PLANT LANDSCAPE CHARACTERISTICS IN ZHEJIANG ECOLOGICAL SCENIC AREAS USING AHP AND FUZZY COMPREHENSIVE EVALUATION METHOD

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Abstract. Traditional analytical methods are inadequate for dealing with the complexity and dynamics of plant landscapes in ecological scenic spots in Zhejiang Province. It is difficult to quantify fuzzy information and dynamic weight distribution effectively in multi-criteria decision-making. To address the above issues, this study proposes a plant landscape feature analysis method that combines the analytic hierarchy process (AHP) and the fuzzy comprehensive evaluation method (FCE). The research results showed that the AHP-FCE model significantly improved the interpretation rate of ecological indicators and the accuracy of aesthetic evaluations compared with traditional methods. It also demonstrated outstanding performance in handling fuzzy information and maintaining data consistency (both over 96.5%). The weight analysis of the criterion layer showed that ecological adaptability (0.400) was the most critical dimension influencing landscape features. This method provides a scientific analytical tool for plant landscape planning and scenic area management. Its research results clearly indicate that, in managing ecological scenic areas, the stability and health of the ecosystem should be prioritized. Then, the aesthetic quality of the landscape can be optimized. This provides a clear decision-making path for achieving the coordinated improvement of ecological sustainability and tourism attractiveness of the scenic area.
Keywords: *AHP, multi-criteria decision making, landscape character assessment, ecotourism, Sustainable landscape management, weight analysis*

Introduction

The building of China’s ecological civilization has entered a crucial phase of carbon emission and pollution reduction, as well as a thorough green transformation of social and economic growth. Eco-tourism has emerged as a significant means for people to unwind connect get in touch with nature as a result of the extensive promotion of ecological civilization development (Morales Pedraza, 2023). As the core element of ecological scenic areas, the quality of plant landscape directly affects the experience of tourists and the sustainable development of scenic areas. Plant landscape refers to the natural or arrangement planting of different forest phases, seasonal phases, and colorful scenery of different plant communities. It is composed of a wide range of plants such as trees, shrubs, grasses and old and famous trees (Cao et al., 2024; Ding et al., 2022). Zhejiang Province, located on the southeast coast of China, is an ecological province rich in plant resources and diverse landscape types. This has earned it the title of a plant treasure house in southeastern China. This study selects ecological scenic spots in Zhejiang Province as a case study, mainly based on their three typicality and representativeness: the transitional and diverse nature of ecological locations, the typical conflicts and coordination between

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human activities and ecological protection, and the completeness of the landscape types. Zhejiang Province is located in the mid-subtropical monsoon zone. The province’s terrain includes coastal plains, hilly basins, and mountains, which create an extremely diverse range of vegetation types and ecosystems. This geographical pattern makes it a microcosm of the ecological landscape in the densely populated areas of eastern China. Studying the characteristics of its plant landscape provides direct reference value for similar areas at the same latitude. Meanwhile, Zhejiang is one of the most economically developed and tourism-active provinces in China. The ecological scenic area is under pressure from both the need for ecological protection and the intense disturbance caused by tourism. Tourists demand high-quality aesthetic experiences and leisure services. Scientific assessment of its plant landscape characteristics in scenic areas has become an important topic in scenic planning, ecological protection, and management decision-making. However, the current analysis of plant landscape characteristics mainly relies on subjective experience or a single indicator, and lacks a systematic and quantitative analysis system. Analytic hierarchy process (AHP) is a multi-criteria decision analysis method used to assist decision makers in ranking or comparing among multiple indicators or factors (D’Adamo, 2023; Mishra et al., 2024). However, there are several ambiguities and uncertainties in plant landscape characterization, making it challenging to properly assess the findings of its thorough study using AHP alone. A comprehensive evaluation (CE) technique founded on fuzzy mathematics is the fuzzy comprehensive evaluation (FCE). According to fuzzy mathematics’ attachment degree theory, this CE approach converts qualitative assessment into quantitative evaluation. It can more effectively address ambiguous and challenging-to-quantify issues and is distinguished by its high systematicity and unambiguous conclusions. It makes up for the deficiency of AHP in fuzzy information processing (Gong, 2023; Muhsen et al., 2023). Aiming at the above problems, the study proposes a method to analyze plant landscape characteristics in ecological scenic areas in Zhejiang by combining AHP and FCE. The study innovatively constructs a hierarchical analysis system that includes four criteria: ecological adaptability, landscape aesthetics, biological diversity and recreational service. Each index’s weights are determined using AHP, and an evaluation is carried out by combining FCE. This can realize the systematic and precise analysis of plant landscape characteristics in Zhejiang ecological scenic areas. The study aims to establish a scientific analytical framework to assess plant landscape characteristics in Zhejiang ecological scenic areas and to enhance the ability to process fuzzy information. By clarifying the indicator weights (IWs) such as ecological adaptability and landscape aesthetics, it provides a scientific basis for plant landscape planning and management in scenic areas.

Related works

FCE can digitize the fuzzy information to get relatively accurate evaluation results. AHP can solve multi-objective complex problems. Therefore, it has been widely used in the fields of resource allocation, risk assessment, engineering evaluation, conflict analysis, and project management (Tavana et al., 2023; Zeng et al., 2023). Bahrami et al. proposed a method of generating an ecological carrying capacity map using AHP and geographic information system in response to the ecological carrying capacity and land use planning issues in Alborz Province, Iran. The research results revealed that slope and land resources had a significant impact on the land use selection in the study area. The planning map indicated that the areas suitable for irrigated agriculture, orchards and

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forestry, grasslands, protected areas, and residential and industrial development were 63,621 ha (11%), 66,730 ha (13%), 79,435 ha (16%), 224,812 ha (44%), and 71,471 ha (14%), respectively. It had practical significance in guiding the effective utilization and protection of land (Bahrami et al., 2024). In response to the complexity of forest management, Başkent et al. proposed a model for identifying and spatially stratifying ecosystem services based on multi-criteria decision analysis methods, particularly the Delphi method and AHP. The research results showed that the spatial stratification of ecosystem services primarily focused on biodiversity conservation (78.5%) and water resource protection (13.3%). The supply of wood production (7.9%) and soil protection (0.04%) was relatively small and did not include climate regulation, ecotourism, or forest products other than wood. This method provided a more efficient spatial zoning strategy for achieving a balance between technological and socio-cultural factors (Başkent et al., 2025). In response to the vulnerability of urban green spaces brought about by rapid urbanization, Li et al. proposed a multi-criteria decision-making method based on AHP and the pressure-state response framework. By analyzing 10 indicators related to the vulnerability of urban green Spaces, the study identified the key factors affecting the vulnerability and classified urban green Spaces into different degrees of vulnerability (Li et al., 2025). Ali et al. proposed a method that combined landscape gene theory, AHP, and FCE to create a ranking index system for protecting traditional settlement landscapes. The study also conducted a systematic assessment of the cultural landscape characteristics of Meicheng Town in the Meishan area. The results showed that terrain and architectural decoration were the main features that needed priority protection, while building materials, traditional culture and folk customs required significant improvement. River and road landscapes offered opportunities to enhance cultural identity and aesthetic quality (AQ) (Ali et al., 2025).

In addition to offering a scientific foundation for landscape design, landscape characterisation can help to coordinate the interactions between plants and their surroundings. It can create sustainable landscapes that satisfy human aesthetic needs as well as ecological laws (Xia et al., 2025; Sulhan et al., 2023; Zhuang et al., 2022). Aboufazeli et al. suggested an artificial neural network model and tool to evaluate the AQ of natural ecosystem landscapes in urban regions and to accomplish the objective of optimum and sustainable usage of urban park settings and services. The technique forecasted the AQ of landscapes with varying water and plant shapes and quantities. The findings showed that, across both the training and test datasets, the multilayer perceptron model had the greatest R^2 value. Urban park landscapes with more striped or clustered trees and water bodies and fewer hedges and grasses might attract park visitors (Aboufazeli et al., 2024). Jahani et al. suggested an evaluation method based on human perception. The study used multilayer perceptrons, radial basis functional neural networks, and support vector machines to simulate the aesthetic qualities of forest areas. According to the study's findings, the multilayer perceptron model was shown to be the most accurate, dependable, and useful model for evaluating the overall quality of a landscape (Jahani et al., 2023). Xu et al. chose ten sample locations to reflect the variety of urban green areas in Xuzhou, eastern China, in an attempt to fill the knowledge gap regarding the impact of seasonality on visual AQ. Seasonal diversity was represented by taking the average of the coefficients of variation of 16 landscape parameters at a location throughout the course of the seasons. The outcomes revealed that fall landscapes were the most popular and winter landscapes were the least popular (Xu et al., 2022). To determine the relationship between a number of water quality indicators

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and a scenic beauty index, Huang et al. looked into a hierarchical analytic procedure based on the evaluation of scenic beauty for each site in a wetland with two water quality indicators. The findings demonstrated that 68.8% of the change in the scenic beauty score could be explained by the model suggested in the study, which focused on DO rise, CODCr removal, and NH3-N removal (Huang et al., 2023). An ordinary least squares regression model was proposed by Gülçin. et al. in order to objectively understand landscape visual aesthetic preferences in relation to landscape type and characteristics. The study used image statistics as explanatory variables to predict visual aesthetic preferences. Landscape types were identified using a landscape character assessment, and a visual field analysis distinguishing between near, middle and far regions was applied. The findings indicated that the most significant elements affecting people's visual aesthetic choices were vegetation and geomorphology, which were followed by water features and man-made buildings and towns (Gülçin et al., 2024).

