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Analysis and Modeling of Yield, CO_2 Emissions, and Energy for Basil Production in Iran using Artificial Neural Networks

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Abstract

The present study attempts to investigate the potential relationship between input energies, performance production of greenhouse basil, and greenhouse gases emitted from this product. The data were collected from 24 greenhouses using a questionnaire and verbal interaction with farmers. Results of the study showed that the total input energy and total output energy for basil production were 119,852.9 MJ/ha and 61,040 MJ/ha, respectively. The highest rate of energy consumption was related to electricity (52,200 MJ/ha), followed by plastic (23,220 MJ/ha) and chemical fertilizers (13,894 MJ/ha). The energy and productivity indices were estimated at 0.45 and 0.21, respectively, which indicated that the efficiency of energy in the agricultural sector was low. In addition, it was found that the pure energy index and total greenhouse gases emitted from basil production were equal to -722,706.9 and 9,595.6 kg (CO_2), respectively. The highest emission of greenhouse gases was attributed to electricity (2,216 kg/CO_2). Results of modeling proved that artificial neural networks can predict basil performance and CO_2 emissions with a high degree of accuracy (R^2=0.99 and MSE= 0.00023).

Keywords:
artificial neural networks, basil, CO_2, energy flow

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INTRODUCTION

In recent years, development and enhancement of advanced agricultural equipment have led to a remarkable increase in the energy use in this sector so that agricultural operations have become heavily dependent on fossil fuel resources. It has been projected that the total human population of the world would reach 10 billion by 2040. Additionally, the global storage of oil is expected to deplete in 40 years. Such conditions would coerce governments into producing larger amounts of food with less resources of energy. Regarding the aforesaid notions, humankind would be forced to supply for 10 billion people. Due to the fact that many arable lands have been filled with crops in recent years, it seems that employing new methods and optimized usage of arable lands would be the only available way to overcome this problem. Food production must be compatible with the population increase; otherwise, friendly living status of humankind would be put at risk. Thus, production methods that can offer higher rates of yield along with lower amounts of energy consumption would be successful. One of the new methods of intensive agriculture is greenhouse cultivation (Alam et al., 2005). This method is capable of boosting production through optimizing the cultivation context as well as is able to consume more energy out of lower level. This method is categorized by some advantages and disadvantages. One of the benefits of the method is more production per unit area so that one can obtain 10 times more production in the same area (Ozkan et al., 2004). Another advantage of this method is cultivated in seasons other than main season. This advantage has led to the fact that the farmer embarks on doing this by exploiting more resources; however, there are disadvantages in the establishment of greenhouse cultivation. The main drawback of this method is excessive consumption of energy by producers so that they make use of higher values of energy for cultivation. Likewise, due to the low cost of energy in Iran, farmers make no efforts to reduce energy consumption rate. Consequently, a large portion of farmers' income is devoted to supply energy. Analyzing the quality of cultivation along with offering solutions for the reduction of energy consumption enables high-level production using lower amounts of energy resources (Canakci et al., 2005). Each method contributing to the reduction of energy consumption decreases total production cost and increases producer's income. The aim of this research was the examination and determination of basil energy consumption using energy indices (energy efficiency, energy ratio, and added pure energy) and the extent of greenhouse gases emitted from this product.

Alam et al. (2005) investigated energy flow in agricultural sector of Bangladesh over the years 1980-2000. Their examinations were focused on human, animal, machinery, electricity, gasoline, fertilizers, and chemical pesticide subsectors. They reported that energy input and output of agricultural products increased from 6.4 to 17.32 GJ/ha and from 72.22 to 130.05 GJ/ha, respectively, during the studied period. It was concluded that the efficiency of energy (the ratio of input to output) was decreased from 11.23% to 8.1%. Thus, energy input increased faster than the output leading to the decrease in efficiency of energy consumption.

