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Optimization of Rice Production Forecasting using Hybrid ANN-PSO

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ABSTRACT

Rice production is a critical component in sustaining national food security, especially Indonesia. The availability of sufficient, affordable, and equitable food is a major challenge for Indonesia. One approach to addressing this challenge is by developing reliable and accurate models for predicting food production. In this study, a hybrid approach that combines Artificial Neural Network (ANN) and Particle Swarm Optimization (PSO) algorithms is used to optimize the performance of modeling and prediction of rice production in Central Java, Indonesia. This study uses secondary data in the form of monthly time series data from the Central Java Provincial Statistics Agency (BPS), Meteorology, Climatology, and Geophysics Agency (BMKG), and satellite imagery data with an observation period from January 2019 to December 2024. The input variables in this study include harvested area, precipitation, number of rainy days, atmospheric pressure, wind speed, NDWI, and NDVI while the output variable is rice production in Central Java. The test results using the ANN model provided an RMSE value of 0.1312 and a MSE of 0.0172, while the ANN-PSO model provided an RMSE value of 0.0259 and a MSE of 0.00067. These results indicate that the PSO algorithm is able to optimize the performance of the ANN model in predicting rice production in Central Java.

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A. INTRODUCTION

Rice production forecasting in developing countries such as Indonesia is crucial for ensuring food security and economic stability. Rice serves as the primary staple for the majority of the population and represents a vital agricultural commodity. Domestic rice production not only sustains national consumption but also contributes significantly to the economy. Over the long term, domestic rice production and global rice prices have been found to significantly affect import volumes (Zaneta & Ayuningsasi, 2025). The results indicate that strengthening domestic production capacity and addressing volatility in international rice prices are essential for ensuring sustainable rice import management. According to official statistics from the Ministry of Agriculture of Indonesia, Central Java ranks consistently among the ten largest rice-producing provinces in Indonesia (Ministry of Agriculture of the Republic of Indonesia, 2024). However, the latest official data from BPS shows that rice production in Central Java has been on a downward trend since 2021, raising concerns about the stability of regional and national food supplies (BPS, 2025).

Rice production is influenced by multiple interacting factors, particularly climate variability (Setiyanto et al., 2024). In regions such as Central Java, diverse agro-climatic conditions and interannual climate fluctuations contribute to significant variability in rice production across planting seasons (Ansari et al., 2021). Changes in rainfall patterns, temperature, and solar radiation have been shown to affect rice yields, thereby increasing uncertainty in production outcomes (Ansari et al., 2021; Modesti & Borsato, 2022). Although integrated climate–crop modeling approaches have been developed, their application is often constrained by data limitations, uncertainty in predictions, and challenges in model validation (Ansari et al., 2023). To overcome these constraints, satellite imagery-based indicators such as the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) have been increasingly utilized for rice production monitoring and forecasting (Farbo et al., 2024; Ajay et al., 2025). Remote sensing data provide spatially explicit and timely information on crop conditions and, when combined with weather data aligned to crop phenological stages, have been shown to improve forecasting accuracy (Brinkhoff et al., 2024; Islam et al., 2021). These advantages highlight the relevance of remote sensing data for developing more robust rice production forecasting models in climatically heterogeneous regions such as Central Java (Setiyanto et al., 2024; Satpathi et al., 2023).

In Indonesia, particularly in Central Java, most rice production prediction studies still rely on statistical approaches such as multiple linear regression (Triyanto et al., 2019), dynamic system modeling (Sardjono et al., 2019), semiparametric time series regression (Fitriyah et al., 2024), and ARIMA (Khofi & Farhan, 2025). While these methods are simple and interpretable, they remain limited in capturing nonlinear and high-dimensional interactions among agro-climatic variables (Fatima & Rahimi, 2024). Regression-based approaches require compliance with classical statistical assumptions. Violations of these assumptions undermine model validity and reliability. Violations of these assumptions undermine model validity and reliability. This indicates the need for more advanced approaches.

