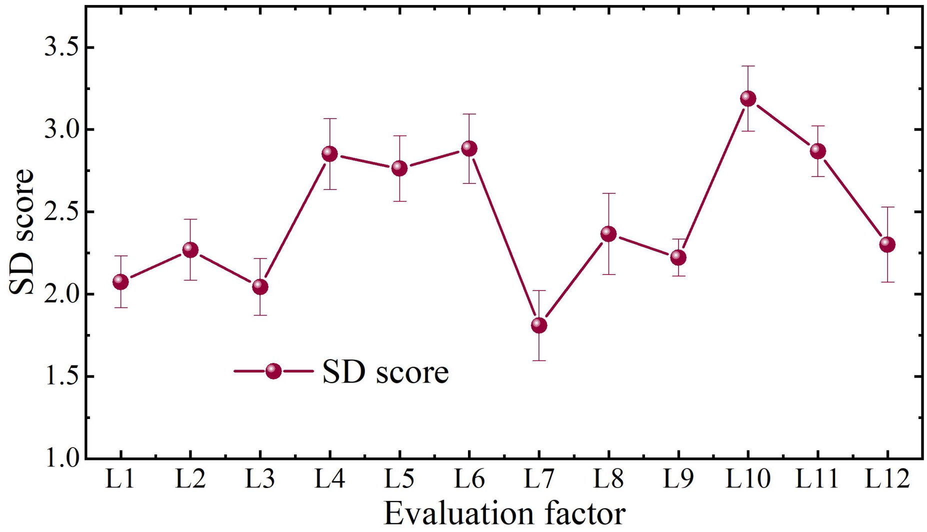

Figure 4. Average value of comprehensive evaluation.

4.2.2. Ecological Effects of Green Space

Based on the greening strategy for public space creation in the Pearl River Delta given in the previous section, this paper further investigates the changes in its ecological effects.The thermal environment data of public space greening are collected from the temperature of the building facade by an integrated thermohygrometer produced by Company D. The air negative ion content of vertical greening and bare walls is collected by a KEC air negative ion detector.In the public space greening creation strategy designed in this paper, it mainly includes five structures (S1~S5): tree-shrub-grass, tree-grass, tree, shrub-grass, and hard paving, then the temperature trend of public space greening under different structures is shown in Fig. 5, and the results of the comparison of the average maximum and minimum temperatures are shown in Table 3.The relative values in the table are based on the observed values of hard paving (S5), and the same as later.

As can be seen from the figure, the overall temperature change trend of the five types of public space greening measures is similar to that of the ambient temperature.Among the four types of greening strategies with plants, the greening consisting of shrub-grass (S4) exhibits the most pronounced daily temperature change, with the temperature gradually increasing with time, from 12.1°C to 18.1°C in the morning from 8 to 12:00 a.m., and reaching 19.5°C in the high-temperature period (14:00 a.m.).This is mainly because the green space composed of shrub-grass is open and less shaded, which is favorable for water evaporation, and it is highest at high temperature and lower at low temperature, which has a weak ability to mitigate changes in the external environment.Arbor-shrub-grass, arbor-grass and arbor-type street green space temperature changes are more moderate, this is because there are trees in all three sites, shading, as well as strong transpiration so that the temperature in the green space environment at high temperatures lower than the shrub-grass type, and due to the protective layer formed by the arbor crowns, the external environmental changes by a certain mitigation capacity, the environment within the green space is relatively stable.The space of hard-paved type is not shaded by trees, receives more light, and the temperature rises faster.The temperature was 11.6°C at 8:00 p.m. and reached 18.4°C at 12:00 p.m. In the evening, because the ground loses heat faster than the green space with greenery, the temperature dropped to 16.3°C, which is the lowest temperature among the five greening strategies.Taking the high temperature period (14:00) as an example for comparison, the temperature of the five types of green space showed a trend of hard paving > shrub-grass > arbor-grass > arbor > arbor-shrub-grass, and among the five types of spatial compositions, the temperature of the green space composed of hard paving was the lowest in the morning and evening, with the most significant temperature change during the day, and the weakest effect of regulating the microclimate.Therefore, increasing plant configurations in green spaces in public spaces plays an important role in maintaining the stability of air temperature in street green spaces throughout the day.On a larger urban scale, the ecological effect of multiple public space green spaces that can enhance the urban environment as a whole is even more significant.

