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Ecological services and improvement strategies of forest healthcare space environment under the background of carbon neutrality

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Abstract: This paper proposes a multidisciplinary optimisation strategy for achieving a ‘carbon sink-healthcare-biodiversity’ triple win. Integrating data, a collaborative evaluation system is established to assess carbon sinks and ecological services using the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model. A spatial planning model optimises the layout of forest healthcare bases, balancing carbon sink efficiency with healthcare functions and employing the Nondominated Sorting Genetic Algorithm II (NSGA-II) algorithm and analytic hierarchy process (AHP) for plan selection. Additionally, a community carbon sink return-sharing mechanism is designed, to enhance government goals, enterprise returns, and community satisfaction. The results show that based on the high ecological benefits of 82% government ecological goal achievement rate and 13.4% annual carbon sink growth rate, the enterprise still maintains a 12.1% return rate and 85% community satisfaction. The multidisciplinary approach achieves a ‘triple-win’ situation of collaborative optimisation of carbon sinks, healthcare, and biodiversity.

Keywords: forest healthcare space; ecological services; carbon neutrality; spatial planning model; benefit sharing mechanism.

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1 Introduction

Against the backdrop of the global carbon neutrality goal and the accelerated ageing of the population, the importance of forest healthcare space as a composite ecological carrier with both carbon sink function and health service value is becoming increasingly prominent. However, current forestry carbon sink projects tend to “focus on carbon storage and neglect service collaboration”. For example, although the single forestation of fast-growing tree species improves short-term carbon sequestration efficiency, it leads to problems such as decreased biodiversity and weakened soil and water conservation functions. In addition, the ecological service value quantification system of the forest healthcare industry has not yet been improved, and policy collaboration and community participation are insufficient, which seriously restricts its comprehensive benefits. In this context, optimising forest management strategies through scientific methods and balancing carbon sink goals and ecological service functions have become key issues that need to be solved urgently.

Forest healthcare is an innovative form of supply-side structural reform in the tourism industry. The key is to achieve significant health benefits by enhancing tourists' perception of the naturalness of the forest environment, enhancing their attachment to the place, and improving their emotional state (Geng et al., 2021; Cui et al., 2022). At present, research on forest healthcare space mainly focuses on the spatial distribution characteristics of forest healthcare resources, influencing factors, and scientific and rational forest healthcare base layout, aiming to promote the effective use of resources and the orderly development of the industry (Sixiao and Jianguo, 2022). Research methods include geographic information system (GIS) analysis, spatial concentration assessment, and analysis of relationships with natural and socioeconomic factors. Forest healthcare spatial research focuses on national demonstration bases' distribution, density, and influencing factors. Spatial analysis methods are used to explore the impact of resources, economy, transportation, etc., on distribution to optimise the layout (Huang et al., 2021). The bases in the Yangtze River Economic Belt are mainly concentrated in the upper reaches of the Yangtze River and surrounding provinces, showing an unbalanced situation. Forest resources and road density significantly affect their distribution, with forest resources having a more significant impact. County-level studies often use the AHP combined with the Delphi method to evaluate suitability (Chen and Zhang, 2023). Some other researchers have used methods such as the nearest neighbour index, geographic concentration index, and kernel density analysis to further explore the spatial distribution characteristics of forest healthcare resources. Their studies have found that the spatial distribution of forest healthcare bases and oxygen bar resources in Guizhou Province shows the characteristics of “overall dispersion and multi-core aggregation”, which is greatly affected by socioeconomic factors (Qiaoyu, 2023). In addition, some studies have found that the distribution of forest parks has a high degree of overlap with the distribution of water resources while having a low degree of overlap with population density, traffic accessibility, and economic development level, providing an important reference for the optimisation of the spatial layout of forest parks (Yang et al., 2021).

The research advantage of multidisciplinary cross-disciplinary methods is that they can integrate theories and methods from different disciplines, comprehensively analyse problems from multiple perspectives, and enhance the depth and breadth of research (Kinnebrew et al., 2021; Yilmaz, 2021). Especially in complex phenomena, they can more effectively capture the influencing factors at all levels and their interrelationships

(Klimska, 2025; Landers and Marin, 2021). Multidisciplinary approaches can also integrate knowledge and perspectives from different fields, such as environmental, economic, and social factors, to comprehensively assess the sustainability of complex systems and provide more in-depth and comprehensive decision support (Hardy et al., 2021). Notably, the integration of advanced computational methods, particularly artificial intelligence (AI) and deep learning, is increasingly recognised for its potential to enhance predictive modelling and decision-making in complex environmental systems like carbon management (Ran et al., 2024; Chen et al., 2024). Crop diversification has a positive effect on improving agricultural production, biodiversity, and ecosystem services, but different diversification strategies have significant differences in their effectiveness in supporting specific ecosystem services (Brillouin et al., 2021). This paper adopts a multidisciplinary approach, combining remote sensing monitoring, Internet of Things (IoT) data collection, and ecological and economic models to construct a collaborative analysis framework. Compared with the traditional single carbon measurement method, the advantages of this framework are reflected in data dynamics (real-time monitoring of forest carbon sink dynamics and environmental parameters through satellite remote sensing and ground sensors, providing high-precision data support for healthcare function assessment), service collaboration (integration of ecosystem service assessment models and health economics methods to quantify the relationship between carbon sinks, soil and water conservation, biodiversity, and healthcare benefits), and policy adaptability (combining policy text analysis with case evidence to explore the multi-subject benefit distribution mechanism and policy collaboration path of forest healthcare space with the carbon neutrality goal). Innovative AI approaches, including visual question-answering systems and multi-model collaborative frameworks, are emerging to address complex challenges in carbon neutrality planning and anomaly detection, potentially informing more adaptive policy design (Wang et al., 2024). Furthermore, research on the strategic application of AI in environmental leadership highlights its role in translating carbon capture initiatives into tangible economic performance, aligning with the need for sustainable enterprise returns within carbon management frameworks (Xia et al., 2024).

