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Does participation in agri-environmental schemes increase eco-efficiency?

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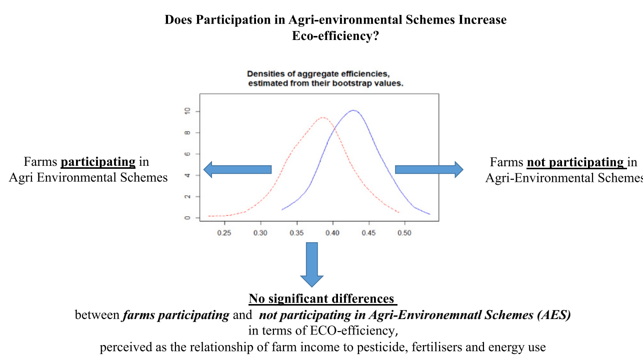
HIGHLIGHTS

- There is potential for enhancing eco-efficiency of Hungarian crop farms.
- No differences in eco-efficiency between non-participating and participating farms
- Results are stable irrespective of the method applied or the timespan analyzed.
- Results pose questions about the efficacy of the Agri-Environmental Scheme

GRAPHICAL ABSTRACT



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ABSTRACT

The literature on the effectiveness of Agri-Environmental Schemes focuses mainly on the environmental effects; only a few studies have focused on economic aspects. The number of papers that address ecological and economic outcomes simultaneously is even more limited. In this paper, we apply the concept of eco-efficiency to integrate these two factors. The aim of the paper is to analyze the impact of participation in the agri-environmental scheme of Hungarian field crop farmers in terms of eco-efficiency. To make unbiased and consistent comparisons we use advances from aggregation and bootstrap theory in Data Envelopment Analysis (DEA) context. The results indicate that there exists a significant potential for enhancing eco-efficiency in Hungarian crop farms. Furthermore, our results reveal that, in terms of eco-efficiency, perceived as the relationship of farm income to pesticide, fertilizers and energy use, no significant differences exist between participating and non-participating farmers. The results are robust to different methods. Our results pose questions about the efficacy of the Agri-Environmental Scheme.

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1. Introduction

According to a study by The Food and Land Use Coalition a staggering USD 700 billion is spent globally every year for Agricultural support (The Food and Land Use Coalition, 2019). In the European union 10 million farms are benefitting from the approx EUR 60 billion funds redistributed through the Common Agricultural Policy schemes. These amounts are dynamically increasing with every 7-year programming period. If one considers that by 2050 global population is expected to reach 9 billion people, clearly, an intensification of agricultural production is needed to meet the demand for food and fibre. Intensification however comes at a great price. Agricultural pressure on the environment is becoming critical, and in some places, combined with Global Warming results in unbearable production and living conditions. Growing concern over the environmental impact of agricultural intensification in Europe has led to the introduction of Agri-Environmental Schemes (AES) in the early 1990s as part of the CAP's. AES incentivizes farmers to adopt environmentally friendly farming practices by financially compensating them for any loss of income associated with measures aimed at benefiting the environment. Budgets for AES are substantial – at least 25 % of the direct payments budget, an estimated 48.5 billion EUR, is planned to be spent on eco-schemes between 2023 and 27 (European Commission, 2021). European taxpayers are expecting policymakers to spend the CAP budget allocated on AES efficiently. Since at present AES is the main tool incentivizing more environmentally friendly farming and takes up a significant share of the CAP budget, it is timely and important to investigate the environmental and economic effects of AES. Early papers examining the impact of AES focuses on various environmental aspects, from greenhouse emissions (Peerlings and Polman, 2008) to impact of fertilizers on the soil (Marconi et al., 2015; Richards et al., 2015), water quality (Poole et al., 2013) of biodiversity (Lindenmayer et al., 2012; Princé et al., 2012). For a comprehensive review about these papers see e.g. (Batáry et al., 2015). One of the main conclusions of these papers is that about half of the schemes fail to deliver any positive effects. In addition, there is concern about the strong geographical bias implicit in the selection of study areas – typically involving Northern and Western Europe (Sutcliffe et al., 2015; Tryjanowski et al., 2011), except Toma et al. (2017) focusing on the EU-wide cross-country comparison. The findings of these studies show that there is a great need for better, locally adapted AES, but information in the literature about the effectiveness of AES on farms' environmental performance is still scarce in Central and Eastern European countries. Later, researchers started to examine economic aspects of AES subsidies (Arata and Sckokai, 2016; Garrone et al., 2019; Baráth et al., 2020; Mennig and Sauer, 2020). More recently, there is a growing body of literature that builds on the concept of eco-efficiency that enable the simultaneous analysis of the environmental (with some limitation) and economic impact of AES, as it is based on the idea of producing more goods and services with fewer resources, and creating less waste and pollution (e.g. Ait Sidhoum et al., 2023a,b; Czyżewski and Kryszak, 2023). Most of these papers, similarly to the papers examining the environmental aspect, also focus on Western European Countries. Moreover, although these papers handle the issues related to selection bias, neglect other important methodological issues.

The aim of our paper is to investigate eco-efficiency differences between participating and non-participating farms in AES on Hungarian field crop farms using the Data Envelopment Analysis (DEA) framework developed by Kuosmanen and Kortelainen (2005) focusing on important methodological issues (theoretical justified aggregation of participating-non-participating groups and to do reliable inference for group efficiency scores) that were usually neglected in the previous literature applying eco-efficiency. Considering the limitations in the literature that examines the effect of AES on economic and environmental performance, and the related methodological issues, our contribution can be summarised as follows: (1) we conduct empirical examination on a Central and Eastern European country; namely, Hungary; (2) we address problems related to the DEA estimator and the aggregation of group efficiency – i.e., we use theoretically justified weights for the aggregation of group efficiency; and, (3) we use bias-corrected efficiency scores, and for the aggregate (group) efficiency context adapted mean and distribution tests. In addition, as a further robustness test of the results we examine the determinants of eco-efficiency, considering AES subsidies to be among the potential drivers of eco-efficiency as well as we also present results estimated applying quasi-experimental setting.

2. Literature review on eco-efficiency in agriculture

In recent years, examining eco-efficiency using DEA has become popular in the literature in many different sectors (Henriques et al., 2022; Kuosmanen and Kortelainen, 2005; Liu et al., 2022; Oggioni et al., 2011; Zhang et al., 2008); however, the number of studies that address agriculture is limited. We provide a brief overview of selected papers that examined eco-efficiency in the EU agricultural sector. In addition to the DEA method, as Orea and Wall (2017) recently showed, stochastic frontier analysis (SFA) can also be used to estimate eco-efficiency. We review both DEA- and SFA-related papers.

Table 1 shows that the number of papers that assess eco-efficiency in agriculture has increased significantly during the last decade. Most of the eco-efficiency papers that analyze European agriculture have focused on the examination of eco-efficiency determinants, except for Masuda (2016). In addition, the geographical diversity of the papers is rather limited: only seven countries are involved in the research from the EU 27. Another key feature is that >40 % of the papers deal with only Spain, and are written by a single Spanish research team. The sectoral distribution of the papers is diverse: they investigate six different subsectors, plus agriculture as a whole. The most popular subsector is the dairy sector. The majority of papers employ regional datasets; five papers use nationwide data. Roughly half of the papers use cross-sectional, mainly small-scale survey-based data. More than half of the papers do not investigate explicitly or implicitly the impact of AES programs on eco-efficiency. In addition, the effects of AES on the eco-efficiency of farms are found to be rather mixed.

The first group of papers apply the DEA approach using a two-step procedure. In the first stage, they estimate eco-efficiency using the DEA method, and in the second stage bootstrapped truncated regression is applied in line with the procedure proposed by Simar and Wilson (2007).

