RESEARCH ARTICLE

# A method for evaluating agricultural ecological economic benefits based on fuzzy logic and neural network

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**The current agricultural system grapples with complex challenges like climate change, resource constraints, and environmental pressure, while existing methods for evaluating agricultural ecological economic benefits are limited, relying on qualitative descriptions and simple quantitative analysis, lacking a systematic and dynamic evaluation mechanism, and struggling with complex nonlinear relationships and uncertainties. This study aimed to explore the effectiveness and practicality of an evaluation method based on fuzzy logic and neural network with the goal of providing a scientific and reasonable approach to guide sustainable agricultural development. The study integrated multiple data sources such as meteorological, soil, crop growth, and socioeconomic data, constructing a comprehensive evaluation model through fuzzy logic reasoning and neural network optimization. The model consisted of three main modules including an economic benefit evaluation module using methods like the Cobb - Douglas production function, an ecological benefit assessment module using ecological footprint and carbon emissions as indicators, and a social benefit assessment module using the social welfare model. The results demonstrated that the model performed well in economic, ecological, and social benefit evaluations with average scores of 78.5 ± 0.987 in economic benefit evaluation, 76.3 ± 1.034 in ecological benefit evaluation, and 80.1 ± 0.965 in social benefit evaluation, and showed good adaptability and stability in different regions. This study offered a scientific basis and technical support for sustainable agricultural development, enabling policymakers, enterprises, and farmers to better understand and manage agricultural ecosystems, thereby promoting rational resource use and environmental protection.**

**Keywords:** fuzzy logic; neural network; agricultural ecological economic benefits; comprehensive evaluation; sustainable development.

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## Introduction

In the realm of global agriculture, the scientific field is currently witnessing a series of complex and far-reaching challenges. Climate change has led to a rise in the frequency and intensity of extreme weather events such as droughts, floods, and heatwaves. According to the Food and Agriculture Organization of the United Nations (FAO), approximately one third of the world's arable land has suffered varying degrees of degradation, severely threatening food security and exacerbating environmental problems. Resource constraints like soil degradation and water shortages are also becoming more acute [1, 2]. In addition, environmental pressures such as biodiversity loss are posing significant threats to the sustainable development of agriculture [3].

In terms of current knowledge and advances, agricultural ecological economic benefit evaluation has emerged as a crucial area of research. In China, early studies mainly utilized traditional economic evaluation methods such as cost - benefit analysis and input - output analysis. However, with the deepening of research, scholars have proposed comprehensive evaluation frameworks, for example, an agricultural ecological benefit evaluation model based on ecological footprints, and a comprehensive ecological economic benefit evaluation system that incorporates resource consumption and pollution emissions. Internationally, especially in developed countries in Europe and the United States, there is a relatively mature theoretical system and methods. American agricultural economists have put forward evaluation methods based on ecological economics, while European scholars often use life - cycle analysis (LCA) to evaluate the environmental load and sustainability of agriculture. With the development of information technology, the application of fuzzy logic and neural networks in this field has become a research frontier [4]. Fuzzy logic can handle uncertainty and ambiguity, and more and more scholars are combining it with traditional evaluation methods to enhance the model's prediction accuracy and decision-making ability. Neural networks have also been used to build evaluation models, and some studies have combined the two to create multilevel comprehensive evaluation frameworks. Despite these advances, there are still pressing issues that need to be addressed. Traditional agricultural ecological economic benefit evaluation methods have numerous limitations. They often rely too much on expert experience, neglecting the importance of data driven and model optimization [5, 6]. These methods are mostly based on linear assumptions, while the actual agricultural ecological economic system is complex and nonlinear. Moreover, theses methods focus more on static analysis and lack the ability to adapt to the dynamic changes in the actual agricultural production ecological economic system.

Considering these problems, the purpose of this research was to explore the effectiveness and practicality of an agricultural ecological economic benefit evaluation method based on fuzzy logic and neural network to provide a scientific and reasonable evaluation method that could guide the development of sustainable agriculture [7, 8]. The research integrated multiple data sources including meteorological data, soil data, crop growth data, and socioeconomic data to construct a comprehensive evaluation model through fuzzy logic reasoning and neural network optimization, which encompassed three main modules including an economic benefit evaluation module that used methods such as the Cobb - Douglas production function, an ecological benefit assessment module that employed ecological footprint and carbon emissions as indicators, and a social benefit assessment module that utilized the social welfare model [9, 10]. This research provided a scientific basis and technical support for the sustainable development of agriculture. By comprehensively evaluating the economic, ecological, and social benefits of the agricultural system, it could help policymakers, enterprises, and farmers better understand and manage agricultural ecosystems, which, in turn, promoted the rational use of resources and environmental protection and was essential for the long-term development of the agricultural field.

