Journal of Agricultural Machinery

Homepage: https://jame.um.ac.ir

Research Article

Vol. 15, No. 1, Spring 2025, p. 23-46

Optimization of Cumulative Energy, Exergy Consumption and Environmental Life Cycle Assessment Modification of Corn Production in Lorestan Province, Iran

M. Soleymani [1*], A. Asakereh [1], M. Safaieenejad [2]

1- Department of Biosystems Engineering, Shahid Chamran University of Ahvaz, Ahvaz, Iran

2- Agricultural Mechanization Management Department of Lorestan Province Agricultural Jihad Organization, Khorramabad, Iran

(*- Corresponding Author Email: m.soleymani@scu.ac.ir)

Received: 06 January 2024 Revised: 06 February 2024 Accepted: 14 February 2024 Available Online: 15 February 2025	**How to cite this article:** Soleymani, M., Asakereh, A., & Safaieenejad, M. (2025). Optimization of Cumulative Energy, Exergy Consumption and Environmental Life Cycle Assessment Modification of Corn Production in Lorestan Province, Iran. *Journal of Agricultural Machinery, 15*(1), 23-46. https://doi.org/10.22067/jam.2024.86234.1221

Abstract

Optimal use of resources, including energy, is one of the most important principles in modern and sustainable agricultural systems. Exergy analysis and life cycle assessment were used to study the efficient use of inputs, energy consumption reduction, and various environmental effects in the corn production system in Lorestan province, Iran. The required data were collected from farmers in Lorestan province using random sampling. The Cobb-Douglas equation and data envelopment analysis were utilized for modeling and optimizing cumulative energy and exergy consumption (CEnC and CExC) and devising strategies to mitigate the environmental impacts of corn production. The Cobb-Douglas equation results revealed that electricity, diesel fuel, and N-fertilizer were the major contributors to CExC in the corn production system. According to the Data Envelopment Analysis (DEA) results, the average efficiency of all farms in terms of CExC was 94.7% in the CCR model and 97.8% in the BCC model. Furthermore, the results indicated that there was excessive consumption of inputs, particularly potassium and phosphate fertilizers. By adopting more suitable methods based on DEA of efficient farmers, it was possible to save 6.47, 10.42, 7.40, 13.32, 31.29, 3.25, and 6.78% in the exergy consumption of diesel fuel, electricity, machinery, chemical fertilizers, biocides, seeds, and irrigation, respectively.

Keywords: DEA, Energy in agriculture, LCA, Renewability, Sustainability

Introduction

The agriculture sector has become increasingly reliant on energy due to the widespread use of agricultural machinery and inputs in mechanized agriculture, particularly in developing countries where there has been a shift from traditional to mechanized farming methods. Mechanization is the main factor in the consumption of non-renewable energy in agriculture (Leiva & Morris, 2001). In addition to reducing non-renewable resources, this situation has also had adverse effects on the environment (Nemecek, Dubois, Huguenin-Elie, & Gaillard, 2011; Nikkhah, Khojastehpour, Emadi, Taheri-Rad, & Khorramdel, 2015). Since the agricultural sector, on the other hand, is responsible for the food security of the growing population, a balance must be struck between the use of resources and the production of agricultural products (Alam, Alam, & Islam, 2005). The consumption of resources should be such that it does not threaten the food security of future generations (Alam *et al.*, 2005).

https://doi.org/10.22067/jam.2024.86234.1221

Increasing agricultural productivity is not possible without the proper, wise, and timely use of inputs. Using more inputs, whether directly or indirectly, leads to a rise in energy consumption. Therefore, to determine effective methods for the optimal use of agricultural inputs, it is necessary to first identify them accurately and comprehensively (Mani, Kumar, Panwar, & Kant, 2007). Energy is one of the most important resources in agricultural activities and due to the limited resources, greenhouse gas emissions, and possible harmful effects on the environment, it should be used optimally and effectively (Alam *et al.*, 2005). On the other hand, the scarcity of natural resources and the impact of intensive agriculture on the environment raise concerns about the ecological sustainability of agriculture. A careful equilibrium must be established between energy usage and its availability in the agricultural sector (Leiva & Morris, 2001).

Today, achieving sustainability in agricultural production systems is one of the main policies in the agricultural sector, with the aim of increasing productivity and reducing adverse effects on the environment. Sustainability in agriculture is achieved when the food needs of the present population is met without threatening the food security of future generations. This type of agriculture emphasizes the protection of the environment and natural resources, and the optimal use of non-renewable resources. To evaluate possible practical measures and promote agricultural sustainability, it is critical to identify the actual flow of various inputs and outputs in agricultural production systems. The optimal use of inputs is one of the principles of sustainable agricultural systems (Ahamed *et al.*, 2011). This situation is even more necessary in the case of energy as one of the most important agricultural inputs, especially in developing countries that are highly dependent on non-renewable resources (Apazhev *et al.*, 2019; Jat *et al.*, 2020; Parihar *et al.*, 2018; Shah *et al.*, 2021). Therefore, identifying optimal patterns of energy consumption in agriculture is necessary and can develop sustainable agriculture as an economic production system (Hatirli, Ozkan, & Fert, 2005). The evaluation of the flow of energy consumption in the production system of agricultural products is the basis of energy analysis. The main goals of energy analysis are to reduce energy consumption, identify non-renewable energy sources for replacement with renewable sources, reduce production costs, and use environmentally friendly production methods as part of an optimal management system (Gezer, Acaroğlu, & Haciseferoğullari, 2003).

Production in agriculture is always associated with the main goal of increasing yield and reducing costs (Gezer *et al.*, 2003). Therefore, optimal energy consumption requires comprehensive planning in this regard. Optimization is a process in which the greatest benefit is obtained by changing the input or output values of a system (Thankappan, Midmore, & Jenkins, 2006). Optimization of energy consumption in agriculture is possible by increasing productivity and maintaining the level of energy input or saving energy consumption without reducing productivity (Bhunia *et al.*, 2021; Vlontzos, Niavis, & Manos, 2014). A lot of research has been done on the optimization of agricultural systems from different perspectives. Optimizing energy consumption is one of these perspectives in which the highest performance with the lowest amount of input energy is desired (Thankappan *et al.*, 2006). However, this approach considers the analysis and amount of energy consumed based on the first law of thermodynamics without considering the quality of energy consumed and does not clearly show the loss of energy in energy conversion processes (Sartor & Dewallef, 2017). For this reason, in recent years, exergy analysis methods that measure the quantity and quality of energy and material flow based on common units have been used (Juárez-Hernández, Usón, & Pardo, 2019). Exergy is the maximum useful work that can be obtained from the system during a process that brings the system into thermodynamic equilibrium with its environment (Juárez-Hernández *et al.*, 2019). Exergy analysis, based on the principles of mass and energy conservation and the second law of thermodynamics, is more useful than energy analysis in determining system efficiency. This procedure provides a useful tool to examine the impact of the use of energy resources on the environment (Ahamed *et al.*, 2011). In previous studies, exergy analysis, cumulative degree of perfection (CDP) and renewability index (RI) were used to evaluate the effects of agricultural production systems on the environment (KhojastehpourTroujeni, Esmailpour, Vahedi, & Emadi, 2018; Yildizhan & Taki, 2018). It also determines the location, types, and magnitude of actual exergy losses (Dincer & Cengel, 2001; Yildizhan, 2018). Exergy is a thermodynamic balance indicator and a unified scale for evaluating different forms of energy carriers and materials, which is suitable for evaluating the sustainability of various production processes and systems (Bösch, Hellweg, Frischknecht, & Huijbregts, 2007; Juárez-Hernández *et al.*, 2019). Several researchers have used the exergy analysis to better understand the efficiency and sustainability of the agricultural production system (Al-Ghandoor & Jaber, 2009; Amiri, Asgharipour, Campbell, & Armin, 2020; EsmaeilpourTroujeni, Rohani, & Khojastehpour, 2021; Juárez-Hernández *et al.*, 2019; Ordikhani, Parashkoohi, Zamani, & Ghahderijani, 2021; Pelvan & Özilgen, 2017; Shahhoseini, Ramroudi, Kazemi, & Amiri, 2021; Yildizhan & Taki, 2018). Saving cumulative exergy consumption (CExC) in agricultural production means less consumption of energy and natural resources and less pollution (Yildizhan, 2018).

Energy consumption in Iran's agricultural sector has almost doubled from 2001 to 2018, mainly due to the increase in the use of agricultural machinery, chemical and mineral materials, and irrigation, as well as the increase in cultivated area, reaching 58.1 million barrels of crude oil equivalent. The sources of this energy are mainly non-renewable (diesel and fossil-based electricity). Accordingly, the agricultural sector in Iran is one of the most important sectors in the emission of pollutants in the environment (for example, more than one-third of N2O emissions in Iran) (Anonymous, 2018). Studies have shown that increasing the use of energy and inputs in agriculture may increase yield, but reduce energy efficiency and exacerbate some of the harmful effects of agricultural systems on the environment (Mohammadi *et al.*, 2013). Therefore, increasing the efficiency of energy consumption in agricultural production systems is very effective to achieve sustainable agriculture. There are various techniques to optimize energy consumption in production units and systems. Data Envelopment Analysis (DEA) is a linear programming method that constructs the efficiency frontier by using the information of production units as the decision-making unit and determines the degree of inefficiency of each decision-making unit based on the distance of that unit to the efficient frontier. DEA has been widely used to measure the efficiency of agricultural production in terms of energy and to determine the optimal amount of input consumption (Bhunia *et al.*, 2021; Kaab, Sharifi, Mobli, Nabavi-Pelesaraei, & Chau, 2019; Powar *et al.*, 2020; Gurdeep Singh, Sodhi, & Tiwari, 2021; Vlontzos *et al.*, 2014).

Several studies have analyzed energy consumption in corn production, mostly based on the first law of thermodynamics (Banaeian & Zangeneh, 2011; Komleh Pishgar, Keyhani, Rafiee, & Sefeedpary, 2011; Mani *et al.*, 2007; Su, Shao, Tian, Li, & Huang, 2021; Yousefi, Khoramivafa, & Mondani, 2014). In this study, optimization of inputs consumption, reduction of energy consumption, and reduction of various environmental effects of the corn production system are investigated based on exergy analysis and life cycle assessment of corn production. The DEA method was used to determine the optimal amount of input consumption based on the CExC and to minimize the environmental effects of corn production while maintaining the current level of performance.

Materials and Methods

The general steps and the boundary of the studied system are shown in Fig. **1**. In the first step, the analysis of exergy and energy in corn production system was performed based on CExC, cumulative energy consumption (CEnC), and exergy and energy evaluation indicators. Finally, the CExC was modeled using the Cobb-Douglas model. In the next step, DEA was used to measure the efficiency of inputs used in each farm (production unit) in terms of CExC and to determine the effective consumption of inputs and CExC in corn farms. The Life Cycle Analysis (LCA) of the corn production system was investigated in the final step.

