RESEARCH ARTICLE

Spatial layout and functional zoning of ecological gardens based on deep learning

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Ecological gardens are an important component of urban sustainability and environmental conservation, which integrate ecological, economic, and social benefits to enhance the quality of life and biodiversity in urban spaces. The optimization of spatial layout and functional area division within ecological gardens plays a critical role in achieving these objectives. Traditional methods of spatial planning often fail to fully address the complexity and dynamic nature of ecological systems. This study aimed to optimize the spatial layout and functional area division of ecological gardens by combining the recurrent neural network (RNN) in deep learning, especially the long and short-term memory network (LSTM), with a multi-target spatial optimization model. The LSTM model was used to process and predict the temporal data in ecological gardens to capture their time dependence and dynamic changes and integrate these prediction results into the multi-objective optimization model to achieve the comprehensive optimization of spatial layout and functional area division. The results showed that the proposed method could effectively improve the ecological, economic, and social benefits of ecological gardens. In terms of spatial layout optimization, Zone 5 showed the highest land use efficiency of 89% and public satisfaction of 79%, while, in the functional area division, the ecological value index of Zone 5 reached 0.89, and the resource utilization efficiency was 93%, reflecting its outstanding advantages in ecological conservation and resource utilization. By evaluating these key indicators, the validity and utility of combining the LSTM model with the spatial optimization model in ecological garden planning were verified. The results suggested that this proposed method could accurately capture the complex spatiotemporal dynamics in ecological gardens and provide scientific basis and optimization strategies for future garden design and management.

Keywords: deep learning; ecological garden; spatial layout; functional area division.

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Introduction

As an important part of the ecological city construction, the ecological garden not only enhances the service function of the urban ecosystem but also improves the quality of life of the residents. With the acceleration of the urbanization process, the traditional garden design method has been difficult to meet the needs of sustainable development, so it is particularly important to explore the new strategy of garden spatial layout and functional area division. The deep learning-based method can process a large number of complex geographical and environmental data and provide more accurate garden design solutions, which is of great significance for optimizing the ecological function of gardens, improving the efficiency of resource utilization and enhancing ecological resilience. Through the introduction of intelligent technology, automation and precision can be realized in garden planning and management, thus effectively addressing the ecological environment challenges in urban development. Therefore, the in-depth study of the ecological garden spatial layout and functional area division technology based on deep learning has important theoretical and practical value for promoting the construction of ecological garden and realizing the sustainable urban development. Ecological garden is a comprehensive garden design method, emphasizing the harmonious coexistence with the natural environment and optimizing the ecosystem services. This concept comes from the combination of traditional garden art and modern ecological principles and aims to create a green space that meets human aesthetic and leisure needs, while also promoting biodiversity, water and soil conservation, and air quality improvement. Spatial layout and functional area division are the core of ecological garden design, aiming to optimize land use efficiency and ecosystem service function through scientific spatial organization and reasonable functional zoning. The theory is based on a deep understanding of the natural properties, ecological processes, and needs of human activities, and achieves a comprehensive balance of ecological, economic, and social benefits through multidisciplinary integration. Traditional spatial layout mainly focuses on the physical characteristics of land and the needs of humans. Through functional zoning, different land uses are reasonably arranged in a specific area to maximize the overall value of land. With the development of ecology and environmental science, this theory gradually introduces the concept of ecological process, emphasizing on considering the structure and function of natural ecosystems in planning.

