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INVESTIGATING ECO-EFFICIENCY OF EU FIELD CROP FARMS – A NEURAL NETWORK APPROACH FOR ASSESSING THE IMPORTANCE OF AGRI-ENVIRONMENTAL SUBSIDIES

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ABSTRACT. Agri-environmental subsidies (AES) are described as a key agricultural policy tool used to promote environmentally friendly farming. The European Green Deal has set ambitious targets for the neutralization of greenhouse gas emissions, which also set higher targets for agriculture's contribution to this goal. Improving agricultural eco-efficiency is seen as one of the most cost-effective ways to achieve sustainable agricultural development. The empirical evidence on the combined environmental and economic significance of AES schemes on the eco-efficiency of EU agriculture is limited. This research aims to assess the eco-efficiency of field crop farms in EU countries and to investigate the importance of AES and other selected economic and policy factors on their eco-efficiency. Data Envelopment Analysis (DEA) was used to assess eco-efficiency for EU field crop farms. Multiple regression analysis and multilayer perceptron (MLP) neural networks were then applied to evaluate the importance of AES and other factors. Analysis of the determinants of eco-efficiency and comparative analysis using t-tests were then used to identify significant differences between different eco-efficiency groups. The study indicated the decline in eco-efficiency of EU field crop farms overall during the time period analyzed. The AES was identified as the most important factor at the level of EU countries, particularly for the countries in the lower eco-efficiency group. This highlights the importance of targeted environmental support measures, AES in particular, especially for newer Member States, to improve agricultural sustainability across the EU.

JEL Classification: Q18, Q57, C45, Q56, C61

Keywords: agri-environmental subsidy, artificial neural network, European Green Deal, sustainable agriculture, agricultural eco-efficiency

Introduction

The agricultural eco-efficiency assessment is driven by the need to contribute to climate change management and to mitigate the impacts of agricultural activities. Assessment of eco-efficiency provides agricultural policymakers with important information for designing policies aimed at sustainable management and efficient use of natural resources in the agricultural sector (Coluccia et al., 2020; García-Agüero et al., 2023). By improving the efficiency of resource use, agriculture can produce more with less, reducing the depletion of essential resources (Aguilera et al., 2020; Hajdukiewicz & Pera, 2023). Eco-efficient agricultural practices minimize the impact of land and water pollution, and greenhouse gas emissions by reducing the need for chemical inputs, promoting sustainable land and water use, lowering carbon footprints, and contributing to climate change mitigation (Fusco et al., 2023; Wang et al., 2022; Batlles-delaFuente et al., 2024). Measuring eco-efficiency in the agricultural sector can provide important information for efficient use of natural resources and sustainable management in agriculture (Colmenares & Cando, 2021; Coluccia et al., 2020). As concerns about preserving and enhancing the EU's natural capital and protecting citizens' health and well-being from climate- and environment-related risks have grown, so has the emphasis on environmentally friendly farming practices at the European level. This trend is reflected in the EU's Common Agricultural Policy (CAP) strategy, the CAP Strategic Plan 2023-2027 and the European Green Deal (Balcerzak et al., 2023). AES implemented under EU's CAP support activities that help protect, restore and enhance natural resources in rural areas, and focus on activities that aim to increase resource efficiency and reduce the climate impact of agriculture (Mottershead et al., 2018; Gavrilă-Paven and Wainberg, 2023; Streimikis and Kyriakopoulos, 2024). Knowledge of the importance of AES, as well as other complementary factors, can contribute to achieving the climate change mitigation targets set by the European Green Deal. Similarly, the contribution of AES could be further enhanced through improved monitoring and more effective impact assessment. Gaining this knowledge would enable the implementation of more targeted policy measures, accounting for the actual influence of these initiatives as well as the needs of the beneficiaries.

The aim of this research is to assess the eco-efficiency of EU field crop farms over the period 2017–2021. More specifically, we analyze the importance of CAP AES and other selected economic and policy factors on the eco-efficiency of field crop farms. The objectives of this study are to analyze the concept of agricultural eco-efficiency and to identify its main determinants. We will assess the eco-efficiency of EU field crop farms and investigate the importance of AES and other selected factors on the eco-efficiency of these farms using multiple regression analysis and artificial neural networks (ANN). A critical aspect of our research will be to compare the results from the regression analysis with those from the neural networks, also to assess the importance of AES and other factors. Finally, we will present our findings and provide recommendations based on the importance of AES and other key factors. The study used data from the Farm Accountancy Data Network (FADN), covering EU field crop farms from 2017 to 2021, with input and output variables weighted by farm averages.

In order to meet the above objectives, first, a literature review was carried out to analyze the main concepts, evidence and existing gaps in this research area, followed by the identification of the indicators and methods required for the study. And after our analysis was conducted in two stages.

The article is structured as follows. The first is a literature review that explores the concept of eco-efficiency and its assessment, highlighting studies on sustainable agriculture, the role of AES and other factors influencing agricultural eco-efficiency. The research methods section describes the methods and techniques used, the data selected and the stages of the research that addressed the research objectives. The Results section presents and analyzes the models developed and the corresponding results. The Discussion section is dedicated to further discussion and comparison of the results with other authors. At the Conclusions section the research findings together with research limitations and directions for future research are summarized.

1. Literature review

1.1. The eco-efficiency concept as a tool to sustainable development of agriculture

Rapidly growing human needs for food, fresh water, timber, fibre and fuel increased air and water pollution, along with climate warming in recent decades (Millennium ecosystem ..., 2005; Mukaila, 2022). The Brundtland Commission introduced the principle of "Producing more with less" and laid the foundations for the introduction of the eco-efficiency concept (WCED, 1987). The Treaty of Amsterdam emphasized the need to integrate environmental considerations into various policy areas (European Community, 1997). Economic sectors were tasked with monitoring and improving their "ecological efficiency."

The concept of eco-efficiency takes into account economic and environmental aspects when improving products, processes and technologies, and allows choosing environmentally friendly solutions:

- relates the pursuit of ecological efficiency to meeting human needs and ensuring quality of life, when the use of natural resources meets the limits of the planet's boundaries (WBCSD, 2006; Firlej et al., 2024);
- the dominant idea is "to produce more with less" (Côté et al., 2006);
- is associated with the production of goods and the provision of services, while aiming to damage the environment as little as possible (Kuosmanen & Kortelainen, 2005);
- the eco-efficient solutions are those that minimize the use of natural resources while maintaining or even increasing production levels (Gołaś et al., 2020).

The concept of agricultural eco-efficiency offers a comprehensive perspective that integrates both economic and environmental dimensions of agriculture. The integration of utilitarian and sustainability principles in economic decision-making is increasingly recognized as a foundation for balancing economic efficiency with environmental responsibility, which underpins the rationale for eco-efficiency in agriculture (Mumcu, 2024). We can distinguish the following goals of this concept highlighted by the researches: it aims to increase the production of high-quality agricultural products while minimizing the consumption of economic and environmental resources, including material costs, agricultural resources, and environmental pollution (Czyżewski et al., 2021; Keating et al., 2010; Li et al., 2022; Wang et al., 2022). By focusing on resource efficiency and promoting sustainable practices, agricultural eco-efficiency both induces productivity and saves essential resources (García-Agüero et al., 2024).

