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Optimising energy efficiency and ecological footprint of an off-season cucumber production agro-ecosystem on different farm levels (case of central Iran)

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Abstact: The present study aimed to use a non-parametric data envelopment analysis (DEA) to estimate the energy efficiency and greenhouse gas (GHG) emissions in off-season cucumber-producing greenhouses in different farm level management systems in Iran. Data were collected using a questionnaire completed by 83 cucumber producers through face-to-face interviews. The results showed that the energy use rate was 75.1%, 82.6%, and 86.2% in small (0.5–0.9 ha), medium (0.9–2 ha), and large farms (≥ 2 ha), respectively. In all the farm levels, the greatest energy use shares belonged to electricity, chemical fertilisers, and human labour, respectively. The results of the DEA revealed that the technical, pure technical, and scale efficiencies of the large farms were 87.3%, 92.8%, and 97.1%, respectively, which were higher compared to other farm level management systems. The ratio of energy savings was estimated at 5.62% and 2.97% for small and large farms, respectively. The results also showed that electricity, chemical fertilisers, and diesel fuel were the most responsible for the GHG emissions. By optimising the energy use, pollution per one/ha one of off-season cucumbers can be mitigated by 1 614.5 and 1 315.0 kg of CO_2/ha in small and large greenhouses; indicating more attention is required in managing the energy inputs in small-sized agro-ecosystems, especially for electricity.

Keywords: CO_2 consumption/emission; cucumber; energy-saving; envelopment analysis; greenhouse gas

Agriculture contributes significantly to greenhouse gas (GHG) emissions and crop production, directly or indirectly requiring a large amount of energy irrespective of the crop type (Vetter et al. 2017; Wu et al. 2017). Curbing GHG emissions and optimising the use of non-renewable energy sources are essential steps towards improving agricultural sustainability and alleviating environmental problems (Wiser et al. 2016). Meanwhile, the world's population has grown in recent decades and continues to grow, which has made it inevitable that natural and underground resources have been overused. Therefore, the only way for a sustainable supply of human food in the future is to reduce GHG emissions and to optimally use the available land, water, and resources (Theurl et al. 2017; Ntinas et al. 2020). Efficiency and productivity can be increased through the more sustainable use

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of resources, including labour, wells access to new technologies, and the better use of inputs and environmental and processing cycles on farms (Ilyas et al. 2019; Wang et al. 2019).

Productivity can be measured using mathematical programming techniques. Data Envelopment Analysis (DEA) is a non-parametric mathematical planning method for calculating the relative efficiency of decision-making units (DMUs). Mardani et al. (2017) reviewed some literature on the use of DEAs in energy and environmental studies. Khoshroo et al. (2018) used the DEA method and Tobit regression to examine the factors affecting energy productivity in grape production in Iran. Malana, Malano (2006) used DEA to evaluate and rank the productive efficiency of wheat cultivation in selected areas of Pakistan and India. Yaqubi et al. (2016) assessed the cost of lowering the marginal costs of major agricultural pollutants using DEA. The results showed that DEA was useful for bench-marking and analysing the efficiency of agricultural units. Ilahi et al. (2019) evaluated the energy consumption pattern in different parts of Pakistan using DEA and reported that the technology level, input energy, and agro-climatic factors were the most relevant parameters of wheat production. They found that the highest input energy was 17.788 GJ/ha and the highest energy ratio was 5.2 for wheat. Concerning the energy balance of greenhouse-grown cucumbers in Iran, Mostashari-Rad et al. (2019) reported that the energy balance, energy productivity, special energy, and net energy were 0.11, 0.14 kg/MJ, 7.30 MJ kg, and –865 665 MJ/ha, respectively, among which fossil fuels accounted for 84% of the input energy. A research study on the use of Constant Return to Scale (CRS) and Variable Return to Scale (VRS) for DEA on melon production revealed that diesel energy and water consumption had the highest share among all the available resources (Sharıfi 2018). The technical, pure, and scale efficiencies were estimated by the models to be 90.37, 95.09, and 94.6%, respectively. Also, the mean technical efficiency of the inefficient units was calculated by the CRS model to be 87%. Another study on energy consumption and CO_2 emissions in potato cultivation showed that the total amounts of energy consumed and CO_2 emitted were 47 GJ/ha and 92.82 kg CO_2/ha, respectively (Pishgar-Komleh et al. 2012). They stated that the highest energy consumption belonged to chemical fertilisers (49%), especially nitrogen (40%). When using the parametric method to estimate the production function in tomato cultivation, it was found that diesel fuel, which produced 2 719.98 kg CO_2/ha, had the largest contribution to environmental pollution. The second and third ranks were for electricity and nitrogen fertilisers, which emitted 729.6 and 409.5 kg CO_2/ha, respectively.

A review of all reports in this field, showed that there is no study on the impact of the farm size on the energy use efficiency and GHG emissions in a greenhouse cucumber production agro-ecosystem. Moreover, no DEA study has been performed to analyse the efficient and non-efficient greenhouse cucumber production agro-system. Therefore, the present research was conducted to analyse the energy use efficiency of a greenhouse cucumber production agro-ecosystem. It also aimed to separate the efficient units from the inefficient ones, to study the hotspots of energy inputs in the inefficient units to propose the amounts of different energy inputs that should be used by inefficient units. Also, the production rate of CO_2 equivalent per unit area and its decline after optimising the input consumption are dealt with.

MATERIAL AND METHODS

Case study. The research was conducted in the fall of 2018–2019 in Tehran province, central Iran (Figure 1), where the cultivated area of the off-season cucumbers is over 2 700 ha (around 35% of the total cultivated area of the country). In general, most greenhouses in these areas are dedicated to cucumber cultivation, although 1 200 ha of the green-

Figure 1. The study site (Tehran region in central Iran)

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houses produce ornamental plants and cut flowers (Anonymous 2018).

