RESEARCH ARTICLE

Deep learning-based landscape design and ecological balance optimization in gardens

Chen Xu*

School of Arts & Design, Yancheng Institute of Technology, Yancheng, Jiangsu, China.

Received: August 19, 2024; **accepted:** December 24, 2024.

As ecological restoration projects become increasingly essential for environmental sustainability, the need to integrate aesthetic appeal with ecological functionality presents a pressing challenge. This study investigated an eco-optimization strategy that sought to address this issue by employing ecological network analysis. The study developed a custom Transformer model to analyze ecological factor data and evaluate the impact of the Eco-Fitness module on ecologically balanced design options. The ecological network analysis identified pivotal ecological nodes and interconnections and was crucial for the preservation and restoration of key ecological functions. The ecological optimization design method significantly improved various indicators of the ecosystem such as the species diversity index from 2.5 to 3.2, the species abundance index from 6.3 to 7.8, and the ecosystem service score from 6.8 to 8.5, indicating that the method had a significant effect in enhancing ecological functions. The abundances of key species increased significantly after the ecological optimization design with *Populus* spp., *Cryptomeria japonica*, and *Medicago sativa* increasing by 80%, 80%, and 50%, respectively, which indicated that the ecological optimization design effectively improved the living conditions of key species and played an important role in species protection. The visual aesthetic score increased from 7.9 in the original state to 8.1, indicating that the ecological optimization design not only improved the ecological function, but also considered the aesthetic value of the landscape, achieving a win-win situation of ecology and aesthetics.

Keywords: transformer; landscaping; ecological design; deep learning; garden.

***Corresponding author:** Chen Xu, School of Arts & Design, Yancheng Institute of Technology, Yancheng 224007, Jiangsu, China. Email: XuChen_xuc@outlook.com.

Introduction

With the acceleration of global urbanization, the importance of urban green space and landscape design has become increasingly prominent. In the process of urbanization, the destruction of natural ecosystems and the reduction of biodiversity have become issues that cannot be ignored. At the same time, the public's demand for a high-quality living environment has continued to grow, which has promoted the development of landscape design to a higher level. Landscape design is not only an art of beautifying the environment, but also an important means to restore and enhance ecosystem services such as air purification, water quality improvement, and biodiversity protection. Therefore, how to incorporate ecological principles into design and achieve a harmonious unity of ecology and aesthetics has become an important topic in the current field of landscape design [1].

In recent years, the field of landscape design has made significant progress in both theory and practice. The application of ecological principles has gradually become the core guiding ideology of design, emphasizing the simulation of natural ecosystems through reasonable plant configuration, terrain shaping, *etc*. to promote ecological diversity, water cycle management, and microclimate regulation. On the other hand, the introduction of new technologies has brought new possibilities to landscape design [2]. In particular, the development of deep learning technology has provided a powerful tool for processing complex spatiotemporal series data. For example, the Transformer model has achieved great success in the field of natural language processing due to its efficient parallel computing capabilities and powerful sequence modeling capabilities [3, 4]. It has also been gradually applied to ecological research, helping researchers to better understand and simulate the dynamic changes of ecosystems. Although certain achievements have been made in the field of garden landscape design, there are still several problems that need to be solved. First, the existing design methods are still insufficient in the application of ecological principles, especially in complex ecosystems. Second, the traditional methods are difficult to process large-scale, high-dimensional ecological data, and more advanced technical means are needed to support them [5, 6]. Third, how to ensure ecological functions while considering visual aesthetics and achieving multi-objective optimization is a major challenge in current design. Finally, the complexity and black box characteristics of deep learning models make it difficult for designers to understand the decision-making process of the model, affecting the practicality and credibility of the model [7].

This study proposed a garden landscape design method that combined ecological principles and technical applications to enhance the ecological value and social benefits of garden landscapes. The research analyzed the limitations of existing landscape design methods and their impact on the ecological environment, identified the shortcomings of current design methods, especially those factors that had a negative impact on ecosystem services, explored the application potential of the Transformer model in processing landscape design data, and studied how to use the model to process complex sequence data such as vegetation type distribution, terrain changes, and hydrological cycles to provide more accurate design decision support [8, 9]. The actual effects of new technologies in landscape design including the feasibility of ecological balance optimization and its positive impact on environmental quality were evaluated in this study, and a set of landscape design guidelines based on ecological principles and technical tools was proposed to provide designers with practical tools and methods to help them better achieve the goal of ecological sustainability in future projects [10]. By integrating ecological principles and advanced technologies, the ecological functionality of garden landscapes would be significantly improved. The multi-objective optimization strategy could ensure that the design scheme had good visual aesthetics while maintaining high ecological benefits. Further, the application of the Transformer model in garden landscape design might provide new technical means for processing complex ecological data. The proposed design guidelines would provide practical tools and methods for garden designers, which would help achieve the goal of ecological sustainability and improve the urban ecological quality and the quality of life of residents [11, 12].

