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Effect of Input Usage on Wheat Yield: An Application of Artificial Neural Networks (ANN)

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ABSTRACT

This study aimed to investigate the effects of inputs such as pesticides, fertilizers, seeds, labor and machine use on wheat yield. The data used in the study were obtained from 177 wheat producers in Diyarbakir Province through a questionnaire, and Artificial Neural Networks (ANN) were used in the analysis of the data. According to the results, the average wheat yield is 5482.03 kg ha^{-1}, and 294.75 kg of seeds, 550.73 kg of fertilizer, 3.59 hours of machinery, 5.37 hours of labor and 2662.43 cc of pesticides were used per hectare for wheat production. According to the results of the ANN analysis, the relative importance of inputs affecting wheat yield was quantified, with the use of pesticides and fertilizer having the most significant impacts. Specifically, the sensitivity coefficients for pesticide use and fertilizer use were found to be 0.23 and 0.14, respectively. These coefficients represent the relative change in wheat yield per unit change in the input parameters.

Keywords: Fertilzer effects, Pesticide effects, Production inputs, Wheat productionn.

INTRODUCTION

Wheat is one of the most important staple foods in the world and, at the same time, one of the most important inputs of the food industry and an important commercial product (Babalık, 2007). According to FAO, in 2021, global cereal production totals 3.07 billion tons, of which 25.10% is wheat. The global wheat harvested area, which was 217.90 Million hectares (Mha) in 2020, increased by 1.31% in 2021, reaching 220.76 Mha. In 2021, India, Russia, China, and the U.S. account for 44.45% of the world's wheat acreage, while these countries account for 47.66% of the world's Mha. Due to the increase in the global wheat harvested area compared to the previous year, wheat production, which was 756.95 million tons in 2020, increased by 1.84% and reached 770.88 million tons in 2021 (FAOSTAT, 2023). Turkey is one of the most important wheat-producing countries in the world due to its ecological structure, producing 20.5 million tons of wheat in the 2020/2021 production season on a wheat cultivated area of 6.92 million hectare. In terms of wheat cultivated area, Konya, Şanlıurfa, Ankara, Diyarbakır, and Yozgat provinces have the top five ranks (TURKSTAT, 2022).

Since wheat is one of the most important products in the consumption patterns of a large part of the world's population, it is necessary to work on the right strategies to increase production of this crop. Since increasing wheat production by expanding acreage is not a viable solution due to the potential limitation of farmland, one of the most effective ways to increase production is to try to improve yield per unit area (Eshraghi *et al*., 2009).

Yield, the mass of crops harvested from a

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given area, is influenced by several factors. These factors are grouped into three basic categories: technological (agricultural practices, management decisions, etc.), biological (diseases, insects, pests, weeds), and environmental (climatic conditions, soil fertility, topography, water quality, etc.). Environmental factors affecting crop yield are divided into two groups: abiotic and biotic. Abiotic stress negatively affects growth and productivity and triggers a range of morphological, physiological, biochemical, and molecular changes in plants. The abiotic constraints include soil properties (soil components, pH, physicochemical and biological properties), and climatic stresses (drought, cold, flood, heat stress, etc.) (Liliane and Charles, 2020). Climatic conditions during the growing season are considered the most important factors for crop yield changes, explaining about 20-60% of global yield changes (Kinnunen *et al*., 2022). Among these factors, another important factor is anthropogenic (use of intensification means) factor. An important aspect of anthropogenic contributions is the increased intensity of land use through the use of fertilizers, pesticides, fuels, and machinery (Schröter *et al*., 2021). Anthropogenic additives make it possible to control the production process to protect the product and improve its quality. In addition to suitable climatic and soil conditions, seed quality, and other inputs used, management practices such as crop nutrition, disease and pest control, irrigation, and tillage also affect the yield of agricultural production (Tiryakioğlu *et al*., 2017).

The use of inputs in agriculture is the most important factor in increasing yield and thus production quantity and improving quality. Inputs such as seeds, fertilizers, farm machinery, etc. are the factors that activate land, labor, and capital. While the optimal use of these inputs has a positive effect on increasing yields, excessive and improper use of these inputs has a negative effect on product quality and environmental sustainability of the product by causing soil and water pollution (Çelik, 2000). In this context, to create an appropriate production plan, it is important to determine the inputs used in the production process that impact productivity the most.

