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PRODUCTIVITY IN THE CONTEXT OF SUSTAINABLE AGRICULTURAL DEVELOPMENT

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GAMYBOS PRODUKTYVUMAS TVARIOSIOS ŽEMĖS ŪKIO PLĖTROS KONTEKSTE

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Abstract

Sustainable agricultural development is one of the most important policy goals in the European Union. Agricultural production and its intensification cause a negative impact on the environment, including climate change. The main goal of sustainable agricultural development is to increase agricultural productivity, reducing the negative impact of this production on the environment. As climate change is one of the most important environmental challenges for sustainable agricultural development, productivity growth should be assessed by introducing greenhouse gas (GHG) emission restrictions. Thus, when evaluating agricultural productivity, it is imperative to simultaneously assess and restrict undesirable production outputs, such as GHG emissions, thus ensuring sustainable agricultural productivity growth.

Extensive scientific research has been done on agricultural productivity and sustainable agricultural development; however, scientists lack consensus regarding undesirable outputs, such as GHG emissions assessments, when studying the efficiency and productivity of agricultural production. Assessing agricultural productivity in sustainable agricultural development requires identifying and assessing environmental constraints, especially related to integrating climate change mitigation into the production function, which is a complex task.

This work aimed to develop methods for evaluating agricultural productivity in the context of sustainable agricultural development. The goal of the dissertation is to develop a model for assessing productivity with undesirable outputs and to apply it for sustainable productivity assessment in agriculture in the EU. The dissertation reviews productivity evaluation methods and discusses various models, emphasising evaluations of undesirable production outputs in the production function.

A new model for evaluating agricultural production with undesirable results was developed based on an expanded production function that includes the main factors of agricultural production (energy consumption in agriculture, capital, labour and land costs in agriculture) and GHG emissions related to energy consumption in agriculture. The new model allows for a new expansion and use of DEA capabilities in the production function, supplementing it with the global slacks-based method (SBM) for efficiency measurement, the Luenberger productivity index, the index of contribution to structural efficiency with the help of which all production factors and GHG emissions can be analysed and studied in detail and the contribution of GHG emissions to overall changes in efficiency and productivity can be evaluated.

Reziumė

Tvarioji žemės ūkio raida yra vienas svarbiausių politikos tikslų Europos Sąjungoje. Žemės ūkio gamyba ir jos intensifikavimas turi neigiamą įtaką aplinkai, o ypač svarbūs tampa klimato kaitos švelninimo klausimai žemės ūkyje. Tvariosios žemės ūkio plėtros pagrindinis tikslas yra siekti žemės ūkio produktyvumo augimo, mažinant neigiamą šios gamybos įtaką aplinkai. Kadangi klimato kaitos švelninimas yra vienas svarbiausių tvariosios žemės ūkio plėtros aplinkosauginių iššūkių, produktyvumo augimas turėtų būti vertinamas įvedant apribojimus šiltnamio efektą sukeliančių dujų (ŠESD) emisijoms. Taigi, vertinant žemės ūkio produktyvumą, labai svarbu kartu įvertinti nepageidaujamų gamybos rezultatų, tokių kaip ŠESD emisijų, įtaką žemės ūkio gamybos produktyvumui, taip užtikrinant tvariojo žemės ūkio produktyvumo augimą.

Yra atlikta nemažai mokslinių tyrimų žemės ūkio produktyvumo bei tvariosios žemės ūkio raidos srityje, tačiau tarp mokslininkų stokojama sutarimo dėl nepageidaujamų rezultatų, tokių kaip ŠESD emisija, vertinimo tiriant žemės ūkio gamybos efektyvumą bei produktyvumą.

Šiame darbe yra siekiama sukurti metodus, leidžiančius atlikti žemės ūkio produktyvumo vertinimus tvariosios žemės ūkio raidos kontekste. Disertacijos tikslas yra parengti gamybos produktyvumo su nepageidaujamais rezultatais vertinimo modelį bei pritaikyti jį žemės ūkio tvariajai raidai vertinti ES. Disertacijoje apžvelgti produktyvumo vertinimo metodai bei aptarti įvairūs modeliai, akcentuojant nepageidaujamų gamybos rezultatų vertinimus. Pasiūlyti nauji metodai, leidžiantys visapusiškai ištirti produktyvumą bei jo augimo veiksnius žemės ūkyje, įvertinus nepageidaujamus rezultatus.

Sukurtas naujas žemės ūkio gamybos su nepageidaujamais rezultatais vertinimo modelis, kurio pagrindą sudaro išplėsta gamybos funkcija, apimanti pagrindinius žemės ūkio gamybos veiksnius (energijos suvartojimas žemės ūkyje, kapitalo, darbo bei žemė sąnaudos žemės ūkyje) bei ŠESD emisijas, susijusias su energijos vartojimu žemės ūkyje. Naujas modelis leidžia gamybos funkcijoje naujai išplėsti bei panaudoti DEA galimybes, ją papildant globaliu perviršio metodu (SBM) efektyvumui matuoti, Luenberger produktyvumo rodikliu, indėlio į struktūrinį efektyvumą indeksu ir, kuriuos taikant galima detaliai išskaidyti ir ištirti visų gamybos veiksnių, taip pat ŠESD emisijų indėlį į bendrus efektyvumo bei produktyvumo pokyčius tiriamuoju laikotarpiu.

Notations

Abbreviations

CAP – Common Agricultural Policy (liet. BŽŪP – Bendroji žemės ūkio politika);
CRS – Constant Returns-to-Scale (liet. Nuolatinė masto grąža);
EC – Efficiency Change (liet, Efektyvumo pokytis);
EU – European Union (liet. ES – Europos Sąjunga);
FADN – Farm Accountancy Data Network (liet. Ūkių apskaitos duomenų tinklas);
GHG – Greenhouse Gas (liet. ŠESD – Šiltnamio efektą sukeliančios dujos);
DEA – Data Envelopment Analysis (liet. Duomenų gaubties analizė);
DDF – Directional Distance Function (liet. Kryptinė atstumo funkcija);
DMU – Decision Making Unit/Country (liet. Sprendimų priėmėjai/Vlastybės);
LPI – Luenberger Productivity Indicator (liet. Luenberger produktyvumo rodiklis);
LSA – Life Cycle Assessment (liet. Gyvavimo ciklo įvertinimas);
PPP – Power Purchasing Parity (liet. Perkamosios galios paritetas);
SFA – Stochastic Frontier Analysis (liet. Stochastinė ribinė analzië);
SBM – Slacks-based Method (liet. Perviršio metodas);
TC – Technical Change (liet. Technologinis pokytis);
VRS – Variable Returns-to-Scale (liet. Kintamoji masto grąža).

Contents

Author's contribution to the publications

Publication[1]	Formal contribution[2]	Conceptualisation	Data curation	Formal analysis	Investigation	Methodology	Software	Validation	Visualisation	Writing – original draft	Writing – review &
Streimikis, Balezentis, 2020	0.500	sole	main	sole	joint	sole		sole	joint	main	joint
Streimikis, Kamali Saraji, 2021	0.500	sole	main	sole	joint	sole	sole	joint	main	main	joint
Streimikis, Miao, Balezentis, 2020	0.333	sole	joint	sole	main	joint	joint	main	joint	main	joint
Streimikis, J. et al. 2022	0.250	sole	joint	sole	main	joint	joint	main	joint	main	joint
Total or max[3]	2.246	sole	joint	sole	joint	sole	joint	main	joint	main	joint

[1] The published articles have been used here with the permission of the relevant publishers.

[2] The formal contribution is calculated as a fraction – $1/N_{\text{authors}}$.

[3] The total sum of the formal contribution values or the highest contribution achieved (in the increasing order: none, joint, main, or sole) in the specified 10 of 14 roles (according to the CRediT taxonomy, https://credit.niso.org/).

All the above-mentioned articles' co-authors have no motive to use this published data to prepare other dissertations.

All the authors of the above-mentioned articles have agreed on the author's contribution statement.

Introduction

Problem Formulation

The scientific literature analysis revealed that although there have been studies dealing with the problem of evaluating productivity with undesirable outputs, all proposed methods of evaluating undesirable outputs of agricultural production have important shortcomings and limitations. No methods have been developed, and no research has been carried out to evaluate the influence of individual agricultural production factors on the overall efficiency of agricultural production and changes in productivity from an environmental (GHG emissions) viewpoint. Therefore, it is necessary to create a new model for assessing agricultural productivity with undesirable outputs, which allows for avoiding the weaknesses and limitations of the proposed methods and comprehensively studying the production factors and obstacles to the growth of agricultural production efficiency and "sustainable" productivity. In addition, an ordinary non-parametric frontier technique like Data Envelopment Analysis (DEA), usually applied to measure productivity and efficiency, suffers from the dimensionality curse. This issue becomes especially cumbersome when undesirable outputs provide additional variables in assessment.

Relevance of the Dissertation

The agricultural sector is one of the most important economic sectors, providing raw materials and food. Although EU policy documents, like Europe 2020, the European Green Deal, and Common Agricultural Policy, consider the sustainable development of agriculture as one of the most important policy goals in the EU, agricultural production intensification negatively impacts the environment. Sustainable agricultural development should ensure the highest possible agricultural productivity and the lowest negative environmental effects of agricultural production, including GHG emissions. Meanwhile, GHG emissions are among the most important environmental challenges for sustainable agricultural development worldwide, including the EU. When evaluating agricultural productivity, it is essential to simultaneously evaluate undesirable outputs, such as GHG emissions on agricultural productivity and efficiency, to ensure sustainable agricultural productivity growth, reducing its negative impact on the environment, including climate change. Low carbon energy transition is a priority area addressed by the Green Deal. Therefore, GHG emission reduction from energy consumption in agriculture is a priority for ensuring sustainable agriculture development.

The Object of the Research

Assessment of agricultural productivity with undesirable outputs in the agricultural sector of the EU.

The Aim of the Dissertation

To prepare a model for evaluating agricultural productivity with undesirable outputs and to apply it to evaluating sustainable agriculture productivity in the EU.

The Objectives of the Dissertation

1. To perform literature analysis and systematise the methods for evaluating efficiency level and productivity changes with undesirable outputs and summarise the results and insights of their application in agriculture;
2. To prepare a model for evaluating productivity with undesirable outputs in agriculture based on the integration of various methods, such as DEA,

Luenberger productivity index, slacks-based method (SBM) for efficiency measurement, super-efficiency DEA and Contribution to Structural Efficiency index;
3. To apply the developed sustainable productivity with undesirable outputs model to the assessment of sustainable agriculture productivity in the EU;
4. To develop policy recommendations for promoting sustainable agriculture development in the EU member states based on the obtained empirical results.

Research Methodology

The main work methods are analysis, synthesis and abstraction of scientific literature, Data Envelopment Analysis (DEA), various productivity indices, such as the global slacks-based method (SBM) for efficiency measurement, the Luenberger productivity index, the index of contribution to structural efficiency, supper efficiency DEA and weak disposability DEA.

Applied non-parametric methods of efficient frontier analysis (DEA) provide opportunities to determine the efficiency and productivity of agricultural production in individual regions with undesirable results based on selected indicators showing overall and individual efficiency of production factors for assessing the change in productivity and production factors (efficiency and technological progress) and the results in GHG emissions; however, they suffer from several weaknesses. New methods, like the Luenberger productivity index and SBM, were used to analyse the impact of individual production factors and undesirable production results on efficiency and productivity changes. The super-efficiency DEA and Contribution to Structural Efficiency index were developed to supplement ordinary DEA and to provide a complete ranking of the countries based on productivity and efficiency, including negative outcomes as the simple DEA suffers from the dimensionality curse, especially in the presence of undesirable outputs providing for additional variables.

Applied weak disposability DEA allows building environmental function of production technology, which integrates additional assumptions about the interrelationship of desirable and undesirable outputs and provides for monetary evaluation of undesirable outputs (GHGs due to energy consumption in agriculture).

Scientific Novelty of the Dissertation

A new model for evaluating agricultural productivity with undesirable outputs has been developed based on an expanded production function that includes the main factors of agricultural production (energy consumption in agriculture, capital, labour and land costs in agriculture) and GHG emissions related to energy consumption in agriculture. The new model allows for a new expansion and use of DEA capabilities in the production function, supplementing it with the global slacks-based method (SBM), Luenberger productivity indicator, super-efficiency DEA and Contribution to Structural Efficiency index, analysing the contribution of all production factors and GHGs to overall changes in efficiency and productivity and finally ranking countries based on sustainable productivity during the set research period.

The developed sustainable productivity assessment model is also supplemented with an environmental function of production technology, which integrates additional assumptions about the interrelationship of desirable and undesirable outputs and allows for the monetary expression of undesirable outputs (GHGs due to energy consumption in agriculture). The undesirable outputs are assessed in monetary terms by calculating GHG emission shadow prices (marginal costs of reducing GHG emissions).

Practical Value of the Research Findings

The prepared model for evaluating productivity with undesirable outcomes was empirically applied for the sustainable productivity assessment of the agricultural sector in the EU member states. Based on the research results, the policy directions for improving agricultural and environmental policy were developed.

The Defended Statements

The following statements based on the results of the present investigation may serve as the official hypotheses to be defended:

1. Sustainable agriculture development can be assessed by applying sustainable productivity assessment based on extended production function with negative outcomes as it includes economic, social and environmental dimensions of agricultural sustainability.
2. The conventional DEA methods suffer from many weaknesses, including dimensionality, which becomes especially cumbersome in the presence of undesirable outputs.
3. The expansion of DEA capabilities by supplementing it with the global slacks-based method (SBM), Luenberger productivity indicator, super-efficiency DEA and Contribution to Structural Efficiency index allows to overcome the main weakness of conventional DEA and to analyse the

contribution of all production factors and GHGs to overall changes in efficiency and productivity.

4. The shadow prices of GHG emission reduction obtained by directional DEA and DDF (Directional Distance Functions) allow for defining lagging and advanced countries in terms of energy efficiency improvements in agriculture.

Approval of the Research Findings

The research results were published in 5 scientific publications, out of which 5 articles were printed in peer-reviewed scientific journals listed in the Clarivate Analytics Web of Science database with an impact factor.

The author has delivered four presentations at three international scientific conferences:

- III International Science Conference SER 2020 "New Trends and Best Practices in Socioeconomic Research". Igalo (Herceg Novi), Montenegro;
- IV International Science Conference SER 2021 "New Trends and Best Practices in Socioeconomic Research". Igalo (Herceg Novi), Montenegro;
- 16th Conference on Sustainable Development of Energy, Water and Environment Systems. Dubrovnik, Croatia.

Structure of the Dissertation

The dissertation contains an introduction, analytical literature review, discussion of research methodology, summary of the results and conclusions, references, appendices with the five scientific articles, and a summary in Lithuanian.

The dissertation consists of 178 pages, 20 equations, 16 figures, 9 tables, and 60 references cited in the dissertation.

The First Chapter provides a literature review on sustainable agriculture, indicators of sustainable agriculture assessment, and sustainable or green productivity measurements based on production function with undesirable outputs. The Second Chapter presents the research methodology and introduces a sustainable productivity assessment model based on extended production functions with undesirable outputs. Luenberger productivity index, SBM, super-efficiency DEA and Contribution to Structural Efficiency index were developed to supplement ordinary DEA and to provide a complete ranking of the countries based on productivity and efficiency, including negative outcomes as the simple DEA suffers from the dimensionality curse, especially in the presence of undesirable outputs providing for additional variables. The Third Chapter presents the results of empirical studies conducted by practically applying a developed sustainable productivity assessment model in the agriculture of the EU member states.

1

Analytical Literature Review on Sustainable Agriculture Productivity

This chapter outlines the results of the analysis performed in the first paper, "Agricultural sustainability assessment framework integrating sustainable development goals and interlinked priorities of environmental, climate and agriculture policies", published in the scientific journal Sustainable Development and the second paper, "Green Productivity and undesirable outputs in agriculture: a systematic review of DEA approach and policy recommendations", published in the scientific journal Economic Research. The First Chapter reviews the literature and research conducted on the dissertation topic.

1.1. Sustainable agriculture

The agricultural sector is crucial for achieving overall sustainable development goals for countries (Cox et al., 2004). There are many policies aiming to promote sustainable agriculture development by stressing the importance of providing enough safe food for the world population and ensuring a sustainable supply of fibre, fuel and other biological products for industries while reducing the negative impact of agricultural production on the environment (Clements, Shrestha, 2004;

Latruffe et al., 2016). The agricultural sector uses a lot of natural resources; therefore, the priorities of sustainable agriculture development are linked to the protection of land and biodiversity, preservation of clean air and water, climate change mitigation and adaptation (Pretty, 2005; McNeely, Scherr, 2003). Consequently, to address these challenges, this sector needs to be innovative, apply new advanced methods in land cultivation, farming and production, and sustainably increase productivity or target sustainable productivity (Velten et al., 2015; Ogaji, 2005).

The term "sustainable agriculture" is based on the classical paradigm of sustainable development introduced by the Brundtland Report in 1987. Based on the literature review, about 70 meanings of sustainable agriculture are available. These definitions reveal diverse priorities and goals, including specific stakeholder preferences at different levels of economic activity (Pretty, 2005).

Due to the diverse terms used in defining sustainability in agriculture or agricultural sustainability, the policy-making process to ensure sustainable agriculture development becomes quite complicated. In general, scientific literature presents sustainable agriculture as an "alternative" agriculture or ecological, low-input, environmentally sensitive, biodynamic, organic, regenerative, permaculture (Dunlap et al., 1993; Clements, Shrestha, 2004; Kesavan, Swaminathan, 2008).

The main dimensions of sustainable agriculture are social, economic and environmental; however, according to Tomich et al. (2004), spatial and temporal dimensions of agricultural sustainability are also essential. Spatial dimensions (national or local level) and temporal dimensions (long-term, mid-term and short-term periods) are important for developing policies to promote sustainable agriculture development.

By summarising findings from the literature review, the main definitions of agricultural sustainability can be characterised as follows: sustainability is an ideology capable of achieving specific goals or defined targets and includes a set of strategies (Hayati, 2017).

Agricultural systems are multifunctional and provide various goods, including food, but more importantly, the agriculture sector is also responsible for providing public goods like the preservation of nature, land, air and water, flood protection, groundwater replenishment, carbon sequestration and the landscape. So, sustainability in agriculture can be considered case-specific and shall be analysed in terms of agricultural productivity and also in terms of public goods, including climate change mitigation, which is of huge importance nowadays (Dobbs, Pretty, 2004).

Sustainable agriculture is oriented to using renewable resources, innovative technologies and advanced practices to ensure sustainable productivity growth. New forms of social capital are also necessary for sustainable or environmental productivity to ensure responsible leadership, resourcefulness, and managerial and innovating capabilities, allowing for increased labour and capital productivity (Olsson, Folke, 2001). The higher social and human capital is more capable of innovating, using new technologies and advanced production practices and achieving sustainable development goals (Uphoff, 2002; Pretty, Ward, 2001).

Another important issue of sustainable productivity growth is using renewable energy or cleaner energy sources in agricultural production to reduce the negative impact of agricultural activities on the environment, including air pollution and climate change. The sustainable agricultural practices need to be implemented to reduce environmental impact.

Therefore, though agricultural sustainability can be defined differently, it finally aims to ensure efficient use of natural and other resources and increase productivity by restraining negative environmental impacts of agriculture production, including GHG emission reduction.

1.2. Sustainability assessment of agriculture

Many sustainability assessment indicators and their frameworks, including composite or integrated sustainable agriculture indicators, were developed to evaluate the sustainability of the agricultural sector on various levels, including farm or country level. All these indicator frameworks provide ample valuable information but do not allow for assessing the main directions of agricultural development in the countries and comparing these directions based on the main drivers and barriers of sustainable agriculture development.

Sustainability assessment of the agricultural sector can also be performed by integrating environmental components into assessments of the productive efficiency of agriculture or another sector. The parametric and non-parametric production frontiers approaches can be used for productivity analysis, including environmental restraints on agriculture productions. This sustainability assessment approach is very helpful as it allows for developing policies and measures to promote sustainable agriculture based on important comparable and consistent information available for a group of countries.

Several main ways are developed for sustainable productivity assessment: application of parametric models requiring a definition of the specific function and use of non-parametric mathematical programming methods like DEA. By applying DEA, it is possible to attain a positive correlation between pollution and desirable outputs. Studies by Hailu and Veeman (2001) and Yang and Pollitt (2009) defined pollution as a free disposable input. Other studies (Korhonen, Luptacik, 2004; Lauwers, 2009) treated undesirable outputs as additional inputs to generate a desirable output (Mahlberg, Sahoo, 2011).

The most advanced approach is to treat pollution as negative outputs based on the weak disposability of environmental technology (Fare, Grosskopf, 2010a, b). Weak disposability assumes that the desirable and undesirable outputs are weakly disposable, i.e., the production possibility set is defined by allowing the scaling down of the undesirable and desirable outputs by the same factor. In addition, the materials balance approach was used in the production theory to overcome the limits of weak disposability (Lauwers, 2009). The most recent approach uses two sub-technologies in production technology: one technology producing the desired outputs and another – undesirable outputs (Forsund, 2009; Murty et al., 2012; Sueyoshi et al., 2017). It is necessary to analyse the green or sustainable productivity assessment approaches to develop proper tools for analysing agricultural productivity in the context of sustainable development.

1.3. Green or sustainable productivity assessment

Although ample research has been done on agricultural productivity and sustainable agricultural development, scientists lack consensus on assessing undesirable outcomes, such as greenhouse gas emissions, when studying the efficiency and productivity of agricultural production. As shown by the extensive research conducted to evaluate agricultural productivity and environmental pollution, to reflect the priorities and problems of agriculture's sustainable development, integrating environmental restrictions, especially related to climate change mitigation, into the production function is an especially complex problem.

Until now, scientists have widely discussed this topic and offered various alternative ways to solve the problem. Pittman (1981), in addition to Hailu and Veeman (2001), proposed to estimate unwanted output in the production function as one of the production factors. Fare et al. (1989) and Kuosmanen (2005) proposed considering unwanted production as weakly disposable with desirable production, i.e., when evaluating production productivity, establish a requirement that desirable and undesirable production decreases proportionally. Murty et al. (2012) proposed a model that identifies the production factors that determine pollution and constructs a separate "pollution function" alongside the production function. Kocisova (2015) assessed agricultural production productivity in the EU using DEA and decomposition analysis, but this study did not consider undesirable production outcomes such as atmospheric pollution or greenhouse gas emissions. Blażejczyk-Majka (2017) also applied DEA to assess the efficiency of agricultural production in EU member countries without considering undesirable outputs of agricultural production. Barath and Ferto (2017) applied DEA and the Fare-Primont index in the study of agricultural production productivity, which allowed for evaluating the substitutability of individual production factors in the production function, but again, unwanted production was not evaluated. Martinho (2017; 2020) also used DEA to assess the agricultural productivity of EU member countries but did not analyse the impact of undesirable production results on productivity changes. Vlontzas et al. (2014) applied a combination of DEA and slacks-based method (SBM) to the assessment of agricultural productivity in EU countries; although the study evaluated two undesirable production outcomes, such as carbon dioxide emissions and nutrient balance, this study did not examine the impact of individual production factors on productivity. Bartova et al. (2018) applied the principle of weakly disposable production in the production function and the DEA and Malmquist-Luenberger productivity index to the analysis of EU agricultural production productivity at the level of EU countries. Although in this study, greenhouse gas emissions were assessed as undesirable outputs, the influence of individual production factors and greenhouse gas emission efficiency on overall efficiency and productivity was not determined.

The main studies dealing with green/sustainable productivity assessments based on undesirable outputs and applying the DEA approach are summarised in Table 1.1.

Table 1.1. Main studies of green productivity assessment with undesirable outputs in the EU agriculture and the application of the DEA approach (Source: Streimikis et al., 2020)

Main studies	Methods	Measurements of changes in productivity	Undesirable outputs
Kocisova (2015)	DEA	–	–
Kocisova et al. (2018)	SBM-DEA	–	–
Błażejczyk-Majka (2017)	DEA	–	–
Martinho (2017)	DEA	–	–
Martinho (2020)	DEA	–	–
Baráth and Fertő (2017)	DEA	Färe-Primont index	–
Vlontzos et al. (2014)	SBM-DEA	–	CO_2 and nitrogen balances
Bartová et al. (2018)	DEA	Malmquist-Luenberger index	GHG emissions

So, the DEA models are the most suitable for assessing agricultural performance with undesirable outputs. In addition, the findings of this review paper indicated that there are different types of DEA models, such as Meta-frontier DEA, Malmquist index (Fei and Lin, 2016), VRS-DEA (Zhang, 2008), DDF-DEA (Makutėnienė, Baležentis, 2015), SBM-DEA (Le et al., 2019), CRS-DEA (Lin and

Fei, 2015), SBM-DEA, LCA (Cecchini et al., 2018), Super-SBM DEA (Pongpanich and Peng, 2016), Multi-objective DEA model (MORO-D) (Angulo-Meza et al., 2019), and most of these methods are useful and applicable for solving the agricultural industries with undesirable outputs though have several weakness and limitations.

1.4. Conclusions of the First Chapter

1. The "PRISMA" protocol has been employed for a systematic literature review. The papers selected based on the PRISMA statement are classified based on agricultural pollution, sustainable agriculture, agricultural economics, environmental performance and resource efficiency. Furthermore, the remaining papers are categorised based on the name of the journal, names of the author/s, methods, area of application, the papers, purposes of using DEA, purposes of study, contribution and research gap, outcomes and results, year of publication and nationality/ies of the author/s.
2. The findings indicated that agricultural pollution is the most attractive application area for scholars. In addition, the results of the present holistic review demonstrated that the DEA model is a strong and evaluated tool for analysing and evaluating the assessment of agricultural efficiency performance with undesirable outputs.
3. All research and proposed methods for assessing agricultural productivity and undesirable outcomes of agricultural production have important shortcomings and limitations. One of the most important limitations is the fact that all the methods used to assess the efficiency and productivity of agricultural production and the research conducted so far were unable to provide methods and suitable models for evaluating the impact of all production factors and undesirable production results on changes in productivity. Therefore, it is necessary to create a new model for evaluating productivity with undesirable outputs, which allows for avoiding the weaknesses and limitations of the DEA and other sustainable productivity assessment methods.
4. Some DEA supplements were found especially useful for dealing with sustainable production analysis in agriculture and including undesirable outputs, such as GHG emissions. Numerous production efficiency assessment methods and indicators were developed to solve several limits of DEA models in assessing sustainable agriculture productivity. They include SBM, the global Luenberger productivity indicator, the Malmquist-Luenberger index, the Fare-Primont index, the Malmquist index, supper

efficiency DEA, and the contribution to structural efficiency index. A more detailed analysis of the applicability and strengths of these DEA supplements is necessary to improve DEA capabilities in addressing sustainable productivity in agriculture for assessing the paths towards sustainable agriculture development, including main drivers and obstacles.

2

Research Methodology for Sustainable Productivity Assessment

This Chapter presents the research methodology and sustainable productivity assessment model formed based on extended production function with undesirable outputs. Luenberger productivity index, SBM, super-efficiency DEA and Contribution to Structural Efficiency index were developed to supplement conventional DEA and to provide a complete ranking of the countries based on sustainable productivity and efficiency, including negative outcomes. The Second Chapter describes methods provided in the third paper, “Creation of climate-smart and energy-efficient agriculture in the European Union: Pathways based on the frontier analysis”, and the fourth paper, “Achievements of the European Union member states towards the development of sustainable agriculture: A contribution to the structural efficiency”, and the fifth paper, “Does the Cost of Energy-related Greenhouse Gas Emission Abatement Depend on the Optimization Direction: Shadow pricing exercise based on the weak disposability technology in the European Union agriculture”, published in the journals indexed in the Clarivate Web of Science Core Collection and co-authored by the dissertation author with other researchers.

2.1. Research rationale and sustainable productivity assessment model based on frontier analysis

Pareto–Koopmans defined that production is efficient if it is impossible to produce more without increasing costs or if it is impossible to use fewer factors of production without reducing production volumes (Mirdehghan, Fukuyama, 2016). At the same time, Farrell (1957) proposed an efficiency ratio to measure the degree to which the actual situation differs from the optimal one. The optimal situation is evaluated with the help of the production function (production possibilities limit). Efficiency is defined as the ratio of actual to optimal productivity. The change in production productivity is measurable as a result of efficiency and technological change.

The main research framework is based on the agricultural production function of the selected region (EU member countries), applying marginal (non-parametric linear programming methods) to determine the effective limit of the agricultural production possibilities of these regions, and after evaluating the undesirable results of agricultural production, such as the greenhouse effect emissions. Environmental production technology can be described by parametric and non-parametric methods. Non-parametric environmental manufacturing technologies have been described by Hailu and Veeman (2001), Färe and Grosskopf (2003) and Murty et al. (2012). The distance of the selected research region (EU member countries) from the limit of efficient agricultural production possibilities would show whether there is potential to achieve better economic outputs with the available resources, i.e., human capital and investment and environmental constraints.

This work proposes the application of non-parametric linear programming methods, such as DEA, because they complement the capabilities of multivariate data analysis and more accurately evaluate the differences in technical agricultural efficiency between the studied regions, allow identifying weak areas and make proposals for agricultural productivity improvement and implementation of environmental policy (Fang et al., 2020; Wang et al., 2020). DEA is better than other non-parametric linear programming methods in filtering out differences in efficiency between technologically similar regions. The main difference is that DEA compares the entire group of regions according to extreme values of efficiency, while the rest of the methods compare the efficiency of different regions only with regions with smaller resources, allowing the values of the economic estimates of some regions to be above the effective production possibilities limit with certain confidence levels. When comparing technologically similar regions, it is more appropriate to look for the leaders of the entire group, based on which it would be possible to conclude the overall agricultural efficiency of the group of regions (Sueyoshi et al., 2017; Urdiales et al., 2016).

So, to assess the efficiency and productivity of agriculture in this work, it is proposed to apply complementary research methods, such as DEA, by supplementing conventional DEA with new methods. The conventional DEA models proposed in the study by Charnes et al. (1978) and Banker and Thrall (1992) are based on radial measures as the composition of inputs and outputs are fixed in the optimisation, and the inefficiency measures are not variable-specific. The new approach introduced by Tone (200) is a slacks-based measure (SBM) that analyses the contributions of each input/output variable to the inefficiency score. This approach was further developed by Cooper et al. (2007) and applied to the examination of environmental performance with undesirable outputs. In addition, the global Luenberger productivity indicator was developed by Wang and Wei (2016) based on SBM and applied by Wang et al. (2016). This indicator allows decomposing the changes in productivity concerning the contributions of each input/output variable.

Therefore, a new model is proposed for evaluating agricultural production with undesirable results, which is based on an extended production function that includes the main factors of agricultural production (energy consumption in agriculture, capital, labour and land costs in agriculture) and greenhouse gas emissions related to energy consumption in agriculture. The model allows estimating the production function using DEA and supplementing it with global technology and a slacks-based method (SBM) for efficiency measurement. This makes it possible to decompose the Luenberger productivity index into the contribution of all production factors and results (including GHG emissions). Efficiency and technological changes can also be analysed with this new tool.

The environmental production technology for the period $t = 1, 2, \ldots, T$ is defined in terms of input quantities $x^{d,t} \in R_+^I$, output quantities $y^{d,t} \in R_+^J$ and undesirable output quantities $z^{d,t} \in R_+^K$. The inputs are intentionally transformed into outputs (desirable ones), whereas the undesirable outputs are unintended (e.g., pollution). The environmental production technology for the period t (i.e., the contemporaneous technology) is defined in terms of the production possibility set:

$$P^t = \left\{ \left(x^t, y^t, z^t \right) \mid x^t \text{ can produce } \left(y^t, z^t \right) \right\}, \tag{2.1}$$

The SBM measures inefficiency (a distance function D) based on excesses/shortages of inputs and outputs. Thus, empirical research will measure inefficiency. The distance function D can take values from 0 to infinity. Inefficiency is the inverse of efficiency, and zero inefficiency means full efficiency. The resulting distance function is denoted as $D(\cdot)$:

$$D^t\left(x^{d,t},y^{d,t},z^{d,t};g\right)=\max\frac{1}{3}\left(\frac{1}{I}\sum_{i=1}^{I}\frac{s_i^x}{g_x^i}+\frac{1}{J}\sum_{j=1}^{J}\frac{s_j^y}{g_y^j}+\frac{1}{K}\sum_{i=1}^{I}\frac{s_k^z}{g_z^k}\right)$$

$$\begin{aligned}
&\text{s.t.}\\
&\sum_{d=1}^{D}\lambda_d x_i^{d,t}+s_i^x=x_i^{d',t}, i=1,2,...,I,\\
&\sum_{d=1}^{D}\lambda_d y_j^{d,t}-s_j^y=y_j^{d',t}, j=1,2,...,J,\\
&\sum_{d=1}^{D}\lambda_d z_k^{d,t}+s_k^z=z_k^{d',t}, k=1,2,...,K,\\
&\lambda_d\geq 0, d=1,2,...,D,\\
&s_i^x,s_j^y,s_k^z\geq 0,
\end{aligned}\tag{2.2}$$

where s^x, s^y and s^z are the slacks associated with inputs, outputs and undesirable outputs, respectively; and g_x, g_y, g_z are the directional vectors for inputs, outputs and undesirable outputs, respectively. In this case, the authors use the proportional distance and set the directional vector to be equal to the observed quantities of the input/output variables.

The Luenberger productivity (LP) indicator reflects changes in productivity, which can be positive or negative. A positive value indicates that production productivity is growing:

$$LP_d^{t,t+1}=D\ \left(x^{d,t},y^{d,t},z^{d,t};g^t\right)-D\ \left(x^{d,t+1},y^{d,t+1},z^{d,t+1};g^{t+1}\right),\tag{2.3}$$

where $D(\cdot)$ is the distance function relative to the global frontier. Therefore, positive (resp. negative) values of *LP* imply positive (resp. negative) productivity growth as an observation approaches the global frontier over time.

Positive Efficiency Changes (EC) are obtained due to the implementation of advanced farming and management practices to better use agricultural production factors and resources:

$$EC_d^{t,t+1}=D^t\left(x^{d,t},y^{d,t},z^{d,t};g^t\right)-D^{t+1}\left(x^{d,t+1},y^{d,t+1},z^{d,t+1};g^{t+1}\right).\tag{2.4}$$

Thus, EC shows whether a certain country improved its performance relative to the contemporaneous frontier, and the positive EC can be observed due to the improved farming and managerial practices when resources are properly used in the production process.

The necessary data for assessing sustainable productivity can be collected for EU member states from Eurostat Agricultural economic accounts, energy balances, and data on greenhouse gas emissions due to energy consumption in agriculture. The studied production factors: energy consumption in agriculture, TJ; costs of fixed capital in agriculture, PGS recalculated at 2005 prices; labour costs in agriculture, annual working hours; land consumption, ha. Desired output expressed as total agricultural output, PGS, recalculated in constant 2005 prices. Undesirable production outputs are expressed as GHG emissions, Mt.

2.2. Further advancements in the sustainable productivity assessment model

Next, the developed sustainable productivity assessment model with undesirable outputs for assessing agricultural productivity in the EU was further advanced to overcome other important limits of conventional DEA.

A model with an environmental function of production technology was supplemented by new methods of efficiency assessment: super-efficient DEA and index of contribution to structural efficiency. This allows for solving the efficiency assessment problem in agricultural productivity when the DEA cannot assess it due to the reduction of discriminatory power, i.e., the ability to reveal differences between various efficiency levels. This problem occurs with numerous variables and observations.

Non-parametric frontier methods, such as DEA, are a good tool to measure the eco-efficiency of environmentally friendly production technology; however, DEA may be unable to measure efficiency due to decreased discriminative power when the ratio of variables to observations is high. This problem becomes particularly complicated when unwanted output (an additional variable) is included.

Thus, the productivity assessment model was further developed to rank EU member states according to ecological efficiency using the super-efficiency DEA and index of contribution to structural efficiency, which is a new method. Super-efficient DEA and similar methods have been proposed to improve discriminative power (reveal differences between various efficiency levels). These methods assume that the production technology of each considered efficient DMU (decision maker/state) is further investigated (and yields results in greater than 1), while inefficient DMUs are not.

The super-efficiency DEA was developed by Andersen and Petersen (1993) as a tool for dealing with situations where the DMU ranking cannot be performed because of the limited sample size. The super-efficiency DEA also suffers from infeasibilities in solving tasks.

Zhu et al. (2019, 2020) proposed an index of contribution to structural efficiency that applies (the same) environmental technology to all DMUs. Therefore, the weak abatement of environmental technology and the contribution to the structural efficiency index were applied to assess the productivity of EU Member States' agricultural sectors in terms of eco-efficiency and GHG emission restrictions.

Environmentally friendly production functions can be defined as:

$$T = \{(x, y, b) : x \text{ can produce } (y, b)\}, \tag{2.5}$$

where: x – inputs; y – desirable outputs; b – undesirable outputs.

DEA function of the weak disposability technology for K-number of DMUs that consume I factors of production to produce J desirable outputs and L undesirable outcomes (GHG emissions) is described by:

$$\widehat{T} = \left\{ (x, y, b) \in \Re^{I+J+L} : \sum_{k=1}^{K} \lambda_k x_{ki} \le x_i, \sum_{k=1}^{K} \lambda_k y_{kj} \ge y_j, \sum_{k=1}^{K} \lambda_k b_{kl} = b_l, \lambda_k \ge 0, \right\},$$
$$i = 1, 2, ..., I, j = 1, 2, ..., J, k = 1, 2, ..., K, l = 1, 2, ..., L, \tag{2.6}$$

where λ_k are the intensity variables that define the production frontier in terms of the observed production plans?

Considering an arbitrarily chosen DMU $k' \in k = 1, 2, \ldots, K$. The two cases of the efficiency measurement can be performed.

First, the output-oriented directional DEA is applied:

$$\begin{aligned}
\rho_{k'} &= \min \frac{1}{1 + \frac{1}{J+L}\left(\sum_{j=1}^{J} \beta g_j / y_{k'j} + \sum_{l=1}^{L} \beta g_l / b_{k'l} \right)} \\
s.t.\ &\sum_{k=1}^{K} \lambda_k x_{ik} \le x_{k'i}, i = 1, 2, ..., I, \\
&\sum_{k=1}^{K} \lambda_k y_{jk} \ge y_{k'j} + \beta g_j, j = 1, 2, ..., J, \\
&\sum_{k=1}^{K} \lambda_k b_{lk} = b_{k'l} - \beta g_l, l = 1, 2, ..., L, \\
&\lambda_k \ge 0, k = 1, 2, ..., K,
\end{aligned} \tag{2.7}$$

where $\rho_{k'} \in (0,1]$ is the efficiency score for a certain DMU k'. The efficiency score of unity indicates full efficiency and declines with increasing inefficiency. This paper uses the proportional output DDF and set $(g_j, g_l) = (y_{k'j}, b_{k'l})$, $j = 1,2,\ldots,J$, $l = 1,2,\ldots,L$.

Generalised Directional Distance Function (DDF) when *k≠ k',* (super-efficient DEA) can be obtained by the following formula:

$$\rho_{k'}^{S} = \min \frac{1}{1 + \frac{1}{J+L}\left(\sum_{j=1}^{J} \beta g_j / y_{k'j} + \sum_{l=1}^{L} \beta g_l / b_{k'l}\right)}$$

$$s.t. \sum_{\substack{k=1 \\ k \neq k'}}^{K} \lambda_k x_{ik} \leq x_{k'i}, i = 1,2,\ldots,I, \tag{2.8}$$

$$\sum_{\substack{k=1 \\ k \neq k'}}^{K} \lambda_k y_{jk} \geq y_{k'j} + \beta g_j, j = 1,2,\ldots,J,$$

$$\sum_{\substack{k=1 \\ k \neq k'}}^{K} \lambda_k b_{lk} = b_{k'l} - \beta g_l, l = 1,2,\ldots,L, \quad \lambda_k \geq 0, k = 1,2,\ldots,K, \lambda_{k'} = 0.$$

The marginal coefficient of contribution to structural efficiency is obtained as follows:

$$I_{k'}^{C} = \frac{1}{2^{K-1} - 1} \sum_{\substack{A \subseteq T^{D} \setminus \{k'\} \\ A \neq \varnothing}} \frac{\rho(A \cup k')}{\rho(A)}, \tag{2.9}$$

where $\rho(\cdot)$ is the efficiency score for aggregate DMU, including or excluding DMU k'.

$I_{k'}^{C} > 1$ indicates that DMU k' positively contributes to structural efficiency. The values below unity indicate that the production plan observed for DMU k' does not improve structural efficiency. Therefore, it is possible to define countries which use the inputs most productively and ensure less intensive environmental pollution due to energy consumption.

The necessary data for sustainable productivity assessment for EU Member States can be obtained from Eurostat energy balance and agricultural statistics. Desired output is all agricultural output (PPS based on 2010 comparative prices); Undesirable output is energy-related GHG emissions (tons of CO_2 equivalent).

Production factors include agricultural land area (ha), labour costs (contract workers = 2036 for working hours), long-term capital (CPS), and final energy consumption (metric tonne oil equivalent).

2.3. Monetary evaluations of undesirable outputs in the sustainable productivity assessment model

The developed sustainable productivity assessment model is supplemented with an environmental function of production technology, which integrates additional assumptions about the interrelationship of desirable and undesirable outputs and allows the monetary expression of undesirable outputs (GHGs due to energy consumption in agriculture). It is found by calculating GHG shadow prices (marginal costs of reducing GHG emissions. The shadow price of GHG emissions shows the marginal costs of their reduction and is very useful in analysing the possibilities of improving the environmental quality of a specific production technology.

The model for evaluating production productivity with undesirable results in agriculture was extended to evaluate the shadow price of undesirable production results (GHG).

A non-parametric method (DEA) was applied in the productivity assessment model. Directional DEA can evaluate the efficiency of decision-making units (states) in moving along the production possibilities curve in different directions, as defined in the sections above. Directions can be calculated by evaluating the data of individual countries or groups of countries.

The main idea in applying environmental technology in DEA is to assess the effect of choosing different directions in moving to the production possibilities curve on the shadow prices of GHG emissions. The weak disposability DEA model developed by Kuosmanen (2005) was applied. The weak disposability technology is among the most often applied in empirical research due to its operationality. It assumes that the desirable and undesirable outputs are weakly disposable, i.e., the production possibility set is defined by allowing the scaling down of the undesirable and desirable outputs by the same factor. This approach was discussed in a detailed way by Färe and Grosskopf (2003). Moving in different optimisation directions yields shadow prices of energy-related greenhouse gas emissions in EU agriculture.

The main formulas and notations are described below.

Environmental production technology:

$$T = \{(x, y, z) : x \text{ can produce } (y, z)\}, \tag{2.10}$$

where x – factors of production; y – desired output; z – undesired output (GHG emissions).

DEA approximation of environmental production technology is provided below:

$$\hat{T} = \left\{ (x, y, b) \in \Re^{I+J+L} : \sum_{k=1}^{K} \lambda_k x_{ki} \le x_i, \sum_{k=1}^{K} \lambda_k y_{kj} \ge y_j, \sum_{k=1}^{K} \lambda_k b_{kl} = b_l, \lambda_k \ge 0, \right.$$
$$\left. i = 1,2,...,I, j = 1,2,...,J, k = 1,2,...,K, l = 1,2,...,L, \right\} \quad (2.11)$$

here, K – decision making units (DMUs) that represent countries; $k = 1,2,\ldots,K$ – number of DMUs; ξ_k, – weights assigned to the DMUs. θ_k – specific abatement factors for DMUs, which are applied to ensure the weak disposability of the desirable and undesirable outputs.

The directional output distance function is described by:

$$D\left(x, y, z; g_y, g_z\right) = \max\left\{\delta : \left(x, y + \delta g_y, z - \delta g_z\right) \in T\right\}, \quad (2.12)$$

where $g = \left(g_y, g_z\right)$ is the directional vector encompassing directions for optimization of desirable and undesirable outputs. The zero value $D(\cdot;\cdot)$ implies full efficiency and positive values imply inefficiency.

Note that the directional output distance function in Eq. 2.12 can be plugged into $\hat{T}$ given by Eq. 2.11.

This provides that the original DEA model takes the following form:

$$
\begin{aligned}
& D(x, y, z;\, g_y, g_z) \;=\; \max_{\delta,\lambda,\sigma} \delta \\
& \text{s.t.} \\
& \sum_{k=1}^{K} \lambda_k y_k^m \ge y_{k'}^m + \delta g_y^m,\ m = 1,...,M \\
& \sum_{k=1}^{K} (\lambda_k + \sigma_k) x_k^n \le x_{k'}^n,\ n = 1,...,N \\
& \sum_{k=1}^{K} \lambda_k z_k^j = z_{k'}^j - \delta g_z^j,\ j = 1,...,J \\
& \sum_{k=1}^{K} (\lambda_k + \sigma_k) = 1 \\
& \lambda_k, \sigma_k \ge 0,\ k = 1,...,K.
\end{aligned}
\quad (2.13)
$$

The dual DEA model will take the following form:

$$D\ (x\ ,y\ ,z\ ;g_y,g_z)=\min_{\pi_y,\pi_x^n,\pi_x^p,\pi_z,\phi}\ \phi-(\sum_{m=1}^{M}\pi_y^m y_{k'}^m-\sum_{n=1}^{N}\pi_x^n x_{k'}^n-\sum_{j=1}^{J}\pi_z^j z_{k'}^j)$$

s.t.

$$\sum_{m=1}^{M}\pi_y^m y_k^m-\sum_{n=1}^{N}\pi_x^n x_k^n-\sum_{j=1}^{J}\pi_z^j z_k^j\le\phi, k=1,...,K$$

$$-\sum_{n=1}^{N}\pi_x^n x_k^n\le\phi, k=1,...,K \tag{2.14}$$

$$\sum_{m=1}^{M}\pi_y^m g_y^m+\sum_{j=1}^{J}\pi_z^j g_z^j=1$$

$$\pi_y^m\ge 0, m=1,...,M$$

$$\pi_x^n\ge 0, n=1,...,M.$$

The dual DEA model includes the assumption that the shadow price of GHG is equal to or greater than 0:

$$\pi_z^j\ge 0,\ \ j=1,2,...,J. \tag{2.15}$$

The shadow values in Eq. 2.14 can be used to calculate the shadow prices of undesirable outputs. The following ratio yields the relative shadow price of the j-th undesirable output:

$$CSP=\frac{\pi_z^j}{\pi_y^m}. \tag{2.16}$$

The directions of DEA optimisation (movement towards the limits of production possibilities) are determined by the following four methods:

Proportional (radial) direction vector:

$$(g_y,g_z)=(y_k,z_k). \tag{2.17}$$

Unit direction vector:

$$(g_y,g_z)=(1,1). \tag{2.18}$$

Aggregate direction vector:

$$(g_y, g_z) = \left(\sum_{k=1}^{K} y_k, \sum_{k=1}^{K} z_k \right). \tag{2.19}$$

Aggregate mean direction vector:

$$(g_y, g_z) = \left(\frac{1}{K} \sum_{k=1}^{K} y_k, \frac{1}{K} \sum_{k=1}^{K} z_k \right). \tag{2.20}$$

Non-negative elements of the directional vectors imply that the desirable outputs are expanded, whereas the undesirable ones are contracted while moving along the directional vector.

