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An Eastern European Perspective

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ISBN 978-3-030-76801-0 ISBN 978-3-030-76802-7 (eBook)
https://doi.org/10.1007/978-3-030-76802-7

This Springer imprint is published by the registered company Springer Nature Switzerland AG.
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Preface

The agricultural sector has been transforming along with economic, environmental, and social dynamics. It is important to track and manage agricultural transformations as they relate to the livelihood of the rural population and food security. Therefore, advanced methodologies and frameworks are needed to fathom the underlying trends in different facets of agricultural production. Concerns about sustainability have also reached the agricultural sector. Such concepts as 3E (energy–economy–environment) framework, climate-smart agriculture, and precision agriculture have been around for some time indicating the need for research on the interaction among resources, economies, and the environment.

The European Union (EU) has acknowledged the important role of agriculture and established the Common Agricultural Policy (CAP) to support its development. The accession of the new member states to the EU marked yet another milestone in the development of sustainable agriculture. Indeed, the new member states face economic, technological, and institutional consequences of the collectivization that had been faced by some countries. Furthermore, the Green Deal and Europe 2030 strategies stress the importance of sustainability in the European economy in general and the agricultural sector in particular.

This monograph addresses the methodological and empirical issues pertinent to the development of sustainable agriculture with a particular focus on Eastern Europe. Economic growth is related to the other dimensions of sustainability by applying integrated methods. The intended audience is researchers in agricultural and production economics, policymakers, and academia in general. The monograph comprises five chapters.

Chapter 1 presents the major concepts relevant to the research and discusses the interlinkages among them. The structure of the monograph and major findings are overviewed.

Chapter 2 discusses the theoretical preliminaries and key concepts surrounding sustainable agriculture. The measures, methods, and empirical cases are discussed and synthesized. The manifestations of sustainability in the strategic objectives for the EU agricultural sector are discussed.

Chapter 3 focuses on the analysis of the efficiency and productivity of the agricultural sector. The measures of efficiency, methodological approaches, and empirical models are discussed. The econometric and optimization techniques are applied for estimation of the production functions and other representations of technology in the case of the EU member states. The major technological properties, their evolution, and their implications are discussed. A robustness analysis is also performed by applying nonparametric regression, ridge regression, restricted estimation, and random coefficient models.

Chapter 4 discusses the main methodological frameworks applied to measure structural change and presents an analysis of structural change in the EU agricultural sector. A combination of the structural change index and shift-share analysis is applied to observe the changing role of agriculture in the EU economic system. Structural changes in EU agriculture are investigated by applying index decomposition analysis. The changes in the structural indicators of the EU agricultural systems are considered by isolating contributions of pure change and structural shifts. This allows the major forces governing structural change in the EU agriculture, member states, and farming structure to be identified.

Chapter 5 proceeds with the measurement of environmental pressures at the farm level. The data from the Farm Accountancy Data Network (FADN) are exploited to establish the theme-based indicator system for estimation of the agri-environmental footprint index (AFI). The AFI follows simple, sound, and transparent index construction procedures and the result of its application is presented along with a case study in Lithuania. A set of 12 indicators customized to the FADN were devised to quantify the environmental pressures. In order to provide a comprehensive and transparent analysis, the results for greenhouse gas (GHG) emissions, use of inorganic fertilizers, and farmers' education level are provided in original values. In addition, a detailed GHG emissions' assessment methodology at the farm level is provided. The AFI allows identifying environmental issues that need to be considered in order to reduce the sector's environmental impact.

This monograph summarizes the research carried out under the research project Activity Analysis Framework for Structural Change–Productivity–Climate Nexus in Agriculture funded by the European Social Fund (Project Leader—Prof. Tomas Balezentis). The project was carried out in 2017–2021. The research was hosted by the Lithuanian Centre for Social Sciences Institute of Economics and Rural Development.

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Acknowledgements

The research and/or technical assistance provided by Prof. Mette Asmild, Prof. Jens Leth Hougaard, Dr Irena Kriščiukaitienė, Dr Rasa Melnikienė, Dr Mindaugas Butkus, and Justas Streimikis is highly appreciated. This research has received funding from the European Social Fund (project no. 09.3.3-LMT-K-712-01-0007) under a grant agreement with the Research Council of Lithuania (LMTLT).

Contents

Abbreviations

AFI	Agri-environmental Footprint Index
CAP	Common Agricultural Policy
CES	Constant Elasticity of Substitution
CF	Carbon footprint
CI	Carbon intensity
COP	Cereals, oilseeds, and protein crops
CRS	constant returns to scale
CV	Coefficient of variation
DEA	Data envelopment analysis
EU	European Union
EW	Equal weighting
FADN	Farm accountancy data network
GDP	Gross domestic product
GHG	Greenhouse gas
GVA	Gross value added
IDA	Index decomposition analysis
IPCC	Intergovernmental Panel on Climate Change
LMDI	Logarithmic Mean Divisia Index
LNIR	Lithuania's National Inventory Report
LU	Livestock units
OLS	Ordinary Least Squares
PCA	Principal component analysis
SCI	Structural Change Index
SFA	Stochastic frontier analysis
SO	Standard output
UAA	Utilized agricultural area
VRS	variable returns to scale

Chapter 1
Introduction and Key Findings

1.1 Problem Setting

The development of the primary sector is important for the global population from the viewpoint of food security and income generation. As is the case in any economic sector, agricultural performance can be tracked by means of multiple indicators reflecting different facets of sustainability. A producer, consumer, or government perspective can be taken. Also, the growth of agricultural production and input use can be taken into consideration. Therefore, this monograph seeks to discuss some of the approaches that have appeared to be the most relevant ones in measuring agricultural performance and development.

The major objective of agricultural activities is an economic one—to produce food at low costs. The OECD/FAO (2020) forecasts that the demand for both crop and livestock products will continue increasing globally throughout 2020–2029. Population growth remains a major driver for such changes. Thus, the agricultural production needs to be adjusted to satisfy the increasing demand and ensure the affordability of food.

The extensive growth mode initially relied on increasing the use of (relatively cheap) agricultural inputs to expand the agricultural production. However, the primary inputs have become scarcer, especially in the developed countries (OECD/FAO 2020). This implies the need for agricultural productivity growth. This topic has been around for decades (Hayami and Ruttan 1971), with technological development seen as the major driver of productivity growth. Fuglie (2018) provided a more recent study on the patterns of agricultural productivity growth across the globe.

The notion of total factor productivity is important in assessing economic performance. Indeed, total factor productivity gains render economic surplus that can be shared among farmers, factor owners, government, and customers (Grifell-Tatjé and Lovell 2015; Veysset et al. 2019). Yet another concept related to total factor productivity is that of efficiency (Latruffe 2010). Basically, efficiency indicates the

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gap between the observed and maximum possible level of productivity. The maximum possible level of productivity can be estimated via a number of approaches. These include parametric and nonparametric methods relying on primal or dual representations of the production technology. The measures of partial factor productivity are also often used to describe the performance of the agricultural sector. Measures of the latter type relate any two indicators (usually output over input) to show the output level per unit of input.

Structural change plays an important role in shaping agricultural production (mode). The structural change mostly manifests itself through changes in farm structure, input structure, and output structure (Chavas 2001). The changes in the farm structure can be related to returns to scale considerations and the question of the optimal farm size. The imperfections in the factor and output markets may create situations where certain groups of farms benefit more than others. In such cases, optimal farm size becomes a blurry concept. Deepening economic integration is likely to accelerate the reallocation of inputs across sectors and regions. For agricultural commodities, economic integration plays an especially important role as the prices of the commodities are established in international markets. The structural changes may also lead to the adoption of different production technologies and adjustment of the output mix. As Chavas (2001) argued, risk aversion appears to be an important factor behind farmers' decisions in regard to the scope of their production.

The increasing scarcity of resources along with the increasing volatility of the climatic conditions has called for a shift towards sustainable agriculture. Sustainable agriculture includes the use of inputs (e.g. agrochemicals, bio-based resources) and farming practices in such a manner that minimum environmental and societal impact is ensured alongside profit maximization (Pretty 2008). It is naturally expected that sustainable agriculture is positively correlated to agricultural resilience. However, this requires the creation of extensive and comparable data sets to guide the decision-making (El Chami et al. 2020). There have also been obstacles related to theoretical and empirical factors (Siebrecht 2020). Therefore, it is important to identify the major concepts underpinning sustainable agriculture and the possibilities for its development in different contexts.

The direct emission from agricultural sector comprises 11% of global greenhouse gas emissions (OECD/FAO 2020). Among other impacts, sustainable agriculture allows greenhouse gas emissions to be mitigated. Sustainable farming practices can also increase carbon sequestration. This leads to mitigation of climate change. In this context, the concept of climate-smart agriculture becomes important as the agricultural sector needs to be both resilient to environmental shocks and operate in a sustainable manner so as to avoid degradation of the ecosystem. A crucial task is to quantify the sustainability level prevailing in farming systems. This requires the development of assessment frameworks at different levels of aggregation.

The issues discussed can be summarized in the structural change–productivity–climate nexus (Fig. 1.1). Agricultural production technology relates the inputs to outputs and defines the production possibilities in the technical sense. Here, productivity impacts the possible output quantities for a given level of inputs.

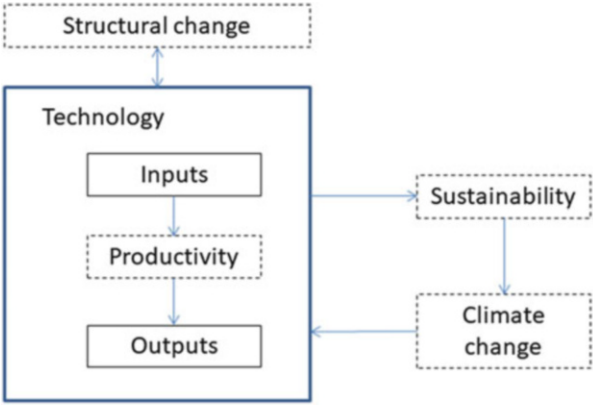

Fig. 1.1 Structural change–productivity–climate nexus in agriculture

As discussed above, technology is developing in line with the external environment and farmers' traits. Structural change itself is influenced by developments in the international markets and the competitive advantages prevailing in certain regions. In addition, agricultural policy can affect the markets of factors and outputs (Swinnen 2018) leading to corresponding structural dynamics. Noteworthy, structural change and structure itself contribute to productivity change (Shen et al. 2018). Thus, structural change may render changes in the input structure, output structure, and productivity. If inputs are used more productively in certain groups of farms, the structural change may result in changes in the average productivity even though farms retain their technologies and the overall input quantity or output volume remains fixed.

The structure (proportions) of inputs and outputs used in the production process depends on the production technology. The scale of production determines the volume thereof. All these circumstances determine the sustainability level of the agricultural production (i.e. the economic, social, and environmental impacts). The environmental impact implies that the ecosystems may be affected by the agricultural production. This gives rise to climate change and adaptation. The concept of climate-smart agriculture becomes important in linking the climate (change) and agricultural production technology. Following this concept, the agricultural technology should be adjusted so as to take into account the risks stemming from climate change.

