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Improving agricultural sustainability through farm mergers: an energy efficiency perspective

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ABSTRACT
The aim of this paper is to investigate agricultural sustainability as a collective issue involving multiple rather than individual farms. Through the utilization of energy consumption as a proxy, we propose a novel methodology that evaluates the impact of farm consolidations on agricultural sustainability while accounting for resource preferences. Our approach incorporates the ordered weighted averaging (OWA) operator within an inverse data envelopment analysis (IDEA) model to identify post-merger farms that meet preset efficiency targets. We employ a DEA cross-efficiency (DEA-CE) procedure to select merger plans that maximize agricultural sustainability for each preference scenario. By analysing a case study of 43 tomato greenhouse farms in Biskra, northern Algeria, our findings demonstrate that mergers can significantly enhance agricultural sustainability, surpassing the potential of individual farms by a factor of over 15. Additionally, the adoption of the most sustainable merger plan can lead to energy savings of more than 69%. Irrespective of the preference scenario, substantial energy savings in machinery, fertilizers, diesel, and electricity ranging from 22.92% to 73.73% were observed. These results emphasize the strategic role of merger processes in promoting agricultural sustainability and optimizing resource utilization.

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Agricultural sustainability; farm mergers; resource optimization; energy efficiency; sustainability assessment; data envelopment analysis (DEA); inverse DEA; ordered weighted averaging (OWA)

1. Introduction

The world population is projected to hit the cap of 8.5 billion in 2030 and grow further to 9.7 billion by 2050 (United Nations, 2022), which amplifies drastically the challenge of meeting the global demand for food (Abu Hatab et al., 2019). With the agricultural sector bearing such a burden, more resources are required for the operations performed on-farm and throughout the agricultural food supply chain, such as water, land, fuel, fertilizers, pesticides, machinery, etc. (Gorjian et al., 2021). The extensive use of these resources leads naturally to an increase of the environmental impact of agriculture, a major issue that has drawn an intense debate on sustainable agriculture (Lampridi et al., 2019). Though a consensus could hardly be reached regarding a common definition of the concept (Binder et al., 2010; de Olde et al., 2017), there is still an agreement among scholars that agricultural sustainability needs to assess environmental, economic, and social aspects associated with agricultural practices (Pham & Smith, 2014). Per se, a sustainable agriculture is expected to be economically viable, ecologically sound, socially just and humane (Zahm et al., 2019). A huge number of publications appeared

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on sustainable agriculture. Recently, Piñeiro et al. (2020) reviewed nearly 18,000 publications only on incentive programmes for sustainable agricultural practices. On another side, Chopin et al. (2021) presented a review of avenues for improving farming sustainability assessment in terms of tools, framing and indicators. The reader is referred to Lampridi et al. (2019) for a systematic review of the literature relating to agricultural sustainability.

At the farms' level, production of goods and/or services, management of resources, and influence on rural dynamics are generally regarded as, respectively, the economic, the environmental, and the social pillars of a sustainable agriculture (Latruffe et al., 2016). Nevertheless, it appears that most of the studies focus more on the environmental rather than on the economic and the social indicators of agricultural sustainability (Dakpo et al., 2016). This trend is notably due to the excessive consumption of natural resources, especially energy, which exacerbates the risk of greenhouse gas (GHG) emissions and hinders environmental sustainability (Liu et al., 2016). Thus, ensuring efficient agricultural energy consumption is an important step towards balancing the need for energy with responsible and sustainable energy management practices (Rasheed et al., 2022).

The evaluation of energy efficiency is a typical multi-criteria decision making (MCDM) problem, which often involves many agricultural production factors (Gésan-Guiziou et al., 2020). The stochastic frontier analysis (SFA) and data envelopment analysis (DEA) are the most commonly used techniques for agricultural efficiency assessment. The DEA approach (Charnes et al., 1978) is a non-parametric approach that is based on linear programming and can evaluate the efficiency of homogenous groups of decision making units (DMUs) defined with multiple inputs and multiple outputs (Oukil et al., 2016). As opposed to the SFA approach (Aigner et al., 1977), DEA does not require prior assumptions on the functional form of the production technology nor the probability distribution of the random error.

Recent applications of SFA to the evaluation of agricultural energy efficiency include the studies of Ali et al. (2019), Khan et al. (2021), Bibi et al. (2021) and Khan et al. (2023). The environmental efficiency of agricultural systems has also been investigated through SFA in Vu et al. (2019), Khan and Ullah (2020), Le et al. (2019) and Tu et al. (2019) but the investigations were carried out from the perspective of undesirable outputs rather than energy inputs.

Studies that apply DEA for the evaluation of agricultural energy efficiency are relatively more abundant. A recent survey reports that DEA applications to agricultural sustainability account for not less than 63% of the extant literature (Zhou et al., 2018), with a remarkable prevalence of the environmental aspects (Dakpo et al., 2016), where energy is the most critical indicator (Hercher-Pasteur et al., 2020). The majority of DEA-based studies that deal with agricultural energy efficiency are carried out for open field agriculture where different crops are cultivated, including sugarcane (Kaab et al., 2019), arecanut (Paramesh et al., 2018), cotton (Singh et al., 2022), rice (Najafabadi et al., 2022; Nayak et al., 2023), almond (Baran et al., 2020), chickpeas (Elhami et al., 2016), paddy (Mohammadi et al., 2015; Nabavi-Pelesaraei et al., 2017), wheat (Esfahani & Rafati, 2022; Ilahi et al., 2019; Pishgar-Komleh et al., 2020; Singh et al., 2019; Singh et al., 2021), peanuts (Hosseinzadeh-Bandbafha et al., 2018), grape (Mohseni et al., 2018), saffron (Saeidi et al., 2022), barley (Payandeh et al., 2021), rice-wheat-green gram (Bhunia et al., 2021), and maize (Mwambo et al., 2021). There are fewer studies in the greenhouse (GH) production, conducted mostly in arid regions, for tomato (Nourani & Bencheikh, 2020; Raheli et al., 2017), eggplant (Nourani & Bencheikh, 2021), button mushroom (Ebrahimi & Salehi, 2015), cucumber (Mardani Najafabadi & Taki, 2020; Soheilifard et al., 2021) and mix GH crops (Elhag & Boteva, 2019; Liang et al., 2019).

The reader is refereed to Kyrgiakos et al. (2023) for a recent review of DEA applications to sustainability assessment in the agricultural sector.

Regardless of the DEA techniques that are adopted, all the aforementioned studies deal with the farms as independent production units, not sharing any resources with each other. More specifically, the farms' relative efficiency is evaluated to capture performance gaps and identify the input factors that may necessitate improvement for each inefficient farm (Sow et al., 2016). The improvement potential is estimated through the slack values of these inputs. Though the slack schemes can lead to efficiency improvement of individual farms, recent studies have established that more savings are possible under Mergers & Acquisitions (M&A) schemes, where a group of farms agree to merge resources for the sake of enhancing collective production capabilities (Oukil, 2023b).

Farm mergers are business deals that involve the consolidation of two or more individual farms seeking various strategic, economic, or operational goals. The scale of these mergers can vary from small family farms to large commercial farming operations. A census of the Food and Agriculture Organization (FAO) across 30 countries reveals that there are approximately 500 million family farms, representing globally not less than 88% of all farms (FAO, 2014). Though most of these farms are small in size – operating under 2 hectares – and produce 80% of the world's food (Graeub et al., 2016), they definitely face constraints related to scale, fragmentation and resource access (Agarwal et al., 2021). Therefore, the potential of farm mergers as an alternative model to small family farms needs to be investigated in terms of the economies of scale, which can result in more savings, an increased production efficiency and an enhanced approach to sustainability and environmental practices.

Farm mergers have generally been promoted within the framework of group farming (e.g. Agarwal, 2018; Agarwal et al., 2021), land consolidation (e.g. Xu et al., 2022; Zeng et al., 2018), and farmers' cooperatives (e.g. Candemir et al., 2021; Grashuis & Su, 2019; Sarkar et al., 2022). Whether these studies are conducted in India (e.g. Agarwal, 2020; Sugden et al., 2021), Ireland (e.g. Cush & Macken-Walsh, 2016), France (Agarwal & Dorin, 2019), or the United Kingdom (Ingram & Kirwan, 2011), it is notable that the common purpose remains the evaluation of the impact of mergers decisions on productivity besides identifying the factors which influence potential changes (improvement/deterioration). In a study carried out in Kerala, India, Agarwal (2018) concluded, through a regression model, that group farming outperforms individual farms in terms of annual output per hectare and net returns, with institutional design, state support, group heterogeneity, commercial crops as the major determinants of positive performance. Using Jiangsu province, China, as a case study, Zeng et al. (2018) applied SFA to assess the effect of land consolidation on the agricultural technical efficiency. Sarkar et al. (2022) adopted the theory of planned behaviour to evaluate the roles of the kiwi-fruit farmer's cooperative in Meixian, China, for fostering environmentally friendly production technologies. Hýblová (2014) analysed agriculture mergers in the Czech Republic from a financial performance perspective and proved that, though the size of the merging entities in terms of balance sheet total decreased, the corresponding performance increased. Considering cow-calf farms, Holmström et al. (2018) highlighted the positive impact of pastures' expansion on Swedish suckler-based beef production due to lower operating costs brought on by economies of scale. Ho et al. (2022) employed DEA to assess the influence of sustainable land management practices on the efficiency for orange cultivation in northwest of Vietnam and concluded that efficiency is strongly correlated with production scale. Llones et al. (2022) applied SFA to show that shared irrigation management among farmers can improve significantly on-farm outcome for rice farms in Northern Thailand. Başer and Bozoğlu (2023) developed a multi-stage approach to prove that a higher farm size has a positive effect on the sustainability of beef cattle farming in Samsun Province, Turkey. Ren et al. (2019) reported similar conclusions. Lozano and Adenso-Díaz (2021) proposed a DEA model to determine the most gainful merger within a set of dairy farms through estimating the total technical efficiency.