In summary, landscape characterization has shown significant value in the fields of ecological landscape planning, risk assessment, and quality management. To further increase the precision and dependability of landscape characterization, several researchers and experts have created numerous enhanced models. To sum up, AHP and FCE are widely applied in their respective fields. However, in the assessment of the complex system of plant landscapes in ecological scenic areas, there are still three key methodological and practical gaps in the existing application combination methods. The first issue is the solidification of weights. Weights determined by traditional AHP are usually static, making it difficult to reflect the dynamic characteristics of plant landscapes that change with the seasons and over the years. This results in a disconnect between the assessment results and the actual management needs of the scenic area. Second, there is insufficient handling of fuzziness and heterogeneity. Existing FCE applications often lack optimization considerations for the spatial heterogeneity of landscape indicators when constructing membership functions. These applications also fail to fully utilize the weight results of AHP to precisely constrain subjective uncertainties in fuzzy assessments. The last issue is the weak coupling between ecological and aesthetic indicators: Many models treat ecological and aesthetic indicators as separate dimensions, failing to reveal their inherent synergies or trade-off relationships through deep methodological coupling. This makes it difficult to guide multi-objective, collaborative optimization practices. Therefore, this study proposes an improved analytical method that deeply integrates AHP and FCE. The innovation of the research method lies in: Not only does it combine the two methods, but it also aims to systematically address the above gaps. It does so by introducing a dynamic weight adjustment mechanism, constructing membership functions for the spatial heterogeneity of landscapes, and establishing a cross-influence assessment framework for ecological-aesthetic indicators. This provides a more adaptive, scientific tool for analyzing and managing the characteristics of plant landscapes in ecological scenic spots in Zhejiang.

Analysis of plant landscape characteristics in Zhejiang ecological scenic areas

Construction of analysis system for plant landscape characteristics in Zhejiang ecological scenic areas

Plant landscape plays a crucial role in ecological scenic areas. In addition to being a vital component of the natural ecosystem, it also serves as a significant assurance of biological variety and ecological balance in picturesque locations (Vaz de Freitas et al.,

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2022). First, plant landscape can shape the cultural connotation and regional characteristics of scenic areas, enhance the immersion and identity of tourists, and thus improve the attractiveness and competitiveness of scenic areas. Second, the seasonal changes, color levels and spatial patterns of plant landscape also provide tourists with rich visual enjoyment and aesthetic experience. Finally, plant landscape can also purify the air, regulate the climate, nourish water and other functions. It can reduce the emission reduction of urban water bodies and reduce urban noise (Vukoičić et al., 2023). Therefore, a scientific analysis of the scenic plant landscape can not only promote ecological protection and sustainable development, but also create a more comfortable recreational environment for tourists. The synergistic growth of ecological, social, and economic advantages can be realized in this way. The establishment of analysis system for plant landscape characteristics in ecological scenic areas can unify the standard and provide convenience for research and comparison. Since the current analysis of plant landscape characteristics in ecological scenic areas focuses on a single perspective, it lacks a complete analytical framework for comprehensive consideration from multiple dimensions. Therefore, the study will construct the key elements of the analysis system for plant landscape characteristics in scenic areas from four aspects: ecological adaptability, landscape aesthetics, biological diversity, and recreational service. The construction steps are shown in *Figure 1*.

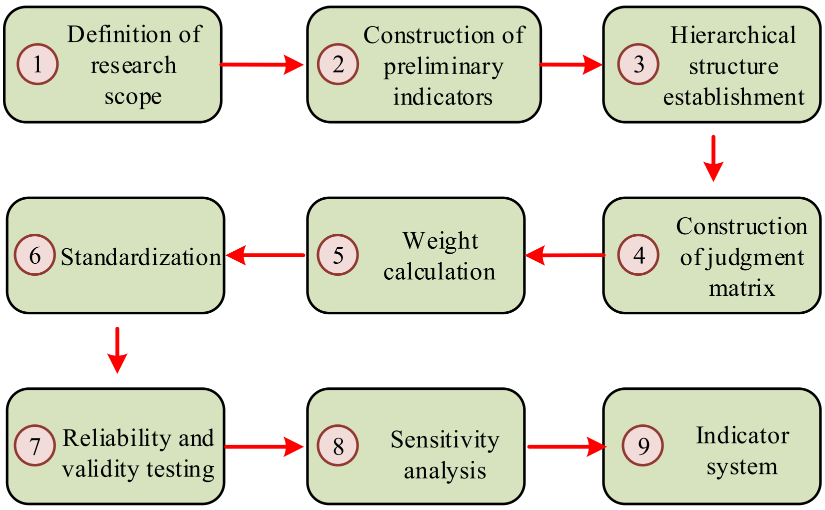

***Figure 1.** Construction steps of the analysis system for plant landscape characteristics in scenic areas. (Icon source: self-drawn)*

Based on *Figure 1,* an analysis system for plant landscape characteristics in ecological scenic areas is constructed as follows. First, the scope and objectives of the research are defined. Then, a preliminary indicator library is established. Core indicators are selected to form a three-level hierarchy: target layer (TL), criterion layer (CL), and indicator layer (IL). Judgment matrices are then constructed to calculate IWs, and a consistency test is performed. Indicators are standardized, and their reliability and sensitivity are tested to finalize the system. The system includes:

TL: Analysis of plant landscape characteristics in Zhejiang ecological scenic areas.

CL: Ecological adaptability (B1), landscape aesthetics (B2), biological diversity (B3), and recreational service (B4).

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IL: 12 specific indicators (C1-C12) covering aspects such as native plant proportion, species richness, and cultural theme expression.

The analysis system for plant landscape characteristics in scenic areas is shown in *Figure 2*.

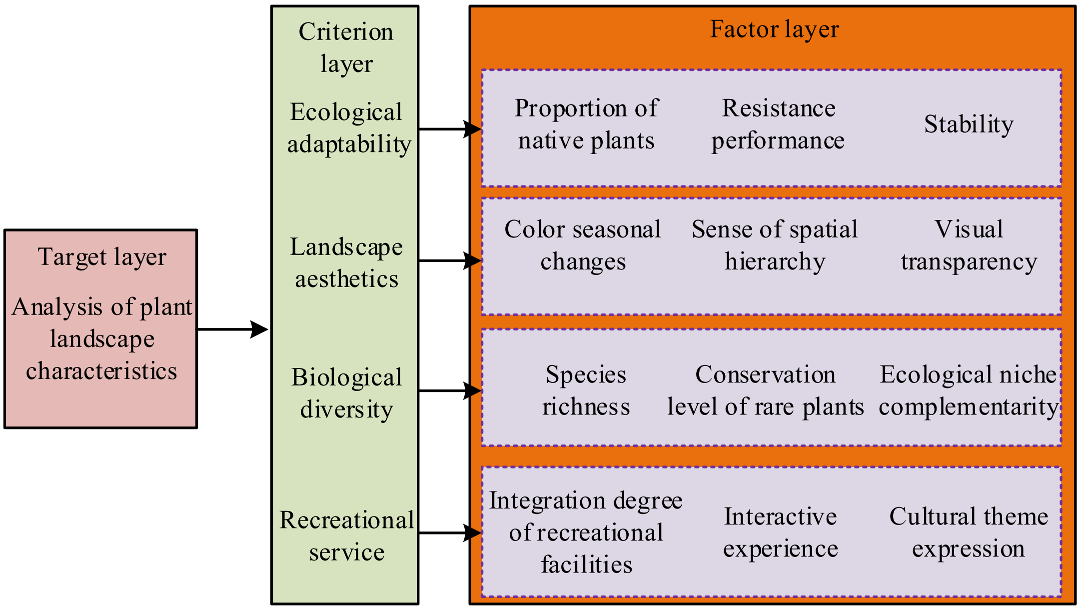

Figure 2. *Analysis system of plant landscape characteristics in scenic area. (Icon source: self-drawn)*

