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SYSTEMIC ISSUES AND EFFICIENCY RESERVES IN EU AGRICULTURE: A SLACK-BASED DEA APPROACH

Purpose. *The purpose of the study is to develop an integrated approach for evaluating the super-efficiency of the agricultural sector in EU countries, considering resource, ecological, and economic dimensions, while identifying systemic challenges and opportunities for efficiency enhancement through slack-based Data Envelopment Analysis (DEA).*

Methodology / approach. *The study uses super efficiency slack-based Data Envelopment Analysis models to evaluate the efficiency of the agricultural sector in EU countries. It incorporates three input-oriented DEA models focusing on resource-based, ecological, and economic dimensions to provide a comprehensive assessment. An aggregated assessment of the efficiency of the agricultural sector in EU countries was proposed based on the geometric mean of the evaluations from the constructed DEA models. A method for identifying systemic issues and opportunities for efficiency improvements in the agricultural sector of 27 EU countries using slack values was proposed.*

Results. *The most efficient countries in the EU agricultural sector according to proposed approach on the base of aggregation of three offered DEA model are the Netherlands, Belgium, Cyprus, Malta, Denmark, France and Ireland, demonstrating high levels of super-efficiency. The main challenges for less efficient countries include excessive land use, low export levels, and insufficient added value of agricultural products. Slack analysis revealed that the largest deviations are observed in land resource utilisation and export volumes.*

Originality / scientific novelty. *The article proposes an approach for evaluating the super-efficiency of the agricultural sector in EU countries by aggregating the assessments of three proposed DEA models. A method for identifying systemic issues in the efficient use of resources in the agricultural sector based on the analysis of slacks in DEA models has been proposed.*

Practical value / implications. *The article provides practical insights for policymakers and stakeholders to optimise resource use and improve the efficiency of the agricultural sector in EU. The results can guide the development of tailored strategies to address inefficiencies, particularly in land use and export performance. The proposed approach provides a methodological framework that can be applied to other regions, promoting sustainable agricultural practices globally and enabling the development of an aggregated efficiency ranking for the agricultural sector.*

Key words: *efficiency of agriculture, DEA models, super-efficiency, resource optimisation, efficiency reserves, slack analysis, EU agriculture.*

1. INTRODUCTION

An evaluation of super-efficiency in the agricultural sector is critically relevant in the context of the European Union's efforts to achieve sustainable development goals under the European Green Deal. Agriculture significantly impacts food security, greenhouse gas emissions, biodiversity, and land use, making its efficient management essential for both economic growth and environmental preservation. The European Union's Common Agricultural Policy (CAP) prioritises sustainable agricultural practices, and assessing the sector's efficiency supports the development of policies that balance economic and ecological objectives.

This study addresses a key challenge for the European Union (EU): optimising resource use in a sector that faces limited land and energy while maintaining competitiveness in global markets. The use of slack-based Data Envelopment Analysis (DEA) models offers a methodologically sound approach to evaluating resource efficiency and identifying inefficiencies at both national and regional levels. These models are particularly relevant in highlighting areas where resource overuse or underutilisation occurs, providing targeted insights for policymakers and stakeholders.

With growing global concerns about climate change and environmental degradation, this research highlights the need for efficient agricultural systems that reduce carbon emissions and promote ecological balance. By identifying leaders such as the Netherlands, Belgium, and Italy, this study emphasises best practices that can serve as benchmarks for less efficient countries. Moreover, the focus on slack values within the DEA framework offers a nuanced understanding of how input reductions or output enhancements can improve efficiency.

The topic is also timely as it addresses regional disparities in agricultural performance across EU member states, which are crucial for achieving cohesion and equitable development. By examining the interplay of economic, ecological, and resource dimensions, the study contributes to the broader discourse on sustainable development and economic resilience. Furthermore, the findings align with global priorities outlined in the UN Sustainable Development Goals, particularly those related to responsible consumption, climate action, and sustainable food systems.

The relevance of this research extends beyond the EU, as it offers a methodological blueprint for evaluating agricultural efficiency in other regions with diverse economic and environmental conditions. In an era of limited resources, the study provides actionable insights for enhancing sustainability and productivity, ensuring that agriculture can meet future demands while preserving the environment. Ultimately, this research supports evidence-based policymaking and reinforces the critical role of efficiency evaluations in shaping the future of agriculture.

Our study has a more methodological focus, as it proposes ways to apply the slack-based DEA approach for the identification of systemic issues and potential for efficiency. The goal of this study is to develop an integrated approach for evaluating the super-efficiency of the agricultural sector in EU countries, taking into account resource, ecological, and economic dimensions. It also aims to identify systemic challenges and opportunities for enhancing efficiency using slack-based Data Envelopment Analysis.

The structure of this paper is as follows: Chapter 2 provides a review of relevant literature. Chapter 3 outlines the methodology, introducing the proposed approach for evaluating agricultural sector efficiency from multiple perspectives – traditional resource-based, environmental, and economic – using DEA super-efficiency slack-based models. Chapter 4 presents the efficiency estimations along with an analysis of systemic issues and opportunities for improvement. These findings are further examined in Chapter 5. Chapter 6 summarises the key conclusions, while Chapter 7 discusses study limitations and suggests directions for future research.

2. LITERATURE REVIEW

The issue of evaluating the efficiency of the agricultural sector is quite popular in scientific literature. The DEA model is one of the most widely used tools for evaluating the efficiency of agribusiness. Pishgar-Komleh et al. (2021) evaluate the eco-efficiency and technical efficiency of the agricultural sector in EU-27 countries from 2008 to 2017 using a Window Slack-Based Measurement Data Envelopment Analysis (W-SBM-DEA) model, incorporating undesirable outputs like greenhouse gas emissions. It highlights significant differences in efficiency scores due to the inclusion of undesirable outputs and identifies the Netherlands, Belgium, Italy, and Malta as the most eco-efficient countries, providing insights for policymakers to improve sustainable agricultural practices. Kyrgiakos et al. (2021) use Window Data Envelopment Analysis to assess input use efficiency in EU agricultural sectors from 2005–2019 and project future efficiency scores, highlighting Estonia, the Netherlands, and Slovenia as the most efficient countries while recommending strategic redesigns for Central European nations to meet upcoming CAP objectives. Taoumi & Lahrech (2023) review methods and tools for evaluating sustainability in the agricultural crop sector, highlighting eco-efficiency and eco-effectiveness approaches, with an emphasis on using DEA and SFA for multidisciplinary assessments of socio-eco-efficiency and socio-eco-effectiveness. Coluccia et al. (2020) evaluate the eco-efficiency of the Italian agricultural sector using Data Envelopment Analysis to highlight regional differences, showing resource conservation strengths in Southern regions and productivity orientation in Northern regions. It emphasises the importance of eco-efficiency as a tool for policymakers to balance economic growth and ecosystem protection, aligning with EU Common Agricultural Policy goals for sustainable agriculture and societal well-being.

Recently, significant attention has been devoted to the issue of evaluating the eco-efficiency of the agricultural sector. Yang et al. (2022) examine the dynamics of agricultural carbon emissions (ACE) and agricultural eco-efficiency (AEE) in China from 2001 to 2018, highlighting regional differences, the role of technological progress, and the need for green-oriented policies to achieve ACE reduction and AEE growth. Wang et al. (2024) evaluate agricultural eco-efficiency in the Yangtze River Economic Belt (2007–2021) using the SBM-undesirable model, revealing spatial heterogeneity influenced by planting structure, machinery intensity, and urbanisation, and emphasising regional coordination for sustainable agricultural development. Akbar et al. (2021), using the SBM-undesirable model, demonstrated that the efficiency in the eastern region of the Yangtze River Economic Belt exceeds that of the central and western regions, while the level of informatization in the central region is higher than in the western region.

