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Prediction model based on neural network and complex plane analysis: a case study of agricultural carbon emissions in Henan Province

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Introduction: Controlling carbon dioxide emissions and pursuing green development are imperative for global sustainable development. Accurately predicting agricultural carbon emissions is crucial for accelerating emission reduction efforts and guiding green technology innovation. This study focuses on forecasting agricultural carbon emissions in Henan Province to provide data-driven support for green agricultural development.

Methods: This research utilizes six key influencing factors—chemical fertilizer, pesticide, and agricultural film usage, among others—to predict total carbon emissions. Two primary analytical approaches were employed: a neural network model (comparing Multilayer Perceptron (MLP) and Radial Basis Function (RBF) models) and a nonlinear surface fitting method (specifically, Gaussian multi-modal fitting) for regression and prediction.

Results: The analysis yielded three main findings: 1) In carbon emission regression, the MLP model demonstrated superior performance with a smaller absolute residual error and significantly higher accuracy ($R^2 = 0.998$) compared to the RBF model ($R^2 = 0.933$), establishing it as more suitable for this forecasting task. 2) The Gaussian multi-modal fitting method effectively predicted the time-varying values of the influencing factors (all $R^2 > 0.9$), enabling reliable further prediction of carbon emissions. 3) Both methods indicate that agricultural carbon emissions in Henan Province follow a quadratic trend over time. The forecast for 2001–2030 reveals a pattern of rapid growth, followed by stable growth, and finally a phase of fluctuating decline.

Discussion: The high-precision prediction results offer a theoretical reference for advancing green agricultural development in Henan Province. Furthermore, they provide empirical, data-based support for promoting the "green production" concept and disseminating low-carbon policies, thereby enhancing the persuasiveness of ecological education. This contributes to establishing a positive ecological governance cycle of "consciousness - voluntary action - effect translation," ultimately aiding the synergistic enhancement of ecological and social benefits.

KEYWORDS

prediction model, neural network, complex plane, ecological values, agricultural carbon emissions

1 Introduction

The emission of carbon dioxide and other greenhouse gases causes the acceleration of global warming. It has become an international consensus to develop low-carbon economy and control carbon emissions. China has set a goal of peaking its carbon dioxide emissions by 2030 and striving to achieve a carbon neutral by 2060. The goal of carbon peak must be realized at all levels. The development of agriculture plays a vital role in the national economy, and the reduction of agricultural carbon emissions is increasingly concerned by the world. Measuring and analyzing the trend of agricultural carbon emissions is of great theoretical and practical significance for energy saving, consumption reduction, control of greenhouse gas emissions, implementation of rural revitalization strategy and construction of ecological civilization. Simultaneously, achieving the Dual Carbon Goals within the agricultural sector necessitates deeply concerted efforts spanning from conceptual awareness to practical action across society. As agriculture constitutes a fundamental industry within the national economy, reducing its carbon emissions requires not merely technological innovation and policy regulation, but more crucially, societal mobilization and value-oriented guidance to forge consensus. This empowers agricultural producers to embed “ecological priority and green development” as a core value and actively translate it into practice.

At present, domestic research on carbon emissions should focus on the calculation and prediction model of carbon emissions. Many scholars have built models from multiple levels to predict the peak and time of carbon emissions (Liu et al., 2022; Qiu et al., 2021; Zhang et al., 2021). Qiao (2021) predicted the development trend of carbon emissions from land use in Guiyang from 2020 to 2035, and put forward countermeasures and suggestions for low-carbon development of Guiyang based on the analysis of the results. Tian et al. (2021) used the extended STIRPAT model to simulate six scenarios and predicted the peak and peak time of carbon emissions in the Yangtze River Economic Belt during 2017–2030. Chu et al. (2020) used GDIM to study the driving factors of China’s agricultural carbon emissions from 1985 to 2017, simulated and predicted China’s agricultural carbon emissions from 2018 to 2030. Zhao et al. (2018) used the log-average segmentation index (LMDI) model to explore the relationship between soil and water resources exploitation and agricultural carbon emissions, and put forward policy suggestions for the future low-carbon development of agriculture in China. Using qualitative time series data from 1985 to 2018, Koondhar et al. (2021) analyzed autoregressive distribution lag, vector error correction model, and a new dynamic ARDL model to explore the green growth of food production under the constraints of agricultural carbon emissions and sown area. The European Green Deal to tackle climate change set a target for 2050. Particular attention is being paid to the agricultural sector, where there is a great need to reduce carbon emissions and rebuild the natural carbon cycle (Scuderi et al., 2021). Governance of carbon emissions necessitates technological approaches coupled with a paradigm shift in societal thinking. Agricultural carbon emissions, as one of the important sources of total carbon emissions, play an

important role in carbon peak, so agricultural carbon emissions increasingly become a research hotspot. Chinese scholars have conducted measurement and analysis of agricultural carbon emissions and their influencing factors at the municipal, provincial, and national levels (Yang et al., 2022; Zhu et al., 2022). In terms of agricultural carbon emission reduction, in addition to input factors, aspects such as farm size (Zhang et al., 2022a) and policy support (Chen and Wang, 2022; Zhu and Huo, 2022) have been found to exert significant impacts.

Many scholars have calculated and analyzed China’s agricultural carbon emission characteristics, carbon emission efficiency and carbon source structure (Shang et al., 2022; Yang et al., 2021), laying groundwork for regional low-carbon development strategies. However, further integration of technical conclusions with guidance mechanisms remains essential. For example, Chen et al. (2021) in Jiangsu Province found significant emission reduction potential in traditional agricultural production - findings that not only indicate opportunities for technical improvements but also demonstrate the need to guide farmers through education to adopt low-carbon production models. Wu et al. (2021) used Gini coefficient to analyze the dynamic evolution of agricultural carbon emission intensity in China, and selected parameter comparison method to measure regional differences in agricultural carbon offset potential in China. Zhang et al. (2022b) used the threshold regression model with agricultural carbon emission as the threshold variable to study the nonlinear relationship between the narrow sense of agricultural production efficiency and agricultural carbon emission intensity. Xiong et al. (2020) utilized the STIRPAT model to identify driving factors of agricultural carbon emissions in Jiangsu Province. Their proposed carbon compensation mechanism—targeting structured urbanization advancement, deployment of low-carbon technologies, and establishment of agricultural carbon offset systems.

In the field of forecasting model research, techniques such as neural networks, nonlinear surface fitting, and Gaussian models have been widely utilized (Papamarkou et al., 2022; Cheng and Titterton, 1994). Their integration can effectively enhance prediction accuracy and strengthen public awareness through data visualization (Titterton, 2004; Hall and Tajvidi, 2000; Buhlmann and Hothorn, 2007). However, despite the extensive application of traditional econometric models like STIRPAT, LMDI, and ARDL in factor decomposition and forecasting, they often rely on linear or parametric assumptions, making it difficult to fully capture the complex nonlinear interactions within agricultural emission systems (George et al., 2012; Goddard et al., 2009; Palmer, 2020). Consequently, a significant research gap remains in combining neural networks with nonlinear surface fitting for agricultural carbon emission prediction. Research in this direction is of great importance for innovating pathways toward green agricultural development and controlling carbon emissions.

Henan Province is located in the Middle East of China, the middle and lower reaches of the Yellow River, is the national grain production core area, the province’s arable land area of 8.15 million hm^2 , per capita arable land 0.075 hm^2 . In addition, the consumption

of chemical fertilizers, pesticides and agricultural film is relatively high in Henan Province. Selecting Henan Province as a case study for agricultural carbon emissions research holds significance beyond its representativeness. As a leading agrarian region, its endeavors in cultivating ecological awareness among farmers and advancing green transformation of agricultural practices carry demonstrative weight for national “Dual Carbon” goal attainment. This research focuses on Henan’s agricultural carbon emissions from 2000 to 2020, employing neural networks and nonlinear surface fitting to construct predictive models (As shown in Figure 1). The study serves dual purposes: providing technical reference for agricultural carbon peaking while exploring how to leverage data for public awareness education. This approach ultimately drives the translation of ecological principles into farming practices, achieving a synthesis of technical rationality and value rationality.

