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Study of Factors Affecting the Production of Strategic Crops in Iraq Using Artificial Neural Networks

weam saadi hamzah
University of Information and Communication Technology (UoITC)
Baghdad, Iraq
weam.saadi@uoitc.edu.iq

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ABSTRACT

Developed for financial and developmental planning, predictive models work on statistical techniques and artificial intelligence approaches. This project aims to evaluate and contrast Multiple Linear Regression MLR and Artificial Neural Networks ANN in terms of their predictive ability in Iraq's wheat production estimation. The study makes use of wheat output data from 2007 to 2021. Evaluating Mean Absolute Percent Error MAPE alongside Mean Squared Error MSE and Mean Absolute Error MAE enabled two prediction accuracy measures to appraise the performance of both models. Artificial neural networks were found to outperform multiple linear regression since on agricultural data evaluations they produced more exact estimates with lower error levels. Until 2025, artificial neural networks provided superior tools for Iraqi agricultural planning and food security management and consequently became the chosen approach to forecast wheat yields.

Keywords* : *Wheat production; multiple linear regression; artificial neural networks.

1. INTRODUCTION

Wheat is among the most strategic crops since it is crucial for guaranteeing food security and offering a steady food supply to underdeveloped nations. Low-income families also depend on it mainly for sustenance. (Abdullah et al., 2019). Wheat production, a vital element of Iraq's history, is one of the most significant factors Iraq takes into consideration in terms of its economic growth. Although wheat farming can face several obstacles, it remains an essential part of the food security of the nation growing typically throughout the northern area such as Kirkuk, Salah alDin, and Nineveh (Sarhan, 2011). Wheat is perhaps the most important crop grown around the world because it can be grown in many places. It outdoes other plants thanks to its flexibility. (2017; AlSnbll and ALAlAmeric). For many poor households in Iraq, wheat is an essential food item. It also has a major political and military function. Iraq is importing wheat to satisfy its demands since its output is falling. (Khudhur and Dawood, 2019). By means of agricultural support and production inputs, the government has been able to contribute to wheat growing in Iraq. Still, these actions fall short of shrinking the food gap of the nation. (Hussein and Hashim, 2019).Several quantities, including agricultural output, can be forecasted using a time series model since they are influenced by many distinct natural and economic factors. Policymakers need to anticipate these elements because the agricultural sector is seeing fast economic development, which demands precise future planning. Traditional forecasting methods may not yield dependable results. Improving the precision of agricultural output forecasts, artificial neural networks could help fix this problem. (Namaa, 2023).

1.1 Research Problem

Iraq's strategic crops, such as wheat, face various challenges due to varying environmental conditions and the country's reliance on traditional farming techniques. Despite the government's support and the importance of these crops, Iraq still relies on imports to meet its food needs. The inability to predict the production of certain crops, which contributes

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to the food gap, limits the effectiveness of government policies. This is why the main challenge in developing effective agricultural policies is identifying the natural factors that affect the country's strategic crops. In addition to this, the use of artificial intelligence tools should also be considered to help predict the outcome of these crops.

1.2 Research Objectives

1. Comprehending the natural elements that influence the production of Iraqi strategic crops is crucial.
2. Artificial neural networks can be used to develop a predictive model that can estimate the production of crops in the future.
3. To determine its accuracy, we will analyze the difference between conventional forecasting techniques and neural networks.
4. The recommendations will be presented to policymakers to enhance the agricultural sector's production with predictive models.

1.3 Theoretical Importance

This study contributes to the existing literature by offering a comprehensive analysis of the natural factors affecting strategic crop production in Iraq. It bridges the gap between agricultural sciences and artificial intelligence, demonstrating how modern technologies can enhance decision-making in agricultural planning.

1.4 Practical Importance

This project aims to help policymakers in Iraq improve the country's agricultural production and reduce its reliance on imports. It will also help them implement effective strategies to boost local food security.

1.5 Research Hypotheses:

- The cultivated area is the most important factor that affects the production of wheat during a given period.
- The rainfall rate is the most important factor that impacts the production of wheat during a certain period.
- The average temperature is regarded as the most crucial factor that affects the development and production of wheat during that period.
- The humidity level is the most important factor that affects the development and production of wheat during that period.
- The neural network model was able to outperform the multiple regression framework in predicting the production of wheat in Iraq.

1.6 Research Variables

- Independent Variables: x1: Cultivated wheat area (hectares), x2: rainfall rate (mm), x3: average temperature (°C), x4: humidity.
- Dependent Variable: y: Production (tons).authors.