Materials and methods

Data sets

The Plant List (http://www.theplantlist.org/) database was used as a representative dataset, which provided detailed information on plant species including their distribution, name, range, and growth habit to help the understanding of plant diversity in a given area. The Terrain Characterization dataset included a variety of information related to terrain, and U.S. Geological Survey (USGS) topographic data (https://www.usgs.gov/programs/national-geospatial-program/topographic-maps) was used as a representative dataset [13, 14]. The other datasets used in this study came from multiple reliable sources including the ecological factor data and meteorological data from the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences (IGSNRR) (http://www.igsnrr.cas.cn/), which provided detailed vegetation type distribution, terrain changes, and historical meteorological records. Remote sensing image data were provided by the National Earth System Science Data Center (NGDC) (http://www.ngdc.org.cn/), which included high-resolution satellite images and drone aerial images for the analysis of spatial layout and landscape characteristics. Ecosystem service data came from the Chinese Ecosystem Research Network (CERN) (http://www.cern.ac.cn/), which provided rich data of species diversity index, species richness index, and ecosystem service score. These datasets were publicly available and had undergone strict quality control and standardization to ensure the reliability and accuracy of the research [15]. A total of 100 GB of data were retrieved from the datasets, which covered a variety of data types to fully support the research on garden landscape design and ecological balance optimization. Specific data types included ecological factor data such as vegetation type distribution, terrain changes, hydrological cycle, *etc.* used to describe the ecological characteristics of garden landscapes, meteorological data such as temperature, humidity, precipitation, *etc.* used to analyze the impact of environmental conditions on ecosystems, remote sensing image data including high-resolution satellite images and drone aerial images used to analyze spatial layout and landscape characteristics, ecosystem service data such as species diversity index, species richness index, ecosystem service score, *etc*. used to evaluate the ecological benefits of design schemes. To ensure the robustness and generalization ability of the model, the data were divided into training set and test set, of which 80% of the data was used for model training and 20% of the data was used for model testing and verification.

Transformer model customization

In applying the Transformer model to ecological factor coding and ecological network analysis, a customized architecture was designed to deal with specific ecological problems. For the input data, there was a need to improve the degree of standardization of the data. Standardization was to allow different ranges of values to be compared on a uniform scale. For non-numerical types of ecological factors such as species categories, an embedding layer could be used to convert them into numerical vectors. Assuming there was a collection of species categories $C=\{c_1,c_2,...,c_n\}$, each category c_i could be mapped into a d-dimensional vector e_i, where d was the embedding dimension. Then $e_i=\text{Embedding}(c_i)$. Location coding was used to provide sequence information to the model. For time series data, position coding was important because it helped the model understand the temporal order in the data. The positional coding could be fixed or learnable, and the coding format was shown in equations (1) and (2) [16].

$$PE(pos,2i)=\sin\left(\frac{pos}{10000^{2i/d}}\right) \tag{1}$$

$$PE(pos,2i+1)=\cos\left(\frac{pos}{10000^{2i/d}}\right) \tag{2}$$

where *pos* was the position. *i* was the dimension index. *d* was the total dimension of the embedding vector. Thus, each position (*pos*) was encoded as a d-dimensional vector. Combining the above steps, an input vector *X* could be constructed to represent a series of ecological factors. Suppose there were *T* time-step data points, and each time-step contained *N* ecological factors, a matrix *X* could be constructed, and each time step *t* could be expressed as equation (3) [17].

$$X_t=[x_{t,1},x_{t,2},...,x_{t,N}] \tag{3}$$

For numerical factors, normalization could be applied directly, while, for typed factors, they were first converted to vector representations through the embedding layer and then joined with numerical factors to form vectors of time step *t.* The position coding was added to the vector for each time step to obtain the final input vector [18]. If $x_{t,i}$ was the *i*-th factor of the *t*-th time step, it could be expressed as follows.

$$X_{t,i} = \begin{cases} \text{norm}(x_{t,i}) + PE(t,i), & \text{if } x_{t,i} \text{ is numerical} \\ e_i + PE(t,i), & \text{if } x_{t,i} \text{ is categorical} \end{cases} \quad (4)$$

In this way, various types of ecological factors could be converted into an input format suitable for the Transformer model. The self-attention mechanism was a core component of the Transformer architecture that allowed the model to focus on different parts of the input sequence to form the output. The self-attention mechanism allowed the model to decide which information was more important by calculating the correlation of each element with all other elements when processing sequence data. This mechanism was particularly well suited for processing ecological factor data, which often contained multiple interrelated features, and self-attention could help models capture the complex relationships between these features. The attention mechanism was defined as Equation (5) [19].

