Technical Efficiency of Agriculture in the EU and Ukraine: A Stochastic Frontier Analysis Based on Factor Income

by *Bohdan Kyshakevych*[*], *Olga Melnyk*[*], *Yaroslav Kotyk*[**], *Yaroslav Lapchuk*[**], *Ivan Vornochak*[**]

Abstract

This paper evaluates the technical efficiency of agricultural sectors in EU and Ukraine using the Stochastic Frontier Analysis methodology. The analysis is based on factor income as the dependent variable and includes labor input, fixed capital consumption, utilized agricultural area, and intermediate consumption as key inputs. The findings reveal that EU countries on average operate under conditions of nearly constant returns to scale, while Ukraine exhibits increasing returns to scale but low efficiency due to underinvestment. The technical efficiency scores highlight significant disparities, with Western European countries outperforming Eastern counterparts. The results offer important policy implications for enhancing agricultural productivity and guiding investment strategies.
Keywords: stochastic frontier analysis, technical efficiency, agricultural sector, factor income, European Union, Ukraine.

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Introduction

The countries of the European Union exhibit considerable heterogeneity in the efficiency of agricultural production, which is influenced not only by natural and climatic conditions but also by the intensity of resource

[*] Department of Foreign Trade and Customs, Lviv Polytechnic National University, Lviv, Ukraine.
[**] Department of Mathematics and Economics, Drohobych Ivan Franko State Pedagogical University, Drohobych, Ukraine.

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utilization, the level of technological advancement, and the scale of government support. For Ukraine – one of the largest agricultural producers in Europe – enhancing production efficiency is of particular relevance, especially in the context of integration into the common European market, constrained financial resources, and the urgent need for structural modernization of the agricultural sector. Conventional productivity assessment methods often fail to adequately disentangle inefficiency from random shocks, potentially leading to biased estimations and suboptimal policy decisions. In contrast, the stochastic frontier analysis (SFA) framework provides a more robust analytical tool by enabling the estimation of technical efficiency while simultaneously accounting for statistical noise and exogenous random effects beyond the control of producers. This methodological advantage facilitates more accurate cross-country comparisons of agricultural performance and allows for the identification of key determinants underlying efficiency gaps or advantages across national agri-food systems.

In the context of intensified global competition, rising quality standards, and the increasing necessity for the sustainable use of natural resources, it becomes critically important to assess how efficiently countries utilize their available production inputs. A comparative analysis of agricultural efficiency using the Stochastic Frontier Analysis (SFA) methodology can serve as a valuable foundation for the development of evidence-based agricultural support policies – both within the European Union and in Ukraine. This approach enables the identification of structural weaknesses in Ukraine's agricultural sector and reveals latent potential for improving its international competitiveness.

Recent trends underscore the growing relevance of efficient use of land, labor, capital, and energy resources as a central pillar of sustainable agricultural development strategies. The absence of rigorous efficiency assessments based on advanced quantitative techniques increases the risk of misallocating public subsidies and investment flows. The application of SFA enables precise estimation of deviations from the production frontier and quantifies the degree of technical inefficiency – thereby providing critical insights for enhancing productivity and profitability in the agri-food sector.

Literature review

Many modern scientific publications are devoted to the problem of assessing the efficiency of the agricultural sector of EU countries. They provide a multi-dimensional understanding of efficiency in agriculture, ranging from technical assessments to subsidy effects and ecological sustainability. There is strong consensus that efficiency improvements are vital for competitiveness and sustainability. However, the path to improvement is influenced by policy design, regional conditions, and technological adaptation. The combination of SFA and DEA remains dominant in empirical studies. Staniszewski & Matuszczak (2023) reviewed 200 studies on environmentally adjusted agricultural efficiency from the Scopus database, focusing on those using DEA or SFA methods, following the PRISMA approach. It identifies key trends, such as a focus on European agriculture and growing interest in Asia, and highlights research gaps, including limited studies from Africa and North America, underexplored horticultural and non-dairy livestock production, and insufficient consideration of behavioral factors, biodiversity, soil quality, and agricultural externalities.

A separate set of studies assesses agriculture's interaction with environmental sustainability. Focusing on 26 EU member states in 2019, Domagała (2021) conducts a comprehensive analysis of economic, energy, and environmental efficiency using an input-oriented DEA model. The study establishes benchmarks, categorizes countries into four eco-efficiency groups, and emphasizes the strategic importance of reducing input usage and emissions for sustainable agricultural advancement. Zhen et al. (2022) examine the relationship between renewable energy consumption, financial development, and technical efficiency on the ecological footprint in 27 EU countries over the period 1980-2018 using CS-ARDL and Westerlund cointegration methods. The findings suggest that while financial development increases ecological pressure, both renewable energy and technical efficiency contribute positively to environmental sustainability, with their interaction further mitigating ecological degradation. Using a DEA framework, Coluccia et al. (2020) assess the eco-efficiency of the Italian agricultural sector by examining the balance between productivity and environmental sustainability across regional divisions. The analysis highlights clear regional contrasts – Southern Italy excels in resource conservation, while Northern Italy leads in productivity – underscoring the necessity for CAP policies that incentivize environmentally responsible practices. Rokicki et al. (2021) focus on the evolution of agricultural energy use patterns across EU countries between 2005 and 2018, examining the diversification of energy sources and their relationship with economic development. Results confirm a steady shift toward renewable energy and reveal strong correlations between energy consumption structures and macroeconomic indicators, especially in leading agricultural economies like France and Poland.