The purpose of this study is to explore improving the comprehensive ecological service function of forest healthcare space by optimising forest management strategies under the background of carbon neutrality. The main contribution is that the ecological service function of forest healthcare space is systematically analysed, providing a theoretical basis and practical guidance for achieving a win-win situation of “carbon sequestration + service”. The innovation is reflected in the construction of a community carbon sink return-sharing mechanism based on horizontal ecological compensation to solve the contradiction of benefit distribution of ‘capital-dominated’ projects.

2 Construction of a collaborative evaluation system for carbon sinks and ecological services

2.1 Multi-source data collection and standardisation

This paper adopts multi-source data fusion technology to integrate satellite remote sensing data, IoT sensor data, and field survey data (Geng et al., 2021; He et al., 2024).

The problem of matching the temporal and spatial resolution between sensor data and satellite remote sensing data is that satellite remote sensing data usually has a large spatial coverage and a fixed time interval, while IoT sensor data can provide higher temporal and spatial resolution. Therefore, in the data fusion process, the temporal and spatial scales of the two need to be adjusted to ensure the comparability and consistency of the data, thereby improving the accuracy of the fusion results. Using Landsat 8 and Sentinel-2 satellite image data, the leaf area index (LAI), normalised difference vegetation index (NDVI), and surface reflectivity of forest vegetation are obtained. These parameters are inverted into forest carbon storage through a random forest regression model (Chen et al., 2022). Specifically, the acquired satellite images are subjected to radiometric correction, atmospheric correction, and geometric correction to eliminate the influence of atmospheric scattering and absorption and ensure data precision. Formula (1) is a formula for radiometric correction (Duan et al., 2021; Di et al., 2021):

$$L_{\lambda} = \frac{\pi \cdot d^2 \cdot (DN \cdot G + B)}{E_{sun,\lambda} \cdot \cos\theta} \quad (1)$$

L_{λ} refers to the surface radiance. DN refers to the original pixel value. G and B refer to the sensor gain and bias parameters. $E_{sun,\lambda}$ refers to the solar irradiance at the top of the atmosphere. d refers to the correction factor for the distance between the sun and the earth. θ refers to the solar zenith angle.

Through image segmentation technology, the texture, shape, and spectral features of forest vegetation are extracted as input variables for carbon storage inversion (Liu et al., 2021; Sakshi and Kukreja, 2023). The random forest regression model is trained using the existing measured carbon storage data, as shown in formula (2):

$$\hat{C} = \frac{1}{N} \sum_{i=1}^N f_i(X_{feature}) \quad (2)$$

$\hat{C}$ refers to the predicted carbon storage. f_i refers to the prediction function of the i th decision tree. $X_{feature}$ refers to the input feature vector.

Table 1 lists the feature weights of carbon storage inversion.

Table 1 evaluates the ecological health and biodiversity of forests through multiple feature parameters. Among them, the weight coefficient of NDVI is 0.38, indicating that it has a high proportion in the evaluation because NDVI directly reflects the coverage and biomass of vegetation, which can better evaluate the growth of vegetation. The weight coefficient of LAI is 0.29, reflecting the density of plant leaves, which is particularly important for understanding the photosynthesis capacity of forests because photosynthesis is the basis of plant growth and energy flow in ecosystems. The weight coefficients of texture entropy and near-infrared reflectivity are 0.18 and 0.15, respectively, which reflect the complexity of forest structure and the moisture content and health status of the canopy, respectively. By combining these parameters and weight coefficients, scientists and decision-makers can have a more comprehensive understanding of the health of forest ecosystems, thereby guiding forest management and protection.

Table 1 Carbon storage inversion feature weights

<i>Feature parameter</i>	<i>Weight coefficient</i>	<i>Physical meaning</i>
NDVI	0.38	It is related to vegetation cover and biomass
LAI	0.29	It reflects photosynthetic capacity through leaf area density
Texture entropy	0.18	It reflects the complexity of forest structure
Near-infrared reflectivity	0.15	It indicates canopy moisture content and health

This paper continues to apply a multivariate regression model to integrate climate factors such as terrain undulation, accumulated temperature, and precipitation as covariates, captures the spatial heterogeneity of carbon storage through feature cross-talk, and improves the inversion accuracy to a 90% confidence interval.

According to the geographical characteristics of the forest healthcare base and the tourist activity area, high-precision sensors are reasonably deployed (Table 2 lists parameters).

In Table 2, the sensor data is transmitted to the cloud server through the low-power wide-area network (LPWAN) technology for real-time analysis and storage (Janssen et al., 2023; Cheimaras et al., 2023). Through the line transect method and the quadrat method, the plant community and animal population in the forest healthcare base are surveyed on the spot to obtain biodiversity indexes.

Table 2 Sensor deployment parameters

<i>Parameter type</i>	<i>Measuring accuracy</i>	<i>Sampling frequency</i>	<i>Coverage radius (m)</i>
Negative ion density	±5%	1 time/min	200
Formaldehyde density	0.1ppb	1 time/5 min	50
Temperature and humidity	±0.5°C, ±3% RH	1 time/s	10

After the sensors are deployed, this paper strictly follows the environmental monitoring sensor calibration specifications for on-site calibration. In actual measurements, the accuracy fluctuation of negative ion density reaches ±8%; the maximum deviation of formaldehyde sensors affected by temperature and humidity is 0.25ppb; the humidity error of temperature and humidity sensors exceeds 5% under canopy shade conditions.

