

Forest Assessment and Management Model Based on Carbon Sequestration

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Abstract. Proper forest management activities can sustainably increase forest carbon stocks to mitigate the effects of climate change. In this paper, we combine CBM-CFS3 model to calculate the amount of carbon sequestration and build a forest valuation model, and integrate various factors to obtain the way to maximize the amount of forest value per unit area. At the same time, this paper analyzes the global macroscopic distribution of forest value in the context of forests with typical characteristics and derives a solution for maximizing forest value under the planning of this model in the context of Jiangxi Forest. The model fully considers the ecological, social and economic values of forests to maximize the benefits of forests while sequestering carbon.

Keywords: Carbon Sequestration, Sustainability, Forest Values, Maximum Benefits

1. Introduction

The Earth's climate system is undergoing a remarkable change characterized by global warming. In order to mitigate the effects of climate change, it is not enough to reduce greenhouse gas emissions, but also to increase the amount of carbon dioxide storage sequestered from the atmosphere by biospheric or mechanical means, i.e. carbon sequestration. Therefore, forests are significant for mitigating climate change [1].

In the long run, reasonable forest management activities can sustainably increase forest carbon stocks. However, in addition to carbon sequestration, forest ecosystems have other multiple functions such as economic, social, and environmental functions. It is complex to reconcile the carbon sink potential of forests with multiple other functions, etc. In this paper, we develop a carbon sequestration model to discuss the carbon stock of forests, and a decision model to determine the appropriate forest use and forest management plan by considering the multiple values of forests from the perspective of society.

2. Forest management model based on the amount of carbon sequestered

2.1. Forest carbon sequestration model

2.1.1 CBM-CFS3 model

For the calculation of total carbon sequestration in the forest at a given time, we use the CBM-CFS3 model, which includes changes in the above-ground and below-ground carbon pools in the simulation, and divides the carbon pool into the biomass organic matter (BOM) and dead organic matter (DOM) pools in general. Its specific structure is shown in Figure 1 [2-3].

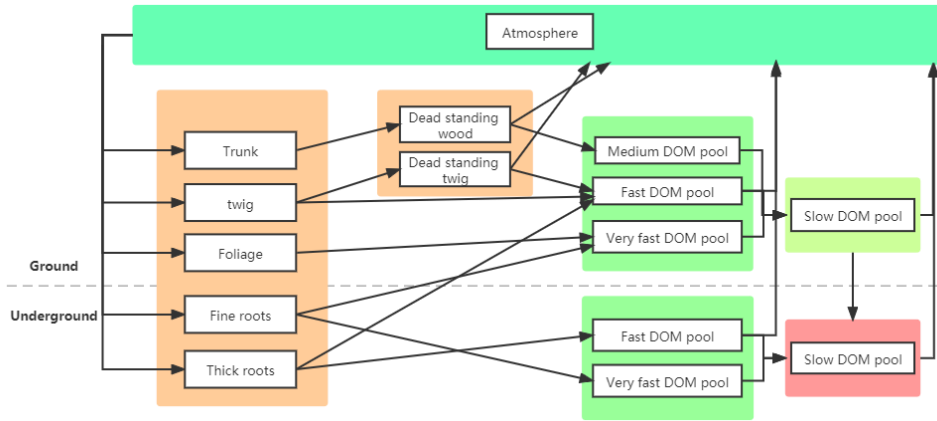


Figure 1. Carbon pool composition and carbon turnover diagram

According to the way the model was constructed [2], it was derived that a given biomass in the model:

$$\Delta BIO_i = gimi - diBIO_i - biBIO_i + biBIO_i \quad (1)$$

where BIO_i is the total biomass carbon of this carbon pool; gi is the net increase in growth; mi is the correction parameter for growth increase; di is the proportion of loss of this carbon pool due to disturbance; bi is the rate of biomass turnover from this pool to the DOM pool; $+biBIO_i$ is the biomass regrowth turnover.