At present, the spatial layout and functional area division of ecological gardens have become the core issue in the field of urban and regional planning. Although traditional methods provide the basic framework, the need for more precision and automation is increasingly prominent with more rapid urbanization and more ecological needs. In recent years, the introduction of deep learning has provided new solutions for processing complex geographic and environmental data. Zhang *et al*. studied the optimization of green spatial landscape layout based on ecological network construction. Through the implementation of deep learning technology, a set of optimization models was proposed, which significantly improved the connectivity and ecological benefits of urban green space in Guiyang, Guizhou, China [1]. Zhao *et al*. applied coupled multi-objective planning (MOP) and flexible land use simulation (FLUS) models to optimize the production-life-ecological space model of the central Yunnan urban agglomeration and demonstrated the effectiveness of deep learning in large-scale spatial data analysis [2]. Driven by deep learning technology, the division of urban functional areas has also made significant progress. Yang *et al*. used the U-Net deep learning model to accurately divide the urban functional areas in the broad urban district of Changchun, Jilin, China and proved the practice of deep learning in enhancing urban planning decision-making [3]. Similarly, Lu *et al*. classified the urban functional areas of Beijing, China through the self-supervised learning method, which could still achieve efficient functional area identification without explicit labeling [4]. Chen and Lu conducted a further study to explore the planning method of shared space in old residential areas based on improving the quality of the ecological environment. This study used deep learning to analyze residents' behavior and spatial use patterns and provided a scientific basis for the reconstruction of old areas [5]. Li *et al*. conducted a multi-scenario simulation analysis for green space of Harbin, Heilongjiang, China and demonstrated the influence of the optimization method based on FLUS model on the green spatial layout [6]. From the perspective of landscape ecological risk assessment, Wang *et al*. demonstrated the application of deep learning in historical data processing and risk assessment by analyzing the landscape ecological risk in the past 40 years, providing strategies and basis for regional ecological protection [7]. Zhan and Zhu demonstrated the potential of deep learning in urban big data analysis through the study of mega urban corridor identification and spatial layout optimization based on point of interest (POI) data, providing new ideas for urban planning [8]. In terms of automated urban planning, Wang *et al*. proposed an automated urban planning model based on human instruction awareness. The model could identify spatial levels and automatically adjust urban planning strategies, demonstrating the prospect of deep learning in urban planning automation [9]. Zhang *et al*. processed complex urban scenes through the heuristic sample learning method, providing effective deep learning application cases for urban functional area mapping, and enhancing the performance of the model in processing high-resolution images and POI data [10]. These past studies demonstrated that deep learning technology was gradually becoming an indispensable tool in urban and regional planning, especially in the spatial layout and functional zoning of ecological gardens. Through continuous technology iteration and application expansion, deep learning is expected to further optimize the design and management of urban ecosystems and provide strong support for sustainable urban development [11-14]. However, the application of deep learning in the spatial layout and functional zoning of ecological gardens still has limitations, especially in the degree of automation and model accuracy and generalization ability of processing complex geographic and environmental data [6, 7, 15].

This research aimed to adopt advanced deep learning techniques to improve the accuracy and efficiency of ecological garden design to support the sustainable development of urban green space. The deep learning model suitable for ecological garden planning was selected and combined with the optimization algorithm of spatial layout and functional area division to collect and process ecological garden data including geospatial data, environmental data, and remote sensing images, and automatically divide functional areas by using deep learning technology. The performance of deep learning model was evaluated in actual ecological garden projects through field application and simulation test. This research would promote the application of deep learning technology in the field of ecological garden planning, improve the scientific and practical nature of garden design, and provide solid technical support for the realization of more sustainable urban development.

Materials and methods

Data collection and preprocessing

The data used in this study included geospatial data, environmental data, and remote sensing images and were obtained from National Center for Geospatial Information (NGIC) (http://www.ngic.gov), China Meteorological Administration (CMA) (http://www.cma.gov.cn), USGS Earth Explorer (https://earthexplorer.usgs.gov), Copernicus Open Access Hub (https://scihub.copernicus.eu), local environmental monitoring stations, and local meteorological bureaus. Geospatial data covered terrain elevation, slope, land use type, and vegetation coverage with a resolution of 1:50,000 and a time range from 2020 to 2023. Environmental data covered daily or hourly data of temperature, precipitation, humidity, wind speed, soil quality including pH and organic matter content, and air quality including PM 2.5 and PM 10 with a time range from 2019 to 2023. Remote sensing image data mainly included normalized vegetation index (NDVI), enhanced vegetation index (EVI), land surface temperature (LST), and land cover changes with a resolution of 10 - 30 meters and a time range from 2021 to 2023.

Data preprocessing

The data preprocessing included data cleaning, standardization, and feature extraction to ensure that all kinds of data were effectively used for the model construction. The data cleaning was suitable for remote sensing image data, environmental data, geospatial data and involved removing the outliers and duplicate values in the data set, filling in missing values using spatial or temporal interpolation to ensure the integrity and accuracy of the data. When processing remote sensing image data, spatial interpolation method was used to fill the missing image value. For missing values in environmental data, linear interpolation or time series regression model was used. In addition, the projection coordinate system of geospatial data was unified during cleaning to ensure that all data were spatially aligned. The standardized treatment aimed to eliminate scale differences between different data sources to improve model stability and prediction accuracy. Using Z-score normalization, all numerical data were converted to a standard normal distribution as below.

$$z = \frac{x-\mu}{\sigma} \quad (1)$$

where μ was the mean of the data. σ was the standard deviation. The standardized data ensured that each variable in the model had the same weight, which helped improve the model's convergence speed and accuracy. The feature extraction step transformed it into a feature vector that could better represent the data features by analyzing the key information in the raw data. For remote sensing images, principal component analysis was used to reduce the dimensions and extract the main components from high-dimensional data. For geospatial and environmental data, features that significantly affected spatial layout and functional division were extracted by calculating spatial autocorrelation indicators and spatiotemporal trend indicators. Through these data preprocessing steps, the quality and consistency of the data were ensured, providing a solid database for the subsequent model construction and analysis.