Formula (3) is the Shannon-Wiener diversity index formula:

$$H' = -\sum_{i=1}^S p_i \ln p_i \tag{3}$$

H' refers to the diversity index. p_i refers to the proportion of individuals of the i th species. S refers to the total number of species.

This paper adopts the spatial interpolation technology and data normalisation method of GIS (Raihan, 2024; AlSaggaf and Jrade, 2023) to unify the spatial scale and numerical range of data to achieve effective fusion of multi-source data, as shown in formula (4):

$$\hat{Z}(s_0) = \sum_{i=1}^n \lambda_i Z(s_i) \quad (4)$$

$\hat{Z}(s_0)$ refers to the predicted value of the point to be interpolated, and λ_i refers to the weight coefficient.

Using the GIS overlay analysis function, data from different sources is overlaid to generate a multidimensional spatial data layer. The fused data is imported into My Structured Query Language (MySQL) to build a comprehensive database.

2.2 Collaborative evaluation model of carbon sink and ecological service

This paper uses the InVEST model to evaluate ecosystem services (Kohestani et al., 2024; Zhang et al., 2024). Using the results of high-resolution remote sensing image interpretation, the study area is divided into different land use types and assigned corresponding carbon density parameters (referring to IPCC AR6 Guidelines).

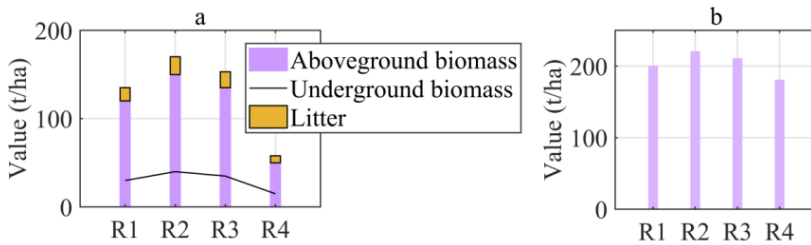
According to different forest types (such as coniferous forests, broad-leaved forests, and mingled forests) and forest age structures, the aboveground biomass, underground biomass, litter, and soil organic carbon density parameters of each type of forest are determined concerning the intergovernmental panel on climate change (IPCC) guidelines and related literature (Legg, 2021; Kikstra et al., 2022).

The InVEST model is based on land use or land cover data and carbon density parameters (in Figure 1) and uses a spatial analysis algorithm to calculate the carbon storage of each grid cell, as shown in formula (5):

$$C_{total} = \sum_{i=1}^n (C_{above,i} + C_{below,i} + C_{litter,i} + C_{soil,i}) \times A_i \quad (5)$$

C_{Total} refers to the total carbon storage. $C_{above,i}$, $C_{below,i}$, $C_{litter,i}$, and $C_{soil,i}$ refer to the aboveground biomass, underground biomass, litter, and soil organic carbon density of the i th category of land. A_i refers to the area of the i th category of land.

Figure 1 Carbon density parameters: (a) aboveground and underground biomass and litter in different forest types and (b) soil organic carbon storage in different forest types (see online version for colours)



In Figure 1, R1–R4 refer to the coniferous forest, broad-leaved forest, mingled forest, and shrubby, respectively. Figure 1(a) and (b) reflect the differences in biomass and

carbon storage among different forest types, revealing the important role of forest ecosystems in carbon cycling and biodiversity.

This paper applies the health economics method to correlate tourists' healthcare experience with health improvement effects to quantify the healthcare benefits of forest healthcare spaces. The regression analysis method is adopted to analyse the relationship between tourists' stay time and the degree of improvement in health indicators and a healthcare benefit evaluation model is established (Ali and Younas, 2021; Bzovsky et al., 2022).

This paper uses the principal component analysis (PCA) method to determine the collaborative weights between carbon sinks, biodiversity, and healthcare functions (Marukat, 2023; Hasan and Abdulazeez, 2021).

The carbon storage, biodiversity index, and healthcare benefit indicators are standardised. The health improvement effect is shown in formula (6):

$$\Delta H = \beta_0 + \beta_1 T + \beta_2 X + \varepsilon \quad (6)$$

ΔH refers to the health improvement index. T refers to the stay time. X refers to the control variable.

Although control variables are used, key confounding factors such as age structure and activity intensity are not explicitly included, and stratified regression may lead to parameter estimation bias due to sample imbalance between groups. Therefore, the standardised data is subjected to PCA to extract the main components and explain the main variation of the data. According to the contribution rate of each principal component, the load coefficients of carbon sinks, biodiversity, and healthcare functions in the main component are calculated as the collaborative weight, as shown in formula (7):

$$\begin{cases} Z_{ij} = \frac{X_{ij} - \mu_j}{\sigma_j} \\ w_j = \frac{\sum_{k=1}^m \lambda_k \cdot |a_{jk}|}{\sum_{j=1}^p \sum_{k=1}^m \lambda_k \cdot |a_{jk}|} \end{cases} \quad (7)$$

Z_{ij} refers to the standardised index. X_{ij} refers to the raw data. μ_j and σ_j refer to the mean and standard deviation of the index, respectively. λ_k refers to the eigenvalue of the k th principal component. a_{jk} refers to the load coefficient of the j th index on the k th principal component.

Table 3 shows the principal component load matrix.