$$\text{Attention}(Q,K,V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (5)$$

where *Q* (query), *K* (key), and *V* (value) were matrices obtained from the input data by linear transformation. d_k was the dimension of the key vector. The query matrix represented the information that would be found. The key matrix provided information about each position and was used to compute the similarity with the query. The value matrix contained the actual content, which was weighted and summed according to the similarity. The input data *X* was converted into a query *Q*, key *K*, and value *V* matrix by three different linear transformations W^Q, W^K, W^V. These linear transformations could be accomplished by simple matrix multiplication as shown in equation (6) [13].

$$Q = XW^Q, \quad K = XW^K, \quad V = XW^V \quad (6)$$

where W^Q, W^K, W^V were the learned weight matrix. The similarity score between query *Q* and key *K* was computed using the dot product attention mechanism as shown in equation (7).

$$\text{scores} = \frac{QK^T}{\sqrt{d_k}} \quad (7)$$

where d_k was the dimension of the key vector and dividing by $\sqrt{d_k}$ was to prevent the dot product score from being too large leading to saturation of the softmax function. The softmax function was applied to the computed score to obtain the attention weights for each position as shown in equation (8).

$$\text{weights} = \text{softmax}(\text{scores}) \quad (8)$$

The softmax function ensured that the sum of the weights for each position was 1. The attention output was then obtained by weighted summation using the attention weights on the value *V* as shown below.

$$\text{output} = \text{weights}V \quad (9)$$

In multi-head attention, the above process was executed in parallel in several different representation subspaces. The results were then stitched together and output through another linear layer. Multi-head attention was computed as follows.

$$\text{Head}_i(Q,K,V) = \text{Attention}(W_i^Q Q, W_i^K K, W_i^V V) \quad (10)$$

where W_i^Q, W_i^K, W_i^V were the linear transformation weight matrix corresponding to the *i*-th header, respectively. The results were spliced as shown in equation (11).

$$\mathrm{MultiHead}(Q,K,V) = \mathrm{Concat}(\mathrm{Head}_1,\ldots,\mathrm{Head}_h)W^O \quad (11)$$

where *h* was the number of heads. W^O was an additional matrix of learned parameters used to convert the spliced vectors to the desired dimensions. The self-attention mechanism enabled the Transformer model to be more flexible and efficient in processing ecological factor data. By calculating the attention weights between different ecological factors, the model could capture the correlation and importance between factors. The multi-attention mechanism further enhanced the model's ability to focus on several different aspects at the same time, which was useful for processing complex and multidimensional ecological data. In this way, the model could better understand the interactions between ecological factors, thus providing more accurate predictions and insights in ecological network analysis. In ecological network analysis, the multiple attention mechanism could help models learn the complex relationships between different ecological factors. When analyzing species interactions, different attention heads could focus on different interaction patterns such as predation, symbiosis, competition, *etc*., thus helping the model capture the dynamics in the network more accurately. An ecological network dataset contained information about multiple species and their interactions that could be predation, symbiosis, competition, *etc*. Our goal was to use these data to predict the strength of interactions between species or to predict the population dynamics of certain species. Each species could be represented as a vector containing various attributes of that species such as survival rate, reproduction rate, food preference, *etc*. For n species, the input data could be represented as a matrix $X \in \mathbb{R}^{n\times d}$, where *d* was the dimension of each species vector. In the multi-head attention mechanism, the query Q_i, the key K_i, and the value vector for each species *i* were computed. The query was a vector of values for each species. For each attention head *h*, the following steps were followed with the flow framework shown in Figure 1. The vector X_i for each species *i* was transformed into a matrix of queries Q_i^h, keys K_i^h, and values V_i^h by three different linear transformations $W^{Q,h}$, $W^{K,h}$, and $W^{V,h}$. The attention score was calculated by calculating the similarity score between the query Q_i^h and the key K_j^h for all other species *j*. The softmax function to the calculated scores was applied to obtain the attentional weights of each species *i* to the other species *j*. Weighted summation was performed using the attentional weights on the values V_j^h to obtain the attentional output for species *i*. Multiple heads of attention were integrated. If *H* attention heads were used, then for each species *i*, *H* output vectors from *H* heads could be obtained. These output vectors needed to be integrated together by splicing. In ecological network analysis, different attentional heads could focus on different interaction patterns, among which head 1 focused on predatory relationships, learning about the interactions between predator and prey, while head 2 focused on symbiotic relationships, learning the interdependence between two species, and head 3 focused on competitive relationships, learning about resource competition between species of the same or different species. In this way, the model learned about different types of interactions and synthesized this information in the final output. For species i, its final output vector could reflect the strength of interactions across multiple dimensions such as predation, symbiosis, and competition.

