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Construction of a model for evaluating the effect of ecological education in national park study activities based on the random forest algorithm

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Abstract This study focuses on the evaluation of the effect of ecological education in the study activities of national parks, and through extensive literature research and actual research, an evaluation index system covering four dimensions of the curriculum system, safeguard conditions, teachers' quality and students' academic knowledge is determined. After determining the subjective and objective weights using the hierarchical analysis method (AHP) and the CRITIC weighting method, respectively, the ecological education effect assessment model was constructed by combining the results of the comprehensive weights derived from the two methods. Taking the ecological education teaching data of 20 colleges and universities in province A as input, the decision tree is constructed first, and then the random forest is constructed and the feature set of the students' ecological education effect is obtained, so as to realize the accurate measurement and evaluation of the ecological education effect. The average absolute percentage error of the evaluation results based on the random forest model is 0.681%, which is 0.647% lower than that of the comparison model, and the absolute value of the relative error fluctuates within the range of [0.030%,2.274%]. It shows that the assessment model in this paper has good accuracy and stability, which helps to promote the high-quality development of research and study activities in national parks.

Index Terms Random Forest Algorithm, Hierarchical Analysis Method, CRITIC Weighting Method, Evaluation of Ecological Education Effectiveness

I. Introduction

With the in-depth development of quality education, cultivating students' diversified development has become one of the priorities of modern education [1], [2]. As a kind of ecological education teaching mode combining knowledge and practice, national park study activities pay more attention to the guidance and development of students' subjective ability, and effectively penetrate students' knowledge into social practice, which not only can deepen students' cognitive understanding of subject matter knowledge, but also make students maintain a positive inquiry mindset in their cognitive experience, so as to achieve the educational goal of the unity of practice and knowledge [3]-[6].

In the traditional development of education, most teachers are subject to the idea of exam-oriented education, focusing too much on the lecture and practice of exam-oriented content, and lack of effective subject guidance and quality cultivation, which leads to bias in the development of students in the main body, and is not conducive to the healthy growth of students [7]-[10]. Park study activities used in daily education, combined with the actual situation of students, the reasonable organization of some practical activities, expanding the scope of students' cognition, building a solid foundation for the development of students, so that students in the process of practical exploration, deepen their understanding and enhance their ability [11]-[14]. At the same time, the correct guidance and implementation of ecological education in park study activities, to a certain extent, can also cultivate students' good behavioral awareness, establish students' healthy development concept [15]-[17]. Compared with traditional teaching activities, park study activities pay more attention to students' exploratory and practical knowledge, so that students can deepen their understanding of knowledge and improve their ability to apply knowledge in practical activities, which is practical and cultivating in the actual way of application [18], [19]. However, in teaching practice, few schools carry out eco-education similar to the national park study activities, the reason behind this is not only because of the lack of innovative consciousness of learning, but also in the lack of trust in eco-education. Based on this, it is of great significance to evaluate the effect of ecological education in national park study activities.

Traditional assessment methods mostly rely on simple qualitative analysis, which is difficult to accurately and comprehensively reflect the educational effect of study activities. This paper utilizes the random forest algorithm, which has strong classification and regression capabilities, to process the complex relationships in the ecological education data, and constructs the ecological education effect assessment model of national park study activities based on the random forest algorithm. Based on the constructed ecological civilization education effect evaluation index system, the AHP-CRITIC method was used to quantify the indicators, and the subjective and objective weights and comprehensive weights of the indicators were calculated separately, avoiding the inaccuracy brought by the assignment of weights by a single method. When feature selection is carried out, information gain is used to rank the importance of features and obtain the degree of influence of different indicators on the effect of ecological education. The model of this paper is also compared with the BPNN model to verify the accuracy and stability of the model of this paper.

II. Model selection and establishment of ecological civilization education effect evaluation system

II. A. Evaluation system of the effect of ecological civilization education

At present, the relevant research on the evaluation system of ecological civilization education in colleges and universities mainly covers the following three aspects: one is to take students as the object of research, so that students can evaluate the proposed evaluation indexes for satisfaction.

For the existing research on the evaluation system of ecological civilization education in colleges and universities, combined with the author's experience, it is suggested that the evaluation system be constructed from the two main subjects of teachers and students. Teachers, as the educators of college education and teaching, can not only summarize the development law of education and teaching by grasping the law of students' growth and success in education and teaching, but also put forward prospective and scientific opinions on the construction of the evaluation system of the effect of ecological civilization education in colleges and universities through their rich experience in teaching and assessment. It is of great significance to conduct research on college teachers' groups to obtain their subjective judgments for the construction of the evaluation system of the effect of ecological civilization education in colleges and universities. Since the research data mainly come from subjective judgment, the hierarchical analysis method (AHP) [20] is a more ideal research method.

