RESEARCH ARTICLE

Evaluation of ecological landscape diversity based on a fuzzy algorithm

Yingying Xiao*

School of Art and Media, Wuhan College, Wuhan, Hubei, China.

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Ecological landscape diversity plays a fundamental role in supporting ecosystem resilience, increasing environmental quality, and guiding sustainable urban planning. With increasing urbanization and ecological degradation, accurate evaluation of landscape diversity has become an urgent issue in the ecological and environmental sciences. Traditional methods often face limitations in addressing the inherent uncertainty and complexity of ecological systems. In this study, the diversity of ecological landscapes was evaluated based on a fuzzy algorithm, and the results provided a reference for the planning and management of various types of ecological gardens. Ten representative ecological gardens including city parks, forest parks, and wetland parks were assessed. The fuzzy algorithm addressed uncertainty in environmental data and established a multidimensional diversity evaluation model. The results indicated that forest parks and nature reserves had higher diversity levels, whereas urban parks and courtyard parks had weaker ecological performance. The evaluation highlighted the link between ecological design and increase in diversity. The proposed fuzzy algorithm-based approach offered a more flexible and accurate tool for landscape diversity assessment. This research contributed to the advancement of ecological evaluation methodology and supported evidence-based design strategies in ecological landscape planning.

Keywords: ecological garden; landscape diversity; fuzzy algorithm.

***Corresponding author:** Yingying Xiao, School of Art and Media, Wuhan College, Wuhan, Hubei 430000, China. Email: 1986xyy1986@sina.com.

Introduction

Ecological landscapes are critical components of urban environments, serving essential functions such as climate regulation, biodiversity conservation, aesthetic enhancement, and the improvement of human well-being. With increasing urbanization and environmental degradation, maintaining ecological integrity within urban green spaces has become a fundamental challenge. Landscape diversity, which refers to the variety and spatial configuration of landscape elements, is a key indicator of ecosystem health, resilience, and sustainability.

Recent developments in environmental science and computational modeling have led to improved methods for biodiversity and landscape analysis. The impact of socioecological and spatial factors on landscape diversity in urban and peri-urban ecosystems has been investigated in numerous studies. Rusciano *et al*. highlighted the influence of social and ecological drivers on community garden innovation [1], while Varga-Szilay *et al*. analyzed the role of demographic factors and gardening practices in shaping urban biodiversity [2]. Other researchers have explored traditional landscape preservation strategies [3], urban–rural ecological differences [4], and the multifunctional value of home and community gardens [5–7]. Brodka *et al*. proposed region-specific diversity protection strategies [8], whereas Liu *et al*. and Sellberg *et al*. emphasized the structural and spatial drivers of plant diversity and ecological connectivity [9, 10]. Studies in Mediterranean and rapidly urbanizing regions further demonstrated the need for localized assessment models [11, 12].

Despite these advancements, significant limitations remain in landscape diversity evaluation. Conventional assessment methods often struggle with incomplete data, subjective judgments, and the inability to fully capture the complexity and uncertainty of ecological systems. These constraints hinder the effective planning, management, and restoration of ecological gardens, especially under dynamic urban and climatic pressures. The primary aim of this study was to develop a quantitative and adaptable framework for assessing ecological landscape diversity. Specifically, the diversity levels across different ecological garden types including urban parks, forest parks, and wetland parks were compared based on multidimensional indicators using a fuzzy algorithm. Relevant data including species richness, vegetation coverage, soil type, and climatic conditions were collected from ten representative ecological gardens through field surveys, remote sensing, and historical environmental records. A fuzzy evaluation model that incorporated fuzzy clustering and rule-based reasoning was constructed after preprocessing and standardization of the collected data. Model parameters were then optimized using a particle swarm optimization algorithm. This research contributed to the advancement of ecological modeling by demonstrating the practical application of fuzzy algorithms in landscape diversity assessment. The proposed model increased evaluation accuracy, reduced subjectivity, and supported evidence-based decision-making in ecological planning. It offered a robust methodological foundation for promoting biodiversity conservation, optimizing landscape design, and advancing sustainable urban ecological development.