For a given DOM carbon library, the model gives:

$$\Delta DOM_i = \sum_{j=1}^n djiS_j + \sum_{j=1}^n bjiS_j + \sum_{k=1}^q a_k Ptki_{DOMk} - a_k DOM_i \quad (2)$$

where DOM_i is the total dead organic matter carbon in that carbon pool; dji is the fraction of the carbon pool affected by various disturbances; S_j is the total carbon in pool j ; bji is the turnover rate from pool j to pool i in the biomass carbon pool or DOM carbon pool; a_k is the decomposition rate of pool k in the DOM pool; $Ptki$ is the proportion of decomposition in pool k to pool i in the DOM; $DOMk$ is the total storage volume of pool k size; n is the total number of carbon pools; q is the number of DOM pools.

The total amount of carbon in the simulated area is calculated in the model as:

$$\Delta ECO = \sum_{j=1}^q \Delta DOM_j + \sum_{j=1}^r \Delta BIO_j \quad (3)$$

In this model, we use $0.5gC/g$ as the carbon content rate to convert biomass into carbon stock by default, and each carbon pool stock is calculated using the annual growth minus loss method.

2.1.2 Biomass-accumulation conversion parameters

We first used the stand stock to find the trunk biomass, which was calculated as follows [3]:

$$B_S = a_s \times vol^{b_s} \quad (4)$$

where vol is the standing volume of live trees in the stand; B_S is the total trunk biomass of live trees in the stand; a_s, b_s are nonlinear model parameters.

And, we determine the trunk, bark, branch, and leaf percentage of trees according to the statistical law formula to further refine the parameter values and give the calculation formula as follows.

$$P = \frac{\alpha}{1 + e^{a_1 + a_2 \times vol + a_3 \times lvol} + e^{b_1 + b_2 \times vol + b_3 \times lvol} + e^{c_1 + c_2 \times vol + c_3 \times lvol}} \quad (5)$$

where α is the statistical amount of trunk, bark, branches, and leaves on the tree; vol is the volume of live wood storage in the stand; $lvol$ is the natural logarithm of $(vol + 5)$.

Based on the proportion of different parts and the trunk biomass, we can further obtain the biomass relationships of different parts of the tree to find a more refined biomass to accumulation conversion parameter.

2.2. Forest Assessment and Management Model

2.2.1 Model Evaluation Metrics

Before model building, we need to establish an objective index system for evaluating the value of forest ecosystem service functions. In this paper, we summarize the existing results and establishes the index system shown in Figure 2 based on the quadratic approach proposed by Millennium Ecosystem Assessment for ecosystem service functions [4].

