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Original Research

Forest Carbon Sequestration Ecological Engineering Afforestation Technology and Carbon Sink Accounting Calculation Model Based on a Genetic Fuzzy Algorithm

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Abstract

In order to explore the role of afforestation technology in responding to climate change, abnormal weather conditions such as snow melting need to be considered alongside evaluating the benefits of forest carbon sink ecological engineering afforestation technology. This paper adopts forest carbon sink ecological engineering afforestation technology based on a genetic fuzzy algorithm and combines static and dynamic economic evaluation indicators to evaluate the benefits. Dividing a wasteland in S City into regions and conducting group experiments, detailed measurements of indicators such as forest carbon storage, vegetation coverage, species richness index, and soil water retention capacity were carried out. The results showed that the experimental group's forest carbon storage, vegetation coverage, and species richness were higher than those of the control group. The economic benefit evaluation indicators such as net present value (NPV), net present value rate (NPVR), internal rate of return (IRR), and benefit-cost ratio (BCR) were also better, proving the effectiveness of afforestation technology in improving forest carbon sink capacity and economic benefits.

Keywords: forest carbon sink, genetic algorithm, fuzzy algorithm, ecological engineering, afforestation technique, computational modeling

Introduction

More and more carbon dioxide is being discharged into the air, and greenhouse gases are constantly increasing. As a result, a series of abnormal events such as rising global temperature, abnormal weather conditions, and snow mountain melting occur frequently, causing panic in public life. Afforestation is a powerful measure to solve this abnormal climate change [1]. At present, many enterprises are also committed to the research of forest carbon sink ecological engineering afforestation technology, but the application of this technology has the problem of low ecological and economic benefits, which has attracted the attention of many enterprises. In order to solve this problem and improve the ecological and economic benefits of forest carbon sink ecological

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engineering afforestation technology, a genetic fuzzy algorithm is a good way. In view of this, it has certain practical significance to analyze forest carbon sink ecological engineering afforestation technology [2, 3].

The development and application of forest carbon sink ecological engineering have sprung up in recent years. Many experts and scholars focus on analyzing past carbon sink data to summarize the experience and provide data support for today. Xiaowei Tong used satellite time series data and showed a widespread increase in leaf area index (a proxy for green vegetation cover) and aboveground biomass carbon, contrasting with the negative trends observed in ecosystem models without human influence [4]. Wang Xianglong analyzed the storage and emissions of greenhouse gases in 2005 and 2010 by comparing changes in land use and forestry. Based on comparing forest resources between Guangdong Province and other provinces with similar geographical and climatic conditions, he discussed the potential of Guangdong Province to improve forest carbon sink in the future [5]. Zhang Zhenqi used the Google Earth Engine platform to discuss the spatial-temporal change characteristics of net ecosystem productivity and its relationship with climate factors in the Sanjiangyuan region from 2001 to 2020 based on climate data [6]. Rebecca L. Morris evaluated current evidence based on the effectiveness of natural and artificial coastal protection and discussed future research needs, including the cost-effectiveness of establishing or restoring habitats for coastal defense compared to artificial structures under the same environmental conditions [7]. Anthony P. Walker synthesized theory and extensive interdisciplinary evidence to demonstrate that increasing carbon dioxide is related to global terrestrial carbon sinks. The theory established with experimental support suggests that carbon dioxide may cause about half of the increase. The global carbon budget, atmospheric data, and forest inventory indicate historical carbon sinks, which are highly responsive compared to experimental and theoretical predictions [8]. Aino Assmuth used a model that includes a forest scale structure to study the economics of carbon storage and determine the choice between rotational forestry and continuous cover forestry. He considered various carbon prices and interest rates and optimized the time and intensity of thinning, as well as the selection of management systems [9]. The analysis of forest carbon sink ecological engineering is rare.

Genetic fuzzy algorithms have some application space in forest carbon sink ecological engineering, such as building assessment models and understanding forest health. Using genetic methods, Zhaohuan Teng constructed a carbon sequestration and forestry assessment model [10]. Koyel Sam explored the degree of disturbance to forest health in the Buksa Tiger Reserve of the Himalayan foothills ecosystem. He applied the analytic hierarchy process based on geographical big data technology to understand the rhythmic spatial disturbance of natural and human factors in the study area. Then, he divided the disturbance map into five regions from extremely high to extremely low [11]. Existing algorithms have been widely used in forest carbon sink ecological engineering, such as genetic algorithms (GA) and support vector machines (SVM), but they each have their own advantages and disadvantages. Genetic algorithms can perform global optimization, but they are prone to falling into local optimality and have a large number of calculations; SVM performs well in high-dimensional space but has a slow processing speed for large-scale data and complex parameter selection. Although fuzzy logic algorithms can handle uncertainty, they rely on a lot of expert experience and rules. In contrast, genetic fuzzy algorithms combine the global search capabilities of genetic algorithms with the processing capabilities of fuzzy logic and can optimize forest carbon sink assessment more efficiently and accurately, reducing dependence on expert experience.

In order to improve the ecological and economic benefits of forest carbon sink ecological engineering afforestation technology, this paper applied genetic fuzzy algorithm to forest carbon sink ecological engineering afforestation technology [12-14] and designed a carbon sink accounting calculation model to analyze the carbon absorption and storage of forests. It was concluded that the forest carbon sink ecological engineering afforestation technology based on a genetic fuzzy algorithm has improved the ecological and economic benefits compared with the conventional forest carbon sink ecological engineering afforestation technology and achieved the expected goal.

The main contributions of this paper are as follows:

1) Proposed forest carbon sink ecological engineering afforestation technology based on genetic fuzzy algorithm: This paper first applied a genetic fuzzy algorithm to forest carbon sink ecological engineering afforestation technology. By optimizing the carbon sink evaluation model and combining static and dynamic economic evaluation indicators, the ecological and economic benefits of the forest carbon sink were improved.