2 Establishment of carbon emission prediction model

2.1 Neural network prediction model

2.1.1 Theory

2.1.1.1 Multilayer perceptron

Multilayer perceptron is a feedforward artificial neural network model which maps multiple input data sets to a single output data set. The schematic diagram is shown in Figure 2. (The relevant data in this study are sourced from the Henan Statistical Yearbook (2000-2021) published by the Henan Provincial Bureau of Statistics,

which includes statistical data on the usage of agricultural materials such as Chemical fertilizers, Pesticides, Agricultural film, Agricultural diesel, Irrigation and Ploughing).

In Figure 2, in the prediction model of total carbon emissions, the input layer is the factor affecting the total carbon emissions, and the output layer is the expected total carbon emissions. The hidden layer does not directly receive signals from the outside world (influence factors), nor does it directly send signals to the outside world (total carbon emissions). Its role in the neural network is to calculate, train and verify the influence factors of the input, so as to obtain the prediction results of total carbon emissions.

2.1.1.2 Radial basis function

The radial basis function (RBF) is a real-valued function whose value depends only on the distance from the origin. Any one meet $\Phi(x)=\Phi(||x||)$ function Φ called radial basis function, the characteristic of standard general using Euclidean distance. In the neural network structure, it can be used as the main function of the full connection layer and ReLU layer.

RBF interpolation can be directly applied to geological exploration, shape design and other fields as interpolation or approximation of scattered data, and also has a good application in the construction of neural network.

Structure of the neural network basic method to assume a certain process belongs to a certain function space function, then connected into a neural grid, minimal potential tends to run for a period of time the network to achieve a dynamic balance, which can find out the function, and select the radial basis function space is a relatively simple easy to use the method of neural network to realize.

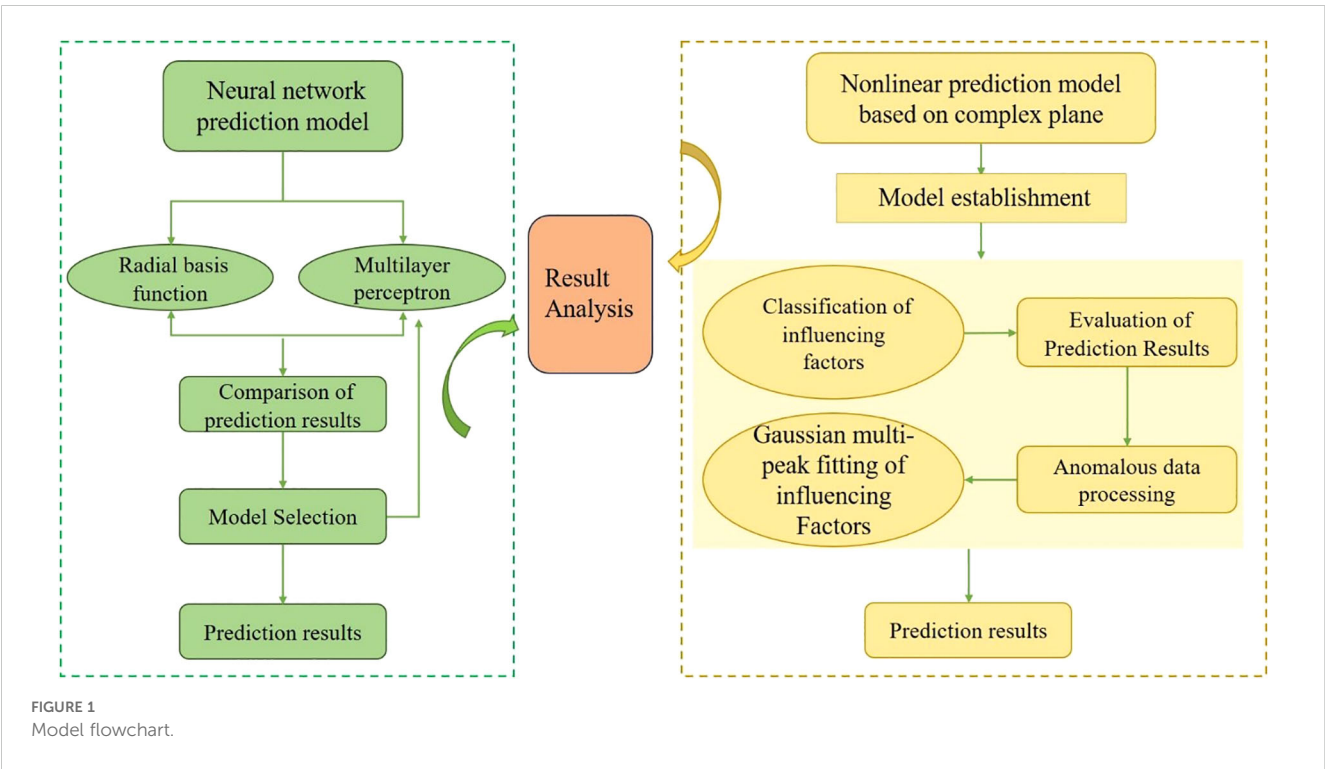


FIGURE 1
Model flowchart.

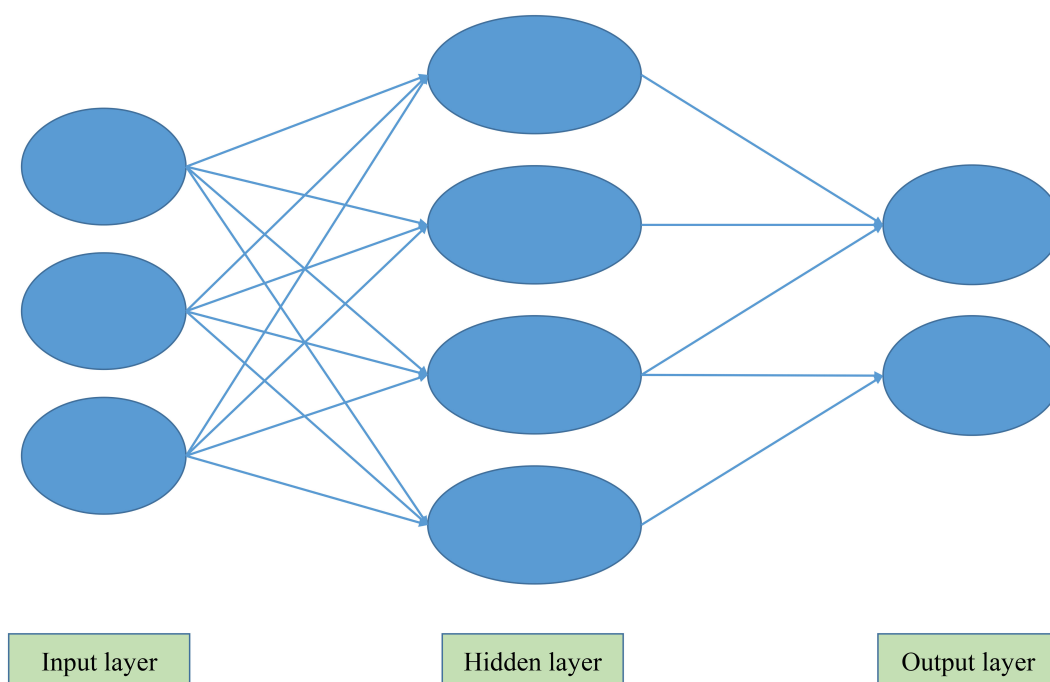


FIGURE 2
Multilayer perceptron.

2.1.2 Model establishment

According to the specific situation of agricultural carbon emissions in Henan Province and with reference to the relevant statistical data of Statistical Yearbook of Henan Province from 2000 to 2021, six factors that have an impact on the total carbon emissions are comprehensively selected: Chemical fertilizer, Pesticides, Agricultural film, Agricultural diesel, Irrigation and Ploughing. The carbon emission coefficient is calculated by referring to IPCC greenhouse gas emission inventory accounting (Pan et al., 2023). SPSS software was used to analyze the correlation between total carbon emissions and influencing factors. Multi-layer perceptron and radial basis function were used to establish the neural network prediction model of total carbon emissions. The model continuously adjusts its weights through iterative training (with the number of training epochs set to 50), thereby reducing errors and improving prediction accuracy. as shown in Figure 3.