Some researchers investigated four types of greenhouse vegetables in Turkey and concluded that the cucumber had the highest energy among four crops (tomato, cucumber, pepper, and eggplant) categorized by 77.134 GJ/ha. The amount of energy consumption of tomato, eggplant, and pepper was 32.127, 68.98, and 80.25 GJ/ha, respectively. The ratio of energy for tomato, pepper, and eggplant was 1.26, 0.99, and 0.61, respectively. This implies that the increase in inputs is not always accompanied by the increase in outputs in case of producing greenhouse vegetables. This causes problems such as global warming, increase in nutrition in soil, and pollution caused by pesticides (Ozkan et al., 2004). Hence, it is necessary to force the producers to determine the extent of using a contributing factor of energy to increase performance without reducing natural resources. The generation and emission of greenhouse gases in the atmosphere were the undesirable repercussions of excessive use of natural resources in the 20th century.

Global warming is concerned with changes in the Earth induced by human-based activities. The Earth has gotten warmer (more than 0.4°C°C) due to non-normal behaviors. Greenhouse gases related to livestock productions in the agricultural sector have been increased by 14%, reaching up to 4.7 billion tonnes. Such an increase is to some extent due to the increase in total agricultural output and is usually observed in developing countries. Agricultural policies tend to enhance systems which are able to produce more energy while consuming lower amounts of energy (Dalgaard, 2000). Several studies have been carried out in relation to energy consumption and environmental effects of agricultural crop production. The main scope of these studies was to evaluate energy consumption in agricultural crop production (Alluvione et al., 2011; Barut et al., 2011). The average energy consumption has been studied in Iran (Mousavi-Avval et al., 2011; Royan et al., 2012; Tabatabaeefar et al., 2009). However, few studies have addressed the environmental effects of greenhouse gases derived from agricultural activities in Iran (Alam et al., 2005). This is the reason why few information is available regarding the amount of fuel and energy consumption as well as the emission of greenhouse gases caused by agricultural operations (Soltani et al., 2013).

Among the issues on which researchers have tended to draw their attention are predicting, estimation, and modeling of energy flow. It is evident that planning and optimizing the inputs would require modeling of this flow. A variety of methods have been employed to model energy flow and the association between farm (input) and farm performance (output). Regression analysis used to be regarded as the main modeling method until Artificial Neural Networks (ANNS) were developed (Safa & Samarasinghe, 2011).

Recently, the number of scientists and engineers who are interested in modeling of energy consumption and related environmental impacts have been increased (Al-Ghandoor et al., 2009). In the energy area, a wide range of models, from geological models in research on natural resources for modeling future energy demand, has been developed (Safa & Samarasinghe, 2011). Several studies have used ANNs for classifying,predicting, and solving problems in the field of energy. Some researchers have analyzed world primary energy resources, including fossil fuels such as coal, oil and natural gas, using feed forward, back propagation ANN (Rahman & Bala, 2010). Application of ANNs to estimate jute production in Bangladesh was reported by Rahman and Bala (2010). They used an ANN model with six input variables, including Julian day, solar radiation, maximum temperature, minimum temperature, rainfall, and type of biomass to predict the desired variable (plant dry matter) (Rahman & Bala, 2010). Pahlavan et al. (2012) developed a network to predict greenhouse basil production. Safa and Samarasinghe (2011) used ANNs for determination and modeling of energy consumption in wheat production. They compared ANNs with Multiple Linear Regression. They found that artificial neural networks can predict energy consumption better than regression models. The artificial neural network is mainly used to predict energy consumption, energy demand, environmental problems, etc. Relative performance of artificial neural networks has been reported by traditional statistical methods.

No study has been carried out in Chaharmahal-Bakhtiary Province on the basil input and output consumed energy. The aim of the present study was to (1) investigate energy consumption for basil production, (2) calculate different indices of energy efficiency of basil product, (3) determine greenhouse gases derived from basil production, (4) predict energy output of basil production, and (5) examine greenhouse gas emissions based on the input energy.