Considering the variety of analysis methods that can be used to determine the factors affecting productivity in agricultural production, Artificial Neural Network (ANN) techniques are one of the effective methods that can be used in this field. Especially with the development of computer technology, ANN has found a wide range of applications in various fields such as environment, economy, engineering and medicine. Moreover, the number of applications of ANN in the field of agriculture has been rapidly increasing in recent years (Akkaya, 2007; Yelmen *et al*., 2021). In particular, the widespread use of computers in all fields has contributed significantly to the development of neural networks. Computers, in which electronic data transmission and some calculations are made, have come to a position that can filter the data over time, obtain information by examining the data, and make comments according to the desired purpose (Küçükönder, 2011). Artificial neural networks operate on the principle of expanding knowledge and experience through learning and achieving results by using what is learned (Öztemel, 2012). Many researchers have conducted studies on yields of various agricultural products using ANN techniques. For example, wheat (Alvarez, 2009; Hardaha *et al*., 2012; Khoshnevisan *et al*., 2013; Taner *et al*., 2015; Dhaka and Lamba., 2015; Niedbała *et al*., 2020), maize (Farjam *et al*., 2014; Matsumura *et al*., 2014; Adisa, 2019; Uno *et al*. 2005), paddy (Jı *et al*., 2007; Taheri Rad *et al*., 2017), and oats (Chantre *et al*., 2014).

There are also several studies in the literature that examine the sensitivity of variables to the production of wheat and other agricultural products. Marginal Physical Productivity (MPP) is perhaps one of the most common methods for sensitivity analysis in econometric models (Khoshroo

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et al., 2018). In the study aimed at determining the most important factors affecting the yield of rainfed wheat, a sensitivity analysis was carried out using the Hill method. In this method, the value of the relative sensitivity coefficient is calculated (Mehnatkesh *et al*., 2017). In the study by Sepehri *et al*. (2019), the technique of eliminating input data was used to evaluate the sensitivity of the model with respect to the input parameters.

This study aimed to use the ANN model to investigate the impact of inputs such as pesticides, fertilizers, seeds, labor, and machinery on the production of wheat, which is the most produced crop in Turkey and the southeast Anatolia Region.

MATERIALS AND METHODS

Research Area

This study was conducted in Diyarbakır Province, which is located in the Southeast Anatolia Region. Diyarbakır Province is located at 37.52 north latitude and 40.13 east longitude. It is surrounded by Batman and Muş province in the east, Mardin province in the south, Şanlıurfa, Adıyaman, Malatya province in the west, and Elazığ and Bingöl province in the north (Anonymous, 2021). According to long-term data (1929-2021), the average temperature in this province is 15.9°C, the average maximum temperature is 22.7°C, the average minimum temperature is 8.9°C, and the average annual precipitation is 494.9 mm yr^{-1} (MGM, 2022). Diyarbakır province has a total of 573614.20 ha of agricultural land in 2021, of which 88.79% (509295.20 ha) are cultivated to wheat, cotton, corn, barley and sugar beet as the main agricultural products. A total area of 290987.5 ha produced 578276 tons of wheat (TURKSTAT, 2022).

Research Data

The main material for the study was obtained from face-to-face surveys with wheat producers in Diyarbakır Province and its districts. 1064 farms producing wheat in Diyarbakır province formed the population of the study. The sample size formula of Newbold (1995) was used to determine the producers to be interviewed in the study.

$$n = \frac{Np(1-p)}{(N-1)\sigma_p^2 + p(1-p)}$$

Where, n: Sample size, N: Number of farms producing wheat in Diyarbakır Province, p: Ratio of wheat producers, and σ_p^2 : Variance.

The p-value can be taken from previous studies or estimated intuitively. Since working with the maximum sample size reduces the possible error, in cases where p is not known, p= 0.5 should be taken to achieve the maximum sample size. Values of p less than or greater than 0.5 reduce the sample size (Aksoy and Yavuz, 2012).

The number of producers to be surveyed was calculated to be 173 with a confidence interval of 99% and a margin of error of 0.09%. A total of 177 producers were interviewed in the study, with 4 replacement producers. In the selection of producers to be interviewed in the region, the suggestions of the experts of the Provincial and District Directorate of Agriculture and Forestry were taken into account.

