RESEARCH ARTICLE

Application of neural network in the evaluation of rural ecological environment governance policy effects

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The deterioration of rural ecological environments driven by industrialization and unsustainable agricultural practices has posed serious challenges to sustainable development and the well-being of rural populations. Various ecological governance policies have been implemented to restore environmental quality and promote rural revitalization. This research scientifically evaluated the effectiveness of these policies using a data-driven framework using a deep learning model integrating spatio-temporal convolutional networks (STCN) and self-attention mechanisms to capture the dynamic, nonlinear, and multi-source characteristics of policy impact data. The model was trained using empirical data from 2018 to 2023 including indicators of water quality, soil pollution, vegetation coverage, agricultural income, and employment rate. The results showed that the proposed model demonstrated high predictive accuracy with mean errors under 2 units for key environmental indicators. Neural networks outperformed traditional methods, particularly in processing heterogeneous and high-dimensional data, providing deeper insights into policy effectiveness. This study offered a scalable and precise solution for evaluating complex environmental interventions and supported evidence-based decision-making in rural ecological governance.

Keywords: neural network; rural ecology; environment governance; policy effect evaluation; deep learning; multi-source heterogeneous data.

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Introduction

Rural ecological environment governance is one of the important contents of achieving rural revitalization and ecological civilization construction and an important link in addressing global ecological and environmental problems. In the past few decades, rapid industrialization and urbanization have brought significant economic growth but also exacerbated ecological and environmental problems in rural areas such as water pollution, soil degradation, and biodiversity reduction [1, 2]. These problems not only threaten the health of rural ecosystems but also pose challenges to the sustainability of agricultural production and the life quality of rural residents. China has successively introduced several rural ecological environment governance policies including rural sewage treatment facility construction, agricultural non-point source pollution prevention and control, and vegetation restoration plans, aiming to improve the rural ecological environment from the source. These policies have provided strong support for promoting green development and ecological civilization construction, but their actual effects still need to be evaluated and verified by scientific methods [3]. Evaluating the effectiveness of rural ecological environment governance policies is an important basis for policy optimization and decision-making improvement. Domestical researchers analyzed the implementation effect of China's rural sewage treatment policy and found that policy support had significantly increased the rural sewage treatment rate, but the regional differences in policy implementation were large, and more precise policy design was needed [4]. European Union's Common Agricultural Policy (CAP) and the United States's Agricultural Protection Program (CRP) are important tools to improve the rural environment. The scientists found that policy implementation had a significant effect on improving soil quality and biodiversity. However, the policy effect was greatly affected by ecological environment and socioeconomic conditions [5].

There are various evaluation methods for rural ecological environment governance policies, but they are mainly concentrated in two categories of quantitative and qualitative methods by constructing an indicator system using the environmental index [6]. The traditional evaluation methods mainly based on statistical analysis and qualitative research usually relying on indicator systems, questionnaires, and case studies based on regression models, causal analysis, and infer policy effects by quantifying the changes in environmental indicators before and after policy implementation. Although these methods can reflect the effectiveness of policy implementation, it is difficult to fully capture the interactive relationship between various factors in the policy implementation process due to the complexity of the ecological environment and the nonlinear characteristics of the data [7]. In addition, with the rapid development of information technology, the amount of data has increased significantly with multi-source, heterogeneous, and dynamically changing, as well as socioeconomic data and policy implementation details [8], which makes traditional analysis tools face bottlenecks in the processing and mining process. Meanwhile, the effects of rural ecological and environmental governance are usually dynamic, and the evaluation needs to consider the short-term and long-term impacts of policy implementation. Traditional static evaluation methods are difficult to reveal the time evolution of policy effects, which limits the guiding role of forward-looking policy improvements. The introduction of advanced artificial intelligence (AI) technologies such as neural networks provides a new approach to policy effectiveness evaluation. With its powerful nonlinear modeling and data mining capabilities, neural networks can extract potential patterns from massive amounts of complex data, providing higher accuracy and explanatory power for policy effectiveness evaluation. Compared with traditional methods, neural networks show significant advantages in processing multidimensional data and capturing dynamic relationships. By combining time series data, neural networks can effectively model the long-term ecological change trends after policy implementation and provide more comprehensive evaluation results [9]. Wang *et al*. used regression analysis to study the implementation effect of agricultural non-point source pollution policies and found that the policy made a significant contribution to the reduction of nitrogen and phosphorus concentrations in water bodies [1]. However, the assumptions of this type of method were relatively strict and it was difficult to deal with the complex nonlinear relationship of policy effects. In addition, statistical analysis methods were highly dependent on data quality, and missing data or noise might lead to biased results. The indicator system is another commonly used policy evaluation method, which usually reflects the policy effect comprehensively by constructing multidimensional evaluation indicators [10]. The advantage of this method is that it can comprehensively evaluate the impact of policies on ecology, economy, and society. However, the construction and weight setting of the indicator system are somewhat subjective, and the results of different studies may lack comparability. As the data dimension increases, this method faces challenges in processing multi-source heterogeneous data. The case analysis method uses case studies of specific policy implementation to explore its mechanism and effect. Researchers used rural ecological policy cases to reveal the successful experience and reasons for failure of policy implementation. However, this approach had limited applicability and was difficult to generalize in different regions or policies [11, 12]. A previous study used convolutional neural network (CNN) models to analyze atmospheric pollution data and successfully predicted the trend of changes in the air quality index [13]. Another study used long short-term memory networks (LSTM) to analyze water quality changes, and the model accurately captured the time series characteristics of dynamic data [14]. These studies showed that neural networks could process multi-dimensional complex data and had significant advantages in predicting and analyzing nonlinear relationships. Neural networks have also been successfully applied in urban governance. Cremin *et al*. used neural network models to evaluate the improvement effect of urban transportation policies on air quality. By combining environmental monitoring and socioeconomic data, the model could accurately identify the key factors of policy effectiveness [15].