2) Designed a carbon sink calculation model: This paper designed a carbon sink calculation model based on the genetic fuzzy algorithm to evaluate forest carbon absorption and storage. Through detailed measurements of indicators such as forest carbon storage, vegetation coverage, species richness, and soil moisture retention capacity in the experimental group and the control group, the advantages of afforestation technology based on a genetic fuzzy algorithm in improving forest carbon sink capacity and ecological benefits were proved.

3) Verified the economic benefits of the algorithm: Using economic evaluation indicators such as NPV, NPVR, IRR, and BCR, this paper demonstrated the advantages of forest carbon sink technology based on a genetic fuzzy algorithm in economic benefits, indicating that it not only improves ecological benefits but also improves the economic benefits of forest carbon sink engineering.

Materials and Methods

Forest Carbon Sink Ecological Engineering Afforestation Technology Based on Genetic Fuzzy Algorithm

Initial Group Generation

Firstly, each decision variable is set to a numerical range, then values are extracted from this range [15]. The value of the decision variable generated by this method follows the standard normal distribution, so the individual distribution in the generated group is relatively concentrated, which contradicts the principle of maintaining the uniform distribution of individuals. However, using probability methods, the algorithm becomes somewhat random, resulting in an uneven distribution of initial individuals, and the algorithm is generally more complex. The initial population method used in this article adopts a mandatory method, dividing n regions into each dimension of the decision variable, with each region taking the same number of values, which ensures that the decision variable is uniformly estimated, which in turn ensures a good distribution of the initial population.

The decision variables generated by different output initial population methods are usually distributed in each sub-partition, while the resulting initial population is more evenly distributed within the target region. The higher the n value of the sub-partition, the better the diversity of the original population and the slower the algorithm convergence. Therefore, this article reasonably determines the number of sub-regions based on the number of decision variables in the algorithm itself.

Cross and Mutation Operations

(1) Cross and Mutation Operators

$\alpha(y_i(s))$ and $\beta(y_i(s))$ describe the changes in adaptation level during group development, reflecting different aspects of individual adaptation quality and forming the basis for adaptive mixing and mutation operation design.

The design of the cross-operator is based on two main aspects: (1) Function T is selected as the operating function. (2) If the estimation uncertainty is high, a higher crossover probability is used to increase the number of new individuals; if the estimation uncertainty is low, a lower crossover probability is used to accelerate the algorithm's convergence. Therefore, the design crossover operator is [16]:

$$q_d(s) = \left(1 + e^{-k_1.s.\left(\alpha(y_i(s))+\beta(y_i(s))\right)}\right)^{-1} \quad (1)$$

Among them, k_1 is the correction factor.

Mutation operations can also introduce new individuals into the algorithm. The design of mutation operators is based on two main aspects: If the estimation uncertainty is high to increase population diversity, the mutation probability must be high; if the estimation uncertainty is low, a lower mutation probability is used to accelerate the algorithm convergence. In the advanced stage of evolution, in order to ensure the convergence of the algorithm, it is necessary to reduce the probability of mutation. Therefore, the design mutation operator is:

$$q_n(s) = 1 - \left(1 + e^{\frac{-k_2 \cdot s}{\alpha(y_i(s))+\beta(y_i(s))}}\right)^{-1} \quad (2)$$

Among them, k_2 is the adjustment coefficient.

(2) Cross Operation Steps

Step 1: The area of each region is determined by the number of species ($d_1, d_2, \ldots, d_m$, total number of species m, where d_j represents the species group of the j-th species). The encoding format is:

$$z = \left(\left[z_{11}, z_{12}, \cdots, z_{1d_1}\right], \cdots, \left[z_{j1}, z_{j2}, \cdots, z_{jd_j}\right], \cdots, \left[z_{m1}, z_{m2}, \cdots, z_{md_m}\right]\right) \quad (3)$$

Step 2: The size of the population corresponds to N.

Step 3: The adaptive function is determined.

In order to facilitate the solution, the weight coefficient method is used to transform multiple objectives into a single-objective problem. The objective function is:

$$h(x) = \sum_{j=1}^{4} \omega_j \left|e_j\right| \quad (4)$$

Among them, e_j is the error between the j-th type of test paper factor and the expected test paper requirements. ω_j is the weight coefficient, and $\omega_j>0$. The weight ω_j of the test paper forming factor is set by the evaluator.

The adaptive function is:

$$r(x) = \frac{1}{1+h(x)} \quad (5)$$

Among them, h(x) is the objective function.

Step 4: N suitable individuals are selected from the values, and N forests are selected for the initial population.

Step 5: The operation is crossed.

N is combined into two or two combinations, and then the following operations are performed:

(1) j = 1, the size of each adaptive function r(x) value is calculated;

(2) If $j \leq m$, two different species j are exchanged, $j = j+1$; if $j > m$, it ends;

(3) The appropriate function r(x) is determined after exchanging the two individuals. If these two r(x) are smaller than both parents, it returns to step (2).

Step 6: The new individual and parents are created into a new group.

Step 7: Decide whether a specific number of iterations has been reached or no new offspring appear. If so, it ends. Otherwise, go to Step 4.

(3) Mutation Algorithm

The algorithm for selecting individuals with the most variable adaptive function values by performing algebra or not using new descendants is as follows:

Step 1: The best individual in the current group is used as the initial individual in the following form:

$$y = \left(\left[y_{11}, y_{12}, \cdots, y_{1d_1}\right], \cdots, \left[y_{j1}, y_{j2}, \cdots, y_{jd_j}\right], \cdots, \left[y_{m1}, y_{m2}, \cdots, y_{md_m}\right]\right) \tag{6}$$

Step 2: The value of an adaptive function is calculated.

Step 3: j = 1, i = 1.

Step 4: Random functions are used to disrupt the order within the j-th species group, denoted as:

$$List = \left(\left[b_{11}, b_{12}, \cdots, b_{1d_1}\right], \cdots, \left[b_{j1}, b_{j2}, \cdots, b_{jd_j}\right], \cdots, \left[b_{m1}, b_{m2}, \cdots, b_{md_m}\right]\right) \tag{7}$$

Step 5: B_j is the j-th species collection meeting the specified requirements in the forest species pool.

$$B_j = B_i - \left\{y_{i1},\ y_{i2},\ \cdots y_{jd_j}\right\} \tag{8}$$

Step 6: The order is taken as $b_{ij} \in List$.

