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Prognostication of total greenhouse gas emissions and economic indices for hazelnut production in Guilan province, Iran

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Abstract

In this study, Artificial Neural Network (ANN) was developed to estimate the total GHG emissions and economic indices of hazelnut production in Guilan province of Iran. In this regard, the data collected from 120 orchardists in the studied region during plant cultivation in 2012-2013 using face-to-face questionnaires. The results indicated that total GHG emissions and hazelnut yield was 77.66 $kgCO_{2eq.}$ ha^{-1} and 450.20 kg ha^{-1}, respectively. Based on grouping of hazelnut orchards according to three sizes level, the large size had the highest emissions and yield compare to another sizes. Moreover, the GHG ratio was 0.17 for all orchards. The economic indices including gross production value, benefit to cost ratio, productivity and net return were calculated as 1575.70 $ ha^{-1}, 1.64, 0.47 kg $\$^{-1}$ and 615.34 $ ha^{-1}, respectively. In this research, the Levenberg-Marquardt learning algorithm was applied for determination of ANN model. With respect to result, the ANN model with 7-4-4-5 structure was determined as best topology which the highest R^2 and lowest RMSE showed the robust model for prediction. In the last section sensitivity analysis was done and its results demonstrated potassium had the highest sensitivity on total GHG emissions and benefit to cost ratio; while nitrogen was the most sensitive input on gross production value, productivity and net return.

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Introduction

Almost 14 percent of global net CO_2 emissions come from agriculture sector. Based on the greenhouse gas (GHG) estimations, it has been estimated that agriculture accounted for 10e12% of the global anthropogenic emission (Smith *Et. al.* 2008). So, the reduction of GHG emissions is very important for improvement of environmental impacts.

In another hand, economic analysis is a systematic approach to determining the optimum use of scarce resources, involving comparison of two or more alternatives in achieving a specific objective under the given assumptions and constraints. Economic analysis takes into account the opportunity costs of resources employed and attempts to measure in monetary terms the private and social costs and benefits of a project to the community or economy.

In recent years many reseracg focused on GHG emission problems in agricultural activity, Soni *Et. al.* (2013) considered the energy use index and CO_2 emissions in rainfed agricultural production systems of Northeast Thailand. In this study, system efficiency, total energy input and corresponding $CO_{2eq.}$ emissions were estimated and compared for different crops. In another study, Ghahderijani *Et. al.* (2013) evaluated the energy consumption and GHG emissions of wheat production in Isfahan province of Iran. Nabavi-Pelesaraei *Et. al.* (2014a) applied DEA method for energy optimization and GHG reduction for orange production in Guilan province of Iran.

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. ANNs have been applied when there is no theoretical evidence about the functional forms. Therefore, ANNs are data-based, rather than model-based. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems (Ghodsi *Et. al.* 2012). ANN can learn the complex transport processes of a system from given inputs and observed outputs, serving as an instrument for universal function approximation The basic advantage of ANN is that it does not need any mathematical model since an ANN learns from examples and recognizes patterns in a series of input and output data without any prior assumptions about their nature and interrelations (Nourbakhsh *Et. al.* 2014). Several studies have been conducted about ANN modeling of GHG emissions and economic indices of agricultural and horticultural crops production. For example, Zangeneh *Et. al.* (2011) modeled ANN for determining of economical productivity, total costs of production and benefit to cost ratio of potato crop and compared with parametric model. Khoshnevisan *Et. al.* (2013) analyzed environmental impact assessment and economic indices of open field and greenhouse strawberry production. Nabavi-Pelesaraei *Et. al.* (2014b) developed ANN model for modeling of CO_2 emissions in tangerine production in Guilan province of Iran. Farjam *Et. al.* (2014) evaluated the energy use and economic indices of corn seed and grain corn production.

With respect to above-mentioned sentences, determining of GHG emissions and economic indices and modeling of them in hazelnut production by ANN in Guilan province of Iran. In other words, the main aim of this research was finding of relation between GHG input, yield and economic indices for creating decision making model and achieved to more economic efficiency the studied area.

