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Combined application of Artificial Neural Networks and life cycle assessment in lentil farming in Iran

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ABSTRACT

In this study, an Artificial Neural Network (ANN) was applied to model yield and environmental emissions from lentil cultivation in Esfahan province of Iran. Data was gathered from lentil farmers using face to face questionnaire method during 2014–2015 cropping season. Life cycle assessment (LCA) was applied to investigate the environmental impact categories associated with lentil production. Based on the results, total energy input, energy output to input ratio and energy productivity were determined to be 32,970.10 MJ ha^{-1}, 0.902 and 0.06 kg MJ^{-1}, respectively. The greatest amount of energy consumption was attributed to chemical fertilizer (42.76%). Environmental analysis indicated that the acidification potential was higher than other environmental impact categories in lentil production system. Also results showed that the production of agricultural machinery was the main hotspot in abiotic depletion, eutrophication, global warming, human toxicity, fresh water aquatic ecotoxicity, marine aquatic ecotoxicity and terrestrial ecotoxicity impact categories, while direct emissions associated with lentil cultivation was the main hotspot in acidification potential and photochemical oxidation potential. In addition, diesel fuel was the main hotspot only in ozone layer depletion. The ANN model with 9-10-6-11 structure was identified as the most appropriate network for predicting yield and related environmental impact categories of lentil cultivation. Overall, the results of sensitivity analysis revealed that farmyard manure had the greatest effect on the most of the environmental impacts, while machinery was the most affecting parameter on the yield of the crop.

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1. Introduction

Lentil (*Lens culinaris*) as a cool-season annual bushy plant or pulse crop is a member of the legume family. Lentils are grown for their high protein content (about 25%) and supply specially the essential amino acids lysine and leucine for human diet. The crop can play a major role in sustaining soil fertility because of its symbiotic nitrogen fixing ability, especially in cereal-based cropping systems. In addition, its straw can be used as animal feed [1,2].

Lentil as a human diet is one of the most common legumes in the regions of Middle East and Asia. Iran ranks tenth in the world in production of lentil with total production of 78,500 tons and a world share of 1.6%. The cultivation area of lentil in Iran is 140,000 ha which ranked the sixth most cultivated area in the world. Esfahan province is one of the most important areas of lentil production in the country.

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Nomenclature

ANN	Artificial Neural Network	LCA	life cycle assessment
ADP	abiotic depletion potential	LCI	life cycle inventory
ACP	acidification potential	LM	Levenberg–Marquardt
DCB	dichlorobenzene	ME	machinery energy
DE	direct energy	MAPE	mean absolute percentage error
ER	energy ratio	MAEP	marine aquatic ecotoxicity potential
EP	energy productivity	NMVOC	non-methane volatile organic compounds
EUP	eutrophication potential	NRE	nonrenewable energy
FAEP	freshwater aquatic ecotoxicity potential	NEG	net energy gain
FYM	farmyard manure	OLDP	ozone layer depletion potential
FU	functional unit	PHOP	photochemical oxidation potential
GWP	global warming potential	RMSE	root mean square error
GHG	greenhouse gas	RE	renewable energy
HTP	human toxicity potential	SE	specific energy
INE	indirect energy	TEP	terrestrial ecotoxicity potential
IE	irrigation energy		

About 12% of the total lentil production in Iran is supplied in this province [3].

In Iran, despite the high cultivation area of lentil, its average yield is about 700 kg ha^{-1} (Anonymous, 2014) which is relatively low in comparison to the average yield of 1800 kg ha^{-1} in Canada [4]. This comparison shows that increasing the average yield can increase the profitability of lentil cultivation and subsequently increase production [4]. Iranian lentil is produced in a semi-mechanized agricultural system. Land preparation, seeding and fertilization operations are generally conducted in a mechanized manner while weeding, spraying and harvesting operations are performed manually. The manual harvesting operations of Iranian lentil is due to the short height of the plant and lack of suitable harvesting machinery that could cut the plant near the soil surface in the generally stony land of farms in Iran. Also the right amount of chemical fertilizers is not consumed in lentil cultivation and their consumption is determined based on the farmer's experience that resulted in relatively high consumption of fertilizers. Therefore the cost, energy use and environmental damages in lentil production are unreasonably high. Regarding these issues, more efficient use of energy and better environmental management in lentil cultivation are important to provide a sustainable production, therefore modeling the environmental impacts associated with lentil production was recognized as important tool for both farmers and decision makers in agriculture.

Life cycle assessment (LCA) methodology is applied for environmental analysis of a product by establishing the inventory of the energy and material inputs vs environmental emissions brought about from each stage of the life cycle of the product, from resource extraction until processing, application, disposal and expressing the results in terms of impact categories [5]. Nowadays, global warming is considered as one of the most serious environmental impact categories man is confronted with. Greenhouse gas (GHG) emissions from agricultural production systems account for 11% of all manmade GHG emissions [4,6]. Thus, LCA is becoming more and more important in the agro-food sector. A review of the literature demonstrated that several researchers have assessed the environmental impacts related to different agricultural products throughout their life cycle using LCA based on cradle to grave approach [7–14].

Despite the importance of lentil production in Iran and considerable amount of research work that has been assessed and predicted the energy use and environmental impacts of agricultural products, the number of publications accessed these topics in the cultivation of lentil or even other legumes is rather small. Abeliotis et al. [15] conducted an LCA study to compare the production of three different varieties of bean in Greece based on three different cultivation methods, i.e., conventional, integrated and organic. Overall results showed that integrated agricultural method could preferably be used to establish the most environmentally friendly production system among the three. Romero-Gámez et al. [8] evaluated the environmental impacts attributed to green beans production in three different cropping systems in Spain including screen house, screen house equipped with misting system and cropping in the open field by applying LCA. Koocheki et al. [16] performed an energy input–output analysis of pulses (lentil, bean and chickpea) production in Khorasan Razavi province of Iran. It must be mentioned that they considered the embodied energy in straw as the output energy, while in the present study only the energy of lentil was considered as the output energy.

Artificial Neural Network (ANN) technique has proved to be of several applications for modeling, simulation and forecasting in the complex nonlinear systems in which there is not any linear or simple relationship between inputs and output(s). Capturing the underlying relationship is known as the process of learning the network [17,18]. ANN models were used to predict energy usage, yield and environmental emissions related to agricultural products in various studies. Khoshnevisan et al. [19] developed an ANN model for estimating output energy and GHG emissions in terms of global warming potential (GWP) of potato production in Esfahan province of Iran as a function of input energies, i.e., human labor, diesel fuel, electricity, seed, machinery, farmyard manure, chemical fertilizers, biocides and irrigation water. They deduced that modeling of both output energy and GWP was performed with a high accuracy. Nabavi-Pelesaraei et al. [20] applied ANN in modeling energy use and GWP of kiwifruit production in Iran based on all inputs within the area. Pahlavan et al. [21] developed an ANN model to estimate the production yield of greenhouse basil in Iran based on energy inputs. Safa and Samarasinghe [18] developed an ANN model for predicting energy consumption in wheat production based on farm conditions, farmers' social considerations and energy inputs in New Zealand. They mentioned that ANN model can predict energy consumption relatively better than the applied multiple linear regression model. In another study, ANN model with Levenberg–Marquardt (LM) training algorithm was applied to predict yield and GWP of watermelon production in Guilan province of Iran [22]. Taghavifar and Mardani [23] developed an ANN model to predict the yield and GWP of apple production in West Azarbayjan of Iran on the basis of input energies. They highlighted that ANN is a powerful and robust tool for studding energy and environmental emissions in agricultural systems.

To the best of authors' knowledge, there is no study up to date on the prediction of yield (output energy) and environmental impact categories of lentil production using ANN models in Iran and even all over the world. Although in all the conducted studies in this field, only one environmental impact category, i.e., GWP was considered. Therefore it is essential to develop an ANN model that can predict simultaneously a number of environmental impact categories and yield based on input energies. Therefore, the main objective of the present study was to estimate the ten environmental impact categories presented by CML2 baseline method and yield of lentil production in Iran using ANN modeling technique. Accordingly, several ANN models were structured and their performance for prediction of output parameters evaluated using the statistical quality parameters. Finally, the sensitivity analysis of the energy inputs on lentil yield and the environmental impact categories were investigated.

