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Application of artificial neural network to predict the environmental impacts of wheat cultivation systems

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Abstract

This study was conducted to analyze and model the environmental impacts using artificial neural networks (ANNs) in wheat production systems. Information needed for this study, related to 2021-2022, data was collected from wheat farms in two parts of conventional and conservation cultivation in Qazvin province, Iran. Life cycle assessment using the ReCiPe 2016 method reported three categories of damage to human health, ecosystem, and resources. The resource damage category for conventional tillage irrigation (76.05 USD_{2013}) has significant pollution. The share of seed emissions, On-Farm emissions, and nitrogen emissions affect the categories of damage to human health, ecosystems, and resources, respectively. The results of ANN for environmental impacts in different wheat production showed the structure 9-8-3 with nine inputs, one hidden layer with eight neurons, and three output parameters have been determined as the best structure for conventional tillage irrigation. Also, rainfed wheat cultivation in conventional tillage showed 6-11-3 with six inputs, one hidden layer with eleven neurons, and three output parameters determined as the best structure. The best structure for irrigated cultivation of conservation tillage is 9-6-3. The suitable structure for rainfed cultivation in conservation tillage is 8-4-3, which has one hidden layer with four neurons. According to the results, the ANN can accurately predict the environmental effects of wheat production. By modeling the environmental effects, it can be found that in the future, sustainable production, will have a suitable plan to reduce environmental pollutants.

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Introduction

In recent years, efforts to make better use of energy resources have come to the attention of governments. The exponential depletion of fossil fuels has led to a shift towards renewable energy sources and sustainable development by increasing consumption and emissions (Ziaei et al., 2015). Renewable energy-based sustainable energy production is a challenging task to replace fossil fuels, achieve a cleaner environment, and challenge the uncertainty of fuel, intensive ecosystems, such as the agricultural sector, produce more than natural ecosystems, higher production is achieved only with the help of significant amounts of auxiliary energy, which is consumed by human labor in planting, irrigation, fertilizer application, control and management of pest, diseases, and weeds (Ahmad et al., 2018). Wheat is the most important agricultural product in the world, but most of the land under wheat cultivation is located in arid and semi-arid regions (Ghasemi-Mobtaker et al., 2020). In its latest report on world agricultural production statistics, the FAO reported 7584,358 hectares of area harvested and 1978 kg ha^{-1} of wheat production in Iran (FAO, 2020). Agriculture has always been dependent on natural resources and therefore has complex relationships with the environment (Kashyap et al., 2021). Evidence suggests that the negative messages of these activities are due to increased input consumption, land use change, and tightening of agricultural operations. As a result of the intensification of environmental pollution, the destruction of natural habitats and the endangerment of biodiversity occur (Tilma et al., 2002). On the other hand, food production and related economic sectors depend on agricultural sustainability. Therefore, the efforts of researchers and scholars are to minimize the consequences of agricultural production in the context of economic benefits (Taherzadeh-Shalmaei et al., 2021). The ability to track the environmental impact of a product or process allows decision-makers to adopt an appropriate policy for all identified environmental impacts (Wang, 2011). Achieving this requires awareness of the various effects that the ecosystem of agricultural systems and their management methods have on the environment (Roy et al., 2009). Among the various methods of studying environmental impact, life cycle assessment is the most accurate approach that assesses all the environmental consequences of a product throughout the production chain. Also, life cycle assessment is a technique for evaluating all inputs and outputs of a product, process, or service, waste assessment, human health effects, and ecological effects, and interpreting evaluation results throughout the product or process life cycle (Kaab et al., 2019a,b). This method has been considered by researchers and has been used around the world in recent decades (Houshyar and Grundmann, 2017). Life cycle assessment can examine the consequences during the process (Saber et al., 2020). This feature means that it not only evaluates the main stage of the process, but also assesses all the infrastructure, raw materials, resources, and energy required to carry out the process and all wastes, pollutants, materials, and energy produced (Rebitzer et al., 2003; Kaab et al., 2021). Along with scientific progress in human societies, agricultural mechanization is also affected by this movement and it is necessary to use scientific methods and tools in production planning. In this regard, forecasting fuel consumption in the production of various products is important. Appropriate solutions are necessary to reduce fuel consumption and having a suitable model will be easier and more transparent. In this study, an artificial neural network (ANN) also transfers the knowledge or law behind the data to the network structure by processing experimental data (Safa et al., 2010). Ghorbani *et al.* (2011) investigated the energy ratio in wheat production in two irrigation systems (as a high input system) and dry farming (as a low input system) in the north of Khorasan province, Iran, were 3.38 and 1.44, respectively. The results showed that the largest share of input energy in the irrigation system is allocated to chemical fertilizers (37.1%) and in the dry farming system, diesel fuel (45%) has a significant share. Total input energy for the production of irrigated wheat 45.3 GJ ha^{-1} has been calculated, applying the right tillage methods and proper selection of agricultural implements are important factors. In this regard, reducing the amount of fuel consumed causes less pollution of the environment. An assessment of fuel consumption for wheat production in Turkey was performed. The total amount of fuel consumed was measured at 67.8 liters per hectare. The best preparation operation with 46.5 liters had the largest share (Canakci and Akinci, 2006). Safa and Tabatabaeefar (2011) evaluated the total fuel consumption in both irrigated and rainfed wheat cultivation systems. The results showed that fuel consumption was 598 and 74 liters per hectare for irrigated wheat and rainfed wheat, respectively. The highest share of fuel consumption in the irrigated wheat harvesting system is related to irrigation operations (78.4%) and the highest share of fuel consumption in the irrigated wheat harvesting system is allocated to the operation (59%). The analysis of ANN was used to predict fuel consumption by considering the social, geographical, and technical variables affecting wheat production. Among the studied variables, the amount of horsepower per hectare and the size of farm plots had the most and the least effect on fuel consumption, respectively. Researchers compared wheat bread production in conventional systems in terms of global warming potential by the life cycle assessment. The production of one kg of bread in the organic system produced 30 kg less CO_2 equivalent than the conventional system (Meisterling et al., 2009). The environmental effects of winter wheat production systems at different levels of nitrogen consumption were studied based on life cycle assessment. Index with consumption of less than 150 kg N ha^{-1} was about 0.22 to 0.26 per ton of wheat grain. The results showed that at lower levels of nitrogen and high levels of nitrogen, land use, and eutrophication were the controlling factors of the life cycle assessment index, respectively. Also, acidification and global warming have been major environmental effects (Brentrup et al., 2004). Life cycle evaluation of the winter wheat and corn production system in China showed a reduction of fossil resources, climate change, acidity, eutrophication, and human and ecological toxicity of water and land systems. Winter wheat production caused more damage to the environment than corn, with a final environmental index of wheat of 0.063 and 0.40 for corn (Wang et al., 2007).

