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Sustainable Systems Engineering Using Life Cycle Assessment: Application of Artificial Intelligence for Predicting Agro-Environmental Footprint

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Abstract: The increase in population has increased the need for agricultural and food products, and thus agricultural production should be increased. This goal may cause increases in emissions and environmental impacts by increasing the consumption of agricultural inputs. The prediction of environmental impacts plays an important role in evaluating pollutant emissions in crop production. This study employed two artificial intelligence (AI) methods: the adaptive neuro-fuzzy inference system–fuzzy c-means (ANFIS–FCM) algorithm as a novel computational method, and an artificial neural network (ANN) as a conventional computational method 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 life cycle of soybean production was assessed in terms of environmental impacts through the IMPACT2002+ method in SimaPro. In the present study, the production of one ton of soybeans was considered the functional unit, and the boundary of the system was considered the gate of the field. 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 $\times$ m^2 $\times$ 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. 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 range of calculated R^2 for the ANFIS-FCM and ANN models were 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; sustainable systems engineering

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Citation: Mohammadi Kashka, F.; Tahmasebi Sarvestani, Z.; Pirdashti, H.; Motevali, A.; Nadi, M.; Valipour, M. Sustainable Systems Engineering Using Life Cycle Assessment: Application of Artificial Intelligence for Predicting Agro-Environmental Footprint. *Sustainability* **2023**, *15*, 6326. https://doi.org/10.3390/su15076326

Academic Editor: Luca Salvati

Received: 4 January 2023
Revised: 1 April 2023
Accepted: 4 April 2023
Published: 6 April 2023

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1. Introduction

The most important factor for good management of agricultural products, such as soybean, is good decision-making. The decision-making process can be undertaken using current conditions and expected future conditions. Hence, there exists a need for a model to predict various parameters of soybean cultivation. Several models may be available for this type of prediction. However, since there is not a clear and specific relationship between inputs and outputs in soybean cultivation, the applied model should ideally have high precision, be fast and computationally inexpensive, and have the ability to solve these issues. Artificial neural networks (ANNs) and ANFIS-FCM are well-known computational systems and methods used to predict the output of complex systems and solve multifaceted nonlinear problems with high accuracy. The methods of machine learning (ML) or artificial intelligence (AI) have been recently considered in the fields of biomass, food, and agriculture by many researchers; therefore, progress in this field is rapidly being made [1–3]. Consequently, it is indispensable to predict environmental impacts for various types of agricultural production and identify appropriate means to reduce emissions and pollutant gases [4].

The agricultural sector directly accounts for around 10–15% of the world's GHG emissions, which rises to about 30% if adding emissions from deforestation and land-use changes [5]. Additionally, based on a special report from the IPCC in 2019, forestry, agriculture, and other land-use sectors had a 23% share of total anthropogenic GHG from 2007–2016 [6]. Iran, with approximately 616,741 million tons of CO_2-equivalent emissions, is not exempt from this rule. It is the country most responsible for global warming (GW) in the Middle East and the seventh most responsible country in the world [7]. Significant population growth, along with the reduction of water resources and productive land area in the country [8], has led Iran's agriculture to compress rapidly over the past few decades. This has led to increasing yield production from existing farmland, which naturally requires more energy, materials, and water to ensure food security for the growing populations. As these inputs (resources) and intensive farming practices increase, GHG emissions, as well as the emission of other harmful gases, increase, which causes various environmental hazards, such as damage to ecosystem quality, human health, and the climate change phenomenon and its related consequences, e.g., reduced agricultural productivity [9].

Currently, various concepts and methods exist for environmental, economic, and/or social assessments of processes, products, or specific activities [10]. Each of these developed tools has the desired characteristics as accompanied by its limitations. As a comprehensive scientific and internationally standardized tool to achieve sustainable production and consumption, the life-cycle assessment (LCA) approach makes it possible to analyze eco-efficiency and optimize agro-systems [11,12]. LCA is a methodology used to determine environmental burdens, considering the usage of resources and the emissions throughout a product's lifetime, i.e., from the stage of material extraction, manufacturing, and utilization, to waste management phases [13]. This method evaluates and quantifies the environmental burdens of a product or process within the scope defined, i.e., system boundary [14]. Accordingly, it can compare the various systems' environmental impacts [15].

LCA enables the diagnosis of environmental problems before damages occur, focusing on agricultural practices and identifying the most critical environmental hotspots [12]. Moreover, this powerful tool can 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 [15].

Various researchers have focused on using combined ML and LCA methods to predict output energy and environmental impacts of agricultural products. Elhami et al. [16] used a combination of artificial neural network (ANN) and LCA methods to assess the model yield and environmental emissions from lentil cultivation. Their studies showed that an ANN model with the structure of 9-10-6-11 is the most suitable network for predicting yield and environmental effects in lentil cultivation.

The combined application of LCA and an adaptive neural fuzzy inference system (ANFIS) for energy modeling and environmental emissions of oilseeds was performed by Mousavi-Avval et al. [17]. They also used artificial neural networks (ANNs) to compare the multi-level ANFIS in their research. They concluded that multilevel ANFIS can be used as a useful tool in predicting the energy, economic, and environmental indicators of agricultural production systems in different regions. Their evaluations also showed that the multilevel ANFIS model was able to more accurately predict the energy, economic, and environmental outputs of canola compared to the ANNs.

Nabavi-Pelesaraei et al. [2] predicted the energy and environmental impacts of paddy production using a combination of AI methods (ANNs and ANFIS) and LCA. The results showed that the ANFIS model based on a hybrid learning algorithm with a correlation coefficient (R) was used to predict output energy of 0.860 and environmental impacts of 0.997. Additionally, an ANN model with a 12-6-8-1 structure predicted energy and environmental impacts with a correlation coefficient (R) of 0.524 and 0.999, respectively.

To predict the life cycle environmental impacts and output energy of sugarcane production in planted or ratoon farms, research was performed by Kaab et al. [3] using two methods of AI, namely ANNs and ANFIS. Overall, their results showed that the ANFIS model is a useful tool for predicting the environmental impact and output energy of sugarcane production in planted and ratoon farms. A comparison of ML approaches to estimate the spatially explicit life cycle of GW and eutrophication of corn production was performed in the U.S. Midwest region in a case study by Romeiko et al. [18]. Their results showed that the gradient-boosting regression tree model had the highest prediction accuracy with cross-validation (CV) values of 0.8 and 0.87 for life-cycle GW and the life cycle eutrophication impacts, respectively.

Iran also has many advantages in the production of agricultural products. One of these products is soybean. It is a major oilseed crop and supply of vegetable oil in Iran mostly planted for edible oil and meal [19]. Such cultivation occurs mainly in the northern and northwestern provinces of the country, i.e., Golestan, Mazandaran, and Ardabil [20]. However, despite the potential to produce this oilseed crop in Iran, it still imports about 95% of its 1.5 million tons of vegetable oil [21]. Hence, to create capacity and promote soybean production in Iran, FAO implemented a Technical Cooperation Project (TCP) in the country in 2017–2019 [22]. In addition to highlighting the importance of further development of this oilseed crop, this issue also provides a good incentive for new research in the field.

Despite the importance of the EIA for sustainable economic growth, it has not had a long history in Iran [23], and although more than two decades (since 1994) have passed since its official introduction in the country, little research has been carried out in the field [24]. However, though 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 investigated. Moreover, based on a literature review, it has been observed that ANNs and ANFIS are the only ML methods used in life-cycle assessments. Therefore, it is essential to introduce a new model that can accurately predict several environmental impacts based on input energies. In this study, the ANFIS-FCM algorithm as a novel computational method based on fuzzy c-means (FCM) clustering was used to predict the environmental performance of soybean based on life cycle input and output data. Finally, a comparison was made between the proposed model and the artificial neural network model using the statistical quality parameters. The present study can guide decision-makers in drafting policies and creating awareness to provide solutions for sustainable production and management. Farmers can also adopt proper crop management in this regard, given the potential contributions of any soybean cultivation system to emissions, environmental protection, and economic benefits.

2. Materials and Methods

2.1. Study Region and Farming System Description

Mazandaran (located at 35° to 36° N latitude, 50° to 54° E longitude) is one of the northern provinces of Iran that is situated on the southern side of the Caspian Sea (Figure 1). Mazandaran Province is one of the most important agricultural hubs in Iran, thanks to its specific geographical location and natural features (weather conditions, surface, and underground water resources, fertile soil, etc.). Soybean cultivation in this region is performed mainly in rotation with wheat, rapeseed, and fallow. In this study, three scenarios were investigated because of their dominance in different regions of the province, as follows:

(1) Soybean cultivation after rapeseed harvest;
(2) Soybean cultivation after wheat harvest;
(3) Soybean cultivation after six months of fallow.

