Biological Forum – An International Journal **7**(1): 1260-1266(2015)

ISSN No. (Print): 0975-1130
ISSN No. (Online): 2249-3239

Applying Artificial Neural Networks for Modeling of Environmental Impacts of Tobacco Production

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(Received 16 March, 2015, Accepted 23 April, 2015)
(Published by Research Trend, Website: www.researchtrend.net)

ABSTRACT: The main aim of this study was the prediction if environmental indices of tobacco production in north of Iran. Data were collected randomly from 90 farms in Mazandaran province by face to face questionnaire method. Initially, Life cycle assessment (LCA) methodology was developed to assess all the environmental impacts associated with tobacco cultivation in the studied area. The ten impact categories including abiotic depletion, global warming potential, ozone layer depletion potential, human toxicity potential, fresh water aquatic ecotoxicity, marine aquatic ecotoxicity, terrestrial ecotoxicity potential, photochemical oxidation, acidification potential and eutrophication potential were selected as target outputs. Farmgate and one ton of harvested tobacco were chosen as system boundary and functional unit. To find the best topology, several ANN models with different number of hidden layers and neurons in each layer were developed. To assess the best performance, a topology with highest coefficient of determination (R2), lowest root mean square error (RMSE) and mean absolute error (MAE) was selected as optimum structure. Accordingly, ANN model with 8-20-10 structure showed the best performance. Evaluation of the results revealed that the developed ANN model (8-20-10structure) appears to be appropriate tool in predicting environmental indices of tobacco production in the studied region.

Keywords: Artificial neural networks, Environmental impacts, Modeling, Tobacco production.

INTRODUCTION

Tobacco (*Nicotiana tabacum* L.) is an important crop plant (Davis and Nielsen 1999) and a member of the nightshade (Solanaceae) family which is one of the largest and most diverse within the angiosperms. This family includes 3,000- 4,000 species (Olmstead *et al.* 2008), of which a considerable number are of major economic importance as crop, vegetable or ornamental species throughout the world such as potato (*Solanum tuberosum*), tomato (*Solanum lycopersicum*), egg plant (*Solanum melonena*), pepper (*Capsicum* species) and Petunia (*Petunia* × *hybrida*) (Mueller *et al.* 2005). Tobacco is one of the most valuable agricultural and industrial products that is produced in over 100 countries in the world with different climatic conditions and plays an important role in the economy of them (Tso, 1990). Although tobacco is counted as an important industrial plant in the world, it has not been paid much attention by researchers because of its negative aspect in cigarette production. Nevertheless, tobacco has different other usage. For instance, nicotine extraction is carried out from this plant in a large scale and tobacco is also used as a model plant in biotechnology (Chawla, 2003).

Tobacco has 4211884 hectares under cultivation in the world and crop produced in this area is 7461994 tons per year, while it has 12230 hectares under cultivation in Iran and 19232 tons production per year. Largest tobacco producers in the world are China, India, Brazil and the United States of America, while Iran ranks 33 in the world in terms of tobacco production (FAO, 2012). Carbondioxide is the main contributor to greenhouse gases released into the atmosphere and there is a significant correlation between agricultural production, energy use and CO_2 emissions (Nabavi-Pelesaraei *et al.*, 2014a). Life-cycle assessment (LCA) is a method of evaluating the environmental effects associated with any given activity, beginning with the initial gathering of raw materials from the earth to the point at which all residuals are returned to the earth. Greater environmental awareness among consumers over the past decade has sharply increased thenumber of organizations conducting LCA studies (Romero-Gámez *et al.*, 2012). The main applications of LCA are in: 1) analyzing the origins of problems related to a particular product; 2) comparing improvement variants of a given product; 3) designing new products; and 4) choosing between a numbers of comparable products (Guinée *et al.*, 2002).