In this regard, assessing energy consumption due to the limited availability of fossil fuels is one of the necessary issues in the current era. The purpose of this study was to estimate the number of environmental impacts related to wheat production systems in different methods, to evaluate the environmental impact associated with input consumption, and provide applied suggestions for modeling emissions and sustainable management in agricultural systems by applying ANN.

Materials and methods

Data collection procedure

Decreased soil fertility, soil compaction under the tillage layer, increased water and wind erosion, severe decomposition of soil organic matter, increased cost and energy of tillage operations, and increased labor costs are among the disadvantages of tillage (McGarry, 2003). Conservation tillage is another type of tillage in which plant debris remains as a cover on the soil surface. The purpose of conservation tillage is to stabilize production resources and improve yields in agriculture. Conservation tillage goals lead to the effective use of natural resources by combining soil, water, and biological resource management. Reducing the working hours of the tractor, reducing fuel consumption economically reducing environmental pollution, minimizing soil compaction, maintaining and storing soil moisture, and increasing organic matter are the benefits of tillage removal (Yalcin et al., 2005). Wheat farms in two parts of conventional and conservation cultivation in Qazvin province, Iran were selected for research. The selection of farms was such to cover all the major production methods in the area in question. The characteristics of the farms and the additional information related to them are presented in Table 1. All management operations performed from seed preparation to harvest were recorded in the studied farms. To collect information about the type and amount of consumption of inputs and outputs, the number of samples was determined from Equation 1 (Cochran, 1977).

$$n=\frac{\frac{z^2pq}{d^2}}{1+\frac{1}{N}\left(\frac{z^2pq}{d^2}-1\right)} \quad (1)$$

Where N is the number of population, z is the reliability coefficient, p is the estimated proportion of an attribute that is present in the population, q is 1-p, and d is the permitted error ratio deviation from the average population.

Table 1. Information on different wheat production systems

Type of cultivation	Type of tillage	Number of farms	Average area (ha)	Average yield (kg ha^{-1})
Irrigated	Conventional Tillage	45	40	5000
Rainfed	Conventional Tillage	35	32	2500
Irrigated	Conservation Tillage	41	25	5100
Rainfed	Conservation Tillage	30	20	3000

Life cycle assessment method

The use of life cycle assessment as an environmental management tool in different ways and titles has been started since the 1960s. This method estimates and evaluates all the resources used to produce the product and all the materials released to the environment through careful and audit (Tzilivakis et al., 2005; Ghasemi-Mobtaker et al., 2022). The purpose of evaluation life cycle in this study was to investigate the environmental effects of wheat production in different management systems. The scope is an expression of the framework in which the study is conducted and should be consistent with the objectives of the evaluation (Iriarte et al., 2010). It will not provide valid information without specifying the purpose and scope of the evaluation. The functional unit in this study was considered based on the production of one ton of seed yield. All inputs and outputs and environmental impacts were measured (Mouron et al., 2006).

Inventory analysis

This is the busiest and most time-consuming stage in the life cycle assessment. The environmental impacts of the studied ecosystems, including emissions to the atmosphere, soil, and water, were estimated according to international standards (Jolliet et al., 2003). The source and reference of data collection play a very important role in the validity and completeness of the data. Information on agricultural products is available in the ecoinvent database used in this study (Renaud-Gentié et al., 2015).