Many articles explore the intersection of agriculture efficiency and sustainability. Kanojia et al. (2024) examine the interplay between agriculture and environmental sustainability, using a Partial-Equilibrium Agricultural Sector Model to assess the impacts of crop and livestock trade on climate, biodiversity, water, and land, while exploring scenarios for mitigating externalities to support the UN Sustainable Development Goals. Chopra et al. (2022) analyse how environmental factors, renewable energy consumption, and regional integration affect agricultural productivity in ASEAN countries, revealing that environmental degradation and natural resource depletion reduce productivity, while renewable energy use enhances it, providing policy recommendations to align agriculture with the Sustainable Development Goals. Pawlak et al. (2021) and Barros et al. (2020) explore the role of circular economy practices in promoting bioenergy in agriculture, highlighting trends from a systematic literature review, with a focus on recent advancements, European leadership, and opportunities in electricity generation and biofuel production from biogas. Ndue & Goda (2021) examine the complex relationship between agriculture and climate change in the EU, highlighting the sector's lagging adaptation performance and proposing a Relative Climate Change Adaptation Index (RCCAI) to assess and accelerate adaptation efforts in alignment with the Common Agricultural Policy. Kyshakevych et al. (2024a; 2024b), as well as Popkova & Sergi (2021), explored the relationships between economic growth, digitalisation in small and medium-sized enterprises, and energy efficiency in the agricultural sector of European countries. Taoumi & Lahrech (2023), Chandio et al. (2023), Shu et al. (2024) examined different dimensions of the relationship between agricultural efficiency and environmental sustainability. Kucher et al. (2020) proposed a comprehensive methodological approach to assessing the economic efficiency of land reclamation projects in the context of sustainable soil management in the agriculture.

Martinho (2020) argued that expanding the variety of energy sources used in the agricultural sector not only reduces costs but also decreases the risks of energy dependence and lessens environmental impact, ultimately fostering sustainable development. Czyżewski & Kryszak (2022) explore sustainable agriculture policies, analysing their impact on food security, economic, social, and environmental sustainability, and proposing solutions to balance agricultural productivity with long-term well-being. Błażejczyk-Majka & Kala (2015) propose a modified combined method integrating parametric and non-parametric approaches to improve the consistency of efficiency assessments, demonstrated through an analysis of agricultural production in the USA and selected EU regions. Minviel & Latruffe (2016) conduct a meta-analysis on the impact of public subsidies on farm technical efficiency, revealing that subsidies are generally linked to lower efficiency, though the effect varies depending on how subsidies are modelled in empirical studies. Boczar & Błażejczyk-Majka (2022) assess the competitiveness of EU wheat producers on the global market using data envelopment analysis, highlighting their dependence on direct payments and the need to reduce mechanisation costs to enhance efficiency.

Batisha (2024) and Dong et al. (2022) investigated issues related to optimizing sustainable agricultural productivity and efficiency, ensuring ecological balance and optimal water resources allocation, improving quality of life, and maximizing economic benefits. The fundamental features of agricultural production and the impact of digitalization in China were examined Guo et al. (2020) and Xie et al. (2024) through stochastic frontier analysis, spatial correlation analysis, and driving mechanism analysis.

Many articles are devoted to advancing DEA methodologies to improve efficiency evaluation by addressing challenges like handling complex data, refining slacks-based measures, and integrating models for broader applicability and computational effectiveness. Tavassoli et al. (2021), along with Khezrimotlagh et al. (2019), focus on developing DEA models designed to handle zero, stochastic, and large-scale data for more robust efficiency analysis. Gerami et al. (2022), as well as Liu et al. (2025) concentrate on refining SBM models to enhance precision and robustness in evaluating efficiency and super-efficiency. Meanwhile, Lee (2021; 2023) prioritises the integration of SBM and Super-SBM models to broaden their applicability and improve computational efficiency, particularly when addressing undesirable outputs.

The literature highlights the widespread use of DEA models to evaluate eco-efficiency and technical efficiency in the agricultural sector, with studies emphasising the importance of integrating environmental sustainability into agricultural practices. These works provide critical insights into regional efficiency disparities, the impact of technological progress, and policy recommendations to align agriculture with sustainable development goals.

While most studies focus on regional, ecological or pure economical efficiency, our research provides a more comprehensive integration of resource, ecological, and economic dimensions, highlighting the interplay between these factors in achieving overall efficiency. Additionally, our slack analysis offers specific recommendations for underperforming countries, which is less emphasised in the reviewed studies.

A review of scientific literature reveals that most studies focus exclusively on technical, ecological, or purely economic efficiency. In this context, a critical challenge in assessing the overall efficiency of the agricultural sector lies in developing a comprehensive evaluation framework that integrates resource, ecological, and economic dimensions. Furthermore, a significant limitation of most existing models and approaches is their lack of attention to providing practical recommendations for improving efficiency.

This study addresses these gaps by identifying the most problematic areas within the EU agricultural sector through the application of slack-based Data Envelopment Analysis. Based on the proposed method for assessing the efficiency of the agricultural sector in EU countries and slack-based Data Envelopment Analysis, this article aims to verify the following hypotheses:

- H1. The export level of agricultural products from EU countries is sufficient in terms of ensuring the efficient functioning of the country's agricultural sector.
- H2. The environmental policy of EU countries does not require adjustments to enhance the efficiency of the EU agricultural sector.
- H3. There is no significant difference in land use efficiency among EU countries.

3. METHODOLOGY

Input-oriented DEA models provide a means to evaluate efficiency in terms of reducing the use of natural resources and minimising environmental impact. This is particularly important in the context of the EU's commitments to sustainable development and CO_2 emission reductions. Amid economic pressures and the need to maintain competitiveness in international markets, EU countries strive to reduce production costs, particularly in the agricultural sector. Input-oriented DEA models help identify resource overuse and enable the development of strategies to optimise their utilisation. The European Union actively supports the implementation of sustainable development policies, particularly through the Common Agricultural Policy, which encourages farmers to adopt practices that reduce environmental harm (Ndue & Goda, 2021).

Input-oriented DEA models are instrumental in assessing how effectively EU countries utilised subsidies and support to lower the consumption of natural resources such as water and energy, thereby enhancing the resilience of the agricultural sector. Input-oriented DEA models are suitable for solving tasks where the goal is to reduce resource use and enhance both environmental and economic efficiency. Output-oriented models, on the other hand, are more appropriate when the primary focus is on increasing agricultural sector productivity and expanding production volumes (Gerami et al., 2022).

Analysing the efficiency of the agricultural sector in European Union countries requires accounting for the specific conditions under which this sector operates. Input-oriented DEA models are the most suitable for assessing the efficiency of the agricultural sector in the EU for several key reasons tied to resource optimisation, environmental requirements, and the EU's economic strategy.

EU countries face limited natural resources, such as land, water, and energy, making their efficient use a priority. Input-oriented DEA models help evaluate how effectively these resources are utilised in the agricultural sector. Reducing resource costs, such as energy, labor, and water, without compromising production volumes, contributes to lowering environmental impact and increasing the sustainability of agriculture.

Super-efficiency extends the standard DEA models with constant returns to scale (CRS), enabling the evaluation of DMUs that are considered efficient ($\theta = 1$) and determining their efficiency level beyond 100 %. This is essential for comparing efficient DMUs with one another, as in the traditional DEA model, all DMUs with $\theta = 1$ are deemed equally efficient. This approach is used to identify best practices among already efficient DMUs (Liu et al., 2025). The use of slacks helps pinpoint specific variables (inputs or outputs) that require improvement, providing valuable insights into areas where optimisation efforts should be directed.

In this interpretation, CRS DEA model use slacks {S} to indicate the extent to which resources (inputs) can be reduced or outputs (products) can be increased to achieve efficiency. Slacks reveal that these resources are underutilised. Reducing only one resource will not make the DMU efficient, as other resources may still be used inefficiently. To achieve full efficiency, all surplus resources must be minimised, as indicated by the slacks. This enables the DMU to operate with the least possible resource costs while achieving maximum output (Lee, 2021).

