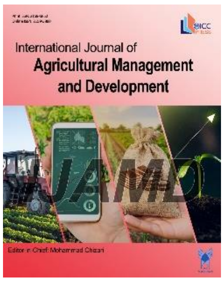

Volume 15, Issue 2, 152508 (64-73)

International Journal of Agricultural Management and Development (IJAMD)

https://doi.org/10.57647/ijamad.2025.16901

The Comparison of Algae Production Systems Based on Energy Consumption and Economic Analysis: The Application of Data Envelopment Analysis

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Original Research

Received:
12 October 2024

Revised:
7 February 2025

Accepted:
12 February 2025

Published in Issue:
30 June 2025

Abstract

This paper examines energy use efficiency and economic performance in different microalgae production systems (open space and greenhouse) using Data Envelopment Analysis (DEA). Experiments were conducted at the laboratory of Islamic Azad University, Arak branch, with 20 samples collected for each production system. Results showed that the average total input energy was 15,920.40 MJ kg^{-1} for open space and 17,691.60 MJ kg^{-1} for greenhouse cultivation. The energy ratio was 0.89 for open space and 0.80 for greenhouse, while the energy productivity index was 0.06 and 0.02 kg MJ^{-1}, respectively. Economic analysis indicated net returns of 204,376.59 \$ kg^{-1} for open space and 269,276.06 \$ kg^{-1} for greenhouse cultivation. Economic productivity was 0.17 kg \$$^{-1}$ for open space and 0.16 kg \$$^{-1}$ for greenhouse. DEA results showed that optimized total energy consumption was 14,476.93 MJ kg^{-1} for open space and 16,355.21 MJ kg^{-1} for greenhouse, representing a 7.55% energy saving compared to current cultivation conditions by converting inefficient practices to efficient ones. Overall, open space cultivation consumes less energy and is more economical than greenhouse cultivation, indicating that promoting outdoor microalgae production is preferable.

Keywords: Energy; Data envelopment analysis; Greenhouse; Microalgae

Cite this article: Kazemi, N. , Gholami Parashkoohi, M. , Mohammadi, A. , Zamani, D.M. , (2025). The Comparison of Algae Production Systems Based on Energy Consumption and Economic Analysis: The Application of Data Envelopment Analysis. *International Journal of Agricultural Management and Development*, 15(2), 64-73.

INTRODUCTION

The biggest challenge worldwide is the supply of energy for various applications. Energy consumption is divided into four sectors: residential, commercial, transportation, and industrial. From heating and cooling homes to lighting offices, driving vehicles, transporting goods, and manufacturing products, energy is essential for all daily activities (Luo et al., 2015). Currently, energy demand is met primarily through fossil fuels. However, limited fossil fuel resources, environmental concerns, population growth, and rising energy demand have compelled many countries to adopt renewable energy (Abbasi & Abbasi, 2012).

Land and water resources are often key limiting factors for large-scale microalgae cultivation. In developed regions, land is limited, making it difficult to secure sufficient area for extensive cultivation (Jiang et al., 2021). Microalgae are among the earliest and simplest chlorophyll-containing organisms, capable of converting inorganic matter into organic matter through photosynthesis. They generally exhibit high growth rates and can produce substantial amounts of oil (Brennan & Owende, 2010). Data Envelopment Analysis (DEA) is a nonparametric method in operations research and economics for estimating the production frontier (Kuosmanen & Johnson, 2010). It is widely used to evaluate production boundaries and experimentally assess the productive efficiency of decision-making units (DMUs) (Geng et al., 2019). DEA is a powerful tool in production economics and operations management, capable of benchmarking the efficiency of service and construction operations. For benchmarking, efficient DMUs identified by DEA provide a partial best-practice frontier, though they do not fully define the production boundary (Akdeniz et al., 2010). Nonparametric techniques, such as DEA, have the advantage of not requiring a specific functional form for the boundary, but they do not establish a general relationship between inputs and outputs. Parametric techniques, in contrast, require specifying a functional relationship between inputs and outputs (Hasilová & Vališ, 2022). Hybrid approaches can combine the strengths of both methods (Kaab et al., 2019a). Therefore, DEA has high potential for optimization in this study. It is a nonparametric, linear programming approach to efficiency estimation that does not require a predefined structural relationship between inputs and outputs. It can also accommodate multiple outputs in the analysis (Mousavi-Avval et al., 2011).