Today, scientists recognize that economic growth and development must be accompanied by decreasing environmental impact and attention to environmental protection (Sadorsky, 2021; Sdrolia & Zarotiadis, 2019; Peña et al., 2023; Niță et al., 2024), so agricultural eco-efficiency could be used as an effective tool for evaluating sustainable agricultural development (Richterová et al., 2021; Wang et al., 2022; López-Serrano et al., 2023). In this way economic and environmental aspects of agriculture are integrated and reduction in recourse consumption and environmental pollution meets the human needs (Simioni & da Silva, 2021; Wang et al., 2022). The economic policy measures aimed at sustainable agricultural development are considered as important external factor that has a decisive influence on agricultural eco-efficiency (Wang et al., 2022). So, AES implemented under EU CAP are seen as a main external driver shaping European agriculture to environmentally sustainable (Coderoni & Esposti, 2018; Eder et al., 2021).

Recent studies highlight the negative impacts of agriculture, which is a major contributor to global climate change. Agriculture's response to high market demand for fresh food and biofuels has led to high-output, intensive agricultural practices which resulted in environmental pollution, overexploitation of resources and ecosystem degradation (Ait Sidhoum, Mennig, et al., 2023; Baum & Bieńkowski, 2020; Gołaś et al., 2020).

The demand for agricultural production cannot overshadow the need to reduce the environmental impact of agriculture. And at this point, the concept of agricultural eco-efficiency is seen as the most cost-effective way to achieve these goals (Coderoni & Esposti, 2018; Eder et al., 2021), which also helps to realise the sustainable use of resources and promotes the development of efficient ecological agriculture (Wang et al., 2022).

The importance of eco-efficiency is also reflected in the 8th Environment Action Programme. This programme reaffirms the EU's long-term vision up to 2030 of living well and within planetary boundaries. The priority objectives of the 2030 Agenda are all related to mitigating climate change, enhancing natural capital, protecting bio-ecological diversity, and increasing eco-efficiency. The Programme sets out the conditions necessary to achieve the priority objectives while emphasising the need to improve resource efficiency and the reduction of environmental impacts while maintaining economic growth (The European Parliament and the Council of the European Union, 2022).

The European Green Deal is aimed to speed up Europe's transition towards a climate-neutral, resource-efficient economy, while recognising that healthy, fully functioning ecosystem is a prerequisite for human well-being and prosperity (European Commission, 2019). Increasing agricultural eco-efficiency targets the specific objectives of The European Green Deal: to restore degraded ecosystems, increase biodiversity, reduce greenhouse gase (GHG) emissions, maintain carbon sinks, promote organic farming, minimize the use of pesticides and fertilisers, and reduce soil degradation. According to Rudnicki et al. (2023), agriculture plays a key rol in achieving the goals of the European Green Deal, and one of the preconditions is the recognition of the eco-efficiency of the mechanism that underpins the activities of the farms in terms of the pro-environmental measures implemented in the CAP.

1.2. Using agri-environmental subsidies to achieve environmental goals in agriculture

The findings of Millennium Ecosystem Assessment reveal negative impact of intensive agricultural practices have a on terrestrial ecosystems and some impacts are irreversible (Millennium ecosystem ..., 2005). The ESs budget for agri-environmental support has been increasing over the last ten years. AES implemented under the EU CAP provide financial support for EU farmers for implementing agri-environmental measures that address mitigation or adaption to climate change issue through increasing biodiversity, improving soil, water, landscape, or air quality. The objectives must deliver environmental benefits, and it is therefore important to assess the environmental performance of the measures.

For the period 2023-27, the EU CAP Strategic Plan is built around ten key objectives (European Commission, 2021). One of the keys is environmental care. The sustainability of agriculture is largely dependent on environmentally sustainable farming practices. The assessment of those environmental measures allows to assess how the climate change goals provided in the EU CAP are achieved.

AES are support measures aimed at promoting environmentally friendly farming practices, enhancing biodiversity, reducing GHG emissions, and mitigating the negative environmental impacts of agriculture. It can be stated that the purpose of the AES is in line with the objectives of the eco-efficiency concept, and therefore the AES is the main financial instrument for increasing the eco-efficiency of agriculture. Researchers are debating the economic and environmental impact of AES implemeted through the EU CAP, on agricultural eco-efficiency and productivity.

The question of the influence of AES on the eco-efficiency of EU farms has been addressed by many authors, but there is no definitive answer yet. The studies of Ait Sidhoum, Mennig, et al. (2023), Stetter et al. (2022), Tzemi & Mennig (2022) demonstrate to have insignificant impact on reducing negative externalities of agriculture or in some cases even adverse effects (Stetter et al., 2022). It should be noted here that these studies were conducted at the level of one region. However, a number of researchers also substantiate the positive effect of AES, contributing to increasing agricultural eco-efficiency (Beltrán-Esteve et al., 2012; Kryszak et al., 2021; Picazo-Tadeo et al., 2011) or reducing the negative externalities (Eder et al., 2021).

A further and more detailed analysis is required - to determine how AES contribute to the implementation of the climate change goals set by EU strategic documents, and in the context of this study - to the agricultural eco-efficiency.

1.3. Assessing agricultural eco-efficiency – a comprehensive review of previous studies

The pursuit of sustainable agricultural development faces an existing contradiction between agricultural productivity and environmental protection. The literature review of earlier studies of agricultural eco-efficiency indicates its rapid develpment stage in recent decade this is linked to the deepening problems of environmental pollution, resource depletion and overarching climate change (Wang et al., 2022).

Previous studies focus on the analysis of the agricultural eco-efficiency both at the farm level of a single country or its region, and by comparing/analyzing the agriculture of several countries or regions.

The studies of agricultural eco-efficiency at the country level cover diverse periods and involves variant countries, the results of these studies indicate differences in eco-efficiency between countries. Early study of Hoang & Alauddin (2012) focused on the environmental and ecological performance of agriculture in thirty OECD Countries during the period 1990-2003, revealing there was a huge potential for inputs savings that could reduce bad environmental outputs caused by nitrogen and phosphorus by more than half, and enhance environmental sustainability. The study suggests that the performance of the country is very much linked to the structure of each country's agriculture sector and agro-envirnonmental policies. Based on results of Moutinho et al. (2018) the agriculture eco-efficiency of 22 EU countries remain overall at the same level in years 2005 and 2010, although some countries improved their eco-efficiency and some got worse, the latter mostly include the newly joined EU countries, however the improvement in eco-efficiency is attributed to CAP policy measures promoting sustainable agriculture practices. There is an improvement of EU member states agricultural eco-efficiency observed through the period 2004-2017, mainly related to positive impact of investment support and AES (Czyżewski et al., 2021). The agricultural eco-efficiency was increasing in NUTS 2 regions within the Visegrad 4 (except Poland) through the years 2013–2017, although 23 regions (out of 32) were not fully eco-efficient, here more efficient input use and new technologies could support with increasing agricultural eco-efficiency (Richterová et al., 2021). Rybaczewska-Błazejowska & Gierulski (2018) investigated eco-efficiency of 28 EU countries agriculture sector in year 2015, the results revealed that more than half of EU's agriculture sectors were eco-inefficient, so better resource management and effective agricultural policy measures in place could lead to more sustainable agriculture. The study of Pishgar-Komleh et al. (2021) assessed the eco-efficiency in agriculture sector in 27 EU countries through the period 2008-2017. The findings of this study revealed higher eco-efficiency scores of old EU members compared to a new ones, slight improvement of average EU eco-efficiency score observed in 10 years period. The results emphasize that the agriculture of the new EU members needs more such agri-support measures that promote sustainable agricultural development.

The analysis of agricultural eco-efficiency studies at the country level reveals clear differences between countries and highlights opportunities for improving environmental sustainability associated with agriculture. In some countries, the growth of agricultural eco-efficiency is observed, partly due to CAP policy measures and AES, but most of the new EU members have lower agricultural eco-efficiency. Environmental measures to promote sustainable farming practices are becoming increasingly important to close the gap in agricultural eco-efficiency between EU countries. Actions include better targeting of such measures, more efficient use of resources and investment in more efficient technologies.