Our study attempted to use input-oriented DEA super-efficiency slack-based models to identify systemic issues and potential for improving the efficiency of the agricultural sector in EU countries. The DEA CRS super-efficiency model with consideration of slacks extends the traditional approach to evaluating the efficiency of DMUs (Decision Making Units) by accounting for both proportional changes in inputs and outputs, as well as surpluses (inputs) or shortfalls (outputs). This provides a more detailed efficiency analysis. The formulation of the DEA CRS super-efficiency model with slacks consideration can be represented as follows (Lee, 2023):

$$\min \theta - \varepsilon\left(\sum_{j=1}^{m} s_j^- + \sum_{r=1}^{s} s_r^+\right), \tag{1}$$

$$\sum_{i=1, i\neq 0}^{n} \lambda_i x_{ij} + s_j^- = \theta x_{0j}, \quad \forall j = 1,2,\ldots,m, \tag{2}$$

$$\sum_{i=1, i\neq 0}^{n} \lambda_i y_{ir} - s_r^+ = y_{0r}, \quad \forall r = 1,2,\ldots,n, \tag{3}$$

$$\lambda_i \geq 0,\ s_j^- \geq 0,\ s_r^+ \geq 0, \tag{4}$$

where x_{ij} – *j*-th input resource for the *i*-th DMU;

y_{ir} – *r*-th output for the *i*-th DMU;

λ_i – weights for the *i*-th DMU;

s_r^+ – slack of the *r*-th output;

s_j^- – slack of the *j*-th input;

θ – efficiency of the DMU.

Slacks can be considered as deviations of a variable from the efficiency frontier in DEA models (Xu et al., 2020). This is a key concept that helps understand the extent to which the input resources or output results of a DMU (Decision Making Unit) fall short of the theoretically achievable level of efficiency defined by the efficiency frontier.

If the slack for a particular input is greater than zero, it indicates that this resource is being overused compared to DMUs located on the efficiency frontier.

Conversely, if the slack for an output is greater than zero, it signifies underutilisation of potential, meaning that this output could be increased without additional input resource expenditure (Yang et al., 2021).

In a DEA model, DMUs are positioned within a multidimensional space of inputs and outputs. If a DMU is not located on the efficiency frontier, slacks represent the distance between its actual position and the nearest point on the frontier. This provides a detailed measure of inefficiency and highlights specific areas where improvements are needed, such as reducing excess input use or maximising output potential.

Input slack reflects the excessive use of a specific resource (Scheel, 2000):

$$s_j^- = x_{j0} - \sum_{i=1}^{n} \lambda_i x_{ji} \, . \tag{5}$$

Output slack reflects the underutilisation of the potential of a specific output:

$$s_r^+ = \sum_{i=1}^{n} \lambda_i y_{ri} - y_{r0} \, . \tag{6}$$

Comparison of traditional DEA model and DEA super-efficiency slack-based models presented in Table1.

Table 1

Comparison of traditional DEA model and DEA super-efficiency slack-based models

Criterion	Traditional DEA model	DEA super-efficiency slack-based models
Core concept	Evaluates the relative efficiency of DMUs within a production possibility set	Extends DEA by allowing efficiency scores above 1 and incorporating slack variables
Efficiency assessment	Scores range from 0 to 1, where 1 indicates efficiency	Can assign scores greater than 1, providing a more precise evaluation
Differentiation among efficient units	Does not distinguish among DMUs that achieve a score of 1	Enables ranking among efficient units, identifying the most efficient ones
Consideration of slack variables	May not fully account for slack variables	Explicitly incorporates all slack variables for a more accurate assessment
Use in ranking	Does not rank efficient DMUs as they all receive the same score (1)	Allows ranking based on super-efficiency levels
Application in analysis	Used for general efficiency analysis but may not be suitable for detailed studies	Suitable for in-depth research, especially for analysing top-performing units

Source: created by the authors.

The variables used in constructing the DEA models are presented in Table 2.

The variable Output (Production value at basic price) reflects the total value of agricultural products created by producers, excluding taxes and including subsidies. Service (Agricultural services output) represents the value of services provided in the agricultural sector. Value (Gross value added at basic prices) is the gross value added at basic prices.

Table 2

Variables of DEA models

Input variables		
1	Energy	Final consumption – agriculture and forestry – energy use, thousand tonnes of oil equivalent (European Commission, 2024d)
2	CO_2	Greenhouse gases in CO_2 equivalent (Agriculture), million tonnes (European Commission, 2024e)
3	Labour	Total labour force input (Agriculture), 1000 annual work units (European Commission, 2024a)
4	Fixed	Fixed capital consumption (Agriculture), million euro (European Commission, 2024c)
5	Area	Utilised agricultural area (tag00025), Main area (1000 ha) (European Commission, 2024b)
Output variables		
1	Output	Production value at basic price (Agriculture), million euro (European Commission, 2024g)
2	Service	Agricultural services output, million euro (European Commission, 2024c)
3	Value	Gross value added at basic prices (Agriculture), million euro (European Commission, 2024c)
4	Export	Agri-export, million euro (European Commission, 2024f)

Source: created by the authors.

For a comprehensive study of the efficiency of the agricultural sector in EU countries, we implemented three sets of input and output variables for the DEA models (Table 3):

- *Model 1* focuses on the primary resources for agricultural activities: energy, labor, capital, and land, with an emphasis on production and productivity;
- *Model 2* incorporates the environmental variable CO_2, enabling efficiency evaluation considering environmental impact;
- *Model 3* excludes energy but includes the economic variable gross value added, making the analysis more focused on the economic returns of the agricultural sector.

The proposed models allow for the analysis of the agricultural sector's efficiency from different perspectives: traditional resource-based, environmental, and economic. The numerical implementation of the constructed DEA models was done using the EMS: Efficiency Measurement System program (Scheel, 2000).

The next stage of our research involves identifying reserves in the agricultural sector of inefficient countries to reach the efficiency frontier. To achieve this, we utilised slacks analysis. Input Slacks refer to the amount of input resources that can be reduced without decreasing output levels. A significant slack for a specific resource may indicate the need for improved management of that resource. Output Slacks represent the potential to increase outputs (e.g., production volume, exports) without incurring additional input costs. These slacks highlight which output variables should be prioritised to enhance efficiency.

Table 3

Sets of input and output variables for DEA models

Indicator	Model 1 Resource-based	Model 2 Ecological	Model 3 Economical
Input			
Energy	+	+	
CO_2		+	
Labour	+	+	+
Fixed	+		+
Area	+	+	+
Output			
Output	+	+	+
Value	+	+	+
Service			+
Export	+	+	+

Source: created by the authors.

The use of slacks helps determine the most effective approach – whether reducing input resources or increasing outputs – to achieve efficiency (Yang et al., 2021). Based on the slacks analysis, the following strategies can be developed:

- for countries with high input slacks (large inputs), develop policies aimed at resource optimisation, such as improving energy efficiency, automating labor processes, or reducing redundant investments;
- for countries with high output slacks (low outputs), prioritise investments in technologies that boost production and export capacity, and enhance marketing strategies to increase export potential;
- for countries with combined slacks, reassess the structure of resource utilisation and improve performance by integrating innovative solutions.

Slacks help identify underutilised reserves (in inputs and outputs), serving as a valuable tool for making strategic decisions aimed at improving the efficiency of each country in the analysis. Since input and output variables in DEA models can have different units of measurement, expressing slacks as percentages of their actual values shifts the focus from absolute magnitudes to relative ones. This allows all variables to be analysed on a uniform scale, enhancing interpretability and facilitating comparisons across different variables.

4. RESULTS

4.1. Evaluation of agricultural sector efficiency based on DEA model. Since the objective of our study is to identify the most pressing issues in the use of resources in the agricultural sector today, we utilised Eurostat statistical data from 2022 for the implementation of the DEA model. This year was chosen because it provides the most recent and comprehensive data available for all the analysed indicators.