In recent years, numerous studies in the fields of energy, economy, and environment have applied DEA for optimization. For instance, Castro and von Zuben (2010) proposed a multi-objective, multi-period mixed-integer linear programming (MILP) model for the biodiesel supply chain, considering sustainability aspects. The model aimed to minimize total cost, greenhouse gas emissions, and the reduction of food availability due to crop substitution for biofuel production.

DEA has proven effective for optimizing facility locations and measuring the relative efficiency of decision-making units (DMUs) (Velasquez, 2013). Bairamzadeh et al. (2016) developed an MILP model to minimize total costs in the bioethanol supply chain produced from lignocellulosic biomass, making decisions on the location, capacity, and technology of biorefineries. Mohseni et al. (2016) first identified suitable locations for biodiesel production facilities using GIS and the analytic hierarchy process (AHP), and then proposed an MILP model to design and plan a microalgae biodiesel supply chain. Environmental objectives in most biofuel supply chain models focus on minimizing greenhouse gas emissions. Han and Kim (2019) proposed a multi-period MILP model with a profit-maximization objective, considering various renewable energy sources, including wind, solar, and biomass. Most studies on microalgae biofuel supply chains have focused primarily on economic aspects, with little attention to sustainability. Arabi et al. (2019) designed a multi-period, non-deterministic supply chain for biobutanol production from microalgae biomass to minimize network costs. Their model addressed decisions such as the location of cultivation, drying, hydrolysis, and workstations in biobutanol refineries and biorefineries. DEA was used to rank locations and reduce computational complexity, but sustainability was not considered in the ranking process.

While designing a biofuel supply chain network can support development and environmental protection, most studies have concentrated on economic objectives. Gumte and Mitra (2019) proposed an optimized supply chain network for producing bioethanol from lignocellulosic biomass, aiming to maximize net present value (NPV). Their results showed that production costs were the largest component, followed by importation, transportation, infrastructure, and inventory costs.

Razm et al. (2019) developed a multi-period, triple-objective MILP model using agricultural wastes and forestry residues as biomass feedstock. Their model aimed to identify suitable locations for new biorefineries and, if necessary, shut down existing refineries. The objectives included maximizing profit (excluding taxes), minimizing greenhouse gas emissions, and achieving maximum social benefit. Using DEA, candidate locations were ranked by efficiency to reduce computational complexity and select the most suitable sites (Mobarezkhoo et al., 2022).

Various studies have addressed microalgae biodiesel production, but none have combined the aforementioned methods to provide a comprehensive perspective on commercial microalgae production. This research determines and optimizes energy consumption and conducts economic analysis across different production systems to establish a consumption pattern using DEA, which identifies an efficient pattern by evaluating the relative efficiency of DMUs. The optimized consumption pattern replaces the current one. By offering solutions and recommendations to improve energy efficiency, this study supports planning for commercial microalgae production through an integrated energy-economic evaluation. The key aspects reviewed include:

Assessment of energy use and economic performance in different microalgae cultivation methods.

Evaluation of energy use efficiency and identification of inefficiencies using DEA to optimize energy consumption. Analysis of economic indices across different microalgae cultivation methods.

Comparison of energy use and economic performance among various cultivation methods.

METHODOLOGHY

Location of case study

Microalgae production experiments in different systems were conducted at the laboratory of Islamic Azad University, Arak Branch. To collect data on the type and quantity of inputs and outputs, the required sample size was determined using Eq. 1 (Cochran, 1977). For each production system (open space and greenhouse), the number of samples was estimated to be 20.

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

Where N is the population size, z is the reliability coefficient, p is the estimated proportion of an attribute present in the population, q is $1-p$, and d is the allowable error or deviation from the population mean.

Algae cultivation greenhouses can be set up in locations such as rooftops, yards, basements, rooms, or traditional greenhouses at low to medium cost. Seeds and basic equipment can be procured with minimal capital. In addition to location, creating suitable environmental conditions is essential for successful cultivation.