Apart from Lozano and Adenso-Díaz (2021), no known study has addressed explicitly farm mergers through DEA. Furthermore, a recent systematic review of research on sustainability in M&A (González-Torres et al., 2020) reveals that DEA has not been used to investigate sustainability of merger processes neither in agriculture nor any other business sector. As such, to the best of the authors' knowledge, the present study introduces for the first time the concept of DEA to the field of sustainability in M&A, regardless of the business field.

On another hand, it is noteworthy that the aim of Lozano & Adenso-Díaz's study is restricted to estimating post-merger efficiency gains by employing the entire input levels of the merging farms. Yet, before sealing the merger deal, the farmers might be interested to know more about the optimal levels of inputs that each merging farm must contribute for the sake of achieving an efficiency target set a priori for the planned merger. In other words, the efficiency score of the planned merger becomes a known parameter of an optimization problem for which the decision variables are the input contributions of the merging farms. Such a statement reflects the essence of an inverse optimization problem and, within a DEA setting, Inverse DEA (IDEA) appears to be the perfect modelling tool (Pendharkar, 2002). Instead of pursuing the estimation of the efficiency for known inputs and outputs of a DMU, IDEA, contrary to the traditional DEA, searches for the optimal input and/or output levels that qualify a DMU to reach a preset efficiency target.

There are relatively fewer studies related to the application of IDEA to M&A. A recent review of the IDEA literature reveals a clear domination of the banking sector (Emrouznejad & Amin, 2023). Other sectors include energy (Lin et al., 2020), higher education (Amin & Oukil, 2019a), hospitality (Oukil et al., 2024) and agriculture (Oukil, 2023b; Oukil, Nourani, et al., 2022; Oukil et al., 2023), In the agricultural sector, Oukil (2023b) is the first study that applied IDEA to investigate prospective gains from the merger of farms. This study's findings reported proportions of potential resource gains ranging between 21% and 72%, on average, with the uppermost gains expected for water and electricity. Also, Oukil, Nourani, et al. (2022) used IDEA to evaluate the impact of farm mergers on energy consumption. The results indicated that the average proportions of potential energy gains range between 20.68% and 78.33% per post-merger GH farm. In spite of succeeding to underline the ability of mergers to enhance resource gains in the agricultural sector, the common drawback of these two studies resides in the implicit assumption that the farm's inputs (resources) are equally important; a feature that is clearly reflected through the adoption of an IDEA model (Gattoufi et al., 2014) whose objective coefficients are all equal. In real-life situations, there are resources that can be regarded as relatively more important than others. The importance scale depends primarily on the decision making settings, which may involve local or global policies, corporate strategies, market trends, or other technical factors that are specific to the farming process. For instance, water is commonly the most important resource for agricultural production but its importance is more emphasized in arid regions because of its scarcity (Al-Mezeini et al., 2020). Electricity, as a requirement for water pumping and distribution, is a key resource for irrigated agriculture, regardless of the agricultural context (Langarita et al., 2017). On the other hand, organic fertilizers are rather essential for a sandy soil, which requires frequent amendments with organic matter to improve its ability to hold onto nutrients (Yu et al., 2012). The role of human labour is strategic to the agricultural sector, but its importance is likely to be greater for territories with low involvement of the local populace, such as Sub-Sahara Africa (Ibidunni et al., 2020). Hence, treating all the resources in the same way is not always appropriate and may lead to biased decisions. Thus, another new aspect that the present study aims to investigate is the impact of resource prioritization on the agricultural sustainability of farm mergers. In light of the reviewed literature, it is the first time that such a topic is studied for either individual or group farming. Considering the preferences of different stakeholders towards the agricultural resources, we develop a new approach that exploits the properties of the Ordered Weighted Averaging (OWA) operator (Yager, 1988) to produce an importance weight for each resource. As a result, we propose an extended IDEA model that enables the decision maker's (DM) preference to be duly integrated into the merger's process.

As environmental sustainability is a collective issue that does require collective actions, the next stage of this study is also concerned with planning the best matches between pairs of farms, in view of maximizing the sustainability of the whole agricultural production sector. In other words, it is hypothetically assumed that the pairs of farms to be merged are not set a priori and the objective is to select collectively the best partners for each merger. To this end, we propose, for the first time, a DEA cross-efficiency (DEA-CE) methodology to determine the most sustainable merger plan for different DM's preference schemes.

Consequently, the present paper contributes to the body of knowledge relating to sustainability over four fronts.

(1) It is the first DEA-based study that investigates sector-wide sustainability from M&A perspective.
(2) The IDEA approach is introduced for the first time as a potent tool for evaluating mergers' sustainability.
(3) A new IDEA model that incorporates the DM's preference is proposed as a way to prioritize the farming resources over the merger decision process.
(4) A new DEA-CE methodology is developed to determine the most sustainable pairs of farms and, hence, yield the most sustainable merger plan..

The proposed methodological framework is implemented on a case study of 43 tomato GH farms from Biskra, Algeria.

The next sections of the paper are set out as follows. In Section 2, the traditional approach of sustainability, based on standard DEA models, is described, followed by the new IDEA model developed for enhancing sustainability through mergers under DM's preferences. Section 3 presents the case study. In Section 4, the results are thoroughly discussed for selected DM's optimism levels. Section 5 is dedicated to a new DEA-CE methodology for building the most sustainable merger plan with various DM's optimism levels. In Section 6, we close the study with concluding remarks, policy implications, some of the study's limitations and potential venues for future research.

2. Methodology

2.1. Traditional sustainability evaluation

Let's consider a sample of K farms, each farm G_k is defined with energy inputs X_{ik} and energy outputs Y_{jk}, where $i = 1, \ldots, I$ and $j = 1, \ldots, J$. Assume that we are interested in evaluating the sustainability of $G_o = (X_{io} Y_{jo})$. The sustainability of G_o depends predominantly on its performance in using the available energy inputs X_{io} to produce energy outputs Y_{jo}. Within the production possibility set comprising the K farms, $G_o^{\prime}$ s performance can be estimated through its relative efficiency score E_o^*, computed via the following input-oriented BCC model (Banker et al., 1984).

$$
\text{(BCC)} \qquad
\begin{aligned}
& E_o^* = \min\ \pi \\
\text{s.t.}\ & \sum_{k=1}^{K} \alpha_k X_{ik} \le \pi X_{io} \qquad i = 1, \ldots, I \\
& \sum_{k=1}^{K} \alpha_k Y_{jk} \ge Y_{jo} \qquad j = 1, \ldots, J \\
& \textstyle\sum_{k=1}^{K} \alpha_k = 1 \\
& \alpha_k \ge 0 \qquad k = 1, \ldots, K
\end{aligned}
$$

E_o^* represents the optimal efficiency score of farm G_o. Thus, G_o is efficient if $E_o^* = 1$, otherwise, it is inefficient. In the case G_o is inefficient, it may need to reduce its energy inputs with an amount S_{io}^* (Oukil et al., 2021; Soltani et al., 2021) where

$$
S_{io}^* = (1 - E_o^*) X_{io} i = 1, \ldots, I \tag{1}
$$

Here, S_{io}^* is the energy saving that is required for input i, $i = 1, \ldots, I$. If $E_o^* = 1$ and $S_{io}^* = 0$ for all $i = 1, \ldots, I$, G_o is strongly efficient. Contrariwise, G_o is weakly efficient if $S_{io}^* > 0$ for one energy input i or more (Oukil & Al-Zidi, 2018).

In the coming sections, we show that, even if G_o is strongly efficient, its merger with another farm may lead to substantial energy savings. As such, we propose a methodology for enhancing sustainability through farm mergers. Although the proposed mathematical model deals with pairwise mergers, its extension to more than two farms remains possible. To enable discarding the impact on the results of possible fluctuations due to market disruptions or other exogenous factors, we also assume that the energy input consumption within the farms is deterministic over the merger planning horizon.

2.2. Enhancing sustainability through mergers

Let's consider the merger of two farms G_A and G_B into a larger farm F_m. Regardless of the efficiency status of G_A and G_B, the targeted efficiency of the post-merger farm F_m is set *a priori* to $\overline{\pi} \ge \max(E_A^*, E_B^*)$. Assuming that F_m retains the total energy outputs of G_A and G_B, i.e. $Y_{jm} = Y_{jA} + Y_{jB}$ ($j = 1, \ldots, J$), the DM is concerned with finding the minimum levels of energy inputs $\delta_{iA} \le X_{iA}$ and $\delta_{iB} \le X_{iB}$ ($i = 1, \ldots, I$), which are needed to operate F_m and achieve the target $\overline{\pi}$. If we also need to integrate the DM's preference into the merger's evaluation, the IDEA model of (Amin & Ibn Boamah, 2020) can be extended as follows:

$$
\text{(E-IDEA)} \qquad
\begin{aligned}
& \min \sum_{i=1}^{I} W_i (\delta_{iA} + \delta_{iB}) \\
& s.t. \\
& \sum_{k \in R} \alpha_k X_{ik} + \alpha_m (X_{iA} + X_{iB}) \\
& -(\delta_{iA} + \delta_{iB}) \times \overline{\pi} \le 0 \qquad i = 1, \ldots, I \\
& \sum_{k \in R} \alpha_k Y_{jk} + \alpha_m (Y_{jA} + Y_{jB}) \\
& \ge (Y_{jA} + Y_{jB}) \qquad j = 1, \ldots, J \\
& \sum_{k \in R} \alpha_k + \alpha_m = 1 \\
& 0 \le \delta_{iA} \le X_{iA}, \\
& \quad 0 \le \delta_{iB} \le X_{iB} \qquad i = 1, \ldots, I \\
& \alpha_k \ge 0,\ k \in R,\ \alpha_m \ge 0
\end{aligned}
$$

The inverse property of E-IDEA stems from the fact that, contrary to traditional DEA optimization models, the targeted efficiency $\overline{\pi}$ is a known parameter of the problem whereas the energy inputs δ_{iA} and δ_{iB} ($i = 1, \ldots, I$) are decision variables whose optimal values must be determined. Here, W_i is the weight of input i, which is integrated into the original model to account for the relative importance of the energy inputs. In real-life problems, the DM may set a preference scale on the inputs, depending on the application context. A specific energy input i may be perceived more important based, e.g. on its market price, its scarcity, its indispensableness to the production process or other considerations pertaining to the decisional context.

