

The Modeling and Optimization of Energy Inputs and Greenhouse Gas Emissions in Watermelon Production Using Artificial Neural Network and Multi Objective Genetic Algorithm

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This study modeled and optimized energy consumption and greenhouse gas emissions (GHGE) for watermelon (*Citrullus lanatus* L.) production in Adana, Turkey. Artificial Neural Networks (ANN) and Multi-Objective Genetic Algorithms (MOGA) were employed for the analysis. The findings revealed that chemical fertilizers accounted for the largest share of energy use (77.0%), followed by diesel fuel (8.4%), with a total energy consumption of 50,100 MJ ha⁻¹. The ANN 10-8-2 architecture provided the most accurate performance (R²). Using the MOGA method, optimum values were determined for minimum total GHGE and maximum watermelon production. The highest amount of production with minimum energy usage was approximately 10,900 MJ ha⁻¹. The GHGE of the best production were calculated as approximately 282 kg CO_{2eq} ha⁻¹. The GHGE reduction potential using MOGA was calculated as 903 kg CO_{2eq} ha⁻¹. Furthermore, the highest reduction in GHGE occurred in nitrogen fertilizer by 52.0%. The results also indicated that the highest amount of production with minimum energy usage is approximately 10,900 MJ ha⁻¹. The GHGE of the best production were calculated as approximately 282 kg CO_{2eq} ha⁻¹. The GHGE reduction potential using MOGA was calculated as 903 kg CO_{2eq} ha⁻¹. Furthermore, the highest reduction in GHGE occurred in nitrogen fertilizer by 52.0%.

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INTRODUCTION

Watermelon is an annual plant that thrives in warm and temperate climates. It can be utilized entirely from its seeds to its rind and is used in various industries such as food, pharmaceuticals, and cosmetics. Approximately 3 million hectares of land worldwide are devoted to watermelon cultivation, producing about 100 million tons annually. Watermelon is the second most cultivated fruit in the world after bananas. China produces 60% of the world's watermelon production, with 60.68 million tons. Turkey follows China with a production of 3.8 million tons. This is followed by India, Brazil, Algeria, Iran, Russia, and the United States follow Turkey, respectively. Turkey's share in global watermelon production is about 3.9%. The average global watermelon yield is 33.6 tons

ha⁻¹, while in Turkey this value is higher at 44.5 tons ha⁻¹ (FAOSAT 2022). Approximately 22.6% of Turkey's total watermelon production occurs in Adana, where yield values reach up to 70 tons per hectare (TUIK 2021).

A sustainable approach to agriculture is achieved through efficient fuel use. This is also important for reducing greenhouse gas emissions (GHGE). Efficient energy (EE) use in agriculture can save fossil fuels and reduce air pollution. Therefore, both production costs and GHGE are reduced while also protecting the surroundings. GHGE occur due to agricultural activities, such as biocides, chemical fertilizers, machinery, electricity, and fuel use (Klikocka *et al.* 2019). Artificial Neural Networks (ANN) deal with event examples, generalize from them, gather information, and use the acquired knowledge to make decisions when encountering unseen examples. ANN has been employed to model energy balance and indices in cultivation (Niedbala 2019). There has been some analysis of energy usage in agricultural producing processes. This has included citrus fruits (Yılmaz and Aydın 2020), mandarin (Dagtekin *et al.* 2019; Bilgili 2021), maize (Farjam *et al.* 2014), winter rapeseed (Niedbala 2019), almond (Yılmaz and Bayav 2022), vetch (Seydosoglu *et al.* 2023), watermelon (Demir 2023), garlic (Baran *et al.* 2023), peach (Demir and Gokdogan 2023), and cherry (Gökdoğan *et al.* 2024), orange (Mohammadshirazi *et al.* 2015; Yelmen 2025).

One of the methods used to solve the optimization process is the Multi-Objective Genetic Algorithm (MOGA) method. The Genetic Algorithm (GA) is a searching method that uses random selection for a function optimization with parameter-space coding. Genetic algorithms have been developed by Holland (1975), with the primary references given by Bäck (1998) and investigations carried out by Goldberg (1997). Few studies have considered optimizing agricultural energy with genetic algorithms. An investigation on the optimization of energy usage in the cultivation of sugar beet had been carried out by Hemmati *et al.* (2013). Cultivation results showed an optimized total energy used for sugar beet production of 32,700 MJ ha⁻¹. Other investigations focused on modeling and the optimization of energy usage and GHGE with ANN and MOGA in eggplant crop production (Pelesaraei *et al.* 2013) and peanut crop production (Nabavi-Pelesaraei *et al.* 2013).

Based on the literature review, there appears to have been insufficient research on ANN modeling and MOGA-based improvement of EE and reduction of GHGE in watermelon farming in Adana county. Therefore, this study aimed to identify energy input (EI) indices for watermelon cultivation, model the energy consumption (EC), and GHGE using ANN, optimize them with MOGA, and identify the most topology for utmost prediction correctness.

MATERIALS AND METHODS

The data used in this study were obtained from interviews conducted with 68 farmers engaged in watermelon (*Citrullus lanatus* L.) cultivation during the March-May 2024 season in Adana. Hundreds of parameters for agricultural activities were compared in 68 farms. Adana is located (36°32' - 38°25' N; 34°39'-36°24' E) in the Mediterranean Region of Turkey (GDM 2024).

Calculation of Energy Indices

To determine energy equivalence of agricultural sector, amount of performance per hectare for watermelon production involving of seeds, pesticides, machinery, fuel, farm yard manure, human work force, chemical fertilizers, and electricity as shown in Table 1 (Demir and Gokdogan 2023).

Table 1. Energy Equivalent of Inputs and Output in Agricultural Production

Inputs	Unit	Energy Equivalent (MJ unit ⁻¹)
Human labor	h	1.96
Machinery	h	62.70
Diesel fuel	L	56.31
Chemical fertilizers		
Nitrogen (N)	kg	66.14
Phosphate (P ₂ O ₅)	kg	12.44
Potassium (K ₂ O)	kg	11.15
Biocides	kg	120
Farmyard manure	kg	0.3
Electricity	kWh	3.6
Seeds	kg	1.9
Output Watermelon	kg	1.9

Equations 1 to 5 were used to determine the energy Indices including those for energy use efficiency (EUE), energy productivity (EP), specific energy (SE), energy density (ED), and net energy (NE). These equations were calculated using Table 1 (Nabavi-Pelesaraei *et al.* 2016; Macedo *et al.* 2021).

$$\text{Energy use efficiency} = \frac{\text{Energy output (MJha}^{-1}\text{)}}{\text{Energy input (MJha}^{-1}\text{)}} \quad (1)$$

$$\text{Energy productivity} = \frac{\text{Product output (kg ha}^{-1}\text{)}}{\text{Energy input (MJha}^{-1}\text{)}} \quad (2)$$

$$\text{Specic energy} = \frac{\text{Energy input (MJha}^{-1}\text{)}}{\text{Product output (kg ha}^{-1}\text{)}} \quad (3)$$

$$\text{Energy density} = \frac{\text{Energy input (MJha}^{-1}\text{)}}{\text{Cost of production (\$ha}^{-1}\text{)}} \quad (4)$$

$$\text{Net energy} = [\text{Energy output (MJha}^{-1}\text{)} - \text{Energy input (MJha}^{-1}\text{)}] \quad (5)$$

In these equations, EO is energy output (MJ ha⁻¹), EI is energy input (MJ ha⁻¹), crop yield has units of (kg ha⁻¹), and production cost has units of (\$ ha⁻¹). Samples were classified into 3 categories (<1 ha, 1-3 ha, >3 ha). In agricultural activities, EUE and SE are complementary values. They are mentioned as direct energy (DE), indirect energy (IDE), renewable energy (RE), and non-renewable energy (NRE) (Demir 2023). The GHGE value for watermelon farming was calculated using Table 2 (Ozbek *et al.* 2024).