The studies discussed unviel the increasing importance of agricultural eco-efficiency in reducing environmental pollution while maintaining agricultural productivity. It is therefore important to analyse the role of AES in the context of the EU CAP in promoting sustainable farming practices, reducing greenhouse gas emissions and addressing the eco-efficiency gap between EU Member States.

Comprehensive reviews of sustainable performance assessment frameworks emphasize the importance of integrating economic, environmental, and social indicators in evaluating agricultural systems, supporting the multidimensional approach adopted in this study (Farchi et al., 2021).

1.4. Factors influencing eco-efficiency in agriculture

The significant amount of EU CAP budget funs are allocated to AES, but there are still debats going around the proper targeting of these subsidies and their contribution in stimulating positive environmental impacts (Scown et al., 2020; Stetter et al., 2022; Tzemi & Mennig, 2022). Reorganization and transformation of agriculture in EU countries takes place at a different pace, various fiscal policy, operating environment, technological factors influence changes in farming activities (Bojnec et al., 2014).

As for the group of economic factors, subsidies on investments were found to have significant positive influence of environmentally sustainable value of EU FADN farms in period 2004-2017, as well as capital to labour ratio (Czyżewski et al., 2021). And yet capital to utilised agriculture area (UAA) ratio had significant negative impact on eco-efficiency. Other production payments stood out having negative impact on eco-efficiency, that included less favoured area payments as well.

When analyzing eco-efficiency of Austrian crop farms in period 2008-2011, the share of rented land had negative impact on farms eco-efficiency, and neither farm size in ha either debt to asset ratio seemed to have no significant impact (Eder et al., 2021). The farm size was also found to have no significant impact on farm eco-efficiency both in studies of Picazo-Tadeo et al. (2011) of farms in Campos County (Spain) and Bonfiglio et al. (2017) of crop farms in Le Marche region (Italy). Czyżewski et al. (2021) also notes that new EU Member States (mainly Central and Eastern Europe) were well less eco-efficient.

When it comes to assessing the influence of AES, this issue is approached in various ways across studies. Empirical research confirms that farm participation in AES programs is positively related to the eco-efficiency of the farm. (Bonfiglio et al., 2017), and have significantly contributed to improvement of soil conservation (Eder et al., 2021). When evaluating the part of agricultural land dedicated to agri-environmental schemes, it demonstrated significantly positive influence on eco-efficiency (Bonfiglio et al., 2017; Picazo-Tadeo et al., 2011). Both studies of Bonfiglio et al. (2017) and Czyżewski et al. (2021) find that the size of AES is an important determinant of eco-efficiency, suggesting that strong support for AES should be maintained.

A review of previous empirical studies allows us to conclude that agricultural eco-efficiency is a widely researched topic, considering its significance in the context of sustainable agricultural development. It is important to note that frequent studies share a common shortcoming — when assessing agricultural eco-efficiency, the negative environmental impacts of agriculture are not included (Ait Sidhoum, Canessa, et al., 2023; Czyżewski et al., 2021; Eder et al., 2021; Richterová et al., 2021). The agricultural eco-efficiency assessment without accounting for these externalities may lead to incomplete or misleading evaluations of agriculture development. Our study will address this gap by incorporating undesirable outputs, such as GHG emissions, into the eco-efficiency assessment. This approach allows us to better capture the environmental impact of farming practices.

When examining the influence of AES on agricultural eco-efficiency, some studies have been limited to analysing farms within a single region (Bonfiglio et al., 2017; Eder et al., 2021; Picazo-Tadeo et al., 2011), some of it examine participation in those subsidies, other studies - the area dedicated to these subsidies schemes. However, the analysis also reveals a common opinion that can be drawn from those studies - future research should focus on analysing the specific determinants of agricultural eco-efficiency, here we pay special interest on the importance of AES, as to an instrument that helps to solve the problem of agricultural impact on the natural environment. The following research hypothesis is addressed:

H: The agri-environmental subsidies are the most important factor influencing eco-efficiency of field crop farms in EU countries.

Thus, with this research, we contribute by investigating the importance of AES and selected factors on the agricultural eco-efficiency using modern machine learning techniques such as ANN, and by offering a way to improve model results by modifying the variables accordingly. The analysis of selected economic and policy factors will provide insights into the context in which AES are implemented and allow for targeted planning and more accurate implementation of CAP support measures.

2. Research methods

In order to achieve the objectives of our research, we have divided our methodological approach into two stages, and the illustrative scheme of our research is presented in *Figure 1*. The steps in these stages are explained in more detail below.

The first stage of our research includes the following steps: (1) the selection of input and output variables, data collection and calculation, (2) the selection of an appropriate DEA model based on our research objectives, (3) the estimation of AEE scores and their statistical analysis.

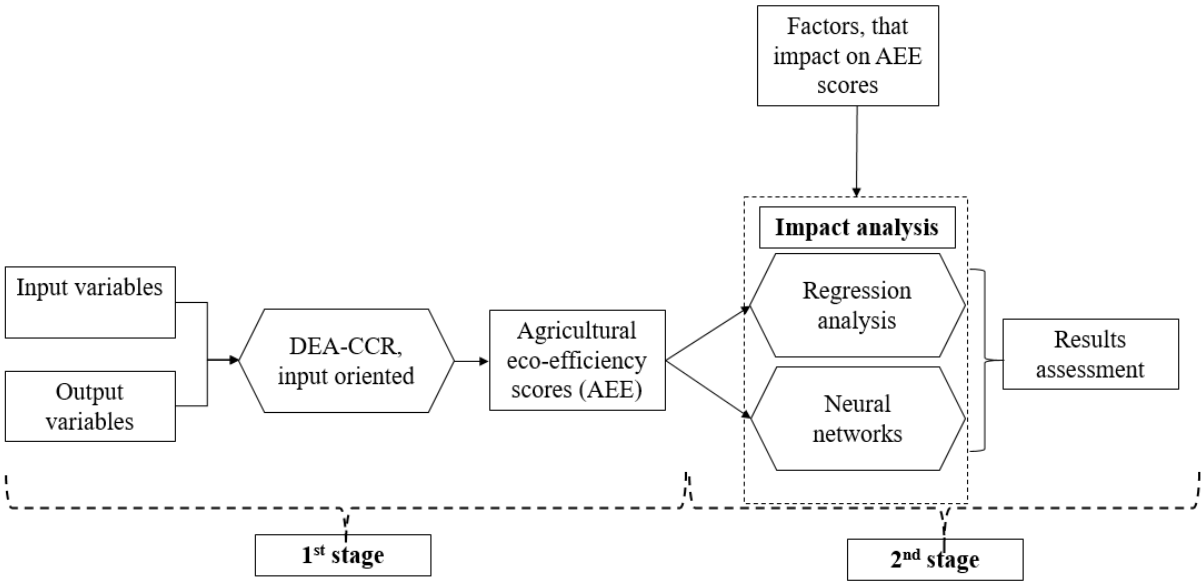

Figure 1. Stages of our analysis
Source: *own elaboration*

The analysis of agricultural eco-efficiency assessment studies in the previous section highlighted the key input and output variables commonly used in these studies. It is important to note that there is no mainstream framework for the selection of variables for eco-efficiency analysis (Wang et al., 2022) and this decision is left to the discretion of the researcher. As the previous studies have shown, eco-efficiency assessment usually includes the variables of produced capital and labour, while the inputs of produced capital include the means of production required for agriculture. The attention here is paid to the inclusion of pollution-causing variables (Vlontzos & Pardalos, 2017). When considering the output variables, we need to consider both desirable and undesirable outputs that are generated by agricultural production. Notably, some studies share a common shortcoming - they fail to account for the undesirable outputs of agriculture when assessing eco-efficiency. Accordingly, Dabkiene (2017) and Mohammadi et al. (2013) state that the use of chemical fertilizers in agriculture is the main source of GHG emissions, and inefficient farms have the potential to reduce the use of chemical fertilizers, thereby reducing environmental pollution. Since the amount of GHG emissions differs between efficient and inefficient research units (Khoshnevisan et al., 2013), incorporating undesirable outputs into eco-efficiency calculations provides a more realistic assessment of agricultural practices and allows to assess the impact of the applied measures on pollution reduction. In this respect, this study aims to fill the gap in previous research by including the variable of undesirable production output – specifically, the pollution from agricultural GHG generated by managed soils.