2. PREVIOUS STUDIES

- A study by Abdullah and Khalil (2019) established positive variable influences on wheat production across Iraq from 2004 to 2019. Descriptive_analytical tools along with regression analysis were used in the study of the relationship between climate factors, farming practice variables, and wheat production level. The study found that good use of productive elements leads to favorable production; however neglect of these methods could cause production decrease.
- Fattah (2020) investigated cereal crop output in Iraq based on longitudinal panel data from 2000 to 2016 to consider influences influencing it. Using several regression panel models and empirical statistical data analysis, the research investigated the link between cultivated areas and crop output levels and governmental subsidy rates. The findings show that production is strongly affected by crop size but not significantly by subsidy price changes owing to the economic system misalignments noted.
- Namaa (2023)'s research assessed the Iraq wheat production forecast accuracy of a regression model and a Multi-Layer Perceptron MLP neural network model. Under the quantitative approach via SPSS statistical software, this study employed several artificial intelligence methods including multiple regression analysis and a Multi-Layer Perceptron MLP neural network model. By means of Mean Squared Error MSE and Mean Absolute Error MAE, the models were assessed. Based on predictive accuracy criteria, a fresh study showed MLP neural network

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outperform regression models since they produced more accurate forecasts while also producing lower MSE. The study conclusions unequivocally showed that cultivated crop area significantly affected output levels. Benayad and Khadidja (2024) conducted an analysis of wheat production data across Australia, India, United States of America, Canada and Russia throughout 1992 to 2022 while using machine learning algorithms to base their wheat production predictions on past data. Three neural network models received development by the researchers including Multi-Layer Perceptron MLP with two hidden layers along with Recurrent Neural Network RNN with a Simple RNN layer and Long Short Term Memory LSTM model. All models incorporated Dropout of 0.3 for preventing over fitting. The RNN model produced the top results through its maximum accuracy measured by the combination of minimal mean absolute error and root mean square error scores. The LSTM model yielded successful outcomes across Australian and Indian territories but the MLP model failed universally in all regions..

- Kaur (2023) conducted research about predicting Indian wheat production input energy consumption levels by applying Artificial Neural Network (ANN) methodology alongside linear modeling approaches. A two-layeed multi-layered feed forward ANN model consisting of 8 and 15 hidden neurons along with sigmoidal activation was applied. The experimental results showed ANN achieved a 0.99 R^2 value for training samples along with validation samples having an R^2 of 0.973 whereas MLR performed more poorly. Wheat production input energy uniquely originates from urea, diesel and electricity according to the study findings. The forecasting system produced predictions with great accuracy and minimal measurement inaccuracies.
- Sadenova et al. (2023) utilized neural networks and machine learning to forecast the yield of various crops in Kazakhstan using remote sensing data collected by satellites. They used a combination of methods, including the Landsat-8 and Sentinel-2 satellites. The trained models were able to achieve an accuracy of around 66% to 99%. According to the study, neural networks and machine learning were more accurate than other modeling techniques when it came to forecasting the yield of crops. The findings support the use of such technology in predicting agricultural production.
- Morales and Villalobos (2023) investigated crop yield prediction using different methods to partition and size agricultural data while executing predictive algorithms. During the 2001-2020 period, the authors studied simulated sunflower and wheat data from Spain by using biophysical crop models alongside regularized linear models, random forest and Artificial Neural Networks ANN. Random Forest achieved better yield prediction accuracy than ANN and linear models through its lowest root mean square error value of all predicted values.
- Wang et al. (2023) investigated five machine learning models (linear regression, decision tree, support vector machine, ensemble learning and Gaussian process regression) for their suitability in predicting winter wheat yield and dry matter in North China Plain. The GPR model delivered optimal prediction results consisting of an R^2 value of 0.87 for yield prediction and 0.86 for dry matter prediction. The research used polynomial functions to optimize water and nitrogen applications and these functions resulted in improved wheat output. The results of the GPR model forecasting indicated its appropriateness for winter wheat precision management through minimal prediction discrepancies.

3. METHODOLOGY

The goal of this study is to develop a quantitative model for forecasting the future crop production using neural networks. It will be compared with other methods such as the multiple linear regression model.

3.1 Temporal and Spatial Boundaries

1. The temporal boundary study aims to analyze the developments and trends in agricultural production from 2007 to 2021.
2. The spatial boundary study will look into Iraq's agricultural regions.