Among the efficient EU countries identified in the resource-oriented model (Table 4) are Belgium, Cyprus, the Netherlands, Ireland, Malta, Greece, Denmark, Italy, Germany, and France. Their super-efficiency scores exceed 100.0 %, indicating optimal resource use and leadership in the agricultural sector. Belgium demonstrates the highest level of super-efficiency (311.6 %), reflecting outstanding productivity due to innovative technologies, efficient resource management, and a strong export orientation. Cyprus (262.1 %) has also achieved a high efficiency level by specialising in high-value-added products and maximising the use of limited land resources. The Netherlands (256.9 %) showcase their efficiency through the adoption of intensive technologies such as greenhouse farming and strong integration into international markets.

Table 4

Evaluation of agricultural sector efficiency in EU countries in 2022 based on DEA model 1 (resource-oriented)

Country	CRS super-efficiency, %	Energy {I}	Labour {I}	Fixed {I}	Area {I}	Value {O}	Output {O}	Export {O}
Belgium	311.6	-	-	-	-	-	-	-
Cyprus	262.1	-	-	-	-	-	-	-
Netherlands	256.9	-	-	-	-	-	-	-
Ireland	172.4	-	-	-	-	-	-	-
Malta	165.4	-	-	-	-	-	-	-
Greece	152.9	-	-	-	-	-	-	-
Denmark	150.4	-	-	-	-	-	-	-
Italy	141.0	-	-	-	-	-	-	-
Germany	118.9	-	-	-	-	-	-	-
France	114.6	-	-	-	-	-	-	-
Slovenia	99.0	0.0	0.0	22.2	0.0	0.0	11.0	-
Spain	98.5	0.0	8.3	0.0	0.0	93.5	0.0	0.0
Lithuania	97.8	0.0	11.0	0.0	1145.0	259.5	0.0	0.0
Bulgaria	92.9	0.0	0.0	0.0	2472.2	20.8	0.0	7494.8
Luxembourg	84.7	0.0	0.0	31.6	0.0	0.0	0.0	0.0
Austria	84.5	0.0	0.0	472.1	0.0	0.0	0.0	7685.7
Slovakia	81.5	0.0	0.0	0.0	791.7	94.5	0.0	0.0
Portugal	79.6	0.0	0.0	0.0	2.6	943.7	0.0	45544.7
Romania	75.4	0.0	269.8	1653.5	1325.9	569.4	0.0	12191.5
Sweden	72.9	0.0	0.0	0.0	579.6	0.0	1283.2	0.0
Estonia	66.8	0.0	0.0	0.0	305.1	0.0	0.0	0.0
Czech Republic	65.2	0.0	0.0	0.0	455.9	0.0	0.0	22983.7
Croatia	63.7	0.0	23.0	0.0	0.0	0.0	575.2	4279.3
Poland	59.2	0.0	0.0	0.0	1876.4	1952.1	0.0	86902.5
Hungary	56.3	0.0	14.1	0.0	0.0	517.9	0.0	48031.2
Latvia	55.2	0.0	0.0	0.0	710.9	0.0	0.0	1713.0
Finland	44.7	17.7	0.0	0.0	0.0	0.0	27.9	0.0

Source: calculated by the authors based on data from Eurostat (2024).

These countries share common success factors, including the adoption of innovations, high product quality, and effective government support. Their high efficiency is also closely linked to robust export strategies and a focus on high-value-added products. For instance, the Netherlands and Belgium leverage advanced technologies, enabling them to operate effectively even with limited land resources.

Mediterranean countries such as Greece, Italy, and Malta specialise in niche products that hold high market value. Meanwhile, Cyprus and Ireland, with their focus on export-oriented products, actively compete in international markets.

These results highlight that leaders in agricultural efficiency emphasise intensive technologies, high product quality, and robust export strategies. Efficient countries can serve as examples for others in resource utilisation, innovation adoption, and the development of agricultural policies aimed at sustainable development.

In DEA Model 2, which focuses on ecological efficiency, the effective countries in the agricultural sector are the Netherlands, Belgium, Ireland, Greece, Italy, Denmark, Slovenia, Germany, Malta, and France (Table 5).

Table 5

Evaluation of agricultural sector efficiency in EU countries in 2022 based on DEA model 2 (ecological)

Country	CRS super-efficiency, %	Energy {I}	Labour {I}	CO_2 {I}	Area {I}	Value {O}	Output {O}	Export {O}
Netherlands	256.9	-	-	-	-	-	-	-
Belgium	225.8	-	-	-	-	-	-	-
Ireland	172.4	-	-	-	-	-	-	-
Greece	154.7	-	-	-	-	-	-	-
Italy	153.8	-	-	-	-	-	-	-
Denmark	150.4	-	-	-	-	-	-	-
Slovenia	123.1	-	-	-	-	-	-	-
Germany	119.7	-	-	-	-	-	-	-
Malta	110.2	-	-	-	-	-	-	-
France	107.8	-	-	-	-	-	-	-
Cyprus	99.1	0.0	0.0	0.0	228.3	0.0	0.0	3221.5
Spain	98.9	0.0	0.0	0.0	11228.3	1453.8	0.0	11104.7
Slovakia	95.2	0.0	0.0	0.0	1021.5	361.4	0.0	0.0
Lithuania	88.3	0.0	0.0	0.0	743.6	299.2	0.0	0.0
Austria	85.8	0.0	0.0	0.0	19.0	0.0	0.0	0.0
Portugal	85.1	0.0	0.0	0.0	312.2	1832.2	0.0	9811.2
Luxembourg	84.7	0.0	0.0	0.1	0.0	0.0	0.0	0.0
Bulgaria	83.4	0.0	0.0	0.0	1820.96	0.0	0.0	3304.0
Sweden	80.0	0.0	0.0	0.0	1358.4	44.0	0.0	0.0
Hungary	77.7	6.6	68.2	0.0	1915.0	2326.8	0.0	15244.9
Romania	75.4	0.0	269.8	1.3	1325.9	569.4	0.0	12191.5
Estonia	68.9	0.0	0.0	0.0	381.63	82.55	0.0	229.6
Croatia	60.7	2.6	56.6	0.0	248.3	76.0	0.0	6706.9
Czech Republic	59.8	0.0	0.0	0.0	748.44	275.34	0.0	0.0
Poland	55.7	90.1	193.0	0.0	100.8	7931.4	0.0	94241.9
Finland	50.1	0.0	0.0	0.0	528.5	137.2	0.0	0.0
Latvia	49.4	0.0	0.0	0.0	536.1	359.3	0.0	1733.9

Source: calculated by the authors based on data from Eurostat (2024).

These countries exhibit high CRS super-efficiency scores exceeding 100 %, indicating a balance between productivity and environmental efficiency. The Netherlands (256.9 %) leads the group of efficient countries due to its active adoption of agricultural innovations that minimise resource use and reduce environmental impact. Belgium (225.8 %) stands out for its effective CO_2 emissions management and strong export orientation, ensuring stable economic growth in the agricultural sector.

Ireland (172.4 %) demonstrates ecological efficiency through its specialisation in high-quality dairy and meat products while minimising environmental costs. Greece (154.3 %) achieves high efficiency by rationally utilising land resources and focusing on niche products such as olives and wine.

These countries show the ability to achieve high performance while adhering to environmental standards. Their high efficiency levels are attributed to the use of innovations, reductions in CO_2 emissions, and optimisation of energy consumption. These examples highlight the importance of an ecological approach in the agricultural sector, which can serve as a benchmark for less efficient countries.

The effective countries in the model focused on the economic returns of the agricultural sector are the Netherlands, Belgium, Cyprus, Malta, Denmark, Slovakia, France, and Spain (Table 6).

The Netherlands (438.9 %) demonstrate the highest level of super-efficiency due to the intensive use of modern technologies and a high export level (26,454), which is a key factor in their success. Belgium (311.6 %) maximises resource efficiency, ensuring high value-added production and substantial export volumes. Cyprus (262.1 %) stands out for its effective utilisation of limited land resources and specialisation in products that are in high demand on international markets.

The analysis of three DEA super-efficiency models (ecologically-oriented, economically-oriented, and resource-oriented) reveals common trends among the efficient countries in the agricultural sector. The leaders in all models are the Netherlands, Belgium, Ireland, Cyprus, Malta, Denmark, France and Spain. These countries demonstrate high levels of efficiency due to balanced resource utilisation, the adoption of innovative technologies, and a strong export orientation.

