DEVELOPMENT OF ECOLOGICAL MANAGEMENT SYSTEM FOR PLANTED FOREST BASED ON ELM DEEP LEARNING ALGORITHM

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Reception: 18/11/2022 **Acceptance**: 07/01/2023 **Publication**: 27/01/2023

Suggested citation:

W., Zhe (2023). **Development of ecological management system for planted forest based on ELM deep learning algorithm**. *3C Empresa. Investigación y pensamiento crítico, 12(1)*, 165-184. https://doi.org/10.17993/3cemp.2023.120151.165-184

ABSTRACT

Plantations play a central and lever role in maintaining the ecological balance of the earth, maintaining the overall function of the terrestrial ecosystem, and promoting the coordinated development of economic society and ecological construction. In order to strengthen the ecological management of plantation forests and improve the ecological level of forest region, the C/S framework is taken as the basic structure, and the programming mode of business model-user interface controller is used, on J2EE platform. The ecological management system of a planted forest is constructed by the evaluation module, the principal component comprehensive analysis module of ecological function value and the demand prediction module of planted forest based on extreme learning machine and deep learning algorithm, and runs under the support of windows system, oracle 15G and above database software. The indexes and factors affecting the ecological function of plantation forests were evaluated and analyzed, and the final management decision was given by the prediction module. The results showed that the plant density significantly affected plant biomass, organic carbon storage, water content and nutrient accumulation, and the comprehensive evaluation indexes of four ecological functions increased from 32.69, 31.84, 33.71 and 35.46 to 86.18, 89.46, 89.83 and 88.76, respectively. Although the degree of influence of the system on lemon strip plants, herbaceous plants, surface litter and soil varies, it still has good feasibility, effectiveness and practicality, and can assist the scientific ecological management of artificial plantation forests.

KEYWORDS

Extreme learning machine; Deep learning algorithm; Plantation forests; Ecological management system; Principal component analysis

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1. INTRODUCTION

As the main body of the terrestrial ecosystem, the forest has always been the focus of debate [1-2]. The function of the forest ecological environment can be direct or indirect. It can be tangible or intangible [3]. The function of forest ecology refers to the natural environmental conditions and effects that are formed by the forest ecosystem and ecological process and maintained by human survival [4].

The management of forest ecology is a systematic and complex project. At present, soil erosion, biodiversity reduction, wetland degradation, land desertification, and other problems are still serious, and the important role of forests in maintaining national ecological security has not been fully played [5-8]. With the development of industrial civilization and the aggravation of global warming, the ecological functions of forests, such as soil and water conservation, water conservation, carbon fixation and oxygen release, air purification and environment beautification, have attracted people's attention [9-10].

Recently, there have been many reports on forest ecological functions, especially on water conservation, carbon sequestration and oxygen release. Therefore, managing forest ecology objectively, dynamically and scientifically can deepen people's environmental awareness, strengthen the leading position of forestry construction in the ecological environment of the national economy, and improve the level of forest ecological environment. It is of great practical significance to accelerate the integration of the environment into the national economic accounting system and correctly handle the relationship between social-economic development and ecological environmental protection [11-13].

Based on the above research background, researchers in related fields are trying to achieve good research results in forest ecological management. Such as literature [14] according to Ukraine and the EU regulatory filing modern requirements for environmental protection and biodiversity conservation and the suggestion, proposing to overcome the ecological problems of radioactive pollution of forest ecosystems from the perspective of environmental management, and create a fire prevention and forest management system based on science, to prevent the personnel and the public excessive exposure from various sources, Prevention of secondary diffusion of radionuclides to relatively clean areas by fire is achieved through the use of hydrodynamic active water extinguishers and the laying of a polyethylene guanidine based barrier in front of the fire line. Literature [15] used mixed methods to conduct ecological management of tropical dry forests on 11079 hectares of land in Colombia. With the participation of 64 experts, the Delphi method was applied to conduct quantitative research on the ecological situation from 2018 to 2020. The results showed that all knowledge management practices identified had a certain impact on ecological management. It also contributes to the generation, transformation, and mobilization of scientific knowledge on each component of the ecological restoration process of tropical dry forests. Literature [16] aims at how to realize the maximization of the value of forest ecological resources to provide theoretical reference to the sustainable development of the global forest resources, using the theory of ecological capital is discussed how to define the concept of forest ecological resources