2. Materials and methods

2.1. Case study region and data collection

This research was conducted in Esfahan province, located between 30°42′ and 34°30′ N latitudes and 49°36′ and 55°32′ E longitudes, in the center of Iran [24]. The study covered the rural areas in the five regions of the province including Chadegan, Fereydonshahr, Fereydan, Tiran and Semirom. The data was collected from 140 lentil farmers using a face to face questionnaire method in 2014–2015 cropping season. The total area of the investigated lentil farms in the studied area was 163.5 ha. The average size of the lentil farms in Chadegan, Fereydonshahr, Fereydan, Tiran and Semirom regions were 1.12, 1.22, 1.38, 0.91 and 0.85 ha, which were not statistically significant. It must be noted that in these regions, apart from lentil, other important crops such as wheat, sugar beet and chickpea were cultivated. Before the data being collected, a pre-test survey was done; thus, a group of farmers randomly selected and interviews conducted. For sampling, simple random sampling method was used. The sample size was determined using Cochran method as follows [25,26]:

$$n = \frac{N \times S^2 \times r^2}{(N-1)e^2 + (S^2 \times t^2)} \tag{1}$$

where 'n' denotes the calculated sample size, 'N' stands for the number of lentil farmers in target population, 'S' presents the standard deviation for the pre-tested data, 'r' denotes the reliability coefficient (1.96 which represents 95% confidence) and 'e' stands for the acceptable error, which was defined to be 5% for a confidence level of 95%.

2.2. Energy balance in lentil cultivation

The input energy sources for lentil production in the region included human labor, machinery, diesel fuel, farmyard manure (FYM), chemical fertilizer, electricity, chemicals (pesticides) and seeds while the produced lentil accounted as the output energy.

In order to convert inputs and output materials into energy forms, the energy equivalent coefficients was used as detailed in Table 1. In this study, the corresponding energy coefficients were extracted from the literature. These coefficients are constant values that do not depend on the product type. For example, diesel fuel and human labor in the production of different products are of the same nature and have constant coefficients for the conversion to their energy forms. Thus, the energy consumption in various agricultural products differs in input values. Expressing the energy consumption in lentil production using standard coefficients resulted in the unique pattern of energy consumption of the crop. Therefore, it will be possible to compare the energy consumption in different products or production systems.

To assess the energy consumption by agricultural machinery in different farm operations, it was assumed that energy use for the manufacturing of agricultural implements and tractors be depreciated during their economic life time [27]. Therefore, the following formula was used to estimate machine energy (ME) per hectare [27,28]:

$$ME = \frac{G \times M_p \times t}{T} \tag{2}$$

where 'ME' is the machine energy (MJ ha^{-1}), 'T' is the economic life of the machine (h), 'G' stands for the mass of the machine (kg) and 't' denotes the operation time of the machine per unit area (h ha^{-1}).

Irrigation energy (IE) was expressed as below [29]:

$$IE = \frac{d \times g \times H \times Q}{\eta_1 \times \eta_2} \tag{3}$$

where 'IE' is irrigation energy (J ha^{-1}), 'g' is gravitational acceleration (9.81 m s^{-2}), 'd' stands for the density of water (1000 kg m^{-3}), 'Q' presents the overall quantity of water (m^3 ha^{-1}) including losses by evaporation, drainage run-off, etc., 'H' denotes the total dynamic head (m), 'η_1' is the pump efficiency and 'η_2' is representing the efficiency of the powering system, either electric motor or diesel engine.

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Table 1 – Energy equivalent of inputs and output in lentil production.

Input–output (Unit)	Energy equivalent (MJ per unit)	References
1. Inputs		
Labor (h)	1.96	[21]
Machinery (kg)		
Tractor	138	[29]
Plow	180	[29]
Disk	149	[29]
Boundaries	160	[29]
Leveler	149	[29]
Planter	133	[29]
Sprayer	129	[29]
Rotary Hoes	148	[29]
Thrashing (h)	62.7	[29]
Seed (kg)	14.7	[16]
Chemicals (kg)		
Herbicide	238	[11]
Insecticide	101.2	[11]
Diesel (L)	47.8	[29]
Electricity (kWh)	11.93	[26]
Chemical fertilizer (kg)		
Nitrogen (N)	78.1	[30]
Phosphate (P_2O_5)	17.4	[30]
Potassium (K_2O)	13.7	[30]
Farmyard manure (kg)	0.3	[54]
2. Output (kg)		
Lentil	14.7	[16]

Other inputs including diesel fuel, human labor, electricity, seed, chemicals, FYM and chemical fertilizers used throughout lentil production were multiplied by their corresponding energy equivalents (Table 1) to calculate their relevant energy consumptions in unit of MJ ha^{-1}.

The energy balance in agricultural crop production is expressed in terms of some energy indices including the energy ratio (ER), energy productivity (EP), specific energy (SE) and net energy gain (NEG). Implementing energy balance of agricultural products can be a very useful tool for decision makers to compare and analyze various alternative products with lentil in the study area. Based upon the energy taken from the inputs vs that derived from output, ER (which is indicative of the energy use efficiency defined as the ratio of output energy to input energies), EP, SE and NEG were calculated as follows [29]:

$$ER = \frac{\text{output Energy}(\text{MJ ha}^{-1})}{\text{Input Energy}(\text{MJ ha}^{-1})} \tag{4}$$

$$EP = \frac{\text{lentil out put}(\text{Kg ha}^{-1})}{\text{Energy input}(\text{MJ ha}^{-1})} \tag{5}$$

$$SE = \frac{\text{Energy input}(\text{MJ ha}^{-1})}{\text{lentil output}(\text{Kg ha}^{-1})} \tag{6}$$

$$NEG = \text{Output Energy}(\text{MJ ha}^{-1}) - \text{Input Energy}(\text{MJ ha}^{-1}) \tag{7}$$

Based on the type of energy sources, energy demand in agriculture can be classified into direct (DE) and indirect (IDE), renewable (RE), and non-renewable (NRE) energies. DE is used directly in agriculture comes from a fossil origin such as diesel fuel, gasoline, liquid petroleum gas, coal and from electricity. IDE refers to the energy used to produce equipment and other materials that are used on the farm. The major IDE is contributed to chemical fertilizers, machinery and water used in irrigation [29]. In this study, DE includes energy derived from human labor, diesel fuel, water used in irrigation and the electricity to power irrigation pumps while INE covers energy that is embodied in seeds, FYM, machinery, chemical fertilizers and chemicals.

RE and NRE are other forms of energy. RE is used to describe energy sources that are replenished by natural processes on a sufficiently rapid time-scale. Thus RE can be used by humans more or less indefinitely, provided the quantity taken per unit of time is not too great. On the other hand, NRE term is used to describe energy sources that exist in a limited amount on earth [30]. In this study, RE sources consist of human labor, seeds, water used up in irrigation and FYM, while NRE in the production of the crop is resulted from the use of diesel fuel, chemicals, electricity, chemical fertilizers and machinery.

2.3. *Life cycle assessment methodology*

LCA of any product is performed based on the cradle to grave approach, i.e., from production of input materials using raw materials to the produced lentil in the farms. This means that the whole process of production is analyzed by considering all inputs (raw materials and energy consumption) and their interactions [31]. LCA specifies the environmental impacts considering all materials emitted into air, soil and water cause environmental burdens [32]. Based on ISO 14040, every LCA methodology consists of four stages i.e. goal and scope definition, inventory analysis of materials or processes, environmental impact assessment and interpretation of the results [33].

