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Application of data envelopment analysis approach for optimization of energy use and reduction of greenhouse gas emission in peanut production of Iran

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A B S T R A C T

The continuous growth in energy demand, the inevitable decline in the availability of fossil fuels, and the rising concern about increasing emissions are all precursors to climate change. The aims of this study comprise the assessment of energy flow and greenhouse gas emission of peanut production in Guilan province, Iran, and then the application of data envelopment analysis to determine optimum energy use pattern for saving energy and reduction of greenhouse gas emission. 120 peanut farms in Guilan province, Iran, an important hub for peanut production, are examined. Data envelopment analysis results show that 22 (18.33%) and 90 (75%) peanut producers are effective units based on constant and variable returns to scale, respectively. The technical, pure technical and scale efficiencies are 0.79, 0.98 and 0.81, respectively. The amount of energy consumption saving by converting inefficient farms into efficient farms is estimated to be 1760 Mega-Joule per hectare. Chemical fertilizer (contributing 48%) has the maximum share to total energy saving in peanut production. Therefore, correct and standard consumption of chemical fertilizer can be a viable solution for energy saving consumption. The total greenhouse gas emissions from peanut farming are computed to be 571.18 and 512.39 kg of carbon dioxide equivalent per hectare for present and optimum farms, respectively. Moreover, the total greenhouse gas emission can be reduced by 58.79 kg of carbon dioxide equivalent per hectare by optimizing energy inputs in peanut farming. This reduction in greenhouse gas emission can be realized by management of diesel fuel, nitrogen and machinery consumption according to optimized input rates introduced by the data envelopment analysis.

1. Introduction

Energy is used for almost all facets of living and in all countries. It enables the existence of ecosystems, human civilizations and life (Ebrahimi and Salehi, 2015). Due to increase of population, lack of sufficient land for cultivation and increase of prosperity, energy consumption in agriculture has increased. The problem is usually resolved by a solution with the maximization of output performance, the minimization of labor-intensive practices, or both together (Esengun et al., 2007). Yet, energy use and carbon dioxide emission have a direct positive correlation, which may lead to global climate change (Lu et al., 2013). Agricultural greenhouse gas (GHG) emission accounts for 10–12% of all man-made GHG emissions (Pishgar-Komleh et al., 2012). As such, to realize sustainable development and mitigate effects of energy consumption on the environment, optimization of energy consumption is one of the most important management requirements in agricultural production systems (Rafiee et al., 2010).

Peanut seed (*Arachis hypogaea* L.), with over 40% oil, is the

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second most important oil seed, just after soybean, in tropical and semi-tropical regions. There are more than 3000 ha of land cultivated with peanuts in Iran, of which 2500 ha are in Guilan province. Major peanut products planted in Guilan province are mostly in Astaneh Ashrafiyeh City and Kiyashahr Port (Nikkhah et al., 2015). Given the economic importance and other benefits of peanut cultivation, farmers try to spend more energy (increased use of inputs, including fertilizers and pesticides, as well as planting, harvesting and mechanized processing) to produce more amount of peanut. Therefore, recognition of optimal energy use pattern in peanut cultivation is essential for appropriate energy consumption, eco-friendly and beneficial peanut production. There are several methods for computing energy efficiency and optimization of consumption. Literature review shows that data envelopment analysis (DEA) is a popular method to determine the efficiency in various fields including energy efficiency in agriculture (Nabavi-Pelesaraei et al., 2017a).

DEA technique is recognized as a non-parametric linear programming method of boundary estimation. DEA is used to determine the relative efficiency of some decision-making units (DMUs) based on multiple outputs and inputs (Mousavi-Avval et al., 2011). Several studies have been undertaken by researchers in respect of agricultural products, taking consideration of the importance of improving energy consumption efficiency and reducing GHG emission. Bolandnazar et al. (2014) employed DEA method to determine the optimal energy consumption and reduce GHG emissions for greenhouse cucumber production in Jiroft city of Iran. Results indicated that 26.7% and 73.3% of farmers were technically and pure technically efficient, respectively. They showed that DEA method could significantly improve the energy efficiency and GHG emissions in greenhouse cucumber production. Optimum energy requirement was 288,168.59 MJ ha^{-1}, indicating that 11% of the total energy input could be saved. Mohammadi et al. (2015) combined DEA with life cycle assessment for benchmarking environmental impacts in rice paddy production. Optimization results by DEA showed average reduction levels of up to 20% and 25% per material input for spring and summer systems, respectively. The corresponding reductions of environmental impacts ranged from 8% to 11% and 19%–25% for spring and summer farms, respectively, depending on the chosen impact category. Ebrahimi and Salehi (2015) used non-parametric DEA techniques to determine efficient and inefficient units in button mushroom production of Iran, and also estimate the amount of storage energy and the reduction in GHG emission. The total optimum energy requirement was 812.75 MJ m^{-2}; indicating that 88.07 MJ m^{-2} of input energy could be saved. Optimization of energy use improved the efficiency, specific energy and net energy by 13.3%, 9.38% and 10.06%, respectively. Elhami et al. (2016) presented a DEA model for saving of energy consumption and reduction of its corresponding harmful effects in chickpea production. The total energy requirement in the optimal situation, by using DEA technique, was 31,511.72 MJ ha^{-1}, showing a reduction by 5.11% compared to the existing situation. Nabavi-Pelesaraei et al. (2017a), by using DEA to identify patterns of efficient and inefficient farms, computed the amount of optimal energy consumption for paddy farm. The amount of GHG emission and other environmental impacts of efficient and inefficient farms were compared. Optimization results indicated that the enhancement of the efficiency of paddy production was mainly in terms of optimal use of toxins and chemical fertilizers. Houshyar et al. (2017) employed DEA models for energy efficiency analysis to measure the amount of dynamic energy consumption and pomegranate production growth during 2009–2015 in the Fars province, Iran. Results showed that the most efficient case occurred if gardeners consumed more renewable energy, especially in the form of farm yard manure. Various studies about the evaluation and optimization of energy use and environmental impacts were undertaken on farms. In these studies, inputs were identified that increased environmental impacts and energy consumption and various methods were suggested to mitigate them. However, due to differences in the production, cultivation pattern and inputs of various agricultural products, these results cannot be used directly to provide a consumption pattern in peanut cultivation.