In Figure 3A, the hidden layer activation function of multilayer perceptron is hyperbolic tangent, namely (Equation 1):

$$\tanh x = \frac{\sinh x}{\cosh x} = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (1)$$

In Figure 3A, the weight calculation method of each input layer is as follows:

1. Set the initial random weight (For the convenience of calculation, we write “deviation” as the first input factor), $\omega_{1n}(1 \times 6)$ and $\omega_{2n}(1 \times 2)$ are the weights of input layer and hidden layer respectively.
2. Multiply each factor of the input layer (x_{1n}) by the weight (w_{1n}).

3. Calculate the output result of hidden layer (Y_1).
4. Calculate the error between the output result of hidden layer and the real result (E).
5. Update weight.

Taking w_{11} as an example, Using the above method, the synaptic weight of the input layer of the multilayer perceptron can be calculated as:

$$\omega_{1n}^T (1 \times 6) = (-0.46, -0.188, 0.165, -0.469, -0.177, 0.055)^T$$

The deviation and synaptic weight of the input layer are -0.215 and -1.679, respectively. The deviation of the hidden layer is -0.307. The factors of the input layer are calculated with weights, combined with a bias, and processed through the hyperbolic tangent function to obtain the hidden layer output, which is then used with the output layer's weight and bias to calculate the total carbon emissions.

In Figure 3B, the hidden layer activation function of the radial basis function is SoftMax, that is (Equation 2):

$$\text{Softmax}(x_i) = \exp(x_i) / \sum_{n=1}^6 \exp(x_n) \quad (2)$$

The results of radial perceptron can be calculated by using the same method as multilayer perceptron. The specific steps will not be repeated.

Figure 4 shows a comparison between the carbon emission results calculated from the neural network model in Figure 3 and the original carbon emission data.

Figure 4 shows the importance of each influence factor under the two neural network models. Figure 4 shows that in the multi-

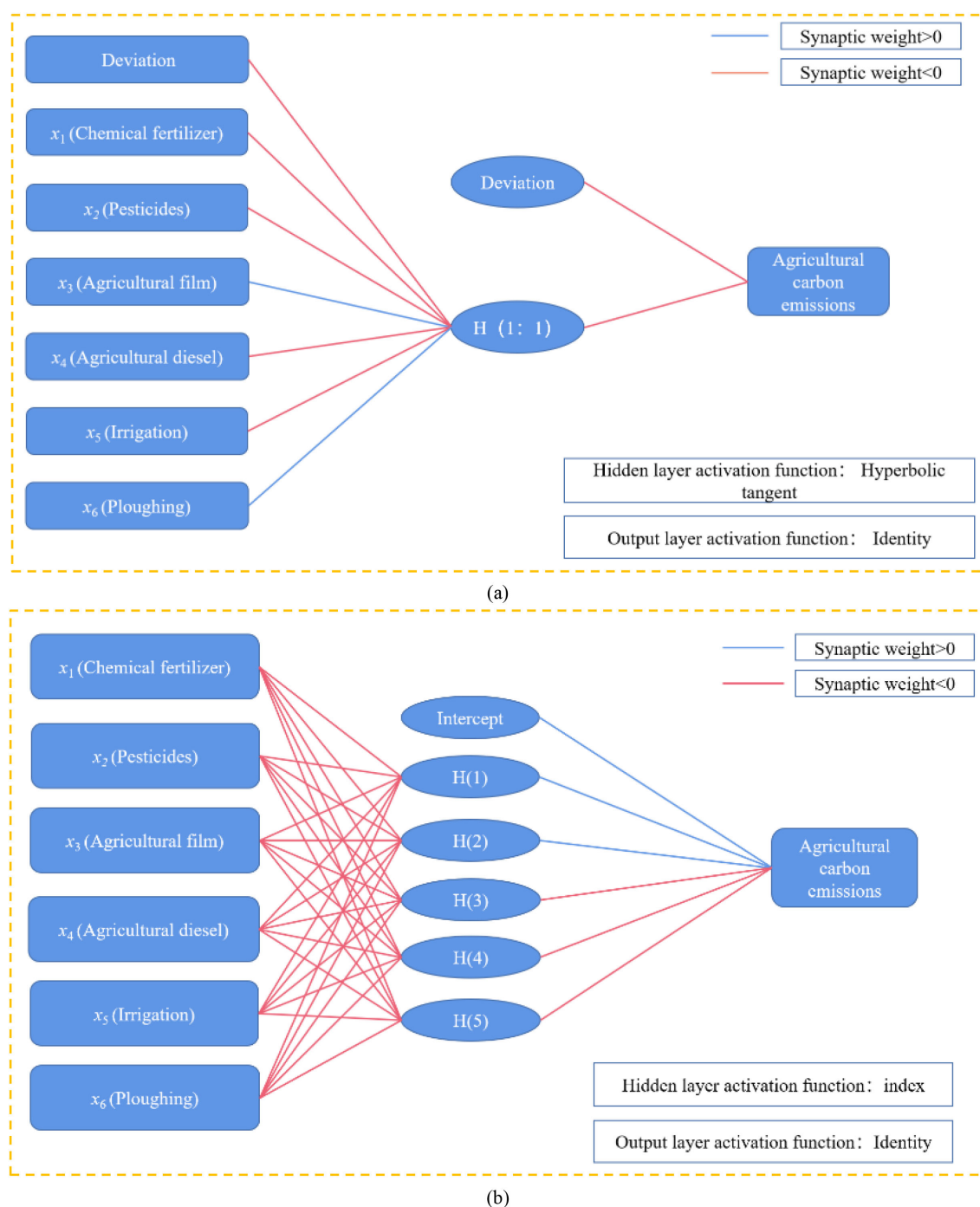


FIGURE 3
Neural network model of total carbon emission prediction. (a) Multilayer perceptron. (b) Radial basis function.

layer perceptron model, the order of importance of influencing factors is Agricultural diesel > Irrigation > Pesticides > Agricultural film > Chemical fertilizer > Ploughing. In the RBF model, the order of importance of influencing factors is Irrigation > Agricultural diesel = Ploughing = Pesticides > Chemical fertilizer = Agricultural film.

The importance of influencing factors reflects their role in neural network models. As can be seen from Figure 4, in the multi-layer perceptron model, the weight difference of each influencing factor is

obvious, among which the importance of agricultural diesel is the highest, the importance of fertilizer and ploughing is less. In the RBF model, the importance arrangement of each influencing factor is relatively close, which is concentrated in the range of 0.13~0.18, indicating that the model is not sensitive to the perception of each influencing factor and cannot distinguish the importance of all influencing factors, resulting in low accuracy of regression prediction.

As can be seen from Figure 4, the carbon emission prediction results obtained by the two neural network models of multi-layer

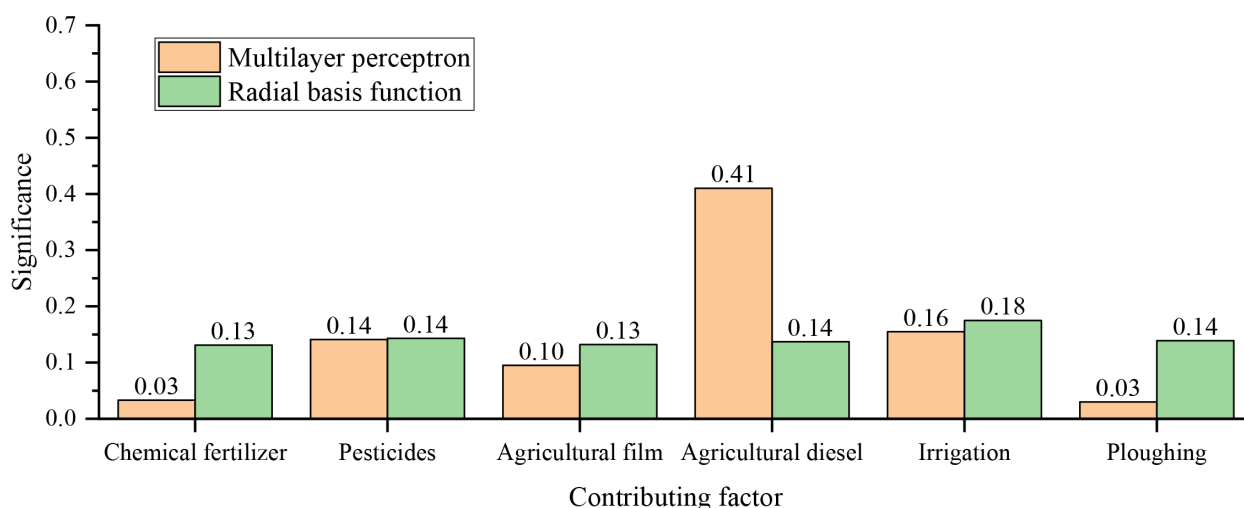


FIGURE 4
Importance analysis of influencing factors.

perceptron and radial basis function have a high similarity with the original recovery result. In order to analyze the fitting degree of the two models in detail, the residual (δ_i) and correlation coefficients (R^2) of the two prediction results should be calculated, as shown in Figure 5.