Sunlight is vital for photosynthesis in algae, so adequate light must be ensured. Temperature is also a critical factor: growth occurs between 20°C and 40°C, and deviations outside this range halt development. Temperatures above 40°C can kill the algae, while temperatures below 20°C stop growth. Cultivation in open spaces exposes algae directly to the external environment, influencing growth conditions (Malyan et al., 2021).

Energy use pattern

Today, energy is not only a crucial component in societal development but also an essential element for national growth and prosperity. It is a fundamental requirement for sustained economic development, social welfare, improved quality of life, and societal security (Oyedepo, 2012). Energy, defined as the capacity to do work, exists in various forms, all capable of performing work. The energy content of each input and output represents its energy equivalent (Hosseinzadeh-Bandbafha et al., 2018b). Microalgae production inputs include human labor, machinery, natural gas, water, and electricity. Data on these inputs and the resulting outputs were collected via a questionnaire administered through interviews. The functional unit was then calculated per 1,000 kg of microalgae produced. Because inputs and outputs have different units, direct comparisons are difficult. Figure 1 illustrates the system boundary for different microalgae cultivation methods.

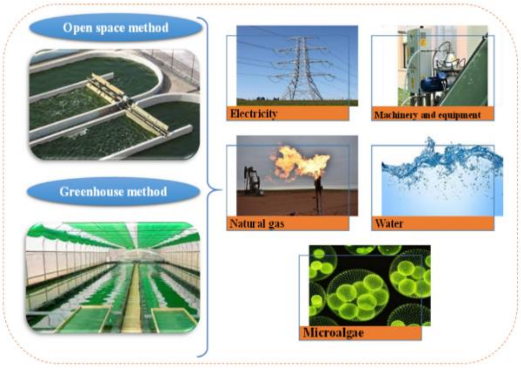


Figure 1. System Boundary for Different Methods of Microalgae Cultivation

To enable comparison, all inputs and outputs were converted into energy equivalents using specific coefficients. The energy equivalents of each input are reported in Table 1.

Energy indicators, including energy ratio, energy productivity, specific energy, and net energy efficiency, were calculated for each microalgae cultivation system (open space and greenhouse). Energy efficiency is defined as the ratio of energy output to energy input of the system (Brentrup et al., 2001). Energy productivity measures the amount of goods or services produced per unit of energy consumed (Yang et al., 2022). Specific energy refers to the energy consumed per unit of production (Hosseinzadeh-Bandbafha et al., 2018a). Net energy gain is the difference between total energy output and total energy input (Eqs. 3–6).

Economic indices

To calculate the cost per production unit, the prices of all inputs must be determined. Variable costs include expenses for natural gas, machinery rental, and labor, while fixed costs include land rent, farmer premiums, and taxes (Rajaeifar et al., 2014). Key economic indicators were calculated using Eqs. 7–9 (Mohammadi-Barsari et al., 2016). Net profit is obtained by subtracting total production costs from gross income per kilogram. The benefit-cost ratio is calculated as total revenue divided by total cost. Productivity, another economic indicator, is defined as the weight of the product per unit of total cost, reflecting the output obtained for each unit of expenditure.

Table 1. Energy Conversion Coefficients Used for Energy Inputs for Different Microalgae Production.

Inputs and outputs (Unit)	Energy equivalent (MJ Unit^{-1})	References
A. Inputs		
1. Human labor (h)	1.96	(Bakhtiari et al., 2015)
2. Machinery and equipment (kg)	9.00	(Hatirli et al., 2005)
3. Electricity (kWh)	12.00	(Bakhtiari et al., 2015)
4. Water (m^3)	1.20	(Kaab et al., 2019b)
5. Natural gas (m^3)	49.5	(Hatirli et al., 2005)
B. Output		
1. Microalgae (kg)	14.20	(Bahadar and Bilal Khan, 2013)

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

$$\text{Energy productivity} = \frac{\text{Production (kg)}}{\text{Input energy (MJ)}} \tag{4}$$

$$\text{Specific energy} = \frac{\text{Input energy (MJ)}}{\text{Production (kg)}} \tag{5}$$

$$\text{Net energy} = \text{Output energy (MJ)} - \text{Input energy (MJ)} \tag{6}$$

$$\text{Net return} = \text{Gross production value}\left(\frac{\$}{\text{kg}}\right) - \text{Production costs}\left(\frac{\$}{\text{kg}}\right) \tag{7}$$

$$\text{Benefit to cost ratio} = \frac{\text{Gross production value}\left(\frac{\$}{\text{kg}}\right)}{\text{Production costs}\left(\frac{\$}{\text{kg}}\right)} \tag{8}$$

$$\text{Productivity} = \frac{\text{Yield(kg)}}{\text{Production costs (\$)}} \tag{9}$$