Step 7: The value of this allele is mutated:

$$x'_{ib_{ij}} \in random\left(B_j\right) \tag{9}$$

The gene strings of the individual mutated species are:

$$X' = \left(\left[x_{11}, \cdots, x_{1b_1}\right], \cdots, \left[x_{j1}, \cdots, x_{j(b_{ij}-1)}, x'_{jb_{ij}}, x_{i(b_{ij}+1)}, \cdots, x_{jd_j}\right], \cdots \left[x_{m1}, \cdots, x_{md_m}\right]\right) \tag{10}$$

Step 8: The appropriate function value r(x') is calculated for the new individual.

Step 9: The new function values are compared: r(x') and r(x). If r(x') > r(x), then x = x'.

Step 10: i = i+1, if i ≤ d_j, it returns to Step 5; otherwise, it is taken to Step 11.

Step 11: j = j+1, if j ≤ m, it is returned to Step 4; otherwise, it must be determined whether the number of variables has reached the upper limit. If it reaches the upper limit, it stops. Otherwise, the number of variants is added to 1, returning to Step 3.

Fuzzy Rule Reasoning

Fuzzy rules can effectively describe the basic characteristics of objects and are an effective form of knowledge, representation, reasoning, and argument [17, 18]. A fuzzy rule library is a key element of a fuzzy system composed of multiple fuzzy rules. Each rule is executed with a certain probability based on the input feature vector, and the execution level of the input feature vector is determined by the current value of the previous x_i and their consistency. In order to ensure the effective extraction of fuzzy rules and high computational efficiency, this article uses a construction method based on fuzzy consistency to extract rules.

Fuzzy correlation rules are a common classical form of elements that satisfy both conditions C and D. This classical form represents an element that satisfies both the C and D conditions. This article uses two indicators, support and confidence, to measure the correlation of rules. The expression formulas for support and confidence are as follows:

$$Supp(C \Rightarrow D) = \frac{C \cap D}{X} \tag{11}$$

$$Conf(C \Rightarrow D) = \frac{C \cap D}{C} \tag{12}$$

The fuzzy logic conjunction operation for all fuzzy numbers existing in set C is represented by the symbol C. C(x) represents the average membership relationship of all fuzzy numbers in the fuzzy logic connection set mentioned above. The calculation formula for C(x) is as follows:

$$C(x) = \frac{\sum_{f \in C} f(x)}{C} \tag{13}$$

Fuzzy if-then rules can be evaluated using fuzzy support and fuzzy confidence as their evaluation criteria. The larger the fuzzy support and fuzzy confidence values, the more appropriate the previous rules that describe the main features of fuzzy rules are when following fuzzy rules.

The steps to determine the basic principles of fuzzy rules in this article are as follows:

In three steps, the fuzzy system assigns input V to output f(x). The first step involves aligning input V in parallel with all fuzzy sets. This step is based on the degree to which input V is associated with each subset to “activate” or “start” the fuzzy rule. The second step is to cover all “part” sets in a reduced proportion to create the final output set. The third step is the solution, where the system calculates the initial value V, which corresponds to the final output point with the highest assigned value.

Forest carbon sink ecological engineering route: Through comprehensive analysis and comparison of the impact of forest and community improvement on the environment, productivity, and biomass of different economic species and species, the best combination of environmental and economic benefits is selected. By showcasing new ecological and economically integrated farming methods and using different intensive farming techniques, new technologies and methods are introduced for reforestation projects. According to the integrated industrialization model of production, supply, and sales, it has been gradually industrialized economically, effectively ensuring that agricultural and forestry reclamation projects can be restored to a stable and abundant state.

Carbon Sink Accounting Calculation Model and Forest Carbon Sink Ecological Engineering Afforestation Technology Effect Evaluation

Carbon Sink Accounting Calculation Model

The different methods of the biomass velocity formula used in this article calculate the carbon storage in trees by calculating the diameter at the breast height of tree species and the height of main tree species with the smallest error. This formula is particularly applicable to natural trees planted in a large area. Using extraction methods, the total biomass of trees and related variables are measured to obtain the biomass change formula.

When selecting the formula for measuring biomass speed, the IPCC (Intergovernmental Panel on Climate Change) reference formula is selected from the project area or other areas with similar environmental conditions in the project area [19]. This method is mainly used to evaluate the biomass of trees.

The market value of forest carbon sink ownership reflects the social cost of forest carbon sink owners to reduce carbon emissions [20, 21]. When limiting carbon dioxide emissions, the social cost of reducing emissions should be equal to the sum of the cost limit of reducing private emissions and the benefits of reducing emissions, as shown in formula (14):

$$\mathrm{td} = \sum_{\mathrm{o}=1}^{\mathrm{m}} \mathrm{qd_o} \cdot \mathrm{p_o} \tag{14}$$

The carbon sink effect of forest carbon sink property rights aims to increase the main body of social emission reduction, and the virtual price of forest carbon sink is the marginal cost of reducing emissions for social actors to reduce emissions. The construction of the simplest linear programming and the solution of the first partial derivative of the Lagrange function show that the price of forest carbon sink property rights is essentially a Lagrange coefficient *γ*, as shown in formula (15):

$$\gamma = \frac{\mathrm{p_j'}}{\mathrm{p_j'} + \mathrm{p_g}} \tag{15}$$

In the formula, p_j' represents the private marginal emission reduction after the forest carbon sink effect reduces social emission reduction costs, and $\mathrm{p_g}$ represents the carbon reduction represented by the forest carbon sink property rights. Therefore, the property price of a forest carbon sink is:

$$\mathrm{FSP} = \frac{\mathrm{dsc}}{\mathrm{dp_g}} \tag{16}$$

The solution to the virtual price decline of forest carbon sinks in the real economy is much more complicated than first-level linear programming [22]. The social cost associated with reducing emissions includes the marginal cost of measuring emissions reduction in different sectors. Dynamic changes in the effectiveness of reducing forest carbon emissions make static planning decisions more prone to errors. A recursive and dynamically predictable global equilibrium model is used to solve the problem of forest carbon sink prices.