Table 3 Principal component load matrix

<i>Indicator</i>	<i>Principal component 1 (Contribution rate 68%)</i>	<i>Principal component 2 (Contribution rate 22%)</i>
Carbon storage	0.82	-0.15
Biodiversity index	0.78	0.32
Healthcare benefit indicator	0.45	0.85

In Table 3, principal component 1 mainly reflects the carbon storage capacity of the ecosystem, contributing 68% of the variance. On this component, the load of carbon storage is as high as 0.82, indicating that it is the main influencing factor of principal component 1, which highlights the important role of carbon storage in maintaining the ecosystem's stability. The load of the biodiversity index on principal component 1 is 0.78. Although it also has a significant impact, it is slightly less important than carbon storage. On the other hand, principal component 2 may be more related to the healthcare benefits of the ecosystem, contributing 22% of the variance. On this component, the load of the healthcare benefit indicator reaches 0.85, indicating that its changes are mainly related to principal component 2.

A sensitivity analysis of the weight assignment results is conducted, and the impact of different weight combinations on the evaluation results is evaluated, ensuring the rationality of the weights. Experts in ecology, environmental science, and health management are invited to evaluate and adjust the weight assignment results to further improve the scientificity and reliability of the weights.

Carbon storage, biodiversity index, and healthcare benefit indicator are incorporated into the collaborative evaluation index system, and corresponding weights are assigned. The weighted summation method is used to calculate the collaborative evaluation index of carbon sinks and ecological services in each area. A spatial analysis is performed on the collaborative evaluation results to identify areas with higher collaborative effects of carbon sinks and ecological services, providing a scientific basis for the optimised layout and comprehensive management of forest healthcare bases, as shown in Table 4.

Table 4 Collaborative evaluation grading

<i>Collaborative service index (CSI) interval</i>	<i>Level</i>	<i>Management recommendation</i>
0.8–1.0	High coexistence	Prioritise protection and restrict development
0.6–0.8	Medium to high coexistence	Develop healthcare tourism
0.4–0.6	Medium coexistence	Optimise carbon sink forest structure
<0.4	Low coexistence	Initiate ecological remediation or afforestation

Table 4 presents the ecological management recommendations corresponding to different CSI intervals, helping guide the ecological protection and utilisation strategies of the area. In the high-collaboration area with a collaborative index between 0.8 and 1.0, ecological functions such as biodiversity, carbon storage, and healthcare benefits are strong. It is recommended that priority be given to protection and restricted development to maintain the ecosystem's stability and service functions. When the collaborative index is in the medium to high-collaboration area between 0.6 and 0.8, the ecosystem function is still relatively strong, and healthcare tourism can be developed moderately to promote sustainable economic development. In the medium-collaboration area of 0.4–0.6, the ecosystem function is moderate, and the carbon sink forest structure should be optimised to enhance the ecosystem's carbon absorption capacity and biodiversity. In the

low-collaboration area with a collaborative index below 0.4, the ecosystem function is weak, and ecological remediation or artificial afforestation needs to be initiated to restore and enhance the ecosystem's function.

2.3 Spatial planning model to optimise layout of healthcare bases

This paper constructs a multi-objective planning model with the dual objectives of maximising carbon sink efficiency and optimising healthcare suitability to achieve a balance between carbon sink efficiency and healthcare function requirements (Yuvashri and Saraswathi, 2024; Sun et al., 2023; Sharma and Kumar, 2022).

The carbon sink efficiency maximisation uses the carbon storage per unit area as the measurement indicator of carbon sink efficiency, and the objective function is expressed as formula (8):

$$\text{Maximize } Z_1 = \sum_{i=1}^n C_i \times A_i \quad (8)$$

C_i is the carbon storage of the i th area, and n is the total number of areas.

The optimal healthcare suitability takes the healthcare suitability index as the measurement indicator of healthcare function. The objective function is expressed as formula (9):

$$\text{Maximize } Z_2 = \sum_{i=1}^n N_i \times A_i \times F_i \times G_i \quad (9)$$

F_i represents the function of the i th area, and G_i represents the health indicator of the i th area.

Ecologically sensitive areas (soil and water loss sensitive areas and biodiversity hotspots) are set as prohibited development areas to ensure the ecosystem's integrity and stability. The constraint condition is expressed as formula (10):

$$A_i = 0, \text{ for all areas within the ecological red line} \quad (10)$$

According to the ecological environment carrying capacity of each area, an upper limit on the number of tourists is set to avoid damage to the ecological environment caused by excessive development. The constraint condition is expressed as formula (11):

$$\sum_{i=1}^n (T_i \times A_i) \leq T_{max} \quad (11)$$

T_i refers to the tourist density of the i th area, and T_{max} is the upper limit of the total tourist carrying capacity of the study area (person).

Considering the livelihood needs of the local community, an upper limit on the proportion of the forest healthcare base development area is set to ensure that the normal production and life of community residents are not affected. The constraint condition is expressed as formula (12):

$$\frac{\sum_{i=1}^n A_i}{A_{total}} \leq R \quad (12)$$

A_{total} is the total area of the study area, and R is the upper limit of the development area ratio under the constraint of community livelihood needs.

The study area is divided into several planning units, and the land use type of each unit (woodland, land for healthcare facilities, other land, etc.) is used as a decision variable. According to the healthcare suitability of each area, the type and scale of healthcare facilities (healthcare centres, trails, and observation decks) are determined.

The NSGA-II algorithm is used to solve the above multi-objective planning model. The algorithm can effectively handle the conflicts between multiple objective functions and generate a set of Pareto optimal solutions for decision-makers to refer to. A set of initial solutions is randomly generated as the starting point of the evolutionary algorithm. According to the objective function and constraints, the fitness value of each solution is calculated. Excellent individuals are selected through selection operations. New individuals are generated through crossover and mutation operations, and optimisation is gradually iterated. Subsequently, a three-stage optimisation process (sensitivity analysis, dynamic parameter adjustment, and Bayesian calibration) is used to determine the optimal parameter combination of NSGA-II, and its robustness is verified through statistical tests and anti-interference tests to ensure that the algorithm can still stably generate high-quality Pareto solutions when the parameters fluctuate. After multiple generations of evolution, a set of Pareto optimal solutions is finally obtained.