The Figure 6 shows that the absolute value of multilayer perceptron residual $|\delta_i| \in [0, 0.06]$, correlation coefficient $R^2 = 0.998$, the absolute value of radial basis function residual $|\delta_i| \in [0, 0.4]$, correlation coefficient $R^2 = 0.933$. The accuracy of multilayer perceptron is obviously higher than that of radial basis function. The results show that the accuracy of the multi-layer perceptron is obviously higher than that of the radial basis function, and it has a good effect on the regression and prediction of total agricultural carbon emissions. Therefore, the multi-layer perceptron is selected for further prediction calculation.

2.2 Nonlinear prediction model based on complex plane

2.2.1 Classification of influencing factors

In this section, the nonlinear surface fitting method is used to analyze the variation rule of total carbon emission with each influencing factor (Zhang et al., 2022). First, SPSS software was used to analyze the linear correlation between total carbon emissions and various influencing factors, as shown in Table 1. In Table 1, A: Agricultural film, B: Chemical fertilizer, C: Ploughing, D: Agricultural diesel, E: Irrigation F: Pesticides, CE: Carbon Emissions.

As can be seen from Table 1, different from the importance of each factor in the neural network model, correlation analysis shows that the Pearson (Aldrich (1995); Tjostheim et al. (2022)) correlation between each factor and the total carbon emission is as follows in

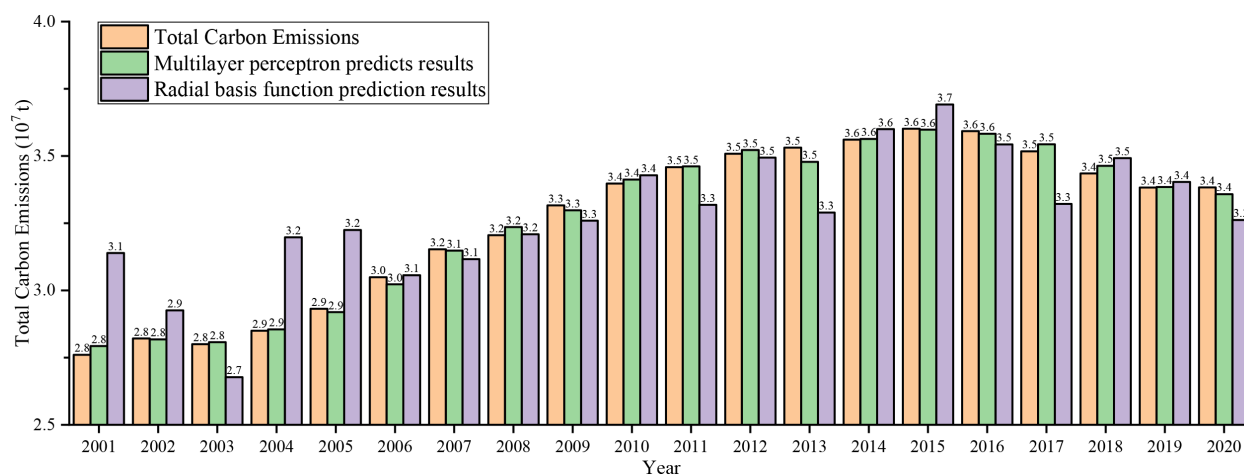


FIGURE 5
Neural network model prediction results.

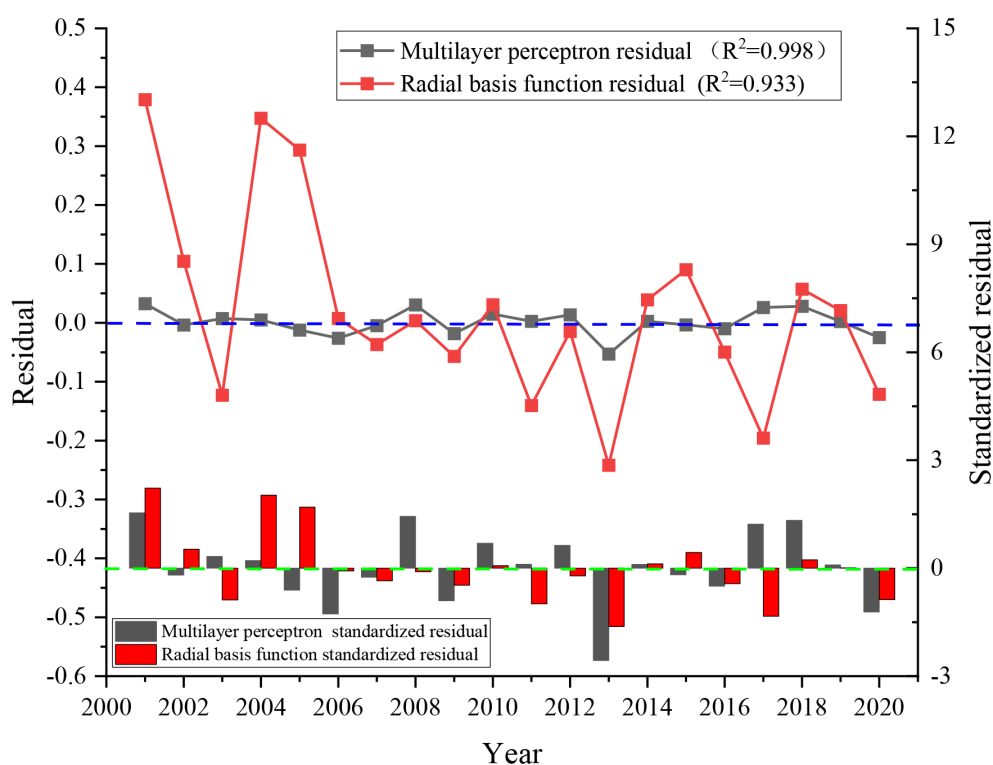


FIGURE 6
Residual analysis of neural network prediction results.

descending order: chemical fertilizer, agricultural film, agricultural diesel, ploughing, pesticide and irrigation.

The six influencing factors are not independent variables. In order to better analyze the impact of these influencing factors on total carbon emissions, the six influencing factors are grouped and multidimensional prediction is made. First, each influencing factor is grouped in pairs to obtain 15 permutations, as shown in Table 2.

Calculate the mean value of the correlation coefficients of the influencing factors of the three groups corresponding to each permutation in Table 2. The greater the mean value, the greater the correlation of the influencing factors in each group in the permutation. The average correlation of the second group was the highest of 0.90, so the second category was selected for calculation: Z_1 was agricultural film and chemical fertilizer, Z_2 was tillage and irrigation, and Z_3 was diesel oil and pesticide. Z_1 , Z_2 and Z_3 correspond to two influencing factors respectively, as shown in Table 3. Assume that Total Carbon Emissions is Z . Since Chemical fertilizer, Agricultural film, Agricultural diesel, Ploughing, Pesticide and Irrigation are not completely independent parameters, in order

to simplify calculation and increase the principle of visibility, imaginary units j and i are introduced, and Z is divided into three parts, namely (Equation 3):

$$Z = Z_1 + jZ_2 + iZ_3 \quad (3)$$

Therefore (Equation 4):

$$|Z| = \sqrt{Z_1^2 + Z_2^2 + Z_3^2} \quad (4)$$

2.2.2 Model establishment

As shown in Table 3, Let a , b and c be the weights of Z_1 , Z_2 and Z_3 respectively, then $Z_2 = \frac{P_2}{P_1} Z_1$ and $Z_3 = \frac{P_3}{P_1} Z_1$. As shown in Equation 5.

$$Z_1 = \frac{P_1}{\sqrt{P_1^2 + P_2^2 + P_3^2}} \cdot Z \quad (5)$$

Three-dimensional nonlinear fitting surfaces of $\{x_1 = \text{Chemical fertilizer}, y_1 = \text{Agricultural film}, Z_1\}$, $\{x_2 = \text{Ploughing}, y_2 = \text{Irrigation},$

TABLE 1 Correlation analysis between total carbon emission and influencing factors.

