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Environmental Impact Assessment and Efficiency of Cotton: The Case of Northeast Iran

Abstract

Cotton is one of the important crops that play an important role in creating a livelihood for rural people in many parts of Iran. Cotton production necessitates a large amount of resources (e.g., fossil energy and agrochemicals, all of which have the potential to damage the environment in various ways). The purpose of the current study was to evaluate the environmental effects of cotton production in the South Khorasan Province of Iran. For this purpose, Life Cycle Assessment (LCA) and Data Envelopment Analysis (DEA) techniques have been applied to investigate the environmental impacts of cotton production. LCA is a practical method to evaluate the environment on the product flow, in which all aspects of the product life cycle are examined by a comprehensive approach. Furthermore, combining the LCA method with other managerial strategies such as DEA could allow researchers to provide decision-makers with more practical and interpretable data. The findings of the efficiency test showed that the average technical efficiency, pure technical efficiency, and scale efficiency were 0.81, 0.92, and 0.87, respectively. Respiratory inorganics (i.e., respiratory effects resulting from winter smog caused by emissions of dust, sulfur, and nitrogen oxides to air) posed the greatest environmental burden in cotton production, followed by non-renewable energy, carcinogens, and global warming. In addition, the highest effects were on human health, and then, on resources and climate change. Energy, on-system pollution, and waste played a crucial role in the environmental impacts of cotton processing. This study suggests improving farmers' knowledge toward the optimum application of chemical fertilizers, or their substitution with green fertilizers, which reduces the environmental effect of growing cotton in the area.

Keywords: Life cycle assessment; Data envelopment analysis; Environmental impact; Respiratory inorganics; Chemical fertilizers.

1. Introduction

Cotton production can pose significant challenges and be associated with high social, environmental, and economic impacts, unless produced in a sustainable manner. About 22% of the world's cotton is now produced by sustainable methods (Altenbuchner et al., 2018). It is predicted that by 2025, the vision of the sustainable cotton challenge will reach more than 50% and a large part of this important product will be produced with methods focused on maintaining environmental sustainability (Smith and Watson, 2018). Cotton's high-water consumption and pollution, soil deterioration, greenhouse gas emissions, and use of hazardous pesticides and fertilizers could damage the ecosystem. Cotton utilizes around 6% of the world's pesticides and 16% of all insecticides, which is higher than any other crop (Zulfiquar et al., 2019). These insecticides are damaging to the environment, contributing to greenhouse gas emissions and polluting thousands of litres of potable water. The most common insecticides used in cotton cultivation, according to the World Health Organization (2018), also include three of the most toxic compounds. These toxic substances result in health risks for cotton farmers and inhabitants of nearby villages, and their use has been causing an increase in miscarriages, malformations, and cancer in those areas (Huang et al., 2022). Therefore, environmental impact prediction is an important tool for the environmental management of cotton production (Solbär and Keskitalo, 2017). As a useful tool for estimating environmental impacts, scientists have developed different analysis techniques to evaluate the product life cycle, assess the impact of manufacturing processes, and include recommendations to enhance all output steps in response to these complicated requirements (Enríquez et al., 2019; Colley et al., 2019; Beagle and Belmont, 2019; Maaoui et al., 2020; Chen et al., 2020). Life Cycle Assessment (LCA) is a practical means to evaluate the environmental influences of production flow, in which all phases of the product life cycle (from the acquisition of raw materials through the production and use phases, to the management of waste) are examined by a comprehensive approach (Brondani et al., 2019; Foteinis and Chatzisymeon, 2016; Wowra et al., 2020). A special aspect of LCA is that during its cycle, it pursues all the environmental impacts of a product or service (Mahmud et al., 2019; Pauer et al., 2019). In other words, all possible environmental impacts in all production stages such as planting, transporting, and processing are included (Zhang and

Rosentrater, 2019). Moreover, a combination of the LCA technique with other managerial techniques like Data Envelopment Analysis (DEA) could enable researchers to offer more practical and interpretable results to decision-makers (Khoshnevisan et al., 2015; Mohseni et al., 2018). The LCA method firstly calculates the return of production units. Then, it evaluates the environmental impacts of production if all units are operated efficiently by reducing the input consumption rate (Khatri et al., 2017).

Cotton is planted in over 100 countries. It accounts for more than 31 million hectares or 2.4% of the world's arable land, impacting approximately 20 million farmers who depend entirely on cotton output and another 30 million farmers who include cotton in their rotation scheme (Ishengoma and Athuman, 2018). Therefore, it seems to be a major source of livelihood for poverty-stricken farmers. Cotton is mostly grown in irrigated situations with a huge risk of disease. For example, some pests are specifically harmful to this crop and its fibber quality.

Cotton seed processing necessitates large amounts of energy, fossil fuels, and agrochemicals, all of which degrade the environment in various ways (Kumar et al., 2016). In fact, following the infiltration of rainwater into the soil, nitrate in the soil, along with other soil contaminants, including chemical toxins, infiltrate groundwater sources and pollute these sources (Jalili et al., 2018; Padilla et al., 2018). In addition, mechanization has expanded the usage of unrenewable resources. The magnitude of such impacts on the environment and utilization of energy in various types differs based on agricultural management activities, surface structures, and circumstances of the agribusiness (Mahlknecht et al., 2020). In addition, intensive input use comes with high production costs in the shape of protection for yield and quality of cotton. All environmental degradation and rising cotton production costs threaten its survival and the profits of farmers in Iran. As a result, the environmental effect of cotton cultivation is constantly in the media, and salinization, desertification, and water pollution are among the major issues of human safety.

1.1. Types of life cycle assessment (LCA)

LCA is described as the methodical analysis of the possible environmental influences of production or services over their life cycle (Jiang and Wu, 2019). There are different evaluation techniques including life cycle impact assessment techniques, which differ in the procedure (e.g., with regard to weighting). Some methods only take into account a single aspect of the environment, such as the total energy demand or the carbon footprint. Other fully integrating techniques (such as the Eco-Indicator) incorporate a number of different environmental impacts into a single key figure (Wiesen and Wirges, 2017). In general, there are three different types of LCAs: 1) screening LCA: a rough estimate and assessment of environmental impacts using average data, based on the most relevant materials and resources; 2) Product LCA: a descriptive analysis of a single product's environmental performance over its entire life cycle; and 3) comparative LCA: a comparison of multiple products or product variants.