Sample selection. A statistical sample of all the off-season cucumber growers in the study region was interviewed about their production practices, inputs used, and output of the greenhouse cucumber production. The sample size was determined using the Bartlett proportional allocation method (Bartlett et al. 2001), by which a statistical sample of 83 greenhouse cucumber growers was determined as a representative of the whole population (Eq. 1).

$$n = \frac{(\Sigma N_h S_h)}{N^2 D^2 + \Sigma N_h S_h^2} \quad (1)$$

where: n – the required sample size; N – the number of holdings in the target population; N_h – the number of greenhouses in the h^{th} category; S_h^2 – the variance of the greenhouses in the h^{th} category; D – permissible error (5% for a 95% confidence interval) that was calculated by Eq. (2):

$$D^2 = \frac{d^2}{z^2} \quad (2)$$

where: d – the sampling precision; z – the confidence coefficient of 1.95 at the 95% confidence level.

To study the effect of the greenhouse farm size on the energy use and ecological footprint indicators in the off-season cucumber production process, the study sample was subdivided into three categories of small-sized greenhouses (SSGs) (0.5–0.9 ha), medium-sized greenhouses (MSGs) (0.9–1.9 ha), and large-sized greenhouses (LSGs) (≥ 2 ha). Accordingly, 34, 27, and 22 of the total 83 cucumber greenhouse farms belonged to the SSGs, MSGs, and LSGs, respectively.

Energy analysis. The total energy equivalents of the different inputs and outputs were computed by using their corresponding energy coefficients (Table 1). The labour energy input was calculated by multiplying the number of man-hours (h/ha) by the labour energy coefficient (MJ/h) (Table 1). The energy used for machinery was estimated by multiplying the duration of the machinery used by its corresponding energy equivalent. Other inputs, including the chemicals fertilisers (nitrogen, phosphorus, potassium, and micro-elements), manure, cucumber seeds, and diesel fuel, were converted to equivalent energy equivalents (MJ/ha) by multiplying their quantities by the corresponding energy coefficients (Pishgar-Komleh et al. 2012).

Energy indicators. The four most important energy indicators including the energy ratio, energy productivity, energy intensity, and net energy gain were determined to compare the energy use performances of the different greenhouse cucumber farms in the study region.

Table 1. Energy equivalents of the inputs and outputs in the cucumber production

Input-output (Unit)	Energy equivalent (MJ/Unit)	References
A. Input		
1. Labour (h)	1.96	Taki and Yildizhan 2018
2. Machinery (h)	13.1	Taki and Yildizhan 2018
3. Diesel fuel (L)	56.3	Pishgar-Komleh et al. 2012
4. Chemical fertilizer (kg)		Mohammadi et al. 2011
4.1. Nitrogen (N)	66.1	
4.2. Phosphate (P_2O_5)	12.4	
4.3. K (K_2O)	11.2	
4.4. Zn, Fe, Cu	120.0	
5. Biocide (kg)		Mohammadi et al. 2011
5.1. Insecticides	101.2	
5.2. Fungicide	238.0	
6. Electricity (kWh)	11.9	Mohammadi and Omid 2010
7. Water for irrigation (m^3)	1.02	Pishgar-Komleh et al. 2012
8. Seed (kg)	1.00	Mohammadi et al. 2011
B. Output		
Off-season cucumber (kg)	0.80	Taki and Yildizhan 2018

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The following energy indices were calculated for each greenhouse cucumber farm (Pishgar-Komleh et al. 2011):

$$\text{Energy use efficiency} = \frac{\text{Output energy (MJ/ha)}}{\text{Input energy (MJ/ha)}} \quad (3)$$

$$\text{Energy productivity} = \frac{\text{Cucumber yield (kg/ha)}}{\text{Input energy (Mj/ha)}} \quad (4)$$

$$\text{Energy intensity} = \frac{\text{Input energy (MJ/ha)}}{\text{Cucumber yield (kg/ha)}} \quad (5)$$

$$\text{Net energy gain} = \text{Output energy (Mh/ha)} - \text{Input energy (MJ/ha)} \quad (6)$$

where: the output energy is the final yield of the cucumbers which was converted from kg to MJ by the coefficient in Table 1. The input energy is the sum of all the input energy in Table 1. The cucumber yield is the final production of the fresh fruit at the end of the season which is calculated by summing the yield of each cucumber harvest during the cultivation time.

Estimation of GHG emissions. Carbon dioxide (CO_2) is considered a major source of global warming and climate change that is emitted by different agricultural activities (Jones et al. 2012). To estimate the amounts of GHG emissions from various inputs used in the greenhouse cucumber production agro-ecosystem, the quantities of all the inputs used during the production process were multiplied by the respective emission coefficients (Table 2). The results were tabulated by taking the inputs into consideration, and the input-output values of the off-season cucumber were determined.

Data envelopment analysis (DEA). In general, the efficiency is measured by parametric or non-parametric methods. Methods that employ econometric models to evaluate the efficiency are called parametric methods because they first estimate a production function (cost, profit, etc.) for the studied units and then, they calculate the optimal production rate for the inputs used by the unit after estimating the parameters of the production function and finding a boundary production function. These points can be determined by assuming a variable return to scale, or the so-called BCC model (named after their creators, i.e., Banker, Charnes, and Cooper). After a series of optimisations, this method determines whether a DMU is located on the efficiency boundary or outside it (Sarıca et al. 2007), thereby separating efficient units from inefficient units (Figure 2).

However, in non-parametric methods, there is no need to explain the form of a specific function to evaluate the efficiency, but these methods use mathematical programming models (objective function optimisation) to determine the efficiency of a DMU (Li et al. 2018). It should be noted that a limitation of the parametric method is that the studied DMUs should have just one output (if they have more than one output, it must be possible to make conversions in their units so that all the outputs can be expressed in a similar unit). In other words, the selected model should have just one dependent variable. However,

Table 2. The greenhouse gas emission (GHG) coefficients (kg CO_2-eq/unit) for various inputs in the greenhouse cucumber production agro-ecosystem

Input	GHG coefficients (kg CO_2-eq/unit)	Unit	References
1. Machinery	0.071	MJ	Khoshnevisan et al. 2013
2. Diesel fuel	2.76	L	Ilahi et al. 2019
3. Chemical fertilizer			Khoshnevisan et al. 2013
3.1 Nitrogen (N)	1.3	kg	
3.2 Phosphate (P_2O_5)	0.2	kg	
3.3 Potassium (K_2O)	0.2	kg	
4. Manure*	0.126	kg	Khoshnevisan et al. 2013
5. Biocide			Ilahi et al. 2019
5.1 Insecticides	5.1	kg	
5.2 Fungicide	3.9	kg	
6. Electricity	0.608	kWh	Ilahi et al. 2019

*Cattle manure

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there is no limit to the number of independent variables. If all the outputs of a DMU cannot be expressed in the same unit, other methods should be used to estimate the efficiency of the DMU.