The post-merger farm F_m is evaluated relatively to the set of peers R, which may include either G_A or G_B, or none. In a *survival,* the acquiring farm, i.e. G_A or G_B, will carry on operating alone with the previous name. In a *consolidation,* G_A and G_B will unite into a new farm, like F_m. Enhancing the farms' sustainability being the main aim of our study, all the mergers will be consolidations, i.e. none of the merging farms will belong to R.

Definition 1: A merger $F_m = (G_A, G_B),\ A \neq B,$ is *sustainable* if $\alpha_m^* = 0$ and $\delta_{iA}^* < X_{iA}$ or $\delta_{iB}^* < X_{iB}$ for one or more input i ($i = 1, \ldots, I$).

Definition 2: A merger $F_m = (G_A, G_B),\ A \neq B,$ is a *major consolidation* if and only if $\alpha_m = 1,\ \delta_{iA}^* = X_{iA}$ and $\delta_{iB}^* = X_{iB}$ for $i = 1, \ldots, I$ and $\overline{\pi} = 1$.

As such, a major consolidation is not sustainable in the sense that it does not lead to energy gains.

Definition 3: Given a sustainable post-merger $F_m = (G_A, G_B),\ A \neq B,$ the potential energy gains of G_A and G_B for energy input i are $\mu_{iA} = X_{iA} - \delta_{iA}^*$ and $\mu_{iB} = X_{iB} - \delta_{iB}^*,$ respectively.

Definition 4: The cumulative energy gains of post-merger $F_m = (G_A, G_B),\ A \neq B,$ for energy input i is $h_{im} = \mu_{iA} + \mu_{iB}$ for a proportion $h_{im}/(X_{iA} + X_{iB})\times$ < ?A3B2show[]? > 100% of the initial energy inputs.

It is important to note that, although model E-IDEA is developed for pairwise mergers, it can be easily extended to the merger of more than two farms.

3. Case study

The new approach is illustrated through a case study of 43 GH farms producing tomato in Biskra, north east of Algeria (Figure 1).

3.1. Study area

Biskra serves as a transitional zone between the northern and the southern parts of the country. With predominantly flat terrain, apart from the surrounding Ziban mountains, the outskirts of Biskra feature small water sources, particularly within the oases and canyons surrounding El Kantara. Located approximately 430 km south-east of the capital city of Algiers, Biskra resides at an average elevation of 88 m above the sea level.

Characterized by a subtropical hot desert climate, Biskra experiences arid and exceedingly hot summers, coupled with very cold winters. During summer, temperatures average around 43.5°C, often peaking above 48°C, with a relative humidity of 12%. Winters bring an average minimum temperature of 4°C, a relative humidity of 89%, and an annual rainfall of 138 mm, occurring over fewer than 31 days each year.

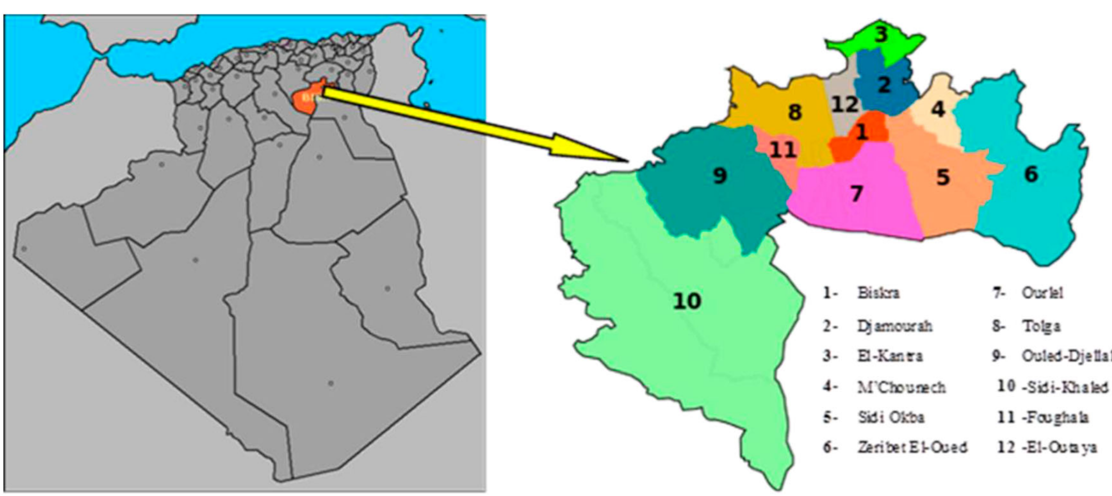

Figure 1. Map of the study area.

Biskra, along with other regions in southern Algeria, has recently witnessed significant development in irrigated crops, primarily relying on groundwater extraction. While renowned as the leading producer of date palm fruits in Algeria, Biskra has arisen as a prominent hub for greenhouse (GH) production as well. Since its introduction to the region in 1984, GH technology has experienced rapid expansion, with the cultivated area growing from 1370 ha in 1999 to 4050 ha in 2013. Despite occupying no more than 4% of the region's entire irrigated land, GH vegetable production in Biskra accounts for over half the country's GH crop market. Among the various crops, tomato GH production holds significant importance, covering nearly 34% of the region's area allocated to GH production.

3.2. Data collection

Primary data were collected in the course of the cropping season of 2017–2018 by conducting face-to-face interviews with 43 farmers. These farmers were nominated in a random manner from six municipalities known for their significant cultivation of tomatoes in greenhouses. The municipalities include M'ziraa, Ainnaga, Sidi-Okba, Elaghrous, Doucen, and Lioua (Figure 1), where lycopersicon esculentum mill is the only type of tomatoes that is cultivated. As such, each GH farm is defined with six inputs, namely *human labour* (X_1), *machinery* (X_2), *fertilizers* (X_3), *pesticides* (X_4), *diesel fuel* (X_5), and *electricity* (X_6), in addition to *yield* (Y), as an output. Table 1 presents the descriptive statistics of the original data sample, prior to its energy conversion.

Human labour refers to the total number of hours spent on field by the workers. The majority of workers are hired from neighbouring municipalities and include both genders, males and females. The workers who ensure the maintenance of the crop are generally employed on permanent job contracts, whereas the harvest and other casual agricultural tasks are allocated on a seasonal contact basis. These two categories are aggregated in the computation of the human labour time.

Table 1. Descriptive statistics for the inputs and output.

Data	Unit	Avg	STD	Min	Max
Inputs					
Human labour	h	3350	1254	930	6615
Machinery	h	28	16	7	100
Fertilizers					
N	kg	237	240	0	1052
P_2O_5	kg	247	210	0	1074
K_2O	kg	218	175	0	944
Manure	kg	49,913	29,417	11,600	177,000
Pesticides					
Fungicides	kg	12	14	0	58
Insecticides	kg	65	98	3	456
Diesel fuel	l	130	180	19	797
Electricity	kWh	6814	6740	0	29,555
Ouput					
Yield	kg	134,512	70,707	40,000	400,000

Farm machinery represents the time that is required for handling mechanized agricultural activities. In Biskra's GH farming, mechanization is limited to tillage, commonly carried out with 45 horse power tractors for drawing iron ploughs. The remaining agricultural tasks are done manually.

Fertilizers comprise the amounts of nitrogen, phosphorus, and potassium as well as manure applied to the soil. In the study's specific context, the application of the fertilizers is performed randomly without prior analysis of the soil or the crop requirements. Accordingly, the survey reveals an over-usage of fertilizers. *Pesticides* are used by most farmers to manage weeds, pests, and illnesses. Here, they are applied every year for preventive purposes rather than treatment, which may also explain the excessive usage amounts per hectare. Here, it is worth noting that nitrogen, phosphorus, potassium and manure are aggregated under the variable Fertilizers (X_3), whereas fungicides and insecticides are combined into Pesticides (X_4). This inputs' aggregation is primarily meant to reduce the number of variables involved in the DEA model and, hence, increase its discriminatory power.

In our study, the GH farms' irrigation system relies fully on groundwater. As the major sources of agricultural energy, *Electricity* and *Diesel fuel* are extensively utilized to operate power generators, which supply electricity to water pumps for abstraction besides pressurization of the water into the irrigation system. Diesel fuel is typically used in areas without access to a power grid or as emergency backup during grid failures. Thus, electricity and diesel fuel are treated as proxies for water consumption. Water consumption has not been included separately among the inputs because all the farmers have reported the same regulated quota for the consumption amount. Having the same input value for all the GH farms will not have any impact on the DEA results.

Table 2 summarizes the input and output values per hectare of land along the energy equivalents for the whole sample.

The energy equivalents are calculated using the corresponding coefficients shown in Table A1 of the

Table 2. Data summary with energy equivalents.

Data	Unit	Quantity per ha	Energy eq. (GJ ha^{-1})	Energy %
Inputs				
X_1	h	144,033.40	282.31	8.07
X_2	h	1195.00	74.93	2.14
X_3	kg	2,176,452.10	1442.26	41.21
X_4	kg	3288.87	391.49	11.20
X_5	l	5581.25	253.39	7.24
X_6	kWh	292,997.01	1054.79	30.14
Totals			3499.17	100.00
Output				
Y	kg	5,784,001.00	4627.20	

Appendices. Figure 2 presents the proportions of energy inputs associated to the tomato GH production sample. The energy proportions per input are displayed in Figure 2 for the whole study sample.

The total energy consumption per GH farm is 81.388 GJ.ha^{-1}, with fertilizers and electricity displaying proportions of 41.21% and 30.14%, respectively, which are the highest. Pesticides follow with a share of 11.20%, while machinery appears as the least energy consuming resource.

4. Results and discussion

4.1. GH farming sustainability evaluation

For each farm G_k, $k = 1, \ldots, 43$, BCC model is solved to compute its optimal efficiency E_k^*, its intensity vector $\boldsymbol{\alpha}_k^*$ and the associated slack values S_{ik}^*, $i = 1, \ldots, 6$. Though the average efficiency of 0.9653 may suggest that the GH tomato production is highly efficient, 14 of the 43 farms, or 32.56%, are inefficient ($E_k^* < 1$) and display overconsumption of energy for all the inputs, as shown in Table 3.