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).In the recent years, many studies considered to environmental impacts assessment and their modelling by intelligence methods. For example, Khoshnevisan *et al.* (2013) analyzed the environmental impact assessment and economic indices of open field and greenhouse strawberry production. Nabavi-Pelesaraei *et al.* (2013) modeled the greenhouse gas emission of eggplant production by ANN. In another study, Nabavi-Pelesaraei *et al.* (2014b) developed ANN model for modelling of CO_2 emissions in watermelon production in Guilan province of Iran. Sadeghzadeh *et al.* (2015) investigated the modeling of environmental impacts of eggplant production by ANN.

Based on the literature, there has been no study on environmental emissions modelling for tobacco production with respect to input emitter flow using ANN. The purpose of this study was to model field emissions of tobacco production in different impact categories. ANNs used for prediction the environmental indices of this production in Mazandaran province of Iran.

MATERIALS AND METHODS

A. Study area

This study was conducted in Mazandaran province. Mazandaran is located in north of Iran. It is located between the latitudes 35-47' and 36-35' N and longitudes 50-34' and 54-10' E and has 1.46 percent of the country's total area (Anon, 2013).Initial data, including agricultural practices, machinery operations, infrastructures, input materials, and energy carriers, were obtained using questionnaires. To determine the sample size formula proposed by Cochran was used (Romero *et al.,* 2012):

$$n = \frac{N(S*t)^2}{(N-1)d^2 + (S*t)^2} \quad \ldots(1)$$

where n is the required sample size, N is the number of tobacco producers in target population, S is the standard deviation, t is the t value at 95% confidence limit (1.96), and d is the acceptable error. As a result, 90 farms were randomly selected for questionnaires.

B. Life cycle assessment

Life cycle assessment follows procedure provided by ISO standards and comprised of four phases: 1) goal and scope definition; 2) inventory analysis; 3) impact assessment; and 4) interpretation (Khoshnevisan *et al.*, 2013).

Goal and scope definition: In the stage of goal and scope definition the intention of the research, anticipated product of the study, system boundaries, and suppositions are all clarified. Setting boundaries and defining the specific lifecycle systems being studied are essential for any LCI or LCA study (Boguski *et al.*, 1996). The purpose of this study was to appraise the environmental performance of tobacco and the environmental impacts related to the use of energy sources, water and raw materials.

Defining a meaningful boundary is very important because the environmental problems of agricultural systems can maintain during postharvest processes when products are taken out of fields. If the farm gate be defined as the system boundary differences in emissions due to transport and processing of products have been ignored. Additionally, effect of differences in the end use of the product and its by-products on net environmental impacts are also ignored. In this study, due to unavailability of complete set of data, farm emissions are considered and it is assumed that all the emissions were related to the input materials which used in tobacco cultivation in the farms. For instance, no significance was attached to transportation. All direct and indirect field emissions were calculated as the proposed method by Nemecek and Kagi (2007). The impact categories used in this study are listed in Table 1. The CML 2 baseline 2000 developed by the Centre of Environmental Science of Leiden University was used as an impact-evaluation method (Khoshnevisan *et al.*, 2013). The emphasis should be laid on the fact that this baseline does not encompass some impact categories like land use, water use, etc. For the environmental impacts analysis of the systems under study, the functional unit adopted was 1 ton of harvested tobacco.

Table 1: Environmental impact categories and measurement units for each category.

Impact categories	**Nomenclature**	**Units**
Abiotic depletion	AD	kg Sb eq.
Global warming potential	GWP	kg CO_2 eq.
Ozone layer depletion potential	ODP	kg CFC-11 eq.
Human toxicity potential	HTP	kg 1,4-DB eq.
Fresh water aquatic ecotoxicity	FAE	kg 1,4-DB eq.
Marine aquatic ecotoxicity	MAE	kg 1,4-DB eq.
Terrestrial ecotoxicity potential	TEP	kg 1,4-DB eq.
Photochemical oxidation	PO	kg C_2H_4 eq.
Acidification potential	AP	kg SO_2 eq.
Eutrophication potential	EP	kg PO_4^{3-} eq.