The Netherlands consistently demonstrate the highest super-efficiency across all models, attributed to their high productivity per unit of resource, robust export base, and integration of innovations. Belgium also maintains strong positions, maximising resource efficiency and focusing on high-value-added products. Cyprus and Malta showcase notable efficiency despite limited resources, highlighting their specialisation in niche, high-value products.

Denmark, France, and Spain stand out for their export orientation and large-scale production, enabling them to maintain efficiency across all aspects of the analysis. Ireland effectively uses its natural resources and specialises in products with high international demand. The implementation of ecological practices is also a common feature among these countries, allowing them to achieve high performance even within the ecologically-oriented model.

Table 6

Evaluation of agricultural sector efficiency in EU countries in 2022 based on DEA model 3 (economical)

Country	CRS super-efficiency, %	Labour {I}	Fixed {I}	Area {I}	Value {O}	Output {O}	Service {O}	Export {O}
Netherlands	438.9	-	-	-	-	-	-	-
Belgium	311.6	-	-	-	-	-	-	-
Cyprus	262.1	-	-	-	-	-	-	-
Malta	165.4	-	-	-	-	-	-	-
Denmark	132.9	-	-	-	-	-	-	-
Slovakia	111.9	-	-	-	-	-	-	-
France	104.0	-	-	-	-	-	-	-
Spain	102.1	-	-	-	-	-	-	-
Ireland	97.1	0.0	0.0	2508.5	0.0	1835.8	0.0	0.0
Bulgaria	93.9	0.0	0.0	1448.4	0.0	1870.6	0.0	31561.0
Italy	93.8	0.0	0.0	0.0	0.0	36315.2	0.0	501970.9
Poland	92.1	523.8	0.0	1442.5	1015.6	0.0	0.0	108544.3
Germany	87.5	0.0	0.0	2312.3	0.0	25654.4	3484.9	0.0
Estonia	85.7	0.0	0.0	196.0	3.5	0.0	0.0	4140.6
Greece	79.7	0.0	0.0	666.9	0.0	2581.5	0.0	29189.6
Hungary	70.7	70.7	0.0	0.0	157.8	0.0	0.0	36489.1
Sweden	69.1	0.0	0.0	408.5	0.0	2615.6	9.8	0.0
Lithuania	67.5	0.0	0.0	809.9	0.0	0.0	0.0	3493.2
Croatia	66.8	32.7	0.0	0.0	0.0	1181.9	0.0	13837.2
Czech Republic	65.6	0.0	0.0	850.4	0.0	0.0	0.0	31032.0
Luxembourg	64.8	0.0	3.9	24.1	0.0	0.0	38.8	206.6
Austria	63.2	0.0	0.0	0.0	0.0	6145.7	213.4	165259.9
Portugal	60.9	0.0	0.0	53.5	61.5	0.0	0.0	21768.6
Latvia	58.3	0.0	0.0	649.2	0.0	0.0	0.0	1901.5
Finland	44.9	0.0	0.0	0.0	0.0	261.3	0.0	0.0
Slovenia	40.4	6.1	0.0	0.0	0.0	159.7	0.0	0.0
Romania	35.3	0.0	0.0	0.0	0.0	7028.9	0.0	19451.2

Source: calculated by the authors based on data from Eurostat (2024).

Overall, efficient countries demonstrate a systematic adoption of modern technologies, cost optimisation, and strong export strategies. Their high levels of efficiency also reflect effective management of labor, capital, and land resources. Ultimately, these countries show that a combination of economic, ecological, and resource balance is key to the successful development of the agricultural sector. Their experiences can serve as a model for other countries seeking to improve the efficiency of their agricultural sectors.

To achieve a comprehensive evaluation of the efficiency of the EU agricultural sector, the average super-efficiency scores across the three DEA models were used (Table 7). Analysing the average super-efficiency values for the three models reveals significant differences in agricultural sector efficiency among countries. High average super-efficiency scores indicate systemic advantages in resource utilisation, environmental adaptation, and economic returns. The most efficient countries are the Netherlands (317.6 %), Belgium (283.0 %), and Cyprus (207.8 %), consistently confirming their leadership positions across all models.

The Netherlands consistently demonstrate the highest efficiency, attributed to their high-tech agricultural sector, optimal resource utilisation, and strong export orientation. Belgium showcases significant balance between economic and environmental efficiency, with a focus on high-value-added products. Cyprus confirms its efficiency through successful specialisation in niche products that meet the demands of international markets.

Table 7

Efficiency rankings of the EU agricultural sector by resource, ecological, and economic approaches and average super-efficiency scores in 2022

Integr. rating	Country	Ratings			Average, %
		Resource approach Model 1	Ecological approach Model 2	Economic approach Model 3	
1	Netherlands	3	1	1	317.6
2	Belgium	1	2	2	283.0
3	Cyprus	2	11	3	207.8
4	Ireland	4	3	9	147.3
5	Malta	5	9	4	147.0
6	Denmark	7	6	5	144.6
7	Italy	8	5	11	129.5
8	Greece	6	4	15	129.1
9	France	10	10	7	108.8
10	Germany	9	8	13	108.7
11	Spain	12	12	8	99.8
12	Slovakia	17	13	6	96.2
13	Bulgaria	14	18	10	90.1
14	Slovenia	11	7	26	87.5
15	Lithuania	13	14	18	84.5
16	Luxembourg	15	17	21	78.1
17	Austria	16	15	22	77.8
18	Portugal	18	16	23	75.2
19	Sweden	20	19	17	74.0
20	Estonia	21	22	14	73.8
21	Poland	24	25	12	69.0
22	Hungary	25	20	16	68.2
23	Croatia	23	23	19	63.7
24	Czech Republic	22	24	20	63.5
25	Romania	19	21	27	62.0
26	Latvia	26	27	24	54.3
27	Finland	27	26	25	46.6

Note. * Effective countries are marked in green.

Source: calculated by the authors.

Mid-range efficient countries, such as Ireland (147.3 %), Malta (147.0 %), and

Denmark (144.6 %), demonstrate effective management of labor and capital while also addressing environmental requirements. Italy (129.5 %) and Greece (129.1 %) maintain their strong positions due to their focus on premium export products and sustainable land-use practices.

Lower average scores, such as those of Romania (62.0 %), Latvia (54.3 %), and Finland (46.0 %), indicate substantial room for improvement. These results may be attributed to less developed infrastructure, insufficient innovation adaptation, or limited export capacity.

Overall, the trend shows that countries with high average super-efficiency scores invest in technology, resource optimisation, and exports. Meanwhile, less efficient countries possess significant potential for improvement through the adoption of modern management practices, development of export strategies, and productivity enhancement. This analysis highlights the importance of a balanced approach to economic, environmental, and resource efficiency.

4.2. Identification of systemic issues and efficiency potential based on slack values. From Table 8, which presents slacks as percentages of the actual indicator values, it is evident that the largest slacks in Model 1 are associated with agricultural product exports. For instance, to reach the efficiency frontier, Portugal needs to increase agricultural exports nearly threefold, Hungary by 2.5 times, and Poland by twofold. This indicates a lack of focus on external markets in these countries.