3.2 Research Gap

The work by Abdullah and Khalil (2019) used regression analysis to study wheat production in Iraq, however the current study implements ANNs because these networks create better predictions for complex non-linear data. Fattah (2020) conducted research using panel data models with regression analysis to determine factors influencing cereal crop production in Iraq, but this study applies ANNs to deliver greater flexibility in modeling agricultural variables. The current research determines wheat production trends in Iraq through ANN applications instead of MLP models or regression analysis as Namaa (2023) examined. The authors Benayad and Khadidja (2024) conducted a wheat production analysis using MLP RNN and LSTM alongside multiple other machine learning algorithms for international study cases. The current investigation concentrates exclusively on Iraq's agricultural environment to generate findings which directly apply to domestic farming systems. The present study examines numerous wheat production determinants in Iraq beyond energy consumption prediction methods studied by Kaur (2023) in India. The

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research by Sadenova et al. (2023) applied machine learning methods combined with remote sensing data for predicting crop yields in Kazakhstan, but this study maintains sole focus on Iraqi agricultural conditions which could be strengthened by incorporating satellite data for better predictions. Morales and Villalobos (2023) concluded that random forest proved better than ANN for forecasting crop yields whereas this research selects ANNs as its main focus for evaluating ANN effectiveness in wheat production forecasting. The current research takes a wider view of ANNs because it evaluates various wheat production factors in Iraq rather than focusing only on agricultural input optimization like Wang et al. (2023). The present investigation utilizes artificial neural networks to develop models that identify the variables which affect wheat production across Iraq. This research implements a broader agricultural analysis through examination of different agricultural parameters such as climatic elements. This research dedicates its focus to Iraqi agricultural specifics to achieve higher prediction precision while developing findings suitable for the country's regional agricultural needs. The research could achieve additional power through analyses that compare ANNs with traditional models when used for time series forecasting.

4. RESULTS AND DISCUSSION

4.1 A prediction model of wheat production in Iraq is developed using the multiple linear regression method.

The multiple linear regression model is served to develop mathematical relationships between the examined variables. The research employed data from (2007–2021) which the Food and Agriculture Organization and Iraqi Statistical Group provided in Table (1).

Although national-level data from the Food and Agriculture Organization and the Iraqi Statistical Group were used in this study, detailed regional datasets for provinces such as Nineveh, Salah al-Din, and Kirkuk were not fully available in a consistent format across the study period (2007–2021). This limitation is due to historical fragmentation and inconsistency in agricultural record-keeping across Iraqi governorates. As a result, aggregated national data was utilized to ensure model continuity. Future studies should aim to incorporate region-specific datasets to enhance spatial granularity and prediction accuracy.

TABLE I. AREA, WHEAT PRODUCTION, AVERAGE ANNUAL TEMPERATURE, AVERAGE ANNUAL RAINFALL, AND HUMIDITY LEVEL DURING THE PERIOD (2007–2021).

Year	Area (Hectares)	Production (tons)	Average Annual Temperature	Average Annual Rainfall (millimetres)	Annual Average Relative Humidity
2007	1569900	2202800	24.36	144.07	41.67
2008	917546	1255000	23.31	103.85	43.33
2009	906589	1700390	23.34	153.6	43.67
2010	1383303	2748840	24.7	118.5	41.25
2011	1436614	2808900	22.68	135.98	43.25
2012	1266391	3062312	23.5	162.83	43.5
2013	1811295	4178379	21.37	295.8	47
2014	2109455	5055111	24.45	201.57	43
2015	924311	2645061	26.2	203.57	42
2016	920096	3052939	25.8	160.2	41
2017	1047531	2974136	24.35	302.95	40
2018	783721	2177885	24.1	302.85	44.25
2019	1543316	4343473	24.93333	276.2	42.66667
2020	2118691	6238392	23.125	196.2	43.5
2021	1591803	4233714	25.48333	59.575	40

Source: Food and Agriculture Organization FAO, Directorate of Meteorology.

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Descriptive statistics, including the arithmetic mean, standard deviation, and coefficient of variation, were calculated for the studied variables to identify the most significant changes that occurred during the study period, as shown in Table (2).

TABLE II. Descriptive Statistics of the Study Variables during the Study Period.