Figure 2 presents a hierarchical grading of the analysis system, where the 12 indicators (C1-C12) are defined as follows: C1 is the percentage of native plant species. C2 is plant adaptability to environmental stressors. C3 is the stability of plant community structure and function. C4 refers to seasonal color richness and ornamental continuity. C5 is the coordination of the vertical structure in plant configuration. C6 is the influence of plant layout on view guidance and landscape penetration. C7 measures species richness and distribution uniformity per unit area. C8 indicates the presence and conservation status of rare or endangered plants. C9 describes niche complementarity and symbiotic relationships within the plant community. C10 evaluates the integration and comfort of the plant landscape with recreational facilities. C11 assesses opportunities for sensory interaction. Moreover, C12 examines whether plant configuration reflects local cultural themes.

Determination of IWs based on AHP

This study uses the AHP to determine IWs for analyzing the characteristics of plant landscapes in Zhejiang's ecological scenic areas. This method breaks down complex problems into hierarchical models. It uses pairwise comparisons and consistency tests to calculate weights for each element. This provides a structured basis for decision-makings (Ayyildiz, 2023; Selvam et al., 2023). The core of AHP involves structuring the problem by overall aim and sub-objectives, then deriving priority weights by solving judgment matrix eigenvectors and synthesizing them through a weighted sum (Vafadarnikjoo et al., 2023). This approach allows for the systematic consideration of

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various factors, minimizing subjectivity, and offering high flexibility for adjustments. These features make it well-suited for this analysis. The steps of determining IWs based on AHP are shown in *Figure 3*.

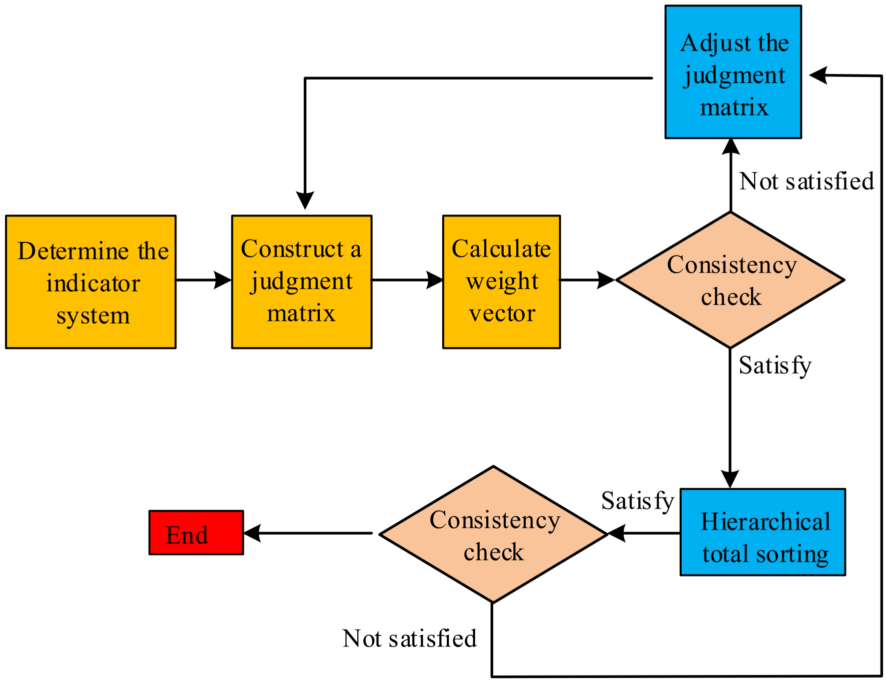

Figure 3. *Steps for determining IWs based on the AHP. (Icon source: self-drawn)*

Figure 3 shows how the IWs in the analysis system for plant landscape characteristics in Zhejiang's ecological scenic areas are determined using AHP. The criteria and sub-criteria (CSC) to be assessed are decided when the decision-making goals have been made clear. The hierarchy of goals, or CSC, is then formed by establishing a hierarchical structure. The CSC is expanded layer by layer until it reaches the lowest level, with the objectives at the top level. Next, a two-by-two comparison of each CSC is performed to derive weights. The relative relevance of each CSC in relation to the higher-level criteria or aim is compared two by two to create a JM. Additionally, each CSC's weights in relation to the higher-level criteria or aim are computed. The final weight values are then obtained by performing a CT on the two-by-two comparison matrix. The study constructs the JM by comparing the same level of indicators two by two using the 1–9 scale approach. *Table 1* illustrates the meaning of the 1–9 scale.

Table 1. *1-9 meaning of scale*

Scale	Meaning
1	Demonstrating the equal relevance of markers i and j
3	Indicator i is somewhat more significant than indicator J
5	Demonstrating that indication i is noticeably more significant than indicator j
7	demonstrating that indication I is more significant and powerful than indicator j
9	This shows that indication i is far more significant than indicator j
2, 4, 6, 8	The median value that reflects the aforementioned assessment

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The JM is constructed according to the criteria for calculating the indicators given in *Table 1,* as shown in *Equation 1*.

$$A=\begin{pmatrix} 1 & a_{12} & \cdots & a_{1j} \\ \vdots & \ddots & \ddots & \vdots \\ a_{i1} & \cdots & \cdots & 1 \end{pmatrix}, a_{ij}=\frac{1}{a_{ji}} \quad \text{(Eq.1)}$$

In *Equation 1*, a_{ij} is the importance of i indicators relative to j indicators. After constructing the JM, the weight vector is calculated. The calculation of the weight vector includes two steps, column normalization and row averaging, which can transform the relative importance in the JM into specific weight values. Column normalization eliminates the difference in the scale by dividing each column element by its column sum. Therefore, different indicators are comparable with each other. The column normalization calculation is shown in *Equation 2*.

$$b_{ij}=\frac{a_{ij}}{\sum_{k=1}^{n} a_{kj}} \quad \text{(Eq.2)}$$

In *Equation 2*, b_{ij} denotes the normalized matrix element. $\sum_{k=1}^{n} a_{kj}$ denotes the sum of all elements in column j. By figuring out the average value of the components in each row, row averaging determines the initial weight of each indication. This step can transform the subjective judgment of experts into objective values, thus quantifying the contribution of each indicator in the overall evaluation. The row average calculation is shown in *Equation 3*.

$$w_i=\frac{1}{n}\sum_{j=1}^{n} b_{ij} \quad \text{(Eq.3)}$$

In *Equation 3*, w_i is the weight of the i th indicator. The weight vector $W=(w_1, w_2, \ldots, w_n)^T$ can be obtained after calculating the average of each row. At this point the weight vector needs to be tested for consistency. CT is a statistical method to compare the consistency of the results obtained by different methods. By determining the JM's consistency index (CI), CT seeks to determine if the JM fulfills consistency. It is necessary to modify the JM till it satisfies the consistency criteria if it does not. It is possible to determine if the matrix satisfies the consistency requirements by computing the greatest eigenvalue, CI, and consistency ratio (CR). The JM satisfies the consistency criteria if the CR is higher than 0.1. On the contrary, it is necessary to readjust the scale value. The maximum eigenvalue calculation is shown in *Equation 4*.

$$\lambda_{\max}=\frac{1}{n}\sum_{i=1}^{n}\frac{(AW)_i}{w_i} \quad \text{(Eq.4)}$$

In *Equation 4*, $\lambda_{\max}$ denotes the maximum eigenvalue. $(AW)_i$ denotes the i th element of the product of matrix A and weight vector W. The CI is calculated, as shown in *Equation 5*.

