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A PSO-OPTIMIZED FUZZY NEURAL MODEL FOR EVALUATING THE COORDINATED DEVELOPMENT OF AGRICULTURAL ECONOMY AND ECOLOGICAL PROTECTION

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Highlights:
- a fuzzy logic and ecological benefit evaluation model is proposed;
- a fuzzy backpropagation neural network model based on particle swarm optimization is studied and constructed to address the weights of fuzzy subjective factors;
- the experiment outcomes denoted that the precision, recall, and F-measure values of the proposed model fluctuate around 0.90, with an mean absolute error and root mean square error of 0.189 and 0.256, respectively.

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Abstract. The coordinated development of agricultural economy and ecological protection is essential for achieving sustainable agriculture, as the resulting ecological benefits have significant implications for both environmental security and economic stability. However, existing ecological benefit evaluation models often suffer from limited indicator coverage and insufficient intelligence in weight assignment, making it difficult to capture the coupled relationship between ecological and economic dimensions. To address these issues, this study proposes a comprehensive evaluation model based on fuzzy logic and a particle swarm optimized backpropagation neural network (PSO-FBP). A multi-level indicator system integrating ecological and economic value is constructed, and fuzzy logic is introduced to manage uncertainty, while PSO enables adaptive weight optimization. The proposed model demonstrates strong learning capability and robustness, enabling a comprehensive quantification of agricultural ecosystem services. A case study of a province shows that waste treatment, agricultural production, and soil conservation are the main contributors to ecological value, confirming the model's effectiveness in real-world agricultural contexts. This research provides a scientific and practical tool for ecological benefit assessment, offering valuable support for decision-making in sustainable agricultural policy.

Keywords: fuzzy logic, PSO-FBP, ecological benefit assessment, agricultural economy, ecological protection, coordinated development.

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1. Introduction

Agriculture is the economic lifeline of a country, and its stable and sustainable development is significant for maintaining social stability and promoting steady progress of the country (Katumo et al., 2022; Akter, 2024). Agriculture and ecological environment are a complex coupled system, and their coordinated development involves various natural resources, socio-economic and technological conditions. Various conditions can work together to form an ecological and economic synergy, generating ecological and economic benefits (Wuest et al., 2021; Hasheminezhad et al., 2021). Ecological benefit assessment mainly involves quantitative analysis and comprehensive evaluation to reveal the specific impact paths of agricultural activities on the ecosystem. Evaluating the ecological benefits generated by the coordinated development of agricultural economy and ecological protection (CDAEEP) helps to scientifically understand the ecological impacts in the process of agricultural development and formulate appropriate policies (Ayyildiz & Taskin Gumus, 2021).

In recent years, scholars have explored various approaches to ecological benefit evaluation models. Akbar et al. (2021) employed the SBM-undesirable model combined with a carbon transfer network to assess agricultural ecological performance across Chinese provinces, providing valuable data support for policy formulation. Czyżewski et al. (2021) used regional farm accounting data to evaluate the impact of the EU's Common Agricultural Policy on ecological efficiency, identifying key sustainability factors. Naseem and Tong (2021) applied panel fixed-effect regression and the two-step system GMM method to examine the relationship among renewable energy consumption, agricultural development, and carbon emissions, offering a quantitative basis for policy decisions. Gashaw et al. (2021) developed a watershed assessment tool based on soil erosion evaluation to measure agricultural ecological efficiency.

Meanwhile, fuzzy logic and its extensions have been widely applied to complex system evaluations across different fields. Soner et al. (2022) proposed a fuzzy analysis-based method to assess environmental risks in ship dismantling processes, contributing to pollution control efforts. Omair et al. (2021) integrated AHP and fuzzy inference systems to rank manufacturing suppliers based on sustainability indices. Kılıc et al. (2022) combined fuzzy AHP and GIS to evaluate the suitability of agricultural land use, effectively mitigating environmental impacts. Mishra et al. (2022) developed a sustainable low-carbon tourism decision-making model based on interval-valued intuitionistic fuzzy logic, enhancing the accuracy of weight calculation and overall decision efficiency.

However, although existing evaluation methods have achieved certain results in the analysis of agricultural ecological benefits, there are still limitations such as excessive reliance on data, insufficient consideration of factors, and lack of intelligence in evaluation methods. At present, the rapid development of artificial intelligence provides solutions to the above-mentioned problems. Fuzzy logic allows variables to take fuzzy values to handle uncertainty and fuzziness. It is suitable for dealing with nonlinear, multivariate, and highly uncertain systems, and researchers from different fields have also discussed this.

In summary, both ecological benefit evaluation models and fuzzy logic have achieved fruitful research results in their respective fields, but there is no relevant work that combines the two to measure the CDAEEP. Therefore, to further improve the comprehensiveness and intelligence of the ecological benefit evaluation model, a fuzzy logic-based ecological benefit evaluation model was proposed. A Particle Swarm Optimization-Fuzzy Back Propagation Neural Network Model (PSO-FBP) based on fuzzy logic and intelligent algorithms was developed to determine the weights of fuzzy subjective factors. The research aims to effectively measure the ecological benefits of coordinated development between agricultural economy and ecological protection through the proposed methods, providing reference value for formulating relevant policies and promoting sustainable development of agriculture.

Compared with existing published machine learning models, the proposed PSO-FBP model combines fuzzy inference mechanisms with a neural network structure and applies particle swarm optimization to jointly optimize weights and parameters. This design improves both the prediction accuracy and generalization performance of the model, while also enhancing its ability to handle fuzzy uncertainty in complex ecological systems, which is often not addressed by traditional black-box approaches.

2. Methods and materials

This section first constructs ecological benefit evaluation indicators for the CDAEEP, and provides relevant mathematical function relationships. Afterwards, fuzzy logic and intelligent algorithms are introduced to optimize the proposed evaluation model.

2.1. Construction of ecological benefit evaluation model for CDAEEP

The measurement of ecological benefits generated by the CDAEEP mainly includes two aspects, namely the measurement of economic valuation of coordinated development and the environmental impact brought by coordinated de-

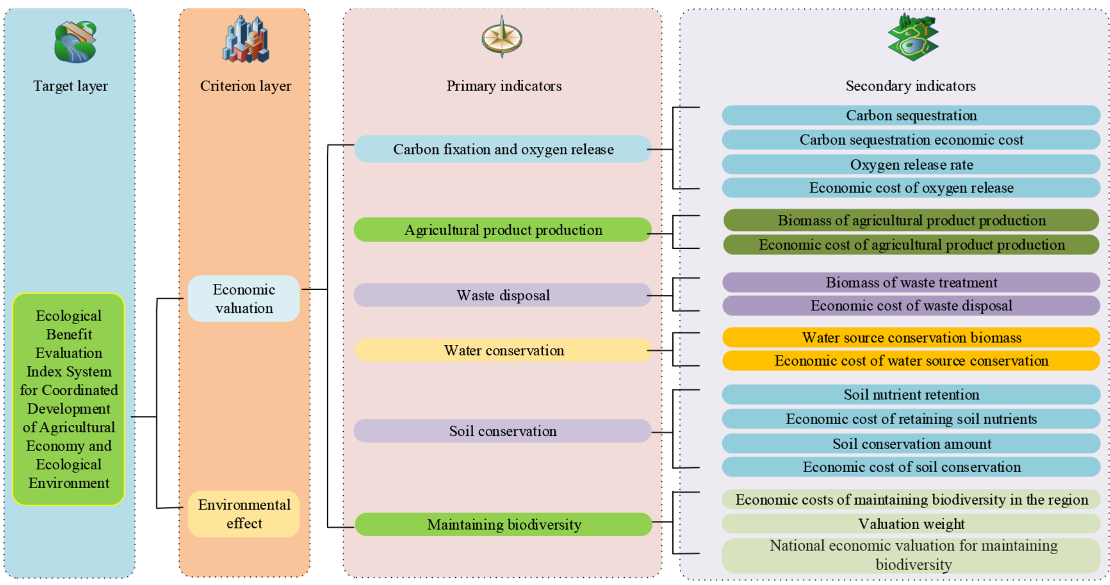

Figure 1. Ecological benefit evaluation indicator system for CDAEEP

velopment. The CDAEEP has both ecological and economic value. In the evaluation of ecological benefits in agricultural production systems, the above two parts should also be included (Groumpos, 2023). However, existing measurement methods have not fully considered the two values, so there is a certain deviation in the measurement results (Liu et al., 2023). Therefore, the study comprehensively considers two aspects of evaluation and measures economic valuation through system dynamics methods to analyze the relationship between various factors. Subsequently, the environmental impact is measured using the life cycle assessment method. By comprehensively evaluating both, it is possible to simultaneously consider the economic and ecological factors of agricultural production systems, and to more comprehensively study and analyze the ecological benefits of their coordinated development (Turunen et al., 2021). Establishing an assessment indicator system is the prerequisite and core for studying and evaluating the ecological benefits of coordinated development between agricultural economy and ecological protection. The research is based on the theory of sustainable development, with agricultural ecology, resource optimization allocation, and circular economy as the foundation. Based on the combination of science and practice, system and comprehensiveness, stability and dynamics, a set of evaluation indicators system is constructed, as shown in Figure 1.