Table 2. Greenhouse Gas Emission Parameters of Agricultural Input

Input	Unit	GHG Coefficient (kg CO _{2eq} unit ⁻¹)
Machinery	MJ	0.071
Diesel fuel	L	2.76
Chemical fertilizer		
Nitrogen (N)	kg	1.3
Phosphate (P ₂ O ₅)	kg	0.2
Potassium (K ₂ O)	kg	0.2
Biocides	kg	6.3
Electricity	kWh	0.608

The GHGE for watermelon culture was determined by Eq. 6 (Karaağaç *et al.* 2019):

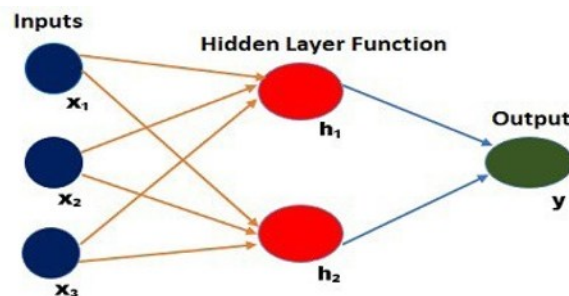
$$GHG_{ha} = \sum_{i=1}^n R(i) \times EF(i) \quad (6)$$

where GHG_{ha} is Greenhouse gas emission (kgCO_{2eq}.ha⁻¹), $R(i)$ is the amount of i input (unit_{input} ha⁻¹), and $EF(i)$ is the GHG emission equivalent of i input (kgCO_{2eq}.unit⁻¹_{input}). The value of I_{GHG} , based on GHG ratio, and Y crop in kg ha⁻¹, was computed utilizing Eq. 7 (Houshyar *et al.* 2015).

$$I_{GHG} = \frac{GHG_{ha}}{Y} \quad (7)$$

Modeling of Artificial Neural Networks

Artificial neural networks (ANN), possessing non-algorithmic and highly parallel processing capabilities, facilitate complex and nonlinear computations easily and rapidly through its learning ability and parallel distributed memory (Fig. 1) (Benti *et al.* 2023). Normalization in artificial neural networks is performed to enable the model to learn faster, more stably, and more efficiently.

**Fig. 1.** Artificial neural network model

ANN is a data input similar to a biological neural system. To solve specific problems, consists of many interconnected neurons. In this research, ANN model was used to train and test 52 and 16 units of watermelon crops, respectively. The selected units were obtained incidental from all examples. Several network structures were selected by evaluating empirical data to identify best predictive model. Numeral of neurons was defined based on input and output layers for watermelon cultivation and GHGE. Various neural network models with multiple layers and structures for the hidden layers have been proposed. Among them is the Levenberg-Marquardt (LM) learning model. All connections between input layers and hidden layers form the weight input matrix. The weight (W) at

each node controlling the output, the input value (X), and evaluated output (O) are adjusted using Eq. 8 (Nabavi-Pelesaraei *et al.* 2016):

$$O = f(T + \sum W_i X_i) \quad (8)$$

Here, T is a certain threshold value for each node and f is a nonlinear sigmoid function. In artificial neural networks, the sigmoid function is an activation function that compresses a neuron's output between 0 and 1. In this study, Root Mean Square Error ($RMSE$), Mean Absolute Percentage Error ($MAPE$), and coefficient of determination (R^2) functions were used to evaluate the model errors (Bhatti and Do 2019). The models were trained using training output and tested using the output and the RMSE criterion was calculated using Eq. 9:

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (y_i - y_i')^2}{N}} \quad (9)$$

The predicted value of R^2 was also determined using Eq. 10.

$$R^2 = \frac{\left[\sum_{i=1}^m (y_i - \bar{y})(O_i - \bar{O}) \right]^2}{\sum_{i=1}^m (y_i - \bar{y})^2 \sum_{i=1}^m (O_i - \bar{O})^2} \quad (10)$$

In Eq. 10, m represents the number of tested outputs, O_i is the predicted output from the ANNs, and y_i is the calculated (observed) output value. The symbol $\bar{y}$ denotes the mean of the calculated output values (y_i), while $\bar{O}$ represents the mean of the predicted output values (O_i) from the ANN. $MAPE$ values were computed using Eq. 11.

$$MAPE = \frac{1}{N} \sum_{i=1}^N |y_i - y_i'| \times 100 \quad (11)$$

N represents number of training vectors, while the output of training vector “ y ” and “ y' ” denote the values that are tracked and simulated.

Multi-Objective Genetic Algorithm (MOGA)

When selecting MOGA parameters, a population size of 50-500, a crossover rate of 0.60-1.0, and a mutation rate of 0.001 to 0.1 were chosen. The main objective of this study was to investigate the integration of ANN and MOGA for modeling and optimization. While comparative modeling could provide additional insights, it is outside the scope of the current study. Genetic algorithms, classified as population-based methods, can efficiently be applied to deal with multiobjective optimization tasks. A typical single-objective genetic algorithm can easily be employed to derive multiple non-dominated solution sets in one execution. The characteristic of genetic algorithms to concurrently explore other parts of the solution space makes them suitable for finding diverse solutions to complex tasks with non-convex, discontinuous, or multimodal solution spaces (Konak *et al.* 2006). The first step for the optimization process using the MOGA method included calculating the production functions. The production functions were established through the energy inputs-output (watermelon production and total greenhouses gas emissions) described in Eqs. 12 and 13:

$$Y_i = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + \alpha_4 X_4 + \alpha_5 X_5 + \alpha_6 X_6 + \alpha_7 X_7 + \alpha_8 X_8 + \alpha_9 X_9 + \alpha_{10} X_{10} + e_i \quad (12)$$

$$G_i = \alpha_0 + \beta_1 X_1 + \alpha_2 \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9 + \beta_{10} X_{10} + e_i \quad (13)$$

Here, X_i represents the corresponding energy inputs: X_1 for human labor, X_2 for machinery, X_3 for diesel fuel, X_4 for nitrogen, X_5 for phosphate, X_6 for potassium, X_7 for biocides, X_8 for farmyard manure, X_9 for electricity, and X_{10} for seeds. Y_i represents watermelon yield, and G_i represents total greenhouse gas emissions.

