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Forest Management and Planning based on ARIMA Carbon Sequestration Model

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Abstract

Climate change presents a massive threat to life as we know it. To mitigate the effects of climate change, we need to take drastic action to reduce the number of greenhouse gases in the atmosphere. Simply reducing greenhouse gas emissions is not enough. We need to enhance our stocks of carbon dioxide sequestered out of the atmosphere by the biosphere or by mechanical means. This ariticle develops a carbon storage model to determine how much carbon dioxide forests and their products are expected to store over time. Therefore, we can take time as a breakthrough and sort according to the timeline to develop the carbon sequestration model. Therefore, we use the ARIMA model to establish a carbon sequestration model and give the appropriate forest management plan. Finally, we viewed whether we need to cut down trees and provide conclusion.

Keywords

Carbon Storage Model; ARIMA; Carbon Sequestration Model; Forest Management.

1. Introduction

Climate change presents a massive threat to life as we know it. To mitigate the effects of climate change, we need to take drastic action to reduce the number of greenhouse gases in the atmosphere. Simply reducing greenhouse gas emissions is not enough. We need to enhance our stocks of carbon dioxide sequestered out of the atmosphere by the biosphere or by mechanical means. This process is called carbon sequestration. The biosphere sequesters carbon dioxide in plants (huge plants like trees), soils, and water environments. Thus, forests are integral to any climate change mitigation effort [1,2].

Forests sequester carbon dioxide in living plants and the products created from their trees, including furniture, lumber, plywood, paper, and other wood products. These forest products sequester carbon dioxide for their lifespan. Some products have a short lifespan, while others have a lifespan that may exceed that of the trees from which they are produced. The carbon sequestered in some forest products combined with the carbon sequestered because of the regrowth of younger forests can allow for more carbon sequestration over time compared to the carbon sequestration benefits of not cutting forests at all.

At the global level, forest management strategies that include appropriate harvesting can benefit carbon sequestration. However, overharvesting can limit carbon sequestration. Forest managers must find a balance between the value of forest products derived from harvesting and the value of allowing the forest to continue growing and sequestering carbon as living trees. In doing so, they must consider many factors such as age and types of trees, geography, topography, and benefits and lifespan of forest products.

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The concerns of forest managers are not limited to carbon sequestration and forest products. They must make forest management decisions based on the many ways their forest is valued. These may include but are not limited to potential carbon sequestration, conservation, and biodiversity aspects, recreational uses, and cultural considerations.

2. Related Work

This article develops a carbon storage model to determine how much carbon dioxide forests and their products are expected to store over time. Therefore, we can take time as a breakthrough and sort according to the timeline to develop the carbon sequestration model. Therefore, we use the ARIMA model to establish a carbon sequestration model and give the appropriate forest management plan.

ARIMA model is one of the most classical and widely used statistical prediction techniques when dealing with univariate time series. It uses the lag value and the lag prediction error to predict the eigenvalue. The ARIMA modle can be seen in Figure 1 [3-5].

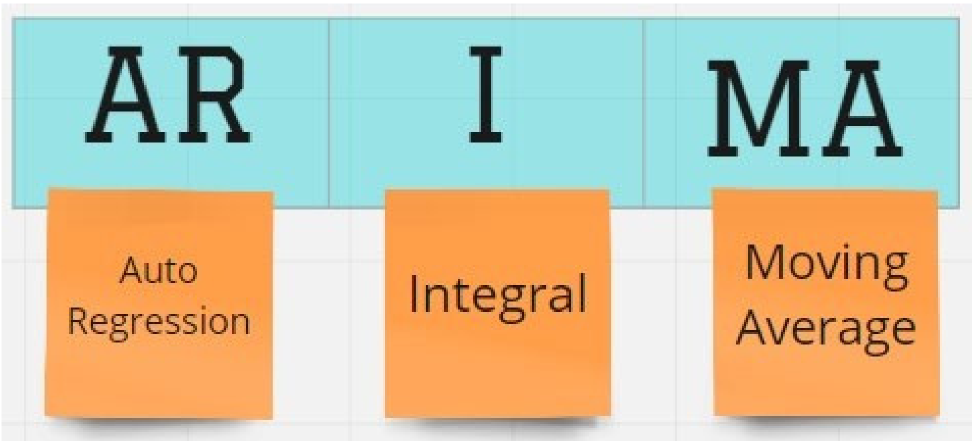

Figure 1. Introduction to ARIMA model

AR: lag using previous values
I: Nonstationary difference
MA: moving average for error items