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capitalization, analyzed from two aspects of forest ecological resources capitalization of inner motivation, and how people change the use of forest resources, the results show that the realization path of capitalization of forest ecological resources can provide theoretical reference for maximizing the value of forest ecological resources and realizing the sustainable development of global forest resources. Literature [17] in 30 provinces as a sample, constructed the index system of forest ecological security and the efficiency of forest management, with the help of the CCR model, the coupling coordination model and the spatial panel model, from 2003 to 2017 China's provincial forest ecological safety and the management efficiency of the forestry coupling coordination degree and its temporal pattern characteristics and influence factors in the measurement and analysis, The results show that, in terms of forest ecological security, the index increases as a whole, and the coupling coordination degree changes from near uncoordinated to intermediate coordinated. This study can provide a theoretical reference framework for China's forest ecological management decisions. According to the consensus on the ecological environment in previous studies and the characteristics of the study area. Literature [18] established a quantitative evaluation index system for the comprehensive ecological environment of forest ecosystem nature reserve based on water, air, soil and biological environment, constructed a weightless cloud model, and provided a weightless evaluation mechanism. The results showed that the results of this study can provide theoretical support for the evaluation of forest ecosystem nature reserves and general evaluation when the weight is difficult to determine or uncertain. Literature [19] in human forest botanical garden as the research object, from the regional environmental quality, development conditions and the scenic area characteristic value of three standard level selected 23 indicators, to evaluate the ecological tourism development potential, using the analytic hierarchy process (AHP) to determine the weight of each index, and using the fuzzy comprehensive evaluation method to three standard level and evaluate the ecological tourism development potential, The conclusion suggested that scenic spots should maintain their advantages, enhance tourism characteristics, strengthen ecological civilization construction, and promote the in-depth development of ecological tourism. The above research results have established a relatively comprehensive and applicable forest ecological evaluation index system from different emphases, which has a certain promoting effect on improving the forest ecological environment and enhancing the ecological level.

Human initial afforestation is mainly in order to production needs, as a part of the agricultural production, with the progress of social productivity, timber demand increasing, under the natural state of forest resource components are insufficient to satisfy the human production and life, people began planting plantation, planted forest ecological level and function is becoming more and more attention [20]. Therefore, this article is based on C/S architecture and the J2EE platform, in the Struts framework with the business model - user interface - controller programming model, under the support of construct artificial planting forest ecological management system, through the synergy evaluation module, the ecological function value of the principal component comprehensive analysis module and the depth of the extreme learning machine learning algorithm of planted forests demand forecast module, Various indicators and factors affecting the ecological function of planted forests were evaluated and analyzed in order to better understand the biodiversity of planted forests and its regulation approaches and mechanisms on ecological function and to provide scientific basis and technical means for guiding the ecological management and sustainable management of planted forests [21].

2. DEVELOPMENT AND DESIGN OF ECOLOGICAL MANAGEMENT SYSTEM FOR ARTIFICIAL PLANTATION FOREST

Based on the C/S framework and J2EE platform, the business model -user interface-controller programming mode of the struts framework is adopted and design the environmental management system for artificial planting forests as shown in Figure 1. The system includes an evaluation module, principal component comprehensive analysis module of ecological function value and planting forest demand prediction module of extreme learning machine deep learning algorithm. The three modules work together to evaluate and analyze the indicators and factors that affect the ecological function of planted forests and provide management and support for decision-makers. The evaluation unit mainly includes three units: single ecological function value evaluation of all planted forest species, total ecological function value evaluation of single planted forest species, and total ecological function value evaluation of all planted forest species. The system server uses windows system, oracle 15G or above database, Tomcat6.0.67 or above server, JDK2.0 or above development package; The client uses IE 9.0 or higher.

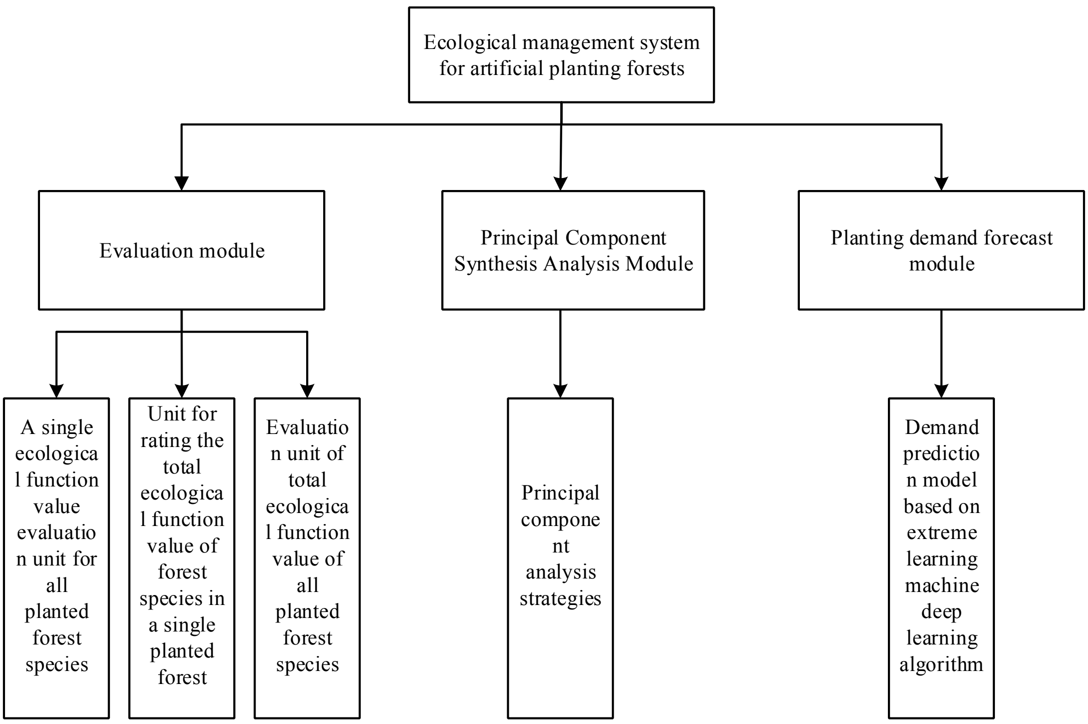

Figure 1. architecture diagram of the environmental management system of artificial plantation forest

