

Study on Forest and Climate Model based on Grey Relational Prediction

Xinzhu Leng*

College of Computer & Information, Science Southwest University, Chongqing, 400799 China

*Corresponding author. Email: lengxinzhu0319@163.com

Abstract. In recent years, global warming and greenhouse gases (representative gas carbon dioxide) have posed a significant threat to people's production and life. Therefore, for this harmful climate phenomenon, this paper first selects 15 forests in the world as the research object and constructs the forest carbon sequestration model based on grey prediction and the forest carbon sequestration management scheme decision-making model based on grey relational analysis. The grey relational analysis method was used to analyze the weight of the influence of six main factors on carbon sequestration. Then, based on considering the capacity of forest carbon sequestration, a decision-making model of forest management scheme based on carbon sequestration was introduced. The differences in carbon sequestration under different forest management schemes were studied, and the changing trend of carbon sequestration with time was discussed. The future trend of carbon sequestration is analyzed on a time scale, and a prediction model based on time change is established to provide a more effective and comprehensive reference for decision-makers.

Keywords: Global warming, forest carbon emissions, gray correlation, prediction model.

1. Introduction

Global warming refers to the increase in the temperature of the Earth's atmosphere and oceans, mainly due to anthropogenic factors. Currently, the main cause of global warming is the excessive emission of greenhouse gases (representative gas carbon dioxide)[1]. During photosynthesis, forests convert carbon dioxide and water into organic matter and release oxygen, thus absorbing large amounts of carbon dioxide, an effect known as the carbon sequestration effect of forests. The carbon sequestered in some forest products, combined with the carbon sequestered by young forest regeneration, can absorb more carbon over time than the carbon sequestration benefits of no deforestation at all. Forests sequester carbon dioxide in the products produced by living plants and trees. These forest products absorb carbon dioxide throughout their lifetimes. Forests, therefore, play an essential role in carbon sequestration. Since harvesting intensity is the main tool for forest management, it becomes essential to determine the optimal harvesting intensity. An appropriate harvest intensity is beneficial to carbon sequestration, while over-harvesting can limit carbon sequestration[2]. Through harvesting, the carbon fixed in forests can be transferred to forest products, which can store and reduce carbon dioxide throughout the life cycle of forest products, have good carbon dioxide offsetting capacity, and affect forest carbon dioxide sinks through consumption inversions [3-6].

Forest managers must balance the benefits of harvesting forest products and the value of allowing the forest to continue to grow and absorb carbon dioxide as living trees. Therefore, forest managers need to consider many factors, such as the age of the trees, climate, topography, and economic returns, to find the optimal harvest intensity point in order to ensure sustainable forest management and provide a theoretical basis and practical approach to the health and stability of forest systems.

2. Calculation of the amount of solid carbon

Step1. Data Searching

Determine the reference sequence that reflects the characteristics of the system behavior and the comparison sequence that affects the system behavior.

Step2. Data Processing

Due to the different physical meanings of various factors in the system, the data dimensions may not be the same, which is not convenient for comparison, or it is difficult to get a correct conclusion during comparison. Therefore, dimensionless data processing is carried out first when grey correlation degree analysis is carried out.

After searching and process, we obtained the data in the following table.

Table 1. Data table of five influencing factors for forests in seven climates

Climate type	Annual precipitation (mm)	Total solar radiation (MJ/m ² *year)	Altitude (m)	Average annual temperature (°C)	Latitude (°)
Tropical rainy climate	1125	7950	1 600	23	0.5
Tropical marine climate	1900	6250	3,011	25	3.75
Subtropical monsoon climate	1500	4344.25	84	22	26.08
Subtropical monsoon climate	630	7095	760	12.5	35.28
Subtropical monsoon climate	2214.3	4750	46	24.5	22.38
Monsoon climate of medium latitudes	1000	5434	2691	-2	42
Monsoon climate of medium latitudes	500	4509.26	1250	-4	48
Temperate marine climate	400	5979.5	227	15.5	37.83
Etesian climate	378	9198	61	13.5	37.8
Temperate continental climate	425	8100	667	14	40.4

tep3. Obtain the grey correlation coefficient between the reference sequence and comparison sequence $\varepsilon(X_i)$