Data Analysis

In the study, farms were divided into 3 groups in terms of wheat area, namely, small, medium, and large farms, and the characteristics of the farms were determined based on these groups (Table 1). The difference between the groups in terms of farm characteristics was statistically tested. For this purpose, the test for normal distribution was first performed using the Kolmogorov-Smirnov test. Since the variables did not have a normal distribution, the Kruskall-Wallis test was applied for comparison.

In the study, ANN was used to determine the effects of various inputs on wheat yield.

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Table 1. Grouping of wheat producers.

Groups (ha of wheat)	Number of farms	% Of farms	Average wheat cultivation area (ha)
0.1- 7.00	55	31.07	5.59
7.10-10.00	63	35.59	8.73
10.00+	59	33.34	17.70
Total	177	100.00	10.75

NeuroSolutions (V.5) software was used for this purpose. ANN, which is built on the electrical model of the human neural network, is one of the methods developed for the purpose of transmitting and processing information, and allows the learning of events by computers (Mikail and Keskin, 2015). Learning, generalization, and parallel processing capacity are the main features that distinguish ANN from other methods, and these features provide advantages such as speed, fault tolerance, and efficiency (Mikail and Keskin, 2015).

As seen in Figure 1, ANN generally has a structure consisting of layers and neurons within those layers. The basic elements of this structure are inputs, weights, summation function, activation function, and outputs (Naseri and Saner, 2017).

In ANN model, information is transmitted from the input layer to the network, processed in the hidden layers, and sent from there to the output layer. In the hidden layer, the network's inputs are multiplied by a weight assigned to each input and then summed. For the network to produce the correct outputs for the inputs, the weights must have the correct values (Duran *et al*., 2017).

In the study, the following steps were followed in the application of ANN.

The inputs used in wheat production are the input variable of the ANN network and wheat yield is the output variable of the model. The details of these variables are given in Table 2. The variables used in the study are continuous variables, and the data obtained in the survey refer to one production season and are a ratio scale.

Since the variables and measurement units used in the study differred from each other, the min-max method was used to assign a value of 0 to the smallest variable value and 1 to the largest (Şengül, 2020). This eliminates scale errors caused by different units of measurement.

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

Sixty per cent of the data used in the study was used as training, 15% as validation, and 25% as test data set.

In the study, Multilayer Perceptrons (MLP) were preferred as an example of feed-forward networks. A multilayer artificial neural network is defined as a network with one or more hidden layers between the input and output layers (Süsler,

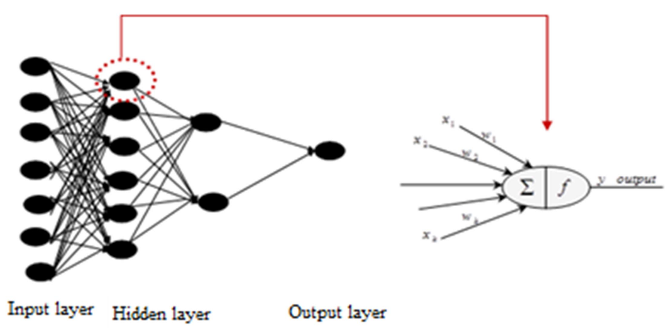

Figure 1. ANN structure (Source: Naseri and Saner, 2017).

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Table 2. Variables used in the ANN application.

Variable	Description	Data min	Data max	Data range
Wheat yield	Amount of wheat produced (kg ha^{-1})	3500.00	6450.00	2950.00
Seed	Amount of seed used (kg ha^{-1})	280.00	340.00	60.00
Fertilizer	Amount of fertilizer used (kg ha^{-1})	510.00	590.00	80.00
Pesticide	Amount of pesticide used (cc ha^{-1})	1500.00	3250.00	1750.00
Machine	Machine operating time (h ha^{-1})	2.30	5.70	3.40
Labor force	Working time of the labor force (h ha^{-1})	4.30	7.60	3.30

2022). The number of neurons in the input layer is considered as the number of input data, and the number of neurons in the output layer is 1 (wheat yield). The number of neurons in the hidden layer was determined by experiments.

Different activation functions, learning algorithms, etc. were tried during the training of the network until it reached the lowest error value. As a result of the experiments, it was found that the SigmoidAxon activation function and the Momentum learning algorithm gave better results than the others.