These papers reveal major eco-inefficiencies with respect to the various processes of production (Picazo-Tadeo et al., 2011), including the use of fertilizers and pesticides (Bonfiglio et al., 2017; Ait Sidhoum et al., 2023a), soil conservation (Eder et al., 2021), waste management (Godoy-Durán et al., 2017), nutrient balance (Pérez Urdiales et al., 2016), phosphorus (March et al., 2016), GHG emissions (Pérez Urdiales et al., 2016) and nitrogen balance (Ait Sidhoum et al., 2023b). While economies of scale have been found to matter (Picazo-Tadeo et al., 2011), eco-inefficiency is apparently closely related to technical inefficiencies in the management of inputs, including soil (Eder et al., 2021; Picazo-Tadeo et al., 2011). Such results imply that the majority of farms could reduce their environmental burden while maintaining their economic value added, irrespective of the sector (ranging from arable farms through dairy farms to horticulture). On the other hand, specific factors have been identified that may have a positive impact on eco-efficiency, such as the younger age (Bonfiglio et al., 2017; Pérez Urdiales et al., 2016; Ait Sidhoum et al., 2023b) and the higher-level education (Picazo-Tadeo et al., 2011) of the farmer, having plans to continue operating (Pérez Urdiales et al., 2016), product specialization (Godoy-Durán et al., 2017; Stępień et al., 2021), the self-sufficiency of inputs (Stępień et al., 2021), and involvement in quality certification schemes (Godoy-Durán et al., 2017) and training programs (Pérez Urdiales et al., 2016). Contractual selling relationships (Stępień et al., 2021), including belonging to cooperatives (Godoy-Durán et al., 2017) appear to enhance eco-efficiency, while rental contracts, as opposed to land ownership, are claimed to have negative environmental consequences due to the short-term maximization of profit (Eder et al., 2021). The self-reported positive environmental habits of farmers appear to have a positive impact (Pérez Urdiales et al., 2016).

The impact of participation in AES on the eco-efficiency is rather mixed: some studies confirm the positive association (Bonfiglio et al., 2017; Eder et al., 2021; Picazo-Tadeo et al., 2011), while other papers find insignificant relationships (Ait Sidhoum et al., 2023a,b).

Another group of papers in the literature combine Life Cycle Assessment (LCA) and DEA to calculate environmental indicators (e.g. Beltrán-Esteve et al., 2017; Cortés et al., 2021; Masuda, 2016). The combined LCA-DEA approach reveals, similarly to the research described in the previous section, the potential for considerable improvements in eco-efficiency. Cortés et al. (2021) claimed that a reduction of input use of up to 53 % would be possible for eco-inefficient Spanish dairy farms, resulting in average impact reductions of 49 % in carbon footprint and 55 % in water footprint, while Beltrán-Esteve et al. (2017) estimated that the organic conversion of Spanish conventional citrus farms would allow a potential reduction in environmental impacts of 80 % without resulting in weaker economic performance. Masuda (2016) pointed out that the reduction in the use of nitrogen fertilizer has great potential for mitigating aquatic eutrophication while maintaining the wheat yield in Japan.

Beltrán-Esteve et al. (2012) analyzed the impact of the Agri-Environmental Scheme for the Protection of Flora and Fauna (F&F) on the eco-efficiency of a sample of dryland farms in the region of Castile and Leon, Spain. Their results show that environmental load could be reduced if all farms adopted F&F Scheme technology. Moreover, the results suggest that the average opportunity cost of the decrease in environmental load is similar to the compensation received by farms included in the F&F Scheme.

DEA and SFA methods are widely used to estimate technical efficiency. The number of papers that apply the SFA method to examine eco-efficiency is considerably less than those that use the DEA method. Orea and Wall (2017) estimated eco-efficiency (similarly as Kuosmanen and Kortelainen, 2005 defined DEA in a frontier setting) using SFA, finding that the SFA model yielded virtually identical eco-efficiency scores to those calculated by DEA. However, comparison of the alternative methods may give substantially different results occasionally (such as in Reinhard et al., 2000, where the SFA efficiency score was 80 %, while the DEA one was 52 %).

More recent attempts have been made to apply SFA to analyze the eco-efficiency of farms. Alem (2023a) estimate eco-efficiency scores and identify determinants of Norwegian dairy farms that accounts for methane emissions. Results show that the average eco-efficiency score, conventional dairy farms could cut input use and CH4 emissions by 5 % while maintaining output. Furthermore, the study find that land tenure, experience, and government subsidies all positively impact eco-efficiency. Related study Alem (2023b) investigates the dynamic eco-efficiency on dairy farms accounting for intertemporal production decisions and CH4 emissions. The mean eco-efficiency score for the dynamic model is 0.94, compared to 0.90 for the static model. The combination of the concept of eco-efficiency with latent-class stochastic frontier analysis and the stochastic meta-frontier approach revealed that

Table 1
Papers on eco-efficiency in agriculture.

Authors	Method[a]	Country	Sector	Sample	Data	AES impacts	Period	Eco-efficiency score	Sample size
Picazo-Tadeo et al., 2011	DEA	Spain	Rain-fed agriculture	Regional	Cross-section	+	2008	0.56	171
Pérez Urdiales et al., 2016	DEA	Spain	Dairy	Regional	Cross-section	n.a.	2010	0.63	59
Bonfiglio et al., 2017	DEA	Italy	Arable farms	Regional	Panel	+	2011–2014	0.55	2944
March et al., 2016	DEA	Scotland	Dairy	Regional	Panel	n.a.	2007–2013	0.57–0.97	n.a.
Godoy-Durán et al., 2017	DEA	Spain	Horticulture	Regional	Cross-section	n.s.	2014–2015	0.89	327
Stępień et al., 2021	DEA	Poland	Small-scale agriculture	Regional	Cross-section	–	2018	0.70	674
Eder et al., 2021	DEA	Austria	Crop	National	Panel	+	2008–2011	0.54	9249
Beltrán-Esteve et al., 2012	DEA	Spain	Rain-fed agriculture	Regional	Cross-Section	+	2008	0.62	241
Beltrán-Esteve et al., 2014	DEA-MF	Spain	Olive oil	Regional	Cross-section	n.a.	2010	0.45–0.49	220
Masuda, 2016	DEA-LCA	Japan	Wheat	Regional	Panel	n.a.	1995–2011	0.55–0.84	n.a.
Beltrán-Esteve et al., 2017	DEA-LCA	Spain	Citrus	Regional	Cross-section	n.a.	2009	0.54–0.58	196
Cortés et al., 2021	DEA-LCA	Spain	Dairy	Regional	Cross-section	n.a.	2019	0.58	108
Reinhard et al., 2000	DEA, SFA	Netherlands	Dairy	National	Panel	n.a.	1991–1994	0.52–0.80	1553
Orea and Wall, 2017	SFA	Spain	Dairy	Regional	Cross-section	n.a.	2010	0.65	50
Stetter et al., 2023	SFA	Germany	Dairy	Regional	Panel	n.a.	2005–2014	0.51–0.79	9224
Stetter and Sauer, 2022	SFA	Germany	Dairy, swine, mixed, crop	Regional	Panel	–	2005–2014	0.49–0.80	9574, 3796, 2558, 5318
Ait Sidhoum et al., 2023a	DEA	Germany, France, Italy, Netherlands	Crop, dairy	National	Panel	n.s.	2006–2011	0.34–0.70	3426, 5232, 4296, 2406, 2166, 984
Ait Sidhoum et al., 2023b	DEA	Germany	Dairy	Regional	Panel	n.s.	2013–2018	0.65	1626
Alem, 2023a	SFA	Norway	Dairy	National	Panel	n.a.	1991–2020	0.954	6229
Alem, 2023b	SFA	Norway	Dairy	National	Panel	n.a.	1991–2020	0.90–0.94	6229

Source: Authors' compilation.
[a] DEA: Data Envelopment Analysis; MF: Metafrontier, LCA: Life Cycle Assessment; SFA: Stochastic Frontier Analysis.

intensive dairy farms convert GHG emissions more efficiently into farm economic output on average than their extensive counterparts (Stetter et al., 2023). Stetter and Sauer (2022) examined GHG mitigation efforts, introducing the concept of emission efficiency and distinguishing between persistent and time-varying efficiency. The authors found considerable differences in farm-level emission efficiencies, but overall emission performance improved over time.