Dataset construction

The dataset of this study consisted of geospatial data, environmental data, and remote sensing image data, which provided high-quality training, validation, and test data for the ecological garden spatial layout and functional area division model through reasonable division strategies. All the data were integrated in time and space to build a unified cube. Each sample point contained multiple data features including topographic elevation, vegetation cover, climate indicators, and features extracted from remote sensing images. To ensure the generalization ability of the model, the dataset was divided in a 7:2:1 ratio for model training, validation, and the testing, respectively. To deal with the problem of data imbalance, especially in the functional area division, the data of each type of functional area was balanced, and the number of various samples was adjusted through undersampling and oversampling technology to ensure the balanced performance of the model in the division of various functional areas.

Visual analysis of dataset

Through the visualization of the dataset, the topographic characteristics, environmental conditions, and vegetation coverage of different regions were revealed, which provided an intuitive basis for model analysis. The topographic data was presented through the digital elevation model (DEM). For the environmental data, heat maps were used to demonstrate the spatial distribution of climate conditions and soil quality. The dynamic changes of vegetation coverage were analyzed through the temporal change chart of NDVI and EVI. Different types of data were superimposed and displayed to comprehensively analyze the correlation between spatial layout and functional area division. Through the visual analysis, the understanding of the spatial layout and functional area division of ecological gardens was further deepened, which provided an important reference basis for the construction and optimization of the model.

Selection of models

Deep learning is a kind of machine learning technology based on artificial neural networks. By layer abstraction and feature extraction of data through multi-layer neural network, it can automatically learn complex data patterns and non-linear relationships. The deep learning includes the construction of the input layer, hidden layer, and output layer, where each layer of neurons processes the input data through the activation function and passes the results to the next layer, thus forming a highly nonlinear functional mapping. In this process, the weight parameters are constantly adjusted by the back-propagation algorithm to minimize the prediction error. The power of deep learning models lies in their ability to process massive high-dimensional data and effectively capture the potential structure and patterns of data through hierarchical representation.

(1) The recurrent neural network model

The recurrent neural network (RNN) model is a kind of deep learning model with significant advantages in processing sequence data and time series prediction, which enables the network to remember the input through the recurrent structure of connecting nodes to retain and utilize this historical information in the computation of the current moment. Unlike traditional feedforward neural networks, RNN enables neural networks to process data with time-dependent or sequential information by introducing recurrent connections, which is widely used in fields such as natural language processing, speech recognition, and time series prediction. The core of RNN laid in the recursive computation of the hidden layer states. Specifically, the hidden state h_t at each time step in an RNN was expressed as follows.

$$h_t = \sigma(W_h h_t - 1 + W_x x_t + b_h) \tag{2}$$

where h_{t-1} was the hidden state from the previous time step. x_t was the input at the current time step. W_h and W_x were the weight matrices for the hidden state and the input, respectively. b_h was the bias term. σ was the activation function. By iteratively applying this recursive formula, the RNN could pass information from past time steps to future ones, creating a dependency on the sequential data. In the output layer, the RNN's output y_t was expressed as follows.

$$y_t = \phi(W_y h_t + b_y) \tag{3}$$

where W_y was the weight matrix from the hidden state to the output. b_y was the bias term for the output layer. ϕ was the activation function of the output layer, usually the softmax function for classification tasks. Through this mechanism, the RNN could generate an output sequence corresponding to the input sequence, enabling the network to perform effectively in tasks like time-series prediction and sequence labeling. Standard RNN has gradient disappearance and gradient explosion problems, which is especially serious when dealing with long sequence data. To address this issue, long-and short-term memory networks (LSTM) and gated cycle units, gated recurrent unit (GRU,) were proposed. LSTM performed well in long sequence modeling by introducing "memory cell" and gating mechanisms, effectively controlling the memory and forgetting of information. The core formula of LSTM included the update formula of input gate, forgetting gate, output gate, and memory unit shown in the following formulas (4) to (9).

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{4}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{5}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{6}$$

$$\tilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{7}$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{8}$$

$$h_t = o_t \cdot tanh(C_t) \tag{9}$$

where f_t was the forget gate. i_t was the input gate. o_t was the output gate. C_t was the current memory cell state. h_t was the hidden state. Through these gating mechanisms, LSTM could selectively retain or forget past information, effectively addressing the dependency issues in long sequences.