Materials and methods

Data collection and case study

The study was performed in central region of Hamedan province which is located in the west of Iran; within 36° 34′and 38° 27′ north latitude and 48° 53′ and 50° 34′ east longitude. Roudsar city in east of Guilan province with about 75% of total hazelnut production had the special place in producing of this nut in the studied area (Anon, 2013). Accordingly, initial data were collected from 120 orchardists by using a face-to-face questionnaire performed in the production year 2012/2013. The questionnaires included input consumption from different sources and yield weight. The hazelnut orchards were classified into small orchards (<1 hectare), medium orchards (between one and three hectares) and large orchards (>3 hectares) in the studied area. From the villages in the area studied, orchards were selected by using a stratified sample randomly. The sample size was calculated using the Cochran method (Kizilaslan, 2009).

Where *n* is the required sample size; *s*, the standard deviation; t, the value at 95% confidence limit (1.96); *N*, the number of holding in the target population and *d*, the acceptable error (permissible error 5%). For the calculation of sample size, criteria of 5% deviation from population mean and 95% confidence level were used. In this study, the sample size was calculated 53 but it was considered to be 60 to ensure the accuracy. In order to estimate the reliability of a psychometric test for samples, the Cronbach method was utilized (Cronbach, 1951). The results of this testing indicated that Cronbach's alpha of questionnaire 83%. Also, the quality of orchardists answers was investigated by regional experts.

GHG inputs consumption

GHG inputs including machinery, diesel fuel, electricity, chemical fertilizers (nitrogen, phosphate and potassium) and biocides (insecticide and fungicide) and output yield values of hazelnut have been used to estimate the GHG ratio. GHG equivalents are shown in Table 1.

Table 1. GHG emissions coefficients of agricultural inputs.

Inputs	Unit	CO_2 coefficient (kg $CO_{2eq.}$ unit^{-1})	Reference
1. Machinery	MJ	0.071	(Dyer and Desjardins, 2006)
2. Diesel fuel	L	2.76	(Ghahderijani *Et. al.* 2013)
3. Chemical fertilizers	kg		
(a) Nitrogen		1.3	(Lal, 2004)
(b) Phosphate		0.2	(Nabavi-Pelesaraei *Et. al.* 2013)
(c) Potassium		0.2	(Ghahderijani *Et. al.* 2013)
4. Biocides	kg		
(a) Insecticide		5.1	(Lal, 2004)
(b) Fungicide		3.9	(Lal, 2004)

Accordingly, the quantity of each GHG input was multiplied by corresponding coefficients; which are given in Table 1. Also, calculating machinery energy related to their manufacturing or hours of use was found to be significant and was considered in the analysis.

Based on the GHG equivalents of the inputs (Table 1) and hazelnut yield, the GHG ratio intensiveness was calculated as follows (Nabavi-Pelesaraei *Et. al.* 2014b):

$$\text{GHG ratio} = \frac{\text{Total GHG emissions (kgCO}_{2eq.}\text{ ha}^{-1})}{\text{Hazelnut yield (kg ha}^{-1})} \quad (1)$$

Economic Indices

The financial analysis of hazelnut production was the one of main aims in this study. The only economic output of the studied systems included hazelnut. All prices of inputs and output were used based on the average prices of production period of 2012–2013.

Benefit to cost ratio, productivity, net return and energy intensiveness were calculated by Eqs. (2)-(5) (Mohammadshirazi *Et. al.* 2012; Tabatabaie *Et. al.* 2013):

$$\text{Gross production value} = \text{Hazelnut yield (kg ha}^{-1}) \times \text{Hazelnut price (\$ kg}^{-1}) \quad (2)$$

$$\text{Benefit to cost ratio} = \frac{\text{Gross production value (\$ ha}^{-1})}{\text{Total production cost (\$ ha}^{-1})} \quad (3)$$

$$\text{Productivity} = \frac{\text{Yield (kg ha}^{-1}\text{)}}{\text{Total production cost (\$ ha}^{-1}\text{)}} \tag{4}$$

$$\text{Net return} = Gross\ \text{production value (\$ ha}^{-1}\text{)} - Total\ \text{production cost (\$ ha}^{-1}\text{)} \tag{5}$$

ANN modeling

ANN are data-processing systems inspired by biological neural system and are used to solve a wide variety of problems in science and engineering, particularly for some areas where the conventional modeling methods fail. A well-trained ANN can be used as a predictive model for a specific application. The predictive ability of an ANN results from the training on experimental data and then validation by independent data. An ANN has the ability to relearn to improve its performance if new data are available (Najafi *Et. al.* 2009). In this study, the Levenberg–Marquardt algorithm was applied for determination of ANN. The Levenberg–Marquardt algorithm blends the steepest descent method and the Gauss–Newton algorithm. Fortunately, it inherits the speed advantage of the Gauss–Newton algorithm and the stability of the steepest descent method. It's more robust than the Gauss–Newton algorithm, because in many cases it can converge well even if the error surface is much more complex than the quadratic situation. Although the Levenberg–Marquardt algorithm tends to be a bit slower than Gauss–Newton algorithm (in convergent situation), it converges much faster than the steepest descent method (Haoand and Bogdan, 2010).