It is also possible to compare different processes and production systems (Martinopoulos, 2020; Yasin and Sun, 2019; Yasin et al., 2018). Yasin and Sun (2019) stated that the textile industry is expanding, as are its technical aspects. As a result, there has been an increase in chemical consumption. In the production and manufacturing of crude materials, considering the stability factor of special textiles with attributed materials has recently been considered (Salehi et al., 2021). There are studies that use LCA outcomes to confirm the environmental choices of technical textiles over conventional textiles using the environmental equality method (Odey et al., 2021). For example, antibacterial textiles are expected to require less wash because of the low-level currency of odour-causing microbes and therefore have less long-term environmental effects than conventional textiles (Manupella et al., 2020). In fact, the influence of environmental technical waste and traditional textile waste cannot be equivalent because of variations in stages such as crude materials and particularly the end-of-life stage. As a result, they investigated two technical textiles with similar weight but with different functionalities using a "gate-to-grave" LCA approach: Wool treated with flame retardant (FR) and polyester treated with silver nanoparticles (AgNPs) (Bashari et al., 2018). According to Yasin and Sun (2019), the impact of technical life cycle textiles is greatest during the use stage, with different materials used and release dates. It was found that there is no relationship between the two types of technical textiles at the end-of-life stage of environmental impact. MSW or even traditional textile waste have no reciprocal relationship with them (Garrels, 2018). By providing an environmental pathway and pre-disposal treatment, Yassin et al. (2018) examined how to increase and enhance the end-of-life phase of flame retardant (FR) textile products. The advanced oxidation process was used to degrade and remove FR from the textile productions. Finally, LCA was performed to determine the environmental effects of the end-of-life stage of FR cotton textiles before and after the disposal of environmental practice. In most of the impact categories studied, LCA results revealed lower impact values, particularly in global warming potential (GWP), air acidification (AA), and other prominent classifications.

LCIA is used from cradle to grave to estimate the possibility of the environmental influence of any product, manner, or activity, from production to disposal. Lack of LCI data in developing or emerging countries is one of the most significant issues with LCI. The production phase has been delocalized to these countries, and this fact must be considered in the context of a global production-consumption chain. Environmental impact assessment entails tracking all inputs (such as energy, water, etc.) and outputs at each stage of the production-consumption chain. Major pollutants in the atmosphere, such as CO2, SO2, NOx, and other particulates, are measured.

To date, inadequate information has been given about the extent of (un)sustainability of the current systems (Ishengoma and Athuman, 2018). Thus, the economic importance of sustainable cotton production necessitates the evaluation of its environmental impacts. However, there is limited research that has studied the effect of cotton development on the ecosystem in semi-arid areas facing drought and water scarcity.

DEA models were used in only a few studies to define a target for ineffective DMUs, i.e., the levels that must be achieved in order to be productive. In addition, the DEA offers the most excellent practices to obtain efficiency. However, there is a chance that this goal will be impossible to achieve from an operational or managerial standpoint. This model gives you more options to find practical and efficient goals during the decision process. As a result, having multiple targets to improve agricultural practices allows farmers to choose between more appropriate courses of act based on their present circumstances and resources. As a result, the current study examines the environmental effects of cotton production, incorporating LCA and DEA techniques to provide more concrete solutions to mitigate the effects of cotton production on the environment. As a result, the incorporation of LCA and DEA can provide more balance in farming practices in order to achieve environmental efficiency, as well as options for producers to enhance their attempts to achieve sustainable products. Overall, this is the primary research to adopt a multi-objective DEA model to define alternative targets for inefficient DMUs in the field of LCA and DEA. We also suggest some criteria to select different targets, one of which is the eco-efficiency index. As a result, this model and its outcomes are novel.

The main aim of this study is to evaluate the environmental effects of cotton production in the South Khorasan Province of Iran by answering the following questions: 1) What are the main effects of cotton cultivation on the environment? 2) Which inputs used in cotton cultivation have the most destructive effects on the environment? To what extent the environmental impacts could be reduced if resources were used optimally?

2. Methodology

The aim of this study is to investigate the environmental impact of cotton production in the South Khorasan Province of Iran by using DEA and LCA techniques. Since the introduction of the LCA and DEA approach, this integration has been widely used in several case studies, especially in agriculture, due to the ease of making an operational and environmental assessment, as well as determining targets for resource consumption and reduction of greenhouse gases emissions. The combined LCA and DEA results can be used to convince farmers to reduce input consumption in the cotton production system in order to obtain operational productivity, decrease costs, and have fewer environmental effects.

In this section, first, the study area is introduced, followed by data collection, data envelopment analysis, life cycle assessment, and estimating gas emissions. To that end, the environmental effects of cotton production were first measured using the inputs used by farmers to produce cotton. Next, using DEAP2.1 software, farmers' efficiency was calculated, and the inputs consumed in the optimal condition of production were estimated by this software as well. Furthermore, the environmental effects of production have been re-estimated when farmers make optimal use of inputs.

As a result, the simulation process in this study was not carried out using SimaPro software. Instead, the results of SimaPro software have been transferred to, and analyzed in an Excel file, because of the high quality and convenience of this software. Fig. 1 shows the step-wise analysis of the current study.

[Insert Fig. 1]

2.1. Study area

South Khorasan Province is the farthest eastern province in Iran, with an average annual precipitation of 134 mm and a mean annual temperature of 17.5°C. It is located between the longitudes of 57°01' and 60°57' E and the latitudes of 30°31' and 34°36' N (South Khorasan Provincial Government, 2016) (Fig. 2). The agriculture sector plays an important role in its residents' employment and earnings. Out of 79843 hectares of agricultural land, only 13% are rain-fed. Out of the 10700 ha of industrial plants, cotton fields comprise the highest acreage of plantations with 9500 ha under cultivation. A quarter of the South Khorasan cotton is produced in the Sarayan region (Jihad Agricultural Organization of South Khorasan, 2015). As one of the most important agricultural regions in the northwestern part of the province, Sarayan County was selected as the sample area.

[Insert Fig. 2]

2.2. Data collection method

A questionnaire, accompanied by discussions with producers and agricultural experts, was employed for collecting the data required for the study in 2017. Cochran's formula was used to determine the sample size (Salehi et al., 2014). Finally, 148 farmers were selected as the sample for data collection. The data were analyzed by DEAP 2.1 and SimaPro software packages.

2.3. Data envelopment analysis (DEA)

Sensitivity analysis is a financial model that determines how changes in other variables, known as input variables, affect target variables (Silvestro et al., 2017). This model is described using the terms like "what if" and "simulation analysis." It is a method of predicting the outcome of a decision based on a set of variables (Fong et al., 2019). Sensitivity analysis is also used to determine how sensitive the decision-making units' (DMUs) solution values and efficiency scores are to numerical observations. By changing the

DMUs' reference set, the proposed new model tests the robustness of DEA efficiency scores (Arabmaldar et al., 2021). For this purpose, in this study, the DEA method has been used.