Table 8

Input and output slacks in model 1 (resource-oriented), %

Country	Energy {I}	Labour {I}	Fixed {I}	Area {I}	Value {O}	Output {O}	Export {O}
Slovenia	0.0	0.0	7.2	0.0	0.0	0.7	0.0
Spain	0.0	1.0	0.0	0.0	0.3	0.0	0.0
Lithuania	0.0	9.2	0.0	39.3	12.8	0.0	0.0
Bulgaria	0.0	0.0	0.0	49.2	0.7	0.0	45.3
Luxembourg	0.0	0.0	28.6	0.0	0.0	0.0	0.0
Austria	0.0	0.0	20.1	0.0	0.0	0.0	12.6
Slovakia	0.0	0.0	0.0	42.8	10.6	0.0	0.0
Portugal	0.0	0.0	0.0	0.1	28.0	0.0	197.1
Romania	0.0	26.3	33.7	10.5	5.7	0.0	47.8
Sweden	0.0	0.0	0.0	19.4	0.0	16.3	0.0
Estonia	0.0	0.0	0.0	30.9	0.0	0.0	0.0
Czech Republic	0.0	0.0	0.0	12.9	0.0	0.0	54.2
Croatia	0.0	13.3	0.0	0.0	0.0	18.1	55.6
Poland	0.0	0.0	0.0	13.2	13.7	0.0	103.6
Hungary	0.0	4.9	0.0	0.0	15.0	0.0	154.2
Latvia	0.0	0.0	0.0	36.1	0.0	0.0	21.6
Finland	2.5	0.0	0.0	0.0	0.0	0.5	0.0

Source: calculated by the authors.

Energy appears to be the most efficiently utilised input in the EU agricultural sector, as reflected by the highest number of zero slacks. However, Romania demonstrates systemic inefficiencies, with excessive use of labor (26.3 %) and capital (33.7 %) alongside a significant export gap (47.8 %). Bulgaria and Slovakia would need to reduce their agricultural land area by nearly half to achieve efficiency, highlighting the need for innovations in land use. Luxembourg and Austria demonstrate excessive capital use (28.6 % and 20.1 %, respectively), suggesting a need for improved investment management.

Overall, the analysis shows that the largest deviations among input variables are associated with capital and land resources, while among output variables, the most significant issue is increasing agricultural exports. Many countries need to focus on more efficient resource management and the development of strategies to support external economic activities to reach the efficiency frontier.

Analysing the results of the ecologically-oriented Model 2 (Table 9) reveals similar challenges faced by EU countries in achieving the status of an efficient DMU. The most common issues in the agricultural sector are excessive use of agricultural land and insufficient export levels.

For instance, Poland needs to double its export levels and increase the gross value added generated by its agricultural sector by almost 50 %. These findings underscore the necessity for enhanced strategies focused on land-use efficiency and export growth to align with ecological and economic efficiency goals.

Table 9

Input and output slacks in model 2 (ecological), %

Country	Energy {I}	Labour {I}	CO_2 {I}	Area {I}	Value {O}	Output {O}	Export {O}
Cyprus	0.0	0.0	0.0	185.6	0.0	0.0	101.0
Spain	0.0	0.0	0.0	45.5	5.0	0.0	7.7
Slovakia	0.0	0.0	0.0	55.2	40.7	0.0	0.0
Lithuania	0.0	0.0	0.0	25.5	14.7	0.0	0.0
Austria	0.0	0.0	0.0	0.7	0.0	0.0	0.0
Portugal	0.0	0.0	0.0	7.9	54.3	0.0	42.5
Luxembourg	0.0	0.0	15.0	0.0	0.0	0.0	0.0
Bulgaria	0.0	0.0	0.0	36.3	0.0	0.0	20.0
Sweden	0.0	0.0	0.0	45.4	1.6	0.0	0.0
Hungary	1.1	23.6	0.0	37.7	67.4	0.0	49.0
Romania	0.0	26.3	7.2	10.5	5.7	0.0	47.8
Estonia	0.0	0.0	0.0	38.7	16.9	0.0	3.6
Croatia	1.1	32.7	0.0	17.1	4.4	0.0	87.2
Czech Republic	0.0	0.0	0.0	21.2	10.6	0.0	0.0
Poland	2.7	13.5	0.0	0.7	55.6	0.0	112.3
Finland	0.0	0.0	0.0	23.3	7.6	0.0	0.0
Latvia	0.0	0.0	0.0	27.2	45.1	0.0	21.9

Source: calculated by the authors.

Similar trends are observed in the results of Model 3 (Table 10), which focuses more on the economic returns of the agricultural sector. The need to reduce agricultural land use and increase export levels are key conditions for most inefficient

EU countries to reach the efficiency frontier. These findings emphasise the importance of optimising land resources and enhancing export strategies to improve the overall economic performance of the agricultural sector.

Table 10

Input and output slacks in model 3 (economical), %

Country	Labour {I}	Fixed {I}	Area {I}	Value {O}	Output {O}	Service {O}	Export {O}
Ireland	0.0	0.0	57.7	0.0	14.2	0.0	0.0
Bulgaria	0.0	0.0	28.8	0.0	29.0	0.0	190.9
Italy	0.0	0.0	0.0	0.0	55.6	0.0	169.7
Poland	36.7	0.0	10.2	7.1	0.0	0.0	129.4
Germany	0.0	0.0	13.9	0.0	34.1	118.4	0.0
Estonia	0.0	0.0	19.9	0.7	0.0	0.0	64.3
Greece	0.0	0.0	12.4	0.0	19.4	0.0	118.7
Hungary	24.4	0.0	0.0	4.6	0.0	0.0	117.2
Sweden	0.0	0.0	13.6	0.0	33.3	2.3	0.0
Lithuania	0.0	0.0	27.8	0.0	0.0	0.0	20.9
Croatia	18.9	0.0	0.0	0.0	37.1	0.0	179.9
Czech Republic	0.0	0.0	24.1	0.0	0.0	0.0	73.2
Luxembourg	0.0	3.5	18.2	0.0	0.0	196.3	6.4
Austria	0.0	0.0	0.0	0.0	61.7	51.4	170.3
Portugal	0.0	0.0	1.4	1.8	0.0	0.0	94.2
Latvia	0.0	0.0	32.9	0.0	0.0	0.0	24.0
Finland	0.0	0.0	0.0	0.0	5.1	0.0	0.0
Slovenia	8.4	0.0	0.0	0.0	10.0	0.0	0.0
Romania	0.0	0.0	0.0	0.0	34.5	0.0	269.8

Source: calculated by the authors.

Figure 1 presents the average geometric slacks for all inputs and outputs of the three DEA models. Large average slack values for certain variables, such as Export (40.40 %) and Area (20.58 %), indicate significant issues in less efficient countries. The substantial gaps in these indicators reflect a pronounced disparity between efficient and inefficient countries, highlighting the need for urgent changes. In the area of exports, this could stem from weak foreign trade policies, insufficient marketing, or high administrative barriers. For land resources, the large gap suggests low land productivity, inadequate adoption of innovations, or issues related to land degradation.

A moderate gap, as observed with variables such as Value (7.44 %) and Output (5.76 %), points to underutilised reserves. This indicates that countries have the potential to increase added value and production volumes but are not fully leveraging their capabilities. To address these shortcomings, it is necessary to implement innovative technologies, invest in the modernisation of production facilities, and support the development of advanced raw material processing.

Small gaps for Energy (0.15 %) and CO_2 (0.47 %) indicate a high level of resource efficiency in most countries. This suggests that there are no significant issues in the areas of energy consumption and emissions, and resources are being used almost optimally. However, it is crucial to maintain this level by further developing renewable energy sources and enhancing environmental standards.