Subsequently, the boundaries of the functions were calculated based on min and max EC values for each input. Fundamental information regarding the EI and GHGE in watermelon farming was coded into Excel 2019, SPSS 20, and MATLAB (R2024a).

RESULTS AND DISCUSSION

Analysis of Energy Use in Watermelon Culture

The energy demand for watermelon farming was roughly 50,100 MJ ha⁻¹. The results indicated that large-scale farm models exhibited best efficiency and productivity in watermelon farming. Furthermore, the findings showed that there was no major distinctness in EI among the three farm size groups (ANOVA). However, when the three farm models were compared in terms of watermelon yield, a significant difference was observed. In other words, while there was a notable difference in EI for large-scale watermelon production, there was no significant difference between small and medium scale farms on account of total EI and output. Table 3 demonstrates that large-scale farms achieve greater productivity than other scales of farms with the same total EI.

Table 3. Energy Input – Energy Output Relationship in the Watermelon Cultivation

Inputs (MJ ha ⁻¹)	Farm Size Groups (ha)			Average (MJ ha ⁻¹)	Percentage (%)
	Small (<1)	Medium(1-3)	Large (>3)		
Human labor	1672 ^a	1631 ^b	1712 ^a	1672	3.34
Machinery	1213 ^c	1311 ^b	1355 ^a	1293	2.58
Diesel fuel	4116 ^b	4144 ^b	4401 ^a	4220	8.42
Chemical					
Nitrogen (N)	33402 ^a	34488 ^a	37341 ^a	35077	69.99
Phosphate (P ₂ O ₅)	1835 ^b	1985 ^{ab}	2052 ^a	1957	3.91
Potassium (K ₂ O)	1468 ^b	1499 ^{ab}	1641 ^a	1536	3.07
Biocides	324 ^a	340 ^a	354 ^a	339	0.68
Farmyard manure	127 ^b	137 ^a	139 ^a	135	0.27
Electricity	3671 ^b	3870 ^b	4103 ^a	3881	7.75
Seeds	3.48 ^b	3.56 ^{ab}	3.69 ^a	3.58	0.01
Total energy input	47832 ^a	49409 ^a	53101 ^a	50114	100.00
Outputs Watermelon	61519 ^c	62383 ^b	66103 ^a	63335	

Note: Different letters show significant difference of means at 5% level.

In watermelon production, nitrogen fertilizer had the highest EC value, accounting for approximately 70.0%. This was followed by fuel 8.42% and electricity consumption 7.75%. Additionally, the shares of other inputs in watermelon farming were lower than the total average EI. Therefore, by managing nitrogen consumption and using farmyard manure instead of chemical fertilizers, EUE in watermelon production can be improved.

In some related studies, the total EI in watermelon farming was reported to be 46,300 MJ ha⁻¹, with the highest EC values in chemical fertilizers (28,600 MJ ha⁻¹) and

fuel (3,030 MJ ha⁻¹) (Banaeian and Namdari 2011). For comparison, the total EI was reported as 45.5 MJ ha⁻¹ for tomatoes (Cetin and Vardar 2008), 30.3 GJ ha⁻¹ for kiwifruit (Mohammadi *et al.* 2010), and 45.2 GJ ha⁻¹ for grapes (Hamedani *et al.* 2011). Other examples include 81.4 GJ ha⁻¹ for greenhouse tomatoes (Ozkan *et al.* 2011), 173 GJ ha⁻¹ for pears (Tabatabaie *et al.* 2013), and 80.2 GJ ha⁻¹ for wheat farming (Safa and Samarasinghe 2011). On the basis of the levels of farm size given in the current study, EUE, EE, SE, NE, and ED results have been seen in Table 4. EUE for growing watermelon is determined to be 1.26. Other similar studies have given EUE of 0.8 for tomatoes (Ozkan *et al.* 2011), 0.96 for cherries (Kizilaslan 2009), 0.15 for strawberries (Banaeian *et al.* 2010), 1.16 for apples (Rafiee *et al.* 2010), 0.665 for garlic (Samavatean *et al.* 2011), 0.51 for pear (Tabatabaie *et al.* 2013), and 0.45 for wheat (Safa and Samarasinghe 2011).

Table 4. Energy Input-Energy Output Ratio in Watermelon Cultivation

Energy Types	Unit	Farm Size Groups (ha)			Average	Percentage (%)
		Small (<1)	Medium (1-3)	Large (>3)		
Energy use efficiency	–	1.29	1.26	1.24	1.26	–
Energy productivity	kg MJ ⁻¹	0.81	0.79	0.78	0.79	–
Specific energy	MJ kg ⁻¹	1.60	1.59	1.59	1.59	–
Net energy	MJ ha ⁻¹	13687	12974	13002	13221	–
Energy density	MJ \$ ⁻¹	10.33	10.13	10.56	10.34	–
Direct energy	MJ ha ⁻¹	9452	9764	10494	9903	19.76
Indirect energy	MJ ha ⁻¹	38379	39645	42607	40211	80.24
Renewable energy	MJ ha ⁻¹	1831	1892	2033	1919	3.83
Non-renewable energy	MJ ha ⁻¹	46000	47517	51068	48195	96.17
Total energy input	MJ ha ⁻¹	47832	49409	53101	50114	100.00

As shown in Table 4, small-size farms in watermelon production have the highest EUE value of 1.29, due to the fact that the ratio of EO to EI is higher. Increase in EO for small farms is significantly greater than the increase in EI compared to medium and large farms. In contrast, the lowest EUE value of 1.24 was calculated for large-scale farms. Therefore, small-scale farms in Adana province, Turkey, are considered more suitable in terms of EUE for watermelon production.

Additionally, EE, SE, NE, and ED were computed to be 0.79 kg MJ⁻¹, 1.59 MJ kg⁻¹, 13,220.61 MJ ha⁻¹, and 10.34 MJ \$⁻¹. The distribution of inputs used in watermelon cultivation for three farm sizes across the DE, IDE, and RE, NRE groups is presented in Table 4. The results indicate that IDE accounts for 80.2% of the total EI, while DE represents 19.8%. Furthermore, only 3.83% of sum EI utilized in watermelon cultivation was derived off renewable energy originated. The main renewable energy sources in watermelon cultivation are chemical fertilizers, fuel, and electricity. Therefore, using renewable inputs such as farmyard manure can increase the share of RE, while productive utilize of diesel fuel and irrigation water can help diminish NRE dependency.

Greenhouse Gas Emissions from Watermelon Cultivation

The total GHGE were found to be 1,250 kg CO_{2eq} ha⁻¹. In a similar study, the CO₂ emission from organic fig production was reported to be approximately 1,109.02 kg CO_{2eq} ha⁻¹ (Oguz *et al.* 2022). Another study calculated total CO₂ emission from okra production as approximately 875 kg CO_{2eq} ha⁻¹ (Sarkar *et al.* 2023). Greenhouse gas emissions from

tomato cultivation were found to be 323 kg CO_{2eq} ha⁻¹ (Sarkar *et al.* 2023). Greenhouse gas emissions are shown in Table 5.