In Figure 1, the indicator system evaluates the ecological and economic benefits of agricultural production systems, including six primary indicators: carbon fixation (CF) and oxygen release (OR), agricultural product production, waste disposal, water conservation, soil conservation, and maintenance of biodiversity. Each primary indicator can be divided into multiple secondary indicators and their influencing factors, such as crop biomass, economic costs, and environmental parameters, to comprehensively reflect the ecological services and economic value of agricultural production systems. Among them, the agricultural product production service function is shown in Equation (1).

$$\begin{cases} EV_{AP} = CAS \times CY \times CUP \\ AP_{biomass} = CY \times (1 - MC) \times EF \end{cases}. \tag{1}$$

In Equation (1), EV_{AP} represents the economic valuation of agricultural product production services; $AP_{biomass}$ represents the biomass of the agricultural product production ecosystem; CAS represents the sowing area of crops; CY represents the yield of crops; CUP represents the unit price of crops; MC represents moisture content; EF represents economic factor. The mathematical expression for water conservation services is shown in Equation (2).

$$\begin{cases} EV_{WC} = (1 - RC) \times rainfall \times RCC \\ WC_{biomass} = (1 - RC) \times rainfall \end{cases}. \tag{2}$$

In Equation (2), EV_{WC} represents the economic valuation of water conservation services; $WC_{biomass}$ represents the biomass of the water source conservation service system; RC represents the runoff coefficient; RCC represents the construction cost of the reservoir. The mathematical expression for CF and OR services is shown in Equation (3).

$$\begin{cases} EV_{CS+OR} = NPP \times CSF \times PCCF \times CSC + NPP \times OPF \times OPC \\ (CS + OR)_{biomass} = NPP \times CSF \times PCCF + NPP \times OPF \end{cases}. \tag{3}$$

In Equation (3), EV_{CS+OR} represents the economic value of CF and OR services; $(CS + OR)_{biomass}$ represents the total amount of organic matter in the CF and OR ecosystem; CS refers to carbon sequestration; OR refers to OR; NPP is the total amount of organic matter produced by plants through photosynthesis minus the portion consumed by plant respiration; CSF represents carbon sequestration capacity; $PCCF$ represents the coefficient that converts fixed carbon into economic value; CSC is the economic input required for carbon sequestration measures; OPF is the coefficient of OR capacity; OPC represents the economic cost of producing oxygen. The functional relationship of soil conservation services is shown in Equation (4).

$$EV_{SC} = Q_{SCOF} \times Q_{NCIS} \times P_{OF} + \left(\frac{SC}{SC_a}\right) \times SEL \times C_{RW}. \tag{4}$$

In Equation (4), EV_{SC} represents the economic valuation of soil conservation; Q_{SCOF} represents the quantity of farmland soil; Q_{NCIS} represents the quality of the soil; P_{OF} represents the price of organic fertilizer; SC_a represents the bearing capacity of the soil; SC represents soil conservation; SEL represents sediment erosion loss; EV_{CS+OR} represents the cost of reservoir engineering. The function expression for waste disposal is shown in Equation (5).

$$EV_{WD} = ECY \times EY_{Nrpu} \times \left(\frac{1}{Ncfm}\right) \times P_{OF}. \tag{5}$$

In Equation (5), EV_{WD} represents the economic valuation of waste treatment; EF represents economic factor; WD represents waste disposal; ECY represents the yield of economic crops; EY_{Nrpu} represents the amount of nitrogen obtained per unit economic output; $Ncfm$ represents the nitrogen content of farmyard manure. The functional relationship for maintaining biodiversity is shown in Equation (6).

$$EV_{BM} = \left(\frac{CIAE_{PEP}}{CN_{PEP}}\right) \times BM_{VPUS}. \tag{6}$$

In Equation (6), EV_{BM} represents the economic valuation for maintaining biodiversity; BM stands for maintaining biodiversity ecosystem services; $CIAE_{PEP}$ and CN_{PEP} respectively represent the potential economic output of the region and the country; BM_{VPUS} represents the biodiversity value of national cultivated land. After constructing the economic valuation measurement function, the study continues to construct the second part of the ecological benefit assessment model, which is the environmental impact measurement function based on the life cycle (Caymaz et al., 2022). When conducting environmental impact measurement, determining the type of environmental impact is a key step in environmental analysis of

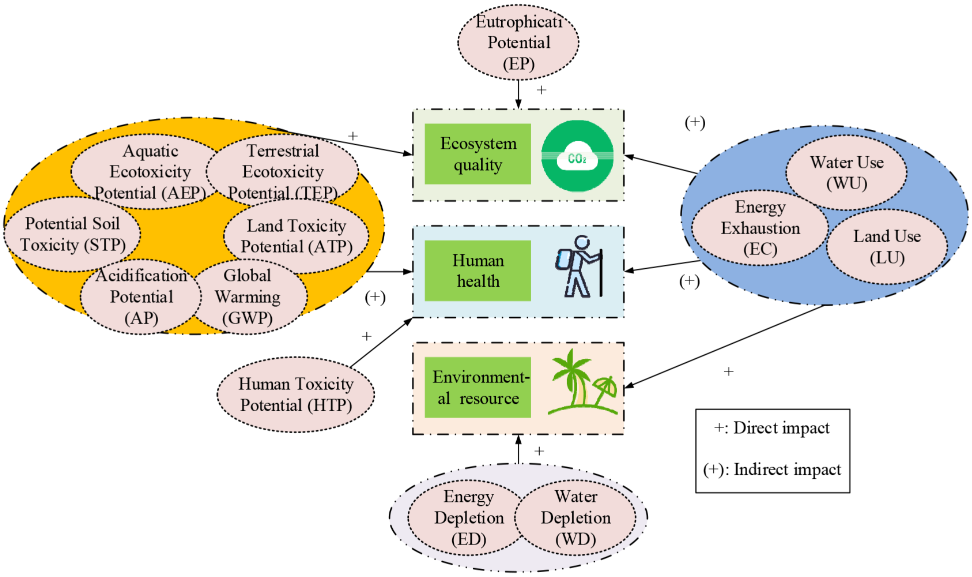

Figure 2. Environmental influence categories of agricultural production systems

agricultural production systems. The study selected indicators as shown in Figure 2 for measurement.

The life cycle method quantifies environmental impacts through the equivalent factor method, which sets a certain ecological impact factor as the baseline value (impact potential value is 1), converts other impact factors through the baseline value, and obtains the relative impact potential values of various ecological impact factors through relative comparison. The calculation formula for various environmental impact potentials is shown in Equation (7).

$$EP(l) = \sum EP(l)_s = \sum \left[Q(l)_s \times EF(l)_s \right]. \tag{7}$$

In Equation (7), $EP(l)$ represents the potential value of Class l environmental impact; $EP(l)_s$ represents the potential impact value of the Class s factor on the Class l environment; $Q(l)_s$ refers to the emissions of ecological impact factors in the Class l environment and the Class s environment; $EF(l)_s$ represents the equivalent coefficient of the Class s impact factor on the Class l environmental impact (Duleba et al., 2021). Therefore, the system flow diagram of the CDAEEP is denoted in Figure 3. Where, the agricultural production system only provides six ecosystem services, and the total economic valuation is obtained by adding up the economic valuations of the six services.