Inventory analysis: Inventory analysis is considered one of the most important stages of an LCA since the stages that follow will be influenced by its results (Allen and Rosselot, 1997). The outcomes of this stage are utilized in the life cycle impact assessment (LCIA). In this stage input materials, energy flows and assumptions considered in the LCI are elaborated. The detailed quantitative data for tobacco production systems upon which the analysis was based on are summarized in Table 2. The application of chemical fertilizers is responsible for several direct emissions as followings: ammonia to air, nitrate leaching to groundwater, phosphorus to water, nitrous oxide (N_2O) to air, and NOx to the air. Among the various methodologies developed to estimate direct emissions of chemical fertilizers, procedures from Brentrup *et al.* (2000), EPA (1995) and Eggleston *et al.* (2006) were used in this study.

The guidelines issued by Eggleston *et al.* (2006) were used in estimating the emissions of nitrous oxide (N_2O) to the air. Accordingly, the application of each 100 kg of N-based fertilizer is assumed to be responsible for emitting 1.25 kg of N_2O into the air. The emissions of NOx were assumed to be 2% and NH_3 emissions 8% of the total amount of N-based fertilizers applied (Galloway *et al.,* 1995). Likewise, it was assumed that 30% of total N fertilizers leached from the soil profile as nitrate (Erickson *et al.,* 2001). The use of diesel fuel and manure causes greenhouse gas (GHG) emissions. Greenhouse gases cause global warming potential and are expressed by kilogram Carbon dioxide equivalent (kg CO_2eq). Extraction of 1 MJ energy from diesel fuel leads to 0.074 kg emission of carbon dioxide equivalent into the air. Also, use of 1 ton manure leads to the release of 0.005 kg CO_2 eq into the atmosphere (Mohammadi *et al.,* 2014).

Table 2: Life cycle inventory data for tobacco production.

Items	Units	Average (unit per ha)
A. Inputs		
1. Machinery	kg	116.2
2. Diesel fuel	L	45.5
3. Chemical fertilizer	kg	
(a) Nitrogen		52.2
(b) Phosphate (P_2O_5)		26.8
(c) Potassium (K_2O)		27.2
4. Pesticide	kg	2.2
5. Electricity	kWh	150.59
6. manure	kg	2980
B. Output		
Tobacco	kg	1796.5
C. Emissions	kg	
1. NO_x (emission to air)	kg	2.2696
2. N_2O (emission to air)	kg	1.4185
3. NH_3 (emission to air)	kg	9.8784
4. CO_2 (emission to air)	kg	189.61
5. NO_3- (emission to water)	kg	34.044
6. P (emission to water)	kg	0.07

Impact assessment: The aim of the Life cycle impact assessment (LCIA) is to evaluate environmental impacts of the system using the set of results from the inventory analysis within the framework of the goal and scope of the study. According to ISO 14044, LCIA proceeds through four steps: 1) selection of impact categories and classification (mandatory); 2) characterization (mandatory); 3) normalization (optional); and 4) weighting (optional). These four steps have been developed in a number of distinctive methodologies including Ecoindicator 99, ReCiPe 2008, and CML developed in The Netherlands, the EPS2000 method developed in Sweden, EcoPoints and EPS 2000 developed in Switzerland and so forth. A literature review revealed that CML 2 baseline 2000 V2.05/world method developed by the Institute of Environmental Science of Leiden University (PRé Consultants, 2013).

Artificial neural networks (ANN): To model environmental impacts, finding the appropriate independent variables was the first step of model creation. Accordingly, all relevant variables and their correlations were studied. Variables were selected on the basis of having no significant correlation between them, although there should be a high correlation between inputs and emissions. The sample size used in this study was 90 farms. Embedded inputs (including machinery, diesel fuel, nitrogen, phosphate, potassium, pesticides, electricity and manure) were chosen as inputs while the ten impact categories were selected as outputs of the model. From 90 units, 68 units were considered as training and 22 units were as testing. These values were selected based on principles of ANN. The election of units was randomized from all samples. Several structures were evaluated using the experimental data to determine the best predicting model by the network. The number of neurons was determined for input and output layer based on number of inputs and outputs for watermelon production. Also, one and two hidden layers were applied for ANN modeling and according to the best results, one of them was proposed for modeling. In this study, Levenberg-Marquardt learning Algorithm was used for training ANNs. The Levenberg-Marquardt algorithm is the most widely used optimization algorithm. It outperforms simple gradient descent and other conjugate gradient methods in a wide variety of problems (Nabavi-Pelesaraei *et al.*, 2014b).