Another cluster of literature focuses on how various subsidy mechanisms influence efficiency. Using stochastic metafrontier analysis, Martinez et al. (2021) explore the effects of different types and levels of agricultural subsidies on the technical efficiency of beef farms in Ireland, France, Great Britain, and Germany. The results demonstrate that fully decoupled subsidies contribute to improved farm efficiency, while partially decoupled payments may obstruct technological progress and slow innovation uptake. Quiroga et al. (2017) explore how four types of CAP (Common Agricultural Policy) subsidy programs influence farm efficiency and environmental sustainability across 98 EU regions, employing the Stochastic Frontier Analysis methodology. While the results confirm that CAP contributes to greater convergence in technical efficiency across Europe, they also reveal that both first-pillar crop subsidies and environmental schemes may unintentionally discourage productivity improvements. Galluzzo (2020) examines the Romanian agricultural sector, evaluating how CAP subsidies influenced technical efficiency between 2007 and 2017. The analysis indicates that targeted support for disadvantaged rural areas yields notable efficiency gains, whereas the impact of decoupled first-pillar payments appears to be relatively limited. Poczta et al. (2020) assess the economic conditions of dairy farms across the EU by classifying them into five categories based on production potential using hierarchical clustering. The research finds that although larger, specialized farms dominate milk production and labor productivity, those with limited structural capacity often struggle to convert financial performance into sustainable income and investment.

A group of articles examines the structural features and comparative performance of agricultural systems. By applying Ward's agglomerative clustering method, Pawlak et al. (2021) compare the agricultural competitiveness of EU countries with that of the United States, using indicators related to production structure and input efficiency. It concludes that only a handful of EU nations – such as Germany, France, and the Netherlands – can effectively compete with the U.S., while many others face structural barriers that limit their agricultural potential. Coca et al. (2023) shift the focus toward the broader performance of EU agriculture under conditions of rising energy and input costs. Instead of traditional output-based evaluations, the study uses correlation analysis among key determinants and uncovers atypical performance trends across member states, arguing that derived indicators can enhance the precision of efficiency assessments at both the national and EU-wide levels. Đokić et al. (2022) evaluate agricultural technical efficiency in EU and Western Balkan countries through the application of stochastic frontier analysis. The study reveals substantial efficiency disparities and stresses the necessity of enhancing internal development factors and farmer education in the Western Balkans to support long-term economic and environmental goals.

A large group of articles is devoted to the analysis of methods and models used in assessing the efficiency of the agricultural sector. Strange et al. (2021) address the topic of benchmarking in forestry by synthesizing findings from 56 studies and highlighting the dominance of DEA and SFA methodologies in assessing efficiency at various scales. Special attention is given to the emerging role of automated data transmission, which opens new opportunities for real-time performance tracking, while also acknowledging the methodological constraints and practical challenges of applying benchmarking in forest management. Zhen et al. (2022) focus on evaluating the technical efficiency of dairy farms across EU member states using FADN data from 2004 to 2019, applying the Stochastic Frontier Analysis methodology. The results demonstrate notable disparities across countries and farm sizes, emphasizing the influence of subsidies, structural factors, and diversification on efficiency levels. Carrer et al. (2022) investigate the determinants and efficiency outcomes of adopting Precision Agriculture Technologies (PATs) on sugarcane farms in São Paulo, Brazil, using a selectivity-corrected stochastic metafrontier model. To assess agricultural efficiency in 27 European countries from 2005 to 2012, Moutinho et al. (2018) employ an integrated methodology combining DEA, SFA, and generalized cross-entropy. Despite methodological differences, both models reliably identify the most and least efficient performers and underscore the role of resource productivity and subsidies in enhancing efficiency.

Aims and objectives

The primary aim of this study is to assess the technical efficiency of agricultural sectors in European Union countries and Ukraine using the Stochastic Frontier Analysis (SFA) methodology, with a particular focus on identifying disparities in efficiency levels and the determinants influencing them.

Objectives of the article are the following:

- to evaluate the technical efficiency of the agricultural sectors in European Union countries and Ukraine using the Stochastic Frontier Analysis (SFA) based on factor income as the dependent variable;
- to test for the presence of technical inefficiency and determine the appropriate functional form of the production frontier using statistical hypothesis testing, including the likelihood ratio test;

− to conduct a comparative analysis across EU countries and Ukraine in terms of efficiency levels, returns to scale and input productivity.