2.2. Optimization of ecological benefit evaluation model based on improved fuzzy logic

In the evaluation of ecological benefits, the distribution of weights is often influenced by subjective factors, and the agricultural ecosystem itself has fuzziness and uncertainty (Azareh et al., 2021; Zhou et al., 2022). To this end, this study introduces fuzzy logic to quantitatively model uncertain information, enhancing the model's adaptability to complex ecological features. Meanwhile, to overcome the problem that the BP neural network is prone to fall into

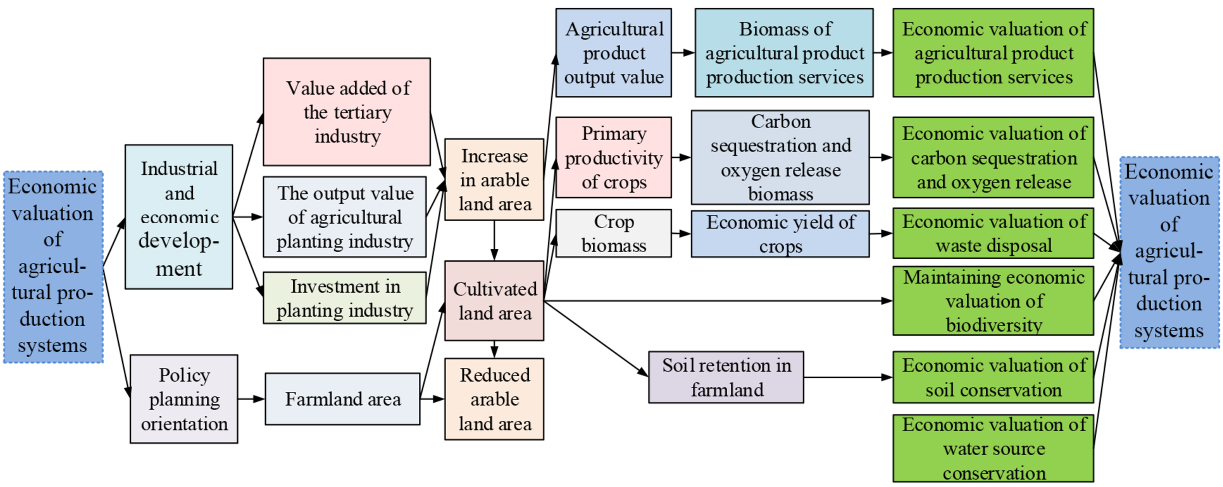

Figure 3. System flow diagram of the CDAEEP

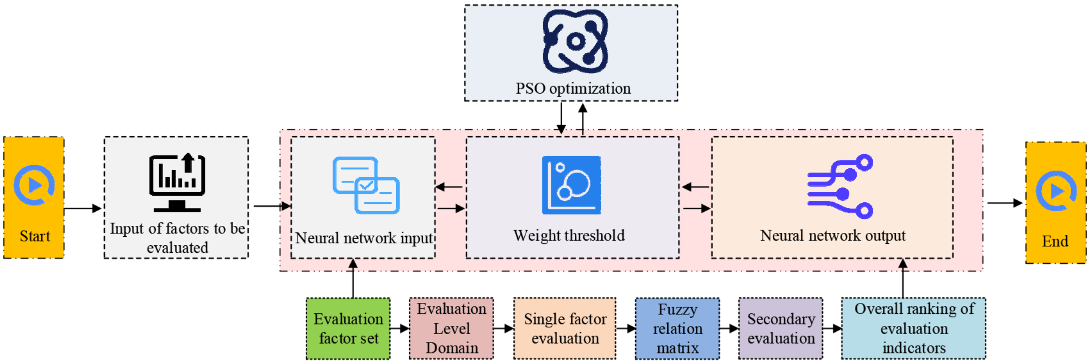

Figure 4. Implementation process of PSO-FBP model

local optimum, the PSO algorithm is adopted for global search optimization of weights and thresholds. PSO has few parameters and converges quickly, making it suitable for handling nonlinear complex systems (Afrasiabi et al., 2022). Therefore, it has good application compatibility when combined with fuzzy reasoning. Finally, the PSO-FBP model was constructed. The core idea of this model is to fully utilize the self-learning ability of BP while processing fuzzy information. The implementation process of the overall model is shown in Figure 4.

As shown in Figure 4, the model first transforms the original ecological evaluation indicators (such as soil conservation, water conservation, and biodiversity) into fuzzy sets using membership functions, based on expert surveys and empirical data, to handle the heterogeneity and uncertainty of multi-source information. Then, a fuzzy inference mechanism is constructed based on a three-layer BP neural network structure, where training samples are used to automatically generate fuzzy rules and realize nonlinear mapping between inputs and outputs. The PSO algorithm is further employed to globally optimize the connection weights and thresholds of the BP network, overcoming the traditional BP network's shortcomings of slow convergence and susceptibility to local optima. On the optimized fuzzy neural network, a fuzzy comprehensive evaluation is performed, and the final ecological benefit grade or score is obtained using the principle of maximum membership. Finally, the model can automatically learn the implicit importance of each indicator from training data, thereby eliminating subjective weight assignment and enabling dynamic adaptation.

Compared with traditional methods, the PSO-FBP model demonstrates significant advantages in weight determination, nonlinear modeling, and adaptability. The model automatically learns feature weights from historical data via neural networks, avoiding the instability caused by subjective weighting; it also captures complex nonlinear relationships among indicators through its multilayer structure, making it more suitable for the highly interactive variables in agricultural ecosystems. In addition, the global optimization capability of the PSO algorithm enhances the model's generalization performance across different regions and time scales. Overall, PSO-FBP enables more effective integration of multi-source heterogeneous data and improves the accuracy and adaptability of ecological benefit evaluation.

Before conducting fuzzy comprehensive evaluation, due to the significant differences in the measurement values of the original index, with different units and dimensions, it is impossible to use the initial values for pattern calculation and final evaluation analysis (Kayacık et al., 2022). In view of this, the study first uses the maximum deviation normalization method to normalize the initial values of each indicator, to avoid the impact of collaborative evaluation. The function expression is shown in Equation (8).

$$\begin{cases} M = \dfrac{Y_{ij} - \min\left(Y_{ij}\right)}{\max\left(Y_{ij}\right) - \min\left(Y_{ij}\right)} \\ N = \dfrac{\max\left(Y_{ij}\right) - Y_{ij}}{\max\left(Y_{ij}\right) - \min\left(Y_{ij}\right)} \end{cases}. \tag{8}$$

In Equation (8), M represents the standardized positive indicator; N represents the standardized negative indicator; Y_{ij} means the indicator value of the j th item under system i; $\max\left(Y_{ij}\right), \min\left(Y_{ij}\right)$ represent the max and mini values of evaluation indicators over a period of time. The larger the M value, the greater the beneficial impact; The smaller the N value, the greater the beneficial impact. It assumes that the set of evaluation factors for the fuzzy comprehensive assessment method is as shown in Equation (9).

$$U = \left\{u, u_2, \ldots, u_n\right\}. \tag{9}$$

In Equation (9), n means the amount of influencing factors in the criterion layer; u_i means the assessment factors of the i th layer. The constructed assessment level domain is shown in Equation (10).

$$V = \left\{v_1, v_2, \ldots, v_n\right\}. \tag{10}$$

In Equation (10), v_i represents the level that can be used for evaluation. In the construction of the fuzzy inference system, triangular membership functions were adopted due to their computational simplicity and interpretability. Parameters of each function were determined using the minimum, maximum, and median values of each indicator, ensuring sufficient coverage and discrimination. Fuzzy rules were automatically derived from training data using a data-driven approach, integrating sample classification labels and neural network weights to form "IF–THEN" rule structures. To improve inference efficiency and semantic consistency, a rule pruning mechanism was applied, removing rules with support below 5% or output ambiguity greater than 0.7.

