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Technical Efficiency of Agriculture in the European Union and Western Balkans: SFA Method

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Abstract: Improvements in productivity and efficiency, together with agricultural modernization, are crucial in the process of future sustainable development. As Western Balkan (WB) countries are in the process of integration into the European Union (EU), the importance of agricultural efficiency in an economic and environmental context and the actuality of the problems of the agricultural sector are very important. In that context, the paper's main goal is to examine agriculture's technical efficiency in the EU and WB. The additional goal is to group analyzed countries by agricultural performances. A stochastic frontier analysis (SFA) is used to calculate the technical efficiency of agriculture. Results have shown a significant difference in technical efficiency between WB and the EU. Furthermore, the cluster analysis has indicated the connection between overall economic development and agricultural development, partially "deformed" by agri-environmental and climate conditions. The exogenous factors do not have a crucial influence on the overall technical efficiency of agriculture in observed countries, indicating that the endogenous factors must be improved. The paper impacts recommendations for optimizing the use of inputs and improving the educations of farmers in WB countries to achieve economic and environmental goals.

Keywords: technical efficiency; agriculture; SFA method; Western Balkans; European Union

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1. Introduction

The current Ukrainian crisis brings the issues of energy supply and inflation to the forefront. An additional problem of this crisis is food supply disruptions and rising prices of agricultural products. Agriculture is a critical link in the food supply chain, and the question of the importance of agriculture is being re-examined. Although this is one of the main reasons for dealing with this topic in general, two other reasons influenced the selection of this topic. First is the importance of agricultural efficiency in an economic and environmental context. Agricultural technological progress and technical efficiency are crucial drivers in promoting improvements in agricultural production, which is the primary source of expanding economic output [1]. According to Morais et al. (2021) [2], the estimation of technical efficiency is frequently used to create programs for performance improvement. Therefore, efficiency enhancement of agricultural production appears worldwide as one of the most significant challenges for agricultural holdings. Almost everywhere, the government tends to help farmers in this process with its agricultural policy. The best example is the European Union (EU) Common Agricultural Policy (CAP), from which the increase in production efficiency had decades of significant support. After decades of supporting the efficiency enhancement of the agricultural sector, the idea of sustainable agriculture in which the social, economic, and environmental objectives should be fulfilled is dominant. However, this role can fulfill only farms that effectively transform inputs into outputs and do not waste the inputs [3]. Similar conclusions are given by Liu et al. (2020) [4] considering Chinese agriculture. This is because improvements in productivity and efficiency, along with agricultural modernization, are considered the decisive factors for the future sustainable development of China's agriculture. Additionally, agricultural production efficiency is the main factor affecting the intensity of agricultural carbon emissions. Therefore, improving production efficiency can suppress the intensity of agricultural carbon emissions [5]. Additionally, according to contemporary developments in CAP, there will be some radical changes in the next period that will influence the whole production system. CAP for 2023–2027 is "greener" than it was previously. Therefore, optimal use of inputs, especially chemicals, will be essential. Second, the agriculture of Western Balkan countries (WB) is particularly interesting. Their agri-food sector has been commonly analyzed in recent years, probably due to the specific political situation in this region. Although all of these countries are in the process of European integration, some consequences of the previous economic system and transition processes still influence agricultural performances. Because of that, it is crucial for all WB countries to provide the best possible positions for their agri-food products during pre-accession negotiations for EU membership and take the necessary steps towards increasing the level of competitiveness in the common EU market [6].

Two papers are significant for this paper due to their focus on the technical efficiency of agriculture. In their study, Đokić et al. (2020) [7] showed that technical efficiency improved in the period 1999–2016 in WB. However, the average relative technical efficiency of agriculture in these countries is noticeably worse than in the EU countries. Similar conclusions are given by Marcikić Horvat et al. (2020) [8]. However, they also indicate that this difference is a consequence of agriculture's unfavorable resource structure, primarily due to high presence of small farms and the slow development of a non-agricultural sector that cannot accept a surplus of labor from agriculture. These papers examined technical efficiency in WB, but both use the data envelopment analysis (DEA) method. Therefore, this research will enable a comparison of the results of DEA and SFA methods for this region.

This paper's main goal is to examine agriculture's technical efficiency in the EU and WB. The additional goal is to group analyzed countries by agricultural performances. Additionally, this research attempts to contribute to the literature by using the SFA method instead of the DEA method, which was often used. The paper is structured as follows. Section two provides a literature review on technical efficiency and agricultural issues in the EU and WB. Section three describes the SFA method and data. The fourth part shows results and discussion divided into two subsections: technical efficiency of agriculture and cluster analysis by agricultural performances. The main conclusions are summarized in the final section.

2. Literature Review

Although many studies on the topic of analysis of technical efficiency refer to the agricultural sector, most are limited to case studies of single countries or single sectors. Moreover, only a few authors have analyzed the technical efficiency of the agricultural sector in several or all European Union countries. Regarding methodology, most research uses the DEA method, while papers with the SFA method are scarce. This literature review will review previous research using these methods, primarily for EU countries, with a particular emphasis on the Central and Eastern European countries (CEEC) and their comparison with the old EU countries. The CEEC analysis is important, bearing in mind that technical efficiency research for the Western Balkans countries is rare and that CEECs are valuable rappers to these countries. At the end of the literature review, the few Western Balkans' technical efficiency research will be reviewed, as will the factors influencing technical efficiency in these countries.

Bakucs et al. (2011) [9] analyzed the technical efficiency of farms specialized in arable production and milk production in eight EU countries (Belgium, Estonia, France, Germany, Hungary, Italy, the Netherlands, and Sweden). Based on the results of the SFA analysis from this research, it was determined that farms from the dairy cattle sector show better results compared to farms specialized in arable production. Nowak et al. (2015) [10]

analyzed the technical efficiency of EU agriculture and its determinants using the DEA method. They found that the technical efficiency of agriculture varies widely: the difference between the countries with the highest and the lowest efficiency is 40%. The determinants of influence on technical efficiency found to be significant are land quality, age of the head of household, and investment subsidies. More recently, in their study of technical efficiency and its determinants in European agriculture, Moutinho et al. (2018) [11] applied DEA and SFA methods and determined that resource productivity and subsidies have a positive and significant effect on technical efficiency, while domestic consumption and the share of areas under organic crops have a negative effect on technical efficiency.

Analysis of the technical efficiency of new EU member states and comparative analysis with old member states was the subject of research of a number of papers. For example, Bojnec et al. (2014) [12] applied the DEA method to evaluate the technical efficiency of 10 EU member states from the CEEC region from 2001 to 2006, a period that included the adaptation and reform processes during accession to the EU. All of the studied countries had a technical efficiency below 1. Bulgaria and Slovakia achieved the highest results, while the Baltic States showed the lowest results. It was determined that technical efficiency in the studied countries is conditioned by the transition process, institutional reforms, policy reforms, as well as technological changes. The size and degree of specialization of the farms were singled out as significant determinants of the influence on technical efficiency. An analysis of the fulfillment of one of the main goals of Agenda 2000, increasing the market orientation of agricultural production, was carried out by Vlontzos and Niavis (2014) [13]. The authors used the DEA and SFA methods to assess technical efficiency, and the results of the study indicated that both models show an increase in the technical efficiency of the agricultural production sector of EU countries. The results also showed that Eastern European countries, which are more recent EU members, have statistically significantly lower technical efficiency compared to older members. Hart et al. (2015) [14] analyzed the impact of trade openness on the technical efficiency of EU agriculture. The study focused on 28 member states over a period from 1980 to 2007 and relied on the SFA method. It was determined that former communist states have lower ratings of technical efficiency compared to southern European states. The results of this study also show that trade openness has a negative impact on the technical efficiency of EU agriculture; however, over time trade openness increases efficiency due to the adaptation of production technology to increased competition. The results also indicate a significant positive impact of foreign direct investment on technical efficiency. Additionally, Náglová and Rudinskaya (2021) [15] analyzed technical efficiency in the EU dairy farms using the SFA method and concluded that new and old member states have almost comparable technical efficiency levels, while old members have a slightly higher level of technical efficiency. Pawłowski et al. (2021) [16] analyzed regional differences in the technical efficiency of farms in the context of overinvestment. The analysis was conducted on the basis of the FADN database for data on farms from Poland for the period 2004–2015. Using SFA, the authors proved that there are significant differences in the average technical efficiency of different overinvested groups, i.e., it was shown that underinvested farms are the least efficient, as well as that greater efficiency was achieved with relatively and absolutely overinvested farms. Záhorský and Pokrivčák (2017) [17] analyzed farm output TE in ten CEEC as well as the total factor productivity development in the period of 2004–2012. They concluded that none of the observed countries were efficient in terms of farm performance. Lithuania was the closest to score 1, while the least efficient was Poland.