Table 5. Greenhouse Gas Emission of inputs used in Watermelon Cultivation

Inputs	Farm Size Groups (ha)			Average (kgCO _{2eq} .ha ⁻¹)	Percentage (%)
	Small(<1)	Medium(1-3)	Large(>3)		
Machinery	86.15 ^b	103.84 ^a	96.18 ^a	95.39	7.66
Diesel fuel	201.74 ^b	203.11 ^b	211.72 ^a	205.53	16.51
Chemical fertilizer					
Nitrogen	656.53 ^b	638.57 ^b	733.94 ^a	676.35	54.32
Phosphate (P ₂ O ₅)	29.51 ^b	28.70 ^b	31.99 ^a	30.07	2.41
Potassium (K ₂ O)	26.34 ^a	25.62 ^b	28.44 ^a	26.80	2.15
Biocides	13.75 ^b	17.00 ^a	13.75 ^b	14.83	1.19
Electricity	187.07 ^a	181.95 ^b	219.12 ^a	196.05	15.75
Total GHGE	1201.09 ^a	1198.78 ^a	1335.14 ^a	1245.01	100.00

Note: Different letters show significant difference of means at 5% level.

In watermelon cultivation, the GHGE share was highest in large-scale farms, although the lowest share was observed in medium-scale farms. However, there was not any statistically (ANOVA) considerable segregation in GHGE amongst three farm groups. With respect to the table, nitrogen fertilizer had the highest share within total GHGE at 54.3%, which was followed by fuel (16.5%) and electricity consumption (15.8%). The contribution of watermelon cultivation inputs to greenhouse gas emissions (GHGE) is illustrated in Fig. 2.

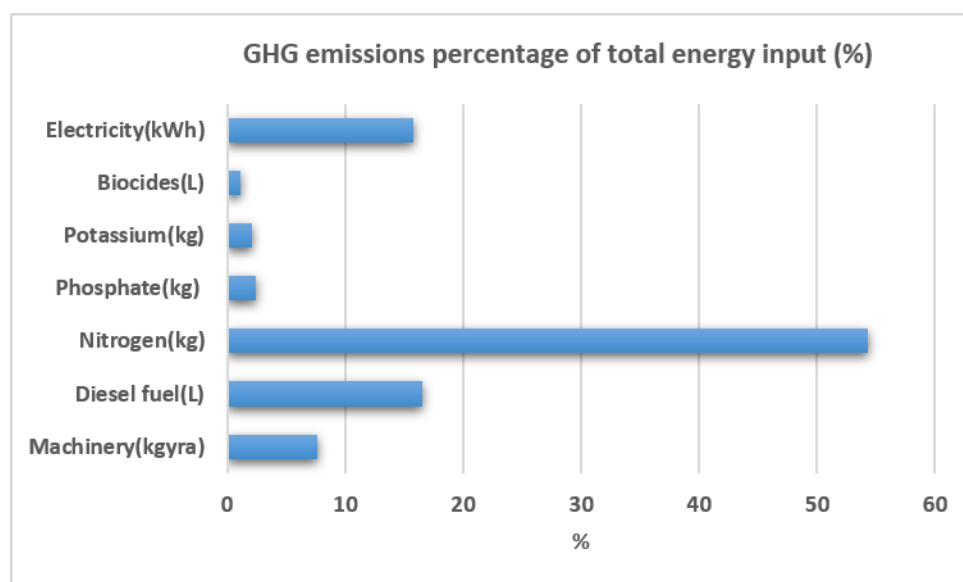


Fig. 2. Contribution of watermelon production inputs to the use of greenhouse gas emission

Through better agricultural management of nitrogen application, lower greenhouse gas emissions (GHGE) can be achieved in the studied area. Considering that Adana province receives sufficient rainfall, reducing irrigation water use electricity consumption

in watermelon production could lead to significant improvements in lowering greenhouse gas emissions.

ANN Model Structure and Evaluation

For the purpose of modeling the production efficiency of watermelon and the GHGE, neural networks were developed. These networks were developed using the MATLAB software (R2024a). This modeling was done based on several parameters such as the range of the layers and neurons in the networks. Additionally, there was involvement of the learning parameters. For this modeling to be done effectively, there is a Levenberg-Marquardt learning algorithm that is used. This training is done with 75% of the data for the training datasets. Further testing is done with 52 samples. As shown in Table 6, statistical scales were used to evaluate the ANN models and predict watermelon production efficiency and GHGE.

Table 6. Results of Different Models

Topologies	Model Categories	Statistics Indices	Output Layer	
			Watermelon Yield	Greenhouse Gas Emissions
10-9-2	Train	R ²	0.929	0.934
		RMSE	0.167	0.079
		MAPE	0.013	0.012
	Test	R ²	0.913	0.947
		RMSE	0.131	0.039
		MAPE	0.012	0.009
10-8-2 (Best)	Train	R ²	0.978	0.982
		RMSE	0.149	0.067
		MAPE	0.006	0.005
	Test	R ²	0.964	0.991
		RMSE	0.118	0.034
		MAPE	0.005	0.001
10-7-2	Train	R ²	0.912	0.922
		RMSE	0.179	0.091
		MAPE	0.017	0.014
	Test	R ²	0.901	0.935
		RMSE	0.143	0.047
		MAPE	0.016	0.015

Through test and fault, top capacity was obtained with use of an ANN model of 10-8-2 structure. The texture of the selected ANN is schematic illustrated in Fig. 3. The MATLAB interface and training data are shown in Fig. 3. The practice and testing consequences are presented in Table 6. The architectural choice was made through a comparative analysis of multiple artificial neural network structures (10-9-2, 10-8-2, and 10-7-2), as presented in the Table. The 10-8-2 model was chosen based on its superior performance metrics (highest R² and lowest RMSE and MAPE). For watermelon performance and GHGE, the best topology with the highest R² and the lowest RMSE and MAPE values demonstrated that both practice and testing stages of the ANN models closely followed the predicted watermelon yield and GHGE values. The R² values ranged between 0.912 and 0.982 for training data and 0.901 and 0.991 for testing data.