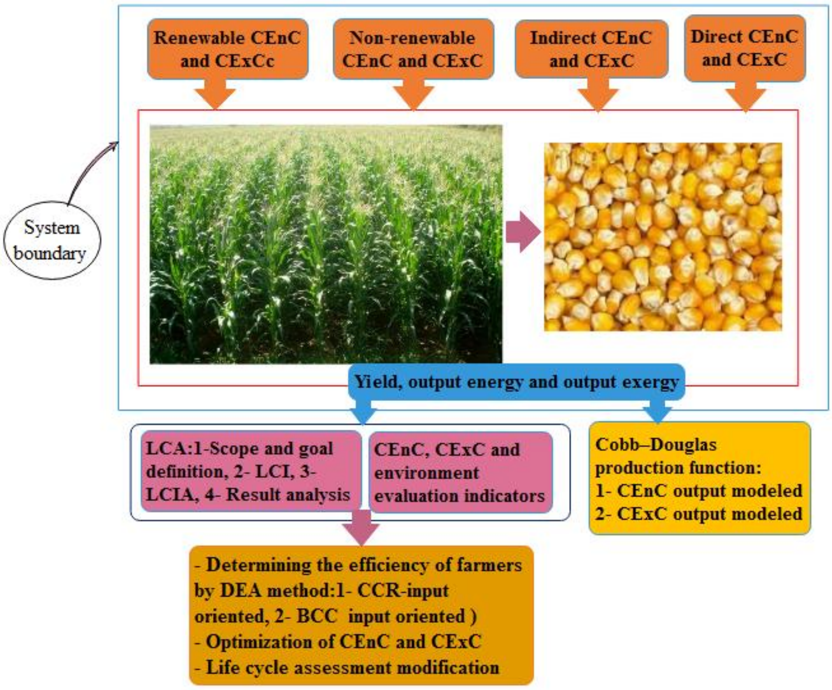

Fig. 1. System boundary and general stages of the study

Data and studied area

The required data were collected from corn farmers in Lorestan province, Iran. About 780 thousand hectares of the province's area are agricultural lands, and it is one of the most important corn production areas in Iran. A total of 214 farmers were randomly selected (Equation (1), (William G. Cochran, 1991)) to interview and collect the necessary data.

$$n = \frac{Nt^2 s^2}{Nd^2 + t^2 s^2} \quad (1)$$

Where:

n – The sample size

N – The size of the statistical population (total corn farmers in the province)

t – The reliability coefficient (1.96 which represents the 95% confidence interval) and the permissible error in the sample size was defined to be 5% for 95% confidence level

d – The precision where (x – X) or mid-confidence interval

S^2 – the variance of the surveyed factor of the population

For exergy analysis, all materials and input energy carriers were quantified based on energy and exergy coefficients. Diesel fuel, electricity, human power, chemical fertilizers, biocides, machinery and tools, irrigation, seeds, and infrastructure (such as irrigation canals) are considered inputs that demand energy or cost at various stages of land preparation, planting, harvesting, and transportation.

Energy and exergy analysis

CExC and CEnC are the sums of total exergy and energy used in all processes required to produce a product, respectively. Therefore, CEnC and CExC were calculated in corn production by considering all categories of inputs and energy carriers. CEnC and CExC in the production of agricultural products are divided into renewable and non-renewable, direct and indirect. Diesel and electricity, which are direct carriers of energy, are direct components of CEnC and CExC in agricultural systems, and the rest of the inputs are of indirect types. On the other hand, agricultural machinery, diesel fuel, chemical fertilizers, biocides and electricity (which is mainly fossil-based in Iran) are non-renewable components of CEnC and CExC in corn production. Table 1 shows the specific equivalents of CEnC and CExC extracted from relevant references. These values for each input are obtained using work and heat interaction processes (EsmaeilpourTroujeni *et al.*, 2021; Yildizhan, 2018). Only inputs for which cost or energy are used were considered in this study, and other inputs and energies such as solar energy, energy received from air and soil, and microorganisms were excluded.

Table 1- CEnC and CExC equivalents of inputs and outputs in corn production system

Items		Specific CEnC		Specific CExC	
		Quantity	Reference	Quantity	Reference
Input	Diesel fuel	56.3 MJ lit^{-1}	(Erdal, Esengün, Erdal, & Gündüz, 2007)	53.2 MJ lit^{-1}	(KhojastehpourTroujeni *et al.*, 2018; Yildizhan, 2018)
	Electricity	12 MJ kWh^{-1}	(Ordikhani *et al.*, 2021)	4.17 MJ kWh^{-1}	(Amiri *et al.*, 2020)
	Nitrogen fertilizer (N)	76.14 MJ kg^{-1}	(Yilmaz, Akcaoz, & Ozkan, 2005)	32.7 MJ kg^{-1}	(Amiri *et al.*, 2020)
	Phosphate fertilizer (P_2O_5)	12.4 MJ kg^{-1}	(Yilmaz *et al.*, 2005)	7.52 MJ kg^{-1}	(Amiri *et al.*, 2020; EsmaeilpourTroujeni *et al.*, 2021)
	Potassium fertilizer (K_2O)	11.15 MJ kg^{-1}	(Ordikhani *et al.*, 2021)	4.7 MJ kg^{-1}	(Pelvan & Özilgen, 2017)
	Herbicides	120 MJ lit^{-1}	(Beheshti Tabar, Keyhani, & Rafiee, 2010)	32.7 MJ lit^{-1}	(EsmaeilpourTroujeni *et al.*, 2021)
	Pesticides	363.6 MJ lit^{-1}	(Kaab *et al.*, 2019)	7.52 MJ lit^{-1}	(Yildizhan & Taki, 2018)
	Fungicides	198 MJ lit^{-1}	(Yildizhan & Taki, 2018)	4.56 MJ lit^{-1}	(Yildizhan & Taki, 2018)
	Machinery	9 MJ kg^{-1} year^{-1}	(Kaab *et al.*, 2019)	7.1 MJ kg^{-1}	(Michalakakis, Fouillou, Lupton, Gonzalez Hernandez, & Cullen, 2021)
	Irrigation	0.00102 MJ kg^{-1}	(Yildizhan & Taki, 2018)	0.00425 MJ kg^{-1}	(Amiri *et al.*, 2020)
	Human labor	1.96 MJ h^{-1}	(Kaab *et al.*, 2019)	-	
	Corn seed	100 MJ kg^{-1}	(Kitani, 1999)	21.7 MJ kg^{-1}	(Juárez-Hernández *et al.*, 2019)
Output	Corn grain	18.3 MJ kg^{-1}	(Ptasinski, 2016)	21.7 MJ kg^{-1}	(Juárez-Hernández *et al.*, 2019)

One of the important indicators in evaluating energy consumption in the production of agricultural products is the ratio of output CEnC to input CEnC, ER (Equation (2)). This index is considered as a criterion for measuring energy usage efficiency in agricultural production systems (Yuan, Peng, Wang, & Man, 2018). The higher the index, the higher the efficiency of energy use (Ordikhani *et al.*, 2021). A value greater than 1 for this index indicates that the energy output of the production system is greater than CEnC (Banaeian & Zangeneh, 2011; Bhunia *et al.*, 2021; Mobtaker, Keyhani, Mohammadi, Rafiee, & Akram, 2010; Mousavi-Avval, Rafiee, Jafari, & Mohammadi, 2011b; Royan, Khojastehpour, Emadi, & Mobtaker, 2012; Gurdeep Singh *et al.*, 2021; Vlontzos *et al.*, 2014). Since only inputs for which energy or cost have been spent are considered, the value of this index can be higher than 1. Other important indicators that are used in the evaluation of energy consumption in agricultural systems include Energy Intensity (EI), Energy Productivity (EP), and Net Energy Gained (NEG), which are calculated using Equations (3), (4), and (5), respectively (Kaab *et al.*, 2019; Ordikhani *et al.*, 2021). EI and EP are the two contrasting indicators. EI shows the amount of CEnC used to produce one unit of product, which is mostly used in the perspective of industrial agriculture, while EP shows the amount of product per unit of CEnC, and is mostly used to compare the production system of different agricultural products. The higher the EP and the lower the EI, the more efficient the agricultural production process is in terms of energy consumption. NEG is equal to the output energy minus CEnC. When NEG is greater than zero, more energy has been produced than consumed. The higher this index is, the more efficient the production system is. A comprehensive study of all these indicators (ER, EP, and EI) is useful to compare and show the potential environmental impacts of agricultural production systems (Khan *et al.*, 2009).

$$Energy\ ratio\ (ER) = \frac{Equivalent\ energy\ produced\ (MJ\ ha^{-1})}{\text{Input CEnC}\ (MJ\ ha^{-1})} \quad (2)$$

$$\text{Energy intensity}\ (EI) = \frac{\text{Input CEnC}\ (MJ\ ha^{-1})}{Yield\ (kg\ ha^{-1})} \quad (3)$$

$$Energy\ productivity\ (EP) = \frac{Yield\ (kg\ ha^{-1})}{\text{Input CEnC}\ (MJ\ ha^{-1})} \quad (4)$$

$$\text{Cumulative net energy gain}(CNEnG) = Output\ \text{CEnC}\ (MJ\ ha^{-1}) - Input\ \text{CEnC}\ (MJ\ ha^{-1}) \quad (5)$$

In the current study, the cumulative exergy approach and obtained Cumulative Degree of Perfection (CDP), as well as renewability index were used to evaluate the renewability and sustainability of corn production processes and the efficiency of exergy consumption (Ahamed *et al.*, 2011; EsmaeilpourTroujeni *et al.*, 2021). The RI is the ratio of renewable resources to non-renewable resources. A higher value of RI means that the production system produces in a more renewable way (Hai *et al.*, 2023). In the calculation of exergy efficiency, all controllable and uncontrollable inputs are considered, while in CDP, only the controllable inputs are considered (EsmaeilpourTroujeni *et al.*, 2021). Since only controllable inputs are usually considered in agricultural systems, CDP is preferable. CDP is equal to the ratio of exergy obtained from the agricultural production system to the CExC of controllable inputs in the agricultural production system (Equation (6), (Ahamed *et al.*, 2011; EsmaeilpourTroujeni *et al.*, 2021)). Since in agricultural production systems, the produced crops are in equilibrium with the environment, the exergy of the crops is considered equal to their chemical exergy (KhojastehpourTroujeni *et al.*, 2018; Yildizhan, 2018). This index, together with the RI, provides a powerful tool for evaluating and comparing the harmful effects of production processes on the environment and is used as an index to monitor the level of environmental sustainability of the processes (EsmaeilpourTroujeni *et al.*, 2021).

$$\text{CDP} = \frac{\text{Exergy in products}\ ((\text{m} \times \text{b})_{\text{products}})}{\sum(m \times CExC)_{raw\ materials} + \sum(m \times CExC)_{fuels}} \quad (6)$$

Where, m represents mass, and b represents chemical exergy

The Renewability Index (RI) is used to determine the renewability of processes, evaluate the intensity of resource stress, and analyze the environmental impact of a production system. This index, which is obtained based on Equation (7) (KhojastehpourTroujeni *et al.*, 2018; Pelvan & Özilgen, 2017; Yildizhan & Taki, 2018), shows the 4 states of processes in terms of renewability. The negative value of this index indicates that the process is completely non-renewable, and the zero value indicates that the restoration work is equal to the amount of exergy produced in the system. Process renewability increases from zero until it reaches its highest value of 1, which represents a fully renewable process. In general, the higher the value of this index for a system, the lower its harmful effects on the environment (KhojastehpourTroujeni *et al.*, 2018; Yildizhan & Taki, 2018).

$$RI = \frac{E_{ch} - W_r}{E_{ch}} \tag{7}$$

Where, E_{ch} and W_r represent the chemical exergy of final products and restoration work, respectively.

Excessive exploitation of resources, especially non-renewable ones, can have harmful effects on the environment. In some cases when the effect is insignificant, nature can tolerate it and neutralize the risks caused by it. In the processing of resources, non-renewable energy sources are destroyed and restoring them to their initial states requires work (Berthiaume, Bouchard, & Rosen., 2001). This restoration work (W_r) is estimated by summing the net exergy consumption in the process and the net exergy consumption for waste treatment. In an agricultural crop production process, the exergy of all consumed non-renewable resources is calculated to estimate the restoration work (EsmaeilpourTroujeni *et al.*, 2021; Pelvan & Özilgen, 2017; Yildizhan & Taki, 2018, 2019).