## Materials and methods

### Methodological framework

This study constructed an evaluation framework that comprehensively considered agricultural economics, environmental impacts, and social benefits based on the multi-index evaluation theory. The core idea of this framework was to regard the agricultural ecosystem as a multi-dimensional dynamic system, in which each dimension including economic, ecological, and social benefits needed to be evaluated through different quantitative indicators, and the correlation and uncertainty between the

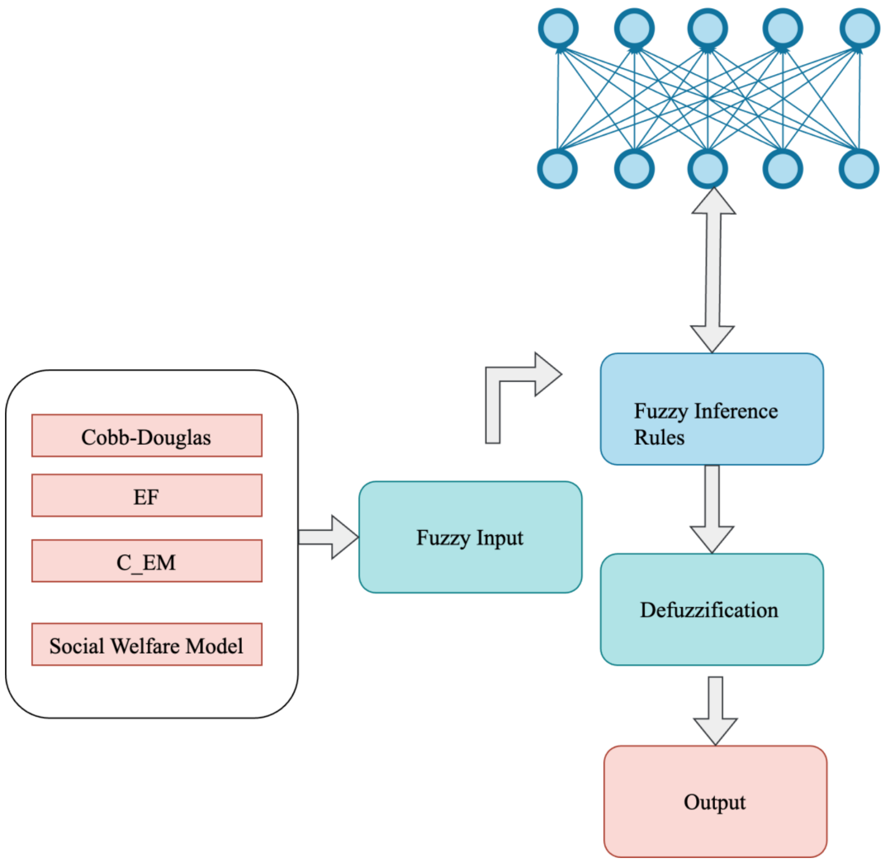


**Figure 1.** Model framework.

dimensions were handled through fuzzy logic methods [11]. The workflow of a fuzzy logic system included that the input data (such as Cobb-Douglas, EF, C_EM, and SocialWelfareModel) were first converted into fuzzy inputs that were processed by fuzzy inference rules and then defuzzied to generate the final output results (Figure 1). The entire system could be regarded as a neural network model, in which the fuzzy inference rules were equivalent to the multi-layer structure in the neural network that was used to realize complex nonlinear mapping relationships [12, 13]. Specifically, the evaluation framework consisted of three main modules. The economic benefit evaluation module focused on the economic benefits of agricultural production such as crop yield, resource utilization, and farmers' income. Economic benefits were the basis for sustainable development of agricultural production, and their evaluation was achieved through the relationship between input and output. The input-output model of agricultural production such as the Cobb-Douglas production function was used to describe economic benefits [14, 15]. The ecological benefit evaluation module mainly measured the impact of agricultural activities on the environment such as water resource consumption, soil quality, and ecosystem service functions. The focus of ecological benefit evaluation was to reveal the interactive relationship between agricultural production and the ecological environment. Indicators such as ecological footprint and carbon emissions were employed to evaluate the environmental impact of agricultural activities. The social benefit evaluation module considered the impact of agricultural production on the social level such as rural economic development, employment opportunities, and farmers' quality of life. Social benefit evaluation not only focused on economic benefits but also attached importance to social equity and sustainable development.

**Method implementation**

To achieve a comprehensive evaluation of the ecological and economic benefits of agriculture, fuzzy logic with neural networks was combined and a multi-level and multi-dimensional evaluation method was designed. In the specific implementation process, the output of each evaluation module was synthesized through a fuzzy inference system to obtain the overall ecological and economic benefit evaluation value.