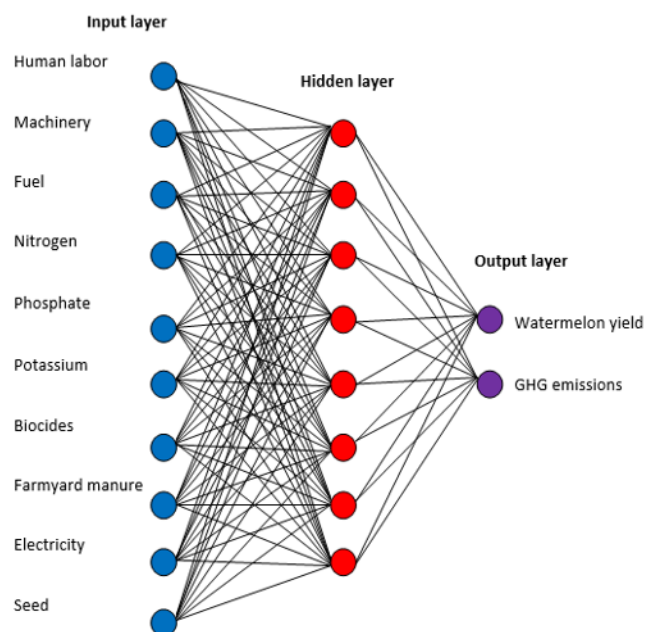


Fig. 3. Artificial neural networks model with 10-8-2 topology

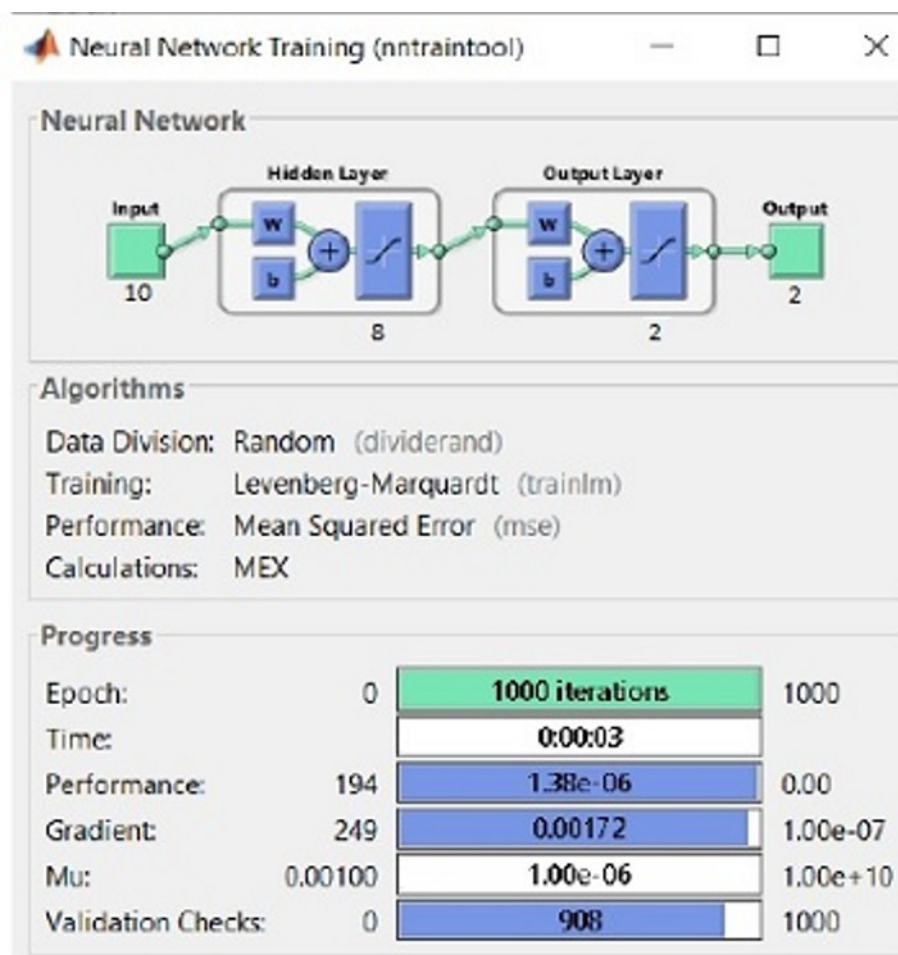


Fig. 4. The MATLAB interface and training data

The R^2 value for training data was between 0.978 and 0.982, while the R^2 value for test data was between 0.964 and 0.991. This indicates that the training and test results were very close, suggesting there was no overfitting (if there were, the training data would be larger than the test data). Therefore, the similarity between test and training performances shows that the model did not exhibit overfitting. In artificial neural networks, an epoch refers to the time it takes for the entire training dataset to pass through the network exactly once. The artificial neural network model created uses a training stopping criterion of 1000 iterations, an error value of "0", and a gradient of $1e-7$. Training reached 1000 iterations in 3 seconds. The MATLAB interface and training data are shown in Fig. 4.

The ANN model 6-9-1 capable of predicting jute cultivation in Bangladesh was developed by Rahman and Bala (2010). For basil production, the best topology was reported as 7-20-20-1 (Pahlavan *et al.* 2012). Another study advanced an ANN to estimate watermelon production efficiency and GHGE (Nabavi-Pelesaraei *et al.* 2016). The outcomes showed that 12-9-9-2 ANN was the best topology for estimating performance and GHGE in watermelon production. The training and testing datasets are illustrated in Figs. 5 and 6. As shown the estimated and actual values are consistent.

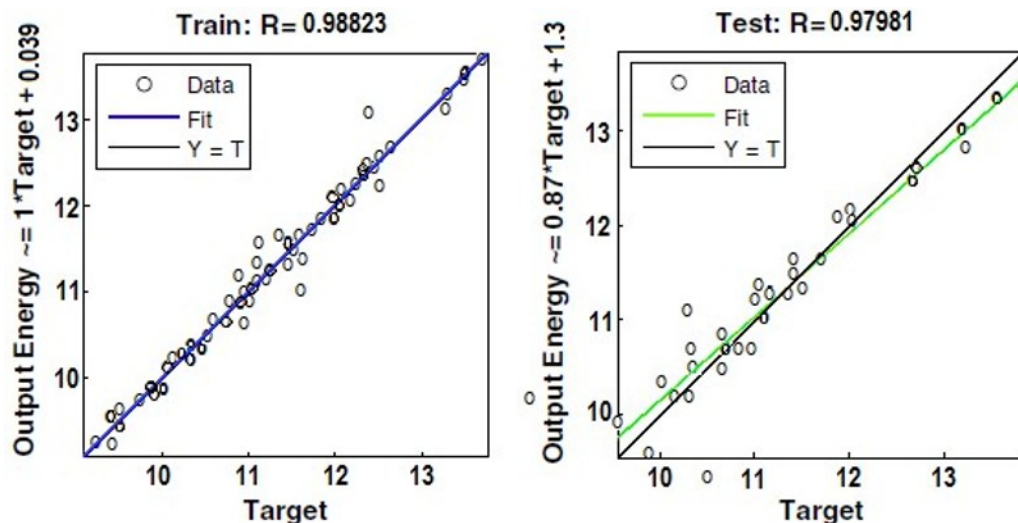


Fig. 5. Correlation between predicted and real outputs energies based on the best topology