It is difficult to obtain and integrate rural ecological environment data including the spatial heterogeneity and time span of data. The existing research often focuses on a single policy or a local area, lacking a systematic evaluation of the comprehensive effects of rural ecological environment governance policies, while most existing models are applied to a single field such as water quality prediction or air pollution analysis and have not yet fully combined multi-task learning (MTL) methods to simultaneously evaluate multi-dimensional policy effects. In addition, although neural networks have powerful data processing capabilities, how to design a suitable model architecture for the complex characteristics of rural ecological governance still needs to be explored in depth. This research proposed a neural network model by combining multi-source heterogeneous data and dynamic analysis to accurately capture the comprehensive effects of rural ecological environment governance policies put forward suggestions for optimizing policies by applying proposed model to typical cases of rural ecological environment governance to verify its feasibility and advantages. The proposed model would effectively deal with the complexity and nonlinear characteristics of ecological data and optimize suggestions for future rural ecological environment governance, providing a scientific basis for policy formulation and adjustment. The results of this study provided not only a new technical path for the effectiveness evaluation of rural ecological governance policies but also data support and decision-making basis for policy and improvement [16, 17], which enriched the theoretical methods in the field of policy optimization evaluation and provided technical support and decision-making reference for the practice of rural ecological environment governance.

Materials and methods

Overall framework design

An evaluation framework based on the latest deep learning technology was proposed by combining spatio-temporal convolutional networks (STCN), graph neural networks (GNNs), self-attention mechanisms, and multi-task learning (MTL) technology to comprehensively evaluate the policy implementation effect. The framework was divided into data preprocessing, feature extraction, modeling, and evaluation. The input was multi-dimensional dynamic tensor data including environmental monitoring, policy input, and spatial features, while the output was a comprehensive policy effect evaluation index. By introducing the self-attention mechanism and MTL framework, this method can not only capture the complex spatiotemporal relationship of policy implementation but also provide multi-dimensional guidance for policy optimization.

Data preprocessing and input representation

The data sources of rural ecological environment governance were complex, usually including environmental monitoring data such as PM2.5 concentration and water quality indicators, policy input data such as funding allocation and policy intensity, and geographic spatial characteristics such as land use distribution and meteorological information, which needed to be standardized, missing value filled, and scaled uniformly [18, 19]. The preprocessed data was organized into a spatiotemporal tensor as follows.

$$\mathbf{X} \in ¡^{T\times N\times D}$$

where T was the number of time steps. N was the number of spatial units. D was the feature dimension. To represent the spatial relationship between geographic units, an adjacency matrix was introduced as below.

$$\mathbf{A}_{ij} = \begin{cases} \exp\left(-\dfrac{\text{dist}(i,j)^2}{\sigma^2}\right) & \text{if (i)and (j)arespatially adjacent} \\ 0 & \end{cases}$$

where $\text{dist}(i,j)$ was the spatial distance. σ was the smoothing parameter of the Gaussian kernel [20].