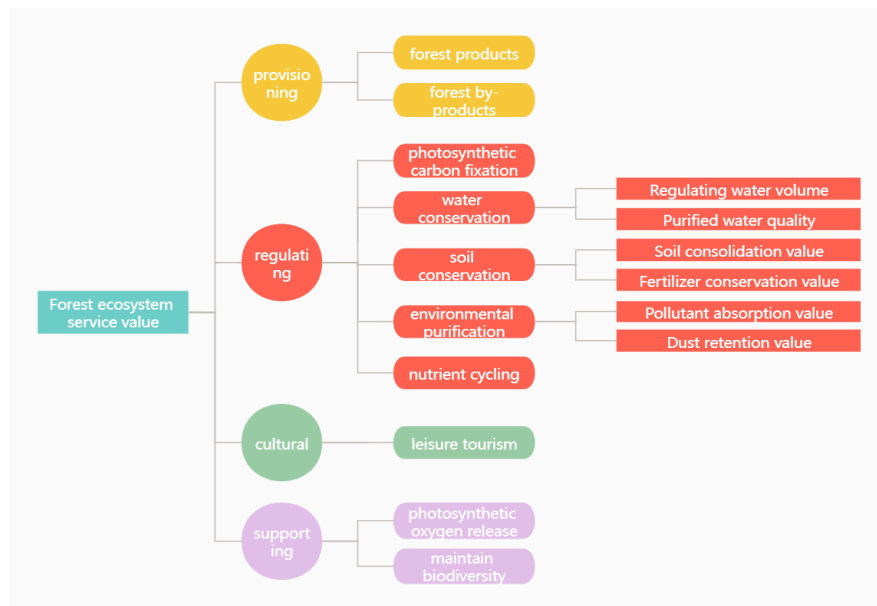


Figure 2. Forest ecosystem service function indicator system

Based on the idea of the standard unit ecosystem ecosystem service value equivalent factor [5-6], we propose the unit area value equivalent of forest assessment indicators. We know that deforestation can directly increase forest products and increase the value of this type of use, but other values of the forest are temporarily and directly lost, i.e., the existence of forest products indicators and the remaining nine indicators are in direct opposition to each other. The sum of the average annual value equivalent per unit area for the remaining nine indicators V_9 is:

$$V_9 = V_2 + U_c + (U_m + U_{wq}) + (U_{sm} + U_f) + (U_p + U_{dc}) + U_n + V_3 + U_0 + U_s \quad (6)$$

where, V_2 indicates the value of forest products per unit area; U_c indicates the amount of fixed carbon per unit forest area per year; $U_m + U_{wq}$ indicates the value of water resources per unit area of forest per year; $U_{sm} + U_f$ indicates the value of land resources per unit area of forest per year; $U_p + U_{dc}$ indicates the value of environmental resources per unit area of forest per year; U_n indicates the amount of nutrients accumulated per year; V_3 indicates the value of recreation and tourism; U_0 indicates the value of oxygen release per unit area of forest per year; U_s indicates the value of conservation of forest species per unit area per year.

2.2.2 Establishment of basic management model

As a forest manager, you decide to cut down $n\%$ of the mature trees in a forest of area S_0 every M years, and immediately after cutting down the trees, you plant saplings. It is assumed that the saplings planted in the forest will take an average of X years to mature into wood. In this way we can obtain a multi-objective linear programming management model.

1)When $M \geq X$,

$$V_0 = \frac{n\% \cdot S_0 V_1 + (1-n\%) \cdot S_0 V_9 X + S_0 V_9 (M-X) + n\% \cdot S_0 C X}{M} \quad (7)$$

2) When $M < X$,

$$\begin{cases} \left\lfloor \frac{X}{M} \right\rfloor \cdot n\% \leq 1 \\ V_0 = \frac{\left\lfloor \frac{X}{M} \right\rfloor n\% \cdot S_0 V_1 + \sum_{i=1}^{\left\lfloor \frac{X}{M} \right\rfloor} (1-in\%) \cdot S_0 V_9 M + \sum_{i=1}^{\left\lfloor \frac{X}{M} \right\rfloor} n\% \cdot S_0 C (iM)}{\left\lfloor \frac{X}{M} \right\rfloor \cdot M} \end{cases} \quad (8)$$

Using the maximum judgment method, i.e., by finding $MAX(V_0)$, the optimal cutting time M and the $n\%$ of the cutting area-optimal management model are thus obtained.

2.2.3 Decision model hierarchy

The decision problem is decomposed into three layers, the top layer is the target layer T , which is the key decision indicators to determine the best use of the forest; the bottom layer is the program layer P , which is the ten evaluation indicators $P_1, P_2, P_3, P_4, P_5, P_6, P_7, P_8, P_9, P_{10}$; the middle layer is the criterion layer C , including the provision of products C_1 , regulation function C_2 , cultural function C_3 , life support C_4 four indicators. The detailed structure is shown in Figure 3.