II. B. Selection of AHP model

Ecological civilization education is an education that dynamically runs through the whole process of cultivating talents, and evaluating the effect of ecological civilization education only by human subjective judgment lacks certain rigor and scientificity. If you want to evaluate the data obtained through subjective, and can not quantitatively represent certain factors, in order to be able to qualitative analysis and quantitative analysis of complex issues combined with systematic analysis, this paper applies the hierarchical analysis method. Hierarchical analysis is a quantitative description of the comparative importance of hierarchical elements based on the subjective judgment structure of a certain objective reality. Specifically, this method divides many factors affecting the ultimate goal problem according to the hierarchy, transforms qualitative problems into quantitative calculations, so as to clarify the logical connection between the elements and analyze their influence on the ultimate goal problem. Evaluation of the effect of ecological civilization education involves many interrelated elements, and the elements can not be quantitatively expressed by simple data, so the research on the evaluation of the effect of ecological civilization education using the AHP model has a certain degree of scientificity and applicability.

II. C. Ecological civilization education effect evaluation system AHP model

II. C. 1) Data acquisition

In order to avoid the subjectivity characteristic of AHP analysis method, according to the constructed evaluation index system, this study chooses teaching experts and teaching leaders in charge in 20 undergraduate colleges and universities in province A as the survey object. The scale adopts Likert 5-level measurement method, and the results of each index data research are weighted average and then rounded to form a judgment matrix.

II. C. 2) Identification and establishment of evaluation indicators

Taking an overview of the relevant studies in the academic world on the selection of evaluation indexes for the effect of ecological civilization education, from the perspective of teaching and educating people and from the perspective of serving the society, teachers and students are not only the main subjects with mobility, creativity and autonomy in the process of education, but also the objects of the other party in the process of teaching and learning. Only when the status of both is recognized and affirmed at the same time, their subjectivity can be maximized, thus achieving the optimal educational effect. Therefore, this paper takes teachers and students together as the dimension of evaluating the effect of ecological civilization education. Curriculum system is the planning of teaching content, teaching organization, teaching method and teaching process by teachers according to the principles of education and teaching, students' cognitive structure and the law of growth and success, in order to achieve the teaching goals, and at the same time, it plays an important role in guaranteeing the participation of teachers and students in education and teaching activities as well as the achievement of educational results. Based on the research results of scholars and the author's own experience in practical education and teaching, this study proposes four dimensions, namely, curriculum system, safeguard conditions, teachers' quality and students' knowledge, with a total of 21 sub-elements as the indicators for evaluating the effect of ecological civilization education.

In order to guarantee the comprehensiveness, systematicity and scientificity of the indicators for evaluating the effect of ecological civilization education, focusing on the students' feeling of being taught and feedback of their actions, and in a good ecological civilization education environment, the AHP hierarchical structure for evaluating the effect of ecological civilization education is formulated from the two main subjects of teachers and students, and the AHP hierarchical structure for evaluating the effect of ecological civilization education is shown in Figure 1.

The model has a total of three layers, the target layer A is the ecological civilization education effect evaluation system. The criterion layer is the curriculum system, safeguard conditions, teachers' quality and students' knowledge, which are labeled with A_1, A_2, A_3 and A_4 respectively. The program layers are 21 items of teaching management, curriculum, teaching content, training objectives, teaching materials, reunion activities, funding, competition platform, supporting equipment, campus design, teaching methods, teaching skills, assessment methods, faculty structure, qualification certificates, practical experience, theoretical knowledge, awareness and concepts, participation in activities, civilized behaviors, learning skills, etc., which are marked with B_1 to B_{21} are marked.