The solution set is mapped into a spatial layout plan containing woodland, healthcare centres, and trail elements. Then, an evaluation index system, including ecological resilience, economic return, and community welfare, is constructed. AHP is used to make multi-criteria decisions on the plan. Finally, the best comprehensive national land space planning plan is selected.

Table 5 lists the NSGA-II algorithm parameter settings.

Table 5 NSGA-II algorithm parameter settings

<i>Parameter name</i>	<i>Parameter value</i>	<i>Description</i>
Population size	100	Number of individuals per generation
Number of iterations	500	Number of evolutionary generations
Crossover probability	0.8	Probability of crossover in individuals
Mutation probability	0.1	Probability of mutation in individuals
Selection pressure	2.0	Tournament selection parameter

Table 5 shows the specific values and corresponding descriptions of the five parameters in detail. The population size is set to 100, which means that 100 individuals participate in the evolution of each generation. Such a scale can provide a diverse solution space and help find a better solution. The number of iterations indicates that the algorithm performs 500 epochs of evolution to gradually approach the optimal solution and ensure the adequacy of the search. The crossover probability means that in each generation, there is an 80% chance of performing individual crossover operations, thereby promoting the recombination of genetic information and increasing population diversity. The mutation probability means that in each generation, 10% of the individuals undergo mutations, and this mechanism can bring new genes. Finally, the selection pressure is 2.0, ensuring that when selecting excellent individuals, solutions with strong adaptability can be effectively retained, thereby improving the overall search efficiency.

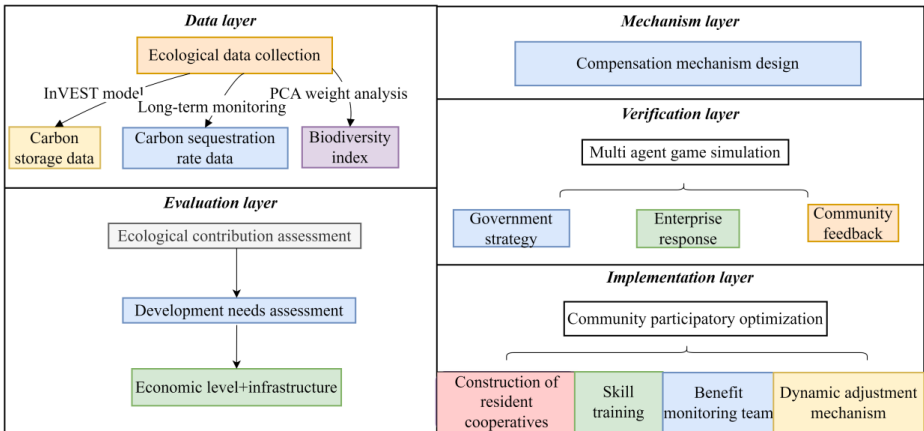
2.4 Community participatory benefit sharing mechanism design

Based on the theory of horizontal ecological compensation, this paper designs a carbon sink return distribution mechanism with ecological contribution as the core to achieve fairness and sustainability in the distribution of benefits in forest healthcare space (Wang et al., 2023; Xi and Jing, 2021). The legal framework of the eco-compensation policy emphasises the clarity of the subjects, including the government as a policy maker and regulator, enterprises as project implementers and operators, and communities as resource guardians and beneficiaries. In terms of rights and obligations, all parties need to clarify their responsibilities and the proportion of benefit distribution to ensure transparency and fairness.

Under the existing carbon trading policy (such as the CCER) framework, the carbon sink benefit distribution mechanism based on ecological contribution may face the problems of inconsistent compensation standards and uneven benefit distribution, which may lead to reduced enthusiasm of ecological protection participants. Therefore, it is recommended to strengthen the measurement and evaluation standards of ecological contribution in policy design to ensure consistency with the CCER benefit calculation method and consider establishing a dynamic adjustment mechanism to adapt to market changes and the evolution of ecological protection goals.

Figure 2 shows the mechanism design.

Figure 2 Mechanism design framework (see online version for colours)



In Figure 2, the carbon sink contribution of each community is evaluated by calculating the carbon storage (t/ha) and carbon sequestration rate (t/ha/year) of the forest area under its jurisdiction. The carbon storage data comes from the InVEST model assessment results, and the carbon sequestration rate is obtained through long-term monitoring data. In addition, the ecological service indicators are comprehensively considered, and the weights of each indicator are determined through PCA to avoid subjective bias.

In the process of benefit distribution, it is also necessary to evaluate the development needs of each community as a reference for the allocation of compensation funds. To verify the effectiveness of the benefit-sharing mechanism, this paper uses MAS to simulate the decision-making behaviour of the government, enterprises, and communities

in the process of benefit distribution. Six communities are randomly selected to implement the mechanism.

In the model, the government, as a policy maker and regulator, aims to maximise ecological benefits and social equity. Enterprises are investors and operators of forest healthcare projects, and their goal is to maximise economic benefits and adjust investment strategies and operating methods according to the government's compensation policy. As the guardian and beneficiary of forest resources, the community aims to maximise its benefits and adjust the protection of forest resources and the enthusiasm for participating in the construction of healthcare projects according to the amount of compensation.