Regression modeling

Regression analysis is a statistical method in which the relationship between two or more quantitative variables is used to predict a variable with the help of another variable or variables. In this study, regression method was used to investigate the relationship between energy consumption and cumulative exergy, and crop yield. For this purpose, the Cobb-Douglas function was chosen due to its simplicity, compatibility with physical logic, and generalization power. This function has been widely used in energy research (Banaeian & Zangeneh, 2011; Bhunia *et al.*, 2021; Mobtaker *et al.*, 2010; Mousavi-Avval *et al.*, 2011b; Royan *et al.*, 2012; Gurdeep Singh *et al.*, 2021; Vlontzos *et al.*, 2014). The best statistically significant estimates and the expected signs of the parameters are obtained from this function, which is expressed as Equations (8) and (9) (Mobtaker *et al.*, 2010).

$$Y = f(x)\exp(u) \tag{8}$$

$$LnY_i = a + \sum_{j=1}^{n} \propto_J lnX_{ij} + e_i \tag{9}$$

where, Y is the corn yield, X is the energy and exergy inputs used in the production processes, α is the coefficient of energy and exergy inputs, e is the error coefficient, and a is a constant value.

To change the inputs and their effects on the output, the returns to scale index was used. This index shows how much the output value changes for each unit increase in all input consumption. The sum of the regression coefficients obtained in the Cobb-Douglas equation indicates the returns to scale index; a value greater than 1 indicates increasing returns to scale, a value less than 1 signifies decreasing returns to scale, and a value equal to 1 denotes constant returns to scale (Mobtaker *et al.*, 2010).

Life Cycle Assessment (LCA)

LCA is a standard and widely used environmental assessment method for evaluating processes, products, and services. LCA is an analytical tool that assesses the environmental burden and impacts related to the entire life cycle of a product or process (extraction and processing of raw materials, manufacturing, distribution and use, and recycling or final disposal of all residuals of main and by-products). LCA is a "cradle to grave" approach to assess all inputs, outputs, and wastes of a product, process, or service, and their impacts on human health and the environment, and finally, interpret the assessment results throughout the entire life cycle (Ordikhani *et al.*, 2021; Prasad *et al.*, 2020). This method serves as an effective approach for assessing the impact of a process on various categories of environmental effects and assists managers in promoting the development of products with minimal adverse environmental impacts (Kaab *et al.*, 2019). A complete LCA is performed in four steps: 1- goal and scope definition, 2- life cycle inventory (LCI), 3- life cycle impact assessment (LCIA), and 4- interpretation of results (Prasad *et al.*, 2020). The purpose of the life cycle assessment in this study was to examine environmental impact groups per kilogram of corn product (as a functional unit). The studied impact categories were: Acidification (AC), Eutrophication (EP), Global Warming Potential (GWP), Ozone Layer Depletion (OLD), Human Toxicity (HT), Fresh Water Aquatic Ecotoxicity (FWAE), Marine Aquatic Ecotoxicity (MAE), Terrestrial Ecotoxicity (TE), and Photochemical Oxidation (PO).

In LCI, all the inputs, outputs, wastes, their amount, and the probable emissions to the environment in the corn production system were determined based on the functional unit (FU). The main inputs at this stage were diesel fuel, electricity, machinery, nitrogen fertilizer, phosphate fertilizer, potassium fertilizer, biocides, irrigation water, and infrastructures, whose environmental impacts were estimated based on existing standards (Finkbeiner, Inaba, Tan, Christiansen, & Klüppel, 2006). Accurate estimation of the amount of pollutants released into the soil, water, and air is challenging. Therefore, instead of measurement, emission factors of pollutants are often used to estimate the average emission of pollutants (Tzilivakis, Warner, May, Lewis, & Jaggard, 2005). Accordingly, the emission factors of pollutants caused by the use of inputs in agricultural production systems were obtained from relevant references (Brentrup, Küsters, Lammel, Barraclough, & Kuhlmann, 2004; IPCC, 2006; Nikkhah *et al.*, 2015; Ordikhani *et al.*, 2021).

The third stage (LCIA) includes the classification and characterization, normalization ranking, grouping, and weighting, of which the first two are mandatory, and the last three are optional. In the classification, impact category groups are defined, and then the released pollutants audited in the LCI stage are placed in the corresponding impact groups based on the type of pollutant released. Then, the coefficient or weight of each pollutant is applied for different impact categories. For this purpose, a characteristic factor is determined for each type of pollutant in the impact groups according to the functioning of the ecosystem (Brentrup *et al.*, 2004; A. Singh *et al.*, 2010). Finally, in the last stage of LCA, interpretation, the results obtained in LCI and LCIA are summarized, important issues are identified, and recommendations are given especially for reducing the harmful effects of hazardous pollutants (Arts, Ruijten, Aelst, Trullemans, & Sels, 2021; Ashby, 2013; Cao, 2017; Hernandez, Oregi, Longo, & Cellura, 2019; Kylili, Seduikyte, & Fokaides, 2018; Papapetrou & Kosmadakis, 2022; Prasad *et al.*, 2020). In the current study, the CML 2 baseline 2000 V2.05/universe technique was used to perform LCA in the Simapro 8.4.0.0. Software.

Data Envelopment Analysis (DEA)

DEA is a non-parametric method for estimating production functions based on a series of optimizations using linear programming (Adler, Friedman, & Sinuany-Stern, 2002). It is a powerful tool in the field of improving productivity and calculating the efficiency of Decision-Making Units (DMUs). This technique was used to evaluate the efficiency of farms in energy and exergy consumption in corn production, and based on this, the efficient amount of energy and exergy consumption was determined, while maintaining the current production level. In this method, DMUs (Adler *et al.*, 2002) can be made efficient in an input or output oriented manner. In the input-oriented mode, by maintaining the output level, the consumption of inputs is minimized, and in the output-oriented mode, by keeping the input values constant, the output value and production are maximized (Mousavi-Avval, Rafiee, Jafari, & Mohammadi, 2011a; Mousavi-Avval *et al.*, 2011b). The production of agricultural products relies on limited and scarce resources. Hence, in similar studies, the use of input-oriented DEA models has been preferred to reduce the inputs used in agricultural production systems (Chauhan, Mohapatra, & Pandey, 2006; Malana & Malano, 2006; Mohammadi *et al.*, 2014; Mousavi-Avval *et al.*, 2011a, 2011b). Therefore, in this research, the input-oriented method was used and the CExC of controllable inputs and corn grain yield were defined as input and output variables, respectively. Each farm was considered as a DMU and the two models of Constant Returns to Scale (CCR) and Variable Returns to Scale (BCC), were used as input-oriented models to calculate efficiency. In the constant returns to scale model, with one percent change in the input values, the outputs also change by one percent (decrease or increase), while in the variable returns to scale model, with one percent change in the inputs, the outputs change with different percentages (increase or decrease) (Mousavi-Avval *et al.*, 2011b; P. Singh, Singh, & Sodhi, 2019). The efficiency of using inputs in the CCR model is called Technical Efficiency (TE), and in the BCC model it is called Pure Technical Efficiency (PTE) (Gurdeep Singh *et al.*, 2021). Scale efficiency (SE) is calculated by dividing the TE by the PTE, and its value is at most 1. When SE is 1, it means that the farmer produces at the most efficient scale, and the TE and PTE of production are equal (Chauhan *et al.*, 2006; Malana & Malano, 2006; Mohammadi *et al.*, 2014; Mousavi-Avval *et al.*, 2011a, 2011b). DEA Solver software was used to calculate efficiency and analyze data.

Results and Discussion

Energy consumption and cumulative exergy

CEnC and CExC in grain corn production systems were calculated to be 68.9 and 29.6 GJ/ha, respectively. Also, CEnC and CExC for the production of one tonne of corn seeds were calculated as 6644 and 2854 MJ, respectively. The results are comparable with the energy consumption for silage corn production in Tehran province, Iran, which is 68.93 GJ ha^{-1} (Komleh Pishgar *et al.*, 2011). As a result of increasing agricultural mechanization and chemical use such as fertilizers, energy consumption for corn production in Iran is increasing and has reached 63.64 GJ ha^{-1}, from 40.98 GJ ha^{-1} in 2001 (Banaeian & Zangeneh, 2011). Electricity, diesel fuel, and nitrogen fertilizer have the largest share in CEnC with 57.58, 10.19, and 12.21%, respectively. In similar studies, diesel fuel, chemical fertilizers, and electricity used in irrigation have been reported as the main energy inputs in corn production (Banaeian & Zangeneh, 2011; Pishgar-Komleh, Keyhani, Mostofi-Sarkari, & Jafari, 2012; Yousefi, Mahdavi, & Mahmud, 2014). Fig. **2** shows the contribution of inputs in energy consumption and cumulative exergy of corn production. As can be seen from this figure in terms of CExC, electricity, diesel fuel, and nitrogen fertilizer are the highest exergy input to the system with 46.57, 22.41, and 12.21%, respectively.

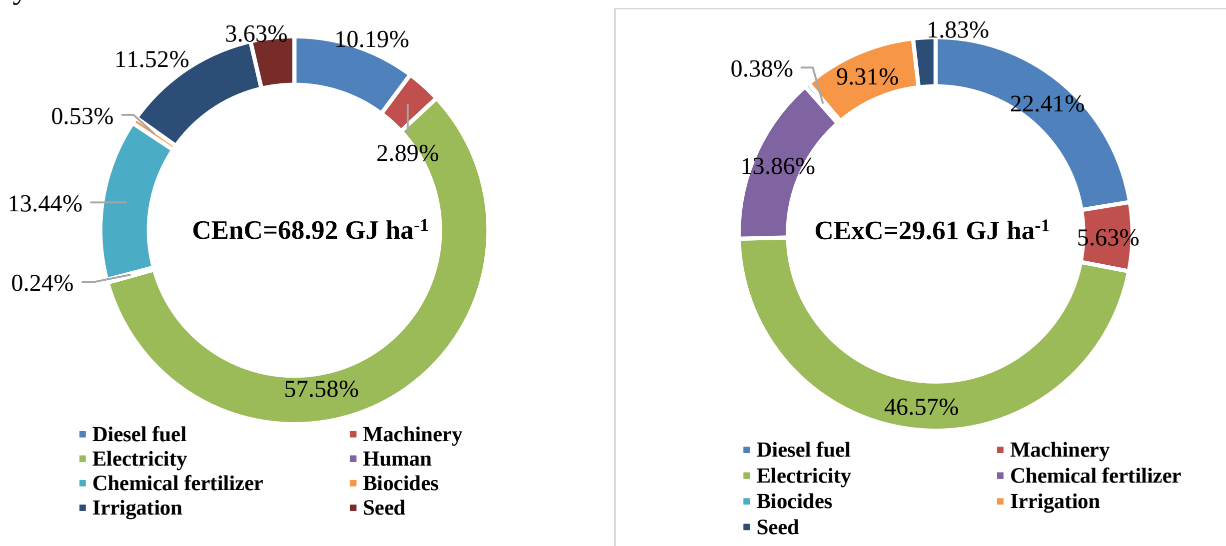

Fig. 2. Contribution of inputs in energy consumption and cumulative exergy in corn production

Autocorrelation of the data, used to estimate the relationship between energy inputs and corn yield, using the Cobb-Douglas production function, was tested by the Durbin-Watson statistic (Hatirli *et al.*, 2005; Mobtaker *et al.*, 2010). The value of this statistic for the model of CEnC and CExC was equal to 1.87 and 1.73, respectively, which shows that the autocorrelation of the data in both models is not significant (α= 5%). The regression results for the Cobb-Douglas model based on CEnC and CExC are shown in Table 2. The value of R^2 for Cobb-Douglas model estimated based on CEnC (model 1) was equal to 0.94, which shows that this model has the ability to predict and explain 94% of the yield changes by 6 inputs of electricity, labor, fuel, machinery, and phosphorus and nitrogen fertilizers. Among the inputs, electrical energy has the greatest effect on yield with a coefficient of 0.578, which means that with an increase of 1 unit of electricity consumed within the model's data range, corn yield increases by about 0.58 units. Phosphorus and nitrogen fertilizers are in the next ranks with coefficients of 0.242 and 0.228, respectively. The negative input coefficients for human energy and nitrogen fertilizer indicate that increasing the consumption of each megajoule of these inputs, based on the analyzed regional data, will lead to a decrease in corn yield by 0.24 units for human energy and 0.06 units for nitrogen fertilizer. In agricultural production modeling studies, machinery, irrigation (electricity), chemical fertilizers, and labor were reported as determining inputs in modeling and explaining yield changes (Hatirli, Ozkan, & Fert, 2006; Mobtaker *et al.*, 2010). The calculated sum of the coefficients for the CEnC-based model reached approximately 0.93, indicating that the yield in the studied area reflects diminishing returns to scale regarding CEnC. Model 2, which was obtained based on CExC, shows that about 94% (R^2) of yield changes can be explained by changes in 5 inputs of diesel fuel, electricity, nitrogen fertilizer, phosphate fertilizer, and biocides. Exergy consumption of inputs of fuel, electricity, and phosphorus fertilizer, respectively, has the greatest impact on corn production yield. The exergy of nitrogen fertilizer in this model has a negative coefficient, and it shows that the yield will decrease with the increase of exergy input of nitrogen fertilizer.

