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Modeling of energy use and greenhouse gas emissions in orange production with artificial neural networks: case study of Turkey

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Abstract. ANN models were utilised in the case of orange (*Citrus sinensis* L.) cultivation in Adana Province to predict greenhouse gas emissions and total energy input. The share of chemical fertilizers in orange cultivation is high and was calculated as 74.47%. Energy consumption and energy output values in large farms have the highest values with 34 972.38 and 35 305.92 MJ ha^{-1}, respectively. Furthermore, there is no significant variance in energy use efficiency among the three different sizes of orange farms. In the orange cultivation, non-renewable energy sources (95.88%) have a significantly larger share than renewable energy sources (4.12%). Energy input in direct energy, indirect energy, renewable energy, and non-renewable energy sources configurations was calculated as 6 819.99, 27 185.07, 1401.98, and 32 603.08 MJ ha^{-1}. The greenhouse gas analysis showed greenhouse gas emissions equivalent to 759.58 kgCO$_{2eq}$ ha^{-1}. 56.84% of greenhouse gas emissions come from chemical fertilizers. The best Artificial neural network model training data used for orange production and greenhouse gas emissions has root mean square error values of 0.141 and 0.063, respectively, while the mean absolute percentage error values are 0.005 and 0.004, respectively. Due to the ability of Artificial neural networks to predict results, it can be effectively used in growing oranges and other plant crops.

Keywords: artificial neural network, energy productivity, greenhouse gas emissions, orange

1. INTRODUCTION

Citrus spp. is a fruit cultivated for many years. According to Barry *et al.* (2020), four primary categories of citrus fruits are commonly consumed worldwide: sweet oranges, tangerines, lemons, and grapefruits. The most widely cultivated fruit group in the world is citrus fruits, with approximately 124 million tons. When the shares in citrus production are considered, orange constitutes 56.12%, tangerine 17.23%, lemon 11.52%, golden balls 5.62%, and other citrus fruits 9.51% (FAOSAT, 2021).

In Turkey, a total of 4.8 million t of citrus fruits were harvested from 140 thousand hectares of land in 2019. Orange, scientifically known as *Citrus sinensis* L., is a type of citrus fruit. It is a winter fruit with an orange color, shiny skin, and circular shape. Orange cultivation takes place on 3.9 million ha of land globally. Brazil owns 16.4% of the area, India owns 15.6%, and China owns 13.1%. According to Ertek *et al.* (2020), Brazil yields 27.6 t ha^{-1}, China yields 25.9 t ha^{-1}, and India yields 12.7 t ha^{-1}. Orange production is rapidly growing worldwide as well as in Turkey. In 2020, Brazil took the lead by producing 17 million t of the total 75 million t of orange production, while India produced 9.9 million t, China 7.5 million t, and the USA 4.8 million t. Turkey held the 7th position with 1.8 million t (Carvalho *et al.,* 2022).

As energy consumption (EC) in agriculture increases, the need for efficient energy use in sustainable agricultural practices also increases. Therefore, both costs and greenhouse gas emissions (GHGE) are reduced at the same time protecting the environment (Klikocka *et al.,* 2019). Artificial neural networks (ANNs) are used to model EC

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and economic indicators in agriculture. In recent years, ANN techniques have been widely used to model agricultural production efficiency and GHGE (Niedbala, 2019). Various examples include corn (Farjam *et al.,* 2014), orange (Nabavi-Pelesaraei *et al.,* 2014), watermelon (Nabavi-Pelesaraei *et al.,* 2016), winter rapeseed (Niedbala, 2019), almond (Yılmaz and Bayav, 2022), watermelon (Demir, 2023), peach (Demir and Gokdogan, 2023), vetch (Seydosoglu *et al.,* 2023), garlic (Baran *et al.,* 2023), and cherry (Gokdogan *et al.,* 2024).