Ecological adaptation module

The ecological adaptability module was a system designed to assess the impact of design solutions on ecological balance. The outputs obtained from

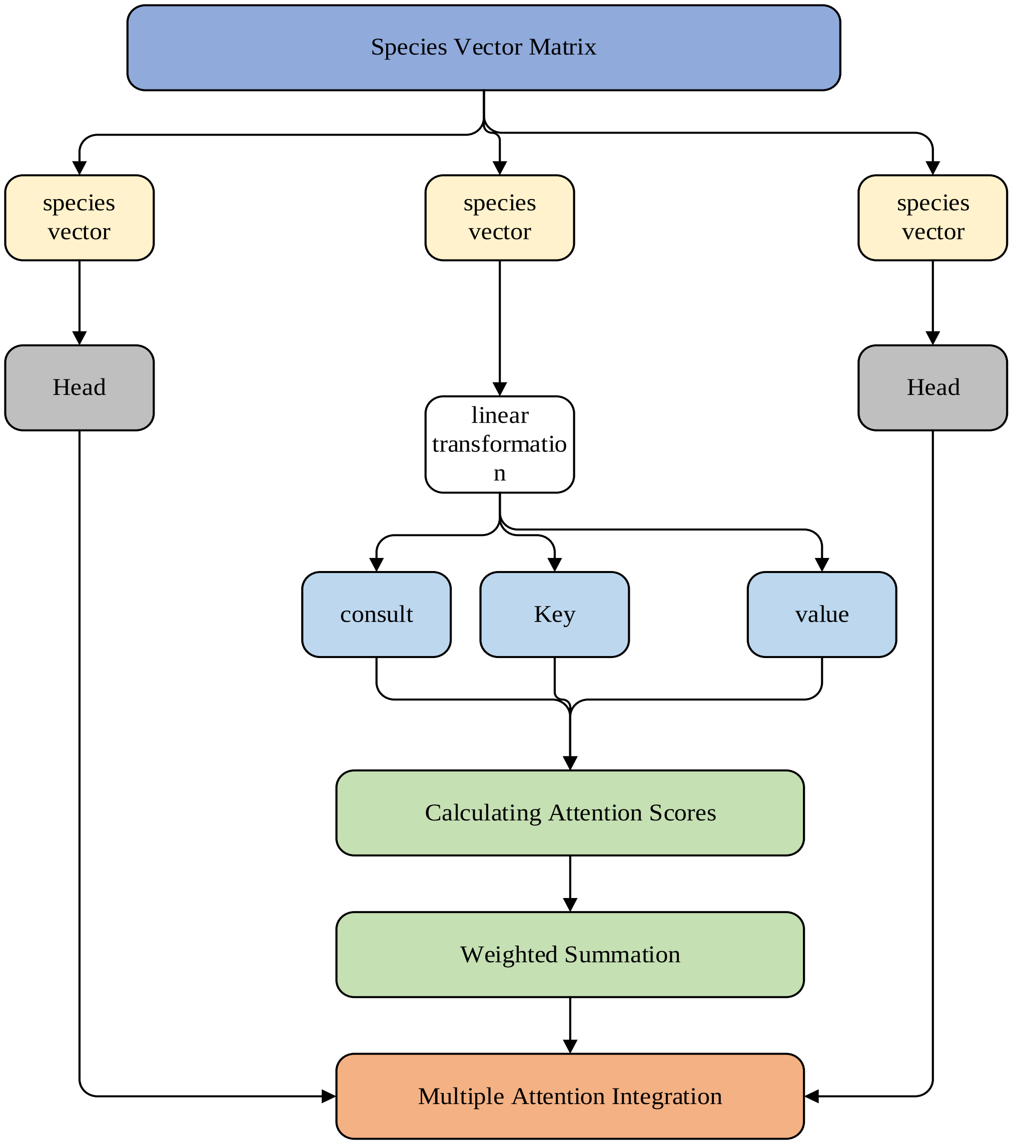

Figure 1. Process framework.

processing the ecological factor data through the previous Transformer model included the strength of species interactions and changes in other ecological indicators. Based on the outputs of the Transformer model, one or more ecological fitness scores were calculated for assessing the impact of the design solution on the ecological balance. These scores included, but not limited to, changes in species diversity, species abundance, and species interactions. By feeding the eco-adaptability scores back into the design process, the design solution was continually adjusted to optimize its impact on the ecological balance, which meant that designers could adapt design solutions based on the results of the scores to minimize negative impacts on the ecosystem and promote the maintenance of ecological balance. The outputs of the Transformer model could be viewed as a prediction of the state of the ecosystem, which included changes in species interactions, species abundance, and other ecological indicators. These outputs could be used as a basis for assessing ecological fitness. Ecological adaptability scoring sought to quantify the extent to which a design solution affected an ecosystem. One or more scoring criteria could be defined to measure the state of ecological balance. For example, a composite score *S* was defined, which consisted of a combination of sub-scores, each of which corresponded to an ecological metric. Specifically, it included species diversity score S_D that measured the change of species diversity, species abundance score S_A that assessed changes in species abundance, and species interaction score S_I that assessed changes in species interactions. The composite score S was calculated as follows.