The model dynamic calculation of general equilibrium theory is widely used for policy modeling and analyzing the impact on trade, carbon emission rate, the environment, and other issues. This document assumes that the social cost of reducing emissions includes two components: the social investment cost of ecological forest environments and the investment cost of carbon dioxide emission reduction technologies in different (non-forest) sectors. The virtual price of forest carbon ownership can be reflected in the impact of changes in forest carbon ownership on reducing social emission costs. Forest carbon wood investment changes are directly related to changes in forest carbon storage. It is assumed that the unit ownership value of forest carbon timber is equal to the contribution of forest carbon timber to the social cost of reducing emissions. Suppose the asset value of the forest carbon sink is measured according to the method of the clean development mechanism to obtain the forest carbon credit line. In that case, it is difficult to capture the increase of the forest carbon sink caused by human activities, such as the change of forest resources and its contribution to the cost of social emission reduction, thus avoiding the complexity of measuring the asset value of the forest carbon sink with the forest resources method.

This article constructs a recursive dynamic computable model that includes forest carbon sink property rights. It mainly includes static modules: income decision-making and expenditure decision-making modules. The dynamic module includes a carbon sink balance module, and the investment module implements corresponding cross-period static models. The basic structure of the model is shown in Fig. 1.

The recursive dynamic computable model designed in this article includes forest carbon sink property rights, an income decision-making module, an expenditure decision-making module, a carbon sink balance module, and a cross-period static model. Among them, the income decision-making module includes the entire chain of capital income, enterprise income, enterprise transfer payments, resident income, and labor income. The expenditure decision-making module includes capital factor investment, labor factor investment, forest carbon sink property rights investment,

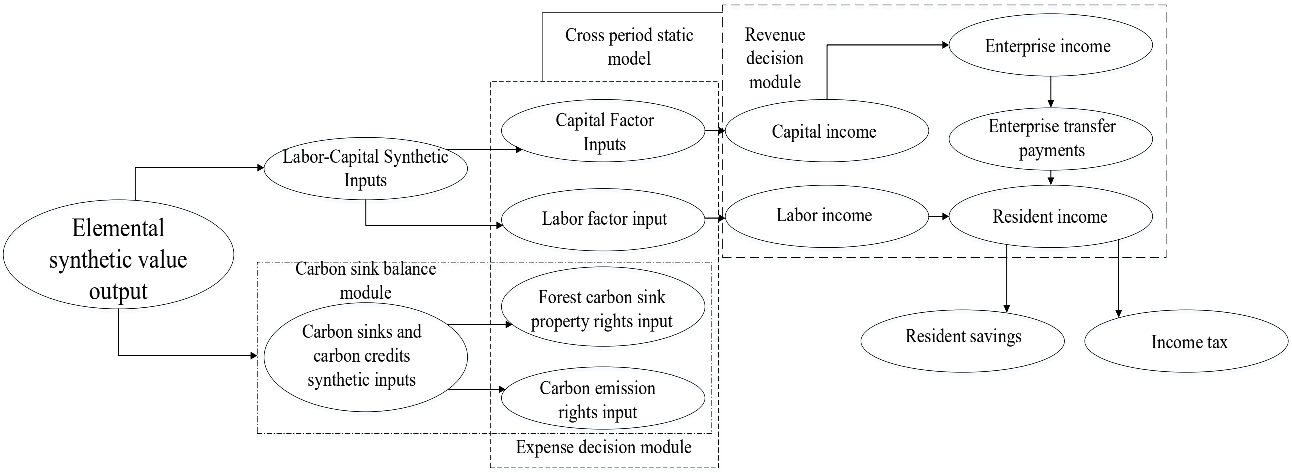

Fig. 1. A recursive dynamic computable model containing forest carbon sink property rights.

and carbon emission rights investment. The carbon sink balance module mainly includes carbon sink and carbon emission rights synthesis investment, forest carbon sink property rights investment, and carbon emission rights investment. The intertemporal static model is the sum of the income and expenditure decision-making modules.

Forest Carbon Sink Ecological Engineering Afforestation Technology Benefit Assessment

Developing forest carbon sink ecological engineering afforestation technology can help improve the carbon sequestration effect in environmental protection, reduce or stabilize the concentration of carbon dioxide in the atmosphere, and slow global warming [23, 24]. Therefore, in order to improve social and environmental benefits, full attention should be paid to the development of forest carbon sinks and ecological forestry technologies in order to reduce threats to the quality of the ecological environment. In addition, it is necessary to strengthen the scientific impact assessment of carbon sequestration afforestation projects, improve the effectiveness of relevant research results, and fully explore the practical significance of carbon sequestration afforestation projects.

In the past, the development and utilization of forest resources were mainly based on the intrinsic value of wood without maximizing their value. In order to change this situation, ecological forest carbon sink projects can be considered, and their afforestation plans can be effectively implemented to achieve comprehensive forest management, using wood and forest carbon sinks as value creators [25]. By determining the optimal harvesting timing, the ultimate goal is to maximize the benefits of forest resources and reduce their value.

(1) Ecological Benefit Assessment

To measure the benefits of forest ecosystems, on the one hand, it is possible to quantitatively understand the ecological benefits of forest ecosystems [26], and on the other hand, it is possible to calculate value and compare and evaluate it with other ecosystems. The results can serve as a basis for formulating compensation standards for forest ecosystem benefits. The ecological value of forests should be scientifically evaluated in order to calculate the positive external value of forests as compensation. Generally speaking, the methods for determining forest ecological value can be roughly divided into physical quality assessment, quantitative assessment, energy value analysis, and ecological modeling methods. The first three methods are based on market theory and can directly quantify the value of ecological services, while the ecological model rules are based on ecological laws. This article adopts a quantitative evaluation method, using vegetation coverage and soil water retention capacity as indicators.