Optimization techniques

The optimization technique (OT) is the practice of accomplishing the most feasible result under specific circumstances. Engineers have to determine the parameters involved in preservation, manufacturing, planning, and so on in order to either maximize the profit or minimize the endeavor. The profit or endeavor can be expressed mathematically as a fitness function of specific parameters. As such, OT is the process of determining the scenario that furnishes the maximum or minimum amount of a fitness function (Kaab et al., 2019a). There is no single technique for solving all optimization problems effectively. So far, a variety of methods have been developed for solving different types of problems. OTs are also mathematical programming methods used in the research on the process. The research on the process can be broadly classified as follows (Masliah et al., 2019): (1) Mathematical programming techniques, which can determine the minimum or maximum function of multiple parameters under prescribed constraints, (2) accidental procedure techniques, which are suitable to analyze quandaries qualified by a specific set of variables in random, and (3) statistical techniques, which are employed to manufacture experimental models or analyze empirical data.

DEA approach

DEA is first used to identify boundary units, after which a constant level is fitted to them. This process establishes the best practical relationship between multiple inputs and multiple outputs, effectively assessing how a specific set of DMUs converts inputs into outputs (Chen & Wang, 2020).

DEA includes four basic models: increasing returns to scale (IRS), decreasing returns to scale (DRS), variable returns to scale (VRS), and constant returns to scale (CRS). Each model can be applied along two axes: input-oriented or output-oriented.

The input-oriented model determines how much inputs can be reduced while maintaining constant output levels and achieving the efficiency frontier. In contrast, the output-oriented model maximizes outputs while keeping inputs constant to reach the efficiency frontier. In agriculture, minimizing inputs is often prioritized for economic and environmental reasons (Zanella, 2014). Charnes et al. (1996) extended DEA by defining performance as the ratio of a weighted sum of outputs to a weighted sum of inputs, using constant CRS and mathematical programming to calculate weights. Banker et al. (1984) further extended DEA to variable returns to scale (VRS), known as the BCC model. The CCR model assumes constant returns to scale and was proposed based on the variable VRS assumption of the BCC model.

DEA models can be classified into input-oriented and output-oriented models. Input-oriented models aim to minimize inputs while maintaining a constant output frontier, whereas output-oriented models focus on maximizing outputs for a given set of inputs. In this study, the input-oriented model is used to identify efficient and inefficient DMUs. Efficiency is measured using three metrics: (1) pure technical efficiency (PTE), (2) scale efficiency (SE), and (3) technical efficiency (TE) (Kaab et al., 2019b). TE reflects the ability of DMUs to maximize output from a given set of inputs or minimize inputs while maintaining output and is computed as follows:

where y_{rj} and x_{ij} denote the output and input values of y_r and x_i for DMU$_j$, respectively, v_i $(i = 1, 2, \ldots, m)$ defines the input weight of x_i, u_r (r = 1, 2, …, s) defines the output weight of y_r, n is the number of DMUs, s and m define input and output numbers, respectively, and θ defines DMU's TE score. It is expressed in matrix-vector dual linear programming format (Kaab et al., 2019b):

$$Maximize\ \ \theta_c = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \qquad (10)$$

$$Subjected\ to:\ \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1,\ j = 1,2,\dots,n$$

$$u_r \ge 0,\ v_i \ge 0$$

$$\text{Minimum:}\ \ \theta_c \qquad (11)$$

Subjected to :

$Y\lambda \ge y_0$

$X\lambda - \theta_c x_o = 0$

$\lambda \ge 0$

where θ_c denotes the DMU's TE score, λ is the $n \times 1$ weight orientation, X denotes an $m \times n$ input matrix, Y denotes an $s \times n$ output matrix, x_o is the $m \times 1$ vector of principal input values employed by the oth DMU, and y_o denotes an $s \times 1$ vector of principal output values. Eq. (10) is under the CCR input particle pattern. PTE is equivalent to TE under the BCC model. The BCC model is employed with the addition of a constraint, namely, λ = 1, in the CCR model under double linear programming format in Eq. (11).