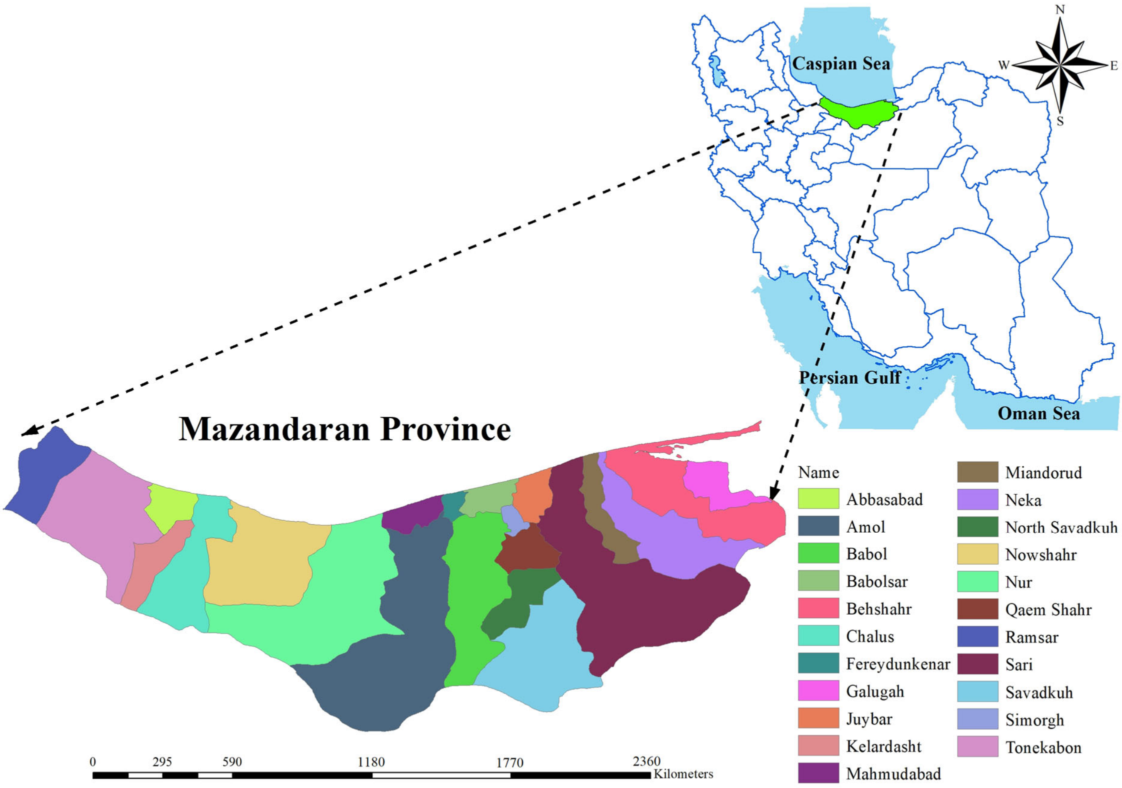

Figure 1. Location of the studied area in the north of Iran.

2.2. LCA of Soybean Production

Based on ISO standards [25], LCA as an appropriate approach to investigating the environmental impacts of agricultural products includes four stages: defining scope and target, life-cycle inventory (LCI), assessing impacts, and results interpretation.

2.2.1. Goal, Functional Unit, and System Boundary

In this study, the FU was mass-based on 1 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) (Figure 2).

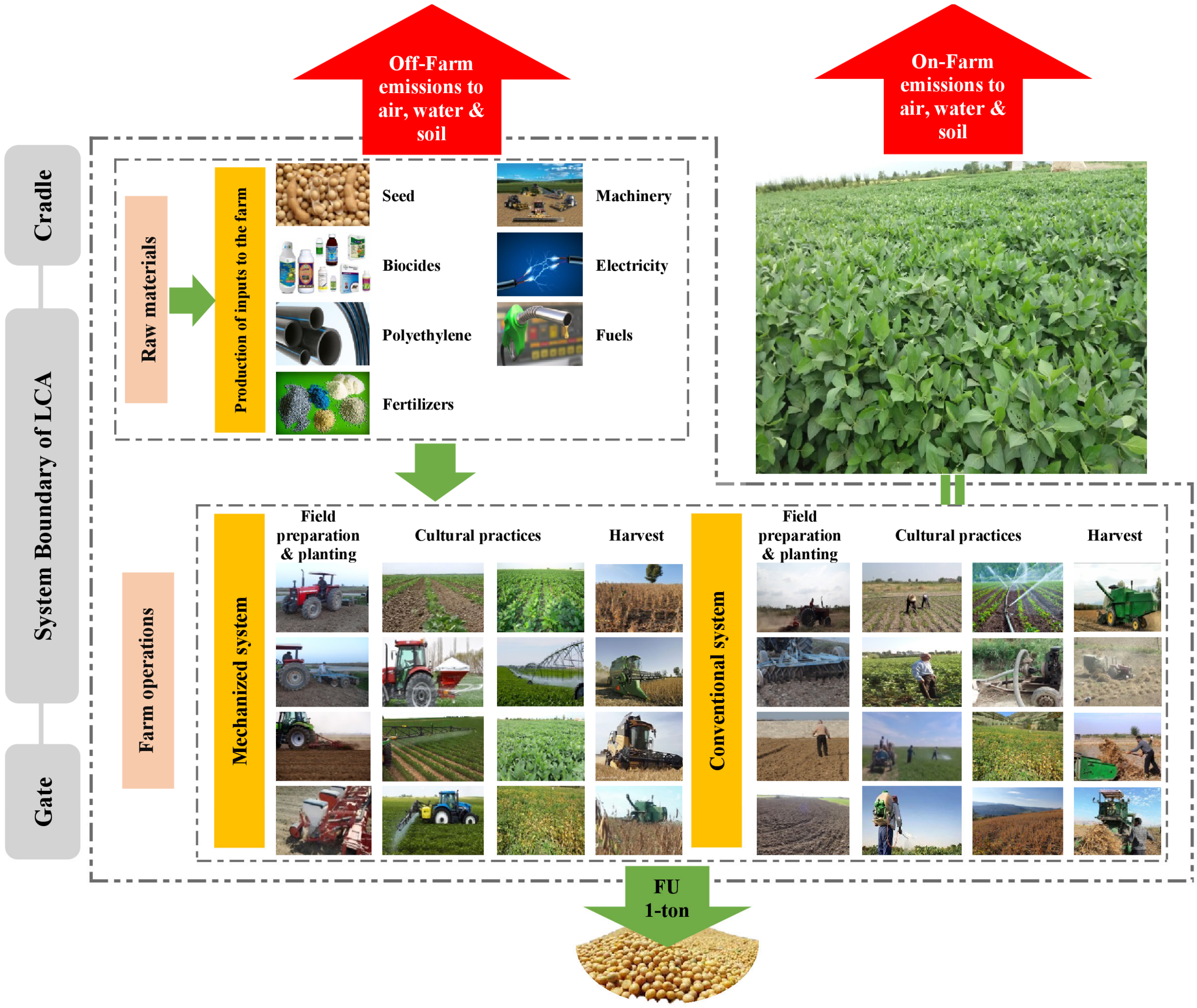

Figure 2. The diagram of cradle-to-farm-gate system boundaries of soybean production.

2.2.2. LCI Analysis and Data Collection

This step of LCA is an inventory of various input/output data for a product about the system under study, including the collection and analysis of these data throughout its life cycle [26]. 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 [25].

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

1. Background systems (cradle-to-gate) data: Data related to this section include the environmental impacts of production, distribution, and transportation of inputs (e.g., biocides, chemical fertilizers, electricity, and fuels). In the present study, the data used in this section were adapted from the EcoInvent3.5 database available in SimaPro software v. 9.0.0.49.
2. Foreground systems (gate-to-gate) data: Data associated with this section include the number of inputs (fertilizers, biocides, and fuels, etc.), and outputs, i.e., soybean seed, and emissions in water, soil, and air caused by input application on the farm (from the planting to harvesting of soybean).

According to Table 1, based on the amount of active ingredient per pesticide, On-Farm emissions from biocides were considered 0.01, 0.09, and 0.9 (kg/kg) for water, air, and soil, respectively [27]. The application of chemical fertilizers (nitrogen, phosphorus, and potassium) is also responsible for several On-Farm emissions. In this context, for the calculation of pollutants in air and water, the standard equations and conversion coefficients of pollutants to the applied value (Table 1) were applied [28]. Additionally, the chemical fertilizers used in the field cause the emission of heavy metals into the soil, resulting in environmental pollution and harm to human health. In the present study, the coefficients presented in Table 2 were used to calculate the heavy metal emissions in the soil [27].

Table 1. Coefficients for computing the emissions caused by agrochemicals (fertilizers and biocides).

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	$\left[\frac{62}{142}\right]$	
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 2. Coefficients for calculating the On-Farm emissions of heavy metals in soil associated with the application of chemical fertilizers in different cultivation scenarios of soybean.

Characteristic	Heavy Metal (mg)						
	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
$\left[\frac{\text{mg Heavy metal}}{\text{kg } P_2O_{5\text{in fertilizer applied}}}\right]$	39.5	90.5	839.0	67.0	88.3	543.0	0.3
$\left[\frac{\text{mg Heavy metal}}{\text{kg } K_2O_{\text{in fertilizer applied}}}\right]$	0.1	4.8	6.2	0.8	2.5	5.8	0.0

The diesel fuel combustion in tractor engines and other agricultural machinery emits some harmful compounds into the air (e.g., CO_2). As shown in Table 3, the EcoInvent database was used to calculate the On-Farm emissions derived from the combustion of diesel fuel [29,30]. Additionally, emission factors for air emissions from kerosene [31–33] fuel combustion are presented in Table 3. Ultimately, all the inputs and outputs (the inventory data), based on the FU of 1-ton product yield (i.e., soybean), were imported to SimaPro software v. 9.0.0.49 for further analysis.