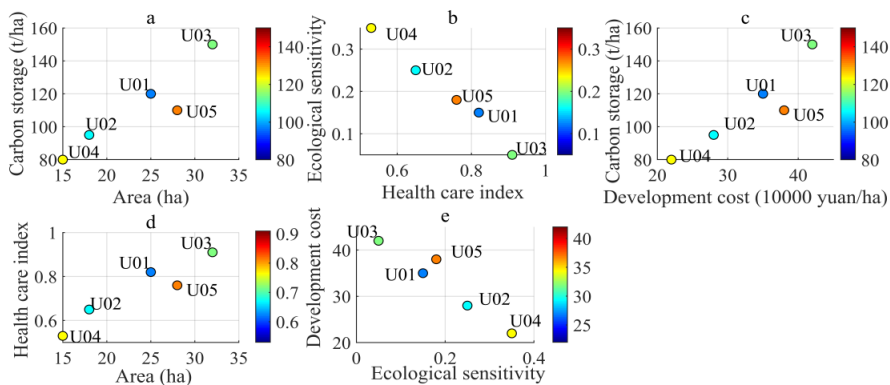
The extended value of the industrial chain includes the direct economic benefits of incorporating forest-derived industries (such as forest medicinal herb planting, eco-tourism supporting services, and nature education curriculum development) and measuring their pulling effects on local employment and farmers' income.

The return function of each subject is set to reach an equilibrium state in multiple rounds of games with continuous adjustment of strategies. In addition, a community resident monitoring group is formed to regularly monitor the ecological, economic, and social benefits of project implementation. A smooth feedback mechanism is also established to collect residents' opinions on project implementation promptly and make improvements based on feedback.

3 Experimental verification and analysis

Figure 3 presents the planning unit attributes from section 2.3.

Figure 3 Planning unit attributes: (a) area vs. carbon storage; (b) healthcare index vs. ecological sensitivity; (c) development cost vs. carbon storage; (d) area vs. healthcare index and (e) ecological sensitivity vs. development cost (10,000 yuan/ha) (see online version for colours)



Ecological sensitivity is graded as 0–0.1 (developable), 0.1–0.3 (restricted development), and > 0.3 (prohibited development). Figure 3 shows the ecological and economic data of five different units to assess their development potential. The data in Figure 3(a)–(e) shows that unit U01 covers an area of 25 hectares, a carbon storage of 120 tons/hectare, a healthcare index of 0.82, an ecological sensitivity of 0.15, and a development cost of

350,000 yuan per hectare. In contrast, the area of unit U02 is smaller, which is 18 hectares, with a carbon storage of 95 tons/hectare, a healthcare index of 0.65, an ecological sensitivity of 0.25, and a development cost of 280,000 yuan/hectare, showing differences in ecological sensitivity and other environmental indicators. Unit U03 has the largest area of 32 hectares, with a high carbon storage of 150 tons/hectare, and has the highest healthcare index of 0.91 and the lowest ecological sensitivity of 0.05. However, it has the highest development cost of 420,000 yuan per hectare, which may reflect the balance between ecological value and development challenges. Unit U04 has the smallest area, only 15 hectares, a carbon storage of 80 tons/hectare, the lowest healthcare index of 0.53, the highest ecological sensitivity of 0.35, and the lowest development cost of 220,000 yuan/hectare. It may have a higher environmental protection value due to its high ecological sensitivity. Finally, unit U05 covers an area of 28 hectares, with a carbon storage of 110 tons/hectare, a healthcare index of 0.76, an ecological sensitivity of 0.18, and a development cost of 380,000 yuan/hectare. The rich data makes it a medium choice for multiple considerations.

Figure 4 presents the spatial planning plan generated in Section 2.3.

Figure 4 Spatial planning plan (see online version for colours)

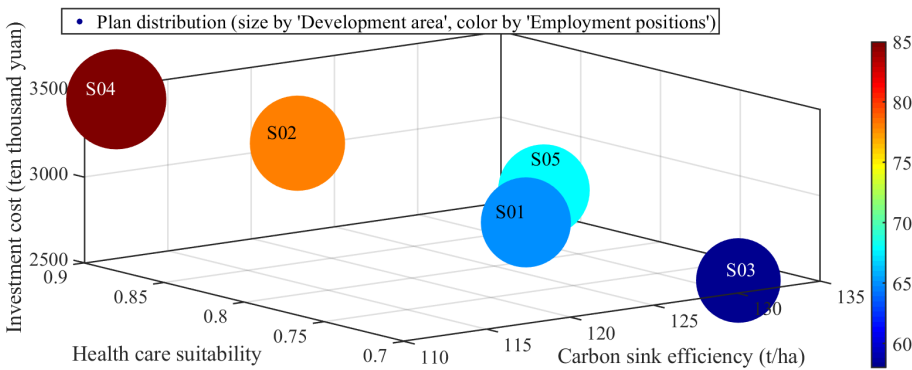


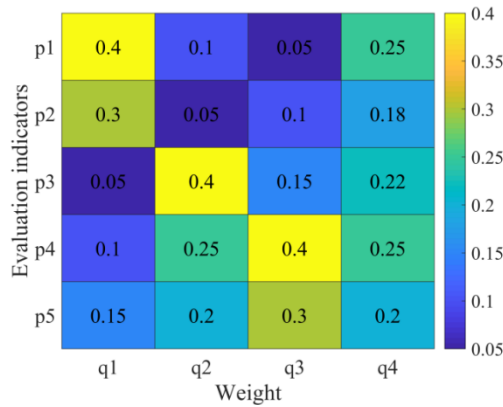
Figure 4 shows the carbon sink efficiency and sustainable development potential of five different plans. Plan S01 has a carbon sink efficiency of 125 tons/hectare, a healthcare suitability of 0.78, a development area of 85 hectares, and an investment cost of 28 million yuan. It is expected to create 65 employment positions. In contrast, although plan S02 has a slightly larger development area of 95 hectares, its carbon sink efficiency is slightly lower than S01, at 118 tons/hectare. It has a higher healthcare suitability of 0.85 and an investment cost of 32 million yuan, and it is expected to create 78 employment positions, showing advantages in environmental adaptability and employment position creation. Plan S03 has the highest carbon sink efficiency, reaching 132 tons/hectare, but has a lower healthcare suitability of 0.72. It has a development area of 75 hectares and the lowest investment cost of 25 million yuan. It is expected to create 58 employment positions, which may be economically attractive due to its low required investment. Plan S04 has the largest development area of 105 hectares. Its carbon sink efficiency is 110 tons/hectare, and it has the highest healthcare suitability of 0.88. However, it is also the most expensive plan, with an investment cost of 35 million yuan and an estimated creation of 85 employment positions, reflecting its balance between