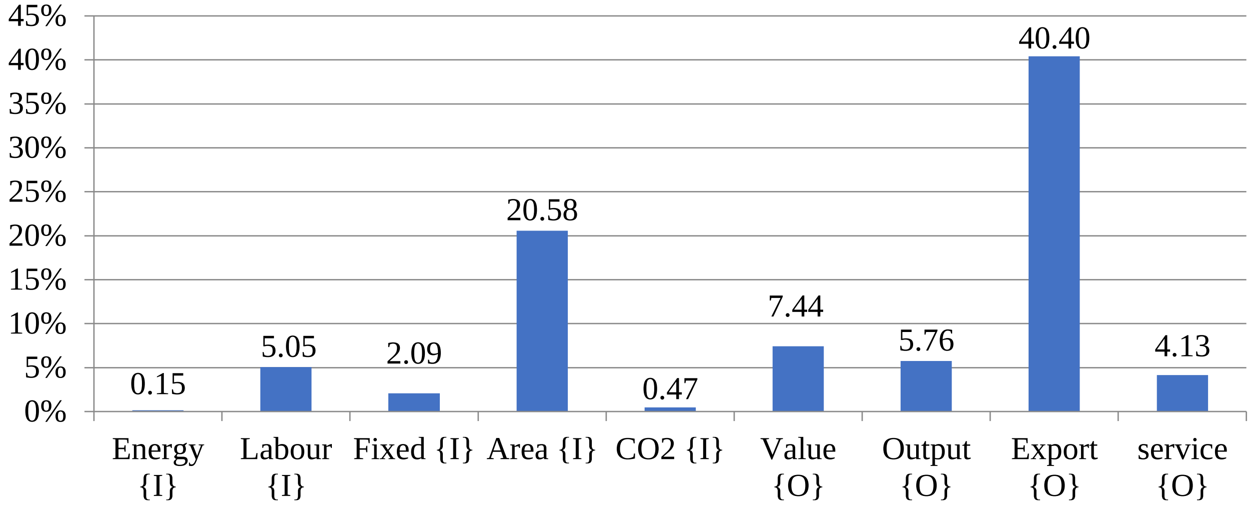

Figure 1. Geometric mean of slacks for input variables {I} and output variables {O} for 2022 year

Source: calculated by the authors.

Thus, large slack values indicate the need to address systemic issues, moderate values highlight the potential to unlock hidden reserves, and small values emphasise the importance of maintaining the already achieved level of efficiency (Figure 2). The existence of significant gaps in export volume and Utilised Agricultural Area among European countries points to substantial disparities in resource utilisation and performance, necessitating tailored strategies for each group of countries.

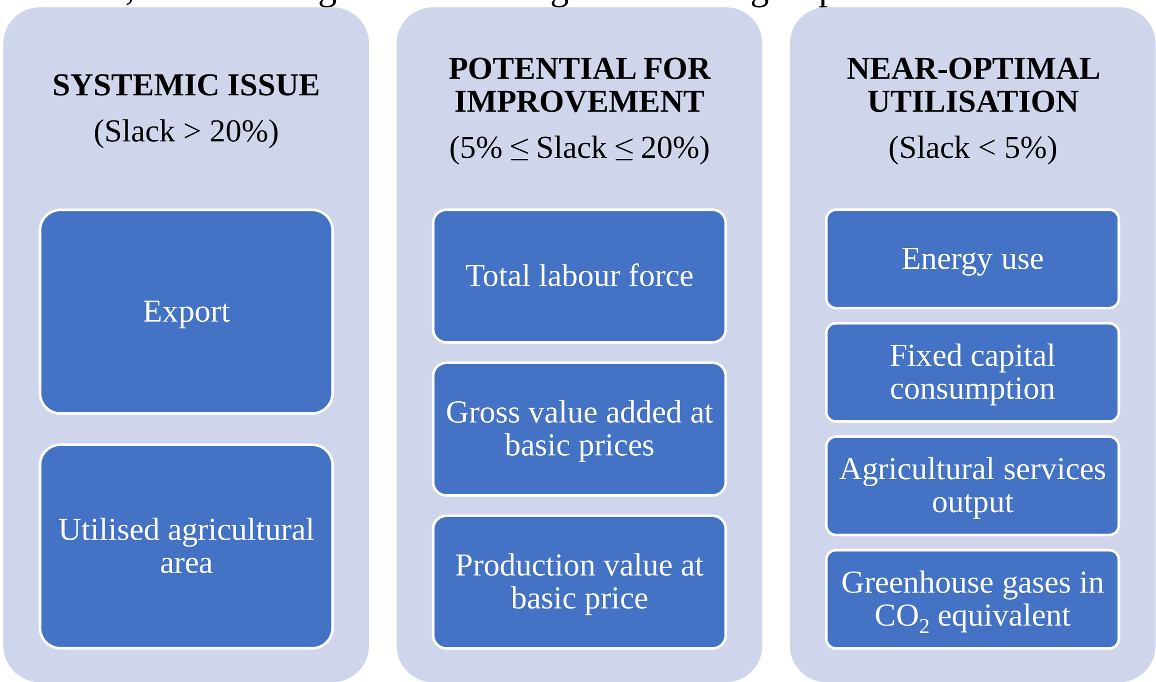

Figure 2. Identification of systemic issues and potential for efficiency improvements in the agricultural sector of 27 EU countries based on slack values

Source: created by the authors.

For less efficient nations, this implies the need to implement innovations, develop export potential, and optimise land use. These measures will help bridge the gaps and enhance the overall efficiency of the agricultural sector in Europe.

Figure 2 clearly illustrates three categories of variables used in the DEA models, highlighting varying degrees of deviation from optimal resource utilisation and performance levels in the agricultural sector of inefficient EU countries. The Figure identifies areas within the agricultural sector that require urgent improvements, particularly systemic issues in inefficient countries, such as exports and agricultural land area. Thus, it can be concluded that Hypothesis H1, which suggests a sufficient level of agricultural product exports from EU countries, was not confirmed.

From Figure 3, where the growth rates of agricultural product exports from EU countries are compared with the growth rates of Gross Value Added in the agricultural sector, a balanced relationship is evident. This relationship helps explain the large slack values observed for inefficient EU countries, which are attributed to the significant disparity in export volumes between efficient and inefficient countries, as indicated by the DEA models.

This highlights a systemic issue with agricultural product exports in the EU, characterised by a considerable gap in export volumes between leading agri-business countries and other nations with efficiency levels below 100 %.

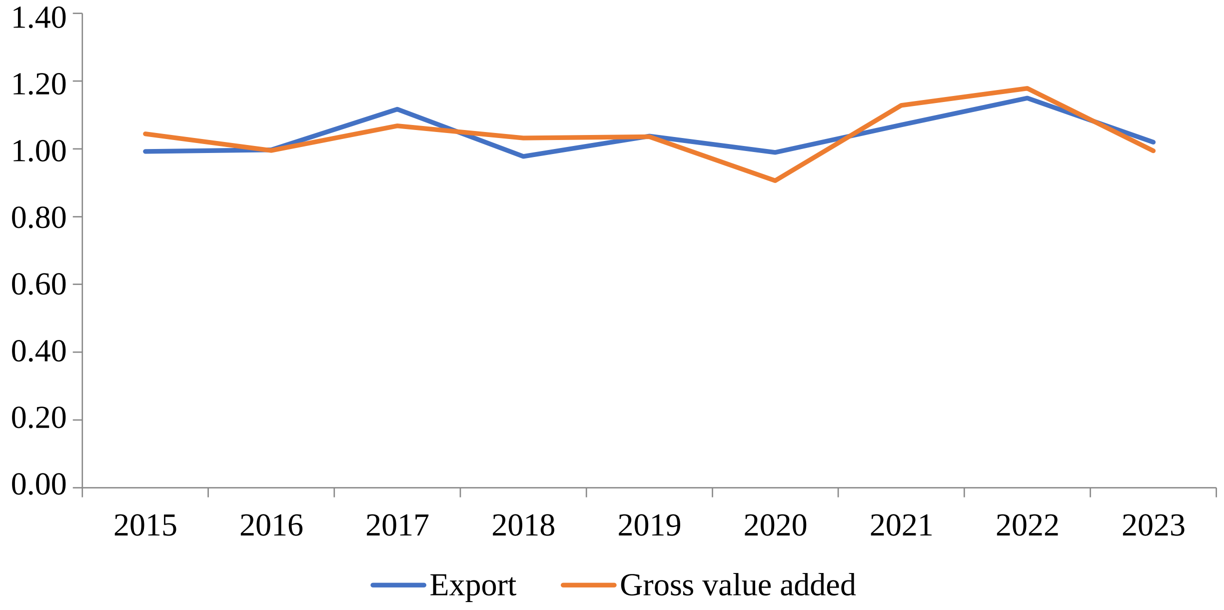

Figure 3. Comparison of growth rates of agricultural product exports with growth rates of Gross Value Added (agriculture) in EU countries, million euros

Source: created by the authors on the base of data Eurostat (2024).

