Predicting of Agro-environmental Footprint with Artificial Intelligence (Soybean cultivation in various scenarios)

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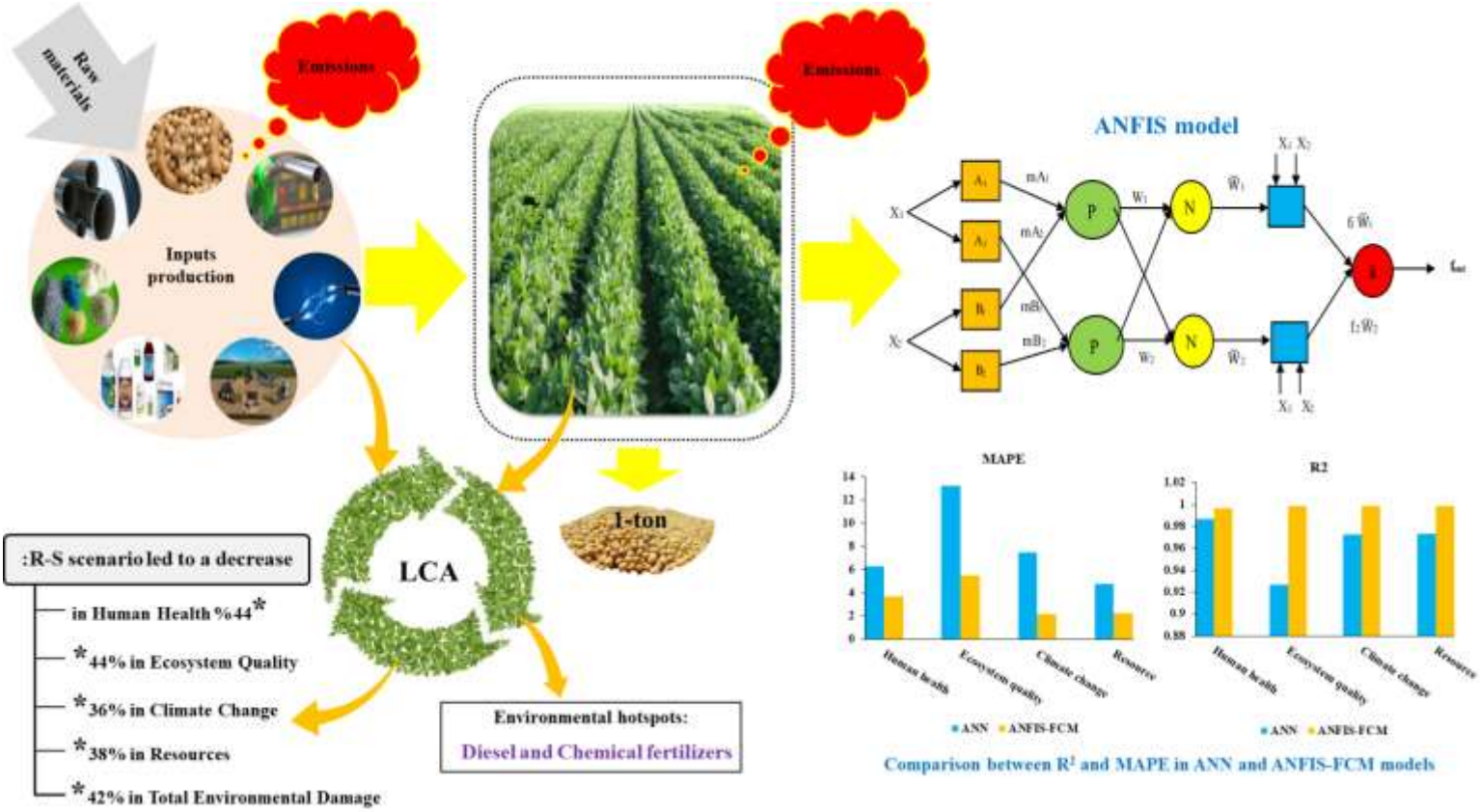
Graphical abstract



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Abstract

This study employed two artificial intelligence (AI) methods called the ANFIS–FCM algorithm as a novel computational method and an artificial neural network (ANN) as a conventional computational method in order to predict the environmental impacts of soybean production in different scenarios (*i.e.*, soybean cultivation after rapeseed (R-S), wheat (W-S), and fallow (F-S)). The 175 data of life cycle assessment (LCA) method were collected from soybean farms. The two methods called the adaptive neuro-fuzzy inference based on fuzzy C-means clustering algorithm (FCM) and the artificial neural network (ANN) were adopted to predict environmental parameters. For this purpose, the life cycle of soybean production was assessed in terms of environmental impacts through the IMPACT2002+ method in SimaPro. According to the results, the production of each ton of soybean in the defined scenarios resulted in 0.0009 to 0.0016 DALY, 5476.18 to 8799.80 MJ primary, 1033.68 to 1840.70 PDF×m^2×yr, and 563.55 to 880.61 kg CO_2-eq damage to human health, resources, ecosystem quality, and climate change, respectively. Moreover, the weighted analysis indicated that various soybean production scenarios led to 293.87–503.73 mPt damage to the environment in which the R-S scenario had the best environmental performance. Notably, the emissions caused by the production and application of the diesel fuel followed by chemical fertilizers, particularly N and P fertilizers, were recognized as the most important environmental hotspots in soybean production. According to the results, the ANFIS–FCM algorithm acted as the best prediction model of environmental indicators for soybean cultivation in all cases related to the ANN. The RMSE and MAPE values obtained from ANFIS–FCM were lower than the values obtained from the ANN model for all environmental indicators. For the ANFIS–FCM and ANN algorithms, R^2 ranged between 0.9967 to 0.9989 and 0.9269 to 0.9870, respectively. It can be concluded that the proposed ANFIS–FCM model is an efficient technique for obtaining accurate environmental prediction parameters of soybean cultivation.

***Keywords*:** ANFIS–FCM algorithm, climate change, environmental damage, human health, LCA, soybean

Highlights

- The ANFIS–FCM algorithm was proposed as a novel computational method for predicting environmental impacts.
- Soybean production scenarios were analyzed from an environmental viewpoint through the LCA.
- The main environmental hotspots were attributed to diesel and fertilizers.
- The R-S scenario proved to be eco-friendlier than the W-S and F-S scenarios.
- The ANFIS-FCM algorithm was identified as the best predictor model of environmental damage in relation to ANN.

Nomenclature

ANNs	Artificial neural networks	m^3	Cubic meter
ANFIS	Adaptive neuro fuzzy inference system	m^2	Square meter
AI	Artificial intelligence	mg	Milligram
C	Carbon	mPt	Milli point
CV	Cross-validation	MJ	Mega joule
CCI	Climate change indicator	MT	Metric ton
Cu	Copper	ML	Machine learning
Cr	Chromium	MAPE	Mean absolute percentage error
Cd	Cadmium	MFs	Membership functions
C_6H_6	Benzene	NC	Number of clusters
CO_2	Carbon dioxide	NO^-_3	Nitrate
CO	Carbon monoxide	NH_3	Ammonia
CH_4	Methane	N_2O	Dinitrogen monoxide
CF	Carbon footprint	NO_X	Nitrogen oxides
DALY	Disability adjusted life years	Ni	Nickel
EIA	Environmental impact assessment	NMVOC	Non-methane volatile organic compound
eq	Equivalents	PAH	Polycyclic hydrocarbons
FCM	Fuzzy C-means clustering algorithm	Pb	Lead
FIS	Fuzzy inference systems	P	Phosphorus
FU	Functional unit	PO_4^{-3}	Phosphate
F-S	Fallow-Soybean	PDF	Potentially Disappeared Fraction
GHG	Greenhouse gases	PGPR	Plant growth promoting rhizobacteria
GW	Global warming	PGPF	Plant growth promoting fungi
GWP	Global warming potential	R^2	Determination coefficient
g	Gram	R-S	Rapeseed-Soybean
ha	Hectare	RMSE	Root means square error
HC	Hydro carbons	SO_2	Sulfur dioxide
Hg	Mercury	Se	Selenium
IPCC	Intergovernmental Panel on Climate Change	TCP	Technical Cooperation Project
ISO	International Organization for Standardization	TJ	Terajoule
kWh	Kilowatt hour	W-S	Wheat-Soybean
kg	Kilogram	yr	Year
LCA	Life cycle assessment	Zn	Zinc
LCI	Life cycle inventory	µm	Micrometer
LCIA	Life cycle impact assessment		

1. Introduction

Different activities in the agriculture sector such as tilling, plowing, irrigation, burning straw, raising livestock, application of chemicals (*e.g.*, fertilizers and biocides), entering energy through machinery, electricity, and fossil fuels (Jaiswal and Agrawal, 2020) are among the most important contributors to the emission of GHGs. The agricultural sector accounts directly for nearly 10–15% of the world's GHG emissions. This number increases to nearly 30% by adding emissions from deforestation and land-use changes (Muller et al., 2011). In 2019, special reports from the IPCC indicated that forestry, agriculture, and other land-uses sectors had had a 23% share of total anthropogenic GHGs since 2007–2016 (IPCC 2019). The reduced emissions of GHGs such as CO_2, N_2O, and CH_4 and their impacts have been considered among the most challenging and hot environmental problems of all nations in recent years. Iran, with an approximately 616,741 million tons of CO_2-equivalent emission, is not an exception. In fact, Iran is the first responsible country for GW in the Middle East and the seventh country in the world (Mansouri Daneshvar et al., 2019). The significant population growth, the scarcity of water resources, and the reduction of productive land areas in the country (Karimi et al., 2018) led Iran's agriculture to compress rapidly over the past few decades. In other words, the increasing production yielded from existing farmland would naturally require more energy, materials and water to ensure food security for the growing populations. Given these inputs (resources) and the increasing intensive farming practices, further GHG emissions and other harmful gases go into the air, something which causes various environmental hazards such as damage to the ecosystem quality, human health, and the climate change phenomenon, which also has its own consequences, *e.g.*, the reduced agricultural productivity (Hu et al., 2019). Due to the importance of this sector in the release of other environmentally hazardous pollutants (*e.g.*, toxic heavy metals) into terrestrial and aquatic ecosystems (Ali et al., 2019) and the increasing interest in environmental quality, it is essential to analyze how farming practices affect the environmental impacts of agricultural products (Houshyar and Grundmann, 2017). Therefore, the EIA and resources utilization must be taken into account to produce sustainable and ecologically sound food, something which is also the goal of food security (Roy et al., 2009; Skaf et al., 2019).

Currently, there are various concepts and methods for environmental, economic, and/or social assessments of processes, products, or specific activities (Čuček et al., 2012). Each of these developed tools has the desired characteristics accompanied by certain limitations. As a comprehensive scientific and internationally standardized tool for achieving sustainable production and consumption, the LCA approach helps analyze eco-efficiency and optimize

agro-systems (Chomkhamsri et al., 2011; Nemecek et al., 2011). In fact, the LCA is a methodology of determining environmental burdens based on the use of resources and the emissions all over the product's lifetime from material extraction, manufacturing, and utilization to waste management phases (ISO 14040 2006). This method evaluates and quantifies environmental burdens of products or processes within the defined scopes, *i.e.*, system boundaries (Brentrup et al., 2004a). It can also compare the various environmental impacts of a system (Bjørn et al., 2018).

The LCA enables the diagnosis of environmental problems before damages occur, focusing on agricultural practices and identifying the most critical environmental hotspots (Nemecek et al., 2011). This powerful tool can also cover a broad range of other environmental issues such as the effects of eco-toxic from metals, aquatic eutrophication, non-renewable resources depletion, toxic impacts on human health, and climate change (Bjørn et al., 2018). Numerous studies employed the LCA to comprehensively examine the role of farming practices on the environment and human health. Table 1 presents an overview of these studies.

Table 1. Some of the recent publications about EIA based on LCA in agricultural production.

Product	Country /region	Functional unit	Remarks	Reference
Tea	Taiwan, Dongshan	1 kg	A. The most important factor in creating an environmental burden was a CCI. B. Consumer use (45.58%) and raw material (35.15%) phases, respectively, had the largest share in the emission of 7.035 kg CO_2eq from conventional tea production.	(Hu et al. 2019)
Oilseeds	U.S, Echo	1 kg	A. The best oilseed result was 660g CO_2eq kg^{-1} for canola following reduced tillage fallow.	(Ankathi et al. 2019)
Rice	Thailand, Surin	1 kg	A. The CCI value caused by the production of 1 kg of paddy rice was estimated to be 2.88 kgCO_2eq.	(Mungkung et al. 2019)
Soybean	Brazil, Rio Grande do Sul	1 kg	A. The most critical environmental impacts were eutrophication.	(Zortea et al. 2018)
Corn wheat	Spain, Lerma basin	1 ha	A. The CF from irrigated corn and non-irrigated wheat production is 0.121 and 0.893kg CO_2eq kg^{-1}, respectively. B. Urea use, with a share of approximately 78%, was the main contributor to the CF in the wheat life cycle. C. Liquid fertilizers application with about 69% was the main factor per kg of CO_2eq produced in irrigated corn production.	(Abrahão et al. 2017)
Maize Wheat Rice	China	Per unit	A. The consumption of energy by machinery, usage of N-fertilizer, burning of straw, consumption of energy for irrigation, and CH_4 emissions from rice paddies are the most important agents in C emissions.	(Zhang et al. 2017)
Soybean	Southern Brazil	1 kg	A. The largest share in the emission of greenhouse gases from soybean cultivation was related to the three agents of seeding (9%), fertilization (19%), and liming (37%).	(Maciel et al. 2016)
Soybean	Latin America	1 kg	A. The highest emissions of GHG came from soybean plantations that were formed from the conversion of the rainforest. B. GHG emissions from the production of 1 kg of soybean were estimated at 0.3 to 0.6 kg CO_2eq, regardless of land-use change.	(Castanheira and Freire 2013)