In Eq. (12), SE represents the additional efficiency potential for attaining an optimized DMU size. Besides, it denotes the efficiency of the DMU's size on productivity. The following shows the relationship among PTE, SE, and TE:

$$SE = \frac{TE}{PTE} \qquad (12)$$

In this study, efficiency scores are expressed within a cross-efficiency matrix. The jth column and ith row denote performance scores of the jth microalgae production environment by applying the ideal weights of the ith microalgae production environment, as computed by the CCR model. An effective microalgae production environment is determined based on its average score, which is obtained from each column of the mutual productivity matrix.

RESULTS AND DISCUSSION

Input-output energy

Table 2 presents the energy use of various inputs in different microalgae cultivation methods.

The average total input energy was 15,920.40 MJ kg^{-1} for the open space method and 17,691.60 MJ kg^{-1} for the greenhouse method, indicating higher energy consumption in the greenhouse system. The output energy for both methods was 14,200 MJ kg^{-1}. Natural gas was the largest energy input, accounting for 12,870 MJ kg^{-1} in the open space method and 17,691.60 MJ kg^{-1} in the greenhouse method. Figure 2 shows the contribution of each energy input, revealing that natural gas represents approximately 80% of total energy input in both systems.

Open systems typically have a depth of 10–50 cm and can be constructed from concrete or covered with polyethylene or PVC (Pragya et al., 2013). Closed systems provide controlled conditions for microalgae growth, improving photosynthetic efficiency and biomass production. However, they involve high initial costs and complex maintenance, resulting in greater energy consumption (Tan et al., 2020). In the greenhouse method, additional equipment increases human labor hours and gas consumption. Optimal production requires careful control of greenhouse conditions.

Table 3 presents the energy indices for different microalgae cultivation methods. The open space and greenhouse methods had energy ratios of 0.89 and 0.80, energy productivity indices of 0.06 and 0.02 kg MJ^{-1}, and specific energy values of 15.92 and 17.69 MJ kg^{-1}, respectively. Net energy gains were −1,720.40 MJ for the open space method and −3,491.60 MJ for the greenhouse method.

Khoo et al. (2013) investigated the potential to efficiently convert lipid-depleted residual microalgae biomass into bioenergy derivatives via thermochemical processes, including gasification at 850 °C, pyrolysis at 550 °C, and torrefaction at 300 °C. Energy indicators were used to quantify the energy input required to produce 1 MJ of bioenergy output.

Experimental results showed net energy balances (NEB) ranging from 0.57 MJ/MJ for bio-oil via pyrolysis to 6.48 MJ/MJ for gas produced via torrefaction. Considering the complete life cycle, the NEBLCA increased to 1.67 MJ/MJ for bio-oil and 7.01 MJ/MJ for gas. Energy efficiencies and life cycle CO_2 emissions were also calculated.

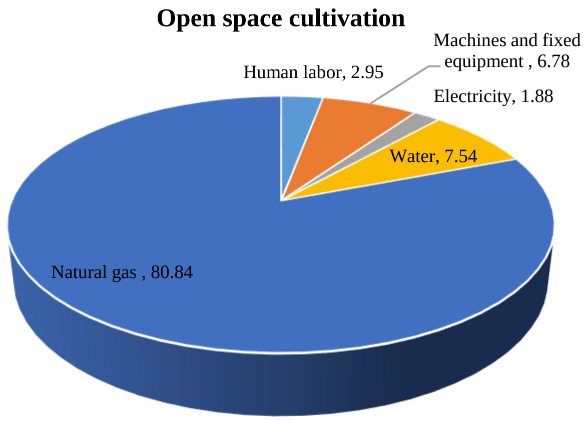
Economic assessment

Table 4 presents the economic indices for different microalgae cultivation methods. The net returns for the open space and greenhouse methods were 204,376.59 $ kg^{-1} and 269,276.06 $ kg^{-1}, respectively. Due to higher income relative to cost, the benefit-cost ratio is more favorable in the greenhouse method. Productivity values were 0.17 kg $$^{-1}$ for open space and 0.16 kg $$^{-1}$ for greenhouse cultivation.