Methods

In the subsequent analysis we employ the Stochastic Frontier Analysis (SFA) to evaluate the technical efficiency of the agricultural sectors in the EU countries and Ukraine. This methodological approach accounts for both systematic determinants and random shocks affecting production performance. The general form of the stochastic production function is specified as follows:

$$LnY_i = f(X_i;\beta) + v_i - u_i, \quad (1)$$

where Y_i - dependent variable (Factor Income);

X_i - a set of independent variables (inputs that affect profitability);

β - model parameters that need to be estimated;

$v_i \approx N(0,\sigma_v^2)$ - random component that takes into account statistical noise;

$u_i \approx |N(0,\sigma_u^2)|$ - the inefficiency component, which is always non-negative, since it models the deviation from the maximum possible profit**.** The main assumptions of this approach are as follows:

- v_i represents a symmetric random error term, assumed to be normally distributed, capturing statistical noise and measurement errors
- u_i denotes a one-sided non-negative inefficiency term, typically assumed to follow an exponential or half-normal distribution.

The level of technical efficiency TE_i is calculated using the following formula:

$$TE_i = e^{-u_i}, \quad (2)$$

where TE_i is technical efficiency ($0 < TE_i \le 1$). If $TE_i \approx 1$, then the country's agricultural sector operates as efficiently as possible.

Stochastic Frontier Analysis (SFA) employs the Maximum Likelihood Estimation (MLE) method, which enables the simultaneous estimation of the production function parameters and the inefficiency components. The Maximum Likelihood Estimation method is based on estimating the parameters β , σ_v^2 and σ_u^2 in such a way as to maximize the likelihood of the observed data.

The log-likelihood function is specified as follows:

$$L(\beta, \sigma_u, \sigma_v) = \sum_{i=1}^{N} \ln\left[\frac{1}{\sigma}\phi\left(\frac{Y_i - X_i\beta}{\sigma}\right)\Phi\left(\lambda\frac{Y_i - X_i\beta}{\sigma}\right)\right], \tag{3}$$

where ϕ(·) – the probability density function (PDF) of the standard normal distribution, Φ(·) – the cumulative distribution function (CDF) of the standard normal distribution.

The estimate of u_i can be obtained using its conditional expectation:

$$E[u_i|\varepsilon_i] = \sigma_u^2\left[\frac{\phi(\varepsilon_i\lambda/\sigma)}{\Phi(\varepsilon_i\lambda/\sigma)} - \frac{\varepsilon_i\lambda}{\sigma}\right], \tag{4}$$

where $\varepsilon_i = Y_i - X_i\beta$ denotes the residuals of the model.

Before estimating the model, it is necessary to choose between different specifications of the production function. Therefore, the first null hypothesis is formulated to determine the appropriate functional form of the profit frontier:

- Null hypothesis (H_0): The production function is linear (Cobb-Douglas).
- Alternative hypothesis (H_1): The production function is nonlinear (Translog).

This hypothesis is tested using the Likelihood Ratio (LR) test, based on the comparison of the log-likelihood values of the restricted and unrestricted models.

$$LR = -2\left(L_{restricted} - L_{unrestricted}\right) \tag{5}$$

where $L_{restricted}$ is the log-likelihood of the Cobb-Douglas model, and $L_{unrestricted}$ is the log-likelihood of the Translog model. If $LR > \chi^2_{critical}$ (the critical value of the chi-squared distribution for the chosen significance level and degrees of freedom), then the null hypothesis H0H_0H0 is rejected, indicating that the Cobb-Douglas model is insufficient and the Translog specification should be used. Conversely, if $LR \le \chi^2_{critical}$, the null hypothesis is not rejected, suggesting that the Cobb-Douglas model is adequate for representing the production frontier.

The second null hypothesis is used to confirm or reject the presence of technical inefficiency in the proposed model:

− Null hypothesis (H_0): The inefficiency component is not present in the model $\gamma = 0$.

− Alternative hypothesis (H_1): $\gamma > 0$, indicating that technical inefficiency is significant.

If the null hypothesis is not rejected, it implies a lack of evidence for technical inefficiency, suggesting that the use of the SFA model is not justified and that a conventional OLS model would be sufficient.

Since γ cannot take negative values, the standard chi-squared distribution is not appropriate; instead, a one-sided test based on a mixed chi-squared distribution is applied. The decision rule is as follows:

- If $LR > \chi^2_{critical}$, the null hypothesis is rejected, indicating that the OLS model is inadequate and the SFA model should be used.
- If $LR \leq \chi^2_{critical}$, there is no statistical evidence of significant inefficiency, and the conventional OLS regression may be considered appropriate.

To assess the efficiency of the agricultural sector in EU countries, four independent variables were employed (see Table 1), namely: total agricultural labour input (Labour), consumption of fixed capital (Fixed), utilised agricultural area (Area), agricultural output (Output), and intermediate consumption in agriculture (Inter).

