*Pol. J. Environ. Stud. Vol. 32, No. 5 (2023), 4789-4798*
DOI: *10.15244/pjoes/168445* ONLINE PUBLICATION DATE: 2023-07-24

*Original Research*

# Trends and Driving Forces of Agricultural Carbon Emissions: A Case Study of Fujian, China

**Yanwei Qi*, Huailiang Liu, Jianbo Zhao, Shanzhuang Zhang, Xiaojin Zhang, Weili Zhang, Yakai Wang**

School of Economics & Management, Xidian University, Xi'an, China

*Received: 18 March 2023*
*Accepted: 16 June 2023*

## Abstract

The prediction of regional agricultural carbon emissions is of great significance for regional environmental protection and sustainable development of regional agriculture. The article proposes a PLS-SA-AdaBoost prediction model combining partial least squares (PLS), simulated annealing algorithm (SA) and adaptive boosting algorithm (AdaBoost), which overcomes the shortcomings of a single model with insufficient prediction accuracy. Through an empirical study of agricultural carbon emissions in Fujian Province, China, the article validates the effectiveness of this combined forecasting model. The results show that the combined PLS-SA-AdaBoost forecasting model has higher accuracy and better performance than other models. The article predicts the future trend and range of agricultural carbon emissions in Fujian Province under five different scenarios.

**Keywords**: agricultural carbon emissions, trends and driving forces, prediction, Fujian, China

## Introduction

Ever-increasing warming of the climate system is now evident from observations of global average temperature rise of air and sea, widespread melting of snow and ice, and global average sea level rise [1, 2]. Meanwhile the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report concluded that most of the observed increase in global average temperature since the mid-20th century is likely due to increased concentrations of anthropogenic greenhouse gases [3, 4]. Available data show that human activities have caused an increase in global greenhouse gas emissions since the era of industrialization, such as an increase of 70% during 1970-2021 [5, 6]. Carbon dioxide serves as the most important anthropogenic greenhouse gas, with a rise of about 80% during 1970-2021 [7, 8].

As the concentration of greenhouse gases in the atmosphere has increased in recent years, the problem of carbon emissions has become an increasing threat to the survival of mankind and the development of social economy, and has become a major concern for all sectors of society [9, 10]. According to statistics, the extensive use of fertilizers, pesticides and fossil energy in agricultural production has made agriculture the second largest source of carbon emissions, in addition to a substantial number of carbon dioxide released in the industrial process [11, 12]. In China, the carbon emissions caused by agricultural production account for 17% of the total national emissions, with a significant impact [13, 14]. On the one hand, with the emergence of various functions of agricultural industry, such as

*e-mail: qi.yanwei@stu.xidian.edu.cn

grain production, ecological balance and social stability, it is increasingly important to ensure the unshakable status of agriculture as the foundation of the national economy [15, 16]. On the other hand, it is necessary to further explore the agricultural carbon source and its amount and quantify the loss of ecological and economic benefits caused by agricultural carbon emissions in order to respond to the development requirements of "transforming agricultural development mode" [17, 18]. This plays a greatly significant basic role in ensuring agricultural food security, maintaining the agricultural ecological environment, formulating agricultural carbon emission reduction indexes for government departments to push forward the process of agricultural low-carbon, with both theoretical and policy significance [19, 20].

Many scholars have conducted research on agricultural carbon emissions, mainly focusing on the following aspects: Firstly, driving factors of agricultural carbon emissions: For instance, the research shows that the influencing factors of agricultural carbon emissions include rural population, economic development level, agricultural technology factors, agricultural industrial structure, urbanization level, rural investment, per capita disposable income of farmers, etc. [21-25]. The research shows that fertilizer, irrigation power and agricultural film are the main factors affecting the growth of carbon emissions at the micro level, while economic factors are the key factors affecting the growth at the macro level [26]. The research shows that the degree of affluence and population effect are the main driving factors of agricultural carbon emissions [27]. Secondly, spatial-temporal dynamic changes of agricultural carbon emissions: For instance, spatial autocorrelation and coupling coordination model is adopted to evaluate the coupling coordination and spatial-temporal dynamic evolution of agricultural carbon emissions and agricultural modernization in China from 2010 to 2020 [28]. The spatial-temporal dynamics of the carbon footprint of major crops in China is studied to evaluate the carbon footprint per unit area (CFA) and carbon footprint per unit yield (CFY) of eight crops from 1990 to 2019 using the carbon footprint method based on the life cycle [29]. The Epsilon Based Measure-Global Malmquist-Luenberger (EBM-GML) model is adopted to measure China's agricultural green technology progress (AGTP) and discuss its dynamic evolution characteristics in the space-time dimension [30]. Thirdly, carbon emission sources in agricultural production: For instance, the research shows that crops including wheat, corn, sugarcane, cotton, pearl millet, sesame, etc. and land use in Pakistan are the main carbon emission sources in agricultural production [31]. The research shows that chemical fertilizers, pesticides, agricultural film, agricultural diesel and cultivation are five carbon emission sources in agricultural production [32]. The research shows that agricultural materials, rice planting, soil $N_2O$, livestock breeding and straw burning are the five carbon sources of agricultural carbon emissions [33]. Fourthly, the relationship between agricultural carbon emissions and economic development: For instance, the research shows that the development of China's agricultural economy has brought about an overall increase of 2% in agricultural trade [34]. With the development, the intensity of agricultural carbon emissions has decreased by 0.1%. The research shows that the agricultural economic growth of Henan Province in China in the past 20 years was realized at the cost of increased agricultural $CO_2$ emissions [35]. The research shows that carbon dioxide emissions will increase by 0.61% for every 1% rise in agricultural economic growth in Nepal [36]. Fifthly, analysis of regional differences in agricultural carbon emissions: For instance, the regional differences in agricultural carbon emissions efficiency are analyzed in China's seven major agricultural regions [37]. A dynamic analysis is conducted on the agricultural carbon emission efficiency of provinces along the "the Belt and Road" in China, which showed that there are significant regional differences in agricultural carbon emission efficiency levels among various regions [38]. A regional analysis of farm carbon emissions is conducted in the United States, assessing carbon emissions from crop production to partial milk supply chains of farms in five production regions in the United States [39]. In general, there are increasingly abundant studies on agricultural carbon emissions and increasingly extensive research content, methods and scope. However, there are few studies on prediction model and demonstration of regional agricultural carbon emissions, which is insufficient to guide for the reduction of regional agricultural carbon emissions and the healthy development of regional agricultural ecology.