Impact assessment

At this stage, the type of impact class is considered and the appropriate method is selected to evaluate the impact (Noya et al., 2015). Implications into three main categories: resource consumption, human health-related consequences, and effective consequences on ecological issues (Pirlo et al., 2014). Acidification potential, global warming, eutrophication, photochemical oxidation, resource degradation, ozone degradation, toxicity, and fresh water use are the most widely used outcomes in this evaluation (Di Maria et al., 2016). The outcome category index means quantifying an outcome category. Indicators are calculated by different methods such as using mathematical relations and coefficients of the effect of each category. Each of the relations has been stated by different authorities (Ruviaro et al., 2012). Due to the importance of environmental issues in wheat production, some indicators of the effective category were estimated with different life cycle assessment models in SimaPro software. After studies on different models and a general comparison of results, the ReCiPe 2016 method was selected. Information about the deafening method can be seen in Figure 1.

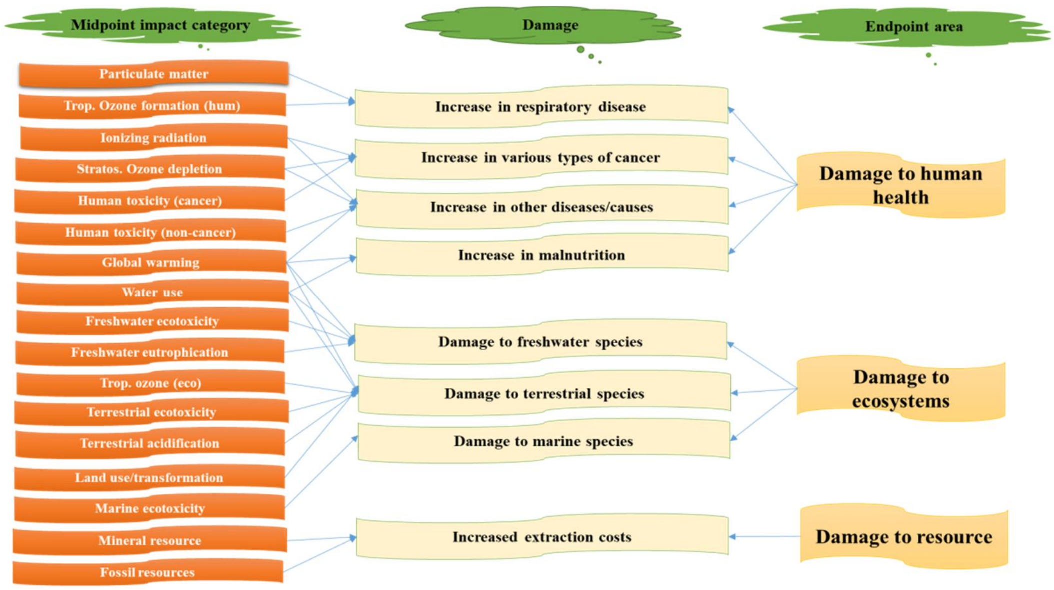


Figure 1. Important categories in the ReCiPe 2016 method

To calculate On-Farm emissions from the use of machinery, diesel fuel combustion, and chemical fertilizers, data are obtained according to Table 2, Table 3, and Table 4. The fuel must be clean and free of any contaminants. Most of the time, the pollution in the fuel occurs when it is not moved properly. Most contaminants include water, dust particles, and microbial growth particles that cause black sludge. Therefore, fuel quality plays an important role in proper operation, increasing service life, and controlling the emission of pollutants in engines (Soam et al., 2017).

Table 2. The equivalent of direct emission of 1 MJ diesel fuel for 1 MJ burning in the ecoinvent database.

Emission	Amount (g MJ^{-1} 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
Polycyclic aromatic hydrocarbons (PAH)	7.85E-05
Hydrocarbons (HC)	6.80E-02
Nitrogen oxides (NO_x)	1.06
Carbon monoxide (CO)	1.50E-01
Particulates (b2.5 µm)	1.07E-01

Table 3. Coefficients for calculating the On-Farm emissions related to the application of inputs in paddy production (IPCC, 2006).

Characteristic		Coefficient (Emission result)
A. Emissions of fertilizers		
1	$\left[\frac{[\text{kg N}_2\text{O} - \text{N}]}{\text{kg N}_{\text{in fertilzers applied}}}\right]\left[\frac{[\text{kg N}_2\text{O} - \text{N}]}{\text{kg N}_{\text{in fertilzers applied}}}\right]$	0.01 (to air)
2	$\left[\frac{\text{kg NH}_3\text{ - N}}{\text{kg N}_{\text{in fertilizers applied}}}\right]$	0.1 (to air)
3	$\left[\frac{\text{kg N}_2\text{O - N}}{\text{kg N}_{\text{in atmospheric deposition}}}\right]$	0.001 (to air)
4	$\left[\frac{[\text{kg NO}_3^- - \text{N}]}{\text{kg N}_{\text{in fertilzers applied}}}\right]\left[\frac{[\text{kg NO}_3^- - \text{N}]}{\text{kg N}_{\text{in fertilzers applied}}}\right]$	0.1 (to water)
5	$\left[\frac{\text{kg P emission}}{\text{kg P}_{\text{in fertilizers applied}}}\right]$	0.02 (to water)
6	$\left[\frac{\text{kg NO}_x}{\text{kg N}_2O_{\text{from fertilizers and soil}}}\right]$	0.21 (to air)
B. Conversion of emissions		
1	Conversion from kg CO_2 – C to kg CO_2	$\left(\frac{44}{12}\right)$
2	Coversion from kg N_2O – N_2 to kg N_2O	$\left(\frac{44}{28}\right)$
3	Conversion from kg NH_3 - N to kg NH_3	$\left(\frac{17}{14}\right)$
4	Conversion from kg NO_3 - N to kg NO_3	$\left(\frac{62}{14}\right)$
5	Conversion from kg P_2O_5 to kg P	$\left(\frac{62}{164}\right)$
C. Emissions from human labor		
1	$\left[\frac{\text{kg CO}_2}{\text{man - h Human labor}}\right]$	0.7 (to air)