The necessary data for sustainable productivity assessment and evaluation of GHG emission reduction shadow prices are as follows: factors of production: work (annual working hours h), land area (hectares), intermediate consumption (PGS 2010, excluding energy costs), energy consumption (tons of oil equivalent); desired production (PGS 2010); undesirable outputs – GHG emissions related to energy consumption (tons of carbon equivalent). Data can be obtained from EUROSTAT agricultural economic accounts, environmental accounts, agricultural statistics and energy balances.

2.4. Conclusions of the Second Chapter

1. Non-parametric frontier methods, such as Data Envelopment Analysis (DEA), can be used to measure eco-efficiency with environmentally friendly production technology. Conventional DEA applied for green/sustainable productivity assessment with negative outputs has many limitations; therefore, this dissertation developed a new sustainable productivity assessment model to overcome these limits.
2. This new model is based on frontier analysis and includes various supplements of conventional DEA. This model allows estimating the production function using DEA and supplementing it with global technology and a slacks-based method (SBM) for efficiency measurement. This makes it possible to decompose the Luenberger productivity index into the contribution of all production factors and results (including GHG emissions). Efficiency and technological changes can also be analysed.
3. DEA may be unable to measure efficiency due to decreased discriminative power when the ratio of variables to observations is high. This problem becomes particularly complicated when undesirable outputs (an additional variable) are included. Super-efficient DEA and structural efficiency methods have been proposed to improve the discriminative

power of conventional DEA (reveal differences between various efficiency levels.

4. Further, the developed sustainable productivity assessment model was supplemented with an environmental function of production technology, which integrates additional assumptions about the interrelationship of desirable and undesirable outputs and allows the monetary expression of undesirable outputs (GHG emissions due to energy consumption in agriculture). Weak disposability technology was chosen, meaning that desired and undesirable outputs (GHG emissions) can decrease proportionally.
5. The directional DEA applied in the model can measure the efficiency of decision-making units towards different directions. These directions can be observation-specific or common to the whole sample. The developed sustainable productivity assessment model ascertains the effects of using the different directions on the GHG emission shadow prices. The shadow price of GHG emissions is beneficial for policy analysis as it shows the marginal costs of GHG emission reduction in agriculture and the possibilities of energy efficiency improvement and GHG emission reduction for a specific agriculture production technology.

3

Sustainable Agriculture Productivity Assessment Results and Conclusions

This chapter presents the results of empirical studies conducted by practically applying a developed sustainable productivity assessment model in the agriculture of EU member states. The Third Chapter describes the main results and findings provided by the third paper, “Creation of climate-smart and energy-efficient agriculture in the European Union: Pathways based on the frontier analysis”, the fourth paper, “Achievements of the European Union member states towards the development of sustainable agriculture: A contribution to the structural efficiency”, and the fifth paper, “Does the Cost of Energy-related Greenhouse Gas Emission Abatement Depend on the Optimization Direction: Shadow pricing exercise based on the weak disposability technology in the European Union agriculture”, published in journals indexed in the Clarivate Web of Science Core Collection. Also, the Third Chapter provides conclusions and policy recommendations for promoting sustainable agriculture development in the EU Member States.

3.1. Sustainable agricultural productivity assessment with Data Envelopment Analysis and Luenberger productivity index in European Union countries

The inefficiency in agricultural production was measured concerning the global frontier. Assuming constant returns to scale (CRS), the changes in the global inefficiency are related to changes in the productivity of analysed EU countries. The additive nature of the SBM of inefficiency allowed for isolating the contributions of individual inputs and outputs towards the overall inefficiency.

The inputs and undesirable output (energy-related GHG emission) show non-zero inefficiencies, whereas the inefficiency score for the desirable output (agricultural output) is zero. This implies that the improvements in agricultural productivity in the EU are mostly related to increasing resource efficiency and improving environmental performance. The average values of the variable-specific CRS inefficiency scores are further analysed to identify the key trends in inefficiency along with the contributions of the individual variables.

The dynamics in the inefficiency scores of EU countries related to the inputs are provided in Fig. 3.1.

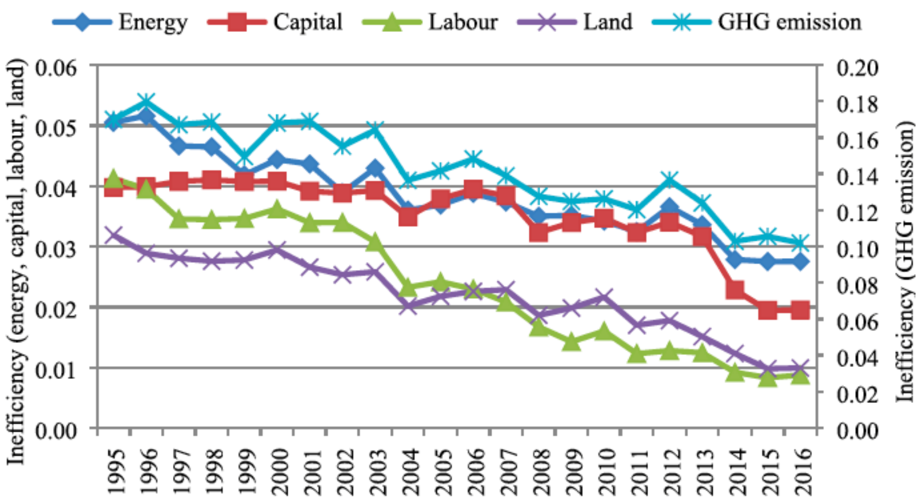


Fig. 3.1. Inefficiency dynamics in EU countries (Source: Streimikis et al., 2020)

As demonstrated in Fig. 3.1, energy use and energy-related GHG emission showed the highest mean inefficiencies over the investigated period.

The Fig. 3.1 results show some differences among the input and output variables in terms of their contributions to the overall inefficiency. Therefore, Table

3.1 provides the average values of inefficiencies along with the trend coefficients (which correspond to the stochastic rates of change) for different periods.

Fig. 3.2 shows the mean inefficiency scores across the EU states for further analysis.

Table 3.1. Inefficiency dynamics in EU countries **(**Source*:* Streimikis et al., 2020*)*

Period	Energy	Capital	Labour	Land	GHG emissions
Average, %					
1995–2016	3.84	3.51	2.37	2.18	14.21
1995–2003	4.52	4	3.55	2.79	16.57
2004–2016	3.38	3.16	1.55	1.76	12.58
Trend (speed of change), pp					
1995–2016	–0.1	–0.09	–0.17	–0.09	–0.34
1995–2003	–0.13	–0.01	–0.1	–0.06	–0.16
2004–2016	–0.08	–0.15	–0.14	–0.1	–0.33

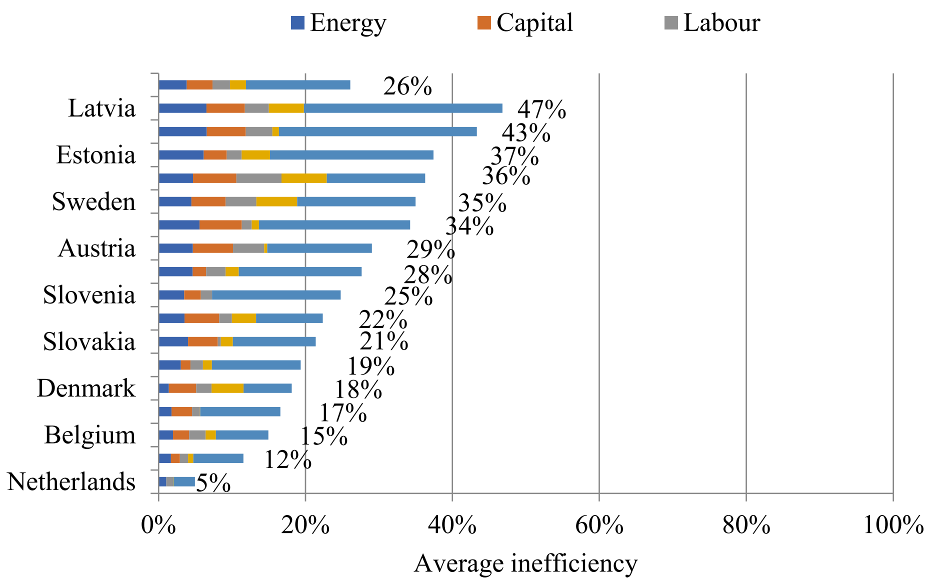


Fig. 3.2. Average inefficiency of EU countries and its decomposition analysis by factors of production (Source: Streimikis et al., 2020)

Latvia, Poland, Estonia and Finland appear as the countries with the lowest levels of agricultural efficiency, whereas the Netherlands, Bulgaria, Belgium and France seem to be the most efficient countries. The decomposition of the inefficiency scores shows that energy use is responsible for the highest share of the overall inefficiency in EU countries.

The analysis of possible convergence in agricultural efficiency requires checking whether the spread in the inefficiency measures declines over time across the EU Member States (Fig. 3.3).

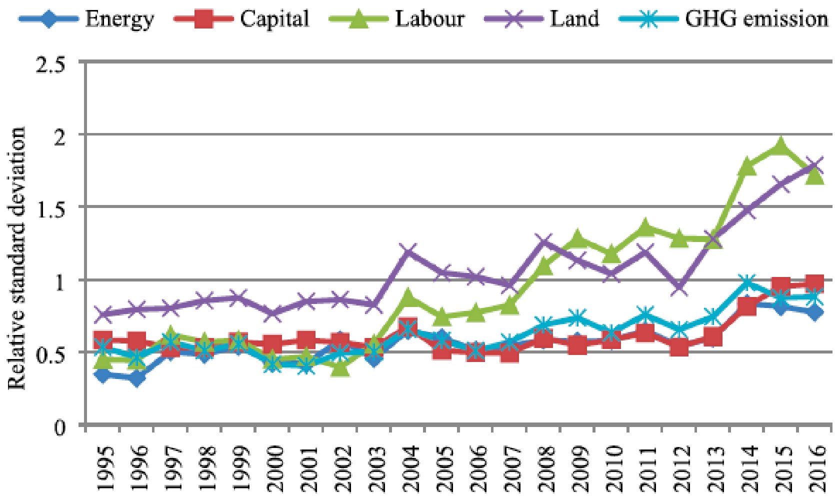


Fig. 3.3. Inefficiency convergence between EU countries
(Source: Streimikis et al., 2020)

Based on Fig. 3.3, all the inputs and outputs showed increasing divergence in terms of the associated efficiency scores. Therefore, the inefficiency of energy consumption has seen an increasing polarization in EU agriculture across the EU countries.

The productivity measures can be decomposed concerning the sources of productivity growth. Due to the additive structure of the SBM, the Luenberger productivity indicator was decomposed with regard to the inputs and outputs. The average values of the Luenberger productivity indicator and its components for the group of selected countries are given in Fig. 3.4.

Fig. 3.4 shows that the cumulative efficiency change effect remained positive throughout most of the period analysed. In general, the contribution of the efficiency change was 0.46% p.a., and that of the technical progress was 0.33% p.a. Therefore, the resources tended to be allocated more efficiently over time across the selected EU countries.

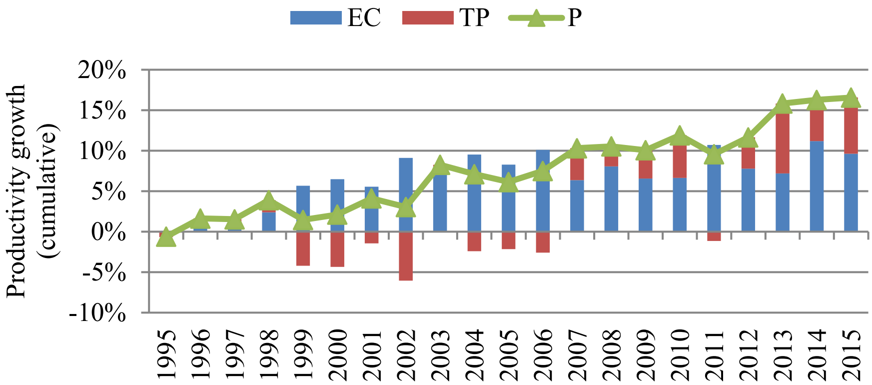


Fig. 3.4. Decomposition analysis of the Luenberger cumulative productivity change indicator (Source: Streimikis et al., 2020)

The productivity growth can be decomposed with regard to the input/output variables. Such an approach allows one to identify the key contributors towards productivity growth along with the major obstacles in EU agriculture. The decomposition is carried out at the country level and is given in Fig. 3.5.

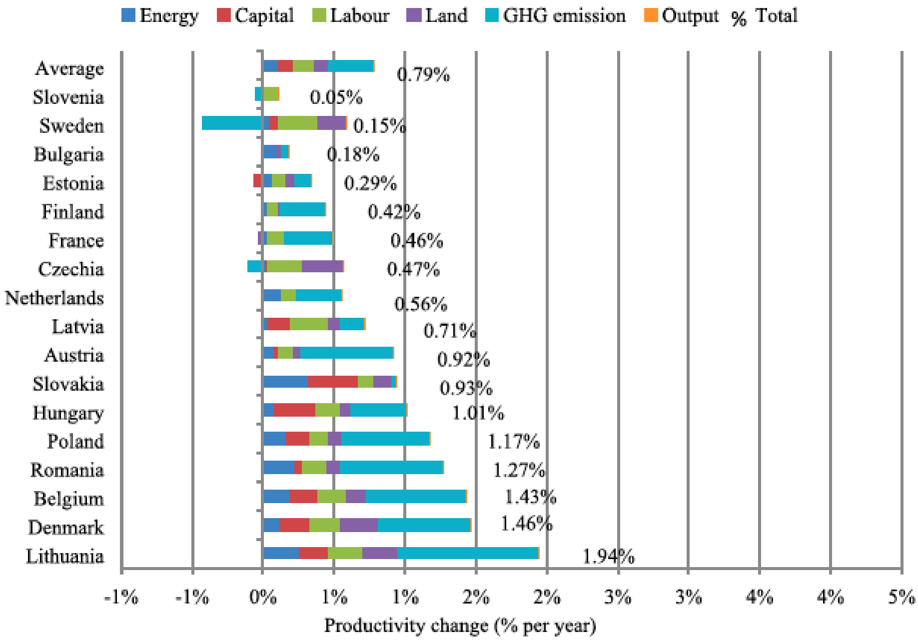


Fig. 3.5. Decomposition analysis of productivity growth at the level of countries 1995–2016 average (Source: Streimikis et al., 2020)

As the contribution of different inputs and outputs towards the productivity growth in the agricultural sectors of the selected EU Member States varies with time, the dynamics in the cumulative average contribution associated with each variable are given in Figure 3.6.

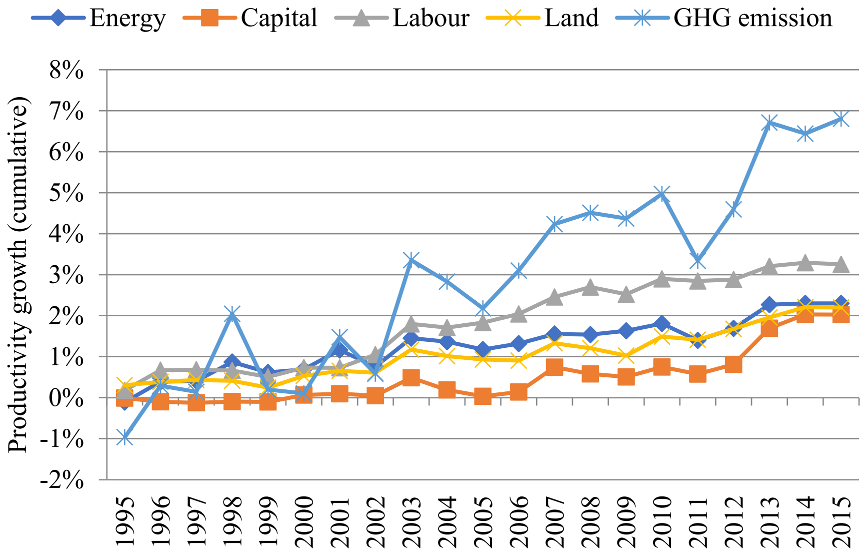


Fig. 3.6. Cumulative average productivity growth by individual factors of production in 1995–2016 (Source: Streimikis et al., 2020)

One can notice that until 2004, all the variables contributed equally to the growth in the agricultural productivity in the EU. However, the capital input remained the least important contributor throughout the period of analysis. The contribution of the energy-related GHG emission kept increasing. The labour input was associated with the second-highest contribution to productivity growth. In addition, the energy-related GHG emission contributed more to the productivity growth than the energy input, showing that energy with lower carbon content was the main factor pushing the sustainable productivity growth up in the agriculture sector of EU countries.

The decomposition of the efficiency change (EC) at the country level is given in Figure 3.7.

The negative EC growth is observed for Estonia, France and Slovenia. It is mainly determined by the energy-related GHG emission and energy use. It is seen from Figure 3.7 that France and Slovenia require not only improvements in the energy mix but also in energy efficiency.

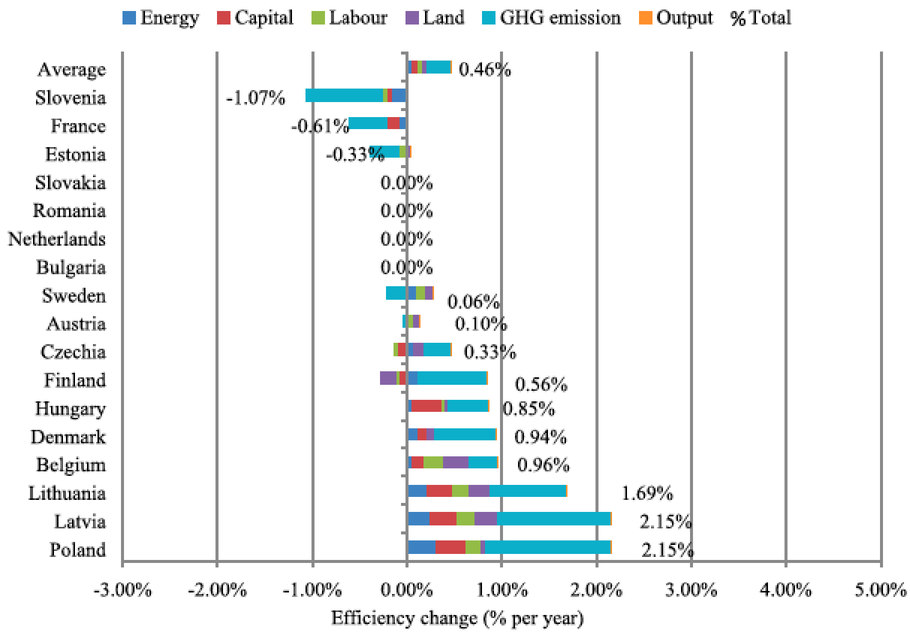


Fig. 3.7. Decomposition of the efficiency change at the country level (average values for 1995–2016) (Source: Streimikis et al., 2020)

3.2. Sustainable productivity assessment with Data Envelopment Analysis and contribution to structural efficiency index in European Union countries

In the first stage of analysis, the performance of the EU agricultural sector in terms of efficiency was analysed at the country level within each year by applying conventional DEA. The results are provided in Table 3.2.

Table 3.2. Efficiency scores of EU member states' agricultural sectors (CRS), 1995–2016 (Source: Streimikis et al., 2022)

State	1995	2000	2005	2010	2016	Average	The trend
Austria	0.89	0.89	0.90	0.95	0.95	0.91	0.005
Belgium	0.81	1.00	1.00	1.00	1.00	0.97	0.007

End of Table 3.2

State	1995	2000	2005	2010	2016	Average	The trend
Bulgaria	1.00	1.00	1.00	1.00	1.00	1.00	0.000
Czechia	0.93	0.94	1.00	0.96	0.94	0.97	0.001
Denmark	1.00	1.00	1.00	1.00	1.00	1.00	0.000
Estonia	0.85	1.00	0.96	0.87	0.73	0.90	–0.003
Finland	0.69	0.67	0.70	0.71	0.68	0.69	0.002
France	1.00	1.00	1.00	1.00	0.93	1.00	–0.001
Hungary	0.86	0.88	0.96	0.84	0.97	0.89	0.003
Latvia	0.62	0.64	0.64	0.70	1.00	0.72	0.018
Lithuania	0.73	1.00	1.00	1.00	1.00	0.96	0.009
Netherlands	1.00	1.00	1.00	1.00	1.00	1.00	0.000
Poland	0.68	0.66	1.00	1.00	1.00	0.84	0.022
Romania	1.00	1.00	1.00	1.00	1.00	1.00	0.000
Slovakia	1.00	1.00	1.00	1.00	1.00	1.00	0.000
Slovenia	1.00	1.00	1.00	1.00	1.00	1.00	0.000
Sweden	0.71	0.72	0.73	0.72	1.00	0.77	0.013
Average	0.87	0.91	0.93	0.93	0.95	0.92	0.004
# of efficiency	7	10	11	10	11	5	–

Next, the output-oriented super-efficiency DEA for ranking the EU Member States is obtained (Table 3.3).

Table 3.3. Efficiency of the agricultural sector of EU member states (CRS super-efficiency DEA scores), 1995–2016 (Source: Streimikis et al., 2022)

State	1995	2000	2005	2010	2016	Average	The trend
Austria	0.89	0.89	0.90	0.95	0.95	0.91	0.005
Belgium	0.81	–	–	–	–	0.93	–
Bulgaria	–	–	–	–	1.80	1.80	–

End of Table 3.3

State	1995	2000	2005	2010	2016	Average	The trend
Czech Republic	0.93	0.94	1.01	0.96	0.94	0.98	0.001
Denmark	–	–	–	1.02	1.14	1.05	–
Estonia	0.85	1.01	0.96	0.87	0.73	0.88	–
Finland	0.69	0.67	0.70	0.71	0.68	0.69	0.002
France	–	–	–	–	0.93	1.08	–
Hungary	0.86	0.88	0.96	0.84	0.97	0.89	0.003
Latvia	0.62	0.64	0.64	0.70	1.01	0.71	–
Lithuania	0.73	1.13	1.21	1.01	1.03	1.02	0.012
The Netherlands	–	–	–	–	–	–	–
Poland	0.68	0.66	–	–	–	0.68	–
Romania	1.13	–	–	–	–	2.56	–
Slovakia	1.33	1.05	1.08	–	1.36	1.23	–
Slovenia	–	–	–	–	–	–	–
Sweden	0.71	0.72	0.73	0.72	–	0.72	–
Average	0.85	0.86	0.91	0.86	1.05	0.97	0.011
# of impossible	5	7	8	8	6	2	–
# of super-efficient	2	3	3	2	5	6	–

Based on the results of supper efficiency DEA plotted in Table 3.3, the use of the super-efficiency DEA allows the ranking of EU countries based on agricultural productivity. There are still several countries for which the super-efficiency model does not yield feasible efficiency scores.

Fig. 3.10 shows the dynamics of average efficiency scores according to conventional and super-efficiency DEA.

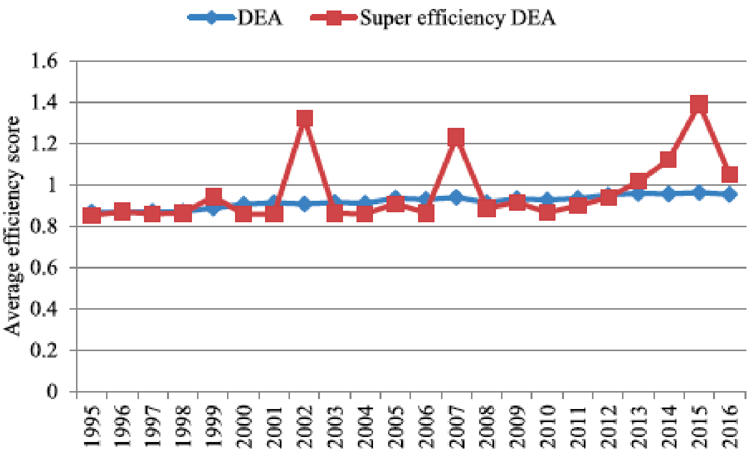


Fig. 3.10. Average efficiency scores for DEA and super-efficient DEA (Source: Streimikis et al., 2022)

As Fig. 3.10 demonstrates, supper efficiency DEA results spike in the average efficiency trend as the infeasible solutions occur and make the ranking based on supper efficiency DEA impossible.

Therefore, further, the contribution to the structural efficiency approach is applied as the ranking becomes impossible for fully efficient observations. As it is possible to consider the two groups of observations, efficient and inefficient, the contribution to the structural efficiency index allows for separating countries based on those contributing to the increase in structural efficiency (with index values exceeding unity) and those not (index values less or equal to unity).

Table 3.4 shows the average efficiency levels for different groups of observations.

Table 3.4. Average efficiency levels by average contribution to structural efficiency (Source: Streimikis et al., 2022)

Contribution	Inefficiency		Average
	Inefficient	Efficient	
$I_{k'}^{C} \leq 1$	0.80	1	0.87
$I_{k'}^{C} > 1$	0.94	1	0.99
Average	0.81	1	0.92

Based on Table 3.4, the efficient observations tend to positively contribute to the aggregate efficiency more often than the inefficient ones.

The distribution of observations in terms of efficiency and contribution to structural efficiency is given in Table 3.5.

Table 3.5. Distribution of observables (agricultural sectors of EU member states) according to efficiency levels and contribution to overall efficiency (Source: Streimikis et al., 2022)

Contribution	Inefficiency		Total
	Inefficient	Efficient	
Absolute frequencies			
$I^C_{k'} \leq 1$	144	75	219
$I^C_{k'} > 1$	16	139	155
Total	160	214	374
Relative frequencies			
$I^C_{k'} \leq 1$	90%	35%	59%
$I^C_{k'} > 1$	10%	65%	41%
Total	100%	100%	100%

The trends of the average contribution to the structural efficiency are provided in Fig. 3.11.

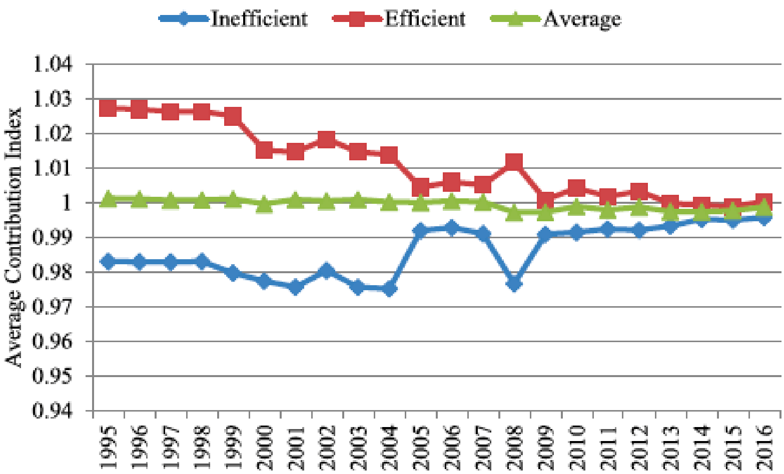


Fig. 3.11. Average index of contribution to structural efficiency for efficient and inefficient observations (Source: Streimikis et al., 2022)

Finally, an EU country-specific analysis of average efficiency and contribution to the structural efficiency is provided in Table 3.6.

Table 3.6. Average efficiency and contribution to structural efficiency of EU Member States, 1995–2016 (Source: Streimikis et al., 2022)

State	Contribution to structural efficiency	DEA average	Number of years of country efficiency	Number of years not possible to solve with the super efficiency DEA	Number of years of positive contribution	Final ranking
Romania	1.023149	1	22	12	22	1
Netherlands	1.02307	1	22	22	18	2
Bulgaria	1.011594	1	22	21	22	3
Slovakia	1.001755	1	22	6	18	4
Slovenia	1.000281	1	22	22	12	5
Denmark	0.997418	0.99808	20	12	3	6
France	1.070929	0.99708	21	18	21	7
Czechia	0.998272	0.97028	7	0	5	8
Belgium	1.007048	0.96935	18	16	19	9
Lithuania	0.995932	0.95689	16	0	4	10
Austria	0.997139	0.91403	0	0	3	11
Estonia	0.996926	0.89864	5	4	0	12
Hungary	0.999253	0.88691	0	0	8	13
Poland	0.914115	0.84153	11	11	0	14
Sweden	0.981677	0.77143	4	4	0	15
Latvia	0.99011	0.72257	2	1	0	16
Finland	0.982399	0.68700	0	12	0	17

The results of the analysis show that even though countries can be ranked in terms of the two efficiency measures, some differences between adjacent ranks are rather insignificant. For instance, Romania and the Netherlands show close-to-nil differences in the average contribution to structural efficiency.

Most of the efficient countries show high numbers of infeasibilities of the super-efficiency DEA. Therefore, these countries show somewhat distinctive patterns of input mix and production scale, which place them outside the production plans of the other countries. Therefore, the measures of the contribution to structural efficiency allow for improved ranking of countries in terms of sustainable agriculture productivity under the presence of heterogeneity in the input mix.

3.3. Assessing shadow prices of reduction of negative outputs in European Union countries

The GHG emission shadow price is determined by the slope of the underlying output isoquant and is related to the GHG emission intensity. Energy-related GHG emission per unit of agricultural output weighted by the output share is important for the construction of the marginal GHG emission abatement cost curve (Fig. 3.12).

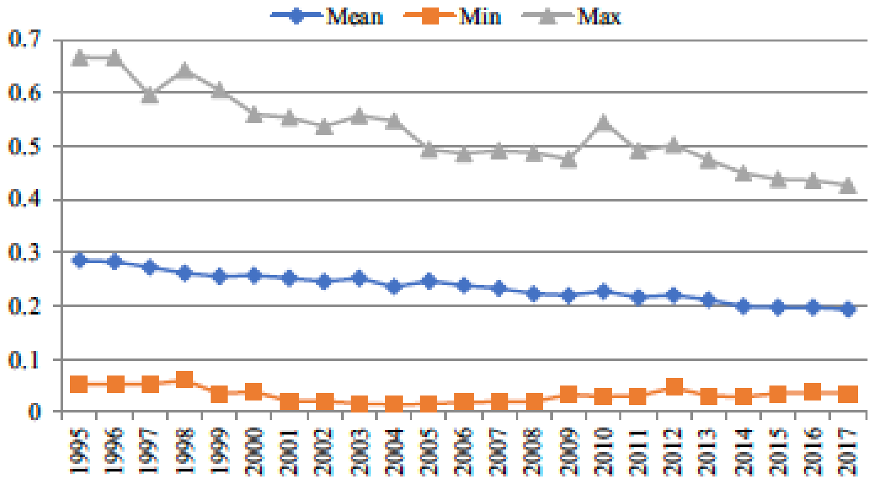


Fig. 3.12. GHG intensity (GHG/agricultural production) in EU countries 1995–2017 (Source: Streimikis et al., 2023)

The three models (Proportional or radial, unit direction and aggregate DDF) defined in Section 2 of this work rendered the estimates of the shadow prices for energy-related GHG emission in the agriculture of EU countries. The aggregate results of GHG emission shadow prices are given in Figure 3.13.

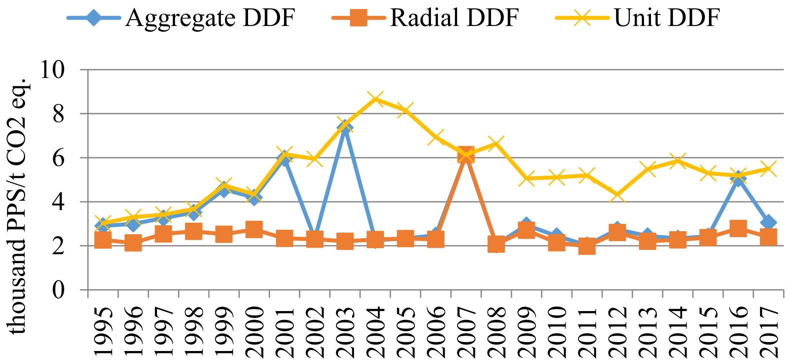


Fig. 3.13. The average shadow price of GHGs related to energy consumption in the EU, 1995–2017 (Source: Streimikis et al., *2023)*

According to Fig. 3.13, GHG emission shadow prices based on the radial DDFs are lower than those based on the non-radial DDFs.

Table 3.7 analyses the country-specific data on the levels and dynamics of GHG emission shadow prices.

Table 3.7. The average shadow price of GHG (PPS 2010/kg CO_2 eq.) and its change (% per year), 1995–2017 (Source: Streimikis et al., 2023)

Country	Aggregate DDF		Radial DDF		Unit DDF	
	Average	Trend	Average	Trend	Average	Trend
Austria	2.4	0.1	2.3	0.0	2.4	0.0
Belgium	1.9	3.8	2.2	3.8	2.2	3.5
Bulgaria	3.1	2.2	2.7	1.4	3.5	1.8
Czechia	2.4	–1.1	2.5	–1.5	2.8	–0.8
Denmark	2.6	3.6	2.6	4.7	2.7	4.9
Estonia	4.5	–4.4	3.3	2.0	5.1	–3.0
Finland	0.7	4.0	1.2	1.0	2.0	0.8
France	3.6	0.8	3.8	–0.3	3.7	1.0
Greece	2.2	11.4	2.0	10.3	3.8	14.8
Hungary	3.5	–1.1	3.4	–0.8	3.7	–0.8
Ireland	2.8	4.2	2.7	3.5	3.0	4.3
Italy	3.1	0.2	3.0	–2.9	2.4	–2.2
Latvia	1.1	13.5	1.2	12.8	2.4	10.6

End of Table 3.7

Country	Aggregate DDF		Radial DDF		Unit DDF	
	Average	Trend	Average	Trend	Average	Trend
Lithuania	4.9	4.0	4.6	5.9	8.8	4.2
Netherlands	1.5	0.7	1.5	0.7	1.3	1.4
Poland	0.0	–	0.0	–	1.1	2.8
Portugal	2.2	–0.2	1.7	–3.7	2.8	3.0
Romania	15.1	–4.9	5.7	0.5	35.0	0.8
Slovakia	7.3	–8.1	5.1	2.0	8.2	–6.4
Slovenia	3.9	–0.1	4.1	4.0	4.9	1.1
Spain	0.2	–2.5	0.2	–4.1	0.4	–2.0
Sweden	0.7	–10.4	0.8	–9.5	1.5	–4.1
UK	2.6	3.3	2.6	3.4	2.6	2.8
Average	3.1	0.9	2.6	1.5	4.6	1.7
Weighted av.	2.0	0.5	1.9	–0.2	2.5	1.2

Based on Table 3.7, the lowest shadow price can be observed for Poland and Spain, irrespective of the DDF applied. The highest shadow price is available in Romania and Slovakia. Countries having lower shadow prices should put more effort into reducing GHG emissions as they have a higher potential to do this.

In Fig. 3.14, the weighted averages of the relative total abatement cost are constructed for the group of EU countries.

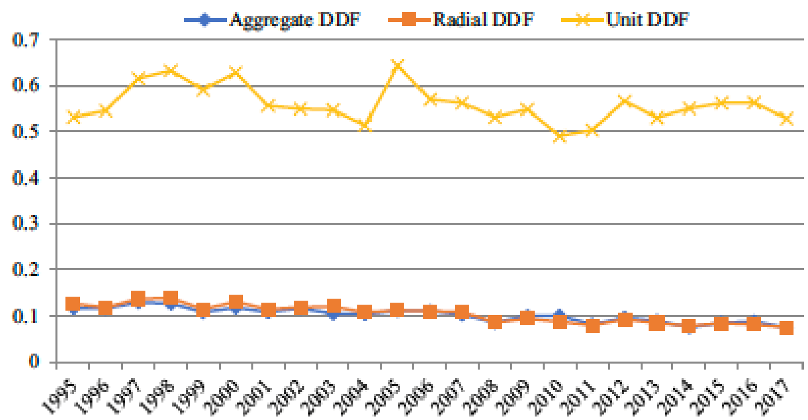


Fig. 3.14. GHG reduction costs (weighted average), i.e., shadow price multiplied by GHG emissions, 1995–2017 (Source: Streimikis et al., 2023)

The GHG emission shadow prices obtained by different DDFs show different levels of the relative total abatement cost. The unit DDF provides for the highest relative total abatement costs.

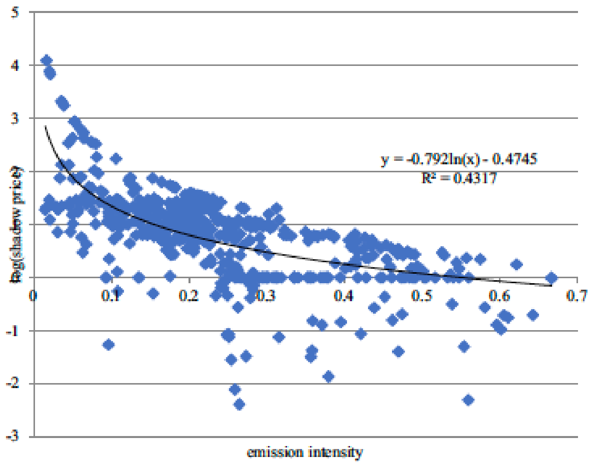
The country-specific relative total abatement costs (measured as a share of the agricultural output) are given in Table 3.8.

Table 3.8. GHG reduction costs and their trend (individual countries), 1995–2017 (Source: Streimikis et al., 2023)

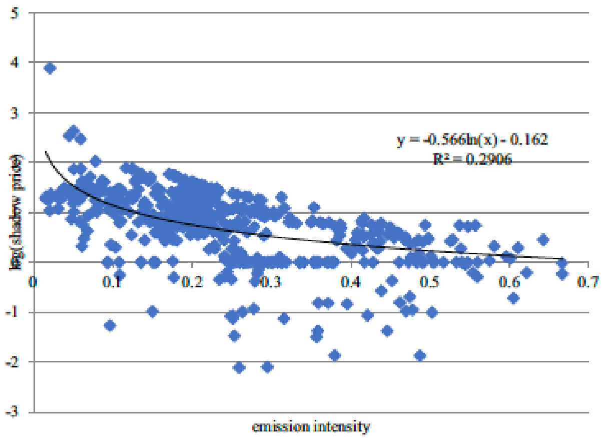
Country	Aggregate DDF		Radial DDF		Unit DDF	
	Aver-age	Trend	Average	Trend	Average	Trend
Austria	0.45	–0.7	0.45	–0.8	0.45	–0.8
Belgium	0.67	0.9	0.75	0.5	0.75	0.5
Bulgaria	0.25	–0.3	0.22	–0.5	0.22	–0.5
Czechia	0.60	–2.4	0.61	–2.7	0.61	–2.7
Denmark	0.77	–0.3	0.73	0.7	0.73	0.7
Estonia	0.86	–1.1	0.72	2.7	0.72	2.7
Finland	0.33	0.6	0.63	–0.6	0.63	–0.6
France	0.75	0.1	0.79	–0.8	0.79	–0.8
Greece	0.26	0.1	0.24	–0.1	0.24	–0.1
Hungary	0.43	–1.4	0.41	–1.2	0.41	–1.2
Ireland	0.45	0.6	0.42	0.3	0.42	0.3
Italy	0.56	–0.6	0.57	–2.3	0.57	–2.3
Latvia	0.27	3.3	0.29	3.3	0.29	3.3
Lithuania	0.36	0.0	0.33	0.6	0.33	0.6
Netherlands	0.71	–0.3	0.71	–0.2	0.71	–0.2
Poland	0.00	0.0	0.00	0.0	0.00	0.0
Portugal	0.35	–0.4	0.27	–1.3	0.27	–1.3
Romania	0.50	–3.8	0.18	–0.4	0.18	–0.4
Slovakia	0.67	–1.7	0.61	2.8	0.61	2.8
Slovenia	0.79	–0.8	0.81	2.6	0.81	2.6
Spain	0.06	–0.2	0.06	–0.3	0.06	–0.3
Sweden	0.29	–3.1	0.34	–3.4	0.34	–3.4
UK	0.60	1.1	0.59	1.1	0.59	1.1
Average	0.48	–0.5	0.47	0.0	0.47	0.0
Weighted av.	0.43	–0.2	0.44	–0.5	0.44	–0.5

As shown, the rankings of countries based on the GHG emission shadow price (Table 3.7) and based on the relative total abatement costs (Table 3.8) differ because the relative total abatement cost involves not only the shadow price information but also covers the magnitude of GHG emission.

Further, the marginal abatement cost (MAC) curves are developed to check the GHG emission intensity elasticity of the shadow prices. The log-log models for the three types of the DDFs are presented in Fig. 3.16.



a – aggregate DDF



b – radial DDF

To be continued

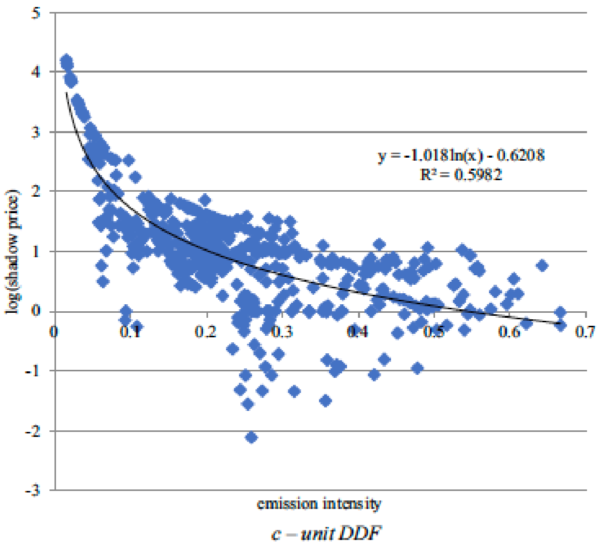


Fig. 3.16. Marginal GHG abatement cost curves (Source: Streimikis et al., 2023)

According to Fig. 3.16, marginal cost curves based on the unit and aggregate DDFs showed elastic responsiveness of the shadow price to the emission intensity. Therefore, a 1% reduction in the GHG emission intensity requires more than around a 1.02% increase in the GHG emission shadow price for unit and aggregate DDF. For the radial DDF, the elasticity drops to 0.57, demonstrating that abatement becomes less costly.

3.4. Conclusions of the Third Chapter

1. Empirical research applying a sustainable productivity assessment model with undesirable outputs has revealed that energy use and energy-related GHG emissions have proven to be important determinants of overall agricultural inefficiency in EU member states.
2. By applying conventional DEA supplements, such as SBM and Luenberger productivity indicators, it was possible to isolate the contributions of individual inputs and outputs towards the overall inefficiency of agriculture production.
3. Inefficiency due to energy-related GHG emissions in Belgium, Austria, Slovakia, Denmark, Sweden, Finland and Lithuania contributed relatively little to overall inefficiency (37–49% of total inefficiency), while such

countries as France, Romania, Slovenia, Czech Republic, Hungary, Estonia and Poland were relatively inefficient in this regard (GHG emissions inefficiency accounted for 60–70% of the total inefficiency in the analysed period. Therefore, countries that use cleaner energy have lower GHG inefficiency (this is the case in Austria, Slovakia and Lithuania). In energy-saving countries, however, the opposite is true. Overall, energy-related inefficiency has decreased in the EU during the investigated period.

4. Productivity growth was disaggregated by factors of production/output variables and sources of growth (i.e., efficiency changes and technical progress). The average annual productivity growth in EU countries was 0.79% during the research period. The largest increase in productivity was observed in Lithuania, Denmark, Belgium and Romania (1.27–1.94% per year). Productivity growth associated with GHG emission reductions dominated in Lithuania, Denmark, Belgium, Romania, Poland, Austria, France, the Netherlands, Hungary and Estonia. These countries have succeeded in reducing energy-related GHG emissions without reducing output levels. This can be achieved by increasing the share of renewable energy sources. Therefore, EU member states have achieved significant growth in sustainable productivity of the agricultural sector.
5. Convergence analysis showed that in 1995–2003, countries were characterised by huge differences and divergence in productivity growth; in 2003–2016, the trends were unclear. Differences in inefficiency rates tended to increase over time between EU countries. However, the variation in inefficiency due to energy consumption and GHG emissions had the smallest variation between countries.
6. The empirical study results can be useful for policymaking to ensure the convergence of EU member states in agricultural efficiency and productivity. Important findings from using DEA supplemented by additional efficiency measures are that sustainable productivity can be increased in all EU countries, regardless of the level of economic development. Support should also be given to lagging countries to promote the use of cleaner energy in agriculture. Specific cases (e.g., Sweden and Slovenia in this study) can be identified as advanced and other countries might follow their model of sustainable productivity growth.
7. The analysis of sustainable productivity in EU countries showed an increase in sustainable agriculture performance in Bulgaria, Denmark, France, the Netherlands, Romania, Slovakia and Slovenia, as measured by conventional DEA; therefore, these countries could not be ranked by the conventional DEA model.