Based on the five-point Likert scale, this study classifies the impact levels of evaluation indicators into five categories: "very low impact," "low impact," "moderate impact," "high impact," and "very high impact." These categories correspond to a gradual progression from negligible ecological benefits (e.g., poor ecological service performance and low resource utilization efficiency), to moderate improvements (e.g., enhanced functions such as soil conservation and water retention), and finally to strong ecological performance with significant positive environmental impact. The numerical thresholds between adjacent levels are set at 40, 60, 80, and 90, respectively, enabling the fuzzy evaluation results to be quantified and categorized accordingly (Jafarzadeh et al., 2023). Subsequently, the weights of each evaluation indicator in the criterion layer are determined and a single factor evaluation is implemented. Subsequently, a fuzzy relationship matrix is established to quantify the evaluated transaction from each factor, as shown in Equation (11).

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{p1} & r_{p2} & \cdots & r_{pn} \end{bmatrix}, \quad r_{ij} = \bar{u}_{ij} / n. \tag{11}$$

In Equation (11), r_{ij} represents the level of membership of the i th assessment factor to the j th assessment level. The total weight of each secondary indicator is the product of the weight of the criterion layer indicator and the corresponding secondary indicator in that criterion layer. The fuzzy operator is $(\bullet, \oplus)$, and this process is shown in Equation (12).

$$B = A(\bullet, \oplus)R = (a_1, \cdots, a_3)(\bullet, \oplus)\begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{p1} & r_{p2} & \cdots & r_{pn} \end{bmatrix}. \tag{12}$$

In Equation (12), $(a_1, \cdots, a_3)$ means the weight of the evaluation indicators in the criterion layer; R is a fuzzy relationship matrix. Finally, it ranks the assessment indices based on the principle of maximum membership degree. In the BP algorithm based on PSO optimization, PSO mainly replaces the gradient descent method of BP through iteration to achieve the optimization process. The position and velocity of the initialized particles are represented by Equation (13).

$$x_i(0) = x_i^{init}, \quad v_i(0) = v_i^{init}. \tag{13}$$

In Equation (13), $x_i(0)$ and $v_i(0)$ represent the initial position vector and initial velocity vector of the i th particle, respectively. The updated velocity and position vectors are shown in Equation (14).

$$\begin{cases} v_i(t+1) = \omega v_i(t) + c_1 r_1 \left(pbest_i - x_i(t)\right) + c_2 r_2 \left(gbest - x_i(t)\right) \\ x_i(t+1) = x_i(t) + v_i(t+1) \end{cases}. \tag{14}$$

In Equation (14), $x_i(t)$ and $v_i(t)$ respectively represent the position vector and velocity vector of the i th particle at the t th iteration; ω represents inertia weight; c_1 and c_2 mean learning factors; r_1 and r_2 mean a random number with a value of $[0,1]$; $pbest_i$ means the individual extreme position of the i th particle; $gbest$ means the global optimal position. The fitness of the algorithm is shown in Equation (15).

$$Fitness(x_i) = \frac{1}{1+E(x_i)}. \tag{15}$$

In Equation (15), $Fitness(x_i)$ represents the fitness value of the location x_i of the i th particle; $E(x_i)$ represents the training error of BP at position x_i. Based on the quantitative analysis results of fuzzy neural networks and the principle of maximum membership degree, the specific impact of each factor on the ecological benefits of CDAEEP can be directly obtained. Therefore, the ecological benefit evaluation model for the CDAEEP is shown in Figure 5. In the figure, the study clarifies the system boundaries and analyzes the key impact factors of the ecological benefits of agricultural production systems. A dynamic model of ecological benefits system was established through system feedback structure and key variable definition, including ecosystem service biomass, economic valuation, etc.

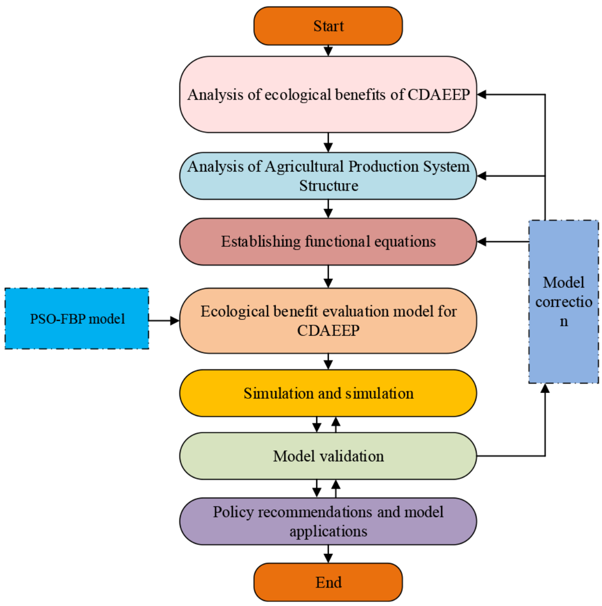

Figure 5. Ecological benefit evaluation model for CDAEEP

3. Results

Taking actual data from a certain province as an example, this section first verified the self-learning performance of the proposed PSO-FBP. Subsequently, based on the proposed ecological benefit evaluation model, an actual application effect analysis was conducted on the ecological benefits of CDAEEP in the province.

3.1. Performance analysis of ecological benefit evaluation model

This study takes Henan Province, China, as the empirical region, selecting its 18 prefecture-level cities as spatial sampling units. The area encompasses diverse agricultural ecological landscapes, including plains, hills, and the Yellow River basin, ensuring strong regional representativeness. The dataset covers the years 2015 to 2022, sourced from Henan's statistical yearbooks, reports from the Department of Agriculture and Rural Affairs, and ecological environment monitoring data. Key ecological service variables include crop production, waste treatment, water conservation, and soil retention, with an annual sampling frequency. To ensure spatial representativeness and enhance the model's generalizability, a spatially stratified sampling strategy was adopted. Specifically, the province was divided into 18 strata based on administrative boundaries, and within each city, 80% of the samples were assigned to the training set and 20% to the test set in chronological order. This approach ensured balanced spatial distribution between the training and test sets and reduced regional bias. For areas with insufficient data, a neighboring-region merging strategy was applied to maintain the validity of stratification. The evaluation level domain was divided into 5 levels, from minimal impact to significant impact. The experimental computing platform was MATLAB 2023b, and the hardware environment was Inteli7 processor, 16GB RAM, and NVIDIAGTX1660 graphics card. The specific parameter settings for the experiment are denoted in Table 1.

Table 1. Specific parameter settings for the experiment

Parameter	Value
Fuzzy neural network layers	3
Particle swarm optimization particle count	30
Maximum number of iterations	100
Learning factors c1 and c2	1.5
Inertia weight w	0.9
Number of evaluation levels	5
Computing platform	MATLAB2023b
Hardware environment	Inteli7, 16GBRAM, NVIDIAGTX1660

The parameter Settings in Table 1 are based on theoretical and experimental verification. Selecting the number of layers of the fuzzy neural network as 3 can effectively capture nonlinear relationships while avoiding excessive complexity. In the PSO parameters, the number of particles is 30, which strikes a balance between computational efficiency and optimization effect. The maximum number of iterations is 100, and the optimal solution can be found within a reasonable time. The inertia weight of 0.9 and the learning factor of 1.5 respectively ensure the balance between global and local search, avoiding local optimal solutions.

Figure 6 shows the trend of the population fitness curve of PSO-FBP during the increase of iteration. In the figure, both the optimal fitness and the mean fitness showed a gradually decreasing trend, indicating that the population gradually approached the optimal solution through multiple generations of evolution. In the initial stage, the fitness sharply decreased, followed by fluctuations within a smaller range, reflecting the fast convergence and stability of the model. As a result, PSO-FBP experienced strong local search ability and good global search performance in searching for the optimal solution, and ultimately tended to stabilize. It has good convergence performance and stable search ability.