Table 4. Coefficients for calculating the On-Farm emissions to the soil of heavy metal related to the application of chemical fertilizers in paddy production (Mostashari-Rad et al., 2021).

Characteristic		Heavy metals						
		Cd	Cu	Zn	Pb	Ni	Cr	Hg
1	$\left[\dfrac{\text{mg Heavy metal}}{kg\ N_{in\ fertilzer\ applied}}\right]$	6	26	203	5409	20.9	77.9	0.1
2	$\left[\dfrac{\text{mg Heavy metal}}{kg\ P_{in\ fertilzer\ applied}}\right]$	90.5	207	1923	154	202	1245	0.7
3	$\left[\dfrac{\text{mg Heavy metal}}{kg\ K_{in\ fertilzer\ applied}}\right]$	0.2	8.7	11.3	1.5	4.5	10.5	0.1

Interpretation of results

The results of the life cycle inventory (LCI) and life cycle impact Assessment (LCIA) are done to conclude in the last stage. Interpretation findings may be used as conclusions and recommendations for decision-makers according to the purpose and scope of application. Life cycle interpretation also aims to provide an understandable, complete, and consistent expression of the results of a life cycle assessment following the definition of the purpose and scope of this study (Iriarte et al., 2010).

ANN model

Inspired by the neural network of the human brain, this network seeks to develop information processing. By processing experimental data, ANNs transfer knowledge or the law behind the data to the network structure, which is called learning. The ability to learn is the most important feature of an intelligent system. A learning system is more flexible and easier to program. So it can better answer new problems and equations (Momenzadeh et al., 2011). Multilayer perceptrons (MLPs), are widely studied and used, especially for supervised learning difficulties. MLP is a hierarchical structure of several perceptrons that does not have the limitations of single-layer networks and learns the mapping of nonlinear functions. MLP consists of at least three node layers. It has one input layer, one hidden layer, and one output layer. All nodes except the input nodes are neurons that use a nonlinear activation function. MLP uses a supervised learning technique for training. Multiple layers and nonlinear activation distinguish it from a linear perceptron (Kaastra and Boyd, 1995). The input elements (ai) and weight (wij), together with the bias (bj), accumulate in the nodes (Equation 1). After imposing the transfer function F to X, an output is generated (Equation 2). The two topics discussed include weight and bias. A set of weighted inputs allows each neuron or artificial node in the production system to generate the corresponding outputs. Artificial intelligence projects typically use internal neural networks that represent weight as a function of biological systems and technologies. A bias node in a neural network is a node that always exists. If the weights are selected correctly, their values must be multiplied by the inputs. The values obtained pass through the output function. Input variables (such as energy equivalents of electricity, sugarcane cutting plant, biocides, fertilizers, diesel fuel, human labor, and machinery) were considered as the input of MLP neural networks. Also, the three environmental impact categories were as outputs. The aim was to obtain the appropriate model with the best weight between the input nodes and the hidden layers and between the hidden and output layer nodes. Optimal weights are obtained through a hidden layer neural network training algorithm. Then, unipolar sigmoid, which is one of the features of these functions, was used (Equation 3) (Kaab et al., 2019a).

$$x = \left(\sum_{i=1}^{n} w_{ij} a_i\right) + b_j x = \left(\sum_{i=1}^{n} w_{ij} a_i\right) + b_j \tag{1}$$

$$F(x) = F\left[\left(\sum_{i=1}^{n} w_{ij} a_i\right) + b_j\right] F(x) = F\left[\left(\sum_{i=1}^{n} w_{ij} a_i\right) + b_j\right] \tag{2}$$

$$f(\theta) = \frac{1}{1+e^{-\theta}} f(\theta) = \frac{1}{1+e^{-\theta}} \tag{3}$$

Model performance evaluation

The prediction accuracy of ANN models was measured by calculating the root mean square error (RMSE) and the coefficient of determination (R^2), using Equations (4 - 5) respectively.

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}} \sum_{i}^{n} (P_i - A_i)^2} \tag{4}$$

$$R^2 = 1 - \sqrt{\frac{\sum_{i=1}^{n} (P_i - A_i)^2}{\sum_{i=1}^{n} A_i^2}} \tag{5}$$

SimaPro V9.1.1.1 software is used to perform analysis on life cycle assessment, and Matlab software is employed in developing an ANN model for the prediction of environmental impacts in wheat cultivation.