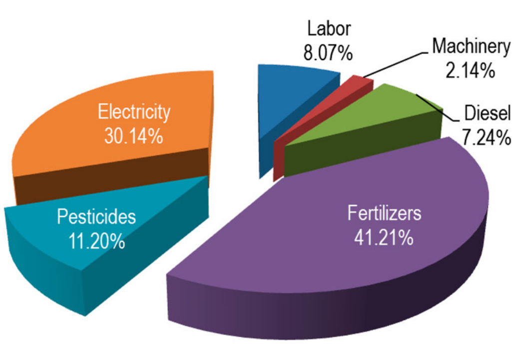

Figure 2. Distribution of the energy equivalents of the tomato GH production.

These results are comparable with those reported in previous studies, such as, e.g. Rahbari et al. (2013) and Oukil, Nourani, et al. (2022) where the mean efficiency scores are, respectively, 0.9955 and 0.9784 for tomato GH production. However, there appears to be more variability for the proportions of inefficient GH farms, which are 29.41% (Oukil, Nourani, et al., 2022) and 13.33% (Rahbari et al., 2013). Such inconsistency can be partially attributed to the differences between the size of the samples of GH farms in comparison with the corresponding number of inputs and outputs in these studies.

To become efficient, each inefficient farm G_k must reduce its energy consumption by S_{ik}^* $(i = 1, \ldots, 6)$ with its energy output unaffected. As a result, the energy savings associated to the GH tomato production are presented in the following Table 4.

The slack analysis reveals a potential of 155.7 GJ ha^{-1} energy savings, where fertilizers have the highest proportion of 41.11%, more than electricity, whose share is 34.60%. Thus, the energy saving index is 4.45% for 3499.17 GJ ha^{-1} energy usage. In other words, the GH tomato production can be declared sustainable if the inefficient farms can save, individually, 4.45% of the total energy consumption. Although the latter index is more than double the value of 2.08% reported in Oukil, Nourani, et al. (2022), it is much lower than the 24.46% of Khoshnevisan et al. (2013).

Whatever the savings achievable at the GH farm individual level, the next section will show that group actions involving more than one GH farm may generate better results.

4.2. Computation of the importance weights

In order to derive a comprehensive judgment regarding the importance of the energy inputs, 15 agricultural experts, including researchers, academicians and professionals, have been presented with a list of 6 inputs and they have been requested to rank them from 1 to 6, where 1 and 6 represent, respectively, the ranks of the inputs that are the most and the least important for the production process The responses are displayed in Table 5.

For instance, we can see that Expert #8 judges that Human labour is the most important production input whereas Pesticides are the least important. Irrigation water being the next important input may suggest that Expert #8's ranking is motivated by the scarcity of the resources rather than any other consideration.

Table 3. Results for the inefficient GH farms.

		Slack values (MJ ha^{-1})					
		Labour	Machinery	Fertilizers	Pesticides	Diesel	Electricity
GH farm	E_k^*	S_{1k}^*	S_{2k}^*	S_{3k}^*	S_{4k}^*	S_{5k}^*	S_{6k}^*
G_{02}	0.9432	463.53	142.58	5225.51	562.52	371.01	210.75
G_{11}	0.9922	85.88	9.73	120.39	22.44	17.61	137.76
G_{14}	0.9600	348.11	58.53	1674.25	470.59	652.69	131.82
G_{15}	0.7818	1450.05	273.67	10,701.78	1303.57	309.62	10,337.48
G_{16}	0.8159	1789.86	346.31	9628.85	2540.50	5615.99	811.26
G_{17}	0.8923	734.75	337.71	2967.51	414.18	611.33	1173.61
G_{18}	0.9566	245.63	45.37	1157.55	108.56	307.97	1645.15
G_{21}	0.9688	220.31	58.77	678.64	63.25	66.49	1479.98
G_{25}	0.8604	850.28	321.03	4490.04	1924.25	198.11	4365.58
G_{28}	0.9277	417.61	120.90	2272.20	286.93	102.59	4110.12
G_{34}	0.8517	996.03	154.97	6025.42	645.35	231.44	14,049.60
G_{36}	0.9396	523.60	113.69	2741.62	2335.89	102.90	1145.17
G_{38}	0.9840	207.83	25.13	454.95	770.88	15.92	433.88
G_{41}	0.6347	3064.29	534.44	15,871.97	2676.91	1140.21	13,843.19

Table 4. Energy savings patterns per resource.

Input	Energy saving (GJ ha^{-1})	Contribution to savings (%)
Labour	11.40	7.32
Machinery	2.54	1.63
Fertilizers	64.01	41.11
Pesticides	14.13	9.07
Diesel	9.74	6.26
Electricity	53.88	34.60
Total	155.70	100.00

Such an approach is emphasized in the ranks assigned by Expert #13 who places Human labour, Irrigation water and Pesticides at the same importance level. Overall, it seems that a similar ranking strategy is adopted by most of the area experts, even if the ranking patterns could be different.

The preference voting matrix Θ that is derived from the ranking matrix ***R*** is presented in Table 6.

The columns of Θ represent the rank positions ρ of the production inputs while each value $\theta_{i\rho}$ provides the number of times the experts voted for input i to be ranked ρth. For instance, 10 out of 15 experts voted for Human labour to be 1st, which may qualify this input to be the most important under an optimistic stance but the least important under a pessimistic stance, though no such conclusion is possible before aggregating the votes over each row. In order to measure the impact of the inputs' importance weights on the GH farms' mergers, we consider three aggregation scenarios, depending on the attitude of the DM: optimistic (α = 0.73), neutral (α = 0.5) and pessimistic (α = 0.27). Hence, we solve the minimax disparity model (WP) presented in Appendix 3 for each optimism level α and $I = 6$, to produce the OWA weight vectors $\boldsymbol{\gamma}$ shown in Table 7.

The aggregate votes corresponding to each of these scenarios are exhibited in Table 8.

For instance, when $\alpha = 0.27$, W_1 is computed as follows:

$$
\begin{aligned}
W_1 &= \sum_{\rho=1}^{I} \gamma_\rho \theta_{1\rho} \\
&= 0.00238 \times 10 + 0.06810 \times 2 + 0.13381 \times 3 \\
&\quad + 0.19952 \times 0 + 0.26524 \times 0 + 0.33095 \times 0 \\
&= 0.5614
\end{aligned}
$$

As expected, W_1, which is the weight of Human labour, is the smallest ($W_1 = 0.5614$) with a pessimistic DM ($\alpha = 0.27$) and the highest ($W_1 = 4.4386$) with an optimistic DM ($\alpha = 0.73$).

Table 5. Ranking matrix ***R*** of the production inputs.

Input	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Human labour	3	1	3	2	1	1	3	1	1	2	1	1	1	1	1
Machinery	3	6	5	6	5	6	3	5	4	1	5	5	6	5	6
Fertilizers	3	4	2	5	4	4	3	4	3	5	3	4	4	4	4
Pesticides	6	3	6	4	6	5	6	6	5	3	4	6	1	6	5
Irrigation water	1	2	1	1	2	2	1	2	2	4	2	2	1	2	2
Electricity	1	5	4	3	3	3	1	3	6	6	6	3	4	3	3

Table 6. Preference voting matrix Θ of the production inputs.

Input	1	2	3	4	5	6
Human labour	10	2	3	0	0	0
Machinery	1	0	2	1	6	5
Fertilizers	0	1	4	8	2	0
Pesticides	1	0	2	2	3	7
Irrigation water	5	9	0	1	0	0
Electricity	2	0	7	2	1	3

4.3. Mergers of GH farms

With a sample of $G = 43$ GH farms, 903 pairwise mergers $F_m = (G_A, G_B)$, $A \neq B$, are possible. The solution of model (E-IDEA) for each potential merger F_m, $m = 1, \ldots, 903$, with $\overline{\pi} = 1$ efficiency target, produces the optimal input blends for each preference scenario. Out of 903 potential mergers, only 742 are found potentially sustainable, i.e. 82.17%. This proportion is the same for all preference scenarios and the corresponding pairs of merging farms are also the same. These results suggest that the importance weights of the energy inputs have no effect on the sustainability status of the mergers. It is also worth noting that 345 sustainable post-merger GH farms, i.e. 46.5%, are hybrid pairs that comprise one efficient along with one inefficient GH farms, while only 75 sustainable mergers, i.e. 10.1%, include solely inefficient GH farms. Nevertheless, the most notable result is indeed the presence of 312 sustainable mergers, i.e. 43.4%, which are pairs of only efficient GH farms. Therefore, regardless of its efficiency status from an individual assessment perspective, a GH farm has potential for energy savings under a merger.

Due to the large number of sustainable mergers and, in the interest of space, Table 9 shows only 10 sustainable mergers under the optimistic stance. In the meantime, the results are discussed for all sustainable mergers under the three preference scenarios.

Consider, for instance, the consolidation of G_{01} and G_{12} into F_6. With an efficiency target $\overline{\pi} = 1$, the optimal energy levels of labour, machinery, fertilizers, pesticides, diesel and electricity required for the post-merger F_6 are $\delta^*_{11} = 5329$, $\delta^*_{112} = 0$, $\delta^*_{21} = 1359$, $\delta^*_{212} = 247$, $\delta^*_{31} = 0$, $\delta^*_{312} = 17734$, $\delta^*_{41} = 1733$, $\delta^*_{412} = 2569$, $\delta^*_{51} = 7558$, $\delta^*_{512} = 0$, $\delta^*_{61} = 5124$ and $\delta^*_{612} = 0$. The fact that $\delta^*_{112} = 0$, $\delta^*_{512} = 0$ and $\delta^*_{612} = 0$ suggests that the collective contributions to the merger F_4 in terms of labour, diesel and electricity, respectively, are at the level of the energy inputs of G_{01} or less.