This review highlights that our knowledge about eco-efficiency in European agriculture is still limited. Generalization of the results of preexisting literature for European agriculture is challenging for several reasons. First, papers are geographically and sectorally concentrated. Second, they tend to use regional and small-scale survey-based cross-sectional data. Finally, information regarding the effect of AES is limited. As AES is one of the main measures employed to mitigate the environmental impact of agriculture, the examination of differences in eco-efficiency between participating and non-participating farms is important and has policy implications.

3. Study area: Hungarian crop sector – some characteristics of the Hungarian crop sector from an economic and environmental perspective

The Hungarian crop sector is an interesting study area regarding the effect of AES on eco-efficiency for several reasons, but especially because there has been a huge difference between the development of the economic and environmental performance of such farms in recent years. In Hungary, the share of agricultural area, in particular arable land, of the total land area is large even in international comparison: 58 % of the territory of the country – i.e. 5.3 million hectares – is under agricultural cultivation (NAK, 2019). Major crops include wheat (0.9 million ha), corn (1 million ha), and oilseeds (0.9 million ha). Structurally, although Hungary is characterized by highly concentrated access to land, it also has a large number of small farms (including many subsistence/semi-subsistence farms). Agriculture is an important contributor to the export performance of Hungary. The country's agricultural trade balance is positive. Agricultural exports account for 9 % of total exports from Hungary. The foreign trade structure of agricultural and food products is relatively constant. Most of the commodities exported in 2020 were grains and grain products (17 %), animal feed (10 %), meat and meat products (9 %), beverages (8 %), fruit and vegetables (6 %), oilseeds (6 %), and vegetable oils (6 %) (ITA, 2021). The development of the economic performance of Hungary's agriculture has been positive overall in recent years. The gradual growth in entrepreneurial income and the fact that this area is closing the gap with the rest of the economy are significant indicators of economic progress (EC, 2020).

However, according to a report by the European Commission (EC, 2020), the state of biodiversity appears to be continuously worsening. The proportion of high-nature-value farmland is continuously decreasing. For arable land, the Farmland Bird Index showed a continuous albeit slowing decline from 100 to 76.06 between 2000 and 2018. Landscape features in Hungary have been actively removed to facilitate agriculture, and today the share of fallow land (3 %) and landscape features (0.4 %) in agricultural area is below the EU average (respectively 4.1 and 0.5 %).

The overall recommendation of the European Commission for Hungary's strategic plan is as follows: "while maintaining competitiveness […] the agricultural sector should gradually change its growth pattern to take advantage of the opportunities of a greener, more modern and more sustainable agriculture."

In this context, the examination of the effect of AES – the main measure designed to mitigate the environmental impact of agriculture – on eco-efficiency (the latter which incorporates both the economic and environmental aspects of production) is important and has policy implications. The results of this examination provide information that can improve the environmental and economic objectives of the future CAP, and help achieve the specific targets of the Farm to Fork Strategy and the Biodiversity Strategy for 2030, and in turn, the Green Deal targets of the EU.

4. Method

The concept of eco-efficiency was first described by Schaltegger and Sturm (1989) and then widely publicized in 1992 in *Changing Course* (Schmidheiny and Timberlake, 1992), a publication by the World Business Council for Sustainable Development (WBCSD) (Ehrenfeld, 2005, p6). In general, eco-efficiency is measured as the proportion of economic value added compared to environmental damage.

The aggregation of environmental pressures into a single environmental damage index is a major challenge for eco-efficiency measurement. Kuosmanen and Kortelainen (2005) showed how data envelopment analysis (DEA) can be adapted for this purpose. Although their method builds on insights from the DEA literature, it deviates from the usual treatments of *firm-level environmental performance analysis* in some important ways (see, e.g., Färe et al., 1989; and for a recent review about the developments, limits, and future prospects of this approach we refer the reader to (Dakpo et al., 2016), in addition information about complementary approaches can be found in (Czyżewski and Kryszak, 2022)). First, the approach of Kuosmanen and Kortelainen takes the standard definition of eco-efficiency (eco-efficiency = economic value added/environmental damage). This definition emphasizes the trade-off between economic and environmental aspects of production (giving equal emphasis to both). Second, it handles the eco-efficiency measurement problem (see below) as it is presented through the fields of *ecological economics* and *industrial ecology* (i.e., differently to in the field of environmental performance analysis). The *environmental performance literature* directly incorporates physical emissions as inputs or outputs into the standard DEA model; in contrast, this approach provides a more ecologically oriented view. We believe that for addressing our current research question, this approach is more adequate.

Following the notation of Kuosmanen and Kortelainen (2005), we denote the economic value added of the production activity as v. Suppose the production activity under consideration induces M different environmental pressures, the severity of which is measured by variables $z = z_1, \dots, z_m$.

For simplicity, all environmental pressures are assumed to be harmful (i.e., $z > 0$) (see Tilman et al., 2002); furthermore, the relationship between biodiversity and disturbance in different contexts is subject to debate; see (EC, 2020; Fox, 2013; Gao and Carmel, 2020; Sheil and Burslem, 2013).

A comprehensive eco-efficiency measure should take into account the phenomenon of the substitution of sources of environmental load, because reducing one pollutant may come at the cost of increasing another. To characterize the substitution possibilities at the most general level, Kuosmanen and Kortelainen (2005) introduced a pollution-generating technology set, as follows:

$$T = \{value\ added\ v\ can\ be\ generated\ with\ damage\ z\}$$

which includes all possible technically and economically feasible combinations of value added v and environmental damage z.

In empirical analysis we are interested in measuring the eco-efficiency of a production unit under evaluation relative to a sample of N comparable units. Let V_n denote the economic value added and Z_n the environmental pressures of unit $n(n = 1, \dots, N)$.

In terms of the above notation, we can express the *eco-efficiency* of unit n formally as:

$$Eco - Efficiency_n = \frac{V_n}{D(Z_n)}$$

where D is the damage function that aggregates the M environmental pressures into a single environmental damage score by employing a linear weighted average of the individual environmental pressures – i.e. $D(z) = w_1 z_1 + w_2 z_2 + \ldots + w_M z_M$, where $w_m (m = 1, \ldots, M)$ represents the weight accorded to environmental pressure, m.

In order to identify the weights w_m, the DEA method is used. DEA identifies weights that maximize the eco-efficiency score of the evaluated farm 'n' belonging to the sample $n = 1, \ldots, N$.

The DEA eco-efficiency score of farm n can be computed by solving the following linear programming problem:

$$Eco\ Efficiency_{n'}^{-1} = \theta_{n'}$$

subject to

$$\nu_{n'} \leq \sum\nolimits_{n=1}^{N} z_n \nu_n$$

$$\theta_{n'} z_{mn'} \geq \sum\nolimits_{n=1}^{N} w_m z_{mn} \; m = 1, \ldots, M$$

$$w_n \geq 0 \; n = 1, \ldots, N$$

The DEA eco-efficiency score, which solves this problem for farm n, θ_n^* can be interpreted as a distance to the eco-efficiency frontier. It shows the maximum potential proportional reduction in all environmental pressures that could be achieved while maintaining the present level of economic value added. The DEA score is equal to one for an eco-efficient farm, whereas values lower than one indicate eco-inefficiency. The further the distance of the farm from the frontier, the lower the eco-efficiency score and the greater the scope for improvement in a farm's environmental performance.