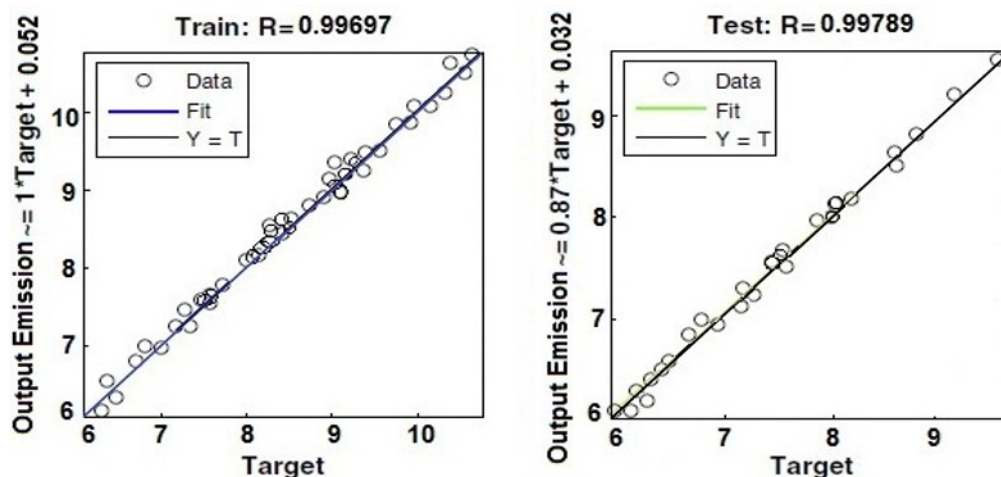


Fig. 6. Correlation between predicted and real outputs GHG emission based on the best topology

The coefficient of determination showed that the advanced network for watermelon cultivation was quite suitable in terms of output energy and GHG emission. The R^2 parameters for watermelon performance and GHGE were found to be 0.988 and 0.997 for the training data, respectively. Furthermore, for the test data, the factor of determination R^2 for watermelon performance and GHGE was 0.980 and 0.998, respectively.

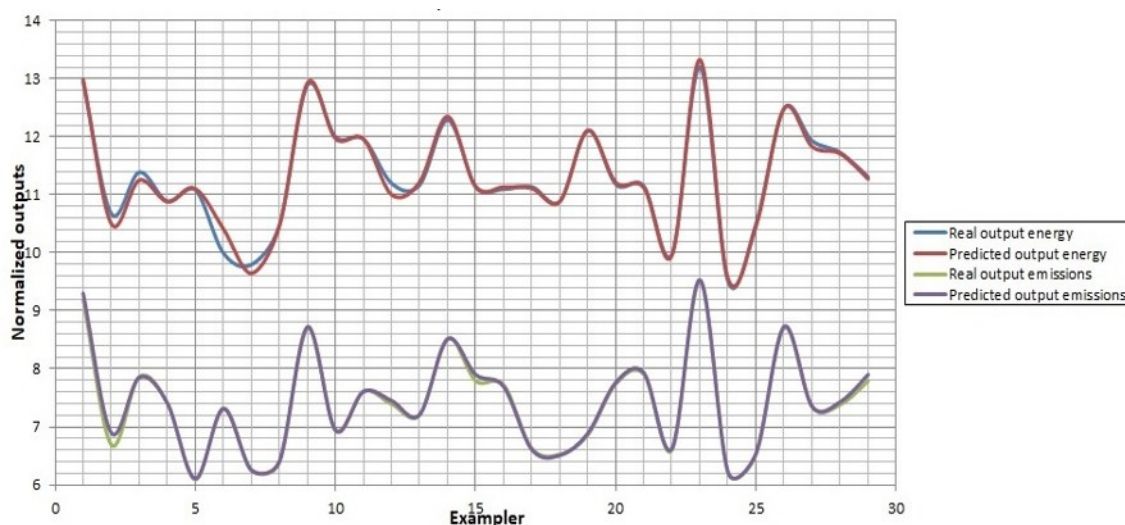


Fig. 7. Predicted and real energy output values

In Fig. 7, the y-axis is used to display normalized outputs. The x-axis is used to display the no of estimated data group. The blue and green curves demonstrate actual outputs. On the other hand, the red and magenta curves represent how well the model tracked the predicted outputs.

In ANNs, sensitivity analysis measures how much small changes in input variables affect the model's output. Sensitivity analysis is performed to test accuracy of a model's results. In sensitivity analysis conducted using ANN, the input variants were listed using a fractional differential study (Table 7).

Table 7. Sensitivity Analysis Results for Input Energies

Inputs	Watermelon Yield	Greenhouse Gas Emissions
Human labor	0.019	0.070
Machinery	0.003	0.002
Diesel Fuel	0.026	0.005
Nitrogen	0.006	0.048
Phosphate	0.009	0.052
Potassium	0.007	0.053
Farmyard manure	0.013	0.051
Biocides	0.007	0.039
Electricity	0.008	0.019
Seed	0.029	0.028

Optimization of Energy Inputs and Greenhouse Gas Emissions

The models for yield and GHGE were optimized with MOGA-based energy inputs. The limitations of the energy inputs are shown in Table 8. The minimum amount of energy

consumed is taken as the lower limit, and the largest amount of energy that can be consumed is taken as the upper limit.

Table 8. Limits of Functions for Multi-Objective Genetic Algorithm (MJ ha⁻¹)

$338.17 \leq X_1 \leq 1186.48$	$113.99 \leq X_5 \leq 861.06$
$144.84 \leq X_2 \leq 2172.54$	$58.97 \leq X_6 \leq 445.42$
$1674.02 \leq X_3 \leq 16740.23$	$58.03 \leq X_7 \leq 1059.68$
$1417.18 \leq X_4 \leq 10174.99$	$2.58 \leq X_8 \leq 6.46$

In addition, the production function was calculated according to Eqs. 12 and 13:

$$Y_f = 3,56 + 0.55X_1 + 0.33X_2 + 0.40X_3 - 0.50X_4 - 0.50X_5 - 0.53X_6 - 0.03X_7 + 0.02X_8 + 0.60X_9 + 1,58X_{10} + e_i \quad (12)$$

$$G_f = -1.39 - 0.03X_1 + 0.75X_2 + 0.74X_3 + 0.98X_4 + 0.98X_5 + 0.38X_6 + 0.06X_7 - 0.05X_8 - 0,70X_9 - 0.01X_{10} + e_i \quad (13)$$

In this study, with MOGA calculated 52 optimal production cases based on maximum watermelon yield and minimum total greenhouse gas emissions (Table 9). Moreover, the best production scenario with minimum energy usage was identified. Thus, production No. 26 was identified as the best production scenario with minimum energy usage. This means that this production scenario had the highest production amount with low production costs and low production-related GHG emissions. The total energy usage and GHG emissions of the best cultivation scenario were identified to be 10,900 MJ ha⁻¹ and 282 kg CO_{2eq} ha⁻¹. In the final part of this investigation, the potential for the reduction of greenhouses gases was computed utilizing the MOGA method. Figure 8 above denotes the percentage contribution to the overall greenhouse gases reduction.