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. (2) (Zhao *et al.*, 2009):

$$O = f\left(T + \sum w_i x_i\right) \quad \ldots(2)$$

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 (Nabavi-Pelesaraei *et al.*, 2014b):

$$E = \frac{1}{p}\sum_p \sum_k \left(t_{pk} - z_{pk}\right)^2 \quad \ldots(3)$$

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 k^{th} element of the output vector when pattern p is presented as input to the network and 't_{pk}' is the kth element of the p^{th} desired pattern vector.

Mean square error (MSE) is very applicable to compare different models; it illustrates the network's ability to predict the accurate output. The MSE can be written as (Safa and Samarasinghe, 2011):

$$\mathrm{MSE} = \frac{1}{\mathrm{n}}\sum_i^n \left(t_i - z_i\right)^2 \quad \ldots(4)$$

Where 't_i' and 'z_i' are the actual and the predicted output for the i^{th} training vector, and 'N' is the total number of training vectors.

Mean absolute percentage error (MAPE) between the predicted and actual values and coefficient of determination (R2) were calculated using the following equations (Tang and Yin, 2012):

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}(t_i - z_i)^2}{\sum_{i=1}^{n} t_i^2}\right) \quad \ldots(5)$$

$$MAPE(\%) = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{(t_i - z_i)}{t_i}\right| \quad \ldots(6)$$

Where 'ti' and 'zi' are the predicted and actual output for the ith farmers, respectively.

Basic information on inputs of tobacco production was entered into Excel 2013 spreadsheets and the Matlab (R2014a) software package.

RESULTS AND DISCUSSION

A. Interpretation of LCA results

A summary of the environmental impacts, assessed on the basis of selected functional unit is shown in Table 3. Farm emissions encompassed emissions to air, water and soil from the field. After calculating all emissions, all of them were converted into the reference substances according to each impact category (characterization factors). For instance in the impact category of GWP all the emissions were converted to CO_2 equivalent according to CML guidelines (Guinée *et al.*, 2002). The results revealed that total GWP was calculated as 655 kg CO_2 eq. Other impacts including AD, ODP, HTP, PO, AP and EP were computed as 2.2 kg Sb eq., 0.0000319 kg CFC-11 eq., 0.286 kg C_2H_4 eq., 10.4 kg SO_2 eq., and 4.54 kg PO43- eq., respectively. Sadeghzadeh *et al.* (2015) in their study on eggplant production computed impact categories GWP, AD, ODP, HTP, PO, AP and EP as 252.99 kg CO_2eq, 0.003 kg Sb eq., 1.54E-05 kg CFC-11 eq., 0.13 kg C_2H_4eq., 1.23 kg SO_2eq., and 3.84 kg PO43-eq., respectively.

Negative value of FAE indicates that the production of tobacco not only has no negative effect in this impact category but also reduce environmental loads in this category. Negative value of FAE is due to application of manure in tobacco production. Generally, application of manure reduce environmental loads in all impact categories except PO (Fig. 1).

Table 3: Environmental impact categories and their value for selected functional unit (1 ton of tobacco production).