8. Even with the application of super-efficient DEA, performing a full ranking of efficient countries was impossible. Such countries as the Netherlands and Slovenia could not be assigned extremely high-performance scores due to infeasibilities. This indicates that such countries have certain combinations of inputs and outputs that are not directly comparable to inputs in other countries.
9. Therefore, the ranking of EU countries was made using the contribution index to overall efficiency. Romania, the Netherlands, Bulgaria, Slovakia and Slovenia were ranked highest in terms of contribution to structural efficiency (in the same order). It should be noted that France and Belgium showed a positive contribution to structural efficiency, although they were not classified as efficient countries. Cooperation with these countries would, therefore, allow other countries to use their agricultural resources more productively and sustainably.
10. The results show that the old and new EU member states are among the countries that received the best ratings. However, among the seven countries that proved fully efficient under the conventional DEA model, four countries joined the EU only in 2004. Thus, even countries with relatively lower levels of economic development (including agricultural productivity) can be ecologically efficient due to less intensive agricultural production and lower energy-related greenhouse gas emissions.
11. The sustainable productivity model was further extended based on DEA for estimating undesirable outputs (GHG emissions) in monetary terms based on shadow prices of GHG emission reduction. The aggregate, radial (output) and unit Directional Distance Functions are applied. The radial DDF varies across the observations and preserves the observed output mix (i.e., agricultural output and energy-related GHG emission), whereas uniform directions are imposed otherwise.
12. The empirical results showed that the shadow prices of energy-related GHG emissions depended on the chosen DEA optimisation direction. Indeed, the output distance function of the proportional (radial) direction showed the lowest level of shadow prices, as it most closely matches the data structure.
13. The lowest average shadow price observed in Poland and Spain indicates that these countries must focus on reducing energy-related GHG emissions in agriculture. Conversely, the highest shadow prices were found in Romania and Slovakia, indicating that these countries do not require much effort to reduce energy-related GHG emissions in the short term as the cheapest potential of GHG emission reduction is already utilised in these countries.

14. Decision-makers formulating support policies for agriculture in the European Union, such as the Common Agricultural Policy, could consider the shadow prices of GHGs when determining support measures (especially the second pillar of the CAP). Also, shadow price analysis can be used for agricultural support programmes providing rural development measures in different regions. Marginal abatement cost curves are also useful for justifying the desired level of energy-related GHG emission reductions in selected countries
15. The results of the empirical application of the developed advanced sustainable productivity assessment model showed that the analytical tools and methods used for analysis need to be considered when planning energy and climate change mitigation policies to adequately address country-specific challenges.

General Conclusions

1. The agricultural sector is related to the socioeconomic and environmental systems. This implies that taking into account multiple dimensions of agricultural performance is required for the evidence-based analysis. The systemic analysis of literature on sustainability assessment in agriculture revealed that the analysis of sustainability and agricultural productivity growth can be implemented within the environmental production technology framework. Here, the undesirable outputs effectively represent the environmental effects of agricultural activities, and productivity and production factors represent the economic and social dimensions of agricultural sustainability.
2. The PRISMA protocol was used for a systematic literature review on sustainable development and agricultural productivity growth. The literature selected based on the PRISMA statement dealt with agricultural pollution, sustainable agriculture, and environmental performance. The DEA models can be adapted in an effective manner to assess agricultural efficiency when the undesirable outputs are controlled for. However, the performed analysis revealed that the conventional DEA models exhibit such limitations as dimensionality when assessing agricultural efficiency and productivity growth. This becomes incredibly cumbersome in the presence of undesirable outputs. An empirical application to the EU agriculture showed that, e.g., the super efficiency DEA was not feasible under the constant returns to scale assumption for some cases.

Therefore, new models are needed to evaluate efficiency and productivity growth with undesirable outputs.

3. DEA is a non-parametric frontier method that can be utilized to determine eco-efficiency using the environmental production technology. These measures can then be used for the analysis of the green productivity growth. However, the conventional DEA models may not be operational when undesirable outputs are involved in the efficiency and productivity growth assessments. To overcome these limitations, novel techniques were adapted to for assessment of the efficiency and productivity growth in the EU agriculture. The proposed new sustainable productivity assessment model involves such extensions as the global production technology and slacks-based measures. This makes it possible to decompose the Luenberger productivity indicator into the contribution of all production factors and outputs, including GHG emissions, when explaining the efficiency change and technological change.
4. The use of the frontier models involving the undesirable outputs allow for the shadow pricing of such outputs. However, the results may depend on the orientation of the model with respect to the input and output variables. The DEA models based on the environmental production technology were tested with different directional vectors when obtaining the monetary values associated with the undesirable outputs (GHG emission due to energy consumption in the EU agriculture). The results relevant to the different directions implied different shadow prices of the GHG emission. This research is useful for policy analysis as it showed the marginal costs of GHG emission reduction in agriculture and the possibilities for abatement of the GHG emission. The shadow prices of GHG emission reduction obtained by this model allowed to identify the best-performing countries and those which require further improvements in the energy mix by fast penetration of renewable energy sources and energy efficiency improvements to achieve sustainable development of the agricultural sector.

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RESEARCH ARTICLE

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Agricultural sustainability assessment framework integrating sustainable development goals and interlinked priorities of environmental, climate and agriculture policies

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Abstract

The agricultural sustainability issues are widely addressed in scientific literature and various reports by international organizations. However, there is lack of harmonized approach in addressing agricultural sustainability issues as different policies are targeting different sustainability issues in agriculture. This article analyses sustainable agriculture development and agriculture sustainability concepts and sustainability assessment approaches and tools developed for agriculture sector. Based on systematic critical literature review, this article develops the new indicators framework for sustainability assessment in agriculture which allows us to achieve harmonization of sustainable development, climate and agricultural policies in European Union (EU). The proposed indicators framework allows us to address the main sustainability issues of agriculture by linking them with sustainable development goals, environmental, climate and rural development policy priorities in EU. The main contribution of this article is linking rural policy goals with sustainable development, climate change mitigation and environmental policy goals by providing agricultural sustainability assessment framework allowing us to track these linkages through indicators system.

KEYWORDS

climate change, framework, indicators, rural development, sustainable development goals, sustainable agriculture

1 | INTRODUCTION

Agriculture is closely linked to the environment. The main challenge for the agricultural sector is to feed the growing world population while mitigating environmental impacts and conserving natural resources for the future (Vasylieva, 2019). As this sector can have a foremost effect on the environment the achievement of sustainable agriculture development is crucial for present and upcoming generations. Agriculture can have negative impacts and positive impacts on environment. The negative impacts are linked air, water and land pollution, degradation of soil and danger for various species. The positive effects of agriculture on the environment can be of following: sequestration of greenhouse gases (GHG) in soil and crops; mitigation of flood risks by adopting certain farming practices. The concept of sustainable agriculture makes it possible to define the main environmental effects of agriculture and the major environmental challenges facing its development (Pretty, 2005a; Pretty, 2005b).

During United Nations (UN) Summit on Sustainable Development, Agenda 2020 and 17 sustainable development goals (SDGs) were adopted and world countries committed to work together on achieving sustainable development path together (Zheng et al., 2019). The European Union (EU) has also adopted 17 UN DSGs for 2030 and has made firm commitments to mitigate climate change. There are several SDGs linked to agriculture, however, the most important for this sector has two goals. SDG goal 15 aiming the protection, restoration and advancement of sustainable usage of terrestrial ecosystems and forests, halting land degradation including desertification and losses of biodiversity as well as goal 13 demands an urgent action to deal with climate change and its negative outcomes.

The measurement of sustainability and the associated metrics have been discussed in the literature ((Chen, Gao, Li, & Song, 2020; Liu, Rong, & Teng, 2019; Mirghaderi, 2020; Savitz & Gavriletea, 2019; Zhu, Sun, He, & Zhao, 2019). There are plenty of studies dealing with sustainable agriculture and agricultural sustainability (Buttel, 2003; Constance, 2010; Food and Agriculture Organization of the United Nations, 2010; Johnson, 2006; Ogaji, 2005; Pretty, 2005a; Rivera-Ferre, Ortega-Cerdà, & Baumgärtner, 2013; Scherr & McNeely, 2008; Swift, Izac, & van Noordwijk, 2004; Tilman, Cassman, Matson, Naylor, & Polasky, 2002; Trewevas, 2002; Uphoff, 2002; Velten, Leventon, Jager, & Newig, 2015) however, there is a gap in scientific literature in addressing all interlinked issues of sustainable development and agricultural sustainability and developing solid framework for sustainability assessment of agriculture in holistic, harmonized way by addressing clear linkages with SDGs and other challenges of sustainable development.

This study aims to analyse the main challenges of sustainable agriculture development or/and agricultural sustainability by linking it with SDGs and to develop sustainability assessment framework for agriculture sector based on country policy priorities. In order to address this goal, the following tasks are set:

- To analyse the literature dealing with sustainable agriculture concepts, sustainability assessment tools and frameworks and approaches.
- To analyse the main SDGs and their interlinkages with agriculture policy aims and priorities.
- To propose sustainability assessment framework for agriculture to address sustainable development, environmental, climate and agriculture policies in harmonized way for EU Member States.

The rest of the article is structured in the following way: Section 2 deals with literature review on sustainable agriculture and sustainability assessment tools and frameworks in agriculture, Section 3 presents the interlinkages between SDGs and agriculture addressed in agriculture policies; Section 4 develops sustainability assessment framework for agriculture; Section 5 provides conclusions and policy implications.

2 | LITERATURE REVIEW

2.1 | Sustainable agriculture and sustainability of agriculture

The agricultural sector is a key sector in terms of achieving SDGs (Conway, 1997; Cox, Picone, & Jackson, 2004). The numerous policy documents in this field stress the importance of nourishing, safe and healthful food for increasing number of world people, while providing more and more farm animals with fibre, fuel and other biological products for industrial use (Clements & Shrestha, 2004; Gliessman, 2005; Latruffe et al., 2016). This important sector must also use more sustainable natural resources to protect land and save biodiversity resources, to preserve clear air and water and to mitigate climate change and adapt to it (McNeely & Scherr, 2003; Pretty, 2005a). Therefore, in order to deal with these tasks and react on opportunities, the agriculture will need to adopt innovative methods in land cultivation, farming, production, supply chain management, etc. and to increase productivity in sustainable mode (Ogaji, 2005; Velten et al., 2015).

The term sustainable agriculture was developed based on Brundtland Report published in 1987 in and is based on the broader paradigm of sustainable development. More than 70 meanings of sustainable agriculture can be found in the literature. They reflect different priorities, diverse goals and specific valuers for specific stakeholders (Pretty, 1995).

Therefore, there are many descriptions of sustainable agriculture due to an extensive disparity in terms of how sustainability in agriculture or agricultural sustainability is outlined and how it is followed in the decision-making process. In scientific literature sustainable agriculture is often linked to 'alternative' agriculture concept, such as ecological, low-input, environmentally sensitive, biodynamic, community, extensive, fresh farm, free breeding, low inputs, organic, regenerative, permaculture, prudent use, etc. (Clements & Shrestha, 2004; Dunlap, Beus, Howell, & Waud, 1993; Gliessman, 2005; Kesavan & Swaminathan, 2008; National Research Council, 2000). There is still an ongoing and deep debate among scholars (Altieri, 1995; Balfour, 1943; Buttel, 1997; Gliessman, 2005; Meredith, 2019; Pretty, 2005a; Reganold, Papendick, & Parr, 1990) whether agriculture sector using specific definitions can be considered as sustainable one. In this atricle agricultural sustainability and sustainability of agriculture are used as synonyms.

The main normative dimensions of sustainable agriculture are social, economic and environmental however, spatial and temporal dimensions of agricultural sustainability are also important (Tomich et al., 2004). Spatial dimensions range from national to local level, and temporal dimensions cover long-term, mid-term and short-term time periods. The main concepts of sustainable agriculture follows the following main principles: sustainability as ideology, sustainability as a set of strategies, sustainability as the capability to continuous outlast and sustainability as the capability to achieve specific goals or defined targets (Hayati, 2017).

Agricultural systems are generally multifunctional and co-produce various goods including food for farmers and markets, but it also provides many public goods like preserve nature, clean air and water, flood protection, groundwater replenishment, carbon sequestration and delivers the landscaping services including leisure and tourism. Therefore, sustainability in agriculture can be considered as case-specific representing first of all an equilibrium between different agricultural and public goods (Dobbs & Pretty, 2004; MEA, 2005; Organisation for Economic Co-operation and Development, 2001).

As sustainable agriculture is oriented toward the usage of mostly natural goods, the innovative technologies and advanced practices need to be developed and locally adapted. This requires also new forms social capital, consisting of belief in relationships expressed in new organizations, new partnerships and networking among institutional and human capital, incorporating leadership, resourcefulness, managerial and innovating capabilities (Chambers, Pacey, & Thrupp, 1989; Olsson & Folke, 2001). Agriculture sector distinguished with high social and human capital is more capable of innovating and achieving SDGs in current time full of uncertainties and risks (Bunch & Lopez, 1999; Pretty & Ward, 2001; Uphoff, 2002).

Because agriculture often has a substantial effect on environment, first of all sustainable agricultural practices need to be designed to protect the environment. Thus, in a broad sense, sustainable agriculture aims to satisfy needs for food and fibre needs, to ensure profitable farm incomes by promoting environmental management and increasing life quality in rural areas. Therefore, though agricultural sustainability can be defined by various definitions but it finally aims to natural resources and rural communities by promoting lucrative, organic and community-friendly farming practices and methods (Dunlap et al., 1993).

Based on extensive literature review (Altieri, 1995; Conway, 1997; Dale, Kline, Kaffka, & Langeveld, 2013; Gliessman, 2004; Gliessman, 2005; Hinchcliffe, Thompson, Pretty, Guijt, & Shah, 1999; Kesavan & Swaminathan, 2008; Li, 2001; McNeely & Scherr, 2003; National Research Council, 2000; Pretty, 1995; Pretty, 1997; Pretty, 1998; Pretty, 2005a; Pretty, 2005b; Reganold et al., 1990; Robinson, 2009; Scherr & McNeely, 2008; Swift et al., 2004; Tilman, 1999; Tilman et al., 2002; Tomich et al., 2004; Velten et al., 2015) the following basic principles of sustainable agriculture can be highlighted:

1. Integration of biological and environmental processes into food supply chains.
2. Minimization of usage of non-renewable resources.
3. Effective usage of farmers' capacities and skills and their collective abilities to work together to resolve sustainable development challenges for agriculture.

Thus, sustainable agriculture is being defined as economically viable and profitable; socially encouraging as life quality of farmers is important and ecologically sound to preserve natural environment and its resources sustaining the society (FAO, 2013). Based on (Food and Agriculture Organization of the United Nations, 2014) definition, the 'sustainable development in agriculture, forestry, fishing, etc., conserves land, water, plant and animal genetic resources, is environmentally non-degrading, technically appropriate, economically viable and socially acceptable'.

Recently, the eco-efficiency and green productivity concept in assessing agriculture sustainability became prominent. The current successful agricultural sustainability initiatives have been developed addressing changes in the following production factors: switching from fertilizer to nitrogen-fixing legumes or replacing pesticides by natural products, etc. (Buttel, 2003; Conway & Pretty, 1991). Very important point in promoting sustainable agriculture systems is better utilization of natural resources like biodiversity, water and land and implementation of new resource savings technologies.

The most critical issues are linked to intensification of agriculture through the usage of all forms of capital (natural, social, human, financial, etc.) joined with the use of the advanced technologies leading to the cost's reduction and resource savings. At the same time, the usage of the best genotypes and top environmental management practices has to be applied to environmental damage and avoid 'unsustainable intensification' of agriculture (FAO, 2010). Though the sustainable agriculture concepts include diverse issues varying at the regional and country context (Balaceanu, 2013), some agreement and commonalities can be defined. Firstly, most of the sustainable agriculture definitions, include three pillars of sustainability—economic, social and environmental; Secondly, all sustainability dimensions and issues are closely interlined and reinforcing each other; Thirdly, the environmental and safety issues are the key in this concept.

2.2 | Sustainability assessment approaches and tools in agriculture

There is plenty of sustainability assessment tools and various frameworks advanced to back up policy-making in achieving agricultural sustainability (Kasem & Thapa, 2012; Marchand et al., 2014; Talukder, Hipel, & van Loon, 2018; Zahm, Viaux, Vilain, Girardin, & Mouchet, 2008; Zrobek, Kovalyshyn, Renigier-Biłozor, Kovalyshyn, & Kovalyshyn, 2020). However, there is the lack of holistic indicators system that allows assessment of agricultural sustainability in different countries. In addition, these frameworks do not offer a robust basis for comparative agricultural sustainability assessment of countries. The policymakers in agriculture requires timely, precise and transparent information and supporting data on many issues linked to agriculture sustainability: production of crops and livestock, implementation of advanced technologies, degradation of land, amount of various kinds of pesticides and fertilizers consumption, a water use and efficiency, labour use, food prices, etc. (United Nations Sustainable Development Solutions Network, 2014).

Even though a great number of indicators for sustainability assessment in agriculture were established, they usually do not take into account all dimensions and indicators on all levels and do not cover all issues of SDGs relevant to agriculture addressed in scientific debate on sustainable agriculture. Because of differences in socioeconomic, geographical and climate conditions among countries, indicators of agricultural sustainability applied in one state are usually not acceptable for other states (Rasul & Thapa, 2004). In conclusion, most indicators of sustainable agriculture development are site specific and constructed in accordance to contemporary socioeconomic situation of the country (Barbier, Markandya, & Pearce, 1990).

Much effort was put to develop relevant indicators of sustainable agriculture on various levels and of different aggregation. The early initiative by (Organisation for Economic Co-operation and Development, 1999) proposed 39 indicators linked to the following sustainable agriculture issues: financial resources of the farms, the usage of water, soil, fertilizers and pesticides, the quality of soil, water and land conservation, GHG emissions, landscape and wildlife biodiversity indicators. These indicators can be employed for assessment of agricultural sustainability at country level. However, these indicators are not appropriate at farm level for assessment of agricultural sustainability (Webster, 1999).

Sands and Podmore (2000) proposed that the index of environmental sustainability for assessing agricultural sustainability in US. This index comprises of 15 sustainability sub-indices covering issues, such as soil depth and organic carbon, the density and of ground water and the depth of ground water. (Gowda & Jayaramaiah, 1998) developed nine indicators for measuring just sustainability of rice production in India. Bouma and Droogers (1998), Rigby, Woodhouse, Young, and Burton (2001), Buchs (2003) and Reytar, Hanson, and Henninger (2014) identified that a set of indicators to assess the ecological, economic and social sustainability issues of agriculture.

EU developed the Indicators for the Economic and Social Dimensions of Sustainable Agriculture framework proposed the following areas of agricultural sustainability: Stock maintenance or protection and renewal for supporting the well-being; Avoiding inefficiency and promoting efficiency in transformation processes; and Intra- and intergenerational equity. Therefore, these three main areas represented as the main objectives of agricultural sustainability for EU Member States and these are still available in recent policy documents on sustainable rural development.

Nevertheless, agricultural sustainability concept can be further expanded. Sustainable agriculture demands for enhanced environment but also continued existence of farms in rural areas by preserving productive functions of European agricultural sector (European Commission, 2000). Thus, in order to guarantee sustainable development, the maintenance of a natural, human and human produced capital in agriculture sector is necessary and to achieve equity and efficiency of production in this sector.

Within this aim it is necessary to define general concerns about conservation of natural resources and to rise society interests in strengthening the social role of agriculture sector for empowering of farm communities and ensuring their preservation (European Commission, 2001, 2002). In 2006 the IRENA operation (Indicator Reporting on the Integration of Environmental Concerns into Agriculture Policy) was initiated by European Environmental Agency (EEA) aiming at elaboration of agri-environmental indicators for observing EU agriculture policies and assessing impact of agriculture systems on environment (European Environment Agency, 2006).

There were also several attempts to develop sustainability indices or aggregated indicators of agricultural sustainability. Specific sustainability indicators are developed on raw data and it is possible to aggregate them. The development of composite agricultural sustainability indicator is built on the integration of specific individual indicators covering different pillars of sustainability (Binder, Feola, & Steinberger, 2010). Aggregation is being performed by integrating several indicators into a single value, represented by applying normalization technique: various multi-criteria decision aiding models ranging from simple weighted summation to complicated fuzzy-techniques (Bausch, Bojorquez-Tapia, & Eakin, 2014). During normalization the weights of indicators comprising integrated indices need to be defined by experts' surveys (Chand, Sirohi, & Sirohi, 2015). There are other combination methods like converting all indicators into the common monetary or physical unit as ecological footprint. Cost–benefit analyses can be applied as aggregation techniques however, they should address the important challenges how to asses in monetary terms non-market goods, such as quality of the air and water or biodiversity changes, etc.

Agricultural sustainability assessment at the farm level covers many tools and frameworks. Different environmental objectives of sustainable agriculture development were assed in these diverse studies. There have been indicators developed for farms, like Environmental Impact Assessment method developed by (Girardin, Bockstaller, & van der Werf, 2000) aiming at evaluation of the influence of agroecosystem practices on environment. Life cycle analysis method for crops, livestock and forestry developed by (Rossier, 1999) and new methodical way of prototyping integrated method for assessment of agricultural sustainability for particular groups of stakeholders (farmers, policy makers) was developed by (Vereijken, 1997). Agroecological system attributes and the statistical simulation modelling methods were applied to cover three groups of environmental objectives. Two environmental objective groups were addressed by and scenario-based approach and response inducing sustainability evaluation approach. The following approaches were developed to address various environmental targets groups: Environmental Sustainability Index, Farmer Sustainability Index, Sustainability Assessment of the Farming and the Environment Sustainable Agricultural Practice and Multi-scale Methodological Framework. (Sabiha, Salim, Rahman, & Rola-Rubzen, 2016; Warhurst, 2002).

3 | SUSTAINABLE DEVELOPMENT GOALS IN AGRICULTURE AND POLICIES

3.1 | Agriculture and sustainable development goals

The 2030 Agenda for Sustainable Development set indicators for assessing sustainability based on its all pillars and including agriculture as well. There are several SDGs linked to agriculture. They are as follows:

1. SDG2 aiming to end hunger, achieve food security and improved nutrition and to promote sustainable agriculture.
2. SDG3 targeting healthy lives and promote well-being for all at all ages.
3. SDG6 seeking availability and sustainable management of water and sanitation for all.
4. SDG12 safeguarding sustainable consumption and production patterns.
5. SDG13 calling for urgent action to combat climate.
6. SDG 15 calling to protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat

desertification, halt and reverse land degradation and halt biodiversity loss.

The SDG2 and SDG13 are the key goals to tackle the current main tasks of sustainable development in agriculture. However, the key SDG indicator for agriculture is SDG 2.4.1 'Percentage of agricultural area under productive and sustainable agriculture' and this indicator was developed based on the long debate by experts for selection of indicators system to address Agenda 2030 targets which are 169. The main problem is, that SDG target 2.4. is one of the most complex: 'By 2030, ensure sustainable food production systems and implement resilient agricultural practices that increase productivity and production, that help maintain ecosystems, that strengthen capacity for adaptation to climate change, extreme weather, drought, flooding and other disasters and that progressively improve land and soil quality'. Based on the pilot tests results, the SDG indicator 2.4.1 was developed comprising from 11 sub-indicators addressed in (Gennari & Navaro, 2019). Those sub-indicators provide the minimal requirements for sustainable food production system necessary to address based on their scientific studies (Abson, Fraser, & Benton, 2013; Pretty, 1995).

The task of minimization of the usage of off-farm, external and non-renewable inputs is addressed by fertilizers and pesticides management sub-indicators of composite indicator (Gennari & Navaro, 2019). The task of integration of natural processes (crop rotation, nutrient cycling and pest/predator relationships) in manufacture processes in agriculture is addressed by sub-indicator on using the biodiversity-supportive practices. The requirement for maximum self-reliance among farmers is addressed by positive sub-indicator of net farm income. The reduction of vulnerability among farmers can be measured by the existence of important risk mitigation instruments which are addressed by associated sub-indicator. The following sub-indicators as farm output value per hectare, conservation of soil, water and biological resources provide for addressing target of long-term sustainability of agricultural production. The target of equitable access to the key productive resource of farmers is addressed by sub-indicator on secure tenure rights over land. The minimum wage rate and a decreasing size of food insecurity address progress toward social justice in agriculture sector. However, such important sustainability issues, such as climate change mitigation are not directly addressed by the main SDG indicator for agriculture. In addition, it is necessary to stress that world countries have selected different indicators to monitor progress toward goal 2 targets based on their priorities of agricultural and environmental policies as well as statistical data availability. For example, EUROSTAT provides comprehensive data on all SDGs for EU Member States to ensure monitoring progress toward sustainable development. The main indicators for SDGs in EU are provided in Table 1.

Attaining healthy diets and safeguarding agricultural systems productivity and sustainability are the main tasks linked to SDG 2 in the EU. In EU the central nutritional issue is obesity not hunger. This obesity is supposed to impact negatively health and well-being and to cause negative influence on health protection systems and economic

TABLE 1 European Union indicators framework to monitor SDG 2

S. No.	Indicator Name	Data Provider
1	Obesity rate	Eurostat
2	Agricultural factor income per work unit (AWU)	Directorate-General for Agriculture and Rural Development
3	Government support to agricultural R&D	Eurostat
4	Area under organic farming	Eurostat
5	Gross nutrient balance on agricultural land	Eurostat
6	Ammonia emissions from agriculture	European Environment Agency
7	Nitrate in groundwater	European Environment Agency
8	Soil erosion by water	Joint Research Centre of European Commission (EC)
9	Common bird index	European Bird Census Council

Source: Adapted from (European Commission, 2019b).

and social development of the EU Member States (MS). In addition, based on EU policy priorities sustainable agricultural systems are necessary to ensure long-term food supply taking into account climate change and a rising population challenges around the world. Though, agricultural productivity has been increasing in EU, the negative environmental influence of farming provides many risks for agricultural production in (European Commission, 2019b). Therefore, taking into account socio-economic situation of EU different indicators for monitoring SDG2 were developed for EU MS. However, one can notice from indicators presented in (Gennari & Navaro, 2019) and Table 2 that in order to address the most important SDGs challenges additional sustainability indicators are necessary in global context and in EU as well. Climate change indictors relevant to agriculture and addressing SDGs 13 are missing in both indicators' frameworks. However, in order to develop agricultural sustainability indicators framework covering climate change risks, the EU environmental and climate policy priorities in agriculture should be discussed.

The next subsection allows to analyse EU agriculture policy goals and to address these goals by specific agricultural sustainability indicators.

3.2 | Agriculture policy priorities in the European Union

For more than 50 years, the Common Agricultural Policy (CAP) makes the background of EU agricultural and rural policy. CAP was proposed in 1960 by the EC with the aim to create a balanced system that would maintain sufficient supply of agriculture products, ensure the increase of productivity and a fair deal for consumers and producers.

TABLE 2 Agricultural sustainability indicators including imate change policy targets

Code	Indicator	Units of Measurement	Linkages with CAP
Economic Indicators			
EC1	Agricultural factor income	Agricultural factor income per [AWU]	+
EC2	Use of energy in agriculture	Final energy use in agriculture [toe]	+
EC3	Final energy intensity of agriculture	Final energy use per value added of agriculture [toe/EUR]	
Environmental Indicators			
EN1	Total GHG emissions from agriculture	GHG emissions in agriculture [Mt CO_2eq]	+
EN2	Total GHG emissions linked to fuel combustion agriculture	GHG emissions linked to fuel combustion in agriculture [Mt CO_2eq]	+
EN3	Carbon intensity of final energy consumption in agriculture	[kg CO_2eq/toe]	
EN4	Share of renewable energy sources in final energy use in agriculture	[%]	
EN5	GHG emissions from agriculture not linked to energy	[Mt CO_2eq]	+
EN6	Carbon intensity of agriculture production	Total GHG emission form agriculture per Value added of Agriculture [ton CO_2eq/USD] 2010	+
EN7	Area under organic farming, %	Area under organic farming [%] of UAA	+
EN 8 & EN9	Gross nutrient balance of agricultural land	Gross nutrient balance (surplus or deficit) on agricultural land by nutrient, kg nitrogen and phosphorous in agricultural soils.	+
EN10	Soil erosion	Soil erosion by water or area [%]	
EN11	Ammonia emissions from agriculture	Ammonia emissions from agriculture, kg per hectare	
EN12	Livestock density	The number of livestock units (LSU) per hectare of utilized.	+
Social Indicators			
SO1	Government support to agricultural research and development	Government support to agricultural R&D and EUR per capita	+

Abbreviations: CAP - Common Agricultural Policy. GHG - greenhouse gases.
Source: Adapted from (International Atomic Energy Agency, 2005) and (Zheng et al., 2019).

The CAP priorities have changed throughout time and environmental, safety, health and climate change issues have evolved (European Commission, 2019a). As a result, the CAP shifted from a market-oriented to production-oriented subsidized system by integrating food safety, environmental and other standards (Balaceanu, 2013). The new CAP reform initiated in 2019 is linked with better addressing climate issues (EURACTIV, 2019).

The foreseen reform of the CAP since 2020 first of all takes into account the financial resources made available. However, the reform is even more ambitious: revising direct support schemes, balancing subsidies and aid for rural development, incorporating ecological issues, or improving the competitiveness of European agriculture. In this context, the positions of the various players involved in this process must be assessed in order to get an improved balance of power at European level.

Summarizing, the CAP is an EU policy providing the financial support to farmers. This is one of first policies of the European Market, which combines national intervention programs into a single structure to ensure that farmers can compete on a level playing field whereas being protected from agricultural and income fluctuations to secure food supply.

Article 39 of the Treaty on EU defines key CAP objectives:

- To achieve growth of supply in agricultural products.
- To increase productivity of agriculture sector by encouraging technical progress and the effectiveness of production factors utilization, putting emphasis on labour.
- To guarantee market stabilization by buying surplus production at guaranteed prices and stock building.
- To ensure reasonable prices for consumers.
- To increase farmers' incomes.

During its existence the CAP offered funding to farmers by supporting the prices of agricultural products. Following the major reform of the CAP in 2005, two main axes of CAP payments are available: pillar 1 or the direct income support and pillar 2 or encouragement for rural development. It is necessary to highlight that direct income support provides large funds than rural development support.

The payments in Pillar 1 or direct payments to farmers aims to remove the motivation for overproduction. These payments based on the land owned by the farmer and are allocated directly from EU funds to national governments which administrate them. Farmers must meet certain requirements and standards of environmental management, animal welfare and traceability in order to receive the payment, these settings are called as 'cross compliance'. EU Member States may also, under certain conditions, use some market support measures.

Support provided by Pillar 2 necessitates co-financing by the governments of the EU Member States. The objectives of this activity are described as follows:

- Promotion of agricultural competitiveness.
- Ensure that natural resources are managed in sustainable way.
- Mitigating climate change.
- Attaining sustainable rural communities' territorial development, covering creation and maintenance of jobs.

Factors, such as improving the welfare of Europe's rural countryside, ensuring food safety, protecting the environment for future generations, especially climate change mitigation and safeguarding better health and animal welfare conditions are very important in shaping future CAP.

EU climate policy priorities for 2030 are the following (European Commission, 2014): to reduce GHG emissions at least 40% from 1990 levels; to rise share of renewable energy sources in final energy consumption, at least to 32% and to improve energy efficiency at least 32.5% from 2005 levels. All these three main issues should be addressed in developing agricultural sustainability indicators framework. The Green Deal package adopted in 2019 (European Commission, 2019c) also envisages the sustainability of agriculture. The managerial issues (food chains) and resource use are mentioned as the objectives.

4 | SUSTAINABILITY ASSESSMENT FRAMEWORK IN AGRICULTURE

Based on literature review it can be stated that the (Food and Agriculture Organization of the United Nations, 2014, 2003, 2019) definition of sustainable agriculture is the most comprehensive and most appropriate for categorizing the most important indicators of agricultural sustainability: 'Sustainable development in agriculture, forestry and fishing, etc. conserves land, water, plant and animal genetic resources, is environmentally non-degrading, technically appropriate, economically viable and socially acceptable'. The main SDGs linked to agriculture are SDG2 and SDG 13. Therefore, the agricultural sustainability indicators framework developed for EU should address these main SDGs and to provide linkages between them.

In turn, to select suitable indicators of agricultural sustainability and to achieve harmonization of climate change and agriculture policies indicators framework for linking sustainable agriculture indicators with climate change issues indicator framework has been developed and presented in Table 2 and Figure 1. The policy actions are selected to address targeted indicators. These policy actions range from climate to agriculture and sustainable development policies.

As one can notice from Table 2 agricultural sustainability indicators linked to climate change were included in the framework-based GHG emission reduction commitments for agriculture sector: They are GHG emission reduction; increase of the share of renewable energy sources in energy use in agriculture; reduction of energy intensity of agriculture.

EC1 indicator can be treated as a partial labour productivity measure of the agricultural sector (European Commission, 2019b). EC2 indicators represents final energy consumption in agriculture and is an indication of mechanization and industrialization of agriculture sector in the country and EC3 indicators represents energy intensity of agriculture. It is evaluated by dividing final energy consumption in agriculture by value added created in agriculture.

EN1 indicators represents total GHG emissions from agriculture. The CO_2 equivalent emissions of all GHG emission from agriculture is a key indicator of climate change in agriculture. It includes GHG emissions from agriculture and GHG form energy consumption in agriculture. EN2 indicator represents total GHG emissions from fuel combustion in agriculture. EN3 indicator shows carbon intensity of final energy consumption in agriculture and is expressed by CO_{2eq}/toe. The high values of carbonization index are linked to high share of fossil fuels and low share of renewables in fuel mix. EN4 indicator represents GHG emissions from agriculture not linked to energy consumption. It is important indicator showing of agriculture input to total GHG emissions in the country. EN5 characterizes the share of renewable energy sources in total final energy use in agriculture. EN6 represents carbon intensity of agriculture expressed by CO_{2eq}/agriculture production. The carbon intensity of agriculture represents the ratio between total GHG emissions from agriculture and is indicator of energy efficiency of agriculture production as well as carbon content of energy use in agriculture. EN7 measures the share of total utilized agricultural area (UAA) employed by organic farming implied by European Council Regulation No 834/2007. EN 8 and EN 9 indicators present the nutrient balance of soil shows the potential surplus or deficit of nitrogen and phosphorous in soil used for agriculture purposes (European Commission, 2019b). EN 10 indicator estimates the losses of soil due to water erosion in percent. EN 11 assesses the ammonia (NH_3) emissions due to agricultural production processes. EN 12 indicates the livestock density index or the number of livestock units (LSU) per hectare of utilized land. SO1 (social indicator) shows the extent of public funding for R&D in agriculture.

Figure 1 illustrates the framework for assessing the linkages among sustainable agriculture indicators linked to climate change mitigation and environmental policies and the CAP. The corresponding policy measures are posited in this context alongside the relevant indicators. The notations of indicators used in Figure 1 refer to those applied in Table 2. Agricultural sustainability indicators are also grouped according to the main policy areas related to energy efficiency and climate change (including better soil management, biomass production, reduction in agricultural

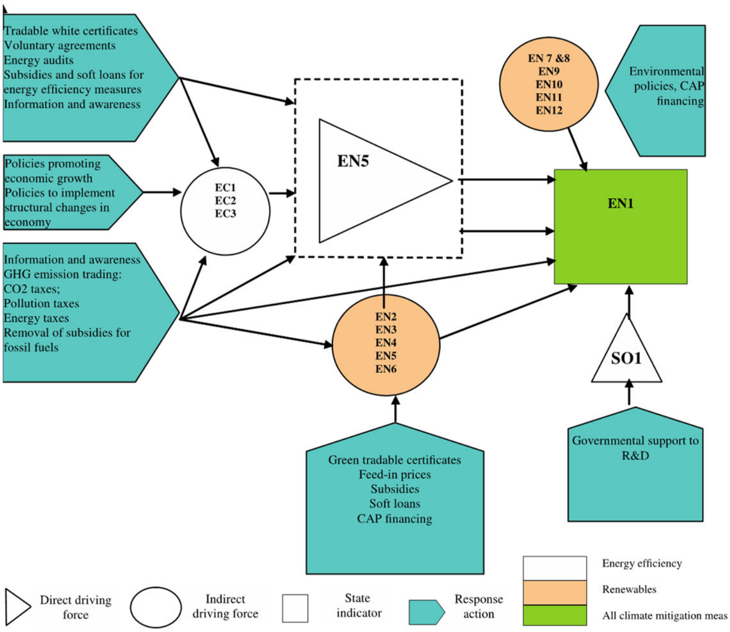

FIGURE 1 Linkages between agricultural sustainability indicators and related policies targeting these indicators. *Source:* Adapted from (Zheng et al., 2019) [Colour figure can be viewed at wileyonlinelibrary.com]

production losses and waste, reduction in afforestation). The geometrical figures in Figure 1 (triangle, ellipse and rectangle) indicate the type of the variables used in the framework.

All agricultural sustainability indicators integrated in this framework are linked to each other via the chain of reinforcing impacts. This allows linking policy priorities in climate change mitigation with agricultural policies and SDGs. The final indicator in agricultural sustainability framework is total GHG emissions form agriculture as in the end all policy actions (aiming at energy efficiency improvements, promotion of renewable energy sources and other climate) influence reduction of GHGs from agriculture sector. All these agricultural sustainability indicators can be collected from EUROSTAT database for all EU MS. Available indicators cover at least 2008–2016 period. These indicators can be used to develop agricultural sustainability index to compare progress achieved by all EU MS in agricultural sustainability progression and approaching SDGs for agriculture by also taking into account targets of relevant policies in climate change mitigation and rural development.

5 | CONCLUSIONS

The main struggle in assessing agricultural sustainability is dynamic issue of agricultural sustainability and interlinked policy issues between sustainable development, rural development, climate change and environmental policies. The measuring of agricultural sustainability at the farm level can deliver the most precise results, however, policies at national level have direct effect on lower level and strongly influence farming practices. Therefore, the most relevant interlinked indicators for developing harmonized agricultural, environmental and climate policies is necessary based on the priorities of countries in these areas.

There are many agricultural sustainability indicators frameworks and approaches developed so far, however, as agricultural sustainability issues are country specific, the agricultural sustainability indicators were developed for EU based on agricultural, environmental and climate policy priorities and SDGs lined to agriculture.

The main SDGs linked to agriculture are SDG2 and SDG 13, so developed agricultural sustainability indicators framework for EU addresses these main SDGs and provides linkages between them and other policy areas. The selected relevant indicators are combined in the framework which allows us to achieve harmonization of climate change and agriculture policies by selecting relevant policy actions for targeted indicators.

The current study has limitations as developed agricultural sustainability assessment framework was not empirically applied and case study was not developed.

However, all selected indicators in developed agricultural sustainability indicators framework can be easily collected from EUROSTAT database for all EU MS. The various multi-criteria decision aiding techniques can be applied to create composite index from these indicators for monitoring and comparative assessment of progress achieved by EU MS toward agricultural sustainability.

The future research guidelines are mainly linked to empirical application of developed agricultural sustainability assessment framework. The composite agricultural sustainability indicators and multi-criteria assessment of the EU Member States in meeting the main sustainable development challenges for agriculture need to be applied.

The developed framework allows us to support sustainable resource use practices in agriculture on all levels by developing more broad harmonized national policies and measures targeting sustainable use of agricultural land, protect rural communities and ensure climatic stability.

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Green productivity and undesirable outputs in agriculture: a systematic review of DEA approach and policy recommendations

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ABSTRACT

Measuring efficiency in the presence of undesirable outputs could be difficult depending on how to treat these outputs; thus, undesirable outputs modelling has been an exciting subject of several studies in the Data envelopment analysis (DEA) literature in the last two decades. The present study aims to illustrate a thorough overlook of studies in which DEA has applied for measuring efficiency with undesirable outputs. Fifty-eight articles were published from 2000 to 2020 have been systematically reviewed through PRISMA protocol. The results indicated that "Journal of Cleaner Production" ranked first with six published articles, and Chinese scholars have the most contributions to this field, with twenty-third articles. Also, almost a quarter of the published articles' scope was related to agricultural pollution, and thirteen articles were published in 2016, the highest number of published articles annually. Taken together, the theoretical and empirical implications of research in the field of Green Productivity are discussed, and some policies were recommended.

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- Systematic literature review on green agricultural productivity;
- Fifty-eight studies dating from 2000 to 2020 were scrutinised;
- How to treat undesirable outputs affects productivity measurement;
- Data Envelopment Analysis found as the primary approach applied;
- Four DEA models named CCR, BCC, SBM, and RAM are widely used in the agri-sector.
- Policy recommendations for promoting green agriculture developed.

1. Introduction

The agriculture sector plays a crucial role in debates on green, circular, and bioeconomy mainstreamed global sustainability concepts (Tsangas et al., 2020). It is

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characterised by several feedstocks appropriate to be improved in terms of material and energy; thus, new opportunities are provided by the circular economy for investors (D'Adamo et al., 2019). The circular economy has two primary goals: improving waste management (or reutilizing), reducing energy consumption (or boosting green energy) (Kapsalis et al., 2019). It is believed that by transforming the agri-sector into circular, apart from the technological sector, circular economy goals could be more achievable; since the agri-sector is one of the most sectors in which a high percentage of biomass has been produced (Jimenez-Lopez et al., 2020). On top of that, renewable biological resources (biomass) and circularity are the critical aspects of the bioeconomy (D'Adamo et al., 2020a); thus, materials recycling, fossil fuel use reduction, and waste management lead the bioeconomy to obtain biofuel, bioenergy, etc., which are vital for achieving sustainable development goals (SDGs) (Duque-Acevedo et al., 2020, Morone & D'Amato, 2019). SDGs could provide a framework of measurable goals and targets and goals, linked directly or indirectly with circular economy principles, to harmonise sustainable development and world economies (Loizia et al., 2021, D'Adamo et al., 2020b).

Economic development and industrialisation rely on high resource input, while the capacities of the environment and resources are neglected, which caused undesirable outputs and ecological crises (Wang et al., 2019). Undesirable outputs comprise wastewater, CO_2 emission, air pollution, etc., which are dangerous for the environment (Tohidi et al., 2014). Undesirable outputs are produced unwillingly in the agricultural sector; thus, policy-makers need to utilise scientific approaches to cope with the undesirable outputs' of production and reduce them (Halkos & Petrou, 2019b, Tohidi et al., 2014). Both undesirable and desirable outputs produce jointly; however, undesirable outputs affect efficiency scores' evaluation of decision-making units (DMUs). Over the last decade, for instance, energy consumption and CO_2 emissions have risen considerably in China, emitting almost 8200 million tons of CO_2 in 2012, produced by industries and agricultural sectors (Sun et al., 2016). Also, waste, an environmental issue having strong relationships whit economic and social dimensions, has increased dramatically over the years (Doula et al., 2019, Doula et al., 2021, Papadopoulos et al., 2021). Zorpas (2020) mentioned various reasons for producing waste in which undesirable outputs, such as CO_2 emissions, were ranked as the most influential reason; also, D'Adamo et al. (2021) mentioned that biomethane could be used as fuel which is an excellent potential for EU leading them towards a green economy; therefore, assessing the environmental productivity in the presence of the undesirable outputs is vital (Dakpo et al., 2014).

There are three popular methods for measuring productivity within a broad context, including index measurement, linear programming, and econometric models (Singh et al., 2000). Index measurement comprises the employing of five ratios for measuring productivity: "single-factor productivity," "multiple factor productivity," "total productivity," "managerial control ratio," and "productivity costing." The most prevalent ratio is the total productivity, in which the productivity is measured as a ratio of various inputs. Linear programming, in which Data envelopment analysis (DEA) is the most prevalent, creates a production frontier and assesses the inputs' contribution to the productivity considering the past performance data (Baležentis et al., 2016). DEA models and econometric models are applicable when large data series are available. In econometric models, statistical models are applied to the data series to estimate productivity. The leaner programming and econometrics models are usually integrated to deal with productivity measurement issues (Singh et al., 2000). The DEA models' main advantages over the other methods are: DEA models could maximise multiple outputs simultaneously, while total productivity index could only maximise one output. DEA is a non-parametric mathematical model; thus, a specific functional form is not required making DEA more flexible and applicable compared to others (Liu et al., 2017). DEA could trace less-productive inputs by employing separate and specific optimisation routines for each input, making DEA more robust than the others.

DEA is a mathematical method proposed by Charnes et al. (1978), and it utilises linear programming methods to turn inputs into outputs to evaluate the performance. Also, any DMUs can freely select any mixture of inputs and outputs to increase their relative efficiency (Kang et al., 2018). By dividing the total weighed output by the total weighted input, the efficiency score or relative efficiency is calculated. The relative efficiency is a non-negative value and calculated concerning linear interactions between the inputs and outputs of the DMUs (Mardani et al., 2018, Zare et al., 2019). Simply put, the relative efficiency shows the level of efficiency of a DMU in a determined level of output concerning the quantity of input, which consumes compared to similar DMUs (Zhou et al., 2019). Shen et al. (2017) mentioned that many researchers used DEA to assess agricultural performance, environmental efficiency, and productivity with undesirable outputs. For instance, Fei and Lin (2017b) utilised Meta-Frontier DEA to tackle the agricultural problems related to carbon dioxide emissions. Li et al. (2013) used constant returns-to-scale (CRS) and variable returns-to-scale (VRS)-DEA to allocate resources to reduce CO_2 emission effectively. Yaqubi et al. (2016) used Directional Distance Functions (DDF)-DEA to assess environmental practices' efficiency and shadow values.