ecological adaptability and social benefits. Finally, plan S05 has a carbon sink efficiency of 128 tons/hectare, a healthcare suitability of 0.80, a development area of 88 hectares, an investment cost of 29 million yuan, and an estimated creation of 68 employment positions. It is an option that strikes a good balance between carbon storage, ecological adaptability, and economic input.

For S01, if a 3-year restoration period + 5-year phased development model is adopted, its carbon sequestration efficiency may increase by 15–20%, while a one-time development may result in a carbon sequestration loss of 30% in the first 3 years.

Figure 5 presents the AHP evaluation weights of plan S05.

Figure 5 AHP evaluation weights (see online version for colours)



In Figure 5, p1–p5 refer to carbon storage change, biodiversity, healthcare income, employment opportunities, and community satisfaction, respectively. q1–q4 refer to ecological weight, economic weight, social weight, and comprehensive weight, respectively. Carbon storage change has the highest weight in ecology (0.4), indicating that ecological protection is valued. However, the economic and social weights are lower, with a comprehensive weight of 0.25, which is a moderate influence. Biodiversity also has a high weight in ecology (0.3) but is less important in economy and society, with a comprehensive weight of 0.18, reflecting its relatively low importance in the comprehensive evaluation. Healthcare income has the highest weight in the economy (0.4). Its weight is 0.15 in society. The comprehensive weight is 0.22, showing a dual role. Employment opportunities have the highest weight in society (0.4). Its weight is 0.25 in economy. The comprehensive weight of 0.25, showing importance. Community satisfaction has a high weight in society (0.3), with a comprehensive weight of 0.2, indicating medium importance.

Table 6 lists the implementation paths of the optimal plan.

In Table 6, the project is divided into five phases. From Phase 1 to Phase 5, each has a specific time node, main tasks, investment budget, and expected benefits. First, in the first phase of 1–2 years, 15 million yuan is invested in the construction of the core healthcare area, which is expected to increase carbon sink by 15% and create 40 employment opportunities. Next is the second phase of 3–4 years, with 8 million yuan focusing on the restoration of ecological corridors to increase biodiversity by 20%. In the third phase, within 5–6 years, 12 million yuan will be invested in improving community supporting facilities, hoping to increase community income by 30%. Then, in the fourth

phase, within 7–8 years, 5 million yuan is invested to build a smart management system, which is expected to improve management efficiency by 40%. Finally, in the fifth phase, in 9–10 years, a budget of 10 million yuan is used for brand promotion and industrial chain extension, to increase the number of tourists by 50%. These phased plans and investment budgets are set to promote ecological construction, economic development, and sustainable development of the community.

Table 6 Optimal plan implementation paths

<i>Implementation phase</i>	<i>Time</i>	<i>Main task</i>	<i>Investment budget (Ten thousand yuan)</i>	<i>Expected benefits</i>
Phase 1	1–2 years	Core healthcare area construction	1500	Carbon sink + 15%, 40 new employment opportunities
Phase 2	3–4 years	Ecological corridor restoration	800	Biodiversity + 20%
Phase 3	5–6 years	Community infrastructure completion	1200	Community income + 30%
Phase 4	7–8 years	Smart management system construction	500	Management efficiency + 40%
Phase 5	9–10 years	Brand promotion and industrial chain extension	1000	Tourist volume + 50%

Figure 6 presents the changes after selecting communities and implementing the mechanism in Section 2.4.

Figure 6 shows the key indicator data of six communities (the selection process of these six communities is carried out based on comprehensive consideration of ecology, economy, social participation, and policy background to ensure that the benefit distribution mechanism can effectively reflect the operation effect of ecological contribution) in the forest healthcare project, directly reflecting the operation effect of the benefit distribution mechanism based on ecological contribution in this paper. In Figure 6(a)–(e), from the perspective of carbon storage, the highest value of 203.1t/ha in Lantian Community S3 corresponds to an ecological service contribution of 0.91 and an ecological benefit growth of 18.9%, confirming the positive correlation between carbon storage and ecological benefits. Although Baiyun Community S4 has the lowest carbon storage (67.5t/ha), it receives a preference for compensation policies due to its development demand index of 0.83, with a compensation amount of 248,000 yuan/year, reflecting the support of the mechanism for lagging communities. S2 represents Lvshui Community. Qingshan Community S1 and Hongye Community S5 achieve 15.2% and 12.6% ecological benefits improvement, respectively, with high carbon storage (152.4t/ha and 118.9t/ha) and ecological contribution (0.87 and 0.81). Meanwhile, the enterprise investment return rates reach 12.5% and 11%, and resident satisfaction exceeds 80%, verifying the collaborative effect of ecological protection and economic development. Huangshi Community S6 presents a typical case of contradiction: although the development demand index is the highest (0.89), the ecological contribution is only 0.63, resulting in the compensation amount (293,000 yuan) and the ecological benefit increase (+5.9%) being in the middle and lower reaches, highlighting the limitations of

only economic compensation. The overall data shows that the implementation of the mechanism can effectively balance the benefits of all parties and provide a quantitative basis for community participatory governance.