Considering satisfactory results of the use of DEA for optimizing energy in various studies, and lack of sufficient study on optimizing energy use in peanut production in Iran, this study was undertaken to identify factors that might lead to the use of surplus energy in peanut field and to provide solutions to increase energy efficiency by employing DEA.

More specific aims are listed as follows:

- Analysis and evaluation of the flow of energy in peanut production.
- Assessment of GHG emission in peanut production and analysis of GHG emission resources in peanut production.
- Assessment of energy efficiency and identification of causes of inefficiency in energy consumption of peanut production by DEA.
- Provision of an optimized energy consumption pattern to reduce energy consumption and GHG emission in peanut production via the identification of causes of inefficiency.

2. Materials and methods

Guilan province, with an annual production of about 10,000 ton of peanuts, is one of the main centers of production in Iran (Ministry of Jihad-e-Agriculture of Iran, 2016). This study is carried out in this area because of the abundance and variety of farms. Guilan province is situated in north Iran, within northern latitudes of 36°34′and 38°27′ and eastern longitudes of 48°53′ and 50°34′. The geographical location of this area is shown in Fig. 1 (Nabavi-Pelesaraei et al., 2017a). The data used in this study were collected from 120 farms in 2012/2013. These farms were selected by using sampling method among other fields. This method is expressed as follows (Cochran, 1977):

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

where n is the required sample size, N is the number of farms per target population (equals to 150), z is the reliability coefficient (equals to 1.96, which represents the 95% confidence level), p is the estimated proportion of an attribute that is present in the population (equals to 0.5), q is 1-p (equals to 0.5), and d is the permitted error ratio deviation from the average population (equal to 0.05). By considering the abovementioned items, the sample size was estimated as 108 farms. In order to be more certain and to increase the accuracy of results, the information of 120 farms are examined.

The key inputs comprise labor, diesel fuel, machinery, biocides, chemical fertilizers and seeds for these farms. The energy equivalent is defined as the energy input taking into account all types of energy utilized in farms (Mousavi-Avval et al., 2011). Table 1 shows the input quantities per hectare of farm. The energy coefficients of inputs represent the energy used for primary production until the end process. The energy equivalents of inputs may vary in different countries. During the process in reviewing various studies in energy field, it is observed that no studies were undertaken specifically to determine the energy equivalent in agriculture of Iran. So the same coefficients of energy equivalent, as those used previously

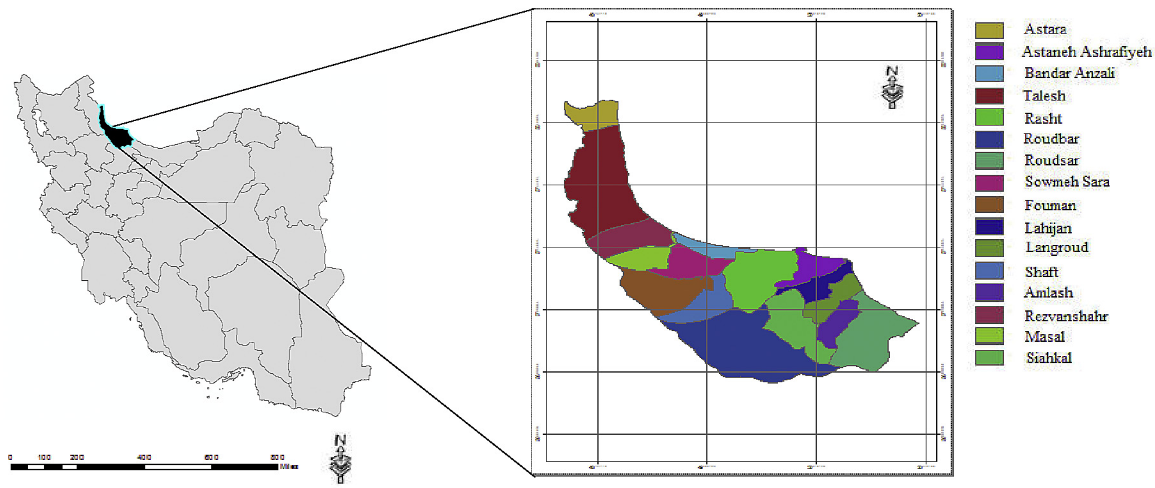

Fig. 1. Location of the studied area in the north of Iran.

Table 1
Energy coefficients and energy inputs/output in various operations of peanut production.

Items (unit)	Energy equivalent (MJ unit^{-1})	Quantity per unit area (ha)	Total energy equivalent (MJ ha^{-1})
A. Inputs			
1. Human labor (h)	1.96 (Nabavi-Pelesaraei et al., 2017b)	636.65	1247.83
2. Machinery (h)	62.70 (Rafiee et al., 2010)	13.44	842.53
3. Diesel fuel (l)	56.31 (Nabavi-Pelesaraei et al., 2017c)	117.84	6635.44
4. Chemical fertilizers (kg)			
(a) Nitrogen	66.14 (Mobtaker et al., 2012)	121.73	8027.74
(b) Phosphate (P_2O_5)	12.44 (Unakitan et al., 2010)	25.95	322.85
(c) Potassium (K_2O)	11.15 (Pahlavan et al., 2011)	31.46	350.78
5. Biocides (kg)	120 (Ozkan et al., 2004)	2.68	520.36
6. Seed (kg)	25 (Nikkhah et al., 2015)	59.99	1499.78
The total energy input (MJ)			19,248.04
B. Output			
1. Peanut (kg)	25 (Nikkhah et al., 2015)	3488.39	87,209.68

in similar studies, are employed in this study. Energy equivalents are computed for all outputs and inputs by using conversion factors (Canakci et al., 2005). The amount of each input is converted to equivalent MJ ha^{-1} energy units (Table 1).