Results and discussion

Life cycle assessment analysis

Equivalents related to each of the inputs (water, air, and soil) are estimated and calculations are performed in SimaPro software. Table 5 shows the results of the second phase of the Life cycle assessment. Emissions of carbon dioxide from diesel fuel are significant in conventional tillage irrigation (562.56 kg). Conservation tillage has less environmental emissions because fewer machines are used. In addition to diesel fuel, nitrogen fertilizer also emits environmental emissions into the air. NH_3 has an emission of 18 to 1790 kg. Nitrates and phosphates from chemical fertilizers contaminate water. Nitrate emissions are higher than phosphate. Improving the efficiency of nitrogen uptake by plants can lead to a reduction in nitrogen leaching, which directly and indirectly reduces N_2O emissions from excess nitrogen in the soil (Smith et al., 2007). Carbon dioxide emissions from human labor are less than carbon dioxide emissions from diesel fuel. Heavy metal emissions to soil were reported, and Lead and zinc have significant emissions to the soil. It should be noted that greenhouse gas emissions due to their special radiative properties cause abnormal global warming, which in turn changes the global climate and the region (Pennington et al., 2004). Consumption of fossil fuels has the greatest impact on the emission of greenhouse gases, especially CO_2, and consequently global warming. Therefore, saving fuel consumption during operations not only reduces costs and conserves national resources, but also reduces the destructive effects of the environment and global warming, and climate change (Martin et al., 2006; Sivakumar et al., 2005).

Table 5. Indirect and direct emissions of different production of wheat in the Qazvin province of Iran based on 1 ha.

Item (unit)	Conventional Tillage		Conservation Tillage	
	Irrigated	Rainfed	Irrigated	Rainfed
A. Indirect emissions				
a. Inputs				
1. Human labor (hr)	90.80	40.00	75.00	38.00
2. Machinery (kg)	22.44	12.00	15.00	10.00
3. Diesel fuel (L)	134.10	90.00	80.00	50.00
4. Nitrogen (N) (kg)	340.00	150.00	250.00	200.00
5. Phosphate (P_2O_5) (kg)	200.00	0.00	100.00	100.00
6. Potassium (kg)	100.00	0.00	100.00	50.00
7. Farmyard manure (kg)	700.00	400.00	500.00	300.00
8. Biocides (kg)	7.00	4.00	8.00	6.00
9. Electricity (kWh)	400.00	0.00	235.00	0.00
b. *Output*				
1. Wheat (kg)	5000.00	2500.00	5100.00	3000.00
B. Direct emissions				
1. Emissions by diesel fuel to air (kg)				
(a). Carbon dioxide (CO_2)	562.56	377.55	335.60	209.75
(b). Sulfur dioxide (SO_2)	0.18	0.12	0.10	0.06
(c). Methane (CH_4)	0.02	0.015	0.013	0.008
(d). Benzene	0.001	8E-04	7E-04	0.0004
(e). Cadmium (Cd)	1.8E-06	1.2E-06	1.1E-06	7E-06
(f). Chromium (Cr)	9E-07	6E-06	5.4E-05	3.4E-05
(g). Copper (Cu)	0.0003	2E-04	1.8E-04	0.0001
(h). Dinitrogen monoxide (N_2O)	0.02	0.014	0.012	0.008
(i). Nickel (Ni)	1.2E-05	8.5E-05	7.5E-04	4.7E-06
(j). Zinc (Zn)	1.8E-04	1.2E-04	0.0001	6.7E-04
(k). Benzo (a) pyrene	5.4E-04	3.6E-04	3.2E-06	2E-06
(l). Ammonia (NH_3)	0.003	0.002	0.002	0.001
(m). Selenium (Se)	1.8E-06	1.2E-05	1.1E-06	7E-06
(n). Polycyclic aromatic hydrocarbons (PAH)	5.9E-04	3.9E-04	0.0003	0.0002
(o). Hydrocarbons, unspecified (HC)	0.51	0.34	0.30	0.19
(p). Nitrogen oxides (NO_x)	8.00	5.37	4.77	2.98
(q). Carbon monoxide (CO)	1.13	0.76	0.67	0.42
(r). Particulates (b2.5 μm)	0.80	0.54	0.48	0.30
2. Emissions by fertilizers to air (kg)				
(a). Ammonia (NH_3) by FYM	170	97.14	121.42	72.85
(b). Ammonia (NH_3) by chemical fertilizers	41.28	18.21	30.35	24.28
3. Emissions by fertilizers to water (kg)				
(a). Nitrate	45.17	19.92	33.21	26.57
(b). Phosphate	4.36	0.00	2.18	2.18
5. Emission by N2O of fertilizers and soil to air (kg)				
(a). Nitrogen oxides (NOx)	71.40	31.50	52.5	42
6. Emission by human labor to air (kg)				
(a). Carbon dioxide (CO_2)	63.56	28	52.5	26.6
7. Emission by heavy metals of fertilizers to soil (mg)				
(a). Cadmium (Cd)	20160	900	10570	10260
(b). Copper (Cu)	51110	3900	28070	26335
(c). Zinc (Zn)	454750	30450	244180	233465
(d). Lead (Pb)	1870010	811350	1367800	1097275
(e). Nickel (Ni)	47956	3135	25875	24605
(f). Chromium (Cr)	276536	11685	145025	140605
(f). Mercury (Hg)	184	15	105	95