Fujian Province, as an economic zone on the west side of the Straits, has the necessary water and heat conditions to develop agricultural production due to its geographical location, good climate and developed water system in the southeast coast, owning great advantages in developing ecological agriculture with its own characteristic [40]. However, the proportion of cultivated land in Fujian Province is small, of which most is terraced and sloping land, known as "Eighty percent of mountains, ten for water and land each", and lack of fertility and organic matter content in the soil [41]. In order to alleviate the contradiction between population growth and limited cultivated land area, Fujian Province has invested more human and material resources in the agricultural production, such as multiple cropping of cultivated land, ploughing, and fattening in recent years. A substantial number of human activities have led to its much higher agricultural carbon emissions than other regions, greatly enhancing the carbon source effect of agricultural production [42]. Therefore, the research of agricultural carbon emissions in Fujian Province is conducive to inspiration for the formulation of policies and standardization of irrational agricultural practice so as to promote the sustainable development of Fujian agriculture [43].

With Fujian Province as an example, considering the agricultural population, economic development, scientific and technological progress and other factors affecting the agricultural carbon emissions in Fujian Province, this paper builds a PLS-SA-AdaBoost prediction model combining partial least squares (PLS), simulated annealing algorithm (SA) and adaptive boosting algorithm (AdaBoost), and verifies the effectiveness of the combined prediction model through demonstrative methods. At the same time, under the five scenarios set in the paper, it predicts the future agricultural carbon emissions in Fujian Province, which is of great practical significance to the reduction of agricultural carbon emissions while increasing agricultural production in Fujian Province as well as the development of low-carbon agriculture.

The innovative points of this paper are as follows:

(1) A combined prediction model based on machine learning is given for the prediction problem of agricultural carbon emissions, and the effectiveness of the model is empirically verified on agricultural data in Fujian Province.

(2) The machine learning prediction model proposed in this paper has a better prediction accuracy compared with other models on agricultural data in Fujian Province.

(3) The combined prediction model proposed in this paper is used to forecast the trend and range of agricultural carbon emissions in Fujian Province under multiple scenarios over the next nine years.

## Material and Methods

### Partial Least Squares (PLS)

Partial Least Squares (PLS) was first proposed by Wolf and Alban, which provides a method of multi-to-multiple linear regression modeling [44]. Especially when there are a substantial number of variables which is in multiple correlations, and a relatively small number of observed data, the model built with partial least squares regression has advantages not found in traditional methods such as classical regression analysis. Partial least squares regression is a new regression analysis method widely used in the analysis and prediction of engineering technology and economic management, multiple regression analysis and modeling.

### Adaptive Boosting (AdaBoost)

The Adaptive Boosting (AdaBoost) is an algorithm that starting from a weak learning algorithm and iteratively learning to obtain a series of weak learners, and then combining these weak learners to construct a strong learner [45]. The key is to change the probability distribution of the training data, call the weak learning algorithm according to different training data distribution, and then integrate the weak learners under a certain weight to get the strong learners.

### Simulated Annealing (SA)

Simulated Annealing (SA) is a stochastic optimization algorithm in essential, which refers to the annealing process of solid substances in physical processes, and then extends to similar combinatorial optimization problems [46]. The annealing cooling process is to cool the heated liquid through parameter control, and finally form an ideal regular solid. During the cooling, the purpose of parameter control is to keep the liquid in a stable state. In case of a sharp drop in temperature and other conditions, the uniform fixation cannot be formed in the end.

### PLS-SA-AdaBoost Model

In order to improve the training accuracy of the prediction model, this paper constructs a PLS-SA-AdaBoost combined model for predicting regional agricultural carbon emissions in Fujian Province based on partial least squares (PLS), simulated annealing (SA) and adaptive boosting (AdaBoost). Wherein, PLS is applied to perform dimensionality reduction of the original input data, so as to remove the multicollinearity in the original input data; SA is adopted for parameter optimization to find the optimal parameter when the model is trained using the regional agricultural carbon emission data of Fujian Province; AdaBoost is used for model training, model prediction and model evaluation. The combined prediction model constructed is shown in Fig. 1.

In order to evaluate the prediction effect and the degree of advantages and disadvantages of the model, indexes including mean square error (MSE), mean

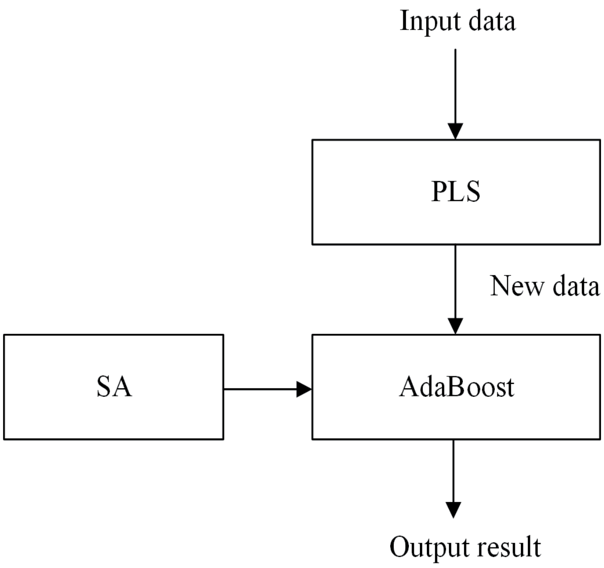


Fig. 1. PLS-SA-AdaBoost combined prediction model.

absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE) etc. are used in this paper. The equation of each evaluation index is as follows:

$$MSE = \frac{\sum_{i=1}^{n}(y-\hat{y})^2}{n} \quad (1)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y-\hat{y}| \quad (2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y-\hat{y})^2}{n}} \quad (3)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y-\hat{y}}{y}\right| * 100 \quad (4)$$

Wherein: $N$ is the number of sample data, $y$ is the true value of regional agricultural carbon emissions in Fujian Province, $\hat{y}$ is the predicted value of regional agricultural carbon emissions in Fujian Province.

## Index System Construction

Ehrlichg and Hdlden first proposed the impact population affluence technology (IPAT) model of environmental impact in the early 1970s [47]. As the model fail to reasonably reflect the impact of human factors on the environment, Dietz et al. have improved the model and constructed the stochastic impacts by regression on population, affluence and technology (STIRPAT) model [48].

Due to few factors affecting carbon emissions for IPAT model to examine, when this paper explores the index system that affects agricultural carbon emissions in Fujian Province, the model is expanded combined with the actual situation of agriculture in Fujian Province in terms of the number of agricultural employees, per capita agricultural GDP level, agricultural mechanization level, disposable income of rural residents, agricultural industrial structure, energy efficiency of agricultural production and area under mechanized cultivation, on the basis of influencing factors of agricultural carbon emissions from economic development, scientific and technological progress, and population. The expanded model form is:

$$lnI = lna + blnP + clnA + dlnT + elnE + flnS + glnN + hlnJ + ln\mu \quad (5)$$

Wherein, $a$, $b$, $c$, $d$, $e$, $f$, $g$, $h$ represents coefficient; $\mu$ is the model error.

The seven indexes selected in this paper that affect agricultural carbon emissions in Fujian Province can reflect the changing trend of regional agricultural carbon emissions. The category, variable content, symbol, unit and other information of these indexes are illustrated in detail in tables, as shown in Table 1:

## Data Processing

Since the selected data sample is composed of seven different indexes characteristic variables, various indexes characteristics owns various dimensions and dimensional units. It is necessary to normalize the data in order to eliminate the dimensional impact between different indicators to enable comparability of different data indexes without affecting the results of data analysis. Min-max standardization method is selected in the experiment of this paper.

Table 1. Factor Variables and Symbolic Meaning.

| Category of Indicators | Meaning of Variables | Symbol | Unit | Supporting Literature |
|---|---|---|---|---|
| Agricultural population | Number of rural populations | $P$ | One hundred million people | [49] |
| Economic development | Agricultural GDP per capita | $A$ | Ten thousand yuan/person | [49] |
| Progress in science and technology | Total power of agricultural machinery | $T$ | Gigawatt | [50] |
| Progress in science and technology | Energy efficiency in agricultural production, diesel use/total output value of agriculture, forestry, husbandry and fishery | $E$ | % | [49] |
| Economic development | Agricultural industrial structure, plantation output value/total agricultural output value | $S$ | % | [49] |
| Economic development | Per capita disposable income of rural residents | $N$ | Ten thousand yuan/person | [50] |
| Progress in science and technology | Area cultivated by machine tillage in the current year | $J$ | 1 million hectares | [50] |
| Regional agricultural carbon emissions | Total agricultural carbon emissions in the region | $I$ | Ten thousand tons | [50] |

Table 2. Statistical Result of the Original Sample Data.

| | Min | Max | Mean | Std |
|---|---|---|---|---|
| *P* | 0.127 | 0.198 | 0.162 | 0.022 |
| *A* | 0.213 | 1.502 | 0.692 | 0.423 |
| *T* | 0.873 | 1.384 | 1.151 | 0.161 |
| *E* | 0.060 | 0.254 | 0.138 | 0.061 |
| *S* | 0.366 | 0.415 | 0.394 | 0.012 |
| *N* | 3.230 | 23.229 | 10.112 | 6.368 |
| *J* | 0.405 | 1.131 | 0.767 | 0.277 |
| *I* | 429.134 | 684.656 | 542.870 | 71.617 |

## Results and Discussion

### Sample Original Data

This paper takes the agricultural production status of Fujian Province from 2000 to 2021 as the research object, of which the data are obtained by the calculation and sorting of records from the Fujian Statistical Yearbook, the China Rural Statistical Yearbook and the China Agricultural Yearbook. There are many indexes variables that affect the agricultural carbon emissions in Fujian Province, including the three factors of agricultural population, economic growth, and technological progress. In this paper, the per capita agricultural GDP level, the disposable income of rural residents, and the agricultural industrial structure are selected as the representatives for economic growth; the level of agricultural mechanization, the energy efficiency of agricultural production, and the area under mechanized cultivation are selected as the representatives for the basic aspects of technology. The descriptive statistical results of the original variables are shown in Table 2.