In these cases, DEA can help solve this problem. To calculate and compare the efficiency of DMUs, DEA allows the DMUs to assign weights to their outputs provided that the assigned weights do not show the efficiency of the DMUs is greater than the value of one, because by definition; the efficiency of a DMU is at most 100% or unity. It is noteworthy that the DEA compares the performance of DMUs that do a similar job or the so-called similar DMUs (Li et al. 2018).

In this study, after completing the questionnaires through face-to-face interviews, the collected data were entered into MS Excel. Then, in addition to examining the energy consumption and yield of all the DMUs, the date were analysed by the DEA method to identify the efficient and inefficient DMUs. The data were analysed by the CRS and VRS models.

Constant return to scale (CRS) model. The DEA innovatively transforms a multi-output and multi-production factor state into a simple single-factor and single-output state. If the data are available on k production factors and M outputs for each of N DMUs, the calculation process will be as below (Li et al. 2018):

$$\underset{s.t.}{Max} \frac{u'y_i}{v'x_i} \tag{7}$$

$$\frac{u'y_i}{v'x_i} \leq 1 \quad i = 1. \ldots N$$

$$u \geq 0, v \geq 0$$

where: u – a vector containing the output weights; v – a vector of the production factor weights; x –a $k \times N$ matrix of the production factors, and y is an M × N matrix of outputs.

These two matrices will represent all the information on N DMUs. Eq. (7) aims to obtain the optimal values of u and v so that the total ratio of the total output weight to the total production factor weight (the efficiency of each DMU) is maximised provided that the efficiency score of a greenhouse must be equal to or smaller than unity. The above function has an indefinite number of optimal solutions. Assuming the dominator to be the value of one, the above model is converted to the following linear programming model:

$$\begin{aligned} &Max\ \mu' y_i \ldots \\ &v'x_j = 1 \\ &v'x_j - x_j \leq 0 \quad j = 1.2 \ldots N \\ &\mu \geq 0.\ \ v \geq 0 \end{aligned} \tag{8}$$

For the sake of a linear transformation, the new parameters μ and v were used instead of u and v, respectively. The above problem can be solved by conventional linear programming techniques. In linear programming, the application of fewer constraints facilitates problem-solving. By solving this form, linear programming represents the technical efficiency (θ) of the DMUs separately.

$$\begin{aligned} &\underset{s.t.}{Min}\ \ \theta \\ &y_i + y\lambda \geq 0 \\ &\theta x_i - x\lambda \geq 0 \text{ and } \lambda \geq 0 \end{aligned} \tag{9}$$

In which λ is an $N \times 1$ vector containing constant information that represents the source weights. The scalar values obtained for θ will be the efficiency

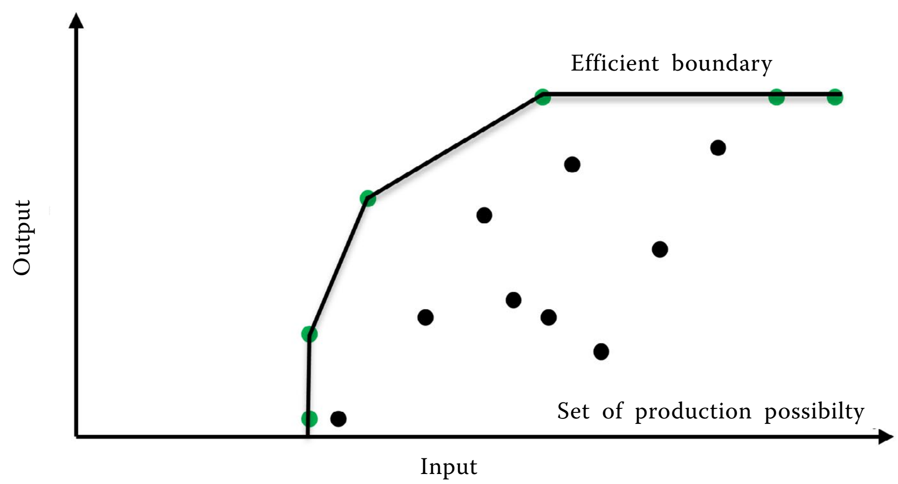

Figure 2. The efficient boundary in the BCC model

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of the greenhouses that satisfy the condition of $\theta \leq 1$. In Eq. (9), the first constraint states whether or not the actual amounts of crop produced by the i^{th} DMU using the production factors can be greater than it. The second constraint implies that the production factors used by the i^{th} greenhouse must be at least equal to the factors used by the source greenhouse.

Variable return to scale (VRS) model. When all the greenhouses are not operated within the optimal scale, the use of the CRS assumption will yield values for the technical efficiency (encompassing scale efficiency) that are disruptive to the analysis. The use of VRS provides a very precise analysis as it calculates the technical efficiency in terms of the efficiency caused by the scale and the efficiency caused by the management (pure technical efficiency) (Charnes et al. 1994; Yong, Chunweki 2003). To this end, the formulation of the linear programming problem with the assumption of the CRS is added with the constraint $NI'\lambda = 1$ (convexity constraint) by which the calculations are made by the assumption of VRS.

$$\begin{aligned} &Min\ \theta \\ &-y_i + y\lambda \geq 0 \\ &\theta x_i - x\lambda \geq 0 \text{ and } \lambda \geq 0 \\ &NI'\lambda = 1 \text{ and } \lambda \geq 0 \end{aligned} \tag{10}$$

This VRS constrained model does not specify whether a DMU is operated in the zone of increasing return to scale or decreasing return to scale. This is, in practice, performed by comparing the constraint of the non-increasing return to scale ($NI'\lambda \leq 1$).

$$\begin{aligned} &Min\ \theta \\ &-Y_i + Y\lambda \geq 0 \\ &\theta X_i - X\lambda \geq 0 \text{ and } \lambda \geq 0 \\ &NI'\lambda \leq 1 \text{ and } \lambda \geq 0 \end{aligned} \tag{11}$$

In other words, the nature of the return type in the scale inefficiency of a certain DMU is determined by comparing the technical efficiency score under the non-increasing return to scale with that under the variable return to scale so that if they are equal, it implies that the unit in question is faced with a decreasing return to scale; otherwise, the condition of an increasing return to scale is held (Banaeian et al. 2010).

