Study on ecological impact of Saihanba Forest Farm Based on Evaluation Model

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Abstract. In order to evaluate the impact of Saihanba on the ecological environment, we selecte 11 factors from three aspects to build the Ecological Environment Health Index (EEHI) evaluation model; Next, We use a combined weighting method combining Hierarchical Analysis, Entropy Weighting method and Coefficient of Variation method to determine the weights of each indicator. Then the EEHI of the Seyhanba area from 1962 to 2020 was calculated using the TOPSIS; Finally, the ecological environment of the Seyhanba area was obtained with a yearly upward trend, and the effect of Seyhanba on the improvement of ecological environment was analyzed in three stages. In order to evaluate the impact of Saihanba on the anti-dust storm capacity in Beijing, we selected 9 indicators from three aspects to build the Sandstorm Resistance Ability (SRA) evaluation model in Beijing; Then, the Main Component Analysis method was used to calculate the SRA in Beijing over the years, and SRA was improved year by year. At the same time, we constructed the Sandstorm Index (SI) to indicate the annual severity of dust storms in Beijing; Finally, the relativity between SRA and SI was calculated using the Pearson Correlation Coefficient and find the correlation coefficient between these was -0.833, as a significant correlation. This show that the improvement of Saihanba's resistance to dust storms in Beijing effectively reduces the severity of dust storms in Beijing.

Keywords: Seyhanba, Ecological Environment, Evaluation Model, Correlation Analysis.

1. Introduction model overview

Saihanba, located in northern Hebei Province, was once a vast wasteland. For more than half a century, three generations of Saihanba Forest Farm people, with perseverance and unyielding responsibility, insist on afforestation and built a million mu of artificial forest sea. Saihanba area in Hebei province, China as early as 1962 began the construction of Saihanba forest farm to improve the ecological environment of the surrounding areas, Saihanba area people after three generations of more than half a century of hard efforts, finally build Saihanba into a national forest park, for Hebei, Beijing, Tianjin, and even the whole north China of ecological environment protection has made great contributions.

2. Model overview

Saihanba Forest Farm is located in the northernmost part of Hebei Province, on the southern edge of the Mongolian Plateau.The audience is 58.6km long from north to south and 65.6km wide from east to west.The terrain is high in the middle, low southeast and northwest and 1010~1940m with an average slope of around 20. Forest area is a cold temperate continental monsoon climate, with less spring precipitation, large evaporation, prone to drought. The following is a relevant map of Saihanba. The vegetation coverage rate of the eastern Saihanba is high and the vegetation coverage rate in the west is low, which shows that Saihanba is in the transition area of monsoon climate and continental climate, which is suitable for coniferous forest growth and provides superior climate conditions for the construction of forest farms.

In order to analyse the impact of Saihanba Forest Farm on the surrounding area ecological environment before and after its establishment, we need to build an evaluation model to evaluate the impact of Saihanba Forest Farm on the surrounding ecological environment. We therefore used EEHI as a measure and built models to evaluate the health of the surrounding ecological environment before and after the establishment of Saihanba.

3. Establish EEHI evaluation model

Ecological environment refers to the whole composed of various ecosystems composed of biological communities and non-biological natural factors, and its status and evolution are closely related to the survival and development of human beings. A simple analysis shows that the impact of an ecological reserve on the ecological environment of the area is related to the environmental data in the city where the reserve is located, to the forest vegetation in the reserve and the biological data, and also to the natural environmental data in the area. Therefore, in order to better and more comprehensively evaluate the Ecological and Environmental Health Index(EEHI) of Saihanba of the ecological environment, we comprehensively selected the urban environment, the forest vegetation and the biology, and the natural environment, and quantified the impact of Saihanba on the ecological environment from these three aspects. A specific assemblage I is given for them:

$I = \{UE、FVB、NE\}$

where UE is the urban environment, where FVB is the forest vegetation and the biology, where NE is the natural environment.