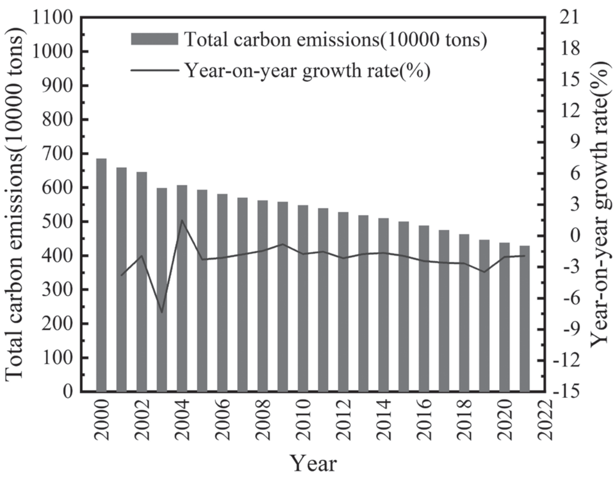


Fig. 2. 2020-2021 Agricultural Carbon Emission and Annual Growth Rate of Fujian Province.

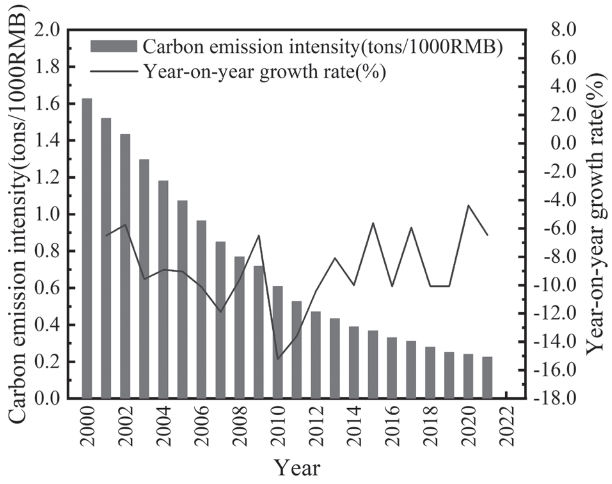


Fig. 3. 2020-2021 Agricultural Carbon Emission Intensity and Annual Growth Rate of Fujian Province.

The agricultural carbon emission and annual growth rate of Fujian Province are shown in Fig. 2.

The agricultural carbon emission intensity and annual growth rate of Fujian Province are shown in Fig. 3.

### Multicollinearity Test

Multicollinearity refers to the existence of correlation among explanatory variables in the model. In the prediction of actual agricultural carbon emissions, explanatory variables tend to own somewhat correlation, and multicollinearity is a common problem existing in multiple regression models. A new index variance inflation factor variance inflation factor (VIF) [51] can be constructed by using the decision coefficient to judge multicollinearity. In the multiple linear regression model, the variance inflation factor of the $i^{th}$ explanatory variable is:

$$VIF_i = \frac{1}{1-R_i^2}, \quad i = 1,2,\dots\dots,k \tag{6}$$

In which, $R_i^2$ is the determinable coefficient obtained by performing linear regression between the $i^{th}$ explanatory variable taken as the explained variable and the other $k-1$ explanation variables.

The larger the variance inflation factor, the closer $R_i^2$ is to 1, the stronger the collinearity between the $i^{th}$ explanatory variable and other explanatory variables. If the value of $VIF_i$ is greater than 10, it indicates that there is severe multicollinearity between explanatory variables. Table 3 shows the multicollinearity test results of various indexes of agricultural carbon emissions in Fujian Province, which can be seen that the $VIF_j$ value of most indexes is greater than 10, indicating that there is serious severe between indexes.

Table 3. Multicollinearity Test.

| Variable | VIF |
|---|---|
| $x_1$ | 219.257 |
| $x_2$ | 1022.393 |
| $x_3$ | 27.815 |
| $x_4$ | 2.742 |
| $x_5$ | 36.259 |
| $x_6$ | 13.769 |
| $x_7$ | 549.279 |

## Partial Least Squares (PLS) for Dimensionality Reduction

Multiple collinearities in the model can be eliminated by dimensionality reduction. In this paper, PLS is adopted to reduce the dimensionality of the index system of the original data. Same as principal component analysis, PLS also achieves dimensionality reduction by extracting principal components, i.e., the original variables are converted to produce a few new variables. These new variables are linear combinations of the original variables. At the same time, these new variables should represent the data structure of the original variables as much as possible and miss as little information as possible. In addition, the new variables, also known as principal components, are not related to each other, namely orthogonal. Five new principal components $t_1$, $t_2$, $t_3$, $t_4$ and $t_5$ are obtained after dimensionality reduction through PLS.

Next, the new principal component after dimensionality reduction will be used as the input data, with which the SA-AdaBoost model are used to predict the agricultural carbon emissions in Fujian Province.

## SA-AdaBoost Model Prediction

### *SA-AdaBoost Parameter Setting*

In this paper, SA is used to find the optimal hyper-parameter in the AdaBoost. The two hyper-parameters to be optimized in AdaBoost are maximum *n_estimators*, and *learning_rate* of weak learners, of which the value range of *n_estimators* is {90, 91, 92, ......, 220}, and the value range of *learning_rate* is {0.01, 0.02, 0.03, ......, 1}. The agricultural carbon emission data of Fujian Province is input into the combined prediction model using a 10-fold cross-validation to find the optimal hyper-parameter of the model under the data set, so that

Table 4. Fitting Result of PLS-SA-AdaBoost Model for Training Set.