There are three basic DEA models, including radial, additive, and slack-based measure (SBM) models. The radial model was proposed by Charnes et al. (1978) is considered the original DEA model, also called the CCR (Charnes, Cooper, and Rhodes) model (Yang & Wei, 2019). In this model, The DMU's efficiency score is measured based on the proportional or radial distance to the efficiency frontier. The radial models are divided into two models: CCR and BCC (Banker, Chames, and Cooper) models. In the BCC model, the production technology shows variable returns to scale (Paradi et al., 2018). Furthermore, the additive model is used if there are multiple inputs and multiple outputs; therefore, the additive model determines all potential of inefficiency through the summation of the total inputs and desirable outputs slacks. The value of variable data could be zeros or negative in the additive model, unlike the radial DEA model (Cooper et al., 2006). Moreover, the SBM model is considered an extension of the additive model developed by Tone (2001). In this model, like the additive model, a mix of multiple inputs and outputs could be considered; however, it could be a unit invariant and generate a standard efficiency score, unlike the additive model.

Measuring productivity is considered a crucial research avenue in economics since it explains how inputs transform into outputs through factors of changes (Baležentis et al., 2021); however, measuring productivity in the presence of undesirable outputs could be difficult depending on how to treat these outputs. The various treatment methods with undesirable outputs in DEA have recently received more attention (Boussemart et al., 2020). Halkos and Petrou (2019b) did attend to present four possible way to cope with undesirable outputs in DEA, including (1) disregarding negative outputs from the production process, (2) regarding negative outputs as inputs, (3) regarding negative outputs as positive outputs, and (4) applying required modifications to take negative outputs into account. They also mentioned a new model named Zero-Sum Gains-DEA (ZSG-DEA) models utilised by Gomes and Lins (2008) to deal with undesirable outputs. Therefore, it is necessary to a clear and comprehensive review of the various treatment methods with undesirable outputs in DEA models be provided due to the effect of the treatment method on productivity; also, capabilities of various DEA models could be highlighted through a comprehensive review motivating scholars to apply them for measuring productivity with undesirable outputs and compare them with the previous research. On top of that, current research gaps in measuring productivity and methodological concerns are highlighted through a systematic literature review providing a clear pathway for future research.

According to the present research results, agricultural pollution is the most attractive topic for scholars, including Falavigna et al. (2013), Kuhn et al. (2018), Yaqubi et al. (2016), Berre et al. (2013), Skevas et al. (2014), Reinhard et al. (2000), Wu et al. (2013), Vlontzos and Pardalos (2017), Buckley and Carney (2013), Coelli et al. (2007), Zare-Haghighi et al. (2014), Dong et al. (2018), Sun et al. (2016), working on productivity measurement with undesirable outputs. In agriculture, water, soil, and Greenhouse Gas (GHG) are three significant pollution sources (Chen et al., 2017). Furthermore, economic activities, such as heat and electricity production, agriculture, and industry, lead nations to achieve socio-economic development (Yu et al., 2020); however, these activities usually produce harmful and toxic material emissions, such as Nitrogen Oxides (NOx), CO_2 emissions, wastewater, Sulfur Dioxide (SO_2), and heavy metals (Wang et al., 2020, Halkos & Petrou, 2019a). Sepehri et al. (2020) also mentioned that Sustainable development goals, economic growth, and human health are affected by agricultural pollution; while, agriculture sectors contribute to the eutrophication phenomenon, greenhouse effect, waterbodies pollution, climate change, stratospheric ozone depletion, global phosphorous, and air pollution (Adegbeye et al., 2020).

State of the art in applying DEA models for measuring agricultural productivity with undesirable outputs through systematic literature review and recommending applicable policies, based on obtained results, to boost green, circular, and bioeconomy could be considered the present study's novelties. Simply put, providing a broad overview of DEA models' application in agriculture productivity with undesirable outputs is the ultimate aim of the present study; therefore, the ultimate aim can be divided into four research issues: (1) which area of agricultural productivity with undesirable outputs has utilised DEA more? (2) which nationality has conducted further research in this area? (3) in which year did scholars publish the most articles? (4) which journals have further published articles in this field? The present study will focus on the significance of DEA in agricultural productivity with undesirable outputs. The main contributions of this article are as follows: (1) improving the understanding of the current scientific knowledge on green productivity and undesirable outputs (2) highlighting why and how DEA models are widely used to measure productivity with undesirable outputs in the agri-sector (3) providing an overview of research limitations and gaps that hinder measuring productivity with undesirable outputs (4) investigating the current status of DEA application for measuring productivity with undesirable outputs concerning the years of publication, authors' nationality, articles' scope, and publication frequency (5) recommending policies and research avenues to provide a pathway for future empirical and theoretical research.

The article's structure is arranged as follows: Section 2 expresses four DEA models being popular in agricultural productivity with undesirable outputs. Section 3 presents the methodology of the present research and how the articles were classified is presented. Section 4 presents the results, including distribution of articles by publication time, author's nationality, and journals. The results were discussed in Section 5. Section 6 presents conclusions, limitations, policies, and future research recommendations.

2. DEA models for dealing with undesirable outputs

In 1978, Charnes et al. presented the first DEA model, namely CCR, to calculate the technical efficiency of DMUs in the form of a non-parametric model, while there are many inputs and outputs (Charnes et al., 1978). Researchers used CCR-DEA, BCC-DEA, SBM-DEA, and Range-Adjusted Measure (RAM)-DEA to calculate agricultural productivity with undesirable outputs. The four mentioned models, which are the most popular agriculture performance model with undesirable outputs, are presented.

2.1. CCR-DEA model

The overall efficiency for a DMU is calculated through the CCR-DEA model if both scale efficiency and pure technical efficiency are combined into a single value. On top of that, the CCR-DEA model never measures absolute efficiency as it is always measured relatively. Also, CCR-DEA is suitable for a situation in which all DMUs are operating at an optimal scale. Assume a manufacturing system with n DMUs, which has three elements, including inputs (X), desirable outputs (G), and undesirable outputs (B). The three matrices X, G, B, and the production possibility set (P) are defined through equation one and λ is the intensity vector (Li et al., 2013).

$$\begin{aligned} & P = \left\{(X, G, B) | x \geq X\lambda, G \leq G\lambda, B \geq B\lambda, \lambda \geq 0\right\}, \\ & X = (X_1, \ldots, X_n) \in R^{m\times n}, \\ & G = (G_1, \ldots, G_n) \in R^{S_1\times n}, \\ & B = (B_1, \ldots, B_n) \in R^{S_2\times n} \\ & \text{S.t.} \\ & \quad x \geq X\lambda \\ & \quad G \leq G\lambda \\ & \quad B \geq B\lambda \\ & X>0, \; G>0, \; B>0 \end{aligned} \tag{1}$$

The output-oriented DEA model coping with undesirable outputs for assessing DMU (x_0, g_0, b_0) is presented below, and σ^* is the inefficiency score of DMUs calculated by equation two (Li et al., 2013). It should be noted that efficiency score can be calculated by $\theta = \frac{1}{1+\sigma}$.

$$
\begin{aligned}
&\sigma^* = max\sigma_0 \\
&\text{S.t.} \\
&x_0 \geq X\lambda \\
&(1+\sigma_0)g_0 \leq G\lambda \\
&(1-\sigma_0)b_0 \geq B\lambda \\
&\lambda \geq 0
\end{aligned}
\tag{2}
$$

2.2. Bcc-DEA model

Variable return to scale frontiers is assumed in the BCC model, while the CCR model assumes a constant return to scale frontiers. Also, overall technical efficiency is measured by the CCR model, while the BCC model measures the pure technical efficiency. Also, as mentioned, the CCR model is not appropriate if DMUs are not operating at an optimal scale; in contrast, the BCC model was developed to deal with situations in which technical efficiencies variables are measured while confounded to scale efficiencies. Assume a manufacturing system with n DMUs is considered, while it has three elements, including inputs (X), desirable outputs (G), and undesirable outputs (B). The three matrices X, G, B, and the production possibility set (P) are defined through equation three and λ is the intensity vector (Li et al., 2013).

$$
\begin{aligned}
&\mathrm{P} = \left\{(\mathrm{X},\mathrm{G},\mathrm{B})|\mathrm{x} \geq \mathrm{X}\lambda, \mathrm{G} \leq \mathrm{G}\lambda, \mathrm{B} \geq \mathrm{B}\lambda, \lambda \geq 0\right\}, \\
&\mathrm{X} = (\mathrm{X}_1, \ldots, \mathrm{X}_n) \in \mathrm{R}^{m \times n}, \\
&\mathrm{G} = (\mathrm{G}_1, \ldots, \mathrm{G}_n) \in \mathrm{R}^{S_1 \times n}, \\
&\mathrm{B} = (\mathrm{B}_1, \ldots, \mathrm{B}_n) \in \mathrm{R}^{S_2 \times n} \\
&\text{S.t.} \\
&\qquad \mathrm{x} \geq \mathrm{X}\lambda \\
&\qquad \mathrm{G} \leq \mathrm{G}\lambda \\
&\qquad \mathrm{B} \geq \mathrm{B}\lambda \\
&X>0,\ G>0,\ B>0
\end{aligned}
\tag{3}
$$

The output-oriented DEA model coping with negatives outputs for assessing DMU (x_0, g_0, b_0) is presented below, and σ^* is the inefficiency score of DMUs calculated by equation four (Li et al., 2013). It should be noted that efficiency score can be calculated by $\theta = \frac{1}{1+\sigma}$.

$$
\begin{aligned}
&\sigma^* = max\sigma_0 \\
&\text{S.t.} \\
&x_0 \geq X\lambda \\
&(1+\sigma_0)g_0 \leq G\lambda \\
&(1-\sigma_0)b_0 \geq B\lambda \\
&\sum_{j=1}^{n}\lambda_j = 1 \\
&\lambda \geq 0
\end{aligned}
\tag{4}
$$

2.3. Slack-Based DEA model

Inputs (outputs) may not behave proportionally in reality, while radial DEA models, such as CCR and BCC, deal with proportional changes in inputs(outputs). Also, radial models neglect slacks in measuring efficiency, while non-radial slacks affect managerial efficiency. In contrast, the slack-based DEA model works directly with slacks and puts aside the proportional changes assumption; however, two primary conditions, including unit invariant and monotone, should be met. Let $X = (x_1, \ldots, x_I) \in R^I_+$ be an inputs' vector, $G = (g_1, \ldots, g_J) \in R^J_+$ be a desirable outputs' vector, and $B = (b_1, \ldots, b_L) \in R^L_+$ be an undesirable outputs' vector. Also, λ^k is an intensity vector, and $k = (k_1, \ldots, K)$ is the index of DMUs. Therefore, the SBM-DEA model accounting for any outputs is presented through equation five (Li et al., 2016).

$$\begin{aligned}
&\rho_t = \min_{s_i^x, s_j^G, s_l^B} \frac{1 - \frac{1}{I}\sum_{i=1}^{I} \frac{s_i^x}{x_i^t}}{1 + \frac{1}{J+L}\left(\sum_{j=1}^{J} \frac{s_j^G}{x_j^t} + \sum_{j=1}^{J} \frac{s_l^B}{x_l^t}\right)} \\
&\text{S.t.} \\
&\sum_{k=1}^{K} \lambda_k X_i^k + S_i^t = X_i^t,\ i = 1, 2, \ldots, I; \\
&\sum_{k=1}^{K} \lambda_k G_j^k - S_j^t = G_j^t, j = 1, 2, \ldots, I; \\
&\sum_{k=1}^{K} \lambda_k B_l^k + S_l^t = B_l^t, l = 1, 2, \ldots, L; \\
&\lambda_k \geq 0,\ k = 1, 2, \ldots, K \\
&s_i^x, s_j^G, s_l^B \geq 0
\end{aligned} \tag{5}$$

where $0 \leq \rho_t \leq 1$ with $\rho_t = 1$ shows total efficiency, while t = 1, 2, …, K. it is presented that the t-th observation presented by input-output (x_i^t, g_i^t, b_i^t) is showed in the production frontier at the point $\left(x_i^t - s_i^{X^*}, g_j^t + s_j^{g^*}, b_l^t - s_l^{b^*}\right)$, where $s_i^{x^*}$, $s_j^{g^*}$, *and* $s_l^{b^*}$ are the optimal value of s_i^x, s_j^g, *and* s_l^b, respectively (Li et al., 2016).

2.4. RAM-DEA model

In the non-radial RAM-DEA, desirable and undesirable outputs could easily be incorporated into a unified model compared to the radial DEA models. Also, RAM-DEA is a linear non-radial model making it more applicable than the non-linear conventional DEA models. RAM-DEA model is specially proposed and applied by Sueyoshi and Goto (2012) and Sueyoshi and Goto (2011) to measure productivity in the presence of undesirable outputs. Let $G_j = (g_{1j}, \ldots, g_{nj})^T$ be a vector of desirable outputs, and $B_j = (b_{1j}, \ldots, b_{nj})^T$ be a vector of undesirable outputs, while for $j = 1, \ldots, n$, G > 0, and B > 0; therefore, in the following, the non-radial RAM-DEA proposed by Sueyoshi and Goto (2011) is presented through equation six.

$$\begin{aligned}
&\text{Max } Z = \sum_{r=1}^{s} R_t^g d_t^g + \sum_{f=1}^{h} R_t^b d_t^b \\
&\text{S.t.} \\
&\sum_{j=1}^{n} g_{rj}\lambda_j^g - d_r^g = g_{rk}, \forall\ r = 1, \ldots, s; \\
&\sum_{j=1}^{n} b_{fj}\lambda_j^b - d_r^b = b_{fk}, \forall\ f = 1, \ldots, h; \\
&\sum_{j=1}^{n} \lambda_j^g = 1; \\
&\sum_{j=1}^{n} \lambda_j^b = 1; \\
&\lambda_j^g \geq 0,\ \lambda_j^b \geq 0,\ d_r^g \geq 0,\ d_r^b \geq 0
\end{aligned} \tag{6}$$

where λ_j^g and λ_j^b are, respectively, intensity variables for desirable and undesirable outputs. Also, d_r^g is a surplus variable for r-th desirable output, d_r^b is a slack variable for f-th undesirable output, and R_r^g and R_f^b indicate the DEA model ranges for desirable and undesirable outputs, respectively, presented through equation seven, while s and h show the number of desirable and undesirable outputs.

$$\begin{aligned}
R_r^g &= \frac{1}{(m+s+h)\left[\max_j(g_{rj}) - \min_j(g_{rj})\right]} \\
R_r^b &= \frac{1}{(m+s+h)\left[\max_j(b_{fj}) - \min_j(gb_{fj})\right]}
\end{aligned} \tag{7}$$

where m represents the number of inputs utilised for yielding desirable and undesirable outputs; therefore, the unified efficiency score of the k-th DMU is calculated through equation eight, while d_t^{g*}, *and* d_t^{b*} are the optimal value of d_t^g, *and* d_t^b, respectively.

$$\theta = 1 - \sum_{r=1}^{s} R_t^g d_t^{g*} + \sum_{f=1}^{h} R_t^b d_t^{b*} \tag{8}$$

3. Research methodology

The present article used the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol to conduct a systematic literature review (SLR). SLR maps and evaluates the current knowledge and gaps in research fields, developing the knowledge base further. SLR follows scientific, replicable, and transparent stages differing from conventional narrative reviews (Murschetz et al., 2020). All publications related to the specific issue could be collected concerning the pre-defined criteria to answer research questions. SLR avoids bias occurring throughout searching, identification, appraisal, synthesis, analysis, and summary of studies using the systematic and explicit procedure (Mengist et al., 2020). Therefore, SLR could provide reliable findings and conclusions due to its capabilities to deal with bias, helping scholars and decision-makers to act accordingly (Saraji & Sharifabadi, 2017). Moreover, apart from PRISMA, there are several methodologies to conduct SLR, such as Search, Appraisal, Synthesis, and Analysis (SALSA). However, PRISMA has some advantages over other methods, such as (1) it has a detailed, precise, and well-described checklist helping scholars in improving systematic review reporting and meta-analyses (2) it is an updated protocol due to its various versions were released time to time, which the newest one was released in 2020; therefore, the present study employed PRISMA protocol to conduct a systematic literature review.

Scrutinizing the current literature is the first step of SLR. In this stage, some substantial scientific databases named Google Scholar, Web of Science (WOS), and Scopus are nominated to find the published articles related to the topic. The search is conducted for grey literature; we search for critical journals and scan the references' lists. The second step, named the eligibility criteria stage, focuses on the study's different characteristics, including the population of interest, study design, time duration, publication year, publication status, and language. Next, the PRISMA focuses on the information sources. This stage explains all related information of resources, such as electronic databases, authors' information, trial registers, and coverage date.

3.1. Searching method

According to the first step of PRISMA, some viable databases, e.g., WOS, Google Scholar, and Scopus, have been selected to comprehensively review the implementation of DEA in agricultural productivity with undesirable outputs. To find the related publications, we search in the selected databases with various keywords such as "DEA and energy efficiency in agricultural with undesirable outputs," "DEA and performance assessment in agricultural with undesirable outputs," "DEA and agricultural pollution with undesirable outputs," "DEA and sustainable agriculture with undesirable outputs," "DEA and agricultural economics with undesirable outputs," "DEA and agricultural industry," "DEA and crop production in agricultural with undesirable outputs," "DEA and resource efficiency," "DEA and agricultural production with undesirable outputs," etc. also, we attempt to involve the recently published articles, and therefore, our selection years are between 2000 and 2020. In the first attempt, based on the above keywords, in total, we identify 276 publication records. In the next stage, we screen the publications based on abstracts and titles to eliminate different items. After eliminating different items in this step, in total, 58 articles remained for the following stages. The PRISMA diagram is shown in Figure 1.

3.2. Publications' eligibility

In this step, the full text of the remaining articles has been reviewed one after another. We choose the articles that used an extension of DEA to compute agricultural productivity and efficiency with undesirable outputs. At this stage, we omit some documents such as essays, Ph.D. and master theses, book chapters, books, other

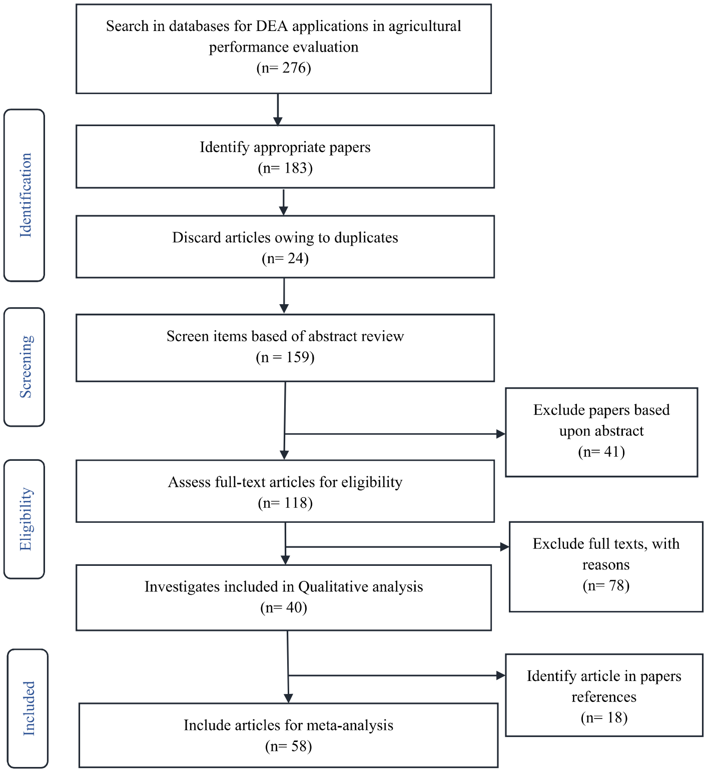

Figure 1. PRISMA flowchart for holistic systematic review.
Source: created by authors.

published resources in other languages except English, and editor's notes. Finally, after the mentioned stages, we choose 58 articles related to the DEA applications in agricultural productivity with undesirable outputs from 36 international scholarly journals between 2000 and 2020.

3.3. Data extraction and summarizing

In this step, firstly, required information has been extracted from the remaining articles. Finally, the remaining articles were classified into different groups (see Table 1) according to the article's primary purpose. Furthermore, all fifty-eight publications are reviewed and summarised based on various views; and are grouped into five

Table 1. Classification articles by their scope.

Categories Based on Scope	Number of Articles	Percentage (%)
Agricultural Pollution	13	22.41%
Sustainable Agriculture	12	20.69%
Agricultural Economics	12	20.69%
Environmental Performance	12	20.69%
Resource Efficiency	9	15.52%
Total	**58**	**100%**

Source: created by authors.

classifications), including agricultural pollution, sustainable agriculture, agricultural economics, environmental performance, and resource efficiency.

4. Results

4.1. Classification articles based on agricultural pollution

A wide variety of agricultural pollution, including air pollution, water pollution, wastewater, CO_2 emissions, etc. considered as significant challenges in countries (Chen et al., 2017). Agricultural activities increase pollutants affecting air quality, environmental performance, water quality, and other areas (Abbasi et al., 2014). Several studies have been conducted to measure productivity in which DEA was used to calculate efficiency of agricultural DMU, while agricultural pollutions were considered undesirable outputs. For instance, Falavigna et al. (2013) used Directional Output Distance Function (DODF)-DEA and Malmquist index to estimate the production possibility for each DMU, while they considered emission quantities of NHO_3 as undesirable outputs, and Kuhn et al. (2018) used SBM-DEA to carry out the difference between waste management in commercials and backyard hog farms, while CO_2 emission as an undesirable output. Table 2 indicates details extracting from the articles were related to agricultural pollution.

4.2. Classification articles based on sustainable agriculture

Sustainability has become attractive among practitioners, scholars, and strategists due to the growing environmental and social concerns (Boussemart et al., 2020). Sustainable agriculture relies on meeting human food, fibre, and biofuel expectations, and it improves the quality of the environment and resource base; the agronomists' living standards, farmworkers, and society to ensure the economic viability of the agricultural sector (Gołaś et al., 2020). Also, sustainable agriculture looks for increasing profitable farm income and promoting environmental stewardship. Therefore, evaluating sustainable agriculture potentials has become attractive for scholars as various methods have been developed for this purpose (Ren et al., 2021). For example, Shen et al. (2018) integrated the by-production model and DEA to calculate the shadow price of CO_2 emission in china's agricultural sectors, since due to the high population of china, having sustainable agriculture is vital, and Vlontzos et al. (2017) developed a synthetic Eco-(in) efficiency index using DDF-DEA model to evaluate the sustainability of the EU agricultural sector over 13 years from 1999 to 2012 on a

Table 2. Classification articles by agricultural pollution.

author (s) and year	Technique	Application area	DEA purpose	Study purpose	Research gap and contribution	Results and outcome
Falavigna et al. (2013)	DODF-DEA, Malmquist index	Agricultural Industry	To estimate the production possibility for each DMU	To evaluate the effect of regional policies in Italian's agriculture	To find a correlation between the level of production sustainability and funds' flows	Italian environmental performances vary among regions and when emissions are considered so that the productivity estimates differ
Kuhn et al. (2018)	SBM-DEA	pork production	To calculate the technical and environmental efficiency	To find the difference between waste management in commercials and backyard hog farms.	To cope with the Pig waste, which is a severe problem for both surface and groundwater resources	Results showed that limited waste disposal choice causes low environmental efficiency and high pollution costs in mid-size hog farms
Yaqubi et al. (2016)	DDF-DEA	Paddy Cultivation	To estimate DDFs	Proposing a hybrid model to assess the environmental inefficiency and shadow value	Need to assess the marginal abatement expenditure of the primary agricultural pollutants.	The Nitrogen surplus and greenhouse gasses have lower marginal abatement cost compared to pesticides and herbicides
Berre et al. (2013)	LCA, DDF-DEA	milk production	to calculate the inefficiency of a DMU with radial or non-radial distance	to assess shadow prices of outputs based on contradictory aims between the society and the farmers	To investigate the relationship between the nitrogen surpluses and the amount of GHG with economic growth	Results indicated that if societies balance farmers' opportunity costs, farmers can decrease pollution significantly.
Skevas et al. (2014)	DDF-DEA	Dutch Arable farming	Calculating the performance of arable farms	Modelling the available effects on farmers' production environment based on an endogenous point of view.	Need to deal with disadvantages of pesticides which is an undesirable output	Results indicated that crop producers should reduce using of pesticides
Reinhard et al. (2000)	Stochastic Frontier Analysis (SFA)-DEA	Dutch dairy farms	To compare with another method of efficiency calculation	to measure holistic environmental efficiency measures for farms dairy located in the Netherlands	to compare efficiency results calculated by two methods	The results indicated many differences between the two mentioned methods.
Wu et al. (2013)	DEA-Game	15 European Union members	To combine with bargaining game to calculate and	To propose a model to investigate the	To reduce and control emissions from agriculture	

(*continued*)

Table 2. Continued.

author (s) and year	Technique	Application area	DEA purpose	Study purpose	Research gap and contribution	Results and outcome
			improve the total efficiency	reduction and reallocation of emission permits	to improve the climatic change.	Results showed that the mechanism could be fair in different areas.
Vlontzos and Pardalos (2017)	DEA Window, ANN	EU farms	to estimate and calculate the efficiency of the environment in the EU countries' primary sectors	To study the long-term performance of EU countries primary sectors in Green House Gas emissions	Need to imply new efficiency assessment due to increasing of market force influence	Results indicated that there are meaningful differences among EU countries in terms of environmental efficiencies
Buckley and Carney (2013)	DEA, Regression Analysis	Dairy and tillage farms	To find that what utilising rates, chemical fertilisers might have been greater than optimum levels	To investigate the chance of reducing chemical fertilizers applications.	Need to study the nutrients transformed into water	Results indicated that there is an inefficiency in the application of chemical fertilizers
Coelli et al. (2007)	CRS-DEA	Pig fishing farms	To estimate the environmental efficiency measure, which is based on the materials balance equation	To propose a novel environmental efficiency based on materials balance condition	Previous models in terms of efficiency measurement might be inconsistent with the basic condition	Results indicated that a significant percentage of nutrient pollution on farms could be diminished in a cost-reducing
Zare-Haghighi et al. (2014)	Non-Radial DEA	Industries	To determine the type of congestion and to estimate its sources and amounts	To develop a non-radial efficiency measure to study the environmental performance of Chinese regions	Need to a novel scheme to measure congestion concerning both desirable and undesirable outputs	Results indicated that seven industries try to reduce pollutions
Dong et al. (2018)	SBM-DEA	Crop production	To evaluate the CO_2 efficiency of crop productions system at the provincial and prefecture-levels	To propose a framework to find the efficiency of inputs and outputs and (GHG) emissions reduction	Need to improve efficiency in agriculture production	Results indicated that there are differences between crop production efficiency among provinces
Sun et al. (2016)	Centralized DEA	China's Regions	to find the optimal path to control CO_2 emissions at the sector level	To propose a novel DEA model concerning various technologies for industrial optimisation	to develop a DEA model based on improved Kuosmanen environmental	Results indicated that the model could determine the optimal way of controlling CO_2 emission efficiently

Source: created by authors.

country level. Table 3 indicates all details extracting from the articles were related to Sustainable agriculture.

4.3. Classification articles based on agricultural economics

Agricultural economics looks for applying economic theories to optimise the production and distribution of agricultural production. Also, Agricultural economics is a branch of economics dealing with land usage, and it emphasises maximising agricultural production and maintaining a good soil ecosystem (Martin, 2019). For instance, the low-carbon economy, a part of agricultural economics, aims to reduce greenhouse gas emissions and save energy consumption to have sustainable agriculture (Streimikiene, 2021). Agricultural economics includes many areas and approaches, including DEA models; therefore, many studies have been carried out to compute energy efficiency and CO_2 emission efficiency concerning low carbon economics policies. For instance, Fei and Lin (2017b) used meta-frontier DEA to find an acceptable policy for agricultural energy saving and to carry out the sources of CO_2 emissions reduction, and Rebolledo-Leiva et al. (2017) integrated Life-cycle assessment (LCA) and VRS-DEA to maximise production and to decrease Carbon Footprint (CF) concerning the economics and ecological perspectives. Table 4 indicates details extracting from the articles were related to agricultural economics.

4.4. Classification articles based on environmental performance

Singh et al. (2020) mentioned that environmental performance is the organization's behaviour concerning the natural environment regarding how it goes about consuming resources to scan pollution emissions strictly. It is considered an introduction of biodegradable ingredients in products, reducing waste and pollution, reducing materials being harmful to the environment, enhancing energy efficiency, etc. (Singh et al., 2019). Due to the importance of environmental performance, several studies used different models, such as DEA, to measure environmental performance. For example, Gutiérrez et al. (2017) used a hybrid multi-stages DEA and regression analysis to calculate rain-fed cereals' efficiency based on actual management circumstances and environmental variables. Le et al. (2019) used the SBM-DEA model to determine the differences in productivity and agriculture efficiency among Asian countries. Table 5 indicates all details extracting from the articles were related to environmental performance.

4.5. Classification articles based on resource efficiency

It is challenging to develop indicators reflecting resource use and its impacts on the environment, economy, and security due to several natural resources characterised by different attributes. However, resource use is distinguished into four categories: usage of material, water, land, energy, and climate change. Modern agriculture faces significant challenges, including extreme water supply and fertiliser impacts (Zamparas et al., 2019a), deforestation (Tsiantikoudis et al., 2019), GHG emissions

Table 3. Classification articles by sustainable agriculture.

author (s) and year	Technique	Application area	DEA purpose	Study purpose	Research gap and contribution	Results and outcome
Shen et al. (2018)	By Production Model- DEA	Agricultural sectors	to determine the gap in the gross agricultural output across different provinces	To apply a new model to calculate the shadow price of CO_2 emission in china's regions	To integrate the approaches of inefficiency decomposition with by-production model	Results indicated that the mixing effect causes inefficiency that needs an improvement in the reallocation of inputs.
Sheng et al. (2016)	Zero-Sum-Gains (ZSG) DEA	Forests	to estimate the national reducing emissions from deforestation and degradation-plus (REDD+) reference levels	To calculate and classify the REDD + reference levels of 89 countries	REDD + implementation needs to study.	Results indicated that the proposed method could estimate the REDD + reference levels efficiently
Angulo-Meza et al. (2019)	Multiobjective DEA model (MORO-D)	organic blueberry orchards	to evaluate the eco-efficiency of units	Proposing a new multi-step model to assess the eco-efficiency of organic blueberry orchards.	Need to calculate environmental effects	Results indicated that the proposed model has some advantages compared to previous models
DE Koeijer et al. (2002)	CRS-DEA	Dutch sugar beet growers	To estimate the sustainable efficiency of farms	Proposing a model to quantify sustainability based on the efficiency theory commonly used in economics.	Need To investigate a vast group of sustainability factors based on production system at farm level	Results indicated that there was a positive relationship between technical efficiency and sustainable efficiency
Babazadeh et al. (2015)	Non-radial DEA	Jatropha curcas L. (JCL)	To calculate the efficiency of each location	To study the efficiency of some areas to cultivate bioenergy crop	Need to study JCL cultivation since it has applicable oily content	Results indicated that the proposed method is practical in terms of location optimization
Sidhoum (2018)	DDF-DEA	arable crop farms	To measure social outputs' shadow prices based on the directional distance function	To propose a framework concerning the state-contingent outputs to measure shadow prices of social outputs	There is not enough study in the field of the quantification of social sustainability and its relationship with the agricultural production efficiency	Results indicated that shadow prices of social outputs, a great value of the farm, are positive

(*continued*)

Table 3. Continued.

author (s) and year	Technique	Application area	DEA purpose	Study purpose	Research gap and contribution	Results and outcome
Vlontzos et al. (2017)	DDF-DEA, Regression	Agricultural Sector	To composite with DDF to estimate the efficiency concerning both desirable and undesirable outputs	To study the sustainability of the EU agricultural sector concerning the Kuznets curve	To investigate the relationship between agricultural sustainability and economic development	Results indicated that the efficiency of the GHG emissions reduction and output development could be improved
Hoang and Alauddin (2012)	CRS-DEA	agricultural production	to measure and decompose the efficiency level in agriculture production	to propose an analytical framework to evaluate the performance differences in economic, environmental, and ecological perspectives	Need to study the relationship between pollution, ecosystem resources, and services.	Results indicated that there is some scope that makes agricultural production eco-friendlier and more sustainable
You and Zhang (2016)	DEA-Tobit Analysis	Agricultural Production	To combine with Tobit model to estimate efficiency and to analyze the factors affecting efficiency	To investigate the eco-efficiency of intensive agriculture in Chinese provinces	To increase the outputs of intensive agriculture without any damage to the environment	The results indicated that six provinces are fully efficient, and some factors like income per capita have affected the efficiency
Pang et al. (2016)	SBM-DEA	Agricultural regions	To combine with Theil index to measure eco-efficiency and the imbalance of regional development	To evaluate the agricultural eco-efficiency using the Theil index approach and DEA	Need to design a new policy to improve eco-efficiency in china	Results indicated that eco-efficiency is different in a different area of china
Hoang and Rao (2010)	CRS-DEA	agricultural production	to calculate efficiency scores based on CRS production technology	To utilise cumulative exergy content to create new efficiency sustainable measures	to propose practical approaches to measure two aspects of sustainable agriculture	Results indicated that sustainable efficiency is likely to be different across countries
Jradi et al. (2018)	Radial-DEA	French vineyards	To propose a unified measure performance evaluation	To study the operational performance of wine estates when the composite factors of carbon footprints are existed	Need to propose a new method to evaluate efficiency under new constraints	Results approved the carbon footprint effect in vineyards

Source: created by authors.

Table 4. Classification articles by agricultural economics.

author (s) and year	Technique	Application area	DEA purpose	Study purpose	Research gap and contribution	Results and outcome
Fei and Lin (2017b)	Meta-frontier DEA	agricultural sector	To calculate the Malmquist energy productivity index	Dealing with the agricultural problems on energy-related CO_2 emissions issues.	To suggest proper policy for agricultural energy saving and to find the sources of CO_2 emissions reduction	Lower CO_2 emission efficiency was indicated in western China compared with eastern and central China
Rebolledo-Leiva et al. (2017)	LCA, VRS-DEA	Agriculture production	To evaluate the environmental and operational performance of multiple units	Proposing a hybrid four-step approach to assess the carbon footprint (CF)	To maximise production and to decrease CF concerning the economic and ecological perspectives	Results indicated that the proposed method could determine eco-efficiency and reduce CF practically
Tao et al. (2016)	Non-separable input/output SBM- DEA	Agricultural Regions	To measure China's provincial green economic efficiencies	To catch the constant trend of green economic efficiencies in specific periods instead of exploring the dynamic efficiency changes.	To deal with CO_2 emission problem in 2030 in china	Results indicated that the interregional differences are more significant in the field of green economic efficiencies.
Li et al. (2016)	Shapley/Sun index, SBM-DEA	EU Countries	to calculate environmental efficiency and shadow prices of CO_2 emission in European agriculture	Proposing an integrated method to the analysis of CO_2 emission based on advanced decomposition and efficiency analysis models	To deal with greenhouse gas (GHG) emissions in Europe	Results indicated that falling energy intensity is the critical factor to decline in CO_2 emission
Andre et al. (2010)	Modified VRS-DEA, Goal programming	Farmer decision making	To calculate efficiency and preference weights	To show a relationship between DEA and a non-interactive elicitation method	To deal with MCDM problems by translating them into DEA terminology	Results indicated that the weights provided by the proposed method are entirely accurate.
Zhang et al. (2011)	DDF-DEA, Malmquist index	Agricultural regions	To estimate TFP growth	To assess China's progress in total factor productivity (TFP)	To investigate the effect of regulation on productivity	Results indicated that more environmental regulations could improve ML productivity growth in China

(*continued*)

Table 4. Continued.

author (s) and year	Technique	Application area	DEA purpose	Study purpose	Research gap and contribution	Results and outcome
Khoshroo et al. (2018)	Non-radial DEA	Turnip production	to assess the efficiencies of the turnip farms, and measure the optimal use of resources	To propose a new method to study the efficiency of turnip farms	To deal with unwelcome emission produced in Iranian turnip farms	Results indicated that the proposed model could work efficiently
Baležentis and Makutėnienė (2016)	DDF-DEA	Pulp, article, and agricultural sectors	To calculate EPI based on the Hicks-Moorsteen indices	to study the environmental performance index (EPI) for economic sectors in Lithuania	Need to investigate the environmental performance of the Lithuanian economy	Results indicated that article and agricultural sectors are the best performing group in the economy sector
Vlontzos et al. (2014)	Non-Radial DEA	EU countries	To provide different estimations of environmental and energy efficiency scores	To assess the efficiency of environment and energy in the primary sectors in the EU	Need to become low carbon and resource-efficient economy in the EU	Results indicated that the efficiency of the environment and energy had been changed due to changes in agricultural policies
Fei and Lin (2017a)	Non-Radial DEA	agricultural sector	Looking for a unified efficiency score to estimate the coordination between inputs and outputs	To find integrated efficiency of inputs-outputs in the Chinese agriculture sector	Need to enhance environmental and energy efficiency to deal with CO_2 and energy challenges	Results indicated that many Chinese's provinces did not perform in the integrated efficiency of inputs-outputs efficiently
Asmild and Hougaard (2006)	VRS-DEA	Pig Farms	To estimate and to analyze the improvement of the efficiency of pig farms	To study the relationship of economics and environmental improvement in pig farms	To study the effect of Danish pig Production surplus on the environment	The empirical results indicated that there are potentials for considerable improvement on the environmental variables.
Pongpanich and Peng (2016)	Super-SBM DEA	Agricultural cooperatives	To combine with SBM DEA to measure and compare the operation efficiency and inefficiency	To propose a novel approach to analyze the operational efficiency in agricultural cooperatives	To study the agricultural corporative in every province in Thailand	the empirical results indicated that there are some problems and benchmarks related to members and farmers

Source: created by authors.

Table 5. Classification articles by environmental performance.

author (s) and year	Technique	Application area	DEA purpose	Study purpose	Research gap and contribution	Results and outcome
Hoang and Coelli (2011)	DDF-DEA	Agriculture production	To calculate efficiency scores and productivity change in crop and livestock production	To utilise nutrient-orientated environmental efficiency (EE) measures to build a nutrient total factor productivity index (NTFP)	To propose a novel framework to provide practical and trustable information in the field of environmental management	Results indicated that the government ought to yield current outputs less than aggregate atrophying power
Gutiérrez et al. (2017)	Two-Stage DEA, Regression	rain-fed cereals	To combine with fractional regression to calculate rain-fed cereals efficiency	To calculate the efficiency of rain-fed cereals based on actual management conditions, environmental variables, and integrating technical	To propose an integrative approach to deal with the many challenges faced by global agriculture.	Results indicated that organic production is more efficient than conventional production
Cecchini et al. (2018)	SBM-DEA, LCA	dairy cattle farms	To integrate with LCA to estimate the efficiency of dairy cattle farms	To study CO_2 emission alleviation based on joint production of milk and GHG emissions using efficiency performance measures	Need To increase farmer economic gain without any conflict with reducing GHG	Results approve a positive correlation between CO_2 -eq efficiency scores and marginal abatement
Lin and Fei (2015)	CRS-DEA, Malmquist index	Agricultural Sectors	To estimate the static emission performance of CO_2 emission	To assess the energy-related CO_2 emissions performance in China's agricultural	There are few studies conducted in terms of analyzing carbon emissions performance and its regional differences	Results indicated that the average annual growth and the aggregated growth of the Malmquist index is 6 and 48 percent, respectively
Ferjani (2011)	DDF-DEA	Dairy Farms	To estimate the Malmquist productivity index using comparing distance functions in two different years	To investigate the effect of environmental policy on-farm performance	To test the Porter hypothesis in Swiss dairy farms	The results indicated that the findings did not reject porter views
Le et al. (2019)	SBM-DEA	Agricultural Sectors	To evaluate the technical and	To investigate the change in productivity and	To find leading countries in terms of TFP growth	Results indicated that there are differences in

(*continued*)

Table 5. Continued.

author (s) and year	Technique	Application area	DEA purpose	Study purpose	Research gap and contribution	Results and outcome
			environmental efficiencies of agriculture	efficiency in agriculture among Asian countries	and environmental efficiency	environmental performance and productivity growth in the agricultural sector among countries
Makutėnienė and Baležentis (2015)	DDF-DEA	Agricultural Sectors	To estimate the efficiency concerning Frontier models	To evaluate the efficiency of a resource, environmental, and economical in the EU agriculture	Need to study productivity and efficiency of agricultural sectors as elements of competitiveness	Results indicated that some countries like Slovenia are the most technically efficient, while others are weak
Baležentis and Makutėnienė (2016)	By-Production, DEA, MCDM	Agricultural Sectors	To compare with the MCDM approach in terms of evaluating countries performance	To propose an MCDM framework to study performance gaps of energy-related CO_2 emission	Need to propose an approach to investigate the effect of the production process on the environment	Results indicated that some countries, including Lithuania, should improve their carbon factors
Nikolla et al. (2013)	CRS-DEA	Farms	To analyzes the efficiency of company units	To study and amalgamate the efficiency of Albanian Farms	To study the efficiency of the production of greenhouse tomato culture	Results indicated that one of the farms is 100% efficient concerning this amount of inputs
Long et al. (2018)	SBM-DEA	Fertiliser Intensity	To calculate the environmental efficiency based on a meta-frontier directional SBM super efficiency method	To compare environmental efficiency in Chinese's provinces	to study the effect of fertiliser on environmental efficiency using intensity	Results indicated that using organic fertiliser can reduce CO_2 emission
Yang et al. (2008)	Shephard output distance function, DEA	swine production	To assess technical efficiency concerning Shephard distance function	To investigate the relationship the environmental regulations and Taiwanese farrow-to-finish swine production	To develop a model which includes undesirable outputs	Results indicated that smaller farms are less technically efficient than larger farms
Zhang (2008)	VRS-DEA	corn production	To calculate the environmental and technical	to study the relationship between demand for green production and eco-efficiency improvement	Need to the policy to improve the environmental performance in agricultural production	Results indicated that improving environmental performance in China is possible

Source: created by authors.

(Kyriakopoulos & Chalikias, 2013, Kyriakopoulos et al., 2010), soil erosion, eutrophication (Zamparas et al., 2019b), and water pollution ((Zamparas et al., 2020). Also, resource use efficiency means allocating and using various scarce resources to reach benefits. Due to the importance of agricultural economics, resource, consumption, and allocation efficiency are the main research stream in this branch of the economy; therefore, Resource consumption and allocative efficiency can be examined through the different approaches, including the DEA model. For instance, Yang and Li (2017) utilised SBM-DEA to evaluate the Total Factor Efficiency of Water resource (TFEW) and the Total Factor Efficiency of Energy (TFEE), and Deng et al. (2016) employed SBM-DEA to calculate the usage efficiency of water in china areas. Table 6 indicates all details extracting from the articles were related to resource efficiency.

4.6. Distribution of articles by journal

Table 7 provides information about the frequency of articles by journals' names. The articles linked to the agricultural performance assessment with undesirable outputs and the DEA models have been chosen through 36 a vast verity of journals from the WOS database, Scopus, Google Scholar. On the surface, "Journal of Cleaner Production" was ranked first with six articles, followed by "Sustainability," "Renewable and Sustainable Energy Reviews," "European Journal of Operational Research," "Agricultural Economics," and "Ecological Indicators" with three articles. The results indicated "Journal of Cleaner Production" made the most contribution in implementing DEA models in agricultural performance assessment with undesirable outputs.

4.7. Distribution of articles by authors' nationality

Table 8 indicates that authors from seventeen countries utilised DEA models in agricultural performance assessment with undesirable outputs, while the Chinese had the most contributions with39.66%. The figure for Australia accounting for the second country is 8.62%. Interestingly, the figure for Iran and Lithuania are the same, with 6.90%. On top of that, the results indicated that Chinese scholars utilised By-production technology and directional distance function (Shen et al., 2017, Fei & Lin, 2017a), the SBM DEA (Kuhn et al., 2018, Deng et al., 2016, Tao et al., 2016, Bian et al., 2014, Dong et al., 2018, Long et al., 2018, Song et al., 2014, Pang et al., 2016, Yang & Li, 2017), the Zero-Sum-Gains DEA (Sheng et al., 2016), meta-frontier DEA (Fei & Lin, 2017b, Fei & Lin, 2016), Malmquist index DEA (Wang et al., 2015, Zhang et al., 2011, Lin & Fei, 2015), DEA-Game (Wu et al., 2013), BCC-DEA (Li et al., 2013), DEA-Tobit (You & Zhang, 2016), centralised DEA (Sun et al., 2016). Australian scholars utilised the directional distance function (Hoang & Coelli, 2011, Azad & Ancev, 2014), CCR-DEA (Coelli et al., 2007, Hoang & Alauddin, 2012), BCC-DEA (Pagotto & Halog, 2016). Iranian scholars utilised the directional distance function (Yaqubi et al., 2016), non-radial DEA (Babazadeh et al., 2015, Zare-Haghighi et al., 2014), BCC-DEA (Khoshroo et al., 2018).