Materials and methods

Data sources and sample selection

A diversified approach for the collection of ecological garden landscape data was adopted to ensure that the data were comprehensive, true, and representative. The data were obtained through field investigations, remote sensing image analysis, meteorological data, and literature data. The focus of the field investigations was representative ecological garden areas in China including urban parks, forest parks, and wetland parks, and ecological indicators such as garden plant species, soil properties, and plant coverage rates were collected. By using satellite remote sensing technology, spatial landscape data such as vegetation distribution, land use type, and green space structure of different ecological garden areas were obtained to provide a spatial–temporal perspective for landscape diversity assessment. The meteorological data included the temperature, humidity, precipitation, and other information about the garden area. The environmental impact of the garden was analyzed using a meteorological station and historical climate data. This research combined regular sampling and onsite questionnaires to ensure the representativeness of data under different seasons and climate conditions [16]. The field questionnaire survey was given to landscape managers, ecological experts, tourists, and other groups to collect subjective evaluations of the use and management of landscape architecture and provide multi-dimensional information for subsequent analysis. Spatial analysis of the landscape data was carried out on a geographic information system (GIS) platform, and the data were used as a geographical reference, which was convenient for analyzing the spatial structure and landscape diversity of the landscape. The data were collected at ten ecological garden sites. Each selected site was characterized by differences in vegetation coverage, species richness, soil type, and landscape function, which included Beijing Olympic Forest Park (Beijing, China), an urban park with an area of 1,500 m², 80 species, 60%

vegetation coverage, and garden soil under a subtropical climate; Qingcheng Mountain Forest Park (Chengdu, Sichuan, China), a forest park with an area of 5,000 m², 200 species, 85% vegetation coverage, and rich soil in a temperate climate; Xixi National Wetland Park (Hangzhou, Zhejiang, China), a wetland park with an area of 3,500 m², 100 species, 75% vegetation coverage, and wetland soil under tropical climate conditions; Beijing Ecological Conservation Zone (Beijing, China), an ecological reserve with an area of 10,000 m², 250 species, 90% vegetation coverage, and forest soil in a temperate climate; Kunming Highland Grassland Park (Kunming, Yunnan, China), a grassland park with an area of 2,000 m², 60 species, 65% vegetation coverage, and grassland soil in a subtropical climate; Guangzhou Waterscape Ecological Park (Guangzhou, Guangdong, China), a garden with waterscape features, an area of 1,800 m², 70 species, 80% vegetation coverage, and water soil under temperate conditions; Hangzhou Theme Ecological Park (Hangzhou, Zhejiang, China), a theme park with an area of 3,000 m², 120 species, 70% vegetation coverage, and garden soil in a subtropical climate; Chengdu Urban Courtyard Demonstration Garden (Chengdu, Sichuan, China), a courtyard park with an area of 1,200 m², 40 species, 50% vegetation coverage, and sandy soil in a temperate climate; Kunming Botanical Garden (Kunming, Yunnan, China), a botanical garden with an area of 2,500 m², 150 species, 80% vegetation coverage, and nutrient soil in a tropical climate; and South China National Botanical Garden (Guangzhou, Guangdong, China), a national forest park with an area of 8,000 m², 220 species, 88% vegetation coverage, and forest soil in a temperate climate. The data was collected over a one-year period from January to December 2023 to capture seasonal variation. Data was acquired from both primary and secondary sources. Primary data were obtained through onsite ecological surveys including species inventories, vegetation cover assessments, and soil sampling. Secondary data were retrieved from China Meteorological Data Service Center (CMDC) (https://data.cma.cn) that provided climate data such as precipitation, temperature, and humidity with a total of 200 entries being downloaded for each site, covering daily weather parameters; National Land Use Remote Sensing Database (NLURSD) (http://www.resdc.cn) that provided high-resolution remote sensing imagery and land use data with a total of 50 processed satellite images per site being used, mainly for vegetation classification and land cover analysis; China Biodiversity Red List Database (CBRD) (http://www.chinabiodiversity.com) that provided reference data on plant species including conservation status and distribution with approximately 300 species records being consulted in total. All the datasets were cleaned and integrated through the GIS platform, which provided spatial referencing and ensured consistency across ecological indicators.