MATERIALS AND METHODS

Data collection and calculation

The scope of production was considered in Chaharmahal-Bakhtiary Province, Iran. Data were collected from 24 greenhouses in the selected region. The data collection was made by questionnaires and the information on the consumed inputs, the employed machines, and the number of workers was gathered using random sampling. Chaharmahal-Bakhtiary Province is

Table 1
Energy Coefficients of Different Inputs and Outputs in Basil Production

Input/output	Unit	Energy coefficient (MJ/unit)	Ref.
A. Input			
1. Human labor	H	1.96	(Mohammad Shirazi et al., 2012)
2. plastic	Kg	90	(Canakci et al., 2005)
3. Irrigation	M3	1.02	(Erdal et al., 2007)
4. FYM	Kg	0.3	(Mousavi-Avval et al. 2011b)
5. Chemical fertilizers	Kg		
N		60	(Chauhan, Mohapatra, & Pandey, 2006)
K_2O		6.7	(Chauhan et al., 2006)
P_2O_5		11.1	(Chauhan et al., 2006)
Fe		120	(Mandal et al., 2002)
6. Chemicals	Kg		
Fungicides		216	(Erdal et al., 2007)
7. Machinery	Kg yr^a	62.7	(Canakci et al., 2005)
8. Diesel fuel	L	43.99	(Coxworth et al., 1995)
9. Electricity	KWh	3.6	(Ozkan et al., 2004)
B. Output			
1. Basil yield	Kg	2.18	Calculated

Table 2
GHG Emissions Coefficients of Agricultural Inputs

Inputs	Unit	GHG Emissions Coefficient (kg CO_{2eq} $unit^{-1}$)	Ref.
N	Kg	1.3	(Lal, 2004)
K_2O	Kg	0.2	(Lal, 2004)
P_2O_5	Kg	0.2	(Lal, 2004)
Machinery	MJ	0.071	(Dyer & Desjardins, 2006)
Diesel fuel	L	2.76	(Pishgar-Komleh et al., 2012)
Electricity	KWh	0.608	(Khodi & Mousavi, 2009)
Fungicide	Kg	3.9	(Lal, 2004)

located within the latitudes of 31°9' and 32°38' N and longitudes of 49°30' and 51°32 E. The input energies of the current study included labor, seed, irrigation water, fertilizer, chemical pesticides, diesel fuel, machinery, plastics, and electricity. To calculate the input and output energies, energy equal coefficients were used as shown in Table 1.

Having determined the share of each energy resource for supplying different inputs, the amount of greenhouse gas (GHG) emissions by the energy resource consumption was calculated in terms of a coefficient (Table 2).

The input energy was calculated based on the principle that human force energy is calculated in agricultural operations. In this regard, it was assumed that each farmer works 210 days and 8 hours per day.

To calculate the energy required for annual manufacturing and machine maintenance, the following equation was used (Hatirli et al., 2005).

$$ME=(G.E)/(T.Ca) \quad (1)$$

where, ME is the energy of machine manufacturing (MJ/ha), G is a constant equal to 158.3 (MJ/kg), Ef is the weight of the tractor (kg), T is the economic life of the tractor (h), and C_a is the effective capacity of the farm (ha/h) which is calculated by Eq. (2):

$$C_a=(S.W.E_f)/10 \quad (2)$$

where, S is the working speed (km/h), W is the effective working width of the machine (m) and Ef is the farm efficiency.

Tractor fuel consumption is obtained in terms of energy by:

Gasoline tractor (lit/h): 0.06 × tractor power in 3.78 PTO

Diesel tractor (lit/h) = 0.73 × gasoline tractor fuel

Power at the PTO is considered as 80% of tractor nominal power.

To calculate the energy of fertilizers, pesticides and seeds, their consumption rate was multiplied by their energy equivalent (Table 1). The input energy of agriculture sector was obtained using the multiplication of a conversion factor by its amount (Table 1).