Impact categories	Units	Values
Abiotic depletion	kg Sb $_{eq.}$	2.2
Global warming potential	kg $CO_{2eq.}$	655
Ozone layer depletion potential	kg CFC-11 $_{eq.}$	0.0000319
Human toxicity potential	kg 1,4-DB $_{eq.}$	229
Fresh water aquatic ecotoxicity	kg 1,4-DB $_{eq.}$	-34.3
Marine aquatic ecotoxicity	kg 1,4-DB $_{eq.}$	202000
Terrestrial ecotoxicity potential	kg 1,4-DB $_{eq.}$	1.02
Photochemical oxidation	kg $C_2H_{4eq.}$	0.286
Acidification potential	kg $SO_{2eq.}$	10.4
Eutrophication potential	kg $PO_{43\text{-}eq.}$	4.54

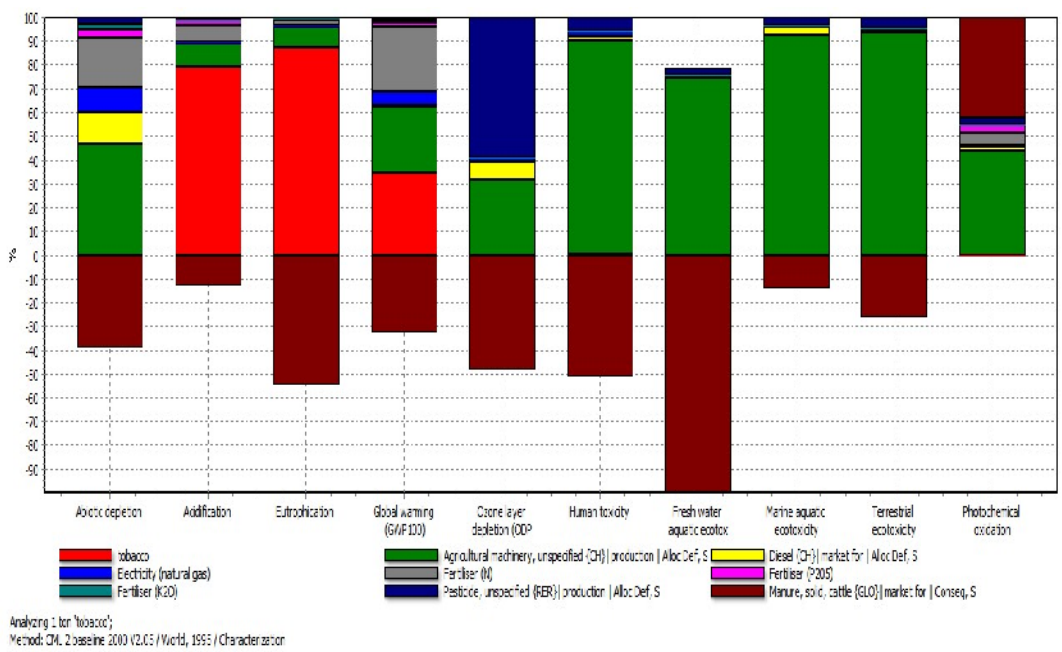

Fig. 1. Contribution of inputs to environmental impact categories.

The distribution of emissions of each input is demonstrated in Fig. 1. The results indicated that: 1) machinery had the highest share of emission in the impact categories AD, HTP, FAE, MAE, TEP, and PO; 2) on-farm emissions had the highest share of emission in the impact categories AP, EP, and GWP; and 3) pesticides had the highest share of emission in the impact category ODP. The import of non-standard machinery was the main reason of machinery share in total emissions. In another hand, irregular consumption of chemical fertilizers (especially nitrogen) and pesticides caused high share of on-farm emissions and pesticides in some impact categories. The lack of true pattern for chemical products application and improper pricing policy (for example low price of chemical fertilizer and pesticides) was main problems in the agricultural system of the study area. Accordingly, true application of farm machinery and chemical products can significantly reduce environmental impacts of tobacco production.

B. ANN results

In this study, several multi-layer perceptron (MLP) networks were designed, trained and generalized, using the Matlab (R2014a) software package. The Levenberg-Marquardt networks were trained using the training sets formed by including 75 percent of data. The Levenberg-Marquardt algorithm were tested applying the testing datasets including 22 samples. The experimental tests consisted of seven inputs and ten outputs. In this paper, an input layer with eight input variables, one hidden layer with twenty neurons and an output layer with ten outputs variables gained the best results (8-20-10 structure). The highest R2 was calculated by the best topology for ten environmental impacts categories (Table 4). Also, this topology had the lowest value of RMSE and MAPE, indicating that the predicted ten environmental impacts by the ANN model tend to follow the corresponding actual ones quite closely.