As agriculture in the EU is highly differentiated, research that focuses on the competitiveness of agriculture and grouping countries of the EU according to similar characteristics is very valuable [18]. New research on the effects of EU integration on the competitiveness of the agricultural sector in the new member states showed that a gap still exists between old and new member states of the EU in the efficiency of utilization of their inputs despite increased labor productivity in new member states [19].

Research on the technical efficiency of agriculture in the Western Balkans, and its comparison with the EU, are very rare in the literature. For example, Marcikić Horvat et al. (2020) [8] compared the relative technical efficiency of agriculture in the Western Balkan and EU countries using the DEA method and concluded that the relative technical efficiency in Western Balkan countries is noticeably worse than in the EU countries. These authors, as the main source of agricultural inefficiency in the Western Balkan countries, found poor results in labor productivity. Another research by Todorović et al. (2020) [20] analyzed the technical efficiency of arable farms in Serbia using the two-stage DEA method. The results of this research showed that the share of rented land, land-to-labor ratio, and financial stress variables are the main determinants of the efficiency of arable farms in Serbia, while subsidies (area payments and input subsidies) have some impact on the technical efficiency of arable farms. The results also highlighted the importance of a future shift of Serbian agricultural support towards CAP, which is especially important if we keep in mind that compared to the EU countries, Serbia's agricultural performance is significantly lagging behind [21].

Đokić et al. (2020) [7] studied the technical efficiency of agriculture and the factors affecting technical efficiency in Western Balkans countries and new EU members. Using the DEA method, the authors found that technical efficiency in all the studied countries improved from 1999 to 2016 and that the factors that have a positive impact on technical efficiency are land per worker, fertilizer per hectare, and membership in the EU, while they singled out the share of areas under organic crops as a factor that negatively affects technical efficiency. Bearing in mind these results of determinants that affect the technical efficiency of agriculture, it is very important in the countries of the Western Balkans to influence the growth of productivity given that there is an obvious gap compared to EU countries [22]. Although the results indicate a positive influence of fertilization on technical efficiency, we should be careful when it comes to the further growth of the use of fertilizers given that more attention will be paid to agri-environmental measures [23], as fertilization contributes to greenhouse gas emissions and pollution [24]. Regarding the membership of the countries of the Western Balkans in the EU, i.e., the harmonization of domestic agricultural policies with the CAP, applied agricultural policies in Western Balkan countries depart from this declared future planning and rather reflect domestic political economy interests [25]. Although previous research showed that organic production negatively affects technical efficiency in the Western Balkans and new EU member states, situation on this issue is not black and white, as organic production is not as efficient as conventional and organic production systems are still in the development phase [7]. Namely, organic agriculture is very important in achieving the Sustainable Development Goals, as it seeks to redesign whole food systems to achieve ecological, economic, and social sustainability [26].

3. Materials and Methods

Econometric literature includes two basic methodological approaches for analyzing technical efficiency, non-parametric and parametric. The non-parametric approach is based on mathematical programming methods, of which DEA is one of the most commonly used methods. The DEA method is a mathematical programming technique based on a non-parametric approach because it does not require a previously defined assumption about the functional form of the production function, which significantly simplifies its application [27]. On the other hand, a crucial disadvantage of this method is reflected in the omission of the model's random error, so it is not possible to define the relative influence of other factors that are not explicitly included in the model.

The parametric approach is based on econometric modeling, in which models of deterministic and models of stochastic frontier production functions are distinguished. The key disadvantage of deterministic models is reflected in the fact that the one-sided error term includes the influence of all those factors that are the cause of deviation from the optimal efficiency regardless of whether or not they are under the control of the production entities or are of an exogenous nature. Accordingly, stochastic frontier production functions allow the introduction of composite error of the model, which separates the influence of factors that are under the control of production entities and the influence of all those factors that are beyond the control of production units [28].

The methodology for estimating the model of the stochastic frontier production function was first presented in the works of Aigner et al. (1977) [29] and Meeusen and van den Broeck, (1977) [30]. Separate studies, carried out independently of one another as the authors knew nothing of each other's work, both highlight the importance of random factors that have an impact on the variability of the output. Relying on the Cobb–Douglas functional form of the model, the stochastic marginal production function in its general form can be represented as follows:

$$\ln y_i = \beta_0 + \sum_n \beta_n \ln x_{ni} + \varepsilon_i.$$

Unlike deterministic models, in which any deviation from the efficiency limit is interpreted as inefficiency, stochastic models show a composite random error of the model (ε_i), which is composed of two components, so that the following applies: $\varepsilon_i = v_i - u_i$. The first component of the composite error of the model (v_i) includes all those random factors that are beyond the control of production entities but are certainly present and have an impact on the realized output. When evaluating the model of the stochastic marginal production function, it is assumed that the component v_i is normally distributed with the homoscedastic variance σ_v^2.

Nevertheless, the composite random error of the model (ε_i) is asymmetric because it holds that $u_i \geq 0$. The u_i component represents a one-sided asymmetric component that includes the influence of all those factors that are under the control of production entities and have an impact on the realized output. In other words, the component u_i represents a measure of realized technical inefficiency.

In this regard, with the basic techniques of econometric analysis, it is possible to test the presence of technical inefficiency. Specifically, as $\varepsilon_i = v_i - u_i$ is valid, the composite random error of the model in the case of the presence of technical inefficiency is asymmetric. If it were not, for the established absence of technical inefficiency ($u_i = 0$), it would be valid that $\varepsilon_i = v_i$, and the random error of the model would be symmetrical. On the other hand, when $u_i > 0$, the composite random error of the model ε_i is negatively asymmetric, indicating the presence of technical inefficiency. Generally speaking, the technical efficiency of production entities can be determined by evaluating different stochastic marginal production function models, which are divided in the methodological approach based on the type of available data (comparative or panel data).

According to Schmidt and Sickles (1984) [31], there are three types of problems when evaluating models based on comparative data. First, the maximum likelihood method relies on an assumption of the distribution of random error components. Second, when evaluating the model of comparative data, it is assumed that there is no connection between the regressor and the component related to inefficiency, which is not in accordance with the reasoning of achieved efficiency [32]. Third, the estimate of technical inefficiency is inconsistent, given that the conditional mean or mode of u $u(v-u)$ never tends to the true value u even though $N \to \infty$, where N is the number of observation units, u is the inefficiency, and v is the random error.