Eq. (12) determines the minimum number of DMUs that should be included in an analysis to guarantee the high reliability of the DEA results (Yong, Chunweki 2003):

$$\text{Number of DMU} \leq 3(I + O) \tag{12}$$

In which I is the number of inputs and O is the number of outputs. The inputs in the present research included six to eight energy inputs; machinery energy, fuel energy, seed, fertilisers, pesticide energy, labour energy, water energy, and transportation energy. The output was also considered to include the crop energy. So, the minimum number of DMUs required for the analysis was equal to:

$$\text{Number of DMUs} \leq 3(1 + 6) = 21 \tag{13}$$

Here, we first used diagnostic statistical methods to find outliers among the data at all three levels and remove them. Finally, 34, 27, and 22 greenhouses were randomly selected from the first, second, and third levels, respectively, and they were analysed by the Frontier Professional Analyst Ver. 5 software package. The technical efficiency (E_{CCR}), pure technical efficiency (E_{BCC}), and scale efficiency (E_S) were related by Eq. (14), shown below, to the value of one another (Banaeian et al. 2010):

$$E_s = E_{CCR}/E_{BCC} \tag{14}$$

The scale efficiency will not exceed the value of one. The CRS model efficiency is called the total technical efficiency because it is not influenced by the scale or size. On the other hand, VRS shows the pure technical efficiency under the variable return to scale. Eq. (14) represents an efficiency analysis that reveals the efficiency sources. That is, it specifies whether the inefficiency is rooted in managerial inefficiency, conditions that show the scale efficiency, or both (Khoshroo et al. 2018).

RESULTS AND DISCUSSION

Figure 3 shows the amounts of various input energy in the greenhouse cucumber production agroecosystem at different farm levels. The highest quantity of the energy used belonged to electricity, which contributed 42.6% of the total energy input

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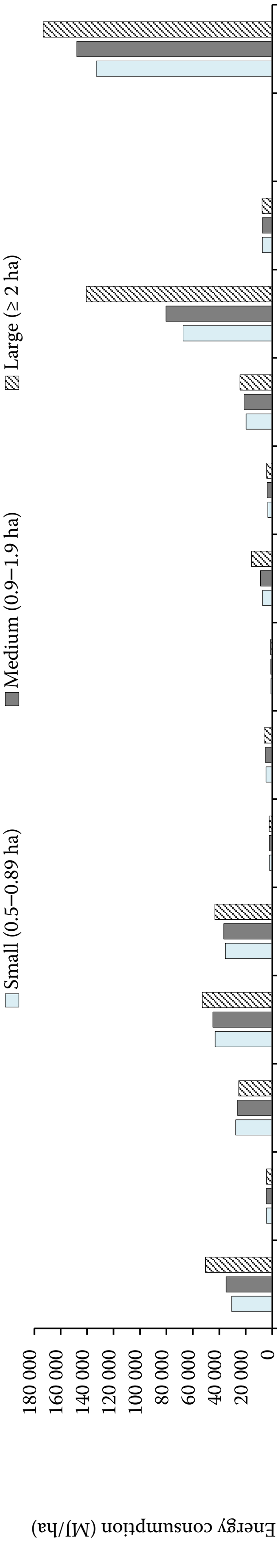
in large-sized greenhouses. Electricity was also first in small-sized (36.5%) and medium-sized (38.0%) greenhouses. The average amount of electricity used in the greenhouse cucumber production agro-ecosystem was determined to be 8 061 kWh, of which, 81%, 12%, and 7% belonged to the pumping irrigation water, heating system, and liquid application of chemical fertilisers, respectively. Therefore, enhancing the water use efficiency and improving the irrigation system must be considered to improve the energy efficiency of the greenhouse cucumber production agro-ecosystem in the study region.

Electricity, chemical fertilisers, and human labour accounted for the highest portions of the total energy input, respectively. Chemical fertilisers were responsible for 20.5%, 19.3%, and 16.3% of the total system energy input in small-sized, medium-sized, and large-sized cucumber production greenhouses, respectively. The contribution of human labour in the total energy input was also determined as 14.5%, 15.0%, and 15.5% in small-sized, medium-sized, and large-sized cucumber production greenhouses, respectively. Therefore, enhancing the chemical use efficiency, particularly for nitrogen chemical fertilisers is essential. Moreover, the labour force management as the third important energy input should be noted in the off-season agroecosystem.

The mean values of the energy inputs of the different sizes of greenhouse cucumber production agro-ecosystem also show that the small-sized off-season cucumber production farms had fewer energy inputs per unit area than the medium and large farms; indicating the better management in the small farms.