Table 2- Estimated coefficients of corn production function based on Cobb-Douglas function

Independent variables	**Coefficient (α)**	**Sig**
Model 1 (CEnC): $\ln Y_i = a_0 + a_1 lnX_{1i} + a_2 lnX_{2i} + a_3 lnX_{3i} + a_4 lnX_{4i} + a_5 lnX_{5i} + a_6 lnX_{6i} + e_i$		
Constant	0.737	0.037
Electricity	0.578	0.000
Phosphate fertilizer	0.242	0.000
Fuel	0.185	0.015
Labor	-0.242	0.000
Machinery	0.228	0.001
Nitrogen fertilizer	-0.065	0.009
Durbin-Watson	1.87	
R^2	0.941	
Returns to scale	0.926	
Model 2 (CExC): $\ln Y_i = a_1 lnX_{1i} + a_2 lnX_{2i} + a_3 lnX_{3i} + a_4 lnX_{4i} + a_5 lnX_{5i} + e_i$		
Fuel	0.469	0.000
Electricity	0.403	0.000
Nitrogen fertilizer	-0.103	0.000
Phosphate fertilizer	0.284	0.000
Pesticides	0.007	0.001
Durbin-Watson	1.73	
R^2	0.938	
Returns to scale	1.06	

Investigating the efficiency of corn production

To optimize the corn production system and determine efficient and inefficient fields based on input and output exergy values using the DEA method, all 214 farms were considered as DMUs, and the input-output exergy for all farms was analyzed based on input-oriented constant returns to scale (CCR-I) and input-oriented variable returns to scale (BCC-I) models. The efficiency results of corn production fields in terms of CExC based on CCR-I and BCC-I models are shown in Table 3. In terms of CExC in the CCR model, about 57% of corn production farms are technically inefficient, and 92 of the 214 surveyed farmers are technically efficient in this model, which shows that the activity of these farmers is constant returns to scale, and operate at the optimal scale of performance. The average efficiency of all farms in the CCR model is 94.7% and the most inefficient farm has a technical efficiency of 74.3%. The obtained efficiency values show that many of the farms in the studied area are significantly inefficient in terms of exergy consumption and do not use inputs correctly and efficiently or do not use the appropriate production methods. In the BCC model, the average efficiency is 97.8%, and 51.87% of farms have pure technical efficiency. Nearly all inefficient farms experience diminishing returns to scale, meaning that each additional unit of exergy input results in less than a one-unit increase in exergy output. Therefore, increasing the use of inputs does not increase exergy efficiency, and in the current method of corn production, inputs are used more than the optimal amount. Understanding the returns to scale associated with redistributing inputs among farms can significantly enhance performance outcomes (Chauhan *et al.*, 2006; Mousavi-Avval *et al.*, 2011a). The SE of farms was 0.968. The units were ranked based on the efficiency values obtained, so that the higher the efficiency value, the higher the farm ranked. One of the valid methods for ranking the efficient units is the benchmarking method, in which an efficient unit is ranked highly if it appears frequently in the reference sets of inefficient DMUs. The information of these DMUs can be used to determine the amounts of inputs used in inefficient units (Adler *et al.*, 2002; Mousavi-Avval *et al.*, 2011a). In this study, the 10 efficient farms with the highest values were DMUs No. 5, 74, 60, 50, 214, 12, 111, 8, 152, and 22, which appeared 55, 53, 39, 37, 36, 23, 20, 20, 19, and 18 times, in the CCR model reference set, respectively.

Table 3- The overall results of the input-oriented DEA method for CExC

Model	Average efficiency	The lowest efficiency	Number of inefficient units	Number of efficient units	Number of reference units
CCR	0.947±0.0683	0.743	122 (57.01%)	92 (42.99%)	16
BCC	0.978±0.0389	0.787	103	111	19
Scale Efficiency	0.968±0.0459	0.946	-	-	-

The highest CExC saving was related to diesel fuel and nitrogen fertilizer with about 1407 (21.21%) and 902 (24.95%) MJ ha^{-1}, respectively. However, the highest percentage of saving in CExC was related to potassium and phosphate fertilizers with 66.51 (34.51 MJ ha^{-1}) and 46.02% (201.70 MJ ha^{-1}), respectively. This shows that inputs, especially potassium and phosphate fertilizers, are used more than required.

The values of CExC and its components based on the input-oriented fixed and variable returns to scale model are shown in Fig. **3**. Based on the analysis of CCR and BCC models, it is possible to reduce the exergy consumption of all inputs in these two models while maintaining the production level. Based on the results of the CCR model and the target values obtained, savings of 6.47, 10.42, 7.40, 13.32, 31.29, 3.25, and 78.6% can be achieved in the exergy consumption of diesel fuel, electricity, machinery, chemical fertilizers, biocides, seeds, and irrigation, respectively, while maintaining the current level of corn production yield. These values in the BCC model were 3.28, 7.22, 5.41, 6.64, 15.31, 1.12, and 6.04%, respectively. The CExC target value, based on the CCR model analysis, is 26833.5 MJ/ha, which represents 2776.6 MJ ha^{-1} (9.38%) of exergy saving. The highest amount of cumulative exergy savings based on the pure technical efficiency model with 1437.2, 484.8, and 429.4 MJ ha^{-1} is related to electricity, nitrogen fertilizer, and diesel fuel, respectively. Meanwhile, the highest percentage of exergy savings of 31.64, 31.29, and 13.41% was related to phosphate fertilizer, biocides, and nitrogen fertilizer, respectively. This suggests an overutilization of inputs within the production system. In face-to-face interviews, most of the farmers believed that the increase in inputs increased the yield, and on this basis, they use more inputs to increase production without improving the production methods. Excessive irrigation and low efficiency of water pumping systems in the study area have led to an increase in the consumption of more than the required amount of water in corn production, which, in addition to wasting water and electricity, often aggravates drainage problems, and reduces soil quality (Mousavi-Avval *et al.*, 2011b; Singh, Gursahib Singh, & Singh, 2004). The lowest percentage of saving in exergy consumption is related to seed input (1.12%), which shows that the farmers of the region use seeds more efficiently than other inputs. The DEA analysis, along with the insights from the reference set and the findings depicted in Fig. **3**, provides valuable recommendations for inefficient farms. By adopting the superior operational practices employed by the reference farms of their peers, these less efficient farms can reduce exergy consumption to align with the target values identified through the DEA method, all while sustaining their current yield levels.

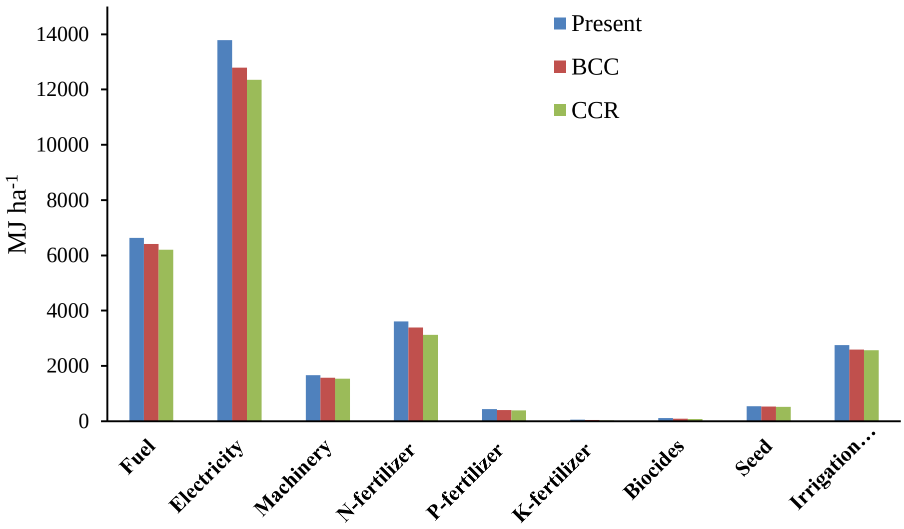

Fig. 3. CExC values of different inputs in the current mode, BCC, and CCR models

Energy, exergy, and environmental indicators

Table 4 shows the values of energy and exergy evaluation indices in the current condition (default), and optimal states based on CCR and BCC models. According to DEA analysis, it is possible to reduce CEnC and CExC by 9.76 and 9.38%, respectively, while maintaining the current production level, by optimally using inputs and improving management and promoting methods used by efficient farms (reference set). The ER index shows that the total system energy output is

2.75 times higher than CEnC. Also, in general, the studied system produces about 121 GJ ha^{-1} of energy (Cumulative Net Energy Gain-CNEnG). As mentioned before, in the analysis of energy and exergy in a production system of agricultural crops (Cumulative net energy gain), only inputs for which costs and energy have been spent are considered. For this reason, ER and CNEnG can be greater than one and zero, respectively. EI and EP indices show that 6.64 MJ of energy is consumed to produce each kilogram of corn, or in other words, about 0.15 kg of corn is produced for each MJ of energy consumed. In similar studies in Iran, ER for corn production has been reported as 4.78 (Pishgar-Komleh *et al.*, 2012), 1.69 to 2.17 (Banaeian & Zangeneh, 2011), and 2.67 (Yousefi, Mahdavi, *et al.*, 2014). Based on the optimization results, an improvement of about 11% in the ER and EP indices of the corn production system is possible only based on following the way of input management by efficient units. CDP, which is often used to check the efficiency of exergy consumption and system stability, was obtained around 7.6. This index for different types of corn production systems in Mexico has been calculated from 1.6 to 1.14 (Juárez-Hernández *et al.*, 2019). The obtained CDP is also higher than that of some agricultural products such as wheat (2.9, (Yildizhan & Taki, 2019)), black tea (0.43, (Pelvan & Özilgen, 2017), rapeseed (2.19, (EsmaeilpourTroujeni *et al.*, 2021)), and strawberry (0.29, (Yildizhan, 2018)), which is mostly due to the high yield and higher exergy output of corn in this study. The larger these indicators are, the more stable the production system and the less environmental consequences. The RI of about 0.87 in this study shows that corn production is a relatively renewable process. The obtained RI index is higher than that of other agricultural products in similar studies (EsmaeilpourTroujeni *et al.*, 2021; Pelvan & Özilgen, 2017; Yildizhan & Taki, 2018, 2019), which is mainly due to the higher output exergy in the corn production system.