2.3.1. *Goal and scope definition*

Goal and scope definition is the first stage in an LCA study. It defines the purpose of the study, describes the functional unit and expected product of the study, the product system and its boundaries, the approach of data collection and its processing and finally the considered environmental impact categories. To achieve a sharper understanding of the goal in LCA studies, the boundaries of the system must be clearly defined. Therefore all operations which contribute to the life cycle of the product, process, or activity of interest are considered within the system boundaries [34]. In this study, the total inputs from the cradle (i.e., production of machinery, fertilizer and pesticide from raw materials) to the farm gate (harvested lentil) was considered as system boundary (Fig. 1). Determining the functional unit (FU) in LCA is a key concept that makes it possible to compare different products in a unique scale [33]. In agricultural systems, generally two functional units are considered, namely the mass-based and land-based. The mass-based FU deals with the unit of mass of a product, e.g. ton or kg of dry material, and land based FU is concerned with the unit of cultivated area, i.e. one cultivated hectare per year [35]. Based on the relatively equal farm size about one hectare and lentil yield in the studied area, considering FU as one cul-

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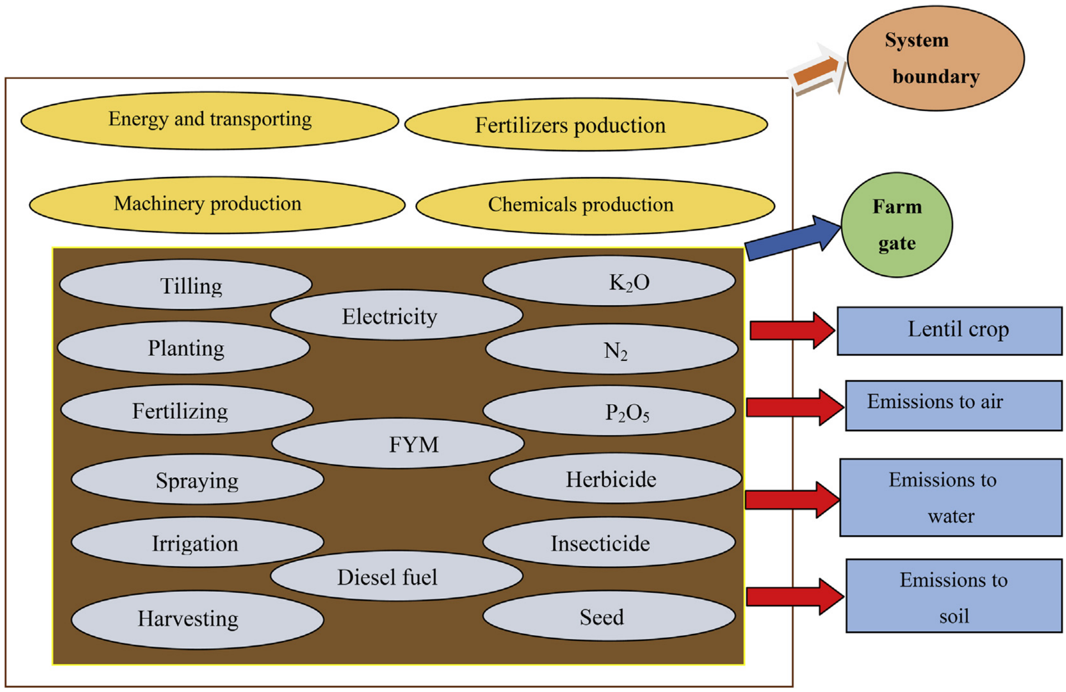

Fig. 1 – The farm gate as system boundary of lentil production.

tivated hectare is useful in analysis of the farms. Therefore, these two FUs were considered simultaneously in this study in order to be able to effectively clarify the environmental performance of LCA of lentil production [19].

2.3.2. *Life cycle inventory (LCI)*

The inventory analysis corresponds to all resources required for lentil production and all the emissions generated from the production process considering the specific FU. In this study, environmental emissions of lentil production were divided into two parts. The first part called indirect emissions refers to environmental impacts of inputs during their production phase. The second part encompassed the direct emissions associated with consumption of inputs in lentil production as presented in Table 2. Direct emissions were due to the diesel fuel consumption, application of fertilizers (chemical fertilizers and FYM) and use of chemicals adopted from literature, environmental reports and EcoInvent database center [36,37], which is explained in the following.

The application of chemical fertilizers resulted in direct emissions including emissions of ammonia, nitrogen monoxide and nitrogen oxides into the air and nitrate leaching to groundwater. Several methodologies have been introduced to estimate direct emissions of chemical fertilizers but EMEP/EAA guidelines from the European Environmental Agency [38] and IPCC guidelines [39] are the most relevant ones.

Crop production in the study region is extensively related to the application of nitrogen fertilizers. Based on IPCC guidelines [39], by application of 100 kg of nitrogen fertilizers, 1.25 kg of N_2O is emitted into the air. Also, Galloway et al. [40] reported that 2% of the total nitrogen fertilizer is emitted

Table 2 – Life cycle inventory data for lentil production.

Inputs	Units	Average	Max	Min	SD
Seed	kg	74.78	90	60	6.37
Chemical fertilizers					
Nitrogen (N)	kg	134.92	200	100	27.41
Phosphate (P2O5)	kg	131.35	180	100	23.81
Potassium (K2O)	kg	75.28	150	0	42.35
FYM	kg	892.75	5000	0	1921.84
Herbicide	kg	2.07	3.26	1.39	0.47
insecticide	kg	3.05	4.66	1.99	0.77
Machinery	kg	5752.96	7320	4430	895.27
Diesel fuel	L	108.39	140	80	611.7
Labor	h	201.10	245	170	29.69
Water for irrigation	m^3	366.82	350	260	132.55
Electricity	kWh	565	800	450	107.07

in the form of NO_x and likewise, 8% of the total nitrogen applied is emitted in the form of NH_3. In addition, it was assumed that 30% of nitrogen fertilizers in the form of nitrate (NO_3^-) are leaching from soil into the groundwater [41]. The use of phosphorus (P) fertilizers resulted in emissions to soil and water. Phosphate (P_2O_5) emissions in the form of phosphorus is calculated through an equilibrium, in which seed and fertilizers are inputs and lentil and accumulated phosphorus in the soil are considered as outputs. About 2.9% of the total phosphorus fertilizers in the soil leaches from soil profile in the form of phosphate. The average amount of phosphorus leached to groundwater was considered as 0.22 kg P-based fertilizers per ha [42]. Pesticides may contain either a single or a combination of two or more active ingredients. Throughout the present study, herbicides and insecticides were considered as a single input referred to as "pesticides". Van den Berg and Ashmore [43] have estimated that 30–50% of applied pesticides in agricultural crop spraying are emitted into the air due to spray drift and volatilization.

Within the lentil production, diesel fuel was used up by tractors in different farm operations. Direct emissions from combustion of diesel fuel into air in farm operations was calculated by multiplying the amount of consumed energy of diesel fuel per hectare by the emission factors based on Ecoinvent database due to its completeness. The values of various emission factors applied in this study derived from data given by Nemecek and Kagi [44] are presented in Table 3. Accordingly, all of the emissions from diesel fuel combustion can be released into air which is obtained by multiplying the emission factors by the amount of consumed energy from diesel fuel per hectare.

2.3.3. *Life cycle impact assessment*

Life cycle impact assessment as the third LCA step investigates the environmental impacts associated with emissions and consumption of resources in a production system. This step consists of a number of compulsory vs voluntary steps. The compulsory steps involve translating the inventory data of input materials and production processes into their contributions to a number of specified environmental impact categories (impact characterization). The voluntary steps are traditionally directed at evaluating the results of impact categories while considering each other (normalization) [45]. Literature review indicated that, CML 2 baseline 2000 V2.05/world 1997/characterization method developed by Leiden University is commonly used in LCA studies of agricultural products. Additionally, application of this method had been the most frequent approach to analysis of the life cycle in the production systems [46]. To perform impact assessment, CML 2 baseline 2000 V2/world method and its ten environmental impact categories were applied in this study. The selected impact categories were eutrophication potential (EUP), abiotic depletion potential (ADP), acidification potential (AP), human toxicity potential (HTP), global warming potential (GWP), freshwater aquatic ecotoxicity potential (FAEP), marine aquatic ecotoxicity potential (MAEP), terrestrial ecotoxicity potential (TEP), photochemical oxidation potential (PHOP) and ozone layer depletion potential (OLDP). The measurement units for these impact categories can be found in Table 4. The prevalence of the selected impact categories was observed in most of the studies [8,10,11].