			C. The two non-tillage and reduced tillage systems had lower GHG levels than other tillage systems.	
Bean	Greece, Prespa National Park	1 kg/1 m^2	A. Integrated agriculture played the most important role among the eutrophication, acidification impacts, and GW potential. B. The two inputs of electricity and manure (sheep), respectively, played the most critical role in environmental impacts.	(Abeliotis et al. 2013)
Tomato	Australia, Sydney	1 kg	A. The main factor in environmental damage was the CCI (84-96%).	(Page et al. 2012)
Sunflower Rapeseed	Chile	1 ton	A. The highest environmental burden was related to the use of chemical fertilizers.	(Iriarte et al. 2010)
Onion	Iran, Bojnord	1 ton	A. In all studied impact categories, electricity and machinery were the two most important inputs to damage the environment. B. The GW index of small farms was almost twice that of large farms.	(Esmaeilzadeh et al. 2020)
Wheat	Iran, Bojnord	1 kg	A. The GW index for irrigated and dryland wheat was 1.22 and 0.72 kg CO_2eq kg^{-1}, respectively.	(Esmaeilzadeh et al. 2019)
Rice	Iran, Amol & Rasht	1 ton	A. Climate change in Rasht and Amol regions was 275.79 and 277.21 kg CO_2eq, respectively. B. The most cumulative energy demand, climate change, and GWP 100a in both regions were observed in the high-input system for semi-mechanized method.	(Habibi et al. 2019)
Oilseeds	Iran, Ardabil	1 ton	A. Production of 1 ton of soybean, rapeseed, and sunflower, 1549, 2132, 2283 kg CO_2eq, respectively, were emitted into the air. B. Soybean demonstrated the best environmental profile because of its higher seed yield, lower production and consumption of chemical fertilizers, electricity, and diesel and fewer field emissions (CO_2, N_2O, NH_3, etc).	(Dekamin et al. 2018)
Rapeseed	Iran, Mazandaran	1 ton	A. GW potential amounts were 1181.6 kg CO_2eq ton^{-1}. B. The acidification and eutrophication potentials were found to be 23.3 kg SO_2eq ton^{-1} and 18 kg PO_4^{-3}eq ton^{-1}, respectively. C. Production of chemical fertilizers and diesel fuel had the largest share in 7023 MJ of damage to the impact category of abiotic depletion (fossil fuels).	(Mousavi-Avval et al. 2017a)
Barley	Iran, Fars	1 kg	A. Irrigated farms had more environmental impacts than rain-fed farms. B. The use of electricity on irrigated farms has been the most significant contributor to the potential for human toxicity and abiotic depletion. C. Total CO_2eq emitted (GW) from irrigated farms was more than the rain-fed farms (2.35 vs. 1.31 kg).	(Houshyar 2017)
Peanut	Iran, Guilan	1 ton	A. The environmental index and resource depletion index for 1-ton production of peanut were 0.62 and 4.30, respectively.	(Nikkhah et al. 2015)

ML and AI have been recently considered in the fields of biomass, food, and agriculture by many researchers. Therefore, achievements in these areas must be rapidly analysed (Amin et al., 2020; Ashapure et al., 2020; Jiang et al., 2020; Talaviya et al., 2020; Mansaray et al., 2020; Misra et al., 2020; Nandy and Singh, 2020; Nica-Avram et al., 2020; Dubois et al., 2021; Guo et al., 2021; Jung et al., 2021; Onsree and Tippayawong, 2021; Samadi et al., 2021).

In particular, various researchers have focused on the use of a hybrid ML–LCA method to predict output energy and environmental impacts of agricultural products. Elhami et al. (2017) integrated an ANN with the LCA to assess the model outputs and environmental emissions from lentil cultivation. According to their results, the ANN with a structure of 9-10-6-11 was the most suitable network for predicting yield and environmental effects in lentil cultivation.

The overall findings of sensitivity showed that farmyard manure and machinery had the greatest effects on environmental impacts and crop yield, respectively.

The hybrid applications of LCA and ANFIS for energy modeling and environmental emissions of oilseeds were implemented by Mousavi-Avval et al. (2017c). They also used ANNs in order to compare the multilevel ANFIS algorithm in their research. They concluded that multilevel ANFIS could be used as a useful tool in predicting energy as well as economic and environmental indicators of agricultural production systems in different regions. Their evaluations also showed that the multilevel ANFIS model managed to more accurately predict energy and economic and environmental outputs of canola compared to the ANNs.

Nabavi-Pelesaraei et al. (2018) predicted the paddy production energy and environmental impacts through a combination of AI methods (ANNs and ANFIS) and LCA. Their results showed that the ANFIS model based on the hybrid learning algorithm predicted the correlation coefficient (R) for the output energy of (0.860) and environmental impacts (0.997). Furthermore, the ANN model with 12-6-8-1 structure predicted energy and environmental impacts with R of 0.524 and 0.999, respectively.

In order to predict the life cycle environmental impacts and output energy of sugarcane production in planted or ratoon farms, Kaab et al. (2019) employed two methods of AI, *i.e.,* ANNs and ANFIS. According to their results, the ANFIS model was a useful tool for predicting the environmental impact and output energy of sugarcane production in planted and ratoon farms. In a case study, Romeiko et al. (2020a) compared the ML approaches to estimate the spatially explicit life cycle of GW and eutrophication of corn production in the US Midwest Region. They reported that the gradient boosting regression tree model had the highest prediction accuracy with the CV values of 0.8 and 0.87 for the life cycle GW and the life cycle eutrophication impacts, respectively.

Iran has achieved many advantages in the production of agricultural products as well. Soybean is one of such products. Mostly planted for edible oil and meal, it is a major oilseed crop and source of vegetable oil in Iran (Satari Yuzbashkandi and Khalilian 2020). Its cultivation occurs mainly in the northern and northwestern provinces of Iran, *i.e.*, Golestan, Mazandaran, and Ardabil (Iran Ministry of Agriculture 2019). However, despite having the potential to produce this oilseed crop, Iran still imports nearly 95% of its 1.5 million tons of vegetable oil (Financial Tribune 2017). Hence, FAO decided to implement a TCP in Iran within the 2017–2019 period in order to create capacity and promote soybean production in this country (FAO 2017). In addition to highlighting the importance of further development of this oilseed crop, the issue provides a good incentive for new research in the field.

Despite the importance of EIA for sustainable economic growth, it has not had a long history in Iran (Yousefi et al. 2015). Although more than two decades have passed since its official introduction in the country in 1994, insufficient research has been conducted in the field (Khosravi et al. 2019). However, although few studies have been reported on the EIA of soybean production in Iran, the effects of different cultivation scenarios on the production of this crop have not yet been analyzed. According to literature review, ANNs and ANFIS are the only ML methods used in the LCA. Therefore, it is essential to introduce a new model that can accurately predict a number of environmental impacts based on the energy inputs. In this study, the ANFIS–FCM algorithm was proposed as a novel computational method based on fuzzy c-means (FCM) clustering to predict the environmental performance of soybean by using the life cycle input and output data. Finally, a comparison was drawn between the proposed model and the artificial neural network in terms of the statistical quality parameters. This study can help decision-makers draft policies and create awareness to provide solutions for sustainable production and management. Farmers can also adopt proper crop management methods based on the potential contributions of any soybean cultivation systems to emissions, environmental protection, and economic benefits.

2. Material and Methods

2.1. Study Region and Farming System Description

Mazandaran Province (located at 35˚ to 36˚ N and 50˚ to 54˚ E) is among the northern provinces of Iran, situated on the southern side of the Caspian Sea (Fig. 1). Mazandaran Province is among the most important agricultural hubs in Iran due to its specific geographical location and natural features (*e.g.*, weather conditions, surface and underground water resources, and fertile soil). Soybean cultivation in this region is performed mainly in rotation with wheat, rapeseed, and fallow. In this study, three following scenarios were analyzed because of their dominance in different regions of the province:

1) Soybean cultivation after rapeseed harvest
2) Soybean cultivation after wheat harvest
3) Soybean cultivation after the six-month fallow

Table 2 presents an overview of different scenario specifications.

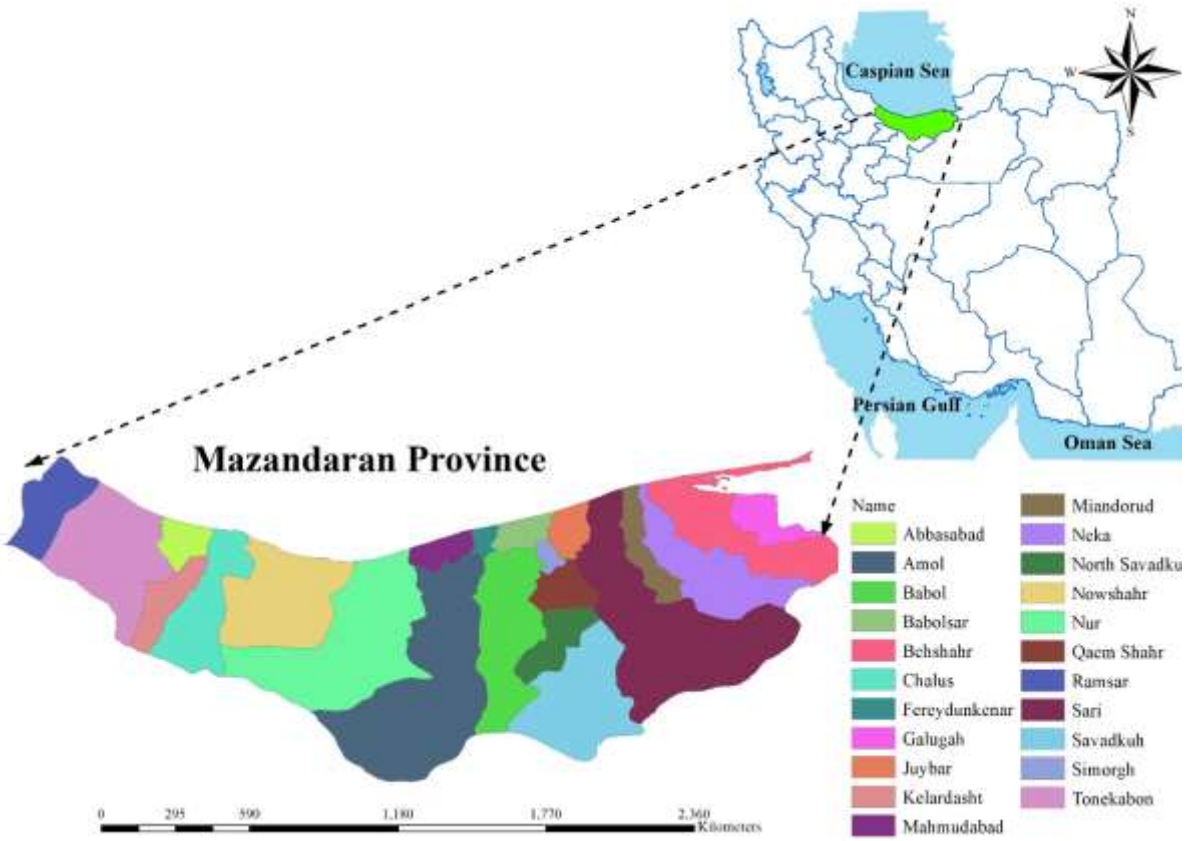

Fig 1. Location of the studied area in the north of Iran.

Table 2. The specification of different scenarios of soybean production in the Mazandaran province of Iran.

Items	Scenarios		
	Fallow-Soybean	Rapeseed-Soybean	Wheat-Soybean
Land preparation	By plow and disk or disk (no plow)		
Seeding	Manual seeding Agricultural machinery (row crop planters)		
Fertilization	By human labor Centrifugal fertilizer spreader		
Weeding	Manual weeding Chemical pesticide (herbicide)		
Sprayer type to control insect, disease, and weed	Backpack sprayer Tractor mounted boom sprayers Sprayer behind tractor		
Irrigation system	Sprinkler irrigation system Traditional irrigation (surface)		
Harvesting	Direct with combine (John Deere) Harvested manually and separated by combine or threshing machine		

Soybean planting date begins in the second decade of May in the area. Soybean cultivation in May, especially in Mazandaran, has the advantage that the sown seeds can benefit from spring rain and grow better. The previous crop (*i.e.*, wheat and rapeseed) should be harvested as soon as possible and planted before July in order to improve the soybean yield (as a second crop). Due to certain problems such as unfavorable weather conditions, lack of timely access to

equipment and machinery for harvesting (first crop), and the preparation duration of inputs, farmers start planting the seeds on different dates in the area. Table 3 shows the approximate planting and harvest dates.

Table 3. Time of planting and harvesting crops in different soybean cultivation scenarios in Mazandaran province, Iran.

Scenarios	First crop (planting time), (harvest time)	Second crop (planting time), (harvest time)
Fallow-Soybean	-	(10/05 - 10/06), (17/10 - 6/11)
Rapeseed-Soybean	(16/09 - 6/11), (15/05 - 31/05)	(16/05 - 6/06), (17/10 - 16/11)
Wheat-Soybean	(6/11 - 6/12), (5/06 - 6/07)	(7/06 - 8/07), (22/10 - 21/11)

2.2. LCA of Soybean Production

Based on ISO standards (ISO 14044 2006), the LCA is considered an appropriate approach to the analysis of environmental impacts of agricultural products. It consists of four stages called defining scope and target, LCI, assessing impacts, and results interpretation.

2.2.1. Goal, FU, and System Boundary

The first step and critical part of the LCA involves defining the purpose and then determining the FU and scope of the study (system boundary). It also states why an LCA is being performed and describes the system under analysis (Brentrup et al. 2004a; Nie 2016). This study aimed to evaluate and compare the environmental burdens of various soybean cultivation scenarios to identify environmental hotspots and provide reduction solutions.

In this study, the FU was mass-based on one ton of soybean produced. The system boundary included agricultural operations and all inputs used by farmers from the cradle (*e.g.*, fuel and biocide production from raw materials) to the farm gate (harvested soybean) (Fig. 2).