As a result of the literature review, it can been seen that there are not enough studies on increasing energy use efficiency and reducing GHGE through ANN modeling in orange cultivation in Adana Province. In this research conducted in Adana Province, Turkey, energy input (EI) indices in orange cultivation were determined and ANN models were developed for energy efficiency and GHGE prediction and evaluated using the best topology for prediction accuracy.

2. MATERIALS AND METHODS

The data utilized in the survey were obtained from 65 farmers producing oranges (*Citrus sinensis* L.) in Adana in the 2023 season. Adana is located in Turkey's Mediterranean Region. Adana is located between 36° 32‘17.8 "N and 38° 25' 21.7" N North latitudes and 34° 39 '34.0 "E and 36° 24' 01.4" E East longitudes (GDM, 2022).

2.1. Calculation of energy indices

To predict the energy equivalent, the yield values of orange crops including seed amounts, biocides, chemical fertilizers, farm manure, electricity, fuel, human labor, and machinery were calculated per ha (Table 1) (Demir and Gokdogan, 2023).

Energy indexes include energy use efficiency (EUE) Eq. (1), energy productivity (EP) Eq. (2), specific energy (SE) Eq. (3), energy density (ED) Eq. (4) and net energy (NE) Eq. (5) computed using Table 1 for their sizes (Nabavi-Pelesaraei *et al.,* 2016; Macedo *et al.,* 2021).

$$\text{Energy use efficiency} = \frac{\text{Energy output}}{\text{Energy input}}, \tag{1}$$

$$\text{Energy productivity} = \frac{\text{Product output}}{\text{Energy input}}, \tag{2}$$

$$\text{Specic energy} = \frac{\text{Energy input}}{\text{Product output}}, \tag{3}$$

$$\text{Energy density} = \frac{\text{Energy input}}{\text{Cost of production}}. \tag{4}$$

$$\text{Net energy} = (\text{Energy output} - \text{Energy input}). \tag{5}$$

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	62.7
Diesel fuel	L	56.31
Chemical fertilizers		
Nitrogen (N)	kg	66.14
Phosphate (P_2O_5)	kg	12.44
Potassium (K_2O)	kg	11.15
Cattle manure	kg	0.3
Pesticides		
Insecticide	kg	199
Fungicide	kg	92
Electricity	kWh	5.9
Output Orange	kg	5.9

Table 2. Greenhouse gas (*GHG*) emission parameters of agricultural inputs

Input	Unit	*GHG* coefficient (kg CO_{2eq} unit^{-1})
Machinery	MJ	0.071
Diesel fuel	L	2.76
Chemical fertilizer		
Nitrogen	kg	1.3
Phosphate (P_2O_5)	kg	0.2
Potassium (K_2O)	kg	0.2
Pesticides		
Insecticide	kg	5.1
Fungicide	kg	3.9
Electricity	kWh	0.608

In the calculation, EO – energy output (MJ ha^{-1}), EI – energy input (MJ ha^{-1}), product output (kg ha^{-1}), and cost of production (\$ ha^{-1}) data were used.

The examples consist of three groups (<1 ha, 1-2 ha, >2 ha). EUE and SE in agricultural activities are complementary indices. They are referred to as direct energy (DE), indirect energy (IDE), renewable energy (RE), and non-renewable energy (NRE) (Demir, 2023). GHGE of orange cultivation was computed (Table 2) (Ozbek *et al.,* 2024).

GHGE in orange cultivation was calculated according to Eq. (6) (Karaagac *et al.,* 2019):

$$\sum_{i=1}^{n} R(i)\ \ EF(i). \tag{6}$$

Here, GHG_{ha} – greenhouse gas emission (kgCO_{2eq} ha^{-1}), $R(i)$ – amount of i input (unit$_{input}$ ha^{-1}), $EF(i)$ – GHG emission equivalent of i input (kgCO_{2eq} unit$^{-1}_{input}$), I_{GHG}, *GHG* rate, *Y* yield in kg per hectare was calculated using Eq. (7) (Houshyar *et al.,* 2015):

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

2.2. Artificial neural network (ANN) modeling

To solve nonlinear mixed problems with ANN, the entered information continues until the input layer neurons and the output layer neurons are reached (Fig. 1) (Benti, 2023).