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$$CI = \frac{\lambda_{\max} - n}{n-1} \quad \text{(Eq.5)}$$

In *Equation 5*, CI denotes the CI. n denotes the matrix order. The CR is calculated in *Equation 6*.

$$CR = \frac{CI}{RI} \quad \text{(Eq.6)}$$

In *Equation 6*, CR represents the CR. RI is the random consistency indicator. The value of RI ranges from 0 to 1. The closer to 1 indicates that the judgment results are more consistent and the calculation results are more reliable. Finally, hierarchical total sorting is performed. The purpose of hierarchical total sorting is to integrate the weights of each level into global weights. This step obtains the final weight of each specific indicator in the overall evaluation by multiplying the guideline level weights with the indicator level weights. The integrated weights are calculated in *Equation 7*.

$$W_t = w_B \times w_C \quad \text{(Eq.7)}$$

In *Equation 7*, W_t denotes the total weight of the indicator. w_B denotes the weight of CL B. w_C denotes the weight of IL C under CL B.

Analysis of plant landscape characteristics in Zhejiang ecological scenic areas combining AHP and FCE

Research on combining AHP and FCE extends beyond traditional simple series applications. Its core advantage lies in achieving the collaborative processing of “precise weights” and “fuzzy information” in the complex system of plant landscapes through functional complementarity and process iteration. The AHP in the research does not provide a static weight result. By introducing the expert’s judgment matrix on seasonal performance, it endows the weight with the potential for dynamic adjustment. This enables the evaluation model to respond better to temporal changes in plant landscapes, solving the problem of “weight solidification”. In the study of FCE, the construction of its membership function fully takes into account the spatial heterogeneity of the indicators. The research uses AHP to obtain not only the weights but also the strict logical relationship of relative importance among the indicators. This relationship is used to constrain and guide fuzzy operations in FCE. The final comprehensive fuzzy operation is essentially a multi-criteria decision-making process. It is not merely an independent evaluation of each indicator. Rather, through the hierarchical structure established by AHP, the four major criteria of ecological adaptability, landscape aesthetics, biodiversity, and leisure services are weighed and integrated within the same decision-making framework. This clearly reveals which criteria improvements contribute the most to overall landscape features. It directly solved the practical problem of “multi-objective collaborative optimization”.

This study employs an integrated AHP-FCE methodology for the quantitative analysis of plant landscape features in Zhejiang’s ecological scenic areas. First, the AHP is used to decompose the system into a hierarchy and calculate the weight vectors of the scientific indicators. These weight vectors then serve as the weight sets in the FCE model. While the AHP ensures objective weighting, the FCE, based on fuzzy

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mathematical theory, effectively handles the ambiguities and uncertainties inherent in landscape evaluations. It does so by determining an affiliation function and synthesizing a fuzzy judgment matrix, which produces comprehensive quantitative results (Huang, 2023; Lin et al., 2025). This combination compensates for AHP's limitations in processing fuzzy information, leading to more accurate and rational evaluation outcomes (Yang et al., 2023). *Figure 4* displays the assessment of plant landscape features in Zhejiang ecological scenic areas.

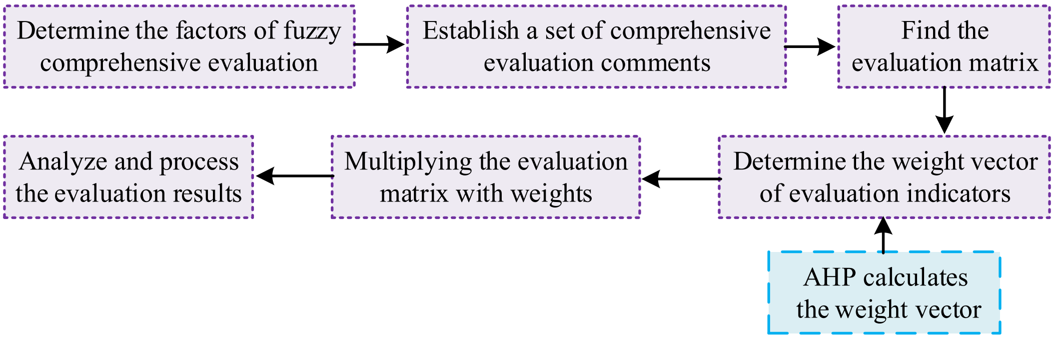

Figure 4. *Evaluation of plant landscape characteristics in Zhejiang ecological scenic areas. (Icon source: self-drawn)*

As outlined in *Figure 4,* the FCE process begins by defining the evaluation levels and their respective affiliation functions for each indicator. An evaluation matrix is then constructed from these affiliation degrees. The IW sets, previously determined by AHP, are applied to this matrix. A fuzzy synthesis operation is performed on the weighted matrix to produce CE results, which are finally defuzzified into specific quantitative scores (Huang, 2023; Lin et al., 2025). This process systematically converts subjective qualitative judgments into a concrete evaluation value. The set of evaluation factors (EFs) of plant landscape characteristics in Zhejiang ecological scenic areas is shown in *Equation 8*.

$$U = \{u_1, u_2, \cdots, u_m\} \tag{Eq.8}$$

In *Equation 8*, U denotes the evaluation index of the evaluated object m, which is the quantity of EFs. The evaluation set, which is a collection of different conclusions the evaluator may draw about the evaluation object, is determined after the EF set of plant landscape features in Zhejiang ecological scenic regions. According to the needs of plant landscape characteristics in Zhejiang ecological scenic areas analysis, the EFs are categorized as excellent, good, qualified, to be improved, and urgent remediation. The evaluation set is shown in *Equation 9*.

$$V = \{v_1, v_2, \cdots, v_f\} \tag{Eq.9}$$

In *Equation 9*, V represents the evaluation set of plant landscape characteristics in Zhejiang ecological scenic areas composed of different decisions. v_f represents the f th evaluation result. f represents the number of evaluations in the evaluation set. The affiliation function is calculated in *Equation 10*.

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$$\mu_k = \begin{cases} 0 & x < L_k \\ \dfrac{x-L_k}{M_k-L_k} & L_k \le x < M_k \\ \dfrac{U_k-x}{U_k-M_k} & M_k \le x \le U_k \\ 0 & x > U_k \end{cases} \tag{Eq.10}$$

In *Equation 10*, μ_k denotes the affiliation of the indicator to rank k. x denotes the actual score of the indicator. L_k denotes the lower threshold of rank k. M_k denotes the middle threshold of rank k. U_k denotes the upper threshold of rank k. The fuzzy relationship matrix R is shown in *Equation 11*.

$$R = \begin{pmatrix} r_{11} & \cdots & r_{1m} \\ \vdots & \ddots & \vdots \\ r_{n1} & \cdots & r_{nm} \end{pmatrix}, \quad r_{ij} = \frac{N_{ij}}{N} \tag{Eq.11}$$

In *Equation 11*, r_{ij} is the DA of the i th indicator belonging to the j th EL. N_{ij} represents the quantity of experts who believe that the i th indicator belongs to the j th rank. N is the total quantity of experts involved in the evaluation. The vector of IWs at each level calculated by AHP is used as the weight set in FCE, and these weights are directly used in the FSO. The calculation of FSO is shown in *Equation 12*.

$$B = W_t{}^\circ R = (b_1,\ldots,b_m), \quad b_j = \min(1, \sum w_i r_{ij}) \tag{Eq.12}$$

In *Equation 12*, W_t denotes the CE result vector. $\circ$ is the fuzzy synthesis operator. b_j overall evaluation belongs to the degree of the j th grade. Comprehensive score S is calculated in *Equation 13*.

$$S = \frac{\sum_j p_j b_j}{\sum b_j} \tag{Eq.13}$$

In *Equation 13*, p_j is the score of the j th EL. The steps of analyzing plant landscape characteristics in Zhejiang ecological scenic areas by combining AHP and FCE are shown in *Figure 5*.