The output energy, or final yield, was about 216 t/ha (173.137 MJ/ha) of cucumbers in large-sized greenhouses, 184 t/ha (147.802 MJ/ha) in medium-sized greenhouses, and 166 t/ha (133.040 MJ/ha) in small-sized greenhouses. With the increase in the greenhouse size from small to large, the input energy increased from 210.491 MJ/ha to 325.222 MJ/ha, respectively. A reason is the traditional view on production and attempts to consume as few inputs as possible in the small-sized greenhouses, which reduces their yield so that the energy balance in small farms was nearly 17.4% of that in large farms because the yield escalation compensates for the higher energy input. The energy ratio was lower in small and medium farms than in large farms. The output of the large-sized green-



	Human labor	Machinery	Diesel fuel	Fertilizer	(a) Nitrogen	(b) Phosphousr	(c) Potassium	Micro fertilizer	Manure	Insecticide	Fungicide	Electricity	Water	Seed	Output
Small (0.5–0.89 ha)	30 543	4 352	27 532	43 086	35 453	2 031	4 631	971	7 188	3 327	19 660	67 463	7 339	1.06	133 040
Medium (0.9–1.9 ha)	34 830	4 293	26 156	44 805	36 635	2 128	5 011	1 032	8 856	3 805	21 273	80 370	7 414	1.08	147 802
Large (≥ 2 ha)	50 452	4 258	25 311	52 906	43 355	2 248	6 191	1 113	15 528	4 177	24 323	140 659	7 609	1.09	173 137

Figure 3. Input and output energies in the cucumber production under the different farm sizes

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houses was at a scale of 173.137 MJ/ha harvested cucumbers while it was 133.040 MJ/ha in small-sized greenhouses.

Table 3 shows the energy use indices for the different greenhouse cucumber farm levels. As seen, large-sized greenhouse farm levels were more efficient than the small and medium-sized farms. The energy productivity of large cucumber greenhouses (0.6671 kg/MJ) was more than the corresponding values in small and medium-sized farm levels (0.7901 and 0.7970 kg/MJ). Moreover, the mean value of the net energy gain of large cucumber farms (–150.988) is more than the corresponding values in small and medium cucumber farms. Therefore, large-sized greenhouse farms had better energy use management compared to small and medium-sized greenhouse cucumber farms.

According to Figure 4, the mean technical efficiency of inefficient cucumber greenhouses at the small, medium, and large farm levels was calculated by the input-oriented CRS model as 75.1%, 82.6%, and 86.2%, respectively. This means that the inefficient DMUs can reach their efficiency boundary by avoiding wastage of 24.8%, 17.3%, and 13.7% of the inputs at these levels, respectively, if their output is kept constant. Thereby, they can save 55% on the total inputs by increasing their efficiency. The efficiency score of the production units implies that each unit should be able to reduce its total inputs by (1–θ)% with no impact on the production, in which θ is the efficiency score of the inefficient unit (22). For example, greenhouse No. 26 in the small-sized group had an efficiency of 68%. This means that it should save 32% on its inputs from all the production factors (with no decline in production) to turn into an efficient production unit. If a production unit turned out to be completely efficient by the VRS model, but poorly efficient by the CRS model, then it is apparently efficient, but it lacks overall efficiency, in which case the overall inefficiency is caused by the scale inefficiency. However, if the efficiency is less than 100% in both the CRS and VRS models, the inefficiency emanates from the scale inefficiency or inefficiency of the DMU conditions, as well as due to the managerial inefficiency (Omid et al. 2011).

Table 4 presents that greenhouses No. 6, 10, 12, 17, 24, 27, and 32 in the 0.5–0.89 ha group, greenhouses No. 3, 16, 27, and 21 in the 0.9–1.9 ha group, and greenhouse No. 12 in the ≥ 2 ha group were locally efficient (i.e., their pure technical efficiency was 1), but their total efficiency was less than 1, and this inefficiency was rooted in the scale or managerial inefficiency. The inefficiency of the other greenhouses was related to the managerial inefficiency and farm conditions, or scale inefficiency (Mohammadi et al. 2014). If a DMU is VRS efficient, its scale efficiency is specified by the output weight. If it is less than 0, the return to scale is increasing, if it is greater than 0, its return to scale is decreasing, and if it is equal to 0, its return to scale isconstant. In an increasing return to scale, the scale of the production unit cannot be reduced, but it can be increased to infinity. The ratio of the output to input for each point on the efficient boundary is non-decreasing versus the input, meaning that the increase in the output is always proportional to the input, at least partially. Table 4 presents the scale efficiency of the greenhouses in three different sizes.

Table 5 displays the results of analysing the ≥ 2 ha greenhouses with the input-oriented CRS model to determine the surplus inputs and yield deficiency. For each inefficient unit, it was specified how much they should reduce the consumption of the surplus inputs to become efficient. For instance, greenhouse No. 1 whose efficiency was 83% should reduce 8 381 units from the labour force, 3 865 units from the machinery, 404 units from the diesel fuel, 23 724 units from electricity, 8 856 units from chemical fertilizers, 701 units from insecticides, 21 807 units from fungicides, 2 245 units from the irrigation water, and 1.1 units from the seeds to place it on the efficiency boundary. Similarly, the amount of reduction in the input use has been determined

Table 3. Energy indices of the cucumber production

Item	Greenhouse size groups (ha)		
	Small farm (0.5–0.8 ha)	Medium farm (0.81–1.9 ha)	Large farm (≥ 2 ha)
Energy use efficiency	0.632 0	0.637 6	0.533 7
Energy productivity kg/MJ	0.790 1	0.797 0	0.667 1
Specific energy MJ/ha	1.265 7	1.254 7	1.499 1
Net energy MJ/ha	–77 451	–84 001	–150 988