Table 6. Classification articles by resource efficiency.

author (s) and year	Technique	Application area	DEA purpose	Study purpose	Research gap and contribution	Results and outcome
Deng et al. (2016)	SBM-DEA	Water Efficiency	To estimate the water consumption efficiency	To investigate the water use efficiency in china provinces	To deal with the undesirable water consumption efficiency and water pollution challenges	Water efficiency is higher in developing provinces
Wang et al. (2015)	Malmquist index, CRS-DEA, Tobit Model	Water efficiency	to calculate the efficiency of agricultural water consumption in the Heihe River Basin	To investigate the changing paths of agricultural water consumption concerning the input-output data over nine years	Need to calculate the agricultural water-use efficiency is a vital factor reflecting the effective water allocation and productivity	Results indicated that the average efficiency of agricultural water consumption is far lower than one in different countries over nine years
Fei and Lin (2016)	Meta-frontier DEA, Malmquist index	Agricultural sector	To calculate the Malmquist energy productivity index	Measuring agricultural energy efficiency and exploring the energy productivity alter in China's agriculture	Need to study energy efficiency in the agricultural sector since it is vital for sustainable agricultural development.	The results showed that the agricultural energy efficiency is completely low, and it is different from place to place
Azad and Ancev (2014)	Luenberger Productivity Indicator, DEA	Water efficiency	To calculate efficiency score for the irrigated enterprises	To calculate trade-offs between the economic gain of water consumption in farming	to construct policy instruments to improve water resource management	Results indicated that a significant difference in the environmental performance of irrigation companies in each area was observed
Li et al. (2013)	CRS and VRS DEA	China's Regions	To calculate relative efficiency under CRS and VRS assumptions	To propose a model to allocate resource and reduce emission effectively	To deal with the environmental pollution in china	Results indicated that the proposed model worked effectively.
Bian et al. (2014)	Three Stages-DEA	Water efficiency	To evaluate water, use efficiency based on CSR assumption	To analyses water consumption performance and to investigate waste management systems in China.	Need to investigate the water shortage crisis and tackle it	Results find some practical action to improve efficiency in china

(continued)

Table 6. Continued.

author (s) and year	Technique	Application area	DEA purpose	Study purpose	Research gap and contribution	Results and outcome
Pagotto and Halog (2016)	ZSG-DEA	Food Industry	to calculate the eco-efficiency performance of selected DMUs based on I-O-approach	to assess the eco-efficiency of various subsectors in the agri-food network in Australian	To study the environmental burdens being available in the food industry	Results indicated that in the life process of food production, some inefficiencies exist.
Song et al. (2014)	SBM-DEA	Water Efficiency	To calculate efficiency of undesirable outputs and estimate desirable and undesirable outputs separately	To extend the SBM model based on network analysis	Need to propose an SBM model to tackle the scenario characterised by constant desirable outputs	The results indicated that the efficiency calculated by the proposed model is smaller than the outputs of the traditional model
Yang and Li (2017)	SBM-DEA	Water Efficiency	to assess TFEW and TFEE	To study the efficiency of water and energy resources in China	Need to investigate wastewater and water pollution produced in the process of manufacture and economic development	Results indicated that by investing in water resource, the Chinese economy could improve

Source: created by authors.

Table 7. Distribution of articles based upon journals.

Journal's Name	NO.	%	Journal's Name	NO.	%	Journal's Name	NO.	%
Journal of Cleaner Production	6	10.34	Applied Energy	2	3.45	Agricultural Systems	1	1.72
Sustainability	3	5.17	Omega	1	1.72	Technological Forecasting & Social Change	1	1.72
Renewable and Sustainable Energy Reviews	3	5.17	Resources, Conservation and Recycling	1	1.72	Journal of Environmental Economics and Management	1	1.72
European Journal of Operational Research	3	5.17	Industrial Crops and Products	1	1.72	Physics and Chemistry of the Earth	1	1.72
Agricultural Economics	3	5.17	European Journal of Agronomy	1	1.72	Environmental Monitoring and Assessment	1	1.72
Ecological Indicators	3	5.17	Applied Economics Letters	1	1.72	Energies	1	1.72
Management Theory and Studies for Rural Business and Infrastructure Development	2	3.45	Environmental Science & Policy	1	1.72	Environmental and Resource Economics	1	1.72
Science of the Total Environment	2	3.45	Journal of Productivity Analysis	1	1.72	PloS One	1	1.72
Ecological Economics	2	3.45	Agricultural Economics Review	1	1.72	Natural Hazards	1	1.72
Mathematical and Computer Modelling	2	3.45	Journal of Applied Mathematics	1	1.72	Journal of Industrial Ecology	1	1.72
Journal of Environmental Management	2	3.45	Discrete Dynamics in Nature and Society	1	1.72	Computers and Electronics in Agriculture	1	1.72
China Economic Review	2	3.45	Journal of Food, Agriculture & Environment	1	1.72	International Journal of Scientific and Research Publications	1	1.72
						Total	**36**	**100**

Source: created by authors.

Table 8. Distribution of articles based upon the nationality of authors.

Country	NO.	%
China	23	39.66
Australia	5	8.62
Iran	4	6.90
Lithuania	4	6.90
Spain	3	5.17
Greece	3	5.17
Italy	2	3.45
The Netherlands	2	3.45
France	2	3.45
Ireland	2	3.45
Taiwan	2	3.45
Albania	1	1.72
Belgium	1	1.72
Switzerland	1	1.72
USA	1	1.72
UK	1	1.72
Chile	1	1.72
Total	58	100

Source: created by authors.

4.8. Distribution of articles by publication time

Figure 2 illustrates the frequency of the publication time. The number of articles written in applying the DEA model in agricultural performance assessment with undesirable outputs rose dramatically over the past two decades. The first article was published in 2000, while in 2019, the number of articles is 58, while more of them was published in 2016, with 13 articles. It is anticipated the number of articles in this field will be increased in the future.

5. Discussion

Results indicated that DEA models showed great promise to be an excellent assessment tool for further productivity measurement in the agricultural sector, especially when it is complicated to determine the production function represented the inputs and outputs relationships. The DEA models’ superiority in dealing with multiple inputs and multiple outputs makes them an exciting research field for scholars interested in productivity measurement with undesirable outputs in agricultural sectors. Not only could DEA models be an alternative for index measurement or econometric models for productivity measurement, but also DEA models could be integrated with various methods, such as game theory (Wu et al., 2013), artificial neural network (ANN) (Vlontzos & Pardalos, 2017), regression (Buckley & Carney, 2013), Tobit analysis (You & Zhang, 2016), LCA (Rebolledo-Leiva et al., 2017), goal programming (Andre et al., 2010) to deal with productivity measurement with undesirable outputs.

Furthermore, the results indicated that there are different types of DEA models such as Meta-frontier DEA, Malmquist index (Fei & Lin, 2016), VRS-DEA (Zhang, 2008), DDF-DEA (Makutėnienė & Baležentis, 2015), SBM-DEA (Le et al., 2019), CRS-DEA (Lin & Fei, 2015), SBM-DEA, Super-SBM DEA (Pongpanich & Peng, 2016), Multiobjective DEA model (MORO-D) (Angulo-Meza et al., 2019) which are helpful and applicable to measure the agricultural productivity with undesirable outputs. DEA

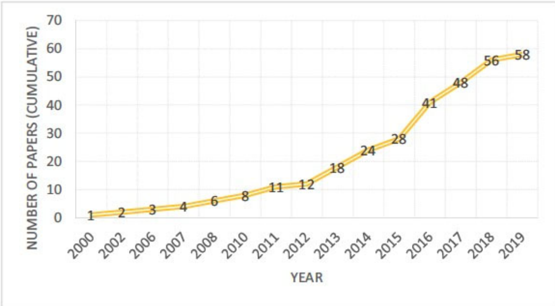

Figure 2. Distribution of articles based upon publication time (cumulative).
Source: created by authors.

models can accommodate multiple inputs and outputs to calculate the relative efficiency of DMUs in agri-sectors, while it is not necessary to set the weights for DMUs since DEA models use a ratio of "weighted outputs sum" to "weighted inputs' sum;" therefore, DEA models could be applied for measuring agricultural productivity due to its superiority in dealing with undesirable outputs, which is consistent with previous studies, such as Baležentis et al. (2016), Zhou et al. (2019), Wang et al. (2019), Halkos and Petrou (2019a), Yang and Wei (2019), Kang et al. (2018), Liu et al. (2017).

6. Conclusion and policy recommendations

The present article's primary purpose is to provide a holistic overview of the DEA's implementation in assessing agricultural productivity with undesirable outputs. In this regard, a systematic review using PRISMA protocol has been conducted to find and review the published articles in agricultural production with undesirable outputs over 2000 to 2020. Primary databases, including Google Scholar, Scopus, and WOS, were searched. This study classified the found articles concerning application areas, including agricultural pollution, sustainable agriculture, agricultural economics, environmental performance, and resource efficiency. Agriculture pollution was ranked first. Also, the selected articles are categorised based on different indicators such as the name of journals, author(s) names, methods, area of implementation, study and DEA purposes, articles' contribution and gaps, outcomes and results, year of publication, and authors' nationalities. In this regard, there were 36 journals had contributed to this article which. The "Journal of Cleaner Production" was ranked the first journal with six publications, followed by "Sustainability," "Renewable and Sustainable Energy Reviews," "European Journal of Operational Research," "Agricultural Economics and Ecological Indicators" journals with three published articles. In terms of country nationality, China was ranked first with 39.66%, followed by Australia, Iran, and Lithuania with 8.62%. And 6.90% respectively.

It could be concluded that DEA models could correctly measure agricultural productivity in the presence of undesirable outputs dut the following advantages: (1)

DMUs could operate under various condition, and DEA avoid this assumption; (2) multiple inputs and multiple outputs could be analyzed simultaneously, and there is no necessity to assign weight by the users in DEA models due to Pareto efficiency used by DEA; (3) the overall efficiency could easily be interpreted, and the most productive units and successful factors could be identified simply due to superiority of DEA in dealing with productivity measurement issues. Also, it is noticeable that the SBM-DEA model was widely used more than other methods, according to table eight. SBM-DEA is appropriate for a situation in which Inputs (outputs) may not behave proportionally. Furthermore, the slack-based DEA model works directly with slacks and puts aside the proportional changes assumption, while radial models neglect slacks in measuring efficiency.

6.1. Policy recommendations

Countries should balance the opportunity cost for the farmers, which is the core principle of agriculture economics. The opportunity cost of farming enables farmers to grow crops, sell, and make money. Society could increase the production profit by decreasing the inefficiency through an undesirable output reduction so that compensation could pay to farmers, considering an opportunity cost for the farmers. Thus, it is unnecessary to produce more without paying a pollution emissions fee, which reduces pollution, a giant leap for sustainable development.

Undesirable outputs, especially in the agri-sector, must be treated carefully. For instance, it is possible to turn nitrogen surpluses, considered an undesirable output, into a desirable input by stocking them into the soil to apply in the future production process. Therefore, setting a price to biomass as pollution or natural fertiliser requires more expertise as either a desirable input or undesirable output. Also, the same could be applied to GHG, such as livestock methane emission as biogas. Biogas is a green form of energy having great potential to use as an alternative to conventional fuel. It can be produced from various sources, such as agricultural waste, manure, and waste dumps.

Assessment of green agriculture productivity using DEA models allows policymakers to promote sustainable agriculture through highlighting various treatment methods with undesirable outputs; then, DEA models could analyze the effect of various subsidy policies concerning the treatment methods with undesirable outputs. Afterward, the empirical results based on DEA models can assess the appropriateness of incorporating subsidy policies and agriculture productivity evaluations.

6.2. Limitations and future research

Like other review articles, this review had some limitations that can be used as recommendations for future works. One of the article's limitations is about the sources of collected articles; this study only selected and collected the published articles from journals of popular databases; therefore, the present article did not consider the published articles from doctoral dissertations and textbooks. Therefore, future studies would consider the published articles of these sources. Another contribution of the article is about the selected journals; in this regard, this study only considered the published articles in English languages, and other published articles in other languages are excluded in this article. Therefore, future works can include the published articles in other languages in the future articles. Another limitation of this review article is related to the classification of the published articles; this study classified the published articles in agriculture into five different application areas; in this regard, it recommends the further works classify the articles in other application areas. Due to this review article’s objective, only the implementation of DEA models in agriculture production performance is considered in this article; therefore, future studies can review DEA’s application in other application areas, industries, organisations, sectors, and firms. Also of this limitation, the current review article only emphasised the implementation of DEA models in the assessment of agriculture production performance; in this regard, the future works can review the application of other methods like fuzzy sets, decision making, optimizations models, neural networks and econometrics approaches and methods in agriculture production performance assessment.

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RESEARCH ARTICLE

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Creation of climate-smart and energy-efficient agriculture in the European Union: Pathways based on the frontier analysis

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Abstract

Creation of the climate-smart agriculture requires efficient resource use and mitigation of the environmental pressures among other objectives. Therefore, it is important to assess the energy efficiency and productivity growth in the European Union's agriculture. This paper analyses the sample of the selected European Union member states. The productive technology including the energy consumption and the resulting greenhouse gas (GHG) emission is constructed. The measurement of the energy efficiency and productivity change relies on the slacks-based measure and Luenberger productivity indicator. The productivity growth was decomposed with respect to the input/output variables and the sources of growth (i.e., efficiency change and technical progress). The average annual productivity growth of 0.79% was obtained for the selected countries during 1995–2016. The highest productivity gains were observed in Lithuania, Denmark, Belgium and Romania (1.27%–1.94% per year). The productivity growth related to GHG emission dominated the contributions by the input/output variables in Lithuania, Denmark, Belgium, Romania, Poland, Austria, France, the Netherlands, Hungary and Estonia.

KEYWORDS
data envelopment analysis, energy efficiency, European Union, resource efficiency, climate smart agriculture, sustainability

1 | INTRODUCTION

The growth in agricultural output has led to increasing food security across the world since the 20th century. As Fuglie, Wang, and Ball (2012) argued, the increase in agricultural output and decline in agricultural commodity prices over the 20th century (even though the last decade saw increasing prices) allowed feeding an increasing population. Such changes that contribute to the wellbeing of the whole population as the means of subsistence become more affordable, and the resources can be directed to the other sectors to further promote economic development (Vasylieva, 2019).

A crucial issue pertinent to agricultural production is the concern about sustainability. As it was mentioned above, the concept of sustainable intensification calls for integrated assessment of input consumption, production of agricultural outputs and the resulting environmental pressures (Fan, Zhang, Chen, & Chen, 2020; Wang et al., 2020). The depletion of the fossil fuels and climate change calls for wider penetration of the renewable energy sources. The latter issue can be addressed within the energy-economy-environment nexus (Jiang, Ji, Qin, & Feng, 2018; Jiang, Qin, Ji, Feng, & Zhou, 2017; Pellegrini & Fernández, 2018). The concerns on climate change have been taken into account when developing models for sustainable development in the other sectors economy as well (Benz, Paulus, Scherer, Syryca, & Trück, 2020; Chen, Gao, Ma, & Song, 2020; Popescu, Andrei, Nica, Mieilă, & Panait, 2019; Sun, Wang, Wang, & Zhang, 2019; Tian, Zheng, Liu, Aggarwal, & Orvis, 2019). As regards the European Union (EU), the European Green Deal strategy has been adopted to promote the climate-neutral economy (European Commission, 2019).

The growth in agricultural output can be maintained due to increasing input consumption or gains in the (total factor) productivity. The increasing use of inputs corresponds to agricultural intensification. Indeed, the increasing input consumption is not desirable in agriculture (this especially applies to the use of agrochemicals). The concept of sustainable intensification has emerged to reconcile the desirable growth in the output levels and mitigation of the undesirable environmental impacts (Wynne-Jones, Hyland, Williams, & Chadwick, 2020). Therefore, the increasing input use should adhere to the principles of sustainable farming.

The growth in agricultural productivity, indeed, is a more sustainable way to increasing agricultural output, food security and wellbeing in general. The latter source of growth has been acknowledged as the major factor behind the increasing agricultural output in the 20th century (Fuglie et al., 2012).

The measures of productivity vary from single-factor ones (e.g., land productivity or labour productivity) to multifactor ones (including the total factor productivity). However, the use of inputs in the production may be subject to differences in input endowments, quality and prices. This may render different contributions to the productivity and output growth by different inputs.

The region- and input-specific differences in contributions to agricultural productivity growth have been reported in the literature. Fuglie (2018) reported that the global increase in agricultural output was 2.24% per annum (p.a.) for 1961–2014 with industrialized countries showing the value of 1.19% p.a. As regards the changes in land productivity, the global average was 2.04% and 1.43% for the world and industrialized countries, respectively. The opposite trend prevailed for the labour productivity (1.14% and 3.23%). This indicates differences in the quality of human capital and modes of agricultural development. Therefore, it is important to embark on the variable-specific analysis to identify the paths and bottlenecks for agricultural development across different regions.

The frontier techniques allow for analysis of economic activities based on an integrated framework (Kubak, Gavurova, & Drotar, 2019): input transformation into outputs and generation of undesirable outputs can be modelled as an environmental productive technology. Among different techniques, data envelopment analysis (DEA) is often used in analysis of the environmental performance (Sueyoshi, Yuan, & Goto, 2017; Urdiales, Lansink, & Wall, 2016). The conventional DEA models introduced by Charnes, Cooper, and Rhodes (1978) and Banker, Charnes, and Cooper (1984) rely on the radial measures, that is, the structure of inputs and outputs remains fixed during the optimization, and the measures of inefficiency are not variable specific. The slacks-based measure (SBM) proposed by Tone (2001) and discussed by Fukuyama and Weber (2009) and Färe and Grosskopf (2010a) considers contributions of each input/output variable to the inefficiency score. Cooper, Seiford, and Tone (2007) discussed the application of the SBM for the analysis of the environmental performance with undesirable outputs.

The DEA models allow estimating the distance functions, which indicate the degree of inefficiency. These functions can be estimated by considering different benchmarks (e.g., observations for different time periods) to approximate the change in productivity and its sources. The global frontier approach (Pastor & Lovell, 2005) allows to establish a common benchmark for multiple time periods and, thus, to derive the corresponding measures of productivity. The global Luenberger productivity indicator was applied by Wang, Xian, Wei, and Huang (2016). The global Luenberger indicator based on the SBM was applied by Miao, Baležentis, Shao, and Chang (2019). The latter setting allows decomposing the changes in productivity with regard to contributions of each input/output variable.

This paper seeks to identify the major drivers of agricultural productivity change[1] in the selected EU member states. To this end, we apply the global SBM-based Luenberger productivity indicator. The research relies on the country-level data.

The rest of the paper proceeds as follows. Section 2 presents the literature review on the analysis of agricultural efficiency and productivity growth in the EU. Section 3 presents the methods used for the analysis. Section 4 presents the data used. The results are discussed in Section 5.

2 | LITERATURE REVIEW

The analysis of agricultural productivity growth is an important research avenue due to the role of agriculture in the economy. Njuki, Bravo-Ureta, and O'Donnell (2019) presented a parametric framework for analysis of the total factor productivity growth based on the random parameters frontier. Skevas (2020) and Baráth, Fertő, and Bojnec (2020) applied the random parameters frontier for efficiency and productivity analysis. Acosta and Luis (2019) also applied stochastic frontier analysis (SFA) for agricultural sector in the world. Njuki and Bravo-Ureta (2019) applied the SFA to develop a single-factor productivity measure.

Among different measures of the productivity growth, the Luenberger productivity indicator is often applied in empirical research. The Luenberger productivity indicator is additive, which allows handling extremely small or zero values in the analysis. What is more, it allows for nonradial analysis as the directional vectors can be applied. Wang and Wei (2016) utilized the Luenberger productivity indicator to measure energy productivity gains. Kerstens, Shen, and Van de Woestyne (2018) discussed the properties of the Luenberger indicator and compared it with the Luenberger–Hicks–Moorsteen productivity indicator. Geylani, Kapelko, and Stefanou (2019) applied the Luenberger productivity indicator in the dynamic setting for enterprise performance analysis. Boussemart, Ferrier, Leleu, and Shen (2020) extended the decomposition of the Luenberger indicator and applied it to the healthcare sector. Therefore, the Luenberger productivity indicator can be applied to different settings and levels of analysis.

[1]Productivity change can be either positive or negative. Following the economic literature, one may also use general term 'productivity growth' which corresponds to, for example, the 'economic growth'.

TABLE 1 The studies on efficiency and productivity change in the European Union (EU) agriculture

Reference	Estimator	Productivity change measure	Environmental pressures	Time period covered
Kočišová (2015)	DEA	–	–	2007–2011
Kocisova, Gavurova, and Kotaskova (2018)	SBM–DEA	–	–	2005–2013
Błażejczyk-Majka (2017)	DEA	–	–	2012
Martinho (2017)	DEA	–	–	2013
Martinho (2020)	DEA	–	–	2014–2016
Baráth and Fertő (2017)	DEA	Färe–Primont index	–	2004–2013
Vlontzos, Niavis, and Manos (2014)	SBM–DEA	–	Carbon dioxide emission and nutrient balance	2001–2008
Bartová, Fandel, and Matejková (2018)	DEA	Malmquist–Luenberger index	GHG emission	2006–2015
This paper	SBM–DEA	Luenberger indicator	Energy-related GHG emission	1995–2016

Abbreviations: DEA, data envelopment analysis; GHG, greenhouse gas; SBM, slacks-based measure.

In this section, we further survey the studies on the analysis of the agricultural efficiency of the EU member states. These studies apply the frontier methods (i.e., the DEA or SFA). The literature survey presented in this paper focuses on the country-level analysis. Table 1 summarizes the relevant literature on the EU member states.

The first group of papers applies the basic DEA models without considerations of productivity or environmental pressures. Kočišová (2015) applied the radial DEA to assess the technical efficiency of the EU agriculture at the country level. The productive technology involved land, labour and capital inputs along with crop and livestock outputs. The research covered years 2007–2011. Kocisova et al. (2018) applied the SBM to analyse the efficiency of the EU agriculture. The productive technology was defined in terms of labour input, agricultural land, crop output and livestock output. The study covered the period of 2005–2015. The results indicated that labour is better utilized if compared with the land input. Błażejczyk-Majka (2017) applied the radial DEA to measure the efficiency of the agricultural sector of the EU member states in 2012. The analysis considered labour, land, 'total inputs' from the Farm Accountancy Data Network (FADN) system (specific costs plus overheads, depreciation and external factors), and fixed capital as the four inputs along with crop, livestock and other outputs. Note that the 'total inputs' and fixed capital both relate to the amount of capital employed in the production process. The FADN data were used.

Martinho (2017) looked into the efficiency of the EU agriculture at the country level by applying the radial DEA. The total agricultural output as well as labour, assets, fertilizers, crop protection products and wages were used to define the productive technology. The monetary variables from the FADN were used. Martinho (2020) applied the DEA to measure the efficiency of the agricultural sectors of the EU member states. The latter study considered energy expenditures as one of the inputs besides labour and fixed assets. The output was the total agricultural output. In this case, the unpaid labour input remained ignored.

The second group of papers includes those applying total factor productivity (TFP) measures and/or considering environmental pressures in the analysis. Among scarce studies on country-level agricultural efficiency appearing in international outlets, the one by Baráth and Fertő (2017) applied the DEA along with the Färe–Primont index, which ensures transitivity. The data from the Food and Agriculture Organization Statistical Database (FAOSTAT) were used. The inputs included labour, land, fixed capital consumption and intermediate consumption. The crop and livestock outputs were considered. The data for 2004–2013 were analysed. Vlontzos et al. (2014) utilized the SBM–DEA to assess the environmental and energy efficiency of the EU agriculture. The inputs included energy expenditures, labour and capital, whereas the outputs included a desirable output (agricultural output) and undesirable outputs (carbon dioxide emission and nutrient balance). The data for 2001–2008 were analysed. Bartová et al. (2018) used the aggregate country-level data from Eurostat to measure the environmental efficiency and productivity change of the EU agriculture. The total agricultural output and greenhouse gas (GHG) emission were used as the desirable and undesirable outputs, respectively. The inputs included labour, land and fertilizers. The period of 2006–2015 was covered. The weak disposability technology, directional DEA and Malmquist–Luenberger productivity index were applied.

The literature analysis suggests that there have been studies dealing with the technical efficiency and productivity growth in the EU agriculture. However, to the best of our knowledge, there have been no studies performing variable-specific decomposition of the environmentally adjusted productivity growth at the country level. What is more, energy was often ignored as an input, or the relevant undesirable output (GHG emission) was not accounted for. In many of the earlier studies, the FADN data were used. These data do not allow for assessing energy inputs or environmental pressures in physical quantities. Therefore, this paper further embarks on the analysis of the energy efficiency and productivity growth in the EU agriculture based on the DEA and Luenberger productivity indicator.

3 | METHODS

The productive technology including the energy consumption and the resulting GHG emission is discussed in this section. The measurement of the energy efficiency and productivity relies on the SBM–DEA and Luenberger productivity indicator. The preliminaries for these measures are also discussed.

3.1 | Environmental production technology

The energy efficiency and productivity change can be measured by constructing the productive technology. In this paper, we follow the nonparametric approach. Let there be D decision-making units (DMUs) (countries) indexed by $d = 1,2,\ldots,D$. The environmental production technology for time period $t = 1,2,\ldots,T$ is defined in terms of input quantities $x^{d,t} \in R^I_+$, output quantities $y^{d,t} \in R^J_+$ and undesirable output quantities $z^{d,t} \in R^K_+$. The inputs are intentionally transformed into outputs (desirable ones) whereas the undesirable outputs are unintended (e.g., pollution). The environmental production technology for time period t (i.e., the contemporaneous technology) is defined in terms of the production possibility set:

$$P^t = \{ (x^t, y^t, z^t) x^t \text{ can produce } (y^t, z^t) \}, \tag{1}$$

where the notations of DMUs are dropped for convenience. The inputs include energy use, and the undesirable outputs include energy-related GHG emission. This allows considering energy efficiency. Then, the global technology (Pastor & Lovell, 2005), P, is defined as a convex hull spanning over the contemporaneous technologies:

$$P = \operatorname{conv}\left(\bigcup_{t=1}^{T} P^t \right). \tag{2}$$

One can also use the alternative definition by Kerstens, O'Donnell, and Van de Woestyne (2019), where no convexity is assumed when constructing the global (or meta-) technology.

The formal definitions outlined in Equations 1 and 2 can then be operationalized by assuming the specific type of the underlying technology. Assuming the nonparametric piecewise linear technology and assuming strong disposability of the undesirable outputs (Hailu & Veeman, 2001), approximation of P^t is obtained as follows:

$$P^t = \left\{ (x,y,z) \middle| \begin{array}{l} \sum_{d=1}^{D} \lambda_d x_i^{d,t} \le x_i, \sum_{d=1}^{D} \lambda_d y_j^{d,t} \ge y_j, \sum_{d=1}^{D} \lambda_d z_k^{d,t} \le z_k, \\ \lambda_d \ge 0, d = 1,2,\ldots,D, i = 1,2,\ldots,I, j = 1,2,\ldots,J, k = 1,2,\ldots,K \end{array} \right\}, \tag{3}$$

where λ is a $1 \times D$ vector of intensity variables. Note that this is a constant return to scale technology. Variable returns to scale technology can be obtained by imposing $\sum_{d=1}^{D} \lambda_d = 1$. The global piecewise linear technology is, therefore, given as

$$P^t = \left\{ (x,y,z) \middle| \begin{array}{l} \sum_{t=1}^{T} \sum_{d=1}^{D} \lambda_d^t x_i^{d,t} \le x_i, \sum_{t=1}^{T} \sum_{d=1}^{D} \lambda_d^t y_j^{d,t} \ge y_j, \sum_{t=1}^{T} \sum_{d=1}^{D} \lambda_d^t z_k^{d,t} \le z_k, \\ \lambda_d^t \ge 0, d = 1,2,\ldots,D, i = 1,2,\ldots,I, j = 1,2,\ldots,J, k = 1,2,\ldots,K, t = 1,2,\ldots,T \end{array} \right\}. \tag{4}$$

In this paper, the strong disposability is assumed for the undesirable outputs. This implies that the undesirable output (energy-related GHG emission) can be scaled without considering the changes in the desirable output. This can be achieved by increasing the share of renewables in the energy mix. The other approaches for modelling the disposability are possible (see, e.g., Fang, 2020).

3.2 | Distance function and efficiency

The productive technology can also be defined in terms of the directional distance function (Chung, Färe, & Grosskopf, 1997). The directional distance function is formally defined as

$$D^t(x,y,z;g_y,g_z) = (\max \beta \mid (x, y + \beta g_y, z - \beta g_z) \in P^t), \tag{5}$$

where g_x and g_y are the directional vectors defining the direction of the movement towards the efficiency frontier. In this instance, assuming the directional vectors are nonnegative ones, the increase in the desirable outputs and contraction of the undesirable ones is modelled. Fully efficient DMUs show $D^t(\cdot) = 0$. The index t in Equation 5 indicates that the distance is measured relative to the contemporaneous frontier for time period t. The global technology can also be used as a reference. In the latter case, the index for t is dropped.

The directional distance function in Equation 5 can be further generalized by allowing nondirected movement and adjustment of all the variables (inputs, outputs and undesirable outputs). These assumptions render the nonradial directional distance function (Zhou, Ang, & Wang, 2012):

$$D^t(x,y,z;g) = (\max w\beta \mid (x,y,z) + g \cdot \operatorname{diag}(\beta) \in P^t), \tag{6}$$

where w is the normalized vector of weights associated with the variables used and diag(·) is the operator for converting a $n \times 1$ vector into the diagonal line of a $n \times n$ square matrix (in general case). Färe and Grosskopf (2010b) showed that Equation 6 can be formulated as an SBM–DEA problem. In this instance, the SBM (Miao et al., 2019; Tone, 2001; Zhou et al., 2012) can be applied to measure the inefficiency of the dth DMU (country):

$$
\begin{aligned}
&D^t\left(x^{d,t}, y^{d,t}, z^{d,t}; g\right) = \max \frac{1}{3}\left(\frac{1}{I}\sum_{i=1}^{I}\frac{s_i^x}{g_x^i} + \frac{1}{J}\sum_{j=1}^{J}\frac{s_j^y}{g_y^j} + \frac{1}{K}\sum_{i=1}^{I}\frac{s_k^z}{g_z^k}\right) \\
&\text{s.t.} \\
&\sum_{d=1}^{D}\lambda_d x_i^{d,t} + s_i^x = x_i^{d',t}, i = 1,2,\ldots,I, \\
&\sum_{d=1}^{D}\lambda_d y_j^{d,t} - s_j^y = y_j^{d',t}, j = 1,2,\ldots,J, \\
&\sum_{d=1}^{D}\lambda_d z_k^{d,t} + s_k^z = z_k^{d',t}, k = 1,2,\ldots,K, \\
&\lambda_d \geq 0, d = 1,2,\ldots,D, \\
&s_i^x, s_j^y, s_k^z \geq 0,
\end{aligned}
\tag{7}
$$

where s^x, s^y and s^z are the slacks associated with inputs, outputs and undesirable outputs, respectively; and g_x, g_y and g_z are the directional vectors for inputs, outputs and undesirable outputs, respectively. In our case, we use the proportional distance and set the directional vector to be equal to the observed quantities of the input/output variables. The linear programming problem in Equation 7 uses P^t as the reference technology. The global technology can be used by adding all the observations to the left-hand side of the constraints (as in Equation 4). In the latter case, the resulting distance function is denoted as $D(\cdot)$.

3.3 | Productivity change

The measures of inefficiency defined in Section 3.2 allow one to assess the performance gaps for a given time period. The dynamics in the performance is also an important issue for decision makers. Acknowledging the intertemporal variation in the underlying productive technology, the measures of efficiency need to be measured against different reference technologies. The change in the performance over time can be represented by the productivity change measures.

As Section 3.1 put it, we resort on the concept of the global technology in this paper. Therefore, the global Luenberger productivity indicator (Wang et al., 2016; Beltrán-Esteve, Giménez, & Picazo-Tadeo, 2019) is applied to measure and decompose the productivity change for the agricultural sectors of the EU member states. The productivity change during $t-(t+1)$ for country d is measured as

$$LP_d^{t,t+1} = D\left(x^{d,t}, y^{d,t}, z^{d,t}; g^t\right) - D\left(x^{d,t+1}, y^{d,t+1}, z^{d,t+1}; g^{t+1}\right), \tag{8}$$

where $D(\cdot)$ is the distance function relative to the global frontier as explained in Section 3.2. Therefore, positive (resp. negative) values of LP imply positive (resp. negative) productivity growth as an observation approaches the global frontier over time.

The Luenberger productivity indicator can be further broken down in to the two components representing technical progress (TP) and efficiency change (EC). The efficiency change is measured by considering the change in the distance to the contemporaneous frontier over time:

$$EC_d^{t,t+1} = D^t\left(x^{d,t}, y^{d,t}, z^{d,t}; g^t\right) - D^{t+1}\left(x^{d,t+1}, y^{d,t+1}, z^{d,t+1}; g^{t+1}\right). \tag{9}$$

Thus, EC shows whether a certain country improved its performance relative to the contemporaneous frontier. Generally, reallocation of resources and improved managerial practices can affect the EC. The distance to the frontier is measured at different time points (for given input/output combinations). Taking the difference of these distances shows how much the performance gap changes over time due to observation-specific performance. Positive (resp. negative) values of EC indicate that an observation improved (resp. reduced) its efficiency. In general, the positive EC can be observed due to the improved farming and managerial practices when resources are properly used in the production process.

The technical progress is defined as the change in the best performance gap from time period t to time period t+1:

$$
\begin{aligned}
TP_d^{t,t+1} &= TG_d^t - TG_d^{t+1} \\
&= \frac{1}{2}\left[D^{t+1}\left(x^{d,t}, y^{d,t}, z^{d,t}; g^t\right) - D^t\left(x^{d,t}, y^{d,t}, z^{d,t}; g^t\right)\right] \\
&- \left[D^{t+1}\left(x^{d,t+1}, y^{d,t+1}, z^{d,t+1}; g^{t+1}\right) - D^t\left(x^{d,t+1}, y^{d,t+1}, z^{d,t+1}; g^{t+1}\right)\right],
\end{aligned}
\tag{10}
$$

The TP indicates whether the best practice is improving over time in the region of a certain observation (country). The movement in the frontier is measured at the input/output combinations (those for time periods t and t+1). The outward movement of the frontier corresponds to increasing productivity at the best-practice observations and is represented by positive TC. A negative value is observed in case the frontier moves inward. The production frontier movement is achieved by means of innovations and is determined by the innovating DMUs (countries).

The global Luenberger indicator based on the SBM–DEA will be applied to the case of the EU agriculture. This allows for tracking the contributions to productivity growth associated with different inputs and outputs. In particular, we are interested in the contributions by energy consumption and energy-related GHG emission. The use of the global technology will allow avoiding the problem of infeasibilities.

4 | DATA

The productive technology for the agricultural sectors of the selected EU member states includes the standard variables used in the agricultural production analysis. The country-level data are used. The data come from Eurostat (Economic Accounts for Agriculture and Energy Balance). The data are available from the Eurostat website (European Commission, 2020). The inputs include energy consumption in terajoules, fixed capital consumption in purchasing power standards, labour in the annual working units and utilized agricultural land in hectares. The desirable output is the total agricultural output in purchasing power standards. The monetary variables are measured in the constant prices of 2005 to ensure comparability. The undesirable output is the energy-related GHG emission.

5 | RESULTS

This section describes the data used for the EU agriculture in the context of productivity analysis. The results on inefficiency and productivity change are provided. The level of inefficiency indicates the position (performance) of individual countries with respect to the global frontier at a certain time period, whereas the productivity change measures the intertemporal dynamics and allows for decomposition of changes.

5.1 | Dynamics in efficiency

The inefficiency[2] can be measured with respect to the global frontier. Assuming constant returns to scale (CRS), the changes in the global inefficiency are related to changes in the productivity. The additive nature of the SBM of inefficiency (cf. Equation 7) allows one to isolate the contributions of individual inputs and outputs towards the overall inefficiency.

The inputs and undesirable output (energy-related GHG emission) show nonzero inefficiencies, whereas the inefficiency score for the desirable output (agricultural output) is zero. This implies that the improvements in agricultural productivity in the EU are mostly related to the increasing resource efficiency and improving environmental performance. The average values of the variable-specific CRS inefficiency scores are further analysed in order to identify the key trends in inefficiency along with contributions of the individual variables.

The dynamics in the inefficiency scores related to the inputs is given in Figure 1. Obviously, the inefficiency due to input use declined over time for the agricultural sectors of the selected EU countries. The gains in efficiency are particularly evident following year 2004. Indeed, this year corresponds to the expansion of the EU and application of improved farming practices in the new member states. The inefficiency due to the energy-related GHG emission (Figure 1) also declined during 1995–2016 in the agriculture of the selected EU member states. Therefore, the resource efficiency and environmental performance have both improved in the EU agriculture. The fluctuations in the GHG emission efficiency come from the two main sources: changes in the energy consumption and energy mix (against the output level). In this case, the climatic conditions and price recovery play the most important roles as these determine the levels of energy inputs and the utilization of the factor inputs (including energy input).

The results depicted in Figure 1 suggest certain differences existing among the input and output variables in terms of their contributions to the overall inefficiency. Therefore, Table 2 reports the average values of inefficiencies along with the trend coefficients (which correspond to the stochastic rates of change). As one can note, the two variables relevant to energy resources—energy use and energy-related GHG emission—show the highest mean inefficiencies

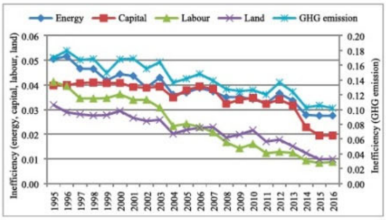


FIGURE 1 Inefficiency for the inputs and energy-related greenhouse gas (GHG) emission (averages for the selected countries)

over 1995–2016. Therefore, the energy efficiency improvement remains a topical issue for the EU agriculture in spite of the positive movements observed throughout the period covered. The energy inefficiency is distinct from the other input variables in that the rate of change declines going from the period of 1995–2003 (−0.13 p.p.) to that of 2004–2016 (−0.08 p.p.), whereas the opposite pattern is observed otherwise.

The results in Table 2 corroborate several findings. First, all the inputs and outputs show negative trends over 1995–2016, which imply decreasing inefficiency. Second, the average values for 2004–2016 are lower than those for 1995–2003. Third, the two variables related to energy resources (energy use and energy-related GHG emission) show the highest inefficiency (mean values of 3.84% and 14.21%) and are followed by capital (3.51%), labour (2.37%) and land (2.18%). Note that the inefficiency associated with the desirable output is zero.

Turning to the country-wise analysis, Figure 2 presents the mean inefficiency scores across the EU member states. Latvia, Poland, Estonia and Finland appear as the countries with the lowest levels of agricultural efficiency, whereas the Netherlands, Bulgaria, Belgium and France seem to be the most efficient countries. The decomposition of the inefficiency scores shows that the energy use is responsible for the highest share of the overall inefficiency in Austria, Czechia, Estonia, Hungary, Lithuania, the Netherlands, Romania and Slovakia. As regards the inefficiency due to the energy-related GHG emission, Austria, Slovakia and Lithuania show relatively low contributions to the overall inefficiency, whereas Bulgaria, France and Slovenia are relatively inefficient in this regard. Therefore, countries with cleaner energy mix can be associated with lower GHG inefficiency in spite of being energy inefficient (this is the case for Austria, Slovakia and Lithuania). The opposite pattern holds for countries, which are energy efficient yet the energy mix induces relatively high emission inefficiency.

The strategic measures envisaged in the Common Agricultural Policy (CAP) seek to ensure the convergence of the agricultural performance within the EU. In order to test the presence of the convergence in the agricultural efficiency, we follow the concept of the σ-convergence, that is, we check whether the spread in the

[2] The SBM applied in this paper (Equation 7) measures inefficiency (score) that is based on the slacks for inputs and outputs. Therefore, we speak of inefficiency when discussing the empirical results. Note that inefficiency is inversely related to efficiency. Therefore, zero inefficiency implies full efficiency.

TABLE 2 The dynamics in inefficiency for the sample of the European Union (EU) member states, 1995–2016

Time span	Energy	Capital	Labour	Land	GHG emission
Average (%)					
1995–2016	3.84	3.51	2.37	2.18	14.21
1995–2003	4.52	4.00	3.55	2.79	16.57
2004–2016	3.38	3.16	1.55	1.76	12.58
Trend (rate of change) (p.p.)					
1995–2016	−0.10	−0.09	−0.17	−0.09	−0.34
1995–2003	−0.13	−0.01	−0.10	−0.06	−0.16
2004–2016	−0.08	−0.15	−0.14	−0.10	−0.33

Abbreviation: GHG, greenhouse house.

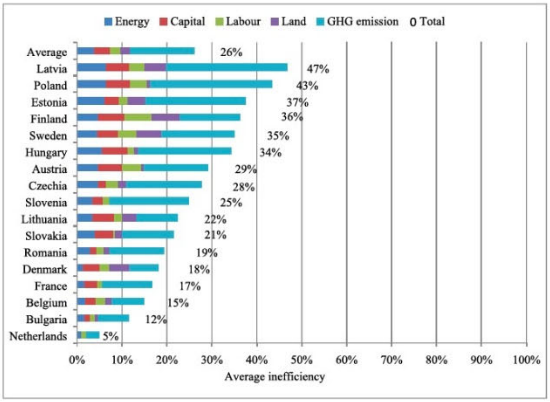


FIGURE 2 The average global inefficiency and its decomposition across the countries, 1995–2016. GHG, greenhouse gas

inefficiency measures declines over time across the EU member states. The results are provided in Figure 3.

All the inputs and outputs showed increasing divergence in terms of the associated efficiency scores. The results imply that inefficiency related to energy consumption and the corresponding GHG emission showed the lowest degree of divergence. Therefore, inefficiency of energy consumption has seen an increasing polarization in the EU agriculture (across the member states), yet it was lower than that observed for inefficiency of labour or land. Especially, the period of 2014–2016 marked an increasing divergence in the energy and GHG emission inefficiency. These changes may have been due to the climatic fluctuations in some of the EU member states, which lead to divergence in the energy use and the related inefficiency.

5.2 | Productivity change

Besides the global inefficiency, which measures the performance of each country at a certain time point, the productivity change can be analysed to obtain the information on the changes in the input consumption and output production over the time. The measures of productivity can be decomposed with respect to the sources of productivity growth, which provides additional insights in the dynamics in the EU agriculture. Due to the additive structure of the SBM, the Luenberger productivity indicator can also be decomposed with regard to the inputs and outputs.

The average values of the Luenberger productivity indicator and its components for the group of selected countries are depicted in Figure 4. The average annual productivity growth is 0.79% for the period of 1995–2016. As Figure 4a suggests, the frontier movements occurred rather frequently, and these movements took different directions. The cumulative effect of the technical progress remained negative up until 2007. The cumulative efficiency change effect remained positive throughout most of the period covered, yet certain years saw a decline in the efficiency. These changes are related climate shocks and market fluctuations, which suppress incentives to exploit the capital acquired to a full extent. In general, the

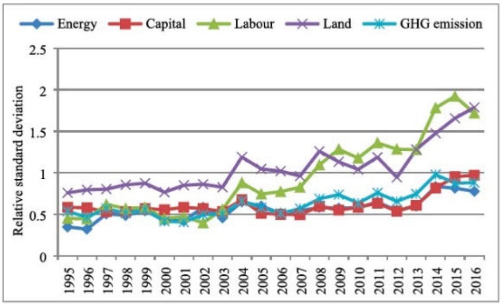
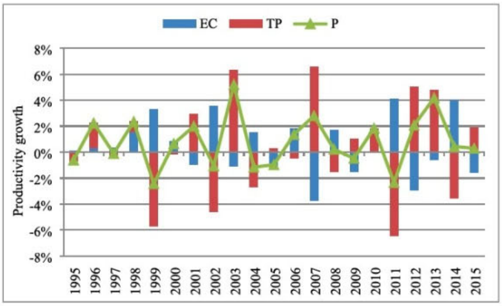
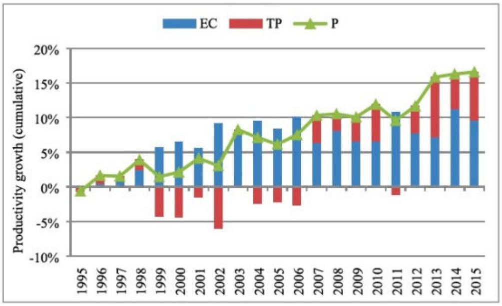


FIGURE 3 The σ-convergence of inefficiency in the European Union (EU) member states, 1995–2016. GHG, greenhouse gas



(a) – decomposition of the productivity change



(b) – decomposition of the cumulative productivity change

FIGURE 4 Decomposition of the Luenberger productivity indicator (base years are shown). (a) Decomposition of the productivity change and (b) decomposition of the cumulative productivity change. EC, efficiency change; TP, technical progress contribution of the efficiency change was 0.46% p.a. and that of the technical progress was 0.33% p.a. Therefore, the individual countries managed to catch-up the frontier and the resources tended to be allocated more efficiently over time across the selected EU countries. The cumulative average productivity growth over the period of 1995–2016 was 16.6% with 9.6% attributed to the efficiency change and 7% to the technical progress. As Figure 4b suggests, the cumulative productivity kept following a positive trend throughout 1995–2016.

As it is the case with the efficiency of the EU agriculture, the productivity growth is also different across the subperiods of 1995–2003 and 2003–2016. The average cumulative productivity growth for the period of 1995–2003 is 2.15%, whereas the corresponding value for 2003–2016 is 10.9%. The technical progress shows much higher contribution towards the growth in the overall productivity over the period of 2003–2016 if contrasted to the earlier subperiod.

The productivity growth can be decomposed with regard to the input/output variables. Such an approach allows one to identify the key contributors towards the productivity growth along with the major obstacles in the EU agriculture. As both the energy use and energy-related GHG emission are included in the analysis, the associated productivity growth measures can bring more light on the energy and environmental productivity. The decomposition is carried at the country level (Figure 5).

