Forest: Who Moved My Carbon Dioxide

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Abstract. In recent years, carbon capture and storage (CCS) has emerged as a hot issue in the international community to study the response to global warming in order to slow down the emission of greenhouse gases due to global warming. Firstly, we established a better forest carbon sequestration model in this paper, and we used the knowledge of spatial informatics to establish a CASA model to estimate the net plant productivity (NPP), and finally obtained the trend spatial distribution of NPP. Subsequently, considering the differences in various factors of forests around the world, we first used k-means cluster analysis to classify each of them, and roughly obtained six major categories.

Keywords: CCS, Forest, NPP, Linear fitting, K-means.

1. Introduction

In recent years, the global warming phenomenon caused by the greenhouse effect resulting from the increase of greenhouse gases has become a popular issue of concern and discussion in the international community. Among the greenhouse gases currently found to be emitted by human activities, carbon dioxide considered to be the primary perpetrator of global warming and has become the primary target for global mitigation of greenhouse gas emissions because of its life span of up to 200 years and its large impact on climate change. To mitigate the effects of climate change, we must take strong actions to reduce greenhouse gas emissions in the atmosphere. Carbon dioxide capture and storage (CCS) is a technology that has emerged in recent years and is being promoted through experiments and has become a hot issue in international research to combat global warming.

Forests sequester carbon dioxide in the products produced by living plants and trees, and they have economic, ecological, and social effects, which are not independent of each other, but have a mutually reinforcing relationship.

2. Assumptions and Justifications

Assuming that the forest we study does not experience major natural disasters.

We assume that the soil pH values are the same everywhere in the one forest we study.

3. Carbon Sequestration Model Based on Remote Sensing Technology

3.1 Data Sources and Pre-processing

Remote Sensing Data: The meteorological satellite Normalized vegetation index($NDVI$)data used in this paper were obtained from the U.S. Earth Resources Observation System (EROS) and all data were revised with geometric correction and atmospheric correction to make the data consistent and comparable.

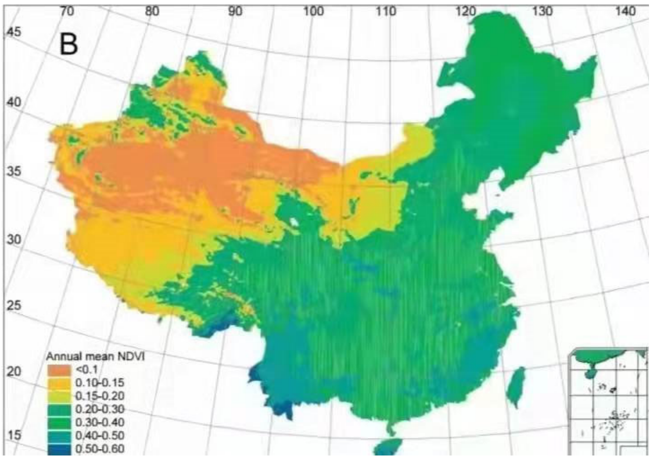

Figure 1 Ground-observed Vegetation Map of China

Meteorological Data: The meteorological data used in this paper were obtained from the China Meteorological Administration (CMA) and include monthly precipitation, monthly average temperature, and monthly total solar radiation, as well as the longitude, latitude and altitude of each meteorological station.

Land Cover Classification Map: The land cover classification map was obtained from the Joint Research Center of the European Union(JRC), and the original classification image was compiled by the Institute of Remote Sensing Applications, Chinese Academy of Sciences, with higher classification accuracy.

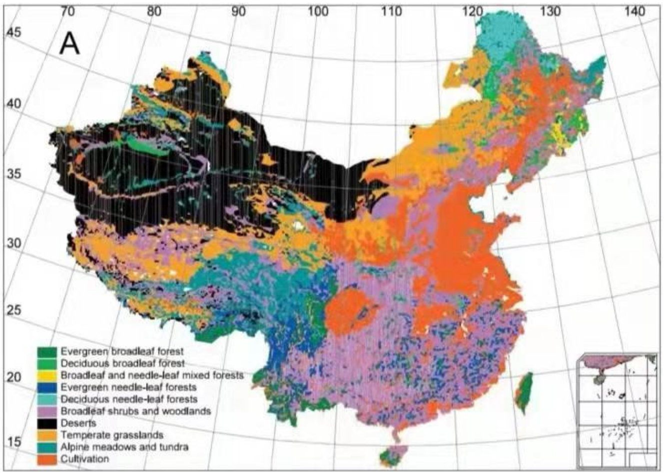

Figure 2 Ground-observed Vegetation Map of China

$\boldsymbol{NEP}$ Measurement Data: The NEP measurements were obtained from the forestry census data of the Ministry of Forestry of China, including vegetation attributes of 17 forest types and 690 observation sites in China, including stand age, leaf area index, total biomass and carbon sequestration, as well as longitude, latitude and altitude of each observation site.

