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Research on How to Improve Carbon Sequestration to Mitigate Climate Change Problems

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Abstract

In this paper, we discuss how to improve carbon sequestration to slow down greenhouse gas emissions has been studied. Specifically, we established a multiple linear regression equation through matlab, and obtained the two most relevant indicators of carbon stock. Under the SPSS grey forecast model, carbon stock is forecasted. In addition, the weight of each indicator in different continents is solved by the entropy weight method. The optimal planning data for each continent is obtained. Finally, a sensitivity analysis was carried out on the established model.

Keywords

Multiple Linear Regression; Gray Forecast Model; Entropy Weight Method; TOPSIS.

1. Introduction

In recent years, humans are suffering from the serious threat of climate change. Countries around the world have taken various means to reduce greenhouse gas emissions, but only this way does not work. We need to value a new means --carbon sequestration, which further to improve the efficiency and intensity of solving climate change problems.

However, we set up two subsystems for carbon sequestration—forest products and forest remained, and set up two indicators for each of these two subsystems [1]. Then, we will use matlab to perform multiple linear regression analysis on these four indicators, and then obtain the correlation coefficients of these four indicators. Through the regression coefficient, we can judge the impact of the indicators on carbon sequestration, and then get the optimal forest management plan. Next, apply the SPSS grey prediction model to make predictions. We established two indicators for the four subsystems, and we obtain the weight of each indicator in different continents through matlab's entropy weight method. We use the weighted data to conduct a TOPSIS comprehensive evaluation to obtain the optimal data for each continent. Finally, we forecast the carbon stock in Superior National Forest a hundred years from now using a grey forecasting model.

2. Model Establishment

2.1. Multiple Linear Regression

Multiple linear regression is a linear regression with two or more independent variables, which can be expressed as:

$$y = a_0 + a_1 x_1 + a_2 x_2 + \cdots + a_k x_k \tag{1}$$

We divide the carbon sequestration's main method into two subsystems the forest products and forest remained. Next, we select two indicators for digital measurement, which is shown in Fig.1.

Figure 1. Indicators of two subsystems

We perform multiple linear regression of these four indicators using matlab. Then, we solve the regression coefficients of these four indicators using the principle of minimum sum of squares of error, $a_0 = -0.7318$, $a_1 = 9.2735$, $a_2 = 0.0008$, $a_3 = 0.7970$, $a_4 = -0.0007$.
Based on the regression coefficients, we obtain the following equation:

$$y = -0.7318 + 9.2735x_1 + 0.0008x_2 + 0.797x_3 - 0.0007x_4 \quad (2)$$

From this, we can conclude that the two indicators — proportion of forest area with a long-term operating plan and average temperature have the strongest effect on carbon stock, while exported deforestation does not even affect it. Ultimately, we can obtain this from the preliminary analysis described above: The most effective forest management plan of is a particular focus on these two aspects of proportion of forest area with a long-term operating plan and average temperature to improve carbon stock content. The forest products make a relatively large contribution to the carbon stock [2].

2.2. Gray Forecast Model

The GM(1,1) model can predict data with few data, incomplete sequences, and low reliability. It does not consider the distribution law or change trend and is suitable for medium and short-term forecasts of exponential growth.

First: Calculate the level ratio. When the level ratio is in the interval $\left(e^{(-2/(n+1))}, e^{(2/(n+2))}\right)$, it means that the data fits the model.

Second: If the original value does not pass the level ratio test, you can pass the "translation conversion", that is, add the "translation conversion value" to the original value, so that the new data meets the level ratio test and calculate based on the data, and then calculate the prediction. When the value is equal, the translation conversion value is also subtracted.

Third: Model construction calculates the development coefficient a, the amount of gray effect b, and calculates the value of the posterior difference ratio W.

Fourth: Predict the data, SPSS predicts 12 periods of data backward by default.

Fifth: Test the model, including relative error test, grade ratio deviation test.

In the GM (1,1) model construction for carbon stock, we first perform a level ratio test to determine the applicability of the data sequence for model construction [3]. The level ratio test values are all within the standard range interval [0.801,1.249], meaning that this data is suitable for GM (1,1) model construction. We then perform the carbon stock prediction for the last 13 years using the data from 2012 to 2019, which is shown in Fig. 2. Finally, we also test the relative error of the model. We find that the maximum model relative error value is 0.008 <0.1, meaning that the model fitting effect can achieve high requirements.