Table 1 - Variables used in the SFA model

Variable	Explanation
Factor	Factor income (Agriculture) [12],[23] Million euro
Labour	Total labour force input (Agriculture) [10],[23] (1 000 annual work units)
Fixed	Fixed capital consumption (Agriculture) [12],[23] Million euro
Area	Utilized agricultural area (tag00025) [11],[24] Main area (1000 ha)
Inter	Intermediate consumption (Agriculture) [12],[23] Million euro

The estimation of the stochastic frontier parameters was conducted using the Maximum Likelihood Estimation (MLE) method, implemented through the FRONTIER 4.1 software package. The statistical basis of the study comprises data on the functioning of the agricultural sector in EU countries for the years 2021, 2022, and 2023 (European Commission, 2024a; 2024b; 2024c), as well as data from the State Statistics Service of Ukraine for the year 2021 (State Statistics Service of Ukraine, 2025a; 2025b).

Experiment and results

The results of hypothesis testing within the framework of the SFA model are presented in Table 2.

Table 2 - Results of hypothesis testing within the SFA model

	Hypotheses tested	LR Statistic	L restricted	L unrestricted	Critic. value
2023	H_0: γ = 0 (No technical inefficiency)	157.61	-231.27	-152.46	1.92
	H_0: Cobb–Douglas functional form	149.80	-198.11	-123.21	12.59
2022	H_0: γ = 0 (No technical inefficiency)	216,18	-342,52	-234,43	1.92
	H_0: Cobb–Douglas functional form	125,98	-241,21	-178,22	12.59
2021	H_0: γ = 0 (No technical inefficiency)	174,92	-243,78	-156,32	1.92
	H_0: Cobb–Douglas functional form	65,82	-178,13	-145,22	12.59

Since the LR statistics exceed the respective critical values for both hypotheses, the null hypotheses are rejected. This provides statistical evidence of inefficiency and supports the use of the translog specification over the Cobb–Douglas functional form:

$$\ln(Factor) = \beta_0 + \beta_1 \ln(Labour) + \beta_2 \ln(Fixed) + \beta_3 \ln(Area) + \beta_4 \ln(Inter) +$$
$$+ \frac{1}{2}\beta_{11}(\ln(Labour))^2 + \frac{1}{2}\beta_{22}(\ln(Fixed))^2 + \frac{1}{2}\beta_{33}(\ln(Area))^2 \frac{1}{2}\beta_{44}(\ln(Intre))^2 +$$
$$+ \beta_{12}\ln(Labour)\cdot\ln(Fixed) + \beta_{13}\ln(Labour)\cdot\ln(Area) + \beta_{14}\ln(Labour)\cdot\ln(Inter) +$$
$$+ \beta_{23}\ln(Area)\cdot\ln(Fixed) + \beta_{24}\ln(Inter)\cdot\ln(Fixed) + \beta_{34}\ln(Area)\cdot\ln(Inter) \qquad (6)$$

The estimation of the stochastic frontier parameters (Table 3) was conducted using the maximum likelihood method with the FRONTIER 4.1 software package.

The estimated value of γ = 0.81 indicates that a substantial proportion of deviations from optimal productivity are attributable to technical inefficiency rather than to random factors such as weather conditions or market fluctuations. This suggests that there exists considerable potential for improving efficiency by addressing the sources of technical inefficiency.

Table 3. Maximum likelihood estimates of regression parameters

	2021			2022			2023		
	Coef.	Standard error	t-statistic	Coef.	Standard error	t-statistic	Coef.	Standard error	t-statistic
β_0	1,429	1,005	1,422	1,986	1,043	1,904	3,479	0,843	4,127
β_1	0,212	0,084	2,524	0,314	0,114	2,754	0,251	0,094	2,670
β_2	0,091	0,026	3,500	0,088	0,026	3,385	0,133	0,065	2,046
β_3	0,413	0,198	2,086	0,546	0,099	5,515	0,411	0,099	4,152
β_4	0,142	0,053	2,679	0,112	0,052	2,154	0,213	0,022	9,682

β_{11}	0,049	0,011	4,455	0,84	0,111	7,568	4,937	2,011	2,455
β_{22}	2,105	0,404	5,210	1,124	0,404	2,782	3,278	0,404	8,114
β_{33}	1,388	0,366	3,792	0,734	0,366	1,913	0,764	0,366	2,087
β_{44}	0,61	0,296	2,061	4,031	1,296	3,110	1,602	0,786	2,038
β_{12}	2,399	0,611	3,926	3,638	0,611	5,954	2,333	0,611	3,818
β_{13}	2,317	1,862	1,244	1,331	0,362	3,677	3,537	1,862	1,900
β_{14}	0,423	0,135	3,133	0,131	0,035	3,743	0,843	0,235	3,587
β_{23}	0,249	0,084	2,964	4,533	0,624	7,264	1,482	0,624	2,375
β_{24}	1,828	0,548	3,336	0,361	0,048	7,521	0,808	0,248	3,258
β_{34}	0,977	0,114	8,570	4,545	0,844	5,385	1,868	0,844	2,213
sigma-squared	0,793	0,369	2,149	0,731	0,364	2,008	0,780	0,239	3,264
gamma	0,812	0,298	2,725	0,765	0,238	3,214	0,820	0,342	2,397

Unlike the Cobb-Douglas specification, the calculation of returns to scale (RTS) in the translog model is more complex and cannot be derived from a simple summation of the β coefficients. In our case, RTS depends not only on the linear coefficients but also on the interaction and squared terms. Consequently, returns to scale are not constant but vary depending on the values of the input variables. For each of the 28 countries analyzed, efficiency can be calculated using the following formula:

$$RTS_i = \sum_{k=1}^{4} \left(\beta_k + \sum_{m=1}^{4} \beta_{km} \cdot \ln\left(x_{mi}\right) \right), \quad i = 1 \ldots 28 \tag{7}$$

The results of the returns to scale (RTS) assessment for EU countries and Ukraine are presented in Table 4. Ukraine in 2021 and Romania in 2023 recorded the highest values of this index, indicating the presence of potential for increasing returns to scale. This can be attributed to the still unrealized efficiency reserves in the utilization of production resources, opportunities for technological modernization, and the enhancement of managerial practices in the agricultural sector.