The input weight matrixes are made up from all the links between input layers and hidden layers and the output weight matrix comprises all the links between the hidden layers and the output layers. Weight (w), which controls the propagation value (x) and the output value (O) from each node, is modified using the value from the preceding layer according to Eq. (6) (Zhao *Et. al.* 2009):

$$O = f\left(T + \sum w_i x_i\right) \tag{6}$$

Where 'T' is a specific threshold (bias) value for each node. 'f ' is a non-linear sigmoid function, which increased uniformly.

The error was calculated at the end of training and testing processes based on the differences between targeted and calculated outputs. The back-propagation algorithm minimizes an error function defined by the average of the sum square difference between the output of each neuron in the output layer and the desired output.

The error function can be expressed as (Deh Kiani *Et. al.* 2010):

$$E = \frac{1}{p}\sum_p \sum_k \left(t_{pk} - z_{pk}\right)^2 \tag{7}$$

Where 'p' is the index of the p training pairs of vectors, 'k' the index of an element in the output vector, 'z_{pk}' the kth element of the output vector when pattern p is presented as input to the network and 't_{pk}' is the kth element of the pth desired pattern vector.

The error identified during the learning process is called the root-mean-squared-error (RMSE) and is defined as follows (Najafi *Et. al.* 2009):

$$\text{RMSE} = \sqrt{\frac{1}{\text{n}}\sum_i^n \left(t_i - z_i\right)^2} \tag{8}$$

Where 't_i' and 'z_i' are the actual and the predicted output for the ith training vector, and 'N' is the total number of training vectors.

The coefficient of determination (R^2) was calculated using the following equations (Pahlavan *Et. al.* 2012):

$$R^2 = 1 - \left(\frac{\sum_{i=1}^n (t_i - z_i)^2}{\sum_{i=1}^n t_i^2}\right) \tag{9}$$

The mean absolute error (MAE) is a quantity used to measure how close forecasts or predictions are to the eventual outcomes (Pahlavan *Et. al.* 2012).

$$MAE = \frac{1}{n}\sum_{t=1}^n \left|(t_i - z_i)\right| \tag{10}$$

Where 't_i' and 'z_i' are the predicted and actual output for the i^{th} orchardist, respectively.

Sensitivity Analysis

Sensitivity Analysis via ANN (SAANN) can rank and select the major and input variables through its analysis. SA with partial differential is based on a calculation of input, weights and output variables from the ANN simulation. The calculation of sensitivity, S is as follows (Sung, 1998):

$$S = \frac{\partial O}{\partial I} = O' \left(\sum_{J=1}^{J} w_{ij}^{1} \; H' \; w_{ij}^{2}\right) \tag{11}$$

$$S = \frac{\partial f(O)}{\partial X} \sum_{J=1}^{J} \left(w_{ij}^{1} \; \frac{\partial f(H)}{\partial X} \; w_{ij}^{2}\right) \tag{12}$$

Where *O* is output and *H* is a hidden node that has to be differentiated, w_{ij}^{1} and w_{ij}^{2} are the weights with respthe the hidden layerirst and second connection of hidden layer. The first connection is for input and hidden layer and the second connection is for hidden node and the output layer (Sung, 1998).

Basic information on GHG inputs and economic indices of tangerine production was entered into Excel 2010 spreadsheets and the Matlab 7.2 (R2014a) software package.