Table 3 – Emission factors for 1 MJ energy production from diesel fuel based on EcoInvent.

Emission	Amount (g/MJ diesel)
Carbon dioxide (CO_2)	74.5
Sulfur dioxide (SO_2)	2.41E−02
Methane (CH_4)	3.08E−03
Benzene	1.74E−04
Cadmium (Cd)	2.39E−07
Chromium (Cr)	1.19E−06
Copper (Cu)	4.06E−05
Dinitrogen monoxide (N_2O)	2.86E−03
Nickel (Ni)	1.67E−06
Zinc (Zn)	2.39E−05
Benzo(a)pyrene	7.16E−07
Ammonia (NH_3)	4.77E−04
Selenium (Se)	2.39E−07
PAH (poly cyclic hydrocarbons)	7.85E−05
Hydro carbons (HC, as NMVOC)	6.80E−02
Nitrogen oxides (NOx)	1.06
Carbon monoxide (CO)	1.50E−01
Particulates (<2.5 μm)	1.07E−01

The index for each impact category is calculated using Eq. (8) [47] as follows:

$$ICI_i = \sum_i [(E_j \text{ or } R_j) \times CF_{ij} \quad (8)$$

where ICI_i is indicator value per functional unit for impact category i; E_j or R_j is the emission of *j* mixture or the consumption of *j* resource on each functional unit; CF_{ij} is the characterization factor for *j* mixture in impact category *i*. The characterization factor in each impact category shows the mixture potential for creating the impact.

The LCA analysis was conducted using SimaPro V8.03 software as one of the most common LCA software for analysis of the environmental burdens of a product through its life cycle.

2.3.4. *Interpretation of the LCA results*

In the fourth stage of the LCA, all the results will be analyzed in order to investigate the environmental conditions resulted from production system and provide solutions. LCA results obtained in this study will be discussed in the results section.

2.4. *Development of ANN models*

Selection of the appropriate inputs parameters of the ANN model is the key step of model development. Nine input energies including human labor, diesel fuel, machinery, chemical fertilizers, chemicals, FYM, electricity, water for irrigation and seeds were considered as inputs to the ANN model, while eleven output parameters, i.e. lentil yield and ten environmental impact categories were considered as model outputs. To ensure the suitability of this selection, the relationship between dependent variables (input energies) and independent variables (outputs of the model) was analyzed statistically by SPSS software. Based on the evaluation results, there were significant correlations between inputs and outputs while the correlations between inputs were not statistically significant.

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Table 4 – Environmental indices categories and measurement units for each category.

Impact categories	Nomenclature	Measurement units
Abiotic depletion potential	ADP	kg Sb eq.
Acidification potential	ACP	kg SO_2 eq.
Eutrophication potential	EUP	kg PO_4^{2-} eq.
Global warming potential[a]	GWP	kg CO_2 eq.
Ozone layer depletion potential	OLDP	kg CFC-11 eq.
Human toxicity potential[a]	HTP	kg 1,4-DCB eq.[b]
Freshwater aquatic ecotoxicity potential	FAEP	kg 1,4-DCB eq.[b]
Marine aquatic ecotoxicity potential	MAEP	kg 1,4-DCB eq.[b]
Terrestrial ecotoxicity potential[a]	TEP	kg 1,4-DCB eq.[b]
Photochemical oxidation	PHOP	kg C_2H_4 eq.

a Considering 100 years.
b DCB = dichlorobenzene.

ANN models are excellent nonlinear modeling tools which can efficiently find the existing deterministic relation between input and output variables by composition of activation functions and weights. In this study, several feed-forward back-propagation neural networks with an input layer, one or more hidden layers and a single layer of output neurons were evaluated and trained using the collected data. In this study, the sigmoid and linear transfer functions were respectively applied for the hidden layers and the output layer. LM training algorithm as one of the most common learning rules in ANN was used for network training. In feed-forward back-propagation neural network, the information flows only in the forward direction, from inputs to outputs. The input vector is directly passed to the node activation output of input layer without any computation. The hidden layer with sigmoid activation function performs intermediate computations. Then, the linear output layer generates the network output. Neurons of the hidden layer with suitable nonlinear transfer functions are applied to process the information by the input nodes received [48].

In this study, the output of the network is given by following equation [49]:

$$y_t = \alpha_0 + \sum_{j=1}^{n} \alpha_j f\left(\sum_{i=1}^{m} \beta_{ij} y_{t-i} + \beta_{0j}\right) + \varepsilon_t \quad (9)$$

where 'n' is the number of hidden nodes, 'm' is the number of input nodes and 'f' stands for a transfer function, i.e., sigmoid function in this study which is defined as $f(x) = \frac{1}{1+\exp(-x)}$. Also, $\{\beta_{ij}, i = 1, 2, \ldots, m; j = 0, 1, \ldots, n\}$ are weights from the input to the hidden nodes, while, the vectors of weights from the hidden to the output nodes are represented as $\{\alpha_j, j = 0, 1, \ldots, n\}$, moreover '$\alpha_0$' and '$\beta_{oj}$' denote the weights of arcs leading from the bias terms, which are of values always equal to 1.

Basic information on inputs and outputs in lentil farms in the form of input and output matrixes was entered into Matlab V7.14 (R2012a) software package to perform ANN analysis. MATLAB software was used to train and test the developed ANNs on a personal computer. The input and output data sets are matrixes composed of vectors specific to each farm. The input vector includes nine input energies while output vector covers eleven output parameters, i.e., yield and ten impact categories in any farm. Moreover, inputs and outputs data were normalized in the range of 0–1 and then returned to original values after the simulation. In this study, data collected from 80, 20 and 40 lentil farmers were respectively used for training, cross validation and testing of the developed ANN models.

For the development of ANN models, several networks were built up and tested using the experimental data to determine the most appropriate ANN arrangement for predicting the output parameters. In this research, 80, 20 and 40 units were respectively used for training, cross validation and testing of ANN models. Accordingly, the most acceptable topology was identified by the highest R^2 value vs the lowest RMSE as well as MAPE values.

To assess the performance of the developed ANN models for estimating the desired output in lentil production, some statistical quality parameters including mean absolute percentage error (MAPE), root mean square error (RMSE) and coefficient of determination (R^2) were employed as follows [18,21]:

$$\mathrm{MAPE}(\%) = \frac{100}{n} \sum_{t=1}^{n} \left| \frac{(t_i - z_i)}{t_i} \right| \quad (10)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (t_i - z_i)^2} \quad (11)$$

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{n} (t_i - z_i)^2}{\sum_{i=1}^{n} t_i^2} \right] \quad (12)$$

where 't_i' and 'z_i' are respectively the actual and predicted values by the ANN model and 'n' denotes the total number of data. Relative percentage deviation between the predicted and measured values was evaluated by MAPE. The MAPE value smaller than 10% was considered to be the acceptable value. The smaller the values of MAPE and RMSE are, the better performance of the ANN model is achieved. The coefficient of determination was used to determine that how well the model approximates the real data points; That is, a model acts more efficiently and accurately when R^2 values are closer to unity.

Sensitivity analysis investigates the influence of input parameters of the model on the model outputs. It can rank and specify the influential input parameters on yield and environmental emissions. To analyze the sensitivity of energy inputs on yield and ten environmental impact categories in lentil cultivation, sensitivity analysis via ANN was conducted using the NeuroSolutions V5.07 software package [50]. In this study, the sensitivity analysis reveals clearly the contribution of input parameters of the best ANN model on the desired outputs, i.e., lentil yield and assessed environmental impact categories. By considering the analysis, it becomes evident that the analysis is of a great assistance in making it feasible to judge what parameters should be considered as the most significant vs the least significant ones during the generation a satisfactory model [21].

