Research and quantitative analysis of ecological development trend of Saihanba forest farm

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Abstract. The cluster analysis method was used to select the more important influencing factors and related data in the ecological environment of Saihanba Forest Farm, and the evaluation was evaluated into three more systematic evaluation indicators. The analytic hierarchy process was used to determine the weight of each influencing factor, and the ecological environment quality evaluation index system of Saihanba Forest Farm was established. This paper takes Beijing 's ability to resist dust storms as an example for evaluation and analysis. Firstly, the entropy weight method-TOPSIS model is used to judge the severity of dust storm changes in Beijing. Secondly, six Saihanba environmental index parameters are selected to establish a mathematical model of Saihanba for Beijing 's ability to resist dust storms. Experiments show that the model provides an important basis for the positive effect of the restoration of Saihanba Forest Farm on Beijing 's ability to resist dust storms.

Keywords: TOPSIS algorithm; Saihanba; Ecological civilization; Sandstorm; The environment.

1 Introduction

1.1 A Subsection Sample

China began to restore the Saihanba Forest Farm in 1962, which has a constructive role in improving the overall coordination mechanism in the field of ecological civilization and building an ecological civilization system. The Saihanba plays a role in fixing sand, protecting water sources, carbon neutralization and oxygenation. It is assumed that the ecological protection model of the Saihanba will be extended to the whole country, which will have a significant impact on the realization of China 's carbon neutralization goal. At the same time, China 's Saihanba ecological protection model also sets an example for the Asia-Pacific region, which has a great impact on absorbing greenhouse gases and reducing carbon emissions. Therefore, quantitative analysis of the role of the Saihanba has an innovative example for the development of civilization, the prosperity of zoology and the promotion in other regions.

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At present, relevant scholars have carried out a lot of research in the field of ecological environment of Saihanba. Qinhai Copper[1] analyzes the current situation of Saihanba National Nature Reserve, comprehensively discusses the problems existing in the ecological environment protection of Saihanba, and puts forward four measures to increase the protection of Saihanba area. Ye Qichao[2] et al. quantified the impact of Saihanba on Beijing 's ability to resist dust storms through the grey prediction model and the model accuracy test. Ge Nan[3] et al. compared and evaluated the plant landscape quality of Hebei Saihanba Forest Park by using SBE method and AHP method. In this study, quantitative analysis was carried out at the same time as the analysis. Taking Beijing sandstorm as an example to verify the impact of the restoration of Saihanba forest farm, the index data were collected and sorted out for the construction of the evaluation model of ecological environment index, the construction of the evaluation model, the analysis model problem, the algorithm calculation, and the quantitative analysis results were obtained.

2 Evaluation methodology

2.1 Cluster analysis method

Cluster analysis[4] can study the similar relationship between different indicators[5] and aggregates the indicators into several classes according to the similarity between the indicators, so that the impact of each indicator on the ecological environment of Sehampa can be better studied.

First we apply the similarity measures of the indicators. In cluster analysis of indicators, the first step is to determine the similarity measure of variables[6]. The similarity measure adopted in this paper is the correlation coefficient, as follows:

Remember the indicatorX_j The value of$(X_{1j}, X_{2j}, \dots, X_{15j})^T \in R^n (j = 1,2, \dots ,15)$, i.e., two indicators can be usedX_j with theX_k correlation as the indicator similarity measure for:

$$r_{jk} = \frac{\sum_{i=1}^{n} (x_{ij} - \bar{x}_j)(x_{ij} - \bar{x}_k)}{[\sum_{i=1}^{n} (x_{ij} - \bar{x}_j)^2 \sum_{i=1}^{n} (x_{ij} - \bar{x}_k)^2]^{\frac{1}{2}}} \tag{1}$$

Secondly we classify the indicators by clustering method, we use the longest distance method to solve the clustering problem, in the longest distance method, the distance between two categories of indicators is defined as:

$$R(G_1, G_2) = \max_{x_i \in G_1, x_k \in G_2} \{d_{jk}\} \tag{2}$$

where$d_{jk} = 1 - |r_{jk}|$ or$d_{jk}{}^2 = 1 - r_{jk}{}^2$, at which point$R(G_1, G_2)$ is related to the value of the similarity measure of the two metrics with the least similarity between the two categories.