As a machine learning method, Artificial Neural Networks (ANN) have exhibited better predictive capability than conventional regression models. Setiawan & Rosadi (2025) successfully developed a rice production prediction model in Sumatra using an Artificial Neural Network (ANN) based on agro-climate data. Model evaluation results showed that the ANN provided the best performance with the lowest average MSE value compared to linear regression and GLM methods. Unlike conventional statistical models, ANN has the capability to learn from input data and capture hidden, nonlinear patterns, even when such patterns are not explicitly visible (Zhang, 2018; Modesti & Borsato, 2022). Its adaptive nature allows ANN to exploit unknown information embedded within datasets. However, ANN also faces challenges, as model performance largely depends on network configuration, training duration, parameter tuning, and trial-and-error processes, which require expertise and can be time-consuming (Ardabili et al., 2019; Abdolrasol et al., 2021; Mijwel, 2021; Scholten et al., 2021).

Although several approaches have been used for rice production forecasting in Indonesia, including statistical methods and conventional Artificial Neural Network (ANN) models, limitations remain in capturing nonlinear interactions between agro-climatic variables and optimizing model performance in regions with high climate variability such as Central Java. To overcome these limitations, this study proposes a hybrid model combining Artificial Neural

Network (ANN) with Particle Swarm Optimization (PSO) to forecast total rice production in Central Java. The PSO algorithm is used to optimize the ANN's synaptic weights improving convergence speed and prediction accuracy (Miao et al., 2021; Garro & Vázquez, 2015). Furthermore, the incorporation of satellite imagery data alongside PSO optimization is further improving the overall performance of rice production forecasting in Central Java.

B. METHODS

In this study, a systematic methodology is adopted to analyze and estimate rice production in Central Java Province using predictive analytical techniques using Hybrid ANN-PSO. The ANN first provides an initial estimate of the model parameters include initial weights and bias. These initial values guide the starting positions of the PSO particles so that they begin closer to the optimal solution. With a more accurate initialization, the PSO algorithm can refine the ANN parameters more efficiently and achieve lower prediction error in forecasting rice production in Central Java (Hamzah et al., 2025). The procedures of the hybrid ANN-PSO method is shown in Figure 1.

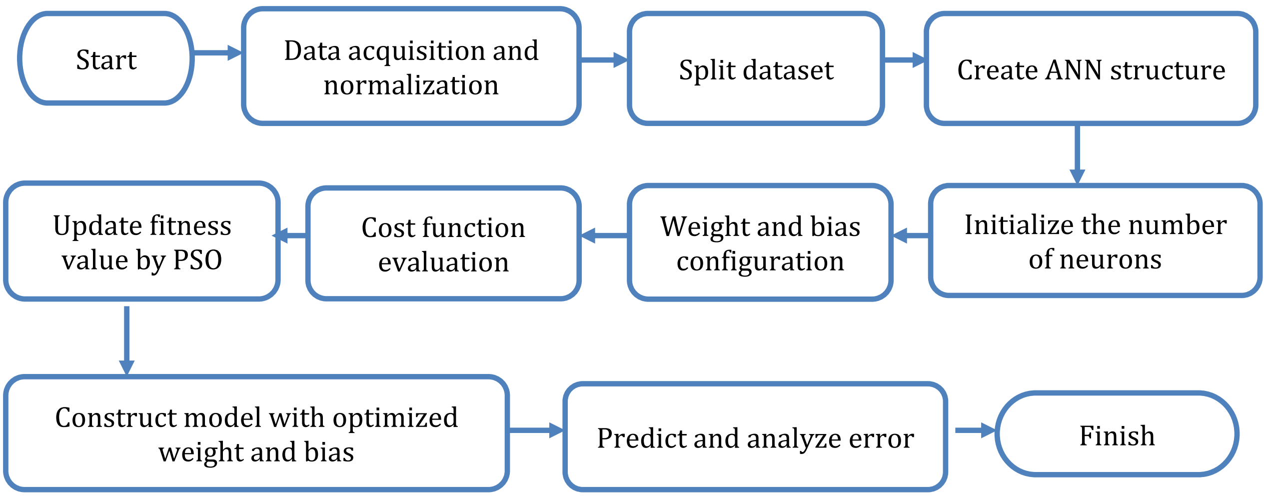

Figure 1. Flowchart of Hybrid ANN-PSO

Figure 1 shows an image of the research flow starting from the data collection stage, data normalization, dividing the dataset into training data and test data, creating an ANN network architecture, using the PSO algorithm for weight and bias optimization, and the evaluation and prediction stages (Shariati et al., 2019):