Feature extraction and modeling

The effectiveness evaluation of rural ecological governance policies needs to capture both spatial correlation and temporal dynamics. This study adopted a modeling strategy of spatiotemporal convolutional networks combined with self-attention mechanisms to extract features and model relationships for multidimensional data. Spatial dependency was modeled by GNNs with its core propagation expressed as follows.

$$H^{(l+1)} = \sigma\left(\tilde{A}H^{(l)}W^{(l)}\right)$$

where $\tilde{A}$ was the normalized adjacency matrix. $H^{(l)}$ was the node feature of the l-th layer. $W^{(l)}$ was a learnable parameter. σ was a nonlinear activation function [21, 22]. The dependency in the temporal dimension was captured by a temporal convolutional network (TCN) as shown below.

$$H_t = \text{Conv1D}(X_{t-w:t}, W)$$

where w was the time window size. W was the one-dimensional convolution kernel parameter. This method could effectively capture long-term dependencies in time series. Spatial and temporal features were jointly modeled by a spatiotemporal convolutional network as follows.

$$H_{t+1} = \sigma(\text{GraphConv}(\text{H}_t) + \text{TimeConv}(\text{H}_t))$$

This structure captured spatiotemporal interaction features through parallel convolution operations, thereby comprehensively characterizing the dynamic changes in policy effects.

Introduction of self-attention mechanism

In the complex context of rural governance policies, different time steps or spatial units might have different weights on the overall effect. This study introduced a self-attention mechanism to dynamically adjust the importance of spatiotemporal features as below.

$$\text{Attention}(\text{Q},\text{K},\text{V}) = \text{Softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V$$

where $(\text{Q},\text{K},\text{V})$ were query, key, and value matrices, respectively, and calculated as follows.

$$\text{Q} = \text{HW}_\text{Q}$$

$$\text{K} = \text{HW}_\text{K}$$

$$\text{V} = \text{HW}_\text{V}$$

The attention mechanism could automatically identify key spatiotemporal nodes and features, improving the accuracy and stability of the evaluation.

MTL framework

A multi-task learning (MTL) framework was adopted to achieve collaborative optimization through a shared representation layer and a task-specific output layer as below.

$$y_i = f(X; \Theta_{\text{shared}}, \Theta_i), \quad i \in \{1,2,\dots,M\}$$

Where Θ_{shared} was the shared feature extraction layer parameter. Θ_i was the task-specific parameter. y_i was the predicted value of task i. The total loss function was defined as the weighted sum of multiple task losses and was calculated as follows.

$$\mathcal{L} = \sum_{i=1}^{M} \alpha_i \mathcal{L}_i$$

where $\mathcal{L}_i$ was the loss function of task *i*, commonly used mean square error (MSE) or cross entropy loss (CE). The weight α_i reflected the importance of the task. This framework could achieve information sharing among multiple tasks and improve the comprehensiveness and accuracy of policy evaluation.

Case selection and data collection

To verify the effectiveness of the proposed rural ecological environment governance policy effect evaluation framework, this research selected the rural ecological environment governance policy of Yancheng city, Jiangsu, China as an empirical case. The region had implemented several ecological environment governance policies, covering water resource protection, land reclamation, vegetation restoration, and other aspects, which included improving water resource utilization efficiency through reservoir construction and water resource protection policies, improving soil quality through vegetation restoration projects, and implementing land reclamation plans to restore cultivated land area. The relevant environmental monitoring data, policy input data, and socioeconomic data were collected, providing rich data resources for the verification of the proposed model. The data used in this empirical analysis came from government, environmental monitoring agencies, and socioeconomic statistics. Environmental monitoring data were obtained from the Yancheng Municipal Environmental Protection Bureau database including 3,420 entries related to water quality, soil pollution, and vegetation coverage from 2018 to 2023. Policy investment data were obtained through the open data platform of Yancheng Government Data Center consisting of 980 entries. Socio-economic data were sourced from the Jiangsu Statistical Yearbook published by Jiangsu Provincial Bureau of Statistics (Nanjing, Jiangsu, China) comprising 1,260 records on agricultural income and rural employment rate. A total of 5,660 data entries were used in the analysis and categorized into three datasets as environmental (60.4%), economic (22.3%), and policy-related (17.3%). These datasets were preprocessed using standardization and missing-value interpolation techniques before being input into the spatiotemporal neural network model for policy effect evaluation.