3. Results and discussion

3.1. Analysis of input–output energy use in lentil production

Various energy inputs used in the production of lentil and their percentage share from the total energy inputs are given in Table 5. The average of total input energy for cultivating one hectare of lentil and the energy output calculated were 32,970.10 MJ ha^{-1} and 29,746.50, respectively. Also, a detailed description of the share of each input energy to the total input energy is shown in Fig. 2. Based on the results, the energy related to chemical fertilizers amounting to 13,855 MJ ha^{-1} contributed the highest share (42.76%) from the total energy input in lentil production within the region. Energy contribution related to chemical fertilizers N, K_2O and P_2O_5 amounted to 76.05%, 16.47% and 7.48% of total energy of chemical fertilizers, respectively. Following chemical fertilizers, the parameters of electricity, diesel fuel and irrigation water were the main energy consuming inputs with values of 20.92%, 15.99% and 12.21%, respectively in lentil production. The total share of all five input energies related to seed, chemicals, machinery, human labor and FYM was 8.12% of total input energy.

Koocheki et al. [16] reported that diesel fuel energy made up 24.36% of total energy, followed by irrigation water (18.79%), chemical fertilizers (18.52%) and electricity (13.27%) for lentil production in Khorasan Razavi province of Iran. As mentioned before, energy and environmental analyses in production of crops from legume family are very sparse, therefore the energy use profile for production of some agricultural products were assessed. Many studies presented similar results and revealed that chemical fertilizers and diesel fuel are the most energy consuming inputs in production of agricultural products [19,21,26,51,52]. Excessive use of chemical fertilizers in agricultural systems generates such environmental burdens as nitrogen loading and carbon emissions in the environment causing degradation of water quality [53]. In Iran, the primary fuel source for electricity generation is fossil fuels, and since the electric power transmission system is outdated; thus, the efficiencies in electricity production and transmission are low. Also, use of old and inefficient agricultural tractors and implements in field operations increases the diesel fuel consumption. For time man-

Table 5 – Amounts of energy inputs and output in lentil production.

Inputs/output	Min (MJ/ha)	Max (MJ/ha)	SD	Average (MJ/ha)	Percentage (%)
A. Inputs					
1. Human labor	333.2	480.2	29.69	394.17	1.21
2. Machinery	246.33	1144.53	199.45	631.7	1.94
(a) Tractor	66.59	517.03	102.38	236.37	0.72
(b) Plow	50	105	9.80	66.85	0.20
(c) Disk	20	85	14.19	47.46	0.14
(d) Boundaries	0	14.4	3.62	7.38	0.02
(e) Leveler	0	6.5	2.38	2.72	0.00
(f) Planter	70	150	18.52	106.41	0.32
(g) Sprayer	0	135	31.26	74.53	0.23
(h) Rotary Hoes	0	75	19.26	45.91	0.14
(i) Thrashing	10	32.8	4.68	18.17	0.05
3. Diesel fuel	3824	6692	611.70	5181.17	15.99
4. Chemical Fertilizers	9550	20,807	2983.84	13854.87	42.76
(a) Nitrogen	7810	15,620	2141.41	10537.92	32.52
(b) Phosphorus (P2O5)	1740	3132	414.40	2285.61	7.05
(c) Potassium (K2O)	0	2055	580.22	1031.34	3.18
5. Farmyard manure (FYM)	0	1500	576.55	267.85	0.82
6.Chemical	535	1250	180.51	803.75	2.48
(a) Herbicide	333	778	112.87	494.37	1.52
(b) (b) Insecticide	202	472	78.19	309.38	0.96
7. Water for irrigation	2849.73	4964.47	484.52	3957.21	12.21
8. Seed	882	1323	93.66	1099.35	3.39
9.Electricity	5400	9600	1284.84	6780	20.92
Total energy input	23713.13	45901.91	5901.19	32970.10	100
B. Output					
Total energy output	26,460	33,075	1751.00	29746.50	100

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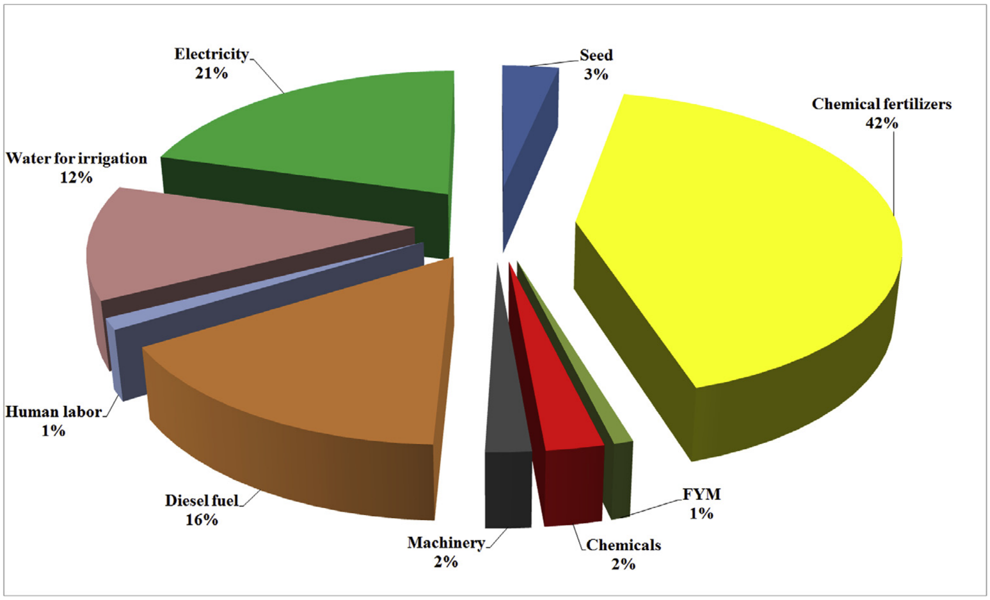

Fig. 2 – The share of total mean energy inputs in lentil production.

agement and economy in fuel consumption, it is essential that the machinery and equipment work at their highest field capacities.

Table 6 presents the values of lentil yield (kg ha^{-1}) and values of energy indices of ER, EP, SE and NEG for lentil production. Also, total input energy consumed in different forms as DE, IDE, RE and NRE (MJ ha^{-1}) are given in this table. The average value of ER index in lentil cultivation was calculated on 0.902 indicating that energy use in lentil production is virtually inefficient in the study region. Other researchers have reported similar results i.e. 0.72 for lentil by considering only lentil in calculation of output energy [16], 0.96 for cherry [25], 1.16 for apple [54] and finally 1.1 for potato [55]. The average yield in the study region was calculated as 2,023.57 kg ha^{-1} while the average yield of 696.6 kg ha^{-1} in Khorasan Razavi province of Iran was reported by Koocheki et al. [16]. This comparison shows that the lentil yield in Esfahan province is relatively high with respect to other regions of the country. The average values of energy indices i.e. SE, NEG and EP in lentil production were calculated as 16.82 MJ kg^{-1}, −3,223.61 MJ ha^{-1} and 0.06 kg MJ^{-1}, respectively. NEG is negative, therefore it could be concluded that, in lentil production, energy is being lost.

The total energy use in the form of DE and IDE were calculated as 16,312.55 (49.47%) and 16,657.54 (50.53%), respectively. It is clear that DE and IDE have same contribution in input energy of lentil cultivation. The share of RE was 17.34% (5718.58 MJ ha^{-1}) while that of NRE form was 82.66% (27,251.52 MJ ha^{-1}), respectively. It is clear from Table 6 that in comparison with RE, the contribution of NRE is higher, thus lentil production is most dependent on NRE sources (such as chemical fertilizers and fossil fuels). Several researchers presented similar results that the contribution of NRE was higher than that of RE for different agricultural products [16,23,53,56].

3.2. *Interpretation of LCA results in lentil production*

On the basis of the models presented by SimaPro software, more than 1600 emissions from raw materials were generated including emissions emitted into air, soil and water. Accordingly, a part of inventory emissions to air, soil and water associated with inputs used in lentil production are tabulated in Table 7. As shown, the emission values related to CO_2, SO_2, CH_4, N_2O and CO were determined as 385997, 124, 15, 14 and 777 g ha^{-1}, respectively. The type of fertilizer is the main

Table 6 – Lentil yield, energy indices and different form of energy in lentil production.