1.2 The European Union Context

The relationships among structural change, productivity, and climate are determined by a plethora of factors. As previously discussed, trade, public policy, and climate change are among the most important factors of agricultural dynamics (for the sake of brevity, we assume that trade includes intersectoral relations and factor movement as well). The empirical research presented in this monograph focuses on the case of the European Union (EU), which is a major food producer. The Common Agricultural Policy of the EU is the main policy instrument and operates through direct payments, market measures, and rural development measures. The requirements for receiving support payments are adjusted in line with the policy objectives.

The EU has also adopted overarching strategies aimed at increasing the sustainability of the economy. The most recent instance of such strategies is the European Green Deal launched in 2019. In the light of the Green Deal strategy, the CAP is also to be adjusted to meet the objectives of sustainability (European Commission 2020). The strategic planning at the country level is expected to ensure linkages among the objectives of the CAP and the Green Deal via National Energy and Climate Plans and CAP Strategic Plans. Thus, the correspondence with the Governance of the Energy Union is to be maintained. The CAP measures relevant to the Farm to Fork Strategy and Biodiversity Strategy are expected to reduce environmental pressures associated with farming activities (the use of pesticides, nutrient leakages, biodiversity). The promotion of organic farming and eco-schemes is yet another strand of CAP measures that is expected to align with the objectives of the Green Deal. Finally, healthy food consumption and a reduction in food waste should contribute to a more efficient use of resources outside the primary sector.

The European Commission (2020) also stressed that already existing databases (e.g. the Farm Accountancy Data Network) should be extended to take into account environment- and climate-related indicators. This would allow for benchmarking of farms in the sense of the three dimensions of sustainability. Thus, it is important to develop methodologies for farm-level and aggregate benchmarking.

1.3 Major Issues and Findings

The present study is arranged into four chapters dedicated to the issues related to structural change, productivity, and climate. These chapters address the aforementioned issues in the context of the EU, whether at the micro- or macrolevel. The focus is often on Lithuania, an Eastern European country that joined the EU in 2004. We believe the discussion will shed light on the agricultural development of the EU and its member states.

1.3.1 Sustainable Development of the Agricultural Sector and Its Interactions with Other Sectors

The concept of sustainable agriculture stresses the need to integrate the environmental effects of agricultural activities into analysis (besides economic and social facets). This approach is crucial for developing policies and corresponding measures that may effectively improve the resource utilization in the light of the climate–water–land–energy–food nexus. Chapter 2 focuses on the theoretical preliminaries of sustainable agriculture and the case of the EU. Much attention is given to energy use that brings environmental consequences as well.

There is a close relationship between sustainable agriculture and sustainable energy development. More specifically, the use of renewable energy sources in agriculture allows the most important environmental, economic, and social objectives stemming from the concept of sustainable agriculture development to be secured. These include climate change mitigation, resource conservation and reduction, avoiding negative environmental impacts, contributing to the security of the energy supply, cost reduction, diversification of farmers' income, the provision of highly productive jobs, and promotion of the social and economic development of rural communities. Therefore, the future shaping of the CAP should be directly linked to the climate–water–land–energy–food nexus: improving the welfare of the rural countryside, safeguarding food security and safety, environmental protection, natural resource saving, climate change mitigation and adaptation, and preservation of animal health and welfare.

The main EU policy priorities outlined in the Green Deal for the creation of a carbon-neutral society and low-carbon transition by 2050 need to be addressed by the two pillars of the CAP. For this reason, a clear understanding of the need to link climate change mitigation and adaptation with the CAP was shown by the EC; however, it is necessary to point out that the linking of climate issues to CAP goals needs to address the broader climate–water–land–energy–food nexus, and this has not been achieved so far in the recent reform of the CAP aimed at developing climate-smart agriculture (Venghaus et al. 2019).

1.3.2 Agricultural Technology, Production, and Productivity

Chapter 3 of this monograph turns to the theoretical preliminaries and empirical applications of the concepts, measures, and models of productivity. Note that productivity is referred to here in a broad sense rather than merely focusing on total factor productivity growth. Indeed, the core of the empirical analysis is the production function that links the input and output quantities. This setting provides information about output elasticities with respect to the inputs (and time).

The empirical analysis focuses on the case of the selected EU member states. Country-level data from Eurostat are used to describe the inputs and outputs employed in the agricultural production process. The production frontier approach is chosen for the analysis. The estimation of the production frontier is carried out both parametrically and nonparametrically. Also, an estimation with regularity conditions imposed is presented. Thus, the results are verified by using different models.

The findings indicate that the efficiency of the agricultural production in the selected EU countries followed an inverse U-shaped trend over the period

1995–2017 even though technical progress was observed. This indicates that the EU countries still need to ensure the spillover of innovations in order to boost the agricultural productivity. Moreover, the output elasticity with respect to capital tended to decline in general. This further shows that overinvestment may be present in EU agriculture. Thus, the support policies (especially the CAP) need to take into account the differences in the total factor productivity and input-related output elasticities in order to ensure efficient use of the resources (including support funds).

1.3.3 Structural Dynamics in Agriculture

Over the last few centuries, the research on the ongoing evolution of agricultural systems has played an important role. Bah (2011) identified a clear nexus between structural change scenarios and the development level of the country. In this context, the recent structural changes in the EU agricultural system after the main enlargement in 2004 contribute to a challenging academic discussion with significant variations in terms of research objects and applied methodological frameworks. Indeed, the previous research often demonstrates a fragmented picture and focuses on individual member states. Therefore, Chap. 4 investigates the evolution of the EU economy and the corresponding developments of the agricultural systems in member states after the main enlargement of the EU.

The dynamics of structural change indices for employment and gross value added (GVA) imply that structural changes in the EU economic system have evolutionary rather than revolutionary characteristics. However, in some member states, the remarkable acceleration of national transformations could be explained by the new business environment, including policy changes, after countries have joined the EU. According to Eurostat, the share of employment and GVA for agriculture, forestry, and fishing economic activity in the EU economy is diminishing, while the direction of the development of the EU economy is in line with previous studies; i.e., the role of the service sector in economic systems is growing (Pannell and Schmidt 2006; Bah 2011). Indeed, the directions and speed of GVA and labour force reallocation in national economies depend on the member states.

The shift-share analysis sheds some light on regional development differences in GVA and employment and allows benchmarking of the actual change with alternative development patterns. For GVA, outcomes depend on the level of inflation; however, several countries demonstrate a performance of agriculture, forestry, and fishing economic activity at a higher rate than the growth rate of the EU economy. In the case of employment, the growth rates of agriculture, forestry, and fishing economic activity are lower than the growth rate of the entire EU economic system. However, the components of local competitiveness for agriculture, forestry, and fishing economic activity in member states demonstrate the diversity in development patterns and confirm the individuality of member states.

Structural changes in the EU agriculture are investigated by employing average measures of utilized agricultural area, standard output, and directly employed labour force on farms. During the period from 2005 to 2016, important shifts in farming types both at the EU level and in member states took place. At the EU level, the increase in the average farm size in terms of the utilized agricultural area and standard output is accompanied by an almost stable situation of the average directly employed labour force on farms.

The remarkable growth in the average farm size is confirmed for specialist field crops and specialist grazing livestock farms. For these farming types, the decomposition of the structural change measures into structural and pure change components shows that the structural changes at the EU level play an important role. At the same time, the largest decline in the average farm size measures is reported for mixed livestock farms. The decomposed results for member states demonstrate significant country-specific variations in peak periods, change rates, and development directions of agricultural systems. The aforementioned results are explained by the individual combination of multiple factors that determine structural changes in member states. Previous studies on the driving forces of structural changes in agricultural systems allow the following critical factors to be identified: historical legacy, technology, agricultural policy, crises and natural disasters, demographic transition, and dynamics in human capital.

1.3.4 Agri-Environmental Footprint as a Measure of Agricultural Sustainability

Agriculture is a sector of special importance in the economy due to its direct connection to the natural environment (cf. Chap. 2). On the one hand, the production processes depend on natural resources of land and water, and on the other hand, agricultural activity often causes pollution and environmental degradation (e.g. resulting in arable land degradation, eutrophication of water, a decrease in biological diversity, and an increase in greenhouse gas emissions). Additionally, energy use efficiency is seen as an important issue in terms of the sector's sustainability with the potential to decrease the use of fossil fuels along with a reduction in environmental impacts. At the same time, the agricultural sector can play a significant role in generating renewable energy, thereby contributing to the transition of the country to a low-carbon economy.

As already mentioned in Sect. 1.2, the measurement of agricultural sustainability at the farm level is important not only from a purely scientific viewpoint but also as a basis for benchmarking that can be used for guiding support policies in practice. Chapter 5 focuses on the construction of the agri-environmental footprint indicator based on farm-level data from the Farm Accountancy Data Network. The case of Lithuanian family farms is considered.

The lowest values for the whole sample were obtained for indicators related to farms' accessibility, environment-friendly farming, wooded areas, and meadow and pasture areas. In order to foster the environmental sustainability of farms, the policy intervention measures need to focus on the enhancement of farmers' entrepreneurship (e.g. rural tourism and conservation of agricultural heritage activities), increasing the areas under climate-friendly farming methods, and enhancing the carbon sink capacity (e.g. by increasing the wooded areas along with meadow and pasture areas).

1.4 Concluding Remarks

The results indicate that there have been serious structural changes in the structure of farms across the EU (Chap. 4). Different chapters of this monograph (Chaps. 2, 3, and 5) explore the causes and outcomes of structural dynamics in agriculture from theoretical and empirical viewpoints. The results suggest that technological change has pushed the production possibility frontier for EU countries and enabled resource conservation along with production growth. However, not every country has been able to exploit these possibilities to the same extent.

The methods discussed in this monograph may be used for benchmarking the progress towards sustainable agriculture at the micro- and macrolevels. The benchmarking may provide important information for decision-makers when devising support measures. It is also important to explore and ensure the congruence among the objectives of sectoral and general strategies (e.g. the CAP and the Green Deal of the EU). Such research needs to adopt both theoretical and empirical approaches.

In order to further develop evidence-based research, standardized and open databases are needed. The variables used in this research can be used for large-scale comparisons in the EU. The data-driven approach can be used to stimulate the creation of a more sustainable agricultural system in the EU through evidence-based support policies.

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Chapter 2
Sustainability of Agriculture: Energy Use and Climate Change Mitigation Issues

Dalia Streimikiene

2.1 Introduction

Climate change plays an important role in the water–land–energy–food nexus. Climate change results from fuel combustion in all sectors of the economy as well as from agricultural activities (Pardoe et al. 2018). It is obvious that rainfall is a main source of water and it is essential for the operation of the agricultural sector and food industries. Also, the production of hydropower is reliant on rainfall. The quantity and timing of rainfall are changing due to climate change. Therefore, there is an inseparable relationship between these ultimate resources for the survival of humans and for climate change (FAO 2011a, b).