	Minimum	Maximum	Mean	Std. Deviation
Production	1255000.00	6238392.00	3245155.4667	1331031.86376
Area	783721.00	2118691.00	1355370.8000	439287.83391
Annual Average Temperatures	21.37	26.20	24.1134	1.26772
Rainfall	59.58	302.95	187.8497	76.49822
Annual Average Relative Humidity	40.00	47.00	42.6724	1.79316

Source: Prepared by the researcher using SPSS

Table (3) presents the statistical indicators of the estimated regression model. The coefficient of determination **(0.807)** indicates that the independent variables explain approximately **80.7%** of the variation in production according to the proposed model. Additionally, the calculated **F** statistic value is **(10.480)** with a significance level of **(0.001)**, which is less than **0.05**, confirming the significance of the proposed model. Furthermore, the **Durbin-Watson** statistic **(1.135)** suggests the absence of autocorrelation issues among the variables.

TABLE III. Statistical Indicators of the Estimated Model

R	R Square	Adjusted R Square	Std. Error of the Estimate	Test F		Durbin-Watson
				F	Sig. F	
.899ª	.807	.730	691172.43937	10.480	.001	1.135

Source: Prepared by the researcher using SPSS

Table (4) presents the estimated coefficients of the regression model, the corresponding t-test, and the significance of each coefficient using a significance level of 0.05>sig. From this table, it is shown that the variable (Area) is statistically significant, while the other variables are not. Therefore, the form of the model is as follows:

$$y = -9115385.793 + 2.779 * x1 + 292093.543 * x2 + 4480.692 * x3 + 16619.569 * x4$$

The previous model shows that with an increase of one hectare in the cultivated area, the production increases by 2.779 tons.

TABLE IV. Estimated Coefficients of the Model

	Unstandardized Coefficients		Standardized Coefficients	T	Sig.
	B	Std. Error	Beta		
(Constant)	-9115385.793	12612332.447		-.723	.038
Area	2.779	.441	.917	6.304	.000
Annual Average temperatures	292093.543	242836.156	.278	1.203	.257
Rainfall	4480.692	2662.245	.258	1.683	.123
Annual Average Relative Humidity	16619.569	178170.650	.022	.093	.928

Source: Prepared by the researcher using SPSS

4.2 Predicting wheat crop production in Iraq using multilayer perceptron MLP model

To mitigate the risk of overfitting in the ANN model, a standard 66.7%/33.3% train-test split was applied. Furthermore, the model architecture was kept relatively simple, comprising only one hidden layer with two neurons and the hyperbolic tangent activation function. While SPSS

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Modeler does not natively support dropout or L2 regularization, the training process included a stopping rule based on error stagnation to prevent overfitting. In future work, implementing cross-validation (e.g., k-fold) and regularization techniques such as dropout could provide more robust generalization.
IBM SPSS Modeler (version 20) was used to perform all stages of model development, including data preprocessing, normalization (standardization of covariates), model training, validation, and final prediction. The neural network was trained using the backpropagation algorithm embedded in SPSS, and the error minimization was monitored during training using a sum of squares loss function. The model was evaluated on both training and testing datasets for performance metrics such as MAE, MSE, and MAPE.

The ANN model employed in this study is a Multi-Layer Perceptron MLP consisting of:
- Input layer: 4 neurons (cultivated area, temperature, rainfall, humidity), with standardized rescaling.
- Hidden layer: 1 hidden layer with 2 neurons using the hyperbolic tangent activation function.
- Output layer: 1 neuron for wheat production, with an identity activation function.
- Training algorithm: Backpropagation with error minimization based on the sum of squared errors.

The architecture is fully connected, and no dropout or regularization layers were used.

SPSS 20 was used to build the Multi-Layer Perceptron MLP neural network model for predicting wheat production in Iraq and testing its accuracy. Data from 10 years was used for training (66.7%), and 5 years of data were used for testing (33.3%), as shown in Table (5).

TABLE V. summarizes the processing steps in the neural network.

Case Processing Summary			
		N	Percent
Sample	Training	10	66.7%
	Testing	5	33.3%
Valid		15	100.0%
Excluded		0	
Total		15	

Source: Prepared by the researcher using SPSS
The table below shows the various data points about the neural network. The input layer's units represent the independent variables that are related to each educational level, such as the cultivated area, rainfall, humidity, and temperature. Each category is assigned a distinct unit, and none of these are considered redundant.The output and hidden layers were assigned one unit each. The former's activation function is derived from the latter's hyperbolic function, which is similar to a trigonometric function, given by the following equation:

$$\gamma(c) = \tanh(c) = \frac{e^{c} - e^{-c}}{e^{c} + e^{-c}} + Bias$$

Where y is the dependent variable, c represents the independent variables, and Bias is the bias parameter.