On average, EU countries exhibit nearly constant returns to scale (RTS_{av} = 0.99), indicating that the agricultural sector operates in a balanced manner. A 1% increase in the use of key production inputs (land, labor, capital, and intermediate consumption) results in a proportional 1% increase in factor income. In other words, such an agricultural sector has reached a mature stage of development, where resources are utilized efficiently, without surplus or deficit. This situation is also typical for stable and advanced agricultural sectors in EU countries with well-established agricultural policies and a high level of government regulation.

Table 4 - Returns to scale (RTS) in the agricultural sectors of EU member states and Ukraine

	2021	2022	2023
Luxembourg	0,9	0,91	0,9
Malta	0,9	0,89	0,88
Cyprus	0,92	0,94	0,92
Belgium	0,95	0,95	0,96
Netherlands	0,95	0,97	0,96
France	0,96	0,97	0,96
Denmark	0,97	0,97	0,98
Germany	0,97	0,98	1
Italy	0,97	0,97	1
Sweden	0,97	0,98	0,95
Austria	0,98	0,98	0,98
Finland	0,98	0,98	0,97
Spain	0,98	0,98	0,97
Ireland	0,99	0,99	1
Greece	1	0,99	1
Portugal	1	1	0,99
Slovenia	1	0,99	0,98
Estonia	1,01	1	1,01
Croatia	1,02	1	1,02
Lithuania	1,02	1,02	1,03
Bulgaria	1,03	1,02	1,05
Latvia	1,03	1,02	1,03
Slovakia	1,03	1,02	1,04
Czech Republic	1,04	1,04	1,04
Poland	1,04	1,05	1,05
Hungary	1,05	1,05	1,04
Romania	1,05	1,06	1,07
Ukraine	1,07		
Geometric Mean	0,99	0,99	0,99

An RTS value greater than 1 in EU countries indicates the existence of potential for scale expansion with increasing returns. This pattern is typically observed in countries experiencing dynamic growth in the agricultural sector, modernization of production, or the active implementation of innovations. According to the obtained results, this situation is characteristic of Central and Eastern European countries, where the agricultural sector is still undergoing an active development phase.

Conversely, an RTS value below 1 signals oversaturation of the agricultural sector or the presence of structural and technological constraints. Additional expansion of production resources does not lead to a proportional increase in factor income. The decreasing returns to scale observed – based on the estimated SFA model – in most Western European countries highlight the need to shift the focus from increasing input volumes to enhancing productivity through innovation, precision farming, digitalization, and intensive technologies.

Since the estimation was based on a translogarithmic functional form, the returns to scale are not constant and depend on the combination of input factors specific to each country. The calculated individual RTS values for EU member states revealed the presence of countries with constant returns to scale as well as cases of decreasing returns, which may indicate resource oversaturation and declining efficiency in certain agricultural systems. This underscores the need for a more individualized approach to agricultural development policy, taking into account the structure of resource endowments and existing technological constraints.

Table 5 presents the results of profit efficiency estimates for the agricultural sectors of EU countries and Ukraine for the year 2021. Due to the unavailability of statistical data for most agricultural performance indicators in Ukraine for 2022 and 2023, efficiency for these years was calculated only for the 27 EU countries.

The undisputed leaders in this ranking are the Netherlands, Belgium, and Denmark. In the pre-war period, Ukraine's agricultural sector demonstrated a technical efficiency level of approximately 0.5, which allowed it to outperform several Eastern European countries, although it remained in the lower tier of the overall ranking. Interestingly, the average efficiency of the agricultural sectors across EU countries has shown a steady increase of approximately 1% per year over the analyzed period.