Indices are powerful tools which enable the comparison of systems and detailed study of them. They are calculated by Equations 3 to 6 (Pishgar-Komleh et al., 2012).

$$\text{Energy uses efficiency} = \frac{Energy\ output(\ MJ\ ha^{-1})}{Energy\ input\ (MJ\ ha^{-1})} \quad (3)$$

$$\text{Energy productivity} = \frac{Basil\ output\ (kg\ ha^{-1})}{Energy\ input(MJ\ ha^{-1})} \quad (4)$$

$$\text{Specific energy} = \frac{Energy\ input(MJ\ ha^{-1})}{yield\ \ (kg\ ha^{-1})} \quad (5)$$

Net energy: this index indicates the net output energy of the farm. The negative value of this number shows that the amount of input energy is not equal to the output energy, so this indicates that energy consumption is inefficient.

$$Net\ energy = Energy\ output(MJ\ ha^{-1}) - Energy\ input\ (MJ\ ha^{-1}) \quad (6)$$

One can divide energy demand in agriculture sector by direct and indirect as well as renewable and nonrenewable sectors (Zangeneh et al., 2010). Direct energies involve the fuel consumed for different agricultural operations, electricity, and working force (labor). Indirect energy includes energy consumed in producing equipments, seeds, fertilizers, and chemicals. Renewable energy is categorized by labor and seeds. Nonrenewable energy comprises fuel energy, fertilizers and pesticides (Erdal et al., 2007).

Artificial neural network

Artificial neural network (ANN) was used to predict the GHG emission and basil yield. ANN models have been successfully used in the prediction of problems in bio-processing and chemical engineering (Mahdavian et al., 2012). In essence, ANN, a system modeled on the human brain, consists of an input layer, some hidden layers, and an output layer. In this study, the back-propagation algorithm was used for the training of all ANN models. ANN with back-propagation algorithm learns by changing the weights and these changes are stored as knowledge. Back-propagation training algorithms, gradient descent, and gradient descent with momentum are often too slow for practical problems because they require smaller rates for stable learning. Moreover, success in the algorithms depends on the user-dependent parameters learning rate and momentum constant. Faster algorithms such as conjugate gradient, quasi-Newton, and Levenberg–Marquardt (LM) use standard numerical optimization techniques. LM method is, in fact, an approximation of the Newton's method.The LM algorithm uses the second-order derivatives of the cost function so that better convergence behavior can be obtained. In the ordinary gradient descent search, only the first order derivatives are evaluated and the parameter change information contains solely the direction along which the cost is minimized, whereas the Levenberg–Marquardt technique extracts a biter parameter change vector. To obtain the best prediction by the network, several architectures were evaluated and trained using the experimental data. This algorithm uses the supervised training technique where the network weights and biases are randomly initialized at the beginning of the training phase. The error minimization process is achieved using the gradient descent rule. A fully connected multilayer perceptron (MLP) was used in this study. Several transfer functions including sigmoid, logarithmic and linear functions together with supervised training algorithms and feed forward