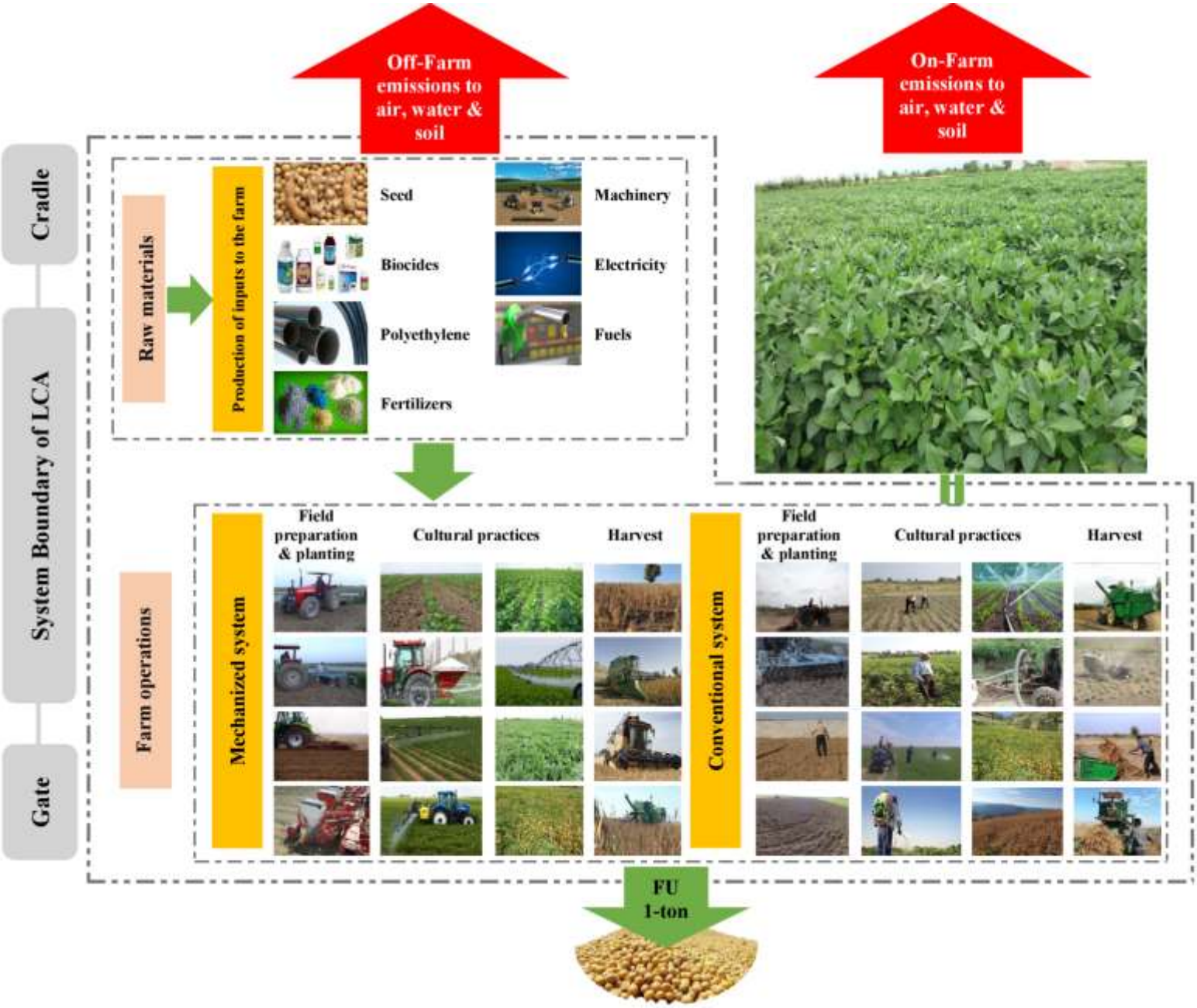

Fig. 2. The diagram of cradle-to-farm gate system boundaries of soybean production.

2.2.2. LCI Analysis and Data Collection

This step of the LCA is an inventory of various input/output data for a product about the studied system, including the collection and analysis of these data throughout its life cycle (Ntiamoah and Afrane 2008). In fact, in this segment of LCA, all quantitative and qualitative data collected (measured, calculated, or estimated for each unit/process) are utilized to quantify the inputs and outputs related to every unit (or process) that enters the system boundary (ISO 14044 2006).

In this study, two datasets were employed to complete the LCI.

1. Background systems (cradle-to-gate) data: In this section, the data include the environmental impacts of production, distribution, and transportation of inputs (*e.g.*, biocides, chemical fertilizers, electricity, and fuels). The data were adapted from EcoInvent3.5 in SimaPro.

2. Foreground systems (gate-to-gate) data: The data associated with this section include the amounts of inputs (*e.g.*, fertilizers, biocides, and fuels) and outputs (*e.g.*, soybean seed, emissions to water, soil, and air) caused by the application of inputs on farms (from the planting to harvesting of soybean).

The initial data were collected from questionnaires and face-to-face interviews with farmers in this study to obtain the information regarding the agricultural inputs consumption. The simple random sampling method and the Cochran formula were also employed to determine the number of farmers or the sample size (Cochran 1977). Table 4 presents all inputs and soybean yields collected from farms as well as On-Farm emissions from the application of these inputs in different cultivation scenarios.

Table 4. LCI of agricultural inputs (per FU= 1 ton) and seed yield of soybean annual production under different cultivation scenarios in Mazandaran province, Iran.

Inventory		Fallow-Soybean	Rapeseed-Soybean	Wheat-Soybean
A. Inputs (Off-Farm)	Unit			
1. Seed	kg	25.68	31.51	32.37
2. Agricultural machinery	kg	4.61	3.18	4.31
3. Fossil fuels	kg			
(a) Diesel		71.66	39.04	79.67
(b) Lubricant		1.35	1.09	1.87
(c) Kerosene		-	10.53	10.50
4. Electricity	kWh	27.5	25.84	11.44
5. Biocides:	kg			
(a) Insecticide				
Indoxacarb		0.04	0.03	0.02
Diazinon		0.38	0.34	-
Chlorpyrifos		-	0.08	0.09
Cypermethrin		0.24	0.19	0.13
Thiodicarb		-	0.38	0.05
Profenofos		-	-	0.31
Fenitrothion		-	0.19	-
(b) Herbicide				
Imazethapyr		-	0.04	-
Haloxyfop-ethoxyethyl		-	0.19	-
Trifluralin		-	-	0.14
Bentazone sodium		0.12	-	-
Paraquat		-	-	0.07
6. Polyethylene	kg	0.84	0.36	0.07
7. Chemical fertilizers	kg			
(a) Nitrogen fertilizer				
Urea (N: 46 - P_2O_5: 0 - K_2O: 0 - S: 0)		50.25	25.03	39.37
Ammonium sulfate (21-0-0-24)		-	3.75	-
(b) Phosphate fertilizer				
Diammonium phosphate (18-46-0)		18.87	6.45	18.89
Single superphosphate (0-16-0-12)		31.73	-	-
Superphosphate triple (0-46-0)		-	16.66	29.47
(c) Potassium fertilizer				

Potassium sulfate (0-0-52-18)		-	2.08	4.31
(d) Sulfur fertilizer				
Bentonite sulfur 70% (0-0-0-70-30)		-	5.55	13.83
Granular sulfur 90% (0-0-0-90-0)		5.86	4.84	3.12
B. Output				
Soybean yield	kg ha^{-1}	2950.00	2853.33	2308.32
C. On-Farm				
1. Emission to air:				
a. Emissions from chemical fertilizers	(kg)			
1. NH_3 emitted from nitrogenous fertilizers		3.22E+00	1.63E+00	2.61E+00
2. N_2O				
N_2O emitted from fertilizer		4.17E-01	2.12E-01	3.38E-01
N_2O released from atmospheric deposition of fertilizers		4.17E-02	2.12E-02	3.38E-02
3. NO_X emitted from N_2O of fertilizers and soil		9.62E-02	4.89E-02	7.81E-02
4. CO_2 released from urea		3.69E+01	1.84E+01	2.89E+01
b. Emissions from biocides	(kg)			
1. Emissions from insecticide				
Indoxacarb		5.00E-04	4.00E-04	3.00E-04
Diazinon		2.03E-02	1.83E-02	-
Chlorpyrifos		-	3.10E-03	3.40E-03
Cypermethrin		8.50E-03	7.00E-03	4.50E-03
Thiodicarb		-	2.71E-02	3.50E-03
Profenofos		-	-	1.27E-02
Fenitrothion		-	8.50E-03	-
2. Emissions from herbicide				-
Imazethapyr		-	4.00E-04	-
Haloxyfop-ethoxyethyl		-	1.80E-03	-
Trifluralin		-	-	5.90E-03
Bentazone		5.00E-03	-	-
Paraquat		-	-	1.30E-03
c. Emissions from fossil fuels	(kg)			
1. Diesel				
CO_2		3.58E+02	1.95E+02	3.98E+02
SO_2		1.16E-01	6.31E-02	1.29E-01
CH_4		1.48E-02	8.06E-03	1.64E-02
C_6H_6		8.36E-04	4.55E-04	9.29E-04
Cd		1.15E-06	6.26E-07	1.28E-06
Cr		5.72E-06	3.11E-06	6.36E-06
Cu		1.95E-04	1.06E-04	2.17E-04
N_2O		1.37E-02	7.49E-03	1.53E-02
Ni		8.02E-06	4.37E-06	8.92E-06
Zn		1.15E-04	6.26E-05	1.28E-04
Benzo(a)pyrene		3.44E-06	1.87E-06	3.82E-06
NH_3		2.29E-03	1.25E-03	2.55E-03
Se		1.15E-06	6.26E-07	1.28E-06
PAH		3.77E-04	2.05E-04	4.19E-04
HC, as NMVOC		3.27E-01	1.78E-01	3.63E-01
NO_X		5.09E+00	2.77E+00	5.66E+00
CO		7.21E-01	3.93E-01	8.01E-01
Particulates, < 2.5 µm		5.14E-01	2.80E-01	5.71E-01
2. Kerosene	(kg)			
CO_2		-	3.39E+01	3.38E+01
CO		-	6.53E-01	6.51E-01
SO_2		-	5.27E-02	5.25E-02
CH_4		-	4.74E-03	4.73E-03
N_2O		-	2.84E-04	2.84E-04
NO_X		-	3.16E-02	3.15E-02

2. Emission to water:

a. Emissions from chemical fertilizers	(kg)			
NO^-_3		3.52E+01	1.79E+01	2.86E+01
P		3.00E-01	2.32E-01	4.86E-01
b. Emissions from biocides	(kg)			
1. Emissions from insecticide				
Indoxacarb		1.00E-04	5.00E-05	3.00E-05
Diazinon		2.30E-03	2.03E-03	-
Chlorpyrifos		-	3.40E-04	3.70E-04
Cypermethrin		9.00E-04	7.80E-04	5.00E-04
Thiodicarb		-	3.01E-03	3.90E-04
Profenofos		-	-	1.41E-03
Fenitrothion		-	9.40E-04	-
2. Emissions from herbicide				
Imazethapyr		-	4.00E-05	-
Haloxyfop-ethoxyethyl		-	2.00E-04	-
Trifluralin		-	-	6.60E-04
Bentazone		6.00E-04	-	-
Paraquat		-	-	1.50E-04
3. Emission to soil:				
a. Emissions from chemical fertilizers	(mg)			
1. From N-fertilizer:				
Cd		1.59E+02	8.08E+01	1.29E+02
Cr		2.07E+03	1.05E+03	1.68E+03
Cu		6.89E+02	3.50E+02	5.59E+02
Hg		2.65E+00	1.35E+00	2.15E+00
Ni		5.54E+02	2.81E+02	4.50E+02
Pb		1.46E+03	7.39E+02	1.18E+03
Zn		5.38E+03	2.73E+03	4.37E+03
2. From P-fertilizer:				
Cd		5.44E+02	4.20E+02	8.78E+02
Cr		7.47E+03	5.77E+03	1.21E+04
Cu		1.25E+03	9.62E+02	2.01E+03
Hg		4.13E+00	3.19E+00	6.67E+00
Ni		1.22E+03	9.39E+02	1.96E+03
Pb		9.22E+02	7.12E+02	1.49E+03
Zn		1.15E+04	8.92E+03	1.87E+04
3. From K-fertilizer:				
Cd		-	1.08E-01	2.24E-01
Cr		-	6.26E+00	1.30E+01
Cu		-	5.18E+00	1.08E+01
Ni		-	2.70E+00	5.60E+00
Pb		-	8.64E-01	1.79E+00
Zn		-	6.70E+00	1.39E+01
b. Emissions from biocides	(kg)			
1. Emissions from insecticide				
Indoxacarb		5.40E-03	4.30E-03	2.90E-03
Diazinon		2.03E-01	1.83E-01	-
Chlorpyrifos		-	3.08E-02	3.35E-02
Cypermethrin		8.46E-02	6.98E-02	4.50E-02
Thiodicarb		-	2.71E-01	3.51E-02
Profenofos		-	-	1.27E-01
Fenitrothion		-	8.46E-02	-
2. Emissions from herbicide				
Imazethapyr		-	3.80E-03	-
Haloxyfop-ethoxyethyl		-	1.83E-02	-
Trifluralin		-	-	5.94E-02
Bentazone		4.97E-02	-	-
Paraquat		-	-	1.33E-02

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In this study, the biocides used by Iranian soybean producers were classified as two groups of herbicides and insecticides (Table 4). According to Table 5, based on the amount of active ingredient per pesticide, On-Farm emissions from biocides were considered 0.01, 0.09, and 0.9 for water, air, and soil, respectively (Durlinger et al. 2017). The application of chemical fertilizers (potassium, phosphorus, and nitrogen) is also responsible for several On-Farm emissions. In this context, for the calculation of pollutants to air and water, the standard equations and conversion coefficients of pollutants to the applied value (Table 5) were adopted (IPCC 2006). Additionally, the use of chemical fertilizers on the field causes the emission of heavy metals into soil, resulting in environmental pollution and harm to human health. In this study, the coefficients presented in Table 6 were utilized to calculate the heavy metals emissions to the soil (Durlinger et al. 2017).