In recent years, DEA has been defined as a measurement means for such a common environmental performance score (Kuosmanen and Kortelainen, 2005). DEA is generally a linear programming methodology to measure multiple efficiencies, and the relative efficiency of DMUs based on industrial inputs and outputs, described as technological performance, has been measured in the industry (Korhonen and Luptacik, 2004). Just recently, with the pioneering works of De-Koeijer et al. (2002), Reig-Martínez and PicazoTadeo (2004), and Gatimbu et al. (2020), DEA has been applied in farming case studies; with the implementation of the DEA system, researchers have begun to see biologically undesirable products as by-products in their models (e.g., Picazo-Tadeo et al., 2011; Avadí et al., 2014), leading to environmental efficiency. Low environmental efficiency arises from small incomes and/or major environmental impacts in any given manufacturing method. Recently, the joint implementation of LCA and DEA (e.g., Vazquez-Rowe et al., 2012) has revealed a way to recognize trade gaps between environmental effects and economic benefits. This procedure also aims at quantifying potential mitigation of environmental impact by possible mitigation of inputs, towards greater eco-efficiency. The aim of the DEA is to measure the relative effectiveness of all DMUs producing similar products in different quantities (Galanopoulos et al., 2006). DEA consists of two separate models called CCR and BCC, named after their developers, i.e., Chames et al. (1978) and Banker, Charnes, et al. (1978), respectively. In the CCR model, total performance is calculated by the integration of mere technological output and size performance into one common factor. In the meantime, technical efficiencies are divided into pure technical efficiency and scale efficiency (Bolandnazar et al., 2014). Pure technical efficiency is the technical efficiency that ignores the influence of the operation scale. Moreover, inefficient farms are compared only with similar farms in terms of scale (Mousavi-Avval et al., 2011). With the assumption of variable scale return, the model measures unit efficiency, and its key benefit is that even productive farms with the same scale are compared with ineffective farms (Ebrahimi and Salehi, 2015). In general, the CCR model is in the form of Eq. (1) (Azizi and Wang, 2013).

$$\text{Max} = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}}$$
$$st:$$
$$\frac{\sum_{r-1}^{s} u_{rj} y_{rj}}{\sum_{i=1}^{m} v_{ij} x_{ij}} \leq 1 \qquad \text{Eq (1)}$$
$$u_r \geq 0, v_r \geq 0$$

where y_{rj} and x_{ij} show the *r*-th output and *i*-th input of DMU j, and *u* and *v* stand for the weight equivalent to each output and input, respectively. x_{io} and y_{ro} are the *i*th input and *r*th output of DMU *o* under study. This model can be converted to the form of Eq. (2):

$$\text{Max} = \sum_{r=1}^{s} u_r y_{ro}$$
$$st:$$
$$\sum_{i=1}^{m} v_i x_{io} = 1 \qquad \text{Eq (2)}$$
$$\sum_{r-1}^{s} u_{rj} y_{rj} - \sum_{i=1}^{m} v_{ij} x_{ij} \leq 0$$
$$u_r \geq 0, v_r \geq 0$$

When the result and input of an E = 1 unit are positive, the unit should be declared to be efficient; otherwise, it would be inefficient (Azizi and Fathi Ajirloo, 2010).

Bankers, Charns, and Cooper (1984) extended the CCR model to the BCC model (Eq.3) to obtain pure technical efficiency (PTE) score by assuming the existence of variable returns-to-scale (VRS).

$$
\begin{aligned}
&\text{Max } E = \sum_{r=1}^{s} u_r y_{ro} + \text{ω} \\
&\text{St:} \\
&\sum_{i=1}^{s} v_i x_{io} = 1 \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + \text{ω} \le 0 \quad \text{j} = 1, \cdots, \text{n}, \\
&\qquad u_r \ge 0, v_r \ge 0, \text{ω};\ \text{free insign}
\end{aligned}
\qquad \text{Eq (3)}
$$

The ww is not bound to the conditional limitation, hence it demonstrates a return to scale aspects of the 'j-th' DMU (Mustafa et al., 2021).

The scale efficiency is specified based on technical efficiency, pure technical efficiency, and their relationships (Zhu et al., 2020).

$SE= TE_{CCR} /TE_{BCC}$ Eq (4)

Scale efficiency shows that inefficiency is partially related to the improper size of DMU, and if DMU approaches the optimum size, total efficiency can be improved (Ebrahimi and Salehi, 2015).

2.4. Life cycle assessment

LCA is a commonly applied technique to measure the environmental value of goods and systems, keeping in consideration the complete life cycle of a product (ISO 14040 2006; ISO 14044 2006), and it refers to the collection and evaluation of inputs, outputs, and possible effects on the ecosystem during a manufacturing process's life cycle (Finnveden et al., 2009). To put it another way, an LCA project examines all the production processes of production, from the derivation of crude materials to the control of waste products. LCA results are used to reduce the adverse environmental impacts.

An important and necessary part of the goal and scope definition to start a life cycle assessment study is to select system boundaries. Its importance is realized when it is considered that the environmental impacts of agricultural systems do not end with crop harvest but may continue during post-harvest processes

(Khoshnevisan et al., 2013b). Although LCA is a "cradle-to-grave" view, it is possible to select a part of the production process. In order to study certain processes more closely, results are reported for the selected boundary on a smaller scale. In fact, the farm gate was considered the system boundary (Fig. 3). Changes in cropping patterns are the primary goals of planners and policymakers in the agricultural sector as a result of the water crisis in the region. Accordingly, farm boundaries are considered as the system boundaries, and all agricultural operations at the farm level, from cultivation to harvest, have been reviewed in this study.

[Insert Fig. 3]

Functional unit determination is the second important phase in an LCA project in any processes or products. The functional unit is the basis for all calculations in the product life cycle. Three different functional units for agricultural product assessments are suggested on the basis of unit area, unit money, or produced material weight (Nemecek et al., 2011). Base region and base mass prevail in LCA research in the agricultural sector (Iriarte et al., 2010; Heller and Keoleian, 2011).

Inventory analysis works on the consumed resources and pollutant emissions in all or part of the product life cycle determined by system boundaries. Inventory analysis is an important phase of LCA whose results are used in the life cycle impacts assessment (Khoshnevisan et al., 2014c). Two sets of data should be studied for this phase. They are known as background and foreground data. The *background* data included the production of any input, and they are extracted from Eco invent databank and SimaPro Software Package (Pre, 2016). The *foreground* data contained the quantity of raw material and the processes in the studied boundary. Table 1 shows the research variables in detail.

[Insert Table1]

To facilitate interpretation results, the data on the emission of important pollutants are summarized in impact categories at the life cycle assessment phase. At this phase, the results of inventory analysis are converted to some environmental indicators (Del Borghi et al., 2014). This phase itself includes some optional and mandatory stages. The mandatory stage is to select impact categories, while normalizing and weighting are the optional stages of the phase. Various institutions and countries have introduced various methods to assess environmental impacts. One of them is a mixture of three techniques, i.e., IMPACT 2002 (Pennington et al., 2005), Eco-Identifier 99 (Goedkoop and Spriensma, 2001), and CML (Khoshnevisan et al., 2014b). By combining these impact indicators, the IMPACT 2002+ method evaluates 15 impact indicators and four endpoint indicators (damage category) (Humbert et al., 2012). At the final phase, all the results were analyzed to draw conclusions and recommendations. At this phase, important issues are defined and assessed in terms of their impact on the LCA results (Buonocore et al., 2015).