Data preprocessing and cleaning

The raw data were standardized, corrected for anomalies, and prepared for analysis. Missing values were handled using mean substitution and k-nearest neighbor interpolation, depending on the variable type. Continuous variables were normalized to a standard normal distribution to eliminate dimensional effects. The outliers were removed using z scores and boxplot diagnostics to ensure robustness. Data cleaning involved detecting and correcting inconsistencies including the removal of duplicate records, correction of input errors, and resolution of temporal conflicts. Remote sensing images were denoised using spatial filters, and time-series meteorological data were screened for instrumentation errors using moving-average smoothing. All the data were georeferenced using GIS tools and subjected to consistency validation prior to modeling.

Model selection and construction

Given the multidimensional, uncertain nature of landscape diversity data, a fuzzy logic-based modeling approach was employed in this study. The fuzzy algorithm allows ambiguous input variables to be handled using membership functions and fuzzy rules. Unlike conventional regression or classification models, fuzzy inference systems are adaptive and well suited for ecological decision-making under uncertainty. Therefore, a fuzzy evaluation framework was constructed and optimized using metaheuristic strategies. The construction of a fuzzy algorithm model included data processing, membership function design, model parameter adjustment, and result analysis. Standardized data processing eliminated the influence of different index dimensions and increased the stability of the model. The appropriate membership function was then designed according to the characteristics of the ecological garden. The membership function mapped the input data to the fuzzy set, selected the Gaussian membership function as the basic function, combined the diversity characteristics of the ecological landscape, and designed a variety of membership function forms to adapt to different landscape types. The Gaussian membership function had a smooth transition effect and was suitable for describing the continuity variables in ecological landscapes such as vegetation coverage and species richness. After designing a membership function, a fuzzy rule base was established. Different fuzzy rules were defined to explain the relationships between different landscape types. The design of the rule base relied on the experience of domain experts and in-depth analysis of the sample data. Each rule reflected the logical relationship between different ecological variables. These rules provided a decision-making basis for the reasoning process of the model. Fuzzy inference performed inference operations on the input data according to the rule base and output fuzzy results. Finally, in the process of defuzzification, the results of fuzzy reasoning were transformed into a concrete numerical evaluation, and the final evaluation result of landscape diversity was obtained. The fuzzy model construction involved defining Gaussian membership functions for input variables such as vegetation coverage (weight = 0.35), species richness (weight = 0.45), and climate adaptability (weight = 0.20). Fuzzy rules were designed based on expert knowledge. These rules guided the fuzzy inference system to output composite diversity scores. The parameters of these functions and the weights of the indicators were later optimized using particle swarm optimization.

Model parameter optimization

The selection of parameters in the fuzzy algorithm had a direct influence on the results, the design of the membership function, weight allocation, and the formulation of fuzzy rules. The parameters were adjusted through optimization to adapt the model to different ecological landscape characteristics. The particle swarm optimization (PSO) algorithm (https://pyswarms.readthedocs.io/) was used to optimize the parameters of the fuzzy algorithm, which was an optimization method based on swarm intelligence to simulate the behavior of birds foraging and find the optimal solution to the problem. The PSO algorithm had a global search ability to avoid falling into local optimal solutions. By updating the position and velocity of the particle, the optimal solution in the parameter space was calculated, and the parameter setting of the model was improved. PSO had two main aspects including optimization of the shape and parameters of the membership function and optimization of the weight of fuzzy rules. Through PSO, the parameters of each membership function were automatically adjusted to reflect the diversity characteristics of different ecological gardens more accurately. The weight distribution was optimized to make the influence of each ecological variable more reasonable. PSO improved model performance and increased stability and accuracy in practical applications. The PSO algorithm was optimized as follows.

$$v_i^{k+1} = wv_i^k + c_1r_1(x_i^{best} - x_i^k) + c_2r_2(x_g^{best} - x_i^k) \quad (1)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (2)$$

where v_i^{k+1} was the particle velocity. x_i^{k+1} was the particle position. x_i^{best} was the individual optimal position. x_g^{best} was the global optimal position. c_1 and c_2 were the learning factors. r_1 and r_2 were random numbers. *w* was inertia weight. By alliterative updating the velocity and position of particles, the PSO algorithm could gradually find the optimal parameters.