- Urban Environment

In today's rapid progress of urbanization construction, an ecological protection area can bring not only a touch of green to the city, but also change the pollution problem of the city for a long time, and bring cleaner air and water to the city. Therefore, we chose the number of days of the urban air quality standard (U1), the average urban PM2.5 concentration (U2), the surface water quality standard rate (U3) and the number of urban dust storms (U4) as the lower indicators of the urban environment.

- Forest Vegetation and Biology

Saihanba Forest Farm is one of the first manually built ecological protected areas in China, which has made great contributions to the cause of forest land protection in China. For more than half a century, the forest vegetation and biomass in Saihanba area have been constantly improving, which has also made great contributions to the construction of ecological civilization. Therefore, we chose: forest coverage (F1), vegetation coverage (F2), and biodiversity index (F3) as the lower indicators of forest vegetation and biology.

- Natural Environment

In addition to the urban and natural resources that we live in, the natural environment of a region is also an important evaluation index. The natural environment of a region can have a variety of ways, but the most important thing is the forest reserves and the ability to purify water and air. Therefore, we chose forest stock (N1), water conservation (N2), carbon dioxide absorption (N3) and oxygen release (N4) as the lower indicators of the natural environment.

We selected a total of 3 superior indicators and 10 subordinate indicators. These indicators can be used to measure the impact of Saihanba on the ecological environment of the region. Therefore, we used these indicators to build the Ecological and Environmental Health Index(EEHI) comprehensive evaluation model, and the determination of the weights of each index will be discussed later.

Because the construction of Saihanba Forest Farm began in 1962 in the last century, at the same time, the construction of artificial forest farm is a long thing, not overnight, so to analyze the impact of Saihanba forest farm on the environment, it is necessary to obtain a large amount of historical data on the surrounding ecological environment. To this end, we collected the index data of Saihanba City from 1962-2020 from the National Statistical Yearbook, Hebei Statistical Yearbook, China Economic and Social Development database and relevant statistical Bulletin, as the research basis for research.

3.1 Normalization of Inferior Indicators

The inferior indicators need to be normalized into the range of [0, 1]. Meanwhile, the inferior indicators need to be transformed to the benefit-type indicators which means that the larger the better. We use different normalization methods to normalize different kinds of indicators according to their characteristics. These methods include the logistic function, the maximum normalization method, the moderate normalization method, the minimum normalization method and the subordinate function of fuzzy mathematics. We are going to show the applications of each method we use.

• Logistic function

This normalization method is applied to indicators which do not have a specific upper limitation, such as forest stock, water conservation. There are some rules of normalization for this kind of indicators. When the original indicator is close to 0, the normalized indicator should be 0; when the original indicator approaches infinity, the normalized indicator should be close to 1. Meanwhile, the normalized indicators should rise sharply when it is close to 0. For these reasons, we choose logistic function to be the normalization function:

$$x' = \frac{1}{1+e^{-b(x-x_0)}}$$

where x is the normalized indicator; is the original indicator; is the minimum standard of the indicator; is a parameter to control the climbing speed of the normalization function. The value of will be determined in the solution of model.

• Maximum normalization method

This method is similar to the maximum normalization method. It is used to normalize the cost-type indicators, such as forest coverage rate, fixed carbon dioxide amount. The way to normalize the indicators is:

$$x = \frac{x}{x_{\max}}$$

where x is the maximum of the indicator.

• Moderate normalization method

Such methods are suitable for those metrics that have the best value or the best interval.When the index data reaches the best value, the higher the score, the further the best value, the lower the score.

$$x' = \frac{|x-x_{op}|}{\max\{|x_{\max}-x_{op}|,|x_{\min}-x_{op}|\}}$$

where xop is the optimal value of the indicator.