As in an agricultural context environmental variables might have a huge effect on the potential reduction of pollution-generating inputs (e.g. regional differences and differences in soil quality), we incorporate these variables into our DEA model as non-discretionary input variables z_k^{ND}.

$$z_{kn'}^{ND} \geq \sum\nolimits_{n=1}^{N} w_k z_{kn} \; k = 1, \ldots, K$$

In this way, the n-th farm is compared with a theoretical farm that has a production environment that is no better that of the n-th farm.

As Simar and Zelenyuk (2007) highlight: after estimating the individual efficiency scores, researchers usually face the questions: What is the efficiency of the entire system? What are the efficiencies of distinct groups within the system? (i.e. participating and non-participating farms in AES program in our case) Which group is more efficient?

To get reliable answers to the above questions, there are at least two critical issues concerning the choice of appropriate methodology: (i) reliable point estimators of group (or subgroup) efficiencies and reliable interval estimators of group efficiencies (Simar and Zelenyuk, 2007).

The first issue can be viewed as an aggregation problem, i.e. obtaining an (appropriate) aggregate efficiency score from individual efficiency scores. But how can we (theoretically consistently) aggregate? Following (Färe and Zelenyuk, 2003, 2007), the simplest example of an aggregate efficiency measure would be the sample mean of the individual estimates (that is also a consistent estimator of the true mean of the population).[1] An important question, however, is whether the simple population mean is indeed of primary interest? The simple equally weighted mean is a useful characteristic of a distribution, but relying only on it in efficiency context may result in dramatic misinterpretation of the results. As Sickles and Zelenyuk (2019) illustrates if we look at the real world, one can observe that most industries are dominated by only a few firms, although there may also be many other small firms in the industry. Using the Sickles and Zelenyuk (2019), banking example in agricultural context: in many countries we see that a handful of farms have a larger share of the industry (sector) than the hundreds of remaining small farms. Imagine, if all those small farms have very high (eco-)efficiency levels, say very close to 100 %, while those few huge farms have low(eco)-efficiency levels, say close to 50 %, although they control most of the industry(sector) share, say at 90 %. In this example, even though the industry is clearly dominated by the very (eco-)inefficient farms, the equally weighted mean of (eco)-efficiency would be close to 100 %, suggesting an almost perfect (eco)-efficiency situation in the sector and in turn no need for policy measures regarding improving farms' (eco)-efficiency. Would the equally weighted mean adequately describe the situation in such an industry (sector)? This example clearly shows that the efficiency scores that enter the averaging should be adequately weighted, with weights reflecting the importance of each farm that generated those scores.

Thus, in this context the most important issue is the choice of the aggregation weights. As different weights could lead to different conclusions, which in turn could lead to biased policy implications, the choice of the weights is highly relevant (Sickles and Zelenyuk, 2019).

The first thoughts regarding weights for measuring aggregate efficiency were discussed by Farrell (1957). He suggested to take the arithmetic average of efficiency scores of individual firms and weight them by the observed output shares of these firms within the group. However, Farrell did not provide any formal justification for such an aggregate scheme, in addition his description was related only to a single output case. As consequence, this approach was rarely used and researchers tended to use simple (equally weighted) averages (Färe and Zelenyuk, 2003).

Later, Färe and Zelenyuk provided the needed theoretical justifications for the Farrell weighting scheme, while also generalizing it to multiple output case (Färe and Zelenyuk, 2003). The key step in their derivation of weights is the assumption about group technology, i.e., the aggregate technology of all firms within a (sub)group. Färe and Zelenyuk (2003) assume a linear aggregation structure of the output sets (more precisely, the Minkowski sum of the individual output or input sets).

The derivation of the weights starts with a (subgroup) revenue function and the authors define the aggregate technical efficiency as the weighted sum of the individual technical efficiencies, where the aggregation weights are the actual revenue (in the case of output orientation) or cost (in the case of input orientation) shares. However, while technical efficiency is typically presumed to be a price independent measure of efficiency, the above defined aggregation weights depend on prices, which is undesirable. To circumvent this problem one might use shadow prices (e.g. (Li and Ng, 1995), or, alternatively, might adopt the standardisation procedure developed by Simar and Zelenyuk, 2006, 2007). In this paper, we follow this later method. For proof and more detailed derivation of this aggregation scheme, we refer the readers to the original papers introducing this approach (see Färe and Zelenyuk, 2003, 2007).

In short, the advantage of these weights is that they are not ad hoc but derived from economic optimization behaviour. Thus, this method provides a mathematically consistent and theoretically justified way of aggregating efficiency scores.

The second issue is how to proceed with reliable inference on such obtained aggregate efficiency scores?.[2] Before the statistical properties of the DEA estimator were known, researchers usually applied the standard inference techniques to analyze the (estimates) of the efficiency score obtained from DEA (Sickles and Zelenyuk, 2019). The most popular example is e.g. a test on the means of efficiency scores using the (asymptotic) normality argument. However, these studies usually ignored the problem of bias of the estimated efficiency scores as well as

[1] As the individual efficiency measures are consistent estimators of the true efficiency scores, the average of them is also a consistent estimator of the true mean of the population distribution of efficiency scores (under certain regulatory condition) (Sickles and Zelenyuk, 2019).

[2] The description in this paragraph mainly based on Sickles and Zelenyuk (2019).

the inherent dependency of the scores. The next wave of studies tried to address these problems suggesting various types of bootstrap for correcting the drawbacks of DEA estimator. The first breakthrough work in this field was the seminal paper of Simar and Wilson (1998), using theoretical reasoning supported by Monte Carlo evidence. They pointed out the incorrectness of the naive bootstrap techniques in the context of bootstrapping individual efficiency scores and suggested an alternative method. This alternative was a version of smooth homogenous bootstrap that was soon extended by Simar and Wilson (2002) to smooth heterogeneous bootstrap. However, the main limitation of the smooth bootstrap was that no theoretical proof was found about the consistency of such an approach (Sickles and Zelenyuk, 2019). The proof of consistency of a bootstrap approach for DEA came some years later, with the seminal work of Kneip et al. (2008) and Jeong and Simar, respectively where they proposed a new alternative: the subsampling bootstrap. A slightly generalized version of subsampling bootstrap was proposed by Simar and Zelenyuk (2007), called group-wise heterogeneous bootstrap. Such a version allows for different groups within the population to have different distributions, where the resampling is done separately for each group, while the DEA estimation is done on the pooled sample. This setting suits well to our research topic. Therefore, we apply it for bias correction of the aggregate efficiency scores and to test the means of groups of farms participating/not participating in AES. In addition, in order to compare the distribution of the analyzed groups of farms we use the (DEA context) adapted Li test introduced by Simar and Zelenyuk (2006) which based also on the group-wise heterogeneous bootstrap approach.

Finally, as some of the core characteristics between participating and non-participating farms are obviously different, the comparison between these groups might also suffer from selection bias. In observational studies, researchers usually apply some quasi-experimental method to correct for selection bias. The most used methods are the propensity score matching (PSM) and/or difference in difference (DiD) methods. There is a growing body of papers that consider selection bias in the estimation of AES effect. For more details, we refer the interested readers to (Ait Sidhoum et al., 2023a,b; Baráth et al., 2020).