The predictive performance of different ANN models is compared using the criteria R^2 (coefficient of determination), MAPE (mean absolute percentage error), RMSE (root mean square error), and the network with the highest R^2 and the lowest RMSE and MAPE is selected as the best model. The mathematical formula for these criteria is given below (Amoozad Khalili *et al*., 2021).

$$R^2 = \frac{\left(\sum_{i=1}^{n}(Y_{ai}-\bar{Y}_{ai})\times(Y_{pi}-\bar{Y}_{pi})\right)^2}{\sum_{i=1}^{n}(Y_{ai}-\bar{Y}_{ai})^2\times\sum_{i=1}^{n}(Y_{pi}-\bar{Y}_{pi})^2}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_{ai}-Y_{pi}}{Y_{ai}}\right|\times 100$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Y_{ai}-Y_{pi})^2}{n}}$$

Where, Y_{ai} and Y_{pi} are observed and predicted values.

- After developing an ANN model suitable for the data set, a sensitivity analysis was conducted to determine the inputs that affect wheat yield. Sensitivity analysis is the study of the degree of effectiveness of the independent variables affecting the model (Turhan *et al*., 2013). NeuroSolutions software was used to perform the sensitivity analysis. The process of sensitivity analysis in this software provides a measure of the relative importance of the neural model's inputs and illustrates how the model output changes in response to variation in an input. By default, the first input is varied between its mean +/- a user-defined number of standard deviations while all other inputs are fixed at their respective means. The network output is computed for a user-defined number of steps above and below the mean. This process is repeated for each input (Anonymous, 2023). The implementation flow of the study is shown in Figure 2.

RESULTS AND DISCUSSION

General Characteristics of Wheat Farms

The average wheat yield in the studied farms was 5482.03 kg ha^{-1}, with the highest average yield in medium-sized farms (5708.10 kg). In small and large farms, this value was calculated as 5507.64 kg/ha and 5216.78 kg ha^{-1}, respectively. This difference between groups proved to be statistically significant ($P< 0.01$). In the studied farms, 294.75 kg of seeds were used per hectare. While the amount of seed used per hectare is close in small and medium farms, more seed is used per hectare in large farms ($P< 0.001$).

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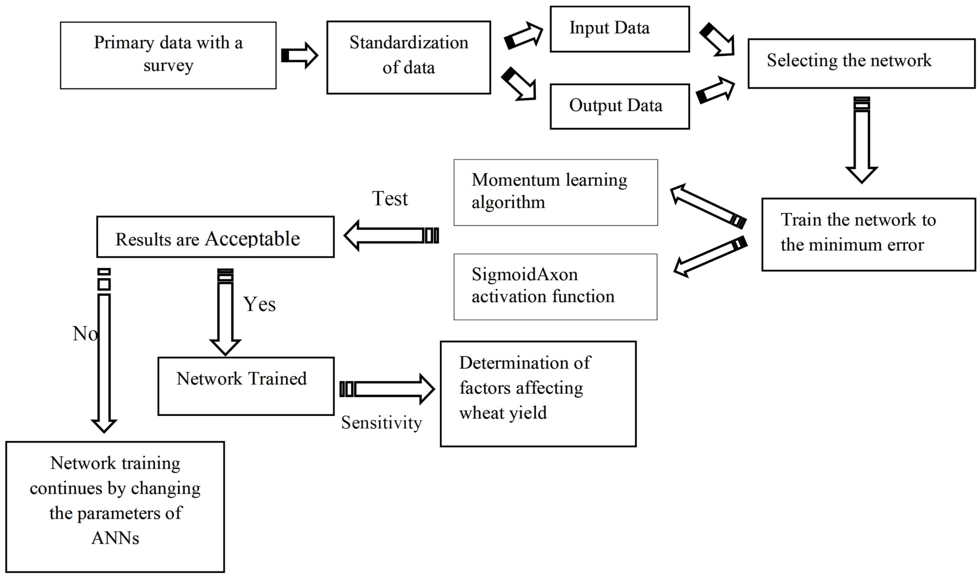

Figure 2. Implementation flow chart of the study.

The average amount of fertilizer used per hectare in the farms was 550.73 kg, with the highest fertilizer use per hectare calculated in large farms with a value of 554.07 kg (P< 0.05). In the studied farms, 3.59 machine hours and 5.37 labor hours were used per hectare. The highest use of machinery was realized in large farms (3.72 h ha^{-1}), while the highest use of labor was in small farms (5.56 h ha^{-1}) (Table 3).

ANN Application

In creating the ANN model in the study, different neuron numbers, activation functions, etc., were tried in the training phase of the network to obtain the lowest error. Different NN architectures that were implemented and compared in the study area are depicted in Table 4.