3. Filter Suitable Merchants based on Supply Characteristics

3.1. Data Preprocessing

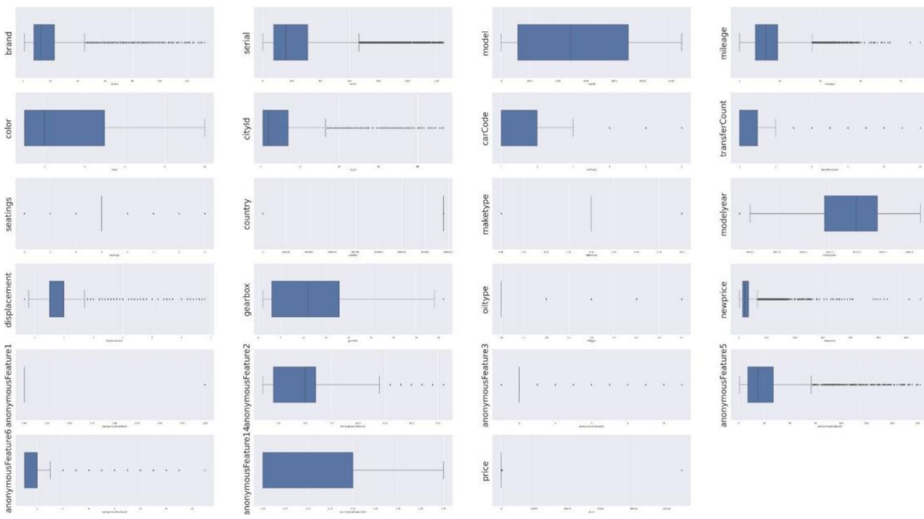

Figure 2. Data set box line diagram

We checked the outliers in the data set and drew the box diagram as Figure 2.

A Then, we checked the distribution of the data, and the results of the distribution map are as figure 3:

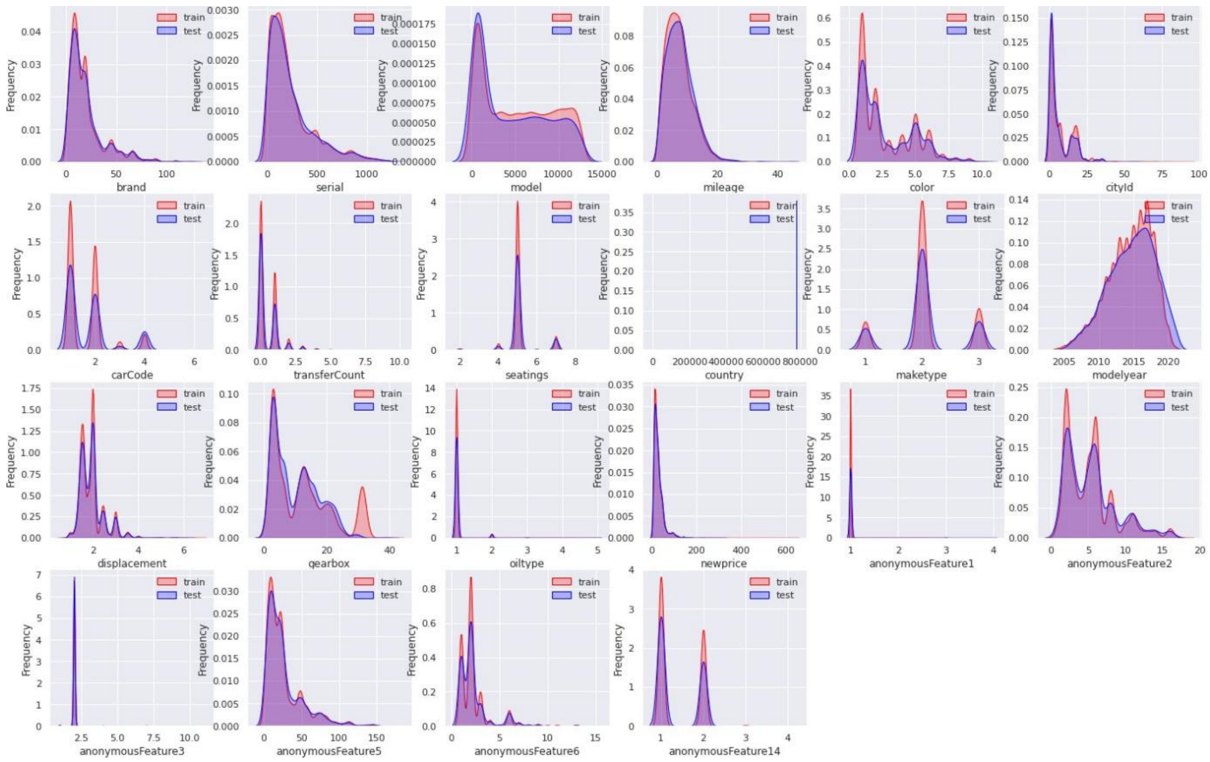

Figure 3. Data set distribution

The histogram distributed by all fields is shown in the following figure 4:

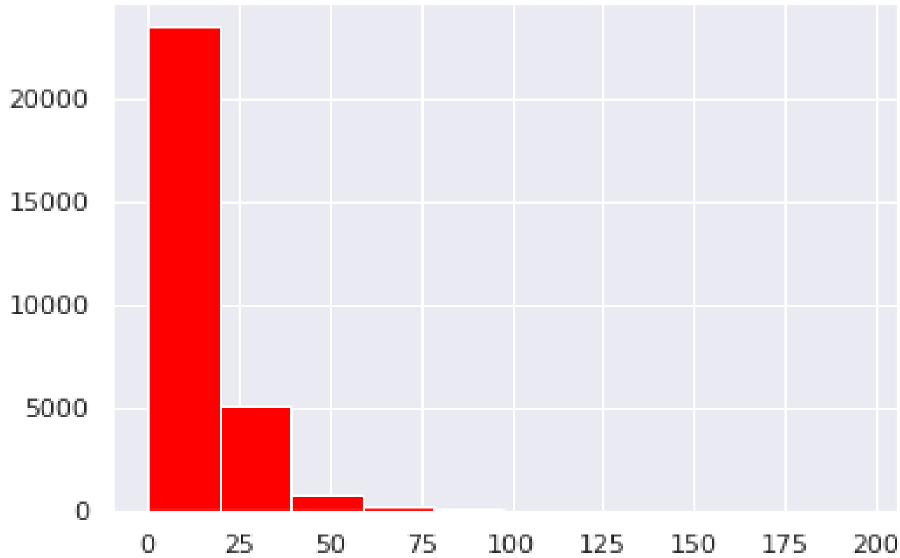

Figure 4. Field distribution histogram

The distribution map is drawn as figure 5:

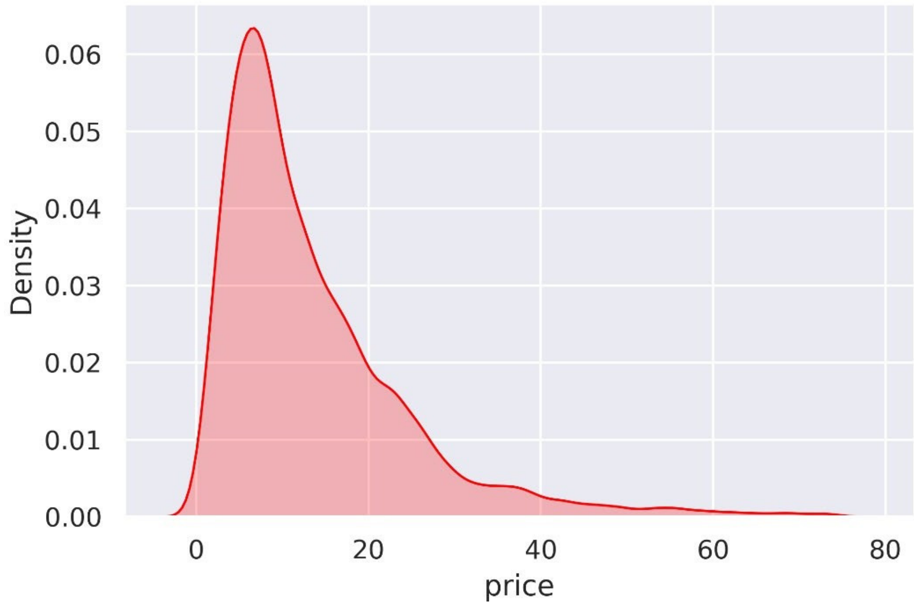

Figure 5. Frequency distribution of price field

The above figure shows that the data distribution does not conform to the normal distribution but is biased data. In regression, we are more sensitive to the data distribution. If it does not conform to the normal distribution, we need to convert the data into an approximately normal distribution.