• Subordinate function

This method is used to normalize the discrete indicators. These indicators can be divided into several intervals with a discrete grade, like national policy and regulatory environment. According to the theory of fuzzy mathematics, we choose the correspondence of the value set and the comment set as:

$$\{Awful, Bad, Normal, Preferable, Excellent\} = \{1,2,3,4,5\}$$

The partial large Cauchy distribution membership function is determined as:

$$f(x) = \begin{cases} \dfrac{1}{1+\frac{a}{(x-b)^2}}, 1 \leqslant x < 3 \\ c\ln x + d, 3 \leqslant x \leqslant 5 \end{cases}$$

We set that when the grade value is 1, the membership grade should be 0.01; when the grade value is 3, the membership grade should be 0.8; when the grade value is 5, the membership grade should be 1. Here, the parameters of the partial large Cauchy distribution membership function can be determined as:

$$\begin{cases} a = 1.1086, b = 0.8942 \\ c = 0.3915, d = 0.3699 \end{cases}$$

Using these normalization method, all the inferior indicators can be normalized. The normalized data form a Y matrix. Here we omit the detailed methods for each inferior indicator.

3.2 Determination of the Weights for Indicators

There are many methods to determine the weight of indicators. In order to make our model more accurate, we decide to use the combination weighting method to calculate the weight of all indicators. Our combination weighting method combines Analytic Hierarchy Process (AHP) in subjective weighting method and Entropy Weight Method (EWM) and Coefficient of Variation Method (CVM) in objective weighting method. Because the AHP judgment is more subjective, it is easy to change by the subjective influence of the decision maker. At the same time, because of the high sensitivity of the data, it may cause errors due to the data itself. Therefore, our combination weighting method synthesizes these methods to help us reduce errors and improve accuracy.

• Analytic Hierarchy Process

1. Establish hierarchical structure model, as shown in figure 2.
2. Construct all judgment matrices in Superior indicator layer and inferior indicator layer

$$A=(a_{ij})_{n\times n}$$

where A is judgment matrix； is the importance of relative to ; is the quantity of inferior indicators in each group. Because of the limited space, we will not show the judgment matrix.

3. Calculate the weight of each layer and perform a consistency check. The results are shown below.

• Entropy Weight Method

After normalization We get a Y matrix. Then, we use the Entropy Weight Method (EWM) to calculate the weight of the inferior indicators.

We calculate the probability matrix P_{ij} .

According to the concepts of self-information and entropy in the information theory, we can calculate the information entropy of each inferior evaluation indicator, hence we can obtain:

$$E_i=-\ln(n)^{-1}\sum_{j=1}^{n}P_{ij}\ln(P_{ij})$$

On the basis of the information entropy, we will further compute the weight of each inferior evaluation indicator we defined before:

$$w_i=\frac{1-E_i}{k-\sum_i E_i} \qquad i=1,2,\cdots,k$$

• Coefficient of Variation Method

Furthermore, we apply Coefficient of Variation Method to weight these five superior indicators. Therefore, we will introduce the application of coefficient of variation method briefly.

Coefficient of Variation Method (CVM) utilizes the information from various indicators and achieve the weight of each superior indicators through calculating, which shows to be an objective approach to give weight.

Owing to the influence of different dimension, it is hard to compare the superior indicators directly, so it needs the coefficient of variation of each superior indicators to measure the difference extent of them. The formula of each indicators can be expressed as:

$$V_i=\frac{\theta_i}{\overline{z}_i} \qquad i=1,2,3$$

where is the coefficient of variation of the superior indicators , which can also be called as standard deviation coefficient, and means the standard deviation of the superior indicators .Then the weight of each superior indicators comes to us:

$$W_i=\frac{V_i}{\sum_{i=1}^{n}V_i} \qquad i=1,2,3$$

• Combination weight

We set the weight calculated by Analytic Hierarchy Process as Wi1. The weight of the inferior indicators calculated by the Entropy Weight Method and the weight of the superior indicators calculated by the Coefficient of Variation Method are set to Wi2.

$$W_i = \frac{W_{i1} + W_{i2}}{2}$$

Calculate EEHI by TOPSIS

TOPSIS method is a method to sort samples based on data. Its basic idea is to construct an ideal goal based on the sample data. For example, in this question is to build a year where each environment index is optimal, and then measure the data of the actual year and the proximity of the ideal year. The closer it is, the better the ecological environment index of the year.Right now we determine the optimal scheme (the year for each ecological environment indicator with the best ecological environment) and the worst scheme (the year with the worst ecological environment).