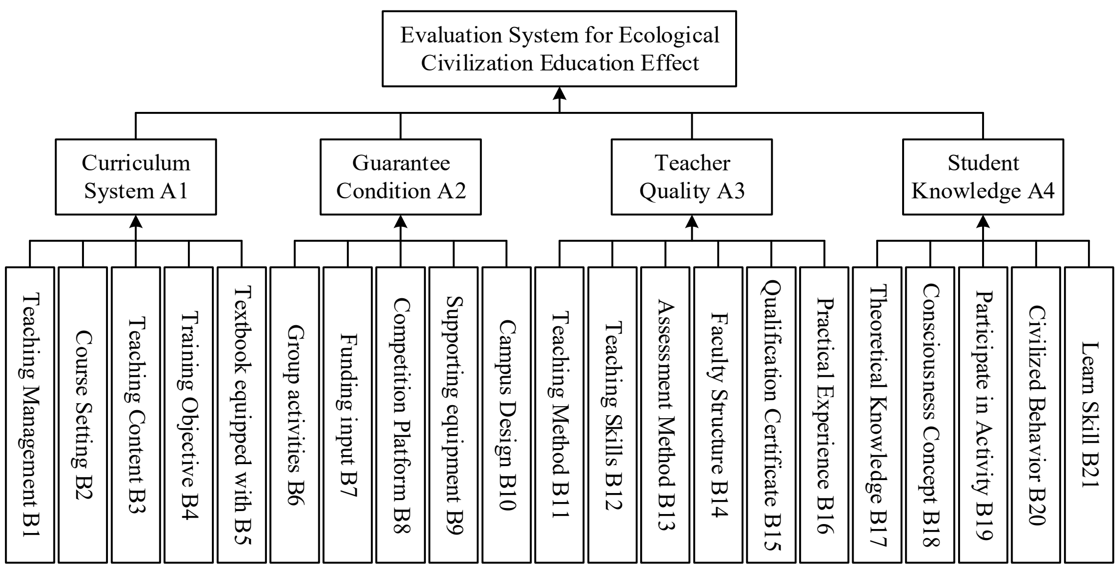

Figure 1: Education effect evaluation architecture

II. D. Determination of indicator weight sets

II. D. 1) Determining indicator weights based on AHP

The hierarchical analysis method (AHP) represents an accurate method for quantifying the weights of decision-making criteria. The principle is to treat a complex problem, which is difficult to study all by quantitative methods, as a big system, analyze the system factors, construct a progressive structure, score the importance of the indicators, construct a judgment matrix, and then carry out a consistency assessment to derive the weight coefficients. The steps are as follows:

(1) Make judgment matrix:

$$A=\begin{bmatrix} a_{11} & a_{12} & \cdots & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & \cdots & a_{2n} \\ \cdots & \cdots & a_{ij} & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ a_{n1} & a_{n2} & \cdots & \cdots & a_{nn} \end{bmatrix} \tag{1}$$

The a_{ij} in the matrix, indicates the relative importance of A_j, A_i, if the former is more important, then $a_{ij} > 1$, if the two are equally important, then $a_{ij} = 1$.

(2) Matrix element importance judgment.

(3) Calculate the weight vector of indicators.

Steps of vector product regularization method:

First, with the help of regularized disposition matrix:

$$\overline{a_{ij}} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} (i, j = 1, 2 \cdots n) \tag{2}$$

where a_{ij} is the data in column j of row i of the judgment matrix A, and $\overline{a_{ij}}$ is the data in column j of row i of the regularization matrix.

Second, add up the elements in the matrix:

$$\varpi_i = \sum_{j=1}^{n} a_{ij} (i, j = 1, 2 \cdots n) \tag{3}$$

Thirdly, for those in the above formula, formalized dispositions are implemented:

$$w_i = \frac{w_i}{\sum_{i=1}^{n} \overline{w_l}} (i, j = 1, 2 \cdots n) \tag{4}$$

Fourth, calculate the maximum eigenvalue of the judgment matrix A:

$$\lambda_{\max} = \frac{1}{n} \sum_{i=1}^{n} \frac{(A\omega)_i}{\omega_i} \tag{5}$$

where n is the order of the matrix, A is the judgment matrix, and w_i is the weight of the i th indicator. $\lambda_{\max}$ is the maximum eigenvalue of the judgment matrix A.

(4) Consistency test

For the vectors obtained earlier, and the eigenvalues, the consistency test is carried out, if it can pass the test, it means that the judgment matrix is reasonable, i.e., there is an explanatory value.

Assuming that CI stands for consistency index, the following is the arithmetic method:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{6}$$

Through the value of n, it is possible to obtain the value of RI, so as to obtain the consistency ratio, i.e., CR = C/RI, and when CR < 0.1, then the test meets the requirements.

II. D. 2) Determining indicator weights based on CRITIC

CRITIC weighting method [21] is an objective weighting method to comprehensively measure the indicators according to the comparative strength and conflict of the evaluation indicators. For the comprehensive evaluation problem of multiple indicators and multiple objects, CRITIC weighting method goes to eliminate the influence of some indicators with strong correlation, reduce the overlap of information between indicators, and is more conducive to obtaining credible evaluation results.

(1) Model construction

Firstly, we select m evaluation objects (the evaluation objects in this study are different years) and n comprehensive evaluation indicators related to urban water supply safety, and establish $m \times n$ order raw data matrix $A = (a_{ij})_{m \times n}$, where $i = 1, 2 \cdots\cdots m; j = 1, 2 \cdots n$. a_{ij} denotes the j th index value of the i th evaluation object.