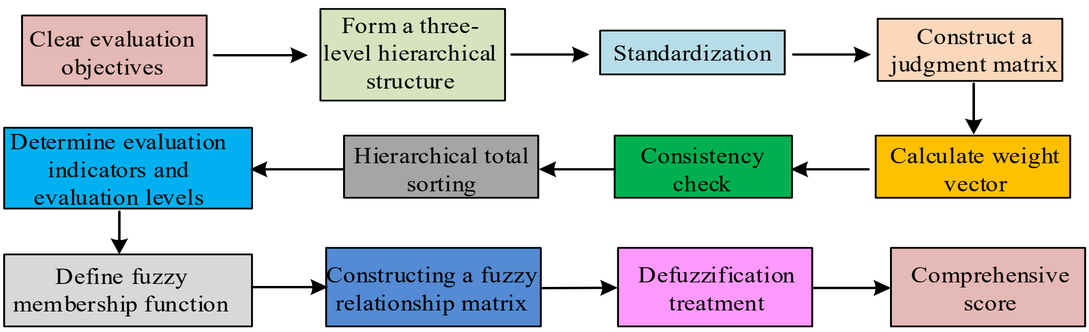

Figure 5. *Analysis steps of plant landscape characteristics in Zhejiang ecological scenic areas using AHP and FCE. (Icon source: self-drawn)*

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Figure 5 shows the analysis of plant landscape characteristics in Zhejiang ecological scenic areas using a combination of AHP and FCE. First, the evaluation objectives are clarified by constructing a three-level hierarchical structure system containing the TL, the CL, and the IL. Second, the JM is built using the 1-9 scale technique to compute the weights and perform CT, and the IWs are established based on AHP. Finally, the EL and affiliation function are defined, and the weights determined by AHP are used as the weight set of FCE. Through FSO and defuzzification, the qualitative evaluation is transformed into quantitative results. The scores of each dimension are finally synthesized and analyzed to comprehensively evaluate plant landscape characteristics.

Analysis effect of plant landscape characteristics in Zhejiang ecological scenic areas

Affiliation of plant landscape characteristics in scenic areas analysis indicators

To ensure the scientificity and practicality of the constructed analysis system, the data basis and index formation process of this study are as follows: The research sites cover five representative ecological scenic spots in Zhejiang Province, including Tianmu Mountain, Yandang Mountain, Qiandao Lake, West Lake Scenic Area, and Nanxi River, to cover different landscape types such as mountains, lakes, wetlands, and cultural heritage sites. The selection and verification of indicators are accomplished through a process that combined literature analysis, on-site investigation, and two rounds of Delphi expert consultation. First, candidate indicators are preliminarily screened out from the literature in fields such as ecology, landscape aesthetics, and recreation management. Subsequently, an expert group consisting of 15 members (including 5 ecologists, 5 landscape planners and 5 scenic area management directors) is formed. Through two rounds of anonymous Delphi questionnaire surveys, the importance and operability of the indicators are scored. Eventually, 12 indicators with high consensus (coefficient of variation < 0.25) are included in the final system. Expert judgment is specifically applied to construct the judgment matrix in the AHP. That is, the expert group is invited to conduct pairwise comparisons of indicators at each level using the 1-9 scale method. The feedback is arithmetic averaged to form a comprehensive judgment matrix, and all passed the consistency test (CR < 0.1). This ensures the objectivity and authority of weight determination.

The DA is crucial in the analysis of plant landscape characteristics in Zhejiang ecological scenic areas. It may have a major impact on the precision and dependability of the analysis's findings. The outcomes of the examination of landscape characteristics can be guaranteed to be more scientific by calculating the DA of the examined indicators in a scientific manner. Therefore, before analyzing plant landscape characteristics in scenic areas, it is necessary to calculate the affiliation of analytical indicators. *Table 2* displays the correlation between plant landscape characteristics in scenic areas analysis indicators.

Combining AHP and FCE for landscape characterization quality

The interpretation rate of ecological indicators and the accuracy rate of aesthetic evaluation of landscape characterization by combining AHP and FCE are compared with other methods. In *Figure 6a*, as the quantity of samples rises, so does the pace at which ecological markers of landscape categorization may be interpreted. The

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ecological indicator explanation rate of combining AHP and FCE for landscape characterization is the highest, and the ecological indicator explanation rate based on principal component analysis is the lowest. When the sample size is 200, the ecological indicator interpretation rate is 0.96 and 0.78, respectively. In *Figure 6b*, the aesthetic evaluation accuracy rate of different methods for landscape characterization also increases with the increase of sample size. The study's proposed method for landscape characterization has the highest accuracy rate for aesthetic evaluation. When the sample size is 200, the highest aesthetic evaluation accuracy is 0.98.

Table 2. *Membership of plant landscape analysis indicators in Zhejiang ecological scenic areas*

TL	CL	Index layer	Excellent	Good	Fair	Need improvement	Urgent renovation
Evaluation of plant landscape characteristics in Zhejiang ecological scenic areas (A)	Ecological adaptability (B1)	Native plant proportion (C1)	0.258	0.342	0.215	0.125	0.060
		Stress resistance performance (C2)	0.185	0.297	0.308	0.142	0.068
		Community stability (C3)	0.320	0.275	0.210	0.115	0.080
	Landscape aesthetics (B2)	Seasonal color variation (C4)	0.412	0.285	0.168	0.095	0.040
		Spatial layering (C5)	0.375	0.310	0.195	0.080	0.040
		Visual Permeability (C6)	0.298	0.352	0.205	0.098	0.047
	Biodiversity (B3)	Species richness (C7)	0.225	0.335	0.285	0.105	0.050
		Rare plant protection level (C8)	0.352	0.298	0.185	0.115	0.050
		Ecological niche complementarity (C9)	0.285	0.315	0.235	0.120	0.045
	Recreational service (B4)	Integration of rest facilities (C10)	0.195	0.375	0.285	0.105	0.040
		Interactive experience (11)	0.168	0.295	0.342	0.135	0.060
		Cultural theme expression (C12)	0.315	0.285	0.225	0.125	0.050

Subjective bias control, classification accuracy, small sample adaptability, and calculation time of combining AHP and FCE for landscape characterization are compared with other methods. In *Figure 7a*, subjective bias control, classification accuracy of landscape characterization by combining AHP and FCE is the highest, 91.3%, 0.96, respectively. Subjective bias control of landscape characterization based on principal component analysis, classification accuracy are the lowest. The reason for this is that principal component analysis is not effective in handling data with nonlinear relationships. At this time the subjective bias control and classification accuracy are 66.4% and 0.78, respectively. In *Figure 7b*, the best performance when combining AHP and FCE for landscape characterization is compared with other methods. The small sample adaptability is 95.1% and the calculation time is 12.5 s.

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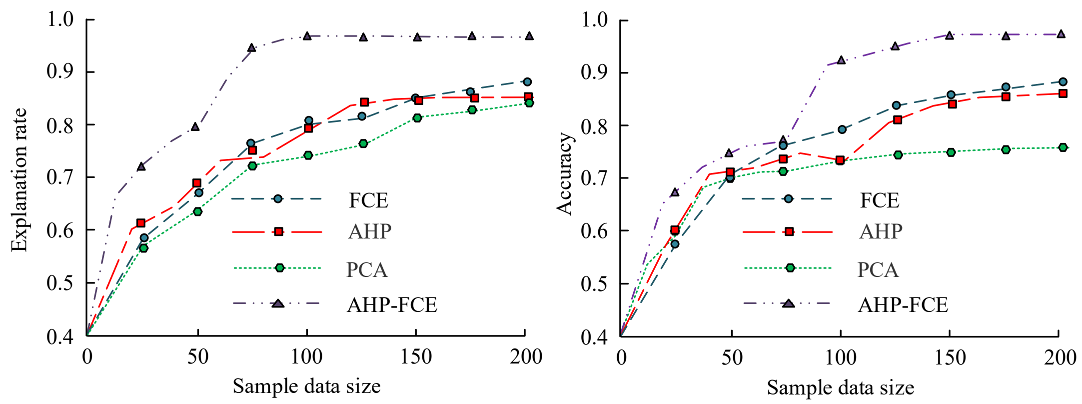
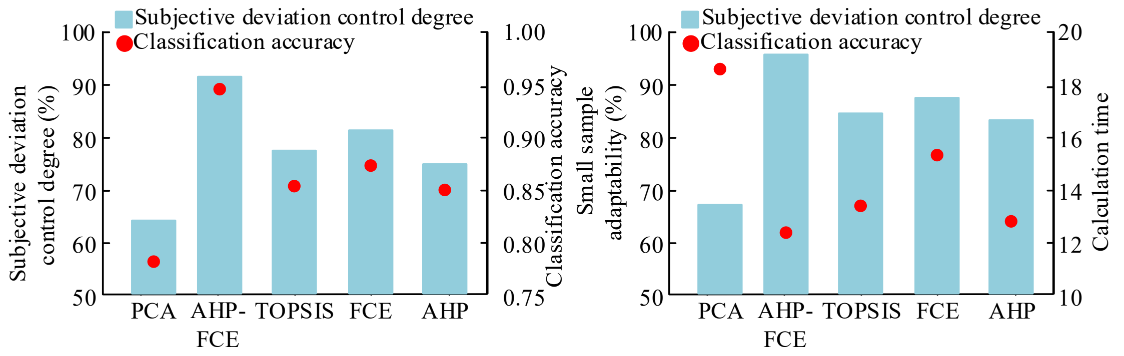