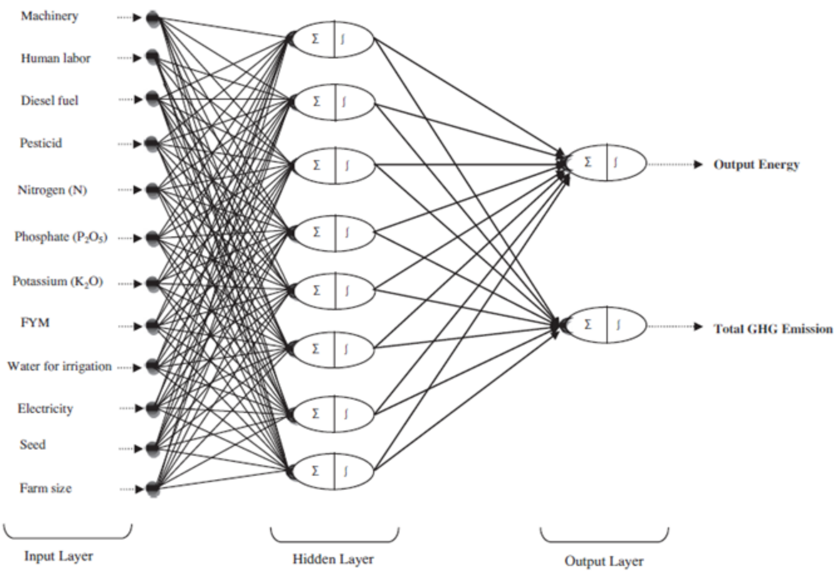

Figure1. Schematic Diagram of Selected Multilayer Feed-Forward Neural Network

back propagation approach was evaluated. To ensure that each input variable provides an equal contribution to the ANN, the inputs of the model were preprocessed and normalized, after which, 70% and 15% of 72 input patterns were devoted to training and validation data sets, respectively. The remaining part of the data wasspecified for the prediction. The learning rate of 0.2 and momentum of 0.1 was adjusted to all the tested networks. Optimum topologies were defined based on the highest R^2 and lowest MSE values. The complexity and size of the network were important, so the smaller ANNs had the priority to be selected. The schematic diagram of the selected multilayer feed-forward neural network is shown in Figure 1. The required codes were developed by MATLAB 2013 software (MathWorks Inc., Natick, Massachusetts, USA).

RESULTS AND DISCUSSION

Estimation of energy consumption

Once the questionnaires were filled out by the participants, values of input consumed energies were determined by studying greenhouses. Likewise, input and output energies were calculated using energy equation coefficients and the results were summarized in Table 3 below. Results indicated that the total consumed energy was 119,852.9 MJ/ha, whereas the output energy was 61,040 MJ/ha. Khoshnevisan et al. (2014b) in a study on strawberry productionreported that the estimated total average of energy input and output was at 35,092.4 MJ/ha and 10,405.9 MJ ha^{-1}, respectively.

As can be seen in Table 3, electricity (43.55%) and plastic (19.37%) are the most important and effective factors in energy consumption followed by chemical fertilizers (11.6%). Among the chemical fertilizers, nitrogen had the highest value (10.61%). The highest electricity consumption was reported in irrigation operations where wells were used for water pumping.

Khoshnevisan et al. (2014a) reported that from among all energy inputs in the production of tomato, natural gas with 66% share was the key input followed by electricity (27%) and chemical fertilizers (4%). This high contribution of natural gas and electricity showed the low efficiency of heating systems and electric pumps utilizedin the production process. Unakitan et al. (2010) found that nitrogen fertilizer (62.79%) and diesel fuel (24.45%) were the most energy consumers in rapeseed production.

a) Includes human labor, electricity, diesel fuel and irrigation

b) Include machinery, FYM, chemical fertilizers, plastic and chemical pesticides

c) Includes human, FYM and irrigation

d) Includes electricity, diesel fuel, machinery, plastic, chemical fertilizers and chemical pesticides

As can be seen in Table 4, one can categorize

Table 3

Energy Input and Output in Basil Production

Input/output	Consumed production (unit area^{-1})	Energy Equivalent (MJ area^{-1})	Percentage
A. Input			
1. Human labor	1100	2156	1.8
2. Seed	35	-	-
3. Irrigation	6900	7038	5.87
4. FYM	18000	5400	4.5
5. Chemical fertilizers		13894	11.6
N	212	12720	-
K_2O	34	227.8	-
P_2O_5	42	466.2	-
Fe	4	480	-
6. Chemicals			8.11
Fungicides	45	9720	-
7. Machinery	20	1254	1.05
8. Diesel fuel	113	4970.87	4.15
9. Electricity	14500	52200	43.55
10. Plastic	258	23220	19.37
Total energy input		119852.9	100
B. Output			
1. Basil yield(kg)	28000	61040	
Total energy output		61040	

the total energy consumption by direct (55.37%), indirect (44.63%) and also renewable (12.18%) and nonrenewable (87.82%) energy sources?. Electricity energy had the highest ratio (43.55%). Moreover, from among the indirect energies, plastic had the highest value (19.37%). Nonrenewable energy had the highest share, and the reason lies on the application of fossil fuels, electric pumps with lower energy consumption efficiency, and the use of chemical fertilizers in higher levels. Energy efficiency, energy productivity, specific energy, and net energy are shown in Table 4. Energy efficiency was measured as 0.45, indicating that the energy consumption for basil production in the studied region is inefficient. This ratio was reported by Pahlavan et al. (2012) as 0.25. The values of energy efficiency, specific energy, and net energy were equal to 0.121 kg/J, 4.77 MJ/kg, and -72,706.9 MJ/area, respectively. These indices were estimated by Pahlavan et al. (2012) as 0.00 kg/J, 9 MJ/kg, and -177,377 MJ/ha, respectively. Unakitan et al. (2010) reported that the shares of renewable and nonrenewable energy resources in the pro-