(2) Normalized data

Each index is categorized as a positive or negative index. For positive indicators, the larger the index value, the better the effect. For negative indicators, the smaller the index value, the better the effect. In order to eliminate the effects caused by differences in the outline of different indicators, it is necessary to standardize the data. The formula is as follows:

For positive indicators:

$$r_{ij} = \frac{a_{ij} - \min\{a_{1j}, a_{2j}, \cdots, a_{mj}\}}{\max\{a_{1j}, a_{2j}, \cdots, a_{mj}\} - \min\{a_{1j}, a_{2j}, \cdots, a_{mj}\}} \tag{7}$$

For negative indicators:

$$r_{ij} = \frac{\max\{a_{1j}, a_{2j}, \cdots, a_{mj}\} - a_{ij}}{\max\{a_{1j}, a_{2j}, \cdots, a_{mj}\} - \min\{a_{1j}, a_{2j}, \cdots, a_{mj}\}} \tag{8}$$

where r_{ij} is the standardized value of the j evaluation indicator in the i program, and a_{ij} is the original value of the j evaluation indicator in the i program.

(3) Calculation of indicator variability

CRITIC expresses indicator variability in the form of standard deviation. AD_j represents the standard deviation of the j th indicator. The standard deviation is used in the CRTIC method to indicate the fluctuation of the differences in the values taken within each indicator, the larger the standard deviation indicates that the greater the difference in the values of the indicator, the more information can be screened, and the stronger the evaluation strength of the indicator itself, the more weight should be assigned to the indicator.

$$AD_j = \sqrt{\frac{\sum_{i=1}^{m}(r_{ij} - \overline{r}_j)}{m-1}} \tag{9}$$

where AD_j is the standard deviation of the j th indicator, and $\overline{r}_j$ is the mean of the j th indicator.

(4) Calculation of indicator ambivalence

The degree of correlation of the indicators can be reflected through the ambivalence, and if it is positively correlated, it means the less ambivalent it is. Let the size of contradiction between indicator j and the rest of indicators be f_j.

$$f_j = \sum_{i=1}^{m}(1 - p_{ij}) \tag{10}$$

where f_j is the ambivalence of the j th indicator.

p_{ij} denotes the correlation coefficient between the object i and the indicator j, where Pearson's correlation coefficient is used, with the following formula.

$$p_{ij} = \frac{\sum_{i=1}^{m}(r_{ij} - \overline{r}_i)(r_{ij} - \overline{r}_j)}{\sqrt{\sum_{i=1}^{m}(r_{ij} - \overline{r}_i)^2 (r_{ij} - \overline{r})^2}}, i \neq j \tag{11}$$

(5) Calculate the amount of information of the indicator

E_j is used to indicate the amount of information contained in the j th indicator. The larger E_j is, the greater the amount of information contained in the j evaluation indicator, and the greater the relative importance of the indicator.

$$E_j = AD_j f_j \tag{12}$$

(6) Calculation of indicator weights:

$$\omega_j = \frac{E_j}{\sum_{i=1}^{n} E_j} \tag{13}$$

where ω_j is the objective weight coefficient of the j th indicator.

II. D. 3) Combined weighting of indicators

The combined weight W_z of the indicators is calculated according to the following formula:

$$W_z = \theta w_i + (1-\theta) w_j \tag{14}$$

where W_z denotes the composite weight of the indicator. w_i denotes the subjective weights calculated by hierarchical analysis, and w_j denotes the objective weights calculated by CRITIC method. θ denotes the linear weighting coefficient, $0 < \theta < 1$. Indicates that the objective weighting is as important as the subjective weighting.

III. Assessment of the effectiveness of ecological civilization education based on random forests

III. A. Relevant theories

III. A. 1) Information gain

Information gain [22] is an important criterion for feature selection, it depends on the feature, different features tend to have different information gain, information gain is defined as how much information the feature can provide to the result of the classification algorithm, the more information provided by the feature means the more important the feature is, corresponding to the greater information gain, which represents the degree of reduction in the information complexity under a condition.

For a feature, the amount of information provided by the feature changes to different degrees when the system uses it and when it is not used, and the difference between the amount of information before and after the change is the amount of information provided by the feature to the system. The amount of information therein is entropy, which is used to measure the uncertainty of a random variable.

Assuming that X is a finite discrete random variable with n possible values, and the i th one is taken with probability P_i, the entropy of the random variable X is defined as:

$$H(X) = -\sum_{i=1}^{n} p(x_i)\log_2 p(x_i) \tag{15}$$

It can be seen that the more possible variations in the random variable X, the more information X provides and the greater the entropy. For classification or clustering problems, the more variations in which category a document belongs to, the more informative the category is. So the information gain provided by the feature A to the classification C or clustering C is

$$IG(A) = H(A) - H(C \mid A) \tag{16}$$

Information gain suffers from the fact that it only examines the usefulness of the attributes for the whole classification system and cannot be specific to a category, which makes it only applicable to the case where the same set of features distinguishes all the categories, and it cannot be done that different categories have different sets of features.

III. A. 2) Random forests

In this paper, classification is used to solve the research problem of the effectiveness of ecological civilization education, and the random forest algorithm is a machine learning algorithm commonly used for classification. Random forest is a classification method that integrates multiple decision trees to train test and predict the sample data set. Random forest algorithm is more acceptable than neural networks, more accurate, more robust to noisy and missing data, faster computing, so the random forest algorithm is more commonly used in data mining.