Model implementation and coding

The model used the Python programming language. Numerical array operations (NumPy) (https://numpy.org) was used for matrix calculation. The scientific computing tools for Python (SciPy) (https://scipy.org) were used for the optimization algorithm, and Matplotlib (https://matplotlib.org/) was used for visual display of the results. The flow chart of model algorithm coding and the entire process included data preprocessing, membership function design, fuzzy reasoning, deblurring, and result analysis (Figure 1).

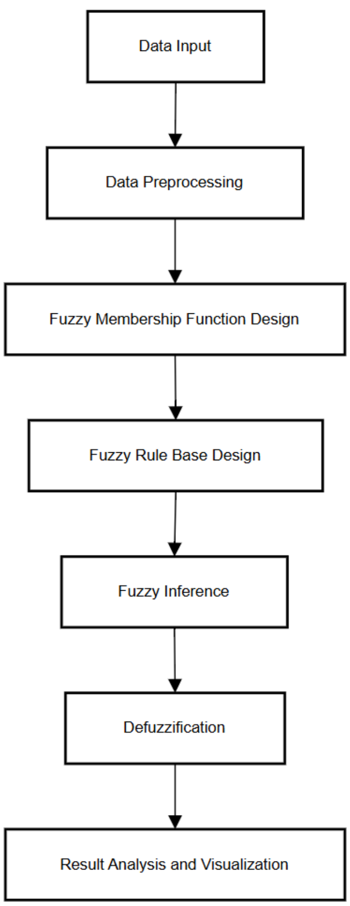

Figure 1. Model algorithm coding flow chart.

Model evaluation indicators

In accordance with the characteristics of ecological landscape diversity assessment, a variety of assessment indicators were selected to measure the accuracy and applicability of the model. Common model evaluation indicators included the accuracy rate, recall rate, and F1 score. In the field of ecology, more consideration was given to a model's ability to identify different landscape types and the accuracy of diversity measurement. In this study, an evaluation index specifically adapted to the characteristics of the fuzzy algorithm was designed. The accuracy rate and recall rate were basic classification performance indicators and were used mainly to evaluate the classification ability of the model. Accuracy compared the proportion of samples that the model correctly predicted to the total sample, and recall focused on the proportion of all true positive samples that the model found. Multiple ecological variables were used in landscape diversity assessments, and F1 scores were used for more comprehensive performance evaluations when the accuracy and recall rates were considered comprehensive. To address the unique uncertainty characteristics of the fuzzy algorithm, a fuzzy accuracy index was introduced to measure the degree of fuzzy matching between the model output results and the actual landscape diversity, reflecting the performance of fuzzy reasoning systems in practical applications. The calculation for the evaluation index was as follows.

(1) Accuracy:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

where *TP* was the real number of examples. *TN* was the true number of counterexamples. *FP* was the false number of positive examples. *FN* was the false number of counterexamples.

(2) Recall rate (recall):

$$\text{Recall} = \frac{TP}{TP+FN} \tag{4}$$

(3) F1 score:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (5)$$

(4) Fuzzy accuracy:

$$\text{Accuracy} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{|f_i - \hat{f}_i|}{f_i + \hat{f}_i}\right) \quad (6)$$

where f_i was the actual observed value. $\hat{f}$ was the predicted value of the model. n was the number of samples.

Model verification and results analysis

The applicability and accuracy of the proposed fuzzy algorithm model were verified, and the model was trained and tested many times by cross-validation. The risk of overfitting was reduced, and the generalization ability of the model was ensured. In each round of cross-validation, the data were divided into a training set and a test set. The model learned on the training set and was evaluated on the test set to obtain more robust evaluation results. In the verification process, other classical algorithms including support vector machine (SVM) and decision tree (https://scikit-learn.org) were selected to compare with the proposed fuzzy algorithm in the evaluation of ecological landscape diversity.