Agriculture is the economy sector at the centre of the climate–water–land–energy–food nexus as it consumes water, land, and energy and produces food and is strongly affected by climate change as well as having an important effect on climate change due to greenhouse gas (GHG) emissions from enteric fermentation, soil nitrification, manure disposal, etc., as well as from fossil fuel burning in agriculture (Rasul and Sharma 2016; Babatunde et al. 2019). Energy use in agriculture creates GHG emissions and the use of clean energy sources like renewables and improvements in energy efficiency are necessary for the development of sustainable agriculture (Bazilian et al. 2011). Agricultural GHG emissions are mainly related to the management of agricultural soils, livestock, and rice production. While the negative impacts of agriculture are serious and can include air and water pollution, soil degradation, etc., agriculture can also have a positive influence on the environment, such as through the sequestration of GHG in crops and soil or mitigating flood risks due to the specific farming practices adopted (Hardy et al. 2012).

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T. Baležentis et al., *Structural Change, Productivity, and Climate Nexus in Agriculture*, https://doi.org/10.1007/978-3-030-76802-7_2

The concept of sustainable agriculture allows the main environmental effects of agriculture to be stressed (Pretty 2005a, b) and policies and measures to be developed for addressing the climate–water–land–energy–food nexus. There is a close relationship between sustainable agriculture and sustainable energy development as the use of renewable energy sources in agriculture allows the most important environmental, economic, and social objectives of sustainable agriculture development to be achieved, such as climate change mitigation, resource savings and the reduction of negative environmental impacts, security of the energy supply, cost savings, diversification of farmers' income, the creation of new job places, and promotion of the social and economic development of rural communities (Ali et al. 2012). Especially, important are climate change mitigation issues linked to energy consumption in agriculture, as the use of renewable energy sources and energy efficiency improvements are the main ways to achieve a reduction in GHG emissions from fuel combustion in agriculture and to achieve the objectives of climate-smart agriculture (Chel and Kaushik 2011). The issues of food security are also important, especially when dealing with climate change mitigation policies and the promotion of renewable energy sources, which are often competing for land with crops and the production of other agricultural products (Pretty 1997; Yang et al. 2009).

Therefore, the agriculture sector is at the centre of the climate–water–land–energy–food nexus debate, and the main task for the development of a sustainable agriculture sector is to provide food for the rising world population while reducing the environmental impact and preserving the most important natural resources for future generations (Granit et al. 2012). Policies to promote sustainable agriculture development or agricultural sustainability need to address the interlinked climate–water–land–energy–food nexus issues highlighted above (Griggs et al. 2013). The Common Agricultural Policy (CAP) plays a major role in the development of the agricultural sector in European Union (EU) member states (MS); therefore, sustainable agriculture development goals supported by the CAP should also address the climate–water–land–energy–food nexus.

In the following sections of this chapter, sustainable, climate-smart agriculture concepts and their links with sustainable energy are discussed by outlining the implications of climate–water–land–energy–food nexus policies for the future development of the CAP.

2.2 Sustainable Agriculture

The sustainability of agriculture or sustainable agriculture is one of the priorities of agriculture policies. The main aim of the agricultural sector is to provide healthy, safe, and nutritious food for an increasing world population, while ensuring that farm animals receive the necessary fibre and other biological products. This important sector of the economy needs to use sustainable natural resources, preserve land, water, and biodiversity, reduce GHG emissions, and adapt to climate change. In striving to address climate–water–land–energy–food nexus challenges and to respond to opportunities, agriculture needs innovative management approaches and business models to increase its productivity in a sustainable way (Velten et al. 2015; Ogaji 2005).

There any many definitions of sustainable agriculture. These definitions incorporate green, ecological, organic, permaculture, biodynamic, extensive, free-breeding, low-input, prudent agriculture, etc. (Pretty 1995, 2005a; Conway 1997; NRC 2000; McNeely and Scherr 2003; Clements and Shrestha 2004; Cox et al. 2004; Gliessman 2004, 2005). There is still an ongoing and strong debate among scholars (Balfour 1943; Lampkin and Padel 1994; Altieri 1995; Trewevas 2002) as to whether these terms can be considered terms for defining sustainable agriculture. The scholars agree that some terms are too narrow to catch all interlinked issues of sustainable agriculture like the climate–water–land–energy–food nexus concept does.

It is necessary to stress that the concept of sustainable agriculture or agricultural sustainability does not imply that some technologies or practices can be excluded on an ideological basis. If technology improves agricultural productivity and does not cause unjustified environmental damage, it can provide in the end some benefits for agricultural sustainability. Agricultural systems that (i) rely on green, ecological, organic, permaculture, biodynamic, extensive, free-breeding, low-input, prudent farming, (ii) supply food and other agricultural products for farmers and other customers, and (iii) provide a variety of valuable public goods, including carbon sequestration, flood protection, groundwater replenishment, biodiversity, landscape niceties, and tourism, leisure and recreation services and amenities can be defined as sustainable ones (Dobbs and Pretty 2004). Therefore, agricultural sustainability can also be considered case-specific and represents first and foremost a balance between different agricultural and environmental services including the climate–water–land–energy–food nexus.

Sustainable agriculture should strive to use natural goods and services, and technologies and practices applied in agriculture need to be adapted locally taking into account natural conditions and various limits. For sustainable agriculture development, new forms of social capital are necessary. The key role in social capital development is the promotion of trust in relationships between people and institutions and the establishment of new horizontal and vertical partnerships between them. Human capital development in agriculture is also important as leadership, resourcefulness, managerial skills, and the capacity to innovate are the main drivers of sustainable society development. In addition, the agricultural sector, having high social and human capital, is more qualified in terms of innovations during the present time characterized by huge uncertainties and risks (Olsson and Folke 2001; Pretty and Ward 2001; Chambers et al. 1989; Uphoff 2002; Bunch and Lopez 1999).

Sustainability in agriculture means combining social and human capital growth, and technological and managerial innovations, with the specific conditions of diverse agricultural systems by balancing costs and benefits of eco-innovations. Because agriculture often has a significant impact on nature, biodiversity, and natural resources including air, water, and land, all sustainable agricultural practices should be designed to save and protect natural resources, maintain and improve soil fertility, and reduce the negative impact of climate change. Accordingly, in a broad sense, agriculture sustainability targets the increase of healthy and high-quality human food and fibre supplied by supporting environmentally safe management practices, the growth of farmers' income, and improvement of the quality of life of farm families and rural communities (Johnson 2006).

Therefore, though sustainable agriculture or agricultural sustainability has many definitions, it ultimately aims to preserve farmers, communities, and natural resources by supporting lucrative, organic, and community-friendly farming practices and methods. The sustainable agriculture concept addresses modern agriculture systems.

Consequently, sustainable agriculture can be described by the following economic, social, and environmental characteristics (Dunlap et al. 1993):

- economically viable or profitable as it ensures cost-effective production;
- socially supportive as it provides farm communities with enhanced quality of life;
- ecologically sound as it preserves natural resources that sustain human and societal development.

Recently, many assumptions have emerged regarding how sustainable agriculture can enable net cost reduction, as for the same amount of food production more lands are necessary if organic agriculture practices are applied. Recent studies showed that innovations and successful sustainability initiatives in agriculture provided important modifications of agricultural production factors by replacing various fertilizers with nitrogen-fixing legumes and substituting pesticides with organic products, etc. (Conway and Pretty 1991; Buttel 2003).

The most important point in addressing the economic dimension of sustainable agriculture development is better utilization of natural resources, such as land, water, and energy, and enhancing climate stability by applying new effective, clean, and environmentally sound technologies, innovative management practices, and new business models. Here, the critical issue is "reinforcement type". Sustainable intensification of agricultural production can be achieved through the efficient use of natural, social, and human capital, pooled with the use of the best genotypes, finest innovative technologies, and paramount environmental management practices enabling costs to be reduced (FAO 2010).

The use of renewable energy-based technologies in the agricultural sector allows GHG emissions to be reduced with a view to achieving climate change mitigation goals. Renewable energy sources (RESs) are able to provide effective and sustainable solutions in the agricultural sector. Such renewable energy sources as solar, wind, biomass, hydropower, and geothermal can be applied for power and/or heat generation in the agriculture sector and contribute to sustainable agricultural development due to the reduction of pollution and conservation of fossil fuel resources.

Based on an extensive literature review (Altieri 1995; Pretty 1995, 1998, 2005a, b; Conway 1997; Hinchcliffe et al. 1999; NRC 2000; Li 2001; Tilman 1999; Tilman et al. 2002; McNeely and Scherr 2003; Gliessman 2004, 2005; Swift et al. 2004; Tomich et al. 2004; Scherr and McNeely 2008; Kesavan and Swaminathan 2008; Velten et al. 2015; Reganold et al. 1990; Robinson 2009;

Dale et al. 2013), the following basic principles of sustainable agriculture or agricultural sustainability are developed:

1. protection and effective use of natural resources such as water, land, biodiversity, and energy resources, as well as climate stabilization;
2. integration of the most advanced biological and ecological practices into food production processes;
3. reduction of the usage of non-renewable resources that are environmentally harmful and have negative effects on the health of farmers as well as consumers;
4. productive use of farmers' skills and know-how, thereby cultivating their self-confidence;
5. productive exploitation of collective abilities of people to work commonly to resolve the main problems in agriculture such as pests, irrigation, and forest and carbon sequestration.

The sustainable development of the agricultural sector is based on addressing holistically economic, social, and environmental dimensions of sustainability by increasing the agriculture productivity and ensuring efficient use of human capital, energy, and natural resources such as water, land, and biodiversity and reducing the negative impact of climate change (Yunlong and Smit 1994).

Thus, sustainable agriculture can be described as environmentally friendly, economically viable, and socially encouraging. The increase in welfare and living standards of farmers is important for the social development of rural communities. Environmental soundness is also very important for sustaining the natural resources necessary for human and societal development (FAO 2019). According to the FAO's (2010) definition, the "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".

Lately, the eco-efficiency and green productivity concept has emerged in the scientific literature and policy debate as the promotion of agricultural sustainability has become a priority in the EU. There are many positive agricultural sustainability initiatives implemented in the EU and other countries across the world aimed at addressing important changes in the use of production factors in the agriculture sector, such as the development and application of advanced resource-saving technologies, using nitrogen-fixing legumes instead of various fertilizers, and switching from chemical pesticides to the use of natural products (Conway and Pretty 1991; Buttel 2003).

Currently, the main driver of agricultural sustainability is efficient use of natural resources, including biodiversity, water, and land. The most acute questions are related to the intensification of agriculture production in terms of natural, social, human, and financial capital use. For this purpose, advanced technologies need to be implemented, providing savings of all capital forms to avoid "unsustainable intensification" of agriculture (FAO 2010).

Although sustainable agriculture development covers various distinctive issues that vary in relation to the regional and country context (Balaceanu 2013), it is necessary to stress that sustainable agriculture or agricultural sustainability definitions must include three pillars of sustainability, namely economic, social, and environmental, and comply with broader sustainable development goals. In addition, it is necessary to stress that agricultural sustainability dimensions are interlinked and reinforcing and that environmental safety guides all other issues in this concept.