1. Data acquisition

This study uses secondary data from Statistics Indonesia (www.bps.go.id), consisting of rice production data in Central Java as the dependent variable and harvested area as the independent variable. In addition, climate data were collected from the Meteorological, Climatological, and Geophysical Agency (www.bmkg.go.id), including rainfall, number of rainy days, air pressure, and wind speed and Satellite imagery data, specifically the Normalized Difference Water Index (NDWI) and Normalized Difference Vegetation Index (NDVI)(European Space Agency (ESA), 2021). All datasets were organized into a monthly time-series format spanning the period from January 2019 to December 2024. The descriptive statistics of the dataset used in this research are presented in Table 1.

Table 1. Descriptive Statistics of Rice Production in Central Java

	Min	1 st Qu	Median	Mean	3 rd Qu	Max
Rice Production	0.16	0.37	0.66	0.78	1.00	2.45
Harvested Area	0.03	0.06	0.12	0.14	0.18	0.42
Precipitation	0.00	95.50	184.50	196.93	284.00	694.00
Number of Rainy Days	0.00	7.00	13.00	12.36	18.00	27.00
Atmospheric Pressure	109.30	1009.28	1010.05	997.63	1010.63	1013.10
Wind Speed	3.00	4.60	5.00	5.99	6.00	16.00
NDWI	-0.58	-0.51	-0.47	-0.46	-0.433	-0.08
NDVI	-0.60	0.48	0.53	0.50	0.57	0.70

Table 1 shows the descriptive statistics for the variables used in this work. Rice production and harvested area present a high variability over time, with mean values slightly higher than their median values. Climate variables also vary considerably, precipitation and the number of rainy days have a wide range, reflecting seasonal differences. There is moderate variation in wind speed, whereas atmospheric pressure is quite stable. Remote-sensing indicators show low values of NDWI throughout, suggesting that there is not much surface water content, while NDVI values mostly fall within the positive range, indicating substantial vegetation cover across the period under study.

2. Data Normalization

All variables must contribute proportionally in the learning process before implementing the ANN model. For this, data normalization was carried out. In this study, the dataset was normalized using the Min–Max Scaling method with a range of [0, 1]. This method does not alter the distribution and structure of the original data, so the information about relationships among variables is preserved without changing its dispersion patterns. Figure 2 visualizes the dataset after normalization.

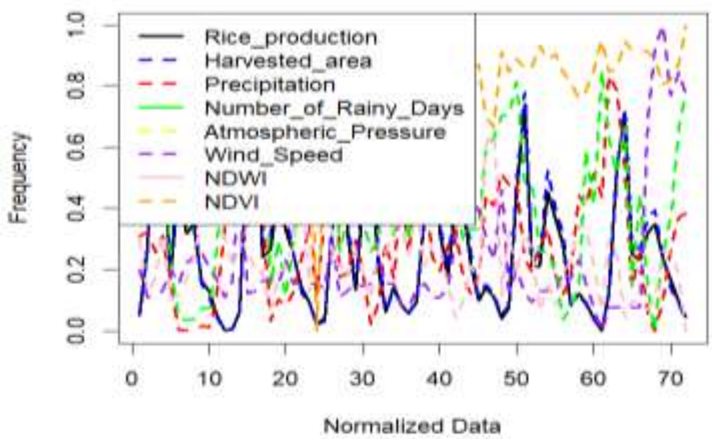

Figure 2. Normalized Data

Figure 2 shows that the standardization of all variables has been successfully executed, with each variable reaching its maximum at 1 and minimum at 0, and the rest of the observations distributed within this interval. The use of normalized data in ANN modeling is expected to be effective in enhancing training efficiency by accelerating convergence and improving the overall prediction accuracy.

3. Data Splitting

The dataset was divided using a hold-out validation approach, where the first 90% of the data were used for training and the remaining 10% for testing. After dividing the data into two parts, it was checked that it was valid and ready for use in rice production predictions.