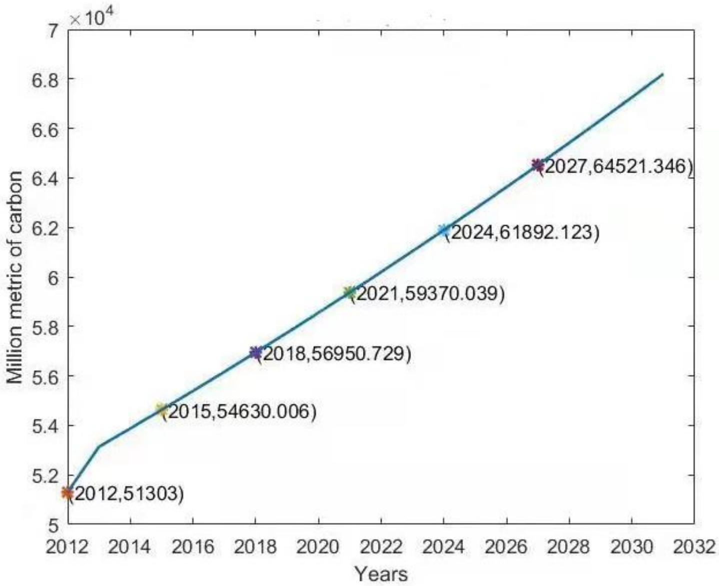

Figure 2. Predicted carbon stock from 2020 to 2032

3. Entropy Weight Method

The principle of the entropy weight method is to determine the objective weight according to the variability of indicators. Generally speaking, the smaller the information entropy of an index is, the greater the variation degree of the index value is, the more information it provides, and the greater the role it can play in the comprehensive evaluation, and the greater its weight is.

Supposing there are $n$indicator$X_1, X_2, \dots, X_n$.Among them, $X_i = \{X_{i1}, X_{i2}, \dots, X_{ik}\}; i = 1, w, \dots n$, K is the number of schemes.

For positive acting indicators:

$$X'_{ij} = (maxX_j - X_{ij})/(maxX_j - minX_j) \tag{3}$$

For negative acting indicators:

$$X'_{ij} = (X_{ij} - minX_j)/(maxX_j - minX_j) \tag{4}$$

According to the calculation formula of information entropy, calculating the information entropy of each indicator E_i, which can be expressed as:

$$E_i = -ln^{-1}(K) \textstyle\sum_{k=1}^{K} p_{ik} ln\, p_{ik} \tag{5}$$

Calculating the weight of each indicator through information entropy w_i, which can be expressed as:

$$w_i = \frac{1-E_i}{n-\sum_{i=1}^{n} E_i} \tag{6}$$

Then, we set up two indicators for these four subsystems respectively, which is shown in Fig.3.

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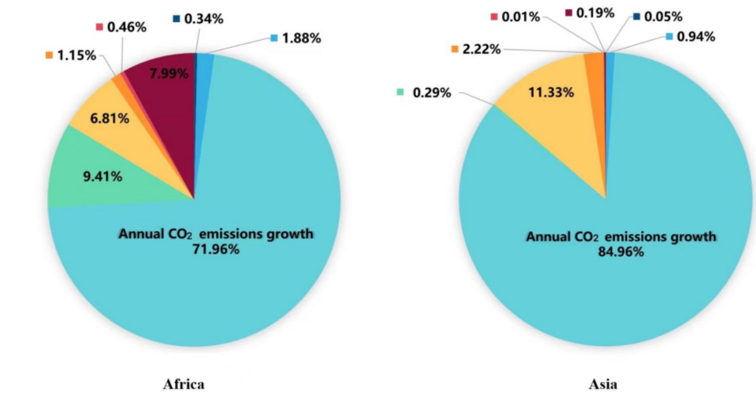
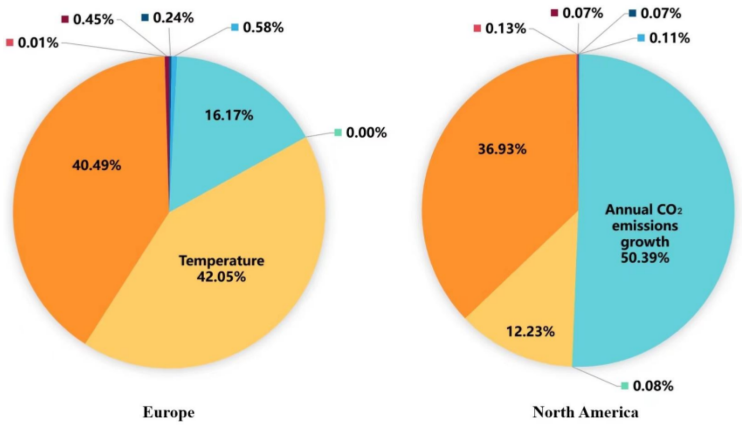
Figure 3. The indicators of four subsystems