Table 3. Emission factors for air emissions from fuel combustion.

Emission	g MJ^{-1} Diesel	Kerosene
CO_2	74.5	71.50 t TJ^{-1}
SO_2	2.41×10^{-2}	0.005 MT MT^{-1}
Pb	-	-
CH_4	3.08×10^{-3}	10 kg TJ^{-1}
C_6H_6	1.74×10^{-4}	-
Cd	2.39×10^{-7}	-
Cr	1.19×10^{-6}	-
Cu	4.06×10^{-5}	-
N_2O	2.86×10^{-3}	0.6 kg TJ^{-1}
Ni	1.67×10^{-6}	-
Zn	2.39×10^{-5}	-
Benzo(a)pyrene	7.16×10^{-7}	-
NH_3	4.77×10^{-4}	-
Se	2.39×10^{-7}	-
PAH	7.85×10^{-5}	-
HC, as NMVOC	6.80×10^{-2}	-
NO_X	1.06	3.00 g kg^{-1}
CO	1.50×10^{-1}	62.00 g kg^{-1}
Particulates, <2.5 μm	1.07×10^{-1}	-

In this study, to determine the information on agricultural input consumption, the initial data were collected by providing questionnaires and face-to-face interviews with farmers. Additionally, the simple random sampling method and Cochran formula were used to determine the number of farmers or sample size [34]. All inputs and soybean yields collected from farmers as well as On-Farm emissions from the application of these inputs in different cultivation scenarios are presented in Table 4.

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

Table 4. *Cont.*

Inventory		Fallow–Soybean	Rapeseed–Soybean	Wheat–Soybean
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. Emissions in air:				
a. Emissions from chemical fertilizers	(kg)			
1. NH_3 emitted from nitrogenous fertilizers		3.22	1.63	2.61
2. N_2O				
N_2O emitted from fertilizer		4.17×10^{-1}	2.12×10^{-1}	3.38×10^{-1}
N_2O released from atmospheric deposition of fertilizers		4.17×10^{-2}	2.12×10^{-2}	3.38×10^{-2}
3. NO_X emitted from N_2O of fertilizers and soil		9.62×10^{-2}	4.89×10^{-2}	7.81×10^{-2}
4. CO_2 released from urea		$3.69 \times 10^{+1}$	$1.84 \times 10^{+1}$	$2.89 \times 10^{+1}$
b. Emissions from biocides	(kg)			
1. Emissions from insecticide				
Indoxacarb		5.00×10^{-4}	4.00×10^{-4}	3.00×10^{-4}
Diazinon		2.03×10^{-2}	1.83×10^{-2}	-
Chlorpyrifos		-	3.10×10^{-3}	3.40×10^{-3}
Cypermethrin		8.50×10^{-3}	7.00×10^{-3}	4.50×10^{-3}
Thiodicarb		-	2.71×10^{-2}	3.50×10^{-3}
Profenofos		-	-	1.27×10^{-2}
Fenitrothion		-	8.50×10^{-3}	-
2. Emissions from herbicide				-
Imazethapyr		-	4.00×10^{-4}	-
Haloxyfop-ethoxyethyl		-	1.80×10^{-3}	-
Trifluralin		-	-	5.90×10^{-3}
Bentazone		5.00×10^{-3}	-	-
Paraquat		-	-	1.30×10^{-3}
c. Emissions from fossil fuels	(kg)			
1. Diesel				
CO_2		$3.58 \times 10^{+2}$	$1.95 \times 10^{+2}$	$3.98 \times 10^{+2}$
SO_2		1.16×10^{-1}	6.31×10^{-2}	1.29×10^{-1}
CH_4		1.48×10^{-2}	8.06×10^{-3}	1.64×10^{-2}
C_6H_6		8.36×10^{-4}	4.55×10^{-4}	9.29×10^{-4}
Cd		1.15×10^{-6}	6.26×10^{-7}	1.28×10^{-6}
Cr		5.72×10^{-6}	3.11×10^{-6}	6.36×10^{-6}
Cu		1.95×10^{-4}	1.06×10^{-4}	2.17×10^{-4}
N_2O		1.37×10^{-2}	7.49×10^{-3}	1.53×10^{-2}
Ni		8.02×10^{-6}	4.37×10^{-6}	8.92×10^{-6}
Zn		1.15×10^{-4}	6.26×10^{-5}	1.28×10^{-4}
Benzo(a)pyrene		3.44×10^{-6}	1.87×10^{-6}	3.82×10^{-6}

Table 4. *Cont.*

Inventory		Fallow–Soybean	Rapeseed–Soybean	Wheat–Soybean
NH_3		2.29×10^{-3}	1.25×10^{-3}	2.55×10^{-3}
Se		1.15×10^{-6}	6.26×10^{-7}	1.28×10^{-6}
PAH		3.77×10^{-4}	2.05×10^{-4}	4.19×10^{-4}
HC, as NMVOC		3.27×10^{-1}	1.78×10^{-1}	3.63×10^{-1}
NO_X		5.09	2.77	5.66
CO		7.21×10^{-1}	3.93×10^{-1}	8.01×10^{-1}
Particulates, <2.5 µm		5.14×10^{-1}	2.80×10^{-1}	5.71×10^{-1}
2. Kerosene	(kg)			
CO_2		-	$3.39 \times 10^{+1}$	$3.38 \times 10^{+1}$
CO		-	6.53×10^{-1}	6.51×10^{-1}
SO_2		-	5.27×10^{-2}	5.25×10^{-2}
CH_4		-	4.74×10^{-3}	4.73×10^{-3}
N_2O		-	2.84×10^{-4}	2.84×10^{-4}
NO_X		-	3.16×10^{-2}	3.15×10^{-2}
2. Emissions in water:				
a. Emissions from chemical fertilizers	(kg)			
$NO^{-}{}_{3}$		$3.52 \times 10^{+1}$	$1.79 \times 10^{+1}$	$2.86 \times 10^{+1}$
P		3.00×10^{-1}	2.32×10^{-1}	4.86×10^{-1}
b. Emissions from biocides	(kg)			
1. Emissions from insecticide				
Indoxacarb		1.00×10^{-4}	5.00×10^{-5}	3.00×10^{-5}
Diazinon		2.30×10^{-3}	2.03×10^{-3}	-
Chlorpyrifos		-	3.40×10^{-4}	3.70×10^{-4}
Cypermethrin		9.00×10^{-4}	7.80×10^{-4}	5.00×10^{-4}
Thiodicarb		-	3.01×10^{-3}	3.90×10^{-4}
Profenofos		-	-	1.41×10^{-3}
Fenitrothion		-	9.40×10^{-4}	-
2. Emissions from herbicide				
Imazethapyr		-	4.00×10^{-5}	-
Haloxyfop-ethoxyethyl		-	2.00×10^{-4}	-
Trifluralin		-	-	6.60×10^{-4}
Bentazone		6.00×10^{-4}	-	-
Paraquat		-	-	1.50×10^{-4}
3. Emissions in soil:				
a. Emissions from chemical fertilizers	(mg)			
1. From N-fertilizer:				
Cd		$1.59 \times 10^{+2}$	$8.08 \times 10^{+1}$	$1.29 \times 10^{+2}$
Cu		$6.89 \times 10^{+2}$	$3.50 \times 10^{+2}$	$5.59 \times 10^{+2}$
Zn		$5.38 \times 10^{+3}$	$2.73 \times 10^{+3}$	$4.37 \times 10^{+3}$
Pb		$1.46 \times 10^{+3}$	$7.39 \times 10^{+2}$	$1.18 \times 10^{+3}$
Ni		$5.54 \times 10^{+2}$	$2.81 \times 10^{+2}$	$4.50 \times 10^{+2}$
Cr		$2.07 \times 10^{+3}$	$1.05 \times 10^{+3}$	$1.68 \times 10^{+3}$
Hg		2.65	1.35	2.15
2. From P-fertilizer:				
Cd		$5.44 \times 10^{+2}$	$4.20 \times 10^{+2}$	$8.78 \times 10^{+2}$
Cu		$1.25 \times 10^{+3}$	$9.62 \times 10^{+2}$	$2.01 \times 10^{+3}$
Zn		$1.15 \times 10^{+4}$	$8.92 \times 10^{+3}$	$1.87 \times 10^{+4}$
Pb		$9.22 \times 10^{+2}$	$7.12 \times 10^{+2}$	$1.49 \times 10^{+3}$
Ni		$1.22 \times 10^{+3}$	$9.39 \times 10^{+2}$	$1.96 \times 10^{+3}$
Cr		$7.47 \times 10^{+3}$	$5.77 \times 10^{+3}$	$1.21 \times 10^{+4}$
Hg		4.13	3.19	6.67

Table 4. *Cont.*

Inventory		Fallow–Soybean	Rapeseed–Soybean	Wheat–Soybean
3. From K-fertilizer:				
Cd		-	1.08×10^{-1}	2.24×10^{-1}
Cu		-	5.18	$1.08 \times 10^{+1}$
Zn		-	6.70	$1.39 \times 10^{+1}$
Pb		-	8.64×10^{-1}	1.79
Ni		-	2.70	5.60
Cr		-	6.26	$1.30 \times 10^{+1}$
b. Emissions from biocides	(kg)			
1. Emissions from insecticide				
Indoxacarb		5.40×10^{-3}	4.30×10^{-3}	2.90×10^{-3}
Diazinon		2.03×10^{-1}	1.83×10^{-1}	-
Chlorpyrifos		-	3.08×10^{-2}	3.35×10^{-2}
Cypermethrin		8.46×10^{-2}	6.98×10^{-2}	4.50×10^{-2}
Thiodicarb		-	2.71×10^{-1}	3.51×10^{-2}
Profenofos		-	-	1.27×10^{-1}
Fenitrothion		-	8.46×10^{-2}	-
2. Emissions from herbicide				
Imazethapyr		-	3.80×10^{-3}	-
Haloxyfop-ethoxyethyl		-	1.83×10^{-2}	-
Trifluralin		-	-	5.94×10^{-2}
Bentazone		4.97×10^{-2}	-	-
Paraquat		-	-	1.33×10^{-2}

2.2.3. Assessing the Impacts of Soybean Production

As the third step of the LCA, impact assessment, which applies LCI results and provides characterization factors, expresses the impacts per amount of inventory [13,35]. In addition, to evaluate potential environmental impacts, this step also provides information on the life-cycle interpretation stage [13].