2.5. Estimating gas emissions

Within the studied system boundary, the consumption of inputs will result in direct emissions of pollutants into the air, water, and soil. These emissions should be calculated and included in assessments (Keyes et al., 2014). One pollutant is NH_3 emitted by chemical fertilizers. NH_3 emission has been calculated by equations introduced by Nemecek et al. (2014b):

$$\mathrm{NH_3} = 17/14 \times \mathrm{N_{min}} \times (\mathrm{EF_a} \times \mathrm{p} + \mathrm{EF_b} \times (1 - \mathrm{p})) \quad \text{Eq (5)}$$

where NH_3 shows ammonium emission levels due to the mineral fertilizer usage expressed in kg per hectare, N_{min} shows N quality of mineral fertilizers, EF_a and EF_b display soil pollution factor with pH < 7 and > 7, respectively (kg NH_3 – N / kg N), and p shows the soil share with pH < 7 expressed in percentage manure use, which results in NH_3 emission whose rate is calculated by the following equation:

$$NH_3 - N = TAN \times (er + c\_app) \times cx \quad \text{Eq (6)}$$

where $NH_3 - N$ shows the emission rate of N as NH_3, expressed in kg per functional unit, *TAN* shows the total ammonium Nitrogen (kg N) that is equivalent to soluble N content (Nemecek et al., 2014b), *er* is the emission rate determined by the type of manure, *c_app* is the corrective coefficient for the emission rate of liquid manure, and *cx* is the correction factor which depends on numerous parameters like manure application season, application intervals, and mixture with soil (Nemecek and Schnetzer, 2011).

The emission element of 0.012 kg NO_x-N/kgN has been considered for calculating the rate of NO_x emission from mineral fertilizers and manure (Rafiee et al., 2016). Nitrous oxide (N_2O) is calculated by the following equation (Faist Emmenegger et al., 2009; Eggleston et al., 2006):

$$N_2O = 44/28 * (0.01 * (N_{tot} + N_{cr} + 14/17 * NH_3 + 14/46 * NO_x) + 0.0075 * 14/62 * NO_3) \quad \text{Eq (7)}$$

where *N2O* shows the emission rate per hectare, *Ntot* shows the total N content of organic and mineral fertilizers (kg N per ha), *Ncr* shows the N content of crop residue (kg N per ha), NH3 and NOx show the losses of nitrogen in the form of ammonia and nitrogen oxides (kg NH_3 and NO_2 per hectare), and *NO3* shows the rate of N lost as nitrate (kg NO_3 per hectare). The rate of nitrate emission to water has been measured by the SQCB-NO_3 model (Nemecek et al., 2014b).

Urea directly emits CO_2 into the atmosphere. Therefore, it is recommended to use the emission coefficient of 1.57 per kg Urea-N (Nemecek et al., 2014a; Rafiee et al., 2016). The emission coefficient of 0.07 was used in the calculation of the rate of phosphate emission into groundwater (Nemecek and Kagi, 2007).

Diesel combustion in tractors and other types of machinery emits different environmental pollutants into the atmosphere. Khoshnevisan et al. (2014b) compared emissions by diesel combustion provided by two databases and found that the Eco invent database included more emission categories. Therefore, the publications of this database were used in the present study.

3. Results and Discussion

Descriptive statistics on the consumption of inputs to produce one hectare of cotton are shown in Table 1.

[Insert Table1]

According to Table 2, mean technological performance, mere technological performance, and scale efficiency were 0.81, 0.92, and 0.87, respectively. In the CCR and BCC modes, 46 and 122 units are effective. Technical efficiency varied in the 0.2-1 range with 0.20 SE. The lowest pure technical efficiency was 0.55 with 0.11 SE. The mean efficiency of units is presented in Table 2. In a study on grapes in Spain, Vazquez-Rowe et al. (2012) showed that 60% of producers were efficient, and inefficient farmers had an efficiency degree of 36-71%. The mean technological, pure, and scale efficiency for the orange output was reported by Nabavi-Pelesaraei et al. (2014) at 0.894, 0.925, and 0.922, respectively. Khoshnevisan et al. (2015) calculated that the mean technological performance for watermelons was 83%. Ebrahimi and Salehi (2015) reported the mean scale efficiency, pure efficiency, and technical efficiency of mushrooms to be 97, 97, and 94%, respectively.

[Insert Table2]

Table 3 shows the environmental indicators calculated for the planting of cotton under two conditions: the consumption of inputs in the current conditions and their consumption in the optimum conditions. As shown in Table 3, if inefficient units adjust their consumption pattern to approach the efficiency boundary, outcomes for influence levels can be decreased by 3.93-19.65%. The minimum reduction, i.e., 3.93%, was for the indicator of carcinogens, and the highest reduction, i.e., 19.65%, was for terrestrial ecotoxicity.

[Insert Table3]

Normalized results are drawn in Fig. 4. Since these indicators are dimensionless, it is possible to compare their magnitudes. As can be seen, respiratory inorganics (i.e., respiratory symptoms from winter smog induced by sulfur, dust, and nitrogen oxide emissions to the air) showed the highest environmental burden on cotton production. The next rankings belonged to the impact of non-renewable energy, carcinogens, and global warming.

[Insert Fig. 4]

As shown in Fig. 5, the environmental charge of electricity had the greatest influence on environmental contamination among the five indicators (global warming, carcinogens, non-carcinogens, non-renewable energies, and respiratory organics). The second highest environmental burden was related to pollution by on-farm emissions which polluted the environment with impact categories (like inorganic breathing, terrestrial acid/nutrient, marine acidification, and global warming).

[Insert Fig. 5]

According to Fig. 6, electricity, in-system emissions, and manure offered the most environmental effects of cotton production in the region. Most effects of electricity were seen in three impact categories- namely carcinogens, non-renewable energies, and global warming. On-farm emission and manure had the greatest impact on respiratory inorganics.

[Insert Fig. 6]

Khoshnevisan et al. (2015) and Khoshnevisan et al. (2013a) expressed the key role of electricity in the environmental impacts of agricultural production in Iran. Electricity is mainly used for water pumping in the agriculture sector. Therefore, the improvement of water use efficiency (WUE) can reduce emissions and environmental impacts considerably. WUE tended to be low in the studied region due to the use of flood irrigation systems and old implements. Stimulating farmers to change the irrigation system and use modern sprinkler irrigation methods can increase WUE and reduce water and electricity consumption significantly, as confirmed by other works (Mohammadi et al., 2014). Another reason for high electricity consumption is the use of old and inefficient pumps. Replacing these pumps will reduce the effect on the atmosphere (Tabatabaie et al., 2012; Nabavi-Pelesaraei et al., 2014). The main sources of on-system emissions are chemical fertilizers, manures, and fuel. However, their optimum usage can reduce environmental pollutants.