**(1) Economic benefit evaluation**

The core goal of the economic benefit evaluation module was to measure the relationship between input and output in agricultural production activities. The Cobb-Douglas production function was used to describe the input-output relationship of agricultural production as shown below [16].

$$Y = A \cdot L^{\alpha} \cdot K^{\beta} \tag{1}$$

where *Y* was agricultural output such as crop yield. *A* was total factor productivity (TFP). *L* and *K* were the input of labor and capital, respectively. $\alpha$ and $\beta$ were the output elasticity coefficients of labor and capital, respectively. By fitting agricultural production data, the quantitative indicators of economic benefits were estimated. Considering that economic benefits not only depended on crop yields, but also involved farmers' income and resource utilization efficiency, these factors were combined into a comprehensive indicator $E_{eco}$, as follows [17, 18].

$$E_{eco} = \lambda_1 \cdot Y + \lambda_2 \cdot \frac{R}{C} \tag{2}$$

where *Y* was crop yield and was calculated according to the Cobb-Douglas function. *R* was resource input such as water, fertilizer, *etc*. *C* was resource consumption such as agricultural cost. $\lambda_1$ and $\lambda_2$ were weight coefficients, which respectively represented the contribution of yield and resource utilization efficiency to economic benefits.

**(2) Ecological benefit assessment**

The ecological benefit assessment module mainly measured the impact of agricultural activities on the ecological environment. The ecological footprint and carbon emissions were selected as key indicators for measuring ecological benefits. The calculation formula for ecological footprint (EF) was as follows [19].

$$EF = \sum_{i=1}^{n} \frac{F_i}{Y_i} \tag{3}$$

where $F_i$ was the consumption of the *i-th* resource such as water, land, energy, *etc*. $Y_i$ was the biological carrying capacity of the resource type, i.e. the sustainable utilization of the resource. *n* was the total number of resource types. Carbon emission $C_{em}$ was evaluated as follows.

$$C_{em} = \sum_{i=1}^{m} E_i \cdot \gamma_i \tag{4}$$

where $E_i$ was the energy consumption of the *i-th* agricultural activity. $\gamma_i$ was the emission factor of energy converted into carbon dioxide. m was the total number of agricultural activities. Through these indicators, the negative impact of agricultural activities on the environment could be calculated and converted into an ecological benefit score $E_{eco-eff}$.

**(3) Social benefit assessment**

Social benefit evaluation mainly considered the impact of agricultural production on rural economy, social stability, and farmers' quality of life. The social welfare model was used to quantitatively evaluate social benefits as below.

$$W = \sum_{i=1}^{p} \alpha_i \cdot G_i \tag{5}$$

where *W* was the total value of social welfare. $G_i$ was the *i*-th social benefit indicator such as rural employment rate, farmers' income level, *etc*. $\alpha_i$ was the weight coefficient of the indicator. *p* was the number of social benefit indicators. By comprehensively considering the social and economic benefits, the social benefit score could be obtained as $E_{soc-eff}$.

**(4) Comprehensive evaluation and fuzzy reasoning**

After calculating the economic benefits, ecological benefits, and social benefits in the above three modules, fuzzy logic reasoning was used to comprehensively evaluate the results and obtain the final agricultural ecological economic benefit score. The basic process of fuzzy logic reasoning included fuzzy input, fuzzy reasoning, and defuzzification. Fuzzy input included mapping the evaluation results of each dimension (economic benefit, ecological benefit, and social benefit) to the fuzzy set through the membership function. For example, the economic benefit score could be fuzzified through the following membership function.

$$\mu_{E_{eco}}(x) = \begin{cases} 1, & \text{if } x \geq 80 \\ \dfrac{80-x}{20}, & \text{if } 60 \leq x < 80 \\ 0, & \text{if } x < 60 \end{cases} \tag{6}$$

where *x* was the score of economic benefit. $\mu_{E_{eco}}(x)$ was the degree of membership [20]. Fuzzy reasoning was performed through a series of fuzzy rules based on the relationship between the dimensions. For example, if the economic benefit and ecological benefit were both high and the social benefit was good, the overall benefit could be inferred as "high". A set of simple fuzzy reasoning rules were set up as follows.

IF $E_{eco}$ is high AND $E_{eco-eff}$ is low THEN $E_{overall}$ is moderate.