As shown in Table 1, the amount of total input energy is 19,248.04 MJ ha^{-1} (with standard deviation of 10,299.33) and peanut yield is 3488.39 kg ha^{-1} (with standard deviation of 2279.14).

2.1. DEA approach

DEA is a method suitable for evaluation and determination of relative efficiency of a certain number of production units. Each production unit is called decision-making unit (DMU) in DEA terminology (Bolandnazar et al., 2014). DEA allows for the relative efficiency measurement of a group of DMUs that utilize different inputs to provide outputs (Pahlavan et al., 2011). By employing this technique, reasons and levels of inefficiency of units can be identified. Hence, DEA technique is employed in this study to identify efficient farms and estimate optimal energy consumption based on peanut producers' performance. Fig. 2 demonstrates the differences between results by regression analysis and DEA. Output and inputs are shown on the horizontal and vertical axes, respectively (Fig. 2).

Eight cases of DMUs having a single input and single output with different output-input ratios are considered as points P1 to P8. The linear regression line for a parametric method is a dotted line, which shows the trend of the data points. In this technique, all

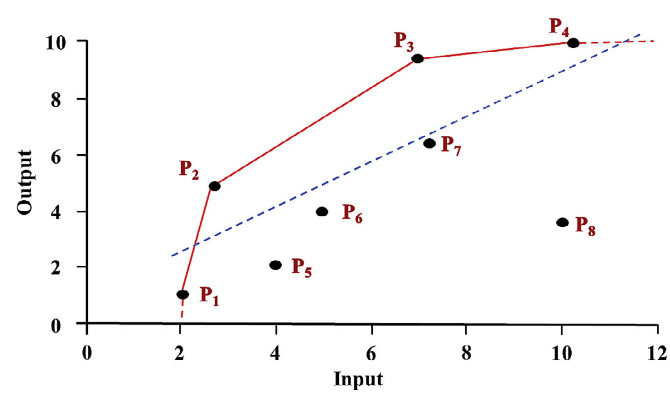

Fig. 2. Difference of DEA and regression analysis.

DMUs situated on or above this line are known as advantageous DMUs (P2, P3 and P4). In the case of a non-parametric approach, a piecewise line is drawn as an envelope above the dataset by connecting the boundary points with straight lines. In addition, P1, P2, P3 and P4 are frontier points in Fig. 2. These points are connected to each other by a solid line that provides the envelope for the dataset. DMUs lying on the boundary line are considered efficient (DMUs 1, 2, 3 and 4) while other DMUs are considered inefficient (Mousavi-Avval et al., 2011).

A comparable statistical method is the central tendency method which appraises DMUs relative to an average DMU, whilst DEA compares each DMU with the "best" DMU. In recent years a high variety of applications of DEA are for appraising the efficiency in different fields and locations (Zhao et al., 2006). A major reason is that DEA has opened up possibilities for use in cases which have been resistant to other approaches because of the complex (often unknown) nature of the relations between multiple inputs and outputs involved in many of these activities (Cooper et al., 2006). Please refer to Charnes et al. (1978) for more in-depth study of DEA.

There are two ways in treating returns to scale (RTS) in DEA (Banker et al., 1984). Charnes, Cooper and Rhodes (CCR) introduced CCR model which had approach of Constant Returns to Scale (CRS) and measured technical efficiency (TE) (Charnes et al., 1978). BCC model was introduced by Banker et al. (1984), which measured TE as the convexity constraint and ensured that the composite unit was of similar scale size as the unit being measured. The resulting efficiency was always at least equal to the one given by the CCR model, and those DMUs with the lowest input or highest output levels were rated efficient. Unlike the CCR model, the BCC model allowed for Variable Returns to Scale (VRS). On the other hand, CCR and BCC models were divided into two types, namely, input-oriented models that had the objective of minimizing inputs while maintaining the same level of outputs, and output-oriented models that were focused on increasing outputs with the same level of inputs (Malana and Malano, 2006). Since in waste management system, there cannot be any control on the amount of outputs materials (here peanut) yet there can be control on inputs, in this study, input oriented DEA models are used to determine efficient and inefficient DMUs.

In DEA, efficiency is defined in three different forms, namely, technical efficiency (TE), pure technical efficiency (PTE) and scale efficiency (SE) (Qasemi-Kordkheili and Nabavi-Pelesaraei, 2014).

TE is defined to be present when evidence shows that it is possible to improve some input or output without worsening some other input or output (Charnes et al., 1978). Also, technical efficiency under VRS or PTE relates to the ability of managers to use firms' given sources and SE refers to exploit scale economies by operating at a point where the production frontier exhibits CRS (Banker et al., 1984). If there appears to be a difference between the TE and PTE scores of a particular DMU, then it indicates the existence of scale inefficiency (Rosman et al., 2014).

As mentioned above the TE can be defined by the ratio of the sum of weighted outputs to the sum of weighted inputs. The mathematical equation for this definition is given as follows (Cooper et al., 2006):

$$TE_j = \frac{u_{1j}y_{1j} + u_{2j}y_{2j} + \ldots + u_{sj}y_{sj}}{v_{1j}x_{1j} + v_{2j}x_{2j} + \ldots + v_{mj}x_{mj}} = \frac{\sum_{r=1}^{s} u_{rj}y_{rj}}{\sum_{i=1}^{m} v_{ij}x_{ij}} \quad (2)$$

In Eq. (2), s is the number of outputs, m is the number of inputs, n is the number of DMUs, TE_j (j = 1, 2, …, n) is the TE of DMU$_j$, u_{rj} (r = 1, 2, …, s) is the weighting of output y_r in the comparison, v_{ij} (i = 1, 2, …, m) is the weighting of input $x_{i,}$ y_{rj} is the amount of service output r produced by DMU j during the observation period, and x_{ij} is the amount of resource input i used by DMU j during the observation period.