The matrix of correlation coefficients between the indicator factors was used as input parameters, and the indicator factors with a relatively large degree of correlation were used as outputs after clustering analysis. Thus, the influencing factors under three types of evaluation indicators were obtained. Firstly, the factors affecting the current state of forest ecosystem: average soil depth, soil porosity, area of soil to reduce erosion, forest stock, vegetation cover; secondly, the factors affecting the function of forest ecosystem: average annual precipitation, amount of reduction of soil erosion, amount of oxygen released, amount of carbon dioxide fixed, frost-free period, amount of absorption of sulphur dioxide; thirdly, the factors affecting the impact of forest ecosystem: richness of tree species , degree of depression, degree of naturalness, and ratio of forest tourism area.

2.2 Hierarchical analysis

Establishment of hierarchical model[7] The problem is decomposed into three levels, with the top level being the target level M, i.e., selecting the most suitable key indicators for evaluating the environmental impacts before and after the restoration of the Se-hampa Dam; the bottom level being the indicator level, i.e., the nine influencing factors D1, D2, D3, D4, D5, D6, D7, D8, D9, D10, D11, D12, D13, D14, D15; and the middle level being the criterion level, including three indicators, namely, the current status of the forest ecology C1, the functions of the forest ecology C2, and the impacts of the forest ecology C3. The middle layer is the guideline layer, including three indicators of forest ecological environment C1, forest ecological environment function C2, and forest ecological environment impact C3, as shown in Table 1.

Table 1. Hierarchical analysis table

Target layer M	Element layer C	Indexing layer D
Forest ecosystems (M)	Status of forest ecosystems (C1)	Average soil depth (D1)
		Soil porosity (D2)
		Reduction of eroded soil area (D3)
		Vegetation cover (D4)
		Common standard deviation (D5)
	Forest ecosystem functions (C2)	Frost-free period (D6)
		Fixed carbon dioxide (D7)
		Amount of oxygen released (D8)
		Average annual precipitation (D9)
		Reduction of soil erosion (D10)
		Sulphur dioxide absorption (D11)
	Forest ecosystem impacts (C3)	Naturalness (D12)
		Crown closure (D13)
		Tree species richness (D14)
		Forest tourism area ratio (D15)

The determination of the standard values of various indicators and the scoring of the indicators refer to the following ways: using the standard values stipulated in national or international standards; referring to the current values of the domestic or foreign environment; quantifying the standard values based on existing theories; and referring to the existing literature.[8] The following are some of the ways: using national standards or international standards; referring to the current value of the domestic or foreign environment; determining the standard value based on the existing theory of quantification; referring to the existing literature.

Each level in turn builds a pairwise comparison judgement matrix $A = (a_{ij})_{n \times n}$ where a_{ij} The values of are taken according to T.L. Saaty[9] adopted to take values in the middle of 1-9 and its reciprocal, and then its eigenvectors are obtained.

First construct the judgement matrix M-C as shown in Table 2:

Table 2. Judgment matrix

M	C1	C2	C3
C1	1.000	3.000	5.000
C2	0.333	1.000	2.000
C3	0.200	0.500	1.000

The maximum eigenvalue M-Cλ_{max} = 3.0034 is obtained by solving the data in Table 2 and the weight vector is.

$$w_i = (0.6484, 0.2296, 0.1220)^T$$

By the formula:

$$CI = \frac{x_{max} - n}{n-1}, CR = \frac{CI}{RI} \tag{3}$$

The calculations yielded $CR = 0.0033 < 0.1$, passing the consistency test.

Secondly, the judgement matrices C1-D,C2-D,C3-D are constructed, and the weight vectors ,maximum eigenvalue λ and consistency index CR calculated from the judgement matrices are listed in the table 3.