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2.1. EVALUATION MODULE DESIGN

The ecological function value evaluation algorithm of the four units of the evaluation module is described as follows:

(1) Single ecological function value evaluation unit of all planted forest species: this unit includes the ecological function of water conservation, soil conservation, and carbon dioxide fixation of planted forest species. The value evaluation formulas of different ecological functions are as follows:

$$M_{hysy} = \sum_{i=1,2,\ldots,n} V_i \tag{1}$$

Where, V_i is the ecological function value of water conservation of n dominant tree species in artificial plantation forests.

$$M_{bytr} = \sum_{i=1,2,\ldots,n} T_i \tag{2}$$

Where, T_i is the ecological function value of soil conservation of n dominant tree species in artificial plantation forests.

$$M_{co_2} = \sum_{i=1,2,\ldots,n} Q_{1i} \tag{3}$$

Where, Q_{1i} is the ecological function value of fixed carbon dioxide of n dominant tree species in artificial plantation forests.

(2) Total ecological function value evaluation of monoculture forest species: this unit contains the total ecological function of different dominant tree species, and the value evaluation formula is as follows:

$$M_{dy} = V_i + T_i + Q_{1i} + Q_{2i} + E_i + K_i \tag{4}$$

Where, Q_{2i} is the corresponding ecological function value of oxygen release of dominant tree species in the planted forest. E_i is the ecological function value of biological storage energy of each dominant tree species in the planted forest; K_i is the ecological function value of biodiversity of each dominant tree species in the plantation.

(3) Total ecological function value evaluation of all planted forests and species: the total ecological function value evaluation algorithm of this unit is as follows:

$$M_z = \sum_{i=1,2,\ldots,n} V_i + \sum_{i=1,2,\ldots,n} T_i + \sum_{i=1,2,\ldots,n} Q_{1i} + \sum_{i=1,2,\ldots,n} Q_{2i} + \sum_{i=1,2,\ldots,n} E_i + \sum_{i=1,2,\ldots,n} K_i \tag{5}$$

Evaluation module by running the business model - user interface - controller programming software, all sorts of forest of planted forest respectively calculated single, single planting forest ecological function value of total sorts of forest ecological function value and all sorts of forest of planted forest ecological function value of three indicators, namely the complete management system of planted forest ecological function value assessment, the evaluation function of ecological management system of artificial plantation forest was realized.

2.2. DESIGN OF PRINCIPAL COMPONENT COMPREHENSIVE ANALYSIS MODULE

The principal component analysis method [22] was adopted to comprehensively and systematically understand the comprehensive strength of the ecological function value of different planted forest types, and many indicators reflecting the ecological function value characteristics of planted forest types were considered from different aspects. The program flow chart of the principal component analysis algorithm is shown in Figure 2. The specific description is as follows:

(1) Data standardization of ecological value evaluation index;

(2) The correlation between ecological value evaluation indicators;

(3) Calculate the covariance matrix of standardized data;

(4) Calculate all the eigenvalues of the covariance matrix, calculate the eigenvectors, determine the number of principal components according to the cumulative ratio of eigenvalues;

(5) Calculate principal component load value and factor score coefficient matrix to determine the principal component expression; To calculate the comprehensive score is to carry out the principal component score, sort the scores according to the size of the score value, and output the most important first several ecological value evaluation indicators.

With the support of Windows system, Oracle 15G or above database, Tomcat6.0.67 or above server, JDK2.0 or above development package and other software, the algorithm program of principal component analysis can run according to the process shown in Figure 2. Principal component scoring is carried out according to the obtained comprehensive score. Several important evaluation indexes of ecological value were obtained, and the analysis function of ecological management system of artificial plantation forest was realized.