Optimum use of non-renewable inputs, especially electricity, diesel fuel, and chemical fertilizers, increases the process's RI. As shown in Figure 2, the highest CExC belongs to these three inputs, which are produced from non-renewable sources.

Table 4- Energy and exergy evaluation indicators in default scenario and optimized scenarios

Items	Unit	Current	CCR		BCC	
			Target	Change (%)	Target	Change (%)
CEnC	MJ ha^{-1}	68924.7	62200.5	-9.76	64537.7	-6.36
ER	-	2.75	3.05	+10.81	2.94	+6.80
EI	MJ kg^{-1}	6.64	5.99	-9.76	6.22	-6.36
EP	kg MJ^{-1}	0.150	0.167	+10.81	0.161	+6.80
CNEnG	MJ ha^{-1}	120923.3	127653.5	+5.56	125316.2	+3.63
DCEnC[a]	MJ ha^{-1}	46867.7 (68.00%)	42266.5 (67.95%)	-9.82	43762.9 (67.81%)	-6.63
ICEnC[b]	MJ ha^{-1}	22057.0 (32.00%)	19934.0 (32.05%)	-9.63	20774.8 (32.19%)	-5.81
RCEnC[c]	MJ ha^{-1}	2662.7 (3.86%)	2570.5 (4.23%)	-3.46	2627.6 (4.07%)	-1.32
NRCEnC[d]	MJ ha^{-1}	66261.9 (96.14%)	59629.9 (95.87%)	-10.01	61910.2 (95.93)	-6.57
CExC	MJ ha^{-1}	29610.0	26833.5		27843.1	
CDP	-	7.60	8.40	+10.35	8.09	+6.35
RI	-	0.871	0.883	+1.41	0.879	+0.90
DCExC[e]	MJ ha^{-1}	20424.6 (68.98%)	18557.9 (69.16%)	-9.24	19210.4 (68.99%)	-05.95
ICExC[f]	MJ ha^{-1}	9185.5 (31.02%)	8275.5 (30.84%)	-9.91	8632.7 (31.01%)	-6.02
RCExC[g]	MJ ha^{-1}	542.5 (1.83%)	524.87 (1.97%))	-3.25	536.4 (1.93%))	-1.12
NRCExC[h]	MJ ha^{-1}	29067.5 (98.17%)	26308.6 (98.04%)	-9.49	27306.7 (98.07%)	-6.06

[a] Direct CEnC, [b] Indirect CEnC, [c] Renewable CEnC, [d] Non- renewable CEnC, [e] Direct CExC, [f] Indirect CExC, [g] Renewable CExC, and [h] Non-renewable CExC

Therefore, their optimal use increases the renewable index. Supplying input from renewable sources will also increase the sustainability and renewability of the system.

Based on the analysis of DEA method, CDP and RI can be improved by about 10.3% and 1.4%, respectively, with optimal and appropriate use of inputs based on existing conditions and facilities. By increasing the efficiency of irrigation and water pumping systems, an effective step can be taken in reducing electricity consumption, which is the main exergy input, and of course increase exergy efficiency. The conventional tillage system in corn production in Iran involves the intensive use of energy-intensive tillage machines such as moldboard plow and deep tillage tolls.

This has caused an increase in the use of agricultural machinery and diesel fuel. As reported in several studies, conservation tillage methods reduce the use of agricultural machinery and reduce fuel consumption compared to conventional tillage (Filipovic, Kosutic, Gospodaric, Zimmer, & Banaj, 2006; Ordikhani *et al.*, 2021). Also, the use of better machinery management techniques can reduce diesel fuel consumption and its harmful effects on the environment (Mousavi-Avval *et al.*, 2011a).

As can be seen from Table 4, the main components of energy consumption and cumulative exergy in the corn production system are direct and non-renewable types of energy. The share of about 96% of non-renewable energies in CEnC and 98% in CExC has caused the strong dependence of corn production on non-renewable resources. In many similar studies, the ratio of DCExC and DCEnC is higher than that of ICEnC and ICExC, and the ratio of NRCEnC and NRCExC is much higher than that of RCEnC and RCExC (Erdal *et al.*, 2007; EsmaeilpourTroujeni *et al.*, 2021; Juárez-Hernández *et al.*, 2019; Mousavi-Avval *et al.*, 2011a; Ordikhani *et al.*, 2021; Rahman & Hasan, 2014; Yildizhan & Taki, 2018). The agricultural production system based on the intensive use of non-renewable resources is not sustainable in the long term and has harmful consequences on human health and the environment (Khan, Khan, Hanjra, & Mu, 2009). Electricity is the main component of CEnC and CExC in the production of corn (to pump water and irrigate fields) and its production in Iran is mainly based on non-renewable fossil resources (Anonymous, 2018). Using renewable electricity instead of fossil electricity in corn production processes like other processes can be one of the ways to reduce environmental consequences and increase RI.

In Iran, mainly due to the lack of economic competition with fossil fuels, renewable energy sources, except for hydropower plants, are still not developed much. However, in recent years, efforts and plans have been made to promote the use of renewable resources for energy production. For example, the production of electricity from wind has increased in recent years, and efforts are underway to make more use of solar energy. It is expected that the share of energy from renewable sources in electricity production in Iran will increase in the future (Anonymous, 2018). Also, promising researches have been conducted on harnessing wind (Jalalvand, Bakhoda, & Almassi, 2014) and solar energy (Parvaresh Rizi & Ashrafzadeh, 2018; Shojaei & Akhavan, 2020) for water pumping, that accounts for the majority of electricity consumption in agriculture. Animal manures and organic fertilizers are currently used commercially in Iran's agricultural sector, and in the past few years, the production of animal manures has increased as a result of the increase in livestock and poultry farms. This way, the renewability index in the default scenario increases to 0.93 and according to the CCR model, it increases to about 0.94. Another suggestion to increase the renewability of the system is to use renewable fuels such as biodiesel instead of diesel and organic fertilizers instead of chemical fertilizers (EsmaeilpourTroujeni *et al.*, 2021; Khan *et al.*, 2009; Mousavi-Avval *et al.*, 2011a; Soltanali, Nikkhah, & Rohani, 2017).

Life cycle assessment

Life cycle assessment based on default (current) values, and optimized values based on BCC model and CCR model was performed, and the results were compared. Natural resources like minerals and fossil fuels are classified as abiotic resources. However, the extraction of these resources often leads to their depletion. Energy production is one of the biggest and most important consumers of natural resources and one of the main factors of consumption and depletion of abiotic resources (Milà I Canals, Burnip, & Cowell, 2006). In agricultural production, the depletion of minerals such as phosphate and potash, alongside fossil fuels, are among the most important subsets of the Abiotic Depletion (AD). From Table 5, it can be seen that to produce one kilogram of corn, 9.513 g Sb *eq* is discharged from abiotic resources. Based on the results of the DEA model, by optimizing input consumption, there is a potential of 10.38% reduction in the effects of depletion of abiotic resources caused by corn production with the current facilities and conditions in the study area. Fig. **4** shows the contribution of the corn production system inputs in the impact categories. About 91% of the "abiotic depletion" category is due to electricity consumption, followed by diesel fuel and chemical fertilizers. Therefore, increasing the efficiency of electrical systems in pumping irrigation water, as well as the use of electricity from renewable sources, is very effective in reducing the depletion of abiotic resources. In a study that assessed the life cycle of the wheat production system, electricity, diesel fuel, and chemical fertilizers were reported as the most important consumers of abiotic resources (Houshyar & Grundmann, 2017).

Acidification, particularly in the form of acid rain, negatively affects terrestrial or aquatic ecosystems (Jacob-Lopes, Zepka, & Deprá, 2021). According to Table 5, the "Acidification" potential is 0.019 g SO_2 eq per 1 kg of corn production. The highest acidification potential due to corn production is related to electricity and on-farm emissions, respectively, which are responsible for about 98% of the total acidification potential. The potential of acidification due to the production of 1 kg of corn based on the optimized values of BCC and CCR models was found to be 17.76 and 17.06 g SO_2 eq, respectively, which shows a reduction of 7.06 and 10.71 percent, respectively.

Enrichment of water environments with dissolved compounds that leads to excessive growth of some living organisms is called eutrophication. In fact, eutrophication is the response of the ecosystem to the excessive increase of natural or artificial substances in a terrestrial or aquatic environment (Houshyar & Grundmann, 2017). The eutrophication potential for the production of each kilogram of corn is about 3.73 g PO_4^{3-} eq. On-farm emissions, mainly due to the loss of chemical fertilizers, especially nitrogen, are responsible for 89.42% of eutrophication. An effective way to reduce eutrophication is to minimize losses of nitrogen and phosphate fertilizers (Bechmann & Stålnacke, 2005; Houshyar & Grundmann, 2017). Life cycle assessment based on DEA model values showed that there is a potential to reduce eutrophication effects by 8.38%.

Table 5- Values of the environmental impacts for 1 kg of corn production

Impact category	Unit	Current condition	BCC model		CCR model	
			BCC	Change (%)	CCR	Change (%)
Abiotic depletion	kg Sb eq	0.009513	0.008844	-7.03248	0.008526	-10.38
Acidification	kg SO_2 eq	0.019105	0.017757	-7.05574	0.017059	-10.71
Eutrophication	kg PO_4^{3-} eq	0.003727	0.003571	-4.18567	0.003398	-8.83
Global warming (GWP100)	kg CO_2 eq	1.36434	1.272863	-6.70485	1.227315	-10.04
Ozone layer depletion	kg CFC-11 eq	1.58E-09	1.46E-09	-7.59494	1.34E-09	-15.19
Human toxicity	kg 1,4-DB eq	0.391071	0.333648	-14.6835	0.321487	-17.79
Fresh water aquatic ecotoxicity	kg 1,4-DB eq	0.095594	0.089181	-6.70858	0.085796	-10.25
Marine aquatic ecotoxicity	kg 1,4-DB eq	304.9183	282.9338	-7.20996	273.1014	-10.43
Terrestrial ecotoxicity	kg 1,4-DB eq	0.002271	0.001815	-20.0793	0.001725	-24.04
Photochemical oxidation	kg C_2H_4 eq	0.000685	0.000635	-7.29927	0.000613	-10.51

Global warming is one of the harmful effects of greenhouse gases, which has led to an increase in the Earth's average temperature and ocean levels. The capacity of gases in absorbing and trapping solar radiation is not the same, and it is evaluated relative to the potential of 1 kg of CO_2 over a period of 100 years. Hence, the global warming potential of a greenhouse gas is expressed in terms of kg carbon dioxide equivalent (kg CO_2 eq). The main cause of the ozone layer depletion is the chemicals produced by human activities, which are called Ozone-Depleting Substances (ODS). As can be seen from Figure 4, electricity has the highest load on GWP with 83.12%, followed by on-farm emissions and diesel fuel with a share of 9.72% and 4.55%, respectively. Diesel fuel, biocides, and chemical fertilizers have the highest load on OLD with 42.67, 31.50, and 17.78%, respectively, and the share of electricity is insignificant (less than 1%). Diesel fuel and on-farm emissions, which are mostly due to the consumption of diesel fuel in agricultural machinery, and chemical fertilizers and biocides, are major contributors to GWP and OLD. Tillage is the main consumer of diesel fuel, followed by harvesting. In the study of the impact of wheat production system on global warming, the most effective factor was fuel consumption in plowing, planting, and harvesting operations (Fallahpour, Aminghafouri, Ghalegolab Behbahani, & Bannayan, 2012; Houshyar & Grundmann, 2017). Optimizing tillage operations and optimal use of plowing tools will reduce fuel consumption and thus reduce its impact on GWP (Lovarelli, Bacenetti, & Fiala, 2017). The results show that the GWP of 1 kg of corn production is about 1.346 kg CO_2 eq. However, based on the findings of DEA, with the optimal use of available resources through the pursuit of efficient farms in the study area (reference group), it is possible to reduce the GWP of corn production by 10.04%. This way, a 15.19 percent reduction in the load on OLD is also achieved.