As the agriculture sector is closely linked to environmental protection and conservation of natural resources, which are equally closely related to climate change issues, the idea of linking climate, water, land, energy, and food issues was initiated by the German government in 2011 at the Bonn Nexus Conference (Hoff 2011). The following concept was advanced as a response to the challenges of climate change and social problems related to population growth, economic development, globalization, and urbanization (Hoff 2011). As one can guess, water, land, energy, and food are the main resources necessary for people and it is expected that the need for these resources will surge sharply because of the increase in populations, especially in developing nations, and the fact that climate change will have a negative impact on the availability of these resources. Lately, the climate–water–land–energy–food nexus has emerged as a popular term due to various global changes and risks linked with climate change and the global pandemic.

Though the climate–water–land–energy–food concept has some shortcomings, there is a need for such a concept for developing systematic concern about the sustainability of societal development and its future. Nevertheless, theoretical, policy, and management studies aimed at addressing the climate–water–land–energy–food nexus are still in their infancy.

Several decades ago, the issues surrounding climate change, water, land, energy, and food security were considered separately before the establishment of the climate–water–land–energy–food nexus concept. However, it is now obvious that new policies and measures aiming to address these important interlinked issues necessary for human survival are indispensable (van Vuuren et al. 2012; Dominković et al. 2016; O'Neill et al. 2017; Keesstra et al. 2018; De Castro and Capellán-Pérez 2018; de Blas et al. 2019; Nieto et al. 2020).

The following steps are possible in addressing the climate–water–land–energy–food nexus. The first step is linked to the integration of water, land, and energy resources in various economic sectors, such as energy, agriculture, and industry. In the next step, the protection of human health, and other welfare services, should be ensured in the exploitation of water, land, energy, and food resources. The third step should involve the development of optimal policy for the interrelated connection between climate, water, land, energy, and food systems. The use of integrated assessment models like MEDEAS (Modelling the Renewable Energy Transition in Europe) is useful in addressing the chain of linkages and mutual impacts of the climate–water–land–energy–food nexus (Zhang and Vesselinov 2017; de Blas et al. 2019; Nieto et al. 2020). The MEDEAS-World model is a global, one-region-aggregated economy–energy–environment model or integrated assessment model providing the world scenario running from 1995 to 2050.

The aim of water–land–food nexus policies is to achieve efficiency of water and land consumption for food production or to increase the productivity of water and

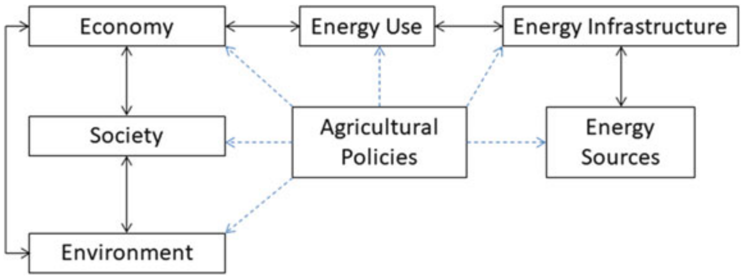

Fig. 2.1 Interlinked areas of the climate–water–land–energy–food nexus. Source: Created by author based on de Blas et al. (2019) and Nieto et al. (2020)

land resource usage in food supply chains. The water–land–food nexus issues have been addressed in several studies (Babatunde et al. 2019; Karimi et al. 2012; Hardy et al. 2012; Qadir et al. 2007). The problems of improving green water usage and preventing depleted residual soil moisture after harvest with squat water use was investigated by Karimi et al. (2012). A study by Akangbe et al. (2011) analysed environmental activities and various social, economic, and governance advances by developing climate models for agriculture to address water, land, and food problems.

The policies aimed at solving water–land–energy nexus problems have been real for many decades as water and land are very important for the energy sector. Hydropower plants (HPPs) use water for power generation, while nuclear power plants consume large quantities of water for cooling purposes. There are hydropower pump storage (HPPS) facilities that are necessary for regulating energy flow, especially with the increase in the share of renewables, and moving to a low-carbon future, the importance of energy storage is increasing. Renewable energy sources require huge quantities of land and are competing with land for food production. Biocrops, solar panels, and wind parks occupy land that could be used for other agricultural, tourism, and recreation purposes, and pos power plants occupy a lot of land, and nuclear waste disposal has serious implications for land usage. Fossil fuel extraction is also linked with land use problems because of some of the negative impacts of mining. In addition, the use of water for food processing and wastewater treatment similarly requires energy. The study of Hardy (2012) showed that agricultural irrigation is linked with high amounts of energy consumption.

The synergy of the water–land–energy–food nexus can be addressed by applying integrated water resource management practices. Karimi et al. (2012) revealed in their study that irrigation practices require high energy consumption and provide for the lower carbon emission of groundwater. Various implications of the regional integration of hydropower, biofuel, and other renewables, reforms of irrigation, and energy market advancements were addressed by Chandel et al. (2015).

In Fig. 2.1, the linkages in the climate–water–land–energy–food nexus are provided along with policies and measures, including various development scenarios, covering all these issues. This figure also indicates the main modules of integrated assessment models providing the framework modelling low-carbon transitions and their various economic, social, and environmental impacts. The developed macroeconomic module within a broader system dynamics model (MEDEAS) has been developed for the whole world from 1995 to 2050 under a business-as-usual scenario that maintains current trends, a green-growth scenario providing the low-carbon transition and implementing Paris pledges, and a post-growth scenario for analysis of low-carbon transition under various GDP development pathways (Nieto et al. 2020).

As one can see from Fig. 2.1, the close linkages between the energy and agriculture sectors are noticeable and future prospects of these sectors' development have serious implications for societal development as well as taking into account climate-neutral societal development aims set by the EU's Green Deal (European Commission 2015, 2019).

As climate change issues are strongly interlinked with the sustainable agriculture concept and have an impact on the water–land–energy–food nexus, the next section provides more insights into climate change mitigation and adaptation issues in agriculture as well as discussing main policy implications.

2.3 Climate-Smart Agriculture

Agriculture is strongly affected by climate change, because of the dependence of farming activities upon climate. The influences of climate change on agriculture include changes in precipitation, rising temperature of air and water, and changes in seasonality across the year. Especially, strong negative effects on agriculture are caused by extreme weather events such as weather storms and flooding, heatwaves, and droughts (Meredith 2019).

In addition, the agriculture sector similarly influences the climate due to greenhouse gas (GHG) emissions from this sector into the atmosphere. GHG emissions from agriculture can be distinguished as GHG emissions from agriculture activities and GHG emissions from fuel combustion in the agricultural sector. However, the agriculture sector can make a significant contribution to climate change mitigation through carbon sequestration.

Climate change mitigation policies are a priority in the EU policy agenda. The European Commission (EC) has established a GHG emissions reduction target by 2050—reduction of GHG emissions by 80–95% compared to the 1990 level in 2018 by adopting the "A Clean Planet for All" road map to 2050 with the aim of achieving a climate-neutral society in the EU by 2050.

The EC also set the target in 2014 to reduce GHG emissions by at least 40% by 2030 compared to 1990. This target was further fragmented into GHG reduction targets for GHG Emission Trading Sectors (ETS) and non-Emission Trading Sectors by 2030: GHG emission reduction by 43% and 30%, respectively, compared to the 2005 level (EC 2015, 2018). The agriculture sector was acknowledged the sector with the lowest' GHG emission mitigation potential, taking into account the need for

Table 2.1 Global warming potential values for 100-year time horizon relative to CO_2

GHG emissions	IPCC Second Assessment Report (IPCC 1996)	IPCC Fourth Assessment Report (IPCC 2007)	IPCC Fifth Assessment Report (IPCC 2014)
Carbon dioxide (CO_2)	1	1	1
Methane (CH_4)	21	25	28
Nitrous oxide (N_2O)	310	298	265

Source: Created by authors based on Matthews (2020)

consistency and a balance between the food supply security and climate change mitigation objectives of the EU.

Therefore, in 2017 the EC issued a communication on the Common Agricultural Policy post-2020, "The future of food and farming", which addresses the main challenges that the agriculture sector is facing (EC 2020). The Common Agricultural Policy post-2020 sets various targets for 2030 to achieve sustainable agriculture development. As pesticides and other hazardous subsidies used in agriculture have a negative influence on soil, water, and air pollution, the EC has established a target for 2030 to reduce consumption of chemical and hazardous pesticides by 50%. As the surplus of nutrients in soils also has a negative impact on air, soil, and water pollution, climate change, and biodiversity, the EC has established a target to reduce nutrient losses by at least 50% and a reduction of fertilizer usage by at least 20% by 2030. Antimicrobial resistance because of the usage of antimicrobials leads to human deaths; therefore, the EC has developed a target to reduce the sale of antimicrobials for farmed animals and for use in aquaculture by 50%. As organic farming is an environmentally friendly agricultural practice, the EC has established the target to achieve 25% of farmland being used for organic farming by 2030.

European Commission Communication (EC 2020) indicates how to overcome main challenges of agriculture by cooperation in R&D and various innovations and learning from each other.

The 2030 Climate and Energy framework requires implementation of the economy-wide GHG emission reduction target of −40% (relative to 1990) by 2030 and that agriculture, due to its low GHG emission reduction potential, is one of the sectors addressed in the Effort Sharing Regulation (ESR) requiring GHG emission to be reduced by 30% in these sectors by 2030 compared to the 2005 year level.

Agricultural GHG emissions consist of methane (CH_4) and nitrous oxide (N_2O). These GHG emissions have to be aggregated to CO_2 equivalent (CO_2eq) to assess the GHG emission reduction targets. In the EU, the aggregation metrics is based on 100-year time horizon global warming potentials (GWP100) provided by the IPCC Fourth Assessment Report (Table 2.1).

The main GHG emissions or by-products of agricultural sector activities are the following:

- methane (CH_4) emissions linked to animal digestion processes and accumulated animal manure;
- nitric oxide (N_2O) emissions related to the usage of organic and mineral nitrogen fertilizers.

The main sources of GHG emissions in the agricultural sector are described below.

Flatulence or enteric fermentation is a part of the digestive process of ruminants such as sheep, goats, and cattle that generates methane emissions due to anaerobic microbes, which decompose and ferment food during the feeding of ruminants due to the low efficiency of the digestion process. So due to this inefficiency, during the digestion process of ruminants, some of the food energy is lost in the form of CH_4 emissions. Measures to reduce CH_4 emissions from enteric fermentation need to be implemented to increase digestive efficiency, which would also have a positive impact on the increase of animals' productivity (Lobell and Burney 2009).

Soil nitrification and denitrification applied in farms generate N_2O emissions. Nitrification is the process of aerobic microbial oxidation of ammonium to nitrates, and denitrification is the process of anaerobic microbial conversion of nitrates to nitrogen gases. The measures to reduce GHG emissions from soil need to be applied by replacing fertilizers that have nitrates in their composition with other means of land fertilization (Ogaji 2005).