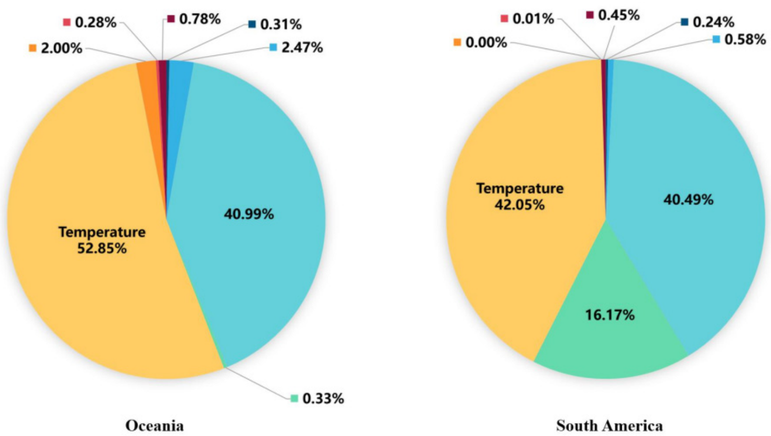
Then, we standardize the initial data of these eight indicators from 2012 to 2019 to calculate information entropy and information entropy redundancy. Finally, we solve the weight of each individual index through the redundancy of information entropy, and the result can be shown in Fig. 4 (a)-(c).



(a)



(b)



(c)

Figure 4. The weight of eight indicators in six continents

As can be seen from Fig.4, the forest managers in different continents should focus on the different value subsystems so that the forest can play the maximum value.

Forward the original matrix. In the TOPSIS method, all indicators must be unified and forwarded, that is, unified into extremely large indicators. Then it is necessary to convert extremely small, intermediate, and interval indicators into extremely large indicators. The formula for converting very small indicators to very large indicators is:

$$max - x \tag{7}$$

Defining the distance between the $i(i = 1,2, \dots, n)$evaluation object and the maximum value:

$$D_i^+ = \sqrt{\sum_{j=1}^{m}(Z_j^+ - z_{ij})^2} \tag{8}$$

Defining the distance between the $i(i = 1,2, \dots, n)$ evaluation object and the minimum value:

$$D_i^- = \sqrt{\sum_{j=1}^{m}(Z_j^- - z_{ij})^2} \tag{9}$$

Then, we can calculate the unnormalized score of the $i(i = 1,2, \dots, n)$ evaluation object:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{10}$$

We first weight the data to obtain new data according to the weight value calculated by the entropy weight method. Then, we solve for D^+ and D^- based on the new data, which respectively represent the distance between the evaluation object and the positive and negative ideal solution. According to the values of D^+ and D^-, the degree of closeness between each evaluation object and the optimal solution (C value) is finally calculated, and the value of C can be ranked , which is shown in Fig.5.

Africa

Year	D+	D−	C	Reasult
2012	202971	5	0.00	8
2013	177660	25311	0.13	7
2014	149684	53287	0.26	6
2015	108122	94849	0.47	5
2016	92103	110868	0.55	4
2017	58722	144249	0.71	3
2018	28623	174348	0.86	2
2019	10	202971	1.00	1

Asia

Year	D+	D−	C	Reasult
2012	1660	4	0.00	8
2013	1471	189	0.11	7
2014	1108	552	0.33	5
2015	1135	525	0.32	6
2016	635	1025	0.62	4
2017	486	1174	0.71	3
2018	234	1426	0.86	2
2019	4	1660	1.00	1

Europe

Year	D+	D−	C	Reasult
2012	2	1547	1.00	1
2013	707	840	0.54	4
2014	576	971	0.63	2
2015	598	948	0.61	3
2016	951	595	0.39	5
2017	1165	382	0.25	6
2018	1286	260	0.17	7
2019	1547	1	0.00	8