Random forest is an integrated learning method integrated by a combination of decision tree classifiers, where each decision tree votes to determine the optimal classification result, and the plurality of categories determines the output category. Decision trees can be viewed as experts for the classification task, and random forest is a collection of multiple experts to do the task. The random forest algorithm integrates decision trees for more accurate classification and is insensitive to outliers, and its generalization error converges with the number of trees, so it is less prone to overfitting. In addition, there are fewer candidate features to consider for each tree division, it is computationally fast, and most importantly, it gives an estimate of the importance of the variables.

III. B. Random forest-based method for assessing the effectiveness of ecological civilization education

For the research on the method of evaluating the effect of ecological civilization education, it is based on the classification of random forest algorithm, and useful features are automatically selected in the classification process. Based on the superiority of the Random Forest algorithm, the Random Forest algorithm, which represents an integrated feature selection method, is particularly applicable in the evaluation of the educational effect of ecological civilization. This section describes the modeling process of using the random forest algorithm to realize the technology of ecological civilization education effect evaluation. The specific process is to construct a decision tree, construct a random forest and obtain a feature set.

III. B. 1) Constructing decision trees

A random forest is a classifier that contains multiple decision trees. Therefore, to utilize the Random Forest method, the first step is to construct a decision tree. A decision tree is a basic classifier that generally classifies features into two classes. The decision tree recursively selects features to divide the dataset until the end of the division into two classes. In this process we utilize information gain to test whether the features produce nodes or not.

Specifically, similar to the modeling of elastic networks, this part takes the study activities in national parks as an example to introduce the process of constructing a decision tree. The indicators in the database reflecting the impact of study activities on students' eco-education effects, i.e., “features”, and accordingly the attribute set of the database is denoted as $A=\{a_1,a_2,...,a_p\}$. Where the database P contains 32 dimensional attributes with multiple possible values for each dimension. In this paper, we first take the class of no research activity and the class of research activity as the sample set, and for the indicator feature a, there are V possible values of a $\{a^1,a^2,...,a^V\}$, if the training set D is partitioned with the indicator a, V branches are generated to generate the node, where the vth branch represents the sample that takes a^V on the feature a, denoted as D_v. $Ent(D)$ is the “information entropy” of D, which is calculated as:

$$Ent(D)=-\sum_{q=1}^{|y|}p_q\log_2 p_q \tag{17}$$

where $p_q(q=1,2,...,|y|)$ denotes the proportion of samples of the q th class in the current sample set D. Considering that different branch nodes contain different number of samples, this paper assigns weights $\frac{|D^v|}{|D|}$ to the branch nodes, then we can calculate the “information gain” obtained by dividing the sample set D with attribute a:

$$Gain(D,a)=Ent(D)-\sum_{v=1}^{v}\frac{|D^v|}{|D|}Ent(D^v) \tag{18}$$

III. B. 2) Random forest-based assessment methodology

Each time a decision tree is built, one data is obtained by repeated sampling for training the decision tree, and the data not utilized to participate in the building of the decision tree is used to evaluate the decision tree classification performance and calculate the prediction error rate of the model. For each decision tree, select the corresponding out-of-bag data to calculate the prediction error rate, randomly add noise interference to the features of all samples of the out-of-bag data X, and calculate the out-of-bag data error again. Assuming that there are N trees in the forest, the average of the differences in the error values of the calculated N trees is used to indicate the importance of the feature X. Random noise is added to study the variation in prediction error rates and important features are selected.

A certain percentage of features are eliminated each time, and the information gain is utilized for attribute selection to obtain a new set of attributes a_*.

$$a_*=\arg\max_{a\in A} Gain(D,a) \tag{19}$$

In this paper, we construct the algorithm for evaluating the ecological education effect of research activities by taking the category of research activities and the category of no research activities as the sample set, and obtain the degree of influence of research activities on the indicators of the ecological education effect of students, so as to evaluate the effect of ecological education. Figure 2 shows the flow of the algorithm in this chapter.