Table 3. Calculation results

C / D	C1	C / D	C2	C / D	C3
	W_j		W_j		W_j
D1	0.2636	D6	0.1948	D12	0.2382
D2	0.4758	D7	0.4288	D13	0.5167
D3	0.0538	D8	0.0497	D14	0.0769
D4	0.0981	D9	0.1142	D15	0.1682
D5	0.1087	D10	0.122		
		D11	0.0904		
λ	5.0719	λ	6.3162	λ	4.1033
CR	0.016	CR	0.0502	CR	0.0387

From the values of CR in Table 3, it can be seen that the matrices C1-D, C2-D, and C3-D have passed the consistency test.

2.3 Conclusions and Analyses

Based on the above data, the total weights assigned to each indicator were calculated according to the following formula resulting in Table 4:

$$W = W_i \times W_j \tag{4}$$

Table 4. Calculation results

D	W	D	W	D	W
D1	0.17091824	D6	0.04472608	D11	0.02075584
D2	0.30850872	D7	0.09845248	D12	0.0290604
D3	0.03488392	D8	0.01141112	D13	0.0630374
D4	0.06360804	D9	0.02622032	D14	0.0093818
D5	0.07048108	D10	0.0280112	D15	0.0205204

In order to test the practical application effect of the constructed evaluation system, this paper selects the data in 1978 to represent the condition before the restoration of the Sehampa Dam, and the data in 2021 to represent the condition after the restoration of the Sehampa Dam. The ecological environment before and after the restoration of the Sehampa is evaluated in practice, and the values of the indicators are obtained directly by using the data of national statistics, yearbook data, existing literature or indirectly extrapolated through the existing theoretical basis.

Table 5. Values associated with 1978 and 2021

vintages D	1978 x_1	2021 x_2
Average soil depth (D1)	16	19
Soil porosity (D2)	35	63
Reduction of eroded soil area (D3)	24	112
Vegetation cover (D4)	155	1036.8
Common standard deviation (D5)	12	80
Frost-free period (D6)	402.5	438
Fixed carbon dioxide (D7)	3028	19740
Amount of oxygen released (D8)	8.2	54.5
Annual evaluated precipitation (D9)	11.2	74.7
Reduction of soil erosion (D10)	58	72
Sulphur dioxide absorption (D11)	68.7	457.95
Naturalness (D12)	94	626
Crown closure (D13)	23	57
Tree species richness (D14)	2	4
Forest tourism area ratio (D15)	2	86

A weighted average model was used to calculate the total score (P) for forest ecosystem quality. Compare the data in Table 4 and Table 5 with the following formula.

$$P = \Sigma W_i X_i \tag{5}$$

Where W_i is the weight of the ith evaluation indicator, andX_i is the value of the ith indicator.

After calculation using the established ecological environment evaluation model, the total score P of the ecological environment quality before restoration of the Sehampa Dam is 348.8702437; and the total score P of the ecological environment quality after restoration of the Sehampa Dam is 2098.909506544. The evaluation results show that the ecological environment of the Sehampa Dam after restoration compared with the pre-restoration period has a good impact on the environment, and the effect is excellent. This is in line with the current status quo of high coverage, abundant resources and good natural environment of the Sehamba forest.

3 Quantitative Evaluation of the Role of the Sehan Dam in Protecting Beijing Against Sand and Dust Storms

3.1 Data-processing calculations for correlation indicators

(1)Average number of days of duration per visit per year vs. average number of days of duration per year

Calculating the average number of days per duration of sandstorms in Beijing over the years has a strong correlation with the change in the severity of sandstorms in Beijing, with the larger the average number of days per duration the more severe and the smaller the less severe.

$$\bar{x} = \frac{\sum_{i=1}^{N} x_i}{N} = \frac{x_1 + x_2 + \cdots + x_N}{N} \tag{6}$$

wherex_1 , .x_2 , ...x_N is the number of days each dust storm lasts in a given year, and *N* is the number of dust storms that occur in Beijing in a given year. It is also possible to calculate the average number of days of duration per year, whenx_1 , ...x_2 , ...x_N is the number of days the sandstorm lasts in each year, and *N* is the number of years.