Items	Unit	Min	Max	Average	SD
Yield	kg ha^{-1}	1800.00	2250.00	2023.57	119.11
Energy use efficiency	–	0.70	1.11	0.902	0.10
Specific energy	MJ kg^{-1}	13.18	20.86	16.29	2.00
Energy productivity	kg MJ^{-1}	0.04	0.07	0.06	0.007
Net energy	MJ ha^{-1}	−13561.90	2722.86	−3223.60	4296.49
Direct energy	MJ ha^{-1}	12426.54	21511.02	16312.55(49.47%)	2264.72
Indirect energy	MJ ha^{-1}	11221.01	25747.1	16657.54(50.53%)	3727.22
Renewable energy	MJ ha^{-1}	4084.53	7929.31	5718.58(17.34%)	981.19
Non-renewable energy	MJ ha^{-1}	19563.01	37972.70	27251.52(82.66%)	5043.70

Table 7 – Some environmental emissions of lentil production per hectare.

Type of emissions	Emission source	Unit	Amount (Unit ha^{-1})
A. To air			
1. Carbon dioxide (CO_2)	Diesel fuel	g	385997.1650
2. Sulfur dioxide (SO_2)	Diesel fuel	g	124.8661
3. Methane (CH_4)	Diesel fuel	g	15.9580
4. Benzene (C_6H_6)	Diesel fuel	g	0.9015
5. Di nitrogen monoxide (N2O)	Diesel fuel	g	14.8182
6. Ammonia (NH_3)	Diesel fuel	g	2.4714
7. Hydrocarbons (HC, as NMVOC)	Diesel fuel	g	352.3195
8. Nitrogen oxides (NO_x)	Diesel fuel	g	5492.0402
9. Carbon monoxide (CO)	Diesel fuel	g	777.1755
10. Particulates (<2.5 mm)	Diesel fuel	g	544.3851
11. Di nitrogen monoxide (N_2O)	Fertilizer	kg	1.686
12. Nitrogen oxides (NOx)	Fertilizer	kg	2.698
13. Ammonia (NH_3)	Fertilizer	kg	10.793
B. To soli			
1. Pesticide	pesticide	kg	2.048
2. Nitrate (NO_3^-)	Fertilizer	μg	81.1108
3. Cadmium (Cd)	Fertilizer	mg	62.6834
4. Cobalt (Co)	Fertilizer	mg	3.3794
5. Zinc (Zn)	Fertilizer	mg	187.1091
6. Lead(Pb)	Fertilizer	mg	35.8289
C. To water			
1. Nitrate(NO_3^-)	Fertilizer	kg	40.48
2. Phosphorus	Fertilizer	kg	29.68

Table 8 – Life cycle impact impacts per two distinctive FUs.

Impact category	Mass based FU: 1 ton	Land based FU: 1 ha
Abiotic depletion	17.98	36.38
Acidification	81.97	165.57
Eutrophication	2.12	4.28
Global warming (GWP100)	3593.72	7259.31
Ozone layer depletion (ODP)	0.00037	0.00074
Human toxicity	2289.75	4625.29
Fresh water aquatic ecotoxicity	62.53	126.31
Marine aquatic ecotoxicity	230051.2	464703.42
Terrestrial ecotoxicity	12.61	25.47
Photochemical oxidation	7.21	14.56

determinant of emissions at all the farm levels. N_2O, NO_x and NH_3 emitted by the fertilizers at 1.68, 2.69 and 10.79 kg ha^{-1} significantly and negatively affect the air in the studied region (Table 7). Nemecek et al. [57] demonstrated that, N_2O and CO_2 emissions from chemical fertilizers made high contributions to GWP. Emissions from pesticide were assumed to end up in the agricultural soils, thus, pesticide emission to soil was tested and found out to be 2.048 kg ha^{-1}. Elements, such as NO_3^-, Cd and Pb that are released from fertilizers, affect both water and soil (Table 7).

The values of environmental impact categories on the basis of the mass based and land based FUs in lentil cultivation are presented in Table 8. The values of environmental impact categories related to one ha of lentil cultivation were approximately two times the relevant impact categories for one ton of produced lentil. This is due to the fact that the yield of lentil is approximately 2 tons per ha. Based upon the obtained results, GWP was estimated at 4284.87 kg CO_2 eq. t^{-1}. Considering the lack of availability of similar research on lentil production in the literature, the results are compared with those of other agricultural crops produced. In a study in Chile, GWP for sunflower and rapeseed productions were estimated about 890 and 820 kg CO_2 eq. t^{-1}, respectively [58]. Bartzas et al. [59] determined that production of barely in Spain and open field production of fresh lettuce in Italy created the total GWP impacts of 171 and 243 kg CO_2 eq. t^{-1}, respectively. Abeliotis et al. [15] reported that the calculated GHG emissions related to the production of three bean varieties in different cultivation methods varied in the range of 86–438 kg CO_2 eq. per ton of product. Romero-Gámez et al. [8] demonstrated that GHG emission varied from 101 to 2890 kg CO_2 eq per ton of bean. The highlighted that the use of both screen house and screen houses equipped with misting systems produced the high air emissions due to the manufacture of steel structures, the processing of concrete, and the manufacture of plastics that constituted these systems. It must be noted that in a similar cropping system to lentil, total GHG emissions of green bean cropping in the open field is 136 kg CO_2 eq t^{-1} which is substantially lower than that of lentil production in the present study. This difference to some extent is due to the different moisture content of green bean and lentil. Overall comparisons shows that the impact categories in this study are different from other studies. This high difference can be interpreted by large application of such agricultural inputs as fertilizers and direct emissions in lentil cultivation.

A percentage contribution of production processes and inputs involved in lentil farming to the selected impact cate-