(2) Economic Benefit Evaluation

Afforestation not only effectively absorbs and restores carbon dioxide but also accurately measures the reduction of greenhouse gas emissions and fully utilizes its demonstration role in local and regional projects. In addition, developing forest carbon sinks can effectively improve the ecological function of forests [27, 28], wind and sand prevention, and soil and water conservation to further promote the restoration of the local ecological environment and enhance local ecological sustainability.

The economic benefits of the forest carbon sink ecological engineering after renovation are evaluated using the combination of static and dynamic economic evaluation indicators [29-31]. Static indicators, including profitability, are mainly based on cash flow analysis. The dynamic evaluation indicators selected for dynamic analysis include NPV, NPVR, IRR, and BCR.

NPV is an important dynamic valuation indicator when the net cash flow of the project implementation year is converted into initial income at the bank interest rate. The higher the net present value, the higher the project's profitability. The calculation formula is:

$$\mathrm{NPV} = \sum_{s=1} \frac{W_s}{(1+l)^s} - \sum_{s=1} \frac{D_s}{(1+l)^s} \tag{17}$$

In the formula (17), NPV is the net present value after s years; W_s is the cost in year s; D_s represents the income in the second year; L is the bank rate (effective interest rate); s is the number of years in the production cycle.

NPVR is the percentage of the present value of an investment project to the initial investment's present value. The calculation formula is:

$$\mathrm{NPVR} = \sum\nolimits_{s=1} \frac{W_s}{(1+l)^s} - \sum\nolimits_{s=1} \frac{D_s}{(1+l)^s} \div \sum\nolimits_{s=1} \frac{W_s}{(1+l)^s} \times 100\% \tag{18}$$

IRR is the profit at which the present value of project capital inflows equals the profit at the time of the flow, that is, NPV = 0. The internal rate of return can intuitively reflect the effectiveness of an investment and represent the maximum return on investment. The higher the internal rate of return, the higher the rate of return.

$$\sum\nolimits_{s=1} \frac{W_s - D_s}{(1+\mathrm{IRR})^s} \tag{19}$$

In the formula (19), IRR is the internal rate of return.

BCR is the ratio of the present value to the present value of all planned services, representing the benefits that can be provided by the unit present value, that is, the ratio of the present value to the present value of planned services.

$$\mathrm{BCR} = \sum\nolimits_{s=1} \frac{D_s}{(1+l)^s} \div \sum\nolimits_{s=1} \frac{W_s}{(1+l)^s} \tag{20}$$

In the formula (20), BCR is the benefit-cost rate.

Results and Discussion

This paper took a wasteland forest in S city as an example and adopted forest carbon sink ecological engineering afforestation technology based on a genetic fuzzy algorithm [32, 33]. Different regions were divided according to the terrain. Based on the investigation of this area, this article divided the barren forest into 12 regions and then into 6 types based on the vegetation characteristics of the region. The specific division results can be seen in Fig. 2.

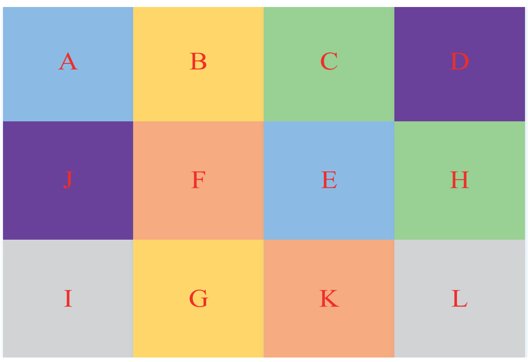

Fig. 2. Regional division results of barren forests.

According to the classification of landform characteristics, Region A and Region E are divided into Region 1, which is basically devoid of vegetation and animals. Region B and Region G are Region 2, with sparse trees and only a few scattered ones. Region C and Region H are Region 3, with less than half of the trees in this area. Region D and Region J are Region 4, with a tree coverage rate of over half. Region F and Region K are Region 5, with a vegetation coverage rate of about 80%, but with a single species. Region I and Region L are Region 6, with a vegetation coverage rate of about 90% and diverse species. Due to the complex and diverse terrain, these 12 areas can be divided into control and experimental groups. Among them, regions A, B, C, D, F, and I are the control group, while regions E, G, H, J, K, and L are the experimental group. The control group uses conventional forest carbon sink ecological engineering afforestation technology, while the experimental group uses forest carbon sink ecological engineering afforestation technology based on a genetic fuzzy algorithm for afforestation [34, 35].

This article analyzed the forest carbon storage of the surveyed areas from 2017 to 2022. The results can be seen in Fig. 3.

a)

b)

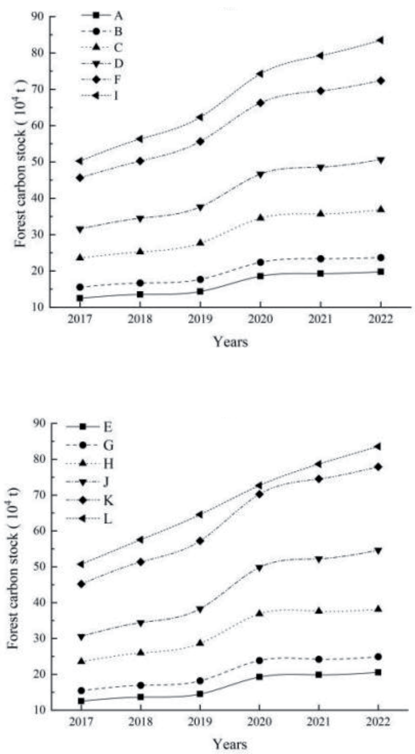

Fig. 3. Changes in forest carbon storage in survey sites from 2017 to 2022. a) Forest carbon storage in the control group, b) Forest carbon storage in the experimental group.