Stored animal manure during the decomposition process produces CH_4 and N_2O emissions. Modern farm management practices can enable the reduction of these GHG emissions.

Greenhouse gas emissions from agriculture are influenced by several important factors, such as economic development trends, implemented regulatory and policy instruments, innovations in farm management, and the dynamics of the number of ruminants available in the country.

GHG emissions in EU member states (MSs) slightly decreased during the 2005–2012 period, but since 2012, a trend of increasing GHG emissions from the agricultural sector can be noticed. In the EU, the MS agricultural sector was responsible for 430 million tonnes of GHG emissions in CO_2eq. A similar amount of GHG was emitted in the EU in 2005. There was a slow improvement in the intensity of GHG emissions per unit of agriculture output, which was offset by increased output levels from the agriculture sector in the EU. The removal of dairy quotas in 2015 had an impact on the increase of GHG emissions from agriculture as the removal of quotas led to a growth in the dairy herd numbers in the EU MSs (Eurostat 2018).

In order to achieve GHG emission reductions from agriculture linked to the EU's effort-sharing sectors agreement set for the year 2030, the expected reduction of GHGs should reach 30% in the period 2005–2030; therefore, this would require GHG emissions to be reduced by 29% during the 2016–2030 period as from 2005 to 2016 just a 1% reduction in GHG emissions was achieved in agriculture.

The current trend in GHG emissions among MSs shows that GHG emissions linked to agricultural activities are going in the wrong direction now, though the situation is different in different MSs as EU MSs have set different GHG emission reduction targets in the effort-sharing sectors. Some MSs have flexibility in meeting GHG emission reduction targets by 2030 as they achieve higher GHG reductions in other effort-sharing sectors like transport and buildings; however, these options should be justified in the Common Agricultural Policy (CAP) Strategic Plans.

The EU's national CAP Strategic Plans have to address climate mitigation issues in agriculture. If some EU Member States can provide justification that climate change mitigation in agriculture is not priority in this case this Member State can skip climate change mitigation in agriculture in their CAP Strategic Plans. There are some problems linked to the "Paris rulebook", which was adopted in 2018 at the COP24 in Poland, as it requires changes in the aggregation metric applied for aggregating all greenhouse gases into CO_2 equivalents, as it is necessary to give a greater weight to methane and a lower weight to nitrous oxide when assessing GHGs by global warming potential.

Thus, the 2030 targets should be assessed by adopting the IPCC Fifth Assessment Report metrics to aggregate different gases to CO_2eq (Table 2.1).

Trends in member state agricultural emissions were calculated by applying IPCC Fourth and Fifth Assessment Report values, which are provided in Table 2.2.

The application of the IPCC Fifth Assessment Report values increases the overall proportion of agricultural GHG emissions in total emissions in the EU-28. There are quite different trajectories in MS GHG emissions from agriculture during the period 2005–2016. Though total EU GHG emissions from agriculture declined by 1.0% or 1.1% if new metrics are applied, in Bulgaria, Hungary, Estonia, Latvia, Poland, Luxembourg, the Netherlands, Ireland, and Austria, GHG emissions from agriculture increased.

In Table 2.2, the countries that face the biggest challenges in reducing GHG emissions in agriculture by 2030 are presented. The reduction/increase in GHG emissions over the 2005–2016 period was subtracted from the required ESR reduction in the 2005–2030 period. IPCC Fifth Assessment Report metrics were applied. MSs with GHG emissions from agriculture as a small share of ESR emissions will be able to protect their agricultural sector from extensive GHG emission reduction if they can afford to reduce significantly GHG emissions from transport, buildings, and small industries. However, it will create big problems for MSs like Ireland, which has a 45% share of ESR emissions.

As one can see from Table 2.2, Luxembourg, the Netherlands, Germany, and Finland will achieve more than a 40% reduction of GHG emissions from agriculture. Austria, Belgium, Denmark, France, Ireland, Sweden, and the UK will have to reduce their GHG emissions from agriculture by 30–39% to achieve the ESR objective. The importance of agricultural GHG emissions in total ESR sector emissions has an impact on the extent of the required GHG emissions reduction from agriculture.

Croatia and Romania achieved a significant reduction of GHG emissions from agriculture during 2005–2016, and in these countries, agriculture contributes pro rata to the required GHG emission reduction from ESR sectors by 2030 if just GHG emissions from agriculture in these MSs remain below the 2016 level.

Table 2.2 GHG emission trends during 2005–2016 in EU MSs and required GHG emission reduction for ESR sectors and agriculture by 2030

EU MS	Change in GHG emissions from agriculture during 2005–2016 period, %	Required GHG emission reduction in ESR sectors set for 2005–2030, %	Required GHG emission reduction for agriculture for 2016–2030, %	
	IPCC Fourth Assessment Report metrics	IPCC Fifth Assessment Report metrics		
EU-28	−1.0	−1.1	−30	−29
Austria	2.6	2.1	−36	−38
Belgium	−4.1	−3.5	−35	−31
Bulgaria	26.3	22.5	0	−22
Croatia	−11.7	−11.3	−7	4
Cyprus	−9.4	−9.1	−24	−15
Czechia	9.2	8.2	−14	−22
Denmark	−2.6	−2.6	−39	−36
Estonia	16.0	14.8	−13	−28
Finland	1.1	1.1	−39	−40
France	−1.7	−1.6	−37	−35
Germany	3.1	2.8	−38	−41
Greece	−12.4	−12.1	−16	−4
Hungary	13.4	12.5	−7	−20
Ireland	2.7	2.9	−30	−33
Italy	−5.3	−4.7	−33	−28
Latvia	13.8	13.9	−6	−20
Lithuania	6.2	4.5	−9	−14
Luxemburg	10.0	10.3	−40	−50
Malta	−13.6	−13.9	−19	−5
Netherlands	4.4	5.7	−36	−42
Poland	1.9	1.7	−7	−9
Portugal	0.4	0.3	−17	−17
Romania	−10.7	−10.9	−2	9
Slovakia	2.4	0.4	−12	−12
Slovenia	−0.2	0.2	−15	−15
Spain	−6.0	−6.7	−26	−19
Sweden	2.3	−2.6	−40	−37
UK	−5.4	−5.3	−37	−32

Source: Created by authors based on Matthews (2020) and Eurostat (2018)

The most important environmental issues for ensuring the sustainability of the agriculture sector are linked to climate change. Thus, climate change mitigation policies and sustainable development agendas recognize the critical role of the agriculture sector in dealing with sustainable development and climate change challenges, and these challenges are expected to get worse in the coming years.

Moreover, the Paris Climate Agreement and the World Summit for Sustainable Development emphasize the significance of ensuring food security and eradicating hunger all around the world in the face of severe risks of climate change. Agriculture plays a key role in adapting to climate change. According to the IPCC assessment report, about 25% of global anthropogenic GHG emissions are triggered by changes in land use, afforestation, and the agriculture sector. Together, millions of people in least developed countries are losing their livelihoods due to climate change, as extreme weather events, droughts, floods, pandemics, etc., have a severe impact on the poorest and most vulnerable people living in developing countries. Almost 80% of the poorest people around the world are living in rural areas, and relying generally on agriculture, fisheries, and forestry, therefore these people are particularly affected by climate change (FAO 2010).

It is necessary to help countries to develop and restructure agricultural systems by limiting their impact on climate change and developing climate-resilient agriculture systems. The United Nations Food and Agriculture Organization (FAO) is mobilizing support worldwide to promote climate-smart agriculture (CSA). The CSA concept is based on three pillars and aims to raise the productivity of the agricultural sector in a sustainable way, to adapt to climate change and increase climate resilience, as well as to reduce GHG emissions from this sector. Promoting an integrated approach to address three pillars of climate-smart agriculture, i.e. productivity, adaptation, and mitigation, requires vertical and horizontal partnerships among all stakeholders involving both private and public actors around the world (FAO 2019).

The CSA concept can enable the challenges of the climate–water–land–energy–food nexus to be addressed and allows the creation of productive, resilient, and smart agricultural systems that are in line with sustainable development goals and are able to deliver targets of food security under climate change and linked risks. It is necessary to stress that common actions and efforts are necessary to form the necessary knowledge and good practices and to disseminate them around the world. Therefore, the implementation of CSA practices provides an essential path towards implementing the Agenda 2030 and Sustainable Development Goals (SDGS) and complying with Paris Agreement commitments (FAO 2010).

The CSA concept and three interlinked pillars of this concept were first endorsed by the FAO in 2010 during the Hague Conference on Agriculture, Food Security, and Climate Change (FAO 2010).

The main pillars of CSA mentioned above are described in more detail below.

The first pillar deals with the growth of agricultural productivity as well as incomes of farmers in a sustainable way. This pillar is directly linked with the climate–water–land–energy–food nexus and seeks to ensure efficient use of production factors in agriculture as well as promoting green productivity in the agriculture sector.

The second pillar deals with the adaptation and resilience of agriculture to climate change. This pillar is also very important for addressing the climate–water–land–energy–food nexus as increasing agricultural productivity on its own will not necessarily enable poor and vulnerable people, including food producers and consumers, to afford sufficient and nutritious food every day. Although the food production in the world can feed everyone on the planet, food waste and other losses, including overconsumption of food, create a situation of inequality where food is not accessible to the people that need it the most or live in hunger. Therefore, a sustainable and climate-smart agriculture should provide sustainable and resilient food systems, integrating all necessary food production and consumption aspects.

The third pillar deals with reducing greenhouse gas (GHG) emissions from agriculture. This can be achieved by using various innovative farm management practices, including energy and resource savings.

In summary, CSA seeks to ensure climate change mitigation and adaptation and food security by delivering the necessary tools for relevant stakeholders by identifying the best local and international agricultural practices and strategies based on local circumstances and varying social, economic, and environmental conditions. Thus, CSA is concerned with on-farm and off-farm activities. The various components that can be incorporated into the climate-friendly agricultural practices of CSA include (Hansen et al. 2007):

- managing farms, crops, livestock, aquaculture, and fisheries to achieve improved resource management, producing more output with fewer inputs, while increasing the agriculture system's resilience to climate change;
- managing ecosystems and landscapes to preserve ecosystems and ensure their services that are vital for increasing the efficiency of resource consumption and resilience of agriculture systems;
- managing services to farmers and land managers to construct an environment that encourages the needed changes.

In addition, it is necessary to stress that CSA cannot be treated as one particular technology or practice that can be functional in agriculture globally, but it is an integrated approach necessitating the assessment of agricultural practices and technologies under specific circumstances to find the most appropriate technologies and exercises for farmers to adopt. CSA also includes decisions regarding necessary policies, strategies, actions, and incentives in a specific economic, social, and political context (Lobell and Burney 2009).

Therefore, the efficiency, climate resilience, and adaptiveness of the agriculture sector as well as climate change mitigation can be achieved through refining the most important constituents of agricultural systems presented below (FAO 2010).