Target Layer T

Criterion Layer C

Program Layer P

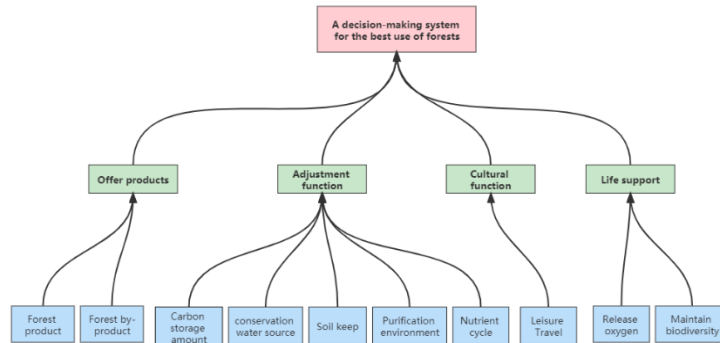


Figure 3. Analytic hierarchy process diagram

2.2.4 Program Evaluation Indicator Matrix

Let the decision domain $U = \{u_1, u_2, \dots, u_m\}$ be the set of forest use options and $P = \{p_1, p_2, \dots, p_{10}\}$ be the set of evaluation indicators. Then the pairs of elements in any pairing of U and P form a Cartesian product set about 10 decision alternatives. Denoting the element pair (u_i, p_j) as f_{ij} , the number of element pairs of $m \times 10$ constitutes the matrix of evaluation indicators for the decision scheme as follows [6].

$$F = (f_{ij})_{m \times 10} \quad (9)$$

2.2.5 Gray correlation of the decision scheme

According to the theory of gray correlation decision making, the correlation between the evaluation scheme indicator vector and the relative optimal scheme indicator vector is used as a criterion to evaluate the merits of the scheme [7].

Let the relatively optimal solution be $u_0 = (f_{01}, f_{02}, \dots, f_{010})$. Then, after normalization, we have

$u_0 = (1, 1, \dots, 1)$. The gray correlation between the evaluation index p_j of design solution u_i and the evaluation index p_j of the relatively optimal solution u_0 is:

$$\gamma_{ij} = \frac{\varepsilon \max_i \max_j |f_{ij} - 1|}{|f_{ij} - 1| + \varepsilon \max_i \max_j |f_{ij} - 1|} \quad (10)$$

where, $\varepsilon \in (0, 1)$ is the resolution factor, which is generally taken as 0.5; $i = 1, 2, \dots, m; j = 1, 2, \dots, 10$.

2.2.6 Decision optimization matrix model

From the above analysis, the gray correlation matrix of the multi-objective decision for the $m \times 10$ forest use options is [6]:

$$\gamma = \begin{bmatrix} \gamma_{1,1} & \gamma_{1,2} & \cdots & \gamma_{1,10} \\ \gamma_{2,1} & \gamma_{2,2} & \cdots & \gamma_{2,10} \\ \vdots & \vdots & \vdots & \vdots \\ \gamma_{m,1} & \gamma_{m,2} & \cdots & \gamma_{m,10} \end{bmatrix} = (\gamma_{ij})_{m \times 10} \quad (11)$$

The weight vector of the 10 evaluation indicators with respect to the total objective is W , then the association vector r consisting of the weighted correlations of each design option u_i with the relative optimal utilization method u_0 is:

$$\gamma' = \gamma W = (\gamma_1, \gamma_2, \dots, \gamma_i, \dots, \gamma_m) \quad (12)$$

where, $\gamma_i = \sum_j^n \gamma_{ij} w_j; i = 1, 2, \dots, m$.

According to the physical meaning of Eq. (12), the larger γ_i , the closer the forest use pattern is to the relative optimal use pattern u_0 . Therefore, when $\gamma_i = \max(\gamma_1, \gamma_2, \dots, \gamma_i, \dots, \gamma_m)$, scheme u_i is the optimal decision scheme.

3. Results

3.1. Decomposition rate and turnover rate parameter setting

In the process of simulating the forest carbon cycle, we set the decomposition rate parameters as shown in Table.1 by combining the biomass carbon pools and DOM carbon pools of different ages, states and species of the corresponding trees.

Table 1. Turnover rate settings in the CBM-CFS3 model

Biomass bank	Turnaround rate(%Cy)
Trunk	0.45-0.67
Twig	3-4
Leaf	45
Fine roots	64.1
Thick roots	2

Except for setting the decomposition rate, the parameters of natural disturbance and management measures and the turnover rate of different carbon pools were set in an optimal way, i.e., the forest was not subject to any external influence during the simulation interval [2].