(2) Optimization model of the spatial layout of the ecological garden

The mathematical expression of the optimization model for the spatial layout of ecological gardens typically involved a multi-objective optimization problem, which constructed an optimized objective function by comprehensively considering multiple factors such as ecological benefits, economic benefits, and social benefits. Let the objective function be $F(x)$, where x was the decision variable vector of the spatial layout. The objective function could be expressed below.

$$Maximize F(x) = \alpha \cdot E(x) + \beta \cdot C(x) + \gamma \cdot S(x) \quad (10)$$

where $E(x)$ was ecological benefits. $C(x)$ was economic benefits. $S(x)$ was social benefits such as resident satisfaction, accessibility to public service facilities, *etc*. The coefficients α, β, and γ were the weight factors for each benefit, set according to specific planning requirements and the preferences of decision-makers. This optimization problem was solved under certain constraints, which commonly included physical limitations of land use, legal and regulatory requirements, and ecological environmental protection standards. By introducing deep learning technology into the optimization process, a RNN model was constructed to predict and adjust the spatial layout, thereby iteratively optimizing the objective function. The objective function in this context was expressed as below.

$$Maximize F(x) = \alpha \cdot E(G(x)) + \beta \cdot C(G(x)) + \gamma \cdot S(G(x)) \quad (11)$$

By constantly adjusting the parameters of the neural network, the optimization process could adapt to the complex ecological garden planning environment and gradually approach the optimal solution.

(3) Mathematical model of functional area division

The mathematical model for functional zoning typically employed optimization or classification models to ensure that the division of functional zones met ecological, social, and economic objectives. Suppose the functional zoning involved n zones with each zone i having a decision variable x_i representing the functional attributes of that zone. The objective function of the model was then expressed as Equation (12).

$$Minimize \sum_{i=1}^{n} \sum_{j=1}^{n} d_{ij} \cdot x_i \cdot x_j \quad (12)$$

where d_{ij} was the distance or other similarity measure between functional zone i and functional zone j. The goal was to minimize the distance between similar functional zones, thereby achieving a reasonable spatial distribution and layout optimization. This model was typically subject to several constraints such as the area, shape of each functional zone, and its proximity to other zones. To further enhance the model's accuracy and practicality, deep learning methods were incorporated into the functional zoning process. A neural network model $H(x)$ was used to predict the functional type of each zone, and by iteratively optimizing and adjusting the model parameters, the results of the functional zoning could become more reasonable and aligned with actual needs. In this case, the objective function of the model was expressed as Equation (13).

$$Minimize \sum_{i=1}^{n} \sum_{j=1}^{n} di_j \cdot H(x_i) \cdot H(x_j) \quad (13)$$

Through the adaptive adjustment of the deep learning algorithm, the model could dynamically optimize the functional area division, so that it could better meet the planning needs of ecological gardens. This mathematical model not only improved the scientific nature and rationality of functional area division but also provided strong technical support for ecological garden planning.

(4) Joint optimization model of spatial layout and functional area division

The joint optimization model of spatial layout and functional area division aimed to comprehensively consider the multiple objectives of ecological garden and improve the overall benefits of garden design through the combination of deep learning and multi-objective optimization technology. In this model, the optimization of the spatial layout was mainly achieved by adjusting the configuration of each area in the garden to maximize the ecological benefits, improve the efficiency of resource utilization, and meet the social needs. The optimization of functional area division focused on reasonably dividing the garden space into different functional areas such as ecological conservation area, leisure and entertainment area, and education science area according to environmental conditions, ecological service functions, and user needs. The joint optimization model integrated the problem of spatial layout and functional division into an optimization framework by defining a comprehensive objective function that usually included the weighted sum of ecological benefits such as biodiversity conservation, carbon sink capacity, *etc*., economic benefits such as cost-benefit ratio, land-use efficiency, *etc*., and social benefits such as landscape aesthetics, public satisfaction, *etc*. The model used iterative optimization algorithms to find optimal solutions that satisfied these objectives simultaneously. In the process of model solving, the deep learning model provided the ability to predict and analyze complex ecological data, while the optimization algorithm ensured that the final design scheme could achieve the optimal level in multiple dimensions by constantly adjusting the strategy of spatial layout and functional zoning division. To ensure the prediction accuracy and reliability of the model, the model results were evaluated by cross-validation methods. The performance of the model was mainly evaluated by the indicators of accuracy, F1 score, and mean square error (MSE). The accuracy was used to measure the prediction accuracy of the model in the spatial layout and functional division. F1 score was used to balance the accuracy and recall rate of the model and evaluate the comprehensive performance of the model in the functional division. MSE was used to quantify the difference between the predicted value and the true value of the model, especially in the application of ecological benefit evaluation. The combination of these evaluation indicators and optimization algorithms ensured that the joint optimization model could realize the optimal spatial layout and functional area division in the planning and design of ecological gardens and meet the comprehensive needs of multiple goals.