The highest productivity gains are observed in Lithuania, Denmark, Belgium and Romania. Among those countries, Lithuania shows the highest inefficiency (cf. Figure 2). The productivity growth related to GHG emission dominates the contributions by the input/output variables in Lithuania, Denmark, Belgium, Romania, Poland, Austria, France, the Netherlands, Hungary and Estonia. These countries managed to reduce the energy-related GHG emission without decline in the output level of input consumption. This can be achieved by upgrade of the energy mix. The energy input is also an important contributor to the productivity growth across many of the countries analysed. The counties showing the highest contribution of the energy input towards the productivity growth include Lithuania, Belgium, Romania, Poland, Slovakia, the Netherlands, Estonia, Bulgaria and Sweden. In general, the average contribution to the productivity growth of energy, capital, labour and land ranges in between 0.1% and 0.15% p.a. The energy-related GHG emission shows the highest average contribution of 0.32%. Therefore, the EU member states have achieved substantial energy productivity gains during 1995–2016.

The productivity gains associated with the energy-related GHG emission are higher than those for the energy consumption. This implies that, besides energy conservation, the progress towards the cleaner energy has been maintained. However, there have been countries indicating unfavourable processes in regard to energy use and the related environmental impacts. For instance, Slovenia shows a slight decline in the agricultural productivity associated with the energy use. As regards the energy-related GHG emission, Czechia, Sweden and Slovenia showed a negative productivity growth. This implies that energy-related GHG emission increased in those countries at the given input and output levels.

The contribution of different inputs and outputs towards the productivity growth in the agricultural sectors of the selected EU Member States varies with time. The dynamics in the cumulative average contribution associated with each variable is depicted in Figure 6. Up until 2004, all the variables contributed equally to the growth in the agricultural productivity. However, the capital input remained the least important contributor throughout the period covered. Contribution by the energy-related GHG emission kept increasing (with certain fluctuations) throughout the whole period covered and, since 2002, has been the major contributor on the average. The labour input was associated with the second highest

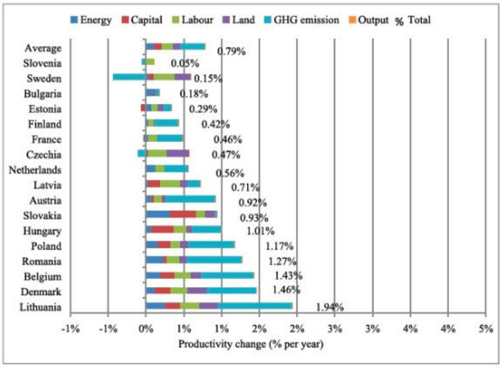


FIGURE 5 Decomposition of the productivity growth at the country level (average values for 1995–2016). GHG, greenhouse gas

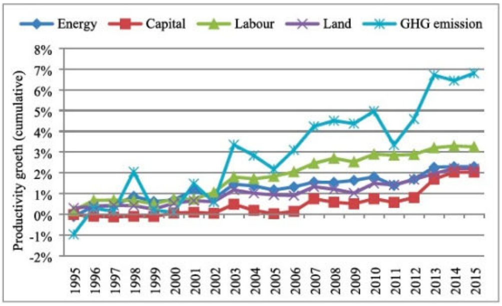


FIGURE 6 Dynamics in the cumulative average productivity growth associated with different inputs and outputs, 1995–2016 (base years are shown). GHG, greenhouse gas

contribution to productivity growth, and the energy consumption followed suit. Therefore, the energy-related GHG emission appeared to contribute more to the productivity growth than the energy input, and this pattern has persisted since 2002. This suggests that cleaner energy (as opposed to the energy conservation) has become a major factor pushing the environmentally sensitive productivity growth up in the EU agriculture.

The productivity change can be decomposed into the components of the efficiency change and technical progress (Section 3.3). The technical progress indicates the movement of the frontier in the direction of the input–output vector observed for a certain country. The further decomposition in regard to the individual inputs and outputs allows one to identify the drivers of technical progress. The country-level decomposition of the technical progress is provided in Figure 7. The largest movement in the frontier is observed for Romania, Slovenia, France and Slovakia (in between 1.27% p.a. and 0.93% p.a.). The negative change is observed for Finland, Poland and Latvia (in between −0.14% p.a. and −1.43% p.a.). The negative technical progress in terms of energy consumption (i.e., the increasing energy use for given level of desirable output and combination of inputs) is observed for Czechia, Sweden, Finland, Poland and Latvia. These countries along with Hungary also experience a negative technical change with regard to the energy-related GHG emission. Thus, these countries face an inward frontier movement indicating loss in energy productivity. The spillover of energy productivity measures should be ensured in the EU agriculture with focus on the aforementioned countries in order to avoid such undesirable processes.

The average contribution to the productivity growth by the *EC* is presented in Figure 8. As one can note, Poland and Latvia appears as the two countries showing the highest catch-up effect (more than 2% p.a.). Lithuania also shows a similar rate of growth (1.69% p.a.). The energy-related GHG emission appears as the major contributor to the

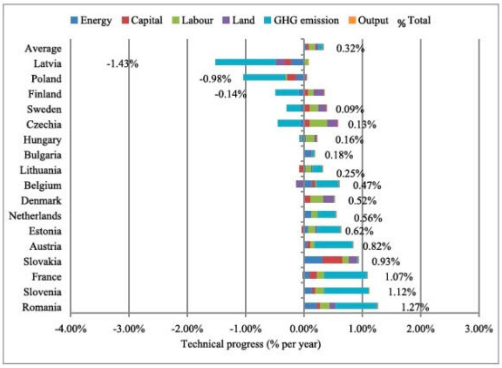


FIGURE 7 Decomposition of the technical progress at the country level (average values for 1995–2016). GHG, greenhouse gas

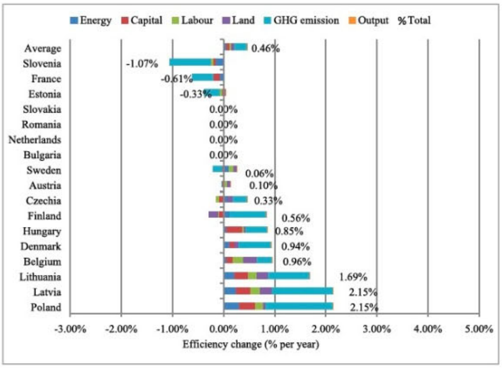


FIGURE 8 Decomposition of the efficiency change at the country level (average values for 1995–2016). GHG, greenhouse gas

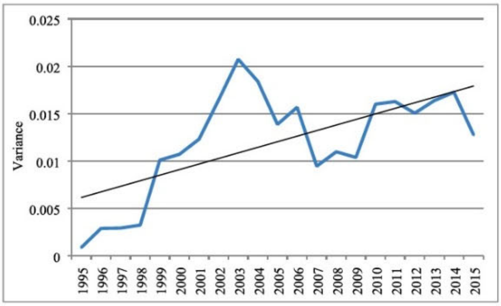


FIGURE 9 Variance of the cumulative productivity growth across the European Union (EU) member states, 1995–2016

EC. Energy also contributes positively in the case of the *EC* growth. However, some countries showed decline in the *EC* due to the energy-related GHG emission (Austria, Sweden, Estonia, France and Slovenia). These countries should be assisted in opting for the cleaner energy options in the agricultural sector. This can be partially achieved via the measures of the CAP.

If contrasted to the case of *EC*, *TP* shows higher contribution of the energy-related GHG emission. This suggests that the frontier countries experience higher productivity gains due to declining carbon intensity, whereas the catch-up in this regard is not as significant. Accordingly, the identification and transfer of the good practice in transition towards cleaner energy in agriculture remains important.

The negative *EC* growth is observed for Estonia, France and Slovenia. Indeed, this is mainly determined by the energy-related GHG emission and energy use (as discussed above). Especially, France and Slovenia requires improvements not only in the energy mix but also in the energy efficiency.

The convergence in the cumulative productivity growth is tested by calculating the variance (Figure 9). The variance went up during 1995–2004 and followed the U shape afterwards. Thus, the expansion of the EU is related to an increase in the productivity convergence.

The CAP of the EU should put more efforts in promoting cleaner energy as the results indicated that inefficiency scores associated with energy use lower than those associated with the energy-related GHG emission. In this context, the establishment of carbon market would also benefit in internalizing the pollution costs and increasing willingness to adopt cleaner energy technologies. At the macro level, the analysis of the carbon price remains important to identify the major directions for development and effectiveness of the support policies. The micro-level carbon accounting practices are also required in order to ensure proper monitoring and accounting. In any case, a wider discussion on the effects of the energy use on the climate change is needed in the EU agriculture.

6 | CONCLUSIONS

The use of resources and environmental impacts of the economic activities have received more attention in the policy making and research due to the increasing concerns of the climate change. The agriculture has also been affected by the climate change, among other factors. Therefore, this paper attempted to analyse the dynamics in the energy efficiency and productivity across the agricultural sectors of selected EU member states.

In order to isolate the effects of the energy use and account for contributions of the other production factors, the frontier-based productivity analysis framework was adopted. The slacks-based model and Luenberger productivity indicator were unified in order to decompose the measures of efficiency and productivity change. The productivity growth was decomposed into efficiency change and technical progress based on the global productive technology.

Energy use and energy-related GHG emission appeared as important contributors to the overall inefficiency. As regards the inefficiency due to the energy-related GHG emission, Belgium, Austria Slovakia, Denmark, Sweden, Finland and Lithuania showed relatively low contributions to the overall inefficiency (37%–49% of the overall inefficiency), whereas France, Romania, Slovenia, Czechia, Hungary, Estonia and Poland were relatively inefficient in this regard (60%–70% of the overall inefficiency). Therefore, countries with cleaner energy mix can be associated with lower GHG inefficiency in spite of being energy-inefficient (this is the case for Austria, Slovakia and Lithuania). The opposite pattern holds for countries that are energy-efficient, yet the energy mix induces relatively high emission inefficiency. In general, the energy-related inefficiency declined over 1995–2016.

The productivity growth was decomposed with respect to the input/output variables and the sources of growth (i.e., efficiency change and technical progress). The average annual productivity growth of 0.79% was obtained for the selected countries during 1995–2016. The highest productivity gains were observed in Lithuania, Denmark, Belgium and Romania (1.27%–1.94% per year). The productivity growth related to GHG emission dominated the contributions by the input/output variables in Lithuania, Denmark, Belgium, Romania, Poland, Austria, France, the Netherlands, Hungary and Estonia. These countries managed to reduce the energy-related GHG emission without decline in the output level of input consumption. This can be achieved by upgrade of the energy mix. Therefore, the EU member states have achieved substantial energy productivity gains during 1995–2016.

The analysis of convergence suggested that there was a divergence in productivity growth during 1995–2003, whereas the period of 2003–2016 saw an uncertain direction. In the case of inefficiency scores, the divergence tended to increase with time. However, the variation of the inefficiency due to energy use and GHG emission tended to show the lowest variation. Therefore, it is still important to ensure the convergence of the EU member states in terms of the agricultural efficiency and productivity.

The results of the study can be useful in guiding the climate-smart and energy-efficient agriculture in the other regions of the world. First, the results indicate that environmental productivity can be increased in both developed and developing countries. Therefore, support should be provided for countries with backward energy mix in order to promote cleaner energy use in agriculture. The particular cases can be identified (e.g., Sweden and Slovenia in this study) as peers for modelling agricultural development in the other regions. Finally, the model applied in this study can be integrated into decision-making systems for energy-efficient agricultural development.

This research can be continued by including more recent data for economic and environmental performance of the EU member states. In addition, the assumptions regarding disposability of the undesirable output could be altered. This would allow exploring the effects of different theoretical models on the empirical results and policy implications.

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Achievements of the European Union member states toward the development of sustainable agriculture: A contribution to the structural efficiency approach

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ABSTRACT

The ranking of decision-making units can be performed by measuring their efficiency. However, the discriminatory power of efficiency measures is sometimes compromised, and complete rankings are not attained. Additionally, environmental performance must be considered when assessing the sustainability of operations. This paper applies the "average contribution to structural efficiency" index to measure the environmental performance of the European Union Member States' agricultural sectors. The contribution index considers all of the possible combinations of observations when assessing states' environmental performance. This process allows for a complete ranking of the countries under consideration. The agricultural performance of Bulgaria, Denmark, France, the Netherlands, Romania, Slovakia and Slovenia, as measured by the conventional data envelopment analysis, approached the production frontier. Therefore, these countries could not be ranked based on the conventional data envelopment analysis model. The application of the contribution index showed that Romania, the Netherlands, Bulgaria, Slovakia and Slovenia were ranked as the best-performing countries. In addition, France and Belgium showed positive contributions to structural efficiency, although they were not classified as efficient countries. Therefore, cooperation with these countries would allow other countries to exploit their agricultural resources in a more productive and sustainable manner.

1. Introduction

The development of the agricultural sector has resulted in multiple benefits for society. The increasing availability of food has allowed people to overcome the problems associated with inappropriate levels of food security and affordability. Increasing productivity has also allowed rural populations to improve their living standards. However, the increasing intensity of input application in agricultural production has also caused concerns over the sustainability of the agricultural sector. To this end, there is a need for integrated frameworks accounting for different dimensions of agricultural development Fuglie (2018). presented an analysis of agricultural productivity change across the world. In particular, the industrialized countries have shown the highest rates of growth in labor productivity (along with a decline in labor input) and lowest growth in agricultural output per land area. The measurement of agricultural productivity growth and efficiency has been performed across various regions with a focus on environmental performance (Deng and Gibson, 2019; Pan et al., 2021).

In the case of the European Union (EU), the agricultural sector has been developing both quantitatively and qualitatively since the end of World War II. Over the last three decades, new EU Member States from the postsocialist bloc have entered the global agricultural market as independent players (Rozelle and Swinnen, 2004). This context has induced a number of socioeconomic transformations across regions, sectors and farm size groups Moutinho et al. (2018). applied stochastic frontier analysis to assess the efficiency of European agriculture.

The measurement of agricultural efficiency and productivity growth requires proper methodological tools. Neoclassical production theory offers the production frontier approach for gaging productive performance. The frontier techniques can be applied for ranking decision-making units (DMUs) in terms of multiple indicators. Data envelopment analysis (DEA) is a nonparametric frontier technique that allows for the estimation of production frontiers without assuming a particular functional form Liu et al., (2013). This approach is appealing in that it

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relies not only on mathematical aggregation but also on neoclassical economic theory (Afriat, 1972; Orea and Zofio, 2019). DEA has been applied in agricultural economics research (Lozano and Adenso-Diaz, 2021). However, DEA can be impeded by the "curse of dimensionality" since efficiency levels increase with increasing numbers of inputs and outputs relative to the number of observations.

The attempts to offer improved discrimination of DMUs in terms of technical efficiency have included super efficiency DEA and cross-efficiency DEA (Doyle and Green, 1994). Super efficiency DEA was proposed by Andersen and Petersen (1993) as a tool for addressing situations in which the ranking of the DMUs cannot be performed effectively due to limited sample sizes. In particular, efficient observations can be attributed to efficiency scores indicating their performance with regard to other DMUs. Super efficiency DEA, however, features certain drawbacks since there can be infeasibilities in the oriented models, and the measures of efficiency are relative to the different frontiers for each observation (i.e., the lack of transitiveness); see Zhu et al. (2019) for a discussion of super efficiency DEA and the related approaches.

Concerns over climate change require addressing the energy-economy-environment nexus (Ye et al., 2018). DEA can also be applied to assess environmental performance (Zhou et al., 2008; Sueyoshi et al., 2017; Toma et al., 2017). This goal can be achieved by assuming a certain environmental production technology and adopting efficiency measures capturing performance gaps (Ma et al., 2019; Zoriehhabib et al., 2021). The problem of dimensionality further increases in this instance with additional variables (viz., undesirable outputs are included in the model). Thus, there is a need to reconcile the quest for environmental performance analysis with complete ranking of DMUs.

To rank the efficiency of DMUs, their impact on structural efficiency can be assessed following Zhu et al. (2019, 2020) Soltani et al. (2021). proposed a multidirectional efficiency approach for ranking DMUs. Structural efficiency refers to the efficiency of the aggregate production unit, indicating the possible reallocation of resources (Karagiannis, 2015). The possible combinations of DMUs are considered to establish the aggregate technology. The contributions to structural efficiency are then evaluated in the spirit of the Shapley value (Shapley, 1953).

In this paper, we seek to apply the marginal contribution to the structural efficiency approach for agricultural sectors from a sample of the EU Member States. This approach has been used for the banking sector (Zhu et al., 2020), yet no applications for agricultural efficiency have been available thus far to the best of our knowledge. Environmental production technology is assumed to represent agricultural activity. The proposed approach allows for a complete ranking of the EU Member States in terms of the performance of their agricultural sectors. The data on economic activity and energy-related greenhouse gas (GHG) emissions are considered.

The paper proceeds as follows: Section 2 presents the methods used for the analysis, Section 3 presents the application of the proposed approach for the agricultural sectors of the EU Member States, and Section 4 concludes the study.

2. Methods

This research relies on the conventional measures of efficiency and the contribution index to structural efficiency. In the latter case, radial DEA is applied for the modified set of DMUs (i.e., production plans). The measures of efficiency, aggregation of the DMUs, and calculation of the contribution index are described in this section.

2.1. Production technology and efficiency

This paper focuses on both the economic and environmental outcomes of agricultural production. Therefore, environmental production technology (EPT) is used for the analysis. The production technology is then defined as:

$$T = \{(x, y, b) : x \text{ can produce } (y, b)\} \tag{1}$$

where x, y and b represent the vectors of input, desirable output and undesirable output quantities, respectively. Convex piecewise linear nonparametric technology can be applied to approximate T. As we address the EPT, weak disposability between the desirable and undesirable outputs can be assumed (Färe et al., 1989). Assuming that there are K decision-making units (DMUs) indexed over $k = 1, 2, \ldots, K$ that consume I inputs to produce both J desirable outputs and L undesirable outputs, the nonparametric representation of T is given as:

$$\widehat{T} = \left\{ (x,y,b) \in \Re^{I+J+L} : \begin{array}{l} \sum_{k=1}^{K} \lambda_k x_{ki} \leq x_i, \sum_{k=1}^{K} \lambda_k y_{kj} \geq y_j, \sum_{k=1}^{K} \lambda_k b_{kl} = b_l, \lambda_k \geq 0, \\ i=1,2,\ldots,I, j=1,2,\ldots,J, k=1,2,\ldots,K, l=1,2,\ldots,L \end{array} \right\} \tag{2}$$

where λ_k are the intensity variables that define the production frontier in terms of the observed production plans. The technology provided in Eq. (2) ensures constant returns to scale.

Cheng and Zervopoulos (2014) proposed the generalized directional distance function (DDF), which measures efficiency with respect to technology established in Eq. (2). In this case, one may choose the direction (i.e., inputs, desirable outputs, undesirable outputs) that should be followed when adjusting the observed production plan to approach the production frontier. Note that the points on the production frontier operate at full efficiency.

Let us consider an arbitrarily chosen DMU $k' \in k = 1, 2, \ldots, K$. We consider two cases of efficiency measurement. First, we apply output-oriented directional DEA (Cheng and Zervopoulos, 2014):

$$\begin{aligned} & \rho_{k'} = \min \frac{1}{1 + \frac{1}{J+L}\left(\sum_{j=1}^{J} \beta g_j / y_{k'j} + \sum_{l=1}^{L} \beta g_l / b_{k'l} \right)} \\ & s.t. \sum_{k=1}^{K} \lambda_k x_{ik} \leq x_{k'i}, i = 1, 2, \ldots, I, \\ & \sum_{k=1}^{K} \lambda_k y_{jk} \geq y_{k'j} + \beta g_j, j = 1, 2, \ldots, J, \\ & \sum_{k=1}^{K} \lambda_k b_{lk} = b_{k'l} - \beta g_l, l = 1, 2, \ldots, L \\ & \lambda_k \geq 0, k = 1, 2, \ldots, K, \end{aligned} \tag{3}$$

where $\rho_{k'} \in (0, 1]$ is the efficiency score for a certain DMU k'. The efficiency score of unity indicates full efficiency, and it decreases with increasing inefficiency. In our paper, we use the proportional output DDF and set $(g_j, g_l) = (y_{k'j}, b_{k'l}), j = 1,2,\ldots,J$, and $l = 1,2,\ldots,L$. In general, we seek to contract the undesirable outputs along with an increase in the desirable outputs. In our case, it corresponds to increasing agricultural output alongside a decline in energy-related GHG emissions in the agricultural sectors.

The ranking of the EU Member States with respect to the performance of their agricultural sectors requires certain adjustments since many countries could be attributed with full efficiency due to the number of input/output variables and sample sizes. To test the possibility of ranking based on the super efficiency DEA, we also apply the super efficiency version of Eq. (3):

$$\rho_{k'}^{S} = \min \frac{1}{1+\frac{1}{J+L}\left(\sum_{j=1}^{J}\beta g_j/y_{k'j}+\sum_{l=1}^{L}\beta g_l/b_{k'l}\right)}$$
$$s.t. \sum_{k=1}^{K}\lambda_k x_{ik} \leq x_{k'i}, i = 1,2,...,I,$$
$$\sum_{k=1}^{K}\lambda_k y_{jk} \geq y_{k'j} + \beta g_j, j = 1,2,...,J, \tag{4}$$
$$\sum_{k=1}^{K}\lambda_k b_{lk} = b_{k'l} - \beta g_l, l = 1,2,...,L$$
$$\lambda_k \geq 0, k = 1,2,...,K, \lambda_{k'} = 0.$$

This equation implies that efficient observations are excluded from the reference set. Therefore, the efficiency score becomes unbounded, i.e., $\rho_{k'}^{S} \in (0, +\infty)$. In particular, the efficient DMUs will be given efficiency scores higher than unity, indicating the degree to which their desirable output production (resp. undesirable output generation) can be contracted (resp. expanded) to reach the efficiency frontier based on the originally inefficient observations.

2.2. Aggregate technology and contribution to structural efficiency

To assess the performance of the EU Member States' agriculture and ensure complete rankings, we suggest applying the contribution index approach (Zhu et al., 2019). Specifically, we construct different combinations of DMUs to check the possible gains in efficiency by adding a DMU under consideration to these combinations.

Let there be set T^D comprising K DMUs. These DMUs can be further aggregated into arbitrary observations $\xi(A)$ or aggregate DMUs, where A is a subset of T^D, i.e., $A \subseteq T^D$. Therefore, a certain aggregate DMU is defined as

$$\xi(A) = \left(\sum_{k\in A} x_k, \sum_{k\in A} y_k, \sum_{k\in A} b_k\right) \in \Re^{I+J+L}. \tag{5}$$

For technology involving K DMUs, there are $2^K - 1$ possible instances of A (excluding the empty set). To calculate the average contribution to the aggregate efficiency, one considers all of the possible instances of A and the resulting aggregate DMUs:

$$T^E = \{\xi(A)|A \subseteq T^D\}. \tag{6}$$

The DEA model given in Eq. (3) is then implemented for a certain DMU $k' \in k = 1,2,...,K$ with $T_{k'}^{E} = \{\xi(A)|A \subseteq T^D \backslash k'\}$ serving as the reference set. Thus, one must solve $2^{K-1} - 1$ problems for each DMU to compute the average contribution to structural efficiency. Specifically, Zhu et al. (2019) proposed the following average contribution index:

$$I_{k'}^{C} = \frac{1}{2^{K-1}-1} \sum_{A\subseteq T^D\backslash\{k'\}, A\neq\emptyset} \frac{\rho(A\cup k')}{\rho(A)}, \tag{7}$$

where $\rho(\cdot)$ is the efficiency score for the aggregate DMU including or excluding DMU k' based on Eq. (3). $I_{k'}^{C} > 1$ indicates that DMU k' positively contributes to the structural efficiency. The values less than unity indicate that the production plan observed for DMU k' does not improve structural efficiency. In our case, we can identify the countries that use the inputs in the most productive manner ensure less intensive environmental pollution due to energy consumption.

3. Results

3.1. Data

We apply the data for EU agriculture at the country level, allowing us to identify the differences in agricultural sustainability and its dynamics across different countries and times. In this research, we do not include some South European countries due to differences in the output structure (some countries are also excluded due to data availability). The time period covered is 1995–2016. While the choice of the time span is less restricted from the viewpoint of the old EU Member States, there have been certain considerations regarding the new EU Member States. Specifically, the Central and Eastern European (CEE) countries faced postcommunist transformations in the early 1990s. As a result, the agricultural sector saw increased volatility of the output level due to abandonment of the backward capacity and the switch from collective to family farming. In addition, data accuracy deteriorated during the transformations. Therefore, we assume that the choice of 1995 as the beginning point allows for a more reasonable analysis in light of the socioeconomic transformations pertinent to the EU countries. The end point of the time span is restricted by the data for the base year of 2005.

The desirable output is the total agricultural output. It is measured in Purchasing Power Standards (PPS) based on the constant prices of 2010. The undesirable output is the energy-related GHG emissions (in tons of CO_2 equivalent). Thus, we relate economic activity to the environmental pressures induced by the energy mix applied in the agricultural sector. This point is important in the sense that the EU CAP and country-specific measures are implemented to manage climate change and sustainable energy development. The inputs include:

- Agricultural land area (hectares);
- Labor input (annual work units equal to 2036 working hours);
- Fixed capital consumption (PPS); and
- Final energy consumption (metric tons oil equivalent).

The data come from the Eurostat database (Eurostat, 2020), primarily from the energy balance and agricultural statistics.

3.2. Efficiency and contribution index

The performance of the EU agricultural sector is analyzed at the country level within each year. Therefore, the production frontiers are established for each time period. Conventional efficiency measures are first applied to assess the degree of efficiency in EU Member States. The results for the output-oriented DEA model (radial measurement) in the assumption of constant return to scale (CRS) are provided in Table 1. These efficiency scores are obtained via Eq. (3) by setting $(g_j, g_l) = (y_{k'j}, b_{k'l})$. As one can note, the objective function in Eq. (3) contains the β variables indicating inefficiency along the direction set by vector g in the denominator. In the case of full efficiency, $\beta = 0$; thus, the efficiency score equals unity. In the present setting, the efficiency score represents the factor by which the output (both desirable and undesirable) should be adjusted (toward different directions).

As one can note, seven countries appeared fully efficient during 1995, and this number increased to 11 in 2005. Five countries remained fully efficient in 2016. Countries showing full efficiency throughout 1995–2016 (based on the CRS DEA) include Bulgaria, Denmark, France, the Netherlands, Romania, Slovakia and Slovenia. Therefore, both economically developed and transitional economy countries fall within this group. These results suggest that the countries cannot be ranked without ties in the ranking. Therefore, the use of the radial DEA model does not allow us to fully rank the agricultural sectors in the EU.

The lowest efficiency scores are observed for Finland, Latvia and Sweden. This outcome implies that these countries should substantially increase their agricultural production and decrease their energy-related GHG emissions. The average efficiency scores for these countries

Table 1
Efficiency scores for the EU Member States' agricultural sectors (CRS DEA), 1995–2016.

Country	1995	2000	2005	2010	2016	Average	Trend
Austria	0.89	0.89	0.90	0.95	0.95	0.91	0.005
Belgium	0.81	1.00	1.00	1.00	1.00	0.97	0.007
Bulgaria	1.00	1.00	1.00	1.00	1.00	1.00	0.000
Czech Republic	0.93	0.94	1.00	0.96	0.94	0.97	0.001
Denmark	1.00	1.00	1.00	1.00	1.00	1.00	0.000
Estonia	0.85	1.00	0.96	0.87	0.73	0.90	−0.003
Finland	0.69	0.67	0.70	0.71	0.68	0.69	0.002
France	1.00	1.00	1.00	1.00	0.93	1.00	−0.001
Hungary	0.86	0.88	0.96	0.84	0.97	0.89	0.003
Latvia	0.62	0.64	0.64	0.70	1.00	0.72	0.018
Lithuania	0.73	1.00	1.00	1.00	1.00	0.96	0.009
Netherlands	1.00	1.00	1.00	1.00	1.00	1.00	0.000
Poland	0.68	0.66	1.00	1.00	1.00	0.84	0.022
Romania	1.00	1.00	1.00	1.00	1.00	1.00	0.000
Slovakia	1.00	1.00	1.00	1.00	1.00	1.00	0.000
Slovenia	1.00	1.00	1.00	1.00	1.00	1.00	0.000
Sweden	0.71	0.72	0.73	0.72	1.00	0.77	0.013
Average	0.87	0.91	0.93	0.93	0.95	0.92	0.004
# of efficient	7	10	11	10	11	5	

Note: "# of efficient" refers to the numbers of fully efficient DMUs. There are 22 time periods in total. Trend represents the slope coefficient of a linear model $\rho_k = a + bt$.

fluctuate between 0.69 and 0.77, indicating that a 30% change in the outputs is needed to approach the frontier.

Regarding the dynamics of the efficiency scores, the overall average shows a slightly upward trend (0.004 per year). All of the countries show nonnegative trends, with the exceptions of Estonia and France. These two countries saw certain downturns in environmental performance during 1995–2016. Latvia, Poland and Sweden show the highest rates of change in the efficiency scores, suggesting that these countries managed to improve agricultural productivity along with a reduction in energy-related GHG emissions relative to the other EU countries Fig. 1. presents the dynamics in the average efficiency scores. Obviously, the use of the super efficiency DEA causes spikes in the average efficiency trend as infeasible solutions occur.

Next, we test the output-oriented super efficiency DEA for ranking the EU Member States (Table 2). The efficient observations are either attributed to scores indicating super efficiency (in the output-oriented case, these scores indicate that a decline in desirable output and an expansion in undesirable output are possible while remaining on the frontier) or infeasibility (implying that an observation cannot be projected onto the resulting frontier in the output direction). The cases of such infeasibilities are represented by blank cells in Table 2.

As mentioned in the Introduction, the use of super efficiency DEA does not fully resolve the problem of incomplete ranking. In our case, we still have five to eight countries for which the super efficiency model does not yield feasible efficiency scores. The superefficient observations (e.g., Bulgaria, Romania, Denmark, France) are compared to different

Table 2
Efficiency scores for the EU Member States' agricultural sectors (CRS super efficiency), 1995–2016.

Country	1995	2000	2005	2010	2016	Average	Trend
Austria	0.89	0.89	0.90	0.95	0.95	0.91	0.005
Belgium	0.81					0.93	
Bulgaria					1.80	1.80	
Czech Republic	0.93	0.94	1.01	0.96	0.94	0.98	0.001
Denmark				1.02	1.14	1.05	
Estonia	0.85	1.01	0.96	0.87	0.73	0.88	
Finland	0.69	0.67	0.70	0.71	0.68	0.69	0.002
France					0.93	1.08	
Hungary	0.86	0.88	0.96	0.84	0.97	0.89	0.003
Latvia	0.62	0.64	0.64	0.70	1.01	0.71	
Lithuania	0.73	1.13	1.21	1.01	1.03	1.02	0.012
Netherlands							
Poland	0.68	0.66				0.68	
Romania	1.13					2.56	
Slovakia	1.33	1.05	1.08		1.36	1.23	
Slovenia							
Sweden	0.71	0.72	0.73	0.72		0.72	
Average	0.85	0.86	0.91	0.86	1.05	0.97	0.011
# of infeasible	5	7	8	8	6	2	
# of superefficient	2	3	3	2	5	6	

Note: "# of infeas." and "# of superefficient" refer to the numbers of infeasibilities in super efficiency DEA and super efficiency scores greater than 1, respectively. There are 22 time periods in total. Empty cells indicate infeasibilities.

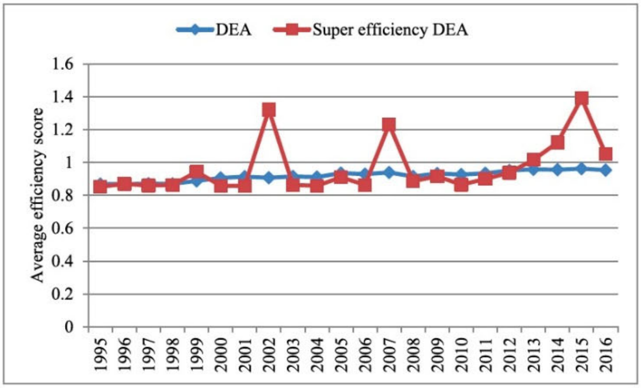

Fig. 1. Average efficiency scores rendered by DEA and super efficiency DEA.

frontiers, and the efficiency scores are not transitive. Countries such as the Netherlands and Slovenia face infeasibilities for the whole period covered, and one cannot obtain meaningful results for them at all.

The trend for the average super efficiency DEA scores also indicates a slight increase in efficiency. However, both conventional DEA and super efficiency DEA do not allow for complete rankings. Therefore, we turn to the contribution to the structural efficiency approach. As discussed before, the ranking becomes problematic for fully efficient observations. Accordingly, one can consider the two groups of observations, namely efficient and inefficient observations. The contribution to the structural efficiency index (as discussed in Section 2.2) also defines the two groups of observations, namely those contributing to the increase in structural efficiency (with index values exceeding unity) and those not contributing (index values less than or equal to unity). Therefore, we address the three issues in what follows: how efficient and inefficient observations relate to the contribution to structural efficiency, what the dynamics for the average contribution to structural efficiency are, and which countries perform the best in terms of efficiency and contribution to structural efficiency.

The relationships among the groups of observations delineated by the levels of efficiency and contribution to the structural efficiency can show whether the efficient observations also contribute to structural efficiency. Indeed, our empirical illustration contains a sample of EU Member States with agricultural sectors differing in terms of scale and input mix. In such a setting, the relationships between efficiency and contribution to structural efficiency become rather complex Table 3. shows the average efficiency levels for different groups of observations. As one can note, the observations associated with positive contributions to structural efficiency are associated with an average efficiency score of 0.99. Regarding the inefficient observations falling within this group, the average efficiency score is 0.94. Turning to the group of observations with a negative contribution to the aggregate efficiency (i.e., the contribution index is equal to or less than unity), the average efficiency scores are lower. Therefore, one can note a link between technical (environmental) efficiency and contributions to structural efficiency.

The distribution of observations in terms of efficiency and contributions to structural efficiency is shown in Table 4, indicating once again that efficient observations tend to positively contribute to aggregate efficiency more often than inefficient ones. Specifically, the share of efficient observations with an average contribution index exceeding unity is 65%, whereas the corresponding share for inefficient observations is only 35%.

The dynamics in the average contribution to structural efficiency indicate how efficient and inefficient observations can ensure better resource allocation. Of course, these calculations are highly theoretical given that the actual reallocation of resources across the countries considered would be extremely cumbersome. Regardless, one can track the trends in the possible improvements in structural efficiency due to changes in the input-mix and scale of operation within different countries. The trends of the average contribution to structural efficiency depicted in Fig. 2 suggest that there has been a decline in the average contribution to structural inefficiency (considering the mean value for the sample of countries within each time period). The efficient and inefficient countries tended to converge in their contributions to structural efficiency. This finding indicates that the input-mix has become more similar across the countries analyzed. The period following the accession of the new EU Member States in 2004 marks a particularly steep decline in the differences between the efficient and inefficient countries (as measured by the average contribution to structural efficiency). Therefore, the expansion of the EU and implementation of the CAP, along with support payments, might be related to increasing convergence among the Member States, yet the overall average contribution to structural efficiency tended to decline.

Table 3
The average levels of efficiency according to the average contribution toward structural efficiency.

Contribution	Inefficiency Inefficient	Efficient	Average
$I_k^C \leq 1$	0.80	1	0.87
$I_k^C > 1$	0.94	1	0.99
Average	0.81	1	0.92

Table 4
Distribution of the observations (agricultural sectors of the EU Member States) across efficiency levels and contribution to the aggregate efficiency.

Contribution	Inefficiency Inefficient	Efficient	Total
Absolute frequencies			
$I_k^C \leq 1$	144	75	219
$I_k^C > 1$	16	139	155
Total	160	214	374
Relative frequencies			
$I_k^C \leq 1$	90%	35%	59%
$I_k^C > 1$	10%	65%	41%
Total	100%	100%	100%

The country-specific analysis of average efficiency and contribution to structural efficiency is presented in Table 5. The countries can be ranked regarding their performance with respect to the conventional DEA model. Since the efficiency scores do not allow for a complete ranking, contribution to structural efficiency is also considered. Thus, the countries are ranked in terms of the efficiency scores in the first stage. Then, in the case of ties for the efficient countries, the average contribution to the structural efficiency is applied. Therefore, a complete ranking is possible.

Five countries (Romania, the Netherlands, Bulgaria, Slovakia, and Slovenia) are fully efficient, and the contribution to structural efficiency becomes the ranking criterion in this instance. The efficient countries show average contributions to structural efficiency ranging between slightly greater than 1 for Slovenia and just 1.02 for Romania. In this ranking, Romania appears to be the best-performing country, obviously related to environmental pressures (as represented by energy-related GHG emissions) since Eastern European countries do not show the highest agricultural productivity. The results in Table 5 suggest that, although countries can be ranked in terms of the two measures of efficiency, some differences between adjacent ranks are rather insignificant. For instance, Romania and the Netherlands show close-to-nil differences in the average contribution to structural efficiency.

It can be noted that most of the efficient countries show high levels of infeasibilities in the super efficiency DEA. Therefore, these countries show somewhat distinctive patterns of input-mix and production scale that place them outside the production plans of the other countries. The analysis performed indicates that the measures of the contribution to structural efficiency could improve the ranking of the DMUs in the presence of heterogeneity in the input mix.

The results of the DEA-based ranking can be compared to the earlier literature with some reservations regarding the different input/output sets, time frames and methods applied. For instance, Bartová et al. (2018) noted that the Netherlands and Denmark achieved the highest agricultural efficiency levels in 2006–2015. These results are also corroborated in the present study. Additionally, the worst performance of Finland is confirmed Vlontzos et al. (2014). also noted that Denmark and the Netherlands show full efficiency. However, the latter study included the gross nutrient balance as an undesirable output. In general, models with larger numbers of inputs and outputs are likely to generate higher efficiency scores due to the nature of DEA.

4. Conclusions

In this paper, we ranked the EU Member States in terms of their agricultural sectors' performance. Environmental production

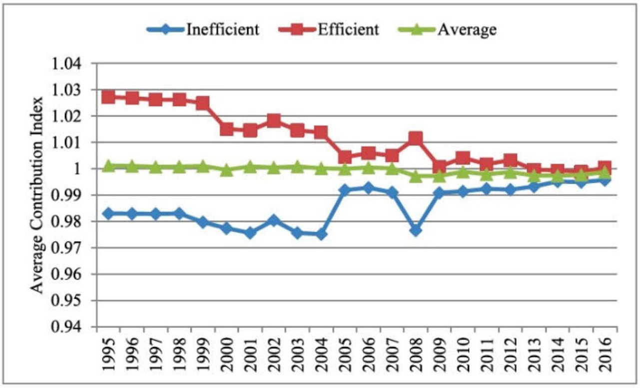

Fig. 2. The average index of contribution to structural efficiency for efficient and inefficient observations.

Table 5
The average efficiency and contribution to the structural efficiency for the EU Member States, averages for 1995–2016.

Country	AverageI_k^C	Average DEA	# of eff.	# of infeas.	# of positive contrib.	Final ranking
Romania	1.023149	1	22	12	22	1
Netherlands	1.02307	1	22	22	18	2
Bulgaria	1.011594	1	22	21	22	3
Slovakia	1.001755	1	22	6	18	4
Slovenia	1.000281	1	22	22	12	5
Denmark	0.997418	0.99808	20	12	3	6
France	1.070929	0.997029	21	18	21	7
Czech Republic	0.998272	0.970281	7	0	5	8
Belgium	1.007048	0.969351	18	16	19	9
Lithuania	0.995932	0.956892	16	0	4	10
Austria	0.997139	0.914025	0	0	3	11
Estonia	0.996926	0.898644	5	4	0	12
Hungary	0.999253	0.886912	0	0	8	13
Poland	0.914115	0.841534	11	11	0	14
Sweden	0.981677	0.77143	4	4	0	15
Latvia	0.99011	0.722572	2	1	0	16
Finland	0.982399	0.687002	0	12	0	17

Note: "# of eff.", "# of infeas." and "# of positive contrib." refer to the numbers of time periods during which a certain country showed full efficiency, infeasibility in super efficiency DEA and positive contributions to aggregate efficiency, respectively. There are 22 time periods in total.

technology was considered. Therefore, energy-related environmental pressures were considered, allowing us to identify the best- and worst-performing agricultural sectors in the EU. The three approaches were applied for the ranking: the conventional DEA, super efficiency DEA and the contribution index. The last measure is relatively new and allows us to assess the average contribution by each country to structural efficiency. The aggregate observations are established in a combinatorial manner with the DEA model solved in each instance.

The empirical results indicate an overall increase in the environmental performance of the EU Member States during 1995–2016. The agricultural performance of Bulgaria, Denmark, France, the Netherlands, Romania, Slovakia and Slovenia, as measured by the conventional DEA, approached the frontier. Therefore, these countries could not be ranked based on the conventional DEA model. The application of super efficiency DEA still did not allow for a complete ranking. Countries such as the Netherlands and Slovenia could not be given super efficiency scores due to infeasibilities, indicating that these countries show particular input-output mixes that are not directly comparable to those for the other countries.

Finally, application of the contribution index allowed for the complete ranking of the countries. Romania, the Netherlands, Bulgaria, Slovakia and Slovenia were ranked as the best-performing countries (in that order) based on their contributions to structural efficiency. Notably, France and Belgium showed positive contributions to structural efficiency, although they were not classified as efficient countries. Therefore, cooperation with these countries would allow other countries to exploit their agricultural resources in a more productive and sustainable manner.

The results indicate that both the new and old EU Member States appeared to be the best-performing ones. However, among the five countries that are fully efficient according to the conventional DEA model, there are four countries that entered the EU in 2004. Thus, countries with relatively lower economic development levels (including agricultural productivity) can be environmentally efficient due to less intensive agricultural production and energy-related GHG emissions. In this regard, benchmarking is helpful in revealing the possibilities for agricultural restructuring at the macro-level.

Further research could aim to analyze the contributions to structural efficiency by considering operation at full efficiency. This approach would allow us to further investigate the possible patterns of resource reallocation. Additionally, the present paper is limited in the time period covered. Further research is needed to assess the dynamics in the efficiency of the EU countries by applying extended datasets.

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CRediT authorship contribution statement

Justas Streimikis: Conceptualization, Data curation, Formal analysis, Investigation, Writing – original draft. **Zhiqian Yu:** Formal analysis, Investigation, Visualization, Writing – review & editing. **Ning Zhu:** Data curation, Software, Writing – review & editing. **Tomas Baležentis:** Conceptualization, Methodology, Writing – original draft.

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ORIGINAL PAPER

Does the energy-related greenhouse gas emission abatement cost depend on the optimization direction: shadow pricing based on the weak disposability technology in the European Union agriculture

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Abstract

The European Green Deal and similar strategies seek to improve sustainability of the agricultural sector via public support programmes. It is important to assess the costs of sustainable energy use in agriculture by exploiting the shadow price approach. However, the earlier literature often ignored the fact that shadow price analysis may be sensitive to the assumed direction of optimization. This paper seeks to disentangle the major patterns in energy-related greenhouse gas (GHG) emission performance in the selected European Union countries by assuming different optimization directions. The country-level data are used to construct the environmental production technology by means of the data envelopment analysis. The different directional output distance functions (aggregate, unit and radial) for the weak disposability data envelopment analysis models are used to quantify the shadow prices of the energy-relevant GHG emission and construct the marginal abatement cost curves. The results indicate spatial and temporal variation in the environmental performance that can be addressed by adjusting the support programmes.

Keywords Shadow price · Data envelopment analysis · Energy-related GHG emission · Agriculture

Mathematics Subject Classification 90C05

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1 Introduction

The creation of the zero-carbon economy has been stressed as an objective of the economic development policies across different regions (Flagg 2015). The integrated assessment models have been established to assess the drivers of decarbonization (Vuuren et al. 2016). These objectives have also been reflected in the strategic documents globally. Recently, such initiatives as Glasgow Agreement have stressed the importance of the climate change mitigation.

Strategy Europe 2020 suggested improving energy efficiency and reducing greenhouse gas (GHG) emission (European Commission 2011). The objectives related to the climate-neutral economy have been stressed by European Commission (2018). This implies even stronger commitment to reduce the GHG emission and other environmental pressures related to productive activities in the EU. Recently, the European Green Deal of the European Union (European Commission 2019) has envisaged such objectives as curbing GHG emission and decoupling economic growth from resource use.

The goals of the climate-neutral and zero-carbon economy can be achieved via modernization of the energy supply (energy-mix changes), improvement of the technologies (carbon factor changes) and energy efficiency, among other measures. The manifestations of the strategies and measures aimed at creation of the zero-carbon economy are present in the literature. Jacobson et al. (2019) stressed the need for adaptation of the energy structure to the objectives of the Green Deal policy. Jetoo (2019) discussed the involvement of stakeholders into the governance frameworks in order to address the climate change concerns. Wood et al. (2020) looked at the consumption- and production-based carbon footprints of the EU economy.

The agricultural sector is an important consumer of energy that also relates to the food security. Thus, the energy-economy-environment-food nexus appears as a framework for analysis of agricultural performance. Given the food security and rural development objectives, the public support is often allocated to agriculture. In the case of the European Union (EU), such support is distributed under the Common Agricultural Policy (CAP). The CAP comprises a number of measures that can be used to impact the structure and volume of agricultural production. Also, the rural development measures can contribute to adjustment of the energy-mix and adoption of the energy-saving technologies. Therefore, the public support can affect the energy efficiency and environmental pressures. This research focuses on the environmental efficiency of the EU Member States agriculture.

