Development of Forest Carbon Sequestration Model

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Abstract. Firstly, the factors affecting carbon sequestration are analyzed based on tree age, precipitation, temperature and light. On this basis, the carbon sequestration model is developed by combining K-means clustering, regression analysis verification and grey prediction model. Finally, the carbon sequestration model is used to predict the trend of carbon sequestration content of six vegetation types in the next two years. The research results provide guidance for sequestration of carbon dioxide.

Keywords: carbon sequestration model; k-means clustering; regression analysis; grey prediction model.

1. Introduction

Forest carbon sequestration is one of the important measures to effectively mitigate climate change [1]. Carbon sequestration can sequester carbon dioxide in the plant, soil and water environment. When the forest grows to a certain age, it can be made into forest products, so that the benefit may be higher. The forest management strategy of appropriate logging is conducive to carbon sequestration, but excessive logging will limit carbon sequestration.

The main factors affecting carbon sequestration are tree age, precipitation, temperature and light intensity [2-5]. Scholars' research on carbon sequestration has produced many achievements [6-8]. However, few studies involve the development of carbon sequestration models. In view of this, the paper studies the effects of tree age, precipitation, temperature and light on carbon sink. Secondly, the carbon sequestration model is developed by combining K-means clustering, regression analysis verification and grey prediction model. Last, the trend of carbon sequestration content of six vegetation types in the next two years is predicted by the carbon sequestration model.

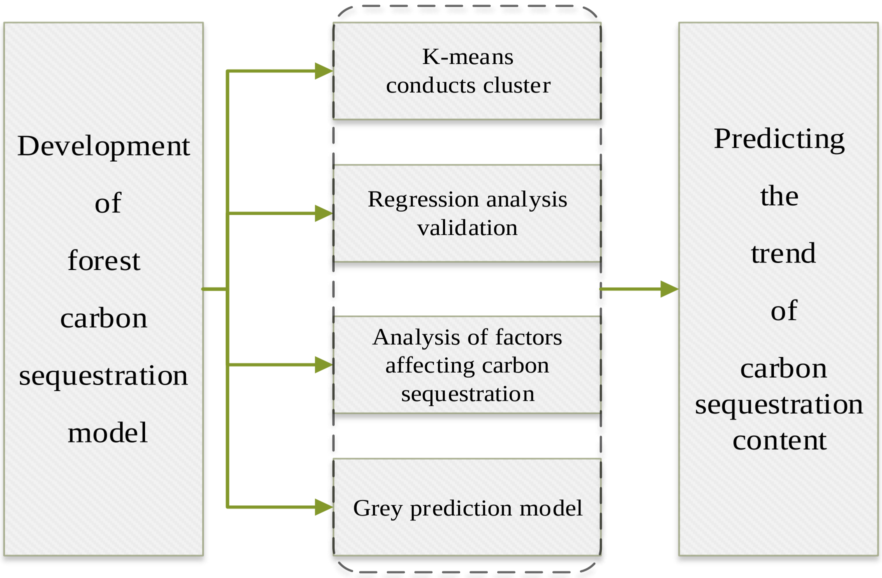

Figure 1 Research route

2. Model establishment and solution

2.1. Carbon sequestration model

2.1.1 K-means conducts cluster analysis on meteorological conditions

K-means clustering was carried out for many variables, and the influence analysis of indicators was represented by Euclidean distance [9].

$$d(x,y)=\sqrt{(x_1-y_1)^2}+\sqrt{(x_2-y_2)^2}\sqrt{(x_3-y_3)^2}+ \\ \ldots+\sqrt{(x_n-y_n)^2} \tag{1}$$

The distance between each object and each cluster center is compared in turn, and the objects are allocated to the cluster closest to the cluster center, and k cluster clusters are obtained$\{S_1,S_2,S_3,\ldots,S_k\}$.