Large slack values for utilised agricultural area and indicate that inefficient EU countries may face the following issues:

- excessive land use in inefficient countries that does not contribute significantly to production;
- inefficient land-use management;
- significant potential for intensification in the agricultural sector;

- insufficient application of innovations;
- ineffective agricultural policies that support farms with large land areas but fail to promote their rational use;
- the presence of degraded or low-productivity lands;
- in some countries, large land areas may be used for extensive livestock farming or other types of agriculture with low output per unit of area.

Moderate slack values may indicate the potential to improve the efficiency of the agricultural sector by either reducing the resources utilised (Total labour force) or increasing Gross Value Added at Basic Prices and Production Value at Basic Price. The remaining indicators used in the DEA models for inefficient countries showed values close to optimal efficiency.

The obtained results can serve as a valuable tool for developing a strategy to advance the agricultural sector, focusing on addressing specific efficiency challenges.

5. DISCUSSION

The results of this study highlight significant efficiency disparities in the agricultural sector across EU countries, which are influenced by resource utilisation, environmental adaptation, and economic strategies. Pishgar-Komleh et al. (2021) similarly highlighted notable efficiency score variations due to the inclusion of undesirable outputs.

The Netherlands, Belgium consistently emerge as leaders due to their high resource efficiency, robust export orientation, and adoption of innovative technologies. These findings are consistent with prior research emphasising the importance of high-tech solutions and niche product specialisation in achieving agricultural efficiency. The Netherlands, Belgium, Italy, and Malta are consistently recognised as leaders in agricultural efficiency across nearly all studies (Pishgar-Komleh et al. (2021); Kyrgiakos et al. (2021), Taoumi & Lahrech (2023)).

The relationship between economic growth, digitalisation, and energy efficiency in the agricultural sector, established previously (Kyshakevych et al., 2024b) is consistent with our findings that high-performing countries leverage innovation and technology for both ecological and economic efficiency. Like our research, Coluccia et al. (2020) highlight the regional differences in agricultural efficiency, with Southern regions excelling in resource conservation and Northern regions focusing on productivity. It Huang et al. (2021) also emphasise notable regional disparities in agricultural efficiency. This supports our observations about the need for targeted regional strategies within countries. Our focus on sustainability aligns with Kanojia et al. (2024) and Chopra et al. (2022), as both highlight the integration of environmental sustainability into agriculture, emphasising renewable energy and circular economy practices, which parallel our recommendations for innovation in resource management and ecological efficiency.

Notably, a comparison of the agricultural sector’s efficiency in EU countries from a decade ago reveals a consistent pattern among the leading nations in this field. Laurinavičius & Rimkuvienė (2017) utilised Data Envelopment Analysis to analyse the efficiency of agricultural sectors in EU countries between 2010 and 2014. By applying DEA-based mathematical models, they measured agricultural productivity across the region. Their findings indicated that Italy, Malta, Spain, Ireland, the United Kingdom, Denmark, the Netherlands, and Germany demonstrated the highest relative efficiency in agriculture. Almost all of the countries mentioned proved to be effective in our study (see Table 6).

Ecological considerations, particularly CO_2 emissions and land-use efficiency, were critical in evaluating performance. Efficient countries demonstrate a strong alignment with EU policies under the European Green Deal, integrating sustainable practices to balance productivity with environmental goals. This suggests that sustainability is not just a policy imperative but also a pathway to economic competitiveness.

While most studies focus on regional, ecological or pure economical efficiency, our research provides a more comprehensive integration of resource, ecological, and economic dimensions, highlighting the interplay between these factors in achieving overall efficiency. We proposed a methodology for identifying systemic issues and potential for efficiency improvements in the agricultural sector of 27 EU countries based on slack values. Additionally, our slack analysis offers specific recommendations for underperforming countries, which is less emphasised in the reviewed studies.

6. CONCLUSIONS

The analysis of the agricultural sector's efficiency in EU countries, based on three constructed DEA super-efficiency models, identified both leading and less efficient countries. The leaders are the Netherlands, Belgium, Cyprus, Malta, Denmark, France, and Ireland, which demonstrated consistently high efficiency levels across all three approaches: resource-based, environmental, and economic.

The Netherlands demonstrated the highest level of super-efficiency due to its high-tech agricultural sector, intensive use of modern technologies, and robust export base. Belgium showcases a balance between economic and environmental efficiency, focusing on high-value-added products. Cyprus and Malta effectively utilise limited natural resources, specialising in niche products that are in demand on international markets.

Denmark, France, and Ireland exhibit efficiency across all aspects of the analysis, driven by their strong export orientation, adoption of eco-friendly practices, and rational land use. Meanwhile, Italy and Greece maintain strong positions by focusing on premium-class exports and sustainable land-use practices.

The analysis of average super-efficiency values based on the proposed approach confirmed a significant disparity among EU countries. The Netherlands, Belgium, and Cyprus remain undisputed leaders with integrated indicators exceeding 200 %. These countries demonstrate a systemic advantage in implementing innovations, optimising resources, and ensuring economic returns.

An important conclusion is that the large slack values for variables such as exports and agricultural land area highlight the existence of systemic issues in less efficient countries. This underscores the need for new strategies focused on reducing excessive resource use and enhancing productivity.

The high efficiency in energy use, the low level of excess CO_2 emissions in most countries, and the small slack value confirm the effectiveness of the EU's environmental policies, thus supporting hypothesis H2. The obtained results cannot confirm Hypothesis H3, which states that there is no significant difference in land use efficiency among EU countries. Since the analysis revealed that the slack in the agricultural product export indicator for less efficient countries falls within the systemic issue zone, this provides grounds to assert that Hypothesis H1**,** which suggests a sufficient level of agricultural product exports from EU countries, cannot be confirmed.

Unlocking the hidden potential of less efficient countries according our models will help balance disparities in the development of the EU agricultural sector. To achieve this, it is essential to adopt modern technologies, invest in infrastructure development, and support advanced raw material processing.

In conclusion, the successful development of the agricultural sector depends on a balanced approach to economic, environmental, and resource efficiency. All three DEA models emphasise the importance of an integrated approach that ensures sustainable development and enhances competitiveness in international markets. This approach should be founded on innovation, cost optimisation, and effective management of natural resources.

7. LIMITATIONS AND FUTURE RESEARCH

This study, despite its comprehensive application of DEA super-efficiency slack-based models, is not without limitations. The limitations of this study are primarily associated with the inherent constraints of the DEA methodology. While DEA is a powerful tool for evaluating relative efficiency, it assumes that all decision-making units (DMUs) operate under similar conditions, which may not fully reflect the diverse economic, environmental, and institutional contexts of EU countries. Additionally, DEA models are highly sensitive to the selection of input and output variables, and the exclusion of relevant factors or the inclusion of less significant ones can influence the accuracy of the results. All conclusions presented in the article are derived exclusively from the indicators utilised in the DEA models. The ranking of countries, however, is influenced by numerous other factors, some of which are challenging to quantify and assess. Another limitation lies in the static nature of the analysis, as the methodology does not capture dynamic changes in efficiency over time.

Future research should address these methodological constraints by incorporating hybrid approaches that integrate DEA with econometric or qualitative methods, offering a more comprehensive understanding of the factors influencing efficiency. Expanding the scope to include variables related to social, institutional, and technological factors would enhance the robustness of the analysis. Furthermore, integrating spatial and temporal dimensions into the models could provide insights into regional disparities and their evolution over time.

The use of a dynamic version of the DEA method, such as the Malmquist Productivity Index (MPI), would be beneficial in our case, as it allows for the assessment of total factor productivity changes over time. This approach would provide deeper insights into efficiency trends, technological progress, and productivity shifts in the agricultural sector of EU countries, complementing the static DEA analysis.

Lastly, comparative studies with alternative efficiency evaluation methods, such as stochastic frontier analysis (SFA), could validate and complement the findings, offering a more holistic perspective on agricultural efficiency in the EU.

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