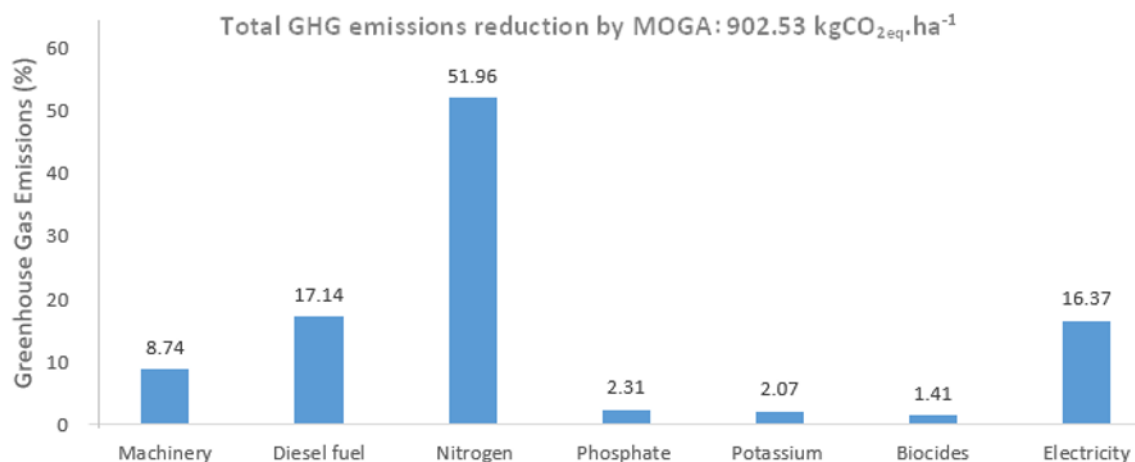


Fig. 8. Distribution of GHGE reduction for each input in watermelon production

According to the results, nitrogen 52.0% had the highest contribution to greenhouse gas reduction, followed by diesel fuel (17.1%) and machinery 16.4%. Therefore, as a first step, reducing diesel fuel consumption and optimizing machinery use through timely maintenance and proper machine selection is recommended. Adopting minimum tillage, no-tillage systems, and the use of biofertilizers in place of chemical fertilizers can significantly reduce both energy consumption and GHGE in the research field.

Table 9. Multi-Objective Genetic Algorithm Results for Optimization of Energy Inputs and GHGE in Watermelon Production

Generation number	Optimum Energy Use (MJ ha ⁻¹)										Total energy use
	Human labor	Machinery	Diesel fuel	Nitrogen	Phosphate	Potassium	Biocides	Farm yard manure	Electricity	Seed	
1	2281	243	1101	8384	604	454	58	45	739	4,98	13914
2	2337	235	1036	10579	609	461	49	42	736	4,47	16088
3	2452	243	1100	11454	629	505	51	43	780	4,64	17262
4	2397	232	1055	10760	600	473	49	41	738	4,50	16349
5	2365	221	1033	8390	556	422	54	43	695	5,14	13785
6	2262	239	1040	8723	602	431	57	46	733	5,24	14138
7	2421	247	1105	9598	622	475	59	47	777	5,41	15355
8	2281	235	1059	8904	593	443	56	46	735	5,27	14357
9	2110	229	1011	7462	548	391	62	41	700	4,5	12560
10	2155	246	1018	7795	594	401	64	44	738	4,6	13061
11	2226	254	1083	8670	615	445	66	45	782	4,8	14191
12	2395	243	1037	7976	586	412	64	43	740	4,7	13502
13	2365	233	1015	9149	558	448	51	45	697	5,3	14567
14	2262	250	1022	9482	604	458	53	49	735	5,4	14920
15	2421	258	1087	10357	625	502	55	49	779	5,6	16138
16	2281	247	1042	9662	596	469	53	48	737	5,4	15140
17	2176	214	1054	7293	551	418	59	43	699	4,72	12512
18	2248	231	1119	7626	597	428	61	46	737	4,81	13097
19	2415	239	1074	8501	617	471	63	47	781	4,98	14214
20	2387	228	1025	7806	588	439	61	46	739	4,84	13325
21	2284	217	1032	6365	544	388	47	48	696	5,48	11626
22	2443	235	1097	6698	590	398	50	51	734	5,58	12299
23	2302	243	1052	7573	610	441	52	51	778	5,75	13108
24	2262	232	1030	6879	581	409	50	50	736	5,61	12233
25	2421	225	1037	8051	558	445	55	42	701	4,88	13540
26	2094	211	1002	5941	532	376	46	39	693	4,38	10939
27	2110	250	1056	9259	625	498	60	45	783	5,15	14692
28	2411	239	1028	8565	596	466	57	44	741	5,00	14152
29	2353	229	1092	9250	551	415	69	46	698	5,65	14708
30	2468	246	1047	6880	597	424	67	49	736	5,75	12520
31	2413	254	1025	7213	617	468	53	50	780	5,91	12880
32	2381	243	1032	8088	588	436	56	48	738	5,77	13616
33	2278	250	1096	7394	552	385	58	44	784	4,62	12845
34	2437	240	1051	5952	598	394	55	47	742	4,71	11521
35	2297	257	1021	6285	618	438	61	48	704	4,88	11734
36	2126	265	1034	7160	589	406	63	46	742	4,74	12437
37	2170	254	1099	6466	545	440	65	48	786	5,38	11879
38	2242	221	1053	7638	591	450	63	51	744	5,48	13059
39	2411	238	1005	7972	611	493	50	52	701	5,65	13538
40	2381	246	1012	8847	582	461	52	50	739	5,51	14376
41	2278	235	1077	8565	537	410	54	46	783	4,78	13989
42	2437	224	1031	9495	583	419	52	49	741	4,88	15037
43	2297	242	1009	9828	604	463	58	50	706	5,05	15261
44	2192	250	1016	10703	575	431	60	48	744	4,90	16024
45	2264	239	1081	10008	593	380	62	50	788	5,55	15470
46	2431	232	1036	7639	613	389	60	53	746	5,64	13206
47	2403	254	1007	7972	584	433	59	54	703	5,81	13475
48	2299	243	1072	8847	540	401	61	53	741	5,67	14261
49	2458	236	1027	8152	586	437	59	40	785	4,96	13785
50	2318	254	1005	6711	606	446	70	43	743	5,05	12201
51	2278	261	1012	7044	577	490	68	44	776	5,22	12555
52	2437	250	1076	7919	570	458	55	42	734	5,08	13545