Model architecture design

RNN was adopted as the core model structure. With the advantage of handling time-series data, RNN was allowed to capture the dynamic changes and temporal dependencies in the spatial layout and functional zoning of ecological gardens. To enhance the model's performance on long-sequence data, LSTM was used as a variant of RNN to address the gradient vanishing problem inherent in standard RNN. The architecture of LSTM included input layers, multiple LSTM layers, and output layers. The input layer received time series data such as environmental change, vegetation index, climate data, *etc*. and the time step of each input sequence. The LSTM layer introduced memory units and gating mechanisms to model the long-term dependence relationship to capture the complex spatial-temporal relationship in ecological gardens. The hidden state at each time step would be passed to the next level, and the final output layer produced predictions of the spatial layout or ribbon division. To improve the generalization ability and stability of the model, the model also integrated regularization techniques such as Dropout to prevent overfitting. Furthermore, to optimize the model performance, the Adam optimization algorithm performed parameter updates to evaluate the prediction accuracy of the model in combination with the cross-entropy loss function. The output of the final model would be used to guide the decision of the spatial layout and functional zoning of ecological gardens to ensure the effectiveness and feasibility of the scheme in practical application.

Model training and parameter optimization

During the training process, Adam optimization algorithm was used for parameter update, which combined the advantages of momentum gradient descent and RMSprop to accelerate convergence and avoid local optima. The learning rate was initially set to 0.001, and a learning rate decay strategy was used to dynamically adjust the learning rate according to the performance of the validation set to improve the generalization ability of the model. The loss function selected the cross-entropy loss and was used to measure the difference between the model prediction results and the true labels. After each iteration, model performance was evaluated by calculating the loss value on the validation set, using an early stop strategy to stop training when the validation set loss no longer dropped to prevent overfitting. During training, model robustness was enhanced using batch normalization and Dropout techniques. Batch normalization alleviated the internal covariate offset by standardizing the distribution of each batch of data, while Dropout randomly discarded part of neurons to prevent the model from overfitting specific data patterns. Through multiple experiments and hyperparameter tuning, the selected model parameter combination performed optimal on the validation set, and the final evaluation on the test set was performed to ensure the generalization ability and prediction accuracy of the model.

Model loss function and optimization algorithm

In deep learning model design, especially in dealing with the complex tasks of ecological garden spatial layout and functional area division, choosing the appropriate loss function and optimization algorithm is crucial to ensure the effectiveness and efficiency of the model. Cross-entropy loss function is widely used in classification problems because of its ability to effectively handle multiple class labels and optimize the performance of the model in prediction accuracy. This loss function guided the model learning by measuring the difference between the probability distribution of the model output and the probability distribution of the true label as shown below.

$$L = -\sum_{c=1}^{M} y_{o,c} log(p_{o,c}) \tag{14}$$

where $y_{o,c}$ was the binary indicator (1 or 0) for whether class c was the correct classification for the observed sample o. $P_{o,c}$ was the predicted probability that the observed sample o belonged to class c. The Adam optimizer was used as an optimization algorithm, which combined momentum and adaptive learning rate techniques to automatically adjust the learning rate of each parameter during training. This optimization device was characterized by high computational efficiency, low memory requirements, and sparsity of the adaptive gradient. The Adam algorithm calculated the first and second moment estimation of the gradient and adjusted the learning rate of each parameter with the formula (15).

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t} + \xi} \hat{m}_t \tag{15}$$

where θ was the model parameters. η was the learning rate. $\hat{m}_t$ and $\hat{v}_t$ were the bias-corrected first and second moment estimates, respectively. ξ was a very small number to prevent division by zero. This approach combining cross-entropy loss function and Adam optimizer provided a robust way to optimize the complex spatial layout of ecological gardens and functional division model, ensuring the stability and efficiency of the model training process.

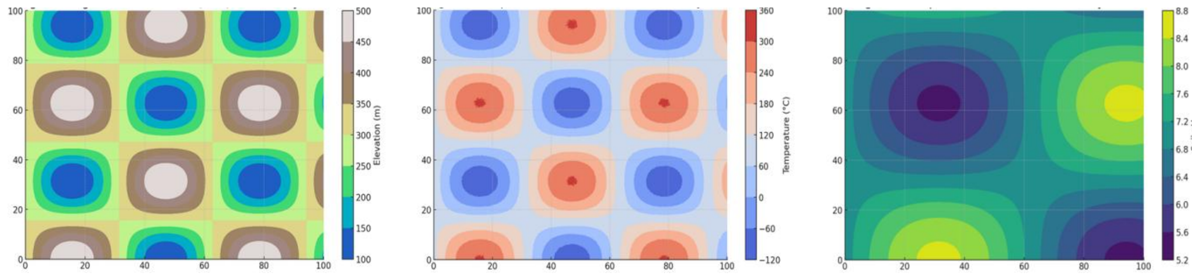
Results and discussion

Visualization of terrain, environment, and remote sensing data

The topographic distribution of the study area showed the elevation changes in different areas, which had important reference value for determining the functional areas in the garden layout (Figure 1a). The temperature distribution of the study area and the distribution of soil pH values were shown in Figures 1b and 1c. These environmental parameters were important for plant selection and layout design in ecological gardens.