The x-axis represents different years, while the y-axis represents forest carbon storage (unit: 10^4t). In Fig. 3, (a) represents the forest carbon storage of the control group from 2017 to 2022, while (b) represents the forest carbon storage of the experimental group from 2017 to 2022. The legends in Fig. 3a) from top to bottom are regions A, B, C, D, F, and I. The legends in Fig. 3b) from top to bottom are regions E, G, H, J, K, and L. During the period from 2017 to 2022, the carbon stock of afforestation using conventional forest carbon sink ecological engineering afforestation technology increased from 1.7908 million tons in 2017 to 2.8681 million tons in 2022, and its carbon stock increased; the carbon storage of forest carbon sink ecological engineering afforestation technology based on a genetic fuzzy algorithm increased from 1.7804 million tons in 2017 to 2.9966 million tons in 2022. The carbon storage of forest carbon sink ecological engineering afforestation technology based on a genetic fuzzy algorithm increased. It can be seen that using a genetic fuzzy algorithm can improve the carbon storage of forests. 2020 was a major turning point, where the carbon storage in each region significantly increased compared to 2019. This indicates that the afforestation work has achieved initial results, and the changes have slowed. However, the overall trend is still rising, which indicates that persisting in long-term forest carbon sink ecological engineering is conducive to carbon storage to achieve the desired goal.

A major source of forest carbon storage is carbon sink absorption. This paper used forest carbon sink ecological engineering afforestation technology based on a genetic fuzzy algorithm to make vegetation absorb carbon dioxide in the air by planting vegetation to prevent the occurrence of harmful events that the temperature rise caused by too high carbon dioxide in the air poses a threat to the life of organisms on the earth. Based on this, this article analyzed the carbon sink absorption (unit: 10^4t). The results are shown in Table 1.

In 2017, the carbon absorption of each region did not exceed 60000 tons. However, with the growth of the year and the continuous promotion of forest carbon sink ecological engineering, the carbon absorption of each region increased. In 2022, the carbon absorption of Region I reached 85200 tons, and Region L's reached 95800 tons. Although the carbon absorption of some areas in the experimental group was lower than that of the control group in 2017, the carbon absorption of each area in the experimental group was higher than that of the corresponding control group in 2022. It can be seen that the application of forest carbon sink ecological engineering afforestation technology based on genetic fuzzy algorithms can improve the ability of vegetation to absorb carbon, thus improving the ecological environment quality of forests.

Vegetation coverage shows, to a certain extent, the effectiveness of forest carbon sink ecological engineering. Planting vegetation in cities is a good measure of afforestation. According to this standard, vegetation coverage was analyzed, and the results were recorded in Fig. 4.

The x-axis represents the year, and the y-axis represents vegetation coverage. The legends represent each region separately. Among them, Fig. 4a) shows the vegetation coverage of Region 1, and Fig. 4b) shows the vegetation coverage of Region 2. Fig. 4c) shows the vegetation coverage of Region 3, and Fig. 4d) shows the vegetation coverage of Region 4. Fig. 4e) shows the vegetation coverage of Region 5, and Fig. 4f) shows the vegetation coverage of Region 6.

Comparing the vegetation coverage rates of various regions, it can be seen that the vegetation coverage rates of the experimental group were generally higher

Table 1. Changes in carbon absorption from 2017 to 2022.

Group	Areas	2017	2018	2019	2020	2021	2022
Control group	A	1.22	1.32	1.42	1.86	1.89	1.93
	B	1.46	1.62	1.72	2.11	2.21	2.65
	C	2.28	2.49	2.61	3.32	3.45	3.54
	D	3.05	3.31	3.61	4.58	4.59	5.62
	F	4.51	4.92	5.51	6.42	6.85	7.21
	I	5.52	5.53	6.01	7.55	8.23	8.52
Experimental group	E	1.13	1.42	1.68	2.08	2.65	3.38
	G	1.22	1.76	1.92	2.65	2.86	3.95
	H	2.31	2.79	3.25	3.95	4.62	4.92
	J	3.51	3.92	4.68	5.64	5.95	6.72
	K	4.72	5.64	6.95	7.95	8.02	8.65
	L	5.35	6.28	7.59	8.54	8.62	9.58