Table 4

Energy Indices for Basil Production inthe Studied Region

Item	Unit	Amount	Percentage%
Energy ratio	-	0.45	-
Energy productivity	Kg MJ^{-1}	0.21	-
Specific energy	MJ kg^{-1}	4.77	-
Net energy gain	MJ area^{-1}	-72706.9	-
Direct energy a	MJ area^{-1}	66364.87	55.37
Indirect energy b	MJ area^{-1}	53488	44.63
Renewable energy c	MJ area^{-1}	14594	12.18
Non- Renewable energy d	MJ area^{-1}	105258.9	87.82

a) Includes human labor, electricity, diesel fuel and irrigation
b) Include machinery, FYM, chemical fertilizers, plastic and chemical pesticides
c) Includes human, FYM and irrigation
d) Includes electricity, diesel fuel, machinery, plastic, chemical fertilizers and chemical pesticides

Table 5
GHG Emission of Inputs in Basil Productiongion

Input/output	GHG Emissions Equivalent(kg Co_{2eq} area^{-1})	Percentage%
Chemical fertilizers	290.8	3.03
Machinery	1.42	0.01
Diesel fuel	311.88	3.25
Electricity	8816	91.88
Chemical pesticides	175.5	1.83
Total GHG emissions	9595.6	100

duction of rapeseed in Turkey were 0.94% and 99.6%, respectively. The shares of direct and indirect energy were 24.69% and 75.31%, respectively. The results presenting estimation of the produced greenhouse gases are shown in Table 5.

The total gas emission from greenhouse basil production in the studied region was 9,595.6 (kg CO_{2eq} area^{-1}). Electricity had a significant role in greenhouse gas emissions (91.88%). Accordingly, diesel fuel (3.25%) and chemical fertilizers (3.03%) had a considerable share in emission of greenhouse gases. Based on the results presented in Table 3, it can be concluded that electricity has the highest energy share. This implies that most utilized tools in greenhouses work with electricity. Some researchers examined the energy consumption in tomato greenhouses and reported that emissions of greenhouse gases was 34,758 kg (CO_{2eq} area^{-1}) and that consumed electricity had the highest share (Khoshnevisan et al., 2014a).

The contents of energy pertinent to inputs and produced products in the agriculture sector as well as the total input and output energy were calculated on basil. Figure 2 shows the share of energy inputs (manufacturing the machinery, irrigation, labor, and inputs).