The so-called degree of correlation is the degree of difference in geometric shapes between curves. Therefore, the difference between curves can be used to measure the degree of correlation. For a reference sequence X_0 , there are several comparison sequences $X_1, X_2, \dots, X_n$. The correlation coefficient $\varepsilon(X_i)$ between the comparative sequence and the reference sequence at each point in the curve can be calculated by the following formula:

$$\varepsilon_{O_i} = \frac{\Delta(m_i, n) + \rho \Delta(\max)}{\Delta_{O_i}(k) + \varphi \Delta(\max)} \quad (1)$$

ρ is the resolution coefficient, and it takes 0.5 as the value. $\Delta(\min)$ is the second-order minimum difference, $\Delta(\max)$ is the two-order maximum difference. $\Delta O_i(k)$ is the absolute difference between each point on the comparison series X_i curve and each point on the reference series X_0 curve.

Step4. Find the correlation degree

Because the correlation coefficient is the correlation degree value between the comparison sequence and the reference sequence at each moment (i.e., each point in the curve), its number is more than one, and the information is too scattered to facilitate overall comparison. Therefore, it is

necessary to concentrate the correlation coefficient of each moment (namely, each point in the curve) into a value, namely, calculate its average value, which is used as the quantitative expression of the correlation degree between the comparative sequence and the reference sequence. The correlation degree formula is as follows:

$$r_i = \frac{1}{N} \sum_{k=1}^N \varepsilon_i(k) \quad (2)$$

The closer r_i is to 1, the better the correlation is.

Step5. Correlation rank

The degree of correlation between factors is mainly described by order of the degree of correlation, not only the degree of correlation. The correlation order is formed by arranging the correlation degree of m subsequence to the same parent sequence in order of magnitude, which is denoted as $\{x\}$, which reflects the "good and bad" relationship of each subsequence to the parent sequence

Matlab code is used to achieve the above steps, and the following results are obtained:

```
relational_degree =  
  
    0.2174    0.1437    0.2002    0.2171    0.2161  
  
rs =  
  
    0.2174    0.2171    0.2161    0.2002    0.1437  
  
rind =  
  
     1     4     5     3     2
```

Figure 1 Matlab code running results diagram

The relational degree represents the correlation between precipitation, total solar radiation, altitude, temperature and latitude, and total forest carbon sequestration from left to right. Rs represents the sequence of correlation from large to small. Rind represents the comparison of correlation between these five influencing factors and total forest carbon sequestration (1,2,3,4, 5 respectively corresponding to precipitation, total solar radiation, altitude, temperature, and latitude). The results show that precipitation and temperature have the greatest influence on total carbon sequestration.

3. Prediction of carbon absorption of forest and its products

The grey prediction model deals with the complex system well and makes up for the deficiency of classical mathematics and statistical mathematics. To determine how much carbon dioxide forests and their products are expected to sequester over time, we looked for multiple data sets. Based on the Miami model, we used precipitation and temperature, which are the two indexes most correlated with carbon sequestration rate, to calculate the carbon sequestration rate according to the following formula and then took the average value as the preliminary small sample data of carbon sequestration.

$$N_t = 3000 / (1 + e^{(1.315 - 0.119t)}) \quad (3)$$

$$N_p = 3000 / (1 + e^{(1.315 - 0.119t)}) \quad (4)$$

N_t is the potential productivity based on temperature ($\text{g}\cdot\text{m}^{-2}\cdot\text{a}^{-1}$), which is the annual average temperature ($^{\circ}\text{C}$), N_p is the potential productivity based on precipitation ($\text{g}\cdot\text{m}^{-2}\cdot\text{a}^{-1}$), p is the annual average precipitation (mm).

Before establishing the grey prediction model, we calculated the amount of carbon sequestration in The Greater Hinggan Mountains of China from 2011 to 2019 by using precipitation, temperature, and two indicators respectively, according to the data in the table below and the Miami model formula,

and then calculated the weight ratio of precipitation and temperature based on the gray correlation method (0.2174: 0.2171) after careful consideration.

First, process raw data into grey to generate sequence (cumulative generation). Then build the Grey Model GM(1,1).

Define the grey derivative of

$$d(k) = x^0(k) = x^1(k) - x^1(k-1) \quad (5)$$

Moreover, $z^1(k)$ is the adjacent values generate a sequence of series x^1 , that is:

$$z^1(k) = ax^1(k) + (1-a)x^1(k-1) \quad (6)$$

So the grey differential equation model of GM(1,1) is that:

$$d(k) + az^1(k) = b \quad (7)$$

a is the development coefficient, $z^1(k)$ is the albino background value, b is the grey action. Then we have the following system of equations:

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

So GM(1,1) can be represented as $Y=Bu$, and we have to figure out the value of a and b . According to the least square principle, we can use linear regression or $(B^T B)^{-1} B^T Y$ (normal equation) to determine the value of a and b .