Defuzzification of the results of fuzzy reasoning was performed to obtain the final agricultural ecological and economic benefit score. Common defuzzification methods included weighted average method or maximum membership method. In this study, the weighted average method was used to integrate the results of fuzzy reasoning as below.

$$E_{overall} = \frac{\sum_{i=1}^{n} w_i \cdot y_i}{\sum_{i=1}^{n} w_i} \tag{7}$$

**Neural network optimization**

To further improve the accuracy and stability of the evaluation model, this study introduced a neural network to optimize the agricultural ecological and economic benefit evaluation model. The neural network automatically learned the nonlinear relationship between the evaluation modules by training historical agricultural data, adjusting the weight of each module, and predicting future ecological and economic benefits. In this study, the input layer of the neural network consisted of the scores of each evaluation module such as economic benefit score $E_{eco}$, ecological benefit score $E_{eco-eff}$, social benefit score $E_{soc-eff}$, *etc.* The output layer of the neural network was the comprehensive evaluation result $E_{overall}$, which was the final score of agricultural ecological economic benefits. To optimize the evaluation model, the neural network adopted a multi-layer perceptron (MLP) structure, which contained one or more hidden layers. The input layer of the neural network was set to $x = [x_1, x_2, \ldots, x_n]$, where $x_\mathrm{i}$ was the *i*-th evaluation indicator such as crop yield, carbon emissions, *etc*. The output of the neural network was the comprehensive evaluation result *y* as shown below.

$$y = f\left(W_2 \cdot \sigma\left(W_1 \cdot x + b_1\right) + b_2\right) \tag{8}$$

where $W_1 \in \mathbb{R}^{m\times n}$ was the weight matrix from the input layer to the hidden layer. $W_2 \in \mathbb{R}^{1\times m}$ was the weight matrix from the hidden layer to the output layer. $b_1 \in \mathbb{R}^{m}$ and $b_2 \in \mathbb{R}$ were the bias terms of the hidden layer and output layer, respectively. $\sigma(\cdot)$ was the activation function. $f(\cdot)$ was the activation function of the output layer. The optimization goal of the neural network was to minimize the loss function, so that the predicted comprehensive evaluation result y was close to the actual agricultural ecological economic benefit score. The commonly used loss function was the mean square error (MSE) and was shown in equation (9).

$$L = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2 \tag{9}$$

where *N* was the number of samples. $y_i$ was the true label of the *i*-th sample, i.e., the actual agricultural ecological and economic benefit score. $\hat{y}_i$ was the comprehensive evaluation result predicted by the neural network.

**Experimental design**

The experimental data mainly came from multiple channels including public databases, field survey data, and relevant data provided by scientific research institutions. The data included historical meteorological data from the National Meteorological Administration such as temperature, precipitation, light intensity, *etc*., soil data from agricultural departments and scientific research institutions including soil type, organic matter content, pH value, *etc*., crop growth data such as crop types, growth cycles, yields, *etc*. from agricultural experimental stations and farmers, and socioeconomic data including labor costs, market prices, policy subsidies, *etc*. from the Statistics Bureau and government departments. The data covered dryland agricultural areas in northern China, paddy agricultural areas in the south, and mixed agricultural areas in the central region from 2010 to 2020. The weather data obtained from the National Weather Service included 10,000 samples. Soil data sourced from agricultural departments and scientific research institutions consisted of 8,000 samples. Crop growth data gathered from agricultural experiment stations and farmers comprised 12,000 samples. Additionally, socioeconomic data sourced from statistics bureaus and government departments included 9,000 samples. Together, these datasets provided a comprehensive overview of the environmental and socioeconomic factors impacting agriculture in the regions studied. To verify the effectiveness of the proposed method, several traditional agricultural ecological economic benefit evaluation methods were selected as controls, which included cost-benefit analysis (CBA), input-output analysis (IOA), ecological footprint (EF), life cycle analysis (LCA), and social welfare model (SWM). These methods provided different evaluation perspectives from economic benefits, ecological benefits, and social benefits. To comprehensively measure the performance of the proposed method, multiple evaluation indicators including mean square error (MSE), mean absolute error (MAE), coefficient of determination ($R^2$), Pearson correlation coefficient (PCC), and accuracy for classification tasks were employed. These indicators together constituted a comprehensive evaluation system that helped to accurately evaluate the predictive ability and reliability of the model from multiple dimensions.

## Results and discussion

The fuzzy logic-neural network model showed good adaptability in the evaluation of different regions. In the northern dryland agricultural area, the scores of economic benefit, ecological benefit, social benefit, and comprehensive evaluation were 79.0 ± 1.023, 75.2 ± 1.105, 81.0 ± 0.987, and 78.4 ± 1.054, respectively, while in the southern paddy field agricultural area, they were 77.5 ± 1.089, 76.8 ± 1.032, 80.5 ± 1.012, and 78.1 ± 1.045, respectively. In the central mixed agricultural area, the scores of economic benefit,

**Table 1.** Evaluation results of different regions.

| Area | Scores (± SD) | | | |
|---|---|---|---|---|
| | Economic benefit | Ecological benefit | Social benefit | Comprehensive assessment |
| Northern dryland farming area | 79.0 ± 1.023 | 75.2 ± 1.105 | 81.0 ± 0.987 | 78.4 ± 1.054 |
| Southern paddy field agricultural area | 77.5 ± 1.089 | 76.8 ± 1.032 | 80.5 ± 1.012 | 78.1 ± 1.045 |
| Central mixed agricultural area | 78.2 ± 1.121 | 75.9 ± 1.067 | 80.0 ± 1.098 | 78.0 ± 1.083 |