Results and discussion

Diversity assessment of different ecological regions

The results of different types of ecological regions demonstrated differences in landscape diversity, which included the plant species, species distribution, ecological structure, and the degree of diversity. The urban parks' diversities were low with abundant plant species. Due to increased human intervention, the stability of the ecosystem was weak, and the ecological relationships between species were relatively simple, which limited the landscape diversity. The diversities of forest parks and national forest parks were high with more natural ecological environments, more complex species diversity, and greater ecological stability and system diversity. Wetland Park had a unique alternating land and water environment with a relatively balanced species distribution and high landscape diversity. Quantitative diversity scores for the ten ecological gardens were generated using the fuzzy evaluation model, which produced a normalized diversity index ranging from 0 to 100, in which higher values indicated greater ecological complexity and landscape richness. The results demonstrated that the Beijing Ecological Conservation Zone scored the highest at 91.2, reflecting its intact forest ecosystem and low degree of human disturbance, while the South China National Botanical Garden and Qingcheng Mountain Forest Park had the second and third highest scores of 90.8 and 88.5, respectively, due to their large size, diverse flora, and high canopy coverage. In contrast, Chengdu Urban Courtyard Demonstration Garden and Hangzhou Theme Ecological Park scored the lowest, at 73.8 and 70.1, respectively, which might be due to limited spatial heterogeneity and intense anthropogenic modification (Figure 2). These outcomes across all ten gardens confirmed that, compared with urban-modified green spaces, protected or seminatural areas consistently exhibited greater diversity. These results revealed the role of ecosystem structure and functional zoning. Forests, wetlands, and protected areas preserved microclimate variations and species associations that supported biodiversity. Urban parks, which were constrained by design and maintenance practices, often prioritized aesthetics over ecological function, thus reflecting lower diversity scores. These findings supported previous studies that emphasized landscape complexity and naturalness as critical drivers of ecological performance [8, 10]. To preliminarily explore the distribution of key variables, a descriptive statistical analysis was conducted and found that the area, species count, and vegetation coverage of the ten ecological gardens substantially differed. Large-scale gardens such as the Beijing Ecological

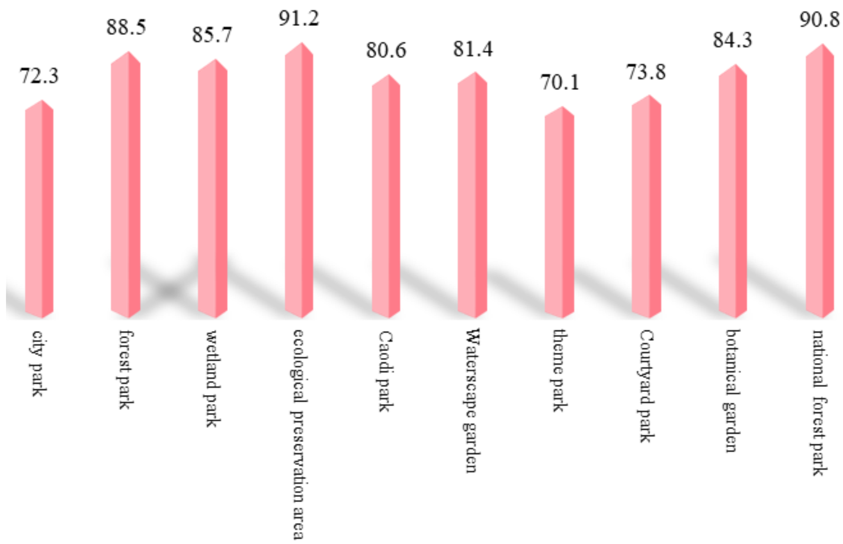

Figure 2. Quantitative diversity scores for the ten ecological gardens.

Conservation Zone (10,000 m²) and South China National Botanical Garden (8,000 m²) had the highest biodiversity values, whereas smaller-scale urban or courtyard parks exhibited lower diversity. The mean vegetation coverage ranged from 50 to 90% with wetland and forest types generally showing higher ecosystem richness and coverage.

The results of the different models in the verification process including accuracy, recall, and F1 score showed that the proposed fuzzy algorithm was superior compared to the other models in terms of all indices with outstanding accuracy, recall rate, and F1 score, which indicated the actual effect on landscape diversity assessment was ideal (Figure 3). The fuzzy algorithm could provide more accurate evaluation results for landscape diversity and maintain high stability and accuracy when dealing with data with high uncertainty. These findings supported the theoretical assumption that ecological diversity was closely linked to spatial scale, vegetation heterogeneity, and land use intensity. The results were aligned with the previous studies in landscape ecology by Brodka *et al*. [8] and Ghadban *et al*. [11], which emphasized that conservation zones and forested regions maintained higher ecological integrity due to minimal fragmentation. These results suggested that urban landscape planning should shift from decorative planting schemes to multifunctional and ecologically integrated designs.