However, similarly to the DEA estimator, standard inferential methods are also not valid for numerous matching estimators (for a detailed discussion of this topic see e.g. Abadie and Imbens, 2006). Researchers using matching methods often apply the conventional i.i.d bootstrap to calculate the standard errors, but Abadie and Imbens (2006) showed that the standard bootstrap is, in general, not valid for matching estimators. Potential solutions for valid inferential methods in this setting are the analytic asymptotic variance estimator of Abadie and Imbens (2006) or modifications of the standard bootstrap, similar to the subsampling methods or a wild bootstrap that was introduced in this context by Bodory et al. (2016).

Therefore, considering these difficulties regarding reliable inferential methods (for both the DEA estimator and matching methods) it is not surprising that, to date, hasn't been introduced any valid inferential method for the combination of matching and DEA estimator.

Despite of these well-known limitations, in the Appendix, we also report results estimated using combined PSM-DiD and DEA methods. However, we want to stress that these results must be interpreted with extra caution.

In sum, although there is a growing body of literature that examines the effect of AES on farms economic and/or environmental performance applying different methods, papers usually neglect two important methodological issues that are empirically highly relevant: (1) the aggregation issues (aggregation individual efficiency scores into group/sectoral aggregates in a theoretically justified way) and (2) issues related to do reliable inference on (group) efficiency scores. The main novelty of our paper is the consideration of these issues.

5. Data

For the empirical analysis, we used Hungarian Farm Accountancy Data Network (FADN) Data for field crop farms from 2015 to 2020. The FADN, or RICA from its French name (Reseaud'Information Comptable Agricole), is an annual survey of European farms.[3]

We used a balanced panel, and the total number of observations in our sample was 2058, 343 per year. We considered a farm to be a participating farm if it was involved in the program for at least half of the analyzed period; that is, we included those farms that participated for at least three years in the program.

For the estimation of the DEA model, we used data on economic value added and environmental indicators. For economic value added, we used Gross Farm Income according to the FADN definition (the difference between total output and intermediate consumption). Our selection of variables that represent the pressure of agricultural activities on the environment in field crop farms (available in our FADN sample) is based on earlier literature (Bonfiglio et al., 2017; Stępień et al., 2021; Ait Sidhoum et al., 2023a). We use three different variables to represent environmental damage caused by agricultural production: (1) farm expenditure on fertilizers, (2) expenditure on crop-protection products, and (3) energy per hectare for field crops farms. We account for these inputs using monetary units following the approach of Stępień et al. (2021). In addition, in the estimation of the DEA model we used also regional dummies at NUTS2 level and soil quality. The unit of soil quality is golden crown (GC, in Hungarian—AK).[4] As the DEA method is sensitive to outliers, in order to avoid results being thus affected we omitted observations belonging to the upper and lower 1 % of the distribution of output and input variables. Table 2 presents some descriptive statistics about the variables used in our empirical analysis.

Table 2
Descriptive statistics.

Variable	Unit of measurement	Obs	Mean	Std. dev.	Min	Max
Non-AES farms						
GFI/ha	€	1749	242.98	126.43	11.76	748.86
Fertilizer/ha	€	1749	56.41	27.35	6.54	136.36
Crop prot/ha	€	1749	40.67	22.30	5.18	115.89
Energy/ha	€	1749	28.62	19.10	1.08	109.55
Soil quality	GC[4]	1472	22.55	6.21	4.00	42.60
AES farms						
GFI/ha	€	309	200.77	126.20	17.66	655.99
Fertilizer/ha	€	309	50.84	26.89	8.23	120.62
Crop prot/ha	€	309	35.04	20.64	5.33	111.27
Energy/ha	€	309	23.89	15.15	3.33	98.50
Soil quality	GC[4]	243	20.59	6.01	8.00	35.00

Notes: 1. crop prot = crop protection; 2. for soil quality we had missing values; 3. Monetary variables are expressed in 2015EUR.

[3] For further information about the FADN survey, including data collection, methodology and FADN survey results, please visit the following website of the European Commission: https://agriculture.ec.europa.eu/data-and-analysis/farm-structures-and-economics/fadn_en.

[4] The golden crown system was introduced in the second half of the past century in Hungary, and it is still in use (http://demogmap.elte.hu/gb/fm-ftf/41.htm). The gold crown value of a certain land means the net income of that area. At the time of the introduction of the system, it was proportional to wheat produced on the area reduced by the transportation expenses to Vienna (Stankovics et al., 2020).

Table 2 shows that both the output and input values are lower for farms that participate in the AES program. It also shows that the standard deviation of every variable is rather high, suggesting that examining aggregate efficiency is more appropriate than equally weighted mean efficiency.

6. Results

6.1. Comparison of the eco-efficiency of AES and non-AES farms

Table 3 highlights several issues. First, it emphasizes that the difference between the bias-corrected efficiency scores and the standard DEA results is rather high, confirming the importance of the bootstrap procedure. Second, it also shows that there is a difference between the aggregate and mean efficiency too, suggesting that in order to obtain a more realistic picture it is worth considering a different weighting scheme to equal weights. Third, it shows that the estimated eco-efficiency of non-participating farms is higher in both cases considering aggregate efficiency or equally weighted mean efficiency. Our main research question is whether this difference is statistically significant. In other words, our null hypothesis of interest is:

$$H_0 : \underline{EE}^{AES} = \underline{EE}^{NON-AES};$$

or following (Simar and Zelenyuk, 2007) in terms of relative difference statistics:

$$H_0 : RD_{AES,NON-AES} \equiv \frac{\underline{EE}^{AES}}{\underline{EE}^{NON-AES}}.$$

Although the quantity of $RD_{AES,NON-AES}$ is not observed, it can be replaced using the estimated DEA scores. The bootstrap confidence interval for $RD_{AES,NON-AES}$ helps to empirically test the above null hypothesis: it should be rejected (at a selected significance level α) if it does not contain unity and not be rejected otherwise. The estimated (0.95 level) confidence interval of the RD statistics for the aggregate eco-efficiency is between 0.95 and 1.31, thus we cannot reject the null hypothesis, i.e., our results show that the difference between participating and non-participating farms is not statistically significant. We also report on a comparison of the equally weighted mean eco efficiency between the groups under analysis, which leads to the same conclusion.

We also consider another way of comparing the eco-efficiency scores we obtained based on estimation and testing the densities of efficiency scores. Fig. 1 shows the density estimates of aggregate efficiencies for the analyzed groups.

There is a clear difference between the distribution of efficiency scores – the density function for non-participating farms is shifted to the right, showing, similarly to in Table 1, that eco-efficiency is higher for non-participating farms (Fig. 1).

Table 3
Bootstrapped aggregate efficiency results and relative difference statistics for the analyzed groups.

	EE	EE_bias corr	bias	SD	BBlow	BBup
	Aggregate efficiency					
Non-AES	0.312	0.198	0.114	0.038	0.122	0.278
AES	0.275	0.169	0.106	0.043	0.084	0.250
Total	0.305	0.196	0.109	0.037	0.127	0.276
	Mean efficiency					
Non-AES	0.329	0.211	0.118	0.038	0.142	0.296
AES	0.290	0.181	0.109	0.044	0.096	0.266
Total	0.321	0.209	0.113	0.037	0.137	0.293
	Comparison (RD statistic)					
Aggeff Ratio	1.136	1.145	−0.009	0.098	0.969	1.310
Mean Ratio	1.125	1.121	0.004	0.095	0.942	1.284

Note: EE = Eco-efficiency (original DEA efficiency estimate); EE_bias corr = the bias-corrected eco-efficiency estimate; bias = the bootstrap bias estimate; standard deviation of the bootstrapped values; Bblow_BBbup: 95 % confidence interval for the bias-corrected efficiency estimates.