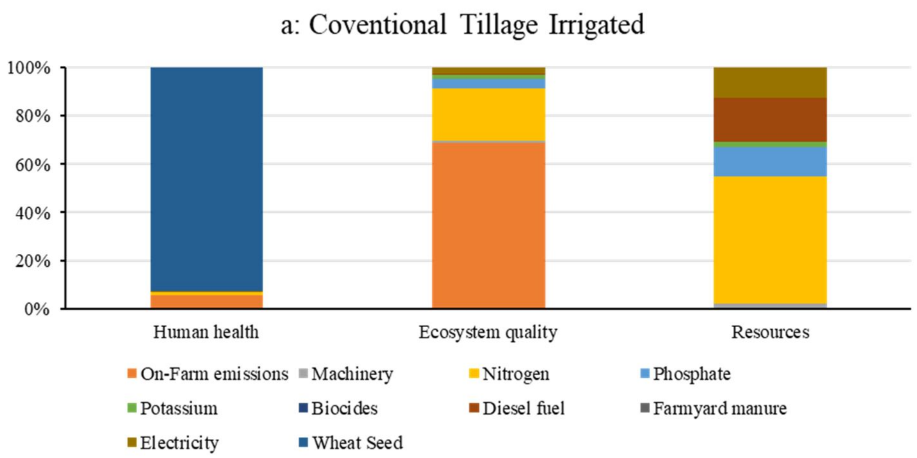
Life cycle assessment results were calculated by SimaPro software, according to the selected method, and three types of damage categories were reported in Table 6. The category of human health damage for conventional tillage irrigation (0.07 DALY) has more environmental emissions than the other three methods. Ecosystem environmental emissions were reported in terms of one ton of wheat. The total conservation tillage publications (11.37E-05 species. yr) is less than the total conventional tillage publications (12.54E-05 species. yr). The resource damage category showed that the environmental emissions of irrigated conservation tillage (50.26 USD_{2013}) are negligible. The most important materials with the potential for acidification in ecosystems are sulfur dioxide and nitrogen oxides, which are mainly produced by the consumption of fossil fuels during agricultural production. However, ammonia from chemical fertilizers in the field is also an important cause of acidification (Engström et al., 2007). Another study in Germany reported that the production of a ton of wheat acidity and global warming were major environmental effects (Brentrup et al., 2004).

Table 6. Values of the environmental impact per one ton in different production systems of wheat.

Impact categories	Unit	Conventional Tillage		Conservation Tillage	
		Irrigated	Rainfed	Irrigated	Rainfed
Human health	DALY [a]	0.07	0.02	0.04	0.06
Ecosystems	species. yr [b]	7.7E-05	4.84E-05	4.91E-05	6.46E-05
Resources	USD_{2013}	76.05	56.70	50.26	59.01

[a] DALY: disability-adjusted life years. Damage of 1 is equal to the loss of 1 life year of 1 individual, or 1 person suffers 4 years from a disability with a weight of 0.25.
[b] species. yr: the unit for ecosystems is the local species loss integrated over time.

Figure 3 shows the share of environmental emissions of each input. Seeds used for 4 methods of wheat cultivation have a great impact on the category of damage to human health. Less than 5% of human health emissions are due to nitrogen fertilizers and On-Farm emissions. Nitrogen fertilizer (25%) has the lowest share of environmental emissions in irrigated conservation tillage. More than 60% of ecosystem damage emissions are due to On-Farm emissions. Diesel fuel consumption and phosphate fertilizer affect the resource damage category. Electricity emissions are visible in irrigated wheat cultivation.