Use the right deviation transformation function of the logarithm to convert the data distribution into an approximately normal distribution, and draw the data distribution diagram as figure 6:

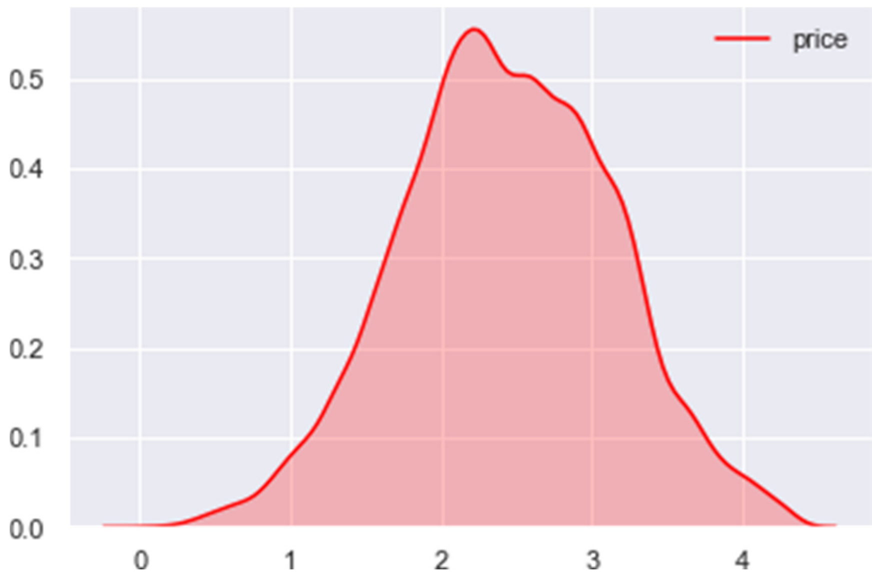

Figure 6. Frequency distribution after normal transformation

Draw the distribution map of the transformed data, and the data distribution is approximately normal distribution. The results are as figure 7:

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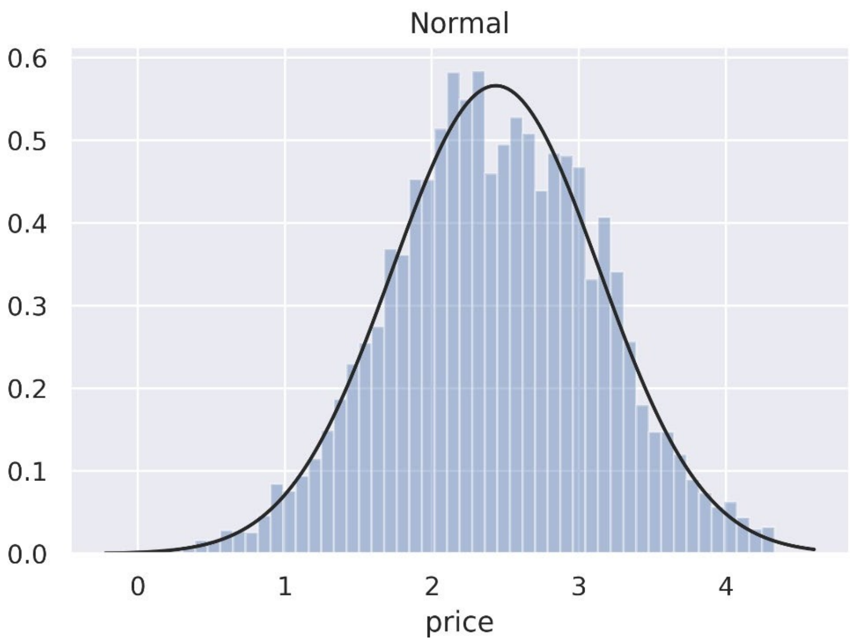

Figure 7. Frequency distribution after data transformation

3.2. Data Preprocessing

ARIMA model requires that the sequence data used must be stable. Therefore, before modeling, we must first judge the stationarity of the given original data. If the original data sequence is unstable, we can convert the unstable data into a stable data sequence by means of difference and logarithm.