At the end of these trials, it was found that the 5-7-1 network architecture had a lower error rate for wheat yield. In other words, the best-fit model for wheat yield data consists of a single input layer (5 neurons), a single hidden layer (7 neurons), and a single output layer (1 neuron) (Figure 3)

The MSE (Mean Squared Error) variation of the training and validation datasets due to iterations during the training of the selected network is shown in Figure 4. The best validation performance was obtained in the 577th iteration, and the MSE value was found to be 0.032439083 in this iteration.

The value obtained from the wheat

Table 3. Characteristics of the farms by groups. [a]

Farm characteristics/ha	0.1-7.00 ha (55)	7.10-10.00 ha (63)	10.00+ha (59)	p	General (177)
Wheat yield (kg)	5507.64	570.810	5216.78	0.003**	5482.03
Seed (kg)	292.36	292.38	299.49	0.000***	294.75
Fertilizer (kg)	544.55	553.02	554.07	0.013*	550.73
Pesticide (cc)	2681.82	2757.94	2542.37	0.165	2662.43
Machine (h)	3.57	3.47	3.72	0.000***	3.59
Labor force (h)	5.56	5.29	5.27	0.046*	5.37

[a] Significance levels * P< 0.05; ** P< 0.01, and *** P< 0.001.

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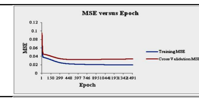
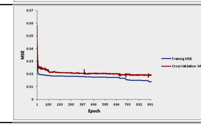
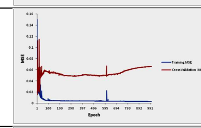
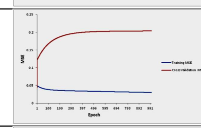
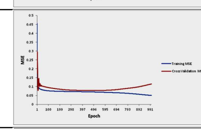
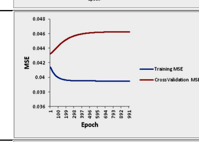
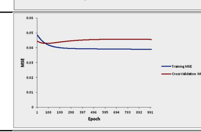
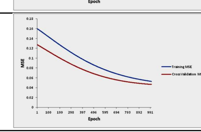
Table 4. Comparison of different NN architectures in the present study.

Topology	Transfer function	Learning algorithm	Performance		Best network
			MSE	r	
5-7-1	Sigmoid	Momentum	0.0353	0.821	
5-7-1	Sigmoid	Conjugate gradient	0.138	0.759	
5-7-1	Sigmoid	Levenberg-Marquardt	0.003	0.747	
5-7-1	Sigmoid	Quick propagation	0.03	0.63	
5-7-1	Tangent	Momentum	0.05	0.47	
5-2-4-1	Sigmoid	Momentum	0.039	0.547	
5-3-4-1	Sigmoid	Momentum	0.0388	0.578	
5-2-4-5-1	Linear sigmoid	Momentum	0.0526	0.105	

producers and the predicted values of the ANN model for the test data set are shown in Figure 5

The estimation performance of the developed ANN model for the test data set is given in Table 5, which shows that the MAPE value was calculated to be 43.45%. Models with MAPE value less than 10% are very good, between 10% and 20% are good, between 20% and 50% are acceptable, and models with MAPE value more than 50% are classified as falsely predicted. The estimated ANN model is at an acceptable level (Moreno *et al*., 2013; Shrestha at al., 2021). In our study, the coefficient of determination was calculated as 0.67. This means that the independent variables in the developed model explain 67% of the variability in wheat yield.

Sensitivity analysis was performed after the ANN model was created. According to the results of the sensitivity analysis, the most effective inputs for wheat yield are, in decreasing order, use of pesticides (0.2290), use of fertilizers (0.1373), labor force (0.0655), seed (0.0403), and machine use (0.0291) (Figure 6; Table 6).