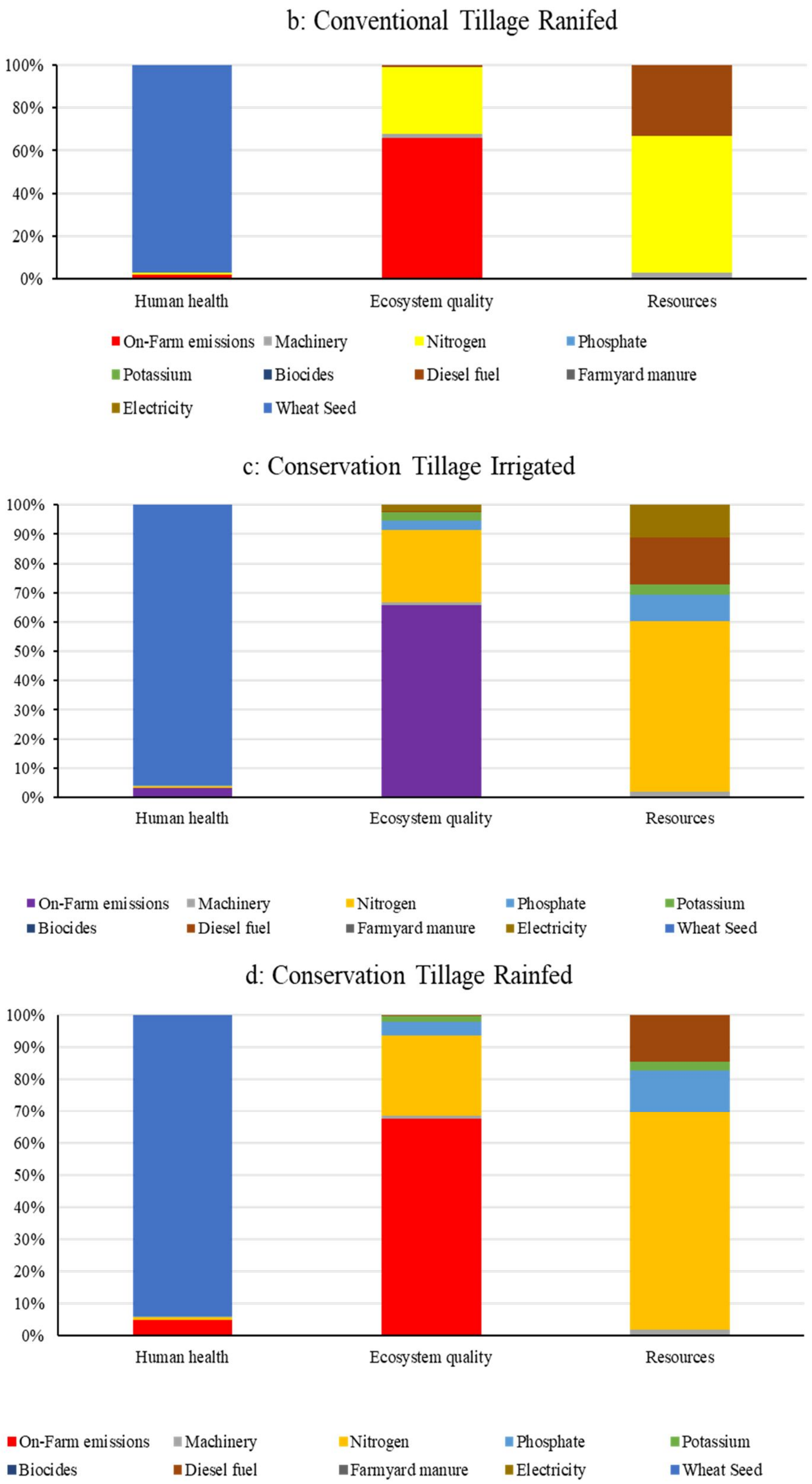


Figure 3. Contribution of different inputs in the damages categories for different production of wheat.

ANN analysis

To achieve the best neural network structure, different numbers of structures with one and two layers and with several neurons from one to 30 in the hidden layer have been trained, tested, and validated, also among the training algorithms used in this research, Levenberg–Marquardt training algorithm was selected. From the dataset used in this model, 70% of the data were considered for network training, 15% of the data for the validation test, and 15% for the test. The statistical measures of the most accurate ANN models in predicting environmental impact for different production of wheat are shown in Table 7. Based on the modeling results for environmental impacts, the structure 9-8-3 with nine inputs, one hidden layer with 8 neurons, and 3 output parameters has been determined as the best structure for conventional tillage irrigation. As a result, rainfed wheat cultivation in conventional tillage showed 6-11-3 with six inputs, one hidden layer with eleven neurons, and 3 output parameters determined as the best structure. The best structure for irrigated cultivation of conservation tillage is 9-6-3. The suitable structure for rainfed cultivation in conservation tillage is 8-4-3, which has one hidden layer with four neurons. Results on MAEP, RMSE, and R^2 are computed for the networks, it can be observed that values of R^2 vary in ranges of 0.870 to 0.945 overall, 0.910 to 0.946 for the training stage, and 0.863 to 0.916 for the testing stage in conventional tillage irrigated. In conventional tillage rainfed, the corresponding values are 0.940 to 0.980 overall, 0.882 to 0.996 for the training stage, and 0.846 to 0.982 for the testing stage. In conservation tillage irrigated, values are 0.892 to 0.961 overall, 0.913 to 0.967 for the training stage and 0.874 to 0.936 for the testing stage. In conservation tillage rainfed, 0.852 to 0.972 overall, 0.893 to 0.989 for the training stage and 0.883 to 0.987 for the testing section. Sensitivity analysis is the study of the influence of the output variables on the input variables of a statistical model. In other words, it is a method to change the inputs of a statistical model in an organized way so that the effects of these changes can be predicted on the output of the model. Nitrogen fertilizer input had the highest amount of sensitivity among other inputs and it was known as the most sensitive input in different tillage systems of wheat production in determining the environmental effects.