Group	A	B	C	D	E	F
CE	0.994	0.995	0.906	0.968	0.776	0.839

TABLE 2 Correlation grouping.

Group 1		Group1 correlation	Group 2		Group 2 correlation	Group 3		Group3 correlation	Mean correlation
A	B	0.99	C	D	0.85	E	F	0.33	0.72
A	B	0.99	C	E	0.78	D	F	0.93	0.90
A	B	0.99	C	F	0.66	D	E	0.61	0.75
A	C	0.91	B	D	0.96	E	F	0.33	0.73
A	C	0.91	B	E	0.80	D	F	0.93	0.88
A	C	0.91	B	F	0.81	E	D	0.61	0.78
A	D	0.96	F	C	0.66	E	B	0.80	0.80
A	D	0.96	F	E	0.33	C	B	0.91	0.73
A	D	0.96	F	B	0.81	E	C	0.78	0.85
A	E	0.78	D	F	0.93	B	C	0.91	0.87
A	E	0.78	D	B	0.96	F	C	0.66	0.80
A	E	0.78	D	C	0.85	F	B	0.81	0.81
A	F	0.81	C	E	0.78	D	B	0.96	0.85
A	F	0.81	C	D	0.85	E	B	0.80	0.82
A	F	0.81	C	B	0.91	D	E	0.61	0.78

$Z_2\}$ and $\{x_3=$ Agricultural diesel, $y_3=$ Tillage, $Z_3\}$ were established respectively, as shown in Figure 7. The fitting formula is shown in Equation 6.

$$\begin{cases} z_1 = 0.89 + 0.031x_1 + 0.1y_1 \\ z_2 = -0.71 + 0.25x_2 + 0.11y_2 \\ z_3 = 0.47 + 0.23x_3 - 0.07y_3 \end{cases} \quad (6)$$

By substituting Equation 6 into Equation 3, the fitting formula of total carbon emission based on six influencing factors can be obtained:

$$\begin{cases} Z = (0.89 + 0.03x_1 - 0.1y_1) + j(-0.71 + 0.25x_2 + 0.11y_2) + i(0.47 + 0.23x_3 - 0.07y_3) \\ |Z| = \sqrt{(0.89 + 0.03x_1 - 0.1y_1)^2 + (-0.71 + 0.25x_2 + 0.11y_2)^2 + (0.47 + 0.23x_3 - 0.07y_3)^2} \end{cases} \quad (7)$$

Equation 7 represents the influence rule of the six influencing factors on the total carbon emission. The calculation results of the real and imaginary parts of Equation 7 are combined with their corresponding years to draw a three-dimensional dot plot, as shown in Figure 8.

The prediction results of the carbon emission model were calculated by Equation 7. To further analyze the trend of total carbon emissions over years, quadratic polynomial fitting was

performed on the prediction curve, and the curve of carbon emissions over years was obtained as follows (As shown in Equation 8):

$$y = 0.89 + 0.031x_1 + 0.1y_1 - 0.71 + 0.25x_2 + 0.11y_2 + 0.47 + 0.23x_3 - 0.07y_3 \quad (8)$$

The influencing factors of agricultural carbon emissions were substituted into polynomial calculation. Figure 9 shows the comparison between the predicted results and the actual agricultural carbon emissions. The overall development trend of the two is unchanged, and the numerical difference is small. As can be seen from Figure 10, the absolute value of multilayer perceptron residual $|\delta_i| \in [0, 0.1]$, and the standardized residual value is mostly located at $[-2, 1.5]$. The correlation coefficient between the calculated actual value and the predicted value $R^2 = 0.974$, indicating that the polynomial can better fit the predicted results of the model.

3 Predicted results

3.1 Backward prediction of each influencing factor

In order to use the model established in section 2 to predict agricultural carbon emissions, it is necessary to first determine the future trend of each influencing factor. Therefore, the Gaussian multi-peak fitting method is adopted in this section to fit the data and time of six factors affecting agricultural carbon emissions.

Before the calculation, the scatter plot was used to test the data of each factor. According to Figure 10, irrigation data in 2013 and

TABLE 3 Weight of group.

Group	Factor of influence		P_n (weight; $n = 1, 2, 3$)
Z_1	A	B	0.99
Z_2	C	E	0.84
Z_3	D	F	0.90

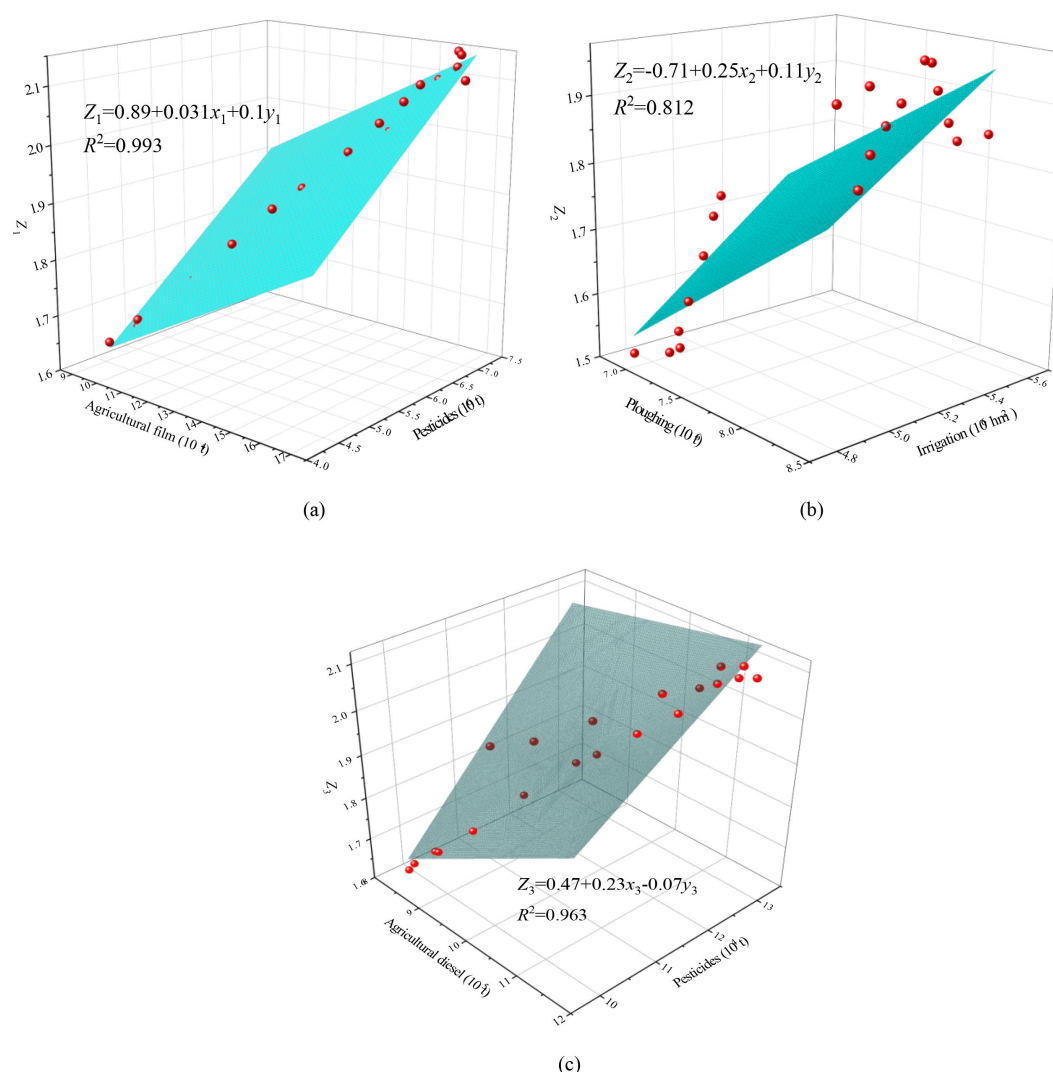


FIGURE 7

The fitting formula of each influencing factor. (A) z_1 fitting formula. (B) z_2 fitting formula. (C) z_3 fitting formula.