From the above calculations we can get a standardized Y matrix, and now we determine the optimal scheme and the worst scheme for each indicator:

$$Y^+ = (\max\{y_{11}, y_{21}, \cdots, y_{n1}\}, \max\{y_{12}, y_{22}, \cdots, y_{n2}\}, \cdots \max\{y_{1m}, y_{2m}, \cdots, y_{nm}\}) \\ = (Y_1^+, Y_2^+, \cdots, Y_m^+)$$

The worst scheme composed of the maximum value of each column element in the :

$$Y^- = (\min\{y_{11}, y_{21}, \cdots, y_{n1}\}, \min\{y_{21}, y_{22}, \cdots, y_{n2}\}, \cdots, \min\{y_{1m}, y_{2m}, \cdots, y_{nm}\}) \\ = (Y_1^-, Y_2^-, \cdots, Y_m^-)$$

Calculate the proximity of each indicator to the optimal scheme and the worst scheme:

$$D_i^+ = \sqrt{\sum_{j=1}^{m} w_j (Y_j^+ - y_{ij})^2}, \quad D_i^- = \sqrt{\sum_{j=1}^{m} w_j (Z_j^- - z_{ij})^2}$$

Calculate the closeness of each indicator to the optimal scheme:

$$EEHI_i = \frac{D_i^-}{D_i^+ + D_i^-}$$

The higher the EEHIi score, the better the ecological environment in this year, and the more obvious the effect of Saihanba Forest Farm improves the environment. Finally, we obtained the ecological and environmental health index of the Saihanba region from 1962-2020, as shown in the figure below.

You can see that the overall EEHI growth curve is similar to the S-type growth curve.The 2020 ecological and environmental health index increased 2.13 times from 1962, indicating that Saihanba has more than tripled the ecological and environmental level in the area.

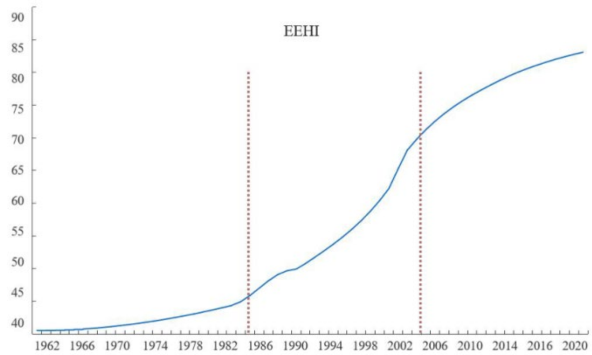

Figure 1: 1962-2020 Ecological and Environmental Health Index score

You can see that the overall EEHI growth curve is similar to the S-type growth curve. The 2020 ecological and environmental health index increased 2.13 times from 1962, indicating that Saihanba has more than tripled the ecological and environmental level in the area.

We can divide the following figure into three stages, the first is the first stage 1962-1985, we can see from the first stage of Saihanba impact on ecological environment growth is slow, ecological environment health index average annual growth rate of less than 1%, this is because in the early stage of forest farm construction, manpower and material resources, and the growth of vegetation organisms need a long cycle, ecological environment repair is also a long process, so not in a few years to improve the environment.