Research on the agriculture sector in Iran emphasizes the high, inefficient consumption pattern and the importance of reform in the use of chemical fertilizers (Mobtaker et al., 2012; Yousefi et al., 2014b; Soltani et al., 2013). Improving the use of chemical fertilizers should be accompanied by the conservation of the quality and quantity of the crop. Therefore, it should be planned to move towards the efficient use of chemical fertilizers. It should be noted that only a small part of mineral nitrogen is absorbed by plants, whose precise amount depends upon soil texture, temperature, and rainfall rate. Crop rotation and water management modifications can play an effective role in enhancing fertilizers' efficiency and reducing the relevant environmental impacts (Safa and Samarasinghe, 2012). Farmers' limited knowledge of chemical fertilizers use and the fact that soil is not analyzed to determine fertilization requirements are some factors responsible for the inefficient application of chemical fertilizers. Actions to address these problems will reduce the fertilization rate and its effect on the atmosphere (Tabatabaie et al., 2013; Pishgar-Komleh et al., 2012). In addition, using green fertilizers and cover crops with large ability to consume nitrates is suggested as a soil supply technique (Pishgar Komleh et al., 2011; Keyes et al., 2014). In most agricultural systems, because green fertilizer fixes atmospheric nitrogen, it is a source of N (Faist Emmenegger et al., 2009; Mohammadi et al., 2015). Manure is a by-product of livestock farms, and its environmental impact in the production stage should be included in the calculations for that sector. Therefore, it is excluded from the calculations for cotton production (Knudsen et al., 2010). Although manure is friendlier to the environment than chemical fertilizers, it is important to note that its application in farms emits some pollutants within the system boundary.

Fig. 7 presents the cumulative results of the impact indicators regarding human security, environmental sustainability, climate change, and resource impact assessment under current and optimized conditions.

[Insert Fig. 7]

As can be seen clearly in the region under the current condition of inputs use, cotton cultivation had the greatest effect on the assessment indicator of health. The effect areas impacting public wellbeing included carcinogens and non-carcinogens, ionizing radiation, degradation of the ozone layer, and organic and inorganic respiratory materials. According to Fig. 4, it is observed that among impact categories influencing human health, respiratory inorganic materials and carcinogens had the strongest effect. Similar results were reported by Rajaeifar and others (2015), Rafiee et al. (2016), and Sanchez et al. (2016). To mitigate this damage category, those impact categories that exhibited the greatest effect should be reduced. In respiratory inorganics, the highest effects were exerted by electricity, on-system emission, and manure, respectively. With respect to carcinogens, electricity revealed the highest effect. Rafiee et al. (2016) also reported that the greatest impact on respiratory inorganics is due to on-system emissions, while electricity had the greatest impact on carcinogens. According to Khoshnevisan et al. (2014c), urea and phosphate fertilizers had the highest impact on human toxicity indicator. Moreover, Khoshnevisan et al. (2014b) proved that electricity had the highest impact on human toxicity indicator.

The resources were the second category of damage. The usage of non-renewable fuels and mineral mining are two components of the capital. The percentage of non-renewable energy consumption was higher than mineral extraction, where electricity again played a major role (Fig. 2). It confirmed the findings of Khoshnevisan et al. (2015), Khoshnevisan et al. (2014c), and Tabatabaie et al. (2012).

The third damage category is climate change, on which only the impact category of global warming is effective. As is evident in Fig. 5, electricity, on-system emission, and manure had the highest effect on this category. However, optimized usage of electricity and manure could reduce this indicator by 7.50%. Rafiee et al. (2016) reported on-system emissions and electricity as the most important causes of global warming in alfalfa and soybean production. The critical role of electricity is also reported in similar studies on the effect of agricultural production on global warming (Yousefi et al., 2014a).

Among damage categories, ecosystem quality has the lowest quantity. In this sense, the results of the present study are in line with those of Mohmad et al. (2014). Regarding the ecosystem quality, terrestrial ecotoxicity had the highest effects, in which manure and electricity played a role. According to Rafiee et al. (2016), livestock farm emissions had the greatest impact on terrestrial ecotoxicity.

4. Policy and Managerial Implications

Cotton is an important source of income for smallholder farmers in Iran because it is a crop that is typically grown very intensively. Non-governmental organizations in Iran are pushing for organic cotton farming to combat the negative effects of cotton production in the country, such as environmental degradation and financial dependence due to high input prices. Farmers can benefit from organic agriculture, according to the findings, primarily due to lower input costs, soil improvements, and reduced exposure to toxic chemicals, which reduces reliance on money lenders. Education will play a crucial role in building capacity and bolstering communities.

Considering the significant amount of pollutants released in the cotton production system in Iran, it is suggested that government subsidies should be paid to farmers in order to reduce the pollutants produced in this product. It is recommended to replace worn agricultural implements with newer implements to have less environmental pollution. It is also recommended to purchase conservation tillage machinery, employ nitrogen-supply sources with lower pollution potential than urea fertilizer, and produce biodiesel and other environmentally friendly fuels to assist in providing part of the farm's energy. While environmental impacts, global warming, increasing acidity, and depletion of fossil resources, water resources, potash, and phosphate resources are crucial, the pollutants emitted from the cotton cultivation in the form of other impact groups also add to adverse environmental costs. Hence, the continuation of the cotton production in Iran with this amount of consumption inputs can have significant environmental impacts. Therefore, there is a need to pay attention to mitigation strategies aimed at reducing pollution in the cotton production in the study area, such as low tillage and no-tillage operations.

According to the results of the study, reducing water and electricity usage and motivating farmers towards conducting soil analysis are recommended as the main reasons for the environmental impacts of cotton output rise in Eastern Iran. Higher pure technical efficiency in comparison with technical efficiency revealed that the cotton production benefiting from the optimum economy of scale could hamper its environmental impacts. Optimum use of water resources could lead to reduced environmental impacts due to controlled electricity usage. These findings may be used to persuade cultivation site managers and operators of the value of reducing input usage while improving operational efficiency.

5. Conclusion

The environment is one of the three main pillars of sustainability. As the concept of sustainability gains prominence across the globe, decision-makers, investors, and individuals will pay more attention to it. Energy efficiency, which is important for any area of existence, plays a key role in countries' growth. Countries must allow effective usage of energy in order to remain successful internationally and achieve sustainable growth. Countries that utilize the resources effectively are economically competitive and have led the way in innovation. Agriculture is one of the sectors that play an important role in achieving these goals. Cotton is an important cash crop in many parts of the world and its value-added products are major export earners for many countries' income, such as Iran. The environmental impacts of cotton production are complex. Previous studies have shown that water use, land use, pollution, and use of chemicals are the most important factors to determine during the cotton-producing phase.

The present research was carried out to determine the environmental effects of cotton output in Eastern Iran and assess its potential for reduction. According to the results for efficiency and the optimum rate of production inputs use, it was shown that the efficient use of resources could allow the mitigation of environmental impacts without the loss of the product. Under optimum conditions, the lowest reduction was observed in the impact category of carcinogens, and the highest reduction was observed in the impact category of terrestrial ecotoxicity. According to the results, the human health indicator had the highest effect on regional cotton production. Moreover, electricity, on-system emissions, and manure had the highest effects on impact categories.