Results and discussion

Analysis of GHG inputs and hazelnut yield

Table 2 indicated the GHG emissions of each input and yield of hazelnut production for three groups of orchard sizes in the Guilan province of Iran. Based on the results, the total GHG emissions and yield of hazelnut were calculated about 78 $kgCO_{2eq.}$ ha^{-1} and 450 kg ha^{-1}, respectively. The highest total emissions and rate of yield belonged to large orchards with 88 $kgCO_{2eq.}$ ha^{-1} and 484.86 kg ha^{-1}, respectively. The high rate consumption of diesel fuel, machinery and nitrogen fertilizer compare to other orchards was the main reason of irregular GHG emissions in the large orchards. Moreover, the less mechanized operation of small orchards was the main cause for decreasing GHG rate in these orchards. It should be noted, the average of GHG ratio was found 0.17. Accordingly, it can be said the one of main disadvantage of agricultural mechanization is the increasing GHG emissions in agricultural activity. In another hand, the decreasing of hard work is the goal in modern agricultural systems. So, the balance between mechanization and traditional system can be controlled the environmental impacts such as GHG emissions in the studied area. According to above-mentioned, it's suggested the applying standard machinery, supervision of chemical fertilizer consumption (especially nitrogen) or replacing farmyard manure instead of them can be effective in reduce of GHG emissions for hazelnut production in Guilan province, Iran. Furthermore, the share of biocides was very low in the total GHG emissions for three groups.

Table 2. Amounts of GHG emissions and yield of hazelnut production based on different orchard size levels.

Items	Units	Orchard size groups (ha)			Average
		Small (<1)	Medium (1-3)	Large (>3)	
A. Inputs					
1. Machinery	$kgCO_{2eq.}$ ha^{-1}	20.60	19.77	24.24	20.61
2. Diesel fuel	$kgCO_{2eq.}$ ha^{-1}	23.64	26.31	29.81	26.28
3. Chemical fertilizers	$kgCO_{2eq.}$ ha^{-1}				
(a) Nitrogen		17.52	19.21	21.70	19.23
(b) Phosphate		3.45	3.78	4.27	3.79
(c) Potassium		4.72	5.18	5.85	5.19
4. Biocides	$kgCO_{2eq.}$ ha^{-1}				
(a) Insecticide		0.77	0.98	1.02	0.94
(b) Fungicide		1.62	1.63	1.62	1.63
The total GHG emissions	$kgCO_{2eq.}$ ha^{-1}	72.31	76.86	88.51	77.66
A. Output					
Hazelnut	kg ha^{-1}	425.59	450.09	484.86	450.20

Nabavi-Pelesaraei *Et. al.* (2013) calculated the GHG emissions for eggplant production about 515.37 $kgCO_{2eq.}$ ha^{-1}. In the similar result, they reported diesel fuel had the highest share in the total GHG emissions; followed by nitrogen fertilizer.

Economics indices results of hazelnut production

Table 3 showed the economics analysis result for hazelnut production in the studied region based on pricing political of 2012-2013. Accordingly, the gross production value was 1575.70 \$ ha^{-1}. Variable and fixed production cost was computed as 557.01 \$ ha^{-1} and 403.35 \$ ha^{-1}, respectively. The total production cost was determined using summation of Variable and fixed production cost (960.36 \$ ha^{-1}). It should be noted, the benefit to cost ratio was 1.64. As can be seen, the one dollar of total cost can be produce 0.47 kg of hazelnut yield in Guilan province, Iran which it's called productivity. The value of profit was calculated as net return (with 615.34 \$ ha^{-1}).

Table 3. Economic indices results of hazelnut production in Guilan province, Iran.

Cost and return components	Unit	Value
Yield	kg ha^{-1}	450.20
Hazelnut price	\$ kg^{-1}	3.5
Gross production value	\$ ha^{-1}	1575.70
Variable production cost	\$ ha^{-1}	557.01
Fixed production cost	\$ ha^{-1}	403.35
Total production cost	\$ ha^{-1}	960.36
Benefit to cost ratio	-	1.64
Productivity	kg \$$^{-1}$	0.47
Net return	\$ ha^{-1}	615.34

Mohammadi *Et. al.* (2010) reported the benefit to cost ratio of kiwifruit production was 1.94. In another study, the benefit to cost ratio and productivity of tangerine production were calculated as 1.62 and 5.19 kg \$$^{-1}$ in Mazandaran province of Iran, respectively (Mohammadshirazi *Et. al.* 2012).

Evaluation and analysis of the model

Several ANN were designed, trained and generalized for prediction of GHG emissions and economics indices of hazelnut production. The results indicated the ANN including one input layer with 7 inputs, two hidden layers with 4 neuron of each layer and one output layer with five outputs based on back propagation algorithm under Levenberg-Marquardt learning algorithm had the best performance for modeling. In other word, the ANN model with 7-4-4-5 structure was computed as best topology which demonstrated in Fig 1.