Model development

A computer server equipped with two Intel Xeon Silver 4214R CPUs (Santa Clara, CA, USA), 128 GB RAM, and one NVIDIA RTX A6000 GPU (NVIDIA Corporation, Santa Clara, CA, USA) was employed for model development and computation. Python 3.9 (https://www.python.org/) was used as the primary programming language with TensorFlow 2.11 (Google LLC, Mountain View, CA, USA) as the deep learning framework. Statistical analysis was conducted using SPSS 26.0 (IBM, Armonk, NY, USA). Model construction included a spatiotemporal convolutional network integrated with a graph neural network and self-attention mechanism. The data were split into 70% for training, 15% for validation, and 15% for testing. MSE was used as the loss function, and Adam optimizer was applied for model training.

Statistical analysis

SPSS version 26.0 (IBM, Armonk, NY, USA) was employed for statistical analysis of this study to assess model performance and validate the relationship between policy implementation and ecological outcomes. MSE was used to measure prediction accuracy, while correlation analysis

Table 1. Comparison of model prediction values and actual values.

Index	Predicted value	Actual value	Error
Water Quality Index	85.6	87.2	1.6
Soil pollution index	30.3	32.1	1.8
Vegetation coverage	72.5	70.8	1.7
Agricultural income	¥12,500/year	¥12,300/year	200 NTD
Employment Rate	78%	77.5%	0.5%

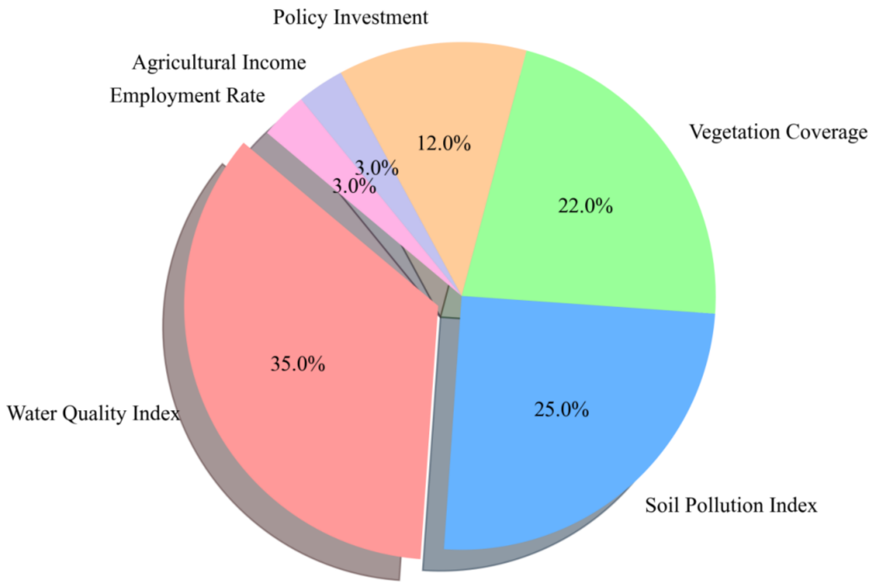

Figure 1. Analysis of key factors affecting policy effects.

was applied to evaluate the strength of association between governance policies and environmental as well as socio-economic indicators.

Results and discussion

Model application and result analysis

By comparing the predicted values with the actual values, the results showed that the proposed model performed well in evaluating the effects of ecological environmental governance. The prediction errors of the water quality index and soil pollution index were small, indicating that the governance policy had a significant effect on improving water quality and soil. In terms of changes in agricultural income and employment rate, the error between the predicted results and the actual values was also small, but the changes were relatively slow, which indicated that it took a long time for economic benefits to manifest (Table 1).

Analysis of key factors affecting the effects of different policies

The water quality and soil pollution index had a larger weight in the policy effect, indicating that the focus of ecological governance policies was mainly on the restoration of water quality and soil, while vegetation restoration also played an important role (Figure 1). Relatively speaking, agricultural income and employment rate accounted for a smaller proportion in the evaluation of policy effects, indicating that changes in these economic indicators took a longer time to reflect.

Table 2. Comparison between traditional methods and neural network models.