In Eq. (2), each DMU determines one set of input and output weights for efficiency valuation. Therefore, there are n sets of input and output weights for n DMUs. By considering 120 DMUs with six inputs and one output to be evaluated in this study, Table 2 shows weighting factors for input and output variables. In Table 2, elements v_{ij} and u_{rj}, illustrate the weighting of input x_i and output y_r for DMU$_j$.

Table 2
The weighting factors for the inputs and output used in DEA models.

Item	DMU$_1$	DMU$_2$	…	DMU$_{120}$
Inputs				
1. Human labor	v_{11}	v_{12}	…	v_{1120}
2. Machinery	v_{21}	v_{22}	…	v_{2120}
3. Diesel fuel	v_{31}	v_{32}	…	v_{3120}
4. Chemical fertilizers	v_{41}	v_{42}	…	v_{4120}
5. Biocides	v_{51}	v_{52}	…	v_{5120}
6. Seed	v_{61}	v_{62}	…	v_{6120}
Output				
1. Peanut	u_{11}	u_{12}	…	u_{1120}

Let DMU$_o$ (o = 1, 2, …, n) be DMU$_j$ to be evaluated on any trial. To calculate the relative efficiency of a DMU$_o$ based on a series of n DMUs, the model is structured as a fractional programming problem as follows (Cooper et al., 2006):

$$\begin{aligned} &\text{Maximize } TE_o = \frac{\sum_{r=1}^{s} u_{ro}y_{ro}}{\sum_{i=1}^{m} v_{io}x_{io}} \\ &\text{Subject to: } \frac{\sum_{r=1}^{s} u_{ro}y_{rj}}{\sum_{i=1}^{m} v_{io}x_{ij}} \le 1, j = 1,2,3,\ldots,n \\ &u_{ro} \ge 0,\ v_{io} \ge 0 \end{aligned} \quad (3)$$

where y_{ro} is the amount of output r produced by DMUo during the observation period, x_{io} is the amount of resource input i used by DMUo during the observation period, u_{ro} is the weight assigned to service output r computed in the solution to the DEA model, and v_{io} is the weight assigned to resource input i computed in the solution to the DEA model. Eq. (3) can be written by a linear programming problem as follows (Cooper et al., 2006):

$$\begin{aligned} &\text{Maximize } TE_o = \sum_{r=1}^{s} u_{ro}y_{ro} \\ &\text{Subject to: } \sum_{r=1}^{s} u_{ro}y_{rj} - \sum_{i=1}^{m} v_{io}x_{ij} \le 0, j = 1,2,3,\ldots,n \\ &\sum_{i=1}^{m} v_{io}x_{io} = 1 \\ &u_{ro} \ge 0,\ v_{io} \ge 0 \end{aligned} \quad (4)$$

Actually, the dual linear programming problem is simpler to solve than Eq. (4) because of fewer limitations. The dual linear programming is written in vector–matrix notation mathematically (Cooper et al., 2006):

$$\begin{aligned} &\text{Minimum } TE_o \\ &\text{Subject to: } \sum_{j=1}^{n} Y_j\lambda_j \ge y_o \\ &\sum_{j=1}^{n} X_j\lambda_j - TEx_o \le 0 \\ &\lambda_j \ge 0 \end{aligned} \quad (5)$$

where y_o is the $s \times 1$ vector of the amount of original outputs produced and x_o is the $m \times 1$ vector of the amount of original inputs used by the oth DMU. Y is the $s \times n$ matrix of outputs and X is the $m \times n$ matrix of inputs of all n units included in the sample. λ is a $n \times 1$ vector of weights and TE_o is a scalar with boundaries of one and zero which determines the TE score of DMU$_o$. Model (5) is known as the input-oriented CCR model.

Model (5) has a feasible solution $TE = 1$, $\lambda_0 = 1$, $\lambda_j = 0$, $j = 1, 2, \ldots, n$ and $j \neq 0$. Hence the optimal TE, denoted by TE*, is not greater than 1. On the other hand, due to the nonzero (i.e., semi positive) assumption for the data, the constraint $\lambda_j \geq 0$ forces λ to be nonzero because $y_0 > 0$ and $y_0 \neq 0$. Hence, from $\sum_{j=1}^{n} X_j\lambda_j - TEx_o \leq 0$, TE must be greater than zero. Putting this all together, it results in $0 < TE^* \leq 1$ (Cooper et al., 2006). Since model (4) is multiplier form of model (5) (envelopment form), model (4) has a feasible solution.

In addition to the CRS model, Banker et al. (1984), by employing the concept of DEA, offered another model called PTE, or BCC model. BCC model calculates the technical efficiency of DMUs under variable return to scale conditions and can separate both technical and scale efficiencies. This model has an important benefit that scale ineffective farms are only compared to effective farms of an identical size (Mobtaker et al., 2012). The BCC model is provided by adding a restriction on λ ($\lambda = 1$) in model (5), resulting in no condition on the allowable returns to scale. This model assumes VRS, indicating that a change in inputs is expected to result in a disproportionate change in outputs (Mousavi-Avval et al., 2011).