In some studies examined, the results were similar to our research findings. In the study conducted in Hatay and Şanlıurfa provinces, it was found that the variables "irrigation status" and "amount of chemical fertilizer

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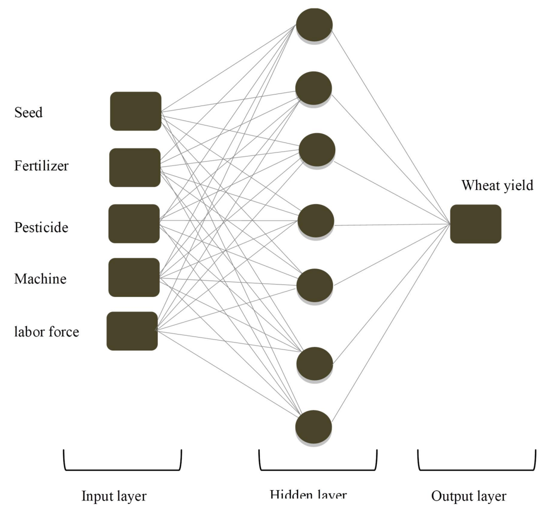

Figure 3. ANN architecture chosen in the study.

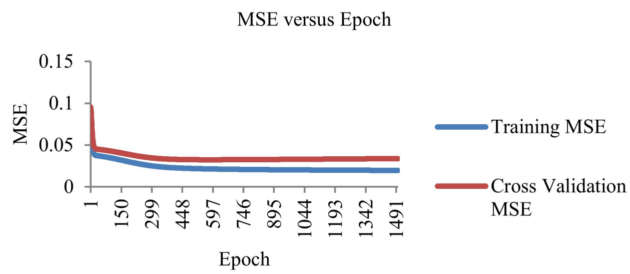

Figure 4. Mean squared error of the training and validation datasets during ANN training.

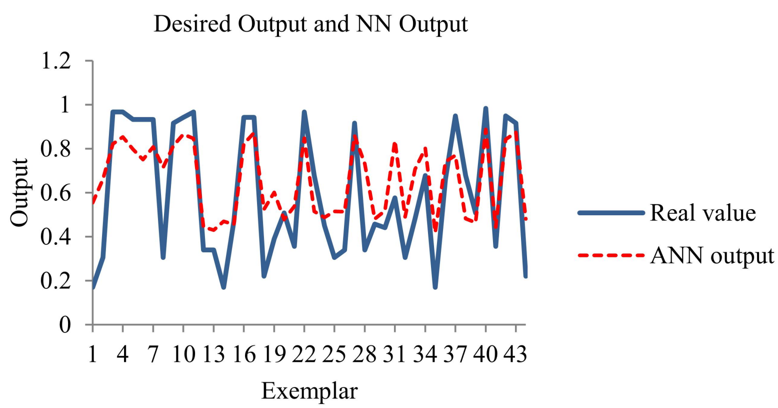

Figure 5. Real and estimated values of the ANN model for the test data set.

Table 5. Prediction performance for the test data set.

Data	MAPE	RMSE	r	R^2
Test dataset	43.455	0.188	0.821	0.674

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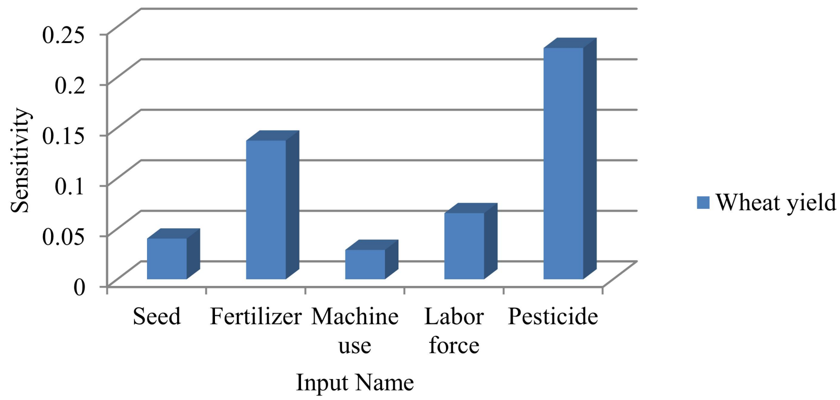

Figure 6. Sensitivity analysis of input variables in ANN model.

Table 6. Sensitivity analysis of variable.

Variable	Sensitivity level	Rank
Seed	0.0403	4
Fertilizer	0.1373	2
Pesticide	0.2290	1
Machine	0.0291	5
Labor force	0.0655	3

applied" were significantly effective in both regions, according to the results of multivariate analysis conducted with 14 variables that could be effective for wheat yield (Tiryakioğlu *et al*., 2017). In the study conducted in Erzurum, it was found that the farmer's education level, plot size, and the effect of nitrogen fertilizer application on wheat yield were significant (Kara and Kadıoğlu, 2014). However, in some studies, different results were obtained because different factors were considered. In a study on the effects of management parameters on yield of forage maize, it was found that the parameters affecting yield were the number of irrigations, the amount of water used, salinity of the irrigation water, salinity of the soil and, finally, the length of the growing season (Sepehri *et al*., 2019). According to the study of Epule *et al*. (2018), which aimed to quantify the role of climatic and non-climatic factors affecting multiple crop yield in Uganda, non-climatic factors, such as forest area dynamics, wood fuels, and tractor use, were more important than climatic factors such as precipitation and temperature (Epule *et al*., 2018).