| Year | Actual value (10000 tons) | Predicted value (10000 tons) | Absolute error (10000 tons) | Rate of error (%) |
|---|---|---|---|---|
| 2000 | 684.656 | 685.341 | 0.685 | 0.001 |
| 2001 | 658.735 | 660.053 | 1.319 | 0.002 |
| 2002 | 645.989 | 647.282 | 1.293 | 0.002 |
| 2003 | 598.338 | 597.142 | 1.195 | 0.002 |
| 2004 | 607.286 | 599.646 | 7.640 | 0.013 |
| 2005 | 593.396 | 591.619 | 1.778 | 0.003 |
| 2006 | 580.852 | 579.691 | 1.161 | 0.002 |
| 2007 | 570.419 | 568.142 | 2.277 | 0.004 |
| 2008 | 562.216 | 564.256 | 2.040 | 0.004 |
| 2009 | 557.633 | 560.612 | 2.979 | 0.005 |
| 2010 | 547.834 | 547.186 | 0.648 | 0.001 |
| 2011 | 539.503 | 541.574 | 2.071 | 0.004 |
| 2012 | 527.830 | 524.672 | 3.157 | 0.006 |
| 2013 | 518.542 | 519.061 | 0.519 | 0.001 |
| 2014 | 509.993 | 508.974 | 1.019 | 0.002 |
| 2015 | 500.114 | 505.029 | 4.916 | 0.010 |
| 2016 | 488.029 | 489.006 | 0.977 | 0.002 |
| 2017 | 475.429 | 474.479 | 0.950 | 0.002 |
| 2018 | 462.871 | 460.562 | 2.309 | 0.005 |

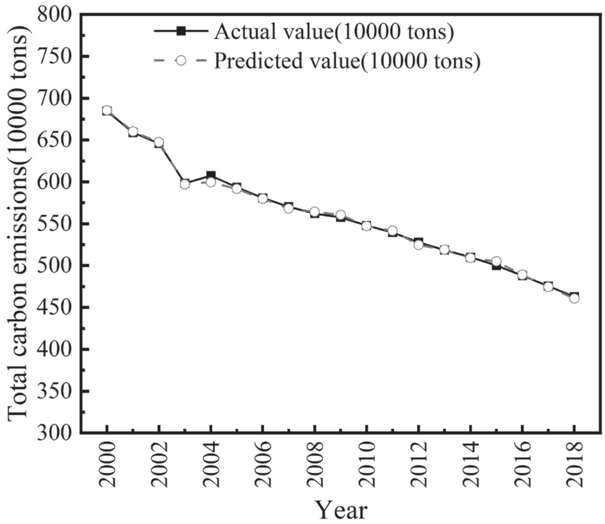


Fig. 4. Training Set Fitting Display.

the mean square error index can reach the minimum. Run the SA-AdaBoost program, and the optimal parameter combination is obtained: *n_estimators*: 108, *learning_Rate*: 0.50, and at this time the mean square error is the smallest: 0.0034.

### *Model Prediction*

Take the data of agricultural carbon emissions in Fujian Province as the data set, divide the data from 2000 to 2018 into training sets, the data from 2019 to 2021 into test sets, train the combined prediction model PLS-SA-AdaBoost through the training set, and then perform the test for the test set with the combined prediction model to evaluate the prediction ability of the model.

The PLS-SA-AdaBoost combined prediction model is used to fit the training set. Table 4 shows the fitting result data of the combined prediction model for the training set, which can be seen a relatively good fitting effect.

Fig. 4 shows the fitting display of the combined prediction model for the training set.

PLS-SA-AdaBoost combined prediction model is used to perform test on the test set, whose results are shown in Table 5. It can be seen that the average error rate of the PLS-SA-AdaBoost prediction model is 0.022, and the predicted value is basically close to the true value, showing a relatively good prediction ability of the PLS-SA-AdaBoost model. Moreover, compared with the SA-AdaBoost not using PLS as well as PCA-SA-AdaBoost model using principal component analysis (PCA) and SA, the PLS-SA-AdaBoost model shows the lowest error rate, which can be seen that PLS-SA-AdaBoost shows better prediction performance than the other two models. And applying PLS and SA to optimize the model parameters is conducive to improving the prediction effect of the model.

In order to verify the effectiveness of the PLS-SA-AdaBoost model proposed in this paper combining PLS, SA and AdaBoost, more models are added for comparison, including support vector regression (SVR), random forest (RF), feed forward networks (FFN), and models not using PLS but SA, using PCA and SA, using PLS and SA, of which measurement indexes of MSE, MAE, RMSE, MAPE, etc. are used for performance evaluation. The comparison results of the performance evaluation of each model are shown in Table 6. It can be found that all performance evaluation indexes of the PLS-SA-AdaBoost model show the best, indicating that the prediction effect of the PLS-SA-AdaBoost combined prediction model is the top.

## Discussion

### *Scenario Analysis and Parameter Setting*

This paper sets five different scenarios, namely high growth rate, average growth rate, low growth rate, minimum positive growth rate, maximum negative growth rate, etc. Then it uses PLS-SA-AdaBoost model to predict the agricultural carbon emissions of Fujian Province in 2022-2030 under these five different scenarios.

### *Prediction of Agricultural Carbon Emissions in Fujian Province*

According to the various scenarios set above, the PLS-SA-AdaBoost model built in this paper is used to predict the agricultural carbon emissions in Fujian Province, as shown in Fig. 5.

It can be seen from Fig. 6 that the predicted agricultural carbon emission of Fujian Province in Scenario 1 shows a trend of earlier decrease and later increase, from 5,178,500 tons in 2022 to 5,264,800 tons in 2030, with a rise of 1.66% in 9 years. In scenario 2,

Table 5. Comparative Analysis of Model Prediction Results.

| Year | Actual value | PLS-SA-AdaBoost | Rate of error | SA-AdaBoost | Rate of error | PCA-SA-AdaBoost | Rate of error |
|---|---|---|---|---|---|---|---|
| 2019 | 446.733 | 455.982 | 0.021 | 465.979 | 0.043 | 465.573 | 0.042 |
| 2020 | 437.617 | 442.500 | 0.011 | 469.108 | 0.072 | 468.291 | 0.070 |
| 2021 | 429.134 | 443.393 | 0.033 | 475.429 | 0.108 | 468.291 | 0.091 |

Table 6. Comparison Result of Each Model in Performance Evaluation.