In this condition, the performance frontier line is not then restricted to pass through the origin, and an increase in inputs may not result in a proportionate increase in outputs in this case (Cooper et al., 2006). Due to convexity, the efficient DMUs form a convex hull on which all inefficient points are projected. Because VRS is more flexible and envelops the data in a tighter way than CRS, PTE is equal to or greater than CRS or the overall TE score. The relationship can be used to measure SE (Omid et al., 2011). According to the above-mentioned relationship between TE and PTE, SE is given below (Nabavi-Pelesaraei et al., 2017a):

$$SE = \frac{TE}{PTE} \tag{6}$$

This decomposition shows the sources of inefficiency. PTE refers to the efficiency in energy consumption while SE shows the impact unit size on system efficiency. In other words, one can say that part of the inefficiency in energy consumption goes to the incorrect selection of unit size, and when DMU moves toward an optimal size the overall efficiency (technical) can be developed at an equal level of approaches (inputs). In this study, for the computation of TE and PTE, scores of units are retrieved from Frontier Analyst 4 software. The Kruskal-Wallis test, as a non-parametric post-test, is also employed to determine significant differences among farm categories as well as agro-climatic zones (Nassiri and Singh, 2009).

Cross efficiency assessment has been widely utilized to identify the most effective DMU or to rank DMUs using DEA. Other available methods for cross-efficiency assessment concentrate on how to measure the uniqueness of output and input weights, yet neglecting the process of accumulation of cross-efficiencies and only addressing them according to the similarities without regard to their respective importance (Wang and Wang, 2013). In this study, scores of efficiency are aggregated in matrix of cross efficiency. The element in the ith row and jth column represents the efficiency score for the jth farmer computed by using the optimal weights of the ith farmer which is computed by the CCR model. The efficient farmers are ranked according to their mean cross efficiency score that is attained by averaging each column of cross efficiency matrix (Nabavi-Pelesaraei et al., 2017).

The credibility of the assumption is an important issue in efficiency studies that the total production process can actually attain the best practice production frontier (Chien and Hu, 2007). In the present study, when measuring energy efficiency, it is assumed that the best practice is accessible to all DMUs. The set on the frontier is the 'best practice' production among the observed DMUs. The inefficient DMUs can reduce inputs by the amount indicated by the arrow and still remain in the input set linear programming using observed data (Boyd and Pang, 2000). The out-of-date technology level and the inefficient production process produced a redundant portion of energy use that needs to be further adjusted. The value of total adjustments, including slack and radial adjustments, was calculated by DEA (Hu and Wang, 2006). The summation of slack and radial adjustments was the total value of 'target' that could be decreased without reduction in output levels. With respect to energy input, the above summation was termed the energy saving target (EST) (Hu and Kao, 2007).

Generally, efficiency is defined in terms of the ratio with which the best practice compares with the actual operation. The indicator of energy efficiency therefore should be the ratios of EST to the actual energy input (AEI). The energy saving target ratio (ESTR) was employed to specify the inefficiency level of energy usage for DMUs under consideration. The equation is presented below (Hu and Kao, 2007):

$$ESTR = \frac{EST}{AEI} \tag{7}$$

In Eq. (7), *EST* is energy saving target and *AEI* is actual energy input. *EST* is the total reduction amount of energy inputs that could be saved without reduction in the output level. Eq. (7) is a standard efficiency definition which is generally defined in terms of the ratio with which the best-practice operation is compared with the actual operation. The minimal value of energy saving target is zero, so the percentage of ESTR will be between zero and 100. A higher ESTR percentage denotes higher energy consumption inefficiency, and thus, a higher energy saving value (Hu and Kao, 2007).

2.2. GHG emission

In this study, in addition to the determination of the energy efficiency of units and the optimal energy use, the reduction of GHG emission as results from the reduced energy consumption is assessed by using DEA. GHG emission coefficients for inputs used in peanut farms are given in Table 3. GHG emission in peanut farms is studied in two cases. In the first case, GHG emission is performed by multiplying the emission coefficient in conventional energy consumption mode. In the second case, GHG emission is attained in the ideal situation and this amount is obtained by multiplying the emission coefficient in the optimal energy consumption mode according to the BCC model. The present and the target amounts of emission are then compared and assessed.

Table 3
GHG emission coefficients of agricultural inputs.

Inputs	Unit	GHG coefficient (kg $CO_{2\ eq.}$ $unit^{-1}$)	Reference
1. Machinery	MJ	0.71	(Pishgar-Komleh et al., 2012)
2. Diesel fuel	L	2.76	(Pishgar-Komleh et al., 2012)
3. Chemical fertilizers	kg		
(a) Nitrogen		1.3	(Taghavifar and Mardani, 2015)
(b) Phosphate (P_2O_5)		0.2	(Taghavifar and Mardani, 2015)
(c) Potassium (K_2O)		0.2	(Taghavifar and Mardani, 2015)
4. Biocides	kg	6.3	(Taghavifar and Mardani, 2015)

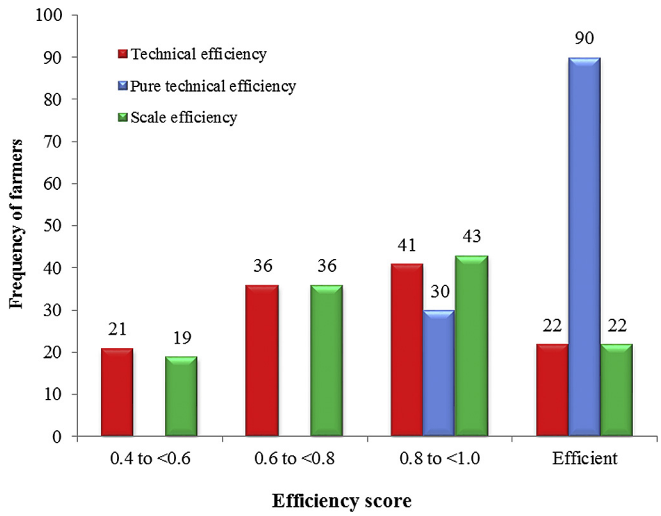

Fig. 3. Efficiency score distribution of peanut producers.

Table 4
Average technical, pure and scale efficiency of peanut farmers.

