

Decision Analysis of Forest Management Based on Carbon Sequestration Model

Chenyi Yang *

Department of Finance, Renmin University of China, Beijing, China

*Corresponding author: yangchenyi@ruc.edu.cn

Abstract. This paper to determine how much carbon dioxide a forest and its products can be expected to sequester over time, building a CASA model to calculate Net Primary Productivity (NPP) of the forest and transfer NPP to carbon sink. Then prove that harvest trees because young forests have stronger carbon sequestration capacity than old forests. Finally, determine that the most effective forest management plan at sequestering carbon dioxide is to harvest old trees and plant new trees at the optimal time provided by model.

Keywords: CASA, Net Primary Productivity, Carbon Sequestration, Forest Management.

1. Introduction

Climate change caused by the rising level of carbon dioxide presents a massive threat to life [1]. So developing technologies to reduce the rate of increase of atmospheric concentration of carbon dioxide (CO₂) from energy, process industry, land-use conversion and soil cultivation is an important issue of the twenty-first century [2]. Of the three options of reducing the global energy use, carbon sequestration implies transfer of atmospheric CO₂ into other long-lived global pools including oceanic, pedologic, biotic and geological strata [3]. Forests sequester carbon dioxide in living plants and in the products created from their trees including furniture, lumber, plywood, paper and so on [4-5]. On the one hand, making trees into products can provide space for regrowth of younger forests and allow for more carbon sequestration over time when compared to the carbon sequestration benefits of not cutting forests at all; on the other hand, it can replace environmentally harmful materials and energy sources, such as fossil fuels [6].

In order to develop guidance for forest managers around the world trying to figure out how to utilize and manage their forests, internally we need to consider many factors such as age and types of trees, geography, topography and so on; externally we need to prove our management plan is the best use of a forest [7-8]. Based on the background information and existing constraints, we develop a carbon sequestration model, which can determine the most effective forest management plan at sequestering carbon dioxide, to calculate the amount of carbon dioxide a forest and its products can be expected to sequester over time [9-10]. Especially, we figure out characteristics and location about a specific forest which determine transition points between management plans that apply to all forests.

2. Carbon sequestration model

2.1 The calculation of NPP based on CASA model

2.1.1 The calculation of light energy utilization rate

- 1 The limitation of vegetation under low temperature and high temperature $F_e(x, t)$

$$F_e(x, t) = 0.8 + 0.02 \times T_{opt}(x) - 0.005 \times [T_{opt}(x)]^2 \quad (1)$$

where $T_{opt}(x)$ represents the optimum temperature for the growth of pixel x in the year, and:

$$F_e(x, t) = 0, \text{ if } T_{opt}(x) \leq -10 \quad (2)$$

- 2 The ambient temperature for the vegetation $T_e(x, t)$

$$T_e(x, t) = \frac{1.184}{1 + e^{0.2 \times (T_{opt}(x) - 10 - T(x,t))}} \times \frac{1}{1 + e^{0.3 \times (T(x,t) - T_{opt}(x) - 10)}} \quad (3)$$

When $T(x, t)$ is 10 degrees Celsius higher or 13 degrees lower than the optimum temperature, $F_e(x, t)$ is equal to half of $T_e(x, t)$ on the condition of the optimum temperature $T_{opt}(x)$ [5].

Influence of moisture conditions on utilization of light energy $W_e(x, t)$

$$W_e(x, t) = 0.5 + 0.5 \times \frac{EET(x,t)}{PET(x,t)} \quad (4)$$

where $W(x, t)$ represents the water stress factor of pixel x in month t ; $EET(x, t)$ represents the actual evaporation of pixel x in month t , which is calculated by Regional Evapotranspiration Estimation Model (REEM); $PET(x, t)$ represents the potential evapotranspiration of pixel x in year t , calculated by Thornthwaite Vegetation Climate Relationship Model [6].