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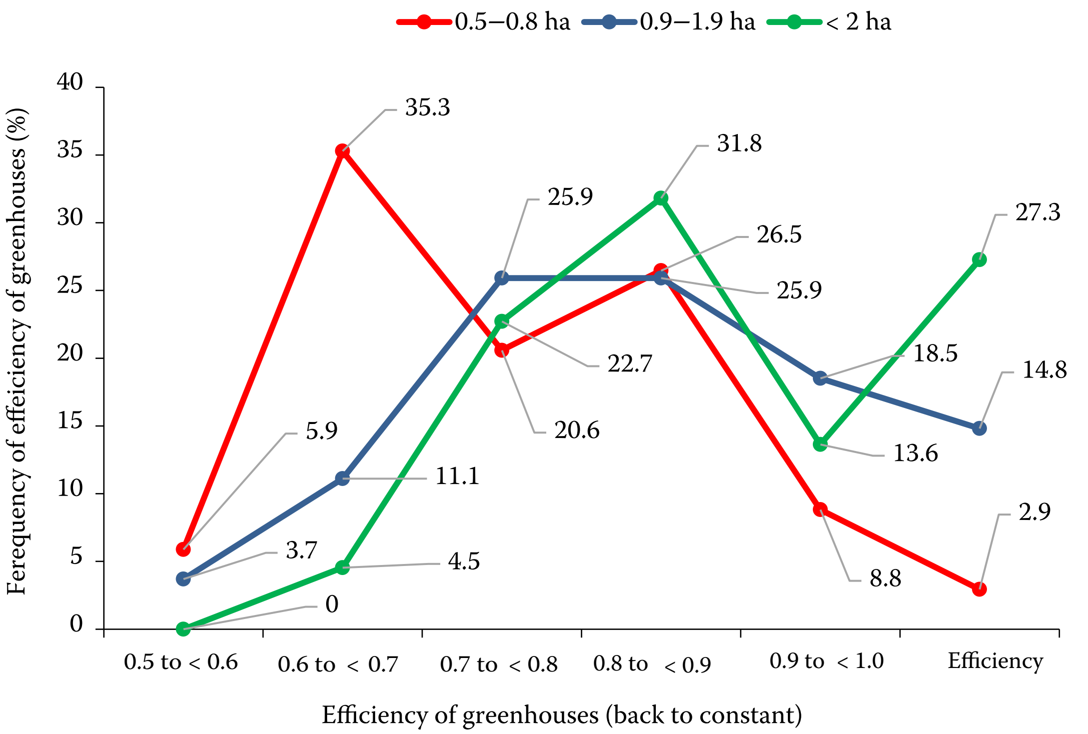

Figure 4. The efficiency score of the cucumber greenhouses with reference units by the CRS model

for the other inefficient units to turn them into efficient units. Similar results were reported by Mohammadi et al. (2011), Khoshroo et al. (2018), and Ilahi et al. (2019) in their studies on energy use optimisation of wheat and turnip production. In a study on corn farms using the CRS and VRS models, Akhtar et al. (2018) reported the mean efficiency of inefficient farms as 0.79 and concluded that by reaching the efficiency boundary, they could save 21% on their energy inputs.

To explore the rate of energy saving in cucumber production by DEA, the energy-saving rate (ESR) index was defined as below (Unakitan et al. 2010; Mousavi-Avval et al. 2011):

$$ESR = \frac{\text{Energy saving}}{\text{Energy consumption}} \tag{15}$$

where: Energy saving is the total energy saved and Energy consumption is the input energy in Table 1.

Table 6 shows the ESR values calculated for the cucumber production in the greenhouses in three different sizes. Accordingly, ESR was estimated at 5.63, 7.47, and 2.97 for the small-sized, medium-sized, and large-sized greenhouses, respectively. This reflects that, by optimising the energy use for all the inputs in the three greenhouse size groups from small to large, the energy can be saved by 11 147, 16 294, and 9 054 MJ/ha, respectively. The DEA reveals that the inputs that need to be saved are electricity, chemical fertilisers, and human labour in the three size groups of greenhouses. In a study on greenhouse tomato production, Ntinas et al. (2020) reported that diesel, electricity, and chemical fertilisers were the primary energy-consuming inputs. To convert an inefficient unit to an efficient unit, the major inputs for energy use optimisation have been reported to be the fertilisers and diesel fuel in wheat production (Ilahi et al. 2019), diesel fuel, electricity, and nitrogen fertilisers in greenhouse cucumber production (Taki, Yildizhan 2018), and machinery and diesel fuel in melon production (Sharıfi 2018), whereas a research study on the wolfberry production indicated that fuel had the greatest potential for saving by using this technique (Akhtar et al. 2018; Wang et al. 2019). Also, a study on a corn cultivar in the Golestan province of Iran, they found that electricity had the greatest room for saving (Pishgar et al. 2011).

Greenhouse gas emissions. Table 7 tabulates the GHG emission rates in the studied greenhouses in Tehran. At all three sizes of cucumber production greenhouses, electricity had the highest contribution to the total GHG emissions among all the energy sources. Its contribution

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Table 4. Technical, pure technical, and scale efficiency in the cucumber production

Small farm (0.5–0.8 ha)					Medium farm (0.9–1.9 ha)					Large farm (≥ 2 ha)				
DMUs	$E_{CRS\ (\%)}$	$E_{VRS\ (\%)}$	$E_{S\ (\%)}$	RTS	DMUs	$E_{CRS\ (\%)}$	$E_{VRS\ (\%)}$	$E_{S\ (\%)}$	RTS	DMUs	$E_{CRS\ (\%)}$	$E_{VRS\ (\%)}$	$E_{S\ (\%)}$	RTS
1	66	71	79	I	1	71	76	89	I	1	76	93	93	I
2	68	63	80	I	2	61	73	80	I	2	92	96	99	I
3	51	72	86	I	3	81	84	59	I	3	100	100	100	C
4	69	79	82	I	4	100	100	100	C	4	77	94	100	I
5	68	82	94	C	5	90	96	96	I	5	83	92	96	I
6	82	81	70	I	6	95	97	100	I	6	100	100	100	I
7	80	85	93	I	7	74	92	94	I	7	65	85	89	I
8	73	98	100	I	8	94	96	98	C	8	100	89	100	I
9	81	91	96	C	9	68	84	94	I	9	80	85	91	I
10	85	88	66	I	10	75	81	90	I	10	100	100	100	C
11	64	88	92	I	11	87	90	91	I	11	73	90	95	I
12	76	83	79	I	12	81	88	89	I	12	90	97	92	I
13	70	51	79	I	13	100	100	100	C	13	82	91	100	I
14	69	70	85	I	14	77	91	92	I	14	91	93	95	I
15	62	91	95	I	15	83	95	96	I	15	80	78	89	I
16	78	84	95	C	16	94	100	97	I	16	100	100	100	C
17	93	100	92	I	17	59	87	98	I	17	100	100	100	C
18	82	67	79	I	18	80	90	95	I	18	84	92	98	I
19	58	88	92	I	19	100	100	100	C	19	91	95	100	I
20	76	91	91	I	20	78	91	93	I	20	76	85	100	I
21	66	100	100	C	21	65	94	91	I	21	89	94	96	I
22	81	76	88	I	22	100	100	100	C	22	92	92	100	C
23	100	100	100	I	23	72	86	91	I	–	–	–	–	–
24	63	95	70	I	24	79	83	93	I	–	–	–	–	–
25	83	73	92	I	25	92	96	91	I	–	–	–	–	–
26	68	60	83	I	26	82	82	90	C	–	–	–	–	–
27	82	97	72	I	27	92	94	92	I	–	–	–	–	–
28	66	60	85	I	–	–	–	–	–	–	–	–	–	–
29	96	45	75	I	–	–	–	–	–	–	–	–	–	–
30	66	91	100	I	–	–	–	–	–	–	–	–	–	–
31	82	82	94	I				–	–	–	–	–	–	–
32	80	82	71	I	–	–	–	–	–	–	–	–	–	–
33	82	81	86	C	–	–	–	–	–	–	–	–	–	–
34	92	82	90	I	–	–	–	–	–	–	–	–	–	–