Particular	Technical efficiency	Pure technical efficiency	Scale efficiency
Average	0.79	0.98	0.81
SD	0.16	0.04	0.15
Min	0.45	0.90	0.46
Max	1	1	1

3. Results and discussion

Fig. 3 exhibits results of BCC and CCR by DEA. It can be observed that, from a total of 120 farmers that are analyzed and evaluated, 22 (18.33%) and 90 (90%) have TE and PTE scores of 1. This means that these farmers are efficient in terms of energy consumption in terms of TE and PTE, respectively. In other words, their potential for energy consumption reduction is 0. As previously mentioned, the score SE is 1 for unit that has full efficiency score in both TE and PTE. Hence, based on the energy consumption, 22 peanut farms have suitable size.

The statistics for three efficiency measures are summarized in Table 4. This table also includes standard deviation, and minimum and maximum scores for each measure. Results of the analysis in these section indicate that mean values of TE, PTE and SE are 0.79 (with standard deviation of 0.16), 0.98 (with standard deviation of 0.04) and 0.81 (with standard deviation of 0.15), respectively. It should be noted that the maximum values are 1 for all these mean scores.

TE, PTE and SE in paddy farms are 0.853, 0.953 and 0.9, respectively (Nabavi-Pelesaraei et al., 2017a). Ebrahimi and Salehi (2015) reported mean TE, PTE and SE for button mushroom production as 0.94, 0.97 and 0.97, respectively. Comparison of average TE scores in this study and those of previous studies indicate that TE in peanut production is low compared to those of soybeans and button mushroom. As such, there is high potential for increasing farmers' TE in peanut cultivation, which can be accomplished by identifying inefficient resources.

Effective farmers are ranked considering results of the CCR model and mean cross efficiency scores. Table 5 shows the mean and standard deviation of cross efficiency scores for 15 most efficient farmers. The maximum average cross efficiency scores are 0.957, 0.954, 0.924, 0.922 and 0.921 for farmer numbers. 50, 2, 63, 4 and 73, respectively. Since these farms have energy consumption with almost similar pattern, differences in cross efficiency scores are not significant for the most efficient units.

Table 5
Average cross efficiency (ACE) score for 15 truly most efficient farmers base on the CCR model.

Farmer No.	ACE	SD	Farmer No.	ACE	SD	Farmer No.	ACE	SD
50	0.957	0.11	25	0.853	0.19	23	0.695	0.17
2	0.954	0.17	55	0.846	0.09	43	0.650	0.22
63	0.924	0.18	53	0.835	0.12	92	0.621	0.18
4	0.922	0.15	96	0.805	0.10	61	0.506	0.16
73	0.901	0.14	97	0.753	0.12	31	0.437	0.19

Table 6 lists physical input-output values for both inefficient and 15 most efficient peanut producers in Guilan province, Iran. Results show that diesel fuel, chemical fertilizers and biocides are used in inefficient units to a greater extent than efficient units. The followings provide some ways to reduce this disparity for inefficient farmers. Farmers can save fuel before it reaches the tractor. Fuel tanks above ground level should be painted with a light color and should be kept shaded to prevent the loss of fuel by evaporation. Farmers should carry out regular maintenance on their engines and tires. Routine replacement of lubricants and air and fuel filters can reduce fuel use while increasing horsepower. Proper pressure and alignment can help minimize resistance, which can reduce fuel efficiency. Farmers can save fuel by shifting to a higher gear and slowing the engine speed (rpm) to maintain the desired speed. Farmers should use their smallest and lightest tractor for light loads and jobs to get the best fuel efficiency. For operations that require more horsepower, farmers should go with a larger tractor to avoid overloading smaller tractors, which increase fuel consumption. Farmers can attain efficiency with effective travel patterns. Besides, quality oils, lubricants and fuel can help increase fuel efficiency, while extending engine life. 35% efficient farmers use human labors and seeds 0.16% and 3.35% more than inefficient farmers, respectively. Moreover, results reveal that the yields of the 15 most efficient units are higher than inefficient units by about 24%.

The optimal energy consumption of peanut production computed using BCC model for different inputs are given in Table 7. The amount of energy saved for each factor is also listed. As seen in Table 7, the optimum energy consumption is 17,487.23 MJ ha^{-1} in peanut production. According to results obtained with the conversion of inefficient to efficient units, 9.15% of the total energy consumption can be saved. The highest energy saving is 13.93% for machinery in peanut production, followed by biocides (10.23%) and chemical fertilizers (9.79%). The total amount of stored energy is shown in the last column of Table 7. Results show that chemical fertilizers (48.49%) and diesel fuel (37.76%) have the highest contribution percentages to the total energy saving. Due to the fact that the amount of rainfall in Guilan province is high and more chemical fertilizer consumption is washed by runoff, the amount and timing of fertilization are the most effective factors in preventing the indiscriminate use of chemical fertilizers. The prevention of increasing use of chemical fertilizers can greatly improve the farmer's efficiency and simultaneously also protect the environment. Considering the climatic and soil conditions of the region, ways to reduce the use of fertilizers are presented as follows. Soil test should be undertaken to determine the appropriate amount and type of fertilizers or other soil amendment to apply to suit the nutritional needs of soil and plant. Fertilizers should not be applied near ponds, wells, or waterways. Fertilizers should be stored in a secure, dry and sheltered location. If fertilizers are exposed and gets wet, they can spread over a local area and contaminate

Table 6
Amounts of physical inputs and output for 15 truly efficient farmers and inefficient farmers.