ANN is a computing paradigm similar to the biological nervous system. There has been a great increase in studies on ANN in recent years. In this study, the ANN model was used for training and testing 48 and 17 units (orange crop units), respectively. Selected units were obtained randomly from all samples. The number of neurons was determined according to the number of input and output layers for orange production and GHG emission. Also, more than one hidden layer modeling has been propounded for ANN modeling. The most widely used Levenberg-Marquardt learning algorithm was used for practice in ANN. The weight (*w*) span value (*x*) and its value at each node controlling output (*O*) were changed using the value corresponding to Eq. (8) (Nabavi-Pelesaraei *et al.,* 2016):

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

Here, *f* is a non-linear sigmoid function. *T* is a specific threshold (bias) value for each node. In this study, parameters of root mean square error (*RMSE*), coefficient of determination (R^2), and mean absolute percentage error (*MAPE*) were utilized (Bhatti and Do, 2019). The models were trained with the training throughput and tested with the test throughput, and *RMSE* was computed using Eq. (9):

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

In addition to *RMSE*, which is valuation used for statistics, R^2 predictive value was also found with Eq. (10):

$$R^2 = \frac{\left[\sum_{i}^{m}(yi-\overline{y})(Oi-\overline{O})\right]}{\sum_{i=1}^{m}(yi-\overline{y})^2\sum(Oi-\overline{O})^2}. \quad (10)$$

Concerning the R^2, *m* is the count of throughput tested, throughput predicted in O_i ANNs, *yi* is the quantity of computed throughput. If *y* is the mean of the computed throughput quantity (*yi*), *O* is the average value of the predicted throughput quantity (O_i) in the ANNs. In addition, *MAPE* values were calculated using Eq. (11):

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

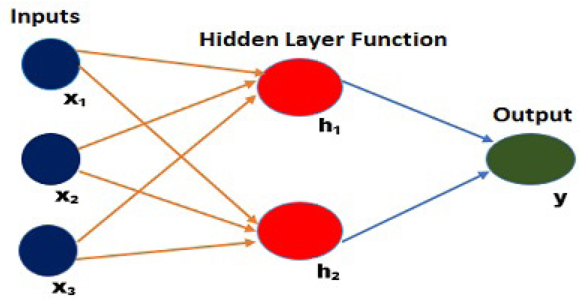

Fig. 1. Artificial neural network model.

N indicates the number of training vectors, and output for the training vector "*y*" and " *y'* " indicates observed and simulated values, respectively. In this study, basic information about EI and outputs (energy efficiency, GHG emission) in orange cultivation was coded into Excel 2016 and Matlab (R2019a), a program used to realize the ANN model.

3. RESULTS AND DISCUSSION

3.1. Analysis of energy use in orange cultivation

In the study, equivalent energy input (EI) and energy output (EO) in three groups of orange cultivation areas were examined (Table 3). The average energy requirement for orange production was approximately 31116.50 MJ ha^{-1}. Orange cultivation has the highest EC and efficiency in the large scale farm models.

While the results revealed that there was no considerable difference between the three farm groups in terms of EI, a considerable difference was monitored when compared in terms of orange cultivation. Among the fertilizers used in the orange production, N has the highest EC at approximately 53.66%, followed by electricity consumption at 6.47% and diesel fuel at 5.64%. Also, the share of the other inputs in orange production is lower than the average EI. Thus, in the orange production with the management of N consumption, EUE can be improved by using farmyard manure instead of chemical fertilizers. The effect of orange production inputs on total energy use is shown in Fig. 2.