The environmental performance of agricultural sector has attracted attention across different countries and from different perspectives. Ball et al. (2002, 2004) discussed the environmental performance index and productivity growth in the context of the US agriculture. Färe et al. (2006) assessed the performance of the US agriculture by calculating the net revenue based on the market prices for the desirable agricultural output and shadow prices for the undesirable ones (water contamination indices). The quadratic output distance was applied to approximate the underlying technology. Tang et al. (2020) applied the quadratic directional distance function for Chinese agricultural sector with regards to different directional vectors. Tang et al. (2021) used the quadratic distance function to estimate the shadow price of GHG emission in the Australian farms. Latruffe et al. (2013) looked into environmental efficiency of Hungarian pig farming. Similarly, Ait Sidhourn et al. (2020) measured farm sustainability based on the non-parametric approach. Dakpo et al. (2019) applied the non-parametric approach to measure productivity growth at the farm level with undesirable outputs included. Thus, the environmental efficiency can be measured at the aggregate and farm level. This choice is often based on the data availability. This paper proceeds with the aggregate data for the EU countries for the same reason.

The environmental production technology is the key concept in modelling the energy-economy-environment nexus. It includes the undesirable outputs besides the desirable ones. The greenhouse gas (GHG) emission can be included as an undesirable output to represent the climate change potential rendered by the production process. The trade-off between the prices of the desirable and undesirable outputs is the shadow pollution cost (Wu et al. 2021b). In case the GHG emission, its shadow price indicates the potential for reduction. The environmental production technologies can be approximated parametrically or nonparametrically. The stochastic parametric estimation is found in Pittman (1981), Reinhard et al. (1999) or Cuesta et al. (2009). The deterministic parametric approach was discussed by Färe et al. (2006). The latter approach requires specification of the functional form of a representation of the technology (usually, translog or quadratic functions are used). The nonparametric estimation relies on the piece-wise linear technology. It is appealing in that a number of economic axioms can be imposed on such technologies without serious computational burden. The nonparametric environmental production technologies can be defined following Hailu and Veeman (2001), Färe and Grosskopf (2003) or Murty et al. (2012). In this paper, we follow the nonparametric estimation.

The directional DEA models and distance functions were developed by Chambers et al. (1996, 1998) mimicking the benefit functions. Chung et al. (1997) adapted the directional DEA to the case of the environmental production technology. The directional DEA can measure the efficiency of decision making units towards different directions. As noted by Färe et al. (2008), the directions can be observation-specific or common to the whole sample. There have been different approaches towards endogenously setting the directions in the DEA proposed. Färe et al. (2013) and Hampf and Krüger (2015) proposed maximizing the distance to the frontier through adjustment of the directional vector. Petersen (2018) suggested minimizing the Euclidean distance to the frontier when adjusting the directional vector. Wu et al. (2021a) surveyed these approaches and argued that the approach by Petersen (2018) is more reasonable from the economic viewpoint. In this paper, we seek to ascertain the effects of using the different directions on the GHG emission shadow prices.

This paper adopts the weak disposability model proposed by Kuosmanen (2005) that assumes observation-specific abatement factors in the environmental production technology. The different directions for optimization are assumed to obtain the shadow prices of the energy-related GHG emission in the EU agriculture. The country-level data are used for the analysis. The analysis of the shadow prices allows identifying the directions of movement towards the carbon–neutral (and, eventually, climate-smart) agriculture.

The paper proceeds as follows. Section 2 focuses on the methodological issues and presents the DEA models applied in this study. The data used are described in Sect. 3. Then, Sect. 4 presents the results (shadow prices, abatement burden and marginal abatement cost curves). Finally, Sect. 5 concludes.

2 Methods

The environmental production technology involves the environmental pressures along with inputs and outputs (as represented by the conventional production technology). In our case, we seek to take the energy-related GHG emission into account and assign it with the shadow price. The modelling of the environmentally-sensitive production involves additional assumptions in regards to the relationships among the desirable and undesirable outputs. The transformation approach (Seiford and Zhu 2002), strong disposability (Hailu and Veeman 2001), weak disposability (Färe and Grosskopf 2003), multi-output technology structure (Cherchye et al. 2015), G-disposability (Rødseth 2017), or by-production technology (Murty et al. 2012). One can further consult Dakpo et al. (2016) for more examples of the studies dealing with undesirable outputs in the context of DEA. More specifically, Zhang and Choi (2014) presented a survey of applications of the directional distance functions (based on DEA and other approaches) for measurement of the environmental efficiency and shadow prices.

The weak disposability technology is among the most often applied ones on the empirical research due to its operationality (however, it does not satisfy the materials balance condition, cf. Forsund 2009). Essentially, it assumes that the desirable and undesirable outputs are weakly disposable, i.e., the production possibility set is defined by allowing the scaling down of the undesirable and desirable outputs by the same factor. The preliminaries for this technology were discussed by Färe and Grosskopf (2003). Later on, Kuosmanen (2005) proposed a more general setting allowing for observation-specific abatement factor linking the quantities of the desirable and undesirable outputs. In this paper, we use the Kuosmanen's model to assess the shadow prices of the energy-related GHG emission in the EU agriculture.

The environmental production technology is formally defined as a set comprising input quantities $x = \left(x_1, x_2, \dots, x_N\right)$, desirable output quantities $y = \left(y_1, y_2, \dots, y_M\right)$ and undesirable output quantities $z = \left(z_1, z_2, \dots, z_J\right)$. The production possibilities given by a certain environmental technology are then defined as

$$T = \{(x, y, z) : x \text{ can produce } (y, z)\} \tag{1}$$

This technology can be represented by input and output isoquants (besides possible dual representations).

The notion in Eq. (1) can be operationalized in a non-parametric way by using the activity analysis framework. Let there be K decision making units (DMUs) that represent countries in our case and let index $k = 1, 2, \dots, K$ keep track of these DMUs. The weights, ξ_k, are assigned to the DMUs. The DMU-specific abatement factors θ_k are used to ensure the weak disposability of the desirable and undesirable outputs. Then, the variable returns to scale DEA technology given by Kuosmanen (2005) takes the following form:

$$\hat{T} = \left\{ (x, y, z) : \begin{array}{l} \sum_{k=1}^{K} \theta_k \xi_k y_k \geq y, \ \sum_{k=1}^{K} \xi_k x_k \leq x, \ \sum_{k=1}^{K} \theta_k \xi_k z_k = z, \\ \sum_{k=1}^{K} \xi_k = 1, \ \xi_k \geq 0, 0 \leq \theta_k \leq 1, k = 1, \dots, K \end{array} \right\} \tag{2}$$

Then, the DEA-based technology in Eq. (2) is linearized by assigning weights λ_k and σ_k to the DMUs so that $\xi_k = \lambda_k + \sigma_k$. The two types of the intensity weights allow for the variable abatement factor and ensure linearity of the model. The intensity variables λ_k are assigned to the 'active' DMUs that have non-zero input–output quantities (i.e., the observed data), whereas intensity variables σ_k are assigned to 'inactive' DMUS (i.e., artificial DMUs that contain observed input quantities and zero outputs). Thus, the netputs can be adjusted to generate the Kuosmanen (2005) weak disposability environmental production technology. In addition, we impose the non-negative shadow prices by modifying the constraint for the undesirable outputs in lines with Leleu (2013). Thus, the linearized technology is formally re-defined as:

$$\hat{T} = \left\{ (x, y, z) : \begin{array}{l} \sum_{k=1}^{K} \lambda_k y_k \geq y, \ \sum_{k=1}^{K} \left(\lambda_k + \sigma_k\right) x_k \leq x, \ \sum_{k=1}^{K} \lambda_k z_k \leq z, \\ \sum_{k=1}^{K} \left(\lambda_k + \sigma_k\right) = 1, \ \lambda_k, \sigma_k \geq 0, k = 1, \dots, K \end{array} \right\} \tag{3}$$

The directional output distance function (Färe et al. 2006) can be adapted to the case of the environmental production technology. By setting the direction, one can assume the trade-offs among the outputs (including desirable and undesirable ones) in the optimization. Note that optimization implies adjustment of the output quantities so that a certain DMU operates on the efficiency frontier (output isoquant). The directional output distance function in general case is given as:

$$D\left(x, y, z; g_y, g_z\right) = \max \left\{ \delta : \left(x, y + \delta g_y, z - \delta g_z\right) \in T \right\}, \tag{4}$$

where $g = \left(g_y, g_z\right)$ is the directional vector encompassing directions for optimization of desirable and undesirable outputs. The zero value of $D(\cdot;\cdot)$ implies full efficiency and positive values imply inefficiency.

Note that the directional output distance function in Eq. (4) can be plugged into $\hat{T}$ given by Eq. (3). This renders the 'estimator' of the directional output distance for a certain DMU k' under the weak disposability technology defined by Kuosmanen (2005) and modified per Leleu (2013):

$$
\begin{aligned}
& D(x_{k'}, y_{k'}, z_{k'}; g_y, g_z) \;=\; \max_{\delta,\lambda,\sigma} \delta \\
& \text{s.t.} \\
& \sum_{k=1}^{K} \lambda_k y_k^m \geq y_{k'}^m + \delta g_y^m, m = 1, \ldots, M \\
& \sum_{k=1}^{K} (\lambda_k + \sigma_k) x_k^n \leq x_{k'}^n, n = 1, \ldots, N \\
& \sum_{k=1}^{K} \lambda_k z_k^j \leq z_{k'}^j - \delta g_z^j, j = 1, \ldots, J \\
& \sum_{k=1}^{K} (\lambda_k + \sigma_k) = 1 \\
& \lambda_k, \sigma_k \geq 0, k = 1, \ldots, K
\end{aligned} \tag{5}
$$

The dual program for Eq. (5) is then given as:

$$
\begin{aligned}
& D(x_{k'}, y_{k'}, z_{k'}; g_y, g_z) \;=\; \min_{\pi_y, \pi_x^n, \pi_x^p, \pi_z, \phi} \phi - \left(\sum_{m=1}^{M} \pi_y^m y_{k'}^m - \sum_{n=1}^{N} \pi_x^n x_{k'}^n - \sum_{j=1}^{J} \pi_z^j z_{k'}^j \right) \\
& \text{s.t.} \\
& \sum_{m=1}^{M} \pi_y^m y_k^m - \sum_{n=1}^{N} \pi_x^n x_k^n - \sum_{j=1}^{J} \pi_z^j z_k^j \leq \phi, k = 1, \ldots, K \\
& - \sum_{n=1}^{N} \pi_x^n x_k^n \leq \phi, k = 1, \ldots, K \\
& \sum_{m=1}^{M} \pi_y^m g_y^m + \sum_{j=1}^{J} \pi_z^j g_z^j = 1 \\
& \pi_y^m \geq 0, m = 1, \ldots, M \\
& \pi_x^n \geq 0, n = 1, \ldots, N \\
& \pi_z^j \geq 0, j = 1, \ldots, J
\end{aligned} \tag{6}
$$

Note that the shadow values associated with the inputs are not restricted in Eq. (6).[1] Thus, Leleu (2013) further modified the second restriction in Eq. (5) by setting $\sum_{k=1}^{K} (\lambda_k + \sigma_k) x_k^n \leq x_{k'}^n$, $n = 1, \ldots, N$. This renders an additional constraint in Eq. (6) that

[1] An anonymous referee points out that one could find possible ranges for the shadow prices for inputs and outputs using an optimal solution, $D*$, by adding an additional constraint $D *= \phi - \sum_{m=1}^{M} \pi_y^m y_{k'}^m + \sum_{n=1}^{N} \pi_x^n x_{k'}^n + \sum_{j=1}^{J} \pi_z^j z_{k'}^j$ to Eq. (6). In our case, such an exit did not render different results.

imposes non-negativity of the shadow values assigned to the inputs, i.e., $\pi_x^n \geq 0$, $n = 1, ..., N$. In this way, the undesirable outputs are treated in a similar manner to the inputs with difference in the associated intensity variables.

The shadow values in the multiplier program (Eq. 6) can be used to calculate the shadow prices of the undesirable outputs. The following ratio yields the relative shadow price of the j-th undesirable output:

$$CSP = \frac{\pi_z^j}{\pi_y^m} \tag{7}$$

The shadow prices of undesirable outputs provide information in regards to the efforts needed for abatement (i.e., marginal abatement costs). This information is useful for analyzing the possibilities for improving the environmental quality given the existing technology.

The directional vector, g, in Eq. (4) governs the direction of movement towards the efficiency frontier. The direction depends on the assumptions on the trade-offs among the outputs. This paper deals with the performance of the EU agricultural sectors. Thus, we assume that the EU countries can follow individual paths towards the efficiency frontier or follow a unified scheme. These assumptions are imposed through adjustment of the directional vector.

The four cases of the directional vectors are tested. First, the observed output quantities are used for each country. In this case, the proportional distance is obtained:

$$(g_y, g_z) = (y_k, z_k) \tag{8}$$

Second, the unit vectors are used for the optimization which implies equal importance of the outputs:

$$(g_y, g_z) = (1, 1) \tag{9}$$

Third, the aggregate output quantities are used as the direction. The latter setting implies that all the countries face the same direction of movement towards the efficiency frontier and this direction is dependent on the overall output levels and proportions:

$$(g_y, g_z) = \left(\sum_{k=1}^{K} y_k, \sum_{k=1}^{K} z_k \right) \tag{10}$$

Equivalently, one may choose using the average output quantities as the directional vector for the directional output distance function. This is a scaled version of the aggregate directional vector discussed above:

$$(g_y, g_z) = \left(\frac{1}{K} \sum_{k=1}^{K} y_k, \frac{1}{K} \sum_{k=1}^{K} z_k \right) \tag{11}$$

In any instance, the elements of the directional vectors are non-negative which implies that the desirable outputs are expanded, whereas the undesirable ones are contracted while moving along the directional vector. In this regard, we unify the objectives of food security and environmental sustainability. As the projection on the efficiency frontier depends on the direction chosen, the different shadow prices may be obtained.

3 Data

This paper assesses the shadow prices of the energy-related GHG emission in the European agriculture. The environmental production technology is approximated in order to gauge the shadow prices. As discussed in the preceding section, the agricultural inputs are used to produce the desirable and undesirable outputs. This framework is adapted to the case of the EU agriculture by incorporating labour (in Annual Work Units), land area (hectares), intermediate consumption (PPS of 2010, less energy expenses) and energy (tonnes of oil equivalent) as the inputs. The desirable output is the agricultural output (measured in PPS of 2010) and the undesirable output is the energy-related GHG emissions (measured in tonnes of CO_2 equivalent). Thus, the data are taken from the economic accounts for agriculture, environmental accounts, agricultural statistics and energy balances provided by Eurostat. The data cover years 1995–2017.

The data are described in Table 1 by providing the country averages and growth rates for each variable. The data indicate that agricultural output tended to increase by 0.9% per year on average for the selected countries. The only cases with negative growth rates were Bulgaria and Greece. Input use followed declining trends in most cases with exception for the intermediate consumption. Indeed, 9 out of the 23 countries analyzed reported a decline in the intermediate consumption (excluding energy expenses). Therefore, some countries managed to expand their agricultural output even though the intermediate consumption went down. The energy input declined to the greatest extent (for the selected countries, the average rate of decline was 4.6% per year). Thus, the energy savings appears as the primal achievement of modernization of the agricultural sector. The second steepest rate of decline is observed for the labour input that declined in all of the analyzed countries. This is related to urbanization that is observed globally and increasing automatization of agriculture.

In spite of the negative energy consumption growth rates observed in all the countries analyzed, there has been positive or zero trends observed for energy-related GHG emission in some countries. This indicates that energy-mix of some countries deteriorated in the sense of climate change mitigation objectives. Therefore, it is important to identify the patterns of the energy-related GHG shadow prices in order to ensure the effective policy making aimed at climate change mitigation.

The major variable of interest in this study is the GHG emission shadow price. It is determined by the shape (particularly, slope) of the underlying output isoquant. The emission shadow price can be related to the pollution intensity to construct the marginal abatement cost curve. Thus, Fig. 1 presents the dynamics in the pollution intensity (energy-related GHG emission per unit of agricultural output weighted by the output share). The data suggest that the energy-related GHG emission intensity declined in the selected EU countries by 1.7% per year on average.

Table 1 Input and output variables for the agricultural sectors of the European countries, 1995–2017

Country	Averages						Trend (% per annum)					
	Output	Intermediate	Land	Labor	Energy	GHG	Output	Intermediate	Land	Labor	Energy	GHG
Austria	5691	3049	3148	146	522	1083	0.6	−0.1	−1.2	−2.2	−0.4	−1.3
Belgium	6537	3558	1370	68	840	2405	2.0	−0.7	−0.2	−2.0	−1.6	−1.8
Bulgaria	8605	5517	5344	555	256	737	−1.0	−4.6	−0.9	−6.0	−3.6	−3.9
Czechia	5991	4016	3778	140	615	1459	0.7	−0.9	−1.1	−3.4	−1.0	−2.4
Denmark	7196	4572	2722	66	702	2193	1.2	0.9	−0.5	−2.7	−0.9	−2.7
Estonia	987	527	926	41	101	219	2.2	3.8	0.4	−6.7	2.2	4.7
Finland	3148	2135	2245	98	733	1615	0.7	−0.3	0.3	−3.4	0.0	−1.0
France	60,411	33,635	29,832	907	4001	12,611	0.2	0.2	−0.1	−2.0	0.4	−0.6
Greece	11,296	4154	4637	538	853	2219	−0.4	−0.5	1.3	−1.9	−7.3	−8.9
Hungary	11,486	6921	5761	555	589	1400	0.5	−1.3	−0.8	−3.2	−1.4	−1.7
Ireland	5488	3612	4432	171	284	903	0.4	0.7	0.1	−1.3	−1.9	−2.7
Italy	47,191	18,750	14,176	1276	2845	8633	0.2	0.0	−1.3	−1.8	−0.7	−1.2
Latvia	1423	796	1940	120	131	408	3.7	5.4	−1.0	−4.5	1.9	0.8
Lithuania	3206	1913	2902	187	120	253	3.1	2.6	−0.5	−3.5	−2.1	−2.0
Netherlands	21,278	11,658	1903	167	3809	10,195	1.1	1.1	−0.4	−1.5	−0.8	0.0
Poland	30,948	15,524	16,166	2323	4106	12,906	1.3	0.5	−1.4	−2.7	−1.8	−1.8
Portugal	7834	4199	3786	355	446	1309	0.4	1.6	−0.5	−2.9	−3.0	−1.7
Romania	30,699	14,616	14,205	2407	456	1060	1.2	1.4	−0.5	−4.8	−1.8	−0.8
Slovakia	3190	2329	2102	105	178	366	0.0	−0.2	−1.4	−7.3	−3.4	4.0
Slovenia	1268	719	493	92	74	253	0.2	−0.6	−0.4	−1.9	−0.2	−0.8
Spain	40,221	16,751	25,445	991	2527	10,870	1.6	1.8	−1.0	−1.6	0.5	1.1
Sweden	4253	2734	3085	73	635	1657	1.0	0.4	−0.1	−2.2	−4.6	−1.0
UK	22,529	13,178	17,224	319	1025	5212	0.3	0.6	0.2	−1.3	−1.6	−1.3

Table 1 (continued)

Country	Averages						Trend (% per annum)					
	Output	Intermediate	Land	Labor	Energy	GHG	Output	Intermediate	Land	Labor	Energy	GHG
Average	14,821	7603	7288	509	1124	3477	0.9	0.5	−0.5	−3.1	−1.4	−1.2

Output and Intermediate consumption are measured in million purchasing power standards (PPS), land area is measured in 1000 ha, labour input is measured in 1000 annual work units, energy input is measured in 1000 tonnes of oil equivalent (TOE) and energy-related GHG emission is measured in 1000 tonnes of CO_2 equivalent; growth rates are based on the stochastic model

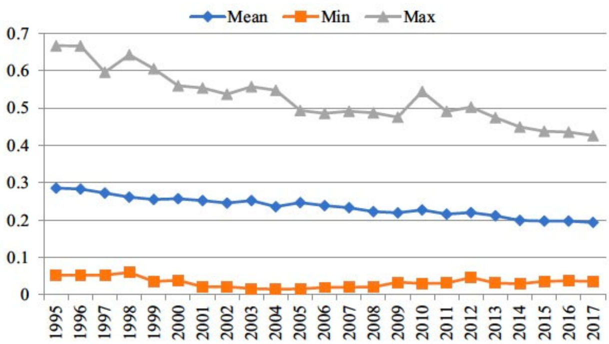


Fig. 1 Dynamics in the energy-related GHG emission intensity in the selected EU countries, 1995–2017. *Note* the mean value is based on the weighted average where the agricultural output shares are used as country-specific weights

The spread of the intensity values also tended to decline over 1995–2017. Looking at the minimum and maximum values for the sample renders two negative trends that correspond to the development of the weighted mean. Specifically, the minimum value of the energy-related GHG emission intensity went down to the lowest extent (a 1% decline per year) if compared to the mean and maximum value (a 1.8% decline per year). This combination indicates that the European agriculture saw at least partial technological progress in regards to energy-saving and/or cleaner energy that allowed achieving both reduction and increasing convergence in the sense of the energy-related GHG intensity.

The weak disposability DEA model will be applied to quantify the shadow prices at the country level. This allows identifying the economic cost of the abatement. The country-level data provide possibility for international comparison and suggestions for international coordination.

4 Results

4.1 Shadow prices of the energy-related GHG emission

The three models defined in Sect. 2 rendered the estimates of the shadow prices for energy-related GHG emission in the European agriculture. The aggregate results are provided in Fig. 2 that shows the trends for the aggregate, radial (output) and unit DDFs. Note that the radial DDF varies across the observations and preserves the observed output-mix (i.e., agricultural output and energy-related GHG emission), whereas uniform directions are imposed otherwise.

The results suggest that no certain trends can be identified for the GHG emission shadow price (Fig. 2) even though a clear decline in the GHG emission intensity is observed (Fig. 1). What is more, the differences among the shadow prices

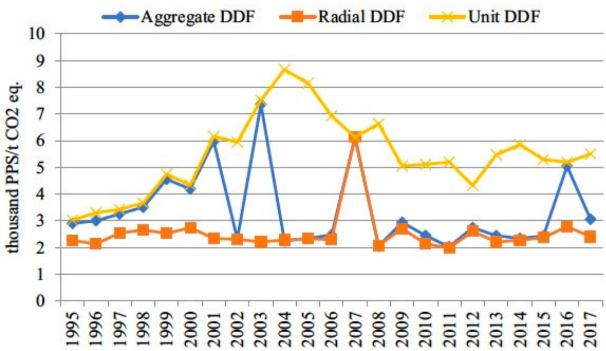


Fig. 2 The mean shadow prices of the energy-related GHG emission in European agriculture, 1995–2017. *Note* the mean value is based on the weighted average where the agricultural output shares are used as country-specific weights

are substantial as the mean shadow price based on the unit DDF appear as more than three times higher than those based on the radial DDF in 2004. In general, the radial DDF showed the lowest level of the shadow price on average with a single spike in 2007. The shadow price based on the unit DDF showed no spikes, yet it returned the highest levels of the average shadow price. The aggregate DDF rendered shadow price that kept fluctuating in between those based on the aforementioned two approaches.

As Ma et al. (2019) suggested, substantial variation exists among the estimates of the carbon shadow prices rendered by different types of the distance functions. Indeed, the shadow prices resulting from application of the more flexible DDFs of non-radial nature are based on greater adjustments in the input- and/or output-mix if opposed to the radial measures. Therefore, the shadow prices based on the radial DDFs are lower than those based on the non-radial DDFs. Yet another circumstance needs to be taken into account is that the present analysis comprises the country-level agricultural production and emission data. Thus, all the production entities are covered, both small and large ones. In this context, the shadow price of the energy-related GHG emission is likely to be inflated if compared to the market-based carbon price that relates to the large producers only.

The country-specific analysis of the levels and dynamics of the energy-related GHG emission in the European agriculture further proceeds in Table 2. The lowest shadow price of the energy-related GHG emission is observed for Poland and Spain irrespectively of the DDF applied. The highest shadow price is observed for Romania and Slovakia. Thus, countries with low shadow prices should put more efforts in reducing the energy-related GHG emission in agriculture, whereas those with high values have already achieved relatively high performance level in this regard.

The dynamics in the energy-related GHG emission shadow price also vary across the countries. The rate of growth of the shadow prices is measured as the trend

Table 2 The average shadow price (PPS of 2010/kg CO_2 eq.) and its trend (% per year) for the energy-related GHG emission across the selected European countries, 1995–2017

Country	Aggregate DDF		Radial DDF		Unit DDF	
	Average	Trend	Average	Trend	Average	Trend
Austria	2.4	0.1	2.3	0.0	2.4	0.0
Belgium	1.9	3.8	2.2	3.8	2.2	3.5
Bulgaria	3.1	2.2	2.7	1.4	3.5	1.8
Czechia	2.4	− 1.1	2.5	− 1.5	2.8	−0.8
Denmark	2.6	3.6	2.6	4.7	2.7	4.9
Estonia	4.5	−4.4	3.3	2.0	5.1	− 3.0
Finland	0.7	4.0	1.2	1.0	2.0	0.8
France	3.6	0.8	3.8	−0.3	3.7	1.0
Greece	2.2	11.4	2.0	10.3	3.8	14.8
Hungary	3.5	− 1.1	3.4	−0.8	3.7	−0.8
Ireland	2.8	4.2	2.7	3.5	3.0	4.3
Italy	3.1	0.2	3.0	−2.9	2.4	−2.2
Latvia	1.1	13.5	1.2	12.8	2.4	10.6
Lithuania	4.9	4.0	4.6	5.9	8.8	4.2
Netherlands	1.5	0.7	1.5	0.7	1.3	1.4
Poland	0.0	–	0.0	–	1.1	2.8
Portugal	2.2	−0.2	1.7	−3.7	2.8	3.0
Romania	15.1	−4.9	5.7	0.5	35.0	0.8
Slovakia	7.3	−8.1	5.1	2.0	8.2	−6.4
Slovenia	3.9	−0.1	4.1	4.0	4.9	1.1
Spain	0.2	−2.5	0.2	−4.1	0.4	−2.0
Sweden	0.7	− 10.4	0.8	−9.5	1.5	−4.1
UK	2.6	3.3	2.6	3.4	2.6	2.8
Average	3.1	0.9	2.6	1.5	4.6	1.7
Weighted av	2.0	0.5	1.9	−0.2	2.5	1.2

Trend is represented by the linear model coefficient normalized with respect to the mean shadow price for 1995–2017; GHG emission volume is used for weighting

coefficient of the linear model divided by the average shadow price for a certain country. This gives a relative measure of the shadow price growth. As one can note, Greece and Latvia show the highest rates of grow expressed in two-digit numbers.

For Greece, the energy-related GHG emission shadow price increased substantially indicating transition towards cleaner energy and energy efficiency in agriculture (the energy consumption in Greek agriculture went down from 1012 thousand toe to 291 thousand toe in 1995–2017; see also the growth rates in Table 1). Latvia followed yet another path of agricultural development. As shown in Table 1, its energy consumption and energy-related GHG emission increased throughout 1995–2017 (growth rates of 1.9% and 0.8% per year, respectively), yet the growth in the agricultural output of 5.4% per year offset the increasing energy consumption and resulted in an increasing GHG emission shadow price.

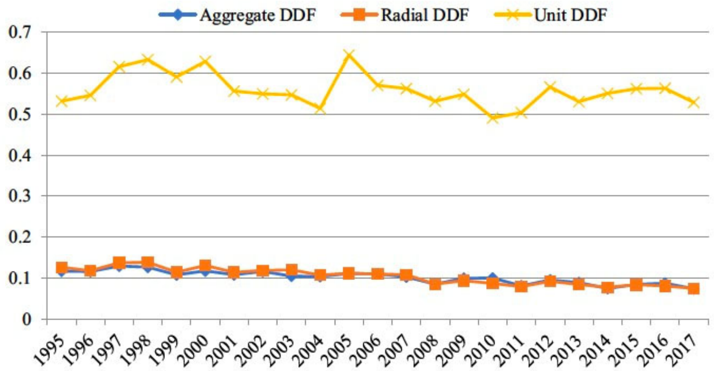


Fig. 3 The relative total abatement cost (weighted average) for 1995–2017. *Note* the volume of the energy-related GHG emission is used to construct the weighting factors

The steepest decline in the energy-related GHG emission shadow price was observed for Sweden (−4.1 to −10.4% per year depending on the direction used). This indicates a deteriorating environmental performance of the agricultural sector. A deeper look into the results outlined in Table 1 suggests that this country experienced a mild increase in the agricultural output (1% per year) and a decrease in the energy-related GHG emission (− 1% per year). Note that the reported growth rates are stochastic ones (i.e., random fluctuations are ignored). Estonia appeared as a country with second-highest rates of decline (4.4% or 3% per year for the aggregate and unit DDF and a 2% annual increase for the radial DDF). This can be explained by an increasing energy use and GHG emission along with modest gains in the agricultural output.

4.2 Relative total abatement cost

The relative total abatement cost is used to assess the potential economic pressure on agricultural sector in the event the emission abatement costs are internalized. First, the total abatement cost is obtained by multiplying the shadow price and the volume of the energy-related GHG emission. Then, the total abatement cost is normalized by the volume of agricultural output. Thus, the relative total abatement cost indicates the share of the total agricultural output foregone in the case of the complete abatement. The relative total abatement cost ensures comparability across space and time. Note that inefficient countries face low shadow prices and, hence, low abatement cost.

The weighted averages of the relative total abatement cost are constructed for the group of the selected countries (Fig. 3). The three DDFs used for obtaining the shadow prices show obviously different levels of the relative total abatement cost: the unit DDF renders the highest shadow prices (Fig. 2) and, consequently,

Table 3 The relative total abatement cost (factor) and its trend (p.p. per year) of the energy-related GHG emission across the selected European countries, 1995–2017

Country	Aggregate DDF		Radial DDF		Unit DDF	
	Average	Trend	Average	Trend	Average	Trend
Austria	0.45	−0.7	0.45	−0.8	0.45	−0.8
Belgium	0.67	0.9	0.75	0.5	0.75	0.5
Bulgaria	0.25	−0.3	0.22	−0.5	0.22	−0.5
Czechia	0.60	−2.4	0.61	−2.7	0.61	−2.7
Denmark	0.77	−0.3	0.73	0.7	0.73	0.7
Estonia	0.86	−1.1	0.72	2.7	0.72	2.7
Finland	0.33	0.6	0.63	−0.6	0.63	−0.6
France	0.75	0.1	0.79	−0.8	0.79	−0.8
Greece	0.26	0.1	0.24	−0.1	0.24	−0.1
Hungary	0.43	−1.4	0.41	−1.2	0.41	−1.2
Ireland	0.45	0.6	0.42	0.3	0.42	0.3
Italy	0.56	−0.6	0.57	−2.3	0.57	−2.3
Latvia	0.27	3.3	0.29	3.3	0.29	3.3
Lithuania	0.36	0.0	0.33	0.6	0.33	0.6
Netherlands	0.71	−0.3	0.71	−0.2	0.71	−0.2
Poland	0.00	0.0	0.00	0.0	0.00	0.0
Portugal	0.35	−0.4	0.27	−1.3	0.27	−1.3
Romania	0.50	−3.8	0.18	−0.4	0.18	−0.4
Slovakia	0.67	−1.7	0.61	2.8	0.61	2.8
Slovenia	0.79	−0.8	0.81	2.6	0.81	2.6
Spain	0.06	−0.2	0.06	−0.3	0.06	−0.3
Sweden	0.29	−3.1	0.34	−3.4	0.34	−3.4
UK	0.60	1.1	0.59	1.1	0.59	1.1
Average	0.48	−0.5	0.47	0.0	0.47	0.0
Weighted av	0.43	−0.2	0.44	−0.5	0.44	−0.5

Trend is represented by the linear model coefficient for 1995–2017; GHG emission volume is used for weighting

the highest relative total abatement cost. All the trends are slightly downward sloped indicating the relative economic pressure related to potential abatement of the energy-related GHG emission declined over 1995–2017.

The country-specific relative total abatement costs (measured as share of the agricultural output) are presented in Table 3. The ranking of countries based on the GHG emission shadow price (Table 2) and that based on the relative total abatement costs differs substantially (rank correlation ranges in between 0.09 and 0.54 depending on the distance used). This is due to the fact that the relative total abatement cost involves not only the shadow price information, but also the magnitude of the energy-related GHG emission. Thus, the countries with high shadow prices and low volumes of the emission can face relatively low abatement cost burden (relative to the agricultural output).

The highest average relative abatement cost for energy-related GHG emission are observed for Estonia, Slovenia, France, Belgium, Denmark and the Netherlands. These countries include both minor and major agricultural producing countries of the EU. Therefore, the commitments towards reduction of the energy-related GHG emission may induce economic pressures of different extent across the selected countries.

4.3 Marginal abatement cost curves

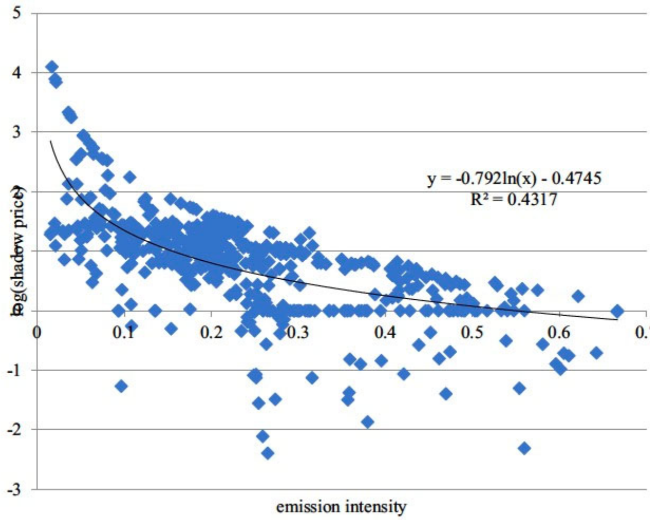
The marginal abatement cost (MAC) curves can be estimated in order to check the emission intensity elasticity of the shadow prices (which is the MAC). Thus, we fit the log–log models for the three types of the DDFs. The MAC curves for energy-related GHG emission in the selected EU countries are presented in Fig. 3. The results are highly dependent on the DDF used.

The MAC based on the unit DDF indicates an elastic responsiveness of the shadow price to the emission intensity. Thus, a 1% reduction in the emission intensity requires some 1.02% increase in the emission shadow price (Fig. 3c). As for the radial DDF (Fig. 3b), the elasticity falls to 0.57 indicating that abatement becomes less costly. The aggregate DDF implies an intermediate intensity estimate of 0.79. The use of the radial DDF, thus, is more relevant for the short-run decision analysis where the output-mix remains fixed.

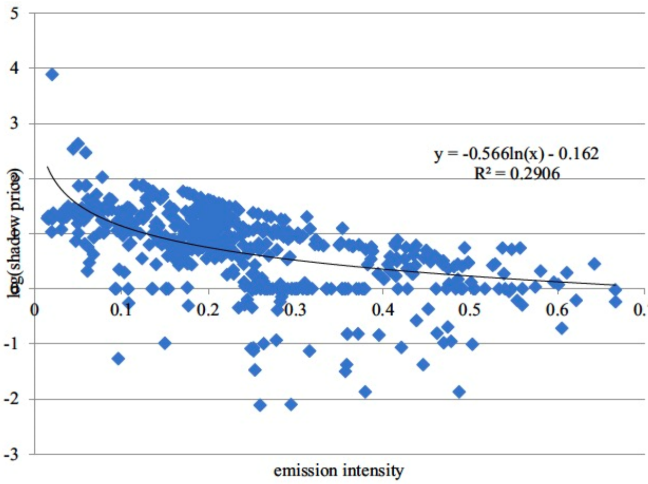
The MACs provided in Fig. 4 provide a general overview of the behavior of the shadow prices. As they are based on the pooled data, some nuances may be masked. To further verify the results, we run a series of panel models that take into account the spatial differences and intertemporal correlation. The fixed effects, random effects and first-difference models are implemented (Tables 5, 6 and 7in Appendix A). The fixed and random effects include two-way effects. The models are estimated with and without lagged dependent variable (shadow price). In general, the panel specifications confirm the inverse relationship between the carbon shadow price and emission intensity. Also, the models vary in the degree of explanatory power (especially, in the case of the radial DDF). Still, the highest elasticity is observed for the unit DDF case.

4.4 Robustness check

The solutions rendered by the linear programs for the DEA may not be unique. Therefore, one can assess the regions in which the shadow prices vary. To address this issue, we adopt additional directional vectors. Specifically, we set either the desirable or undesirable output direction to zero in Eqs. (8–11). This implies that only the desirable output or undesirable output is adjusted during the optimization (i.e., the oriented radial movement). As a result, we explore the two extreme cases for each scenario. The DEA frontier ensures monotonicity. Thus, one may naturally expect that adjusting only the desirable output will lead to a shadow price that is at most equal to that obtained when both desirable and undesirable

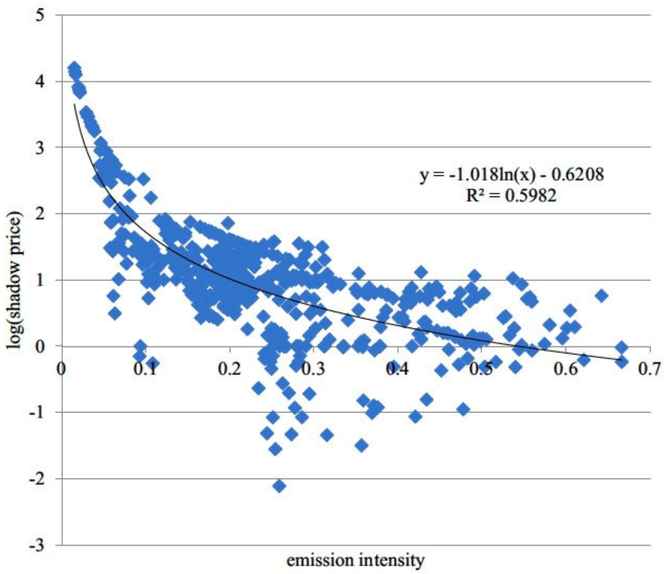


a – aggregate DDF



b – radial DDF

Fig. 4 Marginal abatement cost curves for a sample of the selected EU countries, 1995–2017. *Note* The pooled data are used for fitting the curves. Emission intensity is measured in kg CO_2 eq./PPS



c – unit DDF

Fig. 4 (continued)

outputs are adjusted. The opposite holds if only the undesirable output is adjusted. Figure 5 illustrates the underlying idea.

The average shadow prices of the energy-related GHG emission reported in Table 2. Note that the measures reported in Table 2 correspond to the $g_z>0$, $g_y>0$ case. Table 4 reports the country averages with the oriented radial movement. Note that the oriented cases of the directional vector provide the lower and upper bounds for the shadow prices. For shadow price calculation in this exercise, the exact expression of the oriented directional vector is not important as the present model includes only one undesirable and one desirable outputs. Thus, $g_z > 0$ may be replaced by one or (aggregate) observed undesirable output quantity.

The results in Table 4 suggest that most sensitive to changes in the direction of optimization are the extreme shadow prices. The case of Poland shows a change from zero to 10.9 PPS/kg CO_2 eq. Romania shows a possible range of 2.9 PPS/kg

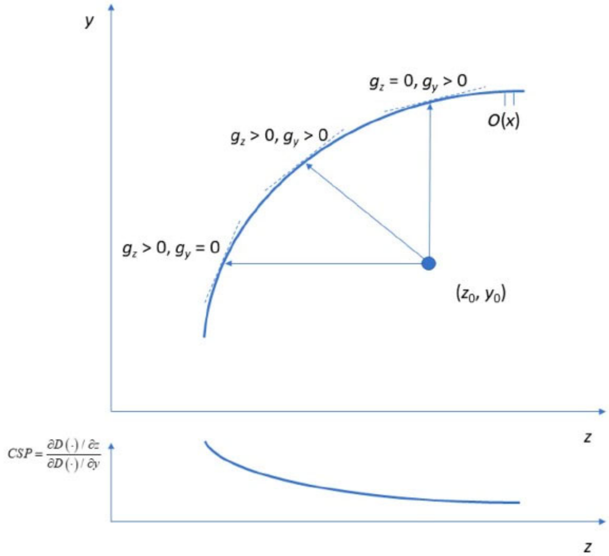


Fig. 5 Directional vector and shadow price

CO_2 eq. to 35 PPS/kg CO_2 eq. The weighted mean indicates the lower and upper bounds of 1.3 PPS/kg CO2 eq. and 4.5 PPS/kg COE eq., respectively. To compare, the weighted averages based on the non-oriented measures fall within the interval of 1.9–2 PPS/kg CO_2 eq. Therefore, the shadow prices based on the non-oriented models rendered by Eqs. (8–11) can be considered as the realistic ones compared to the pessimistic or optimistic results rendered by the oriented models.

5 Conclusions

Mitigation of the climate change requires coordinated actions across sectors of the economy. This paper focused on the shadow pricing of the energy-related GHG emission in the European countries. The country-level data were used to derive the shadow prices and construct the marginal abatement cost curves.

The analysis relied on the nonparametric approach. The directional data envelopment analysis models with different directional vectors were used. Specifically, the

Table 4 The average shadow price (PPS of 2010/kg CO_2 eq.) for the energy-related GHG emission across the selected European countries with different directional vectors and oriented radial movement, 1995–2017

Country	Non-oriented models			Oriented models	
	Aggregate DDF	Radial DDF	Unit DDF	$g_z=0, g_y>0$	$g_z>0, g_y=0$
Austria	2.4	2.3	2.4	2.2	2.5
Belgium	1.9	2.2	1.9	1.3	2.1
Bulgaria	3.1	2.7	3.1	1.8	5.5
Czechia	2.4	2.5	2.4	1.9	3.1
Denmark	2.6	2.6	2.6	1.8	2.8
Estonia	4.5	3.3	4.5	2.2	5.1
Finland	0.7	1.2	0.7	0.2	3.2
France	3.6	3.8	3.6	2.7	3.7
Greece	2.2	2.0	2.5	1.1	3.9
Hungary	3.5	3.4	3.5	3.1	3.9
Ireland	2.8	2.7	2.8	2.4	3.1
Italy	3.1	3.0	3.0	2.1	2.5
Latvia	1.1	1.2	1.1	0.1	3.9
Lithuania	4.9	4.6	5.3	3.2	8.9
Netherlands	1.5	1.5	1.5	1.1	1.7
Poland	0.0	0.0	0.0	0.0	10.9
Portugal	2.2	1.7	2.2	1.0	3.2
Romania	15.1	5.7	16.0	2.9	35.0
Slovakia	7.3	5.1	7.3	2.9	8.2
Slovenia	3.9	4.1	3.9	1.9	4.9
Spain	0.2	0.2	0.2	0.1	1.8
Sweden	0.7	0.8	0.7	0.5	2.5
UK	2.6	2.6	2.6	1.6	2.7
Average	3.1	2.6	3.2	1.7	5.4
Weighted av	2.0	1.9	2.0	1.3	4.5

GHG emission volume is used for weighting

radial, aggregate and unit directional vectors were applied for the directional output distance function. These settings represented different assumptions in regards to the substitutability between the desirable and undesirable outputs.

The results showed that the level of the energy-related GHG emission shadow price depended on the direction taken. Indeed, the radial directional output distance function showed the lowest shadow price levels as it corresponds to the data structure to the highest extent. The highest average shadow price observed in Poland and

Spain implies that these countries require much attention to their energy-related GHG emission in agriculture. On the contrary, the highest shadow prices were observed for Romania and Slovakia which do not require much effort towards curbing the energy-related GHG emission in the short term. The marginal abatement cost curves were also estimated based on the shadow prices rendered by each of the three directional DEA models. The results suggest that energy planning and climate change mitigation policy requires considering the choice of both the analytical tools and measures used for the analysis in order to properly address the challenges specific for different countries.

The decision makers shaping the agricultural support policy in the European Union, the Common Agricultural Policy, could take the carbon shadow prices in the consideration when identifying the support measures (especially, the Pillar 2 ones). The similar experience can also be used for the agricultural support programmes envisaging rural development measures across different regions. The marginal abatement cost curves are also useful in providing rationale for the desirable level of the energy-related emission abatement.

The directional vectors applied in this study are pre-specified ones. Even though they are meaningful in the economic sense, some nuances may be masked in case they are not optimized. Further research could focus on the endogenously chosen directions that are based on optimization approaches, whether global case where all the observations are considered simultaneously or local one where each observation is treated individually. This paper embarked on nonparametric analysis. Further studies could explore the patterns of the energy-related GHG emission in agriculture by using the parametric distance functions. Also, further analysis is possible by exploiting micro-data. This would allow assessing energy consumption in different farming types.

Future research can focus on adjusting the discussed frontier methods by exploring the shadow price calculation based on both parametric (Molinos-Senante et al. 2015) and non-parametric approaches. Within the non-parametric framework, the methods discussed by Cooper et al. (2007) and Aigner and Asmild (2023). The use of the by-production in this context is a particularly important research avenue.

Appendix A: Panel models for the MACs

See Tables 5, 6 and 7.