2014 were significantly different from the overall curve trend and were identified as outliers. In order to make the model more accurate, we eliminate the two outliers and use the Lagrange interpolation method to approximate the function. The specific steps are as follows: take three points before and after the notch to construct the interpolation polynomial $P_5(x)$. After calculation, the remaining term is less than 3.2×10^{-3} , which meets the accuracy requirements. The polynomial was used to recalculate the data at the year =2013 and 2014, and the corrected agricultural film-time scatter plot was obtained, as shown in the red dot in Figure 11.

As shown in Figure 12, the fitting formula of agricultural diesel is as follows (As shown in Equation 9):

$$\begin{cases} y_1 = 8.3213 + \frac{20.1033}{7.1157 \times \sqrt{\frac{\pi}{2}}} \exp\left\{-2\left(\frac{x-2010.7162}{7.1157}\right)^2\right\} \\ y_1 = 8.3213 + \frac{5.1567}{3.7811 \times \sqrt{\frac{\pi}{2}}} \exp\left\{-2\left(\frac{x-2014.9292}{3.7811}\right)^2\right\} \\ y_1 = 8.3213 + \frac{13.2514}{7.0083 \times \sqrt{\frac{\pi}{2}}} \exp\left\{-2\left(\frac{x-2018.0855}{7.0083}\right)^2\right\} \end{cases} \quad (9)$$

According to the above steps, calculate the fitting formula for the remaining influencing factors.

The fitting equation of each influencing factor is obtained through customs clearance calculation to predict the data of the next ten years, and the prediction results are shown in Figure 13.

It can be seen from the above figures that the development trend of each influencing factor presents a trend of gradual development after a rise, and each factor reaches its peak and gradually declines between 2015 and 2025. Through the above function calculation, the predicted results of each factor after 2021 are as follows (Table 4):

3.2 Analysis of carbon emission prediction results

The prediction results of each factor by Gaussian multi-peak fitting in Section 4 were respectively put into the multi-layer

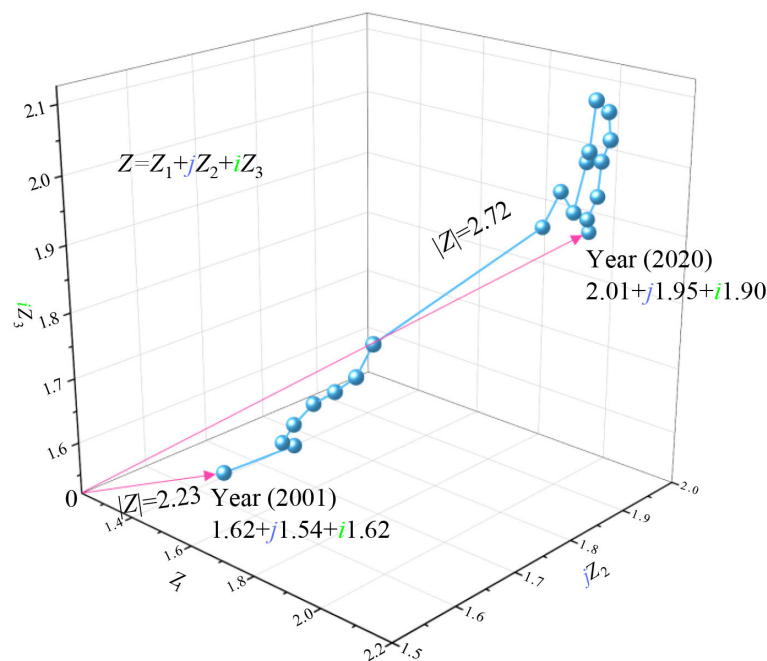


FIGURE 8
Complex plane model diagram.

perceptron model and nonlinear surface fitting model for prediction calculation. The agricultural carbon emission data in the next ten years were obtained and the curve was drawn as follows:

The blue shaded part in the figure is the fitting effect diagram of the actual value. As can be seen from the Figure 14, the first stage was from 2001 to 2012, when agricultural carbon emissions in Henan Province rose rapidly. In the second stage, from 2012 to

2015, agricultural carbon emissions rose slowly and reached a peak, and then showed a downward trend after 2015. Henan Province is the core producing area of grain production in China, and its cultivated land area ranks the third in China. From 2001 to 2012, with the abolition of China's agricultural tax and the rapid development of agriculture in Henan Province, the consumption of chemical fertilizer, agricultural diesel, irrigation and agricultural film in agricultural production increased significantly, resulting in a

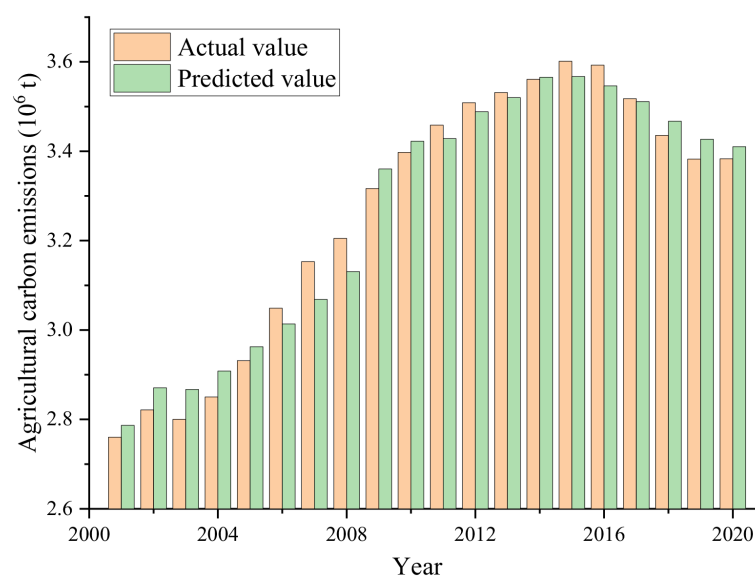


FIGURE 9
Nonlinear surface prediction model results.

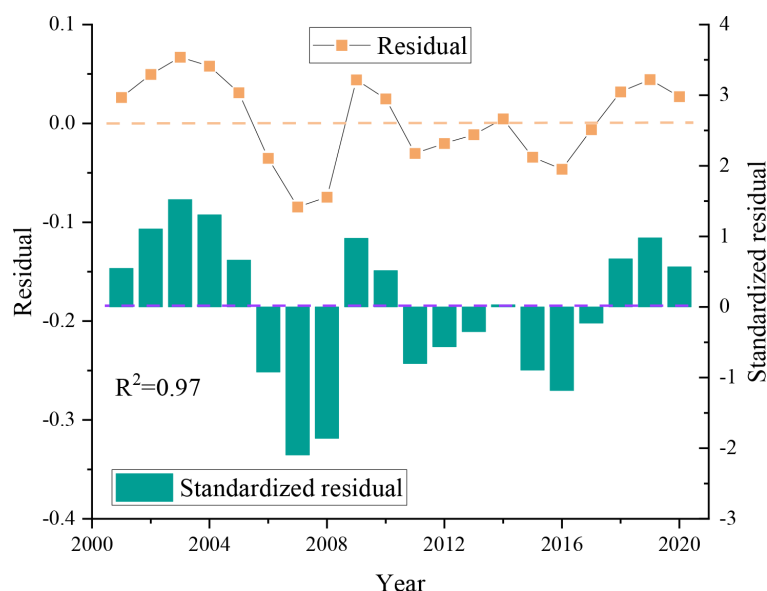


FIGURE 10
Residual analysis of nonlinear surface prediction results.

rapid growth of total agricultural carbon emissions. With the promotion of modern agricultural production system and the gradual improvement of production efficiency from 2012 to 2015, agricultural carbon emissions showed a slow growth, and showed a downward trend after 2015. In the third stage, there is a downward trend from 2015 to 2020, with the promotion of agricultural modernization in Henan Province, there will be a small increase from 2020 to 2023.