The energy inputs of G_{01} and G_{12} at the pre-merger stage are $X_{11} = 6055$, $X_{112} = 6110$, $X_{21} = 1359$, $X_{212} = 1463$, $X_{31} = 6565$, $X_{312} = 24977$, $X_{41} = 1733$, $X_{412} = 6131$, $X_{51} = 8229$, $X_{512} = 851$, $X_{61} = 6534$ and $X_{612} = 28421$. Thus, the potential energy gains for fertilizers, due to the merger F_6, include a portion of the pre-merger energy usage of G_{12}, that is, $\mu_{312} = X_{312} - \delta^*_{312} = 24977 - 17734 = 7243\text{MJ/ha}$ in addition to the entire energy input of G_{01}, which is $\mu_{31} = X_{31} - \delta^*_{31} = 6565 - 0 = 6565\text{MJ/ha}$. Hence, the cumulative energy gains derived for fertilizers are $h_{36} = \mu_{31} + \mu_{312} = 13808\text{MJ/ha}$, which accounts for not less than 43.77% of the collective energy inputs allotted individually to the GH farms G_{01} and G_{12}. Likewise, the gains for labour, diesel, electricity, machinery and pesticides are, respectively, 56.19%, 16.76%, 85.34%, 43.10%, and 45.30%. It is also important to note that G_{01} and G_{12} are both strongly efficient, i.e. $E^*_1 = 1$ and $E^*_{12} = 1$ and no energy savings are needed from neither GH farms while operating individually. Yet, the merger of these farms into F_6 leads to energy savings at the proportion levels given earlier. Table 10 presents the results for 10 post-merger GH farms F_m, $m = 1, \ldots, 10$.

The full picture about the extent of the energy gains is illustrated through the average proportions shown in Figure 3, which include the whole set of sustainable post-merger GH farms F_m,$m = 1, \ldots, 742$.

The average proportions of energy gains are almost the same for machinery, fertilizers, diesel and electricity, nearing 60.92%, 70.32%, 22.92% and 73.73%, respectively, regardless of the preference stance. Under the optimistic and the neutral

Table 8. Aggregate votes W_i.

α	W_1	W_2	W_3	W_4	W_5	W_6
0.27	0.5614	3.7157	2.7300	3.7814	0.8243	2.5986
0.50	2.5000	2.5000	2.5000	2.5000	2.5000	2.5000
0.73	4.4386	1.2843	2.2700	1.2186	4.1757	2.4014

Table 7. OWA weight vectors γ.

α	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6
0.27	0.00238	0.06810	0.13381	0.19952	0.26524	0.33095
0.50	0.16667	0.16667	0.16667	0.16667	0.16667	0.16667
0.73	0.33095	0.26524	0.19952	0.13381	0.06810	0.00238

Table 9. Optimal energy usages (MJ ha^{-1}) of 10 post-merger GH farms with.

Farms			Labour		Machinery		Fertilizers		Pesticides		Diesel		Electricity	
F_m	G_A	G_B	δ^*_{1A}	δ^*_{1B}	δ^*_{2A}	δ^*_{2B}	δ^*_{3A}	δ^*_{3B}	δ^*_{4A}	δ^*_{4B}	δ^*_{5A}	δ^*_{5B}	δ^*_{6A}	δ^*_{6B}
F_1	G_{01}	G_{02}	5078	0	1359	333	0	21,601	1733	3458	7326	0	4637	0
F_2	G_{01}	G_{03}	5357	0	1359	238	0	17,305	1733	2470	7584	0	5179	0
F_3	G_{01}	G_{05}	4799	0	1359	428	0	25,897	1733	4446	7068	0	4095	0
F_4	G_{01}	G_{08}	4659	0	1359	475	0	28,045	1733	4940	6939	0	3824	0
F_5	G_{01}	G_{11}	5357	0	1359	238	1781	15,524	1733	2470	7584	0	5179	0
F_6	G_{01}	G_{12}	5329	0	1359	247	0	17,734	1733	2569	7558	0	5124	0
F_7	G_{01}	G_{14}	5427	0	1359	214	0	16,231	1733	2223	7648	0	5314	0
F_8	G_{01}	G_{15}	5078	0	1359	333	0	21,601	1733	3458	7326	0	4637	0
F_9	G_{01}	G_{22}	5218	0	1359	285	0	19,453	1733	2964	7455	0	4908	0
F_{10}	G_{01}	G_{23}	4659	0	1359	475	1837	26,207	1733	4940	6939	0	3824	0

Table 10. Cumulative energy gains (MJ.ha^{-1}) of 10 post-merger GH farms with related proportions.

	Labour		Machinery		Fertilizers		Pesticides		Diesel		Electricity	
F_m	h_{1m}	%	h_{2m}	%	h_{3m}	%	h_{4m}	%	h_{5m}	%	h_{6m}	%
F_1	9131	64.26	2176	56.27	76,883	78.07	6437	55.36	7429	50.35	5604	54.72
F_2	8122	60.25	1017	38.91	82,768	82.71	9999	70.41	11,995	61.26	5618	52.04
F_3	5741	54.47	2603	59.31	61,404	70.34	14,117	69.56	37,339	84.08	3331	44.86
F_4	5727	55.14	5795	75.97	20,020	41.65	2347	26.02	4127	37.30	14,078	78.64
F_5	11,772	68.72	1017	38.91	4784	21.66	423	9.15	2915	27.76	19,118	78.69
F_6	6836	56.19	1216	43.10	13,807	43.77	3562	45.30	1522	16.76	29,830	85.34
F_7	9330	63.22	1249	44.28	32,186	66.48	9541	70.69	16,896	68.84	4515	45.93
F_8	7621	60.01	922	35.27	34,002	61.15	2516	32.64	2322	24.06	49,265	91.40
F_9	4934	48.60	3477	67.90	29,254	60.06	7644	61.94	8577	53.50	4726	49.06
F_{10}	6609	58.65	1406	43.40	4728	14.43	664	9.04	13,349	65.80	4270	52.76

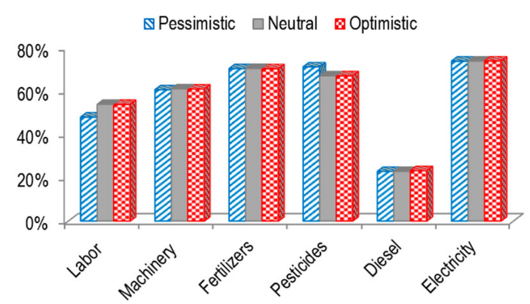

Figure 3. Average proportions of energy gains per input.

scenarios, labour and pesticides have still close proportions, with averages of 66.89% and 53.77%, respectively, slightly different from the pessimistic stance, which is lower for labour (47.92%) and higher for pesticides (71.04%). Such a gap can be partly explained by looking closer at the patterns of energy gains. Indeed, almost 97% sustainable post-merger GH farms of the neutral case show results that are similar to those of the optimistic case. This fraction falls to 57% when the latter results are compared to those of the pessimistic stance. In the meantime, the proportions of energy gains can reach, for some sustainable post-merger GH farms, picks as high as 81.28%, 88.62%, 95.27%, 98.09%, 85.45% and 96.55%, respectively, for labour, machinery, fertilizers, pesticides, diesel and electricity. In other words, there are post-merger GH farms that can be operated with only 18.72%, 11.38%, 4.73%, 1.91%, 14.55% and 3.45% of their current usages of respective energy inputs. The latter proportions are consistent with the findings of Oukil, Nourani, et al. (2022) where the minimum operating requirements for the post-merger GH farms were 19.22%, 7.76%, 2.73%, 2.71%, 10.66%, and 3.28% for labour, machinery, fertilizers, pesticides, diesel and electricity, respectively. Here, the slight gaps between the results can be attributed to the impact of the importance weights assigned to the inputs in the E-IDEA model as well as the size of the GH farms' sample.

To perceive more tangibly the impact of a merger on sustainability, let's consider, for instance, the consolidation of G_{01} and G_{03} into F_2. Under a standard DEA framework, G_{01} and G_{03} are found strongly efficient, that is, none of them needs to reduce its current energy consumption. After merging, the derived post-merger GH farm F_2 could preserve the efficiency level $\pi = 1$ by using only fractions of the collective energy inputs of the original GH farms, as small as 39.75% for labour, 61.09% for machinery, 17.29% for fertilizers, 29.59% for pesticides, 38.74% for diesel and 47.96% for electricity.

These proportions, together with the averages, are enough evidence to support the potential of mergers in enhancing sustainability, notwithstanding the optimistic case. To better corroborate such a statement, it is important to evaluate the impact of a broader scale merger on the sustainability of the whole tomato GH farming sector. To this end, we develop a procedure for building the most sustainable merger plan for each DM's preference stances, as detailed in the next section.

5. Most sustainable merger plan

To develop the most sustainable merger plan, we develop an approach that enables selecting the best post-merger farms based on the potential energy gains h_{im} associated to the inputs of the alternative pairs $F_m = (G_A, G_B),\ A \neq B$.

The energy gains h_{im} satisfy the dictum 'more is better' and qualify to be viewed as an output of the merger process (Oukil & El-Bouri, 2021). Hence, considering each pair F_m as a DMU defined with the outputs h_{im} $(i = 1, \ldots, 6)$, DEA-CE (Sexton et al., 1986) is adopted to rank the pairs F_m prior to selecting the most sustainable merger plan.

5.1. Computing the matrix of CE scores

Here, we introduce the following Sustainable Merger Model (SMM):

$$\text{(SMM)}\quad \begin{aligned} & eff^*_{kk} = \min\ v_k \\ & \text{s.t.} \\ & \sum_{i=1}^{6} h_{ik} u_{ik} = 1 \\ & v_k - \sum_{i=1}^{6} h_{im} u_{ik} \geq 0 \quad m = 1, \ldots, 742 \\ & u_{ik} \geq 0 \quad i = 1, \ldots, 6 \end{aligned}$$

where u_{ik} is the multipliers associated to the ith output and v_k is the measure of returns to scale. As a self-efficiency model, SMM can only categorize the post-merger farms into efficient ($eff^*_{kk} = 1$) and inefficient ($eff^*_{kk} > 1$) and, hence, cannot fully rank the whole set of farms. For this reason, we resort to DEA-CE.