Comparison of ecological indicators

To further validate the performance of the fuzzy algorithm, the fuzzy diversity scores were compared with three conventional ecological indicators including the Shannon–Wiener index, species richness index, and evenness index. The comparison results of the ten ecological gardens showed a consistent pattern across most samples with the Shannon–Wiener index trended closely with the fuzzy score, particularly at sites with well-preserved ecosystems. Xixi National Wetland Park (sample 3) and Beijing Ecological Conservation Zone (sample 4) both exhibited high Shannon–Wiener index values above 3.5 and corresponding fuzzy scores of 0.91 and 0.88, respectively. Species richness showed noticeable variation with Sample 4 and South China National Botanical Garden (Sample 10) exhibiting the highest counts. These were also the sites with high fuzzy scores, indicating that species count played a central role in perceived diversity. The evenness index, while relatively lower at all sites, reflected the dominant distribution of species. In

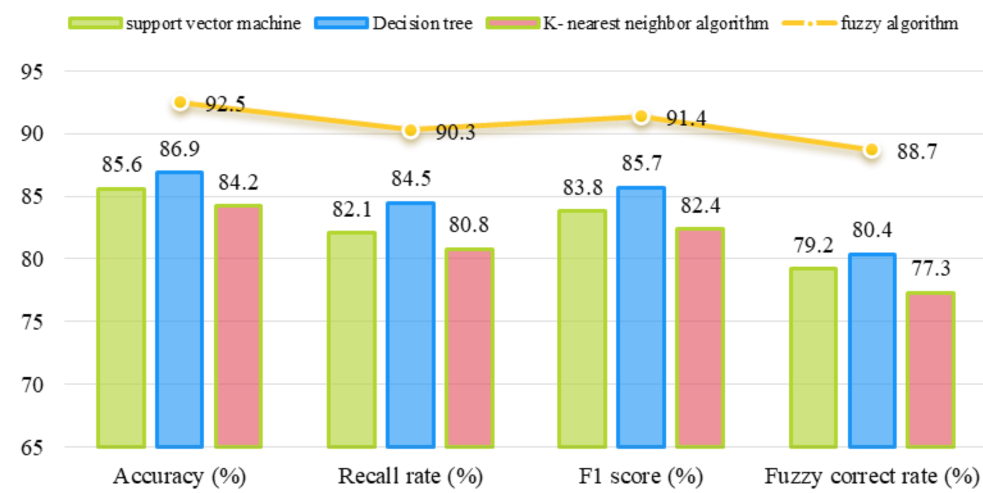

Figure 3. Comparison of different models.

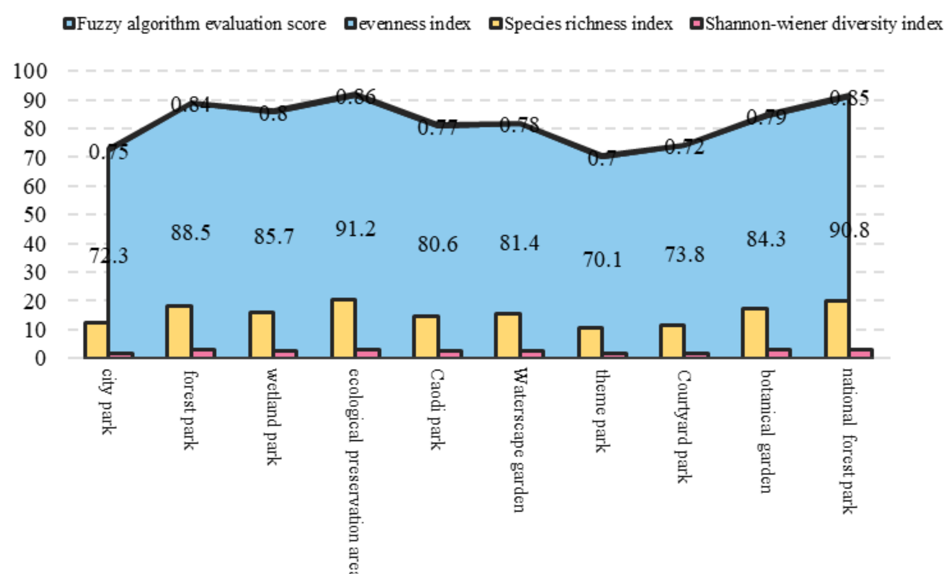

Figure 4. Comparison of different ecological indicators across ten representative ecological gardens.