| Model | MSE | MAE | RMSE | MAPE |
|---|---|---|---|---|
| GA-SVR | 0.02660 | 0.1628 | 0.1631 | 2.6780 |
| PCA-GA-SVR | 0.02209 | 0.1480 | 0.1486 | 2.4349 |
| PLS-GA-SVR | 0.02363 | 0.1530 | 0.1537 | 2.5167 |
| GA-RF | 0.01666 | 0.1286 | 0.1291 | 2.1149 |
| PCA-GA-RF | 0.00368 | 0.0584 | 0.0607 | 0.9615 |
| PLS-GA-RF | 0.00766 | 0.0860 | 0.0875 | 1.4140 |
| GA-AdaBoost | 0.00570 | 0.0714 | 0.0755 | 1.1746 |
| PCA-GA-AdaBoost | 0.00464 | 0.0655 | 0.0681 | 1.0771 |
| PLS-GA-AdaBoost | 0.00338 | 0.0558 | 0.0581 | 0.9175 |
| GA-FFN | 0.98218 | 0.8709 | 0.9911 | 14.3118 |
| PCA-GA-FFN | 0.09741 | 0.2953 | 0.3121 | 4.8596 |
| PLS-GA-FFN | 5.01087 | 2.2290 | 2.2385 | 36.6422 |

the agricultural carbon emission of Fujian Province is predicted to show a slow fall, from 5,206,600 tons in 2022 to 5,098,000 tons in 2030, a decrease of 2.09% in 9 years, with an average annual decline rate of 0.26%. In Scenario 3, the predicted agricultural carbon emissions in Fujian Province shows a relatively rapid decline, from 5,101,300 tons in 2022 to 4,591,400 tons in 2030, a fall of 9.99% in 9 years, with an average annual decline rate of 1.31%. In Scenario 4, the agricultural carbon emission of Fujian Province is also predicted to show a slow decline trend, from 5,243,700 tons in 2022 to 5,064,600 tons in 2030, a decrease of 3.41% in 9 years, with an average annual decline rate of 0.43%. In Scenario 5, the predicted agricultural carbon emission Fujian Province also shows a slow fall trend, from 5,125,200 tons in 2022 to 5,069,600 tons in 2030, with a decrease of 1.08% in 9 years and an average annual decline rate of 0.14%. In conclusion, the agricultural carbon emissions of Fujian Province of China will fluctuate between 5,264,800 tons and 4,591,400 tons in 2030 according to the prediction under five different scenarios.

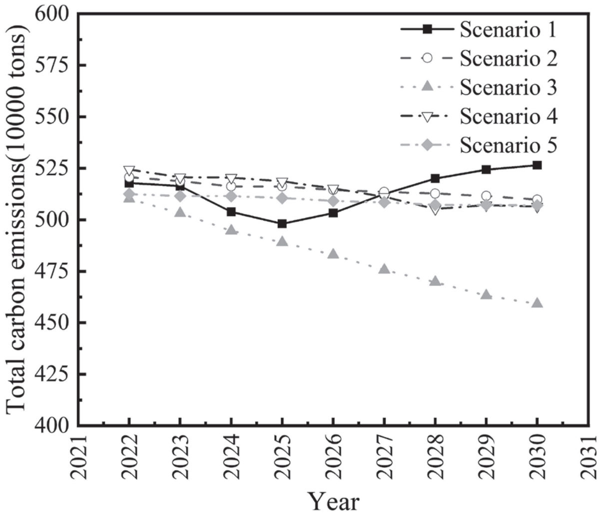


Fig. 5. Prediction of Agricultural Carbon Emissions in Fujian Province from 2022 to 2030.

It can be seen from the prediction results under these five scenarios that in order to control the future agricultural carbon emission level of Fujian Province and enable the green, environmental protection and healthy development of Fujian's agriculture, Fujian Province should try to carry out local agricultural production activities according to scenarios 3, 4 and 5, that is, the indexes including the number of agricultural employees, per capita disposable income of rural residents, and the area under mechanized cultivation should be controlled at the average growth rate, low growth rate and negative growth rate. In this way, the level of agricultural carbon emissions in Fujian Province can be effectively controlled, which is conducive to the healthy and sustainable development of agricultural ecology in Fujian Province.

## Conclusions

This paper constructs the PLS-SA-AdaBoost combined prediction model to compare its performance with other machine learning, neural network and other models and conduct demonstrative research on the agricultural carbon emissions data of Fujian Province with this combined model so as to predict the agricultural carbon emissions of Fujian Province from 2022 to 2030 under five set scenarios. The following conclusions can be drawn through demonstrative research:

1. Agricultural carbon emissions in Fujian are related to seven indexes such as the number of agricultural

workers, per capita disposable income of rural residents, and the area under mechanized cultivation. These seven indexes selected can predict the regional agricultural carbon emissions to a certain extent.
2. The error rate of PLS-SA-AdaBoost model in predicting agricultural carbon emissions in Fujian Province is much lower than that of AdaBoost model not using PLS but SA, as well as that using PCA and SA.

Compared with the other 11 machine learning and neural network models, the PLS-SA-AdaBoost model shows the best performance of measurement indexes of MSE, RMSE, MAE and MAPE, etc. in predicting agricultural carbon emissions in Fujian Province.

## Acknowledgments

This study was funded by National Science and Technology of China (2021ZD0113702).

## Conflict of Interest

The authors declare no conflict of interest.