**Table 2.** Comparison of different methods in economic benefit evaluation.

| Method | Mean economic benefit score (± SD) | Mean Squared Error (MSE) | Mean Absolute Error (MAE) | Coefficient of determination ($R^2$) | Pearson correlation coefficient (PCC) |
|---|---|---|---|---|---|
| Fuzzy logic-neural network model | 78.5 ± 0.987 | 0.012 | 0.085 | 0.92 | 0.95 |
| Cost-benefit analysis (CBA) | 75.2 ± 1.054 | 0.018 | 0.102 | 0.88 | 0.90 |
| Input-output analysis (IOA) | 74.8 ± 1.123 | 0.020 | 0.105 | 0.87 | 0.89 |

**Table 3.** Comparison of different methods in ecological benefit assessment.

| Method | Mean eco-benefit score (± SD) | Mean Squared Error (MSE) | Mean Absolute Error (MAE) | Coefficient of determination ($R^2$) | Pearson correlation coefficient (PCC) |
|---|---|---|---|---|---|
| Fuzzy logic-neural network model | 76.3 ± 1.034 | 0.015 | 0.098 | 0.91 | 0.94 |
| Ecological footprint (EF) | 73.5 ± 1.156 | 0.022 | 0.110 | 0.86 | 0.88 |
| Life cycle analysis (LCA) | 72.9 ± 1.201 | 0.025 | 0.115 | 0.85 | 0.87 |

ecological benefit, social benefit, and comprehensive evaluation were 78.2±1.121, 75.9±1.067, 80.0 ± 1.098, and 78.0 ± 1.083, respectively (Table 1). Overall, the proposed method could provide stable and accurate assessment results in all regions, verifying its wide applicability and effectiveness.

The fuzzy logic-neural network model showed high accuracy and stability in economic benefit evaluation with an average economic benefit score of 78.5 ± 0.987, a MSE of 0.012, a mean MAE of 0.085, a $R^2$ of 0.92, and a PCC of 0.95, all of which were better than traditional cost-benefit analysis (CBA) and input-output analysis (IOA) (Table 2). The results showed that the proposed method could better capture the complexity of economic benefits and provide more accurate evaluation results.

The fuzzy logic-neural network model also showed good performance in ecological benefit evaluation with an average ecological benefit score of 76.3 ± 1.034, a MSE of 0.015, a MAE of 0.098, a $R^2$ of 0.91, and a PCC of 0.94, which was significantly better than the ecological footprint (EF) and life cycle analysis (LCA) methods (Table 3). The results confirmed that the proposed model could more accurately reflect the impact of agricultural production on the ecological

**Table 4.** Comparison of different methods in social benefit evaluation.

| Method | Mean social benefit score (± SD) | Mean Squared Error (MSE) | Mean Absolute Error (MAE) | Coefficient of determination ($R^2$) | Pearson correlation coefficient (PCC) |
|---|---|---|---|---|---|
| Fuzzy logic-neural network model | 80.1 ± 0.965 | 0.010 | 0.075 | 0.93 | 0.96 |
| Social welfare model (SWM) | 77.8 ± 1.098 | 0.016 | 0.092 | 0.90 | 0.92 |