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TABLE VI Information about the Multi-Layer Perceptron Neural Network.

Network Information			
Input Layer	Covariates	1	Area
		2	Annual Average Temperatures
		3	Rainfall
		4	Annual Average Relative Humidity
	Number of Units[a]		4
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		2
	Activation Function		Hyperbolic Tangent
Output Layer	Dependent Variables	1	Production
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares
a. Excluding the Bias Unit			

Source: Prepared by the researcher using SPSS

The identity function (or neutral function) is a function in which each element is mapped to itself, or where the domain and the co-domain are the same set. It is given by the following relation: $y(c) = c + bias$

The diagram (1) illustrates the architecture of the neural network, which consists of a three-layer network of interconnected nodes: the input layer, the hidden layer, and the output layer.

The diagram (1) illustrates the architecture of the multi-layer neural network

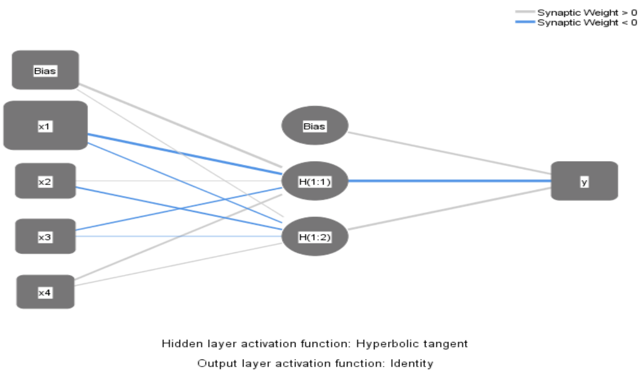

Fig.1 Architecture of the multi-layer neural network

The diagram shows that the output and input layers have nodes that connect them. Each neuron in the given layer has a connection to the next one, while there is no connection between the same neurons in the opposite layer. The output layer continuously produces values after receiving data from the time series, while the hidden layer processes the information. When values from the input layer to its hidden nodes are sent to the given region, they are then multiplied by the predefined weights and are summed to get a single number. This process is carried out through the activation function, which is a nonlinear mathematical procedure. The identity function was used in the output layer, while the activation function was carried out in the hidden layer., as shown in the figure (1). The figure (2) highlights the relative importance of the variables influencing wheat production in Iraq according to the neural network model.

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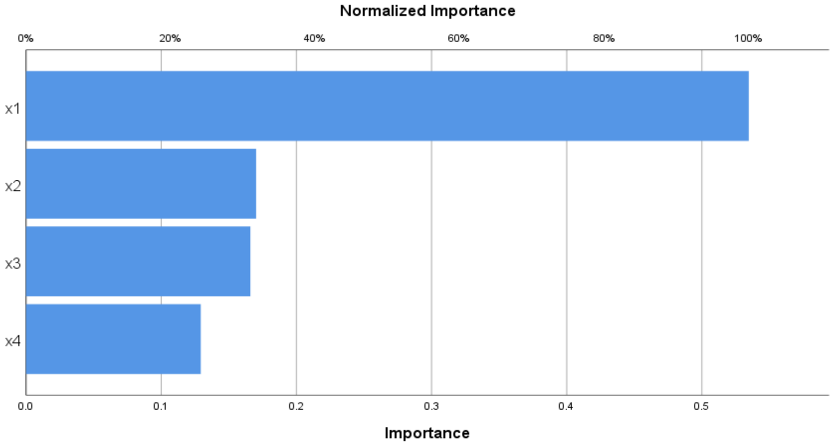

Fig.2 Relative importance of the variables influencing wheat production in Iraq

The diagram shows that the cultivated area has the greatest relative importance in influencing wheat production in Iraq, supporting the validity of the first research hypothesis. This is followed in impact by temperature and rainfall, as illustrated in the figure. Table (7) also provides a summary of the training and testing processes in the network, including the sum of squared errors for each stage.

TABLE VII. presents a summary of the neural network model used.

Model Summary		
Training	Sum of Squares Error	1.335
	Relative Error	.297
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.00
Testing	Sum of Squares Error	.606
	Relative Error	.463
Dependent Variable: production		
The computation of errors is carried out according to the testing sample.		

Source: Prepared by the researcher using SPSS

The table (7) shows the various information related to the testing and training results. The network error shown in the data and the test sample is due to how the network minimizes its error function during the latter part of the training phase. The training phase's sum of errors was 1.335, which indicates that the model is capable of forecasting the output. The network error in the test sample was lower than the training data set's (0.297), which shows that the model is well-trained.