To verify the superiority of PSO-FBP's self-learning ability, the study compared PSO-FBP with traditional BP,

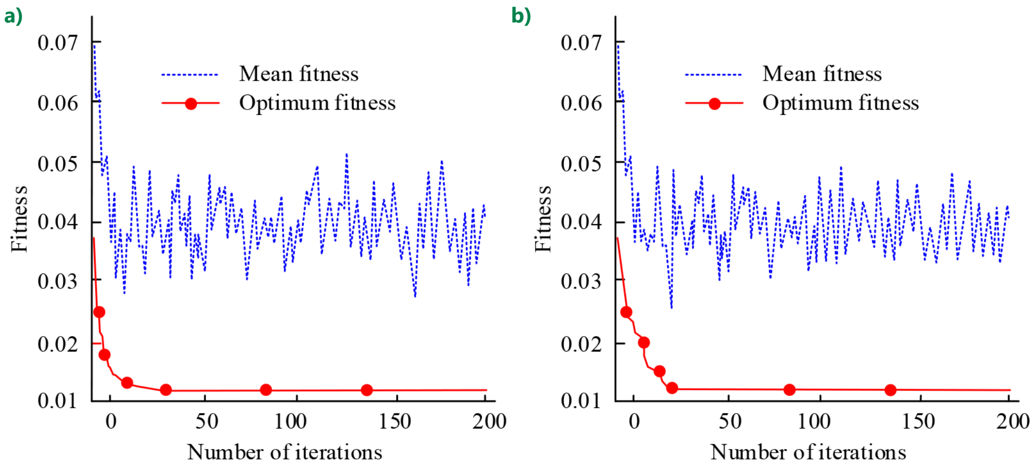

Figure 6. Population fitness curve: a) Fitness curve of training set; b) Fitness curve of test set

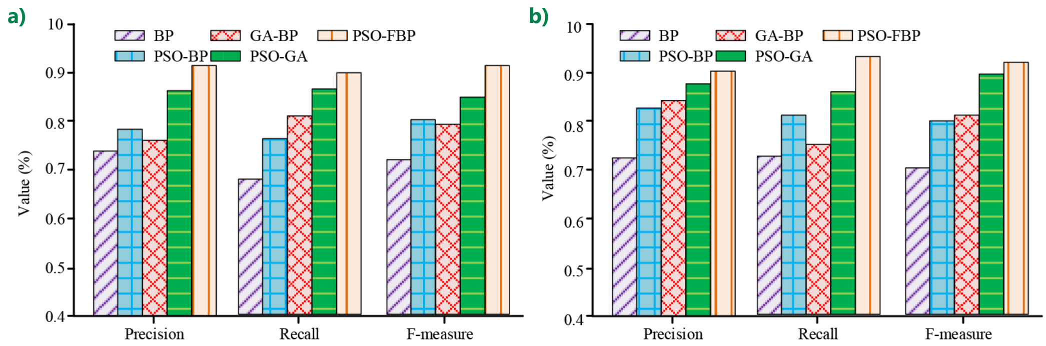

Figure 7. Self-learning results of 5 models on training and testing sets: a) Training set; b) Test set

PSO-BP, GA-BP, and PSO-GA in multiple criteria such as Precision, Recall, and F-measure. Figure 7 showcases the self-learning results of five models on the training and testing sets. In Figure 7a, the three criteria values of PSO-FBP fluctuated around 0.90, all of which were superior to BP, PSO-BP, GA-BP, and PSO-GA. In Figure 7b, the three criteria values of PSO-FBP also fluctuated around 0.90, all better than BP, PSO-BP, GA-BP, and PSO-GA. Therefore, PSO-FBP has stronger stability and higher indicator values.

Figure 8 shows the comprehensive evaluation comparison results of five models. In Figure 8a, the actual and simulated values of PSO-FBP were closer to the trend line, indicating that the difference between the two was smaller and more effective. Observing the other four models, there was a significant deviation from the trend line between their simulated and actual values, with a more discrete distribution, indicating that these four models did not fit well. In Figure 8b, the MAE and RMSE values of PSO-FBP were 0.189 and 0.256, respectively, which were smaller than the other four models, verifying its superior self-learning ability and applicability for benefit evaluation. In addition, traditional BP models had the highest MAE and RMSE values, but their performance was the worst. The main reason was that PSO-FBP improved the shortcomings of traditional models that were prone to falling into local extremes and overfitting data through PSO, and the fuzzy logic in it enabled the model to have adaptive and self-learning capabilities, which can be applied to the ecological benefit evaluation of CDAEEP.

3.2. Analysis of the practical application effect of ecological benefit evaluation model

Ecological benefit analysis evaluates the ecosystem biomass, economic value, and environmental impact of agricultural production systems. The simulation shown in Figure 9 showed that the total economic valuation of agricultural ecosystem services in the province was 4.43335 trillion yuan, with waste treatment contributing the most, accounting for 75.58%; Agricultural product production came second, accounting for 14.11%. Soil conservation accounted for 10.19%. CF and OR accounted for 2.31%. Water conservation and maintaining biodiversity services were relatively low. In addition, comparing the simulation outcomes, there were regional differences in the economic valuation of coordinated development in the province. Mainly due to the uneven natural conditions and economic development in various regions of the province, as well as the different selection of valuation parameters for agricultural ecological services, the results varied. In summary, the model proposed by the research can effectively measure the ecological benefits of coordinated development.

Table 2 showcases the weighted outcomes of environmental impact factors for coordinated development. The data in the table showed that the Aquatic Ecotoxicity Potential (AEP) had the highest score of 3.0589E+16, followed by the Eutrophicati Potential (EP) with a score of 1.68067E+16. The lowest scores for Energy Depletion (ED) and Water Depletion (WD) were 7321.311 and 2079258.501, respectively. Usually, agricultural production

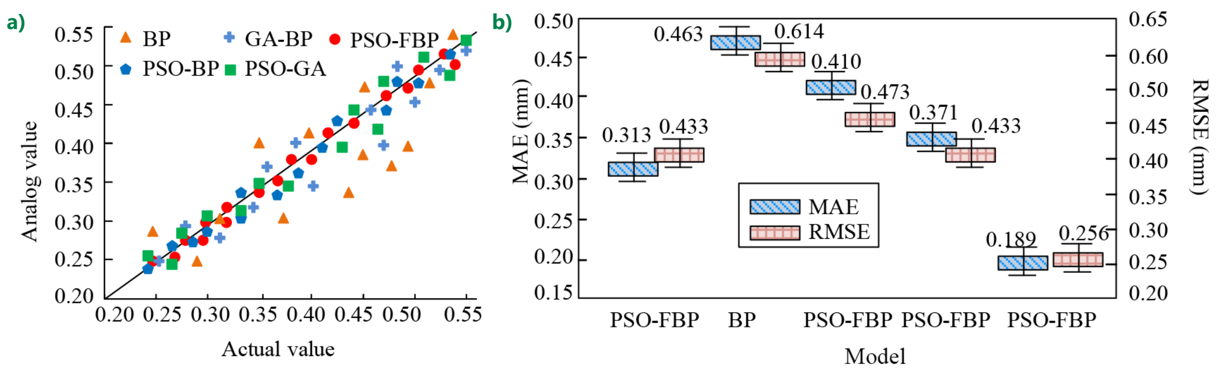

Figure 8. Comprehensive evaluation comparison results of five models: a) Data fitting results; b) MAE and RMSE values for 5 models