Table 4. Network performance of environmental prediction for the best topology.

Environmental indices	R^2	RMSE	MAPE
Abiotic depletion	0.955	0.075	0.066
Global warming potential	0.951	0.063	0.100
Ozone layer depletion potential	0.926	0.073	0.060
Human toxicity potential	0.907	0.067	0.051
Fresh water aquatic ecotoxicity	0.951	0.088	0.101
Marine aquatic ecotoxicity	0.932	0.032	0.037
Terrestrial ecotoxicity potential	0.906	0.072	0.094
Photochemical oxidation	0.929	0.088	0.101
Acidification potential	0.951	0.042	0.064
Eutrophication potential	0.977	0.054	0.100
Abiotic depletion	0.955	0.075	0.066

CONCLUSION

In this study, the ability of ANN model to predict the environmental indices of tobacco production in Mazandaran province in Iran was investigated. Input variables used in ANN models were machinery, diesel fuel, nitrogen, phosphate, potassium, pesticides, electricity and manure while ten environmental impact categories were selected as output parameters. The best topology consisted of an input layer with eight input variables, one hidden layer with twenty neurons in it, and an output layer with 10 output variables (8-20-10 structure). From the results obtained, the developed model gave satisfactory predictions in the studied region and appears to be an appropriate tool for prediction of environmental indices of tobacco production.

ACKNOWLEDGMENT

The first authors express his deep appreciation to Mr. Ashkan Nabavi-Pelesaraei's for helping him revise the study.

REFERENCES

Allen, D.T. and Rosselot, K.S. (1997). Pollution prevention for chemical processes: Wiley-Interscience

Anonymous. (2013). Annual Agricultural Statistics. Ministry of Jihad-e-Agriculture of Iran. [Available from: http://www.maj.ir]. [In Persian].

Boguski, T.K., Hunt, R.G., Cholakis, J.M. & Franklin, W.E. (1996). LCA methodology. In: Curran, M.A. (Ed.), Environmental Life-cycle Assessment. Library of Congress Cataloging-in-Publication Data. pp. 15-33.

Brentrup, F., Küsters, J., Lammel, J. & Kuhlmann, H. (2000). Methods to estimate on-field nitrogen emissions from crop production as an input to LCA studies in the agricultural sector. *The International Journal of Life Cycle Assessment.* **5**(6): 349-357.

Chawla, H. S. (2003). Plant biotechnology: a practical approach: Science Publishers.

Davis, D.L. & Nielsen, M. T. (1999). Tobacco: production, chemistry and technology: Blackwell Science Ltd.

Eggleston, H., Buendia, L., Miwa, K., Ngara, T. & Tanabe, K. (2006). IPCC guidelines for national greenhouse gas inventories. Institute for Global Environmental Strategies, Hayama, Japan.

EPA. (1995) .Compilation of air pollutant emissions factors.

Erickson, J., Cisar, J., Volin, J.& Snyder, G. (2001). Comparing nitrogen runoff and leaching between newly established St. Augustinegrass turf and an alternative residential landscape. *Crop Science.* **41**(6): 1889-1895.

FAO. (2012). Agriculture organization of the United Nations. Statistical database.

Galloway, J.N., Schlesinger, W.H., Levy, H., Michaels, A. & Schnoor, J.L. (1995). Nitrogen fixation: Anthropogenic enhancement environmental response. *Global Biogeochemical Cycles.* **9**(2): 235-252.

Ghodsi, R., Mirabdollah, R., Jalali, R. & Ruzbahman, M. (2012). Predicting wheat production in Iran using an artificial neural networks approach. *International Journal of Academic Research in Business and Social Sciences.* **2**(2): 34-47.

Guinée, JB., Gorrée, M., Heijungs, R., Huppes, G., de Koning, KRA. & Wegener Sleeswijk, A. (2002). Handbook on Life Cycle Assessment. Operational Guide to the ISO Standards. Kluwer, Dordrecht, The Netherlands.