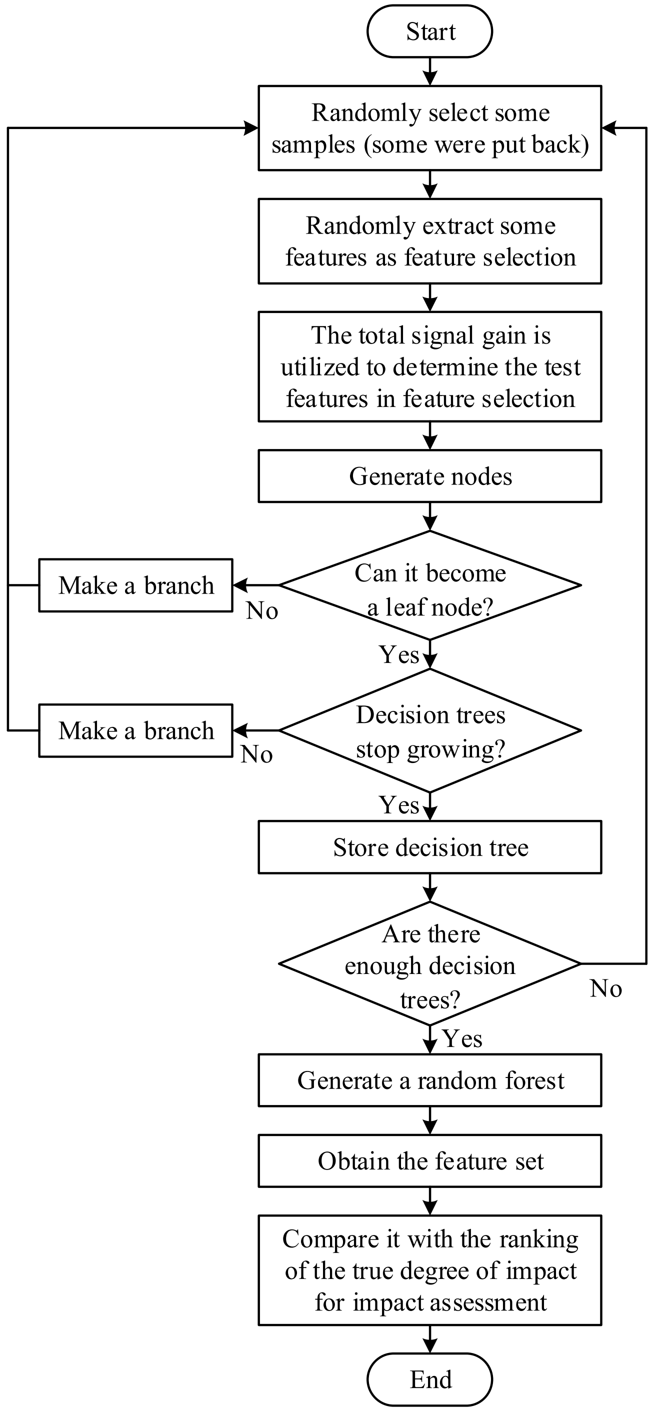

Figure 2: Random forest evaluation algorithm schematic

IV. Calculation of the weights of the indicators of the ecological civilization education effect assessment model

Experts from educational evaluation institutions are invited as scorers, and the profile information of the ecological civilization education effect of the national park study activities of the selected institutions, the scoring method, the assessment judgment matrix and the index scoring form are provided to the scorers. Then, according to the constructed random forest-based ecological civilization education effect assessment method, the AHP-CRITIC method is applied to calculate the weights of the typical assessment, which is firstly applied to the subjective and objective assignment method respectively, and the weights of the two are coupled.

IV. A. Subjective weights of indicators for assessing the effectiveness of ecological civilization education

Based on the AHP method, the quantitative calculation of the indicators was carried out according to the collected expert assignments and in accordance with the constructed assessment judgment matrix. According to the constructed assessment judgment matrix, the data are input into the mceAHP software for calculation, and then consistency test and comprehensive ranking are carried out.

Take the scoring assignment of expert 1 as an example, and list the calculation results of each level. Input the judgment matrix into the mceAHP software to derive the weights, and the weights are retained in 4 decimal places. Verify that each judgment matrix satisfies CR=CI/RI<0.1 and passes the consistency and randomness test values. Based on the weights obtained for the single sorting condition, the calculation was performed to derive the weights of all secondary and tertiary indicators for expert 1.

Repeat the above steps, according to the matrix, all the experts' scoring assignments are imported into mceAHP respectively, the weight results are calculated, and the consistency test is carried out, and it is found that each part of the matrix satisfies CR<0.1, passes the consistency test, and the data are all valid.

After calculating the weight values of all the weighted data, the final indicator weight values are calculated as the average value and normalized to sort the indicators, and the subjective indicator weights are obtained as shown in Table 1. Among them, B16, i.e., practical experience, has the largest weight, which is 0.1546.

Table 1: Index subjective weighting sort

Sort	Index	Weight value	Sort	Index	Weight value
1	B16	0.1546	12	B7	0.0277
2	B9	0.1054	13	B4	0.0268
3	B17	0.0856	14	B21	0.0238
4	B8	0.0799	15	B13	0.0226
5	B19	0.0715	16	B12	0.0226
6	B2	0.0595	17	B11	0.0189
7	B1	0.0577	18	B10	0.0175
8	B3	0.0558	19	B14	0.0165
9	B15	0.0469	20	B18	0.0156
10	B20	0.0458	21	B6	0.0098
11	B5	0.0355			

IV. B. Objective weighting of indicators for assessing the effectiveness of ecological civilization education

Based on the CRITIC method, the data collected for the assignment, were organized and calculated to arrive at the objective weights of the indicators as shown in Table 2. Among them, B16, i.e., practical experience, has the largest weight of 0.0707.