(a) Interpretation rate of ecological indicators (b) Accuracy of aesthetic evaluation

***Figure 6.** Interpretation rate of ecological indicators and accuracy of aesthetic evaluation in landscape characteristic analysis. (Icon source: self-drawn)*



(a) Classification accuracy and subjective bias control of landscape characteristic analysis (b) Small sample adaptability and calculation time for landscape characteristic analysis

***Figure 7.** Subjective bias control, classification accuracy, small sample adaptability, and calculation time in landscape characteristic analysis. (Icon source: self-drawn)*

Table 3 displays the outcomes of the data consistency and fuzzy processing abilities of landscape characterization using various techniques and varying sample sizes. The fuzzy processing ability and data consistency of landscape characterization increase with the increase of sample number. The fuzzy processing ability and data consistency of landscape characterization by combining AHP and FCE are the highest. When the number of samples is 200, fuzzy processing ability and data consistency are 96.9% and 97.5%, respectively. Hierarchical cluster analysis-based method has the highest and lowest fuzzy processing ability and data consistency. When the number of samples is 200, fuzzy processing ability and data consistency are 73.3% and 88.1%, respectively.

The multi-criteria processing power and computational efficiency of combining AHP and FCE for landscape characterization are compared with other methods. In *Figure 8a*. The performance of combining AHP and FCE for landscape characterization is the best, and the performance of principal component analysis-based for landscape characterization is the worst. When the number of samples is 200, the multi-criteria processing ability is 95.2% and 81.1%, respectively. In *Figure 8b*, the computational

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efficiency of the study's proposed method for landscape characterization is the highest. When the number of samples is 200, the highest computational efficiency is 94.9%.

Table 3. *Fuzzy processing ability and data consistency of different methods for landscape characteristic analysis*

Method	Index	Sample size			
		50	100	150	200
AHP-FCE	Fuzzy processing ability (%)	90.2	92.3	95.1	96.9
	Data consistency (%)	92.4	94.9	96.3	97.5
FCE	Fuzzy processing ability (%)	82.9	84.6	86.5	87.7
	Data consistency (%)	87.5	89.4	90.4	92.8
AHP	Fuzzy processing ability (%)	70.1	72.7	73.2	75.6
	Data consistency (%)	85.3	88.2	89.7	91.2
TOPSIS	Fuzzy processing ability (%)	75.2	78.1	81.6	83.4
	Data consistency (%)	86.2	89.3	90.8	92.5
HCA	Fuzzy processing ability (%)	65.7	68.5	71.3	73.3
	Data consistency (%)	80.4	84.8	85.7	88.1

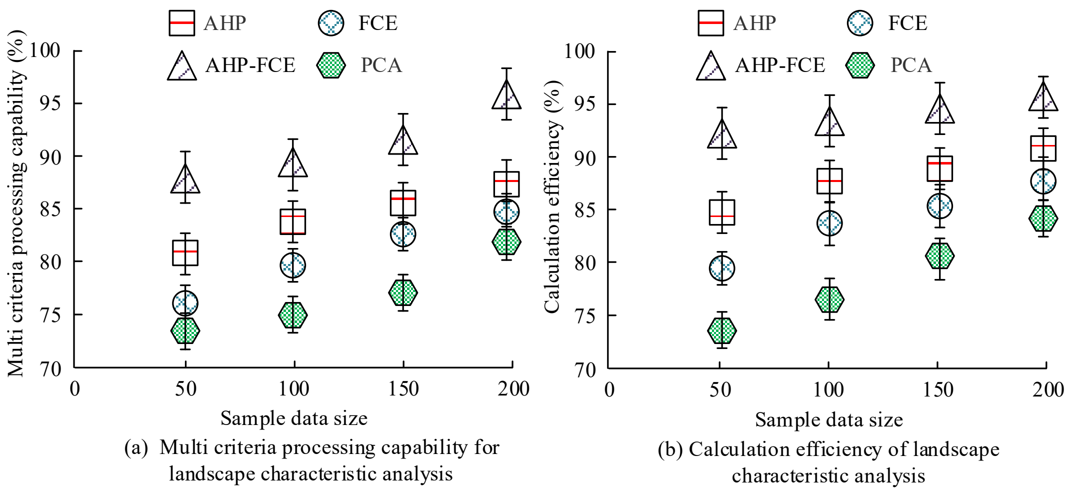

Figure 8. *Multi criteria processing capability and computational efficiency for landscape characteristic analysis. (Icon source: self-drawn)*

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Quality analysis of empirical studies

Table 4 shows the weights of the analyzed indicators of plant landscape characteristics in Zhejiang ecological scenic areas. In the CL, ecological adaptability has the highest weight value of 0.400. It is followed by landscape aesthetics with a weight value of 0.300 while recreational service has the lowest weight value of 0.100. This result indicates that the evaluation of ecological adaptability dimension has the most significant effect on plant landscape characteristics in Zhejiang ecological scenic areas. Therefore, when planning and designing the plant landscape in the scenic area, the primary goal should be to maintain and enhance the stability of the ecosystem. On this basis, the visual aesthetic effect of plant landscape should be emphasized. Finally, the improvement of recreational services should be taken into account. The results of the study are in line with the trend of modern tourists pursuing natural ecological experience.

***Table 4.** Weight table of plant landscape characteristics analysis indicators in Zhejiang ecological scenic areas*

TL	CL	Weight	Index layer	Weight	C-level weight	Rank
Evaluation of plant landscape characteristics in Zhejiang ecological scenic areas (A)	Ecological adaptability (B1)	0.400	Native plant proportion (C1)	0.320	0.128	1
			Stress resistance performance (C2)	0.280	0.112	3
			Community stability (C3)	0.400	0.160	2
	Landscape aesthetics (B2)	0.300	Seasonal color variation (C4)	0.350	0.140	4
			Spatial layering (C5)	0.300	0.090	6
			Visual permeability (C6)	0.350	0.105	5
	Biodiversity (B3)	0.200	Species richness (C7)	0.400	0.080	7
			Rare plant protection level (C8)	0.350	0.070	8
			Ecological niche complementarity (C9)	0.250	0.050	10
	Recreational Service (B4)	0.100	Integration of rest facilities (C10)	0.300	0.060	9
			Interactive experience (11)	0.400	0.040	11
			Cultural theme expression (C12)	0.300	0.030	12

Figure 9 shows the results of quarterly analysis of plant landscape in ecological scenic areas ecological adaptability and landscape aesthetics in Zhejiang in 2024. Among them, the EFs excellent, good, qualified, to be improved, and urgently need to be remedied correspond to a score of 1-5. In *Figure 9a*, the proportion of native plants and stability remained high in the fall, indicating a solid ecosystem foundation. At this time, the rating values are 4.36 and 4.45, respectively. In *Figure 9b*, plant landscape characteristics in Zhejiang ecological scenic areas exhibit significant differences in different seasons. In the fall, the overall performance is optimal, with color seasonal changes and visual transparency standing out, scoring 4.45 and 4.47, respectively. In the winter, color seasonal changes are significantly affected by leaf fall, scoring 4.15 at this time.