In addition, stochastic marginal production function models can be divided based on whether or not they are used to obtain time-invariant and time-varying technical efficiency ratings. The latter group of models is of more recent date and is therefore present to a greater extent in empirical research. The differences between numerous models on the basis of which it is possible to assess time-varying technical efficiency are mainly of a methodological nature. In this regard, according to Kumbhakar, Lien, and Hardaker (2014) [33], the model that takes the following form stands out among the aforementioned group of models:

$$y_{it} = \alpha_0 + \sum_n \beta_n \ln x_{nit} + \mu_i + v_{it} - \eta_i - u_{it}$$

The model defined in this way overcomes certain limitations faced by other stochastic marginal production function models. For instance, the error is made up of as many as four components representing heterogeneity between observation units (μ_i), random effects (v_{it}), persistent or time-invariant technical inefficiency (η_i), and time-variant technical inefficiency (u_{it}). An additional advantage of the model is that error components can be evaluated simultaneously within it or, if they do not show statistical significance, can be excluded from it.

A very significant improvement in the evaluation of the stochastic marginal production function model using the Kumbhakar, Lien, and Hardaker (2014) [28] model compared to other models is that it is possible to evaluate the time-varying technical inefficiency for a time period t, which is not related to the previously calculated inefficiency for the time period t-1. In this way, it is possible to monitor the possible improvement of efficiency for the observation unit i. Additionally, the mentioned model specifically evaluates time-invariant technical inefficiency in the context of the presence of long-term constraints that are under the control of production entities.

The evaluation of the stochastic frontier production function model—which analyzes time-invariant technical inefficiency, time-variant technical inefficiency, and the heterogeneity between the observation units separately—can be performed in three steps using the maximum likelihood method [34].

Given that it is a parametric method, when evaluating the model, it is necessary to introduce certain assumptions regarding the distribution of the random error components. The centered model adapted to the assessment has the following form:

$$y_{it} = \alpha_0^* + \sum_n \beta_n \ln x_{nit} + \alpha_i + \varepsilon_{it},$$

where the following applies: $\alpha_0^* = \alpha_0 - E(\eta_i) - E(u_{it})$, $\alpha_i = \mu_i - \eta_i + E(\eta_i)$, and $\varepsilon_{it} = v_{it} - u_{it} + E(u_{it})$. Parameters α_i and ε_{it} have zero mean value and homoscedastic variance, so the entire model can be evaluated in three steps.

In the first step, by applying the standard procedure inherent in the panel regression analysis of fixed or random individual effects, it is necessary to estimate the unknown regression coefficients of the model $\beta_n s$. Additionally, the initial evaluation of the model gives the evaluated values for α_i and ε_{it}.

In the second step, the time-varying technical inefficiency u_{it} is evaluated. Then, previously estimated values for ε_{it} are used so that $\varepsilon_{it} = v_{it} - u_{it} + E(u_{it})$, where v_{it} follows a normal distribution and u_{it} a semi-normal distribution. For the expected mean value of the time-varying technical inefficiency u_{it}, the following applies: $E(u_{it}) = \sqrt{2/\pi}\sigma_u$. The rating of time-varying technical efficiency in the RTE designation is obtained as follows: $RTE_{it} = exp\{-\hat{u}_{it}\}$.

In the third step, the time-invariant technical inefficiency η_i is evaluated using a similar procedure. The assessment is performed on the basis of the α_i values obtained in the first step, assuming that μ_i follows a normal and η_i a semi-normal distribution, so that the expected mean value for η_i is $E(\eta_i) = \sqrt{2/\pi}\sigma_\eta$. The assessment of persistent technical efficiency, this time in the designation PTE, is carried out in the following manner: $PTE_i = exp\{-\hat{\eta}_i\}$. Finally, the overall rating of technical efficiency is obtained by multiplying time-invariant and time-variant technical efficiency ($OTE = RTE \times PTE$).

Furthermore, it is important to point out that within the second and third step of the model evaluation, it is possible to introduce the assumption of a non-zero mean value for persistent and residual technical inefficiency, which means that—based on the observed model—it is possible to examine the influence of additional explanatory variables on the achieved technical efficiency.

In technical efficiency analysis, one output and five inputs are included. The variables are selected based on previous literature (Table A1). All data are collected from the FAOSTAT database [35]. The value of agricultural production is only output, while the independent variables are:

- **Land** includes arable land and land under permanent crops and pastures.
- **Labor** includes all working-age persons who belong to one of two categories: paid employees (whether at work at that moment or just had a job) or self-employed in agriculture.
- **Capital** is expressed as a gross fixed capital (GFC) formation that represents the total value of a producer's acquisitions, less disposals, of fixed assets during the accounting period plus certain additions to the value of non-produced assets (such as subsoil assets or major improvements in the quantity, quality or productivity of land) realized by the productive activity of institutional units. The most important exclusion from it is land sales and purchases.
- **Mineral fertilizer** usually takes the most significant part in the variable costs of farms and is often used as an indicator of intermediate consumption. Based on FAOSTAT data, the total mineral fertilizer used was calculated as the sum of nitrogen, potassium, and phosphorus used in agriculture, expressed in tons at the national level.
- **Livestock** is calculated using livestock units (LSU), which facilitate aggregating information for different livestock types. This methodology applies the LSU coefficients [36]. LSU coefficients are computed by livestock type and by country. The reference unit used for calculating livestock units (=1 LSU) is the grazing equivalent of one adult dairy cow producing 3000 kg of milk annually, fed without additional concentrated foodstuffs.

Significant differences in the values of the observed variables between the observed states resulted in a logarithmic transformation of the data.

After calculating the technical efficiency, a cluster analysis was performed. Three more variables were added: labor productivity, land productivity, and agricultural area per worker, which together describe the production performance of the country. A hierarchical method was used, and cluster analysis was conducted using the software *Statistica 10*. The cluster analysis results are shown on the map to classify the countries of the EU and the WB according to the performance of agriculture.

4. Results and Discussion

According to the methodological approach, results and discussion are put together but divided into two sections. The first section is focused on technical efficiency, while the second section shows the results of cluster analysis with additional variables.

4.1. Technical Efficiency of Agriculture

The assessment of the Cobb–Douglas production function model, with the aim of determining the technical efficiency of European countries in the agricultural sector, began with an analysis of the fulfilment of the assumption of the presence of multicollinearity (Table 1).

Table 1. Testing the presence of multicollinearity.

Variable	VIF	TOL
lnLivestock	8.94	0.1119
lnFertilizer	8.67	0.1153
lnGFC	6.09	0.1642
lnLand	5.50	0.1818
lnLabour	2.72	0.3678
time	1.03	0.9669
Average	**5.49**	**0.3180**

Source: The authors' calculation.

Table 1 presents the values of the VIF indicators for the independent variables used in the model, which indicate the presence of harmful multicollinearity if greater than 10. In the econometric literature, there is no agreed opinion about the limits of acceptability for the value of the VIF indicator. In this regard, it is necessary to keep in mind the nature of the observed data. With economic indicators, it is to be expected that the independent variables are mutually correlated, so it makes sense to accept a slightly higher value of the VIF indicator. On the other hand, many authors point out that a value of 10 for VIF is a limit, so if VIF is less than 10, it makes sense to continue with the regression analysis [37–39]. In addition to the VIF indicator, the table also presents the reciprocal values of this indicator (values of the TOL indicator). The reciprocal value of a VIF indicator of 0.1 is equivalent to a value of 10 for the VIF [39].

As the VIF indicator values for all independent variables range from 1.03 to 8.94, which is less than 10, it can be concluded that the data used are not burdened by the presence of harmful multicollinearity, so data from that aspect can be included in the model.