4. Artificial Neural Network

The next step is to build a predictive model using an Artificial Neural Network (ANN). The ANN model can be described using the following equation 1:

$$y = g(W^{(2)} f\left(W^{(1)} x + b^{(1)}\right) + b^{(2)}) \tag{1}$$

where:

X : the input vector

$W^{(1)}, b^{(1)}$: The weight matrix and bias vector of the hidden layer

$W^{(2)}, b^{(2)}$: The weight matrix and bias term of the output layer

$f(.)$: The activation function

In this study, the ANN model used consists of 1 input layer, 1 hidden layer, and 1 output layer. The input layer consists of 7 input neurons (according to the attributes used in the data) and one output layer neuron. The number of neurons in the hidden layer is determined using Heaton's rule, which generally recommends that each subsequent hidden layer contain fewer neurons than the previous layer (J. Heaton, 2015). The hidden layer in this study was set at approximately six neurons, calculated as two-thirds of the input neurons plus the output.

5. Parameter optimization with PSO

At this phase, the Neural Network architecture derived from the prior experiment is refined using Particle Swarm Optimization (PSO). The ANN Backpropagation parameters are optimized using the Particle Swarm Optimization (PSO) algorithm. The pbest, gbest, and population size weight parameters used in this study refer to the inertia weight values are tested from 0.1 to 1.0, while the cognitive parameter $PBest$ ($c1$) and social parameter $GBest$ ($c2$) are evaluated in combination, ranging from 1.0 to 4.0 (Li, 2023).

6. Prediction

After obtaining a model with high accuracy for the training data, the model is applied to the test data to assess its ability to generate predictions for future periods. This step enables the assessment of the model's generalization capability beyond the training data. The resulting forecasts provide valuable insights into potential trends in rice production, which can support strategic planning and policy formulation in the agricultural sector.

C. RESULT AND DISCUSSION

In this section, data analysis will be performed using RStudio using the neuralnet and PSO libraries. The initial process before testing the ANN-PSO method is to conduct testing using ANN, which is intended to obtain the best weights and biases that produce the smallest RMSE value. The structure of the ANN (7,6,1) and its weights are shown in Figure 3.

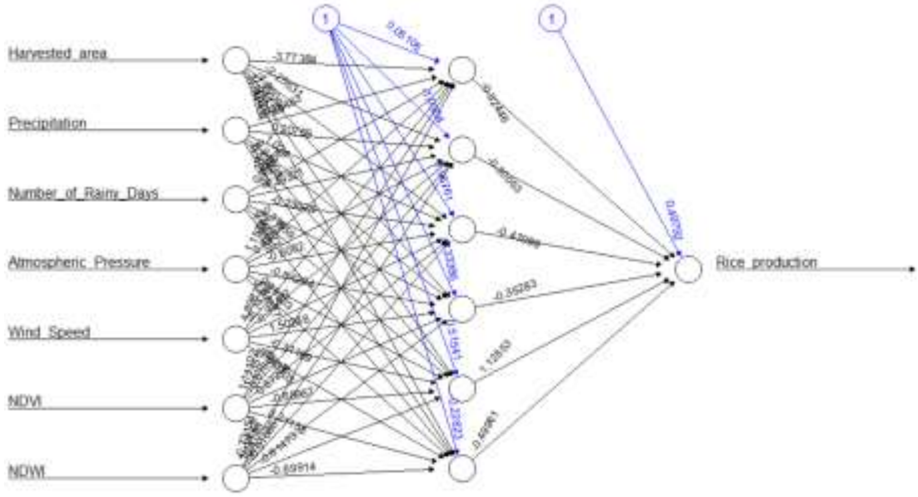

Figure 3. The Architecture of ANN (7,6,1)

Figure 3 illustrates the architecture of the ANN model, consisting of input, hidden, and output layers. Using the same network architecture, optimization will be carried out using the PSO algorithm. This study attempted to adjust several parameter values to achieve high accuracy. For the ANN and Particle Swarm Optimization models, a trial was first conducted by varying the Population Size parameter from 1 to 10, with an inertia value of 0.5 and a fixed maximum number of generations of 30. The following are the results of the experiment for the error values of the ANN-PSO model.