In this study, the IMPACT 2002+ (v2. 15) model was used to determine soybean production's environmental impacts. This methodology is a combination of the CML, Eco-indicator 99, IPCC, and Impact 2002 methods [36]. IMPACT 2002+ combines the midpoint and damage indicators as a life-cycle impact assessment (LCIA) methodology to enhance consistency in the impact pathway modeling [37]. As described in Humbert et al. [38], the model consists of 15 midpoint categories (Figure 3), all of which are expressed in units of a reference substance and are related to four damage indicators of ecosystem quality (PDF $\times$ m^2 $\times$ yr: Potentially Disappeared Fraction (PDF) of species, year (yr), climate change (kg CO_2-eq), resources (MJ primary), and human health (DALY: Disability-Adjusted Life Years).

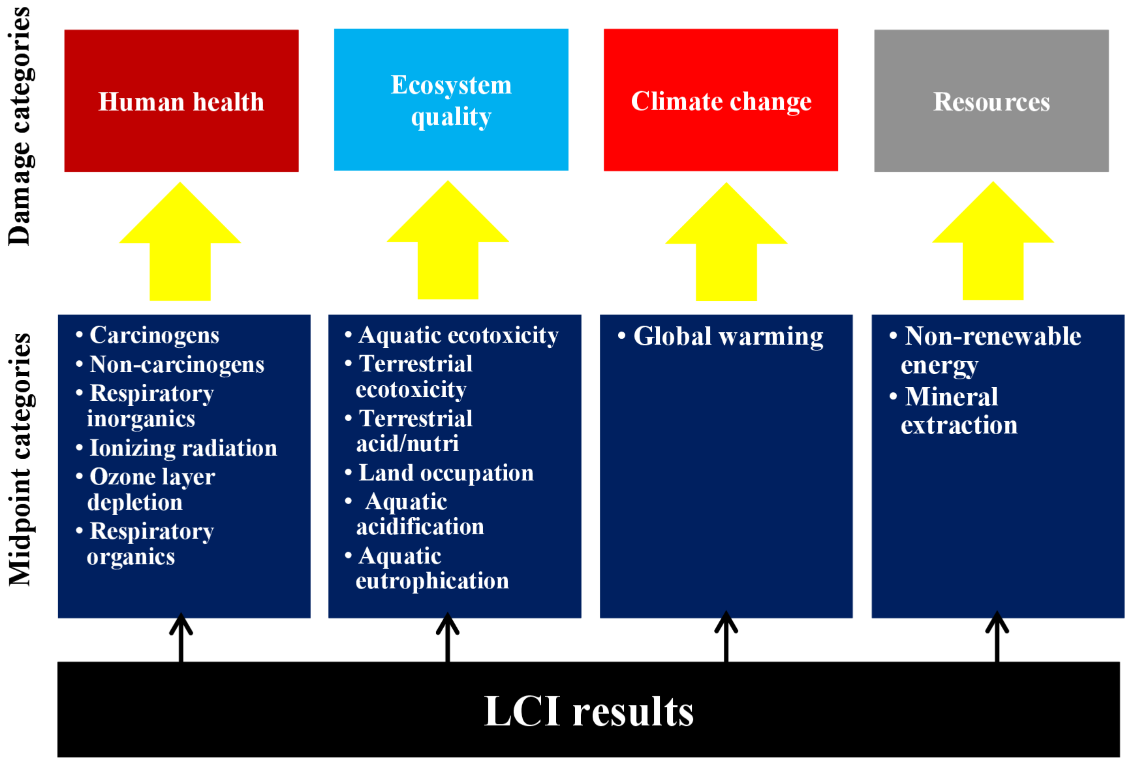

Figure 3. Damage groups and the linked midpoint categories in the IMPACT2002+ method.

2.3. ANFIS-FCM Method

The adaptive neuro-fuzzy inference system (ANFIS) was first proposed by Jang [39]. ANFIS is a neural network that uses the Takagi–Sugeno inference model structure. ANFIS is a powerful modeling technique with a combination of learning rules from ANN_S and linguistic transparency of fuzzy logic theory. Fuzzy inference systems (FIS) are one of the most popular applications of fuzzy logic theory in various fields of economics, science, engineering, and management. In FIS, membership functions (MFs) usually have to be manually adjusted by trial and error, and this model is known as the white box, while in the ANN, achieving the goal is self-learning and acts as a black box. The general picture of ANFIS architecture is described in Figure 4. 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 that can be changed and fixed are shown as squares and circles, respectively.

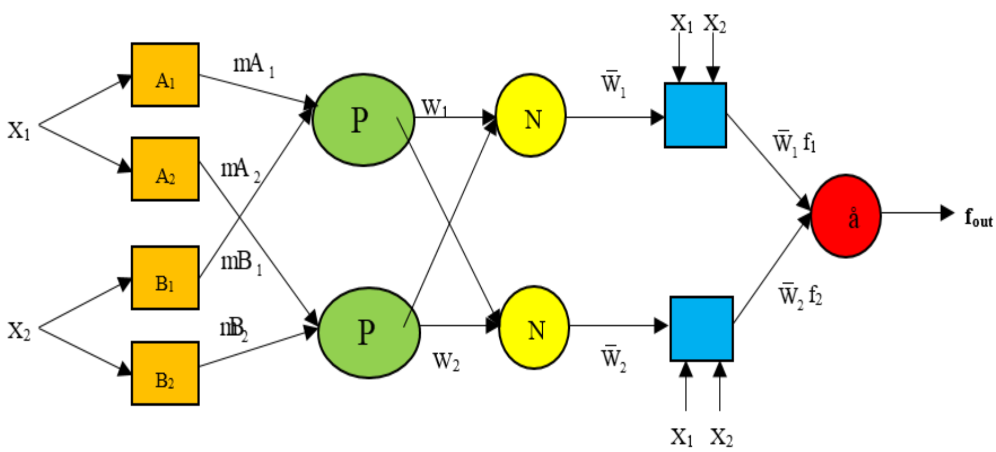

Figure 4. The structure of ANFIS.

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

$$O_{1,i} = \mu A_i(X_1), fori = 1,2 \quad O_{1,i} = \mu B_{i-2}(X_2), fori = 3,4 \tag{1}$$

where X_1 and X_2 are the input variables i, A and B are the linguistic labels characterized with this node, and $\mu(X1)$ and $\mu(X2)$ are the MFs, such as a generalized bell, sigmoid or triangular.

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

$$O_{2,i} = w_i = \mu A_i(X_1).\mu B_{i-2}(X_2), fori = 1,2 \tag{2}$$

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 layer 3 is considered a fixed node. Here, the ratio of the ith rule is firing strength to the sum of all firing strength, calculated as:

$$O_{3,i} = w_i = \frac{w_i}{w_1 + w_2}, fori = 1,2 \tag{3}$$

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

Layer 4: This layer is called defuzzier. In this layer, for every square node, the output from the previous layer is multiplied with the function of fuzzy rules:

$$O_{4,i} = w_i.f_i, fori = 1,2 \tag{4}$$

where $f1$ and $f2$ are the fuzzy if–then rules as follows:

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

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

where, *pi*, *qi*, and *ri* are the parameters set (consequent parameters).

Layer 5: The single circle node in layer 5 in the fifth layer of the output layer is labeled Σ, which calculates using the sum of all inputs of the previous layer:

$$O_{5,i} = \sum_i w_i.f_i, = \frac{\sum_i w_i.f_i}{w_i} = f_{out} \tag{7}$$

The most widely used ANFIS learning rule is "back-propagation", 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 applied to optimize the parameters of the premise part. This learning rule is the same as the back-propagation learning rule in the feed-forward neural networks. Excessive slowness and being trapped in local minima for conventional methods are some of the main problems that can be solved by a 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 rules of ANFIS. The fuzzy c-means (FCM) method determines the number of rules and MFs for input and output variables. The developed K-means algorithm is the FCM method. FCM divides the data set X into C clusters by minimizing the weight distance errors for each data point X_i

relative to all C cluster centroids. Thereafter, the algorithm tries to minimize the objective function, which is a generalization of the least-squares method:

$$j_m = \sum_{c=1}^{c} \sum_{i=1}^{n} w_{ic}^{p} ||x_i - v_c||^2 \tag{8}$$

where n represents the number of data points, c presents the number of clusters, v is the cluster centers, w_{ic} is the degree of membership of x_i in the cluster c, and x shows the input data point. w_{ic} can be calculated with the following formula:

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

where p presents the fuzzifier exponent and k is the number of iteration steps.