Studies in this area including Rahman and Bala (2010) in predicting the dry matter content of hemp in Bangladesh, Mohammadi et al. (2010) in predicting the performance of kiwifruit production in Iran, and Safa and Samarasinghe (2011) in evaluating energy consumption modeling in wheat production. The trend of energy consumption on basil products was discussed using MLP. The best topology was fitted with 7 neurons in the input layer, and 1 neuron in the output layer as 7-20-20-7. The values of R^2 and the root mean square error (RMSE) were calculated to be 0.976 and 0.046, respectively (Pahlavan Bidgoli, 2011). In other studies, Khoshnevisan et al. (2014) predicted potato yield using ANN. Structures 2-8-12 and R^2 (0.99) were selected as the best grid for energy consumption. Khanali et al. (2017) developed ANN models to estimate environmental impact categories and yield in tea production with R^2 values from 0.878 to 0.990. Elhami et al. (2017) employed an ANN model to predict environmental impact categories and yield of lentil cultivation. The selected ANN architecture consisted of two hidden layers with nine neurons in the input layer, ten and six neurons in the hidden layers, and eleven neurons in the output layer. Chen and Jing (2017) predicted the yield by using ANN, and, MAPE (in %), RMSE, and R^2 were found to be 10.38%, 979 kg ha^{-1}, and 0.61, respectively. in the testing phase. Due to the use of training rules, the ANN can predict the environmental impacts of the product with more accuracy and less error. Kaul *et al.* (2005) predicted the yield of soybeans and corn in the United States using average rainfall at different periods of crop growth.

Table 7. The results of different model arrangements by ANN in different production of wheat.

Types of production	Items of the ANN model	Statistics indices	Independent variables			
			Human health	Ecosystems	Resources	The best structure
Conventional Tillage Irrigated	Overall	R^2	0.930	0.870	0.945	9-8-3
		RMSE (%)	0.380	0.430	0.160	
		MAPE (%)	0.080	0.549	0.871	
	Train	R^2	0.910	0.946	0.963	
		RMSE (%)	0.248	0.147	0.116	
		MAPE (%)	0.042	0.180	0.009	
	Test	R^2	0.863	0.916	0.890	
		RMSE (%)	0.341	0.074	0.036	
		MAPE (%)	0.038	0.540	0.740	
Conventional Tillage Rainfed	Overall	R^2	0.940	0.982	0.964	6-11-3
		RMSE (%)	0.221	0.136	0.119	
		MAPE (%)	0.089	0.084	0.074	
	Train	R^2	0.976	0.882	0.986	
		RMSE (%)	0.256	0.352	0.364	
		MAPE (%)	0.008	0.009	0.004	
	Test	R^2	0.978	0.846	0.982	
		RMSE (%)	0.215	0.217	0.289	
		MAPE (%)	0.048	0.076	0.138	
Conservation Tillage Irrigated	Overall	R^2	0.892	0.914	0.961	9-6-3
		RMSE (%)	0.365	0.397	0.471	
		MAPE (%)	0.084	0.074	0.096	
	Train	R^2	0.967	0.943	0.913	
		RMSE (%)	0.371	0.412	0.369	
		MAPE (%)	0.012	0.038	0.068	
	Test	R^2	0.936	0.874	0.910	
		RMSE (%)	0.356	0.210	0.478	
		MAPE (%)	0.025	0.036	0.087	
Conservation Tillage Rainfed	Overall	R^2	0.963	0.852	0.973	8-4-3
		RMSE (%)	0.321	0.478	0.524	
		MAPE (%)	0.049	0.078	0.072	
	Train	R^2	0.989	0.964	0.893	
		RMSE (%)	0.341	0.521	0.298	
		MAPE (%)	0.036	0.089	0.042	
	Test	R^2	0.921	0.883	0.987	
		RMSE (%)	0.361	0.695	0.247	
		MAPE (%)	0.036	0.089	0.048	

Conclusions

In this study, estimation of environmental emissions from life cycle assessment showed that irrigated cultivation of conservation tillage has minimal pollution. In modeling with ANN, the structure 9-8-3 has been determined as the best structure for conventional tillage irrigation. Also, rainfed wheat cultivation in conventional tillage showed 6-11-3 as the best structure. The best structure for irrigated cultivation of conservation tillage is 9-6-3. The suitable structure for rainfed cultivation in conservation tillage is 8-4-3. R^2 and RMSE related to this product have the highest possible accuracy. According to this research, the following suggestions can be recommended for optimizing environmental impacts in agricultural products: The use of modern technologies and suitable agricultural implements such as a multi-purpose machine (combine). As a result, time constraints due to climate change and rainfall are removed during seed preparation and seed sowing. Frequent movements of the tractor and its associated equipment to carry out agricultural operations reduce the compaction of the farm soil and the creation of an impermeable layer. Finally, tractor depreciation and high fuel consumption are reduced due to the reduction of the number of vehicles during field operations. The use of protection systems that require less mechanization and power. Execution of primary tillage operations (plowing) when the soil moisture is adequate, will have a significant effect on reducing environmental pollution. Therefore, it is recommended that plowing be done as soon as possible after harvesting. Electrification of the irrigation engine and increasing the efficiency of transmission and distribution of consumed irrigation water at the field level, is a suitable solution to reduce the consumption of emissions. Development of agricultural mechanization and handing over of advanced tractors to farmers by paying subsidies to farmers and causing worn machinery.

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