Table 5 - Agricultural sector efficiency of EU countries based on the SFA model

Integr. rating	Country	2021	2022	2023
1	Netherlands	0,96	0,97	0,97
2	Belgium	0,97	0,96	0,95
3	Denmark	0,92	0,93	0,94
4	Spain	0,91	0,91	0,93
5	Italy	0,88	0,87	0,9
6	France	0,86	0,85	0,9
7	Germany	0,82	0,81	0,82
8	Malta	0,81	0,83	0,81
9	Greece	0,79	0,76	0,78
10	Ireland	0,78	0,78	0,76
11	Bulgaria	0,74	0,7	0,73
12	Cyprus	0,72	0,74	0,72
13	Slovenia	0,7	0,67	0,72
14	Slovakia	0,67	0,72	0,71
15	Lithuania	0,63	0,65	0,67
16	Luxembourg	0,63	0,62	0,67
17	Austria	0,63	0,6	0,62
18	Portugal	0,55	0,58	0,53

19	Sweden	0,53	0,56	0,52
20	Poland	0,51	0,53	0,52
21	Finland	0,5	0,49	0,5
22	Croatia	0,44	0,52	0,49
23	Estonia	0,45	0,48	0,49
24	Czechia	0,47	0,46	0,47
25	Romania	0,42	0,42	0,42
26	Latvia	0,4	0,39	0,41
27	Hungary	0,41	0,4	0,4
28	Ukraine	0,5	-	-
Geom. mean		0,66	0,67	0,68

Unfortunately, Ukraine's position in the agricultural efficiency ranking among EU countries can be assessed only based on the statistical data available for 2021, as official data for the period of ongoing military aggression have not yet been published. Therefore, efficiency was estimated using the proposed SFA model for the year 2021 (for both EU countries and Ukraine) and for 2022–2023 (for EU countries only).

Overall, territories in Ukraine affected by occupation, military operations, and landmines account for approximately 31.74% of the country's total area. Agricultural land comprises about 70% of Ukraine's territory, with a total area of approximately 41.3 million hectares (State Statistics Service of Ukraine, 2023). As a result of Russian aggression and temporary occupation, around 25–30% of agricultural land (over 12 million hectares) is currently located in zones of active hostilities, occupation, or contamination by landmines. These factors have led to a substantial decline in the production potential of the agricultural sector, weakened Ukraine's export capacity on the global market, and created serious threats to food security not only at the national level but also globally. In addition to economic losses, the situation poses long-term challenges for the restoration of soils and agricultural infrastructure.

When comparing the efficiency of the agricultural sector across regions, Western European countries emerged as the leaders, with an average efficiency score of 0.82 in 2023 (see Figure 1). The lowest efficiency was observed in Eastern European countries, with an average of 0.55. The efficiency of agriculture in Southern EU countries was significantly higher than in the Northern ones – 0.78 and 0.61, respectively. This can be attributed to the favorable climate in Southern Europe, characterized by a long growing season that allows for multiple harvests per year and the cultivation of high-margin crops such as grapes, olives, citrus fruits, and vegetables. In contrast, Northern countries face a shorter agricultural season, greater weather-related risks, and a more limited range of crops.

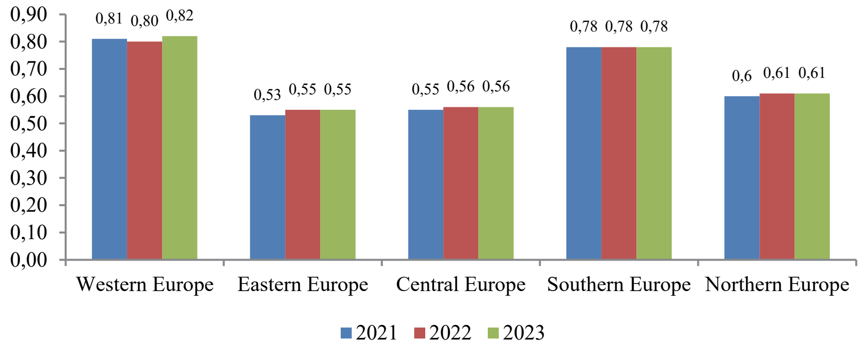

Figure 1 - Average agricultural sector efficiency across EU regions

The availability of vast agricultural land presents significant opportunities while simultaneously posing challenges related to the rational use of these resources. Large land areas require substantial investments in machinery, infrastructure, irrigation systems, and modern agricultural technologies. Insufficient renewal of fixed capital or excessive reliance on extensive farming methods reduces overall efficiency. Ukraine's vast agricultural land represents a strategic advantage in the global agricultural market—provided it is used efficiently. With appropriate agricultural policies and targeted investments, this resource can significantly enhance the country's export potential.

Even without accounting for the temporarily occupied territories, Ukraine currently possesses the largest area of agricultural land in Europe (see Figure 2). However, this considerable predominance in land area partly explains the relatively low efficiency of Ukraine's agricultural sector compared to average EU levels. As shown in Figure 3, the indicator of gross fixed capital consumption (depreciation) in Ukraine is significantly lower compared to countries with smaller or comparable agricultural land areas, such as France and Spain. This reflects insufficient renewal of fixed assets and a low level of capital intensity in agricultural production. While Ukraine's agricultural sector benefits from vast land resources, it fails to provide an adequate level of investment in fixed capital, which may constrain productivity and overall production efficiency. In terms of factor income in the agricultural sector in 2021, Ukraine ranked sixth among the countries analyzed (see Figure 4). However, due to the significantly larger agricultural land area compared to most other countries, Ukraine exhibited a relatively low level of efficiency in its agricultural sector.