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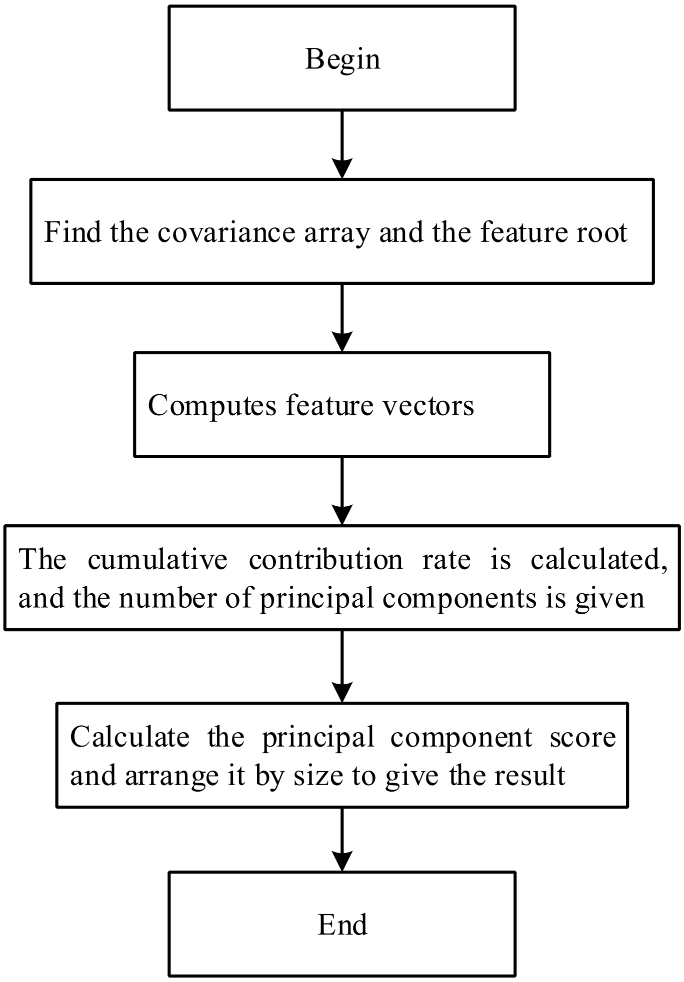

Figure 2. program flow chart of principal component analysis algorithm

2.3. DESIGN OF DEMAND PREDICTION MODULE OF PLANTED FOREST BASED ON EXTREME LEARNING MACHINE DEEP LEARNING ALGORITHM

The prediction module is mainly used for quantitative prediction and analysis of the demand for artificial plantation forests. The change in plantation density is influenced by the social economy, population, natural environment and other factors [23]. So choose gross GDP ($one hundred million), at the end of the total population (ten thousand people), non-agricultural population (ten thousand people), fiscal revenue (one hundred million yuan), financial expenditure (one hundred million yuan), the first industry (one hundred million yuan), the second industry (one hundred million yuan), the third industry (one hundred million yuan), the output value of industrial output value ($one hundred million), construction (one hundred million yuan), the per capita net income (yuan), fixed asset investment ($one hundred million), Urban input (100 million yuan), rural input (100 million yuan), annual precipitation (100 million cubic meters) and other indicators constitute the driving index system of the change of artificial planting forest density (10 thousand trees/ha). There is no simple linear relationship between each driving factor and the density of the planted forest, and there is a correlation in time. Therefore, an extreme learning machine deep learning

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algorithm is adopted to build the demand time series prediction model with the nearest neighbor domain theory [24] as the core, as shown in Figure 3. The prediction process is described as follows:

(1) Extraction of training samples: in order to complete the prediction of planting forest density Y_{t+s} at time $t+s$, k samples most similar to the prediction sequence Q of Y_{t+s} should be extracted from all training samples as the recombination samples, and k recombination samples should be used as the input of the local model. The process of finding the nearest neighbor is the process of measuring the similarity between the prediction sequence Q and all the training samples. Through this step, the best prediction model of planting forest density can be built.

In order to select k nearest neighbors of Q from set S as recombination samples, a method is needed to calculate the similarity of two sets of sequences. Assume that A_1 and A_2 are two time series:

$$\begin{cases} A_1 = \left[X_a, Y_a, X_{a+1}, Y_{a+1}, \ldots \quad {}_{a+q-1}, Y_{a+q-1}, X_{a+q}, Y_{a+q} \right] \\ A_2 = \left[X_b, Y_b, X_{b+1}, Y_{b+1}, \ldots \quad {}_{b+q-1}, Y_{b+q-1}, X_{b+q}, Y_{b+q} \right] \end{cases} \tag{6}$$

F_1 and F_2 are difference sequences of two time series A_1 and A_2 respectively:

$$\begin{cases} F_1 = \left[X_{a+1} - X_a, Y_{a+1} - Y_a, \ldots \quad {}_{a+q} - X_{a+q-1}, Y_{a+q} - Y_{a+q-1} \right] \\ F_2 = \left[X_{b+1} - X_b, Y_{b+1} - Y_b, \ldots \quad {}_{b+q} - X_{b+q-1}, Y_{b+q} - Y_{b+q-1} \right] \end{cases} \tag{7}$$

Assuming that $N_E(A_1, A_2)$ is the standardized Euclidean distance between A_1 and A_2 [25], $N_E(F_1, F_2)$ is the standardized Euclidean distance between F_1 and F_2, we use the mixed Euclidean distance to calculate the similarity of the two groups of time series:

$$N_H(A_1, A_2) = \frac{N_E(A_1, A_2) + N_E(F_1, F_2)}{2} \tag{8}$$

$N_H(A_1, A_2)$ is the mixed Euclidean distance of A_1 and A_2. We calculated the mixed Euclidean distance of each element in the set S and Q, finally obtained z mixed Euclidean distances, and selected k elements $\{S_i\}_{i=1}^{k}$ with the shortest distance as the extracted training samples.