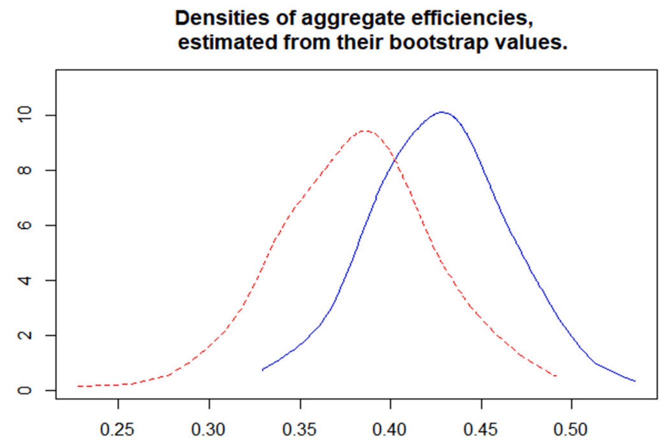

Fig. 1. Densities of aggregate efficiencies. Note: Blue = Non-participating; Red = Participating.

In order to test whether these differences are statistically significant, we apply the adapted Li test introduced by Simar and Zelenyuk (2006). The test statistic is 0.81 and the bootstrapped p-value is 0.38, thus the test confirms our earlier conclusion that there is no significant difference between the eco-efficiency of participating and non-participating farms.

6.2. Does the year of participation matter? - examining the effect of duration of participation

In the next step, we examined whether the number of years of participation in the AES program has any effect on eco-efficiency.

Table 4 contains the RD statistics for the aggregate eco-efficiency scores between non-participating farms and farms participating for different years (AES_1 means that a farm participated for only one year in the program, and AES_2 for two years, etc.) and the adapted Li test.

Table 4 shows that eco-efficiency of non-participating farms is higher in every case, independent of the number of participating years; however, the confidence intervals always contain unity, showing that there is no statistically significant difference between the analyzed groups. The Li statistics confirm these results.

6.3. Does the amount of the environmental subsidy matter?

Following the duration of participation, we also examined whether the value of environmental subsidies per hectare (total utilized agricultural area) affect eco-efficiency. In order to do so, we divided the farms that received an AE subsidy into three groups based on quantiles of the amount of AE subsidy, and we compared these groups with farms did not receive any AE subsidies. Table 5 includes some descriptive statistics about the amount of AE subsidy in the full sample and in the different quantiles.

The total number of observations for farms receiving an AE subsidy was 309 in the sample. The average value of the AE subsidy was 58 euro/ha. The standard deviation is rather high (84 euro/ha), the minimum value is less than one euro/ha, and the maximum is 362 euro/ha (Table 5).

There are huge differences in the amount of AE subsidies between the groups defined by quantiles. Farms in the first quantile received a very small amount of AE subsidies; in the second quantile farms on average received more than ten times that of the latter; whereas the third group received >100 times as much as the first group. These remarkable differences suggest that, in addition to the previous comparisons, it is worth comparing groups of farms that received different amounts of AE

Table 4
Comparison of non-participating farms with groups of farms participating for different durations based on RD statistics and Li-tests.

	Eco-efficiency and bootstrap EE estimates						Li test	
	RD	RD_bias corr	bias	SD	BBlow	BBup	Test statistic	P-value
AES_1	1.116	1.115	0.001	0.103	0.903	1.299	0.517	0.550
AES_2	1.127	1.133	−0.006	0.090	0.953	1.296	−0.750	0.445
AES_3	1.136	1.140	−0.004	0.106	0.955	1.369	−0.573	0.480
AES_4	1.144	1.160	−0.016	0.105	0.935	1.346	−0.756	0.410
AES_5	1.158	1.169	−0.011	0.161	0.791	1.441	−1.060	0.225

Note: EE = Eco-efficiency (original DEA efficiency estimate); EE_bias corr = the bias-corrected eco-efficiency estimate; bias = the bootstrap bias estimate; standard deviation of the bootstrapped values; Bblow_BBbup: 95 % confidence interval for the bias-corrected efficiency estimates.

Table 5
Environmental subsidy per hectare.

	Obs	Mean	Std.dev	Min	Max
Full sample					
Full sample	309	58.26	83.90	0.04	362.18
Quantiles					
quantile_1	103	1.31	0.81	0.04	2.89
quantile_2	103	13.58	12.21	2.91	46.11
quantile_3	103	159.89	73.39	46.91	362.18

subsidy. The results of this comparison are presented in Table 6.

The results of Table 6 suggest that there are no significant differences in eco-efficiency between non-AES farms and the groups of farms belonging to different quantiles. Non-AES farms' eco-efficiency is higher in every case, but the difference is not significant (Table 6).

This result could be attributed to the fact that AES are likely to be claimed by farmers whose typical production strategies already comply with agri-environmental measures and objectives. This represents a challenge to the implementation of AES, and a great deal of literature deals with this issue (a meta-analysis can be found in Lastra-Bravo et al., 2015).

In sum, we can conclude that we find no differences in eco-efficiency between non-participating and participating farms, irrespective of the method that is applied, duration of years, or the amount of AE subsidy received.

6.4. Explaining eco-efficiency

As we found no difference in eco-efficiency between AES and Non-AES farms, we are interested in checking whether we can identify any other determinants that have a significant effect on eco-efficiency. Moreover, we also include AE subsidies in the eco-efficiency drivers in order to test what this method shows about the effectiveness of AE subsidies.

For analyzing such research questions in the context of non-parametric efficiency analysis, semi-parametric two-stage approaches that combine efficiency measurement using DEA with a regression analysis that uses DEA-estimated efficiency scores as dependent variables have become popular (e.g. Bonfiglio et al., 2017; Godoy-Durán et al., 2017; Pérez Urdiales et al., 2016; Stępień et al., 2021).

In the early literature, the second stage is typically a censored (Tobit-like) regression that accounts for the bounded nature of DEA efficiency scores, or just simply OLS. However, Simar and Wilson showed that such approaches have serious issues and proposed two alternatives (algorithm_1 and algorithm_2) based on truncated regression with bootstrap (Simar and Wilson, 2007). A description of the method can be found in many places in the literature (e.g. Badunenko and Mozharovskyi, 2016; Sickles and Zelenyuk, 2019; Simar and Wilson, 2007), so for reasons of space we do not describe it here. In order to remain consistent with our earlier results, we applied algorithm 2, which is computationally more intensive but based on bias-corrected DEA scores, similarly to our earlier analysis. In terms of the potential determinants, we applied the variables most frequently used in the literature (Bonfiglio et al., 2017; Godoy-Durán et al., 2017; Pérez Urdiales et al., 2016; Stępień et al., 2021) that were also available in our sample. Finally, we used eight variables: amount of environmental subsidy per hectare, amount of total subsidy per hectare (without environmental subsidy), number of owners, soil quality, age of manager, crop insurance, share of rented land, and capital-to-labour ratio (to capture farm technology) (Table 7).

The results show, similarly to our earlier calculations, that the AE subsidy does not have a significant effect on eco-efficiency, neither has total subsidies. The number of owners and insurance has a negative effect, while the impact of soil quality and share of rented land is positive. We find no significant effect in the case of age. The capital-to-labour ratio, which captures the technology level of farms, has a positive effect.

Table 6
Comparison of non-participating farms with groups of farms associated with different quantiles of AE subsidy.

	RD	RD_bias corr	bias	SD	BBlow	BBup
NON-AES vs. Qt1	0.974	0.931	0.043	0.141	0.650	1.174
NON-AES vs. Qt2	1.089	1.024	0.065	0.153	0.646	1.295
NON-AES vs. Qt3	0.973	0.807	0.166	0.160	0.432	1.089

7. Robustness tests

We performed several robustness tests to validate the results concerning differences between AES and non-AES farms. Below, we give a short description about it and we present all of the details in the Appendix.