The pink shaded part of the figure shows the projected agricultural carbon emissions of Henan Province from 2021 to 2030. The first three stages show that the prediction results of the two models are close to each other. In the fifth stage, the prediction results of the two models show great differences. The predicted

value of the multi-layer perceptron model is significantly higher than that of the nonlinear surface fitting model, and the downward trend tends to be gentle. This is because the nonlinear surface fitting model is based on the historical function relationship, and the closer the model is to the historical data, the better the prediction effect will be. Conversely, the further the model move away from historical data, the worse the prediction.

With the proposal of carbon neutrality and carbon peaking and the promotion of green sustainable agriculture, agricultural carbon emissions in Henan Province will inevitably show a downward trend. Therefore, the prediction model of agricultural carbon emission proposed in this paper is reasonable.

4 Discussion

Employing neural networks and nonlinear surface fitting with six influencing factors (including chemical fertilizers, pesticides, and agricultural plastic films), this study conducted regression analysis and projection of agricultural carbon emissions in Henan Province. From an interdisciplinary perspective, controlling agricultural emissions constitutes both a technological challenge and a socio-cognitive issue involving transformational producer awareness and societal consensus building.

Amid growing emphasis on green agriculture, the relationship between chemical inputs (e.g., fertilizers/pesticides) and carbon emissions has become a research focal point. Our predictive model offers novel pathways for quantitative analysis. Agricultural carbon emission reduction requires the dissemination of technical optimization protocols and education-driven “green production” principles to farmers. In this process, model predictions can enhance farmers’ intuitive understanding of emission impacts, catalyzing a behavioral shift from passive compliance to active

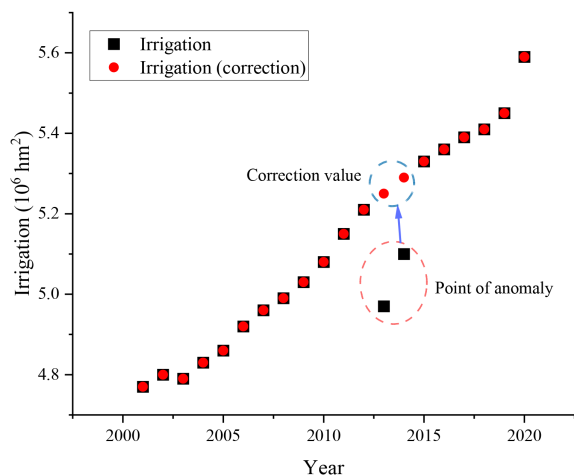


FIGURE 11
Test of outliers.

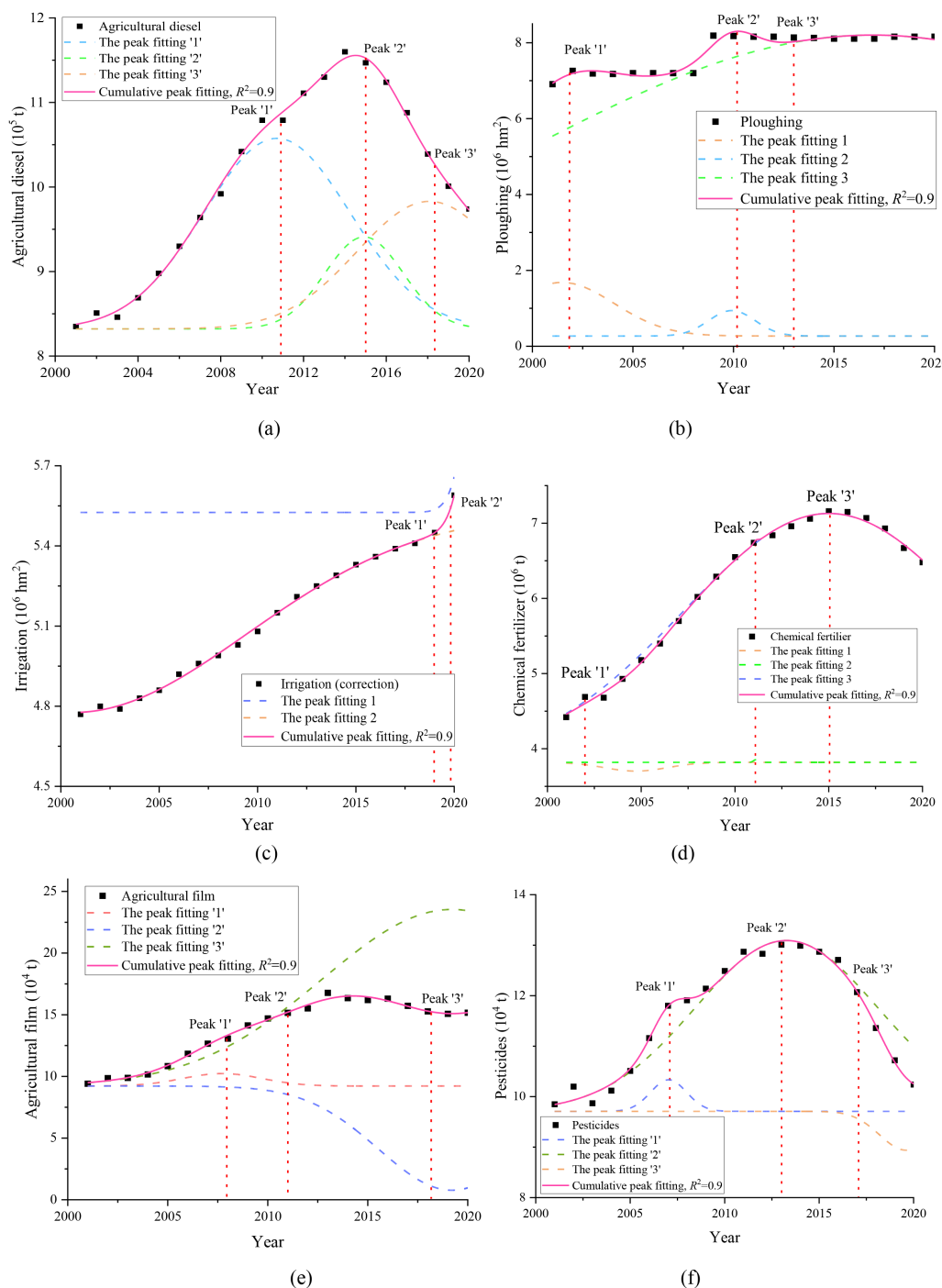
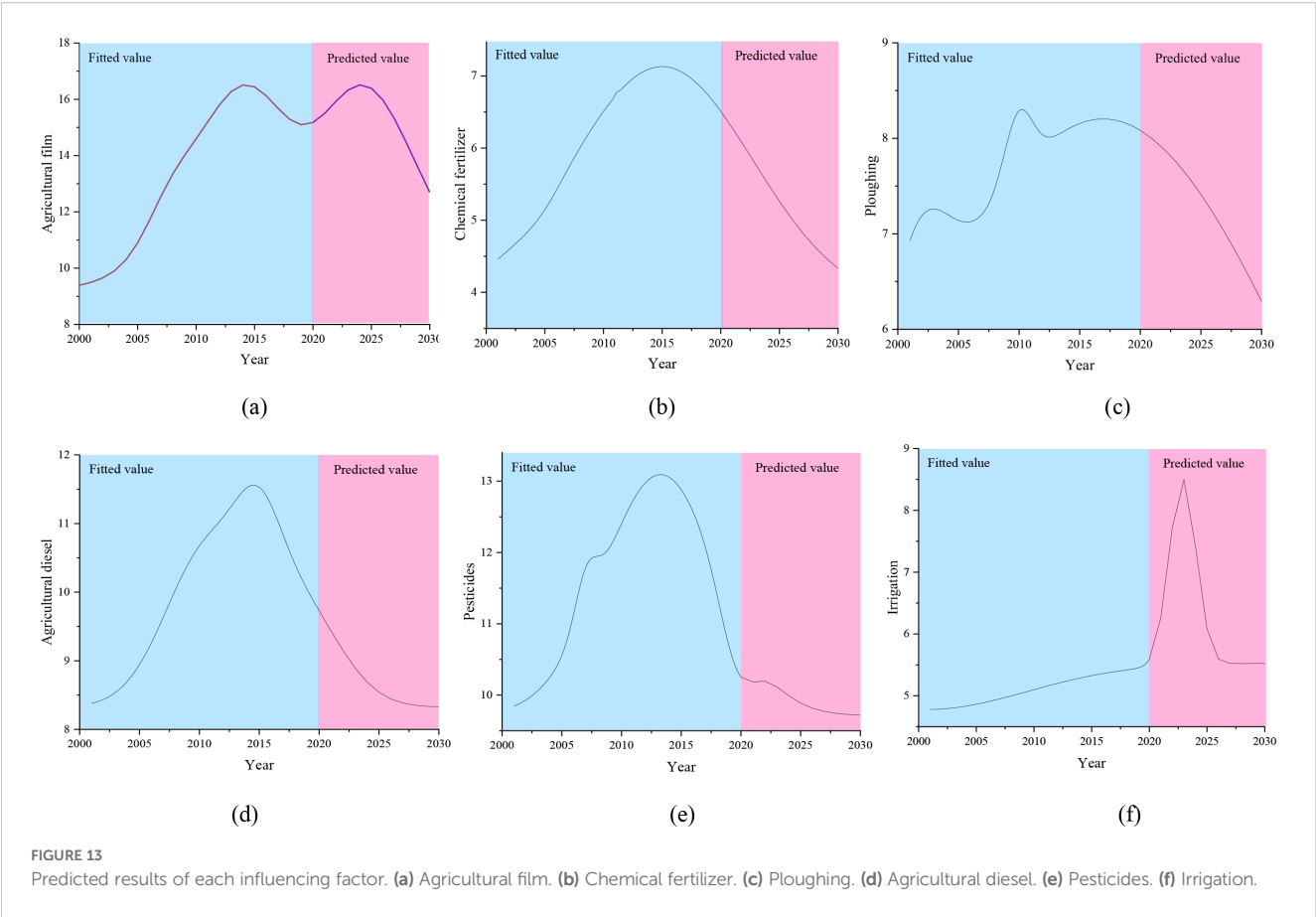