3.2 CASA Model

The basic idea of the CASA model for estimating vegetation NPP is to use the solar radiation obtained by the vegetation and add the vegetation's own utilization to estimate the net vegetation growth[1]. The NPP estimated in the model can be expressed by two factors, the photosynthetically active radiation absorbed by the vegetation, $APAR$, and the actual light energy utilization,ε, with the following equations:

$$\mathrm{NPP}(x,t) = \mathrm{APAR}(x,t) \times \varepsilon(x,t) \quad (1)$$

Where x represents a single image element, t represents the month.

3.3 Estimation of $\boldsymbol{APAR(x,t)}$

The value of $APAR$ is determined by the ratio of solar effective radiation absorbed by the vegetation and the absorption of incident photosynthetically active radiation by the vegetation.

$$\mathrm{APAR}(x,t) = \mathrm{SQL}(x,t) \times \mathrm{FPAR}(x,t) \times 0.5 \tag{2}$$

Where the constant 0.5 indicates the proportion of total solar active radiation (wavelength of 0.4-0.7 μm) that can be utilized by the vegetation to the total solar radiation.

Due to the small number of radiation sites in the study area and the large interpolation error by directly using the site solar radiation data, we adopted the following equation for the estimation of $SQl(x,t)$ in this paper, by reviewing the relevant literature.

$$Q = Q_A(a + bs) \tag{3}$$

Where Q is the total solar radiation; a and b are 0.185 and 0.595[2], respectively; s denotes the percentage of insolation; Q_A denotes astronomical radiation.

Estimation of FPAR

Within a certain range, there is a linear relationship between $FPAR$ and $NDVI$, and this relationship can be determined from the maximum and minimum values of NDVI for a given vegetation type and the corresponding maximum and minimum values of FPAR.

The proportion of effective solar radiation absorbed by vegetation depends on the vegetation type and vegetation cover status[5]. The study proved that the normalized vegetation index ($NDVI$) obtained from remote sensing data can reflect the vegetation cover status well[4]. We found $NDVI$ data with high quality and resolution by searching official websites, etc., and obtained the following relationship by fitting the analysis:

$$\mathrm{FPAR} = \begin{cases} 0 & \mathrm{NDVI} \leqslant 0.075 \\ \min\{1.16 \times \mathrm{NDVI\text{-}0.0439}, 0.9\} & \mathrm{NDVI} > 0.075 \end{cases} \tag{4}$$

3.4 Estimation of Light Energy Utilization

Light energy utilization is the ratio of the chemical potential contained in the dry matter produced per unit area in a given period to the photosynthetically effective radiant energy projected onto that area at the same time. Environmental factors such as temperature, soil moisture status, and atmospheric water vapor pressure difference regulate the NPP of vegetation by affecting the photosynthetic capacity of plants, as calculated by the following equation.

$$\varepsilon(x,t) = T_{\varepsilon 1}(x,t) \times T_{\varepsilon 2}(x,t) \times W_{\varepsilon}(x,t) \times \varepsilon_{max} \tag{5}$$

Where ε_{max} is the maximum light energy utilization under ideal conditions (gC/Mg), and its value is strongly influenced by the vegetation type.

Estimation of Temperature Stress Coefficients

Estimation of $T\varepsilon_1(x,t)$: its reflection of reduced primary productivity due to photosynthetic limitation by plant intrinsic biochemical effects at low and high temperatures.

$$T_{e1}(x,t) = 0.8 + 0.02 \times T_{opt}(x) - 0.0005 \times \left[T_{opt}(x)\right]^2 \tag{6}$$

$T_{opt}(x)$ is the optimum temperature for plant growth, defined as the average temperature (℃) of the month when the $NDVI$ value of a region is at its highest in a year; when the average temperature of a month is less than or equal to -10 ℃, the value is taken as 0.