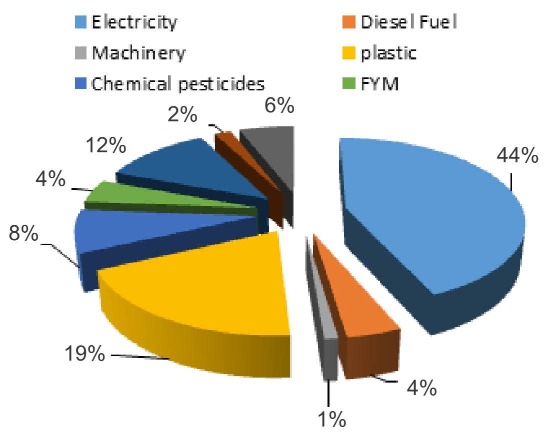

Figure 2.The Share of Energy Inputs of Basil in Chaharmahal-Bakhtiary

According to Figure 2, the share of machinery in energy consumption is equal to 1% (equivalent to 1,254 MJ/ha), which is insignificant regarding to the total input energy followed by the labor, fuel, and organic fertilizer with 2, 4, and 4% shares, respectively.In a study on the energy required for basil production in Isfahan Province of Iran, itwas reported that the total input energy was 236,057 (GJ/ha) and that electricity (75.68%) had the highest share in energy consumption followed by plastic (9.69%) and chemical fertilizers (7.28%) (Pahlavan et al., 2012). Utilizing new pumps with higher energy efficiency in irrigation systems may be suitable to reduce the share of electric energy consumption. Additionally, excessiveuse of chemical fertilizers as the input energy may cause environmental detriments such as underwater contamination (Khan et al., 2009). In this regard, it is suggested to use organic fertilizers, compost, and plant residues.

Results presented in Table 5 indicate that electricity has the highest share in energy consumption of basil production. The ranks in this case are followed by plastic and chemical fertilizers which have a significant share in energy consumption. One can optimize the energy consumption through reducing chemical fertilizers and substituting them with combined control and precision agriculture approaches. In addition, substituting renewable energies with electricity and its optimal utilization can

Table 6
Summary ofANN Model Evaluations

Activation function	Neurons in hidden layer 1	Neurons in hidden layer 2	Training error	R (training)	R (validation)	R (test)	Epoch
Log/Tan	10	0	0.000465	0.9999	0.9999	0.9999	65
Log/Tan	15	0	0.00027	0.9999	0.9999	0.9999	87
Tan/Log	10	0	0.00021	0.9999	0.9999	0.9999	23
Tan/Log	15	0	0.000405	0.9999	0.9999	0.9999	54
Log/ Log	10	0	0.0018	0.9999	0.9999	0.9999	44
Log/Log	15	0	0.00027	0.9999	0.9987	0.9979	34
Log/Tan/Tan	10	6	0.00027	0.9999	0.9999	0.9999	76
Log/Tan/Tan	15	6	0.0153	0.9868	0.9981	0.9989	29
Log/Tan/Tan	20	6	0.0003	0.9999	0.9999	0.9999	17
Log/Log/Tan	10	6	0.000495	0.9999	0.9999	0.9999	91
Log/Log/Tan	15	6	0.000225	0.9999	0.9998	0.9999	62
Log/Log/Tan	20	6	0.000465	0.9999	0.9999	0.9999	43
Log/Tan/Tan	10	6	0.00036	0.9999	0.9999	0.9999	54
Log/Tan/Tan	**15**	**6**	**0.00023**	**0.9999**	**0.9999**	**0.9999**	**87**
Log/Tan/Tan	20	6	0.00033	0.9999	0.9976	0.9999	41

lead to a remarkable decrease in the consumption of this energy resource.When it comes to calculating the indices, energy ratio indices and energy efficiency are 0.45 and 0.21 which shows that energy efficiency was low in agriculture sector and that the net energy was -72,706.9. Furthermore, direct energy and indirect energy were 55.37% and 44.63%, suggesting that direct energy has a high share and that the highest energy consumption was related to renewable energy which can be a menace to the environment.

It was observed that electricity (92%) had the highest share in GHG generation whose reason is using inefficient electric equipment. This requires optimum use of this energy and substituting it with new energies. Followed by electricity are chemical fertilizers and biodiesel fuel (3%). Moreover, in a study by Khoshnevisan et al. (2014a), the total GHG emission was calculated as 803.4 kg CO_{2eq} ha^{-1}, 35083.5 kg CO_{2eq} ha^{-1} for OF, and GH production, respectively. Using organic fertilizers instead of chemical fertilizers can result in a reduction in GHG emissions.

ANN models for predicting the GHG emission and Basil yield

Several topologies were evaluated to obtain the maximum R^2 and minimum MSE values. The results are presented in Table 6. It can be inferred from the table that a network with 2 hidden layers (15 and 6 neurons in first and second layer, consequently) using Levenberg–Marquardt (LM) learning algorithm and tangent-sigmoid transfer function would provide an efficient response, helping to predict the output parameter. A coefficient of determination (R^2) of 0.9999 and a training error of 0.00023 were resulted from the network training. Results showed that an artificial neural network was advantageous in the prediction of basil yield and CO_2 emission. Results of a regression analysis of experimental data and network outputs are illustrated in Figures 3 and 4. The maximum value of R^2 for training, validation, and prediction stages was 0.9999.