Oceania

Year	D+	D−	C	Reasult
2012	8618	12623	0.59	7
2013	21240	3	0.00	8
2014	7051	14189	0.67	5
2015	8380	12860	0.61	6
2016	6607	14633	0.69	4
2017	5277	15963	0.75	3
2018	1	21240	1.00	1
2019	302	20939	0.99	2

North America

Year	D+	D−	C	Reasult
2012	1	23401	1.00	1
2013	13430	10016	0.43	3
2014	16611	6865	0.29	5
2015	8998	14405	0.62	2
2016	22159	1244	0.05	7
2017	16028	7373	0.32	4
2018	23377	484	0.02	8
2019	19007	4396	0.19	6

South America

Year	D+	D−	C	Reasult
2012	1002613	3840150	0.79	4
2013	4842764	17	0.00	8
2014	568353	4274410	0.88	3
2015	4718078	124686	0.03	7
2016	302843	4539921	0.94	2
2017	4443054	399710	0.08	6
2018	40	4842764	1.00	1
2019	4239451	603313	0.13	5

Figure 5. TOPSIS evaluation results of six continents

4. Comprehensive Analysis

For the carbon stock prediction of superior national forest, we apply the grey forecast model. We use superior national forest's data from 2012 to 2019 to fit the corresponding values of carbon sequestration for 7 years after 100 years, which is shown in Fig.6.

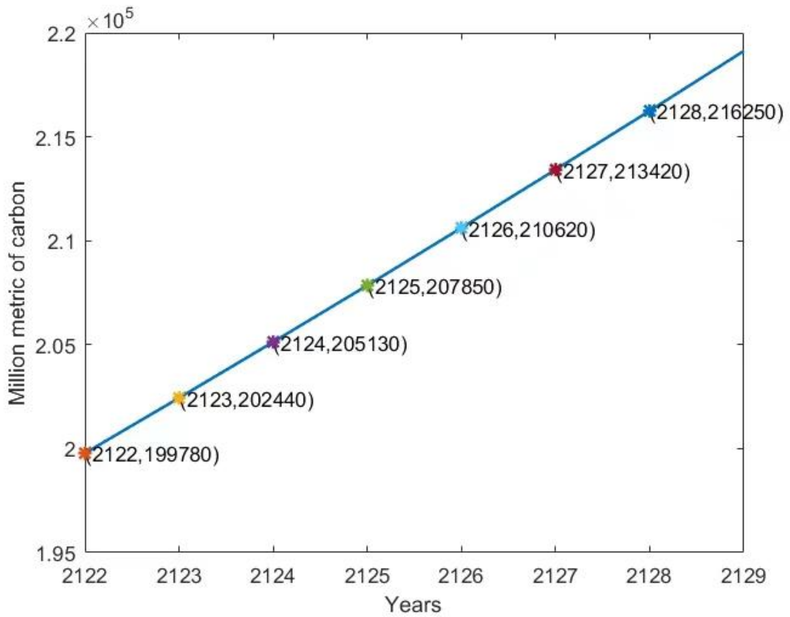


Figure 6. Predicted carbon stock of superior national forest

Therefore, we compare the data from these three indicators of superior national forest in 2020 with the best data in north america, which is shown in Fig.7.

Figure 7. The comparison of three indicators

From Fig.7, we can see that the superior national forest has a significantly positive effect on annual CO2 emissions growth which is significantly lower than the best data. Meanwhile, superior national forest has a slight contribution to the temperature. However, the proportion of forest area with a long-term operating plan of superior national forest is significantly lower than the standard data. This further proves that the relevant managers of superior national forest can cut down more trees to make forest products which play an important role in carbon stock.

Given the considerable uncertainty of proportion of forest area with a long-term operating plan and temperature, we perform a sensitivity analysis of these two parameters. The results show that when proportion of forest area with a long-term operating plan change by 1%, the regression coefficient change by 5% and the weight change by 3%. Meanwhile, when temperature change by 1%, the regression coefficient change by 3.2% and the weight change by 2%, with a small change also.

5. Conclusion

In this paper, we established two indicators for the two main pathways of carbon sequestration--forest remained and forest products, respectively, and performed correlation analysis using multiple linear regression. We found that forest products contributed the most to carbon sequestration. We selected 8 indicators for the forest management plan and analyzed the importance of the indicators using the entropy weight method.

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