First, we conducted all of the above estimations also for different period (which contains different Rural development programming period), i.e. for the period 2010–2015. The results are very similar to the actual ones.

Second, we performed combined PSM and DiD analysis. In order to estimate the propensity scores we estimated a logit model for the pre-treatment year 2015. How many variables to include in a propensity

Table 7
Determinants of eco-efficiency.

	Coef.	Std. Err.*	z	P > z	[95 % CI]	
AE subsidy	0.089	0.142	0.630	0.532	−0.169	0.363
Total subsidies**	0.008	0.064	0.120	0.906	−0.106	0.160
Soil quality	0.241	0.089	2.690	0.007	0.082	0.419
Number of owners	−0.459	0.241	−1.900	0.057	−0.997	−0.047
Age	0.023	0.496	0.050	0.963	−0.951	1.181
Insurance	−0.249	0.072	−3.450	0.001	−0.421	−0.129
Share of rented land	0.375	0.179	2.100	0.036	−0.024	0.676
Capital/labour	0.030	0.003	9.300	0.000	0.024	0.036
Constant	0.118	0.040	2.930	0.003	0.029	0.197

* Notes: Std. Err.: bootstrapped standard errors.
** Total subsidy = Total subsidy received by farms without AE subsidy.

score binary model is widely discussed in the literature. We chose the following farm and farmers' characteristics as covariates in the logit models: economic size unit (esu), age of farm manager, NUTS2 regions, share of unpaid labour, soil quality. (We note that in this case, we estimated our DEA model without soil quality and Nuts2 regions). Then, we used the most applied matching algorithms: kernel normal, kernel epanechnikov, and nearest neighbour matching from 1 (NN1) to 5 (NN5) with replacement. In order to assess matching quality, following Leuven and Sianesi (2003), we checked the following overall covariate balance measures: (1) the mean and median bias of covariates before and after matching; (2) Rubin's B for the absolute standardised difference of the means of the linear index of the propensity score in the treated and matched non-treated groups; and, (3) Rubin's R for the proportion of treated to matched non-treated variance in the propensity score index (Leuven and Sianesi, 2003; Rubin, 2001). Rubin (2001) recommends that B be <25 and that R be between 0.5 and 2 for the samples to be considered sufficiently balanced. When more matching algorithms satisfied the recommended values, we chose those whose mean bias was the smallest. According to these criteria, the kernel (epanechnikov) matching performs the best in our case. The combined PSM/DiD estimation confirms our earlier results and in line with the literature, we haven't found significant effect of AES participation on Eco-efficiency. However, these results must be interpreted with caution, because there is no proofed inference procedure for combined DiD/PSM and DEA method. Therefore, in addition, to the examination of Eco-Efficiency scores, we checked also the effect of participation on the aggregate output and on the aggregate inputs (simply the sum of the cost of the applied input variables (energy, fertilizer, crop protection) in real value). In this case, standard bootstrap procedure provides valid inference, as we don't use DEA model here, and as Abadi-Imbens anticipate the kernel based matching estimators, for which the number of matches increases with the sample size, are asymptotically linear (the same conjecture applies to other asymptotically linear estimators), therefore the standard bootstrap provides valid inference (Abadie and Imbens, 2006, p. 1547). We haven't found significant differences between AES and NON-AES farms in terms of aggregate output and input.

8. Discussion

The results indicate that crop farms show modest levels of ecological efficiency, in line with other studies on the crop sector (Bonfiglio et al., 2017; Eder et al., 2021; Masuda, 2016; Stetter and Sauer, 2022; Ait Sidhoum et al., 2023a). This is supported by the fact that eco-efficiency scores on average are rather low and that there are more farms with middle-low eco-efficiency scores (Fig. 1). However, most farmers have a good chance of improving their eco-efficiency while keeping the degree of value they add constant. In fact, farmers could reduce their environmental pressure by approximately 64 % while maintaining their value-added levels in order to reach the frontier identified by the top farms.

Empirical studies have shown that agri-environmental schemes play a contradictory role in explaining farmers' eco efficiency. Bonfiglio et al. (2017) and Stetter and Sauer (2022) found a negative relationship between AES and farm eco-efficiency, while Eder et al. (2021) reported a positive relationship Stępień et al. (2021) found a non-significant relationship. Agri-environmental schemes in our study do not appear to promote eco-efficiency among Hungarian crop farms.

In line with Ait Sidhoum et al. (2023a,b) results show that there are no differences in eco-efficiency between non-participating and participating farms, irrespective of the method that is applied, duration in years, or amount of AE subsidy. These results contrast with the other previous findings in the literature (Beltrán-Esteve et al., 2012; Bonfiglio et al., 2017; Picazo-Tadeo et al., 2011).

However, this contrast is not surprising at least for two reasons. First, it is well-known in the literature that the environmental effectiveness of AES depends on the compatibility of the scheme's design with respect to the specific region in which it is implemented (Kleijn and Sutherland, 2003; Batáry et al., 2015); therefore, heterogeneous effects are expected in different regions. Second, as Dakpo et al. (2016) highlight, there is no consensus in the literature that extensive farming is more environmentally friendly (Phalan et al., 2016; Balmford et al., 2018), although there is evidence that agricultural intensification has negative local and global consequences (Tilman et al., 2002); the performance of both systems is debated, and more case studies are needed for clarification. Finally, as Ait Sidhoum et al. (2023a,b) point out neglecting the potential selection bias may affect on the impacts of the AES on the eco-efficiency of farms.

9. Conclusions

Sustainable intensification aims to meet rising global food demand while lowering agricultural environmental impact. European policy attempts to resolve this trade-off by imposing environmental limits and paying for more serious commitments resulting from sustainable practices. Sustainable intensification metrics are needed to assess policy efficacy in greening farms.

We assessed the eco-efficiency of crop farms in Hungary. In particular, we are interested in the differences in ecological efficiency between farms participating and not participating in AES. In addition, we looked at the impact of participation duration, AE subsidy per hectare, and eco-efficiency factors. We utilized the DEA approach to combine several environmental pressures. We used the groupwise-heterogeneous bootstrapped method to compare means between groups and the DEA-context-adapted Li-test to compare distributions between groups because standard DEA (eco-)efficiency scores are biased and conventional tests on the means or distributions of efficiency scores between groups are insufficient. In addition, we used price-independent weights, as suggested by Simar and Zelenyuk (2007), to solve any potential problems with group efficiencies with equally weighted averages.

Our main findings are the followings. First we find a low degree of eco-efficiency in Hungarian crops farms indicating a large potential to improve the environmental performance of farms. Second, we find that there are no significant differences in the eco-efficiency of the farms between participating and non-participating in the AES. The results are robust to different methods. Our results have several implications on the efficacy of the AES.

The decision-makers must first consider the fact that AESs have varied effects on how well farms function in terms of the environment. This is particularly significant for creating unique AESs. Second, by improving their policy targeting and taking into consideration factors like farm size and spatiality, policymakers may be able to raise the overall environmental efficacy of AES. Various strategies, such as lowering transaction costs, tying payment amounts to site conditions, and implementing spatially coordinated auctions for conservation contracts or other incentive payments, could be used to encourage farms with high predicted participation effects to take part in AES. In order to increase eco-efficiency while taking environmental concerns into account, policymakers are urged to allow knowledge sharing among farms. To raise the long-term output of farms, socioeconomic variables including increased public support for agricultural extension and farmer training should be considered by policymakers. Several studies report that in order to improve the environmental effects of AES there is a great need for better adaption at the local level (Sutcliffe et al., 2015; Tryjanowski et al., 2011).