Method	Prediction accuracy (MSE)	Model complexity	Calculation time
Traditional statistical analysis methods	0.65	Low	3 hours
Deep learning neural network method	0.12	high	5 hours

Table 3. Implementation and effectiveness of different governance policies.

Policy type	Implementation year	Implementation intensity	Goal completion	Policy effect evaluation (mean)
Water resource protection	2018 - 2021	High	90%	0.85
Land reclamation	2019 - 2022	Middle	75%	0.72
Vegetation restoration	2020 - 2023	High	85%	0.78
Sustainable agriculture	2021 - 2023	Low	60%	0.65
Employment promotion program	2018 - 2023	Middle	80%	0.70

Comparative analysis

To further verify the advantages of the proposed neural network model, this study compared it with traditional evaluation methods that were mainly based on statistical analysis. Two traditional statistical methods were used for comparative study, which included the weighted average method and multiple linear regression analysis. The weighted average method calculated composite scores based on predefined policy impact indicators, while regression analysis was applied to quantify the relationship between policy input variables and outcome indicators such as water quality, soil pollution, and agricultural income. Model comparison was conducted by applying each method to the same dataset and calculating their prediction accuracy using MSE. The comparative results revealed that the proposed neural network model achieved a lower MSE of 0.12 than the traditional methods of 0.65, demonstrating superior performance in handling nonlinear, multi-source ecological data (Table 2). When processing data, the traditional methods usually assumed that there was a linear relationship between data and had difficulty in handling complex nonlinear features. The comparison results of traditional methods and proposed neural network model, especially the differences in prediction accuracy and calculation time, showed that the proposed neural network method was significantly better than the traditional statistical analysis method in terms of evaluation accuracy. Although the traditional methods had a shorter calculation time, the ability to process complex data was obviously insufficient. The deep learning model could automatically identify and process complex nonlinear relationships in the data, thereby improving the accuracy of the evaluation.

Implementation and effectiveness of different governance policies

The implementation of different ecological and environmental governance policies including the implementation year, implementation intensity, completion of relevant targets, and policy effect evaluation results of each policy was analyzed and demonstrated that the water resources protection and vegetation restoration policies had high implementation intensity and high target completion during the implementation process with relatively significant effect. The water resources protection policy showed the highest effect evaluation value, indicating that the implementation of this policy had a significant impact on improving environmental quality. In contrast, the policy effect evaluation of agricultural sustainable development and employment promotion plans was relatively low, which might be limited by capital investment and socio-economic factors (Table 3). The correlation between different ecological and environmental

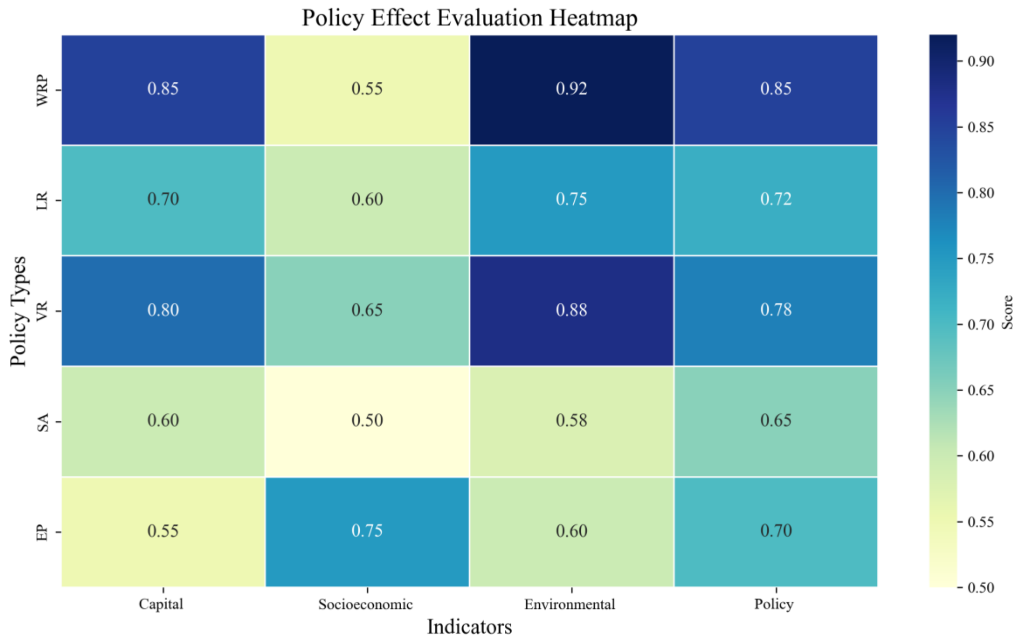

Figure 2. Correlation analysis between different policies and influencing factors.