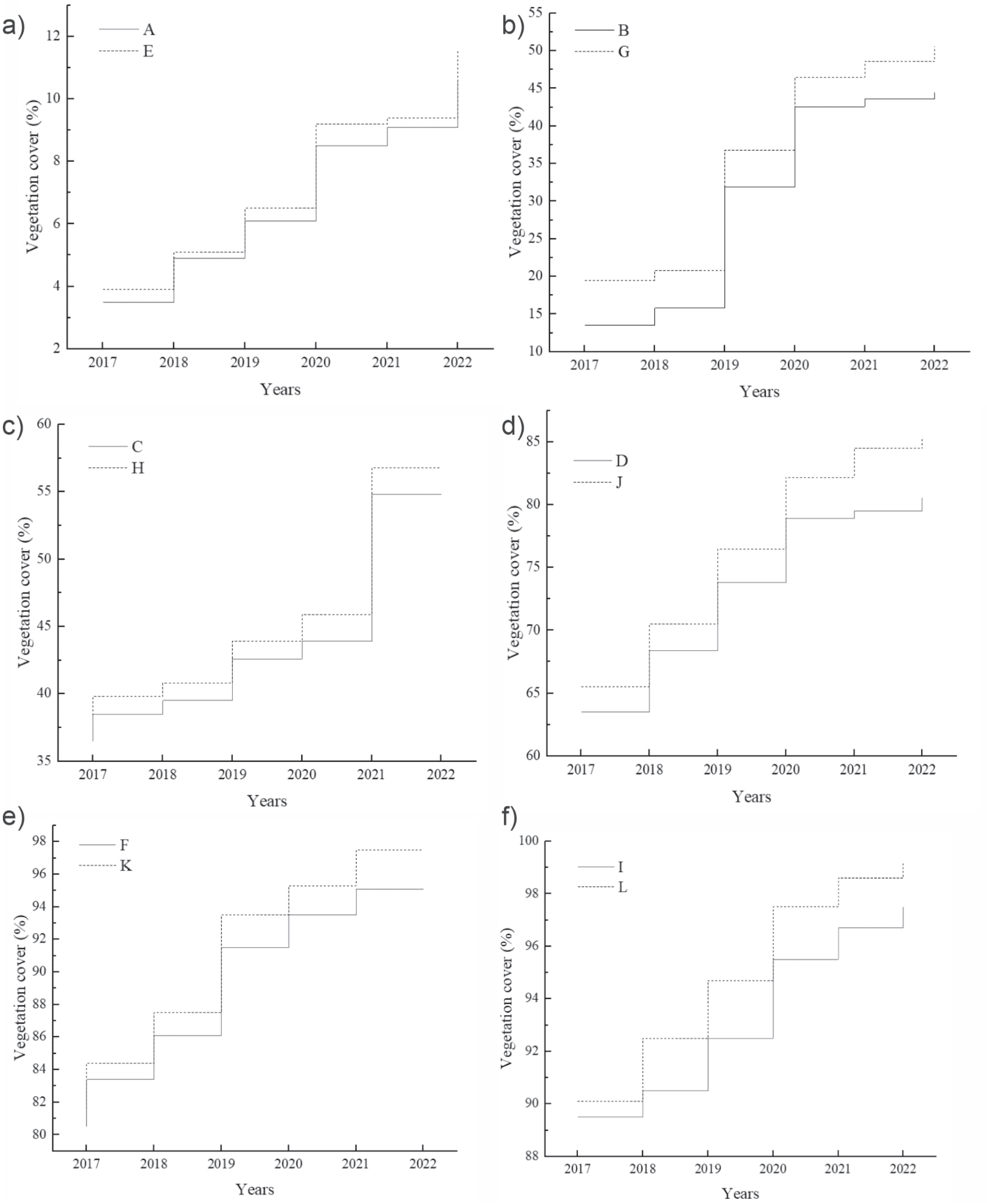

Fig. 4. Vegetation coverage survey results for each region from 2017 to 2022. a) Vegetation coverage in Region 1, b) Vegetation coverage in Region 2, c) Vegetation coverage in Region 3, d) Vegetation coverage in Region 4, e) Vegetation coverage in Region 5, f) Vegetation coverage in Region 6.

than those of the control group. Overall, with the increase of years, the vegetation coverage of each region showed an upward trend. In the 2022 control group, the vegetation coverage of Region A was 10.6%; Region B was 44.5%; Region C was 54.8%; Region D was 80.6%; Region F was 95.1%; and Region I was 97.5%. The vegetation coverage of the experimental group's Region E was 11.6%; Region G was 50.6%; Region H was 56.8%; Region J was 85.4%; Region K was 97.5%; and Region L was 99.2%. The comparison between the two showed that the vegetation coverage of each region in the experimental group was much higher than that of the control group. However, the vegetation coverage of the two regions in Region 1 is still relatively low. The reason for the analysis may be that the soil in these two areas is poor and unsuitable for planting trees.

Biodiversity reflects the survival rate of forests and largely reflects the ecological status of the environment. This paper selected the richness index to analyze the ecological benefits of forest carbon sink ecological engineering afforestation technology. Some areas were basically devoid of life, and only 2022 had been analyzed for biodiversity in the first few years. The richness index is generally limited to 10 points, with high-abundance species above 10 and rare species below or equal to 10. The specific results are shown in Fig. 5.

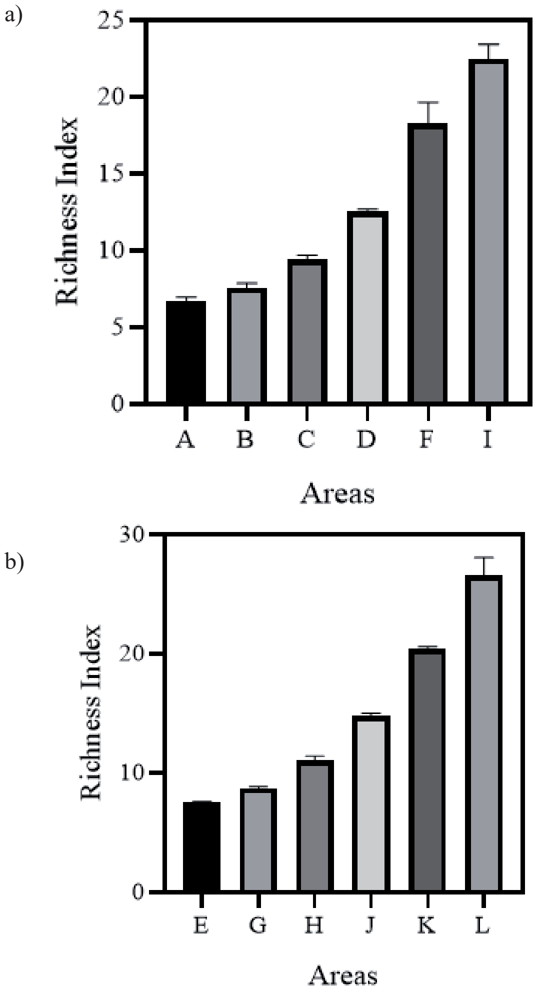

Fig. 5. Abundance index survey results by region. a) Abundance index of the control group, b) Abundance index of the experimental group.

In Fig. 5, the x-axis represents different regions, while the y-axis represents the richness index. In Fig. 5, (a) represents the richness index survey results of the control group, while (b) represents the richness index survey results of the experimental group. After multiple measurements, it is known that Regions A, B, C, E, and G belong to the rare species area, while Regions D, F, I, H, J, K, and L belong to the high-abundance species area. In general, the richness index of the experimental group is higher than that of the control group, which indicates that the forest carbon sink ecological engineering afforestation technology using a genetic fuzzy algorithm is beneficial to increasing species to a certain extent.