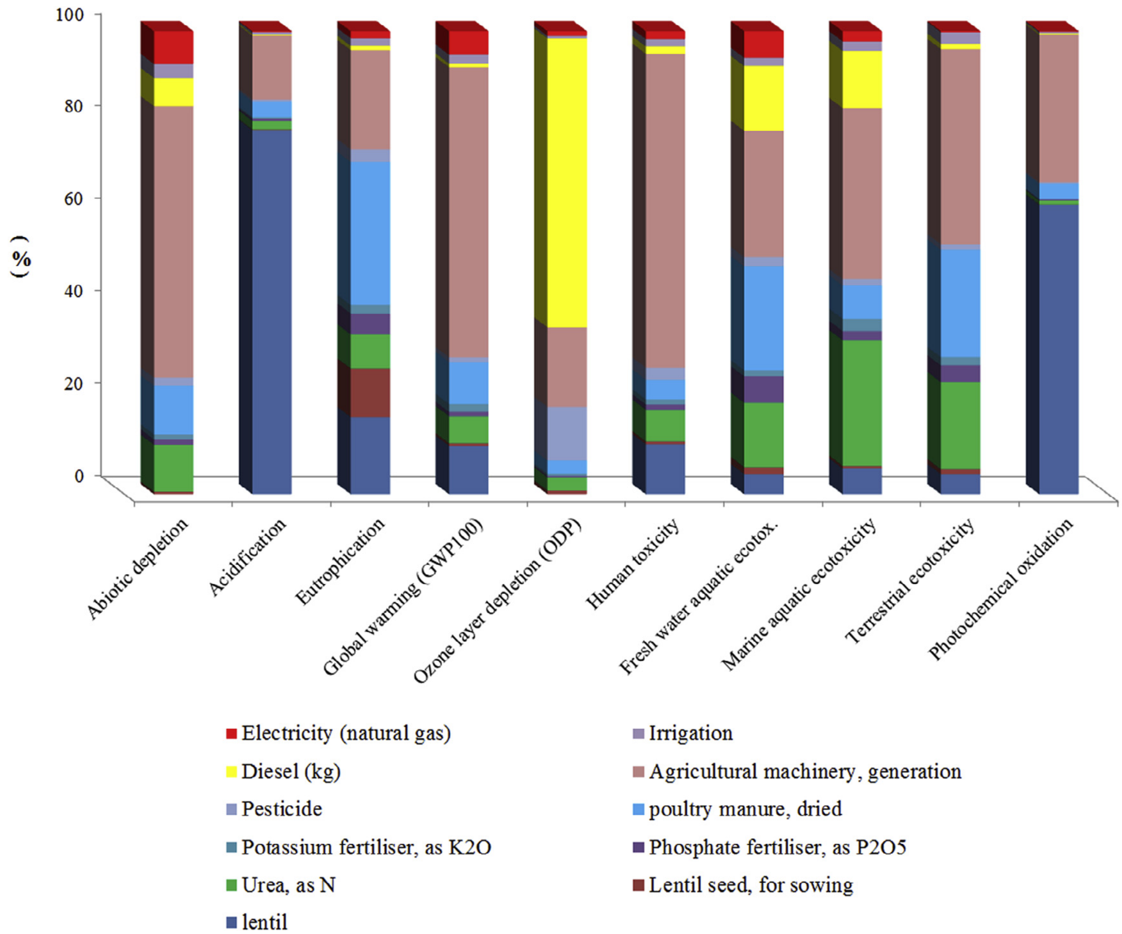

Fig. 3 – Percentage contribution of inputs and processes per environmental impact categories in lentil cultivation.

gories is presented in Fig. 3. The production of agricultural machineries was the one that mostly contributed in the six impact categories, contributing for 67.78%, 62.63%, 58.62%, 42.14%, 36.93% and 27.27% to HTP, GWP, ADP, TEP, MAEP and FAEP respectively. In a similar study on evaluation of the environmental impacts as regards chickpea production in Iran, application of LCA revealed that GWP, ADP, HTP, MAEP and TEP were dominated by agriculture machinery [11]. In order to reduce the environmental burdens related to agricultural machineries, it will be necessary to increase the sizes of the farms by integration, to prevent farms shrinking when a farm is transferred to the next generation and to perform different agricultural operations with combined machineries such as combined equipment for plowing and seed bed preparation. Also in the impact categories of ACP and PHOP, the direct emissions from diesel fuel and chemical fertilizers associated with lentil cultivation were important among all input categories with the shares of 78.62% and 62.49%, respectively. Diesel fuel with the share of 62.21% had the highest environmental impact on OLDP followed by agricultural machinery with 17.16% contribution.

Marucci et al. [60] concluded that the environmental impact from the use of agrochemicals was greater in greenhouse crop production as compared with open-field farming; also, they showed that, on opposite trend existed in terms of herbicide use, with greater quantities applied in the open-field. The MAEP impact category was dominated by machinery and N-based fertilizer while in FAEP, the use of machinery and FYM was important. In LCA of rose cultivation in Ethiopia by Sahle and Potting [45], the production of fertilizers was the main contributor to MAEP, HTP, ADP and TEP. The use of right amount of chemical fertilizers and FYM at different growth stages of lentil cultivation based on the soil testing results and expert's opinions will have a significant impact in reducing direct emissions associated with these inputs. Also, the use of compost produced from agricultural wastes for the fertilization of crops was investigated as a promising alternative waste management option [61]. Regarding the consumption of diesel fuel, the use of clean fuels such as biodiesel and bio-ethanol instead of fossil fuels not only will reduce the negative impacts to environment, but also will provide the higher energy use efficiency [29,62]. In terms of environmental burdens, irrigation water and K_2O chemical fertilizer seemed the least impacting inputs approximately in all of the impact categories.

To better determine the relative magnitude of each impact category within the production of lentil, normalized values of impact categories were utilized. The normalized values of selected impact categories are presented in Fig. 4. Normalization is the calculation of the magnitude of the impact category results with respect to reference values where the different impact potentials and consumption of resources are expressed on a common scale through relating them to

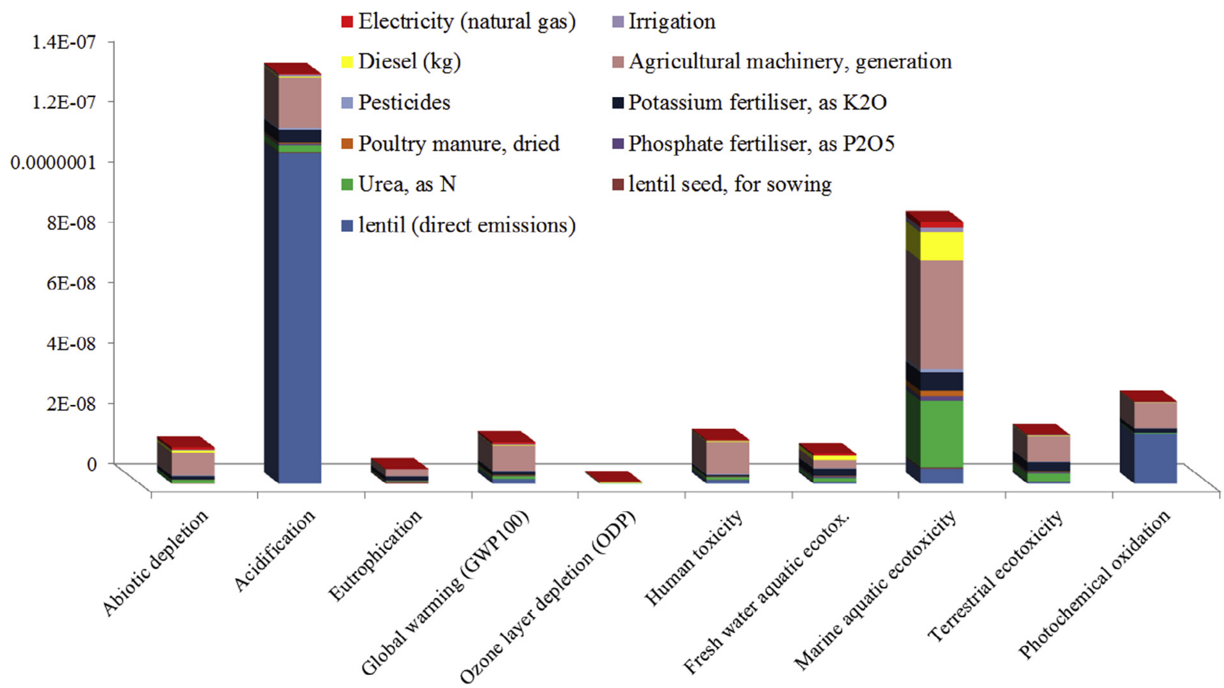

Fig. 4 – Normalized impact categories of lentil production.

a common reference, in order to facilitate comparisons between impact categories. The normalized values of all impact categories are dimensionless, thus their comparison is more readily applicable [34,63]. The magnitude of ACP was significantly higher than that of other impact categories followed by MAEP and PHOP. Since ACP was dominated by direct emission resulted from the application of chemical fertilizers, FYM and diesel fuel, any savings made in consumption of diesel fuel and fertilizers would cause a reduction in the ACP impact category. The normalization in this study moves the attention toward reduction of ACP impact category and reduction of other impact categories at the same time.

3.3. *ANN model development*

Investigation of different ANN models revealed that the best fitted ANN model consisted of an input layer with nine input variables, two hidden layers of each ten and six neurons, respectively, and one output layer with eleven output variables, i.e., 9-10-6-11 structure. The statistical criteria of the best ANN model for predicting yield and environmental impact categories of lentil is tabulated in Table 9. According to the statistical criteria of the developed ANN model, namely R^2 values in the range of 0.8993–0.9956, MAPE in the range of 0.0003–0.2085%, RMSE related to impact categories in the range of 0.0574–0.1292 and RMSE related to yield about 0.1493 kg, it can be concluded that all the considered ANN model provide a very satisfactory prediction results. On the other hand, lentil yield and environmental impact categories predicated by the best ANN model tended to quite closely follow the corresponding actual ones. Accordingly, this model was identified as the most appropriate solution for estimating the lentil production yield and related environmental impact categories.