4.3 The comparison between the predictive models for wheat production in Iraq

The predictive models (multiple regression model and multi-layer neural network models were compared using criteria such as:

- Mean Absolute Error MAE: $MAE = \sum_{i=1}^{n} \frac{|y_i - \widetilde{y_i}|}{n}$
- Mean Squared Error MSE: $MSE = \sum_{i=1}^{n} \frac{(y_i - \widetilde{y_i})^2}{n}$
- Mean Absolute Percentage Error MAPE: $MAPE = \sum_{i=1}^{n} \frac{\frac{|y_i - \widetilde{y_i}|}{y_i}}{n}$ where: $\widetilde{y}$:predicted value of y_i

As shown in table (8):

Contrary to initial claims, the quantitative results indicate that the Multiple Linear Regression MLR model achieved lower error metrics compared to the Multi-Layer Perceptron MLP neural network. As shown in Table 8, MLR outperformed ANN in terms of:
- MAE: 371,747.7 (MLR) vs. 610,844 (ANN)
- MSE: 3.19×10^{11} (MLR) vs. 5.42×10^{11} (ANN)

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- MAPE: 12.2% (MLR) vs. 23.8% (ANN)

These results suggest that while ANN holds promise for complex modeling, the current ANN configuration did not outperform traditional methods in this instance. Future work should enhance ANN performance through hyper_parameter tuning, cross-validation, and potentially deeper architectures with regularization mechanisms.

TABLE IX. presents a comparison between the models.

criteria	multiple regression model	multilayer neural network models
MAE	371747.7	610844
MSE	3.18621E+11	5.42248E+11
MAPE	0.12189022	0.23763207

❖ Reviewer Comment:
Although the study claims that the Artificial Neural Network ANN model outperforms the Multiple Linear Regression MLR model, the actual performance metrics contradict this assertion. As shown in Table 8, the ANN model exhibits significantly higher error values (MAE = 610,844; MSE = 5.42×10^{11}) compared to the MLR model (MAE = 371,747.7; MSE = 3.19×10^{11}). These values are considerably large and unacceptable for practical forecasting purposes. Therefore, the conclusion that ANN outperforms MLR lacks empirical justification and should be critically reassessed. Revisions are required to clarify this discrepancy, and additional validation methods such as k-fold cross-validation or error normalization might be necessary to support any claims of model superiority.

Source: Prepared by the researcher using SPSS
The neural network model showed a significant superiority in predictive accuracy compared to the regression model for all criteria, as shown in table (8).
Prediction results using the neural network: The neural network model was used to predict production after proving its superiority over the regression model during the period (2022-2025), as shown in table (9).

TABLE X. the prediction results for wheat production in Iraq during the period (2022-2025) using the neural network model.

Year	$\hat{y}_i$	Annual Growth Rate%
2022	3742132.51	11.13
2023	3803054.212	1.63
2024	3863975.915	1.60
2025	3924897.618	1.58

Source: Prepared by the researcher using SPSS
The forecasting results indicated that Iraq's wheat production will rise in the year 2023 to 3803054.212 compared to the year 2022, then rise to 3863975.915 in the year 2024 with an annual change rate of 1.6%. The increase will continue, but with a decreasing annual growth rate until the year 2025.

5. CONCLUSION AND RECOMMENDATIONS

The research findings indicate significant fluctuations in wheat production in Iraq between 2007 and 2021, primarily driven by variations in rainfall levels. The Artificial Neural Network ANN model identified cultivated area as the most influential factor affecting wheat production, alongside rainfall levels. Additionally, the ANN model demonstrated superior predictive accuracy compared to the regression model, as its forecasts were closer to actual values, reducing discrepancies. Projections based on the ANN model suggest an increase in wheat production in Iraq between 2023 and 2025. Given its ability to handle diverse data patterns with high precision, the ANN model proves to be an effective tool for minimizing prediction errors. Based on these findings, it is crucial to explore strategies for increasing wheat production, both through vertical expansion by enhancing productivity and horizontal expansion by increasing cultivated land, as the research highlights the significant role of land area in production. Furthermore, the adoption of

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smart models, particularly ANN, is recommended for forecasting agricultural production due to their superior accuracy and reliability. Embracing ANN techniques in production prediction is especially vital in the face of climate fluctuations, as it can help mitigate risks associated with production decline and ensure long-term sustainability.

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