(2)Variance in days of duration

Through the change of the number of days of each sandstorm, i.e. the size of the variance data, we can judge the degree of change and stability of the sandstorms in Beijing. If the variance of the number of days of each sandstorm is larger in a certain year, then it means that the change of the sandstorms in Beijing is large and unstable, and the closer the variance is to 0, then it means that the sandstorms in Beijing are more stable and the changes are small.

It is also possible to further calculate the variance of changes in the average number of days of duration of each year of sandstorms over the years, corresponding to the variance of changes in the ecological indicators of the Sehamba Forest, and to verify the correlation between the occurrence of sandstorms in Beijing and the Sehamba Forest.

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2 = (\frac{1}{N}\sum_{i=1}^{N}x_i^2) - \bar{x}^2 \quad (7)$$

wherex_i can be the number of days of duration of each dust storm in a certain year, corresponding to the$\bar{x}$ which is the average number of days of duration for each occurrence in a given year, and *N* is the number of dust storms occurring in a given year;x_i It can also be the number of dust storm duration days in a year, corresponding to$\bar{x}$ which is the average number of days of duration per year, and *N is the* number of years;

(3)relevance analysis

A visual calculation of whether there is a correlation, how much correlation there is, and how much certainty there is in judging the extent of this correlation. To carry out a correlation analysis, a correlation is generally required, and the magnitude of the correlation coefficient is used to judge the degree of correlation between the independent variable and the dependent variable: strong correlation, weak correlation, no correlation, etc.

$$\rho_{xy} = \frac{Cov(X,Y)}{\sqrt{D(X)}*\sqrt{D(Y)}} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2 * \sum_{i=1}^{n}(y-\bar{y})^2}} \quad (8)$$

Where $Cov(X,Y)$ is$X$ the$Y$ The covariance of$D(X)$, the$D(Y)$ are the covariances of$X$ the covariance of$Y$ The variance of the correlation coefficientρ_{xy} quantitatively portray *the correlation coefficients between X and Y* the degree of correlation, i.e.$|\rho_{xy}|$ The larger the correlation, the greater the degree of correlation; i.e.$|\rho_{xy}| = 0$, corresponding to the lowest degree of correlation.

(4)weighted arithmetic mean

Each indicator has a different correlation, and by assigning larger weights to those with large correlations and smaller weights to those with small correlations, the result of the calculation is a more accurate severity value, with larger values indicating more severity and smaller values indicating less severity.

$$\bar{x} = \frac{\sum_{i=1}^{N} w_i x_i}{\sum_{i=1}^{N} w_i} = \frac{w_1x_1+w_2x_2+\cdots+w_Nx_N}{w_1+w_2+\cdots+w_N} \quad (9)$$

For i=1,..., *N*, each valuex_i has a weightw_i The indicators of the severity of dust storms in Beijing are the average number of days per dust storm per year, the change in the number of days per dust storm per year, and the change in the average number of days per dust storm over the years.[10] There are some other indicators with very small correlation that can be ignored in the calculation.

3.2 Entropy weighting method to calculate coefficients for three indicators

The coefficients of the three indicators were calculated by the entropy weighting method, and the combined scores of the three indicators were used as the severity indicators of dust storms in Beijing. For the average number of days of duration, it was found to be a cost indicator; for the number of days of duration of each sandstorm and the average number of days of duration of sandstorms in the past years, it was found to be a benefit indicator.[11] For the number of days per dust storm and the average number of days of dust storm duration over the years, the analyses showed that they were benefit indicators.