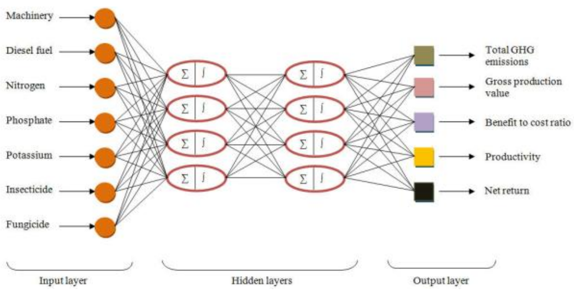

Fig. 1. Schematic diagram of the best topology with 7-4-4-5 structure.

The details of 7-4-4-5 structure are given Table 4. Based on results, the determination of coefficient (R^2) of total GHG emissions, gross production value, benefit to cost ratio, productivity and net return was calculated as 0.986, 0.996, 0.967, 0.951 and 0.893, respectively. Furthermore the lowest RMSE and MAE were found to be for each output in this model.

Table 4. The best result of different arrangement of models.

Items	R^2	RMSE	MAE
Total GHG emissions	0.986	0.044	0.049
Gross production value	0.996	0.081	0.056
Benefit to cost ratio	0.967	0.051	0.071
Productivity	0.951	0.067	0.122
Net return	0.893	0.093	0.034

Nabavi-Pelesaraei *Et. al.* (2014b) reported the ANN with 8-4-1 structure was the best topology for prediction of GHG emissions of tangerine production. In another study, the best structure of ANN for environmental impact assessment of strawberry was determined by model Khoshnevisan *Et. al.* (2013). Their results revealed the ANN model including an input layer (with eight neurons), two hidden layers (with 6 neurons in first layer and 2 neurons in second layer) and an output layer (with ten neurons) had the best structure. Farjam *Et. al.* (2014) reported the best multilayer perceptron network models for predicting economic indices in seed and grain corn production had 6-6-10-4 and 6-4-8-4 topologies, respectively.

Sensitivity analysis

Fig 2 displays the rate of sensitivity of inputs for each ANN model output. The results illustrated the potassium had the highest sensitivity rate for total GHG emissions and benefit to cost ratio; While the nitrogen was the most sensitive input in gross production value, productivity and net return.

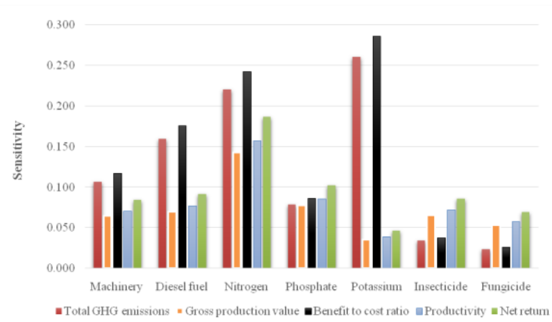

Fig. 2. Sensitivity analysis of various inputs on GHG emissions and economic indices of hazelnut production.

Conclusion

The following conclusions are drawn from the present study:

1- The average of total GHG emissions and hazelnut yield was calculated as 77.66 $kgCO_{2eq.}$ ha^{-1} and 450.20 kg ha^{-1}, respectively. The highest emissions and hazelnut yield belonged to large orchards with 88.51 $kgCO_{2eq.}$ ha^{-1} and 484.86 kg ha^{-1}, respectively. Moreover, the GHG ratio was found 0.17.

2- The results of economic analysis revealed the Gross production value, benefit to cost ratio, productivity and net return were 1575.70 \$ ha^{-1}, 1.64, 0.47 kg $\$^{-1}$ and 615.34 \$ ha^{-1}, respectively.

3- With respect to Levenberg-Marquardt learning algorithm, The ANN developed for modeling of total GHG emissions and economics indices. Accordingly, the results illustrated ANN model with 7-4-4-5 structure was the best topology. This topology had the highest R^2 and lowest RMSE and MAE for all five outputs.

4- The sensitivity analysis of input parameters on outputs revealed that potassium had the highest sensitivity on total GHG emissions and benefit to cost ratio and nitrogen was the most sensitive input on gross production value, productivity and net return.

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