Five variables were selected as input variables in this research. These are: Labour (Annual Working Units per hectare (AWU/ha), Seeds in Euros per hectare (€/ha), Fertilisers and soil improvers in €/ha, Energy in €/ha (that includes motor fuels and lubricants, electricity, heating fuels), Depreciation (of capital assets) in €/ha. In particular, the hectares (ha) used here corresponds to average utilised agricultural area of the farm.

The output variable was defined as GHG benefit and is calculated as the ratio between the desirable undesirable and the undesirable production output (Moutinho et al., 2018; You & Zhang, 2016). Therefore, the ratio of the total output of crops and crop production (€) to the variable of GHG emissions (t of CO2e) stands as an output variable. The growth of such an output variable is then related to the increasing value of the desired output or environmental pollution.

Since the output variable required additional calculation, GHG emissions from field crop farms in each EU country were calculated using the Tier 1 methodology outlined in the IPCC guidelines (IPCC, 2019). Specifically, direct N_2O emissions from managed soils were estimated using Equation 11.1 and Table 11.1. Indirect N_2O emissions due to atmospheric N deposition from evaporation were calculated using Equation 11.9 and Table 11.3. In addition, indirect N_2O emissions due to leaching and runoff were determined using equation 11.10 and table 11.3. Accordingly, the amount of N_2O emissions were converted to CO2 equivalents based on IPCC data on the 100-year global warming potential of N_2O (Forster et al., 2007).

Based on a previous review of agricultural eco-efficiency assessments, Data Envelopment Analysis (DEA) is one of the most frequently chosen approaches. This non-parametric method was used to evaluate the eco-efficiency of decision-making units (DMUs), specifically the EU field crop farms in this context, by defining eco-efficiency as the ratio of a weighted sum of outputs to a weighted sum of inputs. The DEA model is explained in detail by Charnes et al. (1978) and Banker et al. (2004).

In this research in respect to Beltrán-Esteve et al. (2012) and Picazo-Tadeo et al. (2011) we applied constant returns to scale DEA model (hereinafter DEA-CCR), i.e. agricultural activity can be considered operating under conditions of constant return, and the choice of return is more related to the applied farming practices and their impact on ecosystems. The orientation of the model was chosen as input orientation based on repeated assumptions that agricultural producers have more control over the choice of inputs than the output (Czyżewski et al., 2021; Eder et al., 2021; Pishgar-Komleh et al., 2021; Syp et al., 2015). Thus, the eco-efficiency score of an EU country in the DEA-CCR model is the ratio of the weighted sum of its outputs to the weighted sum of its inputs and is calculated for each country relative to the other countries in the dataset. It is expressed as a value between 0 and 1, with a score of 1 indicating that the country is operating eco-efficiently, i.e. maximising its output relative to its inputs. A score below 1 indicates inefficiency, i.e. the country could produce the same output with fewer inputs.

In the last step of the first stage the summary (and descriptive) statistics of input-oriented eco-efficiency scores (DEA-CCR model) of EU field crop farms over the time is presented.

In addition, the sample was divided into two groups based on the 5-year average eco-efficiency scores of EU field crop farms: Group 1, consisting of farms with scores below the mean, representing lower eco-efficiency farms, and Group 2, comprising farms with scores above the mean, representing higher and fully efficient farms. Dividing farms into separate eco-efficiency groups allows us to better explain the differences in the importance of AES and selected factors on the eco-efficiency and to draw more targeted conclusions.

The second stage of the research focuses on assessing the importance of the AES and other selected factors on agricultural eco-efficiency and consists of the following steps: (1) selection of influencing factors and data collection, (2) analysis with multiple regression, (3) corresponding model construction, (4) analysis with ANN, (5) interpretation and evaluation of research results.

The previous review of empirical studies (Bojnec et al., 2014; Czyżewski et al., 2021; Dakpo & Latrufffe, 2016; Eder et al., 2021; Niavis et al., 2018) allowed us to identify the most frequently studied factors influencing agricultural eco-efficiency, including AES. Therefore, the following variables, based on data availability, were selected to explain the eco-efficiency scores of EU field crop farms.

There are seven input variables in the second stage of the research. Namely, AES (AES) in €/ha, Investment subsidies (Invsub) in €/ha, Rented land ha/UAA ha, Size (Size) is the economic size of the farm expressed in €'000 of standard output, Capital (Capital) here stands for average farm capital (excluding land) in €/hour of labour hours, Debt ratio (Debt_ratio) is defined as the the total amount of liabilities in € per the total amount of assets in €. These six variables represent the economic factors of the research. The dichotomous variables Old 0 (representing the countries that joined the EU before 2003) and New 1 (countries that joined the EU since 2004 and after) are dummy variables, that represent policy factor. The output variable is the agricultural eco-efficiency score calculated in the first stage of the research.

Next, the influence of AES and other factors on the eco-efficiency of EU field crop farms was assessed using multiple regression analysis (Studenmund, 2014) so to explain their contribution to the eco-efficiency. Correspondingly, separate multiple regressions for Group 1 and Group 2 were also performed to further explore the importance of factors on different eco-efficiency groups. The goodness of fit of these models was assessed using the coefficient of determination (R^2), the distribution of the residuals of the models was checked using the Shapiro-Wilk test, the heteroskedasticity in the models was checked through inspecting the residual plots.

As an alternative method to multiple linear regression, this study chose to use the ANN. It should be noted that if the database contains high variability of the data and extreme outliers within the dataset, the ANN can be used to obtain more reliable results. The ANN models are used to solve complex agricultural problems, especially when there are multiple non-linear relationships between the phenomena studied, and are applied in the fields of agronomy, agribusiness management and economic development of the agricultural sector. Our research employs the Multilayer Perceptron (MLP) neural network available in SPSS.

As regards the variables in our second database, they are measured in different scales and this can cause learning instability and can hinder the proper initialization of weights in neural networks as well. Since MLP neural network method will yield better models when similar scales for the variables are used, the original variable values of the second database were first standardized by calculating their differences from their medians and then dividing these values by their means of the absolute deviations (MAD). This type of data standardisation will address data-related issues and improve model performance and interpretability.

The impact of factors on the eco-efficiency of EU field crop farms was then assessed using MLP neural networks on the full dataset, and separate MLP neural network models were constructed for Group 1 and Group 2 to investigate the importance of AES and selected factors in different eco-efficiency groups.

When constructing our models, the hyperbolic tangent activation function was used in the hidden layer and the activation of the output layer was based on the softmax function. We tried different versions of MLP neural networks with SPSS, changing the number of hidden layers and the number of neurons. The final models were those that had minimum model error and performed sufficiently well in predicting the eco-efficiency score. Only training data was used in our model due to the limited database. The quality of the created MLP neural network models was measured by the coefficient of determination (R^2).