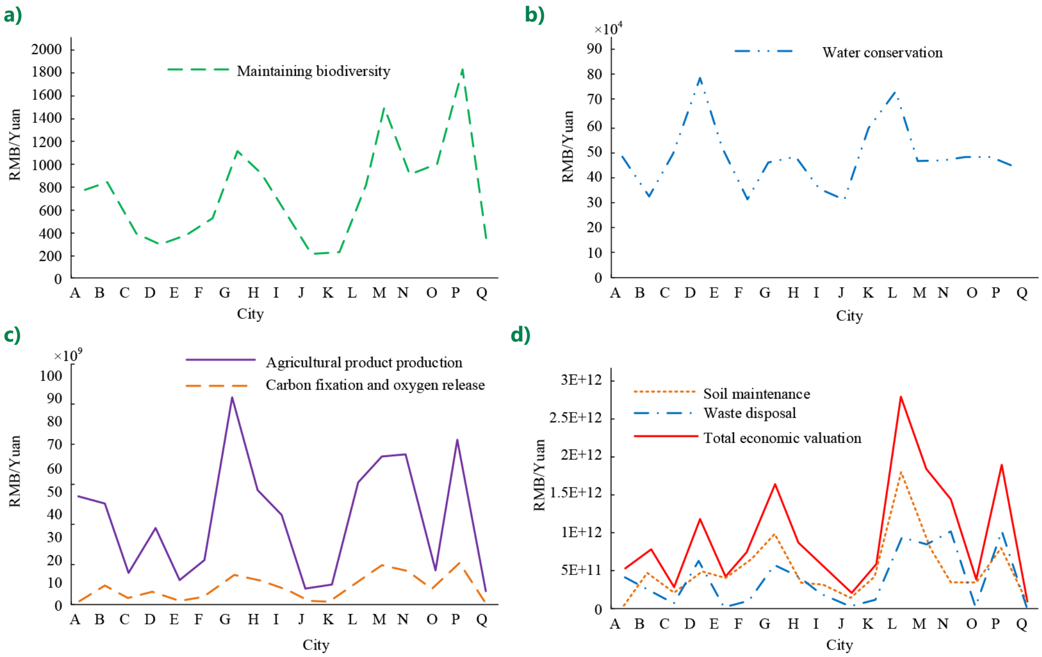

Figure 9. Economic valuation of coordinated development: a) Maintaining economic valuation of biodiversity; b) Economic valuation of water source conservation; c) Economic valuation of agricultural product production and carbonfixation and oxygen release; d) Soil maintenance, waste disposal, total economic valuation

systems provide more ecosystem services, which helps to enhance ecological stability and improve environmental quality. However, as can be seen from the results in the graph, the ecosystem services provided by the agricultural production system have not been effectively transformed into positive impacts on the environment. This indicates that the economic benefits of agricultural production systems often come at the cost of sacrificing the ecological environment.

Figure 10 shows the results of indicator correlation analysis. In Figure 10a, there was a strong negative correlation between AEP and the economic valuation of aquatic conservation, with a correlation coefficient of 0.87. In Figure 10b, there was also a strong negative correlation between EP and soil economic valuation, with a correlation coefficient of 0.89. These negative correlations indicate that there are complex interactions between certain ecological services in agricultural ecosystems and their economic valuations. For instance, the higher the value of aquatic plant protection, the lower the AEP score tends to be. This might be because the long-term benefits of ecological services are difficult to translate into significant

Table 2. Weighted results of environmental impact factors for coordinated development

City	EC	WU	GWP	AP	E+P	HTP	AEP	TEP	ED	WD	STP	ATP
A	1.5E+15	1.0E+15	4.8E+14	1.2E+13	1.68467E+16	5.2E+12	3.0590E+16	1.1E+14	7321.31	2079258.50	5.5E+13	1.2E+13
B	2.1E+15	1.3E+15	6.1E+14	2.1E+13	1.68167E+16	6.1E+12	3.0591E+16	2.1E+14	7315.31	2079250.50	6.1E+13	2.1E+13
C	6.9E+14	2.9E+14	2.1E+14	4.8E+12	1.68067E+16	3.1E+12	3.0592E+16	3.9E+13	7327.31	2079260.50	2.2E+13	5.1E+12
D	2.2E+14	1.05E+14	5.2E+13	1.1E+12	1.68567E+16	2.1E+12	3.0593E+16	2.05E+13	7320.31	2079259.50	1.1E+13	3.1E+12
E	2.05E+14	1.55E+14	9.1E+13	2.2E+12	1.68367E+16	3.05E+12	3.0594E+16	2.1E+13	7322.31	2079262.50	1.6E+13	4.1E+12
F	7.9E+14	4.1E+14	1.45E+14	3.1E+12	1.68767E+16	2.2E+12	3.0595E+16	3.1E+13	7323.31	2079264.50	2.1E+13	3.2E+12
G	1.55E+15	8.4E+14	2.05E+14	4.9E+12	1.68667E+16	4.2E+12	3.0596E+16	4.9E+13	7324.31	2079266.50	2.9E+13	7.1E+12
H	2.6E+15	1.45E+15	7.9E+14	1.05E+13	1.68967E+16	5.1E+12	3.0597E+16	7.8E+13	7325.31	2079268.50	4.1E+13	8.2E+12
I	5.8E+14	2.95E+14	1.05E+14	3.8E+12	1.68267E+16	2.05E+12	3.0598E+16	2.95E+13	7326.31	2079270.50	2.6E+13	4.3E+12
J	1.9E+14	1.3E+14	4.8E+13	1.1E+12	1.67967E+16	1.9E+12	3.0599E+16	1.3E+13	7319.31	2079272.50	1.1E+13	2.1E+12
K	4.6E+14	2.0E+14	8.1E+13	2.1E+12	1.68167E+16	2.5E+12	3.0600E+16	2.0E+13	7322.31	2079274.50	2.5E+13	4.5E+12
L	9.1E+14	5.1E+14	1.65E+14	4.2E+12	1.68367E+16	4.1E+12	3.0601E+16	5.1E+13	7325.31	2079276.50	3.1E+13	6.2E+12
M	3.7E+14	1.8E+14	6.1E+13	1.8E+12	1.68567E+16	3.1E+12	3.0602E+16	1.8E+13	7328.31	2079278.50	2.1E+13	3.8E+12
N	4.9E+14	2.1E+14	7.2E+13	2.2E+12	1.68767E+16	2.8E+12	3.0603E+16	2.1E+13	7331.31	2079280.50	2.8E+13	4.9E+12
O	2.8E+14	1.5E+14	5.1E+13	1.5E+12	1.68967E+16	2.1E+12	3.0604E+16	1.5E+13	7334.31	2079282.50	1.5E+13	3.1E+12
P	3.3E+14	1.7E+14	5.9E+13	1.7E+12	1.68167E+16	2.4E+12	3.0605E+16	1.7E+13	7337.31	2079284.50	1.7E+13	3.7E+12
Q	2.7E+14	1.4E+14	4.9E+13	1.4E+12	1.68367E+16	2.2E+12	3.0606E+16	1.4E+13	7340.31	2079286.50	1.4E+13	2.9E+12

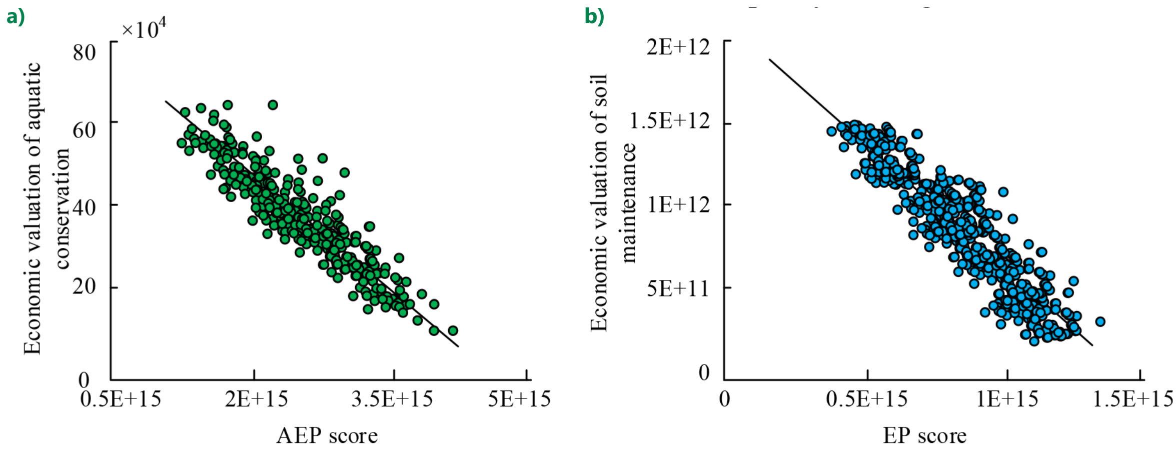

Figure 10. Results of index correlation analysis: a) The correlation between AEP score and economic valuation of aquatic conservation; b) The correlation between EP score and soil maintenance economic valuation

economic gains in the short term. The negative correlation between soil protection and eutrophication potential indicates that increasing investment in soil protection may reduce eutrophication potential, thereby affecting economic benefits. These results emphasize the trade-off between ecological protection and economic development, suggesting that when formulating agricultural policies, we should fully consider the long-term impact of ecological services and the complex relationship between them and economic returns. Therefore, further exploring the temporality and mechanism of ecological services, especially their negative correlation, holds significant reference value for optimizing ecological benefit assessment and policy-making.