Different types of indicators were subjected to different normalisation treatments with the following formulas:

Cost-based indicators are normalised (the larger the original variable, the better):

$$y_i = \frac{x_i - \underset{1<i<n}{min(x_i)}}{\underset{1<i<n}{max(x_i)} - \underset{1<i<n}{min(x_i)}} \tag{10}$$

Benefit-based indicators are normalised (the smaller the original variable, the better):

$$y_i = \frac{\underset{1<i<n}{max(x_i)} - x_i}{\underset{1<i<n}{max(x_i)} - \underset{1<i<n}{min(x_i)}} \tag{11}$$

Combined with the normalised indicators, the sand and dust storm severity scoring model was developed as follows.

$$\Delta_{\mathrm{i}} = w_i r_{i1} + w_i r_{i2} + w_i r_{i3} \tag{12}$$

wherew_i is the weight of the *jth* indicator*, and*r_{ij} which is the value of the *jth* indicator in the *ith* year of sandstorm in Beijing. By solving the weights through the entropy weighting method and substituting them into the above equation, we can get the severity of the sandstorm in the *ith* year.Δ_{i} The severity of the sandstorm in year i can be obtained by solving the weight by entropy weight method and substituting it into the above equation.

After determining the indicators that can effectively describe the characteristics of sand and dust storms in Beijing, the weights of each indicator were solved by the entropy weighting method.

Individual indicators were standardised and then the entropy value of the standardised indicator was calculated as follows.

$$x_i = \max\{x_1, x_2, \dots, x_i\} - x_i \tag{13}$$

There is no negative normalisation:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{14}$$

Then, for each element of its standardised indicator:

$$z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \tag{15}$$

Normalisation in the presence of negative numbers (in fact the following formula is often used in the absence of negative numbers).

$$z_{ij} = \frac{x_{ij} - min\{x_{1j}, x_{2j}, \dots, x_{ij}\}}{max\{x_{1j}, x_{2j}, \dots, x_{ij}\} - min\{x_{1j}, x_{2j}, \dots, x_{ij}\}} \tag{16}$$

Calculate the coefficient of variation for each indicator.
Compute the probability matrix p:

$$p_{ij} = \frac{z_{ij}}{\sum_{i=1}^{n} z_{ij}} \tag{17}$$

Calculate the information entropy e (uncertainty) for each metric:

$$\mathrm{e_j} = \frac{1}{lnn} \sum_{i=1}^{n} p_{ij}\, ln(p_{ij}), (j = 1,2, \dots, m) \tag{18}$$

included among these:

$$k = \frac{1}{lnn} > 0, \mathrm{e_j} \geq 0$$

Calculate the weights of the indicators.
1-e is the information utility value, which is then normalised to the weights: the:

$$d_j = 1 - \mathrm{e_j}, (j = 1,2, \dots, m) \tag{19}$$

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j}, (j = 1,2, \dots, m) \tag{20}$$

Multiply the normalised data by the weights respectively: the:

$$score_j = \sum_{j=1}^{m} w_j z_{ij}, (i = 1,2, \dots, n) \tag{21}$$

The results of the solution are given in the table 6.

Table 6. Weight values of three indicators of sandstorm severity in Beijing

Indicators for the evaluation of severity	Average number of days of duration	Number of days per dust storm	Average number of days of dust storms in a calendar year
weights	0.33837	0.2560	0.4057

As shown in the table above, the weights of the indicators reflected in the severity assessment are:

$$\Delta_\mathrm{i} = 0.43837 r_{1i} + 0.3560 r_{2i} + 0.2057 r_{3i} \tag{22}$$

Where *i* represents the *ith* year, it is easy to see from the values of the weights that the severity is mainly affected by the average number of days of duration and the average number of days of duration of dust storms in the past years, of which the average number of days of duration of dust storms in the past years is the ultimate indicator of the severity of dust storms.

Substituting the data gives us that $\Delta = \Delta_{1978} - \Delta_{2021} = 0.6846$, therefore, from 1978 to 2021, Beijing's dust storms have decreased by 0.8846*100 per cent = 68.46 per cent.