The dataset used for the empirical analysis was obtained from the Farm Accountancy Data Network (FADN) on a panel of EU field crop farms, covering the period 2017-2021. The medium-term period data was selected for several reasons. Firstly, using long-term data could distort eco-efficiency estimates due to overlapping CAP reforms or other policy changes and structural changes in the agricultural sector (Coderoni & Esposti, 2018). Secondly, the data required for the study, specifically the amount of N (kg) in fertilizers applied to the soil, has been available for the most EU member states starting from 2017. During the period covered by the research, the EU consisted of 27 countries. The research does not include the United Kingdom, as it has not been a member of EU since 2020, it would lack data for 2020 and 2021, and since the country is no longer an EU member, the implementation of EU regulations and the EU CAP no longer applies there. However, since the nitrogen data needed for the calculating of GHG emissions was missing for the whole period for Romania, this country was excluded from the dataset. The input and output variables for both the first and the second stages of research are weighted averages by farm, as reported in the FADN. Here field crop farms according to the EU Types of Farming (TF8) classification include these main types of farming: specialist cereals, oilseeds and protein crops, general field cropping, mixed cropping. Previously reviewed studies highlighted the importance of farm homogeneity in efficiency benchmarking, where farms from similar regions and the same farming type were selected for analysis (Eder et al., 2021; Madau et al., 2017). The heterogeneity of European agriculture has also been observed by Bojnec et al. (2014), Moutinho et al. (2018). Therefore, choosing a specific type of farming ensures that technologically similar farms are compared, making the information more comparable and allowing a more accurate assessment of the importance of AES (Beltrán-Esteve et al., 2012).

3. Results

The significance of crop farming in the EU economy has been steadily growing over the past 10 years, regardless of climate change or rising prices for the inputs needed for agricultural production. This is associated with increased yields, demand for plant-based products, as well as rising production prices. Field crop farming, such as cereals, oilseeds, vegetables, and fruits contributed around 50-53% of the total value of agricultural production in the EU agricultural sector in the period 2017-2021 (European Commission, n.d.). Intensive field crop farming is inextricably linked to environmental impacts. According to the report of the European Court of Auditors (European Court of Auditors, 2021), the use of soil nutrients in crop production has increased the amount of GHG emissions emitted, accounting for 33% of all GHG emissions emitted by EU agriculture. The growing amount of GHG emissions is mainly related to the increased use of fertilisers. GHG emissions from crops and grassland accounted for 14% of total GHG emissions from EU agriculture and have not decreased for more than a decade. In this context enhanced eco-efficiency in field crop farming could lead to potential reductions in chemical fertilisers and other polluting inputs, thereby improving GHG emissions performance.

Based on selected input and output variables, the eco-efficiency of field crop farms of a representative sample of EU countries was calculated using the DEA-CCR (input oriented) approach. *Table 1* presents the eco-efficiency scores of field crop farms in EU, where countries are sorted in descending order based on their 5-year means.

Table 1. Descriptive statistics of the DEA-CRS (input-oriented) eco-efficiency scores of EU field crop farms over the period 2017-2021

DMU's	Mean	SD	Change (%) 2017-2021
Belgium	1.000	0.000	0.00%
Denmark	1.000	0.000	0.00%
Greece	1.000	0.000	0.00%
Ireland	1.000	0.000	0.00%
Italy	1.000	0.000	0.00%
Malta	1.000	0.000	0.00%
Netherlands	1.000	0.000	0.00%
Portugal	1.000	0.000	0.00%
Austria	0.977	0.036	0.00%
Spain	0.975	0.034	-9.13%
Hungary	0.942	0.030	-1.49%
Sweden	0.925	0.090	6.26%
Germany	0.920	0.089	-32.10%
Slovenia	0.911	0.097	-10.22%
Luxemburg	0.899	0.066	8.01%
Bulgaria	0.883	0.065	11.52%
Cyprus	0.872	0.057	11.80%
Poland	0.866	0.071	7.24%
France	0.840	0.036	-4.78%
Estonia	0.827	0.105	-5.91%
Lithuania	0.794	0.137	-11.23%
Latvia	0.779	0.115	-31.59%
Czech Republic	0.761	0.029	-3.85%
Slovakia	0.750	0.032	-4.69%
Croatia	0.731	0.040	-6.47%
Finland	0.708	0.050	-19.45%
EU	**0.898**	**0.020**	**-3.13%**

Source: *own compilation*

At the top of the list are fully eco-efficient countries, wherein the average eco-efficiency was equal to 1 throughout the study period and with no change in eco-efficiency and no variability in SD. These countries (Belgium, Denmark, Greece, Ireland, Italy, Malta, Netherlands, Portugal) have consistently high eco-efficiency scores with no fluctuation, which suggests that their agricultural practices are sustainable, they work optimally and maintain the achieved eco-efficiency level.

The countries with their mean between 0.977 and 0.899 are in the middle of the list. The SD values of these countries vary, for example, it is lower in Austria and higher in Luxembourg. Meanwhile, the 5-year changes of these countries vary considerably. Austria, Spain, Hungary, Sweden, Germany, Slovenia and Luxembourg have relatively high eco-efficiency scores, but the stability of their performances varies over time. Positive changes, and higher SD values, in eco-efficiency scores are observed in Sweden and Luxembourg. Austria's eco-efficiency fluctuated over our research period but remained generally stable. Spain, Hungary, Germany and Slovenia show SD variability and negative changes in eco-efficiency over our research period. The eco-efficiency values of field crop farming are in these countries unstable.

The means of the lower performing countries (Bulgaria, Cyprus, Poland, France, Estonia, Lithuania, Latvia, Czech Republic, Slovakia, Croatia, Finland) vary between 0.708 and 0.883. In these countries there is a higher variation of their SD values that is also indicative of the variability of the eco-efficiency scores. There are also clear differences between countries in terms of changes over the period, with most countries experiencing a worsening of the eco-efficiency (Lithuania, Latvia, Finland), whereas the eco-efficiency of Bulgaria, Cyprus and Poland increased over the period.

In general, the annual average eco-efficiency of EU fluctuates slightly over the five-year period, and the scores range from 0.875 to 0.927, this suggesting moderate to high eco-efficiency across the EU (*Table 2*).

Table 2. Summary statistics of EU field crop farms annual average eco-efficiency scores for the period 2017-2021

	2017	**2018**	**2019**	**2020**	**2021**
EU field crop farms	0.913	0.875	0.886	0.927	0.886

Source: *own compilation*

The eco-efficiency score of EU field crop farms for the whole period was 0.898, and the negative five-year change (-3.13%) indicates an unfavourable situation and thus a decrease in eco-efficiency over the period.

Due to the high variability in the eco-efficiency of EU field crop farms, it was decided to compare the eco-efficiency scores between high and fully eco-efficient countries and those with lower eco-efficiency by using the 5-year average eco-efficiency of EU field crop farms (0.898) as the cut-off point. The countries with a 5-year average eco-efficiency scores less than 0.898 were assigned to Group 1 and the rest to Group 2. Group 1 (mean=0.80) mainly included new EU members from Central and Eastern European countries that joined the EU in 2004 and after with the exception of France and Finland. Group 2 (mean=0.97), in turn, mainly included old EU member states. T-tests showed statistically significant differences between the mean eco-efficiency scores of these groups ($p<0.001$). The effect size measured as Cohen's d (-2.12) indicated a large difference between the groups, with Group 1's mean being significantly lower than Group 2's mean, suggesting these two groups are very different in terms of the eco-efficiency.