Additionally, in the FCM algorithm, after initializing the central vectors, the centers are calculated with the following formula:

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

In this study, the input set for the developing model included 14 variables independent of field soybean cultivation, including 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, ecosystem quality, climate change, and resources were given as data output sets. This data set was subdivided into 123 data for training and 52 data for testing. In the modeling process, ANFIS-related functions in Matlab software (version Matlab 2019) were used to generate the model program. In the modeling process, the parameters of the ANFIS model are determined during the learning phase at a specific epoch that verifies that errors are minimal. Experimental datasets are applied to assess the accuracy, effectiveness, and prevention of over-fitting of the trained model. To create the structure of FIS from data in ANFIS, the FCM clustering method was used in this work. These methods were 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) and 30% of the data was used for testing (52 data). In this method, the number of rules and MFs for input and output variables is determined by the FCM method. The number of clusters (NC) created by FCM can be specified in the program. Determining the radius of a smaller cluster usually results in more clusters. This means more rules have been produced in FIS. When the FIS structure type is selected as Sugeno, the input and output membership types are defined as gauss and linear, respectively. Six alternative models are produced by assigning different values to the NC. The NC determines the number of MFs and rules. Simulations are performed for these alternative models to find the optimal FIS structure.

2.4. ANN Method

ANN with a multi-layered feed-forward (MLFF) back-propagation algorithm learns by changing the weights; these changes are stored as knowledge. To obtain the best prediction by the network, several architectures were evaluated and trained to apply 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 [40]. In this study, the neural network structure was modeled with 14 factors, including inputs such as chemical pesticides and fertilizers, agriculture machinery, polyethylene, electricity, diesel, lubricating oil, kerosene, and seed as 14 neurons in the input layer, and the 4 factors of human health, ecosystem quality, climate change, and resources as output layer neurons. Combined parameters, such as the number of hidden layers, the number of neurons, and the number of training cycles during the artificial neural network training process, were determined by trial and error. The total number of input patterns to the network was 123, which were randomly divided into three groups: training (70%), evaluation (15%), and testing (15%). Additionally, the training rate for all cases was 0.2 and the momentum rate was 0.1. The best neural network topology was determined based on two criteria: R and RMSE.

2.5. Model Validation

Statistical parameters were used to evaluate and fit the best model for data. Indices of mean absolute percentage error (MAPE), root means square error (RMSE), and the determination coefficient (R^2) can be expressed as:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \widehat{y}_i}{y_i}\right| \times 100 \tag{11}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \widehat{y}_i\right)^2} \tag{12}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(\widehat{y}_i - y_i\right)^2}{\sum_{i=1}^{n}\left(\widehat{y}_i - \overline{y}\right)^2} \tag{13}$$

where y_i and $\widehat{y}_i$ are the observed and predicted values for the ith testing dataset (respectively), $\widehat{y}$ represents the average of the observed values (respectively), and n represents the total number of data.

3. Results

3.1. EIA of Soybean Production Scenarios

3.1.1. Results of Damage Assessment

The damage categories result for the production of 1 ton of soybean, based on the IMPACT2002+ method presented in Table 5 and illustrated graphically in Figure 5, showed the relative contribution of different inputs to the four environmental damage indicators. Based on the obtained results, On-Farm emissions from soybean production in all cultivation scenarios have the highest share in the three damage categories of human health (>71%), climate change (>50%), and ecosystem quality (>89%). In the following section, we will concentrate on the description of soybean production's environmental damages.

Table 5. The results of damage categories for producing 1 ton of soybean under different scenarios.

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

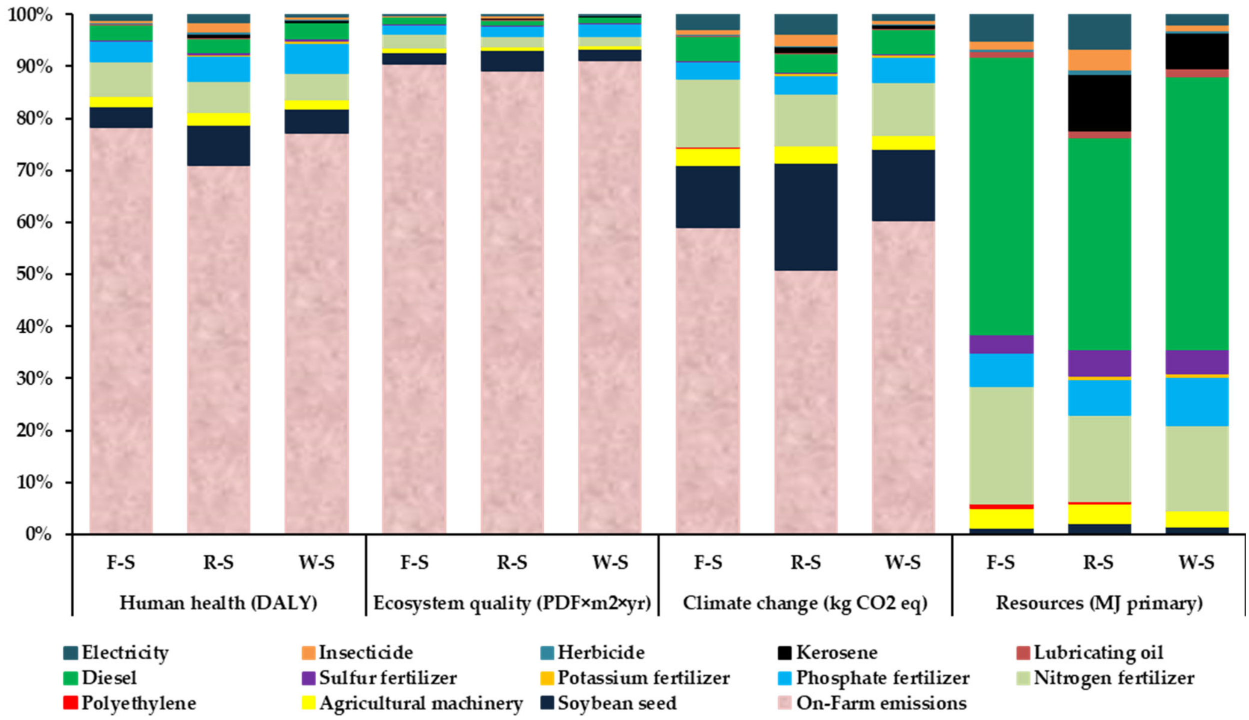

Figure 5. The contribution of On-Farm and Off-Farm emissions to damage categories of soybean production under different scenarios.

As shown in Table 5, in different scenarios of soybean production, the highest CO_2-eq value related to W-S (880.61 kg) was followed by F-S (794.50 kg), and the lowest CO_2-eq value was for the R-S (563.55 kg) cropping system. In this way, the R-S scenario was the best in terms of kg CO_2-eq emissions, which led to a reduction of about 29 and 36% compared to the F-S and W-S scenarios. According to Figure 5, the direct emissions from farm operations played the most important role in increasing GW or climate change in different scenarios of soybean production (about 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, concerning Figure 5, the contribution of indirect emissions from seed production to this category was also significant.

As shown in Figure 3, the resource damage category is related to the two midpoint categories of 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 [41]. According to Table 5, the R-S scenario with a total value of 5476.18 MJ primary had the lowest use of resources. The highest damage to resources was also related to the W-S scenario, which was estimated at 8799.80 MJ primary. As can be deduced from Figure 5, diesel has played the biggest role in creating the environmental burden of this damage category. After diesel, the share of nitrogenous chemical fertilizers was also significant, which varied from about 16–22% in different scenarios.

The results demonstrate that the total amount of damage to ecosystem quality in the wheat–soybean (W-S) scenario is higher than in other scenarios (Table 5). In other words, the production of each ton of soybeans in the R-S, F-S, and W-S scenarios has resulted in damage of 1033.68, 1410.73, and 1840.70 PDF $\times$ m^2 $\times$ yr to the quality of the ecosystem, respectively. This shows that the R-S scenario performed better than the F-S and W-S scenarios by about 27 and 44%, respectively, in terms of ecosystem degradation in the region. The most damage to this category in the production of soybean relates to the field operations, with no considerable share from background processes (Figure 5). It is also notable that the main contributors to On-Farm emissions are heavy metals (mostly Zn) in applied chemical fertilizers; in particular, phosphorus.

As shown in Table 5, the total amounts of human health damage category produced in the F-S, R-S, and W-S scenarios are 0.0015, 0.0009, and 0.0016 DALY, respectively. As can be seen in Figure 5, this difference is mainly due to the high share of direct emissions in different scenarios, i.e., about 71–78%. Given the importance of human health, it is of particular importance to identify the sources of these pollutants so that the right management strategies can be provided to mitigate these emissions by identifying these inputs. The analysis revealed the direct emissions of NO_X and Particulates, <2.5 µm caused by diesel fuel, and NH_3 from nitrogen fertilizers had the most significant role in damage to human health in all scenarios of soybean production, respectively. Like N_2O, the release of NH_3 depends on the number of nitrogen fertilizers consumed on farms [42]. In this way, as the results in Table 5 also show, the R-S scenario can be introduced as the best scenario in terms of damage to human health due to the reduced emission of these On-Farm pollutants. According to the results listed in Table 5, this scenario showed a decrease of about 44 and 40% in damage to human health compared to the other two scenarios, i.e., W-S and F-S, respectively.