RTS – return to scale; I – increasing; C – constant; DMUs – decision-making units; E_{CRS} – constant return to scale efficiency; E_{VRS} – variable return to scale efficiency; E_S – scale efficiency

was 3 438.2 (53.7%), 4 096.4 (57.9%), and 7 169.5 (69.4%) kg CO_2/ha in small, medium, and large farms, respectively. The next ranked in GHG emissions was for diesel fuel, but unlike electricity, its contribution decreased with the increase in the farm size. So that contribution was 21.8%, 18.2%, and 11.0% in small, medium, and large farms, respectively. However, the role of chemical fertilisers, especially N fertilisers, should not be neglected in GHG emissions because a small percentage of the nitrogen utilised in the soil is commuted to nitrous oxide, which has the maximum potency of global warming, that is why nitrogen fertilisers had a major impact on the GHG emissions as well

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Table 5. The excess energy consumption with the CRS model (for up to 2 ha cucumber greenhouses) (MJ/ha)

DMUs	Efficiency (%)	Labour	Machinery	Diesel fuel	Electricity	Chemical fertilizer	Manure	Insecti-cides	Fungicide	Water for irrigation	Seed
1	83	8 381.0	3 856.5	404.1	23 724.9	8 856.2	2 405.7	701.1	21 807.9	2 245.7	1.1
2	86	6 470.5	2 693.2	283.1	17 522.2	7 055.6	1 875.0	562.9	15 027.3	1 566.0	0.7
3	100*	–	–	–	–	–	–	–	–	–	–
4	77	13 756.0	7 906.0	831.9	39 972.9	13 300.1	4 685.2	1 034.5	46 529.0	4 674.1	2.0
5	76	14 547.8	8 425.3	888.5	42 724.0	14 018.5	4 938.6	1 087.3	50 208.5	4 973.3	2.2
6	100*	–	–	–	–	–	–	–	–	–	–
7	65	24 223.4	15 427.1	1 638.7	67 028.8	22 204.0	8 923.5	1 699.1	96 378.1	9 316.3	4.1
8	100*	–	–	–	–	–	–	–	–	–	–
9	80	10 456.2	5 208.3	546.4	31 291.8	10 750.1	3 245.9	846.1	29 988.0	3 046.2	1.3
10	100*	–	–	–	–	–	–	–	–	–	–
11	73	18 355.6	11 615.3	1 229.9	44 537.1	16 889.7	6 704.0	1 295.7	71 842.7	6 951.2	3.0
12	85	6 945.7	2 891.5	304.1	19 883.3	7 578.9	2 000.0	603.8	16 207.8	1 678.4	0.7
13	82	9 384.8	4 673.4	489.4	28 348.5	9 634.4	2 851.5	760.5	26 603.6	2 735.1	1.2
14	79	11 781.0	6 346.4	667.4	35 236.3	11 731.7	3 810.1	917.6	37 085.2	3 734.0	1.6
15	80	10 948.0	5 756.8	604.2	31 813.3	11 009.3	3 555.6	863.6	33 224.8	3 381.8	1.5
16	100*	–	–	–	–	–	–	–	–	–	–
17	100*	–	–	–	–	–	–	–	–	–	–
18	84	7 476.1	3 153.2	331.8	20 702.8	8 128.6	2 186.6	646.3	17 669.1	1 827.8	0.8
19	89	5 839.7	1 571.4	3 922.5	14 721.6	5 190.1	2 269.8	507.5	6 885.3	725.3	0.3
20	76	14 956.6	8 842.1	934.6	45 105.2	14 272.0	4 931.5	1 103.5	53 464.3	5 214.0	2.3
21	91	3 925.3	385.6	3 359.5	10 192.9	4 328.1	1 883.0	348.1	6 779.4	709.4	0.3
22	92	3 530.6	1 344.7	141.4	9738.8	3 951.8	918.4	316.0	7 463.7	779.3	0.3

*Surplus inputs of units that are 100% efficient are about zero. For the sake of summarising the table, the total energy of the chemical fertilisers provided here includes those of nitrogen, phosphorus, potassium, and micro-elements
DMUs – decision-making units

(Yong, Chunweki 2003; Taki, Yildizhan 2010; Pishgar-Komleh et al. 2012; Li et al. 2019).