Table 5. Coefficients for computing the emissions caused by chemicals and fertilizers application.

Characteristic	Coefficient	Emission result
A. Emissions of fertilizers		
$\left[\frac{\text{kg } N_2O - N}{\text{kg } N_{\text{in fertilizer applied}}}\right]$	0.01	To air
$\left[\frac{\text{kg } CO_2 - C}{\text{kg Urea}}\right]$	0.2	To air
$\left[\frac{\text{kg } NH_3 - N}{\text{kg } N_{\text{in fertilizer applied}}}\right]$	0.1	To air
$\left[\frac{\text{kg } NO_3^- - N}{\text{kg } N_{\text{in fertilizer applied}}}\right]$	0.3	To water
$\left[\frac{\text{kg P emission}}{\text{kg } P_{\text{in fertilizer applied}}}\right]$	0.05	To water
Indirect N_2O from atmospheric deposition:		
$\left[\frac{\text{kg } N_2O - N}{\text{kg } N_{\text{in chemical fertilizer applied}}}\right]$	0.001	To air
Direct NO_X emissions from fertilizers and soil:		
$\left[\frac{\text{kg } NO_X}{\text{kg } N_2O_{\text{from fertilizers and soil}}}\right]$	0.21	To air
Conversion of emissions:		
Conversion from kg CO_2-C to kg CO_2	$\left[\frac{44}{12}\right]$	
Conversion from kg N_2O-N to kg N_2O	$\left[\frac{44}{28}\right]$	
Conversion from kg NH_3-N to kg NH_3	$\left[\frac{17}{14}\right]$	
Conversion from kg NO^-_3-N to kg NO^-_3	$\left[\frac{62}{14}\right]$	
Conversion from kg P_2O_5 to kg P	$\left[\frac{62}{164}\right]$	
B. Emissions from biocides		
$\left[\frac{\text{kg active ingredient}}{\text{kg biocide}}\right]$	0.09	To air
$\left[\frac{\text{kg active ingredient}}{\text{kg biocide}}\right]$	0.01	To water

$\left[\frac{\text{kg active ingredient}}{\text{kg biocide}}\right]$	0.90	To soil

Table 6. Coefficients for calculating the On-Farm emissions to the soil of heavy metals associated with the application of chemical fertilizers in different cultivation scenarios of soybean.

Characteristic	Heavy metal						
	Cd	Cu	Zn	Pb	Ni	Cr	Hg
$\left[\frac{\text{mg Heavy metal}}{\text{kg N}_{\text{in fertilizer applied}}}\right]$	6.0	26.0	203.0	54.9	20.9	77.9	0.1
$\left[\frac{\text{mg Heavy metal}}{\text{kg P}_2\text{O}_{5\text{in fertilizer applied}}}\right]$	39.5	90.5	839.0	67.0	88.3	543.0	0.3
$\left[\frac{\text{mg Heavy metal}}{\text{kg K}_2\text{O}_{\text{in fertilizer applied}}}\right]$	0.1	4.8	6.2	0.8	2.5	5.8	0.0

The diesel fuel combustion in the tractor engine and other agricultural machinery emit some harmful compounds into the air (*e.g.*, CO_2). According to Table 7, the EcoInvent database was employed to calculate the On-Farm emissions deriving from the combustion of diesel fuel (Nemecek and Kagi 2007; Khoshnevisan et al. 2014). Table 7 reports the emission factors for air emissions from kerosene fuel combustion (Engineering ToolBox 2009; Majumdar and Gajghate 2011; Ramachandra and Shwetmala 2012). Ultimately, all the inputs and outputs (the inventory data), based on the FU of 1-ton product yield (*i.e.*, soybean), were imported into SimaPro 9.0.0.49 for further analysis.

Table 7. Air emission factors for combustion of fuel.

Emission	g MJ^{-1}diesel	Kerosene
CO_2	74.5	71.50 t TJ^{-1}
SO_2	2.41E-02	0.005 MT MT^{-1}
Pb	-	-
CH_4	3.08E-03	10 kg TJ^{-1}
C_6H_6	1.74E-04	-
Cu	4.06E-05	-
Cr	1.19E-06	-
Cd	2.39E-07	-
N_2O	2.86E-03	0.6 kg TJ^{-1}
NH_3	4.77E-04	-
NO_X	1.06	3.00 g kg^{-1}
Ni	1.67E-06	-
PAH	7.85E-05	-
Zn	2.39E-05	-
Benzo(a)pyrene	7.16E-07	-
Se	2.39E-07	-
HC, as NMVOC	6.80E-02	-
CO	1.50E-01	62.00 g kg^{-1}
Particulates, < 2.5 µm	1.07E-01	-

2.2.3. Assessing Impacts of Soybean Production

The third step in the LCA to perform impact assessment by using LCI results and providing characterization factors expressing the impacts per amount of inventory (ISO 14040 2006; Humbert 2009). In addition to evaluating the potential environmental impacts, this step also provides information on the life-cycle interpretation stage (ISO 14040 2006).

In this study, IMPACT 2002+ (v2. 15) model was employed to determine the environmental impacts of soybean production. This methodology is a combination of CML, Eco-indicator 99, IPCC, and Impact 2002 methods (Jungbluth 2020). IMPACT 2002+ combines the midpoint and damage indicators in the LCIA methodology to enhance consistency in the impact pathway modeling (Hauschild and Huijbregts 2015). According to Humbert et al. (2014), the model consists of 15 midpoint categories (Fig. 3), in which all of these indicators are expressed in units of a reference substance and are related to four damage indicators called ecosystem quality (PDF×m^2×yr: PDF of species, yr, climate change (kg CO_2-eq), resources (MJ primary), and human health (DALY).

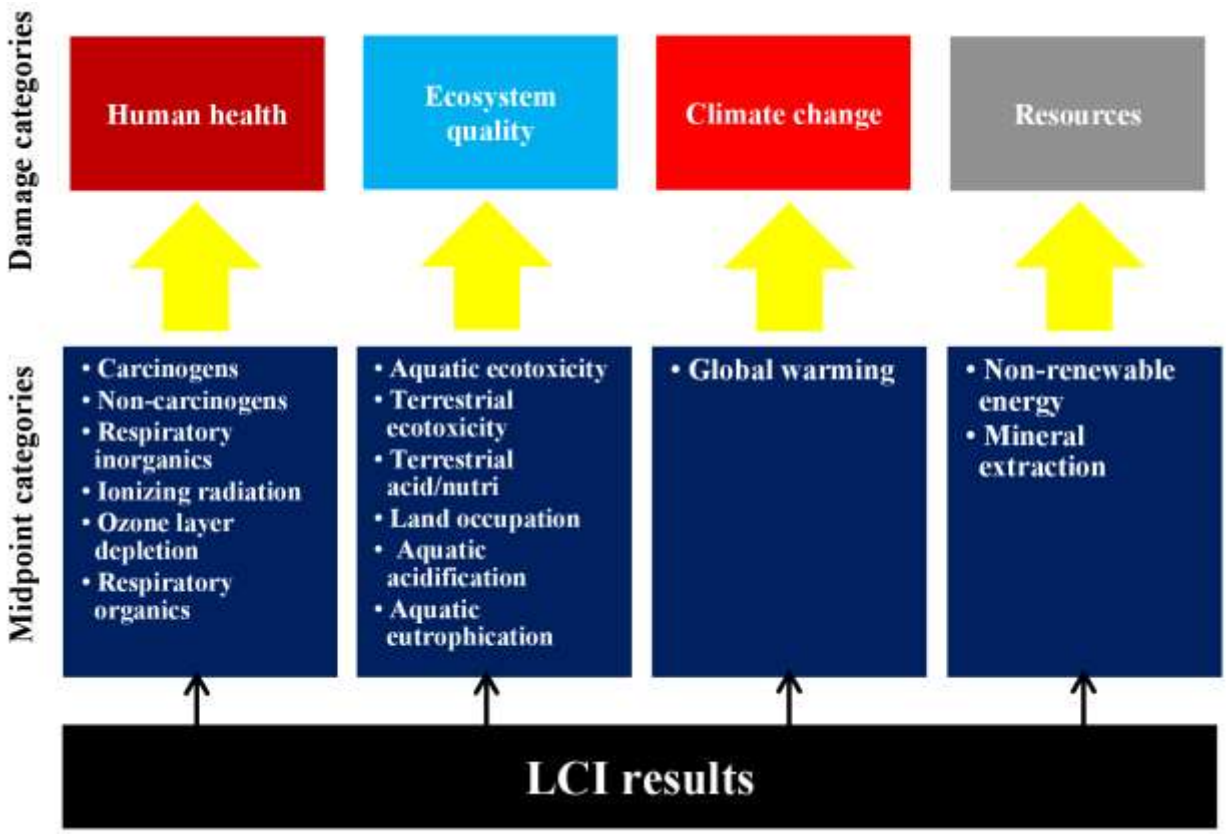


Fig 3. Damage groups and linked midpoint categories in IMPACT2002+ method.

2.3. ANFIS–FCM Method

The ANFIS was first proposed by Jang (1993). The ANFIS is actually a neural network that employs the Takagi-Sugeno inference model structure. In fact, the ANFIS is a powerful modeling technique with a combination of learning rules from ANNs and the linguistic

transparency of fuzzy logic theory. A FIS is among the most popular applications of fuzzy logic theory in various fields of economic, scientific, engineering, and management. In an FIS, MFs usually have to be manually adjusted by trial and error. This model is known as the white box, whereas achieving the goal is self-learning in the ANN and acts as a black box. Fig. 4 demonstrates the schematic view of an ANFIS architecture. This model includes five layers with several nodes described by the node function. The function of each layer is described as follows. The set of parameters in this model, which can be changed and fixed, are shown as squares and circles, respectively.

Layer 1: The first layer consists of an adaptive node with a node function converting the inputs into a fuzzy set through the process of fuzzification:

$$O_{1,i} = mA_i(X_1), \text{for } i = 1,2 \quad (1a)$$

$$O_{1,i} = mB_{i-2}(X_2), \text{for } i = 3,4 \quad (1b)$$

Where X_1 and X_2 are the input variables i, whereas A and B are the linguistic labels characterized with this node. Moreover, μ(X1) and μ(X2) are the MFs such as generalized bell, sigmoid, or triangular values.

Layer 2: Every circle node in Layer 2 represents a fixed node labeled by Π, which multiplies the input signals and sends the output signal.

$$O_{2,i} = w_i = mA_i(X_1).mB_{i-2}(X_2), \text{ for } i = 1,2 \quad (2)$$

Where the $O_{2,i}$ is the output of Layer 2. The output of each node w_i shows the firing strength of a rule.

Layer 3: Every circle node in in Layer 3 is considered a fixed node. Here, the ratio of the *i*th rule in firing strength to the sum of all firing strengths is calculated:

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \text{ for } i = 1,2 \quad (3)$$

Where the $O_{3,i}$ is the output of Layer 3. The $\bar{w}$ is the normalized firing strength of the fuzzy rule.

Layer 4: This layer is called the defuzzier, in which every square node of the output from the previous layer is multiplied by the function of fuzzy rules:

$$O_{4,i} = \bar{w}_i.f_i, \text{ for } i = 1,2 \quad (4)$$

where f_1 and f_2 are the fuzzy if–then rules as follows:

$$\text{Rule 1. IF } X_1 \text{ is } A_1 \text{ and } X_2 \text{ is } B_1, \text{THEN } f_1 = p_1X_1 + q_1X_2 + r_1 \quad (5)$$

$$\text{Rule 2. IF } X_1 \text{ is } A_2 \text{ and } X_2 \text{ is } B_2, \text{THEN } f_2 = p_2X_1 + q_2X_2 + r_2 \quad (6)$$

Where, p_i, q_i and r_i are the parameters (consequent parameters).

Layer 5: The single circle node in Layer 5 in the fifth layer of the output layer is labeled Σ calculated through the sum of all inputs of the previous layer:

$$O_{5,i} = \sum_i \bar{w}_i . f_i , = \frac{\sum_i w_i . f_i}{w_i} = f_{out} \quad (7)$$

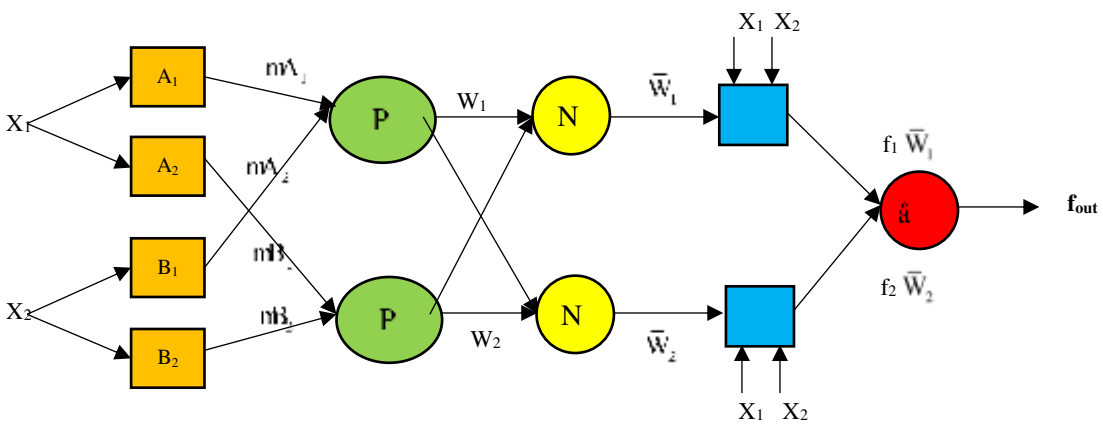


Fig. 4. The structure of ANFIS.

The most widely used ANFIS learning rule is "backpropagation", which calculates error signals recursively from the output layer (Layer 5) and transfers backward to the input nodes (Layer 1). The gradient descent method is employed to optimize the parameters of the premise part. This learning rule is the same as the backpropagation learning rule in the feedforward neural networks. Excessive slowness and trapped in local minima for conventional methods are among the main problems that can be solved through the hybrid learning algorithm.