Under a CE methodological framework, each post-merger farm F_k is enabled to evaluate its peers with its optimal multipliers $(\boldsymbol{u}^*_k v^*_k)$ (Oral et al., 2014; Oukil & Govindaluri, 2020). However, as SMM is likely to have alternative optima, different scores may result for the same CE evaluation and, hence, the uniqueness of the ranking is not guaranteed. One way to alleviate such a drawback is the adoption of a secondary goal for the CE evaluation (Doyle & Green, 1994). Though many secondary goal models are proposed in the DEA literature, we extend the Most Resonated Appreciative (MRA) model (Oral et al., 2015; Oukil & Amin, 2015) as follows.

$$\text{(MRA)}\quad \begin{aligned} & eff^*_{ko} = \min\ v_o \\ & \text{s.t.} \sum_{i=1}^{6} h_{io} u_{io} = 1 \\ & v_o - \sum_{i=1}^{6} h_{im} u_{io} \geq 0 \quad m = 1, \ldots, 742;\ m \neq k \\ & v_o - eff^*_{kk} \sum_{i=1}^{6} h_{ik} u_{io} \geq 0 \\ & u_{io} \geq 0 \quad i = 1, \ldots, 6 \end{aligned}$$

MRA is the only model that generates a customized vector of multipliers for each CE evaluation, which enhances discrimination at an early stage of the ranking process (Amin & Oukil, 2019b; Oukil & Govindaluri, 2017). Here, eff^*_{ko} is the CE score of post-merger farm F_o, as assigned by the assessing farm F_k, using the multipliers $(\boldsymbol{u}^{k*}_o v^{k*}_o)$ that preserve F_k's self-efficiency score at the level eff^*_{kk} (Oukil, Soltani, et al., 2022; Oukil & Amin, 2023). Once each post-merger farm F_k $(k = 1, \ldots, 742)$ completes the evaluation of its 741 peers F_o $(o \neq k, o = 1, \ldots, 742)$, a separate matrix of CE scores $\Psi = (eff^*_{ko})_{742\times 742}$ is obtained for each optimistic stance, with the self-efficiency scores forming the diagonal of Ψ. Matrix Ψ cannot be presented here due to its size (742×742). Next, Ψ is used to compute the ultimate efficiency scores, which are required for ranking the 742 sustainable farms, as explained in the next section.

5.2. Ranking the sustainable post-merger farms

Using the matrix of CE scores Ψ as a ground, we present the successive steps for computing the ultimate efficiency score ε_k corresponding to each post-merger farm F_k.

Let $\boldsymbol{eff^k}$ denote the column of CE scores assigned to F_k in Ψ. The computation of ε_k entails aggregating the elements of $\boldsymbol{eff^k}$ (Oukil, 2018, 2019, 2020, 2022, 2023a). In order to take the preference scenario into account, we employ again OWA aggregation, as explained below.

- **Step 1**: Sort the CE scores

The CE scores of each column $\boldsymbol{eff^k}$ are sorted in ascending order to enable attaching more importance to smaller scores assigned to post-merger farm F_k by its peers F_o ($o \neq k, o = 1, \ldots, 742$). The smaller eff^*_{ok} the more important is farm F_k perceived by farm F_o. Let $\boldsymbol{f^k} = (f_{1k} f_{2k} \ldots f_{742k})$ be the vector of sorted CE scores for column, where $f_{1k} < f_{2k} < \ldots < f_{742k}$.

- **Step 2**: Generate the vector of OWA weights

Model (WP) is used to generate the aggregation weights γ_ρ, $\rho = 1, \ldots, 742$. Three different optimism levels are considered for each preference scenario, namely $\alpha = 0.6671$, $\alpha = 0.5$ and $\alpha = 0.3329$ depending on whether matrix Ψ corresponds to the optimistic, neutral and pessimistic stance.

The solution of WP is a vector $\boldsymbol{\gamma}$ of 742 weights $\gamma_\rho \in [0.00000013, 0.00269528]$, $\sum_{\rho=1}^{742} \gamma_\rho = 1$, with decreasing values for $\alpha = 0.6671$ and increasing values for $\alpha = 0.3329$.

For $\alpha = 0.5$, all the weights γ_ρ are equal.

- **Step 3**: Compute the ultimate efficiency score

With the OWA weights on hand, the ultimate efficiency score ε_k can be computed for post-merger farm F_k through aggregating the CE scores of vector $\boldsymbol{f^k} = (f_{1k} f_{2k} \ldots f_{742k})$ by using formula (3) as $\varepsilon_k = \sum_{\rho=1}^{742} \gamma_\rho f_{\rho k}$.

Once steps 1 to 3 are completed for each post-merger farm k ($k = 1, \ldots, 742$), these farms are ranked from the most to the least sustainable. Table 11 presents an excerpt of the 10 leading farms under each optimistic stance.

To evaluate the effect of the DM's preference on the variability of the ultimate efficiency scores, we run a two-tail Student test at 5% significance level with paired samples. Each sample consists of 742 ε_k-values of same post-merger farms under different optimistic stances. Thus, three tests are run separately, with the outcomes exhibited in Table 12.

Based on the p-values, there is not enough evidence to reject the hypothesis that the difference between the means of the ultimate efficiency scores' populations is significant. Hence, at 5% significance level, we can assert that the DM's preference has an impact on the variability of the ultimate efficiency scores.

Would the same conclusion stand with the ranking patterns?

The smaller the ultimate efficiency score ε_k the better the ranking of the efficient post-merger farm F_k. Hence, as shown in Table 11, F_{166} is the leading post-merger farm for the pessimistic as well as the neutral samples whereas the optimistic sample is led by F_{61}. Again, we may need to investigate whether the DM's preference affects the variability of the ranking patterns. Here, we perform a two-tailed Wilcoxon signed-ranks test for paired samples at 5% significance level to test the following null hypothesis:

> H_0: The ranking patterns produced under both stances are identical.

The tests' results are summarized in Table 13, where $T = \min(T^+, T^-)$ with T^+ and T^- representing, respectively, the rank sums associated to positive and negative differences.

At 5% significance level, we can conclude that the ranking patterns produced under the neutral and the pessimistic stances are not identical. The same conclusion stands for the neutral and the optimistic stances. However, p-value > 0.05 suggests

Table 11. Ranking patterns of the 10 leading post-merger GH farms.

Pessimistic					Neutral					Optimistic				
F_k	G_A	G_B	ε_k	Rank	F_k	G_A	G_B	ε_k	Rank	F_k	G_A	G_B	ε_k	Rank
F_{166}	G_{05}	G_{38}	1.200	1	F_{166}	G_{05}	G_{38}	1.116	1	F_{61}	G_{02}	G_{38}	1.041	1
F_{417}	G_{16}	G_{38}	1.305	2	F_{417}	G_{16}	G_{38}	1.170	2	F_{417}	G_{16}	G_{38}	1.043	2
F_{416}	G_{16}	G_{36}	1.370	3	F_{30}	G_{02}	G_{05}	1.232	3	F_{166}	G_{05}	G_{38}	1.048	3
F_{167}	G_{05}	G_{39}	1.379	4	F_{164}	G_{05}	G_{36}	1.259	4	F_{733}	G_{38}	G_{41}	1.056	4
F_{162}	G_{05}	G_{34}	1.380	5	F_{162}	G_{05}	G_{34}	1.262	5	F_{257}	G_{08}	G_{38}	1.074	5
F_{163}	G_{05}	G_{35}	1.382	6	F_{167}	G_{05}	G_{39}	1.262	6	F_{714}	G_{35}	G_{38}	1.079	6
F_{414}	G_{16}	G_{34}	1.398	7	F_{163}	G_{05}	G_{35}	1.267	7	F_{141}	G_{05}	G_{08}	1.082	7
F_{415}	G_{16}	G_{35}	1.410	8	F_{416}	G_{16}	G_{36}	1.270	8	F_{256}	G_{08}	G_{36}	1.093	8
F_{164}	G_{05}	G_{36}	1.435	9	F_{414}	G_{16}	G_{34}	1.272	9	F_{704}	G_{34}	G_{35}	1.094	9
F_{30}	G_{02}	G_{05}	1.446	10	F_{714}	G_{35}	G_{38}	1.274	10	F_{163}	G_{05}	G_{35}	1.096	10

Table 12. Tests of the effect of preference on the variability of the ultimate efficiency scores.

Test samples	Mean	STD*	*p*-value
Pessimistic vs. Neutral	0.589	1.082	10^{-43}
Pessimistic vs. Optimistic	−11.243	140.691	0.0298
Neutral vs. Optimistic	−11.832	140.676	0.0222

*Standard deviation.

Table 13. Tests of the effect of preference on the variability of ranking patterns.

Test samples	*T*	Mean	STD*	*p*-value
Pessimistic vs. Neutral	120,262.50	133,773.00	5711.14	0.0180
Pessimistic vs. Optimistic	125,896.50	135,976.50	5781.62	0.0813
Neutral vs. Optimistic	118,478.50	135,976.50	5781.56	0.0025

*Standard deviation.

that the ranking patterns of the optimistic and the pessimistic stances are identical. Although the latter conclusion applies only to the case study, it is apparently reliable enough to refute the hypothesis that the DM's preference may affect the mergers' ranking.

5.3. Building the most sustainable merger plan

To build the most sustainable merger plan, the best mergers are selected according to the rank orders while discarding subsequent pairs that overlap with previously selected pairs. As such, the pairs of farms, presented in Table 14, are selected as the potential most sustainable mergers for each preference stance.

Overall, the most sustainable merger plans developed for the three preference stances are different although exhibiting similarities for some of the selected post-merger farms.

In the pessimistic plan, $F_{417} = (G_{16}, G_{38})$ has not been selected in spite of ranking 2nd because F_{417} has G_{38} in common with $F_{166} = (G_{05}, G_{38})$. The same applies to the neutral plan where six pairs are discarded, namely F_{417}, F_{30}, F_{164}, F_{162}, F_{167} and F_{163}, which share either G_{38} or G_{05} with the leading post-merger farm F_{166}. Thus, the exclusion of better ranked post-merger farms is essentially based on the occurrence of an overlap between these pairs and the ones that are previously selected. Such exclusion criterion applies also to F_{417}, F_{166}, F_{733}, F_{257} and F_{714}, which occupy the next five positions of the optimistic ranking pattern but share, at least, one GH farm with F_{61}. Therefore, the next pair to be selected is $F_{141} = (G_{05}, G_{08})$, because it does not overlap with $F_{61} = (G_{02}, G_{38})$.