3.3. Analysis of the Superiority of Ecological Benefit Evaluation Models

To verify the effectiveness of the proposed PSO-FBP model in agricultural ecological benefit evaluation, two widely used traditional weighting methods—Entropy Method and Fuzzy AHP—were selected as benchmarks. Under the same data conditions, ecological benefit scores were calculated using the three methods, and expert ratings were used as reference to evaluate classification consistency and numerical errors. The results are presented in Table 3.

Table 3. Comparison of weighting-based evaluation methods

Method	Accuracy (%)	MSE	MAE	Spearman Correlation	Weight Entropy
Entropy Method	71.3	0.084	0.173	0.69	2.12
Fuzzy AHP	74.6	0.076	0.161	0.76	1.95
PSO-FBP	88.2	0.041	0.096	0.87	1.36

As shown in Table 3, the PSO-FBP model outperforms the traditional Entropy Method and Fuzzy AHP in all key metrics, including accuracy, error control, and rank consistency. It achieves a classification accuracy of 88.2%, with an MSE of 0.041 and MAE of 0.096, both significantly lower than the benchmarks. The Spearman correlation coefficient reaches 0.87, indicating a high level of agreement between the model output and expert ratings. Moreover, PSO-FBP generates the lowest weight entropy, reflecting more discriminative and stable weight distributions. A Wilcoxon signed-rank test was conducted to assess statistical significance, and the differences in error metrics were found to be significant ($p < 0.01$), confirming the model's performance advantage and its strong generalizability and reliability.

To further evaluate the PSO-FBP model's capability in nonlinear modeling and handling complex variable interactions, two commonly used machine learning models—Random Forest (RF) and Extreme Gradient Boosting (XGBoost)—were adopted for comparison. Under the same data conditions, all three models were trained to classify ecological benefit levels, and their performance was assessed using four standard classification metrics: Precision, Recall, F1-score, and AUC. The results are shown in Table 4.

Table 4. Performance comparison with advanced machine learning methods

Method	Precision	Recall	F1-score	AUC
RF	0.793	0.762	0.773	0.851
XGBoost	0.814	0.789	0.801	0.873
PSO-FBP	0.861	0.832	0.845	0.902

As shown in Table 4, the PSO-FBP model outperforms both RF and XGBoost across all four metrics. The higher Precision indicates a lower false positive rate in identifying high ecological benefit areas, thus enabling more accurate selection of priority zones for conservation or policy support. The higher Recall suggests that the model is able to identify a greater proportion of truly high-benefit regions, reducing the risk of omission and improving the coverage of ecological resource allocation. The F1-score, which balances Precision and Recall, is highest for PSO-FBP, demonstrating its advantage in multi-objective evaluation scenarios. Finally, the improvement in AUC reflects stronger differentiation among ecological levels and better overall classification stability. A paired t-test conducted on F1-score values showed that the performance improvements of PSO-FBP over RF and XGBoost are statistically significant ($p < 0.05$), confirming its robustness and practical value in intelligent and fine-grained ecological benefit evaluation.

4. Limitations and future research directions

Although the proposed PSO-FBP model demonstrates strong performance in ecological benefit evaluation within agricultural systems, several methodological and application-related limitations remain. First, the model is developed based on data from prefecture-level cities in Henan Province, which introduces regional dependence. Given the heterogeneity of agricultural ecosystems across different regions in terms of resource structures and policy contexts, future research should incorporate multi-regional datasets to enhance the model's generalizability and applicability. Second, due to the limited spatial resolution of the available data, this study does not include diagnostic visualizations such as spatial residual plots, uncertainty propagation, or fuzzy rule dependency diagrams. Future work will introduce high-resolution geospatial data and interpretability mechanisms to strengthen model transparency and diagnostic capacity. Third, the current model assumes a linear relationship between ecological and economic variables, overlooking potential nonlinear coupling effects. Future research may incorporate more sophisticated nonlinear modeling strategies and include additional environmental variables to better capture complex interactions within agricultural ecosystems, thereby improving predictive performance and application scope.

From the application perspective, this study focuses primarily on short-term and static evaluations of ecological benefits, without accounting for the delayed and long-term impacts of ecological measures. Future work should incorporate longitudinal monitoring data and establish dynamic evaluation frameworks to capture temporal variations and predict long-term effects more accurately. In addition, the model currently lacks integration of policy intervention factors, limiting its utility in simulating ecological responses under varying policy scenarios. Future studies could introduce policy variables or scenario-based simulations to support more informed cost-benefit trade-offs and optimize policy decision-making. Moreover, the fuzzy rules within the model are automatically learned by the neural network. While this enhances nonlinear modeling capability, it also compromises semantic interpretability and increases sensitivity to initial membership function partitioning. Future efforts should consider incorporating attention mechanisms, interpretable neural architectures, or fuzzy rule visualization tools to improve rule traceability and transparency. It is also necessary to employ expert consensus methods such as the Delphi technique and quantitative rule confidence evaluation to ensure consistency and credibility of the rule base, particularly when resolving trade-offs between productivity and ecological sustainability. These improvements will contribute to the model's scientific rigor and practical reliability in decision-support contexts.

5. Conclusions and discussion

To raise the comprehensiveness and intelligence of the ecological benefit evaluation model, a PSO-FBP-based ecological benefit evaluation model was proposed. The research experimental outcomes indicated that PSO-FBP had good convergence effectiveness and stable search ability in finding the optimal solution, manifested in its strong local search ability and good global search performance, and ultimately tended to be stable. Taking a certain province as an example, the actual analysis outcomes indicated that the total economic valuation of agricultural ecosystem services in the province was 4.43335 trillion yuan, of which waste treatment accounted for 75.58%, agricultural products accounted for 14.11%, soil conservation accounted for 10.19%, and CF and OR accounted for 2.31%. The weighted results of environmental impact factors indicated that the AEP score was the highest, at 3.0589E+16, and the EP score was the second, at 1.68067E+16. Therefore, the ecological benefit evaluation model constructed through research can effectively measure the ecological benefits of coordinated development between agricultural economy and ecological protection, providing reference for formulating agricultural policies.

Compared with existing studies, the PSO-FBP model shows stronger comprehensive advantages in method design and result interpretation. Li (2023) explored the coordinated development of ecology and economy in the Yellow River Basin from a macro perspective, but only put forward policy and industrial suggestions, lacking quantitative modeling and empirical verification. Although the socio-environmental coordination index constructed by Ge et al. (2023) reveals the development trend of poverty-stricken areas, the linear weighting method is difficult to reflect the nonlinear coupling and multi-source heterogeneous characteristics within the ecosystem. Although a nonlinear transition mechanism was introduced, it did not involve the modeling of fuzzy and uncertain information and the adaptive generation of evaluation index weights. In comparison, PSO-FBP integrates fuzzy logic, self-learning network structure and particle swarm optimization algorithm. It has stronger modeling ability when dealing with data fuzziness and complex variable interactions. It can dynamically learn the importance distribution of different indicators, improving model performance while enhancing the accuracy and stability of policy application.

Based on the above conclusions, policy suggestions for enhancing the ecological benefits of farmland can be approached from multiple aspects. Firstly, policies should enhance the self-repairing capacity of agricultural ecosystems, encourage the reduction of pesticide and chemical fertilizer use, promote organic agriculture and low-impact agricultural technologies, and strengthen the self-repairing function of agricultural ecosystems, including aspects such as soil and water conservation and water source conservation. Secondly, the government should attach importance to ecological restoration work such as carbon footprint, organic carbon footprint and waste treatment regulation services, promote the recycling of agricultural waste, strengthen soil structure monitoring and improvement, and enhance soil health and the production capacity of crops. Finally, policies should encourage the application of green and innovative technologies, such as precision agriculture, intelligent irrigation, and biological control technologies, to reduce environmental pollution, enhance production efficiency, and strengthen farmers' training and support for new technologies. Through these measures, the coordinated development of agricultural economy and ecological protection can be achieved, ensuring the sustainability of agriculture and the improvement of ecological benefits.