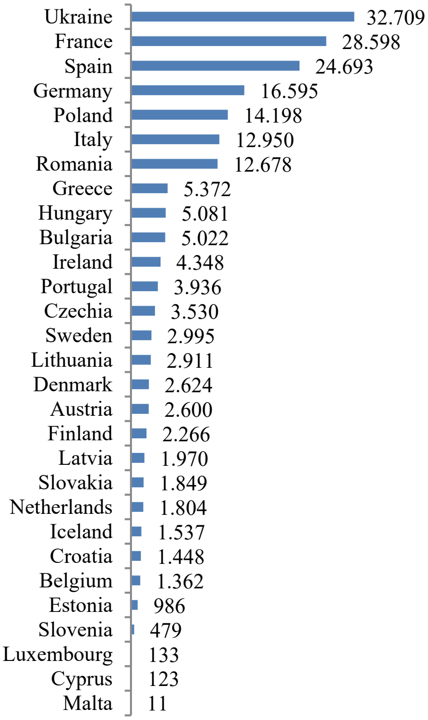

Figure 2 - Agricultural land areas in EU and Ukraine in 2023, thousand hectares

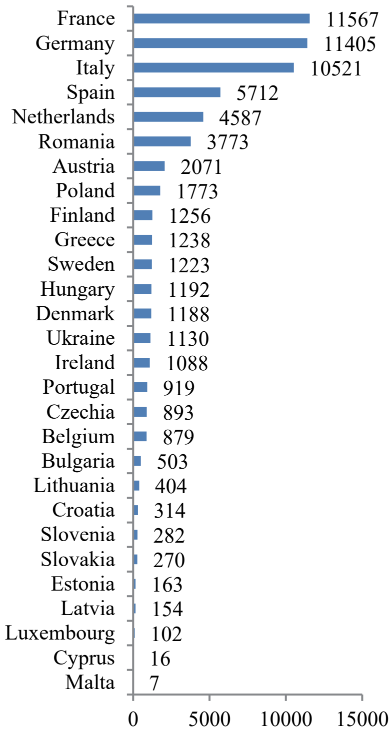

Figure 3 - Gross fixed capital consumption in agriculture in 2021, million euros

Intermediate consumption is an important indicator of resource expenditure and reflects the costs of materials, energy, services, seeds, and feed – resources that directly influence the volume of output or profit. In agriculture, intermediate consumption refers to the value of all goods and services used in the production process for generating agricultural output during the reporting period, which were entirely consumed in that process (i.e., not retained as assets or inventory). In the production function, intermediate consumption serves as a key short-term input factor alongside labor, land, and capital. In essence, intermediate consumption represents material resources that are directly transformed into output – either in the form of produced goods or factor income. In Ukraine, the level of intermediate consumption is relatively high (see Figure 5).

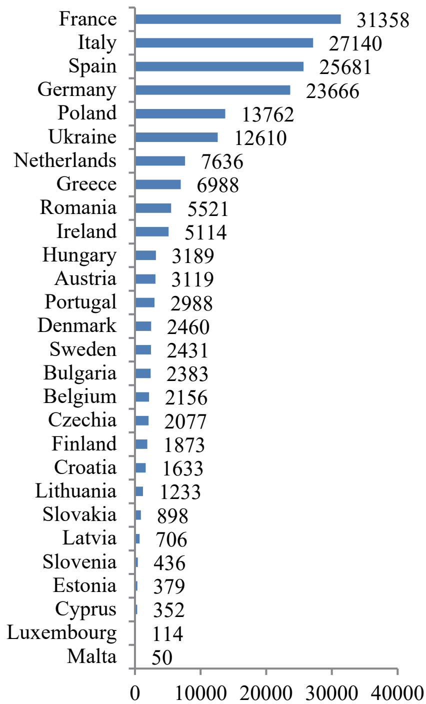

Figure 4 - Factor income in agriculture in 2021, million euros

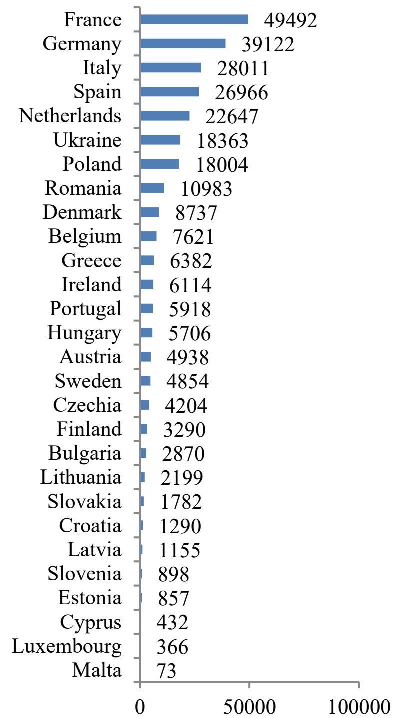

Figure 5 - Intermediate consumption in the agricultural sector in 2021, million euros