Under the pessimistic stance, all the GH farms are paired except G_{09}, G_{32} and G_{42}. Two additional exceptions, i.e. G_{01} and G_{04}, are found for both the neutral and the optimistic cases. Practically, pairwise mergers are still possible among the excluded GH farms but remain not sustainable. Remarkably,

Table 14. Most sustainable merger plans.

Pessimistic					Neutral					Optimistic				
F_m	G_A	G_B	Rank	Gains (GJ ha^{-1})	F_m	G_A	G_B	Rank	Gains (GJ ha^{-1})	F_m	G_A	G_B	Rank	Gains (GJ ha^{-1})
F_{166}	G_{05}	G_{38}	1	223.88	F_{166}	G_{05}	G_{38}	1	223.88	F_{61}	G_{02}	G_{38}	1	205.79
F_{416}	G_{16}	G_{36}	3	179.93	F_{416}	G_{16}	G_{36}	8	179.93	F_{141}	G_{05}	G_{08}	7	165.50
F_{58}	G_{02}	G_{35}	22	231.27	F_{58}	G_{02}	G_{35}	22	231.27	F_{704}	G_{34}	G_{35}	9	247.56
F_{374}	G_{14}	G_{34}	23	200.88	F_{710}	G_{34}	G_{41}	25	210.71	F_{418}	G_{16}	G_{39}	25	127.08
F_{71}	G_{03}	G_{08}	48	160.49	F_{71}	G_{03}	G_{08}	47	160.49	F_{723}	G_{36}	G_{41}	54	177.26
F_{550}	G_{22}	G_{41}	121	142.68	F_{379}	G_{14}	G_{39}	85	119.36	F_{77}	G_{03}	G_{15}	146	205.04
F_{404}	G_{15}	G_{39}	143	125.58	F_{515}	G_{21}	G_{25}	175	124.85	F_{284}	G_{11}	G_{25}	195	95.07
F_{574}	G_{24}	G_{28}	209	110.46	F_{393}	G_{15}	G_{26}	220	130.21	F_{521}	G_{21}	G_{31}	214	100.67
F_{217}	G_{07}	G_{25}	235	98.68	F_{642}	G_{28}	G_{31}	251	116.99	F_{609}	G_{26}	G_{28}	250	119.62
F_{425}	G_{17}	G_{21}	273	92.42	F_{264}	G_{10}	G_{22}	258	105.17	F_{262}	G_{10}	G_{14}	253	120.28
F_{453}	G_{18}	G_{26}	349	108.49	F_{433}	G_{17}	G_{29}	319	134.10	F_{426}	G_{17}	G_{22}	321	83.91
F_{288}	G_{11}	G_{29}	388	121.53	F_{451}	G_{18}	G_{24}	390	90.21	F_{579}	G_{24}	G_{33}	401	62.29
F_{493}	G_{20}	G_{23}	434	112.56	F_{279}	G_{11}	G_{20}	412	107.92	F_{456}	G_{18}	G_{29}	485	166.25
F_{191}	G_{06}	G_{31}	510	75.59	F_{222}	G_{07}	G_{30}	479	72.21	F_{222}	G_{07}	G_{30}	562	72.21
F_{698}	G_{33}	G_{37}	557	95.35	F_{701}	G_{33}	G_{40}	513	89.62	F_{509}	G_{20}	G_{40}	616	144.32
F_{627}	G_{27}	G_{30}	566	84.86	F_{311}	G_{12}	G_{23}	591	76.67	F_{340}	G_{13}	G_{27}	633	75.92
F_{302}	G_{12}	G_{13}	609	70.17	F_{340}	G_{13}	G_{27}	620	75.92	F_{311}	G_{12}	G_{23}	658	76.67
F_{027}	G_{01}	G_{43}	648	67.87	F_{196}	G_{06}	G_{37}	629	98.91	F_{486}	G_{19}	G_{37}	686	96.18
F_{269}	G_{10}	G_{40}	655	94.33	F_{491}	G_{19}	G_{43}	672	77.43	F_{202}	G_{06}	G_{43}	687	88.53
F_{117}	G_{04}	G_{19}	734	43.25										

almost 50% of the selected pairs consist solely of GH farms that are strongly sustainable, no matters the preference case. Such a result brings more support to the potential of mergers in enhancing sustainability, even if the merging entities are individually efficient.

5.4. Managerial implications

At this stage of the analysis, it is important to evaluate the impact of the prospective merger plans on environmental sustainability. Table 15 summarizes the total energy savings for each merger plan.

The results reveal that the most sustainable merger plan is more likely under the pessimistic stance, where the largest energy savings are 2440.26 GJ ha^{-1}. The neutral merger plan is probably the least sustainable with almost 15 GJ ha^{-1} less savings. Thus, with the current energy usage estimated to 3499.17 GJ ha^{-1}, the energy savings indices are 69.74%, 69.33% and 69.45% for the pessimistic, neutral and optimistic sustainable merger plans, respectively. Hence, there is potential for more than 15 times improvement of the GH production sustainability. Specifically, Figure 4 displays the proportions of savings for each preference scenario.

Regardless of the sustainable merger plan, the energy savings on each input are close to each other and follow almost a similar pattern. Fertilizers and electricity are prevailing, with proportions that exceed 40.5% and 33.8%, respectively. The lowest proportions are found for machinery, whose shares are less than 1.9%. Relatively higher proportions are expected for labour and diesel at levels of more than 5.8% and 4.7%, respectively. The proportions of energy savings on pesticides fall between 12.1% and 12.7%. Interestingly, these sustainability patterns comply with the current distribution of energy usage (refer to Figure 2), which suggests that the proposed merger plans can be an important step towards an optimal energy consumption and, hence, more sustainable agricultural production.

In practical terms, chemical fertilizers energy savings can be achieved by adopting more precise

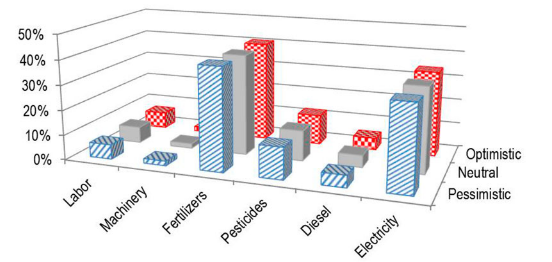

Figure 4. Proportions of energy input savings per sustainable merger plan.

fertilization practices. Conducting seasonal soil analyses can assist in determining the most adequate quantities on a weather basis. However, replacing chemical fertilizers with organic or microbial alternatives is certainly the preferable choice. The Integrated Pest Management (IPM) method can be adopted as a long-term pest management approach.

Diesel fuel is typically used to power electric generators in areas without access to a power grid or as emergency backup during grid failures. To minimize reliance on diesel and electricity, the adoption of renewable energy sources is recommended. Given the region's high solar irradiation all over the year, solar panels can possibly be installed to provide a cleaner and more sustainable energy alternative. Alternatively, the energy needed for irrigation can be reduced by using low-flow resistance foot valves for pumps besides rigid PVC pipes for the suction and delivery operations. More energy savings are also possible through an appropriate substitution of undersized pipes in addition to employing less elbows and friction-causing fittings.

Implementing conservation tillage practices significantly decreases the need for machinery throughout various agricultural tasks. These practices also improve soil structure through the retention of vegetative matter, facilitating carbon storage in the soil.

However, it is crucial not to overlook the human aspect of the entire process. GH farmers should receive training on implementing new practices and

Table 15. Energy savings for sustainable merger plans.

Merger plan	Labour GJ ha^{-1}	Machinery GJ ha^{-1}	Fertilizers GJ ha^{-1}	Pesticides GJ ha^{-1}	Diesel GJ ha^{-1}	Electricity GJ ha^{-1}	Energy savings GJ ha^{-1}
Pessimistic	143.43	44.98	999.02	309.36	117.28	826.18	2440.26
Neutral	158.52	45.68	982.40	296.70	118.58	823.98	2425.87
Optimistic	160.57	44.76	986.30	294.29	115.64	828.61	2430.17

be educated about the importance of energy mitigation as a global imperative for sustainable farming.

6. Concluding remarks

The present study investigated the impact of mergers among farms on environmental sustainability from different preference perspectives, with a focus on energy consumption. Based on experts' judgments, a preference vector, produced through an OWA-based approach, is incorporated into an IDEA model to estimate the energy input requirements for a preset sustainability target under three preference stances: pessimistic, neutral and optimistic.

Using a case study of 43 GH farms for an efficiency target $\overline{\pi} = 1$, the proposed IDEA model is solved for pairwise consolidations under each preference scenario. The results revealed that 742 post-merger farms are potentially sustainable, where 43.4% are pairs involving only sustainable GH farms, i.e. GH farms that have been declared individually efficient and, hence, do not require energy input savings.

Thus, we can establish that neither the sustainability status of the merging DMUs nor the preference of the DM have an influence on the sustainability status of the post-merger DMUs.

In terms of energy inputs, the results of the case study show average proportions of gains that are almost the same with the three preference scenarios for machinery, fertilizers, diesel and electricity, reaching 60.92%, 70.32%, 22.92% and 73.73%, respectively. A slight deviation is noted, under the pessimistic stance, for energy gains on labour and pesticides, which still remain relatively high. In all cases, the energy gains per post-merger farm can reach proportions as high as 80.78%, 88.62%, 95.27%, 97.29%, 85.45% and 96.55%, respectively, for labour, machinery, fertilizers, pesticides, diesel and electricity. These proportions, together with the corresponding averages, substantiate the potential of mergers to enhance sustainability, regardless of the preference stance.

The next stage of the present study is concerned with maximizing the collective sustainability effort through determining the most sustainable merger plans under different preference stances. A DEA-CE model is developed to select the sets of post-mergers with the best matching pairs of GH farms under each preference stance.

The most sustainable merger plans that are built under the three preference stances include different post-merger farms even if similarities can be found. Almost half of the selected pairs entail individual GH farms that are strongly efficient. This result brings more support to the potential of mergers in enhancing sustainability, no matters the efficiency status of the merging farms.