The second stage of the research begins with statistical summary of the factor variables of EU field crop farms. At this point, Malta was excluded from the research as it was considered to be an outlier according to its standardised factor variables values, and this, in turn, may be due to Malta's exceptional geographical conditions, its limited resources, and dominating small and micro-farm holdings compared to the rest of the EU countries (European Commission, n.d.).

Hence, for describing better our field crop farms in terms of the analysis of the impact factors, their descriptive statistics is presented in *Table 3*. These statistics are presented separately the data for all EU field crop farms (N=125), Group 1 and Group 2 (N=70). The grouping of the dataset is based on the cut-off point of the 5-year average eco-efficiency estimate (0.894 after removing Malta), which did not affect the distribution of the remaining countries between the groups.

Table 3. Descriptive statistics of factors affecting the eco-efficiency of EU field crop farms

Factor variables	All countries (N=125)			
	Mean	Median	SD	Min-Max
Inputs				
Old 0, New 1	0.440	0	0.498	0-1
AES	52.423	29.362	58.545	5.787-241.754
Invsub	25.328	9.451	45.248	0.000-332.159
Rent	0.550	0.510	0.187	0.145-0.888
Size	106.259	72.400	84.700	16.300-346.600
Capital	48.586	28.696	41.126	7.908-212.576
Debt_ratio	0.173	0.182	0.141	0.000-0.507
Output				
AEE score	0.898	0.934	0.114	0.609-1
Factor variables	Below the EU mean (N=55) Group 1			
	Mean	Median	SD	Min-Max
Inputs				
Old 0, New 1	0.818	1	0.389	0-1
AES	31.417	14.906	35.339	5.787-141.525
Invsub	20.096	13.348	21.618	0-109.585
Rent	0.626	0.661	0.210	0.275-0.888
Size	107.885	71.900	98.709	22.8-346.6
Capital	32.302	25.644	22.813	7.908-103.396
Debt_ratio	0.229	0.241	0.138	0.007-0.452
Output				
AEE score	0.801	0.788	0.096	0.609-1
Factor variables	Above the EU mean (N=70) Group 2			
	Mean	Median	SD	Min-Max
Inputs				
Old 0, New 1	0.143	0	0.352	0-1
AES	68.929	43.318	67.484	7.973-241.754
Invsub	29.438	7.412	57.225	0.00-332.159
Rent	0.489	0.480	0.140	0.145-0.759
Size	104.981	73.450	72.550	16.300-277.400
Capital	61.381	55.384	47.484	8.125-212.576
Debt_ratio	0.130	0.116	0.128	0.000-0.507
Output				
AEE score	0.968	1	0.062	0.747-1

Source: *own compilation*

When comparing Groups 1 and 2, we notice that,

- Group 2 had significantly higher means for variables AES, Invsub and Capital.
- Group 1 had slightly higher means for the variables Rent, Size and Debt_ratio.
- The medians of the variables also showed that Group 2 tends to have higher values for the AES and Capital variables, and this indicates clear differences between the groups, while according to the Rent and Size variables, there was more consistency between the groups.
- Group 2 has a much higher SD values of AES, this indicating a wider spread of AES values (as is the case for the Invsub variable). The higher SD values of the variable Capital in Group 2 also show that these values vary considerably compared to Group 1. As regards the variable Size of the groups, Group 1 shows a greater variability in the size of farms while Group 2 is more consistent.

- When comparing the minima and maxima of the variables, Group 2 had much higher maximum values for AES, Invsub and Capital. Group 1 seems to have slightly higher rent values overall, with a narrower range in Group 2. A greater variability in size was also observed in Group 1, which included farms that were both smaller and larger than those in Group 2.

In general, Group 1 appears to be more stable and homogeneous concerning its variable values, and it also showed more limited ranges across the variables except for Size and Rent. Group 2 shows more diversity and more extreme variable values, especially for AES, Invsub and Capital. The equality of means between the Groups is compared using t-test (*Table 4)*.

Table 4. Mean equality tests of factor variables affecting the eco-efficiency of EU field crop farms between Group 1 and Group 2

Test Statistic	Inputs							Output
	Old 0, New 1	AES	Invsub	Rent	Size	Capital	Debt_ratio	AEE score
t-test	-10.155	3.737	1.147	-4.355	-0.190	4.176	-4.157	11.764
p-value	<0.001	<0.001	0.253	<0.001	0.850	<0.001	<0.001	<0.001

Source: *own compilation*

The t-test also revealed statistically significant differences between the means of the variables AES, Capital, Rent and Debt_ratio across Group 1 and Group 2. The means of the variables AES and Capital are greater in Group 2, whereas the means of Rent and Debt_ratio are greater for Group 1. No significant differences were found between the groups for the variables Invsub and Size, this indicates that the groups are similar at this point.

Multiple regression analysis was used to investigate the influence of the selected factors. The analysis results of the panel data of EU countries field crop farms (2017-2021) in the case of the full data set and separately for Group 1 and Group 2 are presented in *Table 5*.

Table 5. Results of the panel data of EU field crop farms using multiple linear regression analysis (2017-2021)

Input variables	Dependent variable – eco-efficiency score of EU countries field crop farms		
	All farms (N=125)	Group 1 (below) (N=55)	Group 2 (above) (N=70)
Constant	0.997***	0.747***	0.987***
Old 0, New 1	-0.131***		
AES	0.000*	-0.001	0.000**
Invsub	0.001*		
Rent		0.209**	
Size		-0.001**	
Capital			
Debt_ratio	-0.206***		
Model fit – R^2	*0.347*	*0.223*	*0.097*

Significance at the 5%, 1%, and 0.1% level is indicated by *, **, and ***. Only final regression models are presented.
Source: *own compilation*

When analysing the full dataset, the impact variables being an "Old 0" or "New 1" EU Member State and Debt_ratio were significant at the 0.1% level, and the increases in these variable values would have a strong negative influence on the eco-efficiency of field crop farms.

Whereas Invsub and AES showed a small but still statistically significant positive effect on the eco-efficiency. As regards group 1, the significances of the variables Rent and Size were observed and Rent has a positive effect on the eco-efficiency, while Size has a small negative effect, both at the 1% level. AES in this model is marginally not significant (p=0.062). A small but statistically significant positive effect of the variable AES was noticed in group 2, while the other variables were insignificant and excluded from the model. The fit of the models, as indicated by R^2 values, were low, i.e. R^2=0.347 for the whole dataset, R^2=0.223 in group 1, and R^2=0.097 in group 2, indicating substantial unexplained variances in these regression models. Additionally, the distribution of the residuals was checked in all three models using the Shapiro-Wilk Test. A slight deviation from normality was observed in residuals of the full dataset model (p = 0.002). The residuals were normally distributed in the model of group 1 (p = 0.612), while the distribution of residuals in the model of group 2 (p <0.001) suggests strong violation of the normality assumption. Heteroskedasticity of the residuals in the models was also detected according to the visual inspection of the plots, and these residuals displayed a non-random pattern.

In the next step of the research, we applied artificial neural networks (MLP in particular) by using SPSS with the standardized factor variables as described in the Research methods section. This was done to overcome the high variability and extreme values in the dataset, as indentified during the statistical analysis. All the MLP neural networks included three layers. The input layer had eight neurons (one categorical with two categories and six continuous variables), and they forwarded the inputs to the hidden layer. The outputs of the hidden layer neurons were connected to an output layer. The data is passed through the layers by using the weighted connections. The hidden layer also uses a hyperbolic tangent activation function, while the output layer uses the softmax function.

We constructed separate MLP neural networks for full data set, Group 1 and Group 2. The results, provided by SPSS are presented in *Table 6*.