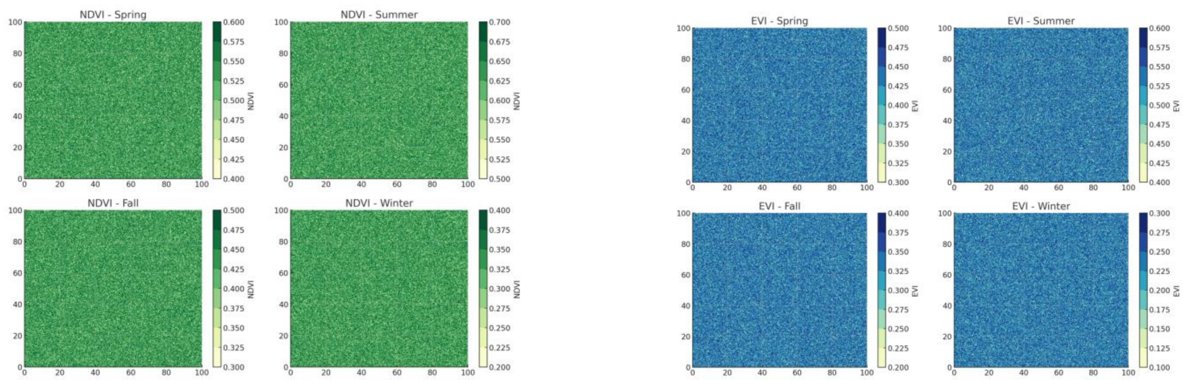
Seasonal variation trends of NDVI (a) and EVI

The seasonal trends of NDVI and EVI demonstrated the vegetation status at different



(a) (b) (c)

Figure 1. Visualization of digital elevation model (DEM) (a), temperature distribution (b), and soil pH distribution (c) across the study area.



(a) (b)

Figure 2. Seasonal variation trends of NDVI (a) and EVI (b) in the study area.

time periods in the study area (Figure 2). These indicators played an important role in assessing the ecological benefits of ecological gardens.

Key indicators of different functional zones

The main characteristic indicators of each functional area such as topography, climate, and vegetation cover were shown in Table 1. This superposition analysis of multidimensional data helped to identify the spatial associations between different functional areas and provided a scientific basis for functional area division. Based on different environmental factors of altitude, temperature, soil pH, NDVI, and EVI, the study areas were divided into five different functional areas from Zone 1 to Zone 5. Zone 1 was low elevation, high temperature, more neutral soil pH values, and low NDVI and EVI values, which indicated that the area was suitable for heat-tolerant plants, possibly for tourist reception and leisure areas, or for areas with more human activities and relatively less vegetation cover. Zone 2 was moderate altitude with suitable temperature, acidic soil, and moderate NDVI and EVI values, which was suitable for planting plants that needed a mild climate and slightly acidic soil and might be used for flower display, scientific research, and education areas and other functions. Zone 3 had higher elevation, lower temperature, moderate soil pH values, and higher NDVI and EVI values, indicating better vegetation coverage, suitable for the growth of alpine plants. This area might be used for ecological protection areas or ecological restoration areas, mainly for vegetation restoration and ecological protection. Zone 4 was high altitude, low temperature, moderate soil pH value or slightly acidic soil, high NDVI and EVI values, good vegetation cover, suitable for protective ecological areas such as

Table 1. Key indicators of different functional zones.

Functional Zone	Elevation (m)	LST (°C)	Soil pH	NDVI	EVI
Zone 1: Tourist and leisure	150-200	22-28	6.5-7.0	0.4	0.3
Zone 2: Flower display and research	200-250	20-25	5.5-6.0	0.5	0.4
Zone 3: Ecological protection	250-300	18-24	6.0-6.5	0.6	0.5
Zone 4: Wetland restoration	300-350	16-22	5.5-6.5	0.7	0.6
Zone 5: High-altitude ecological protection	350-400	14-18	5.0-6.0	0.8	0.7

wetland restoration areas or specific ecological protection areas. Zone 5 Located in areas with extremely high altitude or special climatic conditions with low temperature, acidic soil pH values, high NDVI and EVI values, and abundant vegetation cover, which was suitable for plant diversity conservation or special ecological function zones such as habitats for rare species. The division of these functional areas helped to rationally plan the spatial layout of ecological gardens according to different environmental characteristics and ensured the maximum ecological benefits of each functional area. Meanwhile, these data could provide a scientific basis for the future ecological garden design and support the ecological restoration and protection work.