Table 2: Objective weighted sort

Sort	Index	Weight value	Sort	Index	Weight value
1	B16	0.0707	12	B17	0.0445
2	B9	0.0625	13	B12	0.0416
3	B17	0.0625	14	B20	0.0414
4	B18	0.0608	15	B15	0.0406
5	B6	0.0571	16	B1	0.0393
6	B19	0.0535	17	B4	0.0371
7	B3	0.0519	18	B13	0.0355
8	B14	0.0516	19	B7	0.0345
9	B21	0.0516	20	B5	0.0345
10	B2	0.0471	21	B11	0.0342
11	B10	0.0466			

IV. C. Comprehensive weighting of indicators for assessing the effectiveness of ecological civilization education

Integrate the subjective weight 1 and objective weight 2 of the ecological civilization education effect assessment indexes, calculate the integrated weight 3 according to the obtained weights of the 2 indexes, and sort them according to the weight level, and the sorting results are shown in Table 3. The results of the calculation of the 3 weights of the 21 indicators are compared in the form of a curve diagram, and the comparison results are shown in Figure 3.

The graph clearly reflects the distribution of the weights of the 3 indicators. It is clear from observation that most of the weights of the indicators obtained from the AHP method and the CRITIC method for the assessment of the effect of ecological civilization education are similar, but there are also some indicators with large differences in weights. The comprehensive weight curve is between the weight 1 and weight 2 curves, which can achieve the neutralization purpose. Therefore, when applying the ecological civilization education effect assessment model constructed by AHP-CRITIC method, the calculated comprehensive coupling weights should prevail.

Table 3: The main objective index weight integration and comparison

Sort	Index	Weight 1	Weight 2	Weight 3
1	B16	0.1546	0.0707	0.1054
2	B9	0.1054	0.0625	0.0788
3	B8	0.0799	0.0625	0.0710
4	B19	0.0715	0.0535	0.0618
5	B17	0.0856	0.0445	0.0602
6	B3	0.0558	0.0519	0.0540
7	B2	0.0595	0.0471	0.0521
8	B1	0.0577	0.0393	0.0464
9	B20	0.0458	0.0414	0.0424
10	B15	0.0469	0.0406	0.0410
11	B21	0.0238	0.0516	0.0401
12	B18	0.0156	0.0608	0.0398
13	B5	0.0355	0.0345	0.0377
14	B12	0.0226	0.0416	0.0364
15	B14	0.0165	0.0516	0.0362
16	B4	0.0268	0.0371	0.0357
17	B10	0.0175	0.0466	0.0343
18	B7	0.0277	0.0345	0.0340
19	B13	0.0226	0.0355	0.0328
20	B6	0.0098	0.0571	0.0305
21	B11	0.0189	0.0342	0.0294

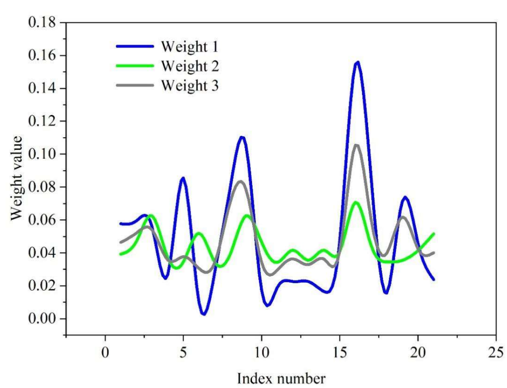

Figure 3: Comparison of weights

V. Results of the assessment of the effect of ecological civilization education on study activities in national parks

V. A. Sample Desired Output Value Determination

Combining the weights of the indicators, the evaluated value of the effect of ecological civilization education in the selected 20 institutions is derived based on the calculation formula, which will be used as the expected value of the evaluation process. The final expectation value obtained is shown in Table 4.

Table 4: The value of the education effect of ecological civilization

School number	Expected value
1	0.3444
2	0.3416
3	0.3394
4	0.338
5	0.3357
6	0.3334
7	0.3322
8	0.3304
9	0.3292
10	0.3284
11	0.3266
12	0.3254
13	0.3242
14	0.3230
15	0.3216
16	0.3206
17	0.3199
18	0.3185
19	0.3184
20	0.3172

V. B. Analysis of the results of the evaluation of the effect of ecological civilization education

The evaluation data of the ecological civilization education effect of 20 institutions selected in this paper construct the ecological civilization education effect evaluation model.