The majority of individual GH farms are paired, except a few. The excluded ones can still form mergers, which are de facto not sustainable.

The total energy savings of the sustainable merger plans exceed 69% for all preference scenarios, representing more than 15 times relating outcomes under the individual GH farm sustainability framework. The distribution of these energy savings among inputs follows almost the same pattern. Fertilizers and electricity prevail with proportions of over 40.5% and 33.8%, respectively, followed by 12.1% to 12.7% for pesticides. Relatively lower proportions are observed for labour and diesel, with more than 5.8% and 4.7%, respectively, whereas machinery records the lowest share of less than 1.9%. Interestingly, the sustainability patterns conform to the energy usage distribution. For that reason, the proposed merger plans can be an important platform for an optimal energy consumption and, hence, more sustainable agricultural production.

6.1. Policy implications

This study's findings underscore the imperative for the development of progressive policies to reinforce sustainability within the GH farming sector. In practical terms, such a step is particularly vital to ensure a meaningful engagement of diverse stakeholders throughout the GH agricultural production supply chain.

One key policy recommendation revolves around incentivizing GH farmers to adopt energy-efficient practices within the context of potential mergers. These incentives might encompass state-level direct and indirect subsidies, tax exemptions besides relaxation of import duties. The GH farmers could be eligible for these incentives as they embrace energy-saving initiatives, contributing to reduced GHG emissions and optimal resource consumption. These initiatives may involve (1) the procurement of biodegradable plastic films and versatile construction materials for infrastructure development; (2) the transition from chemical to environmentally friendly organic or microbial fertilizers; (3) the adoption of integrated pest management (IPM) strategies for sustainable pest control; (4) the installation of solar panels to harness cleaner, renewable energy sources as an alternative to fossil fuels; and (5) the incorporation of cutting-edge technologies and techniques for fertilization and irrigation, including the implementation of smart irrigation systems (Zaier et al., 2015).

Recognizing the central role of the human factor in merger dynamics entails an additional set of policies, which should be primarily dedicated to raising awareness among GH farmers regarding the benefits of mergers. These policies may consist of the organization of comprehensive awareness campaigns aimed at promoting mergers and highlighting their potential to optimize energy usage and mitigate environmental impacts. Furthermore, state-sponsored training sessions could be developed to provide GH farmers with the knowledge and skills required for collaborative management in post-merger GH farms. Additionally, an incentivizing framework could be established, featuring an annual award to commend and incentivize the best-performing post-merger GH farms.

Though, it is paramount to underscore that prior to the adoption of merger-related policies, extensive investigations are necessary to gauge GH farmers' readiness to participate in merger initiatives and identify market-driven incentives that are likely to spur their willingness to join such plans. Conducting these investigations will provide crucial insights for crafting policies that effectively address the unique needs and challenges of GH farmers while advancing sustainability within the sector.

6.2. Future research directions

While this study has made substantial progress in highlighting the benefits of GH farm mergers, it has also brought to light several key research areas that warrant further investigation. These future research directions would build upon the foundation laid by this study and expand our understanding of the complex dynamics surrounding GH farm mergers.

- *Consider the geographical locations of the farms*

The geographical distribution of GH farms is a crucial aspect that has been inadvertently overlooked in the present study but holds significant relevance for the prospects of mergers. Current assumptions suggest that mergers are feasible irrespective of the farms' physical locations, leading to the representation of pairwise consolidations as a complete graph with $N = G(G-1)/2$ edges for G farms (Oukil, 2008). However, this approach raises practical challenges, particularly for large values of G, due to the computational cost associated with solving N IDEA models. Furthermore, proximity issues among merging GH farms may render the field implementation of optimal energy-saving solutions impracticable. Future research should consider addressing these limitations by adopting a more realistic approach that accounts for the sparse graph structure depicted through the GH farms' network. In this context, only adjacent farms would be considered as merger candidates, potentially leading to geographically advantageous and more feasible merger plans.

- *Conduct a profitability analysis of the mergers*

The implementation of energy-efficient measures within post-merger GH farms incurs additional costs, necessitating a deeper exploration of pertaining economic aspects. Such analysis can be critical in supporting merger decisions and providing more accurate estimates of each partner's share of the incremental expenses. To achieve this objective, researchers can envisage an energy-cost efficiency analysis that incorporates cost-weighted energy inputs. This approach will produce a robust framework for quantifying the dollar value of the merger per unit of energy input, offering stakeholders a more comprehensive financial perspective (Amin & Ibn Boamah, 2020).

- *Assess the long-term impact of the mergers*

The present study has been carried out over a single cropping season, which may restrict the temporal scope of its findings. Understanding the long-term implications of GH farm mergers is essential for assessing their sustainability and adaptability. Future studies should investigate the impact of mergers over extended time horizons, encompassing multiple periods to account for the dynamic nature of the system (Moghaddas et al., 2022). This multi-period analysis will provide valuable insights into the evolving dynamics of merged GH farms, aiding in the development of strategies for long-term success.

- *Extend the sample size and the methodology*

It is known that the discriminatory power of the standard DEA approach is attenuated when the number of inputs and outputs is too large, compared to the number of DMUs (GH farms in our case). As such, the number of inputs considered for the present study has been reduced through aggregation for the sake of increasing discrimination. Future studies may provide better insights if the inputs are used without aggregation but with larger samples of GH farms. On the methodology side, the IDEA model can be extended to include GHG emissions as undesirable inputs and/or outputs. Another research direction may consider the integration of the mergers' gain estimation and the building of the most sustainable merger plan into a unified framework.

- *Expand the application scope*

Although this study's practical context was focused on agricultural GH production, its methodological framework holds potential for applications in other agricultural sectors where energy consumption is a critical concern, such as livestock production systems (Sefeedpari et al., 2020) and dairy farms (Nacer et al., 2016). Prospective research could also explore the implementation of the proposed approach across non-agricultural sectors to better identify the energy efficiency challenges of mergers.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendices

Appendix 1. List of abbreviations

BCC	Banker, Charnes, and Cooper
CE	Cross-Efficiency
DEA	Data Envelopment Analysis
DM	Decision Maker
DMU	Decision Making Unit
E-IDEA	Extended Inverse DEA
FAO	Food and Agriculture Organization
GH	Greenhouse
GHG	Greenhouse Gas
IDEA	Inverse DEA
LP	Linear Programming
M&A	Merger & Acquisition
MCDM	Multi-Criteria Decision Making
MRA	Most Resonated Appreciative
OWA	Ordered Weighted Averaging
SFA	Stochastic Frontier Analysis
SMM	Sustainable Merger Model

Appendix 2

Table A1. Energy equivalent coefficients in tomato GH production.

Data	Unit	Energy equivalent (MJ Unit^{-1})	References
Inputs			
Human labour	h	1.96	Hamedani et al. (2011)
Machinery	h	62.70	Singh (2002)
Diesel fuel	l	45.40	Bojacá et al. (2012)
Fertilizers	kg		
Nitrogen N		60.60	Ozkan et al. (2011)
Phosphate P_2O_5		11.10	Ozkan et al. (2011)
Potassium K_2O		6.70	Ozkan et al. (2011)
Manure	kg	0.30	Khoshroo et al. (2013)
Pesticides	kg		
Fungicides		216.00	Mohammadi and Omid (2010)
Insecticides		101.20	Mohammadi and Omid (2010)
Electricity	kWh	3.60	Ozkan et al. (2011)
Output			
Tomato	kg	0.80	Ozkan et al. (2011)

Appendix 3. OWA aggregation operator

An OWA aggregation operator of dimension l is a mapping $f_\gamma: R^l \rightarrow R$, associated with a weigh vector $\boldsymbol{\gamma} \in [0,1]^l$ and defined as $f_\gamma(\boldsymbol{\theta_i}; \boldsymbol{\gamma}) = \sum_{\rho=1}^{l} \gamma_\rho \theta_{i\rho}$ where $\theta_{i\rho}$ is the value of the ρth largest factor of the vector of arguments $\boldsymbol{\theta_i} = (\theta_{i1}\, \theta_{i2} \ldots \theta_{il})$ and γ_ρ its associated OWA weight (Saeidi et al., 2015). In our case, we use the following minimax disparity model (Wang &

Parkan, 2005) to generate the OWA weight vector $\boldsymbol{\gamma}$.

$$
(\mathrm{WP}) \quad
\begin{aligned}
& \min \ d \\
& s.t. \\
& \sum_{\rho=1}^{l-1} \left(\frac{l-\rho}{l-1} \right) \gamma_\rho = \alpha \quad \alpha \in [0,\ 1] \\
& \sum_{\rho=1}^{l} \gamma_\rho = 1 \\
& -d \ \le \gamma_\rho - \gamma_{\rho+1} \le d \quad \rho = 1,\ \ldots, l-1 \\
& \gamma_\rho \ge 0 \qquad\qquad\qquad \rho = 1,\ \ldots, l
\end{aligned}
\qquad (A1)
$$

The objective of model (WP) consists of minimizing the deviation d between successive aggregation weights γ_ρ and $\gamma_{\rho+1}$, $\rho = 1, \ldots, l$. Such a deviation is duly formulated through constraints (A1). The DM's optimism level is reflected by the parameter α, also known as orness value (Yager, 1995).

In each vector of votes $\boldsymbol{\theta_i} = (\theta_{i1}\theta_{i2}\ldots\theta_{il})$, relating to energy input i, the importance of each vote $\theta_{i\rho}$ is implicitly induced by the associated rank ρ, i.e. the smaller the value of ρ the more important is the vote $\theta_{i\rho}$. Therefore, the vector of weights $\boldsymbol{\gamma}$ can be used directly to aggregate the votes of $\boldsymbol{\theta_i}$ into a single vote W_i without an *a priori* ordering, where

$$
W_i = \sum_{\rho=1}^{l} \gamma_\rho \theta_{i\rho} \qquad (A2)
$$

The aggregate vote W_i reflects the relative importance of input i from the perspective of a DM whose optimism level is α. High values of W_i imply that a large number of experts voted for energy input i to be among the leading inputs.