Jonker and Faaij (2013) developed a limitation growth model to determine microalgae productivity under different climate profiles. Total direct and indirect energy consumption ratios for heat, fuel, and electricity production from microalgae were calculated.

Table 2. Energy Consumption of Various Inputs Used in Different Methods of Microalgae Cultivation

Items	Quantity		Total energy equivalent (MJ kg^{-1})	
	Open space	Greenhouse	Open space	Greenhouse
A. Inputs				
1. Human labor	240.00	210.00	470.40	411.60
2. Machinery and equipment	120.00	130.00	1080.00	1170.00
3. Electricity	25.00	30.00	300.00	360.00
4. Water	1000.00	750.00	1200.00	900.00
5. Natural gas	260.00	300.00	12870.00	14850.00
The total energy input (MJ)	-	-	15920.40	17691.60
B. Output	-	-	-	-
1. Microalgae	1000.00	1000.00	14200.00	14200.00



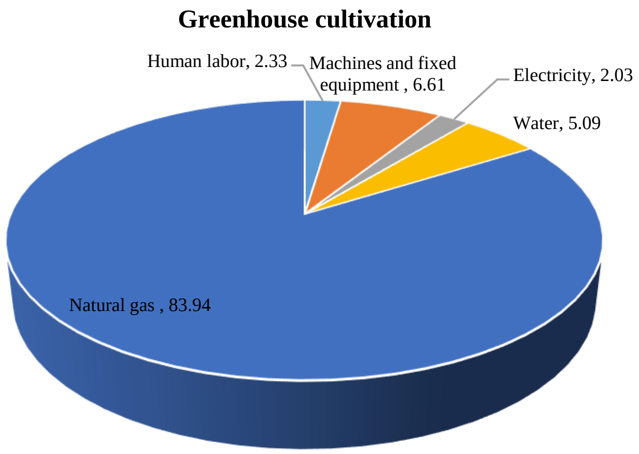


Figure 2. Shares of Energy Sources in Different Microalgae Cultivation Methods

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For raceway ponds, the optimal direct energy consumption ratio was 0.06 and the indirect ratio 0.74, while for horizontal tubular systems, the optimal direct ratio was 0.32 and the indirect ratio 117. Implementing improvement options could reduce indirect energy consumption by 50% for both systems under optimistic scenarios. Key contributors to energy consumption were CO_2 supply for raceway ponds and circulation power for horizontal tubular systems. The minimum fuel production costs were 136 €2010/GJ for raceway ponds and 153 €2010/GJ for horizontal tubular systems, compared to 5–20 €2010/GJ for non-renewable gasoline and diesel. Considering potential improvements, overall bioenergy production costs could be reduced by one-fourth. Current results indicate that microalgae cultivation is not suitable for dedicated bioenergy production under the studied cultivation, harvesting, and conversion conditions. Coproduction with high-value products may be more viable, though this was not addressed in the present study.

DEA assessment

Table 5 shows that the average scores of TE, SE, and PTE were 0.853, 0.946, and 0.910 for the open space method, and 0.912, 0.936, and 0.905 for the greenhouse method, respectively. The results indicate that SE exhibited the highest standard deviation in the open space method, primarily due to a lack of knowledge of proper cultivation practices and suboptimal resource allocation. The large dispersion in TE suggests that farmers used excessive or inefficient inputs.

Khai and Yabe (2011) reported a TE of 0.816 for paddy production in Vietnam, while Elhami et al. (2016) calculated TE, PTE, and SE values of 0.94, 0.99, and 0.94 for chickpea production in Isfahan province, Iran. The CCR and BCC models are illustrated in Figure 3. According to the CCR model results, TE scores of 1 were observed in 7 units for the open space method and 11 units for the greenhouse method. The BCC model results indicate PTE scores of 1 for 15 units in open space cultivation and 13 units in greenhouse cultivation. SE scores of 1 were achieved in 9 units for open space and 7 units for greenhouse cultivation.