Khoshnevisan et al. (2014a) studied artificial neural networks and the fuzzy-neural deduction system in an attempt ot to model consumed energy in producing greenhouse tomato in Isfahan Province of Iran. Comparison of artificial neural networks and the fuzzy-neural deduction system suggest that ANFIS was more accurate in modeling through making use of fuzzy rules. Other researchers employed artificial neural networks to determine the energy consumption in wheat production (Safa & Samarasinghe, 2011). They compared the artificial neural network using multivariate linear regression and

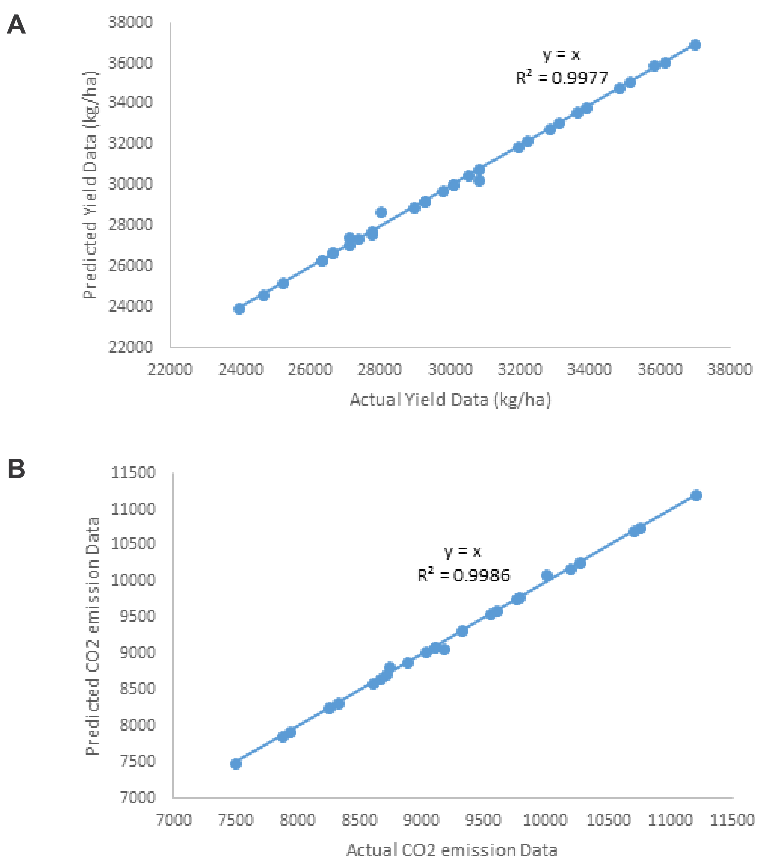

Figure 3. **(A)** Predicted Outputs Versus Measured Yield Values **(B).** Predicted Outputs versusCo2Emission Measured Values

found that these networks were better predictors of energy consumption compared to regression mode.

CONCLUSION

The relationship between input and output energy in production of greenhouse basil was studied. The total consumed energy in basil production was recorded as 119,852.9 (MJ area-1). Electricity energy had the highest share in input energies followed by plastic and chemical fertilizers. Hence, one can declare that this greenhouse is not justifiable in terms of consumption rate, efficiency, and energy efficiency. The reasons would be counted as the lack of observing the true principles of greenhouse insulation with outer space, the existence of inefficient water pumps, excessive use of fertilizers, and low-costing side of energy inputs in Iran, which require propermanagement. Carefulmanagement of inputs can reduce environmental risks. The results of model showed that the trained neural network was accurate in estimating the performance of basil and CO_2 emission (R^2=0.9999 and MSE= 0.00023). The best network was categorized by topology of 15 neurons in the first layer and 6 neurons in the second layer.

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