2.1.2 The calculation of absorbed photosynthetic active radiation

- 1 Total annual astronomical radiation SOL_0

SOL_0 can be calculated by the following formula:

$$SOL_0 = \frac{24}{2\pi} E_{sc} \left(\frac{r_0}{r}\right)^2 \left[u \sin \delta \sum_{i=1}^n (\omega_{si} - \omega_{ri}) v \cos \delta \sum_{i=1}^n (\omega_{si} - \omega_{ri}) - w \cos \delta \sum_{i=1}^n (\cos \omega_{si} - \sin \omega_{ri}) \right] \quad (5)$$

where SOL is the daily astronomical radiation Under the undulating terrain, in units of MJm^{-2} ; E_{sc} is the solar constant; r_0/r is the corrected coefficient of the sun-earth distance on the day; n is the discrete number of illuminable hour angles, δ is the solar declination angle; ω_{si} and ω_{ri} are the starting and ending solar hour angles ($^\circ$) of the illuminable time period respectively; u, v, w are characteristic factors related to terrain and geography:

$$\begin{cases} u = \sin \varphi \cos \alpha - \cos \varphi \sin \alpha \cos \beta \\ v = \sin \varphi \sin \alpha \cos \beta + \cos \varphi \cos \beta \\ w = \sin \alpha \cos \beta \end{cases} \quad (6)$$

- 2 Total annual solar radiation SOL

$SOL(x, t)$ represents the total radiation of pixel x in t year, in MJm^{-2} , which is linearly fitted by the total astronomical radiation and the percentage of sunshine.

$$SOL = SOL_0(a + bs) \quad (7)$$

where s is the percentage of sunshine; a, b are the empirical coefficients.

- 3 Photosynthetically active radiation component FPAR

Photosynthetically active radiation component (FPAR) is the main driving factor in the process of estimating vegetation NPP by CASA model. At present, there are many methods to invert FPAR

based on vegetation index. Commonly used vegetation indices include NDVI and Ratio Vegetation Index (RVI), etc. The calculation formula of FPAR inversion from NDVI is:

$$FPAR = \frac{NDVI - NDVI_{(i,min)}}{NDVI_{(i,max)} - NDVI_{(i,min)}} \times (FPAR_{max} - FPAR_{min}) + FPAR_{min} \quad (8)$$

where the values of $FPAR_{max}$ and $FPAR_{min}$ are 0.95 and 0.001 respectively, and the values of $NDVI_{(i,max)}$ and $NDVI_{(i,min)}$ are the 95% and 5% percentiles of the NDVI of the i th land type respectively.

Absorbed Photosynthetic Active Radiation ($APAR$) is determined by total solar radiation (SOL) and photosynthetically active radiation component ($FPAR$):

$$APAR(x, t) = 0.5 \times SOL(x, t) \times FPAR(x, t) \quad (9)$$

2.1.3 CASA model

Net primary productivity (NPP) is the amount of carbon retained in an ecosystem (increase in biomass), equal to the difference between the amount of carbon produced through photosynthesis (GPP) and the amount of energy that is used for respiration (R) [3].

Carnegie Ames Stanford Approach (CASA) model quantifies NPP of vegetation by simulating the process of light energy utilization, which can better reflect the productivity of vegetation, and is widely used in NPP monitoring and research [4]. The function is

$$NPP(x, t) = \epsilon(x, t) \times APAR(x, t) \quad (10)$$

2.2 Transfer NPP to carbon sink

Carbon sink $CK(x, t)$ ($Mg \cdot C \cdot ha^{-2} \cdot a^{-1}$) and Net Primary Productivity $NPP(x, t)$ ($g \cdot C \cdot ha^{-2} \cdot a^{-1}$) has the following relationship:

$$CK(x, t) = -4.0 \times NPP(x, t)^2 + 0.0026NPP(x, t) - 0.243 \quad (R^2 = 0.64) \quad (11)$$

Since carbon sink represents the amount of carbon dioxide absorbed, we can determine how much carbon dioxide a forest and its products can be expected to sequester over time through carbon sink calculated from the above model.

2.3 Determine harvesting time based on NPP

If we can maximize the volume of carbon sequestration of a small area according to NPP, the volume of carbon sequestration of the entire forest will be maximized. According to Figure 1.

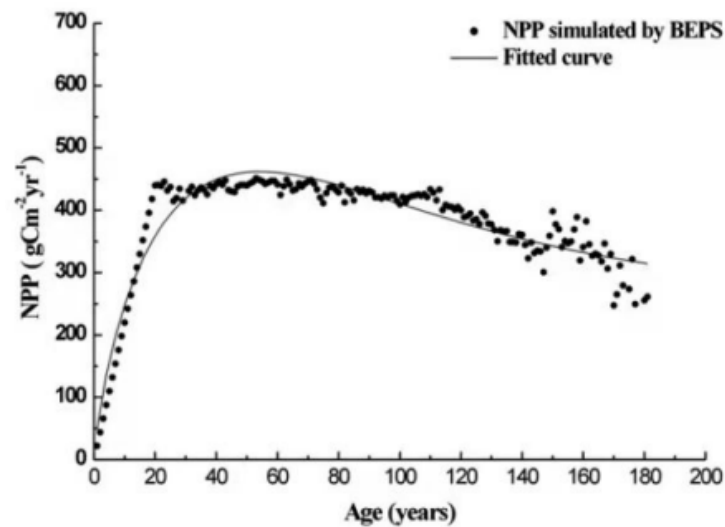


Figure 1. The relationship between tree age and NPP

And based on the research of Shaoqiang Wang, young forests are more capable of sequestering carbon than old forests.