CSA systems enable improved soil and nutrient management by manure and residues of crops composting, better adaptation of nutrients to the needs of plants, application of deep insertion technology, or use of legumes for the fixation of natural nitrogen. With the application of innovative farming methods and practices that are able to raise organic nutrients, it is possible to reduce the need for environmentally harmful synthetic fertilizers, which in addition are unaffordable for small farms due to their high cost.

Improved water collection and use (e.g. pools, dams, retention ledges) and increased efficiency of water usage for irrigation systems are key factors in promoting the productivity and efficiency of the agriculture sector, along with using increasing rainfall resources. In developing countries currently, 20% of farmland is irrigated, but yields can be 130% higher if there are effective rainfall collection systems installed. It is important to expand effective water management technologies and techniques, especially for small farmers.

Pest and disease control needs to be improved as there is an evident negative impact of climate change on animal and plant pests and the prevalence of diseases, as well as on the growth of the number of invasive species and genus. Recently, due to the high temperatures, wheat yellow rust strains have emerged in several regions. This is an example of the risks linked to the adaptation of various pathogens to climate change. New aggressive strains are spreading around the planet at a high speed and causing epidemics in newly established crop sites, which were previously unaffected by yellow rust and have not yet adapted to it, and resistant varieties of crops. As the areas of wheat fields distributed in Asia are becoming warmer now, various pathogens are expected to spread further, triggering huge losses for agriculture and increasing the risks for food security.

Improved ecosystem resilience guarantees the desirable ecosystem services that enable the resilience of agricultural systems, growth of productivity and efficiency in agriculture, and the reduction of GHG emissions. The main measures to achieve this are the control of pests and diseases, microclimate control, waste decomposition, nutrient cycle regulation, and crop pollination. There are innovative natural resource management and production practices, including the mentioned measures that are able to improve effectively the provision of ecosystem services.

Improved genetic make-up increases the resistance of animals and plants to negative climate impacts like extreme temperatures, drought, floods, pests, and diseases. It also allows regulation of the extension of the growing season or growing cycle as well as the response to substances like fertilizers, water, and feed. Thus, the conservation of crops' genetic resources is crucial for promoting resistance to climate change, cultivating resource efficiency and productivity, shrinking the growing and production cycles, and ensuring better yields in terms of quality and nutrition on each land. So it is very important to grow varieties of species adapted to ecosystems and farmers' needs.

Effective harvesting and early processing of agricultural products and supply chains can diminish the post-harvest losses and reserve quantity, quality, and nutritional usefulness of agricultural products. Effective harvesting can also enable more efficient usage of by-products like animal feed for the production of renewable energy sources and/or to increase soil fertility. As food supply chains are getting longer and more complicated now, it is necessary to promote the efficiency and effectiveness of food processing, packaging, storage, and transportation efficiency, to maintain its quality and reduce its carbon footprint. Early food processing enables food surplus to be kept as a stock for a bad harvest year or allows for multiple sales and a reduction of food wastage. This results in a greater food supply and generation of farmers' income during a bad harvest season. Food processing also delivers new job places and increases income prospects.

In general, humans and ecosystems are quite vulnerable to climatic changes like floods or droughts. Although some climate change impacts can provide some positive impacts in some regions like Northern Europe, most effects are expected to be negative, and in particular, they might be harmful for regions that are already badly affected by climate change impacts like hot climate areas, especially in least developed countries already suffering from food shortages and hunger. Vulnerability can be exacerbated by different types of impacts in different regions (FAO 2019). With regard to negative climate change impacts, a number of adaptation measures can be taken in farming practices, such as innovative planting, harvesting and watering, fertilizing of plants, diversifying crops and applying different varieties, and other advanced management practices.

Climate change mitigation measures in agriculture can mitigate GHG emissions, and adaptation measures are able to minimize the damage caused by climate change effects. Together climate change mitigation and adaptation measures can enable the establishment of a society and agriculture systems more resilient to climate change. Adaptive measures in the agricultural sector include various technological solutions to improve farm management and structural adjustments and policies and measures like the development of climate change adaptation strategies and plans.

Climate change adaptation measures in agriculture can be divided into farm-level and sector-level measures.

On the farm level, there are several short- and medium-term adaptive measures, which are presented below (EURACTIVE 2019):

- adjusting planting and treatment operations at farms;
- protection of plants and animals from hot and cool weather and frost through technical solutions like refining ventilation, heating and cooling systems in greenhouses, and livestock shelters;
- selection of crops and other species that are well adapted to the changes of length of the growing cycle and are more resilient to high or low temperatures and different humidity conditions;
- increase in adaptation capacities of crops through genetic diversity measures and the opportunities provided by new biotechnologies;
- increase of pest and disease control effectiveness by providing improved monitoring, more diverse rotation of crops, and by applying integrated management techniques for pest control;
- increase in water utilization efficiency by lowering water wastage, refining water irrigation methods and practices, and ensuring effective water recycling and storing systems;
- making soil management more effective by increasing retention of water to maintain necessary moisture of soil and better landscaping like providing animal shelter;
- introduction of temperature-tolerant animal breeds and adapting animal nutrition habits to heat changes;
- sectoral-level adaptation measures are provided below (EURACTIVE 2019):
- identification of the most vulnerable areas and evaluation of crops, changing alternatives and varieties as necessary to respond in a timely manner to climate change;

- encouragement of R&D aimed at developing best crop selection practices and expansion of varieties of species adapted to the best way to mitigate climate change impacts;
- enhancing adaptive capacity by raising awareness of farmers and providing necessary knowledge and advice for improvement of farm management practices and implementation of innovative approaches in agricultural systems.

The key factors enabling the promotion of climate-smart agricultural transformation for small farmers are linked to better coordination and integration of interlinked climate change mitigation, sustainable agricultural development, and food security issues. Policies and measures in all three interlinked areas of CSA affect small- and large-scale producers as well as enabling climate change mitigation and effective use of production factors. However, the absence of consistency can block synergies that are necessary to be successful, and pursuing declared CSA policy goals may not be effective and may contradict each other (European Environmental Bureau 2019).

Currently, climate change policy at national level in the EU is implemented by developing the National Adaptation Action Plans (NAPA) and the Nationally Adequate Mitigation Action (NAMA) plans as well as by preparing national climate change strategies. Food security and agricultural development plans are set out in National Development Strategies and Poverty Reduction Strategy Papers (PRSPS). These policies need better harmonization and integration with the Common Agricultural Policy in Europe (Environmental Bureau 2019).

At international level, there is also a need for better integration of sustainable agricultural development, food security, and climate change policies and measures including funding. This integration is also in line with the climate–land–water–energy–food nexus.

There are usually parallel policy dialogues ongoing on food security and on addressing climate change issues. The agricultural communities are also active in the debate on climate change policies and measures, which would have a major impact on the agriculture sector. It is essential to establish mechanisms for enhancing dialogue between policymakers and farmers and other stakeholders on food security, sustainable agricultural development, and climate change mitigation and adaptation (Rivera-Ferre et al. 2013).

Climate change risks are creating new funding needs such as required investments and innovative institutions. To achieve synergies between adaptation and mitigation, there are a few possible alternatives to attain terrain synergies to be created over the long-term time frame; however, for shorter periods such as up to 10 years, the major challenge will be the volatility of farmers' income. For example, crop and grassland refurbishment projects frequently result in long-term loss of farmland, reducing land under cultivation or grazing in the short term, but eventually increasing productivity and stability in the long term (Scherr and McNeely 2008).

Including crop residues is likely to enhance the fertility of soils and increase the capacities of water retention systems, thus raising the yields in the medium and long term may result in a different trade-off in the short term. Nevertheless, in conditions with livestock at the centre of the food supply chains, residues used for the food crop system may be offset against their use as animal feed. Policy decisions are needed to enable these transitions, and funding is the key issue in this context. There are two major topics that arise: exploration of non-traditional sources for financing of necessary transitions and the development of proper instruments for insurance (European Environmental Bureau 2019).

Sustainable restructuring of the agricultural sector requires joint action on food security and significant investment (Constance 2010). Uncertainty about possible losses and dangerous risks as well as amplified costs of inactivity related to climate change problems show the need for urgent and more aggressive transformation efforts in agriculture. Addressing the funding challenges to deal with climate change risks will necessitate innovation and joint action, as well as policies and measures to deal with existing and foreseeable adaptation and mitigation gaps, including the availability of different sources of funding and finding better ways of linking necessary actions to attract funding for climate change mitigation and adaptation in the agricultural sector.

Although agriculture and food security have attracted more funding in recent decades, they are not widely considered to be central to the climate change crisis. The possibilities of agriculture to attract financing for climate change actions in the future are related to greater recognition of climate change mitigation potential in agriculture, including deforestation, carbon sequestration and its adaptation potential, and the resilience capacity to respond to climate change and to ensure food security prospects for future generations as well.

The use of climate change mitigation funding to support the low-carbon transformations of small-scale agricultural systems calls for moving beyond the carbon offset systems of developed industrialized world countries and the introduction of preferential financing for agricultural activities in developing countries that generate common benefits like climate-sustainable agricultural products supply chains. Therefore, appropriate and timely funding is able to provide necessary transitions in the agriculture sector that were hampered before by the shortage of financial flows. Mitigation funding is also a valuable resource, if applied for creating synergies between all policies targeting the agriculture sector and addressing the climate–water–land–energy–food nexus (European Commission 2019).

2.4 Sustainable Energy and Agriculture

There are close linkages between sustainability issues in energy and agriculture sectors as the main sustainable energy development, and climate change mitigation issues in the energy sector can be addressed by promoting the use of renewable energy sources like hydro or wind parks, which are mainly located in rural areas and require huge amounts of land resources. The use of biomass for energy production also requires some trade-off between land allocation for energetic plant growing and satisfying other land needs for biomass and energy production and land used for agriculture production like crops or cattle breeding.

This section aims to reveal these close relationships between sustainable agriculture, sustainable energy, and climate change.

The EU has set an ambitious target for 2050—to reduce GHG emissions by 80–95% compared to 1990 levels. The Energy Roadmap 2050 explores the low-carbon transition of the energy sector for achieving the set GHG emission reduction target, while also enhancing the competitiveness of the energy sector and increasing the security of the energy supply (EC 2015, 2018).

The global Sustainable Development Goals (SDGs) have been established as the blueprint for achieving a better and more sustainable future for current and future generations. Through the promotion of renewables, three SDGs can be met, namely:

- SDG 7: Affordable and clean energy;
- SDG 12: Responsible consumption and production; and
- SDG 15: Life on land, if renewable energy allows for continued irrigation.

Energy demand has grown rapidly in the last few decades in the agriculture sector, with just the economic crisis of 2008 having an impact on decreasing the rates of energy consumption in agriculture. Several decades ago, many agricultural activities, especially in developing countries, were performed manually (Giampietro and Ulgiati 2005). The Green Revolution following the industrial revolution that started in the 1960s enabled extensive use of fossil fuel-based energy in agriculture.