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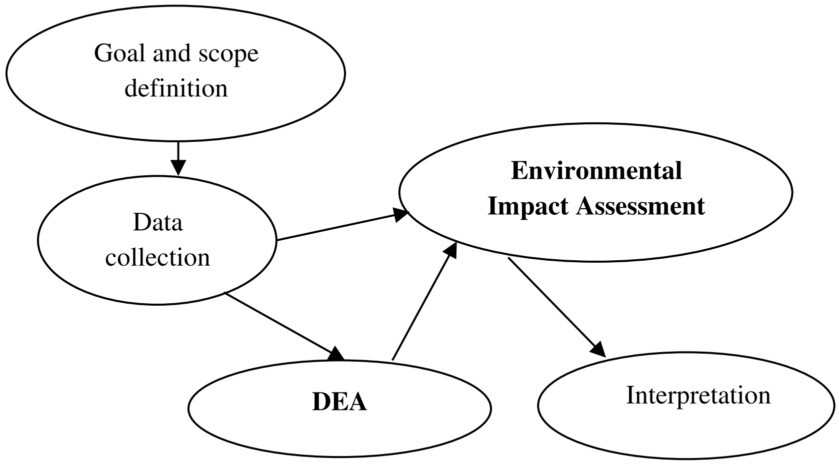

Fig. 1. The main framework and stages of the study.

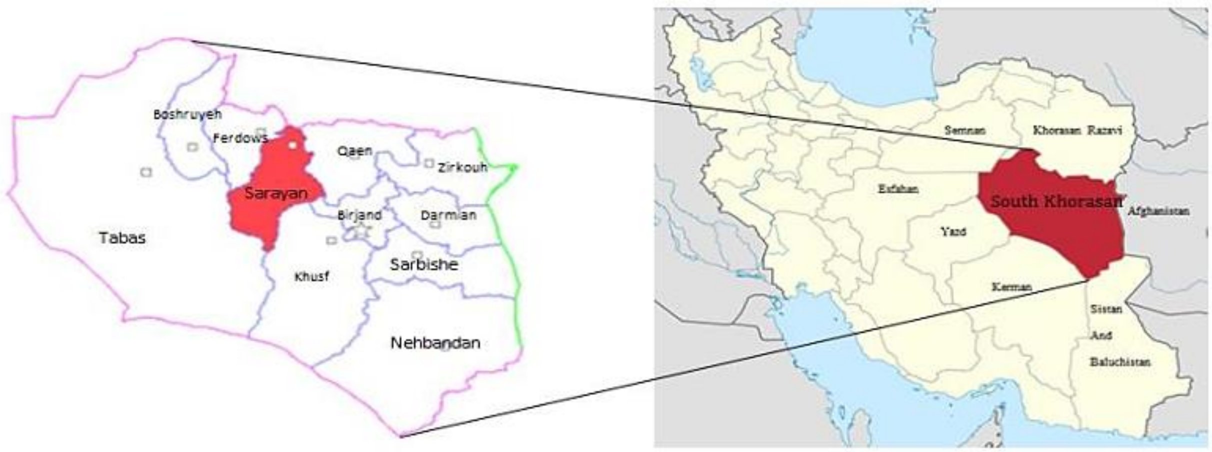

Fig. 2. Map of the study area (South Khorasan Provincial Government, 2016).

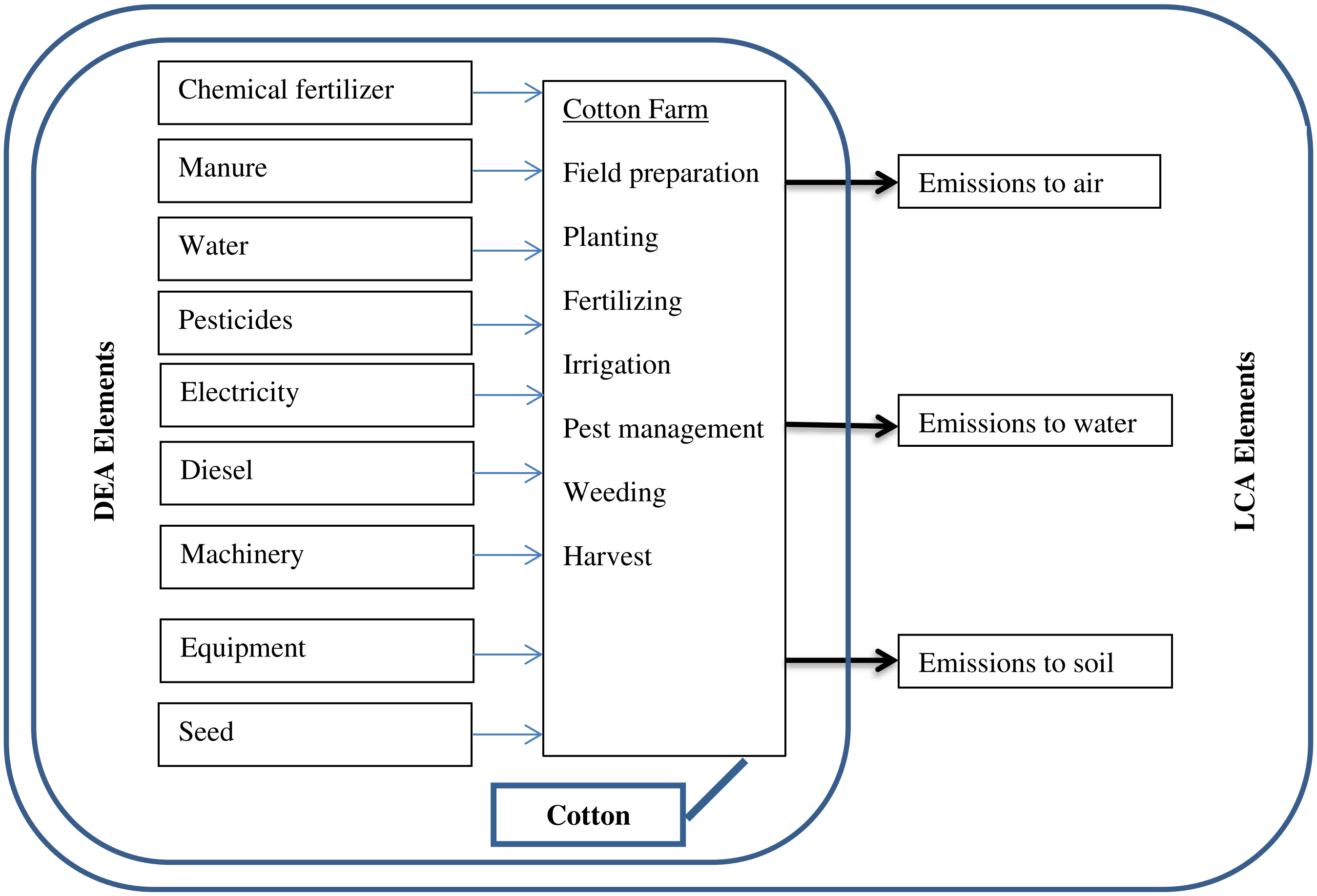

Fig. 3. System boundary of cotton production in southeastern of Iran.