governance policies and various influencing factors including capital investment, socio-economic development, and environmental quality showed that the water resource protection policy had the highest correlation with environmental quality as 0.92, indicating that the water resource protection policy had a great effect on improving water quality and soil pollution. Vegetation restoration and land reclamation had a strong correlation with environmental quality as 0.88 and 0.75, respectively, indicating that vegetation restoration and soil remediation had a positive effect on environmental improvement. Capital investment had the greatest impact on water resource protection and vegetation restoration policies as 0.85 and 0.80, respectively, which meant that the effectiveness of these policies depended largely on financial support. In terms of socio-economic development, agricultural sustainable development and employment promotion plans had a high correlation of 0.60 and 0.75, respectively, indicating that these two policies were closely related to local economic growth and help improve residents' income and employment levels (Figure 2).

The advantages and applicability of neural networks

The proposed neural network-based rural ecological environment governance policy effect evaluation framework demonstrated obvious advantages in improving the evaluation accuracy. Neural networks, especially spatiotemporal convolutional neural networks (STCN), could effectively process data from different sources and dimensions and capture the complex relationships therein. Through multi-level feature extraction and learning, the model showed excellent ability in processing spatiotemporal features and nonlinear relationships. However, the training of neural networks required a lot of computing resources, and overfitting might occur when the amount of data was small. Therefore, combining traditional methods with deep learning technology for hybrid evaluation was an ideal strategy that could make up for the shortcomings of deep learning models when data was insufficient. The impact trends of the rural ecological environment governance policy on environmental and economic indicators showed that the water quality index increased year by year over time from 75.3 in 2018 to 87.2 in 2023, indicating that

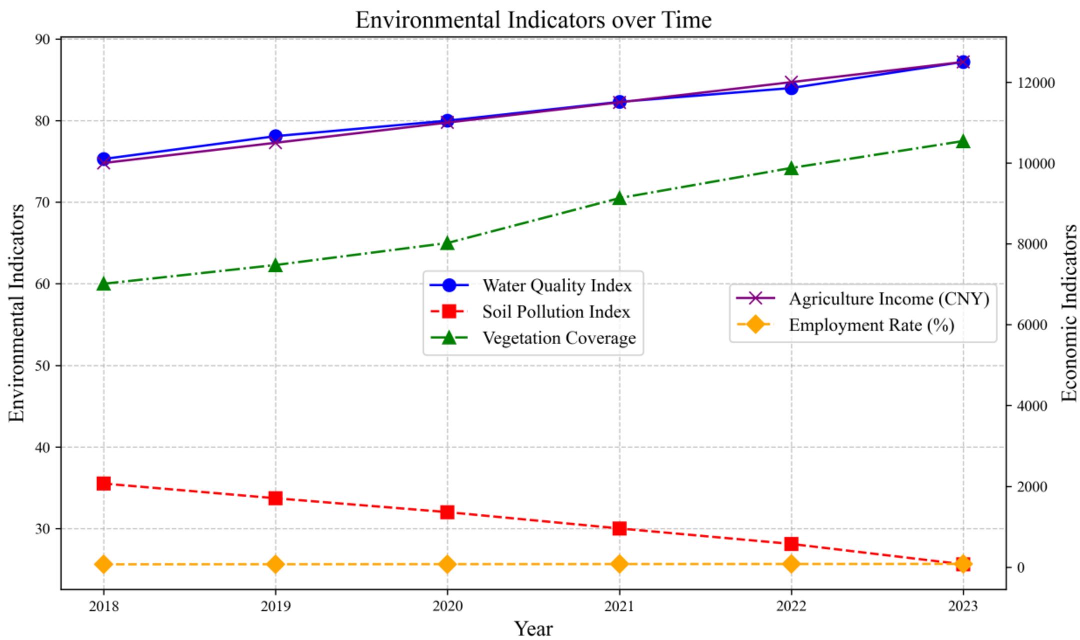

Figure 3. Impact trends of ecological environmental governance policies on environmental and economic indicators.