During these times, agricultural activities aimed at increasing yield were very reliant on the use of fossil fuels (Johansson et al. 2012). An in-depth understanding of the agricultural system is necessary to evaluate the amount of energy necessary in the agricultural sector as well as for complete supply chains of agricultural products (Jordan 2013). The life cycle of carbon emissions of agriculture products linked to energy consumption plays an important role in developing climate change mitigation policies in agriculture.

The energy needs of the agriculture sector are diverse and incorporate such activities as the supply of fertilizers, water irrigation and pumping systems, machinery, and manufacturing processes (Wiedmann 2009). The constant increase in energy demand has a negative impact on the rising costs of productions in all sectors, including agriculture. It is obvious that agriculture is central for rural areas and an important economic resource for many countries, providing economic activities and income for rural areas. Therefore, the biggest share of food production comes from the rural areas. The people living in rural areas are employed in the production, processing, and storage of agricultural product, and all these activities need energy resources. Water supply and irrigation systems are vital for the agriculture sector and food production, and water pumping from the ground requires a lot of energy (Shinde and Wandre 2015). Water resources are necessary for such agricultural activities as irrigation and livestock, and they are responsible for the highest share of energy used in agriculture. Consequently, water pumping and water supply in agriculture are the main sources of energy needs and also account for substantial cost in this economic activity, thereby raising the prices of food and other agricultural products.

The main factors that have an impact on the cost of irrigation and water pumping are related to water and energy availability and the way they are used. The cost of irrigation and water pumping can be cut by applying modern and innovative water- and energy-saving irrigation practices as well as using renewable and clean energy sources for water irrigation (Chandel et al. 2015). Historically, water management systems in agriculture functioned by applying fossil fuel like diesel or electricity produced from fossil fuels and supplied to the grid. However, climate change and the rapid shrinking of fossil fuel resources all over the world led to fast penetration of alternative fuels in the agriculture sector as well. Moreover, the problems linked to environmental degradation and the severe impacts of climate change meant that renewables were found to be an excellent replacement for the fossil fuel used in agriculture for water management and other purposes. Additionally, population growth has an impact on food consumption and raises the risks for food security. Therefore, there is a need to address these issues together by improving agricultural production systems and replacing fossil polluting fuels with clean renewable energy sources and ensuring food security through climate change mitigation as burning fossil fuel is the main source of GHG emissions. The climate–water–land–energy–food nexus is relevant in this context, and renewables also compete with crops and other agricultural activities for land and water resources, and climate change issues affect all these problems as well.

The minimization of food wastage is very important as well. Energy and water savings and efficient use of land are very important for the costs of agriculture production and food security; however, food wastage issues should be among the priorities in ensuring food security. Food wastage happens in several phases, including harvest, post-harvest, and the marketing stage. Analysis of the situation in developing countries revealed that the food waste problem is the most acute in the post-harvest phase, leading to huge economic losses for those countries (Prakash et al. 2016).

One can imagine that fresh products can easily get damaged. Accordingly, to keep products fresh for longer, low-temperature storage technologies are being applied; however, this is very expensive and requires a lot of energy and especially a reliable energy supply to avoid damage. As an alternative, a drying technology was created for preserving fresh products and reducing food losses and wastage (Sharma et al. 2009). The dried products can be maintained for a longer period of time without damage. Nevertheless, this drying technology also requires a lot of energy (Kumar and Tiwari 2007). High energy consumption in particular is linked with the drying of agricultural products, and in developed countries across the world, almost 10% of the energy used in the agriculture sector is used for drying processes (Kudra 2004). Until 1970, all these drying processes were powered by energy based on fossil fuels. After the oil crisis, renewable energy sources became more popular for powering the drying process in the agriculture sector. Therefore, renewable energy sources provide good opportunities for environmentally friendly drying processes in agriculture (Babatunde et al. 2019).

Today, agriculture and farming activities are carried out in a mechanized way. The machines applied in these processes also require a lot of energy. Machines and mechanisms are used for the preparation of field crops, planting and harvesting, chemical spraying, and fertilization of land. Moreover, the production of fertilizers necessary for agriculture requires a lot of energy.

Numerous and various types of renewable energy installations deliver useful options for new business models and cooperations in energy supply from renewable energy sources. Renewable energy sources also provide good opportunities for the creation of new job places and stimulation of the economic growth and social development of rural communities. Replacing fossil fuels with renewables also contributes significantly to the increase of energy supply security, especially in remote rural areas. Many renewable energy-based technologies can deliver energy to farmers for heating, cooling, and other farmers' energy consumption needs. These renewable energy sources spread across rural communities are mainly based on bioenergy, solar, wind, and geothermal energy.

It is also possible to apply heat pumps and heat recovery systems linked to heating and cooling systems and manure storage and for farmers to apply different renewable energy-based technologies together.

Renewable energy generated on the farm can be supplied to electricity grids as farmers can also act as energy prosumers. There are various options for consuming renewables on the farm and sector levels as well as various renewable energy generation options and microgeneration technologies based on renewable energy sources.

The decrease of renewable energy technology costs over time provides several beneficial options for farmers to get involved in renewable energy production and to develop new business models. Taking into account EU energy and climate targets, the increase in the usage of renewable energy sources in agriculture is a beneficial prospect for farmers as well as a priority of energy and climate change mitigation policy. Nevertheless, this diverse assortment of opportunities and alternatives available to farmers also creates multifaceted questions linked to available renewable energy potential and its exploration impacts taking into account natural conditions such as landscape, soils, water resources, climate, the size of the farm, applied management practices and technologies, the degree of mechanization, and also the following socio-economic drivers: the availability of investment flows, and institutions supporting and providing advances for farmers. The energy system and available energy infrastructure also play a crucial role in the prospects of renewables deployment in agriculture and rural communities. Therefore, these complicated and closely related issues raise a lot of challenges for farmers. Information and knowledge dissemination as well as financial support are necessary for farmers engaging in the use of renewables on their farms as many barriers still exist (Lu et al. 2020).

The market uptake of new renewable energy-based technologies is driven by a number of elements, including increasing support for renewable energy sources and policies and measures implemented around the world. Reducing greenhouse gas emissions is one of the most essential reasons for promoting renewable energy sources. A greater share of renewable energy in final energy consumption permits countries to meet their climate change mitigation targets. Investors around the world are gradually seeing new RES-based technologies as a lucrative investment opportunity with higher returns and benefits. Thus, while new, renewable energy technologies are already successfully competing with conventional energy sources in many parts of the world, there are still many barriers to the further development of these new technologies. Thus, the rapid market uptake of new energy generation technologies is hampered by a number of social, economic, technological, and regulatory barriers. Researchers have highlighted these barriers as the main causes inhibiting the widespread use of new energy generation technologies based on renewable energy sources (Zyadin et al. 2014; Nasirov et al. 2015).

Public resistance and the unfavourable assessment of renewable energy projects are important social barriers to the faster market uptake of these new technologies. This resistance is largely due to an absence of understanding of the benefits of such technologies. Other social barriers are linked to the acquisition of land for renewable energy infrastructure, as the land allocated for this could be successfully used for agriculture, tourism, etc. (Paravantis et al. 2014; Zhao et al. 2016). Much of the agricultural land, including arable land, is being converted into roads, building structures, and other necessary infrastructure for the operation and maintenance of renewable energy generators. This is why other sectors, such as agriculture, tourism, and fisheries, suffer (Boie et al. 2014; Edomah et al. 2017). A lack of public consciousness and other information barriers preclude quick market uptake of new energy generation technologies and do not allow a level playing field with regard to traditional energy production technologies (Raza et al. 2015).

Researchers have highlighted a very important "not in my back yard" or "NIMBY" syndrome in their research, which is evident when examining renewable energy projects that face societal resistance to a variety of issues, such as negative impacts on the environment and the landscape and related conflicts with local communities (Nasirov et al. 2015). Another major problem is the loss of other revenue due to land being reserved for large RES projects. Developed countries generally face a severe lack of capacity and education about renewable energy, in addition to a lack of skilled labour for the development of RES projects. Important obstacles, such as the inability to perform proper operation and maintenance work, also cause many problems and even lead to the collapse of the RES project immediately after the project implementation phase. Therefore, researchers agree that the lack of experienced professionals and training institutes hinders the wider penetration of new RES technologies in the market (Karakaya and Sriwannawit 2015). Key policy measures have been identified to overcome social barriers to the development of new energy production technologies, such as demonstration projects, information campaigns to raise awareness, training, and capacity building (Sovacool 2009; Paravantis et al. 2014; Kilinc-Ata 2016; Seetharaman et al. 2019).

Economic and financial barriers to the expansion of new energy generation technologies are related to high start-up capital needs, a lack of financial institutions and investors in renewable energy projects, subsidies available for traditional fuels, and the resulting unfair competition with regard to energy price between conventional and renewable energy sources (Byrnes et al. 2013; Raza et al. 2015). Economic and financial barriers have so far failed to ensure the widespread penetration of new renewable energy technologies in the market. Thus, high start-up capital costs are an important economic barrier, as the acquisition of RES technologies requires large initial investments. Because of the limited efficiency of RES generators, RES projects encounter a long payback period (Lyu and Shi 2018). Therefore, RES projects often remain unworkable precisely for these reasons (Painuly 2001). Due to the fewer financing institutions offering loans and providing financing for RES projects, RES project developers face problems such as securing financing for these projects. A lack of institutional experience and poor access to effective risk management mechanisms, such as guarantees, make it difficult for developers of RES projects to find suitable financial instruments. This suggests that investment in renewable energy projects is seen as very risky (Ohunakin et al. 2014).

Another problem is that the government support for fossil fuels often exceeds RES grants, putting RES-using technologies at a competitive disadvantage (Byrnes et al. 2013). External costs are also an important economic obstacle to fast market uptake of new energy generation technologies. Total energy supply costs include research, production, distribution, and consumption costs. However, the external costs of the negative environmental impact being high for traditional fossil fuels are not mirrored in their price. Thanks to declining fossil fuel prices, they even compete more successfully with RES. Researchers identified the subsequent economic and financial policies that can remove economic barriers to rapid market uptake of new energy generation technologies: subsidies and grants for renewable energy projects, green certificates, and greenhouse gas emissions trading; GHG taxes or tax incentives for companies using RES; administratively fixed electricity purchase prices for RES-using energy producers, and price auctions, preferential loans, etc. (Zhang et al. 2014; Harrison 2015; Sun and Nie 2015; Zeng et al. 2018).