The first step in the assessment of the model of the stochastic marginal production function was the assessment of the panel model of fixed and random individual effects (Table A2). Then, in order to select the appropriate model specification, the Hausman test was applied, the results of which are presented in Table 2. The corresponding test statistic is 77.25, which is significantly higher than the critical value of the χ^2 distribution for six degrees of freedom and the significance threshold α = 0.01. Therefore, the null hypothesis, which assumes a stochastic specification of the model, must be rejected. In other words, the conclusion is that the panel regression model of fixed individual effects corresponds to the data used, based on which the assessment of technical efficiency will be made.

Table 2. Hausman test of model specification.

Test	Null Hypothesis	Test Statistics	*p*-Value
Hausman test	Random individual effects model	$\chi^2(6) = 77.25$	0.0000

Source: The authors' calculation.

The values of the parameters λ and ρ also speak in favor of the fixed effects panel model. Their desirable values signal the justification of the assessment of the stochastic marginal production function model [40]. The parameter λ ($\lambda = \sigma\_u/\sigma\_v$), which in the methodological sense indicates the extent to which the obtained residuals derive from realized inefficiency, has a value of 8.0850. As its value for the fixed individual effects model is greater than 1, the conclusion is that the use of the model of the stochastic marginal production function to evaluate the technical efficiency for the observed observation units is justified. The same applies to the parameter ρ ($\rho = (\sigma\_u^2)/\sigma^2$), which represents a part of the total variability that can be said to be a consequence of technical inefficiency. In other words, 98.48% of the total variability of the fixed effects model can be explained as a consequence of technical inefficiency.

Additionally, one of the basic assumptions related to the justification of the application of the stochastic marginal production function is the verification of the distribution of the u_i component related to technical inefficiency. The obtained results indicate the negative asymmetry of the u_i component, which is statistically significantly different from the normal distribution. This is a desirable scenario in the assessment of technical efficiency. The measure of asymmetry of the component u_i is -1.0762, and the statistical significance is confirmed by the χ^2 test, whose test statistic is 67.26 and is significantly higher than the critical value of the χ^2 distribution for 2 degrees of freedom and the significance threshold α = 0.01.

The Levin–Lin–Chu test was used to check the presence of a unit root in order to determine the stationarity of the variables [41]. The test has the null hypothesis that all the panels contain a unit root. The obtained results presented in Table 3 indicate that the null hypothesis must be rejected for all variables, which is desirable scenario.

Table 3. Levin-Lin-Chu unit root test.

Variables	Null Hypothesis	Test Statistics	*p*-Value
lnVA	Presence of unit root	−96,160	0.0000
lnLabour	Presence of unit root	−73,080	0.0000
lnLand	Presence of unit root	−115,310	0.0000
lnGFC	Presence of unit root	−93,710	0.0000
lnFertilizer	Presence of unit root	−160,470	0.0000
lnLivestock	Presence of unit root	−83,910	0.0000

Source: The authors' calculation.

Modified Wald test results for groupwise heteroskedasticity in a fixed effect regression model are presented in Table 4. Here, the overall statistic $\chi^2(31) = 1394.86$ has a $p = 0.0000$. This leads to strongly rejecting the null hypothesis for any confidence level. Therfore, a phenomenon of heteroskedascitcity is present.

Table 4. Modified Wald test for groupwise heteroskedasticity in fixed effect regression model.

Test	Null Hypothesis	Test Statistics	*p*-Value
Modified Wald test	$H_0 : \sigma_i^2 = \sigma^2$	$\chi^2(31) = 1394.86$	0.0000

Source: The authors' calculation.

The problem of heteroskedasticity is overcome by estimating a panel regression model with fixed effects and robust standard error (Table A3).

Regarding the variables that define the production function, it is important to point out that all independent variables show a statistically significant influence on the realized value of agricultural production, except labor and fertilizer. Additionally, productivity growth was identified, which for the studied period from 2008 to 2019 is 1.06%.

As already mentioned, in order to obtain a rating of technical efficiency with desirable properties, the Kumbhakar, Lien, and Hardaker (2014) [28] model was used, which is linked to a separate rating of individual effects and persistent and residual technical (in)efficiency. In Table 5, the overall rating of technical efficiency is presented together with the previously mentioned components.

Table 5. Evaluation of technical efficiency.

TE	Number of Observations	Mean	Standard Deviation	Minimum
Residual	372	0.8459	0.0524	0.6634
Persistent	372	0.5597	0.2220	0.1013
Total	372	0.4734	0.1900	0.0818

Source: The authors' calculation.

It was found that the overall rating of technical efficiency is 47.34%. The reason for such a low rating of overall technical efficiency may be a significant difference in the indicators used between the studied countries. Additionally, it is noticeable that the residual (time-variant) technical efficiency significantly exceeds the persistent (time-invariant) technical efficiency. The rating of residual technical efficiency is 84.59%, while the rating of persistent technical efficiency is 55.97%.

In other words, it is noticeable that persistent technical inefficiency is significantly dominant in relation to residual technical inefficiency. Therefore, the overall assessment of technical efficiency is to the greatest extent profiled by factors that are under the control of agricultural producers—that is, factors that are related to long-term aspects of business. The econometric literature recognizes the mentioned group of factors as indicators that mostly relate to the characteristics of agricultural producers and the characteristics of agricultural holdings. On the other hand, based on the results of the analysis, it can be concluded that exogenous factors, such as administrative measures of agricultural policy or climatic conditions, do not have a decisive influence on the overall technical efficiency of the studied countries related to the agricultural sector.

Based on the above-mentioned data, Figure 1, presented below, provides a graphical representation of the total, residual, and persistent technical efficiency for observed European countries from 2008 to 2019. Lower level of total efficiency in some years can be connected with unfavorable weather conditions in Europe.

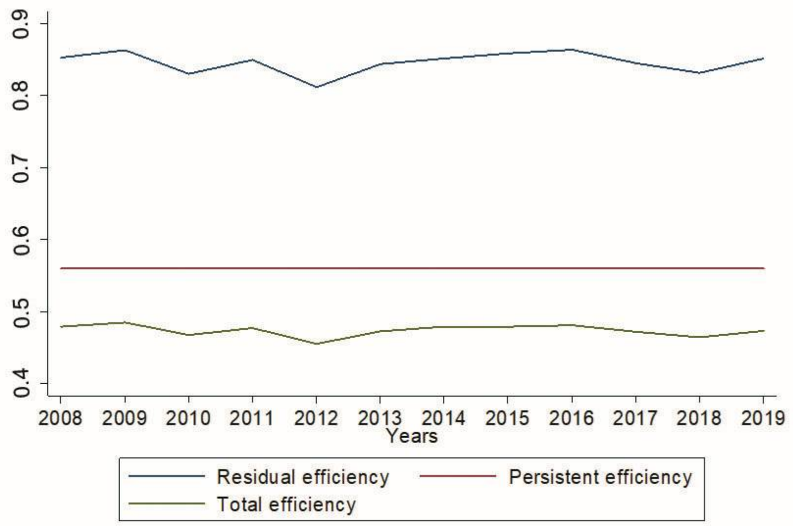

Figure 1. Estimate of the total, persistent, and residual technical efficiency from 2008 to 2019. **Source:** The authors' calculation.

Figure 2, presented below, provides insight into the distribution of the overall technical efficiency rating for the studied period. A high variability in the obtained grades can be noted, which is supported by a relatively high interquartile difference coefficient of 31.95%.