Table 2. Experiments with Varying Population Size

Population	Max of Generation	Inertia Weight	□□□□□ (□1)	□□□□□ (□2)	RMSE
1	30	0.5	1.0	1.0	0.016354108
2	**30**	**0.5**	**1.0**	**1.0**	**0.00772903**
3	30	0.5	1.0	1.0	0.012250295
4	30	0.5	1.0	1.0	0.009543195
5	30	0.5	1.0	1.0	0.009944599
6	30	0.5	1.0	1.0	0.013104034
7	30	0.5	1.0	1.0	0.009725330
8	30	0.5	1.0	1.0	0.011179719
9	30	0.5	1.0	1.0	0.008514028
10	30	0.5	1.0	1.0	0.008589879

The population size analysis in Table 2 shows that changing the population size from 1 to 10 significantly affects PSO performance. The effect of population size initially increases accuracy, but at a certain point actually causes a decrease in performance. In this study, the smallest RMSE value of 0.00773 was achieved when the population size was set to 2, indicating that a small swarm size was sufficient to explore the search space effectively under a fixed maximum generation of 30. This smaller population size can be sufficient for datasets with limited sample sizes and subtle temporal patterns, while larger swarms can lead to overexploration and slow convergence. A moderate population balances exploration and exploitation, while avoiding overfitting and excessive computational complexity in swarm-based optimization processes (Idris & Mustofa, 2025). The second experiment in this study was conducted by changing the maximum number of generations parameter value from 10 to 100, with a population size of 2 and an inertia weight of 0.5. The following are the experimental results using ANN-PSO with changing the maximum number of generations parameter value.

Table 3. Experiments with Varying Maximum Number of Generation

Population	Max of Generation	Inertia Weight	□□□□□ (□1)	□□□□□ (□2)	RMSE
2	10	0.5	1.0	1.0	0.019715262
2	20	0.5	1.0	1.0	0.011302419
2	30	0.5	1.0	1.0	0.009357753
2	40	0.5	1.0	1.0	0.015067706
2	50	0.5	1.0	1.0	0.010853126
2	60	0.5	1.0	1.0	0.013301699
2	70	0.5	1.0	1.0	0.009316999
2	80	0.5	1.0	1.0	0.011971060
2	**90**	**0.5**	**1.0**	**1.0**	**0.007528582**
2	100	0.5	1.0	1.0	0.017280260

As shown in Table 3, the RMSE value decreased as the number of generations increased, reaching the lowest value of 0.00753 at 90 generations. This result suggests that increasing the number of generations improves the optimization process up to a certain point, after which the performance may degrade due to excessive exploration. Hence, the maximum number of generations was set to 90 for the subsequent experiments. The results of this study align with those of Chanakot & Phoksawat (2024), who emphasized the importance of a range of 50–100 generations to achieve a balance between exploration and accuracy without overfitting. Therefore, selecting the right number of generations is key to optimizing a PSO-based model for prediction. The third experiment aims to evaluate the effect of variations in inertia weights, cognitive parameters (c1), and social parameters (c2) on the performance of PSO optimization in Li(2023). Selecting the right PSO parameters is crucial in improving PSO-based accuracy. The five best parameter combinations with the lowest RMSE values are shown in Table 4.

Table 4. Experiments with Varying Pbest, GBest, and Inertia Weight

PBest (C1)	GBest (C2)	Inertia Weight	RMSE
3.5	1.0	0.3	0.00628859
4.0	4.0	0.2	0.00646029
3.5	2.0	0.3	0.00659900
3.5	2.5	0.2	0.00671875
2.5	2.0	0.1	0.00675695

The experimental results show that the combination of attribute weights of $PBest$ $(c1)$ = 3.5, $GBest$ $(c2)$ = 1.0, and an inertia weight of 0.3 produces the smallest RMSE of 0.00628859 out of 490 combinations of parameter variations. In this study, the model produces the best accuracy when the inertia weight value is 0.3, which is selected from a range of values 0.1 to 1.0. This is in accordance with research by Widians et al. (2024) which states that inertial weights that are too large can inhibit convergence because particles take too long to explore, while weights that are too small can cause premature convergence to a local solution. Based on the results of the PSO parameter combination with the lowest error rate, the next step was a final evaluation to compare the performance of the standard ANN model with the model optimized using Particle Swarm Optimization (PSO). The results of the model performance comparison are shown in Table 5 below:

Table 5. Comparison of RMSE and MSE of ANN and ANN-PSO models

	Train		Test	
Method	**MSE**	**RMSE**	**MSE**	**RMSE**
ANN	0.0038318	0.06190153	0.01721755	0.1312157
ANN-PSO	0.0019931	0.04464463	0.00067462	0.0259736

Based on Table 5, the MSE and RMSE values obtained from the Hybrid ANN-PSO are lower than those of the standard ANN. This indicates that the Hybrid ANN-PSO model has better predictive performance compared to the ANN model. From the weighting results obtained, forecasting is then carried out using test data. In this section, the forecasting results from the ANN and Hybrid ANN-PSO methods will be compared with the testing data. The comparison graph of actual data and predicted results is given in Figure 4.