Items (unit)	15 truly most efficient farmers (unit ha^{-1}) (A)	Inefficient farmers (unit ha^{-1}) (B)	Difference (%) (B–A)*100/B
A. Inputs			
1. Human labor (h)	525.90	525.07	−0.16
2. Machinery (h)	9.87	19.45	49.24
3. Diesel fuel (l)	87.72	143.81	39.00
4. Chemical fertilizers (kg)	135.02	211.99	36.31
5. Biocides (kg)	2.18	3.36	35.29
6. Seed (kg)	60.74	58.77	−3.35
B. Output			
1. Peanut (kg)	3693.19	2972.07	−24.46

Table 7
Optimum energy requirement and saving energy for peanut production.

Input	Optimum energy requirement (MJ ha^{-1})	EST (MJ ha^{-1})	ESTR (%)	Contribution to the total saving energy (%)
1. Human labor	1176.26	71.57	5.74	4.06
2. Machinery	725.13	117.41	13.93	6.67
3. Diesel fuel	5970.71	664.92	10.02	37.76
4. Chemical fertilizers	7871.90	853.90	9.79	48.49
5. Biocides	288.24	32.85	10.23	1.87
6. Seed	1455.19	44.59	2.97	2.53
Total energy	17,487.23	1760.81	9.15	100

groundwater, or can be washed away into waterways via storm drains.

Nabavi-Pelesaraei et al. (2017a) reported the total energy saving was 21.15% in paddy farms of Guilan with herbicides to attain the highest energy saving with 30.77%, potassium fertilizers (29.69%) and phosphate and nitrogen fertilizers (29.64%) being in next places.

Table 8 displays improvements in energy production indices. The energy consumption efficiencies are 4.53 and 4.99 for present and optimum units, respectively. The percentages for present and target units are 11.11%, −9.42%, 2.59% and −9.49% for energy productivity, specific energy and net energy, respectively. Table 8 lists direct, indirect, renewable and non-renewable energies for present and optimum units. The percentage differences between present and target units are −9.34%, −9.01%, −4.22% and −9.97% for direct, indirect, renewable and non-renewable energies, respectively. According to cases mentioned in Table 8, there is a significant difference in the amount of non-renewable energy consumption in present and target units. Given the importance of this type of energy, farmers are recommended to reduce chemical fertilizers and diesel fuel works as much as possible.

As can be seen in Table 8, in the fields under consideration, renewable sources of energy only include human labors and seeds. Human labors are involved in all stages of land preparation, irrigation, tillage, pest control, planting, and harvesting. This energy source is used as machinery operator, farm worker and farm manager in peanut farms. The use of skillful operator (especially the driver of the tractor) and skillful worker (especially the irrigation worker) and the provision of welfare conditions for workers can greatly increase the efficiency of human labors' work in a certain time-period and optimize the use of this energy source. For optimal use of seeds, the first and most important action is accurate adjustment of planter seeds that will largely avoid wasting seeds. Few renewable sources of peanut production are currently used in Guilan province in Iran. However, due to the unfavorable effects of non-renewable energy use, the use of more renewable resources, such as solar, wind, biomass, etc., should be prevalent in these fields. In order to eliminate environmental damage, the use of non-renewable resources should also be optimized.

The potential reduction in GHG emission is computed and the difference between amounts of current emission and optimal situation is determined by using DEA technique. In both cases, the amounts of GHG emission from peanut farms are shown in Table 9. As seen in Table 9, the total GHG emission is 512.39 and 571.18 kg $CO_{2\ eq.}$ ha^{-1} for present and target units, respectively. In other words, optimal energy use in peanut farms that is determined by DEA technique result in a reduction of 58.79 kg $CO_{2\ eq.}$ ha^{-1} of GHG production less than normal state. Thus it is confirmed that the reduction in energy consumption can lead to a reduction in GHG emission.

Table 9
Amounts of GHG emission for efficient farmers and inefficient farmers.

Inputs	Present farmers (kg $CO_{2\ eq.}$ ha^{-1})	Optimum farmers (kg $CO_{2\ eq.}$ ha^{-1})	GHG reduction (kg $CO_{2\ eq.}$ ha^{-1})
1. Machinery	59.82	51.48	8.34
2. Diesel fuel	325.23	292.64	32.59
3. Chemical fertilizer			
(a) Nitrogen	157.79	142.75	15.04
(b) Phosphate (P_2O_5)	5.19	4.70	0.49
(c) Potassium (K_2O)	6.29	5.69	0.60
4. Biocides	16.86	15.13	1.73
Total GHG emission	571.18	512.39	58.79

Table 8
Improvement of energy indices for peanut production.

Items	Unit	Present quantity	Optimum quantity	Difference (%)
Energy use efficiency	–	4.53	4.99	10.15
Energy productivity	kg MJ^{-1}	0.18	0.20	11.11
Specific energy	MJ kg^{-1}	5.52	5	−9.42
Net energy	MJ ha^{-1}	67,961.64	69,722.45	2.59
Energy intensiveness	MJ $\$^{-1}$	1.58	1.43	−9.49
Direct energy[b]	MJ ha^{-1}	7883.27 (40.96%)[a]	7146.77 (40.87%)	−9.34
Indirect energy[c]	MJ ha^{-1}	11,364.77 (59.04%)	10,340.46 (59.13%)	−9.01
Renewable energy[d]	MJ ha^{-1}	2747.62 (14.27%)	2631.45 (15.05%)	−4.22
Non-renewable energy[e]	MJ ha^{-1}	16,500.42 (85.73%)	14,855.78 (84.95%)	−9.97
Total energy input	MJ ha^{-1}	19,248.04 (100%)	17,487.23 (100%)	−12.95

[a] Numbers in parentheses indicate percentage of total optimum energy requirement.
[b] Includes human labor, diesel fuel.
[c] Includes seeds, chemical fertilizers, biocides, machinery.
[d] Includes human labor, seeds.
[e] Includes diesel fuel, Biocides, chemical fertilizers, machinery.