3.3 Data on indicators related to the Seyhan Dam weighting

Then association analysis, similar to the classic case of "beer and nappies": in the 1980s, Wal-Mart in the invention of bar codes, wireless scanning guns, computer tracking inventory technology, has accumulated a large number of customer consumption records, through the use of data mining technology to analyse the unexpected discovery of the highest frequency of purchase of goods together with nappies The most frequently purchased item together with nappies was the seemingly unrelated beer. The discovery of this correlation rule for Wal-Mart to develop a sales strategy provides an important basis, through the two kinds of commodities placed in the position and price adjustments, greatly enhancing the sales volume of the two. The two products' placement and prices were adjusted to greatly increase the sales of the two products.

Therefore, a multi-indicator evaluation model based on TOPSIS was established [12], which score that reflects the influence of each indicator on the decline of sand and dust storm severity. The hierarchical analysis method was used to exclude several indicators with small weights, and six indicators, namely, the amount of water in the Sehampa Dam, the volume of forest reserves, the area of forest cover, the forest coverage, the carbon dioxide absorption, and the amount of oxygen release were selected as the influencing factors, and the data of the six indicators, namely, the amount of water in the Sehampa Dam, the volume of forest reserves, the area of forest cover, the forest coverage, the carbon dioxide absorption, and the amount of oxygen release, were subjected to the homothetic processing of the indicator attributes, and the normalised initial matrix was constructed. Normalised initial matrix[13].

For the normalisation of very small indicators.

$$x_i = \max\{x_1, x_2, ..., x_i\} - x_i \tag{23}$$

Data standardisation:

$$z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} {x_{ij}}^2}} \tag{24}$$

Standardised matrix:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{25}$$

Then the optimal and worst options are identified.

The scoring matrix *Z, which* has been normalised and normalised, contains all very large data. We can then take out the ideal optimal solution and the worst solution from it. Thus we take out each indicator, i.e. the largest number in each column, to form the vector of ideal optimal solutions, i.e:

$$z^+ = [z_1^+, z_2^+, \dots, z_m^+] = [max\{z_{11}, z_{21}, \dots, z_{n1}\}, max\{z_{12}, z_{22}, \dots, z_{n2}\}, \dots, max\{z_{1m}, z_{2m}, \dots, z_{nm}\}] \quad (26)$$

Similarly, take the smallest number in each column to compute the ideal worst solution vector:

$$z^- = [z_1^-, z_2^-, \dots, z_m^-] = [min\{z_{11}, z_{21}, \dots, z_{n1}\}, min\{z_{12}, z_{22}, \dots, z_{n2}\}, \dots, min\{z_{1m}, z_{2m}, \dots, z_{nm}\}] \quad (27)$$

z^+That's it.z_{max} It is.z^- That's it.z_{min} (LAUGHS)

On the basis of obtaining the ideal optimal solution and the ideal worst solution it is possible to calculate the score for each solution, based on the scoring formula above:

$$\frac{z_i - z_{min}}{z_{max} - z_{min}} \quad (28)$$

Then calculate the proximity of each evaluation object to the optimal solution and the worst solution.

distance from the optimal solution:

$$d_i^+ = \sqrt{\sum_{j=1}^{m} \left(z_j^+ - z_{ij}\right)^2} \quad (29)$$

Distance to the worst solution:

$$d_i^- = \sqrt{\sum_{j=1}^{m} \left(z_j^- - z_{ij}\right)^2} \quad (30)$$

Calculate the closeness of each evaluation object to the optimal programme.

$$S_i = \frac{d_i^-}{d_i^+ + d_i^-} \quad (31)$$

The collected data of six indicators [14], as shown in Fig. 1 Fig. 2 below, were substituted into TOPSIS algorithm for solving. The information on forest cover and area covered from 1962 to 2021 in Sehamba was obtained from Sehamba Mechanical Forestry Farm.