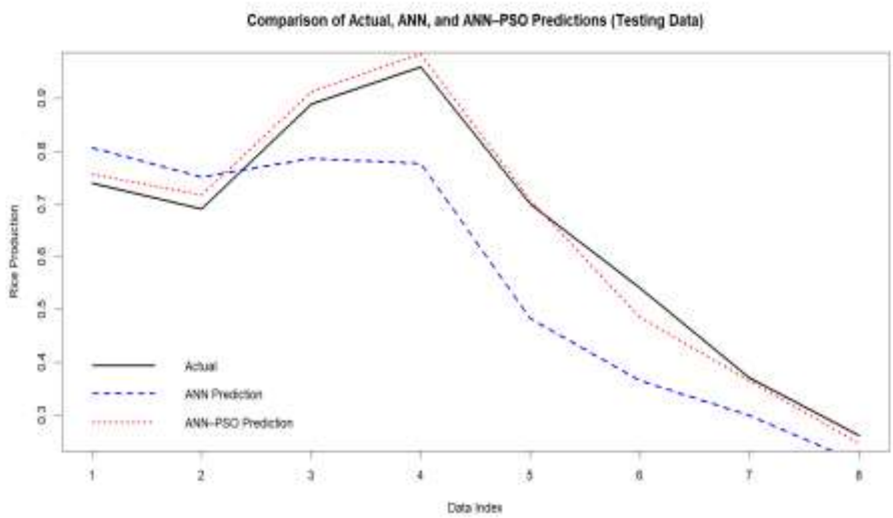

Figure 4. Comparison of Actual Testing Data and Prediction Results of ANN and ANN–PSO

Figure 4 illustrates the comparison between the actual values and the predictions generated by the ANN and ANN–PSO models on the testing dataset. Although neither model perfectly matches the actual data, the ANN–PSO predictions show a closer alignment with the overall trend and better capture the upward and downward patterns of the actual values compared to the standard ANN model. This visual observation is supported by the quantitative evaluation presented in Table 6, which the ANN–PSO model achieves lower MSE and RMSE values than the ANN model.

Table 6. Comparison of ANN and Hybrid ANN-PSO Prediction Results

Actual	ANN	ANN-PSO
0.74	0.8065504	0.7563370
0.69	0.7508992	0.7172494
0.89	0.7867128	0.9134234
0.96	0.7767660	0.9839770
0.70	0.4831741	0.7075362
0.54	0.3647963	0.4853964
0.37	0.2989820	0.3648298
0.26	0.2089468	0.2458940
MSE	0.0172175	0.0006746
RMSE	0.1312157	0.0259736

Table 6 presents a comparative evaluation of the forecasting performance of the ANN and Hybrid ANN–PSO models on the test dataset. The Hybrid ANN–PSO model provides values closer to the actual rice production values than ANN. In some test observations, the ANN model tends to underestimate production, while the Hybrid ANN–PSO produces estimates with a smaller deviation from the actual values. This improvement is confirmed by the error metrics, where the Hybrid ANN–PSO achieves significantly lower MSE (0.0006746) and RMSE (0.0259736) compared to ANN (MSE = 0.0172175; RMSE = 0.1312157). These results indicate that integrating PSO into ANN training significantly improves prediction accuracy.

D. CONCLUSION AND SUGGESTIONS

This study successfully developed a rice production prediction model in Central Java using a hybrid Artificial Neural Network (ANN)-PSO based on agriclimate data and satellite imagery. Model evaluation results showed that ANN-PSO provided the best performance with the lowest average MSE value compared to the ANN method. This demonstrates that adding the PSO algorithm to the ANN model can produce more accurate predictions. Further research can be developed using more real-time data and under conditions of extreme climate anomalies. This is expected to not only improve the model's predictive reliability but also deepen its theoretical contribution to the development of a hybrid machine learning framework for agricultural forecasting.

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