$$S = w_D \cdot S_D + w_A \cdot S_A + w_I \cdot S_I \tag{12}$$

where (w_D, w_A, w_I) were the corresponding weight coefficients used to adjust the relative importance of each sub-score. Species diversity was an important indicator of ecosystem health. Shannon diversity index was used to assess species diversity as below.

$$S_D = -\sum_{i=1}^{n} p_i \log(p_i) \tag{13}$$

where p_i was the relative abundance of species *i*. *n* was the total number of species. After a design change, its effect on species diversity could be assessed by comparing the old and new diversity indices. Changes in species abundance could also affect ecological balance. The species abundance score was assessed by calculating the difference in species abundance as shown in equation (14).

$$S_A = \sum_{i=1}^{n} |a_{i,new} - a_{i,old}| \tag{14}$$

where $a_{i,new}$ and $a_{i,old}$ were the abundance of species *i* before and after the design change, respectively. Species interactions were crucial for ecological networks and could be quantified using the Transformer model's multiple attention mechanism as follows.

$$S_I = \sum_{i=1}^{n} \sum_{j=1}^{n} |w_{ij,new} - w_{ij,old}| \tag{15}$$

where $w_{ij,new}$ and $w_{ij,old}$ scores were the strengths of interactions between species *i* and species *j* before and after the design change, respectively.

Ecological balance optimization strategy

The ecological balance optimization strategy aimed to ensure that the ecological restoration project was both aesthetically pleasing and ecologically functional, as well as capable of long-term stable development through technical means such as ecological network analysis, multi-objective optimization, and dynamic simulation with the specific strategy framework (Figure 2).

(1) Ecological network analysis

The goal of ecological network analysis was to identify key ecological nodes and connections in an ecosystem to facilitate the protection and restoration of important ecological functions. Through this approach, which species or areas were critical to the health of the entire ecosystem could be determined. Key ecological nodes were those species or sites that occupied an important position in an ecological network. These nodes typically had a high degree of centrality, i.e., they had more connections or greater influence in the ecological network. Degree centrality measured the number of direct connections of a node. For node *i*, its degree centrality D_i was expressed as equation (16).

$$D_i = \sum_{j \neq i} A_{ij} \tag{16}$$

where A_{ij} was an element in the adjacency matrix indicating whether there was a direct interaction between species *i* and species *j*. $A_{\mathrm{ij}} = 1$ indicated that there was an interaction, while $A_{\mathrm{ij}} = 0$ indicated that there was no