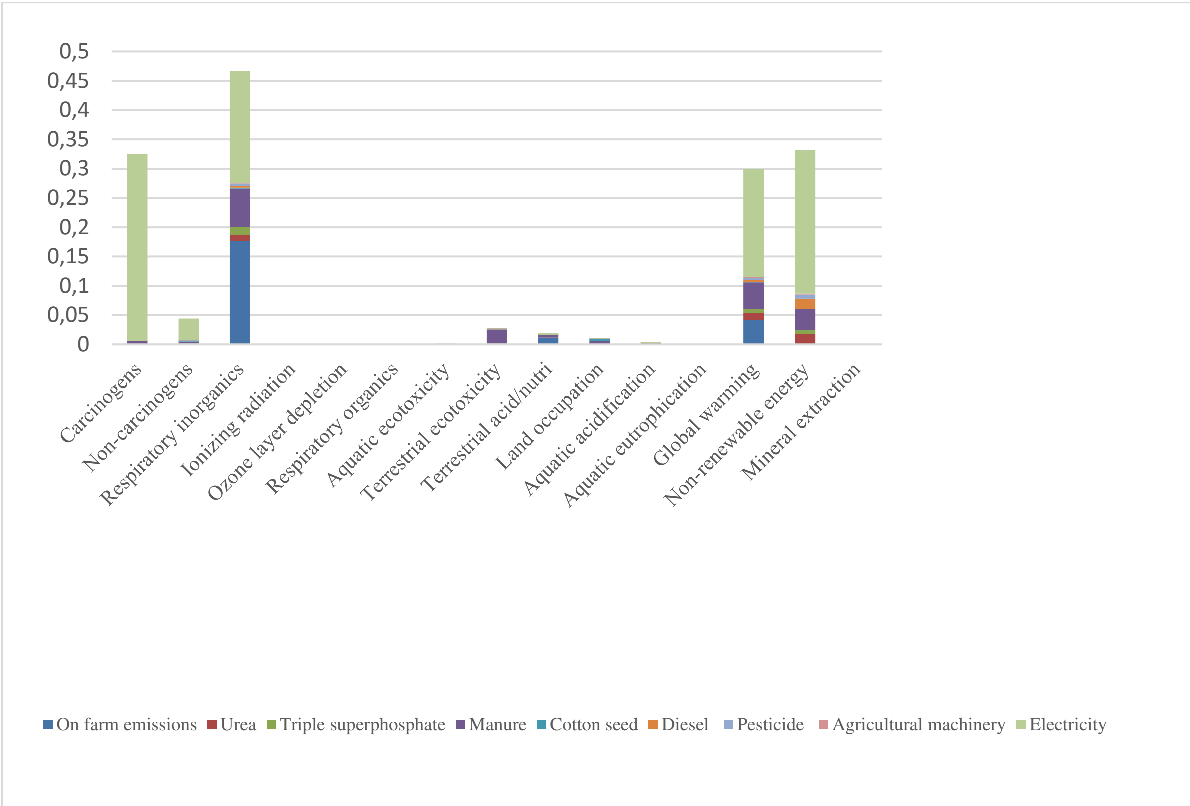

Fig. 4. Normalized impact indicators studied for cotton production.

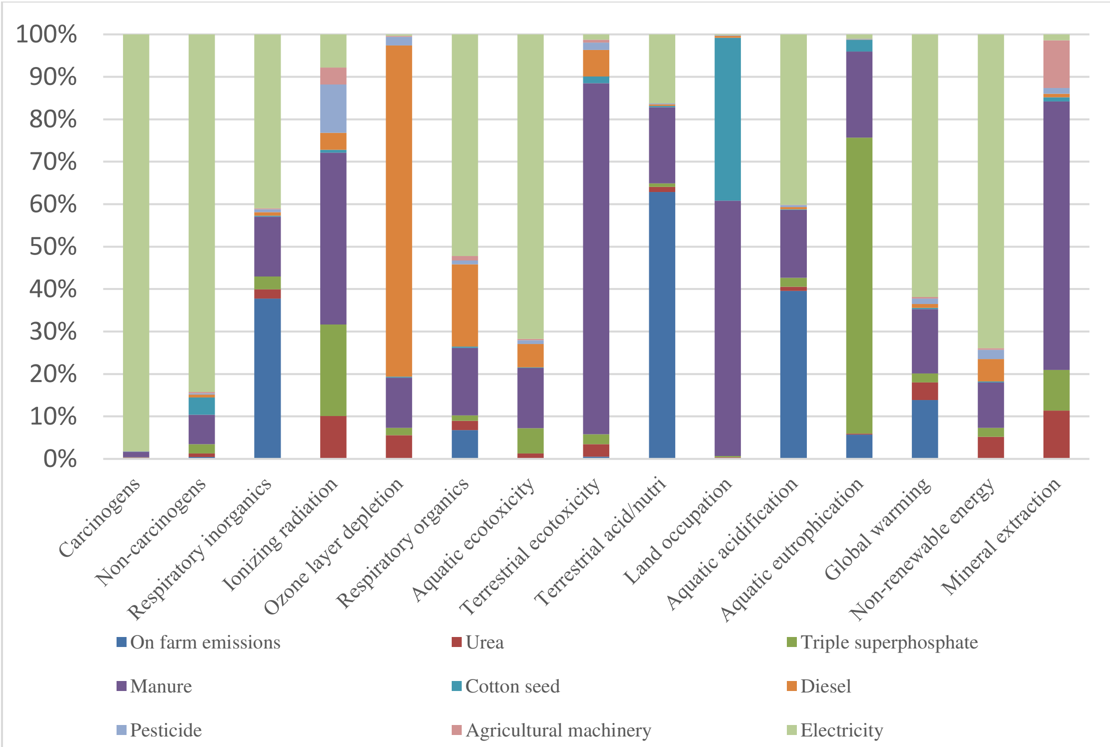

Fig. 5. Impact categories studied for cotton production and the extent of different inputs' effects on each category.