Estimation of $T_{\varepsilon 2}(x,t)$: indicates the trend that the light energy utilization of plants gradually becomes smaller when the ambient temperature changes from the optimum temperature $T_{opt}(x)$ to high or low temperature, which is because the high respiratory consumption at low and high temperatures will definitely reduce the light energy utilization, and the light energy utilization will definitely decrease when growing under conditions that deviate from the optimum temperature. The calculation formula is as follows:

$$T_{\varepsilon 2}(x,t)$$

$$= \frac{1.184}{\left\{1+\exp\left[0.2\times\left(T_{\mathrm{opt}}(x)-10-T(x,t)\right)\right]\right\}\times\left\{1+\exp\left[0.3\times\left(-T_{\mathrm{opt}}(x)-10+T(x,t)\right)\right]\right\}} \quad (7)$$

When the average temperature $T(x,t)$ of a month is 10℃ higher or 13℃ lower than the optimum temperature $T_{opt}(x)$, the value of $T_{\varepsilon 2}(x,t)$ of that month is equal to half of the value of $T_{\varepsilon 2}(x,t)$ when the monthly average temperature $T(x,t)$ is the optimum temperature $T_{opt}(x)$.

Following consideration of the complex and variable topography of some regions, this paper interpolates the temperature by three variables, namely longitude, latitude, and altitude, using multiple regression analysis and residual method[5]. The interpolation method not only takes into consideration the influence of altitude on meteorological elements, but also uses the difference between station data and interpolated data for correction, which improves the interpolation accuracy.

Estimation of Water Stress Impact Coefficient $\boldsymbol{W_\varepsilon(x,t)}$

The water stress impact coefficient Wε(x,t) reflects the effect of the effective water conditions available to the plant on light energy utilization. Wε(x,t) gradually increases with the increase of effective water in the environment, and it takes values ranging from 0.5 (under extreme drought conditions) to 1 (under very wet conditions).

$$W_\varepsilon(x,t) = 0.5 + 0.5 \times \frac{EET(x,t)}{EPT(x,t)} \quad (8)$$

Based on equations (1) to (8) above, we estimated the NPP in China from 1982 to 1999, and thus we completed the calculation of the NPP and derived the spatial distribution of the annual NPP trend in China from 1982 to 1999, as shown in Figure:

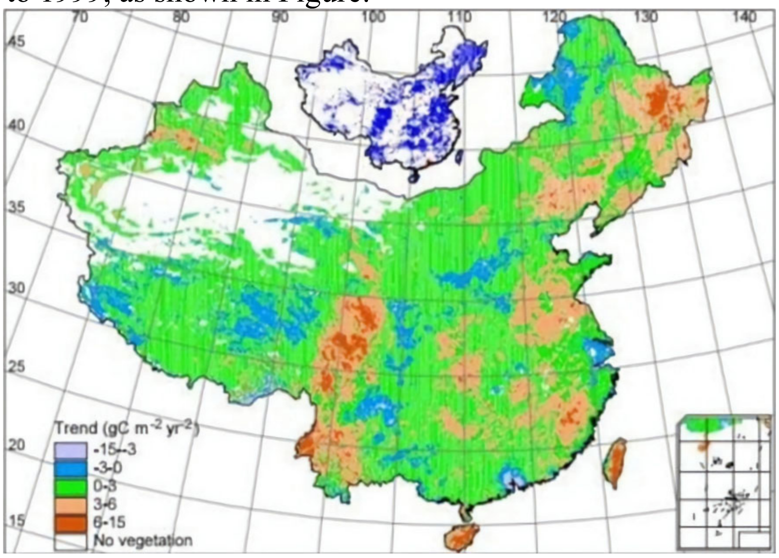

Figure 3 Spatial Distribution of Annual $\boldsymbol{NPP}$ Trends

The inset at the top of the figure shows the significant increase (blue) or decrease (red) in $NDVI$ over 18 years.

3.5 Linear Fit for Carbon Sequestration

Above we obtained the net primary productivity (NPP) of plants through the CASA model, and then we performed a quadratic linear fit of forest carbon sequestration (NEP, y) and net primary productivity (NPP, x) based on the data in 4.1 to derive the relationship between them, and it was practically concluded that the square of the correlation coefficient (R^2) of the following equation is closest to 1, so the best fit is achieved.

$$y = -4.0 \times 10^{-6}x^2 + 0.0026x - 0.243 \quad (9)$$

The equation indicates that the amount of carbon sequestered increases gradually with the increase of NPP; when NPP increases to a certain value, the carbon sink reaches a maximum. This process can be explained by plant physiology. For example, the NPP of tropical rainforests is very large, but the net dry matter accumulated is not much due to the rapid respiratory decomposition, i.e., the carbon sequestration is not large; The grassland in arid-semi-arid zone has a low NPP and the dry matter accumulated is also low; While the carbon sequestration of temperate forests is large.

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