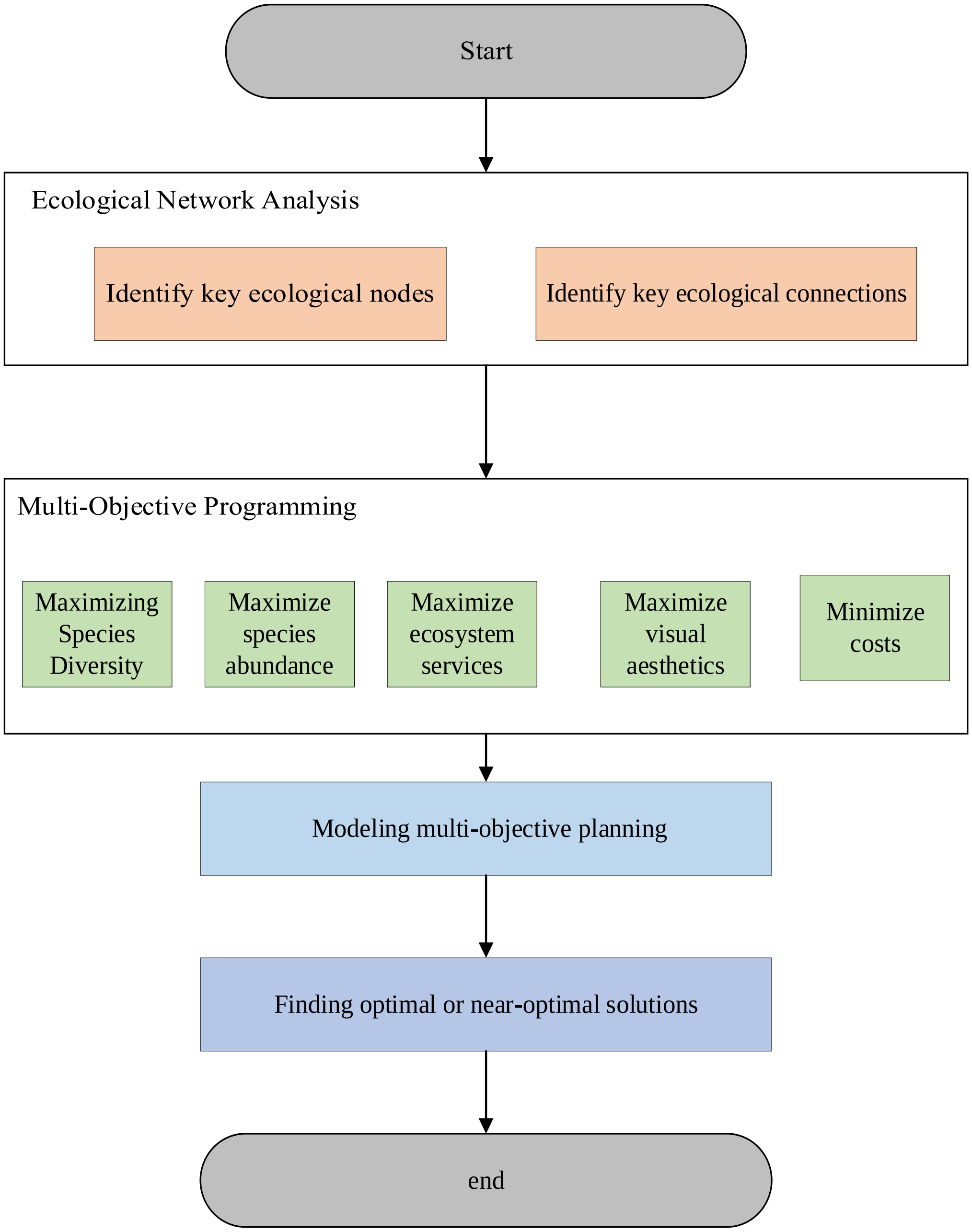

Figure 2. Ecological balance optimization strategy framework.

interaction. The median centrality measured the proportion of a node that was the shortest path between other nodes. For node *i*, its median centrality B_i could be expressed as equation (17).

$$B_i = \sum_{s \neq i \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}} \tag{17}$$

where σ_{st} was the number of shortest paths from node *s* to node *t*. $\sigma_{st}(i)$ was the number of paths containing node *i* in these paths. By comparing the centrality values of all nodes, nodes with higher centrality were selected as key ecological nodes. In addition to identifying key nodes, key ecological connections also needed to be identified, which were critical to the overall structure of the ecological network. Connection strengths were calculated by the multi-attention mechanism of the Transformer model. For the connection strength between species *i* and species *j*, W_{ij} could be expressed as below.

$$W_{ij} = \sum_{h=1}^{H} \text{Attention}_h (Q_i^h, K_j^h, V_j^h) \tag{18}$$

where *H* was the number of attention heads. Attention_h was the attention function of the h-th head. (Q_i^h, K_j^h, V_j^h) were the query, key, and value vectors, respectively.

(2) Multi-objective planning

Multi-objective planning was an important component of ecologically optimized design, aiming to balance conflicts between different design objectives such as the balance between ecological function and visual aesthetics. In ecological restoration projects, multiple objectives needed to be considered at the same time such as increasing species diversity, protecting key species, and enhancing ecosystem services, while also ensuring that the landscape was aesthetically pleasing and functional. Multi-objective planning could help find an optimal solution or a set of near-optimal solutions among these objectives. In eco-optimized design, the objectives of multi-objective planning usually included maximizing species diversity by increasing the species diversity of ecosystems to enhance their stability and resilience, maximizing species abundance by increasing the number of keystone species to facilitate the restoration of ecological functions, maximization of ecosystem services to enhance ecosystem functions and services such as air purification, water quality improvement, and carbon fixation, maximizing visual aesthetics to ensure that design solutions were aesthetically pleasing to meet the needs and preferences of the public, and minimizing the cost of project implementation while meeting ecological and aesthetic goals. The multi-objective planning model was established as follows.

$$\begin{aligned} \text{Maximize:} \quad & S_D \cdot w_D + S_A \cdot w_A + S_I \cdot w_I \\ \text{Subject to:} \quad & C \le c_{\max} \\ & S_D \ge d_{\min} \\ & S_A \ge a_{\min} \\ & S_I \ge i_{\min} \end{aligned} \tag{19}$$

where (S_D, S_A, S_I) were the species diversity score, the species abundance score, and the species interaction score, respectively. (w_D, w_A, w_I) were the corresponding weighting factor. *C* was the project cost. $(c_{\max}, d_{\min}, a_{\min}, i_{\min})$ were the maximum value of the cost and the minimum value of each score, respectively. In this way, multi-objective planning not only helped find the optimal compromise between design alternatives, but also ensured that ecological restoration projects achieved the best possible ecological balance.