Table 6. Summary of MLP neural network models performance and architecture of EU field crop farms (2017-2021)

Model properties	Dependent variable – eco-efficiency score of EU countries field crop farms		
	All farms (N=125)	Group 1 (below) (N=55)	Group 2 (above) (N=70)
Model architecture			
Hidden layer	1	1	1
Number of neurons in the hidden layer	7	10	10
Importance of the variables			
AES	100.0%	100.0%	71.1%
Capital	73.7%	90.4%	68.9%
Debt_ratio	69.7%	22.1%	94.9%
Size	56.1%	58.5%	62.5%
Invsub	54.1%	98.9%	100.0%
Rent	35.3%	48.3%	34.4%
Old 0, New 1	35.1%	49.2%	40.9%
Model fit – R^2	*0.712*	*0.641*	*0.713*

Source: *own compilation*

The limitation of our ANN modelling here was that cross-validation, the usual procedure within the ANN, was not performed due to the relatively small data set. This could be considered as a limitation of our research, which was also justified because our primary goal was only to train the model.

We studied the normalised importances of the input variables for predicting the eco-effciency score of EU field crop farms separately for each dataset. As for the whole EU dataset, AES is the critical impact factor and has the highest normalised importance of 100 per cent. Capital the second factor with an importance of 73.7 per cent. The next one is Debt_ratio which importance is 69.7 per cent. Both Size (56.1%) and Invsub (54.1%) variables have moderate importance when predicting eco-efficiency score. The least important variables are Rent (35.3%) and “Old 0” or “New 1” EU Member State (35.1%), and thus they play minor role in eco-efficiency prediction.

For Group 1, the most important factor for predicting the eco-efficiency score is the variable AES with the highest normalised importance of 100 per cent. But nearly as important is the variable Invsub (98.9%) whose high importance value indicates it also to be as a key predictor. The variable Capital is also highly important, contributing 90.4 per cent of importance. The variables Size, “Old 0” or “New 1” EU Member State and Rent revealed moderate importance of 58.5 per cent, 49.2 per cent and 48.3 per cent respectively. Debt_ratio has minimal importance.

Regarding Group 2, which includes EU countries with an eco-efficiency score above the EU 5-year average, the most important variable for explaining and predicting the eco-efficiency score is the Invsub variable with 100 per cent normalised importance. Debt_ratio is also highly important (94.9%), in contrast to its low importance in Group 1. The variable AES has the importance of 71.1 per cent and still remains as relevant impact factor although it is not the most important compared to the other group. Capital is nearly as important as AES (68.9%), contributing substantially for prediction of eco-efficiency score. Size is also relevant (62.5%), but its importance is moderate. The least important variables are “Old 0” or “New 1” EU Member State and Rent in this group.

After standardising the original values of the input variables, our neural network models significantly outperformed the corresponding regression models. The R^2 value for the whole dataset was 0.712, and thus the model explains a large proportion of the variance in the eco-efficiency score of EU field crop farms. The high R^2 values for Group 1 (0.641) and Group 2 (0.713) also indicated good model fit for both subgroups.

In summary, the application of the DEA-CCR method has provided an estimate of the eco-efficiency of the EU countries field crop farms. After dividing the countries into two groups, high and full eco-efficiency and medium and low eco-efficiency, it was found that there are significant differences between these groups in terms of AES, the amount of capital, the share of rented agricultural land and the debt ratio. In general, the analysis of the influence of factors using MLP neural networks largely confirmed our research hypothesis - AES is the most important factor influencing eco-efficiency at the level of EU countries, although its importance for countries with different levels of eco-efficiency turned out to be unequal, i.e. it is the most important factor for field crop farms in EU countries with lower efficiency, while it is not a critical factor for high and full eco-efficiency countries.The importances of other factors of eco-efficiency also differed between the groups. Our methodological approach to standardise the factor variables before applying ANN proved successful, and the MLP models yielded significantly higher predictive abilities compared to the multiple linear regression models. Hence the use of ANN may be considered as an appropriate tool for analysing the importance of factors affecting the eco-efficiency.

4. Discussion

The results of our research provided us with the eco-efficiency score of EU field crop farms for the period 2017-2021, which mainly covered the implementation of measures from the second programming period of the CAP. The general trend of EU field crop farms average yearly scores shows some volatility in eco-efficiency, the highest value reached at 2020 (0.927) but still decline in eco-efficiency is observed at the end of the period (0.886).

It is noteworthy that when analysing the scientific literature, there is a lack of research on agricultural eco-efficiency in the EU in the last 5-10 years, especially in the case of crop farming, where we struggled to find previous studies to compare with our eco-efficiency scores of EU field crop farms. Therefore, our results are discussed with the available research on EU agricultural eco-efficiency.

The 5-year average eco-efficiency score of 0.898 in our study although is higher but still consistent to the EU-27 eco-efficiency score (average 0.80-0.85) assessed by Pishgar-Komleh et al. (2021) for the period 2008-2017. This study used similar input and output variables, although all agricultural activities, but at the same time it included the undesirable output of agriculture - GHG emissions. As for the eco-efficiency results of agriculture in the 25 EU Member States in the period 1993-2013, the average was 0.676 (Toma et al., 2017), and this is well below our results, even though the study didn't include undesirable outputs of agriculture.

In our study, we split the database into two groups into which we assigned countries according to their eco-efficiency score. In the case of our study, the lower efficiency group 1 consists mainly of the new EU member states that joined the EU in 2004 and after, with the exception of France and Finland. Meanwhile, members of the old EU as well as Malta, Slovenia and Hungary were more efficient or fully efficient. This is in line with the mentioned studies (Pishgar-Komleh et al., 2021; Toma et al., 2017), where greater average eco-efficiency scores for the old EU members compared to the new EU members were observed. The same tendency is observed in egriculture eco-efficiency of 26 EU member states for the period 1990-2019, where eco-efficiency leaders where mainly old EU member states, while lower than EU average performed new EU member states and also Finland, Sweden and Belgium (Domagała, 2021). Meanwhile, studies analyzing the eco-efficiency of individual countries or regions have revealed the following eco-efficiency scores: avergae of 0.34 in Germany and 0.36 in France of farms specialising in field crops in the period 2006-2011 (Ait Sidhoum, Canessa, et al., 2023), a relatively low average level of eco-efficiency of 0.548 was determined for crop farms in the LeMarche region of Italy, in the period 2011-2014 (Bonfiglio et al., 2017), and in 2008 the average level of eco-efficiency of crop farming in Campos county was 0.56 (Picazo-Tadeo et al., 2011). However, our findings show a higher eco-efficiency of German, Italian and Spanish field crop farms - all of these countries were classified in the higher eco-efficiency group, which in turn may be related to the longer accessibility of EU CAP support.

Overall, the increase in the eco-efficiency score from 0.676 (1993-2013) to 0.85 (2008-2017) and up to 0.898 (2017-2021) in our study at EU level could be attributed to the CAP and the fact that this policy was implemented earlier in the old EU members, while the newly acceded members started to apply the CAP rules and restrictions related to the implementation of environmental requirements only from the date of accession. Over time, agriculture in the new EU countries has also been operating under CAP conditions for longer and receiving payments set by the policy for the same environmental purposes. It can therefore be concluded that there is an increasing trend in eco-efficiency compared to the early studies. Bojnec et al. (2014) bring out the differences in agriculture in the new EU member states, i.e. agricultural structures and reforms, farm size and specialisation, institutional and economic context, compared to the old EU members, as a result of which the agricultural sector in most of the new

EU member states has not reached the level of efficiency typical of the old EU members. And this is in line with our findings.

Ensuring high agricultural eco-efficiency is one of the ways to contribute to sustainable agricultural growth and development. Thus, understanding which factors have a critical impact will help us to better target CAP measures.