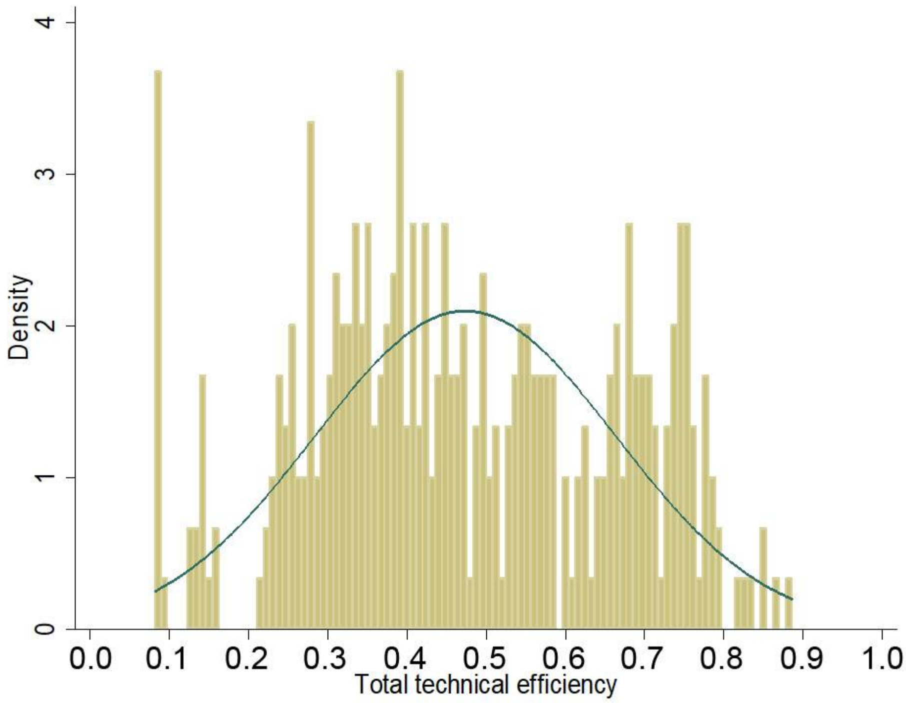

Figure 2. Estimate of the total technical efficiency from 2008 to 2019. **Source:** The authors' calculation.

In Table A4 overall technical efficiency of agriculture by country is presented. Results are similar to those of other studies [7,8] in the context of differences between the EU and

WB countries (average 0.52 compared to 0.3), but the level of TE in the WB is higher in case of the DEA method than the SFA. The same conclusion is presented in Odeck (2007) [42]. However, these estimates suggest that inefficiency exists in the agricultural sector of the WB and that there is considerable space for improvement in input uses that can enhance the competitiveness of the agri-food sector. Agricultural policy measures should encourage more intensive agricultural production, which could create a better foundation for progress in the food industry [43]. This could be an alarm for policymakers in the WB. However, in the long run, it is essential to consider the environmental goals of agriculture. In order to achieve sustainable development goals of national economies, the higher education system could contribute significantly [44]. Universities, especially agricultural faculties, can play a unique role in achieving these goals.

4.2. Cluster Analysis

As mentioned before, cluster analysis is performed in the second step, and characteristics of the clusters are shown in the Table A5. Figure 3 shows the results of the cluster analysis of the overall development level of agriculture from the aspect of production performance. Five clusters were obtained by including factors such as the technical efficiency of agriculture, resource structure, and land and labor productivity. Cluster 1 represents the highest level and Cluster 5 the lowest level of production performance. Considering the factors involved, the results are relatively expected. Only two countries belong to Cluster 1—Belgium and Denmark, which, in addition to The Netherlands, are known to have a developed agricultural sector in all aspects, which is reflected in the high level of production performance. Finland is one of two highly developed countries located in Cluster 3.

Cluster 1 and Cluster 2 represent the most developed part of European agriculture, including the most developed countries of Western Europe. For the relatively diverse cluster 3 (extending from Scandinavia through the former socialist countries to Italy), the level of production performance of agriculture can be stated. It is interesting to note that of the former socialist countries, this cluster mainly includes those countries that have retained large farms, such as the Czech Republic, Slovakia, and Estonia. On the other hand, Cluster 4 includes those countries from the CEEC whose agricultural sector is characterized by small farms—Poland, Slovenia, Croatia, Bulgaria, and two less developed “old” EU members—Greece and Portugal—where small farms also dominate. Finally, in Cluster 5, in addition to Romania (characterized by small farms), there are Western Balkan countries that have not yet gained full membership in the EU. The research results confirm the already-known connection between overall economic development and agricultural development. This correlation is partially “deformed” by agri-environmental and climate conditions, which significantly affect the level of production performance. This is the case with Sweden and Finland, two highly developed countries located in Cluster 3 (similar results are provided by Reiff et al. (2016) [45].

Figure A1 shows the absolute amount of funds that EU members and potential candidate countries receive from common funds intended for agriculture and rural development. Although it is clear that the largest countries with the most significant agricultural sector also withdraw the largest part of the funds, the presentation can be interesting for the following reasons. First, it is a striking fact that even small countries from Western Europe with small agricultural sectors, such as Ireland and Portugal, withdraw significant funds—more than some members from Central and Eastern Europe with similar agricultural sector capacities. The lowest level of support goes to potential EU member countries, which on one hand is understandable. On the other hand, it makes it difficult for these countries to adapt (primarily in terms of competitiveness) their national agricultural sectors to business conditions in the future common European market.

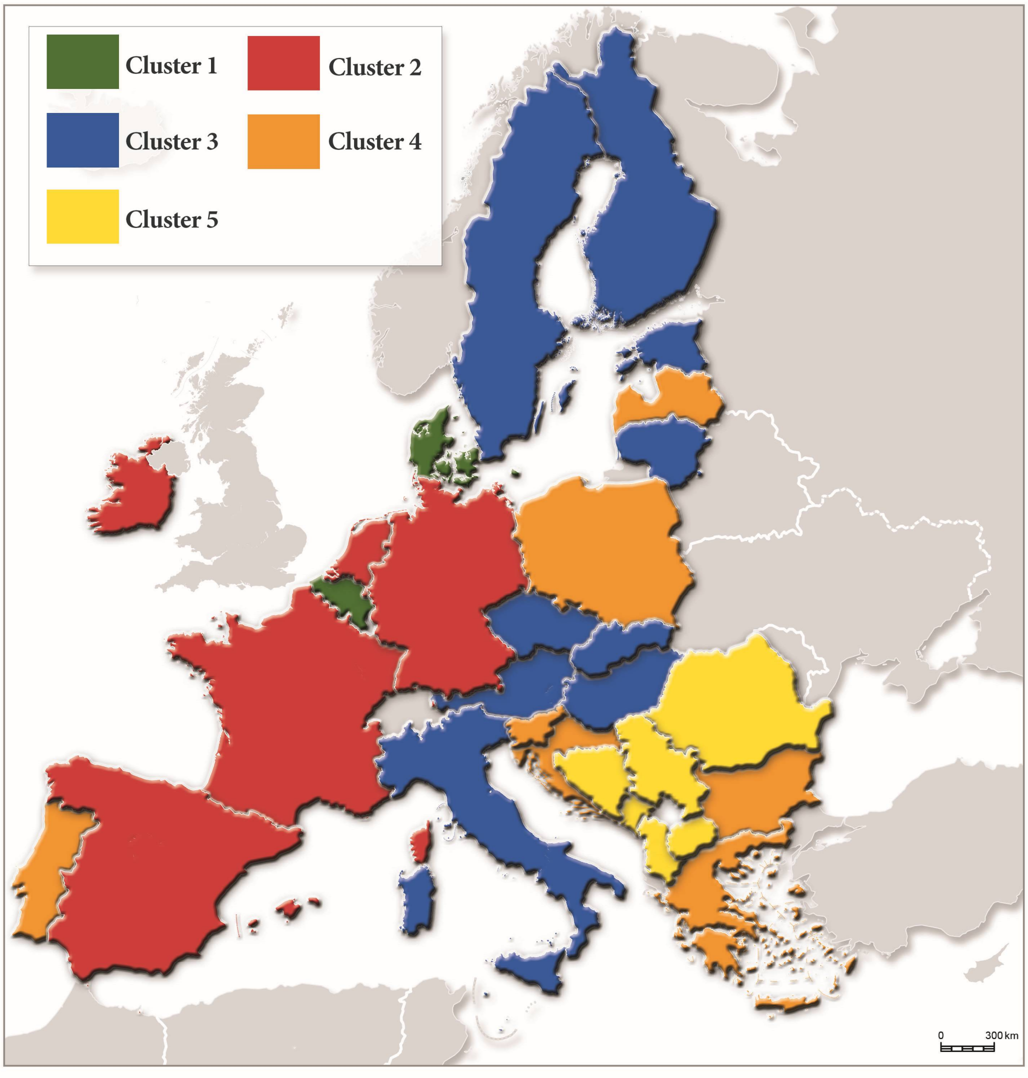

Figure 3. Cluster analysis. **Source:** The authors' calculation.