This paper applies the Random Forest package in R3.3.1 software under window7 system to train and test the model. The parameters are set as ntree=500, nodesize=2, mtry=7. Relative error (RE) is selected to test the accuracy of the prediction results. The formula was calculated as:

$$RE_{(i)} = \frac{y_i^* - y_i}{y_i} \times 100\% \tag{20}$$

where y_i^* and y_i are the predicted and actual values respectively, the prediction results of Random Forest model are shown in Table 5.

The prediction results of the Random Forest model fluctuate less up and down, and the relative error is maintained within [-3%,3%], so the prediction results are more stable and accurate.

In order to determine that the model has validity, this paper additionally selected the neural network (BPNN) for comparative analysis.The parameters of the BPNN model are set as follows: the number of iterations is 200, the learning rate is 0.1, the training error is 0.00004, and the number of neurons in the implicit layer is 60.The test results of the BPNN model are shown in Table 6.

The average absolute percentage error of Random Forest model is 0.681%, while the average absolute percentage error of BPNN model is 1.328%. And the absolute range of relative error of Random Forest model is controlled within [0.030%,2.274%], while the absolute range of relative error of BPNN model is within [0.063%,4.142%]. In 20 sets of samples, it can be seen that compared with the BPNN model, the error fluctuation of the RF model is smaller, and the evaluation accuracy is higher, with a certain degree of stability.

In summary, the random forest evaluation model can effectively solve the problem of evaluating the effect of ecological civilization education, and its evaluation accuracy and generalization ability are better than the neural network model. For the future evaluation of the effect of ecological civilization education, the model can be used for evaluation, i.e., the teaching indicators of each region are brought into the model, and the evaluation value of the effect of ecological civilization education in the region is obtained after the model parameters are set.

Table 5: Random forest evaluation model test results

School number	Expected value	Test value	Relative error
1	0.3444	0.3440	-0.116%
2	0.3416	0.3398	-0.527%
3	0.3394	0.3379	-0.442%
4	0.3380	0.3439	1.746%
5	0.3357	0.3341	-0.477%
6	0.3334	0.3333	-0.030%
7	0.3322	0.3379	1.716%
8	0.3304	0.3254	-1.513%
9	0.3292	0.3275	-0.516%
10	0.3284	0.3263	-0.639%
11	0.3266	0.3233	-1.010%
12	0.3254	0.3180	-2.274%
13	0.3242	0.3227	-0.463%
14	0.3230	0.3215	-0.464%
15	0.3216	0.3211	0.155%
16	0.3206	0.3209	-0.094%
17	0.3199	0.3224	-0.781%
18	0.3185	0.3189	-0.126%
19	0.3184	0.3189	-0.157%
20	0.3172	0.3184	-0.378%

Table 6: BPNN evaluation model test results

School number	Expected value	Test value	Relative error
1	0.3444	0.3491	1.365%
2	0.3416	0.3410	-0.176%
3	0.3394	0.3426	0.943%
4	0.3380	0.3520	4.142%
5	0.3357	0.3318	-1.162%
6	0.3334	0.3354	0.600%
7	0.3322	0.3190	-3.974%
8	0.3304	0.3333	0.878%
9	0.3292	0.3316	0.729%
10	0.3284	0.3300	0.487%
11	0.3266	0.3312	1.408%
12	0.3254	0.3127	-3.903%
13	0.3242	0.3228	-0.432%
14	0.3230	0.3237	0.217%
15	0.3216	0.3175	-1.275%
16	0.3206	0.3178	-0.873%
17	0.3199	0.3151	-1.500%
18	0.3185	0.3183	-0.063%
19	0.3184	0.3150	-1.068%
20	0.3172	0.3215	1.356%

VI. Conclusion

This paper conducted an in-depth study on the key influencing factors and evaluation models affecting the effectiveness of ecological education in research and study activities in national parks, and achieved the following research results.

(1) Starting from the two main subjects of teachers and students, a set of indicators for evaluating the ecological education effects of national park study activities has been constructed. This indicator system comprehensively considers four dimensions: curriculum system, support conditions, teacher quality, and student knowledge. It includes 21 indicators such as teaching management, curriculum setup, and teaching content. Based on the analytic hierarchy process and the CRITIC method, the comprehensive weights obtained can achieve a neutral weighting purpose. The indicator with the maximum weight across the three methods is practical experience, which verifies the scientific nature of the comprehensive weighting method for assigning weights to the indicators.

(2) A random forest-based model for evaluating the eco-education effect of study-learning activities in national parks was constructed. Data related to the teaching of ecological education in 20 undergraduate colleges and universities in Province A were collected, and the data of the research activity category and the no research activity category were used as the input dataset for training, respectively. It is found that the average absolute percentage error of the evaluation results of the random forest model is 0.681%, which is reduced to 0.647% compared with that of the BPNN model, and its overall error fluctuation range is small, and the evaluation accuracy is high and more stable. It confirms the scientific validity of the proposed ecological education effect evaluation model based on random forests in evaluating the ecological education effect of students in national park study activities.

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