the water resource protection policy had gradually achieved significant results. The soil pollution index demonstrated a downward trend from 35.5 to 25.6, indicating that the policies of land reclamation and pollution control had been gradually implemented, while vegetation coverage also showed a significant increase from 60% in 2018 to 77.5% in 2023. The agricultural income showed an increasing trend year by year, reaching ¥12,500/year in 2023, which was a significant increase compared with ¥10,000/year in 2018. In addition, the employment rate had also steadily increased from 70% in 2018 to 80% in 2023, indicating that governance policies had led to full employment of the rural labor force (Figure 3). The annual changing trends of environmental and economic indicators showed that the soil pollution index demonstrated a year-on-year downward trend, indicating that soil remediation and pollution control measures had made significant progress. Meanwhile, vegetation coverage showed a clear upward trend, reflecting the successful implementation of vegetation restoration projects and the gradual improvement of the ecological environment. For economic indicators, the agricultural income showed a trend of sustained growth, reflecting the positive impact of ecological environment improvement on farmers' income. The agricultural output value also grew steadily from 15,000 tons in 2018 to 18,200 tons in 2023, reflecting the gradual recovery of the rural economy under ecological governance (Figure 4).

Conclusion

This research proposed an evaluation framework based on neural networks by deeply analyzing the key factors in the evaluation of rural ecological environment governance policy effects. The results showed that the proposed neural networks had significant advantages in processing complex environmental and socio-economic data. Through model training and verification, this study successfully demonstrated the application potential of neural networks in multi-dimensional data analysis, especially in evaluating the effectiveness of different policy types. Traditional evaluation methods such as statistical analysis and evaluation based on indicator systems often ignored the nonlinear relationship between data and the heterogeneity

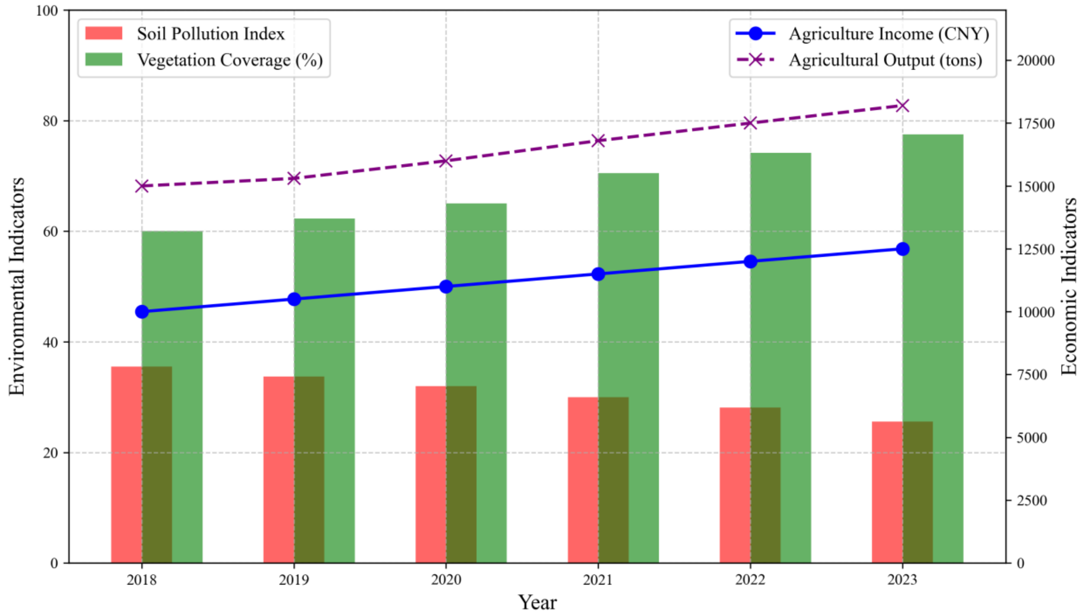

Figure 4. Comprehensive results of the implementation of rural ecological environment governance policies.

of multi-source data, resulting in limitations in evaluation results. Neural networks could effectively capture these complex relationships through multi-level nonlinear transformations and provide more accurate policy effect evaluation results. Through experimental data verification, the neural network model was superior to traditional methods in predicting accuracy of policy effects, especially when it involved comprehensive analysis of multiple environmental indicators and socio-economic indicators. The neural network could reveal the impact of different factors on policy effects more comprehensively and deeply.

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