5. Conclusions

It is possible to summarize a few key conclusions. First, the overall technical efficiency is relatively low (47.34%), probably due to a significant difference in the indicators used between the studied countries. Second, the persistent technical inefficiency is more significant than the residual technical inefficiency, indicating that the overall assessment of technical efficiency is, to the greatest extent, profiled by factors that are under the control of agricultural producers. Third, the exogenous factors, such as administrative measures of agricultural policy or climatic conditions, do not have a crucial influence on the overall technical efficiency of agriculture in observed countries. Fourth, there is a significant difference between the EU and WB countries (an average of 0.52 compared to 0.3). Additionally, compared to other studies, it can be concluded that the level of technical efficiency in the WB is higher in the case of the DEA method than in SFA. Finally, the cluster analysis confirms the connection between overall economic development and agricultural development, which is partially "deformed" by agri-environmental and climate conditions (as in the case of the Scandinavian countries).

The contribution of the results of the article indicates that the WB countries have a significant lag behind the EU countries, especially its "old" members, which have experienced a multidecade policy of supporting the efficiency enhancement of agriculture. Therefore, policymakers in WB countries should strive for a policy of efficiency improving agriculture. In the pre-accession period, this would be a rational strategy because the convergence of efficiency levels would facilitate the position of WB countries' agriculture in the future common European market. There is room to improve technical efficiency. This is particularly important because of the optimization of the use of inputs to achieve agricultural policy's economic and environmental goals. In addition, improving the education of farmers would most likely significantly contribute to realizing these goals given that the results showed the importance of endogenous factors. In short, policymakers should consider greater integration of economic and business knowledge into the existing education system, especially in rural areas. That is, in order to improve the efficiency of farmers, a certain synergy between educational and agricultural policies may be necessary.

It is necessary to consider the limitations of evaluating the technical efficiency of agricultural activity as a whole. Therefore, in order to determine the factors influencing technical inefficiency, especially in countries with a low rating of technical efficiency, it is necessary to consider technical efficiency at the sector level. In this way, it is possible to clearly identify sectors characterized by low productivity, which can benefit agricultural policymakers. Additionally, technical efficiency as a relative indicator depends on the units of observation in the sample. In other words, the technical efficiency must be seen as a relative estimation in relation to the observation units that achieve the optimal estimation of technical efficiency.

The focus of future research will be the possibilities of the education system's contribution to the goals of agricultural policy as well as the discovery of critical factors that determine the level of technical efficiency in European countries. It can be expected that this type of research volume will increase significantly due to the political crisis, which endangered the European food chain. In this context, the methodology used in the article can be useful, as it is fully applicable to other countries and/or regions. In other words, the article represents a solid basis for research on a similar topic but with a different scope.

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Appendix A

Table A1. Literature review of most frequent usage of variables.

Authors/Year	Method	Country/Region	Output Variables	Input Variables
Latruffe at al. (2011) [46]	DEA	Hungary and France	Total output Milk produced COP output Other output	Utilized land, labor, capital, and intermediate consumption
Bojnec et al. (2014) [12]	DEA	Ten EU countries	Gross value added in $	Labor, number of agricultural tractors, agricultural area, total fertilizers, and number of animal livestock units

Table A1. *Cont.*

Authors/Year	Method	Country/Region	Output Variables	Input Variables
Vlontzos and Niavis (2014) [13]	DEA and SFA	EU countries	total agricultural output	Agricultural land, labor and fixed capital consumption
Baráth and Fertő (2015) [47]	SFA	Hungary	total output	Labor, utilized agricultural area, total fixed assets in value, and total specific costs in value
Hart et al. (2015) [14]	SFA	28 EU countries	agricultural GDP	Land, capital, fertilizer, labor, time, dummy variable country
Nowak et al. (2015) [10]	DEA	27 EU countries	total output	Labor, capital, and land
Záhorský, T. and Pokrivčák, J. (2017) [17]	DEA	10 CEEC countries	crop output animal output	Labor, utilized agricultural area, buildings, and fixed equipment, materials and total livestock units
Moutinho et al. (2018) [11]	DEA SFA	27 EU countries	net added value	Inputs, labor force, utilized agricultural area, and energy consumed in the technical
Todorović et al. (2020) [20]	DEA	Serbia	total output	Total labor, utilized agricultural area, seed and plant costs, fertilizers, crop protection, farming overheads, depreciation, external costs, total assets, total liabilities
Đokić et al. (2020) [7]	DEA	Western Balkans and the New Member States	total output	Agricultural land, labor, and capital
Náglová and Rudinskaya (2021) [15]	SFA	25 EU countries	total factor productivity	Land, labor, capital, and material

Source: The authors' presentation.

Appendix B

Table A2. Panel regression model of fixed and random individual effects.

Parameter	Variable	Fixed Effects Model		Random Effects Model	
		Coefficient	Std. Error	Coefficient	Std. Error
β_0	Constant	−15.3896 a	3.8088	−23.3721 a	2.8338
β_1	lnLabour	0.0727 b	0.0362	0.1260 a	0.0301
β_2	lnLand	0.1262 a	0.0483	0.1600 a	0.0404
β_3	lnGFC	0.0864 a	0.0199	0.0979 a	0.0193
β_4	lnFertilizer	0.0430 c	0.0232	0.0579 b	0.0227
β_5	lnLivestock	0.4766 a	0.0806	0.6688 a	0.0450
β_6	time	0.0106 a	0.0015	0.0128 a	0.0013
σ_u		0.5328		0.2681	
σ_v		0.0659		0.0659	
$\lambda = \sigma_u / \sigma_v$		8.0850		4.0683	
$\rho = \sigma_u^2 / \sigma^2$		0.9849		0.9430	
Number of observations		372		372	
Number of countries		31		31	
		a statistical significance at level α = 0.01			
		b statistical significance at level α = 0.05			
		c statistical significance at level α = 0.1			

Source: The authors' calculation.

Table A3. Panel regression model of fixed individual effects with robust standard error.

Parameter	Variable	Fixed Effects Model	
		Coefficient	Robust Std. Error
β_0	Constant	−15.3896 b	60.643
β_1	lnLabour	0.0727	00.568
β_2	lnLand	0.1262 c	00.635
β_3	lnGFC	0.0864 a	00.175
β_4	lnFertilizer	0.0430	00.382
β_5	lnLivestock	0.4766 a	01.463
β_6	time	0.0106 a	00.023
σ_u		0.5328	
σ_v		0.0659	
$\lambda = \sigma_u / \sigma_v$		8.0850	
$\rho = \sigma_u^2 / \sigma^2$		0.9849	
Number of observations		372	
Number of countries		31	
a statistical significance at level α = 0.01			
b statistical significance at level α = 0.05			
c statistical significance at level α = 0.1			

Source: The authors' calculation.

Table A4. Overall technical efficiency of agriculture by country.