The second stage was from 1986 to 2005, when the annual environmental health growth rate was fast, reaching about 3%. This is because, with the continuous development of China's economy, the government's support for Saihanba construction has not only increased, and it began to invest more manpower and material resources to speed up the construction of Saihanba Forest Farm. At the same time, some vegetation planted in the early stage has gradually grown into big trees, and has begun to play a role in improving the environment. Therefore, the role in improving the ecological environment is also increasing year by year.

The third phase is from 2006-2020, during which the ecological and environmental health index increased slowly, with your average growth rate of about 1%, slowing down from the previous stage. This is because with the continuous construction of Saihanba Forest Farm, the forest area of the area reaches basic saturation, if the number of vegetation will destroy the ecological balance. At the same time, it is not conducive to the construction of fire belts, roads and infrastructure.

4. Establish SRA evaluation model

With the continuous construction of Saihanba Forest Farm, the forest area of the forest farm is constantly increasing. These forest vegetation can purify air, protect soil and soil and sand. These can all help to resist the wind and sand. First, the forest can well absorb dust in the air, so as to achieve the effect of air purification. Once the dust content in the air drops, it will naturally reduce the occurrence of dust storms; then, large forests can fix soil and soil, prevent soil loss, water conservation, and play a great role in promoting the downstream ecological environment protection.; Finally, a large forest is the natural protection barrier, which can largely resist the sandstorms, so that it will no longer go south. To sum up, we chose air quality, soil and soil protection ability, and sand resistance as the superior indicators of the dust storm resistance ability assessment model.

$$I = \{UE、FVB、NE\}$$

where UE is the urban environment, where FVB is the forest vegetation and the biology, where NE is the natural environment.

4.1 Evaluation Model of SRA based on Principal Component Analysis

It can be seen from the above quantitative evaluation index system of anti-sandstorm capacity, the urban anti-sandstorm capacity is a multi-cause and one causal process, with a large number of indicators affecting on the results, and the relationship between each indicator is complex.

A comprehensive evaluation method in the main cost analysis has the advantage of dimensionality reduction analysis of a large number of variables. According to these characteristics, we decided to use 9 index data to build the anti-sandstorm capacity evaluation of Beijing based on the main component analysis method. The specific process is as follows:

1. The raw data were standardized.
2. The correlation coefficient matrix R was calculated.
3. Eigenvalues and eigenvectors were calculated.

$$y_1 = u_{11}\tilde{p} + u_{21}\tilde{a} + u_{31}\tilde{f} + u_{41}\tilde{l} + u_{51}\tilde{m} + u_{61}\tilde{h} + u_{71}\tilde{v} + u_{81}\tilde{n} + u_{91}\tilde{w}$$
$$y_2 = u_{12}\tilde{p} + u_{22}\tilde{a} + u_{32}\tilde{f} + u_{42}\tilde{l} + u_{52}\tilde{m} + u_{62}\tilde{h} + u_{72}\tilde{v} + u_{82}\tilde{n} + u_{92}\tilde{w}$$
$$\vdots$$
$$y_9 = u_{19}\tilde{p} + u_{29}\tilde{a} + u_{39}\tilde{f} + u_{49}\tilde{l} + u_{59}\tilde{m} + u_{69}\tilde{h} + u_{79}\tilde{v} + u_{89}\tilde{n} + u_{99}\tilde{w}$$

4. Information and cumulative contribution rates of the eigenvalue m were calculated.

$$b_j = \frac{\lambda_j}{\sum\limits_{k=m}^{m} \lambda_k}, j = 1, 2, \cdots, m$$

5. Select p (p≤9) main components to calculate the comprehensive score.

$$SAR_{tmp} = \sum_{j=1}^{p} b_j y_j$$

The composite scores were normalized to limit the range of values to [0,1].

$$SAR = \frac{SAR_{tmp} - \min(SAR_{tmp})}{\max(SAR_{tmp}) - \min(SAR_{tmp})}$$

Combining the quantitative definition of influencing factors in this model, it is known that the higher the final comprehensive score, the stronger the anti-sandstorm capacity, so the index directly evaluated is positively correlated with its anti-sandstorm capacity.