Energy saving

Table 6 presents the optimized energy use and savings for microalgae cultivation systems (open space and greenhouse). According to DEA results, total optimized energy consumption in the open space method is 14,476.93 MJ kg^{-1}. Converting inefficient practices into efficient ones in the open space method leads to an energy saving of 1,443.47 MJ kg^{-1} (9.06%) compared to current practices.

For the greenhouse method, optimized energy consumption is 16,355.21 MJ kg^{-1}, representing a 7.55% reduction compared to current cultivation. The largest energy savings in the greenhouse system were in water (26.67%) and electricity (18.17%), while in the open space system, the greatest saving (16.89%) was in electricity. Overall, DEA demonstrates significant potential for reducing energy consumption by improving efficiency in both cultivation methods.

Table 3. Energy Indices of Different Microalgae Cultivation Methods

Items	Open space	Greenhouse
Energy use efficiency (ratio)	0.89	0.80
Energy productivity (kg MJ^{-1})	0.06	0.02
Specific energy (MJ kg^{-1})	15.92	17.69
Net energy gain (MJ)	-1720.40	-3491.60

Table 4. Economic Indices of Different Microalgae Cultivation Methods

Items	Open space	Greenhouse
Total value from production ($ kg^{-1})	210341.00	275520.00
Total cost from production ($ kg^{-1})	5964.41	6243.94
Net return ($ kg^{-1})	204376.59	269276.06
Benefit-to-cost ratio (ratio)	35.26	44.12
Productivity (kg $\$^{-1}$)	0.17	0.16

Table 5. Average Efficiency Items of Different Microalgae Cultivation Methods

Items	TE		PTE		SE	
	Open space	Greenhouse	Open space	Greenhouse	Open space	Greenhouse
Average	0.853	0.912	0.946	0.936	0.910	0.905
Standard deviation	0.070	0.060	0.090	0.040	0.080	0.030
Minimum	0.683	0.652	0.693	0.647	0.651	0.694
Maximum	1.000	1.000	1.000	1.000	1.000	1.000