We found that N fertilisers accounted for 10.90% of the GHG emissions in small farms, 10.21% in medium farms, and 8.03% in large farms. The results of optimising the pollutants emitted by the inputs used to produce 1 ha of cucumbers using the CRS model revealed that the energy use optimisation in greenhouses sized 0.5–0.8 ha can reduce the pollutant emissions of the cucumber production by 1 614.5 kg CO_2/ha. This value is 2 138.2 and 1 315.0 kg CO_2ha for the medium and large-sized greenhouses, respectively. These results corroborate the reports of Bakhtiari et al. (2015), Khoshroo et al. (2018), Elhami et al. (2016), and Taleghani et al. (2020). A higher share of electricity in GHG emissions, especially in large-sized greenhouses, can be attributed to the long distance between water storage ponds and the greenhouse and the need to pump water over a long distance. It can also be associated with the higher area of pesticide and fertiliser applications and the use of heavier heating systems with higher electricity use (furnaces are 5 to 1 in large-sized greenhouses versus 3 to 1 in small-sized ones). The portion of total GHG emissions, which has been reported to come from electricity in greenhouse crop production, varies among studies from about 28.4% in the Taki and Yildizhan (2018) study to about 33.5% in the Mohammadies and Omids (2010) study and 26.9% in the Taleghani et al. (2020) study. However, it should be noted that, in these reports, among the greenhouse crop production inputs, the highest amount of GHG emissions is related to the electricity followed by diesel fuel. As was already mentioned, unlike electricity, the contribution of diesel fuel decreased with the increase in the greenhouse size, which can be ascribed to the fact that larger

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Table 6. ESR index with the CRS model in greenhouse cucumber production

Inputs	Small farm (0.5–0.8 ha)			Medium farm (0.9–1.9 ha)			Large farm (≥ 2 ha)		
	Energy consumption (MJ/ha)	Optimum energy requirements (MJ/ha)	ESR (%)	Energy consumption (MJ/ha)	Optimum energy requirements (MJ/ha)	ESR (%)	Energy consumption (MJ/ha)	Optimum energy requirements (MJ/ha)	ESR (%)
Labour	30 543.48	3 0087.00	1.49	34 830.3	32 386.8	7.02	50 452.1	48 056.4	1.75
Machinery	4351.9	4 262.18	2.06	4 292.7	4 191.6	2.36	4 257.7	4 103.5	3.62
Diesel fuel	27 531.52	26 819.63	2.59	26 155.6	25 811.5	1.32	25 310.9	24 781.3	2.09
Chemical fertilizer	43 085.99	38 992.82	9.50	44 805.4	40 459.3	9.70	52 906.1	51 054.4	3.50
Insecticides	3 327.31	2 944.67	11.50	3804.7	3 321.5	12.7	4 176.5	3 767.2	9.80
Fungicide	19 660.09	17 792.38	9.50	21 273.1	18 996.8	10.7	24 322.6	24 235.1	0.36
Electricity	67 463.22	64 022.60	5.10	80 369.9	74 181.4	7.70	140 658.5	129 654.2	5.81
Irrigation water	2 446.49	2 341.29	4.30	2 471.4	2 359.9	4.51	2 536.2	2 442.1	3.71
Seed	1.06	0.92	12.80	1.08	0.95	12.5	1.09	0.95	12.6
Total input	19 8411.0	187 263.4	5.62	218 004.5	201 710.2	7.47	304 621.9	295 567.6	2.97

ESR – energy-saving rate

greenhouses may consume diesel fuel at a higher efficiency owing to the operator's higher pace of work and easier manoeuvre during different agronomic operations in the greenhouse.

CONCLUSION

The key results of the research are briefly listed below:

(1) Electricity, chemical fertilisers, and the labour force are the most important contributors to the energy use in the greenhouse cucumber production agro-ecosystem in Tehran province. The large cucumber greenhouses were more efficient than the small and medium-sized production units. Therefore, using energy-efficient electrical systems particularly for pumping irrigation water in the small and medium-sized greenhouse cucumber agro-ecosystem is essential. Moreover, enhancing the nitrogen use efficiency by using specific bio-fertilisers and providing some nitrogen use by animal manures are among the useful approaches to boost the energy use efficiency in small and medium-sized cucumber production greenhouses in the study region.

Table 7. Reduction of greenhouse gas (GHG) emissions of the inputs in the cucumber greenhouses by the CRS model

Inputs	GHG emission (kg CO_2/ha)					
	GHG emissions by cucumber production			Optimization of GHG emissions by the CRS model		
	0.5–0.8 ha	0.9–1.9 ha	≥ 2 ha	0.5–0.8 ha	0.9–1.9 ha	≥ 2 ha
Machinery	309.3	305.7	302.7	246.9	231.1	280.2
Diesel fuel	1 349.1	1 282.5	1 241.6	1 069.3	907.6	1 132.8
Nitrogen	697.5	720.6	852.5	544.6	510.2	734.5
Phosphorus	33.3	34.2	36.3	25.8	24.1	32.1
Potassium	83.4	90.8	111.1	64.2	61.9	95.5
Insecticide	168.1	192.0	210.6	122.4	138.8	181.4
Fungicide	322.3	349.7	399.3	234.7	252.4	344.8
Electricity	3 438.2	4 096.4	7 169.5	2 478.7	2 807.7	6 207.3
Total input	6 399.2	7 068.9	10 320.6	4 786.7	4 933.7	9 008.6

(2) The mean technical efficiency of inefficient small, medium, and large greenhouses was calculated as 75.1%, 82.6%, and 86.2%, respectively. This implies that by the optimal use of energy sources and avoiding wastage of 24.8%, 17.3%, and 13.7% of inputs at the three farm sizes, respectively, and keeping the output constant, the inefficient DMUs can reach the efficiency boundary and save 55% on the total inputs by increasing their efficiency.

(3) GHG emission rates at the three levels of 0.5–0.89 ha, 0.9–1.99 ha, and ≥ 2 ha were 6 399.2, 7 068.9, and 10 320.6 kg CO_2/ha, respectively. By optimising the energy consumption using the CRS model, the GHG emissions per 1 ha of cucumber cultivation can be reduced by 1 614.5, 2 138.2, and 1 315.0 kg CO_2/ha in small, medium, and large farms, respectively. Such a decrease in a province like Tehran can play a key role in reducing the environmental pollution and the accumulation of harmful compounds in the atmosphere.

(4) The DEA has proven to be a robust instrument to estimate the optimal rate of energy use in different agricultural units so that it can be applied to all crops. However, the results show that a proper strategy should be considered for each crop and the results and recommendations should be presented to agricultural producers and planners.

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