The ANFIS fuzzy c-means clustering is the most common hybrid learning method of fuzzy clustering. In this structure, the behavior of the data describes the ANFIS rules. The fuzzy c-means (FCM) method determines the number of rules and MFs for input and output variables. In fact, the developed *k*-means algorithm is an FCM method, which divides the data set X into *c* clusters by minimizing the weight distance errors for each data point xi related to all *c* cluster centroids. Hence, the algorithm minimizes the objective function which is a generalization of the least squares method:

$$j_m = \sum_{c=1}^{c} \sum_{i=1}^{n} w_{ic}^{p} \left\| x_i - v_c \right\|^2 \qquad (8)$$

Where n represents the number of data points, and c denotes the number of clusters, whereas v is the cluster centers, and w_{ic} is degree of membership of xi in the cluster c. Finally, x indicates the input data point. Moreover, w_{ic} can be calculated through the following formula:

$$w_{ic} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\left\| x_i - v_i \right\|}{\left\| x_i - c_k \right\|} \right)^{2/(p-1)}} \qquad (9)$$

Where p denotes the fuzzifier exponent, and k is the number of the iteration step.

Moreover, after the central vectors are initialized in the FCM algorithm, the centroids are calculated through the following formula:

$$v_i = \frac{\sum_{i=1}^{n} w_{ic}^{p} x_i}{\sum_{i=1}^{n} w_{ic}^{p}} \qquad (10)$$

In this study, the input set for the developing model includes 14 variables that are independent of field soybean cultivation. These variables are defined as the type of soybean cultivation (after wheat cultivation, rapeseed cultivation, and fallow land), seed, agricultural machinery, polyethylene, nitrogen, phosphate, potassium, sulfur, herbicide, insecticide, electricity, diesel, lubricating oil, and kerosene (Table 4). Human health, resources, climate change, and ecosystem quality are given as data output sets. This dataset is subdivided into 123 data for training and 52 data for testing. In the modeling process, the ANFIS-related functions of MATLAB were adopted to generate the model program. In the modeling process, the ANFIS parameters are determined during the learning phase at a specific epoch which verifies that errors are minimal. Experimental datasets are then employed to assess the accuracy, effectiveness, and prevention of overfitting of the trained model. The FCM clustering method was adopted in this study to develop the FIS structure from data in the ANFIS. These methods are applied to develop and select the best LCA prediction model for soybean cultivation. In this study, 70% of the data was used for training (123 data), whereas 30% of the data was used for testing (52 data). In this method, the quantities of rules and MFs for input and output variables are determined by the FCM method. The NC created by the FCM can be specified in

the program. Determining the radius of a smaller cluster usually results in more clusters. This means that more rules have been produced in the FIS. When the FIS structure type is selected as a Sugeno model, the input and output membership types are defined as Gaussian and linear models, respectively. Six alternative models were then produced by assigning different values to the NC, which determines the number of MFs and rules. Simulations were performed for these alternative models to find the optimal FIS structure.

2.4. ANN Method

The ANN with multilayered feedforward backpropagation algorithm performs the learning process by changing the weights. These changes are stored as knowledge. In order to obtain the best prediction by the network, several architectures were evaluated and trained by applying the experimental data. The hidden layer can consist of one or more layers. The number of neurons in each layer varies and is usually determined by trial and error (Agatonovic-Kustrin and Beresford 2000). In this study, the neural network structure was modeled with 14 factors of inputs such as chemical pesticides and fertilizers, agriculture machinery, polyethylene, electricity, diesel, lubricating oil, kerosene, and seed used as 14 neurons in the input layer as well as four factors of climate change, resources, human health, and ecosystem quality used as neurons in the output layer. Combined parameters such as the number of hidden layers, number of neurons, and number of training cycles during the artificial neural network training process were determined by trial and error. In total, there were 123 input patterns in the network. They were randomly divided into three groups: training (70%), evaluation (15%), and testing (15%). The training rate for all cases was 0.2, whereas the momentum rate was 0.1; moreover, the best neural network topology was determined by using R^2 and RMSE.

2.5. Model Validation

Statistical parameters were employed to evaluate and fit the best model for data. The indices of MAPE, RMSE, and the R^2 can be expressed as:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100 \qquad (11)$$

$$MSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \qquad (12)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2} \qquad (13)$$

Where y_i and $\hat{y}_i$ denote the observed and predicted values for the *i*th testing dataset, respectively. In addition, $\bar{y}$ refers to the average of the observed values, whereas *n* represents the total number of data.

3. Results and Discussion

3.1. EIA of Soybean Production Scenarios

3.1.1. Results of Damage Assessment

Table 8 presents the damage categories caused by the production of 1-ton soybean based on the IMPACT2002+ method, and Fig. 5 demonstrates the relative contributions of different inputs to the four environmental damage indicators. According to the results, On-Farm emissions from soybean production in all cultivation scenarios had the highest share in three damage categories of human health (>71%), climate change (>50%), and ecosystem quality (>89%). The following subsections address the environmental damage caused by the soybean production.

3.1.1.1. Climate Change

According to Table 8, the highest CO_2-eq value came from the W-S (880.61 kg) followed by the F-S (794.50 kg) in different scenarios of soybean production, whereas the lowest CO_2-eq value was obtained from the R-S (563.55 kg) cropping system. According to Fig. 5, the direct emissions from farm operations played a major role in increasing GW or climate change in different scenarios of soybean production (nearly 51-60%). This increase was mainly due to the release of CO_2 from diesel combustion in all farms and then the emitted N_2O, albeit in smaller amounts compared to CO_2. Likewise, according to Fig. 5, the contribution of indirect emissions from seed production to this category is also significant.

This phenomenon as the major environmental challenge of the present age (Pandey and Agrawal 2014), resulting in an uncontrolled population growth and the excessive and unprincipled exploitation of natural resources. As a supplier of increasing human food needs, this sector will increase GHG emissions and worsens the phenomenon of climate change by increasing the consumption of inputs such as nitrogen and phosphorous fertilizers, diesel fuel, and manure (Jaiswal and Agrawal 2020). Nitrogen is considered among the most important nutrients for plant growth and higher yields. Spreading manure and used as chemical fertilizers on farmlands, it leads to a number of important emissions that affect GW (Durlinger et al. 2017). Amongst these emissions, N_2O is of great importance due to its longevity in the atmosphere (more than 114 years) and its GWP (298 times larger than CO_2). The main sources of N_2O emissions in the soil are mainly due to agricultural activities including the use of

nitrogen fertilizers in the soil, fossil fuels combustion, and some of the natural mechanisms that occur in aquatic and terrestrial ecosystems (Signor and Cerri 2013). Therefore, any strategies proposed to reduce the atmospheric concentration of GHG should be focused on the agricultural sector as an important source of their emissions.

In a similar study on the LCA for oilseeds production in Ardabil Province (Iran), the amounts of CO_2-eq emitted per ton of products for rapeseed, sunflower, and soybean were reported 2132, 2283, and 1549 kg, respectively. Moreover, the study reported that more than 70% of these emissions (GW) were caused by electricity production, manure, and chemical fertilizers (Dekamin et al. 2018). The comparison of results indicated clearly that the GWP index for soybean production was much higher in Ardabil Province than in Mazandaran, something which is due to the higher consumption of these inputs and more intensive management to produce this product. In another study conducted in South Korea, (Lee and Choe 2019) reported the amounts of CO_2-eq emitted from soybean production in conventional and organic farms as 1657.55 and 2045.11 kg ton^{-1}, respectively. Like the present study, N_2O emission from the consumption of manure and chemical fertilizers and CO_2 from fossil fuel combustion accounted for the largest shares of total CO_2-eq emitted from these farms. In fact, manure, fuel, and fertilizer were the main contributors to GHG emissions and poor energy efficiency in Korean soybean production. They proposed the optimal use of these inputs in order to diminish the emissions. In another LCA analysis in Iran, Khanali et al. (2018) analyzed the EIA of edible canola oil production in Isfahan Province. Their findings showed that the direct emissions from the field operations played a key role in GW, mainly due to the use of chemical fertilizers, manure, and diesel fuel. They attributed the increase in this impact category to unsuitable management practices, *i.e.*, improper tillage patterns and incorrect use of these inputs. Similarly, Mousavi-Avval et al. (2017b) analyzed the environmental LCA of rapeseed production in Mazandaran Province and reported that On-Farm emissions with 844.8 kg of 1181.6 kg CO_2-eq ton^{-1} emitted or GWP (as the only impact category affecting climate change) were the main contributors. Nemecek et al. (2011) conducted a study to assess the LCA of farming systems in Switzerland and revealed that N_2O and CO_2 emitted from fertilizers and fossil fuels had the greatest impacts on GWP, respectively. In similar surveys on the LCA of soybean production in different parts of the world such as Northern Great Plains, USA (Moeller et al. 2017), U.S. Midwest (Romeiko et al. 2020b), Southern Brazil (Zortea et al. 2018), Mato Grosso State, Brazil (Raucci et al. 2015), and Jilin Province, China (Knudsen et al. 2010) the amounts of CO_2-eq emitted were reported 602 g kg^{-1}, -11.4 to 22 kg kg^{-1}, 0.734 kg kg^{-1}, 0.186 kg kg^{-1}, and 263 kg ton^{-1}, respectively. Although the GHG emission in different

agro-ecosystems varies depending on climatic and soil conditions, the type of management practices also has a significant effect on the amount of these emissions and their environmental impacts. Due to the roles of diesel, chemical fertilizers (as the most crucial environmental hotspots) in damaging the climate change category, improvement measures should focus on the consumption management of these inputs.

3.1.1.2. Resources

According to Fig. 3, this damage category is related to the two midpoint categories called mineral extraction and non-renewable energy. These midpoints mean "MJ additional or surplus energy (or kg-eq iron)" and "MJ total primary non-renewable energy (or kg-eq crude oil)", respectively (Sajid et al., 2016). According to Table 8, the R-S scenario with a total value of 5476.18 MJ primary made the lowest use of resources. In all scenarios, the findings revealed that diesel and nitrogen fertilizers had the greatest impacts on the resource category, respectively. In other words, these inputs are the main environmental hotspots in damage to this category (Fig. 5). These results are consistent with the findings reported by Knudsen et al. (2010) in Jilin Province, China. Accordingly, the production of agro-chemicals and traction at farms with nearly 73% and 27% of the total non-renewable energy used in soybean production (1,710 MJ t^{-1}), respectively, were the main contributors of the environmental burdens caused by this index. To improve the environmental profile of soybean production, they suggested a minimum consumption of nitrogen fertilizer and efficient management of manure by covering manure storage, providing adequate aeration, and reducing nutrients losses and NH_4 emission. In Swiss farming systems, mechanization processes, *i.e.*, soil cultivation and harvest, accompanied by mineral fertilizers, in particular N fertilizers, had the highest demand for non-renewable energy resources. The reason why N fertilizers had the highest energy demand of all inorganic fertilizers was the high consumption of fossil fuels in the process of NH_3 synthesis (Nemecek et al. 2011). Another study was conducted to analyze the EIA of barley production in Southwest Iran, Fars Province, based on the LCA methodology. Their results showed that large amounts of N fertilizers were used by farmers in the area without soil testing and accurately determining plant fertilizer requirements. In order to reduce the consumption of N fertilizers and maintain soil fertility, the researchers suggested planting green crops such as alfalfa and clover, crop rotation, and soil analysis. In terms of abiotic depletion, diesel combustion in agricultural machinery was the main contributor in barley production. Conservation tillage systems, new machines, and suitable cultivars were also recommended to reduce the environmental burdens of barley production (Houshyar 2017). The depletion of abiotic resources is the use of resources such as minerals (*e.g.*, phosphate rock) or fossil fuels,

which can reduce the access of future generations to these resources. Since these resources have inherent values for human beings and access to them in the future is economically and socially important (Brentrup et al. 2004a), further monitoring and research efforts should be made to properly manage and reduce the consumption of these valuable resources. In a similar study, the incompatibility of farm equipment and machines with the target product as well as the use of old machinery on the farms led to the high consumption of fossil fuel, *i.e.*, diesel for peanut production. Therefore, it is possible to reduce diesel consumption and higher efficiency by replacing old machines with the new and modern ones in addition to conservation tillage (minimum or no-tillage). As a result, its environmental impacts were decreased (Nikkhah et al. 2015).

3.1.1.3. Ecosystem Quality

The results demonstrate that the total amount of damage to the ecosystem quality was higher in the W-S scenario than in other scenarios (Table 8). The most damage to this category in the production of soybean relates to the field operations with no considerable share from background processes (Fig. 5). It is also notable that the main contributors of On-Farm emissions are heavy metals (mostly Zn) in applied chemical fertilizers, especially phosphorus. Regarding damage to ecosystem quality, these inputs were the main environmental hotspots due to the highest emissions. These results double the importance of fertilizer consumption management in the soybean farms of Mazandaran Province. In this regard, Zortea et al. (2018), Khanali et al. (2018), Brentrup et al. (2004b), and Ntiamoah and Afrane (2008) also noted the efficient management of fertilizers in the production of soybean, rapeseed, wheat, and cocoa, respectively. Similarly, Khanali et al. (2018) reported that the use of phosphorus fertilizers in canola cultivation was the main environmental hotspot in the edible oil produced in Iran. In another study analyzing the impacts of heavy metals on human toxicity of corn cultivation in southern Belgium, cancer and non-cancer impacts were mostly attributed to Cr and Zn emissions from organic and mineral fertilizers, respectively (Gerbinet et al. 2019). Similarly, Matsuura et al. (2017) attributed the impacts of human toxicity and freshwater eutrophication (as the impact categories affecting human health and ecosystem quality) in the soybean-sunflower production system to heavy metals and phosphate emitted from high phosphorus fertilizers consumption in soybean cultivation. These results reflect the importance of optimizing usage of fertilizers for the cleaner production of these crops. However, due to the sharing of some resources such as the biological stabilization of nitrogen by soybean and more efficient use of land, the soybean-sunflower cropping system outperformed than the sum of monocultures in environmental aspects. According to the results, the agricultural sector through

525 the use of chemical fertilizers, especially phosphorus, was considered an anthropogenic source
526 for the release of heavy metals into the environment. By emitting these pollutants into water
527 and soil, not only are natural ecosystems damaged, but they also endanger human health by
528 entering the food chain (Ali et al. 2019). Apart from being an important anthropogenic source
529 for the release of heavy metals, phosphorus is considered an important nutrient for crop
530 production (Gupta et al. 2014). In addition, since most countries in the world (nearly more than
531 90%) lack the significant reserves of phosphate rock as the main source of production of most
532 phosphate fertilizers due to the fact that no element can be replaced instead of phosphorus in
533 biochemical processes (Ohtake and Tsuneda 2019), it is important to manage the consumption
534 of this non-renewable resource. Hence, to achieve sustainable agriculture, bio-fertilizers and
535 renewable inputs can be employed to improve soil fertility and minimize environmental
536 hazards (Verma et al. 2013). These inputs can maintain long-term soil fertility and stability
537 through different mechanisms such as biological N fixation, conversion of insoluble
538 phosphorus in the available form for plants, and increased access to macro and micronutrients
539 in the rhizosphere (Mahdi et al. 2010). Plant growth promoting microbes such as PGPF and
540 PGPR are the examples of these bio-fertilizers.