Because damage categories have different units, it is still difficult to select the most environmental scenario. Accordingly, damage categories were weighted according to the IMPACT 2002+ method to obtain a single score (in milli Point unit (mPt)) based on which decisions could be made. Based on the results obtained from the weighting analysis, the total environmental damage for soybean production under various cultivation scenarios was 293.87–503.73 mPt. Moreover, the human health damage category had a critical role in the total environmental impacts of around 43–47%.

3.1.2. Comparison of Environmental Damages among Various Scenarios

From Figure 6, it is evident that the R-S scenario showed greater environmental compliance than the other scenarios. More specifically, compared to W-S (as the most applied scenario in Mazandaran), R-S led to a reduction of around 44, 44, 36, 38, and 42%, respectively, in human health, ecosystem quality, climate change, resources, and total environmental damage.

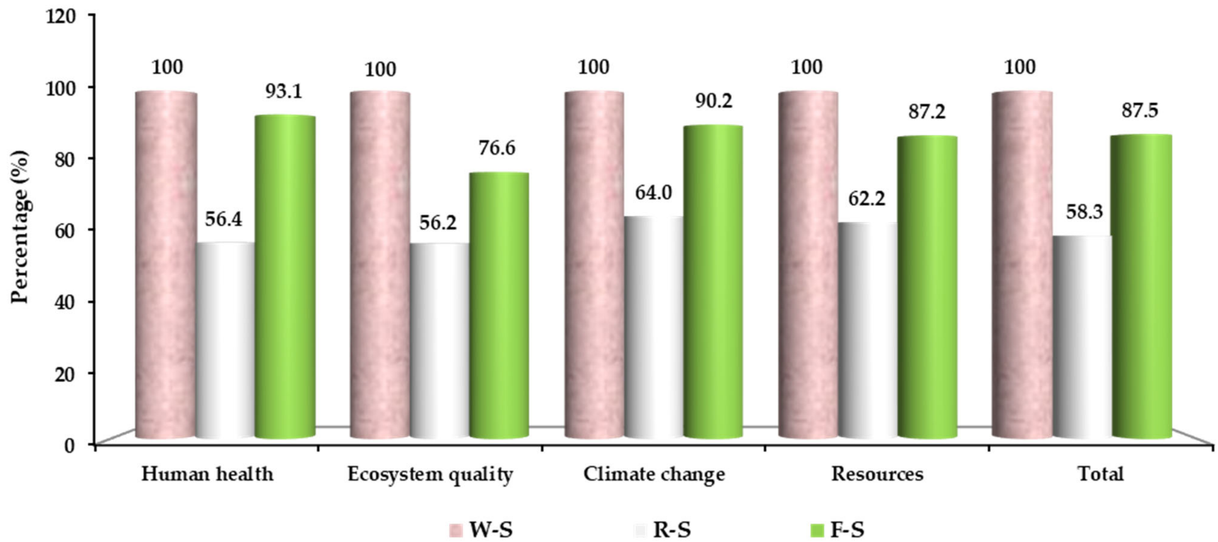

Figure 6. The weighted environmental damages of soybean production (FU = 1 ton) in different cultivation scenarios.

3.2. *Evaluating of ANFIS-FCM and ANN Models*

The ANFIS-FCM models and performance results are given in Table 6. As can be seen, it is not easy to conclude that with more clusters, better performance results can be obtained. For environmental parameters, i.e., human health, climate change, and resources, the best performance of the model was obtained in the lower clusters (FCM2). On the other hand, for ecosystem quality, the best performance forecast of the model in cluster 3 was obtained (FCM3). The criterion for selecting the best model is fewer differences in the RMSE of training and testing of models. For example, in ecosystem quality, the RMSE values obtained for training, testing, and all data sets were 31.20, 42.02, and 34.83, respectively. Therefore, the ANFIS-FCM3 model was considered with three optimal rules in ecosystem quality. Increasing the number of clusters causes over-fitting of the model. For instance, in the FCM7 model, although the training error was the lowest (RMSE = 20.98), the testing error reached its highest level (RMSE = 1776.55). This trend can be seen for other environmental parameters in the ANFIS-FCM model by increasing the number of rules and cluster models.

Table 6. The performance of ANFIS-FCM models for prediction of environmental impact.

Environmental Impacts	Model Name	Number of Clusters	Number of Input MF	Number of Output MF	Number of Rule	Epochs	RMSE			R		
							Training	Testing	All Data	Training	Testing	All Data
Human health (DALY)	**FCM2**	**2**	**[222]**	**[2]**	**2**	**5**	$\mathbf{4.43 \times 10^{-5}}$	$\mathbf{5.35 \times 10^{-5}}$	$\mathbf{5.70 \times 10^{-5}}$	**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
Ecosystem quality (PDF × m^2 × yr)	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 (kg CO_2-eq)	**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 (MJ primary)	**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	23,009.21	12,662.90	0.9996	0.3624	0.4370
	FCM7	7	[777]	[7]	7	15	118.98	616.83	353.69	0.9997	0.9954	0.9978

Additionally, the parameters of the most accurate ANN network models in predicting environmental impacts for soybean production are shown in Table 7. The results of MAEP, RMSE, and R for the neural networks were calculated. Feed-forward backpropagation neural networks with the Levenberg–Marquardt training algorithm for ANN models were used. Sigmoid "tansig" and "purelin" linear functions were used as activation functions in the hidden and output layers, respectively. The best ANN structures were 14-10-7-1, 14-11-6-1, 14-10-10-1, and 14-12-8-1 for human health, ecosystem quality, climate change, and resources, respectively. It can be seen that the coefficient of determination values differ from 0.9863 to 0.9938 in the 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 the ANN models.

Table 7. 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 shown in Figure 7, the calculated coefficients of determination (R^2) to predict the environmental impacts obtained by the ANFIS-FCM models were higher than the ANN models. The R^2 ranges for the ANFIS-FCM and ANN models were between 0.9967 to 0.9989 and 0.9269 to 0.9870, respectively. Two other parameters that were used to evaluate the accuracy of the model are RMSE and MAPE. The lower value of these parameters indicates higher model accuracy. The RMSE and MAPE values obtained in ANFIS-FCM were lower compared to the ANN model for all environmental indicators. The MAPE values for the ANFIS-FCM and ANN models were obtained at 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. Additionally, results revealed the values of the RMSE were 5.35×10^{-5}, 34.90, 18.57, and 186.98 in ANFIS-FCM and 1.09×10^{-4}, 234.12, 63.84 and 858.51 in the ANN model for human health, ecosystem quality, climate change, and resources, respectively.

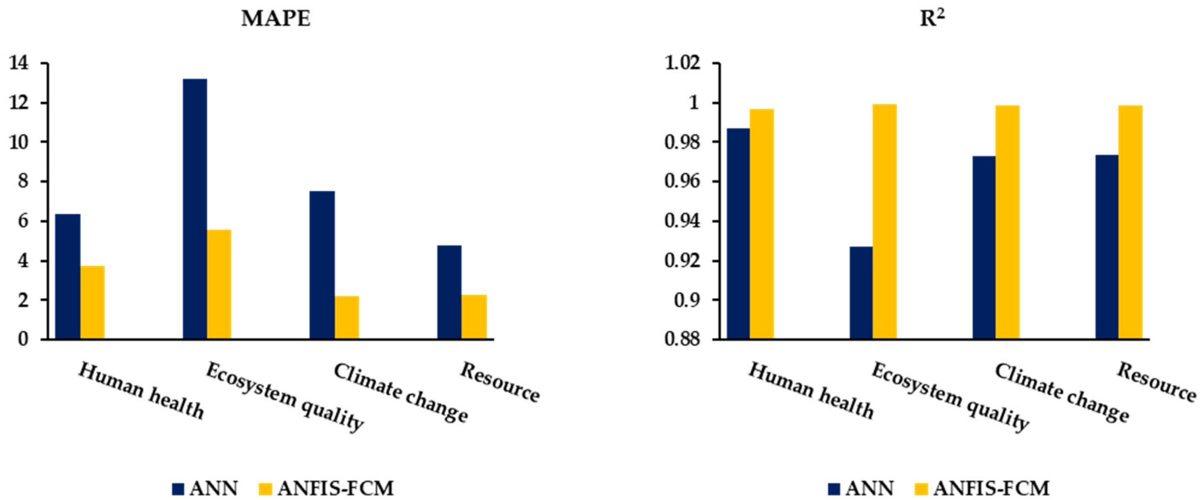

Figure 7. Comparison between R^2 and MAPE in ANN and ANFIS-FCM models.

In general, according to the results of the ANN and ANFIS-FCM models, it is concluded that the ANFIS-FCM model performed better than ANN in all aspects for the prediction of environmental impacts in soybean farms. Additionally, Figure 8 illustrates the environmental indicator prediction results in the ANFIS-FCM model versus actual environmental indicator data for climate change, ecosystem quality, 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 Figure 9. The range of calculated R^2 for predicting all environmental parameters is very close to each other (Figure 9).