(2) Prediction model derivation of extreme learning machine deep learning algorithm: the deep learning algorithm of extreme learning machine integrates the idea of self-coding [26] and encodes the output by minimizing reconstruction error so that the output can approach the original input infinitely. This structure provides an abstract representation of the input and thus captures the deep features of the original input. Figure 3 describes the prediction modeling process of the algorithm for the output planting forest density Y_{t+s} at time $t+s$. The extracted training sample $\{S_i\}_{i=1}^{k}$ is

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taken as the input of the network. It is assumed that the network is composed of the hidden layer of h layer, and $W = \{W_1, W_2, \dots, W_{h+1}\}$ represents the weight parameters to be learned in the network.

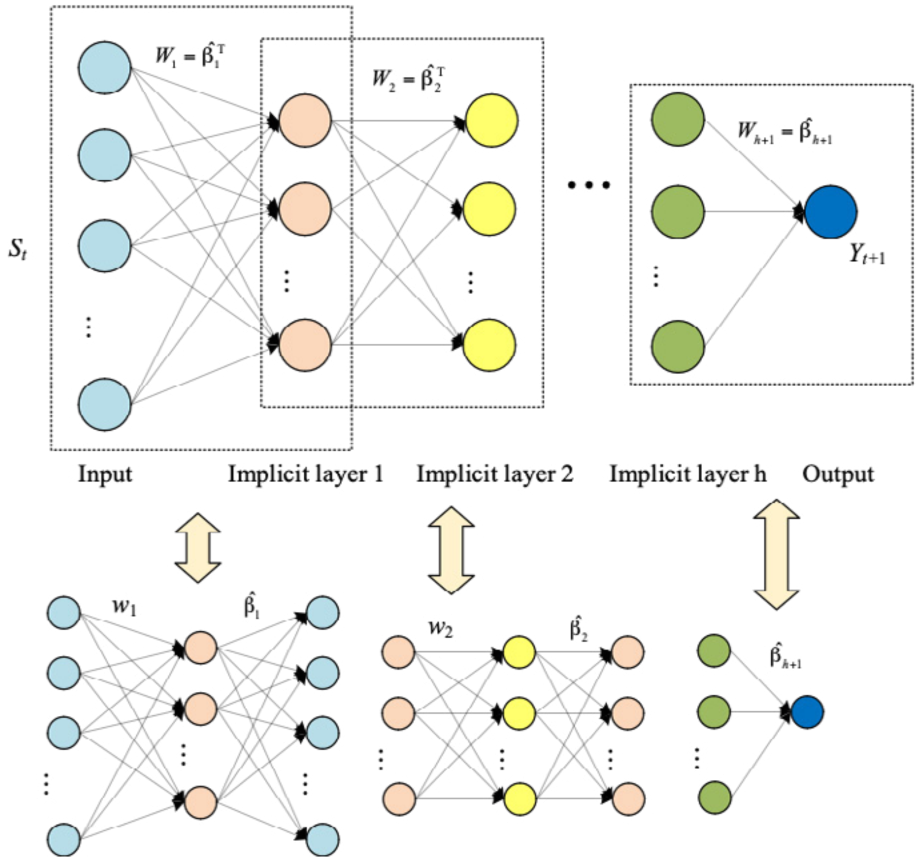

Figure 3. architecture diagram of a prediction model based on extreme learning machine deep learning algorithm

Each layer in the network can be decoupled as an independent extreme learning machine [27], and the target output of each extreme learning machine is equal to the input of the extreme learning machine. In this way, the low-dimensional representation of the input data can be obtained, that is, the hidden layer output of the extreme learning machine, and this output can be used as the input of the next extreme learning machine. The output weight $\hat{\beta}$ of the extreme learning machine is calculated by the following formula:

$$\hat{\beta} = H^T \left(\frac{I}{\lambda} + H^T H \right)^{-1} T \tag{9}$$

Where, λ is the rule item; H is the output matrix of the hidden layer of an extreme learning machine.

Then the weight parameter $W_k \left(k = 1, \dots, \right)$ is calculated by the following formula:

$$W_k = \hat{\beta}_K^T \left(k = 1, \dots, \right) \tag{10}$$

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Finally, the feature expression is obtained, that is, the output of the hidden layer of layer h, as the hidden layer of an independent extreme learning machine, and the output weight $\hat{\beta}_{h+1}$ of the extreme learning machine is obtained by similar calculation. The weight parameter W_{h+1} of the network is calculated by the following formula:

$$W_{h+1} = \hat{\beta}_{h+1} \tag{11}$$

According to the obtained network weight parameter $W = \{W_1, W_2, \cdots, W_{h+1}\}$, the prediction model architecture of extreme learning machine deep learning algorithm is defined. After the training sample data is input into the input layer of the prediction model, layer by layer calculation is carried out according to the determined network structure, and Y_{t+s} of planted forest density can be calculated, which provides decision basis for ecological management of planted forest.