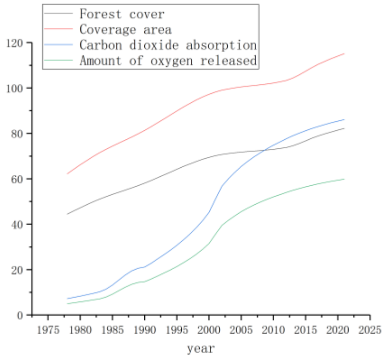

Fig. 1. Data of four related indicators of Saihan Dam

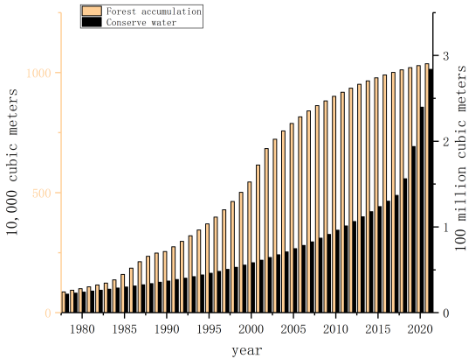

Fig. 2. Data for two relevant indicators for the Saihan Dam

The table 7 of weight values associated with the reduction in the severity of sand and dust storms in Beijing was derived by ranking the data according to the magnitude of the closeness, and the data of the relevant indicators of the Sehampa Dam were ranked.

Table 7. The weights of six indicators related to the severity reduction of sandstorms in Beijing.

norm	quantity of water retained	forest tree stock	forest cover	forest cover	Carbon dioxide uptake	Oxygen release
weights	0.3617	0.3272	0.1622	0.0254	0.1143	0.0093

The above table 7 shows the weights of the indicators embodied in the TOPSIS multi-attribute evaluation, and from the value of the weights, the amount of water retained in the Sehampa Dam is the most important indicator affecting the decrease of the severity of sandstorms in Beijing, followed by the forest volume.

3.4 Reach a verdict

The proportion of the role of the Saihan Dam in the protection of Beijing against sand and dust storms can be obtained by substituting the results of the calculation into the following formula:

$$Y=\frac{x_{2021}-x_{1978}}{x_{1978}}\times 100\% \tag{32}$$

of whichx_{2021} is the severity of sand and dust storm occurrence in 2021 when the Sehamba is defending Beijing against sand and dust storms.x_{1978} is the severity of sandstorm occurrence in Beijing in 1978. Substitute to get:

Y=-(2.31 per cent-1.78 per cent)/1.78 per cent*100 per cent=-29.78 per cent

Since the results are negative, the restoration of the Sehamba Forest played a role in suppressing the sandstorms in Beijing. In 1978, the Sehamba Dam suppressed the sandstorms in Beijing by 1.78%, and in 2021, the Sehamba Dam suppressed the sandstorms in Beijing by 2.31%, which is calculated to be about 29.78% reduction of sandstorms in Beijing as a result of the restoration of the Sehamba Forest from 1978 to 2021. 29.78 per cent.

4 Conclusions

This paper evaluates the important role played by the Sehan Dam in resisting wind and sand, protecting the environment, and maintaining ecological balance and stability. Suitable indicators were selected, relevant data were collected, and the construction and analysis of the evaluation model of the ecological and environmental indicators of the Sehampa Forest Farm were carried out to quantitatively evaluate the impact of the restoration of the Sehampa Dam on the environment, i.e., a comparative analysis was made of the environmental conditions before and after the restoration of the Sehampa Dam. It also analyses and evaluates the important role played by the restoration of the Sehamba Forest Farm in Beijing's resistance to sandstorms and dust storms, using Beijing's ability to resist sandstorms and dust storms as an example, and quantitatively evaluates the role of the Sehamba in Beijing's resistance to sandstorms and dust storms. This paper finds a large amount of data from China's official data websites, which are scientific and accurate [14], which has scientificity and accuracy and improves the credibility and accuracy of the algorithm. At the same time, it combines the local climatic conditions, industrial land use and city scale, etc., and can draw correct conclusions more accurately. However, at the same time, the actual calculation should consider a large number of index data, but in order to facilitate the calculation, the less relevant indexes are ignored, which makes the calculation results may have differences, and we expect peer researchers to make corrections.