Analysis of spatial layout and functional area division

In the analysis of the spatial layout, the joint application of the RNN, especially LSTM, and the spatial optimization model formed a powerful analytical framework. This combination made the model not only handle complex temporal data, but also dynamically optimize the overall layout of the garden space. The LSTM model processed and predicted various time sequence data in ecological gardens by capturing the time dependence of the data and generating future trend predictions. These prediction results were then combined as input into spatial optimization models to guide decision making in spatial layout and functional partitioning. The spatial optimization model used the temporal prediction data output by the LSTM model to optimize the spatial configuration of each functional area to maximize the ecological, economic, and social benefits. The functional score distribution of the spatial layout results generated by the combination of the LSTM and the spatial optimization model showed that the layout of different regions went through the timing analysis of LSTM (Figure 3). The multi-objective optimization of the spatial optimization model reflected the coordination of ecological functions and social needs of each region (Table 2).

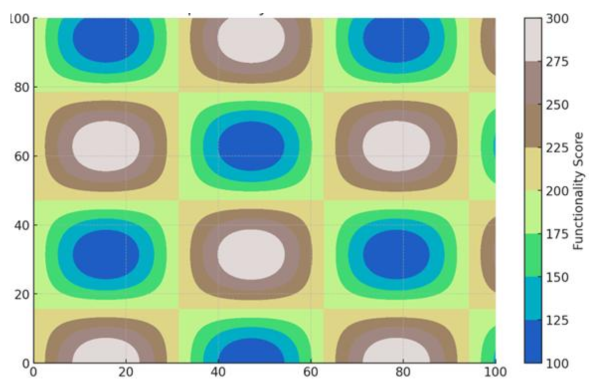


Figure 3. Spatial layout result.

In the analysis of the results of functional area division, the precise division and optimal configuration of ecological garden functional area were realized through the combination of models. The division of functional areas was based on the optimization of several key indicators including ecological value, resource utilization efficiency, social impact, and sustainability. The results showed that Zone 5 had the highest ecological value index of 0.89, indicating that the ecological function of this region was given the most effective play, and it was suitable for the division of functions such as conservation and ecological restoration. The ecological value indexes of Zone 2 and Zone 4

Table 2. Spatial layout evaluation metrics.

Zone	Biodiversity index	Carbon sequestration (tons/year)	Land use efficiency (%)	Public satisfaction (%)
Zone 1	0.78	150	85	75
Zone 2	0.82	145	88	78
Zone 3	0.79	148	87	76
Zone 4	0.81	152	86	77
Zone 5	0.80	149	89	79

Table 3. Functionality zone analysis metrics.

Zone	Ecological value index	Resource efficiency (%)	Social impact score	Sustainability index
Zone 1	0.85	90	70	0.80
Zone 2	0.88	92	72	0.85
Zone 3	0.83	88	69	0.79
Zone 4	0.87	91	71	0.82
Zone 5	0.89	93	73	0.86

were at 0.88 and 0.87, respectively, showing good ecological benefits. The resource utilization efficiency demonstrated that Zone 5 had the optimal performance in resource utilization efficiency as 93%, which indicated that the land resources in this area had been maximized, and the spatial allocation of functional areas had been optimized. Zone 2 and Zone 4 also showed high resource efficiency of 92% and 91%, respectively, which were suitable for the division of efficient functional zones. The social impact score of Zone 5 was in leading position of 73, reflecting the public's high recognition of the functional configuration of the region, while Zone 2 followed by a score of 72, indicating that the functional division of the region better met the social needs. The sustainability index showed that the Zone 5 had the highest sustainability index of 0.86, indicating that the functional division of the region had a high sustainability in long-term development, while the Zone 2 and Zone 4 also had a high sustainability index of 0.85 and 0.82, respectively, showing a balance in environmental and social benefits (Table 3). The results demonstrated that the optimization model of functional zoning had successfully realized the balance of ecological benefits, resource utilization, and social demand in each region, and the accuracy and scientific nature of functional zoning were further improved through the prediction of LSTM model. Zone 5 outstanding performance on multiple indicators demonstrated the effectiveness and utility of the model in functional division (Figure 4).