In previous research, EI was declared to be approximately 46 349 MJ ha^{-1} for orange production, the highest EC was attributed to chemical fertilizers 28 566.22 MJ ha^{-1}, and diesel fuel consumption was 3 025.77 MJ ha^{-1} (Nabavi-Pelesaraei *et al.,* 2014). EUE, EP, SE, NE, and ED are given in Table 4 according to the farm size levels specified in this study. EUE for orange production was determined as 1.01. The EUE results of other research are as follows: 2.49 for sesame (Ozbek *et al.,* 2024) and 0.95 for cherry (Gokdogan *et al.,* 2024). In another study, EI and EO in cotton cultivation were calculated as 54 617.62 and 65 984.42 MJ ha^{-1}, respectively (Baran *et al.,* 2021). In cherry, these values were calculated as 14 934.30 and 14 234.67 MJ ha^{-1} (Gokdogan *et al.,* 2024).

Table 3. Energy input – Energy Output relationship in the orange cultivate

Inputs (MJ ha^{-1})	Farm size groups (ha)			Average (MJ ha^{-1})	Percentage (%)
	Small (<1)	Medium (1-2)	Large (>2)		
Human labor	12026	1471	1476	1444	4.64
Machinery	1366	1550	1640	1515	4.87
Diesel fuel	1211	1817	1812	1754	5.64
Chemical					
Nitrogen (N)	14249	16306	19979	16697	53.66
Phosphate	913	2004	2237	1932	6.21
Potassium	3782	4671	4457	4544	14.60
Cattle manure	551	614	585	603	1.94
Pesticides					
Insecticide	136	244	294	242	0.78
Fungicide	158	387	418	369	1.19
Electricity	1948	2010	2070	2013	6.47
Total energy input	255211	31079	349728	31116	100.00
Output Orange	22860	31720	35305	31402	

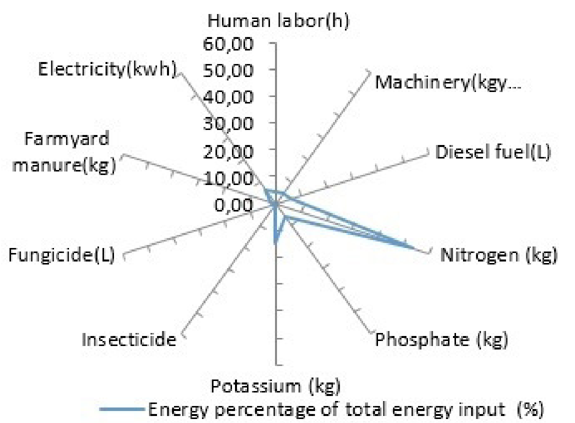

Fig. 2. Effect of orange production inputs on total energy use.

As can be seen in Table 4, small-scale farms have the lowest EUE in orange production (0.90) since the ratio of EO to EI is the lowest. Accordingly, the energy use in orange production on small-scale farms in Adana Province in Türkiye is not efficient. In addition, EP, SE, NE, and ED were calculated as 1.01 kg MJ^{-1}, 1.00 MJ kg^{-1}, 286.30 MJ ha^{-1} and 2.21 MJ \$$^{-1}$, respectively. According to the results, 79.94% of the total EI share is IDE and 20.06% is DE. Moreover, 4.12% of the total EI used in orange cultivation was provided from quite low RE sources (Table 4). Therefore, the share of NRE in terms of EC in orange cultivation is considerably higher than RE sources. Efficient use of fuel and irrigation can reduce the rate of NRE. The results obtained are consistent with the literature for different crops.

Table 4. Energy input-energy output ratio in the orange cultivate

Energy types	Unit	Farm size groups (ha)			Average	Percentage (%)
		Small (<1)	Medium (1-2)	Large (>2)		
Energy use efficiency	–	0.90	1.02	1.01	1.01	-
Energy productivity	kg MJ^{-1}	1.22	1.01	0.91	1.01	-
Specific energy	MJ kg^{-1}	0.73	1.01	1.12	1.00	-
Net energy	MJ ha^{-1}	-2660	640	333	286	-
Energy density	MJ \$$^{-1}$	1.82	2.20	2.45	2.21	-
Direct energy	MJ ha^{-1}	55185	6723	7494	6819	20.06
Indirect energy	MJ ha^{-1}	22407	27299	30430	27185	79.94
Renewable energy	MJ ha^{-1}	10694	1302	1452	1401	4.12
Non-renewable energy	MJ ha^{-1}	268571	32719	36473	32603	95.88
Total energy input	MJ ha^{-1}	27926	34022	37925	34005	100