Pahlavan et al. [21] reported that an ANN model with 7-20-20-1 structure was the best network for predicting basil production yield. Khoshnevisan et al. [10] demonstrated that an ANN model including an input layer with 11 neurons, two hidden layers with six neurons in the first hidden layer and ten neurons in the second hidden layer and an output layer with two neurons was the best network for estimating the total yield and GWP in the strawberry production system. Their results revealed that the obtained structure can predict the desired outputs with high accuracy. Khoshnevisan et al. [19] for predicting the output energy and GWP of potato production, applied the best fitted ANN model consisted of an input layer with twelve inputs, one hidden layer with eight neurons and an output layer with two output variables, i.e.,

Table 9 – Network performance of lentil yield and environmental prediction for the best topology.

Item	R^2	MAPE (%)	RMSE
Yield	0.9039	0.0382	0.1493
ADP	0.9726	0.1209	0.1276
ACP	0.9823	0.0041	0.1145
EUP	0.9850	0.0197	0.1109
GWP	0.9834	0.0003	0.1024
OLDP	0.9956	0.0111	0.0574
HTP	0.8993	0.2085	0.1944
FAEP	0.9641	0.1781	0.1244
MAEP	0.9793	0.1042	0.1053
TEP	0.9844	0.0901	0.0948
PHO	0.9744	0.0659	0.1292

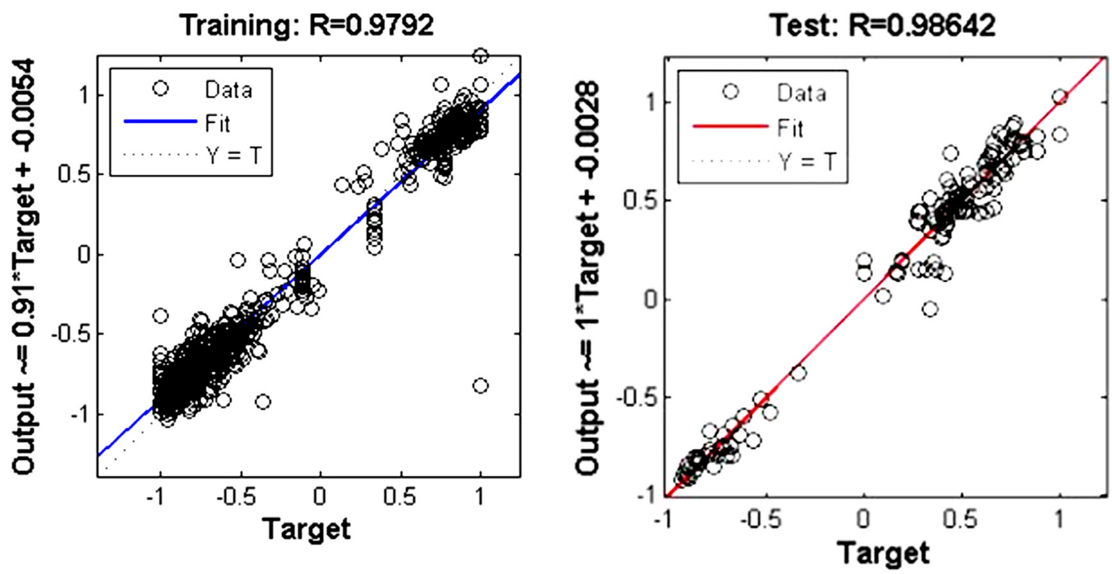

Fig. 5 – Comparison between measured and estimated values of yield and environmental impact categories of lentil production using best developed ANN model.

Table 10 – Sensitivity analysis results for input energies.

Sensitivity	Yield	ADP	ACP	EUP	GWP	OLDP	HTP	FAEP	MAEP	TEP	PHO
Seed	5.150	0.139	0.218	0.051	17.003	0.00030	14.752	0.176	2323.010	0.122	0.021
Fertilizers	10.098	0.509	0.614	0.198	79.230	0.00070	71.333	5.755	9195.634	0.956	0.048
FYM	11.0800	**2.452**	**4.454**	**1.012**	**446.166**	**0.00370**	79.410	**23.890**	21660.367	**3.464**	**0.316**
Chemical	1.3035	0.588	0.975	0.221	86.709	0.00020	28.066	5.264	6259.28	0.851	0.075
Machinery	**17.8013**	1.528	1.692	0.407	119.936	0.00015	**155.743**	12.057	**25316.397**	2.243	0.181
Diesel fuel	11.2343	0.295	0.436	0.137	49.490	0.00060	54.276	0.439	6596.823	0.321	0.040
Labor	6.4066	0.266	0.292	0.084	46.796	0.00220	46.197	0.273	6146.356	0.269	0.036
Irrigation	4.4657	0.461	0.685	0.170	17.494	0.00250	44.454	2.967	7078.624	0.616	0.060
Electricity	0.9541	0.387	0.510	0.108	31.656	0.00001	26.755	2.812	5295.476	0.517	0.502

12-8-2 ANN structure. This network had the least MAPE for output energy and GWP and the highest R^2 and the least RMSE for GWP. In an ANN model developed by Taghavifar and Mardani [23] the best network was the 8-16-2 structure. The R^2 values of 0.9879 and 0.9827 were obtained for yield and GWP prediction of apple production in Iran, respectively. Nabavi-Pelesaraei et al. [20] predicted energy use and GWP of kiwifruit production using an ANN model with 12-9-9-2 structure. The R^2 values of the best network were calculated as 0.987 and 0.992 for yield and GHG emissions, respectively, demonstrating the high accuracy of the model. Nabavi-Pelesaraei et al. [22] predicted yield and GWP of watermelon production using ANNs. They reported that selected ANN model was of the potential of predicting yield and GWP by respective coefficients of determination of 0.96 and 0.99.

Fig. 5 demonstrates the scatter plots of the predicted yield and environmental impact categories versus actual values for the training and testing data sets. The predicted and actual values were found out in good agreement with each other. Coefficients of determination for these indices demonstrated the potential capability of the developed ANN model for prediction of yield and environmental impacts in lentil production in the studied area.

3.4. *Sensitivity analysis*

Considering the best selected ANN model, a sensitivity analysis was performed to assess the prediction validity and capability of the developed models. The results of the sensitivity analysis are given in Table 10. The sensitivity values of the most effective input parameter on each output parameter are shown in bold type. As clearly shown, machinery related energy had the highest effect on lentil yield with sensitivity value equal to 17.80, followed by diesel fuel and FYM energies. It was also found that the sensitivity concerning electricity on lentil yield was the lowest among all inputs. In the case of environmental impact categories, all the indices except HTP and MAEP were discerned as sensitive to the FYM energy. Furthermore, the highest sensitivity was determined for agricultural machinery for both impact categories of HTP and MAEP.

4. Conclusions

The total input energy and output energy in lentil production were calculated as 32,970.10 and 29,476.50 MJ ha^{-1}, respectively. On the average, the share of DE was 49.47% of total energy input expended in lentil production, while the contribution of IDE being 50.53%. The share of input as RE and NRE energies were recorded as 17.34% and 82.66%, respectively. Chemical fertilizers (42.76%), electricity (20.92%) and diesel fuel (15.99%) demonstrated their pivotal roles in total energy consumption. The high contribution of chemical fertilizers energy in total energy consumption (42.76%) revealed the high potential for reducing fertilizer application. The most significant impact categories are related to agricultural machinery employed in seedbed preparation and in sowing operations. Therefore, an application of either no-tillage or reduced tillage systems could reduce the use of machinery, thus diminishing some of these impacts. The direct emissions in lentil cultivation resulted from high application of chemical fertilizers and diesel fuel contribute considerably to some environmental impacts, notably ACP and PHOP. Also, diesel fuel would considerably dominate in OLDP. Therefore, it suggested establishing a sustainable and environmental friendly lentil production system in the region with application of alternatives such as no-till and reduced tillage systems, use of clean fuels instead of fossil fuels and more efficient fertilizers application by integrated nutrient management. The ANN model with 9-10-6-11 structure was determined as the most appropriate model for predicting the lentil yield and its related environmental impacts.

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