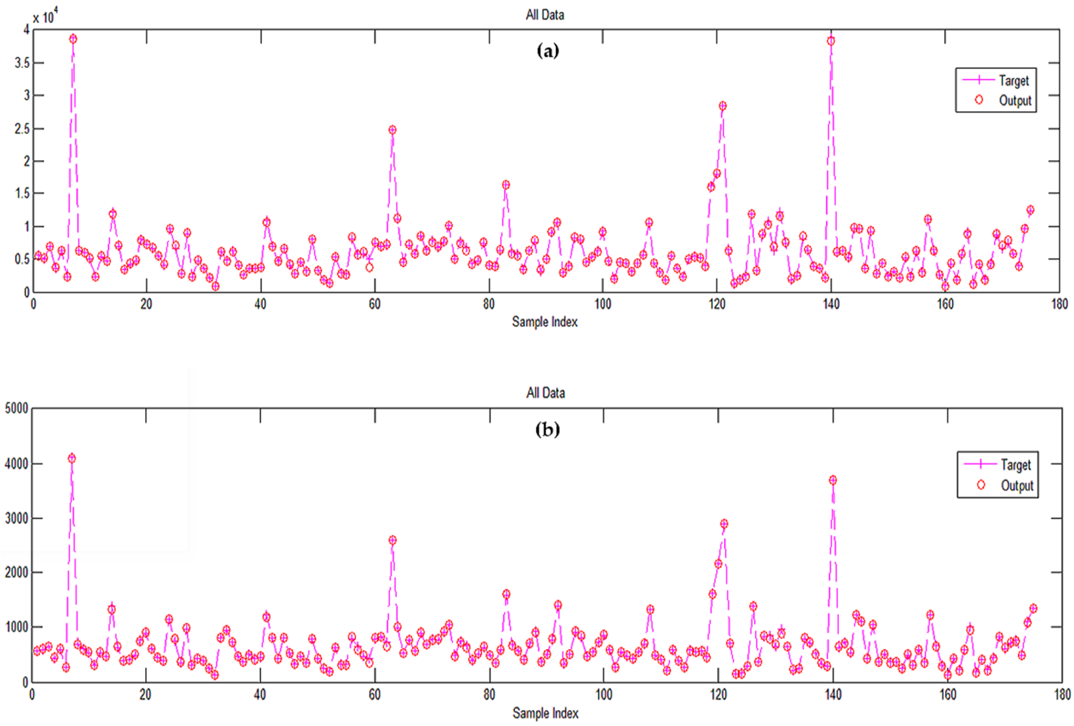

Figure 8. *Cont.*

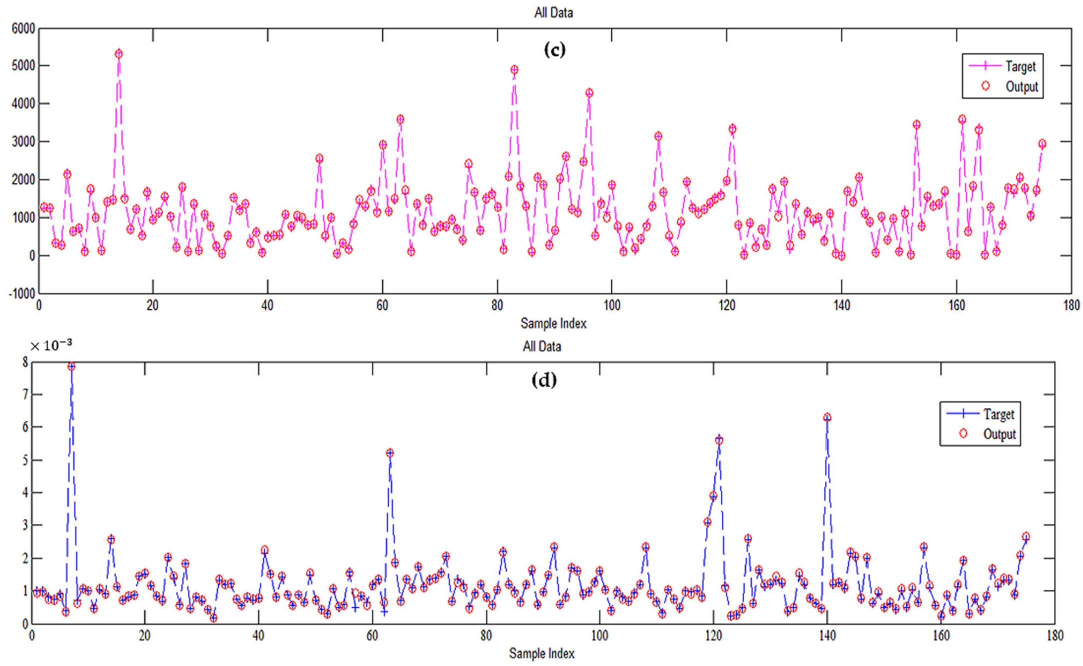

Figure 8. Prediction values versus actual data for (**a**) resources, (**b**) climate change, (**c**) ecosystem quality, and (**d**) human health.

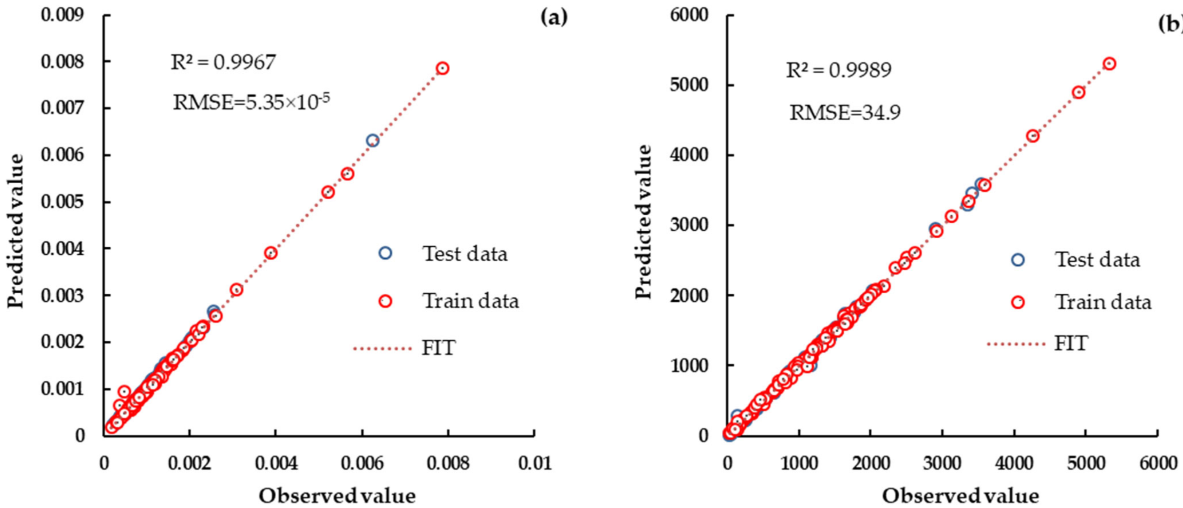

Figure 9. *Cont.*

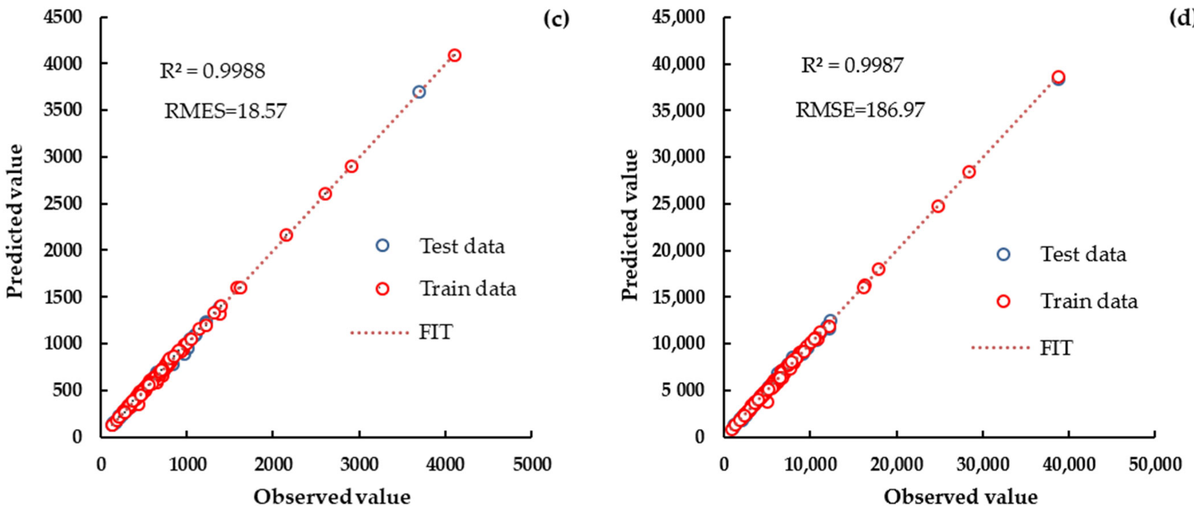

Figure 9. Comparison between observed and predicted values for (**a**) human health, (**b**) ecosystem quality, (**c**) climate change, and (**d**) resources.