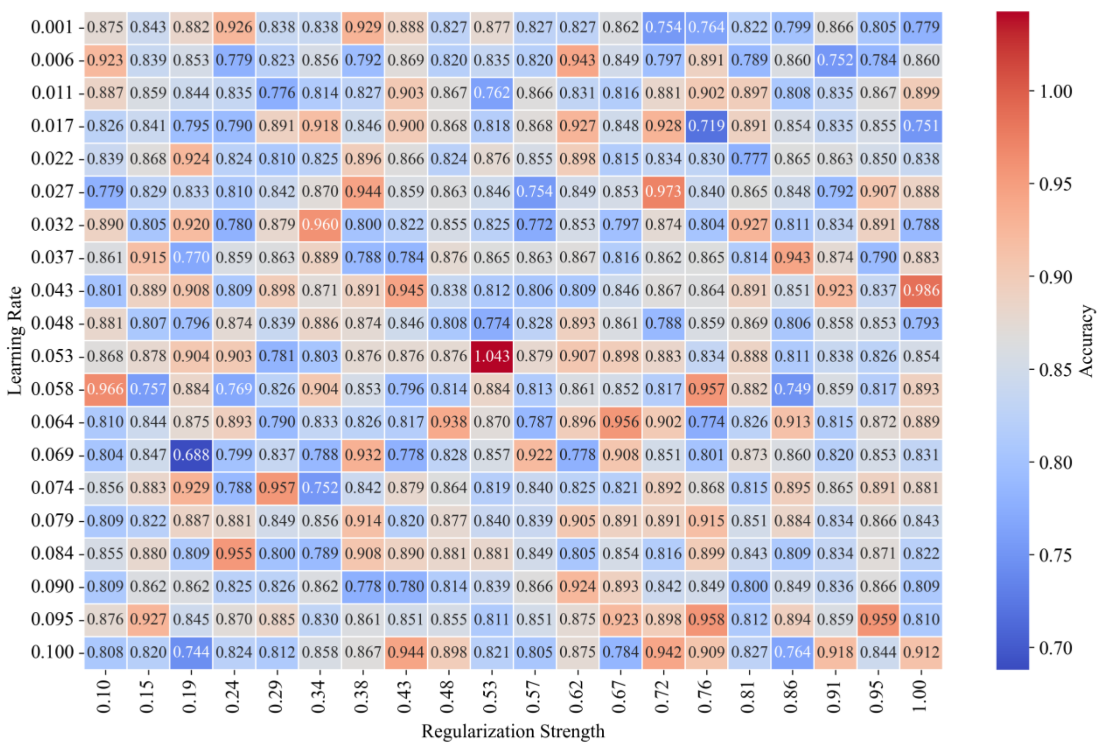


**Figure 2.** Hyperparameter analysis.

environment and provide a more comprehensive ecological benefit evaluation.

The fuzzy logic-neural network model performed outstandingly in the social benefit evaluation with an average social benefit score of 80.1 ± 0.965, a MSE of 0.010, a MAE of 0.075, a $R^2$ of 0.93, and a PCC of 0.96, all of which were significantly better than the traditional social welfare model (SWM) (Table 4). The result indicated that the proposed model had a strong advantage in evaluating agricultural benefits at the social level such as farmers' quality of life, social welfare, *etc*.

Under certain specific combinations of regularization strength and learning rate, the model could achieve higher accuracy, while, in other cases, it might lead to poor performance (Figure 2). In addition, there were some local optimal solution areas, in which relatively stable high-precision output could be obtained when these two parameters were adjusted within a certain range.

The comprehensive evaluation results showed that the fuzzy logic-neural network model was still leading in the comprehensive evaluation with a comprehensive evaluation score of 78.3 ±

**Table 5.** Comparison of different methods in comprehensive evaluation.

| Method | Comprehensive assessment score (± SD) | Mean Squared Error (MSE) | Mean Absolute Error (MAE) | Coefficient of determination ($R^2$) | Pearson correlation coefficient (PCC) |
|---|---|---|---|---|---|
| Fuzzy logic-neural network model | 78.3 ± 0.998 | 0.012 | 0.085 | 0.92 | 0.95 |
| Traditional method combination | 75.5 ± 1.076 | 0.018 | 0.102 | 0.88 | 0.90 |