Table 5 Panel estimation of the MACs for the EU agriculture (aggregate DDF)

Model	Fixed effects 1	Fixed effects 2	Random effects 1	Random effects 2	First-difference 1	First-difference 2
Intercept			−0.68**	−0.07	0.002	0.01
$\log(GHG/Out)_t$	−1.03***	−0.62***	−0.91***	−0.27***	−0.72***	−0.80***
$\log(GHG/Out)_{t-1}$		0.39***		0.61***		−0.33***
Country effects	+	+	+	+		
Time effects	+	+	+	+		
Adj. R^2	0.13	0.27	0.40	0.63	0.03	0.13
N	463	463	427	427	441	405

*** and ** indicate significance at 1% and 5% levels of significance respectively; observations with zero shadow price were omitted; logged shadow price is the dependent variable; first differences of the dependent and independent variables are used for the first-difference models

Table 6 Panel estimation of the MACs for the EU agriculture (radial DDF)

Model	Fixed effects 1	Fixed effects 2	Random effects 1	Random effects 2	First-difference 1	First-difference 2
Intercept			−0.29	0.07	0.02	0.02
$\log(GHG/Out)_t$	−0.61***	−0.37***	−0.65***	−0.17**	−0.33*	−0.51***
$\log(GHG/Out)_{t-1}$		0.45***		0.63***		−0.33***
Country effects	+	+	+	+		
Time effects	+	+	+	+		
Adj. R^2	0	0.24	0.26	0.58	0	0.13
N	466	430	466	430	466	466

***, ** and * indicate significance at 1%, 5% and 10% levels of significance respectively; observations with zero shadow price were omitted; logged shadow price is the dependent variable; first differences of the dependent and independent variables are used for the first-difference models

Table 7 Panel estimation of the MACs for the EU agriculture (unit DDF)

Model	Fixed effects 1	Fixed effects 2	Random effects 1	Random effects 2	First-difference 1	First-difference 2
Intercept			−0.81**	−0.14	0.00	−0.0004
$\log(GHG/Out)_t$	−1.26***	−0.76***	1.13***	−0.27**	−0.99***	−1.06***
$\log(GHG/Out)_{t-1}$		0.44***		0.75***		−0.10***
Country effects	+	+	+	+		
Time effects	+	+	+	+		
Adj. R^2	0.33	0.54	0.60	0.86	0.10	0.17
N	510	477	510	477	510	454

***, ** and * indicate significance at 1%, 5% and 10% levels of significance respectively; observations with zero shadow price were omitted; logged shadow price is the dependent variable; first differences of the dependent and independent variables are used for the first-difference models

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Declarations

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Summary in Lithuanian

Įvadas

Problemos formulavimas

Atlikta mokslinės literatūros analizė atskleidė, kad nors pasaulyje publikuota tyrimų produktyvumo su nepageidaujamais rezultatais vertinimo problemai spręsti, tačiau visi mokslinėje literatūroje siūlomi nepageidaujamų žemės ūkio gamybos rezultatų vertinimo metodai turi svarbių trūkumų ir apribojimų. Nėra sukurta metodų bei atlikta tyrimų, kurie leistų įvertinti atskirų žemės ūkio gamybos veiksnių įtaką bendram žemės ūkio gamybos efektyvumui ir aplinkosauginių (šiltnamio dujų emisijų) požiūriu įvertinto produktyvumo pokyčiams. Todėl būtina sukurti naują produktyvumo su nepageidaujamais rezultatais vertinimo modelį, leidžiantį išvengti pasiūlytų metodų silpnybių ir apribojimų, bei visapusiškai ištirti žemės ūkio gamybos efektyvumo ir tvariojo produktyvumo augimo veiksnius bei kliūtis. Be to, įprasta neparametrinė ribinė analizė, tokia kaip duomenų apgaubties analizė (DEA), taikoma produktyvumui ir efektyvumui matuoti, pasižymi daugiadimensiškumo problema. Ši problema tampa ypač sudėtinga, kai nepageidaujami rezultatai įtraukiami tarp vertinimo kintamųjų.

Darbo aktualumas

Žemės ūkio sektorius yra vienas svarbiausių ekonomikos sektorių, teikiantis žaliavas ir maistą kitiems sektoriams. Nors tvarioji žemės ūkio raida yra vienas svarbiausių politikos tikslų ES (Europa 2020; Europos žaliasis susitarimas, Bendroji žemės ūkio politika), žemės ūkio gamybos intensifikavimas daro neigiamą įtaką aplinkai. Tvarioji žemės ūkio raida turėtų užtikrinti didžiausią galimą žemės ūkio produktyvumą bei mažiausius negatyvius žemės ūkio gamybos padarinius, tokius kaip aplinkos tarša. Šiltnamio efektą sukeliančių dujų emisijos yra vienas svarbiausių tvariojo žemės ūkio vystymosi aplinkosauginių iššūkių. Vertinant žemės ūkio produktyvumą, labai svarbu kartu įvertinti nepageidaujamų rezultatų, tokių kaip šiltnamio dujų emisijos, įtaką žemės ūkio gamybos produktyvumui, siekiant užtikrinti tvariojo žemės ūkio produktyvumo augimą, mažinant neigiamą poveikį aplinkai, taip pat klimato kaitai. Perėjimas prie mažanglės energetikos yra prioritetinė sritis įgyvendinant Žaliąjį kursą, todėl šiltnamio efektą sukeliančių dujų emisijų mažinimas dėl energijos vartojimo žemės ūkyje yra ypač svarbus tikslas siekiant užtikrinti tvarią žemės ūkio plėtrą.

Tyrimo objektas

Žemės ūkio produktyvumo su nepageidaujamais rezultatais vertinimas ES žemės ūkio sektoriuje.

Darbo tikslas

Parengti gamybos produktyvumo su nepageidaujamais rezultatais vertinimo modelį bei pritaikyti jį žemės ūkio tvariajam produktyvumui vertinti ES.

Darbo uždaviniai

Darbo tikslui pasiekti reikalinga spręsti sekančius uždavinius:

1. Atlikti mokslinės literatūros analizę ir susisteminti efektyvumo ir produktyvumo pokyčių su nepageidaujamais rezultatais vertinimo metodus bei apibendrinti rezultatus bei jų taikymo žemės ūkyje įžvalgas;
2. Parengti produktyvumo su nepageidautina produkcija žemės ūkyje vertinimo modelį, pagrįstą įvairių metodų, tokių kaip duomenų apgaubties analizė, Liuenbergerio produktyvumo indeksas, perviršio metodas, super efektyvi duomenų apgaubties analizė ir struktūrinio efektyvumą indeksas efektyvumo matavimui.
3. Sukurtą tvaraus produktyvumo su nepageidaujamais produktais modelį pritaikyti darnaus žemės ūkio produktyvumo vertinimui ES;
4. Remiantis gautais empirinio tyrimo rezultatais, parengti rekomendacijas tvariosios žemės ūkio raidos politikos formavimui ES šalyse narėse.

Tyrimų metodika

Pagrindiniai tyrimų metodai yra mokslinės literatūros analizė, sintezė ir abstrahavimas, Duomenų apgaubties analizė (DEA), įvairūs produktyvumo indeksai, tokie kaip perviršio metodas (SBM), Luenberger prodyktyvumo rodiklis, indėlio į struktūrinį efektyvumą indeksas, superefektyvi DEA, silpno sumažininimo DEA.

Neparametriniai efektyvios ribos analizės metodai (DEA) suteikia galimybes nustatyti atskirų regionų žemės ūkio gamybos efektyvumo ir produktyvumo su nepageidaujamais rezultatais įverčius pagal pasirinktus rodiklius, rodančius bendrą bei atskirų gamybos veiksnių efektyvumą, įvertinti produktyvumo kitimą bei jo veiksnius (efektyvumas bei technologinė pažanga) ir taršos rezultatus. DEA, papildyta SBM bei Luenberger produktyvumo indikatoriumi, leidžia išskaidyti atskirų gamybos veiksnių bei nepageidaujamų gamybos rezultatų įtaką efektyvumui ir produktyvumo pokyčiams. Be to, DEA rezultati gali būti išderinti dėl didelių duomenų imčių, reikalingų gamybos funkcijai įvertinti tam tikru tikslumo lygiu. Kintamųjų skaičius auga eksponentiškai atsižvelgiant į funkcijos įvesties kintamųjų skaičių ir ši problema tampa ypač sudėtinga, kai yra nepageidaujamos produkcijos (papildomas kintamasis). Todėl reitingavimui pagal ekologinį efektyvumą tvariojo produktyvumo vertinimo atveju įvedamas indėlio į struktūrinį efektyvumą indeksas bei superefektyvios DEA rodiklis.

Pritaikytas silpno sumažinimo („weak disposability") DEA modelis, kurį taikant, judant skirtingomis optimizavimo kryptimis, gaunamos šešėlinės su energija susijusių šiltnamio efektą sukeliančių dujų emisijų mažinimo kainos žemės ūkyje, leidžiančios įvertinti ŠESD mažinimo kaštus žemės ūkyje, esant skirtingoms gamybos technologijoms.

Panaudoti „Excel" su „Solver" ir „Visual Basic" programiniai paketai.

Darbo mokslinis naujumas

Sukurtas naujas žemės ūkio produktyvumo su nepageidautina produkcija vertinimo modelis, pagrįstas išplėsta gamybos funkcija, apimančia pagrindinius žemės ūkio gamybos veiksnius (energijos suvartojimą žemės ūkyje, kapitalą, darbo ir žemės sąnaudas žemės ūkyje) ir ŠESD emisijas, susijusias su energijos vartojimu žemės ūkyje. Naujasis modelis leidžia naujai išplėsti ir panaudoti DEA galimybes gamybos funkcijoje, papildant ją globaliu perviršio („slacks-based") metodu (SBM), Luenberger produktyvumo rodikliu, itin efektyviu DEA ir indėlio į struktūrinį efektyvumą indeksu, leidžiančiu išanalizuoti visų gamybos veiksnių, taip pat ir šiltnamio efektą sukeliančių dujų, indėlį į bendrus efektyvumo ir našumo pokyčius ir pagaliau suskirstyti šalis pagal tvarų produktyvumą per nustatytą tyrimo laikotarpį.

Sukurtas tvariojo produktyvumo vertinimo modelis taip pat papildytas gamybos technologijos aplinkosaugine funkcija, kuri integruoja papildomas prielaidas apie pageidautinos ir nepageidautinos produkcijų tarpusavio ryšį ir leidžia gauti nepageidautinos produkcijos (šiltnamio efektą sukeliančių dujų, atsirandančių dėl energijos suvartojimo) piniginę išraišką. Nepageidautina produkcija, vertinama piniginė išraiška skaičiuojant šešėlines ŠESD emisijų kainas (ribines ŠESD emisijų mažinimo išlaidas), leidžia formuoti politikos rekomendacijas tvariajai žemės ūkio raidai skatinti.

Darbo rezultatų praktinė reikšmė

Parengtas gamybos produktyvumo su nepageidaujamais rezultatais vertinimo modelis empiriškai pritaikytas tvariojo žemės ūkio sektoriaus produktyvumo vertinimui ES valstybėse. Remiantis tyrimo rezultatais buvo parengtos žemės ūkio ir aplinkosaugos politikos tobulinimo politikos kryptys, kurios padėtų didinti išteklių naudojimo ES žemės ūkyje efektyvumą ir kartu spręsti su klimato kaitos švelninimu susijusias aplinkosaugos problemas, tvariojo žemės ūkio produktyvumo augimą.

Ginamieji teiginiai

1. Tvariosios žemės ūkio plėtros vertinimas gali būti atliekamas taikant tvariojo produktyvumo modelį, pagrįstą išplėstine gamybos funkcija su neigiamais rezultatais, nes ji apima ekonomines, socialines ir aplinkosaugines žemės ūkio tvarumo dimensijas.
2. Įprasti DEA metodai turi daug trūkumų dėl diskriminacinės galios sumažėjimo, kai egzistuoja didelis kintamųjų skaičiaus, ypač kai yra vertinami nepageidaujami rezultatai.
3. DEA galimybių išplėtimas, papildant gamybos funkciją globaliu perviršio („slacks-based“) metodu (SBM), Liuenbergerio produktyvumo rodikliu, superefektyvia DEA, indėlio į struktūrinį efektyvumą rodikliu leidžia įveikti pagrindinę įprastos DEA daugiadimensiškumo silpnybę ir detaliai ištirti visų gamybos veiksnių, taip pat ŠESD emijų indėlį į bendrus efektyvumo ir produktyvimo pokyčius.
4. ŠESD emisijų šešėlinės kainos, gautos taikant silpno sumžinimo duomenų apgaubties analizę ir kryptinius atstumo nuo gamybos galimybių ribos vektorius („Directional Distance Functions“), leidžia apibrėžti atsiliekančias ir pažangias šalis žemės ūkio energijos vartojimo efektyvumo didinimo bei ŠESD emisijų mažinimo požiūriu.

Darbo rezultatų aprobavimas

Tyrimo rezultatai publikuoti 5 moksliniuose leidiniuose, iš kurių 5 straipsniai išspausdinti recenzuojamuose mokslo žurnaluose su cituojamumo indeksu, įtrauktuose į Clarivate Analytics Web of Science duomenų bazę.
Disertacijos autorius skaitė keturis pranešimus trijose tarptautinėse mokslinėse konferencijose:

- 3-ioji Tarpatutinė mokslinė konferencija SER 2020 „New Trends and Best Practices in Socioeconomic Research “. Igalo (Herceg Novi), Juodkalnija.
- 4-oji Tarpatutinė mokslinė konferencija SER 2020 „ New Trends and Best Practices in Socioeconomic Research “. Igalo (Herceg Novi), Juodkalnija.
- 16-oji tarptautinė mokslinė konferencija „Conference on Sustainable Development of Energy, Water and Environment Systems “. Dubrovnikas, Koratija.

Disertacijos strukūra straipsnių pagrindu

Disertaciją sudaro įvadas, analitinės literatūros apžvalga, tyrimo metodologijos aptarimas, rezultatų ir išvadų santrauka, literatūros sąrašas, priedai su penkiais moksliniais straipsniais, santrauka lietuvių kalba.

Disertaciją sudaro 178 puslapiai, 20 lygtys, 16 paveikslai, 9 lentelės ir disertacijoje cituojamos 60 nuorodos.

1. Tvariojo žemės ūkio produktyvumo analitinė literatūros apžvalga

Nors yra atlikta nemažai tyrimų žemės ūkio produktyvumo bei tvariosios žemės ūkio raidos srityje, tarp mokslininkų stokojama sutarimo dėl nepageidaujamų rezultatų, tokių kaip šiltnamio efektą sukeliančių dujų emisijos ir kt., vertinimo tiriant žemės ūkio gamybos efektyvumą bei produktyvumą. Kaip rodo atlikta išsami tyrimų, skirtų žemės ūkio produktyvumui bei aplinkos taršai vertinti, analizė, yra labai sunku tinkamai aplinkosauginiu požiūriu įvertinti žemės ūkio tvariosios raidos prioritetus ir problemas. Iki šiol mokslininkai plačiai diskutuoja šia tema bei siūlo įvairius alternatyvius problemos sprendimo būdus.

Pittman (1983) bei Hailu ir Veeman (2001) pasiūlė nepageidautiną produkciją gamybos funkcijoje įvertinti kaip vieną iš gamybos veiksnių. Fare et al. (1989), Kuosmanen (2005) pateikė pasiūlymą nepageidautiną produkciją laikyti silpnai sumažinama („weakly disposable“) lyginant ją su pageidautina produkcija, t. y., vertinant gamybos produktyvumą, nustatyti reikalavimą, kad pageidautina ir nepageidautina produkcija mažėja proporcingai.

Murty et al. (2012) pasiūlė modelį, kuriame nustatomi taršą lemiantys gamybos veiksniai ir sudaroma atskira „taršos funkcija“ šalia gamybos funkcijos. Kocisova (2015) atliko ES žemės ūkio gamybos produktyvumo vertinimą, taikydama DEA ir dekompozicinę analizę, tačiau šiame tyrime nebuvo nagrinėjami nepageidaujami gamybos rezultatai, tokie kaip atmosferos tarša ar šiltnamio efektą sukeliančių dujų emisijos. Błażejczyk-Majka (2017) taip pat pritaikė DEA ES šalių narių žemės ūkio gamybos efektyvumui vertinti, neatsižvelgdama į nepageidaujamus žemės ūkio produkcijos rezultatus. Barath ir Ferto (2017) žemės ūkio gamybos produktyvumo tyrime pritaikė DEA ir Fare–Primont indeksą, kuris leido įvertinti atskirų gamybos veiksnių pakeičiamumą gamybos funkcijoje, tačiau vėlgi nepageidautina produkcija nebuvo įvertinta. Martinho (2017) taip pat panaudojo DEA ES šalių narių žemės ūkio produktyvumui vertinti, tačiau neanalizavo nepageidaujamų gamybos rezultatų įtakos produktyvumo pokyčiams. Vlontzos at al. (2014) pritaikė DEA ir perviršio modelio (SBM) kombinaciją ES šalių žemės ūkio produktyvumui vertinti, tačiau nors tyrime buvo įvertinti du nepageidaujami gamybos rezultatai, tokie kaip anglies dioksido emisijos ir maistinių medžiagų balansas, šiame tyrime atskirų gamybos veiksnių įtaka produktyvumui nebuvo nagrinėta. Bartova et al. (2018) pritaikė nepageidautinos produkcijos silpno sumažinimo („weakly disposable“) gamybos funkcijoje principą bei DEA ir Malmquist–Luenberger produktyvumo indeksą ES žemės ūkio gamybos produktyvumo analizei ES šalių lygmenyje. Nors šiame tyrime kaip nepageidautina produkcija buvo įvertintos šiltnamio efektą sukeliančių dujų emisijos, atskirų gamybos veiksnių bei šiltnamio dujų emisijų efektyvumo įtaka bendram efektyvumui ir produktyvumui nebuvo nustatyta.

Visi atlikti tyrimai ir siūlomi žemės ūkio produktyvumo bei nepageidaujamų žemės ūkio gamybos rezultatų vertinimo metodai turi svarbių trūkumų ir apribojimų. Vienas svarbiausių apribojimų yra tai, kad visi iki šiol taikyti žemės ūkio gamybos efektyvumo ir produktyvumo vertinimo metodai bei atlikti tyrimai nesugebėjo pateikti tinkamų modelių visų gamybos veiksnių bei nepageidaujamų gamybos rezultatų įtakos produktyvumo pokyčiams įvertinti. Todėl būtina sukurti naują produktyvumo su nepageidautina produkcija vertinimo modelį, leidžiantį išvengti pasiūlytų metodų trūkumų ir apribojimų bei išplėsti DEA galimybes žemės ūkio produktyvumo su nepageidaujamais rezultatais visapusiškai analizei bei vertinimui. Tuo tikslu siekiama panaudoti įvairius papildomus produktyvumo rodiklius, konstruojant aplinkosaugines gamybos funkcijas taikant DEA.

2. Tvariojo produktyvumo vertinimo tyrimo metodika

Pareto–Koopmans pateikė apibrėžimą, kad gamyba yra efektyvi, jeigu neįmanoma pagaminti daugiau, nepadidinus sąnaudų, arba neįmanoma panaudoti mažiau gamybos veiksnių, nesumažinus gamybos apimčių (Mirdehghan, Fukuyama, 2016). Tuo tarpu Farrell (1957) pasiūlė efektyvumo koeficientą, leidžiantį įvertinti, kiek faktinė situacija skiriasi nuo optimalios. Optimali situacija įvertinama taikant gamybos funkciją (gamybos galimybių ribą). Efektyvumas nustatomas kaip faktinio ir optimalaus produktyvumo santykis, o gamybos produktyvumo pokytis yra išmatuojamas kaip efektyvumo bei technologinio pokyčio rezultatas.

Taigi, tvarusis žemės ūkio produktyvumas gali būti tiriamas, taikant ribinius (neparametrinius tiesinio programavimo) metodus ir siekiant nustatyti efektyvią pasirinkto regiono žemės ūkio gamybos galimybių ribą, kartu įvertinus nepageidaujamus žemės ūkio gamybos rezultatus, tokius kaip šiltnamio efektą sukeliančių dujų emisijos. Pasirinkto tyrimo regiono (ES šalių narių) nuotolis nuo efektyvios žemės ūkio gamybos galimybių ribos parodytų, ar yra potencialas pasiekti geresnius ekonominius rezultatus, įvertinus šiltnamio efektą sukeliančių dujų emisijų apribojimus, su turimais ištekliais, t. y. žmogiškuoju kapitalu ir investicijomis bei aplinkosauginiais apribojimais.

Konstruojant tvariojo produktyvumo vertinimo modelį žemės ūkyje, pasirinkti neparametriniai tiesinio programavimo metodai (duomenų gaubties analizė), nes jie papildo daugiamačių duomenų analizės galimybes ir tiksliau įvertina techninio žemės ūkio efektyvumo skirtumus tarp tiriamų regionų, leidžia identifikuoti silpnąsias sritis ir pateikti pasiūlymus žemės ūkio bei aplinkos politikai. Duomenų gaubties analizė (DEA) geriau nei kiti neparametriniai tiesinio programavimo metodai padeda išgryninti technologiškai panašių regionų efektyvumo skirtumus (Hailu, Veeman 2001; Färe, Grosskopf, 2003; Murty et al., 2012).

DEA lygina visą regionų grupę pagal ekstremalias efektyvumo reikšmes, o likę metodai skirtingų regionų efektyvumą lygina tik su mažesnius resursus turinčiais regionais, leidžiant dalies regionų ekonominių įverčių reikšmėms būti virš efektyvios gamybos galimybių ribos su tam tikrais pasikliovimo lygmenimis α. Lyginant technologiškai panašius regionus tikslingiau ieškoti visos grupės lyderių, kurių pagrindu būtų galimybė daryti išvadas apie bendrą regionų grupės žemės ūkio efektyvumą (Sueyoshi et al., 2017; Urdiales et al., 2016).

Taigi efektyvumui ir žemės ūkio produktyvumui tirti šiame darbe yra siūloma taikyti vienas kitą papildančius tyrimo metodus, tokius kaip DEA ir įvairūs produktyvumo rodikliai bei aplinkosauginės technologijos, siekiant identifikuoti problemines sritis ir gauti naudingos informacijos tvariosios žemės ūkio raidos skatinimo ir klimato kaitos švelninimo politikai formuoti.

Pasiūlytas naujas žemės ūkio gamybos su nepageidaujamais rezultatais vertinimo modelis, kurio pagrindą sudaro išplėsta gamybos funkcija, apimanti pagrindinius žemės ūkio gamybos veiksnius (energijos suvartojimas žemės ūkyje, kapitalo, darbo bei žemės sąnaudos žemės ūkyje) bei šiltnamio dujų emisijas, susijusias su energijos vartojimu žemės ūkyje. Modelis leidžia įvertinti gamybos funkciją taikant DEA ir wepapildant globalia technologija ir perviršio („slacks-based“) metodu (SBM), Luenberger produktyvumo rodikliu, superefektyvios DEA bei indėlio į struktūrinį efektyvumą rodikliais, skirtais žemės ūkio tvariajam produktyvumui bei efektyvumui matuoti.

Tarkime, kad X yra gamybos veiksnio sąnaudos, o Y – gamybos apimtis, o (faktinis) produktyvumas = Y/X. Tarkime, kad optimalus sąnaudų kiekis yra $X^* < X$; tada optimalus produktyvumas = $Y/X^* > Y/X$. Dažniausiai gamybos procese naudojamas daugiau nei vienas gamybos veiksnys, pagaminamas daugiau nei vienas produktas. Tuomet apskaičiuojami agreguoti kiekiai $X = f(x1, x2, \ldots, xm)$ ir $Y = g(y1, y2, \ldots, yn)$. Agregavimui naudojami svoriai (t. y. funkcijų f ir g koeficientai), kurie yra gaunami taikant ribinius metodus, tokius kaip DEA.

SBM perviršio vertinimo metodas išmatuoja neefektyvumą (atstumo funkcija) remiantis įvesties ir rezultatų perviršiais / trūkumais (Cooper et al., 2007). Taigi empirinio tyrimo metu bus matuojamas neefektyvumas. Kryptinė atstumo funkcija gali įgauti reikšmes nuo 0 iki begalybės. Neefektyvumas yra atvirkščias dydis efektyvumui, o nulinis neefektyvumas reiškia visišką efektyvumą.

Luenberger produktyvumo (LPI) rodiklis atspindi produktyvumo pokyčius, kurie gali būti teigiami ir neigiami. Teigiama reikšmė rodo, kad gamybos produktyvumas auga, ir atvirkščiai (Wang, Wei, 2016; Wang et al., 2016).

Toliau sukurtas gamybos produktyvumo su nepageidaujamais rezultatais vertinimo modelis su aplinkosaugine gamybos technologijos funkcija papildomas naujais efektyvumo vertinimo metodais: superefektyvia DEA ir indėlio į struktūrinį efektyvumą indeksu. Tai leidžia spręsti ŽŪ efektyvumo vertinimo problemą, kai DEA analizė nepajėgi įvertinti efektyvumo dėl diskriminacinės galios sumažėjimo, t. y. gebėjimo atskleisti skirtumus tarp įvairių efektyvumo lygių. Ši problema pasireiškia esant dideliam kintamųjų ir stebėjimų skaičiui ir tampa labai sudėtinga, kai yra įtraukiama nepageidautina produkcija (papildomas kintamasis).

Superefektyvi DEA analizė ir panašūs metodai buvo pasiūlyti siekiant pagerinti diskriminacinę galią (atskleisti skirtumus tarp įvairių efektyvumo lygių). Taikant šiuos metodus daroma prielaida, kad kiekvieno nagrinėjamo efektyvaus DMU (sprendimų priėmėjo / valstybės) gamybos technologija yra tiriama toliau ir gaunami rezultatai yra didesni nei 1, o neefektyvių DMU – ne.

Taigi, taikant superefektyvią DEA, efektyvūs sprendiniai yra eliminuojami iš pagrindinės aibės kiekvienam DMU. Neefektyvūs sprendiniai neturi įtakos, todėl jų nebūtina eliminuoti. Taip efektyvumo matas tampa neapribotas.

Taip pat įvedamas indėlio į struktūrinį efektyvumą indeksas, kuris taiko (tą pačią) aplinkosauginę technologiją visiems DMU. Indėlio į struktūrinį efektyvumą indeksas skaičiuojamas kaip visų galimų atvejų agregavimo variantų įtraukus ir neįtraukus atskiras DMU vidurkis. Skaičius >1 rodo, kad atskiras DMU pagerina struktūrinį efektyvumą.

Toliau produktyvumo vertinimo modelis papildomas aplinkosaugine gamybos technologijos funkcija, kuri integruoja papildomas prielaidas apie pageidaujamų ir nepageidaujamų rezultatų tarpusavio ryšį, ir vertinama nepageidaujamų rezultatų (ŠESD dėl energijos suvartojimo žemės ūkyje) piniginė išraiška. Ji randama skaičiuojant ŠESD šešėlines kainas (ribiniai ŠESD emisijų mažinimo kaštai).

Kitame etape į gamybos produktyvumo su nepageidaujamais rezultatais vertinimo žemės ūkyje modelį įvedama aplinkosauginė gamybos technologijos funkcija, kuri integruoja papildomas prielaidas apie pageidaujamų ir nepageidaujamų rezultatų tarpusavio ryšį. Tyrimui pasirinkta silpno sumažinimo (angl. weakly disposable) technologija, t. y. pageidautina produkcija ir nepageidaujami rezultatai (ŠESD) mažėja proporcingai. Šešėlinė ŠESD emisijų kaina rodo jų sumažinimo ribinius kaštus. Ši informacija labai svarbi norint analizuoti aplinkos kokybės gerinimo galimybes taikant konkrečią gamybos technologiją.

Kryptinė DEA, pritaikyta aplinkosauginei technologijai, gali įvertinti sprendimų priėmimo vienetų (valstybės) efektyvumą judant prie gamybos galimybių kreivės įvairiomis kryptimis. Kryptys gali būti skaičiuojamos vertinant atskirų šalių duomenis arba šalių grupes.

Šiame tyrime buvo siekiama išsiaiškinti skirtingų krypčių pasirinkimo, judant prie gamybos galimybių kreivės, poveikį ŠESD emisijų šešėlinėms kainoms. Buvo pritaikytas silpno sumažinimo („weak disposability“) DEA modelis, sukurtas Kuosmanen (2005). Judant skirtingomis optimizavimo kryptimis gaunamos šešėlinės su energija susijusių šiltnamio efektą sukeliančių dujų emisijos ES žemės ūkyje kainos.

Skaičiavimui reikalingi duomenys: ES šalių narių duomenys iš *Eurostat* Žemės ūkio ekonominių sąskaitų, energijos balansų, šiltnamio dujų emisijų dėl energijos suvartojimo žemės ūkyje duomenys. Tiriami gamybos veiksniai: energijos suvartojimas žemės ūkyje, TJ; pastovaus kapitalo sąnaudos žemės ūkyje, PGS, perskaičiuotos 2005 m. arba 2010 m. kainomis; darbo sąnaudos žemės ūkyje, metinės darbo laiko valandos; žemės sąnaudos, ha. Pageidautina produkcija išreikšta bendra žemės ūkio produkcija, PGS, perskaičiuota pastoviomis 2005 m. kainomis. Nepageidautina produkcija išreikšta šiltnamio efektą sukeliančių dujų emisijomis, Mt.

3. Tvariojo žemės ūkio produktyvumo vertinimo rezultatai

Šiame skyriuje pateikiami empirinių tyrimų, atliktų taikant sukurtą orginalų tvaraus produktyvumo vertinimo modelį ES valstybių narių žemės ūkyje, rezultatai.

Žemės ūkio gamybos neefektyvumas buvo matuojamas atsižvelgiant į gamybos galimybių ribas. Įtraukus prielaidą apie nuolatinę masto grąžą, ribiniai neefektyvumo pokyčiai yra susiję su analizuojamų ES šalių produktyvumo pokyčiais. Pritaikytas perviršio metodas neefektyvumo analizei leido atskirti atskirų sgamybos veiksnių ir rezultatų indėlį į bendrąjį žemės ūkio gamybos neefektyvumą.

Atlikti skaičiavimai atskleidė, kad ES žemės ūkio produktyvumo padidėjimas yra daugiausiai susijęs su gamybos veiksnių naudojimo efektyvumo didinimu ir aplinkosauginio veiksmingumo gerinimu. Vidutinės neefektyvumo balų vertės toliau analizuojamos, siekiant nustatyti pagrindines neefektyvumo tendencijas žemės ūkio gamyboje ir atskirų kintamųjų įtaką bendram produktyvumui. S3.1 lentelėje pateikiamos vidutinės neefektyvumo reikšmės kartu su tendencijų koeficientais (atitinkančiais stochastinius kitimo tempus) įvairiais laikotarpiais.

S3.1 lentelė. Neefektyvumo dinamika ES šalyse **(**Šaltinis*:* Streimikis et al., 2020)

Laikotarpis	Energija	Kapitalas	Darbas	Žemė	ŠESD emisijos
Average, %					
1995–2016	3,84	3,51	2,37	2,18	14,21
1995–2003	4,52	4	3,55	2,79	16,57
2004–2016	3,38	3,16	1,55	1,76	12,58
Trendas (pokyčių greitis, procentiniai punktais)					
1995–2016	–0,1	–0,09	–0,17	–0,09	–0,34
1995–2003	–0,13	–0,01	–0,1	–0,06	–0,16
2004–2016	–0,08	–0,15	–0,14	–0,1	–0,33

Pradžioje ES žemės ūkio sektoriaus veiklos efektyvumas buvo analizuojamas šalies lygiu kiekvienais metais taikant įprastinę duomenų apgaubties analizę. Gauti rezultatai pateikti S3.2 lentelėje.

S3.2 lentelė. ES valstybių narių žemės ūkio sektorių efektyvumo balai (pastovaus masto grąža), 1995–2016 (Šaltinis: Streimikis et al., 2022)

Valstybė	1995	2000	2005	2010	2016	Vidurkis	Trendas
Austrija	0,89	0,89	0,90	0,95	0,95	0,91	0,005
Belgija	0,81	1,00	1,00	1,00	1,00	0,97	0,007
Bulgarija	1,00	1,00	1,00	1,00	1,00	1,00	0,000
Čekija	0,93	0,94	1,00	0,96	0,94	0,97	0,001
Danija	1,00	1,00	1,00	1,00	1,00	1,00	0,000
Estija	0,85	1,00	0,96	0,87	0,73	0,90	–0,003
Suomija	0,69	0,67	0,70	0,71	0,68	0,69	0,002
Prancūzija	1,00	1,00	1,00	1,00	0,93	1,00	–0,001
Vengrija	0,86	0,88	0,96	0,84	0,97	0,89	0,003
Latvija	0,62	0,64	0,64	0,70	1,00	0,72	0,018
Lietuva	0,73	1,00	1,00	1,00	1,00	0,96	0,009
Nyderlandai	1,00	1,00	1,00	1,00	1,00	1,00	0,000
Lenkija	0,68	0,66	1,00	1,00	1,00	0,84	0,022
Rumunija	1,00	1,00	1,00	1,00	1,00	1,00	0,000
Slovakija	1,00	1,00	1,00	1,00	1,00	1,00	0,000

S3.2 lentelės pabaiga

Valstybė	1995	2000	2005	2010	2016	Vidurkis	Trendas
Slovėnija	1,00	1,00	1,00	1,00	1,00	1,00	0,000
Švedija	0,71	0,72	0,73	0,72	1,00	0,77	0,013
VIdurkis	0,87	0,91	0,93	0,93	0,95	0,92	0,004
# efektyvių rezultatų skaičius	7	10	11	10	11	5	-

Toliau buvo panaudotas superefektyvios duomenų apgaubties analizės ES valstybių narių reitingavimui pagal žeemės ūkio gamybos efektyvumą (S3.3 lentelė).

S3.3 lentelė. ES valstybių narių žemės ūkio sektoriaus efektyvumas taikant superefektyvią duomenų apgaubties analizę, 1995–2016 m. (Šaltinis: Streimikis et al., 2022)

Valstybė	1995	2000	2005	2010	2016	Vidurkis	Trendas
Austrija	0,89	0,89	0,90	0,95	0,95	0,91	0,005
Belgija	0,81	–	–	–	–	0,93	–
Bulgarija	–	–	–	–	1,80	1,80	–
Čekija	0,93	0,94	1,01	0,96	0,94	0,98	0,001
Danija	–	–	–	1,02	1,14	1,05	–
Estija	0,85	1,01	0,96	0,87	0,73	0,88	–
Suomija	0,69	0,67	0,70	0,71	0,68	0,69	0,002
Prancūzija	–	–	–	–	0,93	1,08	–
Vengrija	0,86	0,88	0,96	0,84	0,97	0,89	0,003
Latvija	0,62	0,64	0,64	0,70	1,01	0,71	–
Lietuva	0,73	1,13	1,21	1,01	1,03	1,02	0,012
Nyderlandai	–	–	–	–	–	–	–
Lenkija	0,68	0,66	–	–	–	0,68	–
Rumunija	1,13	–	–	–	–	2,56	–
Slovakija	1,33	1,05	1,08	–	1,36	1,23	–
Slovėnija	–	–	–	–	–	–	–
Švedija	0,71	0,72	0,73	0,72	–	0,72	–
Vidurkis	0,85	0,86	0,91	0,86	1,05	0,97	0,011
# superefektyvių rezultatų skaičius	5	7	8	8	6	2	–

Remiantis S3.3 lentelėje pavaizduotais superefektyvios duomenų apgaubties analizės rezultatais, galima iš naujo suranguoti ES šalis pagal žemės ūkio produktyvumą. Tačiau yra keletas šalių, kurioms superefektyvi duomenų apgaubties analizė nepateikia įverčių dėl duomenų pobūdžio.

Toliau apskaičiuotas ir S3.4 lentelėje pateiktas ES šalių vidutinis indėlio į struktūrinį efektyvumą indeksas.

S3.4 lentelė. ES valstybių narių vidutinis efektyvumas ir indėlis į struktūrinį efektyvumą indeksas, 1995–2016 m. (Šaltinis: Streimikis et al., 2022)

Valstybė	Indėlis į struktūrinį efektyvumą	DEA vidurkis	Efektyvių valstybių metų skaičius	Metai, kai superefektyvi DEA nepateikia sprendimo	Metai, kai indėlio į struktūrinį efektyvumą rezultatas yra teigiamas	Galutinis rangavimas
Rumunija	1,023149	1	22	12	22	1
Nyderlandai	1,02307	1	22	22	18	2
Bulgarija	1,011594	1	22	21	22	3
Slovakija	1,001755	1	22	6	18	4
Slovėnija	1,000281	1	22	22	12	5
Danija	0,997418	0,99808	20	12	3	6
Prancūzija	1,070929	0,99708	21	18	21	7
Čekija	0,998272	0,97028	7	0	5	8
Belgija	1,007048	0,96935	18	16	19	9
Lietuva	0,995932	0,95689	16	0	4	10
Austrija	0,997139	0,91403	0	0	3	11
Estija	0,996926	0,89864	5	4	0	12
Vengrija	0,999253	0,88691	0	0	8	13
Lenkija	0,914115	0,84153	11	11	0	14
Švedija	0,981677	0,77143	4	4	0	15
Latvija	0,99011	0,72257	2	1	0	16
Suomija	0,982399	0,68700	0	12	0	17

Analizės rezultatai rodo, kad nors šalis galima reitinguoti pagal du efektyvumo matavimo metodus, kai kurie gautų rezultatų skirtumai yra nereikšmingi. Pavyzdžiui, Rumunijoje ir Nyderlanduose vidutinis indėlis į struktūrinį efektyvumą beveik nesiskiria. Todėl indėlio į struktūrinį efektyvumą metodas leidžia geriau reitinguoti šalis pagal tvaraus žemės ūkio produktyvumą, kai tuo tarpu kiti metodai neduoda rezultatų.

Toliau tyrime pritaikyti trys kryptiniai atstumo vektoriai (proporcinis arba radialinis, vienetinis ir agreguotas), leido apskaičiuoti šešėlines su energija susijusių šiltnamio efektą sukeliančių dujų emisijų kainas ES šalių žemės ūkyje. Agreguoti ŠESD emisijų šešėlinių kainų rezultatai pateikti S3.5 lentelėje.

S3.5 lentelė. Vidutinės šešėlinės ŠESD kainos (perkamosios galios standartais 2010/kg CO_2 ekvivalento) ir jų pokytis (Šaltinis: Streimikis et al., 2023)

Country	Agreguotas krypties vektorius		Radialinis krypties vektorius		Vienetisnis krypties vektorius	
	Vidurkis	Trendas	Vidurkis	Trendas	VIdurkis	Trendas
Austrija	2,4	0,1	2,3	0,0	2,4	0,0
Belgija	1,9	3,8	2,2	3,8	2,2	3,5
Bulgarija	3,1	2,2	2,7	1,4	3,5	1,8
Čekija	2,4	–1,1	2,5	–1,5	2,8	–0,8
Danija	2,6	3,6	2,6	4,7	2,7	4,9
Estija	4,5	–4,4	3,3	2,0	5,1	–3,0
Suomija	0,7	4,0	1,2	1,0	2,0	0,8
Prancūzija	3,6	0,8	3,8	–0,3	3,7	1,0
Graikija	2,2	11,4	2,0	10,3	3,8	14,8
Vengrija	3,5	–1,1	3,4	–0,8	3,7	–0,8
Airija	2,8	4,2	2,7	3,5	3,0	4,3
Italija	3,1	0,2	3,0	–2,9	2,4	–2,2
Latvija	1,1	13,5	1,2	12,8	2,4	10,6
Lietuva	4,9	4,0	4,6	5,9	8,8	4,2
Neyderlandai	1,5	0,7	1,5	0,7	1,3	1,4
Lenkija	0,0	–	0,0	–	1,1	2,8
Portugalija	2,2	–0,2	1,7	–3,7	2,8	3,0
Rumunija	15,1	–4,9	5,7	0,5	35,0	0,8
Slovakija	7,3	–8,1	5,1	2,0	8,2	–6,4
Slovėnija	3,9	–0,1	4,1	4,0	4,9	1,1
Ispanija	0,2	–2,5	0,2	–4,1	0,4	–2,0
Švedija	0,7	–10,4	0,8	–9,5	1,5	–4,1
Jungtinė Karalystė	2,6	3,3	2,6	3,4	2,6	2,8
VIdurkis	3,1	0,9	2,6	1,5	4,6	1,7
Svertinis vidurkis	2,0	0,5	1,9	–0,2	2,5	1,2

Kaip matyti S3.5 lentelėje, Lenkijoje ir Ispanijoje galima pastebėti žemiausią šešėlinę ŠESD kainą, nepaisant taikomo krypties vektoriaus. Didžiausia šešėlinė ŠESD kaina yra Rumunijoje ir Slovakijoje. Šalys, kurių šešėlinės ŠESD kainos yra mažesnės, turėtų dėti daugiau pastangų mažindamos šiltnamio efektą sukeliančių dujų išmetimą, nes jos turi didesnį potencialą tai padaryti. Tuo tarpų šalys, turinčios aukštas šešėlines ŠESD kainas yra pasiekusios didelį energijos efektyvumo lygį ir dar labiau sumažinti ŠESD emisijas dėl energijos vartojimo joms yra brangu.

Bendrosios išvados

1. Žemės ūkio sektorius yra susijęs su socio-ekonominėmis ir gamtinės aplinkos sistemomis. Dėl to yra svarbu atsižvelgti į įvairias žemės ūkio veiklos dimensijas atliekant įrodymais grįstą analizę. Sisteminga literatūros apie tvarumo vertinimą žemės ūkyje analizė atskleidė, kad žemės ūkio tvarumo ir produktyvumo augimo vertinimas gali būti atliekamas panaudojant aplinkosaugine gamybos technologija. Ši technologija apima nepageidaujamus gamybos rezultatus, leidžiančius išmatuoti žemės ūkio poveikį gamtinei aplinkai, o produktyvumas ir gamybos veiksniai atspindi ekonomines ir socialines tvarios žemės ūkio tvarumo dimensijas.
2. PRISMA protokolas buvo naudojamas sistemingai apžvelgti literatūrą apie žemės ūkio tvarumo ir produktyvumo vertinimą. Literatūros šaltiniai buvo atrinkti remiantis PRISMA teiginiais ir suskirstyti į šias tematines grupes: žemės ūkio tarša, tvarus žemės ūkis ir aplinkosaugos veiksmingumas. DEA modeliai gali būti veiksmingai pritaikomi vertinant žemės ūkio efektyvumą įtraukiant nepageidaujamus rezultatus. Tačiau atlikta analizė atskleidė, kad įprastiniai žemės ūkio efektyvumo ir produktyvumo augimo vertinimo DEA modeliai turi tokių apribojimų kaip dimensiškumas, kuris tampa ypač aktualus, kai įtraukiami nepageidaujamą produkciją aprašantys kintamieji. Empirinė ES žemės ūkio sektoriaus efektyvumo analizė parodė, kad, pavyzdžiui, superefektyvumo DEA modelis esant pastoviosios masto grąžos prielaidai negali įvertinti kai kurių valstybių efektyvumo. Todėl, norint įvertinti efektyvumo ir produktyvumo augimo rodiklius esant nepageidaujamiems gamybos rezultatams, reikalingi nauji DEA modeliai.
3. DEA yra neparametrinis ribinis metodas, kurį galima panaudoti ekologiniam efektyvumui nustatyti naudojant aplinkosauginę gamybos technologiją. Efektyvumo matai gali būti panaudojami „žaliojo“ produktyvumo augimui apskaičiuoti. Visgi, įprastiniai DEA modeliai gali neveikti kai į efektyvumo ir produktyvumo augimo analizę yra įtraukiami nepageidaujami gamybos rezultatai. Siekiant įveikti šiuos apribojimus, disertaciniame darbe buvo pritaikyti nauji DEA modeliai ES žemės ūkio sektoriaus efektyvumo ir produktyvumo augimo vertinimui. Pasiūlytas naujas tvariojo produktyvumo vertinimo modelis apima tokius plėtinius kaip globalioji gamybos technologija ir perviršio matavimu. Šis metodas leidžia išskaidyti Luenberger produktyvumo rodiklį visų gamybos veiksnių ir rezultatų (įskaitant šiltnamio efektą sukeliančių dujų emisiją) atžvilgiu ir taip paaiškinti efektyvumo bei technologinius pokyčius.
4. Gamybos galimybių ribinių modelių, apimančių nepageidaujamus gamybos rezultatus, taikymas leidžia įvertinti šių rezultatų šešėlines kainas. Tokios analizės rezultatai gali priklausyti nuo modelio orientacijos gamybos veiksnių ir rezultatų

atžvilgiu. DEA modeliai, skirti aplinkosauginei gamybos technologijai, buvo pritaikyti pinigine išraiška matuojant nepageidautinos produkcijos (ŠESD emisijos dėl energijos vartojimo ES žemės ūkyje) kainą su skirtingais kryptiniais vektoriais. Su skirtingais kryptinais vektoriais susiję modeliai parodė skirtingas šešėlines ŠESD emisijos kainas ir leido išmatuoti sprendimus priimančių vienetų efektyvumą taikant skirtingas judėjimo link gamybos galimybių ribos kryptis. Šis tyrimas yra naudingas politikos analizei, nes jis atskleidė ribinius šiltnamio efektą sukeliančių dujų emisijų mažinimo žemės ūkyje kaštus ir parodė skirtingas ŠESD emisijos mažinimo galimybes ES šalyse narėse. Tyrimo metu įvertintos šešėlinės šiltnamio efektą sukeliančių dujų emisijos mažinimo kainos leidžia nustatyti pažangias valstybes ir tas, kurioms reikalingas tolesnis energijos vartojimo efektyvumo didinimas bei švaresnės energijos balansas žemės ūkio sektoriuje, didinant atsinaujinančių energijos išteklių panaudojimą ir taip užtikrinant tvarią žemės ūkio raidą.

Justas ŠTREIMIKIS

PRODUCTIVITY IN THE CONTEXT OF SUSTAINABLE AGRICULTURAL DEVELOPMENT

Doctoral Dissertation

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GAMYBOS PRODUKTYVUMAS TVARIOSIOS ŽEMĖS ŪKIO PLĖTROS KONTEKSTE

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