FIGURE 12 Gaussian multi-peak fitting results. (a) Agricultural diesel. (b) Ploughing. (c) Irrigation. (d) Chemical fertilizer. (e) Agricultural film. (f) Pesticides.

participation (Lyu et al., 2023; Guo et al., 2023). In Henan—China's core grain production region—integrating our predictions (e.g., post-2015 emission declines linked to policy interventions) into rural education programs could strengthen farmers' trust in decarbonization policies, thereby improving compliance. Furthermore, Gaussian multi-peak projections indicate agricultural plastic film usage remains at elevated levels,

warranting intensified promotion of biodegradable alternatives' environmental merits. During usage decline phases, consolidating emission reductions through demonstration projects and experience-sharing prevents rebound. Such “temporally adaptive” education strategies enhance guidance relevance and efficacy.

Compared to the models employed in this study, deep learning models enable a shift from “verifying preset hypotheses” to



“discovering complex patterns from data,” thereby providing a more powerful scientific tool for agricultural low-carbon development research in terms of accuracy, depth, and decision-making support value (Chai et al., 2022). Future research should integrate deep learning models to enhance their practical predictive guidance capabilities, while also incorporating subjective variables, such as “policy awareness” and “ecological values”, to explore the synergistic mechanisms between technical forecasting and value-based guidance.

This will ultimately establish a virtuous cycle where data empowers education, and education accelerates emission reduction.

5 Conclusion

Based on six influencing factors—including chemical fertilizers, pesticides, and agricultural plastic films—this study employs neural

TABLE 4 Prediction results of each influence factor.

Year	A	B	C	D	E	F
2021	15.50	6.30	8.04	9.48	6.27	10.20
2022	15.94	6.05	7.93	9.20	7.73	10.21
2023	16.33	5.79	7.79	8.94	8.50	10.13
2024	16.51	5.53	7.64	8.74	7.42	10.01
2025	16.40	5.29	7.46	8.59	6.09	9.90
2026	15.97	5.06	7.27	8.49	5.60	9.83
2027	15.29	4.85	7.06	8.43	5.53	9.78
2028	14.46	4.66	6.83	8.40	5.53	9.76
2029	13.56	4.49	6.59	8.38	5.53	9.74
2030	12.70	4.36	6.34	8.38	5.53	9.73

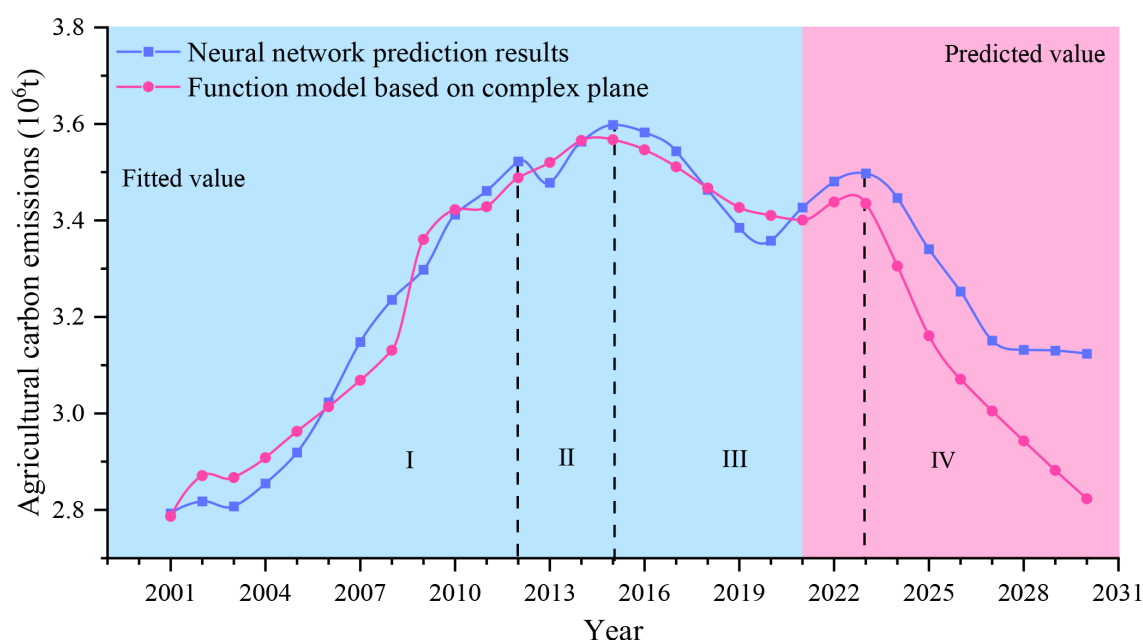


FIGURE 14
Projections of agricultural carbon emissions.

network modeling and nonlinear surface fitting to conduct regression analysis and projection of agricultural carbon emission totals in Henan Province. The research provides dual insights for advancing agricultural green development, offering both intellectual guidance for policy formation and actionable pathways for implementation. Key findings are as follows:

- 1) The total carbon emissions prediction model based on two neural network methods of multilayer perceptron and radial basis function was established. The absolute value of residual error of multilayer perceptron model is less than that of radial basis function model, instructions in regression and prediction of carbon emissions, multi-layer perceptron model has a better effect. It's Its identification of critical drivers, particularly highlighting agricultural diesel and irrigation, accentuates the dominant role of diesel consumption in carbon emissions.
- 2) Combine the results of neural network and nonlinear surface fitting method, the total carbon emission of Henan Province is predicted. It is concluded that the total carbon emission of Henan province shows a quadratic change law with time. Based on the time axis, the development of total agricultural carbon emissions in Henan Province from 2001 to 2030 shows the characteristics of rapid growth, stable growth and fluctuation decline.
- 3) Through comparative data analysis, the prediction results objectively reflect the transformative outcomes of agricultural development models. In the practice of agricultural carbon emission reduction, educational initiatives should prioritize promoting biodegradable

alternatives through policy interpretation and cost-benefit analysis to enhance farmers' environmental awareness. Simultaneously, it is essential to consolidate outcomes through demonstration projects and peer-to-peer knowledge exchange, achieving precisely calibrated "time-limited educational interventions" that foster multi-stakeholder participation in cultivating social norms of ecological consciousness.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material. Further inquiries can be directed to the corresponding author.

Author contributions

JH: Writing – original draft. YP: Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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