3.2. AHP method to determine weights

By combining the AHP method with the previously assessed values of each index, we obtained the weighting table, the details of which are shown in Table.2.

Table 2. A decision-making system for the best of forests

Subsystem	Indicator	Weights
Offer products	Forest product	0.126
	Forest by-product	0.112
	Carbon storage amount	0.146
	Conservation water source	0.113
Adjustment function	Soil Keep	0.062
	Purification environment	0.072
	Nutrient cycle	0.057
Cultural function	Leisure travel	0.093
Life support	Release oxygen	0.105
	Maintain biodiversity	0.094

3.3. Analysis of forest value volume

Based on the above model, the value equivalents per unit area of the ten assessment indicators of all forests were clustered and calculated to obtain Figure 4. The value equivalents per unit area of the ten assessment indicators were ranked as follows: carbon sequestration, forest products, forest by-products, water conservation, oxygen release, biodiversity maintenance, recreation and tourism, environmental purification, soil conservation, and nutrient cycling.

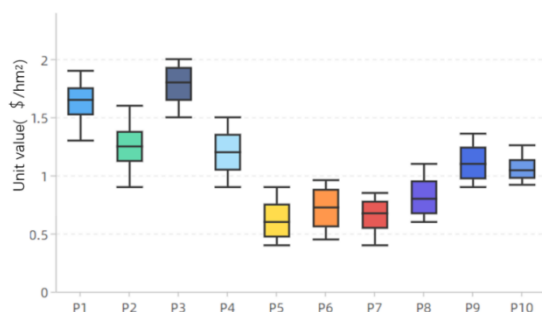


Figure 4. Ten indicators unit area value volume

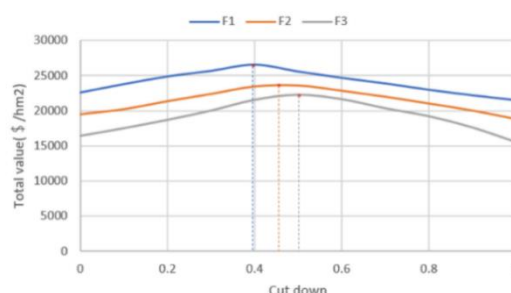


Figure 5. Location feature value volume

At the same time, based on the geographic location and forest distribution, we selected three locations as the forest samples to find the transition point: Virgin Lomi Forest, Changbai Mountain Forest, and Amazon Jungle, which are typical coniferous forest, mixed deciduous and coniferous forest, and evergreen broad-leaved forest, respectively. These three forests represent the characteristics of forests in different locations, and we can determine the transition points by these three forest model characteristics [8]. From Figure 5, we can see that the lower the latitude, the higher the average total value of the forest, while its transition point has a smaller deforestation value than the higher latitude, and vice versa for the higher latitude.

3.4. Model Example Analysis

We used Jiangxi Forest as an example [9] and brought it into our established model for analysis. According to the carbon sequestration model, the total amount of carbon sequestered in Jiangxi forest was simulated using three different rotation periods [1] of 15, 25, and 50 years, and in the 150-year simulation, we obtained that the total biomass carbon using the short rotation harvesting method was 0.97 times higher than that of the normal rotation and 1.52 times higher than that of the long rotation, respectively. We analyzed that the average maturity period of trees in Jiangxi Forest is 20 years, and the optimal harvesting period is 25 years (Figure 6), when the maximum carbon sequestration accumulation can be obtained.

In addition, we further combined the decision model to explore the quantitative relationship between deforestation and total forest ecosystem values, and obtained Figure 7.