Optimum GHG Emissions (kgCO ₂ eq. ha ⁻¹)							
Machinery	Diesel fuel	Nitrogen	Phosphate	Potassium	Biocides	Electricity	Total GHG emissions
17	52	199,70	1,53	6,94	2,66	32,65	312
18	50	195,88	1,38	5,53	2,43	34,59	308
17	52	225,13	1,43	6,39	1,97	41,66	345
17	51	207,47	1,38	5,89	2,12	37,27	321
16	55	194,83	1,58	4,98	2,15	31,32	306
19	55	189,31	1,61	4,76	2,62	30,35	303
18	58	218,57	1,67	5,63	2,15	37,42	340
18	56	200,90	1,62	5,12	2,31	33,03	316
14	52	203,63	1,40	6,76	1,78	37,01	316
17	52	198,12	1,43	6,54	2,25	36,04	313
15	55	227,37	1,48	7,40	1,78	43,10	351
15	53	209,71	1,43	6,90	1,94	38,72	327
15	57	197,07	1,63	5,99	1,97	32,77	312
18	58	191,55	1,66	5,77	2,43	31,80	309
17	60	220,81	1,72	6,64	1,97	38,86	347
17	58	203,14	1,67	6,13	2,12	34,48	322
17	54	205,87	1,45	6,15	2,38	32,18	319
20	55	200,36	1,48	5,93	2,85	31,21	316
18	57	229,61	1,53	6,79	2,38	38,27	353
18	55	211,95	1,49	6,29	2,54	33,89	329
14	60	199,30	1,69	5,38	2,57	27,94	310
17	60	193,79	1,72	5,16	3,03	26,97	307
16	62	223,05	1,77	6,02	2,57	34,03	345
16	60	205,38	1,72	5,52	2,72	29,65	321
14	52	200,75	1,50	7,16	2,20	33,63	311
12	50	186,12	1,35	4,59	1,76	26,41	282
16	54	194,19	1,58	7,80	2,20	39,72	315
15	53	223,45	1,54	7,30	2,35	35,33	338
15	57	205,78	1,74	6,39	2,38	29,39	317
18	57	193,14	1,77	6,17	2,85	28,41	308
17	60	187,63	1,82	7,04	2,38	35,48	310
17	58	216,88	1,78	6,53	2,54	31,09	333
12	54	199,22	1,42	5,60	2,50	32,24	307
16	54	201,94	1,45	5,37	2,65	31,26	312
14	57	196,43	1,50	6,24	2,13	38,33	315
14	55	225,69	1,46	5,74	2,59	33,94	338
15	59	208,02	1,66	4,83	2,13	31,65	322
18	60	195,38	1,69	4,61	2,28	30,67	312
16	62	189,87	1,74	5,47	2,31	37,74	315
16	60	219,12	1,69	4,97	2,78	33,35	338
15	56	201,46	1,47	6,61	2,31	27,41	310
18	57	204,18	1,50	6,39	2,47	26,43	315
16	59	198,67	1,55	7,25	2,73	33,50	318
16	57	227,93	1,51	6,75	2,40	29,12	341
16	62	210,26	1,71	5,84	2,55	33,09	330
19	62	197,62	1,74	5,62	2,03	32,12	319
18	64	192,11	1,79	6,48	2,49	39,19	323
17	62	221,36	1,74	5,98	2,03	34,80	345
13	63	203,70	1,52	6,52	2,18	28,85	319
16	63	199,06	1,55	6,29	2,21	27,88	316
15	65	196,82	1,61	7,16	2,68	34,95	323
15	64	199,55	1,56	6,66	2,21	30,56	319

CONCLUSIONS

This study aimed to evaluate artificial neural net (ANN) models to make predictions based on energy input (EI) consumption by optimizing the EI and greenhouse gas emissions (GHGE) in Adana province, where watermelon is grown in the Mediterranean region of Türkiye.

1. Evaluations were made in terms of EI and energy output (EO), yield, Renewable energy (RE), energy efficiency (EE), specific energy (SE), and net energy (NE). For watermelon cultivation, the total EI was computed as 50,100 MJ ha⁻¹, with 77.0% attributed to chemical fertilizers. The EO was computed at 63,300 MJ ha⁻¹. Large-scale farms showed high EC and EO at 53,100 and 66,100 MJ ha⁻¹, respectively. Differences between EI and EO were not significant among the three farm size levels. The mean measures of EUE, EE, SE, NE, and ED were determined to be 1.26, 0.79 kg MJ⁻¹, 1.59 MJ kg⁻¹, 13,200 MJ ha⁻¹, and 10.30 MJ\$⁻¹.
2. Results revealed that medium sized farms had significantly higher ER, EE, and NE values in comparison to other farms, indicating that energy was used efficiently in watermelon cultivation. It was also concluded that ER can be further improved by enhancing vegetative performance or reducing energy consumption.
3. The EUE index indicates that watermelon production is an energy-intensive process. In terms of energy generation, farm productivity can be increased by using less EI through reduced diesel fuel and natural gas consumption, electricity savings, and various energy-saving techniques while increasing output energy.
4. In watermelon production, the share of NRE sources 96.2% was much higher than that of RE sources (3.83%). The total EI composed of DE, IDE, RE and NRE was 9,900, 40,200, 1,920, and 48,200 MJ ha⁻¹, respectively.
5. The GHG analysis showed that the total GHG emissions were 1,240 kg CO_{2eq} ha⁻¹. Chemical fertilizers had the greatest part of GHGE (58.9%), followed by fuel (16.5%) and electricity (15.8%). Moreover, differences in GHGE among the three farm sizes were not statistically significant.
6. In watermelon growing, the proportion of NRE (96.2%) was substantially larger than that of RE (3.83%). The total EI including DE, IDE, RE, and NRE was 9,900, 40,200, 1,920, and 48,200 MJ ha⁻¹, respectively. Results of the GHGE indicated that total GHG emissions amounted to 1,240 kg CO_{2eq} ha⁻¹. Among those components, chemical fertilizers (GHGE) had the largest percentage (58.9%) contribution to overall GHGE followed by fuel (16.5%) and electricity (15.8%). Furthermore, differences in GHGE were not significant across the three farm sizes.
7. For this purpose, multiple ANN models were developed to estimate energy consumption. The results showed that the 10-8-2 Levenberg-Marquardt ANN model was the most accurate model to estimate watermelon production efficiency and GHGE. R² for training datasets for both watermelon performance and GHGE were 0.978 and 0.982. RMSE was 0.149 and 0.067 for watermelon performance and GHGE, respectively. MAPE was 0.006 and 0.005 for watermelon performance and GHGE, respectively. A well-trained ANN model can be applied to estimate energy consumption of other crops. In accordance with EUE examine results, the ANN model was deemed to be advantageous in modeling EI in watermelon production with high accuracy.
8. Multi-objective optimization results showed that MOGA evaluated 52 production units, including maximum yield and minimum total greenhouse gas emissions, as optimal units; however, the best production was selected based on minimum energy consumption. The total EC and GHGE of the best output were estimated at

approximately 10,900 MJ ha⁻¹ and 282 kg CO_{2eq} ha⁻¹. Furthermore, nitrogen fertilizer accounts for the largest portion of greenhouse gas reductions, at 51.96%. This saves on fertilizer consumption and significantly reduces greenhouse gas emissions.

Conflict of Interest

The authors declare no conflict of interest.

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