Another major impact category is photochemical oxidation, which is a dangerous chemical air pollutant that causes various problems such as eye irritation and damage to some materials and products. This phenomenon mostly occurs in the presence of emissions from the combustion of fossil fuels, sunlight, and low humidity (Baumann & Tillman, 2004). The production of 1 kg of corn may cause a photochemical oxidation potential of 0.685 g C_2H_4 eq, 98% of which is due to the use of electricity (Fig. **4**). Life cycle assessment based on optimized values using DEA showed that there is a potential to reduce 10.51% of the potential of photochemical oxidation caused by corn production through optimizing the input consumption of inefficient farms.

In toxicity categories that include Human Toxicity (HT), Fresh Water Aquatic Eco-toxicity (FWAE), Marine Aquatic Eco-toxicity (MAE), and Terrestrial Eco-toxicity (TE), electricity is one of the most influential inputs. The share of electricity in the MAE impact category is about 99%. In the TE category, on-farm emissions have the highest share with 51.09%, while in the BCC and CCR models, its share decreases to 42.83% and 41.86%, respectively, but the share of electricity increases. The contribution of inputs in different subcategories of toxicity impact category is shown in Fig. **5**. The DEA results show that with the optimal use of inputs, 10.25 to 24.05% of the effects of toxicity categories caused by corn production can be reduced.

The comparison of the normalized environmental effects of producing 1 kg of corn under current conditions (default scenario) and the optimized values using the input-oriented BCC and CCR models based on the CML 2 baseline 2000 V2.05 / Netherlands, 1997 model is shown in Fig. **5**. It can be seen that corn production has the highest load on MAE, AC, and FWAE impact categories, respectively, while the lowest load is on OLD. This figure also shows that the DEA method can reduce all environmental impact categories by 9% to 24% by optimizing inputs.

Conclusion

Relatively high yield of corn and higher exergy output in the corn production system have led to the achievement of a production system with efficient exergy consumption (CDP=7.6). Additionally, according to the obtained RI index (0.87), in general, the corn production process in the study area is relatively renewable. However, it can be improved by optimal use of inputs, especially non-renewable inputs such as electricity, diesel fuel, and chemical fertilizers. Electricity is the main component of CEnC and CExC in corn production, and replacing non-renewable sources of electricity with renewable sources can lead to reduced environmental consequences and improved energy indicators. Other important inputs affecting the renewability and sustainability of the corn production system, which must be used very carefully and efficiently, are diesel fuel and chemical fertilizers.

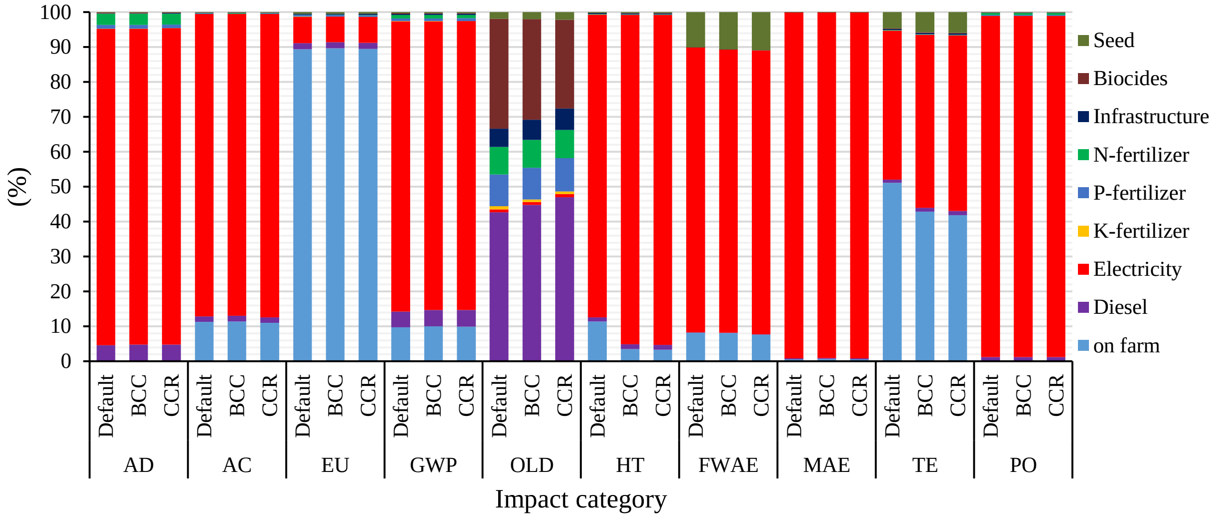

Fig. 4.The contribution of inputs in different impact categories in corn production system

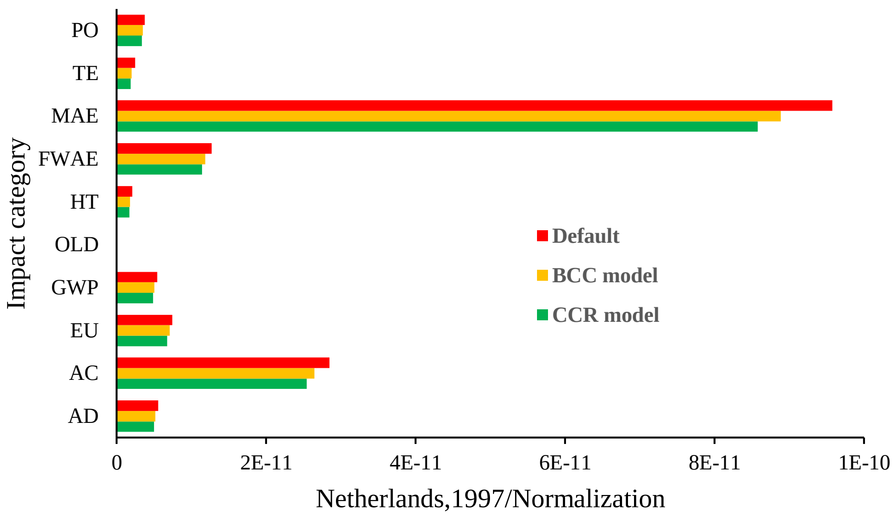

Fig. 5. Comparison of environmental impact categories of 1 kg of corn production in three scenarios (Method: CML 2 baseline 2000 V2.05/the Netherlands,1997/Normalization)

DEA is an effective method for finding efficient farms and recommending best practices aimed at minimizing exergy consumption to meet specified targets. Results showed that the average efficiency of all farms in terms of CExC in CCR and BCC models was 94.7 and 97.8%, respectively. Based on the DEA results, it was possible to save 6.47, 10.42, 7.40, 13.32, 31.29, 3.25, and 78.6%, respectively, in the exergy consumption of diesel fuel, electricity, machinery, chemical fertilizers, biocides, seeds, and irrigation, while maintaining the current yield level, only by promoting methods used by efficient farms. Consequently, CEnC and CExC have decreased by 9.76 and 9.38%, respectively. Furthermore, there was a potential for reductions of about 10, 17, 8, 10, and 11% respectively in the impact categories of “depletion of abiotic resources”, “acidification”, “eutrophication”, “GWP”, and “photochemical oxidation”. The improvement of ER, EP, CDP, and RI energy indices was also about 11, 11, 10.3, and 1.4%, respectively.

Acknowledgments

The authors would like to thank Shahid Chamran University of Ahvaz and the financial support of the Vice Chancellor for Research and Technology of Shahid Chamran University of Ahvaz in the form of a fund (SCU.AA1403.26966).

Conflicts of interest/Competing interests

The authors declare they have no financial interests.

Availability of data and materials

The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

Authors Contribution

M. Soleymani: Responsible for conceptualization, Methodology, Analysis, and Writing the manuscript

A. Asakereh: Provided technical advice and guidance throughout the research process and assisted with exergy and environmental analysis

M. Safaieenejad: Responsible for Study design, and Data collection

References

1. Adler, N., Friedman, L., & Sinuany-Stern, Z. (2002). Review of ranking methods in the data envelopment analysis context. In *European Journal of Operational Research*, *140*, 249-265. North-Holland. https://doi.org/10.1016/S0377-2217(02)00068-1
2. Ahamed, J. U., Saidur, R., Masjuki, H. H., Mekhilef, S., Ali, M. B., & Furqon, M. H. (2011). An application of energy and exergy analysis in agricultural sector of Malaysia. *Energy Policy*, *39*(12), 7922-7929. https://doi.org/10.1016/j.enpol.2011.09.045
3. Al-Ghandoor, A., & Jaber, J. O. (2009). Analysis of energy and exergy utilisation of Jordan’s agricultural sector. *International Journal of Exergy*, *6*(4), 491-508. https://doi.org/10.1504/IJEX.2009.026674
4. Alam, M. S., Alam, M. R., & Islam, K. K. (2005). Energy Flow in Agriculture: Bangladesh. *American Journal of Environmental Sciences*, *1*(3), 213–220. https://doi.org/10.3844/ajessp.2005.213.220
5. Amiri, Z., Asgharipour, M., Campbell, D. E., & Armin, M. (2020). Extended exergy analysis (EAA) of two canola farming systems in Khorramabad, Iran. *Agricultural Systems*, *180*, 102789. https://doi.org/10.1016/j.agsy.2020.102789
6. Anonymous. (2018). *Energy Balance Sheet of Iran*. Tehran: Iran Ministry of Energy Deputy of Electricity and Energy Affairs.
7. Apazhev, A. K., Fiapshev, A. G., Shekikhachev, I. A., Khazhmetov, L. M., Khazhmetova, A. L., & Ashabokov, K. K. (2019). Energy efficiency of improvement of agriculture optimization technology and machine complex optimization. In *E3S Web of Conferences* (Vol. 124, p. 05054). EDP Sciences. https://doi.org/10.1051/e3sconf/201912405054