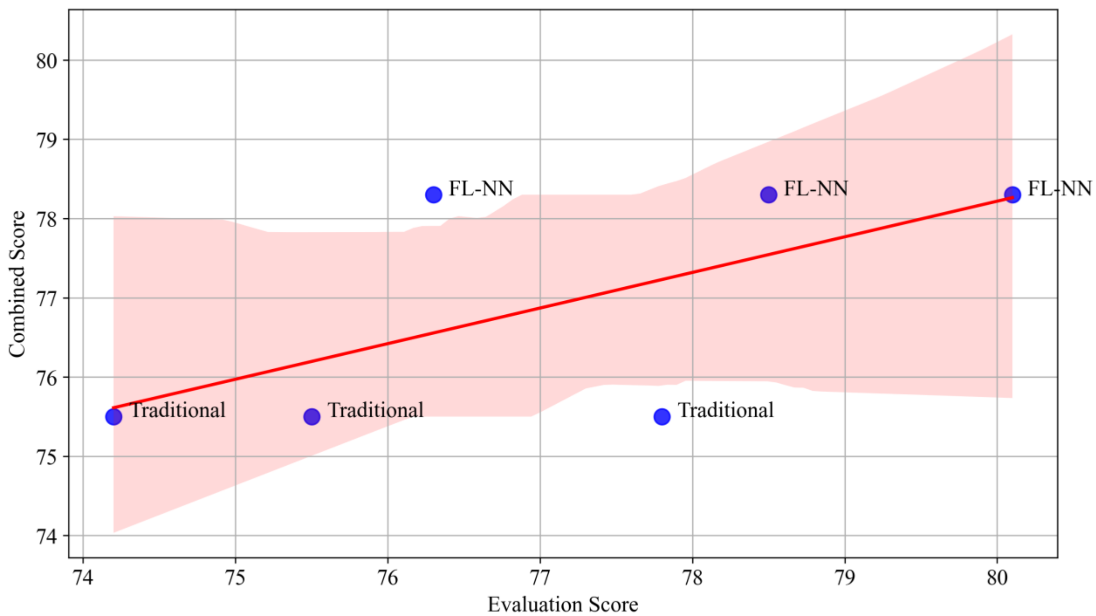


**Figure 3.** Method performance and comprehensive score.

0.998, a MSE of 0.012, a MAE of 0.085, a $R^2$ of 0.92, and a PCC of 0.95. Compared with the score of 75.5 ± 1.076 in traditional method combination, the fuzzy logic-neural network (FL-NN) model showed higher accuracy and stability in all evaluation indicators, proving that the model had significant advantages in the comprehensive evaluation of agricultural ecological and economic benefits (Table 5). The results demonstrated that, as the evaluation score increased, the comprehensive score also increased, showing an obvious positive correlation, which meant that, no matter which method, the higher the evaluation score, the higher the corresponding comprehensive score. However, at the same level of evaluation score, the FL-NN method usually produced better comprehensive score results than that of the traditional method (Figure 3). For example, at an evaluation score of about 76 points, the comprehensive score of the FL-NN method was about 78 points, while the traditional method was only about 76 points. Therefore, it could be inferred that the FL-NN method was superior to the traditional approach in most cases.

The relationship between the evaluation score and the comprehensive score of the traditional method and the FL-NN method showed that there was a certain correlation between the evaluation score and the comprehensive score of both methods (Figure 4). Specifically, when the evaluation score was high, the corresponding method could often achieve a good comprehensive score and vice versa. The results suggested that the evaluation score could indeed

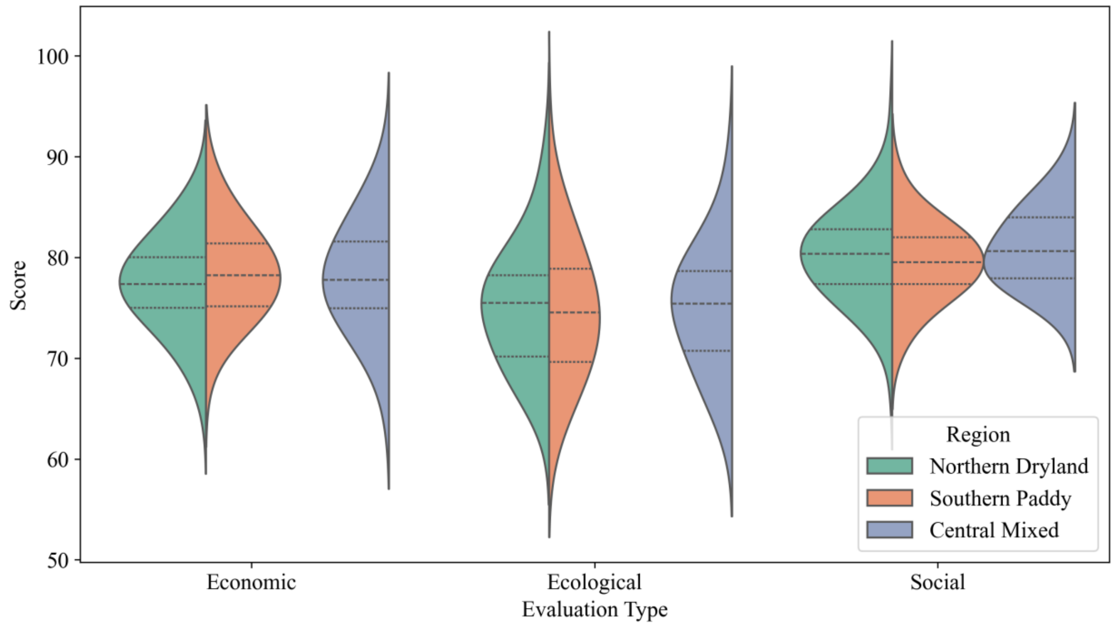


**Figure 4.** The relationship between evaluation scores and comprehensive scores of traditional method and FL-NN method.