## References

1. WOOLWAY R.I., KRAEMER B.M., LENTERS J.D., MERCHANT C.J., O'REILLY C.M., SHARMA S. Global Lake responses to climate change. Nature Reviews Earth & Environment, **1** (8), 388, **2020**.
2. LOEB N.G., JOHNSON G.C., THORSEN T.J., LYMAN J.M., ROSE F.G., KATO S. Satellite and ocean data reveal marked increase in Earth's heating rate. Geophysical Research Letters, **48** (13), 093047, **2021**.
3. SUN Y., ZHANG X., DING Y., CHEN D., QIN D., ZHAI P. Understanding human influence on climate change in China. National science review, **9** (3), 113, **2022**.
4. KNUTSON T.R., CHUNG M.V., VECCHI G., SUN J., HSIEH T.L., SMITH A.J. Climate change is probably increasing the intensity of tropical cyclones. Critical Issues in Climate Change Science, Science Brief Review, 4570334, **2021**.
5. GVAMFI B.A., AGOZIE D.Q., BEKUN F.V. Can technological innovation, foreign direct investment and natural resources ease some burden for the BRICS economies within current industrial era?. Technology in Society, **70**, 102037, **2022**.
6. WHELAN M.J., LINSTEAD C., WORRALL F., ORMEROD S.J., DURANCE I., JOHNSON A.C., TICKNER D. Is water quality in British rivers "better than at any time since the end of the Industrial Revolution"?. Science of the Total Environment, 157014, **2022**.
7. VAZ JR S., DE SOUZA A.P.R., BAETA B.E.L.Technologies for carbon dioxide capture: A review applied to energy sectors. Cleaner Engineering and Technology, 100456, **2022**.
8. GUR T.M. Carbon dioxide emissions, capture, storage and utilization: Review of materials, processes and technologies. Progress in Energy and Combustion Science, **89**, 100965, **2022**.
9. ZHAO X., MA X., CHEN B., SHANG Y., SONG M. Challenges toward carbon neutrality in China: Strategies and countermeasures. Resources, Conservation and Recycling, **176**, 105959, **2022**.
10. RAIHAN A., TUSPEKOVA A. Dynamic impacts of economic growth, energy use, urbanization, tourism, agricultural value-added, and forested area on carbon dioxide emissions in Brazil. Journal of Environmental Studies and Sciences, **12** (4), 794, **2022**.
11. ALI R., ISHAQ R., BAKHSH K., YASIN M.A. Do agriculture technologies influence carbon emissions in Pakistan? Evidence based on ARDL technique. Environmental Science and Pollution Research, **29** (28), 43361, **2022**.
12. KHAN Z.A., KOONDHAR M.A., TIANTONG M., KHAN A., NURGAZINA Z., TIANJUN L., FENGWANG M. Do chemical fertilizers, area under greenhouses, and renewable energies drive agricultural economic growth owing the targets of carbon neutrality in China?. Energy Economics, **115**, 106397, **2022**.
13. TANTIWATTHANAPHANICH T., SHAO X., HUANG L., YOSHIDA Y., LONG Y. Evaluating carbon footprint embodied in Japanese food consumption based on global supply chain. Structural Change and Economic Dynamics, **63**, 56, **2022**.
14. RAHMAN M.M., ANAN N., MASHUD A.H.M., HASAN M., TSENG M.L. Consumption-based $CO_2$ emissions accounting and scenario simulation in Asia and the Pacific region. Environmental Science and Pollution Research, **29** (23), 34607, **2022**.
15. ZHU X., PENG C. China's Anti-poverty: Explorations Since the 18th CPC National Congress. In 40 Years of China's War on Poverty, 109, **2022**.
16. CHEN Y., ZHU M. Spatiotemporal Evolution and Driving Mechanism of "Production-Living-Ecology" Functions in China: A Case of Both Sides of Hu Line. International Journal of Environmental Research and Public Health, **19** (6), 3488, **2022**.
17. CHEN W., CHEN W. Agricultural Development Mode: Relevant Theoretical Research at Home and Abroad. Challenges and Opportunities for Chinese Agriculture: Feeding Many While Protecting the Environment, 17, **2020**.
18. CHEN W., CHEN W. The transformation of agricultural production system in line with "Resource and Ecologically Sound Agriculture". Challenges and Opportunities for Chinese Agriculture: Feeding Many While Protecting the Environment, 183, **2020**.
19. WANG X. Managing land carrying capacity: key to achieving sustainable production systems for food security. Land, **11** (4), 484, **2022**.
20. PAWLAK K., KOLODZIEJCZAK M. The role of agriculture in ensuring food security in developing countries: Considerations in the context of the problem of sustainable food production. Sustainability, **12** (13), 5488, **2020**.
21. HU C., FAN J., CHEN J. Spatial and Temporal Characteristics and Drivers of Agricultural Carbon Emissions in Jiangsu Province, China. International Journal of Environmental Research and Public Health, **19** (19), 12463, **2022**.
22. ZHANG M., KAFY A. A., XIAO P., HAN S., ZOU S., SAHA M., ZHANG C., TAN S. Impact of urban expansion on land surface temperature and carbon emissions using