8. Arts, W., Ruijten, D., Aelst, K. Van, Trullemans, L., & Sels, B. (2021). The RCF biorefinery: Building on a chemical platform from lignin. *Advances in Inorganic Chemistry*, 77, 241-297. https://doi.org/10.1016/BS.ADIOCH.2021.02.006
9. Ashby, M. F. (2013). Eco-audits and eco-audit tools. *Materials and the Environment*, 175-191. https://doi.org/10.1016/B978-0-12-385971-6.00007-5
10. Banaeian, N., & Zangeneh, M. (2011). Study on energy efficiency in corn production of Iran. *Energy*, *36*(8), 5394-5402.
11. Baumann, H., & Tillman, A. M. (2004). *The Hitch Hiker's Guide to LCA. An orientation in life cycle assessment methodology and application*. *Studentlitteratur Lund*. Studentlitteratur AB.
12. Bechmann, M., & Stålnacke, P. (2005). Effect of policy-induced measures on suspended sediments and total phosphorus concentrations from three Norwegian agricultural catchments. *Science of the Total Environment*, *344*(1-3 SPEC. ISS.), 129-142. https://doi.org/10.1016/j.scitotenv.2005.02.013
13. Beheshti Tabar, I., Keyhani, A., & Rafiee, S. (2010, February). Energy balance in Iran's agronomy (1990-2006). *Renewable and Sustainable Energy Reviews*. Pergamon. https://doi.org/10.1016/j.rser.2009.10.024
14. Berthiaume, R., Bouchard, C., & Rosen., M. A. (2001). Exergetic evaluation of the renewability of a biofuel. *Exergy, An International Journal*, *1*(4), 256-268.
15. Bhunia, S., Karmakar, S., Bhattacharjee, S., Roy, K., Kanthal, S., Pramanick, M., …, & Mandal, B. (2021). Optimization of energy consumption using data envelopment analysis (DEA) in rice-wheat-green gram cropping system under conservation tillage practices. *Energy*, *236*, 121499. https://doi.org/10.1016/j.energy.2021.121499
16. Bösch, M. E., Hellweg, S., Frischknecht, M. A. J., & Huijbregts, R. (2007). Applying cumulative exergy demand (CExD) indicators to the ecoinvent database. *The International Journal of Life Cycle Assessment*, *12*(181).
17. Brentrup, F., Küsters, J., Lammel, J., Barraclough, P., & Kuhlmann, H. (2004). Environmental impact assessment of agricultural production systems using the life cycle assessment (LCA) methodology II. The application to N fertilizer use in winter wheat production systems. *European Journal of Agronomy*, *20*(3), 265-279. https://doi.org/10.1016/S1161-0301(03)00039-X
18. Cao, C. (2017). Sustainability and life assessment of high strength natural fibre composites in construction. *Advanced High Strength Natural Fibre Composites in Construction*, 529-544. https://doi.org/10.1016/B978-0-08-100411-1.00021-2
19. Chauhan, N. S., Mohapatra, P. K. K. J., & Pandey, K. P. (2006). Improving energy productivity in paddy production through benchmarking—An application of data envelopment analysis. *Energy Conversion and Management*, *47*(9-10), 1063-1085. https://doi.org/10.1016/j.enconman.2005.07.004
20. Dincer, I., & Cengel, Y. A. (2001). Energy, entropy and exergy concepts and their roles in thermal engineering. *Entropy*, *3*(3), 116-149. https://doi.org/10.3390/e3030116
21. Erdal, G., Esengün, K., Erdal, H., & Gündüz, O. (2007). Energy use and economical analysis of sugar beet production in Tokat province of Turkey. *Energy*, *32*(1), 35-41. https://doi.org/10.1016/j.energy.2006.01.007
22. EsmaeilpourTroujeni, M., Rohani, A., & Khojastehpour, M. (2021). Optimization of rapeseed production using exergy analysis methodology. *Sustainable Energy Technologies and Assessments*, *43*, 100959. https://doi.org/10.1016/j.seta.2020.100959
23. Fallahpour, F., Aminghafouri, A., Ghalegolab Behbahani, A., & Bannayan, M. (2012). The environmental impact assessment of wheat and barley production by using life cycle assessment (LCA) methodology. *Environment, Development and Sustainability*, *14*(6), 979-992. https://doi.org/10.1007/s10668-012-9367-3
24. Filipovic, D., Kosutic, S., Gospodaric, Z., Zimmer, R., & Banaj, D. (2006). The possibilities of fuel savings and the reduction of CO_2 emissions in the soil tillage in Croatia. *Agriculture, Ecosystems and Environment*, *115*(1-4), 290-294. https://doi.org/10.1016/j.agee.2005.12.013
25. Finkbeiner, M., Inaba, A., Tan, R. B. H., Christiansen, K., & Klüppel, H. J. (2006, January). The

new international standards for life cycle assessment: ISO 14040 and ISO 14044. *International Journal of Life Cycle Assessment*. Springer. https://doi.org/10.1065/lca2006.02.002
26. Gezer, I., Acaroğlu, M., & Haciseferoğullari, H. (2003). Use of energy and labour in apricot agriculture in Turkey. *Biomass and Bioenergy*, *24*(3), 215-219. https://doi.org/10.1016/S0961-9534(02)00116-2
27. Gurdeep Singh, P., Sodhi, G. P. S., & Tiwari, D. (2021). Energy auditing and data envelopment analysis (DEA) based optimization for increased energy use efficiency in wheat cultivation (*Triticum aestium* L.) in north-western India. *Sustainable Energy Technologies and Assessments*, *47*, 101453. https://doi.org/10.1016/j.seta.2021.101453
28. Hai, Q., Zhiliang, D., Xinshang, Y., Li, Y., Zhao, Y., & Xiaotian, S. (2023). Extended exergy accounting for assessing the sustainability of agriculture: A case study of Hebei Province, China. *Ecological Indicators*, *150*, 110240.
29. Hatirli, S. A., Ozkan, B., & Fert, C. (2005, December). An econometric analysis of energy input-output in Turkish agriculture. *Renewable and Sustainable Energy Reviews*. Pergamon. https://doi.org/10.1016/j.rser.2004.07.001
30. Hatirli, S. A., Ozkan, B., & Fert, C. (2006). Energy inputs and crop yield relationship in greenhouse tomato production. *Renewable Energy*, *31*(4), 427-438.
31. Hernandez, P., Oregi, X., Longo, S., & Cellura, M. (2019). Life-Cycle Assessment of Buildings. *Handbook of Energy Efficiency in Buildings: A Life Cycle Approach*, 207-261. https://doi.org/10.1016/B978-0-12-812817-6.00010-3
32. Houshyar, E., & Grundmann, P. (2017). Environmental impacts of energy use in wheat tillage systems: A comparative life cycle assessment (LCA) study in Iran. *Energy*, 122, 11-24. https://doi.org/10.1016/j.energy.2017.01.069
33. IPCC. (2006). *IPCC guidelines for national greenhouse gas inventories.* Hayama, Japan.: Institute for Global Environmental Strategies.
34. Jacob-Lopes, E., Zepka, L. Q., & Deprá, M. C. (2021). Methods of evaluation of the environmental impact on the life cycle. In *Sustainability Metrics and Indicators of Environmental Impact* (pp. 29–70). Elsevier. https://doi.org/10.1016/b978-0-12-823411-2.00003-7
35. Jalalvand, M., Bakhoda, H., & Almassi, M. (2014). Wind Energy Potential Assessment for Electric Pumps of Agriculture in Broujerd. *Journal of Agricultural Machinery*, *4*(2), 368-377. (in Persian). https://doi.org/10.22067/jam.v4i2.34821
36. Jat, H. S., Jat, R. D., Nanwal, R. K., Lohan, S. K., Yadav, A. K., Poonia, T., …, & Jat, M. L. (2020). Energy use efficiency of crop residue management for sustainable energy and agriculture conservation in NW India. *Renewable Energy*, *155*, 1372-1382. https://doi.org/10.1016/j.renene.2020.04.046
37. Juárez-Hernández, S., Usón, S., & Pardo, C. S. (2019). Assessing maize production systems in Mexico from an energy, exergy, and greenhouse-gas emissions perspective. *Energy*, *170*, 199-211. https://doi.org/10.1016/j.energy.2018.12.161
38. Kaab, A., Sharifi, M., Mobli, H., Nabavi-Pelesaraei, A., & Chau, K. wing. (2019). Use of optimization techniques for energy use efficiency and environmental life cycle assessment modification in sugarcane production. *Energy*, *181*, 1298-1320. https://doi.org/10.1016/j.energy.2019.06.002
39. Khan, S., Khan, M. A., Hanjra, M. A., & Mu, J. (2009). Pathways to reduce the environmental footprints of water and energy inputs in food production. *Food Policy*, *34*(2), 141-149.
40. KhojastehpourTroujeni, M., Esmailpour, M., Vahedi, A., & Emadi, B. (2018). Sensitivity analysis of energy inputs and economic evaluation of pomegranate production in Iran. *Information Processing in Agriculture*, *5*(1), 114-123. https://doi.org/10.1016/j.inpa.2017.10.002
41. Kitani, O. (1999). *Energy and biomass engineering, CIGR handbook of agricultural engineering*. American Society of Agricultural and Biological Engineers. https://doi.org/10.13031/2013.36411
42. Komleh Pishgar, S. H., Keyhani, A., Rafiee, S., & Sefeedpary, P. (2011). Energy use and economic analysis of corn silage production under three cultivated area levels in Tehran province of Iran.

Energy, *36*(5), 3335-3341.

43. Kylili, A., Seduikyte, L., & Fokaides, P. A. (2018). Life Cycle Analysis of Polyurethane Foam Wastes. *Recycling of Polyurethane Foams*, 97-113. https://doi.org/10.1016/B978-0-323-51133-9.00009-7
44. Leiva, F. R., & Morris, J. (2001). Mechanization and sustainability in arable farming in England. *Journal of Agricultural and Engineering Research*, *79*(1), 81-90. https://doi.org/10.1006/jaer.2000.0686
45. Lovarelli, D., Bacenetti, J., & Fiala, M. (2017). Effect of local conditions and machinery characteristics on the environmental impacts of primary soil tillage. *Journal of Cleaner Production*, *140*, 479-491. https://doi.org/10.1016/j.jclepro.2016.02.011
46. Malana, N. M., & Malano, H. M. (2006). Benchmarking productive efficiency of selected wheat areas in Pakistan and India using data envelopment analysis. *Irrigation and Drainage*, *55*(4), 383-394. https://doi.org/10.1002/ird.264
47. Mani, I., Kumar, P., Panwar, J. S., & Kant, K. (2007). Variation in energy consumption in production of wheat-maize with varying altitudes in hilly regions of Himachal Pradesh, India. *Energy*, *32*(12), 2336-2339. https://doi.org/10.1016/j.energy.2007.07.004
48. Michalakakis, C., Fouillou, J., Lupton, R. C., Gonzalez Hernandez, A., & Cullen, J. M. (2021). Calculating the chemical exergy of materials. *Journal of Industrial Ecology*, *25*(2), 274-287. https://doi.org/10.1111/jiec.13120
49. Milà I Canals, L., Burnip, G. M., & Cowell, S. J. (2006). Evaluation of the environmental impacts of apple production using Life Cycle Assessment (LCA): Case study in New Zealand. *Agriculture, Ecosystems and Environment*, *114*(2-4), 226-238. https://doi.org/10.1016/j.agee.2005.10.023
50. Mobtaker, H. G., Keyhani, A., Mohammadi, A., Rafiee, S., & Akram, A. (2010). Sensitivity analysis of energy inputs for barley production in Hamedan Province of Iran. *Agriculture, Ecosystems and Environment*, *137*(3-4), 367-372. https://doi.org/10.1016/j.agee.2010.03.011
51. Mohammadi, A., Rafiee, S., Jafari, A., Dalgaard, T., Knudsen, M. T., Keyhani, A., …, & Hermansen, J. E. (2013). Potential greenhouse gas emission reductions in soybean farming: A combined use of Life Cycle Assessment and Data Envelopment Analysis. *Journal of Cleaner Production*, *54*, 89-100. https://doi.org/10.1016/j.jclepro.2013.05.019
52. Mohammadi, A., Rafiee, S., Jafari, A., Keyhani, A., Mousavi-Avval, S. H., & Nonhebel, S. (2014, February). Energy use efficiency and greenhouse gas emissions of farming systems in north Iran. *Renewable and Sustainable Energy Reviews*. Pergamon. https://doi.org/10.1016/j.rser.2013.11.012
53. Mousavi-Avval, S. H., Rafiee, S., Jafari, A., & Mohammadi, A. (2011a). Improving energy use efficiency of canola production using data envelopment analysis (DEA) approach. *Energy*, *36*(5), 2765-2772. https://doi.org/10.1016/j.energy.2011.02.016
54. Mousavi-Avval, S. H., Rafiee, S., Jafari, A., & Mohammadi, A. (2011b). Optimization of energy consumption for soybean production using Data Envelopment Analysis (DEA) approach. *Applied Energy*, *88*(11), 3765-3772. https://doi.org/10.1016/j.apenergy.2011.04.021
55. Nemecek, T., Dubois, D., Huguenin-Elie, O., & Gaillard, G. (2011). Life cycle assessment of Swiss farming systems: I. Integrated and organic farming. *Agricultural Systems*, *104*(3), 217-232. https://doi.org/10.1016/j.agsy.2010.10.002
56. Nikkhah, A., Khojastehpour, M., Emadi, B., Taheri-Rad, A., & Khorramdel, S. (2015). Environmental impacts of peanut production system using life cycle assessment methodology. *Journal of Cleaner Production*, *92*, 84-90. https://doi.org/10.1016/j.jclepro.2014.12.048
57. Ordikhani, H., Parashkoohi, M. G., Zamani, D. M., & Ghahderijani, M. (2021). Energy-environmental life cycle assessment and cumulative exergy demand analysis for horticultural crops (Case study: Qazvin province). *Energy Reports*, *7*, 2899-2915. https://doi.org/10.1016/j.egyr.2021.05.022
58. Papapetrou, M., & Kosmadakis, G. (2022). Resource, environmental, and economic aspects of SGHE. *Salinity Gradient Heat Engines*, 319-353. https://doi.org/10.1016/B978-0-08-102847-6.00006-1