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References

1. Qinhai copper. Research on ecological environment and sustainable development in Saihanba area of Chengde [J]. Shanxi Agricultural Economy, 2023 (01): 130-132.
2. Ye Qichao, Zhang Kaiyu, Yang Panyao, et al. Ecological protection construction and environmental impact assessment - A case study of Saihanba [J]. Leather production and environmental protection technology, 2023,4 (08), 71-74.
3. Ge Nan, Li Hongxiang, Cao Feng, et al. Evaluation of plant landscape quality in Hebei Saihanba Forest Park based on SBE-AHP method [J]. Journal of Central South University of Forestry and Technology, 2023,43 (4) : 182-190.
4. Niu Geng, Ji Yu,Zhang Zhihui, Wang Wenbo, Chen Jikai, Yu Peng. Clustering analysis of typical scenarios of island power supply system by using cohesive hierarchical clustering based K-Means clustering method[J]. Energy Reports,2021,7(S6).
5. Ali Jawad, Alkenani Ahmad N. Vector Similarity Measures of Dual Hesitant Fuzzy Linguistic Term Sets and Their Applications [J]. Symmetry, Volume 15, Issue 2.2023. pp 471-471.
6. Chenpeng Wu, Ze Wang, Chun Miao. Study on the Comprehensive Evaluation of Population Quality in Anhui Province Based on the Principal Component Analysis Model[J]. The Frontiers of Society, Science and Technology,2023,5(11).
7. Liu Changle, Li Shujiang, Nie Weiliang, et al. Study on three benefit evaluation techniques of forest ecosystem [J]. Forestry Science and Technology, 2004 (03): 20-22.
8. Thomas L. SAATY. Decision making-the analytic hierarchy and network processes (AHP/ANP)Jj. Journal of Systems Science and Systems Engineering, 2004(01):1-35
9. Zhu Shengdong, Jiang Wei. A Comprehensive Evaluation of Environmental Quality for Health Ecotourism in Huangshan National Forest Park[J]. Mobile Information Systems,2022,2022.
10. Baviera Puig Amparo, García Melón Mónica, López Cortés Isabel, Ortolá María Dolores. Combining sensory panels with Analytic Hierarchy Process (AHP) to assess nectarine and peach quality[J]. Cogent Food & Agriculture,2023,9(1).
11. Piao Jinling, Chen Wen, Wei Ke, Cai Qingyu, Zhu Xiaowan, Du Zhencai. Increased sandstorm frequency in North China in 2023: Climate change reflection on the Mongolian plateau[J]. frequency in North China in 2023: Climate change reflection on the Mongolian plateau[J]. The Innovation,2023,4(5).
12. Gheibollahi Hamid, Masih-Tehrani Masoud. a multi-objective optimisation method based on NSGA-II algorithm and entropy weighted TOPSIS for fuzzy active seat suspension of articulated truck semi-trailer[J]. Proceedings of the Institution of Mechanical Engineers,2023,237(17).
13. Miqdam T. Chaichan, Hussein A. Kazem, Ali H. A. Al Waeli, Kamaruzzaman Sopian, Mohammed A. Fayad, Wissam H. Alawee, Hayder A. Dhahad, Wan Nor Roslam Wan Isahak, Ahmed A. Al Amiery. Fayad, Wissam H. Alawee, Hayder A. Dhahad, Wan Nor Roslam

Wan Isahak, Ahmed A. Al Amiery. Sand and Dust Storms' Impact on the Efficiency of the Photovoltaic Modules Installed in Baghdad: A Review Study with an Empirical Investigation[J]. Energies,2023,16(9).
14. Beijing Municipal Bureau of Statistics, National Bureau of Statistics Beijing Survey Team. Beijing Statistical Yearbook 2022[EB/OL]. https ://nj.tjj.beijing.gov.cn/nj/main/2022-tjnj/zk/e/zk/indexch.htm,2022.