The corresponding bleaching model is

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

Moreover, the resulting is:

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

Use $t+1$ to replace t . It is the predicted value. Matlab code is used to achieve the above steps to obtain the following line graph:

```
input the number of prediction:5
absolute percentage error: 12.9868%
the predicted value: 1187.1303    1184.4799    1181.8354    1179.1969    1176.5642
```

Figure 2 Matlab code running results diagram

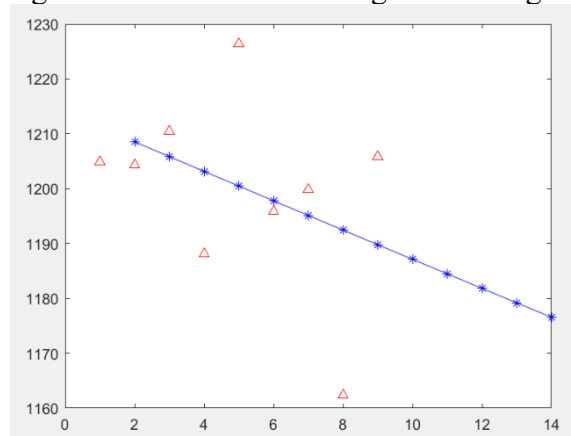


Figure 3 Matlab program running results line chart

We finally find the five predicted values 1187.1303, 1184.4799, 1181.8354, 1179.1969, and 1176.5642. Moreover, the absolute percentage error is 12.9868%.

4. Model CHecKout

There are generally three methods to test the accuracy of the grey model: the relative error size test method, the correlation degree test method, and the posterior error test method. The commonly used method is the posterior difference test.

Take the predicted x^1 and subtract it to get x^0

$$x^0(k) = x^1(k) - x^1(k-1), k = 2, 3, \dots, n \quad (11)$$

Residual calculation:

$$e(k) = x^0(k) - x^0(k), k = 1, 2, \dots, n \quad (12)$$

Calculate the variance S_1 of original sequence x^0 and the variance S_2 of residual e :

$$S_1 = \frac{1}{n} \sum_{k=1}^n (x^0(k) - \bar{x})^2$$

$$S_2 = \frac{1}{n} \sum_{k=1}^n (e^0(k) - \bar{e})^2 \quad (13)$$

Calculate the posterior ratio

$$C = \frac{S_2}{S_1} \quad (14)$$

Check the table to observe the effect. The model accuracy level table is below.

Table 2. Model accuracy level

Model accuracy level	Variance-mean ratio(C)
1(good)	$C \leq 0.35$
2(qualified)	$C \leq 0.5 \text{ \& } C > 0.35$
3(poor)	$C \leq 0.65 \text{ \& } C > 0.5$
4(disqualification)	$C > 0.65$

We know that the absolute percentage error is 12.9868%, which is under 0.35. So, this model accuracy level is good.

Table 3. Forecast of annual average carbon sequestration in Greater Khingan Mountains from 2020 to 2024

Year	Fixed carbon content(g.m-2.a-1)
2022	1187.1303
2021	1184.4799
2022	1181.8354
2023	1179.1969
2024	1176.5642

We get with time through modeling, calculation, and program implementation, and we get with time, the forest from 2020 to 2024 and its products are expected

to be sealed 1187.1303, 1184.4799, 1181.8354 1179.1969, and 1176.5642 g·m⁻²·a⁻¹ of carbon dioxide. Moreover, the absolute percentage error is 12.9868%, which is under 0.35. So, this model accuracy level is good.

5. Conclusions

To improve the phenomenon of global warming, carbon sequestration is necessary. Therefore, this paper first selects 15 forests in the world as the research object, uses the grey relational analysis method to analyze the weight of six main factors on carbon sequestration, and compares it with professional data to verify the effectiveness of the model. Based on considering the capacity of forest carbon sequestration, a decision-making model of forest management scheme based on carbon sequestration was introduced, and the differences of carbon sequestration under different forest management schemes were studied. Grey prediction model discusses the changing trend of carbon

sequestration with time. The future trend of carbon sequestration is analyzed on the time scale, and a prediction model based on time change is established.

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