Discussion

The findings of this study offer valuable insights into the technical efficiency and scale dynamics of agricultural production across EU member states and Ukraine. The use of a translog stochastic frontier model allowed for a nuanced interpretation of how multiple input factors – land, labor, fixed capital, and intermediate consumption – contribute to factor income in the agricultural sector. One of the key contributions of this analysis lies in the observation that, on average, EU countries operate under nearly constant returns to scale (RTS ≈ 0.99), implying an efficient balance between input use and output generation. This outcome is consistent with earlier research by Kocisova and Sedliaciková (2022), who emphasized the stabilizing role of institutional and technological maturity in the EU's western agricultural systems. Similarly, Đokić et al. (2022) found that countries such as the Netherlands, France, and Germany consistently exhibit high efficiency levels, largely due to long-term investments in modernization and sustained agricultural policy support. Conversely, the increasing returns to scale (RTS > 1) observed in Central and Eastern European countries, as well as in Ukraine (RTS = 1.07), align with findings from Galluzzo (2020), which analyzed Romania's agricultural sector. These results suggest underutilized potential that could be unlocked through structural reforms, enhanced access to capital, and adoption of precision agriculture technologies. In this context, the findings reinforce arguments presented by Zhen et al. (2022), who highlighted those improvements in technical efficiency – particularly when combined with renewable energy integration – can yield environmental and economic co-benefits.

However, the efficiency score for Ukraine (TE ≈ 0.50) remains below the geometric mean of the EU sample (TE ≈ 0.66-0.68). While Ukraine ranks sixth in factor income in absolute terms, its relative efficiency is diluted by the sheer scale of agricultural land. This indicates a low level of capital intensity and limited renewal of fixed assets, reinforcing the conclusions of Martinez et al. (2021) and Quiroga et al. (2017) regarding the critical role of subsidy mechanisms and investment incentives in influencing farm-level performance. As these studies suggest, mere availability of land or labor is insufficient, efficient transformation of inputs into outputs hinges on modernization and institutional support.

The present study also affirms the importance of intermediate consumption as a short-term determinant of technical efficiency. This result supports prior studies (e.g., Moutinho et al., 2018; Coluccia et al., 2020) showing a strong association between intermediate input use and both profitability and productivity in agri-food systems, particularly in the Mediterranean and Southern regions of the EU. The observed regional disparities – namely, higher efficiency in Southern Europe compared to Northern and Eastern counterparts – reflect ecological and climatic conditions highlighted by Domagała (2021), who emphasized the significant impact of climate suitability and crop specialization on output efficiency. Additionally, our results emphasize the significance of tailoring agricultural policies to regional contexts. Variations in efficiency across EU countries mirror the typologies outlined by Poczta et al. (2020) and Pawlak et al. (2021), emphasizing the combined influence of structural features, policy measures, and environmental limitations on national-level results. Countries with decreasing RTS should prioritize innovation, digitalization, and sustainability, while those with increasing RTS, require targeted support to realize scale economies and modernization gains.

Overall, the outcomes of this research confirm the robustness of the SFA framework in disentangling inefficiency from random shocks, and they underscore the necessity for differentiated and evidence-based agricultural strategies. The implications are particularly relevant for Ukraine's post-war recovery planning. Investments in capital stock, institutional reform, and access to innovation will be essential in transforming its extensive land base into a source of sustainable productivity and global competitiveness.

Conclusions

This study provides a detailed assessment of the technical efficiency of the agricultural sectors in the European Union and Ukraine using stochastic frontier analysis (SFA) based on the translog production function. Ukraine possesses one of the largest areas of agricultural land among European countries, which creates substantial production potential. However, gross fixed capital consumption (depreciation and technical renewal) per hectare is below the EU average. This indicates the need for increased investment in the modernization of machinery, equipment, irrigation systems, and other fixed assets to enhance the efficiency of land use.

According to the estimated SFA model, the agricultural sector in EU countries exhibits, on average, nearly constant returns to scale (RTS ≈ 0.99), indicating balanced and efficient use of production resources without overexploitation or shortage. This pattern is particularly characteristic of economically developed Western European countries with strong governmental support and substantial investment in modernization. In contrast, Central and Eastern European countries show increasing returns to scale (RTS > 1), suggesting significant potential for growth in efficiency through resource consolidation, modernization, and the implementation of innovations.

Technical efficiency in the EU agricultural sector demonstrates a consistent upward trend, growing by approximately 1% annually. The highest efficiency levels were observed in the Netherlands, Belgium, and Denmark, while Eastern European countries continue to lag behind, with efficiency levels around 0.55–0.60. Ukraine's agricultural sector recorded a technical efficiency score of 0.5 in 2021, which allowed it to outperform some Eastern European countries, although it remained in the lower range of the overall ranking. At the same time, Ukraine's high RTS value (1.07) indicates strong potential for efficiency improvements through modernization and institutional reforms. Regional differences in agricultural sector efficiency across the EU underscore the need for individualized agricultural policies. Countries experiencing resource saturation and low RTS should focus on innovation, digitalization, and intensive technologies, while those with high RTS should prioritize support for scaling up and modernization.

Thus, the results of this study may serve as a basis for defining strategic directions for the development of Ukraine's agricultural sector in the context of European integration, shaping state support mechanisms, and designing policies aimed at stimulating investment in the recovery and modernization of agricultural production.

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