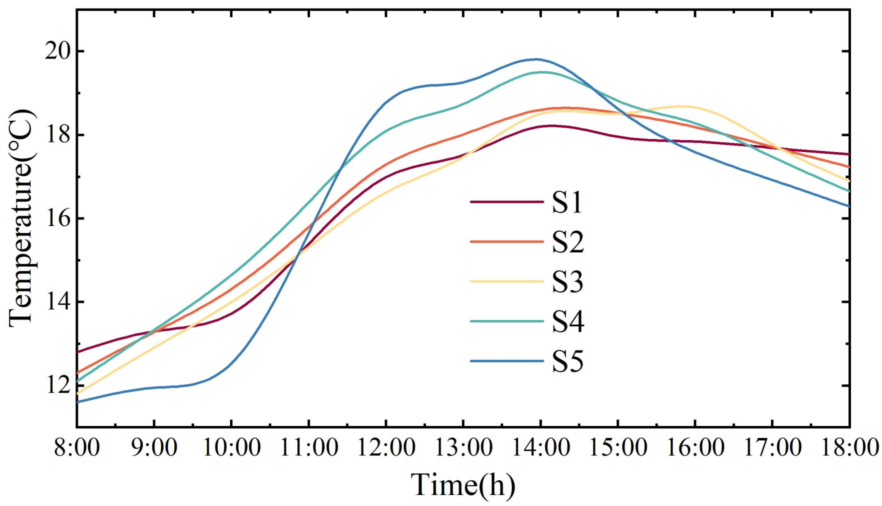

Figure 5. The trend of green temperature change in public space.

Table 3. The comparison results of the average max and min temperatures.

Structure	Max temperatures (°C)		Min temperatures (°C)	
	Observed value	Relative value	Observed value	Relative value
S5	19.8	100.00%	11.6	100.00%
S1	18.2	91.92%	12.8	110.34%
S2	18.6	93.94%	12.3	106.03%
S3	18.5	93.43%	11.8	101.72%
S4	19.5	98.49%	12.1	104.31%

In addition, this paper further conducts statistics for the negative air ions of different types of public space green spaces, and obtains the results of the comparison of the highest and lowest negative ion concentrations of different types of public space green spaces as shown in Table 4.As can be seen from the table, there is a large gap between the highest negative ion concentration and the lowest negative ion concentration of the five different internal composition spaces.The observed values of the highest negative ion concentrations of the arboreal-shrub-grass, arboreal-grass, arboreal and shrub-grass type green spaces were 1314.37, 1305.29, 1511.53 and 1093.48 anions/cm^3 in that order, and the magnitude of the negative ion concentrations compared with those of the hard paved ones reached 152.28%, 151.22%, 175.12%, and 126.69%, respectively.Overall, except for the part of the area without greening, the strongest negative ion concentrations were produced by green spaces composed of trees, followed by tree-grass type, then tree-shrub-grass type, and finally shrub-grass type.There is a difference in the value of negative air ions concentration in space types composed of different plants, the more plants and the greater the degree of depression the higher the negative air ions concentration.Therefore, tree species with large crowns and dense foliage are selected for plant configuration in green spaces in public spaces, such as African mahogany, rubber ficus, and mango in the tree-grass type in the study site.Improvement of air quality as a way to improve the environment.

Table 4. Comparison of the highest and lowest negative ion concentrations.

Structure	Max negative ion concentration (N/cm^3)		Min negative ion concentration (N/cm^3)	
	Observed value	Relative value	Observed value	Relative value
S5	863.15	100.00%	411.23	100.00%
S1	1314.37	152.28%	625.16	152.02%
S2	1305.29	151.22%	552.45	134.34%
S3	1511.53	175.12%	678.39	164.97%
S4	1093.48	126.69%	436.98	106.26%

4.2.3. Green Vision Satisfaction Survey

In this paper, Adobe Photoshop was used for data counting.All the green plants appearing in the image were selected and their percentage of the whole image was calculated as green visibility.The branches of plants and green structures are not included in the selection.The data obtained from 500 images from multiple observation points were entered into an Excel spreadsheet corresponding to the number of the observation point and the average greenness was calculated.