K-means algorithm defines the prototype of class cluster with center, which is the mean value of all objects in the class cluster in each dimension. Its calculation formula is as follows:

$$C_l=\frac{\sum X_i \in S_l}{|S_l|} \tag{2}$$

Where, C_l represents the center of the first cluster, $1\le l\le k$, $|S_l|$ represents the number of objects in the first class cluster,X_i represents the ith object in the first class cluster, $1\le i\le |S_l|$.

2.1.2 Regression analysis validation [10]

The determination coefficient is an indicator to measure the closeness of the direct relationship between the dependent variable and the independent variable, and represents the percentage of changes in the dependent variable explained by the independent variable. It ranges from 0 to 1. Also called goodness of fit test, coefficients are also called judgment coefficients.

$$r=\frac{\sum(\hat{y}-\bar{y})^2}{\sum(y-\bar{y})^2}=1-\frac{\sum(y-\bar{y})^2}{\sum(y-\bar{y})^2} \tag{3}$$

Correlation coefficient is an indicator used to measure goodness of fit between variables, and the calculation formula is as follows:

$$\rho_{xy}=\frac{\mathrm{Cov}\,(x,y)}{\sqrt{D(x)}\sqrt{D(y)}} \tag{4}$$

The ratio of the covariance to the square root of the variance of x and y.

After calculating the regression coefficient, the significance test of the regression coefficient was carried out, and the significance test of the regression coefficient was carried out by t parameter. The formula is as follows:

$$S_b=\frac{SE}{\sqrt{\sum(x-x_m)^2}},t_b=\frac{b}{S_b} \tag{5}$$

2.1.3 Analysis of factors affecting carbon sequestration

The carbon sequestration of forests is closely related to the age composition of forests. The general forest can be divided into young forest, middle forest, near mature forest, mature forest and overmature forest according to their ages. The carbon sequestration rate is the largest in the middle forest ecosystem, while the carbon absorption and release of mature forest/overmature forest are basically balanced because their biomass basically stops growing. The carbon sequestration of forests increases with the increase of precipitation. Forest sequestration is also affected by topography. Terrain affects the distribution and growth of forest vegetation types to a certain extent by influencing temperature, precipitation, light and soil properties, and thus affects the carbon input of forest ecosystems. In addition, the degree of human disturbance varies with different slopes and elevations. With the increase of slope or altitude, the chance and degree of human disturbance decreases, and the vegetation biomass is large and the carbon sequestration capacity is high vegetation growth time is long, biomass is large, carbon storage is also large, carbon density also increased (Figure. 1).