3.2. Greenhouse gas emissions in orange cultivation

GHGE from the three groups of orange cultivation is shown in Table 5. GHGE was found to be 759.58 kgCO_{2eq} ha^{-1}. In a similar study, it was reported that CO_2 emission in tomato production was calculated as approximately 322.75 kg CO_{2eq} ha^{-1} (Sarkar *et al.,* 2022). In another study, GHG emission in okra farming was calculated as 875.41 kg CO_{2eq} ha^{-1} (Sarkar *et al.,* 2022). In organic fig cultivation, the total greenhouse gas emission was calculated as 1109.02 kg CO_{2eq} ha^{-1} (Oguz *et al.,* 2022). The distribution of GHGE in this study is given in Table 5.

While the portion of GHGE in orange cultivation has the highest share in large farms, GHGE has the lowest share in small-scale farms. In the table, there is no significant difference in GHGE between the three different farm groups in orange production. According to the table, the nitrogen fertilizer has the highest ratio (41.89%) in the total GHGE, followed by diesel fuel (14.09%) and electricity consumption (13.77%). The contribution of orange production inputs to the use of GHGE is shown in Fig. 3.

In the case of sufficient rainfall, reduction of irrigation water (electricity consumption) and good agricultural management (reduction of chemical fertilizers) in orange production can reduce GHGE.

3.3. ANN model structure and evaluation

Various nets were trained in the Matlab (R2019a) program using the method of the Levenberg-Marquardt algorithm to predict orange production and GHGE and provide the best model. Using training sets, prediction models contain 75% of data. Test data sets containing 48 samples were used to test the developed network. As seen in Table 6, statistical indicators were used to predict orange production yield and GHGE to evaluate the ANN models. After

Table 5. Greenhouse gas (GHG) emission of inputs used in orange cultivation

Inputs	Farm size groups (ha)			Average (kg CO_{2eq} ha^{-1})	Percentage (%)
	Small (<1)	Medium (1-2)	Large (>2)		
Machinery	75.75	90.09	106.44	94.63	12.46
Diesel fuel	79.37	99.10	118.83	107.01	14.09
Chemical fertilizer					
Nitrogen	280.07	320.51	392.70	318.19	41.89
Phosphate (P_2O_5)	14.68	32.23	35.98	30.07	3.96
Potassium (K_2O)	67.84	83.79	79.95	83.51	10.99
Pesticides					
Insecticide	3.51	6.27	7.55	6.11	0.80
Fungicide	6.74	16.43	17.74	15.45	2.03
Electricity	99.28	102.47	105.50	104.60	13.77
Total GHG emissions	627.24	750.89	864.69	759.58	100.00

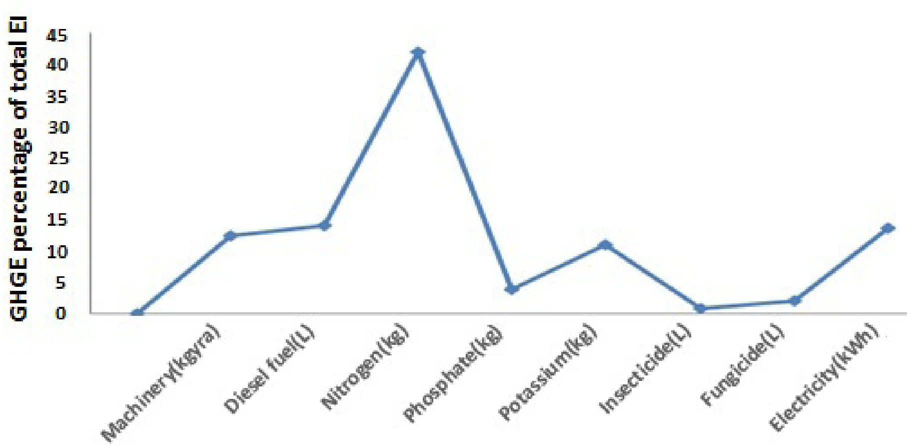

Fig. 3. Contribution of orange production inputs to the use of greenhouse gas emission.