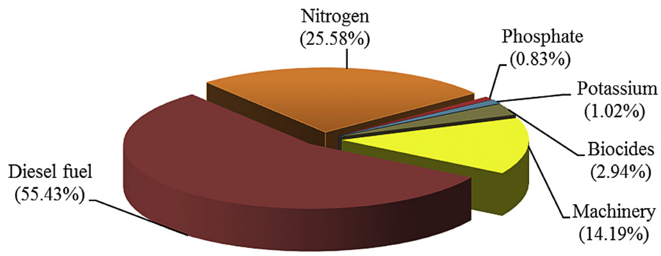

Fig. 4. Total potential reduction of GHG emission for peanut production.

Fig. 4 gives the potential GHG reduction of each input with optimal consumption for peanut farms. As seen in Fig. 4, the highest shares in reducing GHG emission are related to diesel fuel, nitrogen and machinery with 55.43%, 25.58% and 14.19%, respectively. These inputs also have the highest amount of energy savings. Results of the survey indicate that the largest energy consumer for peanut farms has the highest amount of GHG emission in Guilan province. Thus, benchmarking the target units can be an effective step to enhance the present farms' situation from both energy and environmental points of view. Utilizing inappropriate machinery, especially for plowing operations, is the main reason for these results. The absence of experts and lack of professional supervision in cultivation of peanuts are the root problems in the region. According to the above, monitoring the consumption of diesel fuel and using agricultural machinery can improve fuel consumption and convert inefficient units to efficient units. For this purpose, cooperation of governmental organizations (especially the Ministry of Jihad-e-Agriculture) as importers of agricultural machinery can improve the sustainable development of machinery use. In addition, monitoring of consumption levels of nitrogen fertilizer orders by experts and then delivering it to farmers can be effective in reducing the consumption of this input to a large extent and can lead to optimal use of nitrogen fertilizers and GHG emission for peanut production in the province of Guilan, Iran. Optimal use of energy sources and energy reduction in peanut production can lead to energy security, mitigation of the social and economic impacts of high energy prices and concerns about climate change. Finally, energy efficiency in peanut production based on DEA model can bring additional multiple advantages which extends far beyond the reduction of energy bills or emissions. Increase energy efficiency can also bring improvements to the production process, such as lower operational and maintenance costs, increased production yield, open outlets in new food markets that require certification of sustainability or energy performance and safer working conditions, all of which increase the productivity, overall efficiency and profitability of farms of peanut of Guilan province, Iran. Eventually, the above will lead to creating jobs for people living in Guilan province and will pave the way for achieving sustainable agriculture principles in peanut production.

An important issue that arises here is that: “Is it possible in reality to achieve the target energy consumption (provided by DEA) and subsequently to reduce GHG emissions?” Results of the survey on peanut production show that most machineries and appliances, especially tractors, are time-worn and have high fuel consumption. As long as they are used, diesel fuel consumption cannot be reduced to target. Due to inappropriate infrastructure and climatic characteristics of the area, there is a lot of leaching resulting from high use of chemical fertilizers. So long as this problem is not overcome, leaching of chemical fertilizers cannot be prevented. Thus, it can be said that, in order to achieve energy and GHG emission reductions in reality, it is still a major problem that requires effort as well as cost reduction.

GHG emissions in mushroom production for efficient and inefficient farmers were 23.84 and 32.86 kg $CO_{2\ eq.}$ m^{-2}, respectively, which showed a potential reduction of 19.11% (Ebrahimi and Salehi, 2015). Soni et al. (2013) reported that transplanted rice contributed the highest CO_2 emission (1112 kg $CO_{2\ eq.}$ ha^{-1}) to agricultural production systems in this region. Bolandnazar et al. (2014) showed that, in cucumber production, an improvement of energy use efficiency of 1614.89 kg $CO_{2\ eq.}$ ha^{-1} could be attained with the optimum energy consumption by DEA.

4. Conclusions

In this research, optimized energy consumption in peanut farms is computed by using non-parametric DEA. The reduction in GHG emission via reducing energy consumption is studied. The data used in this study are collected from 120 peanut farmers in Guilan province, Iran. After determining the target units, the GHG emission from present and optimal farmers are computed and compared. Results of studies show that, out of 120 farmers, 90 farmers (75%) are efficient in terms of total PTE, while 22 units (18.33%) are effective in terms of total TE based on BCC and CCR models, respectively. Results of DEA models indicate that, with appropriate energy consumption to achieve efficiency in energy consumption, about 1761 MJ ha^{-1} (9.15%) will be saved for inefficient units. The greatest amount of stored energy with energy efficiency is related to chemical fertilizers (48.49%) in peanut production, whilst diesel fuel is in the second place (37.76%). Besides, GHG emission will be reduced by 58.79 kg CO_2 per hectare of peanut farms by optimizing the energy consumption. It should be noted that the highest shares of GHG emission reduction are related to diesel fuel (55.43%) and nitrogen fertilizer (25.58%). Therefore, GHG emission can be improved by diesel fuel, nitrogen, machinery consumption management and energy use optimization. According to results of this study in peanut production in Guilan, due to the specific climate of the region, in order to increase efficiency, field passes, including strategic tillage, one-pass operations, and shallow tillage with wide implementation should be reduced. Moreover, matching equipment power to scale is essential. In order to avoid wastage of valuable natural resources and to mitigate environmental issues, there is a necessity to develop and demonstrate the balanced use of synthetic fertilizers. This will help increase the peanut production in a sustainable way. High peanut production needs more amount of plant nutrition. As no single source is able to supply amount of nutrients which are required by the peanut and the integrated use of all sources is a must to supply balanced nutrition to plants. The use of fertilizers in balanced amount improves nutrient deficiency, enhances soil fertility level, improves fertilizer and water use efficiency, increases peanut production, enhances environmental safety and ultimately also improves farmers' incomes. To enjoy the benefits of balanced use of fertilizers, key emphasis should be given to use good quality seeds, timing and number of irrigations and better agronomic practices with greater emphasis on timeliness and precision in farm operations.

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