So harvesting trees at the right time, processing them into forest products and planting new trees can sequester more carbon. The extra carbon sequestration. Let the carbon sequestration amount of trees in x pixels cut down at time t be more than the carbon sequestration amount that is not cut down as $c(x, t)$:

$$c(x, t) = NPP(x, t) + NPP(x, y_0 - t) - NPP(x, y_0) \quad (12)$$

where Pixel x , t is the age of the tree, unit: year, $NPP(x, t)$ represents the net initial value productivity of pixel x in t year, unit: gm^{-2} ; y_0 is the average lifespan of trees in x pixels.

Therefore, the optimal tree harvesting time $t_0(x)$ in x pixels satisfies:

$$t_0(x) = \max_{t \in (0, y_0)} c(x, t) \quad (13)$$

So the most effective forest management plan at sequestering carbon dioxide is to harvest old trees and plant new trees at the optimal time provided by our model.

3. More comprehensive forest management decision model

Due to regional factors such as climate and precipitation, there are different growth conditions for forests in different regions. Obviously, under more favorable conditions, forests will grow better and absorb more carbon. So one-size-fits-all guidance is simply not possible as the make-up of forests, and we need to consider transition points.

Taking China's Northeast Forest as an example, in order to determine the transition point, we select the monthly average precipitation, monthly average temperature, total population and GDP of Heilongjiang as the characteristics of forest growth. We use Principal Component Analysis (PCA) to assign scores to each area. The higher the score, the more suitable the area is for tree growth, and the fewer trees should be cut down; on the contrary, the area with a low score means that the external conditions are less suitable for tree growth than other areas.

1 Bartlett and KMO's test

For KMO value, the judgement criteria is shown in Table.1.

Table.1. KMO test criteria

KMO value	Applicability of analysis
0.90-1.00	very good
0.80-0.89	good
0.70-0.79	general
0.60-0.69	poor
0.50-0.59	very poor
<0.50	no effect

For Bartlett's test, if the significance (p value) is less than 0.01, the null hypothesis will be rejected, which means that principal component analysis can be done. If the null hypothesis is not rejected, it means that these variables may provide some information independently and are not suitable for principal component analysis. Our test results are as shown in Table.2:

Table.2. KMO and Bartlett test results

KMO test	KMO value	0.643
Bartlett's test	chi-squared approximation	1453.937
Bartlett's test	df	325
Bartlett's test	p	1%

The results of the test are significant, so there is a correlation between the variables, which meets the requirements of principal component analysis.

2 Select principal components

Calculate the eigenvalues and eigenvectors of the covariance matrix from the samples, and then calculate the contribution of the eigenvalues of each factor. The variance interpretation table is as shown in Table.3:

Table.3. The variance interpretation table(top ten only)

Factors	Characteristic root	Variance proportion	Accumulation
1	9.837	37.83%	37.83%
2	8.243	31.70%	69.54%
3	2.211	8.51%	78.04%
4	1.677	6.45%	84.49%
5	1.152	4.43%	88.92%
6	0.693	2.67%	91.59%
7	0.579	2.23%	93.82%
8	0.401	1.54%	95.36%
9	0.303	1.17%	96.52%
10	0.233	0.90%	97.42%

When the total variance explained rate is greater than 85%, the components can be considered to represent the data. Generally speaking, the higher the variance explained rate, the more important the principal component is, and the higher the weight ratio should be. From Table. 3, we can see that the variance contribution rate of the top five eigenvalues has exceeded 85%, so we select five principal components.

3 Choose transition points

After obtaining the principal component composition formula and weight, we calculate the principal component score and comprehensive score of each variable. According to the ranking of comprehensive scores, and considering local actual policies and other factors, we can selectively harvest trees, and the lower ranking areas are the transition points of the forest management plans.

4. Carbon sequestration forecasting

4.1 Current state of carbon sequestration

Using formula (10), we calculate China's Northeast Forest NPP in 2020 and present it in a visual way. According to Figure 2.