Experimental design

To comprehensively assess the effectiveness of eco-optimization strategies in landscape design, the eco-optimization design approach was compared with the traditional design approach in terms of ecological benefits. The experimental group applied eco-optimization strategies such as eco-network analysis, multi-objective optimization, and dynamic simulation to enhance ecological functions, while the control group used traditional design methods focusing on visual aesthetics and functionality and were provided by Landscape Architecture Firm (New York City, New York, USA), a professional landscape design company provided comprehensive landscape design services including the design of residential, commercial, and public spaces. The traditional methods focused on traditional design concepts and techniques, mainly on beauty and functionality, but less consideration to ecological benefits. The key steps of the experiments included clarifying the design task by including ecological objectives such as enhancing species diversity, protecting key species, and enhancing ecosystem services, and modeling and evaluating a damaged lake ecosystem in a real-world scenario selected for

Table 1. Comparison of eco-efficiency between traditional and eco-optimized design methods.

Design methodology	Species diversity index	Species abundance index (SABI)	Ecosystem service scores	Visual aesthetics score
Traditional design	2.5	6.3	6.8	7.9
Eco-optimized design	3.2	7.8	8.5	8.1

Table 2. Changes in abundance of key species before and after design.

Design phase	*Populus spp.*	*Cryptomeria japonica*	*Medicago sativa*
Original state	10	5	8
After traditional design	12	6	9
After eco-optimized design	18	9	12

the purpose of restoring its ecological balance and creating a public recreational space. The data of ecological factors and visual aesthetics scores were collected followed by training a customized Transformer model and performing ecological adaptability score calculations.

Results and discussion

The results of the comparison between the traditional design method and the eco-optimized design method in terms of eco-efficiency showed that the eco-optimized design outperformed the traditional design method in species diversity index, species abundance index, and ecosystem service score, which were improved by 0.7, 1.5, and 1.7 points, respectively (Table 1). The results indicated that the eco-optimized design method had a significant effect in enhancing ecological functions. Meanwhile, the visual aesthetics scores were also improved, indicating that the eco-optimized design did not neglect the aesthetics of the landscape while focusing on the ecological benefits, achieving a win-win situation for both ecology and aesthetics.

The changes in abundance of key species *Populus* spp., *Cryptomeria japonica*, and *Medicago sativa* before and after the design demonstrated that the abundance of key species increased significantly through the eco-optimized design, in which the abundance of *Populus* spp. increased by 80%, *Cryptomeria japonica* increased by 80%, and *Medicago sativa* increased by 50% (Table 2). This result indicated that the eco-optimized design effectively enhanced the survival conditions of the key species, which was important for the conservation of these species.

The changes in ecosystem service scores before and after design showed the increase trend from 5.5 in the original state to 6.8 after the traditional design and to 8.5 after the eco-optimized design (Figure 3). The improvement of the score reflected the enhancement of the ecosystem service function, which indicated that the eco-optimized design not only improved the ecological environment, but also enhanced the services provided by the ecosystem to human beings such as improving air quality and regulating climate. The results also showed the change in visual aesthetic scores before and after the design. Although the eco-optimized design focused on the enhancement of eco-efficiency, the visual aesthetics score also increased from 6.5 in the original state to 8.1 after the eco-optimized design, which indicated that the eco-optimized design not only enhanced the ecological function, but also considered the