3. APPLICATION OF THE SYSTEM

3.1. OVERVIEW OF THE STUDY AREA

An artificial plantation forest area with an area of about 2,000 square kilometers and a planting density of 9.64 million trees per hectare in 2017 was selected as the research target. The research area is located at 110°13 '~111°35' east longitude and 36°46 '~37 °52' north latitude, 983-1684m altitude and mountainous area. It is a typical hilly and gully region with complex terrain and closed traffic. The main type of soil is the yellow soil developed from the parent material of loess, with fine particles and deep soft soil, which is conducive to farming. The main vegetation types include agricultural land crops, grasslands, and shrubland. The main grassland species are alfalfa, long miscanthus, thyme, ice grass, iron pole, pig hair down, Chinese asparagus herb, two cracks, and so on. Shrub species mainly include Salix psammophila, peach, apricot, caragana korshinskii. Caragana korshinskii is widely planted in this region because of its drought resistance, cold resistance, sand resistance and good soil and water conservation. There are large typical experimental and demonstration areas of the caragana korshinskii plantation. The system was put into use in 2018. According to the prediction model of extreme learning machine deep learning algorithm, the reasonable planting density of artificial planting forest in this region is 23.24 million trees/ha. Caragana korshinskii will be planted in 2021.

3.2. SELECTION, MEASUREMENT AND CALCULATION OF ECOLOGICAL FUNCTION EVALUATION INDEX OF PLANTED FOREST

In order to verify the ecological management effect of the system on the region, the ecological function of the forest region is evaluated from four aspects [28-31]: plant biomass, organic carbon storage, nutrient accumulation, and water retention capacity.

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The evaluation system and the measurement method of secondary indicators are shown in Table 1. The first-level indicators include (1) plant biomass: caragana korshinskii and herbaceous aboveground biomass and litter biomass; (2) organic carbon storage: the aboveground and ground litter of caragana korshinskii and herbaceous plants and soil organic carbon storage; (3) total nitrogen and total phosphorus reserves of caragana korshinskii plants and herbaceous plants aboveground and litters; soil nutrient index: soil total nitrogen, nitrate nitrogen, ammonium nitrogen, and available phosphorus contents; (4) water content of caragana korshinskii plants and herbaceous plants aboveground, litter and soil.

Table 1. evaluation system and component determination method

Primary indicators	secondary indicators	Determination method
biomass	Aboveground biomass	Model estimation method
	Aboveground and litter biomass	Weighing method
Organic carbon storage	Aboveground and surface litter and soil organic carbon storage	The external heating method of potassium dichromate oxidation
Accumulation of nutrients	Total nitrogen storage in aboveground and litter	Concentrated sulfuric acid - hydrogen peroxide digestion
	Total phosphorus storage in aboveground and litter	Vanadium molybdenum yellow colorimetry
	Contents of total nitrogen, nitrate nitrogen and ammonium nitrogen in soil	Semi-trace Kjeldahl nitrogen determination
	Soil available phosphorus content	Sodium bicarbonate extraction - molybdenum antimony resistance colorimetric method
Water retention	Water content of aboveground and litter	Weighing method
	Soil moisture content	

The contents of different components were determined, and the first-order index of ecological function was measured using average value method[32-33]. Assuming that the actual measured value of the j secondary index of sample plot i is Xij, and the mean value and standard deviation of the j secondary index among all sample plots of the same factor are uj and σj respectively, the calculation formula for the score of the j secondary index of sample plot i is as follows:

$$Zij = \left(Xij - uj\right)/\sigma j \tag{12}$$

Thus, the ecological functional comprehensive index of each level index can be deduced:

$$EMFi = \sum_{1}^{f} Zij / f \tag{13}$$

Where, f is the number of all second-level indicators contained in plot i.

4. RESULTS AND ANALYSIS

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4.1. PLANT BIOMASS, ORGANIC CARBON STORAGE AND WATER CONTENT OF ARTIFICIAL PLANTATION FOREST

The aboveground biomass of caragana korshinskii, herbaceous plants and litters were selected as the parameters to evaluate the plant biomass of the planted forest. Figure 4 shows that plant biomass is significantly affected by planting density of planted forests. Before the application of ecological management system, the aboveground biomass and litter biomass of caragana korshinskii and herbage were only 8.19t/hm^2, 6.47t/hm^2 and 5.84t/hm^2, respectively. After applying the system for ecological management, through comprehensive evaluation of the ecological function of the sample land, they are 10.67t/hm^2, 2.51t/hm^2, 1.34t/hm^2, 12.55t/hm^2, respectively. After the application of ecological management system, organic carbon storage increased significantly, reaching 30.43t/hm^2 in 2021, the aboveground biomass and litter biomass of herbage increased, and the aboveground biomass and litter biomass of herbage increased, reaching 40.64t/hm^2, 8.76t/hm^2 and 7.66t/hm^2 in 2021, respectively. The aboveground organic carbon storage of caragana korshinskii and herbage, litter organic carbon storage and soil organic carbon storage were selected as parameters to evaluate the ecological function of organic carbon storage. Caragana korshinskii, herbage, litter and soil organic carbon storage were 7.19t/hm^2, 6.48t/hm^2, 26.71t/hm^2, respectively. Water retention is an important ecological function of planted forests. In this study, four indexes of caragana korshinskii plants, herbaceous plants, ground litters and soil water content were selected as parameters to evaluate the water retention capacity of caragana korshinskii plantations. As shown in figure 4, you can see that plantation planting density of caragana korshinskii and plant litter moisture content is less affected, there was no significant difference before and after the application in the system, but the herbs and soil moisture content in 2017 and 2021 significant difference under different planting density and planting density increase, herbaceous plants and soil water content is increased greatly, in 2021, they will reach 62.58% and 59.43% respectively. To sum up, the environmental management system is based on the results of the evaluation of the single ecological function value of all planted forests, the total ecological function value of all planted forests and the total ecological function value of all planted forests. By reasonably adjusting the planting density in the forest region, the coverage rate of surface vegetation was expanded, and the ecological function indexes were improved. The comprehensive indexes of plant biomass, organic carbon storage and water content of the planted forest increased from 32.69, 31.84 and 35.46 in 2017, respectively. Increasing to 86.18, 89.46 and 88.76 in 2021, there is an obvious synergistic effect between planting density and ecological function in the forest region, and artificial planting forest has a better ability to provide and maintain multiple ecological functions simultaneously.