59. Parihar, C. M., Jat, S. L., Singh, A. K., Kumar, B., Rathore, N. S., Jat, M. L., …, & Kuri, B. R. (2018). Energy auditing of long-term conservation agriculture based irrigated intensive maize systems in semi-arid tropics of India. *Energy*, *142*, 289-302. https://doi.org/10.1016/j.energy.2017.10.015
60. Parvaresh Rizi, A., & Ashrafzadeh, A. (2018). Techno-economic Analysis of Solar Irrigation: Comparison with Conventional Energy Sources for Irrigation. *Journal of Energy Planning And Policy Research*, *4*(2), 201-228.
61. Pelvan, E., & Özilgen, M. (2017). Assessment of energy and exergy efficiencies and renewability of black tea, instant tea and ice tea production and waste valorization processes. *Sustainable Production and Consumption*, *12*, 59-77. https://doi.org/10.1016/j.spc.2017.05.003
62. Pishgar-Komleh, S. H., Keyhani, A., Mostofi-Sarkari, M. R., & Jafari, A. (2012). Energy and economic analysis of different seed corn harvesting systems in Iran. *Energy*, *43*(1), 469-476. https://doi.org/10.1016/j.energy.2012.03.040
63. Powar, R. V., Mehetre, S. A., Patil, P. R., Patil, R. V., Wagavekar, V. A., Turkewadkar, S. G., & Patil, S. B. (2020). Study on Energy Use Efficiency for Sugarcane Crop Production Using the Data Envelopment Analysis (DEA) Technique. *Journal of Biosystems Engineering*, *45*(4), 291-309. https://doi.org/10.1007/s42853-020-00070-x
64. Prasad, S., Singh, A., Korres, N. E., Rathore, D., Sevda, S., & Pant, D. (2020, May). Sustainable utilization of crop residues for energy generation: A life cycle assessment (LCA) perspective. *Bioresource Technology*. Elsevier. https://doi.org/10.1016/j.biortech.2020.122964
65. Ptasinski, K. J. (2016). *Efficiency of Biomass Energy: An Exergy Approach to Biofuels, Power, and Biorefineries*. *Hoboken, NJ: Wiley*. https://doi.org/10.1002/9781119118169
66. Rahman, S., & Hasan, M. K. (2014). Energy productivity and efficiency of wheat farming in Bangladesh. *Energy*, *66*, 107-114. https://doi.org/10.1016/j.energy.2013.12.070
67. Royan, M., Khojastehpour, M., Emadi, B., & Mobtaker, H. G. (2012). Investigation of energy inputs for peach production using sensitivity analysis in Iran. In *Energy Conversion and Management 64*, 441-446. Pergamon. https://doi.org/10.1016/j.enconman.2012.07.002
68. Sartor, K., & Dewallef, P. (2017). Exergy analysis applied to performance of buildings in Europe. *Energy and Buildings*, *148*, 348-354. https://doi.org/10.1016/j.enbuild.2017.05.026
69. Shah, S. M., Liu, G., Yang, Q., Casazza, M., Agostinho, F., & Giannetti, B. F. (2021). Sustainability assessment of agriculture production systems in Pakistan: A provincial-scale energy-based evaluation. *Ecological Modelling*, *455*, 109654. https://doi.org/10.1016/j.ecolmodel.2021.109654
70. Shahhoseini, H. R., Ramroudi, M., Kazemi, H., & Amiri, Z. (2021). Sustainability assessment of autumn and spring potato production systems using extended exergy analysis (EEA). *Energy, Ecology and Environment*, 1-12. https://doi.org/10.1007/s40974-021-00222-5
71. Shojaei, M., & Akhavan, S. (2020). Economic assessment of photovoltaic (PV) water pumping system in drip-irrigated fields. *Iranian Water Researches Journal*, *14*(1), 19-28.
72. Singh, A., Pant, D., Korres, N. E., Nizami, A. S., Prasad, S., & Murphy, J. D. (2010). Key issues in life cycle assessment of ethanol production from lignocellulosic biomass: Challenges and perspectives. *Bioresource Technology*, *101*(13), 5003-5012. https://doi.org/10.1016/j.biortech.2009.11.062
73. Singh, Gursahib, Singh, S., & Singh, J. (2004). Optimization of energy inputs for wheat crop in Punjab. *Energy Conversion and Management*, *45*(3), 453-465. https://doi.org/10.1016/S0196-8904(03)00155-9
74. Singh, P., Singh, G., & Sodhi, G. P. S. (2019). Applying DEA optimization approach for energy auditing in wheat cultivation under rice-wheat and cotton-wheat cropping systems in north-western India. *Energy*, *181*, 18-28. https://doi.org/10.1016/j.energy.2019.05.147
75. Soltanali, H., Nikkhah, A., & Rohani, A. (2017). Energy audit of Iranian kiwifruit production using intelligent systems. *Energy*, *139*, 646-654. https://doi.org/10.1016/j.energy.2017.08.010
76. Su, X., Shao, X., Tian, S., Li, H., & Huang, Y. (2021). Life cycle assessment comparison of three

typical energy utilization ways for corn stover in China. *Biomass and Bioenergy*, *152*, 106199.

77. Thankappan, S., Midmore, P., & Jenkins, T. (2006). Conserving energy in smallholder agriculture: A multi-objective programming case-study of northwest India. *Ecological Economics*, *56*(2), 190-208. https://doi.org/10.1016/j.ecolecon.2005.01.017
78. Tzilivakis, J., Warner, D. J., May, M., Lewis, K. A., & Jaggard, K. (2005). An assessment of the energy inputs and greenhouse gas emissions in sugar beet (*Beta vulgaris*) production in the UK. *Agricultural Systems*, *85*(2), 101-119. https://doi.org/10.1016/j.agsy.2004.07.015
79. Vlontzos, G., Niavis, S., & Manos, B. (2014, December). A DEA approach for estimating the agricultural energy and environmental efficiency of EU countries. *Renewable and Sustainable Energy Reviews*. Pergamon. https://doi.org/10.1016/j.rser.2014.07.153
80. William G. Cochran. (1991). *Sampling Techniques* (3rd Editio). New York: John Wiley and Sons.
81. Yildizhan, H. (2018). Energy, exergy utilization and CO_2 emission of strawberry production in greenhouse and open field. *Energy*, *143*, 417-423. https://doi.org/10.1016/j.energy.2017.10.139
82. Yildizhan, H., & Taki, M. (2018). Assessment of tomato production process by cumulative exergy consumption approach in greenhouse and open field conditions: Case study of Turkey. *Energy*, *156*, 401-408. https://doi.org/10.1016/j.energy.2018.05.117
83. Yildizhan, H., & Taki, M. (2019). Sustainable management and conservation of resources for different wheat production processes; cumulative exergy consumption approach. *International Journal of Exergy*, *28*(4), 404-422. https://doi.org/10.1504/IJEX.2019.099295
84. Yilmaz, I., Akcaoz, H., & Ozkan, B. (2005). An analysis of energy use and input costs for cotton production in Turkey. *Renewable Energy*, *30*(2), 145-155. https://doi.org/10.1016/j.renene.2004.06.001
85. Yousefi, M., Khoramivafa, M., & Mondani, F. (2014). Integrated evaluation of energy use, greenhouse gas emissions and global warming potential for sugar beet (*Beta vulgaris*) agroecosystems in Iran. *Atmospheric Environment*, *92*, 501-505. https://doi.org/10.1016/j.atmosenv.2014.04.050
86. Yousefi, M., Mahdavi, A., & Mahmud, D. K. (2014). Energy consumption, greenhouse gas emissions and assessment of sustainability index in corn agroecosystems of Iran. *Science of the Total Environment*, *493*, 330-335.
87. Yuan, S., Peng, S., Wang, D., & Man, J. (2018). Evaluation of the energy budget and energy use efficiency in wheat production under various crop management practices in China. *Energy*, *160*, 184-191. https://doi.org/10.1016/j.energy.2018.07.006

نشریه ماشین‌های کشاورزی
https://jame.um.ac.ir

مقاله پژوهشی
جلد ۱۵، شماره ۱، بهار ۱۴۰۴، ص ۴۶-۲۳

بهینه‌سازی مصرف انرژی و اکسرژی تجمعی و ارزیابی چرخه حیات زیست‌محیطی تولید ذرت در استان لرستان

محسن سلیمانی[1*]، عباس عساکره[1]، مجتبی صفایی‌نژاد[2]

تاریخ دریافت: ۱۴۰۲/۱۰/۱۶
تاریخ پذیرش: ۱۴۰۲/۱۱/۲۵

چکیده

بهینه‌سازی مصرف نهاده، کاهش مصرف انرژی و اثرات مختلف زیست‌محیطی سیستم تولید ذرت در استان لرستان بر اساس تحلیل اکسرژی و ارزیابی چرخه حیات زیست‌محیطی مورد بررسی قرار گرفت. بر اساس نتایج به‌دست‌آمده و با توجه به معادله کاب-داگلاس، برق، سوخت دیزل و کود نیتروژن، بیشترین سهم را در مصرف اکسرژی تجمعی در سیستم تولید ذرت داشته‌اند. نتایج DEA نشان داد که میانگین راندمان تمام مزارع از نظر مصرف اکسرژی تجمعی در مدل‌های CCR و BCC، به‌ترتیب ۹۴/۷ و ۹۷/۸ درصد است. همچنین نتایج نشان داد که نهاده‌ها به‌ویژه کودهای پتاسیم و فسفات بیش از نیاز مصرف می‌شود. همچنین می‌توان ۶/۴۷، ۱۰/۴۲، ۷/۴۰، ۱۳/۳۲، ۳۱/۲۹، ۳/۲۵ و ۶/۷۸ درصد به‌ترتیب در مصرف اکسرژی سوخت دیزل، برق، ماشین‌ها، کودهای شیمیایی، سموم، بذر و انرژی آبیاری، با حفظ سطح عملکرد فعلی و تنها با ترویج روش‌های مورد استفاده توسط مزارع کارآمد، صرفه‌جویی کرد.

واژه‌های کلیدی: LCA، DEA، انرژی در کشاورزی، پایداری، تجدیدپذیری

۱- گروه مهندسی بیوسیستم، دانشکده کشاورزی، دانشگاه شهید چمران اهواز، اهواز، ایران
۲- گروه مدیریت مکانیزاسیون کشاورزی، جهاد کشاورزی استان لرستان، خرم‌آباد، ایران
(*- نویسنده مسئول: Email: m.soleymani@scu.ac.ir)

https://doi.org/10.22067/jam.2024.86234.1221