Table 6. Result of different models

Topology	Model categories	Statistics indices	Output layer	
			Orange yield	Greenhouse gas emissions
10-7-2	Train	R^2	0.911	0.925
		RMSE	0.154	0.068
		MAPE	0.011	0.010
	Test	R^2	0.904	0.935
		RMSE	0.122	0.027
		MAPE	0.010	0.008
10-6-2 (Best)	Train	R^2	0.974	0.986
		RMSE	0.141	0.063
		MAPE	0.005	0.004
	Test	R^2	0.959	0.989
		RMSE	0.114	0.031
		MAPE	0.004	0.002
10-5-2	Train	R^2	0.907	0.918
		RMSE	0.182	0.094
		MAPE	0.019	0.016
	Test	R^2	0.903	0.937
		RMSE	0.147	0.049
		MAPE	0.019	0.017

trial and error processing, the best performance was obtained with an ANN model with a 10-6-2 topology with a statistical indicator. The structure of the selected ANN is shown schematically in Fig. 4. Training and test results are shown in Table 6. Therefore, the best topology in orange farming and GHGE, the highest R^2, and the lowest RMSE and *MAPE* values tend to closely follow the predicted orange farming and GHG emission in the ANN models, both training and testing. The amount of R^2 varies in the range of 0.907-0.986 for the training data and 0.903-0.989 for the test data.

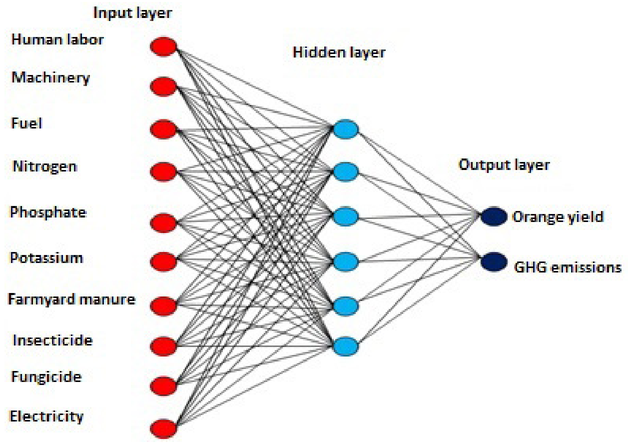

Fig. 4. Artificial neural networks model with 10-6-2 topology.

An ANN model of winter rapeseed yield was developed to predict indices EC, and it was found that the best model was the 21-13-6-1 topology. The best R^2 and MAE values showing the superiority of this ANN model to the prediction models were 0.98 and 0.00943, respectively (Niedbala, 2019). The coefficient of determination (R^2) for watermelon yield and GHGE of the ANN model with an 11-10-2 structure was calculated as 0.969 and 0.995, respectively (Nabavi-Pelesaraei *et al.,* 2016). For the ANN model (R^2) with a 6-3-9-1 topology, the coefficient of determination for grain corn yield and GHGE was calculated as 0.982 (Farjam *et al.,* 2014). The distribution graph of the predicted EO, GHG emission in orange cultivation, training, and test data sets for real values are shown in Figs 5 and 6. The predicted and real output energy values are consistent with each other. The determination coefficient for these indices showed the suitability of the output energy of the developed network and the GHG emission in orange farming in the areas examined. For the training data, the R^2 coefficient of orange yield and GHGE was found to be 0.974 and