high-density urban sites such as Chengdu Courtyard Park (Sample 8), the evenness index decreased significantly, indicating uneven species distribution. These were also the sites where the fuzzy score was the lowest, capturing ecological imbalance (Figure 4). These outcomes validated the fuzzy evaluation model's sensitivity to ecological structure and heterogeneity. Unlike traditional indices that relied primarily on species counts and proportions, fuzzy algorithms integrated multidimensional variables such as soil type and climate adaptability, thus offering a more holistic and context-aware representation of ecological diversity. This comprehensive comparison revealed a strong positive correlation between the fuzzy model and classical biodiversity metrics as well as the model's superior ability to reflect functional ecological complexity under conditions of uncertainty. These results indicated strong concordance between the fuzzy model and classical diversity metrics with Pearson correlation coefficient larger than 0.89. However, the fuzzy algorithm offered additional analytical advantages that it captured nonlinear relationships and integrated multidimensional inputs such as soil type and climate adaptability, which were often excluded from traditional indices. The model's holistic approach reflected the functional diversity of ecosystems rather than merely compositional metrics.

Practical significance and application scenarios of the results

The diversity of the ecological landscape affects the survival and reproduction of biological populations, which is related to the stability and sustainable development of the ecological environment. Quantitative assessments of landscape diversity in different ecological regions provided a basis for ecological protection, urban planning, and green space design. The evaluation results provided a basis for the management of ecological reserves. By evaluating the diversity of different ecological regions, managers could identify regions with poor ecosystem stability and take corresponding protective measures. The diversities of forest parks and national forest parks were high, and the ecosystem health in these areas was good. Urban parks and courtyard parks were needed to strengthen ecological design and plan to increase biodiversity and improve the ecological environment. In urban planning and green space design, the results of landscape diversity assessments provided planners with the direction of optimal design. Against the background of accelerating urbanization, the ecological function of urban green space has been weakened, and a reasonable ecological landscape is conducive to restoring ecological balance. Through diversity assessment, the sites with incomplete ecological functions in green space could be identified, and the diverse plants should be introduced to improve the ecological structure and increase the ecological value of urban green space. In the landscape design of wetland parks, waterscape gardens, and other special ecological environments, the fuzzy algorithm provided a flexible model for diversity evaluation and the complexity of multiple factors to address the uncertainty in the environment, which provided scientific and operable decision support tools for landscape managers and was helpful for improving the ecological quality of landscapes and promoting sustainable urban development. These results confirmed the fuzzy model's superior adaptability to ecological data heterogeneity. While traditional models were sensitive to feature selection and noise, the fuzzy inference system maintained interpretability and accommodated uncertainty through its rule-based structure. This advantage was particularly relevant in landscape ecology, where measurement inconsistency and partial data were frequent. The integration of fuzzy logic with PSO optimization enabled dynamic parameter tuning, increasing predictive reliability in real-world applications.

Conclusion

Based on the fuzzy algorithm, the diversity of ecological landscapes was systematically evaluated, and the application effects in different ecological regions were explored. An analysis of different types of ecological landscapes including city parks, forest parks, and wetland parks revealed that the diversity levels of various types of ecological areas differed. The fuzzy algorithm could address the uncertainty and complexity of ecological data, providing a flexible and efficient tool for assessing the ecological diversity of landscapes. The diversity evaluation model used in data collection and processing showed strong applicability and comprehensively considered the influence of different ecological factors, providing a scientific basis for ecological garden management. The evaluation results revealed the diversity status of ecological landscapes in various ecological regions, which provided a direction for future ecological protection and landscape design. In the design of urban parks and garden greenbelts, through the results of a diversity assessment, the plant configuration and landscape structure could be optimized more accurately, and the stability and resilience of the ecosystem could be improved. This study provided a theoretical framework and method support for the diversity assessment of ecological landscapes, which had important practical significance. It had guiding value for future ecological garden design and urban greening planning.

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