References

Afrasiabi, A., Tavana, M., & DiCaprio, D. (2022). An extended hybrid fuzzy multi-criteria decision model for sustainable and resilient supplier selection. *Environmental Science and Pollution Research*, *29*(25), 37291–37314. https://doi.org/10.1007/s11356-021-17851-2

Akbar, U., Li, Q. L., Akmal, M. A., Shakib, M., & Iqbal, W. (2021). Nexus between agro-ecological efficiency and carbon emission transfer: Evidence from China. *Environmental Science and Pollution Research*, *28*, 18995–19007. https://doi.org/10.1007/s11356-020-09614-2

Akter, M. S. (2024). Harnessing technology for environmental sustainability: Utilizing AI to tackle global ecological challenges. *Journal of Artificial Intelligence General Science* (*JAIGS*), *2*(1), 61–70. https://doi.org/10.60087/jaigs.v2i1.97

Ayyildiz, E., & Taskin Gumus, A. (2021). Pythagorean fuzzy AHP based risk assessment methodology for hazardous material transportation: An application in Istanbul. *Environmental Science and Pollution Research*, *28*(27), 35798–35810. https://doi.org/10.1007/s11356-021-13223-y

Azareh, A., Rafiei Sardooi, E., Choubin, B., Barkhori, S., Shahdadi, A., Adamowski, J., & Shamshirband, S. (2021). Incorporating multi-criteria decision-making and fuzzy-value functions for flood susceptibility assessment. *Geocarto International*, *36*(20), 2345–2365. https://doi.org/10.1080/10106049.2019.1695958

Caymaz, T., Çalışkan, S., & Botsalı, A. R. (2022). Evaluation of ergonomic conditions using fuzzy logic in a metal processing plant. *International Journal of Computational and Experimental Science and Engineering*, *8*(1), 19–24. https://doi.org/10.22399/ijcesen.932994

Czyżewski, B., Matuszczak, A., & Majchrzak, A. (2021). Environmental sustainable value in agriculture revisited: How does Common Agricultural Policy contribute to eco-efficiency? *Sustainability Science*, *16*(1), 137–152. https://doi.org/10.1007/s11625-020-00834-6

Duleba, S., Kutlu Gündoğdu, F., & Moslem, S. (2021). Interval-valued spherical fuzzy analytic hierarchy process method to evaluate public transportation development. *Informatica*, *32*(4), 661–686. https://doi.org/10.15388/21-INFOR451

Gashaw, T., Dile, Y. T., Worqlul, A. W., Bantider, A., Zeleke, G., Bewket, W., & Alamirew, T. (2021). Evaluating the effectiveness of best management practices on soil erosion reduction using the SWAT Model: For the case of Gumara watershed, Abbay (Upper Blue Nile) Basin. *Environmental Management*, *68*(2), 240–261. https://doi.org/10.1007/s00267-021-01492-9

Ge, Y., Hu, S., Song, Y, Zheng, H., Liu, Y., Ye, X. (2023). Sustainable poverty reduction models for the coordinated development of the social economy and environment in China. *Science Bulletin*, *68*(19), 2236–2246. https://doi.org/10.1016/j.scib.2023.08.015

Groumpos, P. P. (2023). A critical historic overview of artificial intelligence: Issues, challenges, opportunities, and threats. *Artificial Intelligence and Applications*, *1*(4), 197–213. https://doi.org/10.47852/bonviewAIA3202689

Hasheminezhad, A., Hadadi, F., & Shirmohammadi, H. (2021). Investigation and prioritization of risk factors in the collision of two passenger trains based on fuzzy COPRAS and fuzzy DEMATEL methods. *Soft Computing*, *25*(6), 4677–4697. https://doi.org/10.1007/s00500-020-05478-3

Jafarzadeh, G., Shaffiee, H., Memarpour, G., Guido, G., & Vitale, A. (2023). Road safety assessment and risks prioritization using an integrated SWARA and MARCOS approach under spherical fuzzy environment. *Neural Computing and Applications*, *35*(6), 4549–4567. https://doi.org/10.1007/s00521-022-07929-4

Katumo, D. M., Liang, H., Ochola, A. C., Lv, M., Wang, Q., & Yang, C. (2022). Pollinator diversity benefits natural and agricultural ecosystems, environmental health, and human welfare. *Plant Diversity*, *44*(5), 429–435. https://doi.org/10.1016/j.pld.2022.01.005

Kayacık, M., Dinçer, H., & Yüksel, S. (2022). Using quantum spherical fuzzy decision support system as a novel sustainability index approach for analyzing industries listed in the stock exchange. *Borsa Istanbul Review*, *22*(6), 1145–1157. https://doi.org/10.1016/j.bir.2022.10.001

Kılıc, O. M., Ersayın, K., Gunal, H., Khalofah, A., & Khalofah, M. (2022). Combination of fuzzy-AHP and GIS techniques in land suitability assessment for wheat (Triticum aestivum) cultivation. *Saudi Journal of Biological Sciences*, *29*(4), 2634–2644. https://doi.org/10.1016/j.sjbs.2021.12.050

Li, L. (2023). Research on ecological environmental protection and high-quality coordinated economic development in the Yellow River Basin. *Open Access Library Journal*, *10*(5), 1–8. https://doi.org/10.4236/oalib.1110102

Liu, K., Sun, Y., & Yang, D. (2023). The administrative center or economic center: Which dominates the regional green development pattern? A case study of Shandong Peninsula urban agglomeration, China. *Green and Low-Carbon Economy*, *1*(3), 110–120. https://doi.org/10.47852/bonviewGLCE3202955

Mishra, A. R., Chandel, A., & Saeidi, P. (2022). Low-carbon tourism strategy evaluation and selection using interval-valued intuitionistic fuzzy additive ratio assessment approach based on similarity measures. *Environment, Development and Sustainability*, *24*(5), 7236–7282. https://doi.org/10.1007/s10668-021-01746-w

Naseem, S., & Tong, G. (2021). A system-GMM approach to examine the renewable energy consumption, agriculture and economic growth's impact on CO_2 emission in the SAARC region. *GeoJournal*, *86*(5), 2021–2033. https://doi.org/10.1007/s10708-019-10136-9

Omair, M., Noor, S., Tayyab, M., Maqsood, M., Ahmed, W., Sarkar, B., & Habib, M. (2021). The selection of the sustainable suppliers by the development of a decision support framework based on analytical hierarchical process and fuzzy inference system. *International Journal of Fuzzy Systems*, *23*(7), 1986–2003. https://doi.org/10.1007/s40815-021-01073-2

Soner, O., Celik, E., & Akyuz, E. (2022). A fuzzy best–worst method (BWM) to assess the potential environmental impacts of the process of ship recycling. *Maritime Policy* & *Management*, *49*(3), 396–409. https://doi.org/10.1080/03088839.2021.1889066

Turunen, J., Elbrecht, V., Steinke, D., & Aroviita, J. (2021). Riparian forests can mitigate warming and ecological degradation of agricultural headwater streams. *Freshwater Biology*, *66*(4), 785–798. https://doi.org/10.1111/fwb.13678

Wuest, S. E., Peter, R., & Niklaus, P. A. (2021). Ecological and evolutionary approaches to improving crop variety mixtures. *Nature Ecology* & *Evolution*, *5*(8), 1068–1077. https://doi.org/10.1038/s41559-021-01497-x

Zhou, B., Chen, J., Wu, Q., Pamučar, D., Wang, W., & Zhou, L. (2022). Risk priority evaluation of power transformer parts based on hybrid FMEA framework under hesitant fuzzy environment. *Facta Universitatis*, *Series*: *Mechanical Engineering*, *20*(2), 399–420. https://doi.org/10.22190/FUME220223013Z