4. Discussion

The increase in population in recent years and its growing trend in future years has increased the need for agricultural and food products, and thus the agricultural production should be increased. This goal can lead to increases in GHG emissions, and the subsequent phenomenon of climate change, by increasing the consumption of inputs such as nitrogen and phosphorous fertilizers, diesel fuel, and manure [43]. Nitrogen, as one of the most important nutrients for plant growth and higher yields, mainly by spreading manure and using chemical fertilizers in farmlands, leads to several important emissions that affect GW [27]. Amongst these emissions, nitrous oxide (N_2O) has great importance due to its longevity in the atmosphere (more than 114 years) and its GWP (298 times higher than CO_2). The main sources of N_2O emissions in the soil are mainly due to agricultural activities, including nitrogen fertilizers applied in the soil, fossil fuel combustion, and some of the natural mechanisms that occur in aquatic and terrestrial ecosystems [44]. Therefore, any strategy 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 of oilseeds production in Iran, Ardabil Province, the amount of CO_2-eq emitted per ton of product for rapeseed, sunflower, and soybean was 2132, 2283, and 1549 kg, respectively. Moreover, the study reported that more than 70% of these emissions (GW) were due to electricity production, manure, and chemical fertilizers [45]. By comparing these results, it is clear that the GWP index for soybean production in Ardabil province is much higher than in Mazandaran, which is due to the higher consumption of these inputs and more intensive management to produce this product. In another study in South Korea [46], the amount of CO_2-eq emitted from soybean production in conventional and organic farms was 1657.55 and 2045.11 kg ton^{-1}, respectively. Like the present study, N_2O emissions from the consumption of manure and chemical fertilizers and CO_2 from fossil fuel combustion accounted for the largest share of total CO_2-eq emitted from these farms. Manure, fuel, and fertilizer were the main contributors to GHG emissions and poor energy efficiency in Korean soybean production. To diminish these emissions, the authors proposed the optimal use of these inputs. Research to assess the LCA of farming systems in Switzerland [12] revealed that N_2O and CO_2 emitted from fertilizers and fossil fuels had the highest impact on GWP, respectively. Similar surveys on the LCA of soybean production in different parts of the world, such as the Northern Great Plains, USA [47], the U.S. Midwest [48], Southern Brazil [49], Mato Grosso State, Brazil [50], and Jilin Province, China [51], showed that the amount of CO_2-eq emitted was calculated as 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. Accordingly, although the emission of GHG in different agroecosystems 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 impact. Hence, due to the role of diesel, and chemical fertilizers (as the most crucial environmental hotspots) in causing damage to the climate change category, improvement measures should focus on the consumption management of these inputs.

The findings revealed that in all scenarios, diesel and nitrogen fertilizer had the highest impacts on the resource category, respectively. In other words, these inputs are the main environmental hotspots in damage to this category (Figure 5). These results are consistent with the findings of Knudsen et al. [51] in Jilin Province, China. Based upon this study, the production of agro-chemicals and traction at farms, with about 73% and 27% of the total non-renewable energy used in soybean production (1710 MJ t^{-1}), respectively, were the main contributors to 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 and providing adequate aeration, reducing nutrient losses and NH_4 emissions. In Swiss farming systems, mechanization processes, i.e., soil cultivation and harvest, accompanied by mineral fertilizers, particularly N fertilizers, showed the highest demand for non-renewable energy resources. The reason why N fertilizers have the highest energy demand of all inorganic fertilizers is the high consumption of fossil fuels in the process of NH_3 synthesis [12]. Depletion of abiotic resources refers to the use of resources such as minerals (e.g., phosphate rock) or fossil fuels, which reduces the access of future generations to these resources. Since these resources have inherent value for human beings and access to them in the future is economically and socially important [14], more monitoring and research are needed 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 new and modern ones, as well as by conservation tillage (minimum or no-tillage), and, as a result, decrease its environmental impacts [52].

In terms of damage to ecosystem quality, chemical fertilizers were the main environmental hotspots due to their emissions. These results emphasize the importance of fertilizer consumption management in Mazandaran soybean farms. In this regard, Zortea et al. [49], Khanali et al. [53], Brentrup et al. [42], and Ntiamoah and Afrane [26] also noted the need for the efficient management of fertilizer in the production of soybean, rapeseed, wheat, and cocoa, respectively. Similarly, Matsuura et al. [54] 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 the usage of fertilizers for the cleaner production of these products. 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 had better environmental performance than the sum of monocultures. As the results of this study showed, the agricultural sector, through the use of chemical fertilizers, especially phosphorus, is one of the anthropogenic sources for the release of heavy metals into the environment. By emitting these pollutants into water and soil, not only are natural ecosystems damaged, but they also endanger human health by entering the food chain [55]. Apart from being an important anthropogenic source for the release of heavy metals, phosphorus is vital as an important nutrient for crop production [56]. In addition, most countries in the world (more than 90%) do not have significant reserves of phosphate rock as the main source of production of most phosphate fertilizers, considering that no element can be replaced instead of phosphorus in biochemical processes [57], so it is important to manage the consumption of this non-renewable resource. Hence, to achieve sustainable agriculture, biofertilizers and renewable inputs can be used to improve soil fertility and minimize environmental hazards [58]. These inputs can maintain long-term soil fertility and stability through mechanisms such as biological nitrogen fixation, conversion of insoluble phosphorus in the available form for plants, and increased access to macro- and micronutrients in the rhizosphere [59]. Plant-growth-promoting microbes, such as plant-growth-promoting rhizobacteria (PGPR) and plant-growth-promoting fungi (PGPF), are examples of these biofertilizers.

According to the present study, the use of agrochemicals (herbicides and chemical fertilizers) and the burning of diesel fuel in farm machinery were the main contributors to the environmental burdens caused by sugarcane growth and harvesting in Mexico. In this study, the use of NPK fertilizers in farms had a significant contribution to the endpoint categories (climate change, ecosystem quality, human health, and resources). For dealing with this problem and to correctly estimate the amounts of fertilizer used on farms, they proposed an artificial-intelligence-based decision support system. Furthermore, they suggested the presence of agricultural experts due to the difficulty of interpreting soil test results for farmers [60]. In a similar study in Mazandaran Province, high consumption of nitrogen fertilizers and diesel fuel were the main contributors to the environmental burdens of rapeseed production in the area. They revealed that the integration of legumes, such as beans, in rotation with rapeseed could be a management strategy to reduce dependence on chemical fertilizers and thus produce more environmentally friendly rapeseed in the region [61]. Pulses increase soil productivity by reducing soil pathogens, decreasing soil erosion, and biological stabilization of nitrogen, thereby improving crop yields in rotation. In addition, pulses are environmentally friendly products due to their reduced use of inputs such as irrigation and agrochemicals, i.e., pesticides and fertilizers. Legume-based cropping systems enhance the sustainability of production systems by increasing soil biodiversity, soil health and quality, crop productivity, soil restoration, and food security [62,63].

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. The use of two artificial intelligence simulation models, ANN and ANFIS-FCM, showed that the use of these models could predict the impacts of reducing chemical fertilizers and fuel consumption on the number of emissions of pollutants and categories of environmental damage in soybean production. These forecasts can predict the best levels of agriculture inputs according to damage categories to be used by farmers. In addition, the predicted results can help to formulate different programs in farms for the future so that the optimization of emissions of pollutants and energy consumption does not cause harm to performance.

5. Conclusions

In the current study, the life-cycle assessment method was used to predict environmental impacts from soybean cultivation in different scenarios using developing models based on ANFIS-FCM and ANN. Based on the result obtained, the total environmental impact of soybean production in the studied area was in 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. Out of these values, about 43–47% was related to the human health damage category, which was mainly due to the consumption of diesel and chemical fertilizers. According to the results, ANFIS-FCM was chosen as a better model than ANN models due to the higher accuracy of its statistical indicators. Additionally, the RMSE and MAPE values achieved in ANFIS-FCM were lower compared to the ANN model for all soybean cultivation environmental prediction performances. Generally, the results of this study are important for the environmental burden control of soybean production. However, the results showed that soybean cultivation after rapeseed (R-S) has the smallest environmental impacts compared to the W-S and F-S scenarios. In addition, the ANFIS-FCM model can be a more useful tool than ANN to predict high-precision environmental indicators for agricultural production.

Author Contributions: Conceptualization, F.M.K. and A.M.; methodology, F.M.K. and A.M.; software, F.M.K. and A.M.; validation, Z.T.S. and H.P.; formal analysis, F.M.K.; investigation, H.P.; resources, M.V.; data curation, M.V.; writing—original draft preparation, F.M.K.; writing—review and editing, H.P., A.M. and M.V.; visualization, A.M.; supervision, H.P. and M.N.; project administration, Z.T.S. and H.P.; funding acquisition, Z.T.S. All authors have read and agreed to the published version of the manuscript.

Funding: This paper is extracted from the results of a Ph.D. thesis at Tarbiat Modares University and received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets obtained and analyzed in the present study are available from the corresponding author upon reasonable request.

Acknowledgments: This study is part of a Ph.D. thesis. We gratefully acknowledge the financial support provided by the Department of Agronomy at Tarbiat Modares University, Tehran, Iran. We also would like to thank the farmers, honorable officials of Sari Agricultural Sciences and Natural Resources University, and the Agricultural Jihad Organization of Mazandaran Province for fruitful cooperation during the data collection for this study.

Conflicts of Interest: The authors declare no conflict of interest.

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	Hydrocarbons	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	PDF	Potentially Disappeared Fraction of Species

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