Our study highlights some limitations of eco-efficiency studies. Measuring the environmental impacts are usually constrained by the data availability. It is important to note that the ecological impacts of the AES may not necessarily result in improved efficiency in the utilization of fertilizers, crop protection, and energy. Therefore, in agreement with Ait Sidhoum et al. (2023a), the absence of more explicit measures of environmental sustainability, including greenhouse gas emissions, nitrogen balances, or soil erosion rates, is a constraint in our analysis. To get more comprehensive and international comparable studies the

European farm accountancy data network should be augmented with more specific data on agricultural procedures and management practices.

CRediT authorship contribution statement

LB: Methodology, Software, Writing - Original draft, Concept; **IF**: Writing - Review & Editing; **ZB**: Writing - Review & Editing; **JF** and **EV**: Data preparation; **ED**: Data Curation; **NZS**: literature review; Visualisation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A

Appendix 1
Bootstrapped aggregate efficiency results and relative difference statistics for the analyzed groups. 2010–2015.

	EE	EE_bias corr	bias	SD	BBlow	BBup
	Aggregate efficiency					
Non-AES	0.343	0.240	0.104	0.031	0.180	0.293
AES	0.304	0.209	0.095	0.038	0.130	0.272
Total	0.335	0.236	0.099	0.030	0.179	0.289
	Mean efficiency					
Non-AES	0.375	0.266	0.108	0.032	0.205	0.321
AES	0.329	0.232	0.098	0.037	0.156	0.297
Total	0.364	0.262	0.102	0.030	0.205	0.311
	Comparison (RD statistic)					
Aggeff Ratio	1.128	1.132	−0.004	0.093	0.946	1.311
Mean Ratio	1.133	1.128	0.005	0.087	0.956	1.296

Note: EE = Eco-efficiency (original DEA efficiency estimate); EE_bias corr = the bias-corrected eco-efficiency estimate; bias = the bootstrap bias estimate; standard deviation of the bootstrapped values; Bblow_BBbup: 95 % confidence interval for the bias-corrected efficiency estimates.

Appendix 2
Comparison of non-participating farms with groups of farms participating for different durations based on RD statistics and Li-tests. 2010–2015.

	Eco-efficiency and bootstrap EE estimates						Li test	
	RD	RD_bias corr	bias	SD	BBlow	BBup	Test statistic	P-value
AES_1	1.128	1.132	−0.004	0.093	0.946	1.311	2.38	0.01
AES_2	1.100	1.123	−0.023	0.097	0.925	1.300	0.72	0.44
AES_3	1.097	1.117	−0.020	0.098	0.932	1.317	0.81	0.38
AES_4	1.144	1.160	−0.015	0.139	0.876	1.410	0.55	0.61
AES_5	1.094	1.144	−0.051	0.133	0.861	1.380	0.13	0.91

Note: EE = Eco-efficiency (original DEA efficiency estimate); EE_bias corr = the bias-corrected eco-efficiency estimate; bias = the bootstrap bias estimate; standard deviation of the bootstrapped values; Bblow_BBbup: 95 % confidence interval for the bias-corrected efficiency estimates.

Appendix 3
Comparison of non-participating farms with groups of farms associated with different quantiles of AE subsidy. 2010–2015.

	RD	RD_bias corr	bias	SD	BBlow	BBup
NON-AES vs. Qt1	1.078	1.090	−0.012	0.139	0.803	1.332
NON-AES vs. Qt2	1.037	0.999	0.038	0.142	0.694	1.259
NON-AES vs. Qt3	1.108	1.028	0.080	0.175	0.661	1.291

Appendix 4
Parameter estimates of logit-models explaining program participation.

Variables	Coefficients	Std. Err.	z	P > |z|	95 % confidence interval	
Economic size	−0.0003	0.0006	−0.5300	0.5970	−0.0014	0.0008
Soil quality	−0.0402	0.0159	−2.5300	0.0110	−0.0714	−0.0090
Age	−0.0133	0.0084	−1.5800	0.1150	−0.0299	0.0032
Unpaid labour share	−0.6003	0.3229	−1.8600	0.0630	−1.2332	0.0326
Nuts 2 regions:						
2	−0.0069	0.4805	−0.0100	0.9890	−0.9487	0.9349
3	0.2521	0.4601	0.5500	0.5840	−0.6496	1.1538
4	0.6595	0.4557	1.4500	0.1480	−0.2337	1.5527
5	0.0350	0.4939	0.0700	0.9440	−0.9331	1.0031
6	0.1887	0.4599	0.4100	0.6820	−0.7127	1.0901
7	0.1491	0.4459	0.3300	0.7380	−0.7248	1.0230
Capital to labour ratio	0.0000	0.0000	1.7100	0.0880	0.0000	0.0000
Constant	0.6626	0.7959	0.8300	0.4050	−0.8974	2.2226

Appendix 5
Overall covariance balance measures using different matching.

Matching algorithms	Before matching				After matching			
	Mean bias	Median bias	Rubin's B	Rubin's R	Mean bias	Median bias	Rubin's B	Rubin's R
Kernel normal	16.17	5.51	70.96	24.54	5.51	4.92	24.54	0.82
Kernel epanechnikov	16.17	3.48	70.96	12.21	3.48	2.50	12.21	1.18
caliper	16.17	12.40	70.96	55.86	12.40	7.97	55.86	0.67
NN: 1	16.17	11.37	70.96	58.97	11.37	10.42	58.97	1.06
NN: 2	16.17	11.16	70.96	50.28	11.16	11.73	50.28	1.25
NN: 3	16.17	4.81	70.96	22.30	4.81	4.44	22.30	0.85
NN: 4	16.17	6.66	70.96	28.77	6.66	7.04	28.77	1.00
NN: 5	16.17	4.90	70.96	18.54	4.90	4.93	18.54	0.77

Note: Mean and median bias are summary indicators; they shows the mean and median value of the absolute standardised bias before and after matching. Standardised bias (SB) is an indicator that was suggested by Rosenbaum and Rubin (1985). For each covariate X it is defined as the difference of sample means in the treated and matched control subsamples as a percentage of the square root of the average of sample variances in both groups. $SB_{before} = 100{*}\frac{(\overline{X_1} - \overline{X_0})}{\sqrt{0.5{*}(V_1(X) + V_0(X))}}$; $SB_{after} = 100{*}\frac{(\overline{X_{1M}} - \overline{X_{0M}})}{\sqrt{0.5{*}(V_{1M}(X) + V_{0M}(X))}}$. where X_1 (V_1) is the mean (variance) in the treatment group before matching and X_0 (V_0) the analogue for the control group. X_{1M} (V_{1M}) and $X_{0M}(V_{0M})$ are the corresponding values for the matched samples (Caliendo and Kopeinig. 2008).

Appendix 6
Difference in Difference (DiD) estimation results.

	DiD	Std. error	z-Score	p-Value
AES_1				
Eco-Eff	0.006	0.020	0.300	0.764
Output	18.746	16.077	1.166	0.244
Inputs	−0.852	7.119	0.120	0.905
AES_2				
Eco-Eff	0.003	0.022	0.159	0.874
Output	12.081	17.569	0.688	0.492
Inputs	−3.361	7.906	0.425	0.671
AES_3				
Eco-Eff	−0.001	0.021	0.038	0.970
Output	10.010	17.701	0.566	0.572
Inputs	−2.724	9.169	0.297	0.766
AES_4				
Eco-Eff	0.013	0.018	0.739	0.460
Output	23.153	20.714	1.118	0.264
Inputs	−2.509	10.572	0.237	0.812
AES_5				
Eco-Eff	0.017	0.067	0.254	0.799
Output	42.335	38.054	1.113	0.266
Inputs	31.367	33.394	0.939	0.348

Note: Eco-Eff: bias corrected eco-efficiency scores; Output = Gross Farm Income (the difference between total output and intermediate consumption), Inputs: sum of energy, fertilizer, crop protection costs in real value.

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