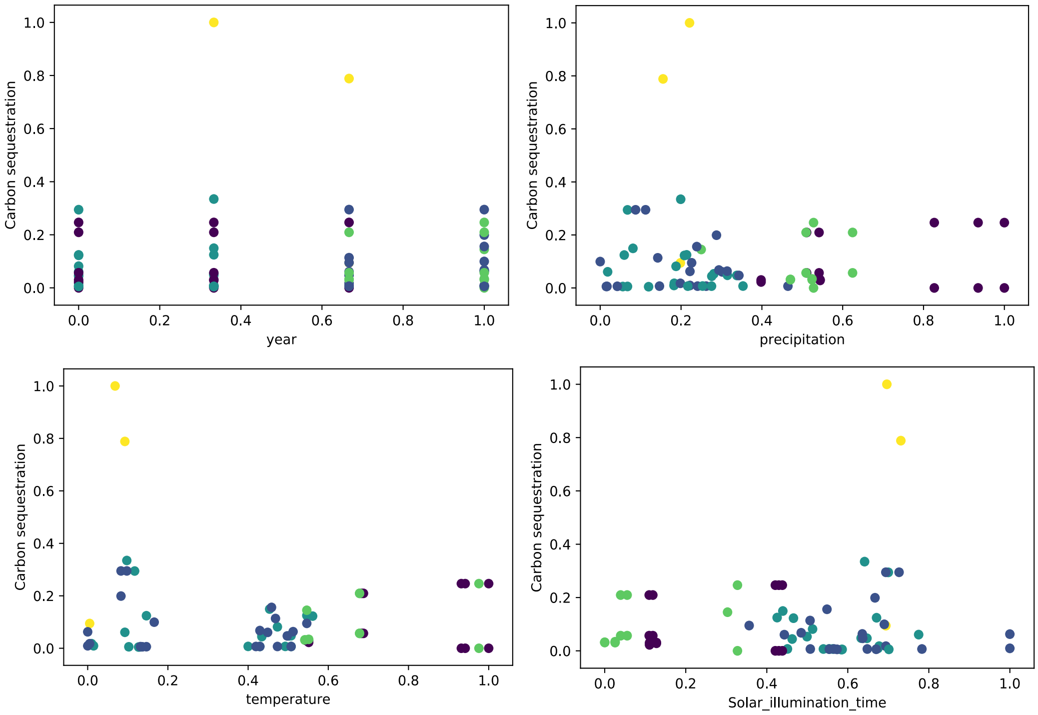

Figure 2 Cluster analysis diagram of index and carbon sequestration

2.1.4 Grey prediction model (GM) [11]

Modeling with GM requires validation of the data, starting with the calculation of the level ratio of the sequence.

$$\lambda(k) = \frac{x^0(k-1)}{x^0(k)}, k = 2,3,\ldots,n \tag{6}$$

If all the stage ratios fall within the tolerable coverage range $X = (e^{\frac{-2}{n+1}}, e^{\frac{2}{n+1}})$, then the sequence x^0 can be established and the GM model can be established for gray prediction. Otherwise, it is necessary to do appropriate transformation of the data, such as translation.

Define the gray derivative of $x^{(1)}$ as $d(k) = x^0(k) = x^1(k) - x^1(k-1)$., and let $z^1(k)$ generate a sequence of x^1 neighbors, $z^1(k) = ax^1(k) + (1-a)x^1(k-1)$, the grey differential equation model of GM(1,1) is defined as $d(k) + az^1(k) = b$, a is called development coefficient, $z^1(k)$ is called whitening background value, b is called gray action.

$$\begin{aligned} x^0(2) + az^1(2) &= b \\ x^0(3) + az^1(3) &= b \\ &\cdots \\ x^0(n) + az^1(n) &= b \end{aligned} \tag{7}$$

List (7) as a matrix:

$$\mu = \begin{bmatrix} a \\ b \end{bmatrix}, Y = \begin{bmatrix} x^0(2) \\ x^0(3) \\ \cdots \\ x^0(n) \end{bmatrix}, B = \begin{bmatrix} -z^1(2) & 1 \\ -z^1(3) & 1 \\ \cdots & \\ -z^1(n) & 1 \end{bmatrix} \tag{8}$$

Then GM can be expressed $Y = B\mu$. Using linear regression or $(B^TB)^{-1}B^TY$ to find the values of a and b (the value of a is 0.5) using the principle of least square.

The corresponding bleaching model is:

$$\frac{dx^1(t)}{dt} + ax^1(t) = b \tag{9}$$

The resulting solution to $x^1(t)$ is :

$$x^1(t) = (x^0(1) - \frac{b}{a})e^{-a(t-1)} + \frac{b}{a} \tag{10}$$

Make t+1=t:

$$x^1(t+1) = \left(x^0(1) - \frac{b}{a}\right)e^{-a} + \frac{b}{a},$$
$$k = 1,2,3\ldots,n-1 \tag{11}$$

Generally, there are three methods to test the accuracy of grey model, which are relative error size test, correlation test and posteriori error test. The commonly used method is posterior difference test.