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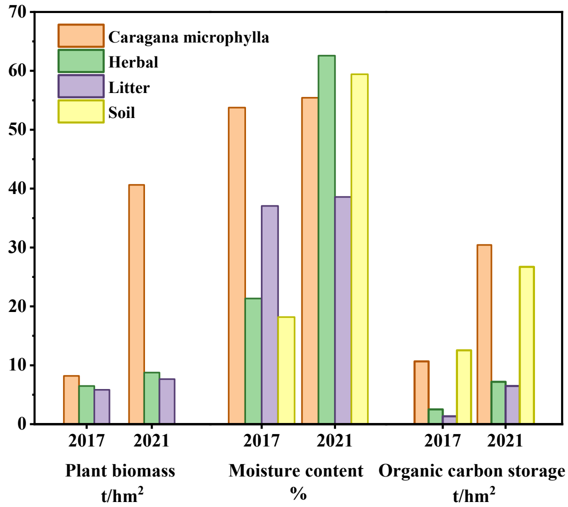

Figure 4. schematic diagram of ecological function change of plantation forest

4.2. NUTRIENT ACCUMULATION IN PLANTATION FORESTS

Total nitrogen and total phosphorus reserves of caragana korshinskii and herbaceous plants, total nitrogen and total phosphorus reserves of litters, and soil nutrient content indexes (soil total nitrogen, available phosphorus, nitrate-nitrogen, ammonium nitrogen) were selected as the parameters to evaluate the ecological function of nutrient accumulation in planting areas. Figure 5 (a) shows that the planting density of caragana korshinskii significantly affected the plant total nitrogen storage of the planted forest. The total nitrogen storage of caragana korshinskii was significantly higher than that of herbaceous plants and litters. Before the system was put into use, the planting density was small, and the total nitrogen reserves of caragana korshinskii, herbaria korshinskii and litters were low, only 135.46kg/hm^2, 11.13kg/hm^2 and 8.54kg/hm^2. However, after the system was put into use, the total nitrogen reserves of three kinds of plants were greatly increased. In 2021, the ecological function of total nitrogen accumulation was 763.08kg/hm^2, 25.66kg/hm^2 and 51.73kg/hm^2, respectively. The ecological function of caragana korshinskii was the most obvious before and after application of the system. Compared with total nitrogen, the total phosphorus reserves of plants in the planted forests with different planting densities changed more gently, but the functional degree of plants was still that the total phosphorus reserves of caragana korshinskii were significantly higher than that of herbaceous plants and litters. Before the use of systematic management of forest ecology, the total phosphorus reserves of the three are 8.46kg/hm^2, 1.23kg/hm^2 and 0.64kg/hm^2, respectively. After management, total phosphorus reserves reach 36.16kg/hm^2, 1.43kg/hm^2 and 2.22kg/hm^2, respectively. There was no significant difference in total phosphorus storage of herbaceous plants and litters under different planting densities.

It can be seen from Figure 5 (b) that with the increase in plantation density, soil total nitrogen content also showed a corresponding upward trend, but the increase was not