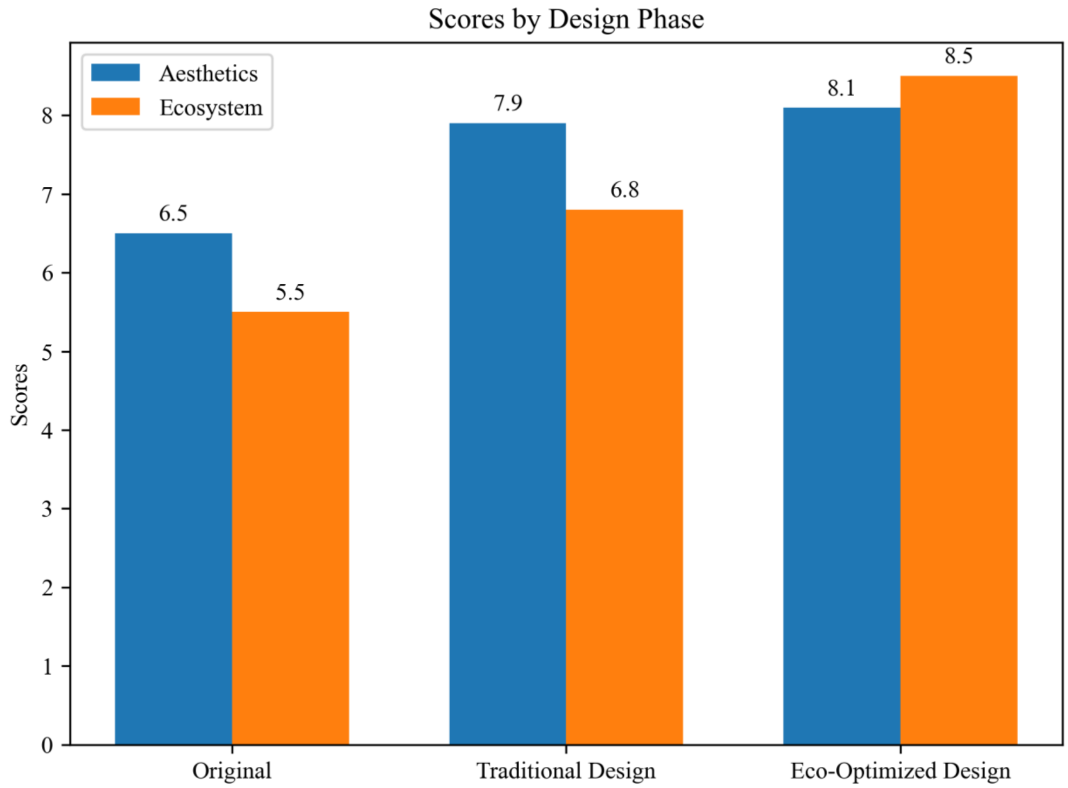

Figure 3. Changes in ecosystem service scores before and after design.

aesthetics value of the landscape, making it ecological as well as aesthetically pleasing.

By combining techniques such as ecological network analysis, multi-objective optimization, and dynamic simulation, the eco-optimal design approach aimed to improve the functionality and stability of the ecosystem while maintaining the visual aesthetics of the landscape. Located in a damaged lake ecosystem, this project aimed to restore ecological balance and provide public recreational space. By applying eco-optimization strategies, a design solution that met ecological functions while maintaining landscape aesthetics was proposed. In the ecological optimization design case of this study, special attention was paid to the enhancement of ecological connectivity by adding several small wetlands and connecting waterways, which facilitated the migration and dispersal of species and enhanced the connectivity of the ecological network. At the same time, the strategy focused on the key species protection and attracted them to settle by creating suitable habitats and selectively planting specific plants. Recreational spaces including bird-watching platforms and walking trails had been carefully planned to ensure the integrity of ecological functions and provide places for the public to interact with nature. To ensure the sustainability of the design, a number of management measures including water quality monitoring, biodiversity monitoring, and the use of native plants were implemented to minimize long-term maintenance costs. The results of the changes in ecological network health measures and species diversity indices before and after the design in an integrated manner provided a comprehensive assessment of the effects of the ecologically optimized design. The increase in mean degree centrality from 4.2 in the original state to 5.2 after the eco-optimized design indicated an increase in connectivity between individual nodes such as different habitats or species in the ecological network, which implied that interactions and energy flows between species were more

Table 3. Changes in ecological network health measures and species diversity indices before and after designing.

Design phase	Evenness centrality	Mean mesocentricity	Average clustering coefficient	Species Diversity Index
Original state	4.2	0.05	0.55	2.3
After traditional Design	4.5	0.06	0.57	2.5
After eco-optimized design	5.2	0.08	0.62	3.2

frequent, and the overall connectivity of the ecosystem was improved. This increased connectivity facilitated the migration of species and efficient allocation of resources, thus improving ecosystem stability and resilience. The increase in mean median centrality from 0.05 in the original state to 0.08 in the ecologically optimized design reflected the increased importance of certain nodes in the ecological network as "bridges" or "critical paths". These nodes had more significant roles in ecological processes such as the location of certain key species in the food web that might have a significant impact on the functioning of the entire ecosystem. The increase in median centrality suggested that optimal ecological design could strengthen these critical roles, thereby enhancing the efficiency and health of ecological networks. The increase in the average clustering coefficient from 0.55 in the original state to 0.62 after the eco-optimized design showed the tendency of species groups to form tight clusters in ecological networks. The increase in clustering coefficient implied that more interactions and collaborative relationships were formed between species, and that species within these clusters were better able to support and protect each other, thus enhancing the diversity and complexity of the ecosystem. The increase in species diversity index from 2.3 in the original state to 3.2 after the eco-optimized design was a direct indicator of the success of the eco-optimized design (Table 3). The increase in species diversity not only reflected the increase in the number of species in the ecosystem, but also indicated the enhancement of ecosystem function and multi-level utilization of ecological niches. This increase in diversity helped the ecosystem to better cope with environmental changes and external pressures and maintain long-term ecological balance.

The research demonstrated that the eco-optimization design method had achieved significant results in enhancing the ecological benefits of landscape gardening. Compared with the traditional design method, the eco-optimized design significantly improved the species diversity index and species abundance, enhanced the function of ecosystem services, and improved the visual aesthetics. The results proved that the proposed models, especially the Transformer-based ecological adaptive assessment model, had significant advantages in dealing with complex ecological data and improving the ecological effects of design solutions. The effective application of the model provided a scientific basis for landscape design and strong technical support to realize the harmonious unity of ecological function and visual aesthetics, and laid a solid foundation for the future development of eco-friendly landscape design.

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