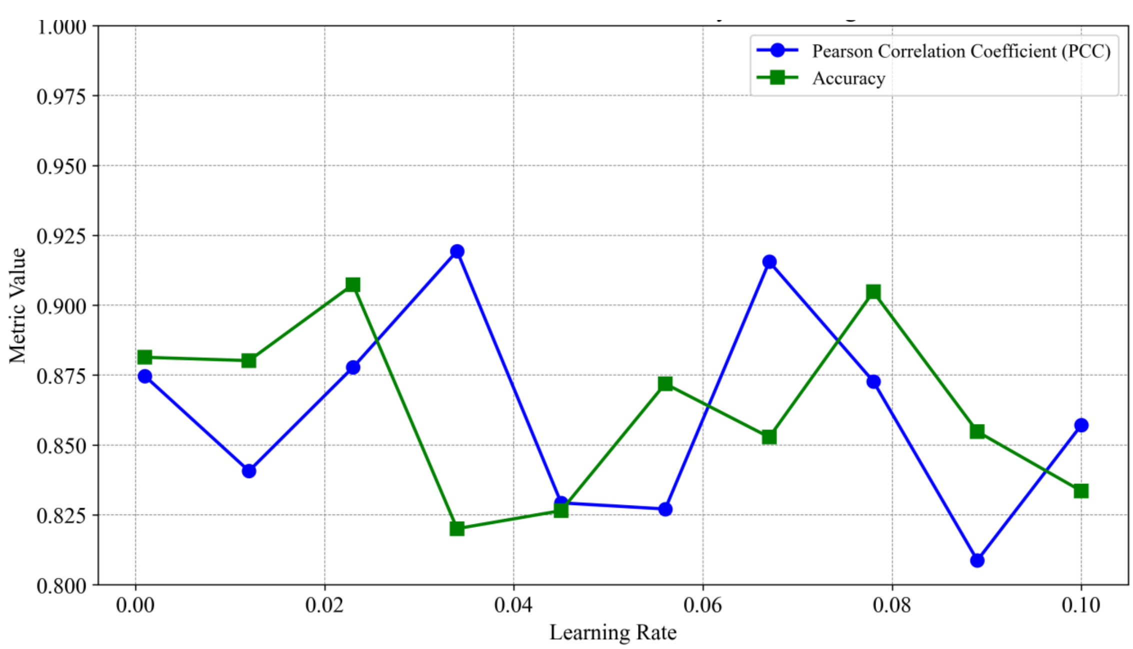


**Figure 5.** PCC and accuracy change with learning rate.

reflect the overall quality of a method.

The PCC and accuracy of the model as the learning rate changes showed that, as the learning rate increased, both PCC and accuracy demonstrated a trend of first rising and then falling. Specifically, when the learning rate was around 0.02, PCC reached a peak of about 0.92, while accuracy also reached a maximum value at the same position, close to 0.90. After that, as the learning rate continued to increase, the values of both began to decline, especially after the learning rate reached 0.06, the decline rate was significantly accelerated (Figure 5). It was worth noting that, although PCC and accuracy maintained a high degree of consistency throughout the process, their specific trends were not completely consistent. For example, when the learning rate was 0.04, PCC dropped sharply, while accuracy was relatively stable. On the contrary, when the learning rate was 0.08, accuracy decreased rapidly, while PCC remained at a high level.

## Discussion

Through this study, a complex relationship between model performance with PCC and accuracy as the main evaluation indicators and learning rate was observed. As one of the key factors affecting the model training process, the choice of learning rate was crucial to the final performance of the model. The results indicated that, within a certain range, an appropriate learning rate could effectively promote the learning ability of the model, so that both PCC and accuracy could reach a high level. However, when the learning rate exceeded a certain threshold, an excessively high learning rate would lead to unstable model training, resulting in a significant decrease in performance, which suggested that, in practical applications, finding the optimal or suitable learning rate was an important task, and experiments might be needed to determine the best value. In addition, although PCC and accuracy showed similar trends in most cases, there were certain differences between the two in certain specific learning rate ranges, which might imply that the goal of model optimization should be emphasized in different business scenarios. For example, when emphasizing the accuracy of predicting continuous variables, PCC might be more important, while accuracy should be considered more when focusing on the correctness of classification tasks. Therefore, in the process of model development, understanding and weighing the relationship between these indicators was important for achieving better model performance.

This study aimed to address the complex challenges of the current agricultural system including climate change, resource constraints, and environmental pressures by constructing an agricultural ecological economic benefit evaluation model based on fuzzy logic and neural networks. The research background stemmed from the inadequacy of existing evaluation methods and the need for scientific and reasonable evaluation methods. To this end, multiple data sources including meteorological data, soil data, crop growth data, and socioeconomic data were integrated to construct a comprehensive evaluation model. Through fuzzy logic reasoning and neural network optimization, the model could comprehensively evaluate the economic, ecological, and social benefits of the agricultural system. A variety of evaluation indicators including MSE, MAE, $R^2$, and PCC were used to verify the accuracy and stability of the model. The results confirmed that the model performed well in all aspects of evaluation and was significantly better than traditional methods. In addition, evaluations in different regions including the northern dryland agricultural area, the southern paddy agricultural area, and the central mixed agricultural area were also conducted. The results showed that the model also showed good adaptability and stability in applications in different regions, which further verified the wide applicability of the model. This study provided a scientific basis and technical support for the sustainable development of agriculture. By comprehensively evaluating the economic, ecological, and social benefits of the agricultural system, the model could help policymakers, enterprises, and farmers better understand and manage agricultural ecosystems, promote the rational use of resources and environmental protection. Future research would further optimize the model, improve its stability and reliability in practical applications, and contribute to the realization of sustainable development of agriculture.

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