Khoshnevisan, B., Rafiee, S.& Mousazadeh, H. (2013). Environmental impact assessment of open field and greenhouse strawberry production. *European Journal of Agronomy.* **50**: 29-37.

Mohammadi, A., Rafiee, S., Jafari, A., Keyhani, A., Mousavi-Avval, S. H. & Nonhebel, S. (2014). Energy use efficiency and greenhouse gas emissions of farming systems in north Iran. *Renewable and Sustainable Energy Reviews.* **30**: 724-733.

Mueller, L.A., Solow, T.H., Taylor, N., Skwarecki, B., Buels, R., Binns, J., Wright, M.H., Ahrens, R. & Wang, Y. (2005). The SOL Genomics Network. A comparative resource for Solanaceae biology and beyond. *Plant Physiology.* **138**(3): 1310-1317.

Nabavi-Pelesaraei, A., Abdi, R., Rafiee, S. & Bagheri, I. (2014a). Determination of efficient and inefficient units for watermelon production-a case study: Guilan province of Iran. *Journal of the Saudi Society of Agricultural Sciences.* http://dx.doi.org/10.1016/j.jssas.2014.11.001

Nabavi-Pelesaraei, A., Abdi, R. & Rafiee, S. (2014b). Neural network modeling of energy useand greenhouse gas emissions of watermelonproduction systems. *Journal of the Saudi Society of Agricultural Sciences.* DOI: http://dx.doi.org/10.1016/j.jssas.2014.05.001.

Nabavi-Pelesaraei, A., Shaker-Koohi, S.&Dehpour, MB. (2013). Modeling and optimization of energy inputs and greenhouse gas emissions for eggplant production using artificial neural network and multi-objective genetic algorithm. *International Journal of Advanced Biological and Biomedical Research.***1**(11): 1478-1489.

Nemecek, T. & Kagi, T. (2007). Life cycle inventories of agricultural production systems. Eco invent report No. 15 Dübendorf, CH: Swiss Centre for Life Cycle Inventories; [Available from: http://www.ecoinvent.org/documentation/reports/].

Nourbakhsh, H., Emam-Djomeh, Z., Omid, M., Mirsaeedghazi, H. & Moini, S. (2014). Prediction of red plum juice permeate flux during membrane processing with ANN optimized using RSM. *Computers and Electronics in Agriculture.* **102**: 1-9.

Olmstead, R.G., Bohs, L., Migid, H.A., Santiago-Valentin, E., Garcia, V.F. & Collier, S. M. (2008). A molecular phylogeny of the Solanaceae. *Taxon.* **57**(4): 1159-1181.

PRé Consultants. (2013). Introduction to LCA with SimaPro.

Romero-Gámez, M., Suárez-Rey, E., Antón, A., Castilla, N. & Soriano, T. (2012). Environmental impact of screenhouse and open-field cultivation using a life cycle analysis: the case study of green bean production. *Journal of Cleaner Production.* **28**: 63-69.

Sadeghzadeh, A., Yousefinejad-Ostadkelayeh, M. & Nabavi-Pelesaraei, A. (2015). Modeling and sensitivity analysis of environmental impacts for eggplant production using artificial neural networks. *Biological Forum.* **7**(1): 375-381.

Safa, M. & Samarasinghe, S. (2011). Determination and modelling of energy consumption in wheat production using neural networks: "A case study in Canterbury province, New Zealand". *Energy.* **36**(8): 5140-5147.

Tang, H.W.V. & Yin, M.S. (2012). Forecasting performance of greyprediction for education expenditure and school enrollment. *Economics of Education Review.* **31**: 452-462.

Tso, T.C. (1990). Production, physiology, and biochemistry of tobacco plant: Ideals.

Zhao, Z., Chow, T.L., Rees, H.W., Yang, Q., Xing, Z. and Meng, F.R. (2009). Predict soil texture distributions using an artificial neural network model. *Computers and Electronics in Agriculture.* **65**(1): 36-48.