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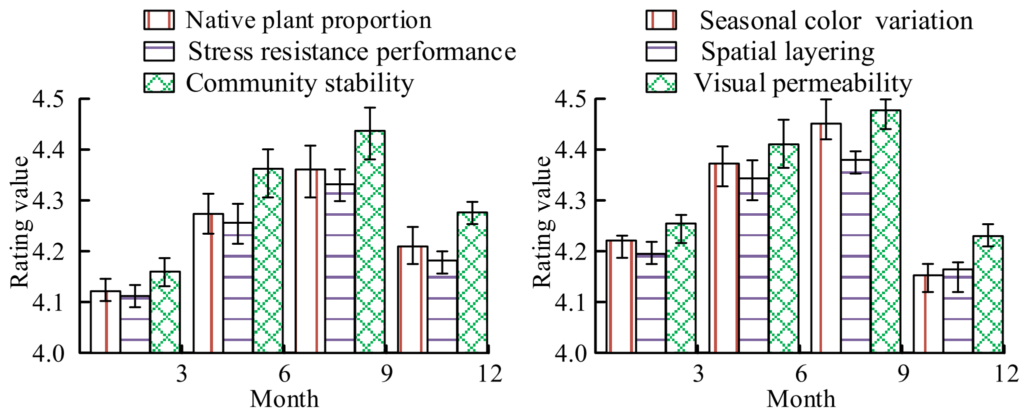
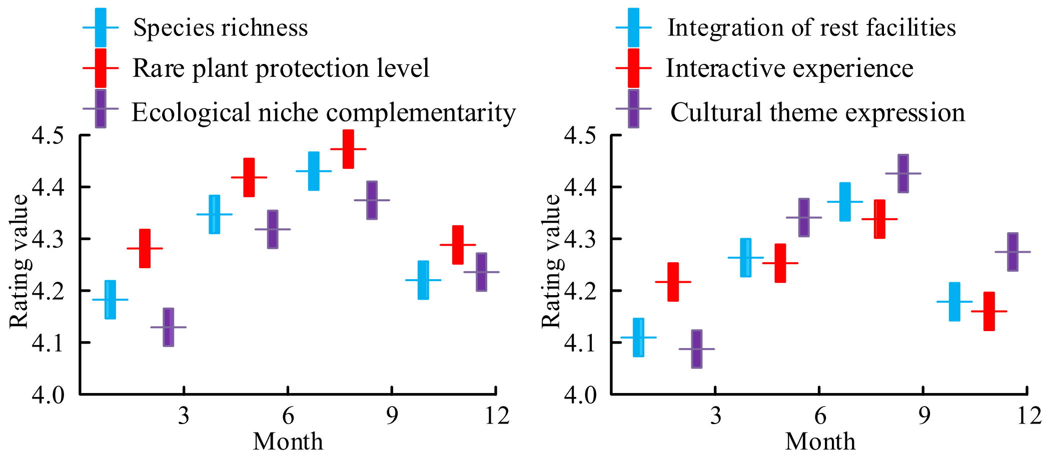


(a) 2024 ecological adaptability score (b) 2024 landscape aesthetics rating value

Figure 9. *Quarterly analysis results of plant landscape ecological adaptability and landscape aesthetics in Zhejiang ecological scenic areas in 2024. (Icon source: self-drawn)*

Figure 10 shows the results of seasonal analysis of biological diversity and recreational service in plant landscape in ecological scenic areas in Zhejiang in 2024. In *Figure 10a*, the functional characteristics of Zhejiang plant landscape in ecological scenic areas showed obvious seasonal changes. Among them, the best performance is observed in the fall, when the species richness and conservation level of rare plants reach the peak. This indicates that the conservation of biological diversity is effective. At this time, the rating values are 4.43 and 4.47, respectively. In winter, affected by plant dormancy, the species richness decreases. At this time, the rating value is 4.21. In *Figure 10b*, the integration degree of recreational facilities, interactive experience, and cultural theme expression in the Spring Festival have the worst overall performance. At this time, the rating values are 4.13, 4.11, and 4.08, respectively.



(a) 2024 biodiversity assessment value (b) 2024 Recreation service evaluation value

Figure 10. *Quarterly analysis results of plant landscape biodiversity and recreational services in Zhejiang ecological scenic areas in 2024. (Icon source: self-drawn)*

Table 5 shows the results of FCE of plant landscape characteristics in Zhejiang ecological scenic areas. The scenic areas performs well in ecological adaptability and

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landscape aesthetics. The scores of stability, proportion of native plants, and visual transparency are high, with the values of 4.351, 4.342, and 4.297, respectively. This reflects the good ecological foundation and landscape effect. The performance of recreational service is relatively poor. In particular, the interactive experience and integration degree of recreational facilities need to be improved, with ratings of 4.108 and 4.144, respectively. The findings indicate that while the scenic plant landscape has attained a high degree of ecological protection and aesthetic value, more work has to be done to improve the humanized design of service activities and the interactive experience. Nonetheless, more work has to be done to improve the experience's interaction and the humanized design of service activities.

Table 5. *FCE results of plant landscape characteristics in Zhejiang ecological scenic areas*

TL	CL	Evaluation value					Appraisal of value
		Excellent	Good	Fair	Need improvement	Urgent renovation	
Evaluation of plant landscape characteristics in Zhejiang ecological scenic areas (A)	Ecological adaptability (B1)	0.512	0.328	0.142	0.015	0.003	4.342
		0.487	0.351	0.145	0.012	0.005	4.318
		0.523	0.312	0.148	0.011	0.006	4.351
	Landscape aesthetics (B2)	0.465	0.362	0.153	0.015	0.005	4.282
		0.442	0.378	0.162	0.013	0.005	4.254
		0.481	0.341	0.158	0.014	0.006	4.297
	Biodiversity (B3)	0.498	0.335	0.152	0.010	0.005	4.326
		0.472	0.356	0.154	0.013	0.005	4.295
		0.428	0.382	0.172	0.012	0.006	4.230
	Recreational service (B4)	0.382	0.401	0.195	0.016	0.006	4.144
		0.356	0.412	0.208	0.018	0.006	4.108
		0.402	0.385	0.186	0.020	0.007	4.162

Conclusion

The study proposed an analysis method of plant landscape characteristics in Zhejiang ecological scenic areas combining AHP and FCE. This was done to enhance the ecological service function of the scenic area, optimize the aesthetic value of the landscape, enhance the attractiveness of tourism, guarantee the safety of biological diversity, and achieve the development goal of harmonious coexistence between human and nature. The study firstly constructed a hierarchical analysis system containing four criteria: ecological adaptability, landscape aesthetics, biological diversity, and recreational service. Then, AHP was utilized to determine the weights of each index. Finally, an FCE was carried out by combining FCE. The results showed that combining AHP and FCE for landscape characterization had the highest subjective bias control and classification accuracy of 91.3% and 0.96, respectively. Comparing with other methods, combining AHP and FCE had the best performance in landscape characterization. The small sample adaptability was 95.1%, and the calculation time was 12.5 s. The functional characteristics of Zhejiang plant landscape in ecological scenic areas showed obvious seasonal changes. The best overall performance was in the fall. Species richness and conservation level of rare plants reached their peaks, indicating the effectiveness of conservation of biological diversity, and the scores were 4.43 and 4.47

in winter due to plant dormancy. The scores were 4.43 and 4.47 respectively, and the species richness decreased in winter due to plant dormancy. At this time, the score value was 4.21. From a management perspective, the discovery with the highest weight of ecological adaptability clearly states that resources should be prioritized for the restoration of native plants and maintenance of community stability. This is fundamental to ensuring the ecological resilience and long-term sustainable development of scenic spots. Meanwhile, the significant improvement in aesthetic assessment accuracy and the high autumn landscape scores provide a scientific basis for tourism management departments. They can optimize the tourist experience and develop seasonal brands by precisely configuring landscapes with rich seasonal changes. This directly converts ecological advantages into tourism appeal and economic benefits. The results and methodological system of the research have significant reference value for ecological landscape planning and management in China and other regions around the world. The research constructs a four-level assessment framework of "ecological adaptability, landscape aesthetics, biodiversity, and leisure services." This framework captures the core functions and values of plant landscapes in ecological scenic spots, and it is universally applicable. The methodology of the deep integration of AHP-FCE has the core advantage of handling multi-objective and fuzzy decision-making problems. This logic is also applicable to the assessment of other types of ecological Spaces such as national parks, urban forests, and rural landscapes. The finding revealed that maintaining the health of the ecosystem should be a fundamental prerequisite in the management of ecological landscapes in any region because ecological adaptability holds the highest weight. This has universal warning significance for correcting the one-sided approach of "emphasizing landscape over ecology".

The proposed method performs well in analyzing the characteristics of plant landscapes in scenic areas. However, this study has certain limitations, primarily due to the inherent characteristics of the methodology. The first point is the reliance on expert opinions. Although the Delphi method and consistency test ensure the rigor of the process, the determination of AHP weights essentially still depends on the subjective judgment of experts. The second point is the computational complexity of the FCE algorithm. As the index system and the size of the evaluation sample grow, the computational load of FCE will increase significantly. This could limit its use in real-time management decisions requiring a quick response. Therefore, future research efforts will focus on introducing a broader stakeholder participation weight survey or attempting to coupling objective data with subjective weights to construct a more universal and dynamic weight system. The research uses machine learning algorithms to simulate the CE logic of AHP-FCE. This approach improves computational efficiency by an order of magnitude while maintaining evaluation accuracy.