By simulating the observation behavior of human beings, the green visual acuity can more intuitively reflect the value of the visible green at a certain shooting point, and can reflect the relationship between the human visual experience and psychological experience at a certain point.In order to prove and study the specific relationship between the green visibility and human visual and psychological experience, the group selected 10 groups of photos every 10% from low to high according to the average green visibility of the observation point, a total of 100 points, 500 photos for random questionnaire surveys, in accordance with the greening of the public space construction "particularly poor","poor", "average", "good" and "especially good".The scores of all the people were summed up, and each photo finally corresponded to a total score of heart assessment, and its relationship with the average green visibility rate of the observation point was analyzed.The correlation between the total score of residents' satisfaction with the greening construction of public space reflected in the photo groups and the corresponding average green visibility rate of the observation points was analyzed by SPSS software.Figure 6 shows the linear relationship between average green visibility and greening satisfaction.

As can be seen from the figure, there is an obvious positive correlation between the total score of greening satisfaction and the average green visibility (R2=0.843), and it is considered that the total score is greater than 0, which is considered to be a green visibility rate of "qualified" standard.From the curve, it can be seen that the residents believe that the "qualified" green visibility rate should be around 13.5%.When the curve begins to converge and the changes moderate, it can be considered that the green visibility rate has reached the "good" standard, which is about 29.2% of the green visibility rate in the curve.Therefore, when optimizing the greening of public space, focusing on the greening rate higher than 29% can significantly enhance the residents' greening satisfaction and better create a good ecological effect of public space.

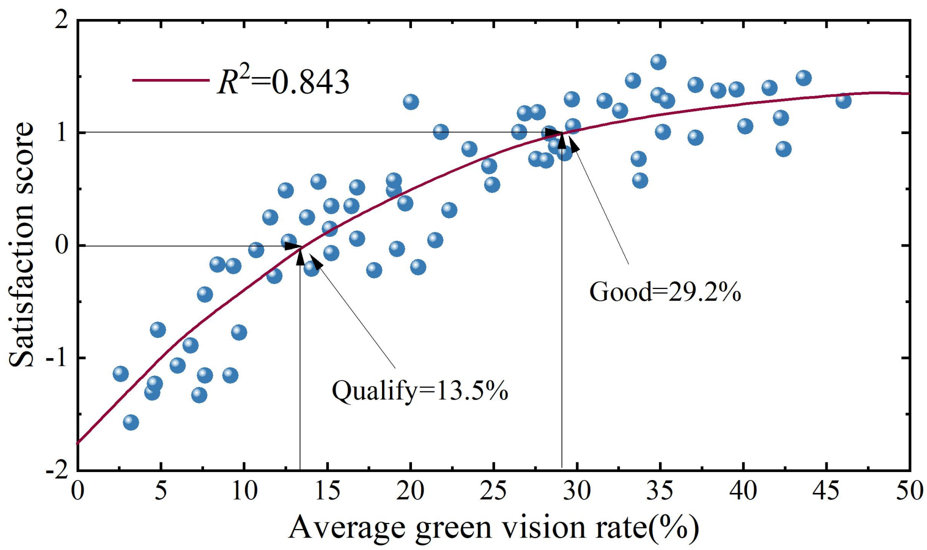

Figure 6. Average green view rate and greening satisfaction.

5. Conclusion

In this study, a public space greening information extraction model was constructed based on deep learning technology, and a public green space creation strategy was constructed to analyze its green space optimization effect.It was found that compared with the original ResNet network, SRResNet improved 0.61%, 1.31%, and 0.63% in overall accuracy, mIoU, and FWIoU, respectively, and the number of parameters was reduced by 76.84%, which can better realize the extraction of greening information in public space.The mean value of SD of public space greening in the Pearl River Delta is 2.47 points, the overall ecological effect of public space greening is good, and the green visibility rate of 29% or more can significantly improve the satisfaction of residents.As a result, when optimizing the greening of public spaces, it is necessary to focus on the consideration of vertical spreading of multiple types of greening plants, so as to better create a good public greening space, and further enhance the satisfaction and happiness of residents.

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