To a certain extent, the soil's water retention capacity reflects its state and effectiveness, which is closely related to the ecological environment. Analyzing this indicator can reflect the state and quality of forests. Therefore, this index can be used to evaluate the ecological benefits of forest carbon sink ecological engineering afforestation technology. This article chose to measure the saturated soil moisture content to analyze this indicator, and samples were taken from each region. The survey results are shown in Fig. 6.

In Fig. 6, the x-axis represents different regions, and the y-axis represents the saturated soil moisture content. The legends from top to bottom represent the control and experimental groups, respectively. The saturated soil moisture content of Regions 1, 2, 3, 4, 5, and 6 in the control group was 12%, 29%, 31%, 35%, 41%, and 46%, respectively. However, each region's saturated soil moisture content in the experimental group was 19%, 37%, 42%, 46%, 53%, and 62%, respectively. Because the higher the soil moisture content, the more beneficial it is for plant growth, it can be seen that the experimental group's region is more prone to tree planting and

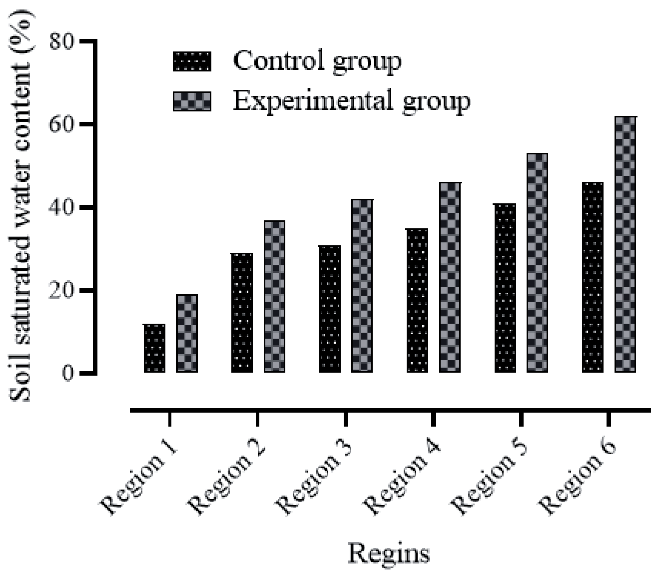

Fig. 6. Measurement results of soil water retention capacity.

Table 2. Evaluation results of economic benefits of forest ecological engineering.

Economic efficiency indicators	Groups	Region 1	Region 2	Region 3	Region 4	Region 5	Region 6
NPV (10^4yuan)	Control group	13.6	26.3	38.2	49.5	62.3	76.2
	Experimental group	16.5	32.5	56.5	72.2	82.6	101.2
NPVR (%)	Control group	42.4	53.2	61.2	69.5	76.5	80.1
	Experimental group	50.5	59.2	70.6	82.8	89.4	95.4
IRR (%)	Control group	2.2	3.1	4.2	6.8	7.9	8.5
	Experimental group	2.6	3.8	4.8	7.5	8.9	10.6
BCR	Control group	1.02	1.24	1.34	1.52	1.64	1.72
	Experimental group	1.16	1.32	1.54	1.72	1.82	1.86

growth. Moreover, the soil moisture content in both the experimental group and the control group's Region 1 is less than 20%, which further reflects that the soil in Region 1 is unsuitable for planting trees. Therefore, planting plants suitable for the growth of this area can be considered.

NPV, NPVR, IRR, and BCR are all important indicators for evaluating the economic benefits of forest ecological engineering. Analyzing these indicators can show the economic status of forest ecological engineering. Therefore, this article analyzed these indicators. The results can be seen in Table 2.

The total NPV of each region in the control group was 2.661 million yuan, while the total NPV of each region in the experimental group was 3.615 million yuan. The NPV of the experimental group was nearly 1 million yuan more than that of the control group, which indicates that applying the genetic fuzzy algorithm to forest carbon sink ecological engineering afforestation technology can greatly improve the economic benefits of forests and make people profit while protecting the environment.

The average NPVR of each region in the control group was 63.82%, while the average NPVR of each region in the experimental group was 74.65%, indicating that using a genetic fuzzy algorithm can improve the return on unit investment and create economic value. The reason for the analysis is that trees grow from scratch and become more numerous, and the value of trees themselves creates economic value for the region.

The IRR and BCR values of each region in the experimental group are higher than those of the control group. Therefore, it is easy to see that adopting two forest carbon sink ecological engineering afforestation technologies has brought certain economic benefits. However, in comparison, forest carbon sink ecological engineering afforestation technology based on a genetic fuzzy algorithm can bring more economic benefits.

By comprehensively comparing the NPV, NPVR, IRR, and BCR values of each region under two afforestation techniques, it can be found that the use of genetic fuzzy algorithms can create more economic value for forests. This indicates that applying genetic algorithms and fuzzy reasoning algorithms can improve the vitality of forests and increase people's income.

Conclusions

In order to improve the ecological and economic benefits of forest carbon sink ecological engineering afforestation technology, this paper applied a genetic fuzzy algorithm to forest carbon sink ecological engineering afforestation technology and designed a carbon sink accounting calculation model. Taking a piece of wasteland in S city as an example, different regions were divided based on their geomorphic characteristics. The carbon absorption capacity, ecological benefits, and economic benefits of forest carbon sink ecological engineering afforestation technology were analyzed, and it was concluded that using a genetic fuzzy algorithm could not only improve the carbon storage and carbon absorption of forests but also improve the ecological and economic benefits of forests. The next step is to plant trees that are conducive to developing a forest economy based on the characteristics of forest landforms, further improving the economic and ecological benefits of forests and striving to maximize benefits. However, the research also has certain shortcomings, such as the limitations of the experimental area, the imperfect data collection and processing methods, etc. In the future, we will further expand the experimental area and improve the data collection and processing methods in order to obtain more accurate and comprehensive research results and provide a more solid scientific basis for promoting and applying this technology.

Conflict of Interest

The authors declare no conflict of interest.

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