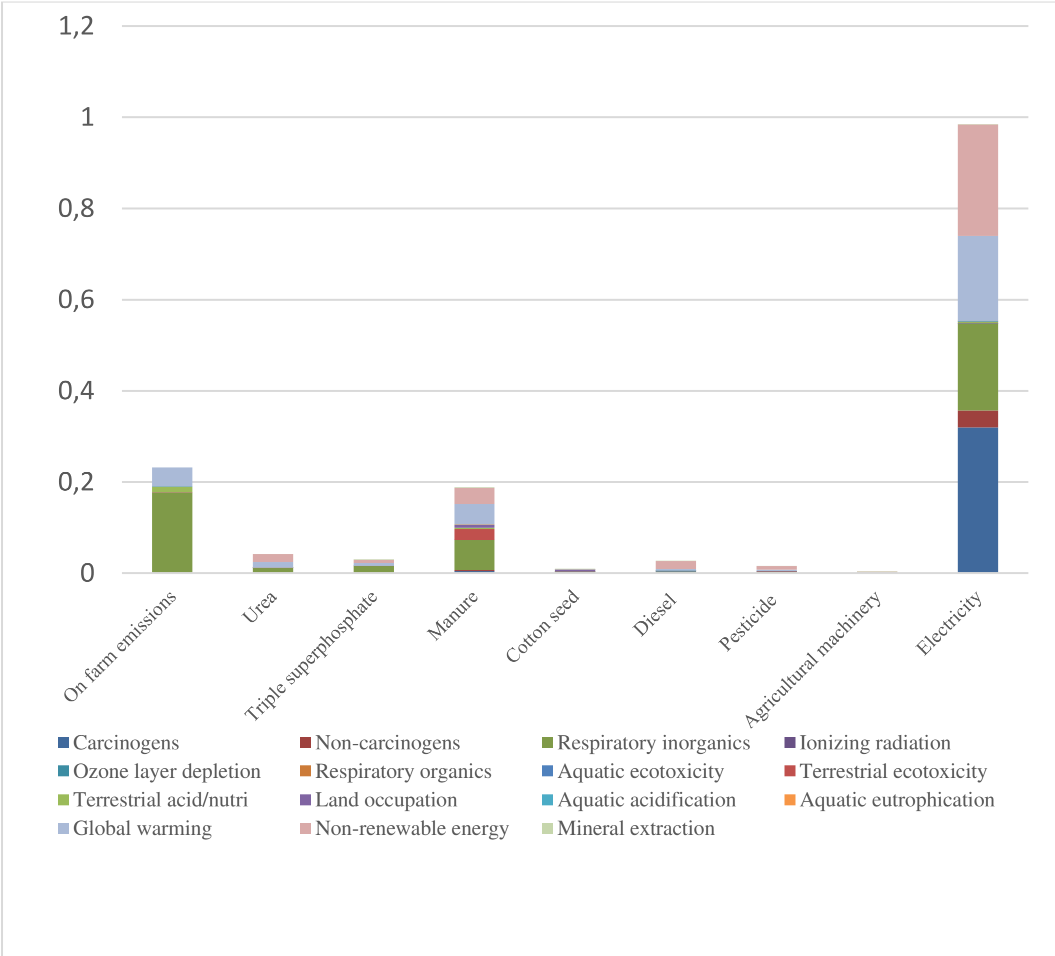

Fig. 6. Effect of each input on the assessed impact indicators in cotton production.

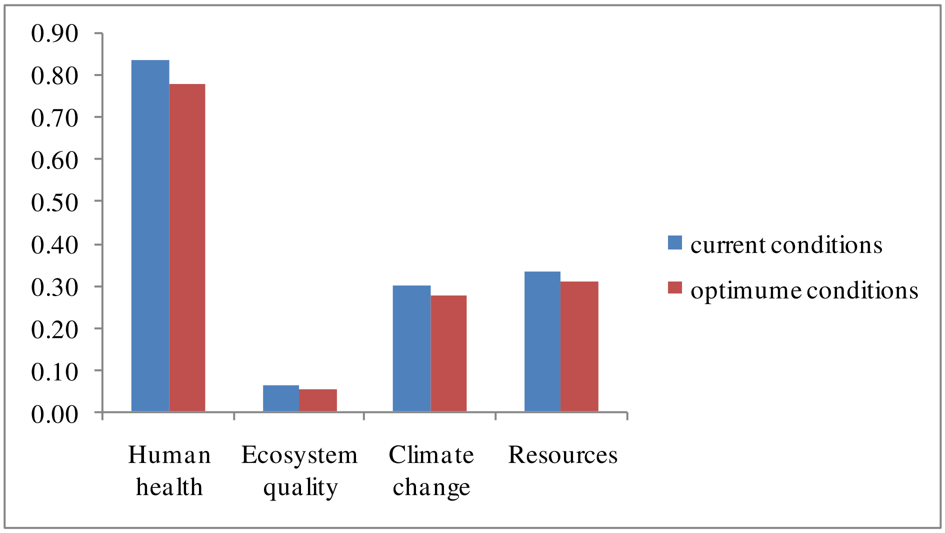

Fig. 7. Damage category of cotton production in eastern Iran.

Table1

The life cycle inventory variables applied in the study

Input	Unit	Average
N- fertilizer	kg	185.48
P- fertilizer	kg	155.54
Farmyard manure	kg	2246.29
Seed	kg	90.97
Electricity	kWh	5605.86
Diesel	L	141.26
Herbicide	kg	0.19
Insecticide	kg	11.14
Machinery	kg	3.67
Equipment	kg	2.59
Water	L	7296070.07
Yield	kg	2260.57

*- One hectare of cotton farm

Table2

Descriptive statistics for efficiency scores of cotton farms

	Technical efficiency	Pure technical efficiency	Scale efficiency
Average	0.81	0.92	0.87
Std. Deviation	0.20	0.11	0.17
Max	1.00	1.00	1.00
Min	0.20	0.55	0.21
Efficient DMU	46	122	122
Efficient DMU%	31.08	82.43	82.43

Table 3
Comparison results of impact indicators for cotton cultivation under current conditions and optimum input use

Impact indicators	Unit/ton	Current condition	Optimum condition	Improvement %
Carcinogens	kg C2H3Cl eq	824.17	791.76	3.93
Non-carcinogens	kg C2H3Cl eq	111.54	105.62	5.31
Respiratory inorganics	kg PM2.5 eq	4.73	4.32	8.51
Ionizing radiation	Bq C-14 eq	12227.09	10400.25	14.94
Ozone layer depletion	kg CFC-11 eq	0.00	0.00	9.33
Respiratory organics	kg C2H4 eq	1.41	1.30	7.88
Aquatic ecotoxicity	kg TEG water	381161.52	354190.30	7.08
Terrestrial ecotoxicity	kg TEG soil	48555.03	39016.17	19.65
Terrestrial acid/nutrient	kg SO2 eq	253.64	227.28	10.39
Land occupation	m2org.arable	123.90	104.74	15.47
Aquatic acidification	kg SO2 eq	50.90	46.36	8.93
Aquatic eutrophication	kg PO4 P-lim	1.88	1.65	12.12
Global warming	kg CO2 eq	2969.60	2746.90	7.50
Non-renewable energy	MJ primary	50338.38	47047.80	6.54
Mineral extraction	MJ surplus	24.11	19.99	17.11