Country	OTE	Country	OTE	Country	OTE
Albania	0.3133	France	0.7318	N. Macedonia	0.3795
Austria	0.4417	Germany	0.7572	Poland	0.6622
Belgium	0.6346	Greece	0.6760	Portugal	0.4626
Bosnia and Herzegovina	0.2514	Hungary	0.6817	Romania	0.4987
Bulgaria	0.5496	Ireland	0.3101	Serbia	0.5443
Croatia	0.4043	Italy	0.7914	Slovakia	0.3619
Czechia	0.4649	Latvia	0.3125	Slovenia	0.2415
Denmark	0.5612	Lithuania	0.3943	Spain	0.7713
Estonia	0.2842	Montenegro	0.1414	Sweden	0.3864
Finland	0.3537	Netherland	0.6964		

Source: The authors' calculation.

Table A5. Characteristics of the clusters.

	OTE	Agricultural Land per Worker (ha/Worker)	Labor Productivity ($/Worker)	Land Productivity ($/ha)
Cluster 1	0.60	32	148,860	5090
Cluster 2	0.65	31	76,973	3556
Cluster 3	0.46	25	37,127	1609
Cluster 4	0.47	14	17,901	1481
Cluster 5	0.35	10	8635	1116

Source: The authors' calculation.

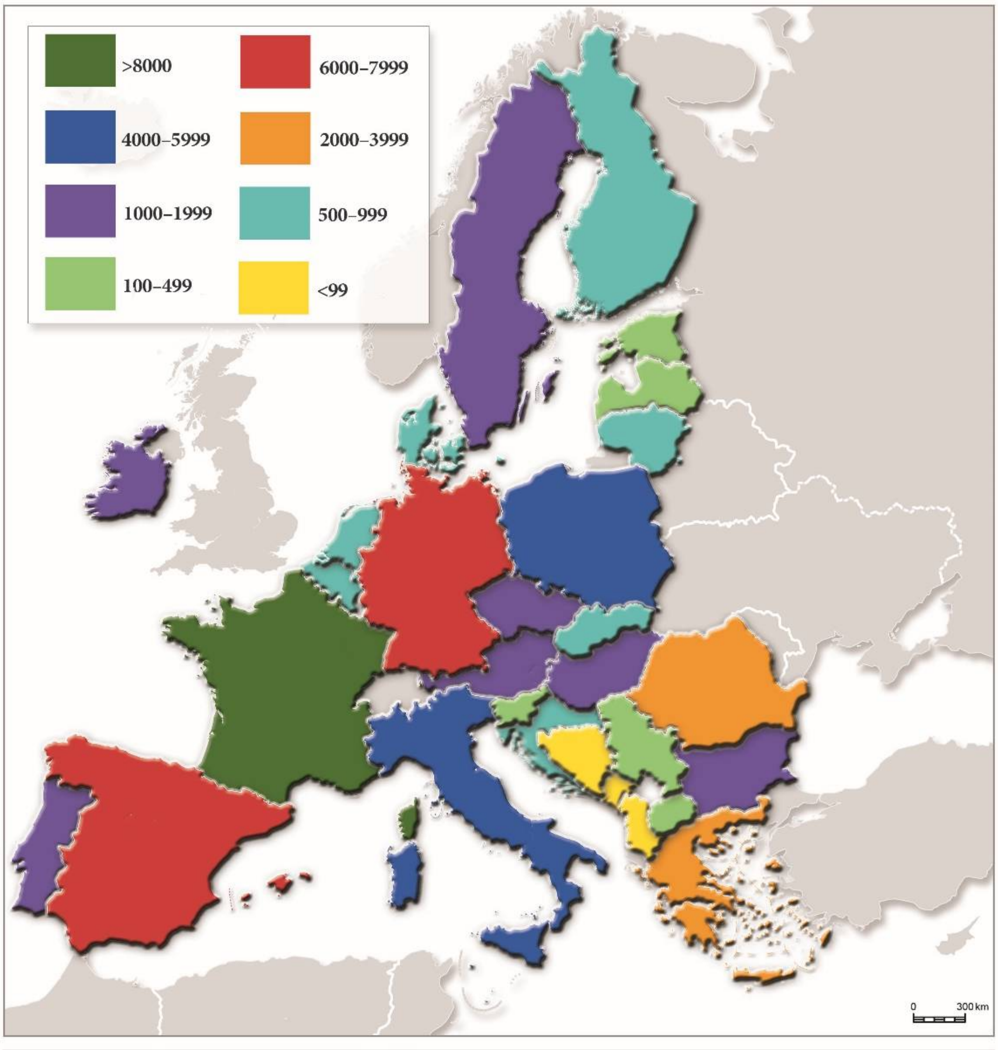

Figure A1. Agricultural support by country in the EU and WB. **Source:** The authors' presentation based on [48,49].

References

1. Zhao, Z.; Peng, P.; Zhang, F.; Wang, J.; Li, H. The Impact of the Urbanization Process on Agricultural Technical Efficiency in Northeast China. *Sustainability* **2022**, *14*, 12144. [CrossRef]
2. Morais, G.A.S.; Silva, F.F.; Freitas, C.O.D.; Braga, M.J. Irrigation, Technical Efficiency, and Farm Size: The Case of Brazil. *Sustainability* **2021**, *13*, 1132. [CrossRef]
3. Lazíková, J.; Lazíková, Z.; Takáč, I.; Rumanovská, L'.; Bandlerová, A. Technical Efficiency in the Agricultural Business—The Case of Slovakia. *Sustainability* **2019**, *11*, 5589. [CrossRef]
4. Liu, J.; Dong, C.; Liu, S.; Rahman, S.; Sriboonchitta, S. Sources of Total-Factor Productivity and Efficiency Changes in China's Agriculture. *Agriculture* **2020**, *10*, 279. [CrossRef]
5. Zhu, Y.; Huo, C. The Impact of Agricultural Production Efficiency on Agricultural Carbon Emissions in China. *Energies* **2022**, *15*, 4464. [CrossRef]
6. Matkovski, B.; Zekić, S.; Đokić, D.; Jurjević, Ž.; Đurić, I. Export Competitiveness of Agri-Food Sector during the EU Integration Process: Evidence from the Western Balkans. *Foods* **2022**, *11*, 10. [CrossRef] [PubMed]
7. Đokić, D.; Zekić, S.; Jurjević, Z.; Matkovski, B. Drivers of technical efficiency in agriculture in the Western Balkans and New EU Memeber States. *Custos Agronegocio Online* **2020**, *16*, 2–15.
8. Marcikić Horvat, A.; Matkovski, B.; Zekić, S.; Radovanov, B. Technical efficiency of agriculture in Western Balkan countries undergoing the process of EU integration. *Agric. Econ.* **2020**, *66*, 65–73. [CrossRef]
9. Bakucs, Z.; Ferto, I.; Latruffe, L.; Desjeux, Y.; Soboh, R.; Dolman, M. Comparative Analysis of Technical Efficiency in European Agriculture. In Proceedings of the 2011 International Congress, Zurich, Switzerland, 30 August–2 September 2011.
10. Nowak, A.; Kijek, T.; Domańska, K. Technical efficiency and its determinants in the European Union. *Agric. Econ.* **2015**, *61*, 275–283. [CrossRef]