Evaluation of the joint optimization model

From the data of the model, the optimized accuracy was 0.92, which indicated that the model could accurately identify and divide the functional areas in the ecological gardens in most cases with high overall reliability. F1 score was 0.88, which closed to 1.0, indicating that the model was able to correctly identify positive samples in the classification task and effectively cover all positive samples. Further it also indicated that the model performed well in both aspects, especially in the ability to effectively handle various complex situations when dealing with functional area division. The MSE was 0.015, which meant that the prediction accuracy of the model in functional area division and spatial layout optimization was very high with minimal error and showed the high efficiency and reliability of the model in dealing with complex data of ecological gardens. The values of these evaluation indicators suggested that the

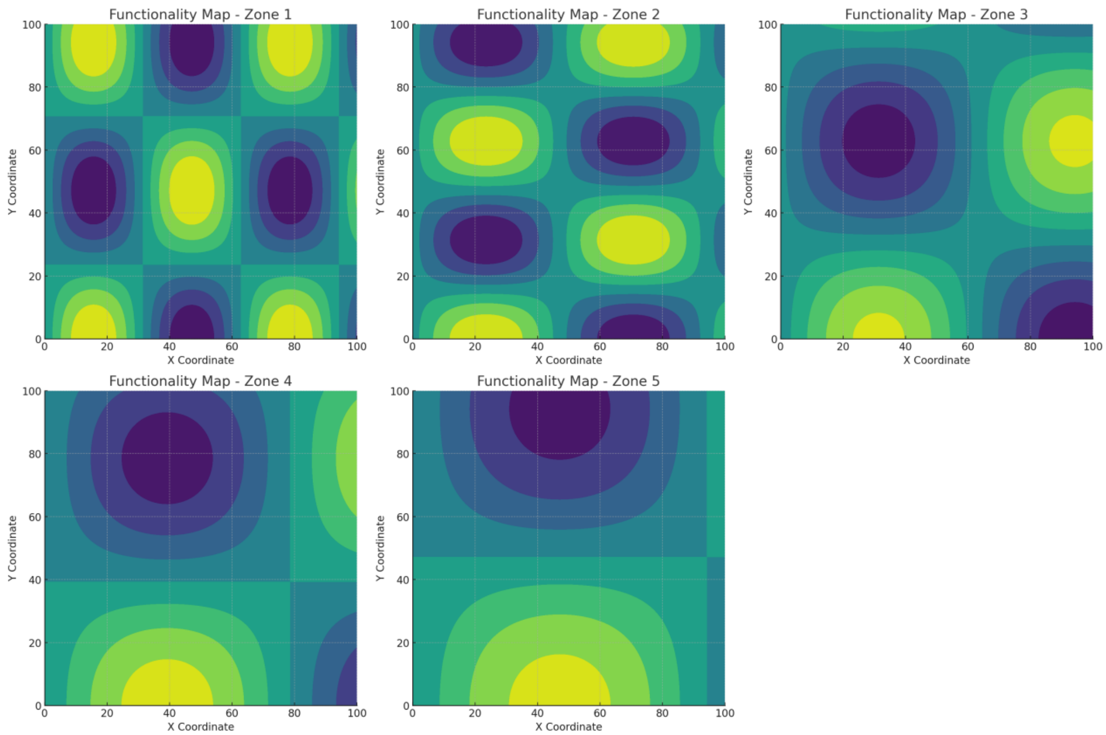


Figure 4. Functionality map.

proposed model performed well in the spatial layout and functional area division tasks and could provide accurate and reliable prediction and a scientific basis for the design and optimization of ecological gardens. In this study, LSTM and the spatial optimization model were successfully realized to optimize the spatial layout and functional area division of ecological gardens. The LSTM model captured the temporal data in the ecological garden, predicted the future trend, and combined with the spatial optimization model to dynamically adjust the spatial configuration of the garden and maximize the ecological, economic, and social benefits. The model evaluation results showed that the joint optimization model had high accuracy and reliability, indicating that the model could effectively identify and divide the functional areas in ecological gardens and improve the prediction accuracy. The results of functional zoning also showed that Zone 5 performed well in multiple evaluation indicators, especially in terms of ecological value and resource utilization efficiency, demonstrating the effectiveness of the model in functional zoning optimization. However, this research still faces some challenges that more computational resources may be required when processing large-scale data, and the quality of the data and the choice of input variables have an important impact on the model results. Future studies need further optimizing data processing and model input to improve the adaptability and scalability of models.

Conclusion

This study successfully optimized the spatial layout and functional zoning of ecological gardens by integrating RNN, particularly LSTM networks, with multi-objective spatial optimization models. The results demonstrated that using LSTM models to predict time-series data in ecological gardens combined with multi-objective optimization models could significantly enhance the ecological, economic, and social benefits of gardens. In the optimization of spatial layout, Zone 5 performed exceptionally well across several key indicators, particularly in land use efficiency and public satisfaction, fully validating the model's effectiveness. In functional zoning, Zone 5 achieved the highest ecological value index with a resource efficiency of 93%, showing outstanding performance in ecological conservation and resource utilization. Overall, the combination of LSTM models with spatial optimization models could accurately capture complex spatiotemporal dynamics, optimize the layout and functional zoning of ecological gardens, thereby demonstrating high practicality and potential for broader application.

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