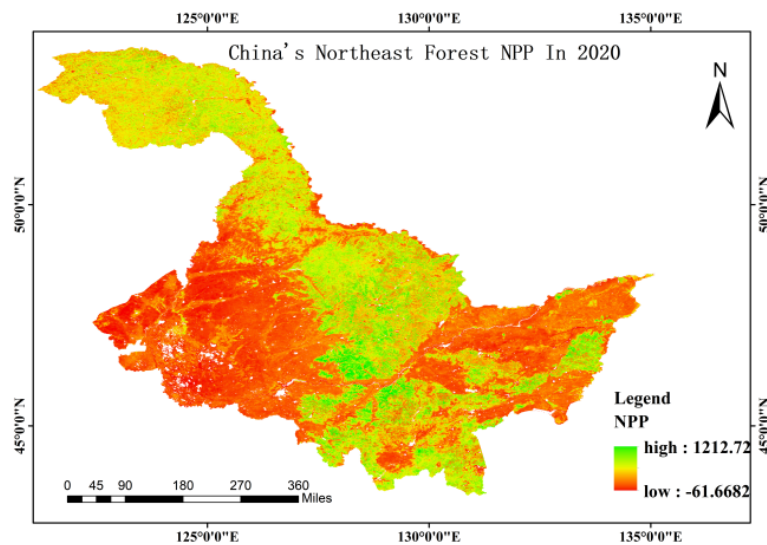


Figure 2. China's Northeast Forest NPP in 2020

4.2 Trend analysis

we draw a scatter plot and fit a best line. According to Figure 3.

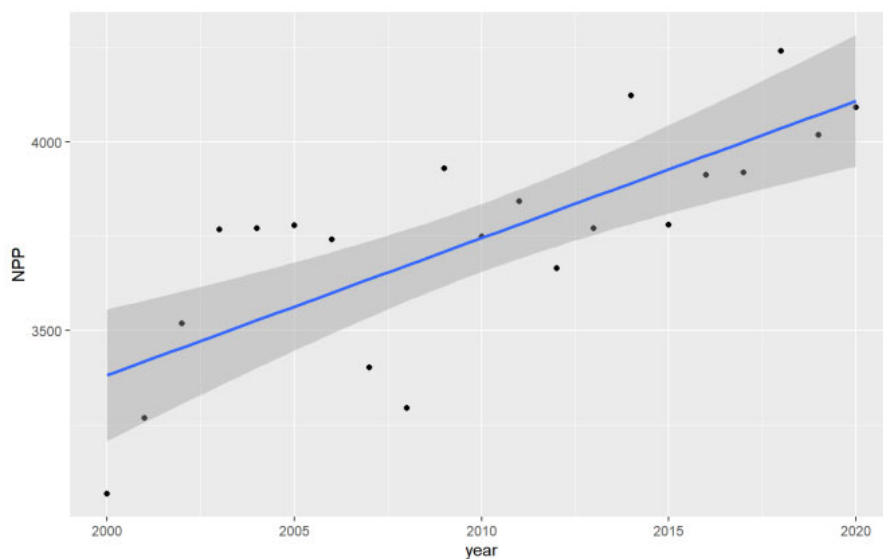


Figure 3. Trend of NPP in China's Northeast Forest

We can find that the average annual NPP per pixel shows an upward trend; at the same time, the trend test is tested through Cox-Stuart's S2 statistic, and the p value of the test is 0.001, meaning the result is very significant. This shows that China's Northeast Forest is currently in the growth stage. (After consulting the data, we find that the abnormal situation of NPP production in 2007 and 2008 was caused by El Niño in 2007-2008.)

5. Model evaluation

Compared with the macro management system, this model achieves delicate management, which is more convenient and efficient. We have innovated the management of forests based on the CASA model, balancing the values of ecology, humanity, economy and other aspects. This model considers of solar radiation, moisture, temperature and different tree types and can be implemented on any forest, that is, as the forest's information changes over time, our model holds true.

However, this model can't calculate the amount of carbon sequestration or provide management plans for forests without satellite remote sensing data.

6. Conclusions

In order to provide forest management plans, we have established a series of complete models to quantify forests' carbon sequestration capacity, economic value, ecological value and so on. Using principal component analysis, we select top 5 principal components and set lower ranking areas as transition points of forest management plans.

In conclusion, our work realizes using silviculture to achieve carbon sequestration in the true sense and is applicable to most forests all over the world.

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