ADF test is a commonly used method to judge the stationarity of data. It is a relatively strict method. Next, we use ADF test to judge whether the time series is stable. The python operation results are shown in the figure 8:

	value
Test Statistic Value	0.807369
p-value	0.991754
Lags Used	1
Number of Observations Used	31
Critical Value(1%)	-3.661429
Critical Value(5%)	-2.960525
Critical Value(10%)	-2.619319

Figure 8. ADF test results before differential processing

It can be seen from the above figure that the t statistic is greater than the critical value of any confidence, and the p value is greater than 0.05. Therefore, it is considered that the sequence is non-stationary. Therefore, the sequence is processed by difference. It is found that the sequence after difference is basically stable and passes the ADF test. The test results are shown in the following figure 9:

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	value
Test Statistic Value	-3.522762
p-value	0.007421
Lags Used	0
Number of Observations Used	31
Critical Value(1%)	-3.661429
Critical Value(5%)	-2.960525
Critical Value(10%)	-2.619319

Figure 9. ADF test results after differential processing

The main task of model identification and order determination is to determine the three parameters p, d and q. According to the recognition rules of time series, the order of ARMA model is determined by the combination of ACF diagram, PACF diagram, equatorial information criterion (AIC criterion) and Bayesian criterion (BIC criterion).

The full name of AIC criterion is the criterion of minimizing the amount of information. The calculation formula is as follows:

AIC = = 2 * (number of model parameters) - 2ln (maximum likelihood function value of the model)

AIC criterion has some shortcomings. When the sample size is large, the information provided by the fitting error in AIC criterion will be amplified by the sample size, but the penalty factor of the number of parameters has nothing to do with the sample size (always 2). Therefore, when the sample size is large, the model selected by AIC criterion does not converge with the real model, which usually contains more unknown parameters than the real model. BIC Bayesian information criterion makes up for the deficiency of AIC. The calculation formula is as

$$\text{BIC} = \ln(n) * (\text{number of parameters in the model}) - 2\ln (\text{maximum likelihood function value of the model}) \quad (1)$$

```
                           Results: ARMA
====================================================================
Model:              ARMA             BIC:                 -89.4537
Dependent Variable: y                Log-Likelihood:      51.658
Date:               2021-01-20 12:54 Scale:               1.0000
No. Observations:   32               Method:              mle
Df Model:           3                Sample:              12-31-1979
Df Residuals:       29                                    12-31-2010
Converged:          1.0000           S.D. of innovations: 0.048
No. Iterations:     24.0000          HQIC:                -93.373
AIC:                -95.3166
----------------------------------------------------------------------
               Coef.    Std.Err.      t      P>|t|     [0.025   0.975]
----------------------------------------------------------------------
const          0.1487     0.0130   11.4221   0.0000    0.1232   0.1743
ar.L1.y       -0.0346     0.3180   -0.1087   0.9135   -0.6578   0.5887
ma.L1.y        0.5940     0.2520    2.3571   0.0184    0.1001   1.0880
-----------------------------------------------------------------------------
                Real           Imaginary          Modulus          Frequency
-----------------------------------------------------------------------------
AR.1          -28.9419            0.0000          28.9419             0.5000
MA.1           -1.6834            0.0000           1.6834             0.5000
====================================================================
```

Figure 10. Model estimation results

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Where n is the sample size. The best combination of P and Q can be selected by using AIC and BIC. The group with the smallest AIC and BIC value should be selected as the ideal order.
The model estimation results are shown in the figure 10.

4. Conclusion

Many people say that cutting down trees is evil behavior because it will destroy the balance of the natural environment. At the same time, it will not be able to absorb carbon dioxide and reduce the production of oxygen. However, such a one-sided view of this issue is very wrong. The relevant data show that the excellent felling of trees is more conducive to controlling the balance of the ecological environment and can help the more favorable combination of carbon dioxide. we develop a carbon storage model to determine how much carbon dioxide forests and their products are expected to store over time. Therefore, we can take time as a breakthrough and sort according to the timeline to develop the carbon sequestration model. Therefore, we use the ARIMA model to establish a carbon sequestration model and give the appropriate forest management plan.

Declare

The two authors of this article contributed equally to the article. Both authors are first authors.

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