1.Find $\hat{x}^0(k)$ using the reduction generation of the predicted$\hat{x}^1(k)$:

$$\hat{x}^0(k) = \hat{x}^1(k) - \hat{x}^1(k-1), k = 1,2,\ldots,n \tag{12}$$

2. Calculate residuals:

$$e(k) = x^0(k) - \hat{x}^0(k), k = 1,2,\ldots,n \tag{13}$$

3. Calculate the variance of the original sequence and the variance of the residual:

$$S_1 = \frac{1}{n}\sum_{k=1}^{n}(x^0(k) - \bar{x})^2;$$
$$S_2 = \frac{1}{n}\sum_{k=1}^{n}(e^0(k) - \bar{e})^2 \tag{14}$$

4. Calculate a posteriori ratio:

$$C = \frac{S_2}{S_1} \tag{15}$$

5. Mean square error ratio C:

Table 1: Mean square error ratio C

Model accuracy level	Mean square error ratio C
Level 1 (excellent)	$C \leqslant 0.35$
Level 2 (good)	$0.35 < C \leqslant 0.5$
Level 3 (fail)	$0.5 < C \leqslant 0.65$
Level 4 (poor)	$C > 0.65$

2.1.5 Result Analysis

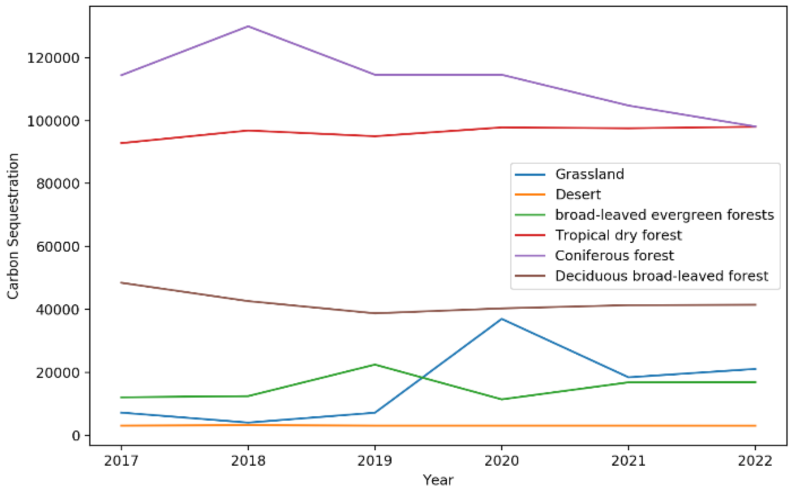

Figure 3 Carbon sequestration of six forest types

Carbon sequestration data from 2017 to 2020 to forecast the two-year carbon sequestration of six vegetation types is used [12].

As shown in the Figure.3, the carbon sequestration of coniferous forest and deciduous broadleaved forest showed a downward trend on the whole, while that of deciduous broadleaved forest was basically unchanged. The carbon sequestration of other forest types showed an upward trend on the whole, rising in fluctuation. In particular, the carbon sequestration of coniferous forest is the highest and that of desert is the lowest.

3. Model evaluation and promotion

3.1. Advantages

1.The model adopts accurate and reliable data to ensure the reliability of the results. The research results have high reference value.

2.The model adopted in the study has a high accuracy, which enables prediction of future forest carbon sequestration within an acceptable error range

3.2. Shortcomings

1. The factors considered in the risk model are not comprehensive enough to accurately predict more complex situations

2.A linear model has a small amount of data and may produce large errors when the time span is large

3.3. Model extension

1.The model established in this paper argues for a wider applicability. The model will be extended to more specific temperature zones and more countries, and more specific forest management plans will be developed according to the differences in geographical location and culture of different temperature zones and countries.

2.Anyway, we plan to factor the life cycle of tree species into the model in order to make the prediction more accurate and the results more referable. Since trees sequester different amounts of carbon in different life cycles, breaking down the life cycle makes the model more accurate and more consistent with reality.

3.Investing in a model to optimize its code and algorithms increases decision-making and prediction speed, boosting efficiency.

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