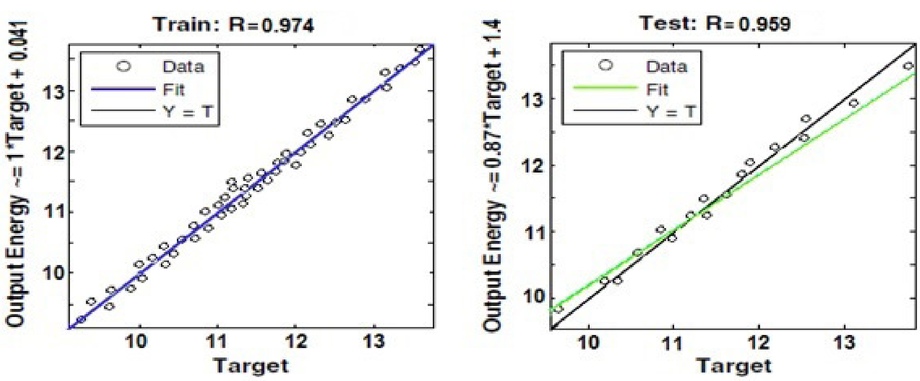

Fig. 5. Correlation between predicted and real outputs energies based on the best topology.

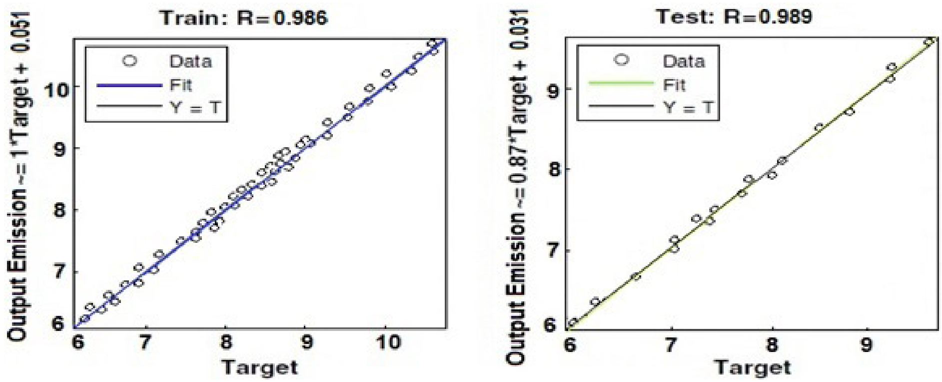

Fig. 6. Correlation between predicted and real outputs greenhousegas emission based on the best topology.

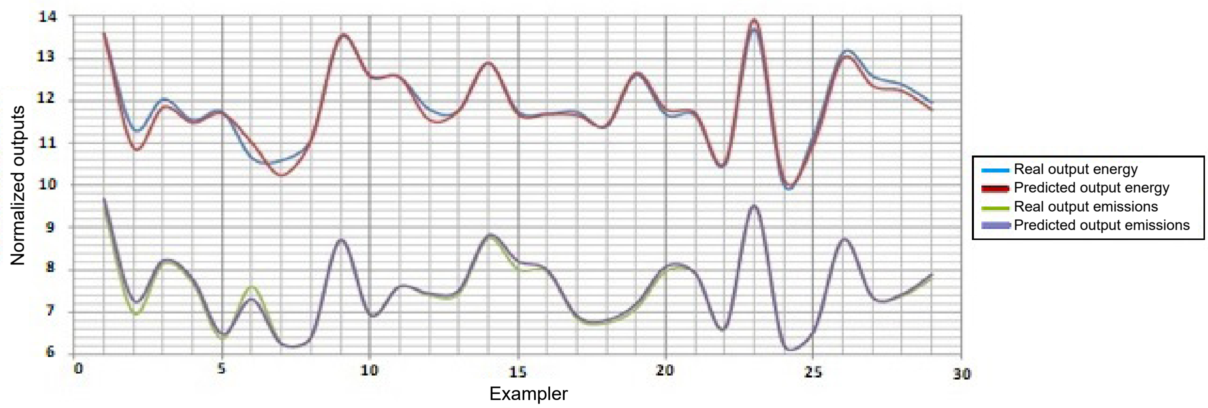

Fig. 7. Predicted and real output energy values.