Results of our study showed that use of pesticides and fertilizers are the most important factors affecting wheat yield. Agrochemicals are chemicals used in various agricultural applications to control pests, weeds, and diseases in plants (Sharma *et al*., 2019). Wheat is a plant that generally responds well to fertilizer. Half of the nitrogen fertilizer and all of the phosphorus fertilizer should be given at sowing. The other half of nitrogen fertilizer should be given as top dressing during tillering stage (Yıldız *et al*., 2013).

Pesticides and fertilizers are used to increase productivity, but the excessive use of these materials causes problems for the environment and human health. Therefore, different measures are taken in different countries to limit the use of pesticides in

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agriculture. For example, EU member states have developed some binding legislation on the use of pesticides. (Lobin *et al.* 2017)

CONCLUSIONS

With the continuous increase in the world population, the demand for food is increasing day by day, and the world agriculture may face serious difficulties in the coming years to meet the increasing demand for food. In parallel with this increase in demand, the issue of food security has taken on new dimensions and is one of the most important problems facing countries. Since self-sufficiency is one of the principles of food security, this can be achieved by increasing food production (Hoseinzadeh *et al*., 2012). In this respect, wheat is the most widely grown cereal in the world and plays an important role in ensuring food security.

In this study, a survey of 177 producers was conducted to determine which inputs affect wheat yield in Diyarbakır. The ANN method was used in analyzing the data. The study found that wheat yield was more sensitive to the use of pesticides and fertilizers. If these two inputs are applied in proper doses, in an appropriate manner, and at the right time, the efficiency increases. The unconscious use of pesticides and other permanent organic pollutants in agricultural areas causes serious health risks to living beings by directly or indirectly polluting the air, water, soil, and the general ecosystem. Therefore, producers should be made aware that the excessive use of pesticides and fertilizers is harmful to human and environmental health. Also, soil analysis should be conducted and the type of fertilizer to be used, the time of application, and the application dose should be determined. To minimize the use of pesticides, the importance of integrated control methods should be emphasized through extension studies. In addition, pesticide use can be avoided by developing pest-resistant varieties through breeding studies.

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تأثیر استفاده از نهاده بر عملکرد گندم: کاربرد شبکه های عصبی مصنوعی (ANN)

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چکیده

هدف این پژوهش بررسی اثرهای نهاده‌هایی مانند سموم دفع آفات، کود، بذر، نیروی کارگری و استفاده از ماشین آلات بر عملکرد گندم بود. داده‌های استفاده شده در این بررسی از ۱۷۷ تولیدکننده گندم در استان دیاربکر از طریق پرسشنامه به دست آمد و در تجزیه و تحلیل داده ها از شبکه های عصبی مصنوعی (ANN) استفاده شد. بر اساس نتایج، میانگین عملکرد گندم ۵۴۸۲/۰۳ کیلوگرم در هکتار است و برای تولید گندم در هکتار ۲۹۴/۷۵ کیلوگرم بذر، ۵۵۰/۷۳ کیلوگرم کود، ۳/۵۹ ساعت ماشین‌آلات، ۵/۳۷ ساعت کارگری و ۲۶۶۲/۴۳ سانتی مترمکعب سموم دفع آفات در هکتار استفاده می‌شود. بر اساس نتایج تحلیل شبکه عصبی مصنوعی، اهمیت نسبی عوامل ورودی مؤثر بر عملکرد گندم کمی‌سازی شده است. در این میان، استفاده از سموم دفع آفات و کود بیشترین تأثیر را داشته‌اند. به طور مشخص، ضرایب حساسیت برای استفاده از سموم دفع آفات و کود به ترتیب ۰.۲۳ و ۰.۱٤ به دست آمده‌اند. این ضرایب، تغییر نسبی در عملکرد گندم را در ازای هر واحد تغییر در پارامترهای ورودی توصیف می کنند.

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