541 ***3.1.1.4. Human Health***

542 According to Table 8, the total amounts of human health damage category produced in F-S, R-
543 S, and W-S scenarios were reported 0.0015, 0.0009, and 0.0016 DALY, respectively.
544 According to Fig. 5, this difference is mainly due to the high shares of direct emissions in
545 different scenarios, *i.e.* nearly 71-78%. Given the importance of human health, it is essential to
546 identify the sources of these pollutants, for the right management strategies can be formulated
547 to mitigate these emissions by identifying these inputs. The analysis revealed the direct
548 emissions of NO_X and Particulates, < 2.5 μm caused by the diesel fuel, and NH_3 from nitrogen
549 fertilizers having the most significant role in damage to human health in all scenarios of
550 soybean production, respectively. Like N_2O, the release of NH_3 depends on the amounts of
551 nitrogen fertilizers consumed on farms (Brentrup et al. 2004b). In a similar LCA study in
552 Mazandaran Province, the optimal use of chemical fertilizers, especially nitrogen, was
553 recommended to mitigate the environmental impact of rapeseed production in that area
554 (Mousavi-Avval et al. 2017c).

555 According to the present study, the use of agrochemicals (herbicides and chemical
556 fertilizers) and the burning of diesel fuel in farm machinery were the main contributors of the
557 environmental burdens caused by sugarcane growth and harvesting in Mexico. In this study,
558 the use of NPK fertilizers in farms made a significant contribution to the endpoint categories

(ecosystem quality, human health, climate change, and resources). The researchers proposed an artificial intelligence-based decision support system to solve this problem and correctly estimate the amounts of fertilizer used on farms. They also suggested the presence of agricultural experts due to the difficulty of interpreting soil test results for farmers (Meza-Palacios et al. 2019). In a similar study in Mazandaran Province, high-consumption rates of nitrogen fertilizers and diesel fuel were the main contributors of the environmental burdens of rapeseed production in that area. They revealed that the integration of legumes such as bean in rotation with the rapeseed could be a management strategy to reduce dependence on chemical fertilizers and thus produce more environmentally-friendly rapeseed in the region (Mousavi-Avval et al. 2017a). Pulses increase soil productivity by reducing soil pathogens, decreasing soil erosion, and maintaining biological stabilization of nitrogen, thereby improving crop yields in rotation. In addition, pulses are environmentally-friendly products due to the less use of inputs such as irrigation and agrochemicals, *i.e.*, pesticides and fertilizers. In fact, legume-based cropping systems enhance the sustainability of production systems by increasing crop productivity, soil restoration, soil health and quality, soil biodiversity, and food security (Rawat and Tripathi 2019). In this regard, MacWilliam et al. (2014) assessed the economic and environmental aspects of the pulse-based systems in Western Canada and showed that the inclusion of pulse crops (lentil and dry pea) in the rotation of oilseed-cereal was beneficial due to the reduced input requirements (*e.g.*, fertilizers) and increased yields. According to their results, rotations containing dry pea and lentil mitigated the impact on human health, ecosystem quality, GW, and resource use.

The analysis revealed that diesel fuel combustion and the use of chemical fertilizers, especially nitrogen and phosphorus, were the major causes of environmental damage inflicted by soybean production. In other words, if we want to have an agro-ecosystem with minimal environmental impacts in line with the goals of sustainable production in the region, there should be a serious revision of the consumption pattern of these inputs. Some of the management strategies that can mitigate the environmental impact of soybean production are as follows:

- Diesel:
  - Applying special planting and harvesting machinery for crop production
  - New engine standards
  - Conservation tillage (minimum or no-tillage)
  - Cleaner fuels

- Replacing old machines with the new and modern ones such as combination machine

➢ Fertilizers:

- Soil testing to accurately determine the plant fertilizer requirements
- Using bio-fertilizers such as PGPF and PGPR
- Soybean seed inoculation with nitrogen-fixing bacteria (*Rhizobium japanicum*) in soils where the bacterium is not found naturally (*e.g.*, Iran)
- Using the green manure and plant residues
- Placing nitrogen-fixing plants in crop rotation pulses such as faba bean and clover
- Precision agriculture
- Agricultural experts should inform farmers about the environmental impacts of fertilizers and proper management of their use.
- Selecting suitable cultivars
- Splitting nitrogen fertilizers and managing the time of use
- Placing phytoremediation plants in crop rotation to purify the soil from heavy metals

Table 8. Results of damage categories for 1-ton soybean production under different scenarios.

Scenarios	Climate change (kg CO_2-eq)	Human health (DALY)	Ecosystem quality (PDF×m^2×yr)	Resources (MJ primary)
Fallow-Soybean (F-S)	794.50	0.0015	1410.73	7669.47
Rapeseed-Soybean (R-S)	563.55	0.0009	1033.68	5476.18
Wheat-Soybean (W-S)	880.61	0.0016	1840.70	8799.80

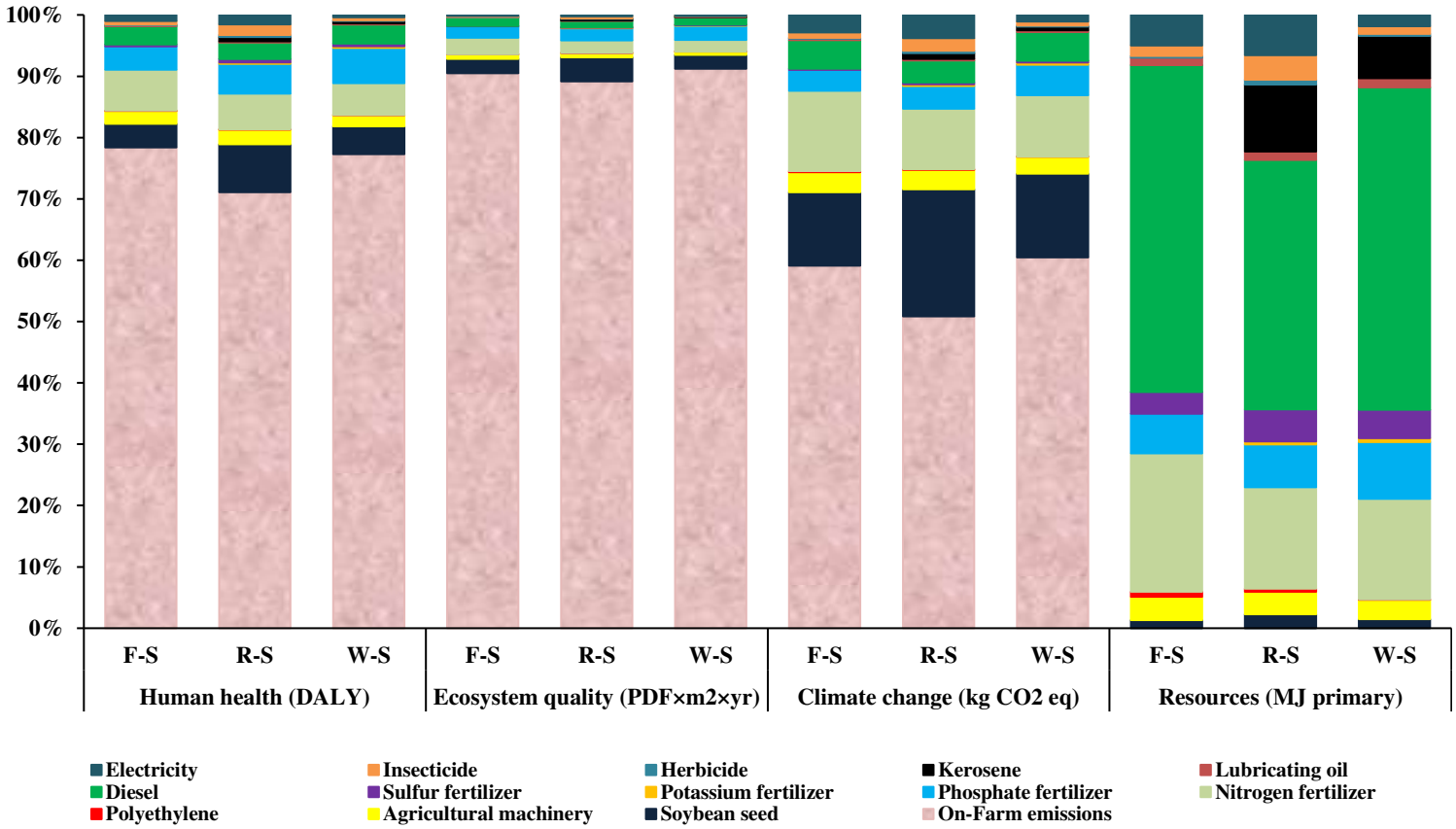


Fig 5. The share of Off-Farm and On-Farm emissions to damage categories of soybean production under different scenarios.

Since damage categories have different units, it is still difficult to select the most environmentally-friendly scenario. Accordingly, damage categories were weighted in accordance with IMPACT 2002+ to obtain a single score (in milli Point unit (mPt)) based on which the right decision can be made.

3.1.2. Results of Weighting

Fig. 6 indicates the weighting analysis of different scenarios in producing 1-ton soybean. Based on the results, the total environmental damage for soybean production under various cultivation scenarios were reported to range from 293.87 to 503.73 mPt. Moreover, human health damage category had a critical role in the total environmental impacts of nearly 43–47%.

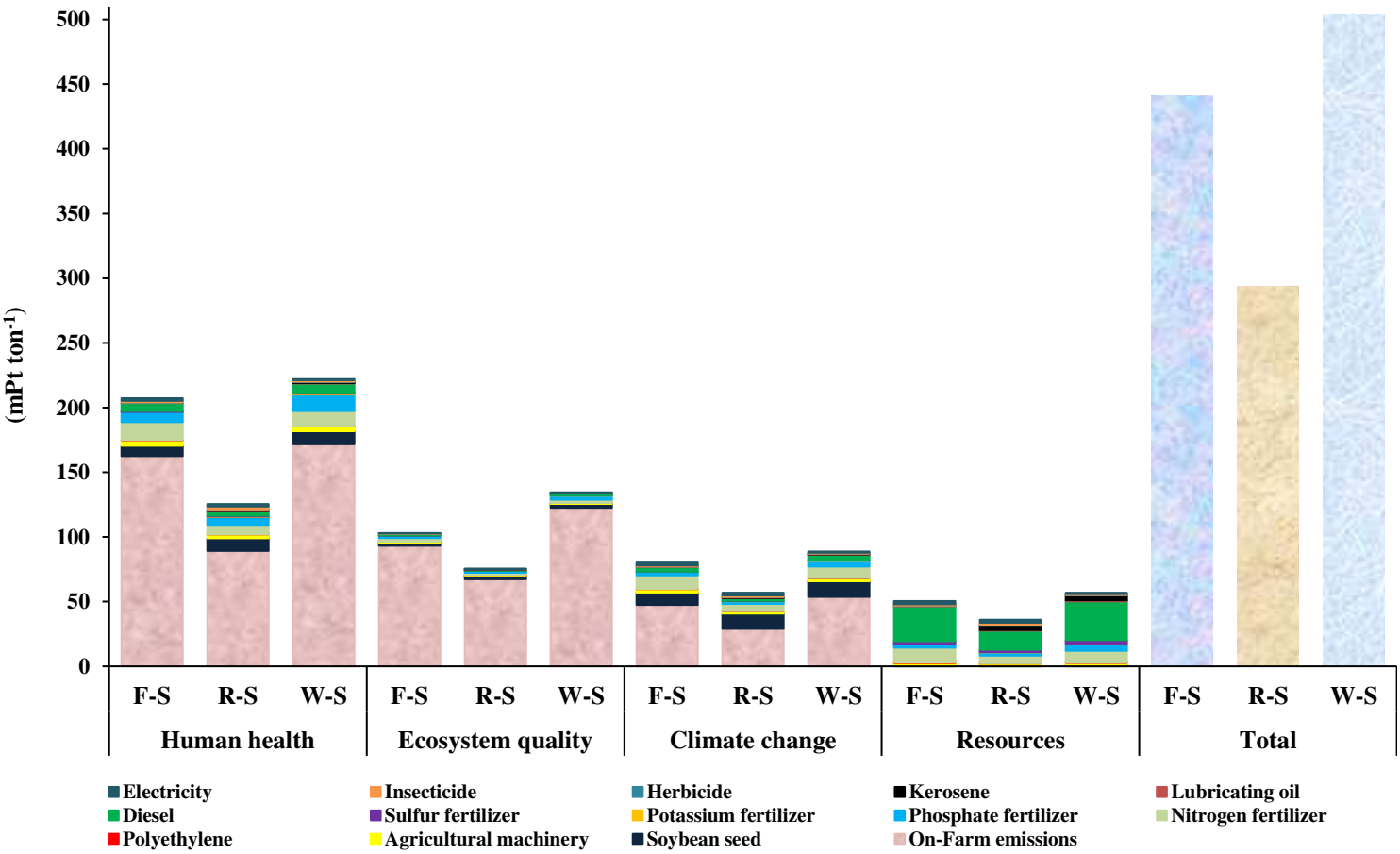


Fig 6. Distribution of damage categories weighting in soybean production under different cultivation scenarios.