0.986. Also, the coefficient of determination R^2 of orange yield and GHGE for the test data was found to be 0.959 and 0.989.

In Fig. 7, the perpendicular axis indicates uniform outputs; it shows the predicted number of data sets on the horizontal axis. Blue and green lines represent the actual output values. The red and magenta color lines show the accuracy of the model as the predicted values were close.

3.4. Sensitivity analysis (SA)

Sensitivity analysis is carried out to test the accuracy of the consequence of a model. In the SA with ANN, entry variants were listed by handling fractional differential study (Table 7).

Table 7. Sensitivity analysis results for input energies

Inputs	Orange yield	Greenhouse gas emissions
Human labor	0.016	0.058
Machinery	0.002	0.001
Diesel fuel	0.024	0.003
Nitrogen	0.004	0.045
Phosphate	0.006	0.050
Potassium	0.006	0.051
Farmyard manure	0.011	0.048
Biocides	0.008	0.034
Electricity	0.009	0.017
Seed	0.026	0.027

4. CONCLUSIONS

The aim of the study was to assess the ANN model's accuracy in predicting GHGE and EI for orange farming in Adana. The EI in orange farming was computed as totaled 31 116.50 MJ ha^{-1} due to the use of chemical fertilizers (74.47%), with an Energy output (EO) of 31 402.8 MJ ha^{-1}. Large farms have the highest EC and EO values with 34 972.38 and 35 305.92 MJ ha^{-1}, respectively. Furthermore, the difference in performance between the EUE is not important for the three different scales of orange plantations. The average values for EUE, EP, SE, NE, and ED were calculated to be 1.01, 1.01 kg MJ^{-1}, 1.00 MJ kg^{-1}, 286.30 MJ ha^{-1}, and 2.21 MJ \$$^{-1}$, respectively. The findings indicate that medium farms have notably higher EUE and NE, compared to other farms. This demonstrates that energy is effectively utilized in the process of growing oranges. Furthermore, it is concluded that improving vegetative efficiency or decreasing EC can further enhance energy efficiency. The EUE index indicates that growing oranges requires a significant amount of energy. Regarding energy production, operational efficiency and its EO can be increased by implementing various strategies such as reducing EI (diesel fuel, natural gas), saving electricity.

In the field of orange cultivation, NRE sources account for a significantly larger portion (95.88%) than RE sources (4.12%). The EI values for DE, IDE, RE, and NRE configurations were calculated as 6819.99 MJ ha^{-1}, 27185.07 MJ ha^{-1}, 1401.98 MJ ha^{-1}, and 32603.08 MJ ha^{-1}, respectively. The analysis of greenhouse gas (GHG) emissions indicated 759.58 kg CO_{2eq} emitted per hectare. The largest contribution to GHGE is from chemical fertilizers at 56.84%, followed by diesel fuel at 14.09% and electricity at 13.77%. Additionally, there is no substantial difference in GHGE among the three farm groups. Several ANNs were created in this research to simulate EC, with the most effective being the ANN model utilizing the Levenberg-Marquardt Algorithm. This model, with a 10-6-2 structure across all energy indices, is superior in predicting orange production efficiency and GHGE. In the best topology, training data, R^2 values for the yield of orange production and GHGE were 0.974 and 0.986, respectively, while the *RMSE* values were 0.141 and 0.063, and the *MAPE* values were 0.005 and 0.004, respectively. It was concluded that a well-trained ANN could be widely applied to other crops and other areas of work, thanks to its considerable predictive ability.

According to the EUE analysis results, it was determined that the ANN model is advantageous in terms of modeling energy indices in orange production with high accuracy. In sensitivity analysis, the share of seed and human labor in the prediction of efficiency and GHGE, respectively, in orange farming has the highest share in terms of EI and CO_2 emissions. In terms of EUE in orange cultivation, various measures should be taken to reduce the consumption of chemical fertilizers, fuel, EC, and GHGE.

Conflict of interest: The authors declare no conflict of interest

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