The results of our MLP neural network model indicate that AES are the most influential factor in the lower eco-efficiency group, highlighting their importance as a critical determinant. As regards AES, the previous paragraph described the new EU members' greater need for these subsidies, as for old EU member states this factor is the third place of importance. The positive influence of AES on the agriculture eoc-efficiency is highlighted by Bonfiglio et al. (2017), Czyżewski et al. (2021), Dakpo & Latrufffe (2016), both at the single region level and EU countries level. Given the results on the importance of AES between the eco-efficiency groups, and the fact that there is a statistically significant difference in the number of AES in each group, strong support is needed for agri-environmental measures for countries with lower eco-efficiency, which are predominantly new EU member states, while ensuring the widest possible participation in these measures.

The second most important factor in lower eco-efficiency group is investment subsidies, indicating the need for further investment support. While in the higher eco-efficiency group, investment subsidies are considered the most important factor. These our findings are in line with Czyżewski et al. (2021), the investment subsidies had positive influence on the eco-efficiency of EU new member states as well as AES, and the eco-efficiency of agriculture could be futher enhanced through investment subsidies.

The ratio of capital to labour hours was the third most important factor in the lower eco-efficiency group and the fourth in the other group, i.e. increasing the amount of capital would reduce labour intensity and allow more efficient use of farm resources. Findings of Czyżewski et al. (2021) aprove these assumptions - capital endowment, combined with reduced labor intensity had positive impact on the eoc-effciency of agriculture.

The debt ratio was the second most important factor in the higher eco-efficiency group and the least important in the other group, also the means were statistically significantly different between the groups, indicating a different structure of farm financing between the coutries of these groups. According to Kurdyś-Kujawska et al. (2021), the structure of farm financing depends on the availability of capital sources, the cost of capital and production risk. This suggests that more efficient countries with lower mean of debt ratios have accumulated sufficient assets to finance their activities from their own resources. Compared to other studies, no significant effect of the debt ratio on eco-efficiency was found (Eder et al., 2021).

According to our results, the economic size of the farm has medium importance in both eco-efficiency groups revealing it is not a critical factor of agriculture eco-efficiency, that is in line with findings of Bonfiglio et al. (2017) and Picazo-Tadeo et al. (2011) whose studies did not identify a significant effect of farm size on farm eco-efficiency at the level of one country.

In studies analysing the influence of rented land, it is observed that farms working on their own land are more likely to be involved in agri-environmental schemes (Biffi et al., 2021). The last decades show an increase in the size of farms in the EU, and when there is a shortage of agricultural land for sale, it is mostly rented. However, according to our results, the share of rented land is an insignificant factor affecting eco-efficiency, but this variable is significantly higher in less efficient countries, which is partly consistent with the findings of Eder et al. (2021), where the share of rented land had a significant negative effect on soil conservation. Being an old or new EU member state was a less important factor in both groups, although it was more important in countries with lower eco-efficiency.

Thus, the difference in eco-efficiency between our two groups is related to the main factors influencing eco-efficiency described above. The differences in the eco-efficiency of farms from old and newly accessed EU members can be partly attributed to the unequal impact of the EU CAP, market liberalisation and farm restructuring.

Conclusion

The objectives of this research were to assess the eco-efficiency of EU field crop farms and to investigate how AES and selected economic and policy factors affect the eco-efficiency of EU agriculture.

We addressed a gap in the literature by conducting a study specifically focused on EU field crop farms, as most existing studies focused only on crop farms in a single region, dairy farms, or the agricultural sector of EU countries. The eco-efficiency of EU field crop farms was assessed using the DEA-CCR method, considering the methods reviewed in the literature for such assessments. However, to assess the influence of factors on the eco-efficiency, we decided to use ANN in addition to multiple regression. To develop better performing ANN models, we standardised the original variable values by calculating their differences from their medians and then dividing these values by the MAD. The model fitting results we obtained indicate that this data processing approach, combined with the application of the ANN method, provides significantly better eco-efficiency prediction results and offers more advantages than traditional regression methods.

The study identified two distinct groups based on eco-efficiency scores. The lower efficiency group consisted mainly of the newer EU members, plus France and Finland. In contrast, the higher efficiency group consisted mainly of older EU members, with the exception of Malta, Slovenia and Hungary.

This division is in line with previous research and reflects persistent differences in agricultural eco-efficiency between older and newer EU members. The difference is likely due to the earlier implementation of the CAP in older Member States, which allowed for a longer period of adaptation to environmental requirements and access to related financial support.

In particular, our results show higher eco-efficiency for German, Italian and Spanish crop farms compared to previous country-specific studies. This improvement may be related to these countries' longer history with EU agricultural policies and regulations.

The research highlights that while there's an overall upward trend in eco-efficiency across the EU, differences persist between old and new member states. These differences are rooted in different agricultural structures, farm sizes, specialisations and institutional and economic contexts. Despite progress, the agricultural sector in most of the new EU Member States has not yet reached the efficiency levels typical of the older Member States.

Using the MLP neural network model, we found that AES emerge as the most critical factor influencing the eco-efficiency of EU agriculture, especially for countries in the lower eco-efficiency group. This group, consisting mainly of newer EU member states, shows a greater need for these subsidies compared to older member states. Generally, our research hypothesis that AES subsidies are the most important factor influencing eco-efficiency of field crop farms in EU countries was confirmed. This finding is in line with previous studies and underlines their importance in improving the eco-efficiency of agriculture.

Investment subsidies were the second most important factor for the lower eco-efficiency group and the most important for the higher efficiency group. This underlines the continued need for investment support in all EU Member States to improve the eco-efficiency of agriculture. Other important factors were the capital-labour hours ratio and the debt ratio, although their importance varied between the two eco-efficiency groups. Farm size and the share of rented land were found to have less influence on eco-efficiency. Crop production accounts for a significant share of EU agriculture and is associated with pollution and land degradation. Therefore, the factors influencing the eco-efficiency of crop farms can help to select appropriate complex measures that would help to reduce the consumption of material and natural resources and move the crop production sector towards higher eco-efficiency.

A limitation of our study relates to the use of ANNs, as the modelling of the MLP neural network did not undergo a cross-validation procedure due to the relatively small dataset. However, we only aimed to train the model.

Future research could be pursued in two directions. As regards the assessment of the eco-efficiency of agriculture, it could be extended to include more types of negative outputs of agricultural activities to reflect the aggregated pressure on the environment. In this context, these could be N balance, water pollution, Shannon diversity index. For this, it is necessary to find ways to obtain the necessary data if it is calculated at a lower than national level. Another line of research relates to further analysis of the impact of AES on eco-efficiency, and future research will focus on exploring a computational approach that would allow to determine the optimal level of AES that would contribute to the growth of eco-efficiency estimates.

To this end, we have contributed to existing research by assessing the latest available data on EU agricultural performance and providing recent estimates of eco-efficiency. Our study also included the undesirable outputs of field crop farming in the assessment of the eco-efficiency score, thus addressing the limitations of previous studies, as well as offering an up-to-date perspective on the eco-efficiency of EU field crop farms during the second CAP programming period. In light of these findings, it's crucial to provide strong support for agri-environmental measures, especially in countries with lower eco-efficiency. Increased farmer participation in AES measures could contribute to improving agricultural eco-efficiency of the EU, especially in the new member mtates. In addition, investment support should be maintained to further increase the eco-efficiency of agriculture across the EU.

The results of our study highlight the positive impact of the long-term implementation of the AES on agricultural eco-efficiency across the EU, while underlining the challenge in reversing its decline.

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