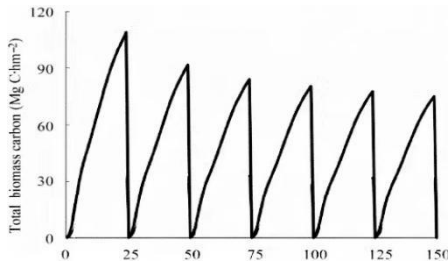


Figure 6. Carbon sequestration during 25 years

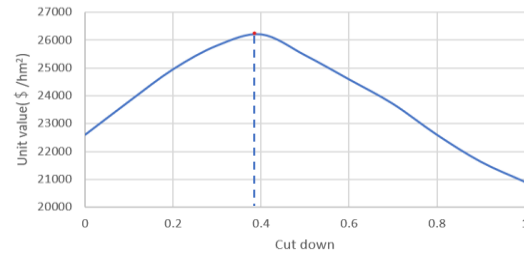


Figure 7. Jiangxi Forest unit area value

According to the assessment management model, our management scheme is that the Jiangxi forest should be specified to be cut for a period of 25 years and the cutting volume should be 38% of the forest trees. After that, we use the decision optimization matrix model to verify that the final γ value obtained from this kind of decision is the maximum value in γ_i and it is verified that this scheme is the optimal decision scheme under the current model [10].

4. Discussion

Since the forest assessment and management model is a multi-objective linear programming model, the determinants of the ten assessment indicators we are determined in the model, but the coefficients in their determinants will also change accordingly with changes in the market and technology, and eventually lead to changes in the optimal solution of the model.

Here, we mainly select one of the more volatile coefficients for sensitivity analysis [5], and we select the practical price of wood as the object of analysis by consulting authoritative data, assuming that the determined price is P_0 and the subsequent market price is P . We define a new quantity: the rate of price change $\gamma = \frac{P-P_0}{P_0}$.

With the multi-objective linear programming model, the optimal cutting time M and the optimal cutting volume can be obtained simultaneously, and since they are equivalent here, we analyze the stability of the model only through the relationship between M and γ . We observe the change in the mean absolute percentage error MAPE of M by changing the value of γ . After our data analysis, the γ -MAPE relationship is obtained as shown in Table.3.

Table 3. The mean absolute percentage error

MAPE (%)	Forecasting ability
<10	High ability
10-20	Good ability
20-50	Reasonable ability
>50	Weak ability

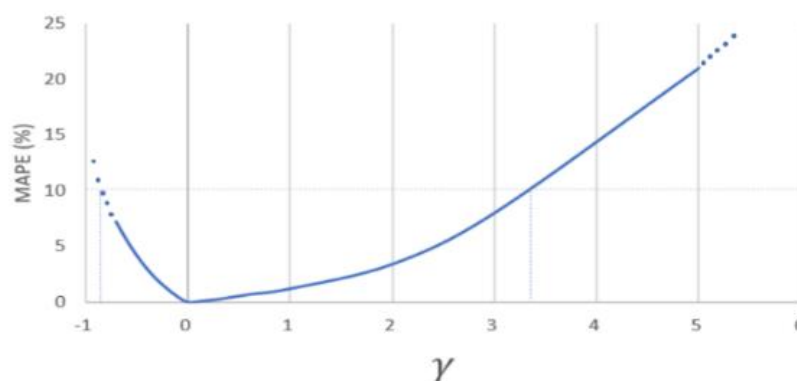


Figure 8. γ -MAPE relationship diagram

Analyzing Figure 8, we can see that the MAPE values are below 10% for γ values in the $(-0.86, 3.37)$ interval, and there are a large number of other regions where the MAPE values are below 20%. According to the MAPE table, our model has high stability when the γ value is in a certain region. Combined with the characteristics of the market price P , its fluctuation range will always be within the optimal range for the model. Therefore, the stability of our model is very high.

5. Conclusion

This paper adopts the CBM-CFS3 model to establish the correlation between several factors and the amount of carbon sequestration. And based on this, a forest management decision model is constructed, and other social values as well as ecological values of forest ecosystems are fully considered, and ten indicators are selected using the quadratic method to establish an assessment system. Then this paper uses hierarchical analysis to establish a matrix optimization model, while improving the basic management model based on the gray correlation model, and analyzing the correlation between indicators to more objectively determine the weights between indicators, so as to establish a more appropriate forest management plan.

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