3.1.3. Comparison of Various Scenarios in Environmental Damage

According to Fig. 7, it is evident that the R-S scenario was in greater environmental compliance than the other scenarios. More specifically, compared to the W-S scenario (as a most applied scenario in Mazandaran), the R-S scenario led to reduction rates of nearly 36, 44, 44, 38, and 42% in climate change, ecosystem quality, human health, resources, and total environmental damage, respectively.

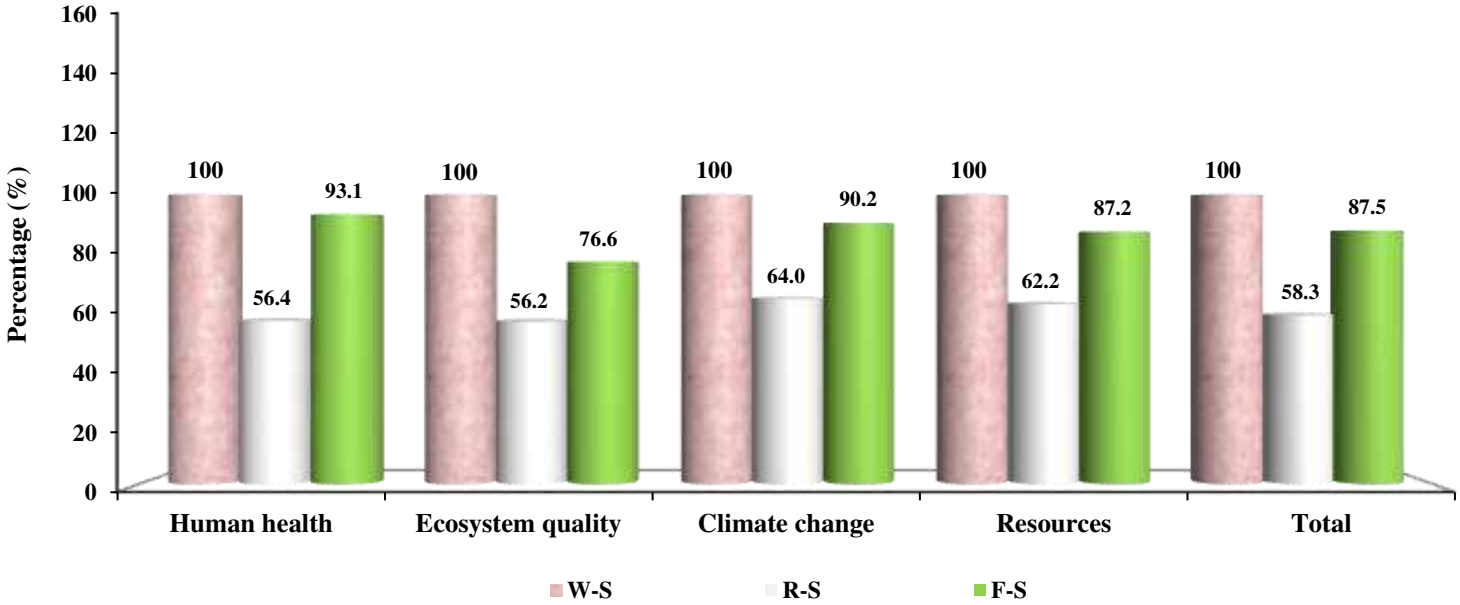


Fig 7. The weighted environmental damages of soybean production (FU=1 ton) in different cultivation scenarios.

3.2. Evaluating ANFIS–FCM and ANN models

Table 9 reports the performance results of the ANFIS–FCM and ANN models. Evidently, it is not easy to conclude that better results can be obtained with more clusters. For environmental parameters, *i.e.*, climate change, resources, and human health, the best performance of the model was obtained in the lower clusters (FCM2). At the same time, the best performance forecast of the model was obtained from Cluster 3 for the ecosystem quality (FCM3). The criterion for selecting the best model is defined as having fewer differences in the RMSEs of training and testing of models. For example, in terms of ecosystem quality, RMSE values were reported 31.20, 42.02 and 34.83 for training, testing, and all datasets, respectively. Therefore, the ANFIS–FCM3 model was considered with three optimal rules in the ecosystem quality. Increasing the number of clusters caused over-fitting in the model. For example, in the FCM7 model, although the training error was the lowest (RMSE=20.98), the testing error reached its highest rate (RMSE=1776.55). This trend can be seen in other environmental parameters in the ANFIS–FCM model by increasing the number of rules and clusters.

Table 9. The performance of ANFIS-FCM models for prediction of environmental impact.

Environmental impacts	Model name	Number of cluster	Number of input MF	Number of output MF	Number of rule	Epochs	RMSE			R		
							Training	Testing	All data	Training	Testing	All data
Human health	**FCM2**	**2**	**[222]**	**[2]**	**2**	**5**	**4.43×10^{-5}**	**5.35×10^{-5}**	**5.70×10^{-5}**	**0.9983**	**0.9996**	**0.9985**
	FCM3	3	[333]	[3]	3	2	5.17×10^{-5}	6.26×10^{-4}	3.47×10^{-4}	0.9986	0.7765	0.9369
	FCM4	4	[444]	[4]	4	2	4.20×10^{-5}	6.34×10^{-4}	3.51×10^{-4}	0.9991	0.7680	0.9353
	FCM5	5	[555]	[5]	5	15	4.77×10^{-5}	6.26×10^{-4}	3.47×10^{-4}	0.9988	0.7706	0.9365
	FCM6	6	[666]	[6]	6	15	4.96×10^{-5}	2.23×10^{-3}	1.27×10^{-3}	0.9987	0.6035	0.6807
	FCM7	7	[777]	[7]	7	2	2.86×10^{-5}	4.51×10^{-3}	2.49×10^{-4}	0.9996	0.8750	0.9668
E c o s	FCM2	2	[222]	[2]	2	15	35.47	45.70	38.86	0.9993	0.9997	0.9996

	FCM3	**3**	**[333]**	**[3]**	**3**	**5**	**31.20**	**42.02**	**34.83**	**0.9994**	**0.9998**	**0.9997**
	FCM4	4	[444]	[4]	4	5	32.23	61.97	43.44	0.9994	0.9996	0.9995
	FCM5	5	[555]	[5]	5	5	27.68	1741.04	958.42	0.9995	0.6118	0.7369
	FCM6	6	[666]	[6]	6	2	20.22	1741.50	958.54	0.9997	0.6110	0.7367
	FCM7	7	[777]	[7]	7	2	20.98	1776.55	977.83	0.9997	0.5731	0.7215
Climate change	**FCM2**	**2**	**[222]**	**[2]**	**2**	**15**	**17.85**	**20.12**	**18.57**	**0.9994**	**0.9993**	**0.9994**
	FCM3	3	[333]	[3]	3	2	15.11	38.43	24.63	0.9995	0.9987	0.9990
	FCM4	4	[444]	[4]	4	20	12.51	110.58	61.74	0.9997	0.9861	0.9938
	FCM5	5	[555]	[5]	5	2	10.06	2230.00	123.01	0.9998	0.9356	0.9731
	FCM6	6	[666]	[6]	6	1100	5.88	523.28	288.01	0.99999	0.6359	0.8614
	FCM7	7	[777]	[7]	7	1100	6.27	291.03	160.24	0.9999	0.8395	0.9513
Resources	**FCM2**	**2**	**[222]**	**[2]**	**2**	**100**	**178.50**	**205.17**	**186.98**	**0.9993**	**0.9993**	**0.9993**
	FCM3	3	[333]	[3]	3	2	162.87	302.96	222.92	0.9994	0.9984	0.9990
	FCM4	4	[444]	[4]	4	1100	72.67	902.58	500.40	0.9999	0.9885	0.9954
	FCM5	5	[555]	[5]	5	1100	59.20	477.53	267.41	0.9999	0.9972	0.9987
	FCM6	6	[666]	[6]	6	2	128.06	23009.21	12662.90	0.9996	0.3624	0.4370
	FCM7	7	[777]	[7]	7	15	118.98	616.83	353.69	0.9997	0.9954	0.9978

Table 10 reports the parameters of the most accurate ANN network models in predicting environmental impacts of the soybean production. The results of MAEP, RMSE, and R^2 for the neural networks were calculated. Feedforward backpropagation neural networks with the Levenberg–Marquardt training algorithm for ANN models were also employed. The sigmoid "tansig" and "purelin" linear functions were used as activation functions in the hidden and output layers, respectively. The best ANN structures was reported 14-12-8-1, 14-10-10-1, 14-11-6-1, and 14-10-7-1 for resources, climate change, ecosystem quality, and human health, respectively. Evidently, the coefficient of determination differed from 0.9863 to 0.9938 in overall data, 0.9666 to 0.9977 for the testing, 0.9688 to 0.9929 for the validation, and 0.9945 to 0.9996 for the training in ANN models.

Table 10. The performance of ANN models for prediction of environmental impact.

Environmental impacts	Best topology of ANN	Epochs	R				RSME			
			Training	Validation	Testing	All data	Training	Validation	Testing	All data
Human health	14-10-7-1	11	0.9984	0.9859	0.9866	0.9938	5.69×10^{-5}	2.17×10^{-4}	1.33×10^{-4}	1.09×10^{-4}
Ecosystem quality	14-11-6-1	9	0.9994	0.9854	0.9666	0.9863	31.97	504.00	325.66	234.12
Climate change	14-10-10-1	13	0.9945	0.9929	0.9879	0.9929	57.21	93.24	57.05	63.84
Resources	14-12-8-1	17	0.9996	0.9688	0.9977	0.9866	141.13	2146.36	500.88	858.51

According to the statistical indices in Fig. 8, the resultant R^2 to predict the environmental impacts obtained from the ANFIS–FCM models were higher than the values reported by the ANN models. The R^2 range for ANFIS–FCM and ANN models were reported to be from 0.9967 to 0.9989 and 0.9269 to 0.9870, respectively. Two other parameters used to evaluate the model accuracy were RMSE and MAPE. The lower the value of these parameters, the

higher model accuracy. The RMSE and MAPE values obtained in ANFIS–FCM were lower than those of the ANN model for all environmental indicators. The MAPE values for the ANFIS–FCM and ANN models were reported 3.71, 5.54, 2.18, and 2.26 and 6.35, 13.22, 7.51, and 4.76 for human health, ecosystem quality, climate change and resources, respectively. The results also revealed that the values of the RMSE were 5.35 $\times 10^{-5}$, 34.90, 18.57, and 186.98 in the ANFIS–FCM model and 1.09 $\times 10^{-4}$, 234.12, 63.84, and 858.51 in the ANN model for human health, ecosystem quality, climate change, and resources, respectively.