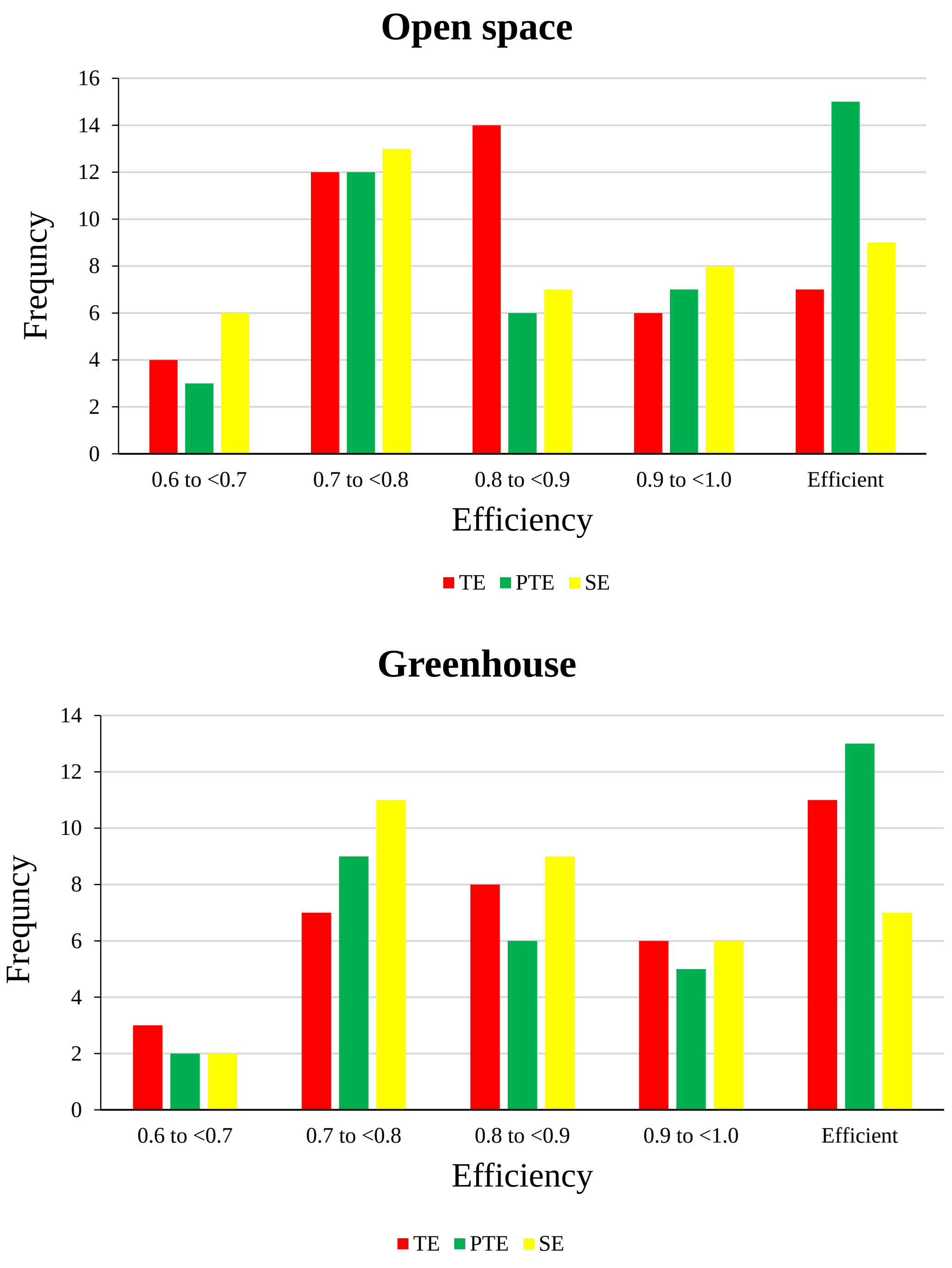

Figure 3. The Efficiency Score Distribution in Different Microalgae Cultivation Methods

Table 6. Optimum Energy Requirement and Saving Energy In Different Microalgae Cultivation Methods

Inputs	Optimum energy requirement (MJ ha^{-1})		Saving energy (MJ ha^{-1})		Saving energy (%)	
	Open space	Greenhouse	Open space	Greenhouse	Open space	Greenhouse
1. Human labor	459.22	364.58	11.17	47.01	2.37	11.42
2. Machinery and equipment	964.92	1050.27	115.07	119.72	10.65	10.23
3. Electricity	249.32	294.55	50.67	65.44	16.89	18.17
4. Water	1007.48	659.92	192.51	240.07	16.04	26.67
5. Natural gas	11795.96	13985.87	1074.03	864.12	8.34	5.81
Total energy input	14476.93	16355.21	1443.47	1336.38	9.06	7.55

CONCLUSIONS

This study evaluated energy use and economic performance in different microalgae cultivation methods, using DEA to optimize energy consumption. For the open space and greenhouse methods, energy ratios were 0.89 and 0.80, energy productivity was 0.06 and 0.02 kg MJ^{-1}, and specific energy was 15.92 and 17.69 MJ kg^{-1}, respectively. Natural gas was identified as the most significant energy input across cultivation methods.

Economic analysis showed that the benefit-cost ratio was higher in the greenhouse method, while productivity was 0.17 kg \$$^{-1}$ for open space and 0.16 kg \$$^{-1}$ for greenhouse cultivation. Optimized energy consumption in the open space method was 14,476.93 MJ kg^{-1}, achieving an energy saving of 1,443.47 MJ kg^{-1}, or a 9.06% reduction compared to current practices. In the greenhouse method, optimized energy consumption was 16,355.21 MJ kg^{-1}, representing a 7.55% decrease.

Overall, the open space method was found to be more economical in terms of energy and cost. Further studies are recommended to model algae production in different cultivation systems to project future energy consumption.

ACKNOWLEDGMENTS

The authors wish to thank of the Department of Biosystem Engineering, Tak.C., Islamic Azad University, Takestan, Iran for financial support.

Authors Contribution
Naser Kazemia: Data curation, Validation, Writing-Original draft, Reviewing and Editing, Mohammad Gholami Parashkoohi: Methodology, Reviewing and Editing, Supervision, Ahmad Mohammadi: Validation, Writing- Reviewing and Editing, Supervision, Davood Mohammad Zamani: Investigation, Writing-Reviewing and Editing, Formal analysis, Software.

Availability of data and materials
The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Conflict of interests
The authors declare that they have no competing interests.

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