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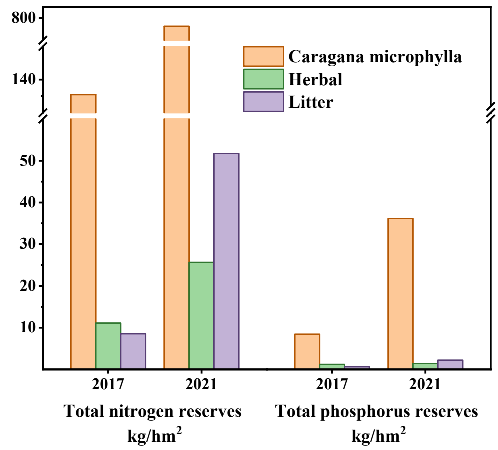
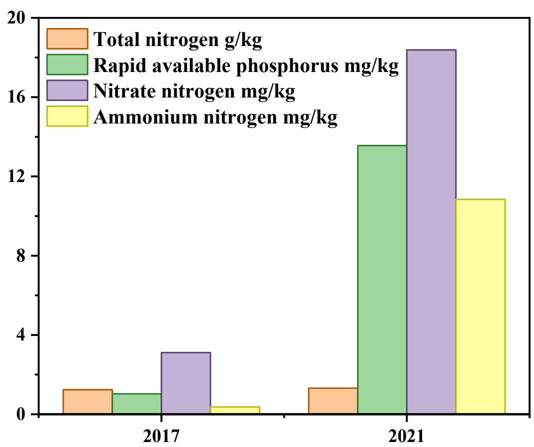
obvious, only increased by 0.08g/kg. Therefore, the application of an ecological management system had no significant effect on soil total nitrogen content. Before the application of the system, the contents of soil available phosphorus, nitrate-nitrogen, and ammonium nitrogen content were only 1.03mg/kg, 3.11mg/kg and 0.37mg/kg. When the system gave a reasonable planting density and implemented it, the contents of the three nutrients in the soil were as high as 13.56mg/kg, 18.38mg/kg and 10.84mg/kg, respectively. This is because, with the support of a principal component analysis strategy and extreme learning machine deep learning algorithm, the management system reasonably increases the number of caragana korshinskii plants per unit area, and makes the biomass of caragana korshinskii and litters at a high level. Therefore, it directly promotes the increase of total nitrogen and total phosphorus reserves of caragana korshinskii plants and litters. In addition, by increasing the surface vegetation coverage and improving the input of soil resources, the nutrient contents of soil such as nitrogen and phosphorus were increased, and the nutrient accumulation ecological functional composite index of the cultivated forest increased from 33.71 in 2017 to 89.83 in 2021.



(a) plant and litter nutrient content



(b) soil nutrient content

Figure 5. schematic diagram of nutrient accumulation

https://doi.org/10.17993/3cemp.2023.120151.165-184

5. DISCUSSION

This study focuses on the study of the environmental management system of artificial planting forests. The data input into the system, through the function evaluation and prediction, helps to achieve the best combination of forest species selection, planting area and ecological environmental benefits. The next step for further in-depth research is as follows:

(1) Combined with 3S technology, global positioning system is used for real-time positioning, remote sensing for data collection and update, geographic information system for spatial analysis and comprehensive processing, so as to rapidly update ecological related data and reduce the cost of manpower and material resources;

(2) For the model base of this study, optimization model and early warning model need to be added in the future. From the perspective of ecological economics, it is expected to think about how to arrange the species structure of planted forest and analyze the optimization between its related functions and generated services. Forewarning of the loss of ecological function of plantation forest;

(3) For the system, there is currently a lack of expert experience and practical knowledge, which needs to be enriched and strengthened in the future. In addition, artificial intelligence technologies such as neural networks, support vector machines and time series analysis can also be used to acquire knowledge in the system.

6. CONCLUSION

Afforestation is one of the main ways of ecological restoration and land reclamation. Whether the restoration mode is suitable or not needs long-term observation to see its restoration effect. The ecological health of the planted forest also varies with the recovery time. Therefore, this paper takes C/S as the basic framework and J2EE as the development platform. With the support of principal component analysis method and extreme learning machine deep learning algorithm, the Struts framework and business model-user-interface controller programming mode are adopted in this paper. An environmental management system consisting of an evaluation module, principal component comprehensive analysis module and planting demand prediction module has been developed. Through carrying out experimental research activities on the effect of ecological management of forest region by the system in the study area, the following three conclusions have been obtained:

(1) Single system USES all sorts of the forest of planted forest ecological function value evaluation, the single planting Lin total sorts of forest ecological function value evaluation, all sorts of the forest of planted forest ecological function value evaluation three units constructing evaluation module, to provide better practice ecological management database and decision basis, and planted forest density and obvious synergistic effect between different ecological functions.

(2) Using principal component analysis comprehensive system understanding of different sorts of the forest of planted forest ecological function value of

https://doi.org/10.17993/3cemp.2023.120151.165-184

comprehensive strength, help considering from different sides reflects growing forest category characteristics of many types of ecological function value indicators, the artificial planting forests can have better ability to provide and maintain multiple ecological functions at the same time.

(3) Based on the extreme learning machine deep learning algorithm, the demand prediction module of planted forest designed by extreme learning machine takes the nearest neighbor domain theory as the core, making the output infinitely close to the original input, and giving the reasonable planting density of planted forest in this region as 23.24 million trees/ha. The biomass, organic carbon storage, nutrient accumulation and water content in the study area were increased to 57.06t/hm^2, 70.81t/hm^2, 924.38kg/hm^2 and 216.03% from 20.5t/hm^2, 27.07t/hm^2, 171.21kg/hm^2 and 130.35%. The corresponding ecological functional composite index increased from 32.69, 31.84, 33.71, 35.46 to 86.18, 89.46, 89.83, 88.76, respectively.

7. DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/ supplementary material, further inquiries can be directed to the corresponding author.

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9. CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.