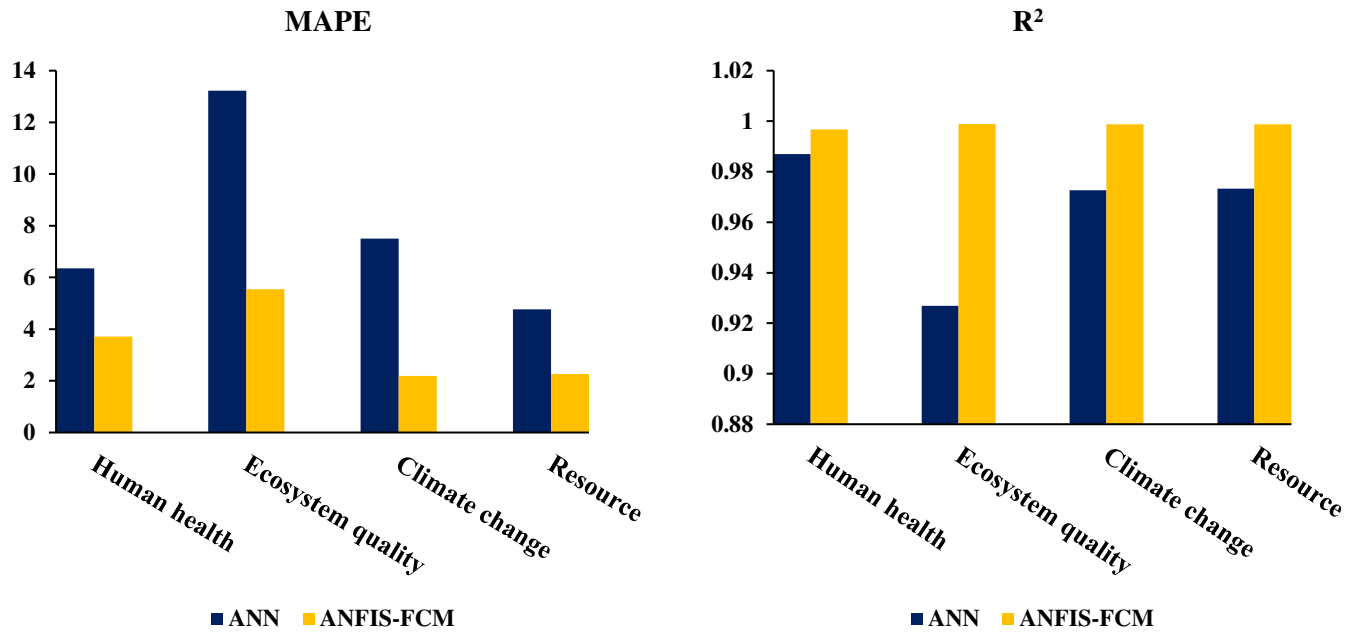
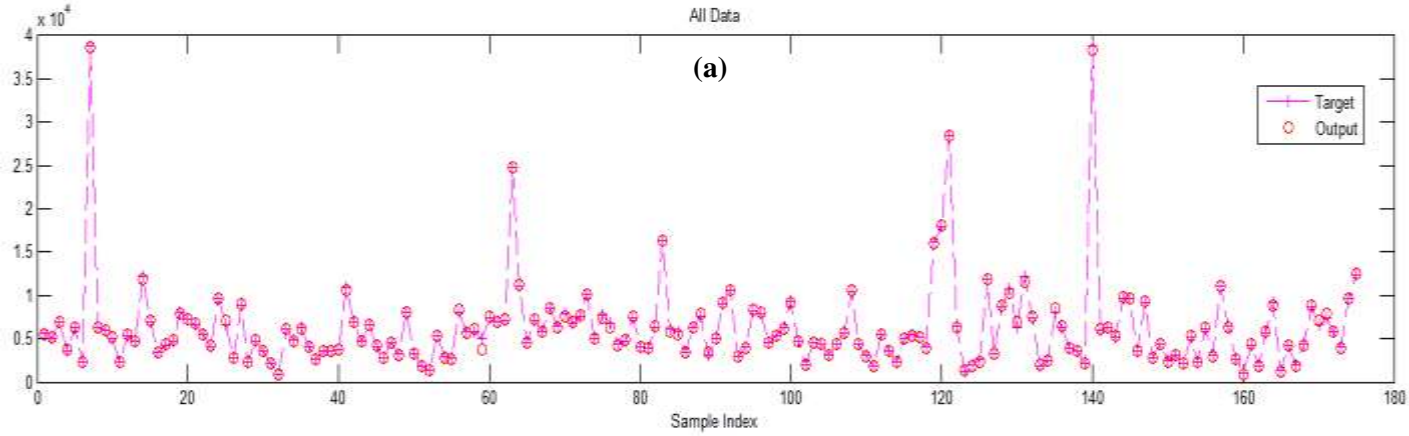
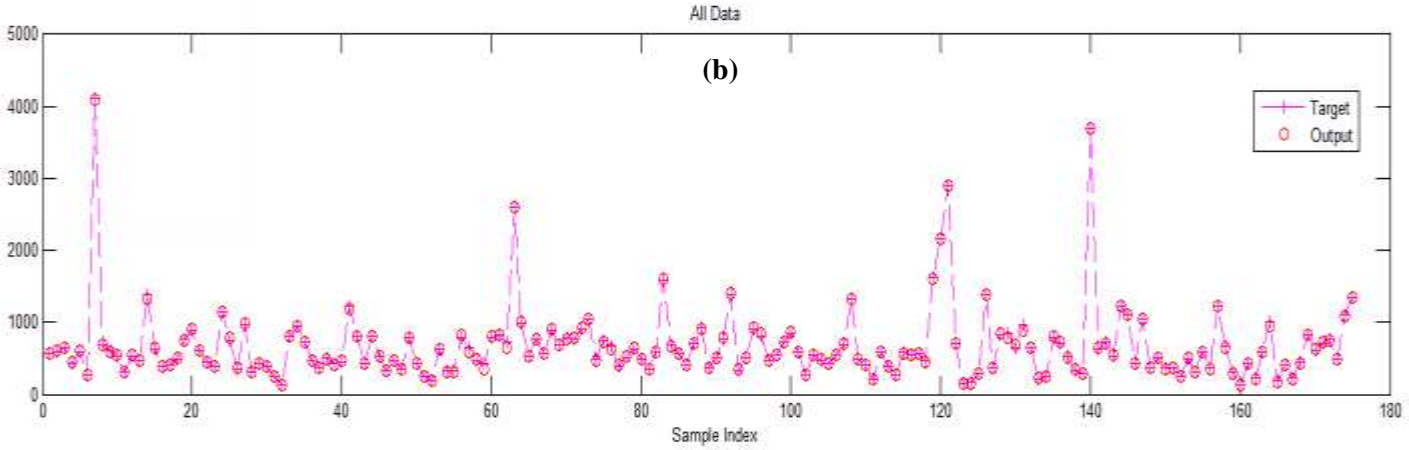
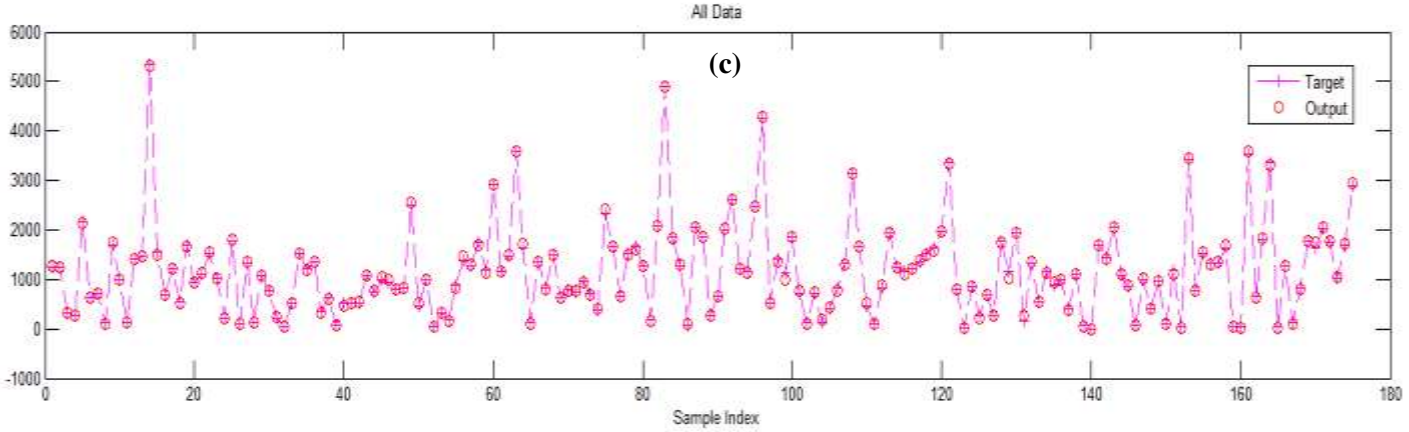


Fig. 8. Comparison between R^2 and MAPE in ANFIS-FCM and ANN models.

In general, according to results of ANFIS-FCM and ANN models, it is concluded that ANFIS-FCM model outperforms better than ANN in all aspects for prediction of environmental impacts in the soybean farms. Also, Fig. 9 illustrates the environmental indicators prediction results in ANFIS-FCM model versus actual environmental indicators data for ecosystem quality, climate change, human health, and resources. The prediction results show that it is fully consistent with the actual results. A more complete distinction between them can be seen in Fig. 10. The range of calculated R^2 for predicting all environmental parameters is very close to each other (Fig. 10). By comparing the statistical parameter MAPE, it can be concluded that the proposed model predicts the environmental parameter climate change better than other parameters with 2.1% MAPE.


All Data
x 10^4
(a)
Target
Output
Sample Index


All Data
(b)
Target
Output
Sample Index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(c)
Target
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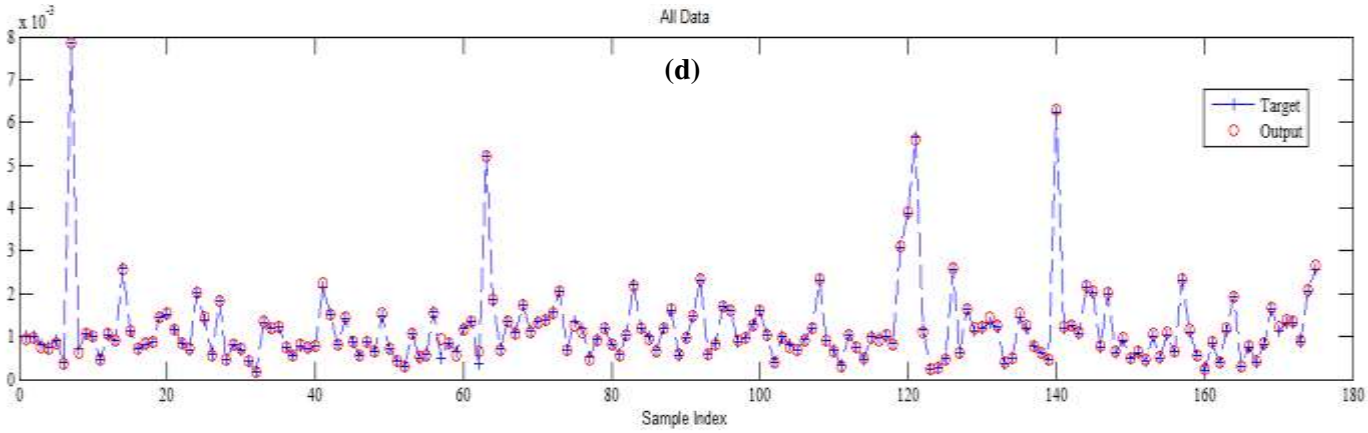

Fig. 9. Prediction values versus actual data for (a) resources, (b) climate change, (c) ecosystem quality, and (d) human health.
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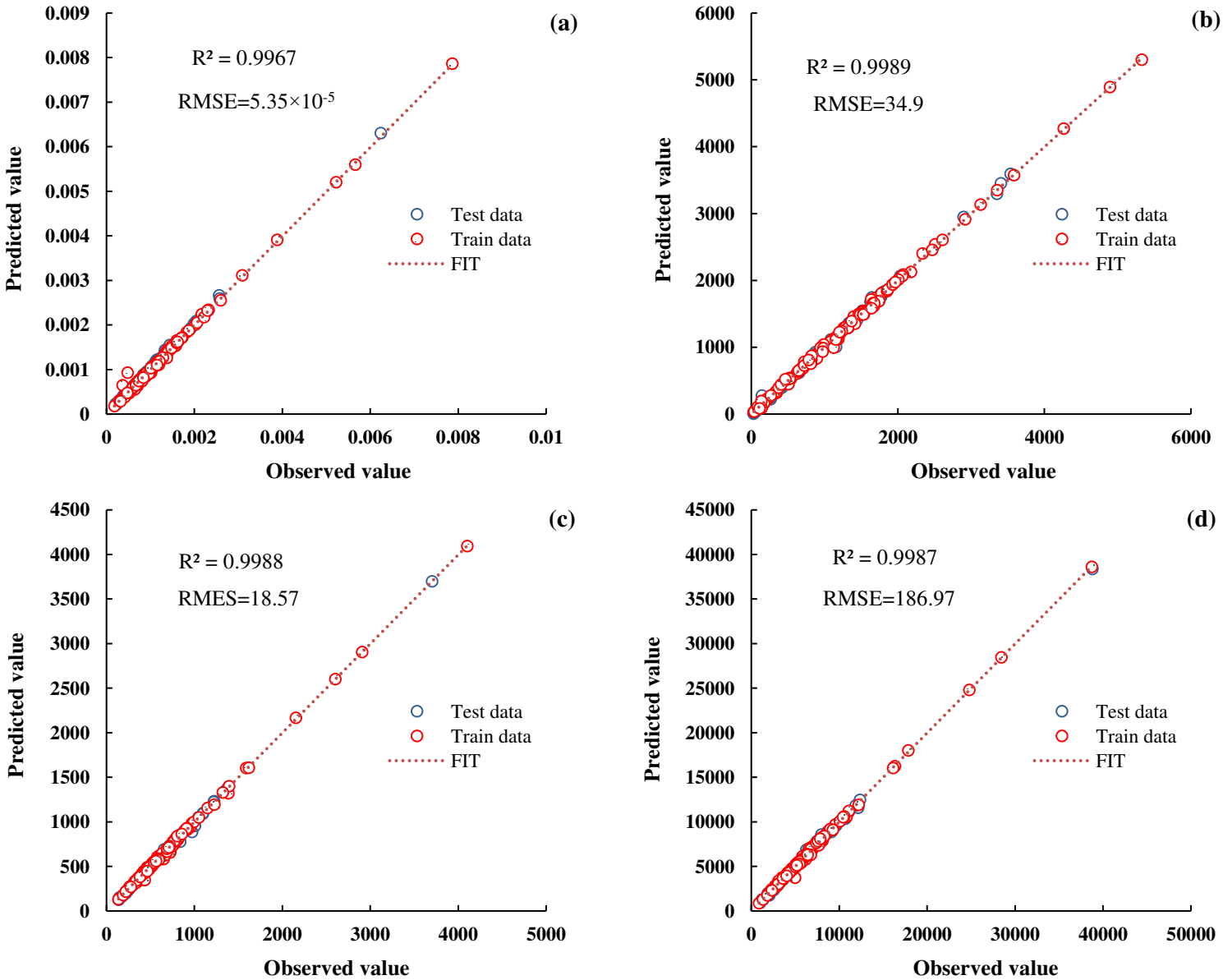

Fig. 10. Comparison between observed and predicted values for (a) human health, (b) ecosystem quality, (c) climate change, and (d) resources.

4. Conclusion

In this study, the life cycle assessment method was employed to predict environmental impacts (ecosystem quality, climate change, human health, and resources) of soybean cultivation in different scenarios by developing certain models based on ANFIS–FCM and ANN models. According to the results, the total environmental impacts of soybean production in the studied area were reported within the range of 293.87–503.73 mPt ton^{-1}, the lowest and highest of which were related to the R-S and W-S scenarios, respectively. Moreover, nearly 43–47% is related to human health damage category, which was mainly due to the consumption of diesel and chemical fertilizers. According to results, the ANFIS–FCM model was selected as a better model than ANN models due to the higher accuracy of statistical indicators. The values of calculated R^2 for the ANFIS–FCM and ANN models ranged from 0.9967 to 0.9989 and 0.9269 to 0.9870, respectively. Moreover, the RMSE and MAPE values yielded by the ANFIS–FCM model were smaller than those reported by the ANN model for all soybean cultivation environmental prediction scenarios. In general, since the environmental assessment of soybean agriculture is of great importance, the ANFIS–FCM model can be employed as a useful tool to help predict the accurate environmental indicators of agricultural production.

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Consent to participate: Not applicable.

Consent to publication: Not applicable.

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