machine learning algorithms in Wuhan, China. Urban Climate, **47**, 101347, **2023**.
23. TAN S., ZHANG M., WANG A., ZHANG X., CHEN, T. How do varying socio-economic driving forces affect China's carbon emissions? New evidence from a multiscale geographically weighted regression model. Environmental Science and Pollution Research, **28**, 41242, **2021**.
24. ZHANG M., ZHANG Z., TONG B., REN B., ZHANG L., LIN X. Analysis of the coupling characteristics of land transfer and carbon emissions and its influencing factors: A case study of China. Frontiers in Environmental Science, **10**, 2579, **2023**.
25. KE Y., XIA L., HUANG Y., LI S., ZHANG Y., LIANG S., YANG Z. The carbon emissions related to the land-use changes from 2000 to 2015 in Shenzhen, China: Implication for exploring low-carbon development in megacities. Journal of Environmental Management, **319**, 115660, **2022**.
26. HUANG W., WU F., HAN W., LI Q., HAN Y., WANG G., WANG Z. Carbon footprint of cotton production in China: Composition, spatiotemporal changes and driving factors. Science of the Total Environment, **821**, 153407, **2022**.
27. RADWAN A., HONGYUN H., ACHRAF A., MUSTAFA A.M. Energy use and energy-related carbon dioxide emissions drivers in Egypt's economy: Focus on the agricultural sector with a structural decomposition analysis. Energy, **258**, 124821, **2022**.
28. XIA M., ZENG D., HUANG Q., CHEN X. Coupling Coordination and Spatiotemporal Dynamic Evolution between Agricultural Carbon Emissions and Agricultural Modernization in China 2010-2020. Agriculture, **12** (11), 1809, **2022**.
29. FAN J., GUO D., HAN L., LIU C., ZHANG C., XIE J., YIN L. Spatiotemporal Dynamics of Carbon Footprint of Main Crop Production in China. International Journal of Environmental Research and Public Health, **19** (21), 13896, **2022**.
30. DENG Y., CUI Y., KHAN S.U., ZHAO M., LU Q. The spatiotemporal dynamic and spatial spillover effect of agricultural green technological progress in China. Environmental Science and Pollution Research, 1, **2022**.
31. REHMAN A., MA H., OZTURK I., AHMAD M.I. Examining the carbon emissions and climate impacts on main agricultural crops production and land use: updated evidence from Pakistan. Environmental Science and Pollution Research, **29** (1), 868, **2022**.
32. LONG D.J., TANG L. The impact of socio-economic institutional change on agricultural carbon dioxide emission reduction in China. Plos One, **16** (5), 0251816, **2021**.
33. HUANG X., XU X., WANG Q., ZHANG L., GAO X., CHEN L. Assessment of agricultural carbon emissions and their spatiotemporal changes in China, 1997-2016. International Journal of Environmental Research and Public Health, **16** (17), 3105, **2019**.
34. ZANG D., HU Z., YANG Y., HE S. Research on the relationship between agricultural carbon emission intensity, agricultural economic development and agricultural trade in China. Sustainability, **14** (18), 11694, **2022**.
35. WANG Z., LV D. Analysis of Agricultural $CO_2$ Emissions in Henan Province, China, Based on EKC and Decoupling. Sustainability, **14** (3), 1931, **2022**.
36. RAIHAN A., TUSPEKOVA A. Nexus between economic growth, energy use, agricultural productivity, and carbon dioxide emissions: new evidence from Nepal. Energy Nexus, **7**, 100113, **2022**.
37. ZHANG X., LIAO K., ZHOU X. Analysis of regional differences and dynamic mechanisms of agricultural carbon emission efficiency in China's seven agricultural regions. Environmental Science and Pollution Research, **29** (25), 38258, **2022**.
38. ZHANG H., GUO S., QIAN Y., LIU Y., LU C. Dynamic analysis of agricultural carbon emissions efficiency in Chinese provinces along the Belt and Road. PloS one, **15** (2), 0228223, **2020**.
39. THOMA G., POPP J., SHONNARD D., NUTTER D., MATLOCK M., ULRICH R., KELLOGG W., KIM S. D., NEIDERMAN Z., KEMPER N., ADOM F., EAST C. Regional analysis of greenhouse gas emissions from USA dairy farms: A cradle to farm-gate assessment of the American dairy industry circa 2008. International Dairy Journal, **31**, 29, **2013**.
40. HOAGLAND P., YANG J., BROADUS J. M., CHU D. K. China Sea Coastal and Marine Nonfuel Minerals: Investigation and Development. In Resources and Environment in Asia's Marine Sector, 219, **2018**.
41. ZHONG L., WANG J., ZHANG X., YING L., ZHU C. Effects of agricultural land consolidation on soil conservation service in the Hilly Region of Southeast China–Implications for land management. Land Use Policy, **95**, 104637, **2020**.
42. ZHU Y., HUO C. The Impact of Agricultural Production Efficiency on Agricultural Carbon Emissions in China. Energies, **15** (12), 4464, **2022**.
43. XIE C. Exploring the Effective Path of Combining Rural Revitalization and Ecological Civilization Construction: Fuzhou City, Fujian Province as an Example. Scientific and Social Research, **4** (7), 31, **2022**.
44. LI X., MA J., LI S. A novel face recognition method based on Principal Component Analysis and Kernel Partial Least Squares. In 2007 IEEE International Conference on Robotics and Biomimetics (ROBIO). 1773, **2007**.
45. FENG D.C., LIU Z.T., WANG X.D., CHEN Y., CHANG J.Q., WEI D.F., JIANG Z.M. Machine learning-based compressive strength prediction for concrete: An adaptive boosting approach. Construction and Building Materials, **230**, 117000, **2020**.
46. JAVIDRAD F., NAZARI M. A new hybrid particle swarm and simulated annealing stochastic optimization method. Applied Soft Computing, **60**, 634, **2017**.
47. MAGEE C.L. A taxonomy for technology models used in environmental impact studies. Procedia CIRP, **69**, 412, **2018**.
48. XU F., HUANG Q., YUE H., HE C., WANG C., ZHANG H. Reexamining the relationship between urbanization and pollutant emissions in China based on the STIRPAT model. Journal of Environmental Management, **273**, 111134, **2020**.
49. XIONG C., CHEN S., XU L. Driving factors analysis of agricultural carbon emissions based on extended STIRPAT model of Jiangsu Province, China. Growth and Change, **51** (3), 1401, **2020**.
50. CUI H., ZHAO T., SHI H. STIRPAT-Based Driving Factor Decomposition Analysis of Agricultural Carbon Emissions in Hebei, China. Polish Journal of Environmental Studies, **27** (4), **2018**.
51. MILES J. Tolerance and variance inflation factor. Wiley statsref: statistics reference online, **2014**.