11. Moutinho, V.; Madaleno, M.; Macedo, P.; Robaina, M.; Marques, C. Efficiency in the European agricultural sector: Environment and resources. *Environ. Sci. Pollut. Res.* **2018**, *25*, 17927–17941. [CrossRef] [PubMed]
12. Bojnec, Š.; Ferto, I.; Jambor, A.; Toth, J. Determinants of technical efficiency in agriculture in new EU member states from Central and Eastern Europe. *Acta Oeconomica* **2014**, *64*, 197–217. [CrossRef]
13. Vlontzos, G.; Niavis, S. Assessing the Evolution of Technical Efficiency of Agriculture in EU Countries: Is There a Role for the Agenda 2000? *Agric. Coop. Manag. Policy* **2014**, 339–351. [CrossRef]
14. Hart, J.; Miljkovic, D.; Shaik, S. The impact of trade openness on technical efficiency in the agricultural sector of the European Union. *Appl. Econ.* **2015**, *47*, 1230–1247. [CrossRef]
15. Náglová, Z.; Rudinskaya, T. Factors Influencing Technical Efficiency in the EU Dairy Farms. *Agriculture* **2021**, *11*, 1114. [CrossRef]
16. Pawłowski, K.P.; Czubak, W.; Zmyślona, J. Regional Diversity of Technical Efficiency in Agriculture as a Results of an Overinvestment: A Case Study from Poland. *Energies* **2021**, *14*, 3357. [CrossRef]
17. Záhorský, T.; Pokrivčák, J. Assessment of the Agricultural Performance in Central and Eastern European Countries. *AGRIS Online Papers Econ. Inform.* **2017**, *9*, 113–123. [CrossRef]
18. Nowak, A.; Różańska-Boczula, M. The Competitiveness of Agriculture in EU Member States According to the Competitiveness Pyramid Model. *Agriculture* **2022**, *12*, 28. [CrossRef]
19. Jarosz-Angowska, A.; Nowak, A.; Kołodziej, E.; Klikocka, H. Effect of European Integration on the Competitiveness of the Agricultural Sector in New Member States (EU-13) on the Internal EU Market. *Sustainability* **2022**, *14*, 13124. [CrossRef]
20. Todorović, S.; Papić, R.; Ciaian, P.; Bogdanov, N. Technical efficiency of arable farms in Serbia: Do subsidies matter? *New Medit* **2020**, *19*, 81–97. [CrossRef]
21. Jurjević, Ž.; Bogićević, I.; Đokić, D.; Matkovski, B. Information technology as a factor of sustainable development of Serbian agriculture. *Strateg. Manag.* **2019**, *24*, 41–46. [CrossRef]
22. Matkovski, B.; Kalaš, B.; Zekić, S.; Jeremić, M. Agri-food Competitiveness in South East Europe. *Outlook Agric.* **2019**, *48*, 326–335. [CrossRef]
23. Zekić, S.; Matkovski, B.; Kleut, Ž. Analiza agroekoloških indikatora u Srbiji i zemljama Evropske unije. *Anali Ekon. Fak. Subotici* **2018**, *54*, 45–57. [CrossRef]
24. Tagarakis, A.C.; Dordas, C.; Lampridi, M.; Kateris, D.; Bochtis, D. A Smart Farming System for Circular Agriculture. *Eng. Proc.* **2021**, *9*, 10. [CrossRef]
25. Erjavec, E.; Volk, T.; Rednak, M.; Ciaian, P.; Lazdinis, M. Agricultural policies and European Union accession processes in the Western Balkans: Aspirations versus reality. *Eurasian Geogr. Econ.* **2021**, *62*, 46–75. [CrossRef]
26. Šeremešić, S.; Dolijanović, Ž.; Tomaš Simin, M.; Vojnov, B.; Glavaš Trbić, D. The Future We Want: Sustainable Development Goals Accomplishment with Organic Agriculture. *Probl. Ekorozw.* **2021**, *16*, 171–180. [CrossRef]
27. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [CrossRef]
28. Kumbhakar, S.C.; Knox Lovell, C.A. *Stochastic Frontier Analysis*; Cambridge University Press: Cambridge, UK, 2003.
29. Aigner, D.J.; Knox Lovell, C.; Schmidt, P. Formation and Estimation of Stochastic Frontier Production Function Models. *J. Econom.* **1977**, *6*, 21–37. [CrossRef]
30. Meeusen, W.; van den Broeck, J. Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error. *Int. Econ. Rev.* **1977**, *18*, 435–444. [CrossRef]
31. Schmidt, P.; Sickles, R.C. Production Frontiers and Panel Data. *J. Bus. Econ. Stat.* **1984**, *2*, 367–374.
32. Mundlak, Y. Empirical Production Function Free of Management Bias. *J. Farm Econ.* **1961**, *43*, 44–56. [CrossRef]
33. Kumbhakar, S.C.; Lien, G.; Hardaker, J.B. Technical Efficiency in Competing Panel Data Models: A Study of Norwegian Grain Farming. *J. Product. Anal.* **2014**, *41*, 321–337. [CrossRef]
34. Colombi, R.; Martini, G.; Vittadini, G. *A Stochastic Frontier Model with Short-Run and Long-Run Inefficiency Random Effects*; Working Paper Series; University of Bergamo: Bergamo, Italy, 2011.
35. FAOSTAT. Available online: https://www.fao.org/faostat/en/ (accessed on 8 August 2022).
36. FAO. Guidelines for the Preparation of Livestock Sector Reviews. Available online: https://www.fao.org/3/i2294e/i2294e.pdf (accessed on 8 August 2022).
37. Hair, J.F.; Black, W.C.; Babin, B.J.; Anderson, R.E. *Multivariate Data Analysis*; Pearson: Upper Saddle River, NJ, USA, 2010.
38. James, G.; Witten, D.; Hastie, T.; Tibshirani, R. *An Introduction to Statistical Learning (with Applications in R)*; Springer: Berlin/Heidelberg, Germany, 2013. [CrossRef]
39. Pallant, J. *A Step by Step Guide to Data Analysis Using IBM SPSS*; Taylor & Francis Group: London, UK, 2020.
40. Battese, G.E.; Corra, G.S. Estimation of a production frontier model: With application to the pastoral zone of eastern Australia. *Aust. J. Agric. Econ.* **1977**, *21*, 169–179. [CrossRef]
41. Levin, A.; Lin, C.-F.; Chu, C.-S.J. Unit root tests in panel data: Asymptotic and finite-sample properties. *J. Econom.* **2002**, *108*, 1–24. [CrossRef]
42. Odeck, J. Measuring technical efficiency and productivity growth: A comparison of SFA and DEA on Norwegian grain production data. *Appl. Econ.* **2007**, *39*, 2617–2630. [CrossRef]
43. Matkovski, B.; Zekić, S.; Jurjević, Ž.; Đokić, D. The agribusiness sector as a regional export opportunity: Evidence for the Vojvodina region. *Int. J. Emerg. Mark.* **2021**. [CrossRef]

44. Krstić, M.; Filipe, J.A.; Chavaglia, J. Higher Education as a Determinant of the Competitiveness and Sustainable Development of an Economy. *Sustainability* **2020**, *12*, 6607. [CrossRef]
45. Reiff, M.; Surmanová, K.; Balcerzak, A.P.; Pietrzak, M.B. Multiple Criteria Analysis of European Union Agriculture. *J. Int. Stud.* **2016**, *9*, 62–74. [CrossRef]
46. Latruffe, L.; Fogarasi, J.; Desjeux, Y. Efficiency, productivity and technology comparison for farms in Central and Western Europe: The case of field crop and dairy farming in Hungary and France. *Econ. Syst.* **2012**, *36*, 264–278. [CrossRef]
47. Baráth, L.; Fertő, I. Heterogeneous technology, scale of land use and technical efficiency: The case of Hungarian crop farms. *Land Use Policy* **2015**, *42*, 141–150. [CrossRef]
48. EUROSTAT. Available online: https://ec.europa.eu/eurostat (accessed on 8 August 2022).
49. Agricultural Policy Plus—APP. Available online: http://app.seerural.org/ (accessed on 27 October 2022).