4.2 Correlation Analysis based on Pearson

Evaluate the severity of the sandstorm in Beijing over the years.We first need to build an index that can measure the annual severity of dust storms in Beijing. Therefore, for this reason, we collected the number of dust storms, sandstorm number and average sandstorm level in Beijing from 1962-2020, and used to assess the annual sandstorm severity of Beijing with the following formula. To balance the magnitude of the number of sandstorm days, we gave them 0.3 and 0.7, respectively, while, considering the average dust storm level and counting the fingers to before [0, 1]. Finally, it can be concluded that the larger the dust storm index, the more severe the dust storm in the year.

$$SI = \frac{0.3SD + 0.7NS + MSI}{\max\{SD_i\}}$$

Where, SD is sandstorm days, NS is number of sandstorm, MSL is mean sandstorm lever.

We analyzed the specific evaluation scores of SRA and SI over the years 1962 to 2020, and obtained the following figure:

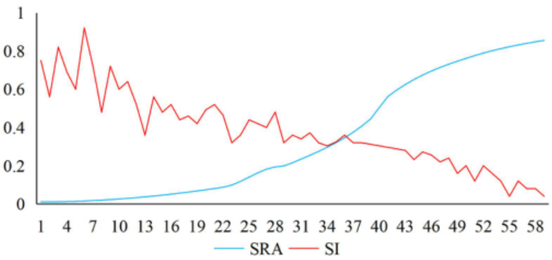

Figure 2: SRA and SI curves

From the figure, we can see that with the improvement of Saihanba's ability to resist sandstorms in Beijing year by year, the severity of sandstorms in Beijing is also declining. Therefore, we can preliminary judgment that the two are negatively related. To quantitatively analyze the role of Saihanba in resisting dust storms in Beijing, we performed a Pearson phase analysis to analyze the two relationship. We took the evaluation value SRA of Saihanba for resisting dust storm capacity in Beijing as variable X, took Beijing sandstorm severity as the most variable Y, and performed Pearson correlation analysis.

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_x \sigma_y} = \frac{E((X-\mu_x)(Y-\mu_y))}{\sigma_x \sigma_y}$$

Pearson's correlation coefficient, takes the value of [-1,1], the greater the absolute value, the stronger the correlation. According to the results shown above, the significance value is 0.000 <0.05, and the Pearson correlation value is-0.833. Due to the numerical size of 0.833> 0.6, -0.833** shows two ** on the data, indicating a strong correlation and a significant correlation at the 0.01 level. Therefore, we can know that the impact of Saihanba on the sandstorm resistance capacity in Beijing is significantly and negatively correlated with the sandstorm severity in Beijing, with a correlation coefficient of-0.833.

Reading the relevant literature, we can know that Saihanba, as a shelterbelt, can serve as a natural physical barrier, to resist a large amount of sand from the middle, and greatly reduce the intensity of dust storms. At the same time, Saihanba, as a forest park, can effectively conserve water sources, enhance the soil fixation capacity in the area, reduce the sand content of rivers in Beijing, and bring a large number of clean water sources to the local area. All of these can help Beijing fight against sandstorms.

5. Summary

In order to assess the ecological and environmental health degree of a region, we comprehensively selected 11 indicators, and the evaluation results are more accurate. The severity of dust storms in Beijing was quantified, and the relationship between the ability of Saihanba to withstand dust storms in Beijing and the severity of Beijing was quantitatively analyzed. Using the cost-benefit ratio to determine the scale of the ecological protection reserve of each city is somewhat innovative. Some missing or no errors of data may cause a small bias in the results of the model. In determining which cities need to adopt unified evaluation models for each city to establish ecological protection areas, the particularity of individual cities is not considered, and the model needs to be improved.

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