Figure 6 Changes in communities after implementing the mechanism: (a) carbon storage; (b) ecological service contribution; (c) development demand index; (d) enterprise investment return rate and resident satisfaction and (e) relationship between ecological benefit change rate and compensation amount (see online version for colours)

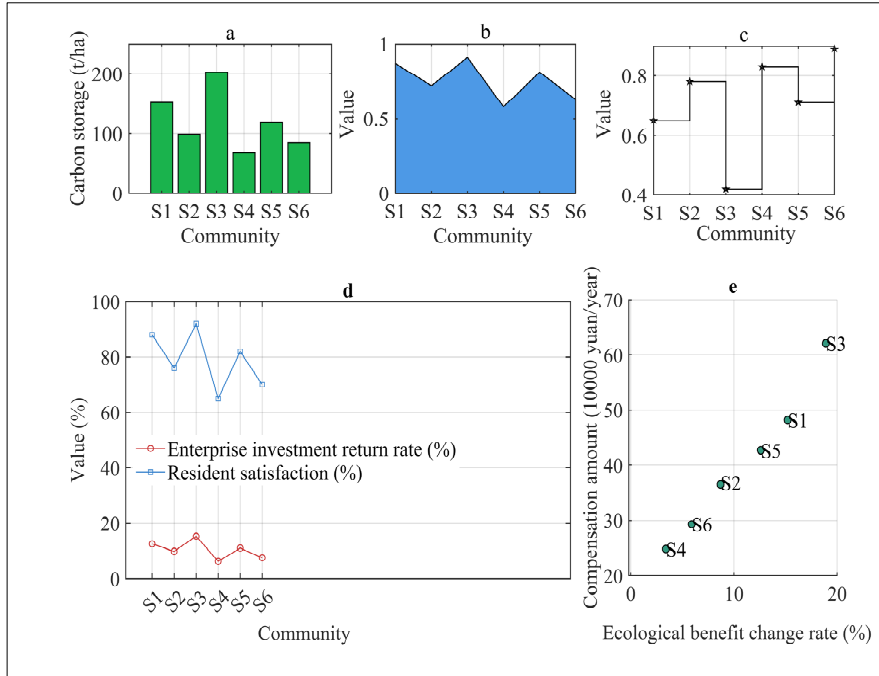
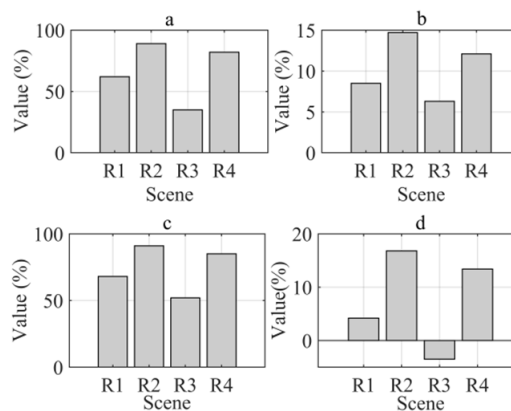


Figure 7 compares scenario simulations based on the MAS model

Figure 7 Comparison of scenario simulations based on the MAS model: (a) government ecological goal achievement rate (%); (b) average enterprise return rate (%); (c) average community satisfaction (%) and (d) annual carbon sink growth rate (%)



In Figure 7, R1–R4 refer to the baseline scenario, scenario 1 (high compensation), scenario 2 (overdevelopment), and scenario 3 (equilibrium mechanism), respectively. Figure 7(a)–(d) show that in the baseline scenario, the government ecological goal achievement rate is 62%, and the annual carbon sink growth rate is 4.2%. This shows that although the original mechanism can maintain basic operation, the enterprise return rate of 8.5% and the community satisfaction of 68% are not ideal. In scenario 1, the compensation standard is increased to make the ecological goal achievement rate soar to 89%, and the annual carbon sink growth rate reaches 16.8%. Meanwhile, the enterprise return rate of 14.7% and the community satisfaction of 91% reached a peak, but it may face financial pressure in the long term. In sharp contrast, in scenario 2, overdevelopment causes the enterprise return rate to drop sharply to 6.3% in the third year. The carbon sink has a negative growth of 3.5%, and community satisfaction is only 52%, verifying the unsustainability of short-sighted development. The most valuable reference is the equilibrium mechanism in scenario 3. Based on the high ecological benefits of 82% government ecological goal achievement rate and 13.4% annual carbon sink growth rate, the enterprise return rate of 12.1% and the community satisfaction of 85% are still maintained. For example, with this mechanism, the ecological benefits of the Hongye Community increase by 12.6%, and resident satisfaction reaches 82%, indicating that by dynamically adjusting the compensation policy and optimising the investment intensity and community participation, a triple-win situation of government supervision, enterprise profits, and community welfare can be achieved, providing empirical evidence for the sustainable development of forest healthcare space.

4 Conclusion

This paper constructs a collaborative evaluation system for carbon sinks and ecological service functions through multi-source data fusion and transforms its core indicators (spatial distribution of carbon storage and incremental potential of carbon sinks) into multi-objective functions and constraints of the spatial planning model, forming a quantitative bridge of ‘evaluation-optimisation’. An innovative two-layer spatial optimisation model that couples carbon sink efficiency grading and healthcare suitability analysis is proposed, and a multi-scenario constraint algorithm is used to generate differentiated layout plans. In the policy verification phase, the agent-based modelling is combined to simulate the behaviour strategies of different subjects and a participatory scenario workshop is designed to visualise the community benefit game. Although a data-driven planning paradigm is established in this paper, the model parameters still rely on expert experience calibration, and dynamic adaptability needs to be improved through long-term monitoring.

Conflicts of Interest

All authors declare that they have no conflicts of interest.

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