REFERENCES

[1] Aboufazeli, S., Jahani, A., Farahpour, M. (2024): Aesthetic quality modeling of the form of natural elements in the environment of urban parks. – Evol. Intell. 17(1): 327-338. DOI: 10.1007/s12065-023-00844-0.

[2] Ali, M. B., Jamal, S. (2025): Modelling the present and future scenario of urban green space vulnerability using PSR based AHP and MLP models in a metropolitan city Kolkata Municipal Corporation. – Geology, Ecology, and Landscapes 9(3): 1141-1159. DOI: 10.1080/24749508.2024.2392377.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_331351

[3] Ayyildiz, E. (2023): Interval valued intuitionistic fuzzy analytic hierarchy process-based green supply chain resilience evaluation methodology in post COVID-19 era. – Environ. Sci. Pollut. Res. 30(15): 42476-42494. DOI: 10.1007/s11356-023-25353-6.
[4] Bahrami, M., Sarmadian, F., Pazira, E. (2024): Integrating AHP (Analytic Hierarchy Process) and GIS (Geographic Information System) for precision land use planning and ecological capacity assessment in Alborz Province, Iran. – EQA-International Journal of Environmental Quality 64: 48-67. DOI: 10.6092/issn.2281-4485/20020.
[5] Başkent, E. Z., Başkent, H. (2025): Integrating technical, socio-economic, and sustainability dimensions for spatial stratification of ecosystem services using the AHP method. – Environmental Management 75(10): 2777-2794. DOI: 10.1007/s00267-025-02224-z.
[6] Cao, Z., Mustafa, M., Mohd Isa, M. H. (2024): The role of artistic quality in a heritage architectural style in modulating tourist interest and aesthetic pleasure: a case study of Hui-style architecture in the Hongcun Scenic Area, China. – J. Herit. Tour. 19(6): 896-918. DOI: 10.1080/1743873X.2024.2315678.
[7] D'Adamo, I. (2023): The analytic hierarchy process as an innovative way to enable stakeholder engagement for sustainability reporting in the food industry. – Environ. Dev. Sustain. 25(12): 15025-15042. DOI: 10.1007/s10668-023-03298-7.
[8] Ding, Y., Liu, Z., Jiao, Y. (2022): A bi-scale assessing framework for aesthetic ecosystem services of villages in a world heritage site. – J. Mt. Sci. 19(3): 874-891. DOI: 10.1007/s11629-021-6945-6.
DOI: 10.47852/bonviewGLCE3202761.
[9] Gong, M. (2023): Retracted: Fuzzy multiple attribute decision making method for multimedia teaching effectiveness comprehensive evaluation in college English with double-valued neutrosophic numbers. – J. Intell. Fuzzy Syst. 45(4): 5697-5707. DOI: 10.3233/JIFS-230678.
[10] Gülçin, D., Yalçınkaya, N. M. (2024): Correlating fluency theory-based visual aesthetic liking of landscape with landscape types and features. – Geo-Spat. Inf. Sci. 27(1): 237-256. DOI: 10.1080/10095020.2023.2291234.
[11] Huang, Y. (2024): Developing a fuzzy comprehensive assessment model for English translation for college students. – J. Comput. Methods Sci. 24(3): 1709-1725. DOI: 10.32604/cmc.2024.047892.
[12] Huang, Y., Li, T., Jin, Y. (2023): Correlations among AHP-based scenic beauty estimation and water quality indicators of typical urban constructed WQT wetland park landscaping. – Aqua 72(11): 2017-2034. DOI: 10.2166/aqua.2023.123.
[13] Jahani, A., Saffariha, M., Barzegar, P. (2023): Retracted article: Landscape aesthetic quality assessment of forest lands: an application of machine learning approach. – Soft Comput. 27(10): 6671-6686. DOI: 10.1007/s00500-023-07829-2.
[14] Li, S., Yang, L., Fang, J. (2025): Comprehensive evaluation of urban river ecological bank protection based on AHP-TOPSIS method. – Environmental Technology 46(8): 1201-1214. DOI: 10.1080/09593330.2024.2380395.
[15] Lin, J., Li, Q., Wang, Y. (2025): Comprehensive evaluation of intrinsic safety of railway facilities and equipment based on improved cloud model-fuzzy Petri net. – Proc. Inst. Mech. Eng., O J. Risk Reliab. 239(2): 298-309. DOI: 10.1177/1748006X231212345.
[16] Mishra, A. P., Singh, S., Jani, M., Singh, K. A., Pande, C. B., Varade, A. M. (2024): Assessment of water quality index using analytic hierarchy process (AHP) and GIS: a case study of a struggling Asan River. – Int. J. Environ. Anal. Chem. 104(5): 1159-1171. DOI: 10.1080/03067319.2023.2267458.
[17] Morales Pedraza, J. (2023): The role of renewable energy in the transition to green, low-carbon power generation in Asia. – GLCE 1(2): 68-84.
[18] Muhsen, Y. R., Husin, N. A., Zolkepli, M. B. (2023): A systematic literature review of fuzzy-weighted zero-inconsistency and fuzzy-decision-by-opinion-score-methods:

assessment of the past to inform the future. – J. Intell. Fuzzy Syst. 45(3): 4617-4638. DOI: 10.3233/JIFS-230456.

[19] Selvam, R. A., Antony Jebamalai, A. R. (2023): Application of the analytical hierarchy process (AHP) for flood susceptibility mapping using GIS techniques in Thamirabarani River basin, Srivaikundam region, Southern India. – Nat. Hazards 118(2): 1065-1083. DOI: 10.1007/s11069-023-06031-9.

[20] Sulhan, O. F., Sevik, H., Isinkaralar, K. (2023): Assessment of Cr and Zn deposition on Picea pungens Engelm. in urban air of Ankara, Türkiye. – Environ. Dev. Sustain. 25(5): 4365-4384. DOI: 10.1007/s10668-022-02638-3.

[21] Tavana, M., Soltanifar, M., Santos-Arteaga, F. J. (2023): Analytical hierarchy process: revolution and evolution. – Ann. Oper. Res. 326(2): 879-907. DOI: 10.1007/s10479-023-05319-0.

[22] Vafadarnikjoo, A., Badri Ahmadi, H., Liou, J. J. H. (2023): Analyzing blockchain adoption barriers in manufacturing supply chains by the neutrosophic analytic hierarchy process. – Ann. Oper. Res. 327(1): 129-156. DOI: 10.1007/s10479-022-04983-y.

[23] Vaz de Freitas, I., Sousa, C., Ramazanova, M. (2022): Feeling a historic city: Porto landscape through the eyes of residents and visitors. – Int. J. Tour. Cities 8(2): 529-545. DOI: 10.1108/IJTC-08-2021-0167.

[24] Vukoičić, D., Ristić, D., Milinčić, U. (2023): Assessment of the attractiveness of natural resources and landscapes of the Kopaonik National Park (Serbia): framework and importance for tourism development. – Pol. J. Environ. Stud. 32(1): 281-295. DOI: 10.15244/pjoes/152845.

[25] Xia, H., Chen, F. (2025): Recognition and optimization of landscape genes in traditional settlements: a case of Meishan area. – Journal of Environmental Engineering and Landscape Management 33(1): 85-96. DOI: 10.3846/jeelm.2025.22946.

[26] Xu, W., Jiang, B., Zhao, J. (2022): Effects of seasonality on visual aesthetic preference. – Landscape Res. 47(3): 388-399. DOI: 10.1080/01426397.2021.1999996.

[27] Yang, H., Luo, Q., Sun, X. (2023): Comprehensive evaluation of urban waterlogging prevention resilience based on the fuzzy VIKOR method: a case study of the Beijing-Tianjin-Hebei urban agglomeration. – Environ. Sci. Pollut. Res. 30(52): 112773-112787. DOI: 10.1007/s11356-023-30190-8.

[28] Zeng, S., Gu, J., Peng, X. (2023): Low-carbon cities comprehensive evaluation method based on Fermatean fuzzy hybrid distance measure and TOPSIS. – Artif. Intell. Rev. 56(8): 8591-8607. DOI: 10.1007/s10462-023-10412-8.

[29] Zhuang, Q. D., Hussein, M. K., Ariffin, N. F. M. (2022): Landscape character: a knowledge mapping analysis using CiteSpace. – Int. J. Environ. Sci. Technol. 19(10): 10477-10492. DOI: 10.1007/s13762-022-04275-9.