Researchers have also identified various technological barriers to the rapid market uptake of new renewable energy technologies: a lack of infrastructure, insufficient capacity for operation and maintenance of RES generators, and inadequate research and development efforts. In addition, RES-based power plants require advanced energy storage capacities because of the intermittency of RES technology operations (Gullberg et al. 2014; Zhao et al. 2016). Important infrastructure barriers reflect the lack of infrastructure for the integration of RES into the energy supply system, as there are many problems with system flexibility and limited grid access to RES-based energy generators (Boie et al. 2014; Raza et al. 2015). It must be emphasized that the cost of developing the infrastructure required for RES technologies, incorporating transmission lines and other necessary equipment to connect to the grid, is very high. In addition, due to complex technologies and established procedures and guidelines, including reliability and other standards, it is not possible to make extensive use of RES technologies (Nasirov et al. 2015). The lack of research and development prevents RES technologies from competing effectively with conventional fossil fuel power generation technologies. In addition, the already mentioned high risks associated with RES technologies prevent businesses and governments from investing sufficiently in R&D activities. In addition, there is no culture of operation and maintenance, which is also an important obstacle to the development of RES technologies, as these technologies are new and still under development, so there is very little practical experience. The following key policy measures have been identified to remove technological barriers to the development of new energy production technologies: public support for renewable energy infrastructure, such as energy storage, financing, supply of equipment, and parts needed to operate renewable energy technologies, import taxes, VAT abolition and tax breaks (Boie et al. 2014; Edomah et al. 2017).

Regulatory barriers are also significant in hampering the rapid deployment of new technologies. The market uptake of new energy generation technologies requires strong political will and properly developed regulatory frameworks supporting the development of RES. However, in many developing countries, there is strong political resistance to renewable energy projects, such as institutional corruption and lobbying for fossil fuels or nuclear energy (Ohunakin et al. 2014). Researchers have acknowledged these regulatory and institutional barriers to the development of new RES technologies: a lack of national policies to maintain renewable energy, bureaucratic burdens, and over-regulation, split incentives, unrealized government targets for renewable energy, a lack of standards and certificates, etc. (Stokes 2013; Sun and Nie 2015). A strong regulatory policy for the energy industry is needed to remove regulatory barriers to the deployment of new technologies using RES. In the absence of effective policies, the various market participants, government institutions, and departments do not have a clear understanding of the implementation of the necessary support measures. However, the most urgent problems are related to unpredictable energy policy and insufficient political assurance in RES development projects and insufficient support for them (Zhang et al. 2014). The other regulatory barriers are the following: the lack of a clear division of obligations, multifaceted authorization procedures, other hurdles with permits and land acquisition, limited planning rules, etc.

Insufficient fiscal incentives are also a significant issue hindering the development of new energy production technologies (Sun and Nie 2015). Other barriers include information asymmetries and a lack of information, fragmented initiatives, a lack of transparency, subsidies for conventional fuels, and failure to integrate external energy production costs into energy prices (Browne et al. 2015). Bureaucratic procedures for the introduction of new energy production technologies are considered to be the biggest barrier to investment in renewable energy projects (Huang et al. 2013). Additional regulatory barriers include inefficient policy development or inconsistent policies, unclear energy purchase agreements, and other agreements. It must be emphasized that the various obstacles to the development of new energy production technologies often overlap.

Although many countries have defined renewable energy targets in their long-term strategies, there is a clear gap between policy objectives and the actual results achieved (Malik et al. 2019). Policymakers lack an understanding of realistic goals, and there are many gaps in the accomplishment itself. New policy schemes need to be developed that provide a clear understanding of the regulation needed to give businesses confidence in future policies to promote new energy generation technologies. There are a number of policy measures to remove regulatory barriers: the share of RES in final energy, in power and heat generation balance, in transport and other obligations and mandates; public procurement of power from renewables and the establishment of renewable energy quotas and other commitments (Boie et al. 2014; Cadoret and Padovano 2016; Kilinc-Ata 2016; Papież et al. 2018; Malik et al. 2019).

Table 2.3 presents the most important hurdles to fast market uptake of new energy generation technologies and the means to overcome these barriers.

As can be seen from Table 2.3, overcoming social, economic, technological, and regulatory barriers to the development of new energy generation technologies requires targeted policies that effectively deal with these barriers. Nonetheless, the success and impact of this policy in disabling barriers to new energy production technologies need to be appraised on the basis of actual examples while also taking into account behavioural and psychological barriers that are site-specific and culturally based.

Thus, all measures to promote new energy generation technologies can be divided into these main groups: target setting and strategic commitments for RES development; financial instruments; administratively priced pricing measures such as feed-in prices or feed-in premiums for power from renewable energy sources; carbon, energy, or fuel taxes; market-based flexible instruments such as GHG emissions trading or green and white certificates; competitive pricing tools such as auctions; RES portfolio standards; obligations, such as the share of renewable energy sources in transport fuels, RES heat quotas; requirements for the installation of water boilers using solar energy; zero-emission vehicle obligations, building codes, and standards; energy performance requirements for energy efficiency or RES; banning the use of fossil fuels for heating; information tools, such as information campaigns and energy labelling; standards and certification for buildings and equipment like low-carbon fuel standards and vehicle emission standards; constant provision of information on energy consumption by means of meters or in bills; capacity building like demonstration projects, research, and development; public procurement; alternative fuel or charging infrastructure for carbon-free transport development, voluntary programmes, and other initiatives.

Farmers in Eastern European countries in particular face extra challenges such as fragmentation of land, the small size of agricultural holdings, and the low investment capacity of farmers. In addition, the changes in policy incentives have a negative impact on farmers' willingness to use renewable energy sources. Nevertheless, the usage of RES at European farms is an attractive option due to the finance available from EU Structural Funds for the promotion of renewable energy penetration, and also, it is a good opportunity to expand jobs and to diversify the income of farmers and also to increase the sustainability of agricultural systems by facing the increase in economic pressures because of agricultural products' price volatility.

The usage of renewables in the agricultural sector allows to avoid many problems linked to the usage of fossil fuel as renewables do not cause environmental pollution and, GHG emissions and reduce dependency on imported fossil fuels and creates new jobs, especially in rural communities. Therefore, the use of RES in the agricultural sector is associated with many social, economic, and environmental benefits. Renewable energy also provides a long-term revenue opportunity for farmers and rural communities. There are many available good practices of farmers engaged in

Table 2.3 Barriers to quick market uptake of new energy technologies

	Main barriers	Description of the barriers	Policy tools
Social barriers	Barriers to public awareness rising and spread of information about RES benefits	Insufficient information on the benefits of all types of RES; lack of awareness about RES technologies; insufficient information provision on the limited negative environmental impact of RES.	Various tools for information spreading and enhancement of education: public informative campaigns; application of various social media channels; employment of social marketing techniques; coaching on benefits of RES in schools, universities; in the workplace and capacity building Standards and certification and growing consumer confidence. Various pilot or demonstrating projects relevant to verifying site suitability Greater satisfaction of various stakeholders should be achieved by enhanced communication and information about RES benefits provision like new jobs, reduced GHG emissions, and other environmental damages Voluntary agreements of companies with state institutions might be very useful, including various corporate social responsibility initiatives
	NIMBY of Not in My Back Yard pattern of behaviour	NIMBY phenomenon describes the situation then people support renewable energy in general, but not in their neighbourhood, so renewable energy projects face individual citizens' resistance, which is called NIMBY syndrome.	
	Loss of income	Large-scale RES projects require large areas of landscape, so RES projects require a lot of land. To achieve this, income is lost by arable land, fishing, and tourism business.	Awareness raising and information-spreading tools: public informative campaigns; use of social media channels and social marketing means for disclosure of information about positive impact of RES technologies and their various external, including environmental, benefits.

(continued)

Table 2.3 (continued)

	Main barriers	Description of the barriers	Policy tools
	Shortages in highly experienced professionals and experts	Non-existence of technical specialists (designers, financiers, construction, operation and maintenance specialists). Lack of training institutions hinders RES technologies from better penetrating this market.	The integration of courses on RES technologies in higher education and vocational training syllabuses might be useful for capacity building and preparation of highly skilled cadres and professionals in the RES field.
Economic barriers	Necessary initial capital investment quite high	The lack of initial capital for investments in RES and the long payback period of these projects create an extra hurdle.	RES projects are supported from various funds, especially from European Union Structural Funds. Also, there are various financial support measures available for RES: grants, subsidies; soft loans; loan guarantee
	Lack of funding institutions	There are fewer financial agencies to finance renewable energy projects, so investing in renewable energy projects is seen as riskier business.	
	Subsidies for fossil fuels exceed subsidies for RES	Government support for fossil fuels in excess of support for renewable energy sources is hampering the development of RES.	Elimination of environmentally harmful subsidies like various currently available subsidies for fossil fuels or nuclear energy
	Non-integrated external costs of fossil fuel-based energy generation	External costs of fossil fuel production due to adverse impacts on health and the environment are not integrated in the energy price, making fossil fuel energy more competitive on the market.	Policies to include the external costs of energy production in the cost of energy supply are necessary: the increase of environmental taxes; subsidies for RES; tax incentives and credits for renewable energy sources
	The decreasing world prices for fossil fuels	Currently declining fossil fuel prices negatively affect the market uptake of renewables.	
Technological barriers	Limited infrastructure for the development of renewable energy sources	RES generators are traditionally located in remote locations where additional transmission lines are needed to incorporate RES	Government support for renewables infrastructure. Installation of alternate infrastructure, such as energy storage installations, energy

(continued)

Table 2.3 (continued)

	Main barriers	Description of the barriers	Policy tools
		generators into the grid, and networks need to be upgraded, and this would affect the cost of RES projects.	charging infrastructure, reduction of import tax on equipment required for RES technologies, and VAT reduction
	The complexity of technologies is mainly related to the interruptibility of their work and the requirements of energy storage	The insufficient standards, and practices for working with new energy technologies, which are characterized by high intermittency, have negative impact on market uptake of RES. The main technical problem facing RES technologies today is the need for energy storage, and this also affects the growth of energy generation costs. There is also the lack of RES technology equipment, spare parts, and other components that have an influence on the rise of energy generation costs.	
	There is a lack of investment and opportunities for research and development of RES-based technologies	Investment in RES technology research and development is insufficient to safeguard the competitiveness of renewables compared to conventional fossil fuel-based technologies. RES technologies are riskier and require additional research and development capacity.	Public financing of research and development activities, RES demonstration projects
Regulatory barriers	Unsuccessful government measures	Unstable energy policies, lack of effective policies for the integration of RES and weak governmental agencies, due to lack of adequate knowledge, human resources and expertise.	Increasing the competitiveness of renewable energy sources requires a stable long-term regulatory policy, containing financial instruments such as administratively fixed prices for

(continued)

Table 2.3 (continued)

	Main barriers	Description of the barriers	Policy tools
	Insufficient financial initiative	The lack of economic and financial incentives leads to elevated costs that hinder the development of the RES industry.	electricity produced from RES; technology certificates, subsidies, and soft loans for RES projects; and loan guarantees In addition, policies are needed that offer a clear understanding of important regulatory issues.
	High administrative and bureaucratic complexity	Ineffective coordination between various institutions and other bureaucratic hurdles takes a long time to develop a renewables projects, and RES project creators incur higher costs in obtaining permits and necessary licences.	Removing of various administrative barriers by giving priority to connecting to grid renewable energy-based generators
	Irrational governmental pledges	A huge gap exists between the political goals set by local governments and the real results that are possible to achieve in RES deployment.	Obligations for the share of RES in fuels; procurement of renewable electricity, RES-using vehicles; RES quotas and commitments Established specific technology targets supplemented by other policy schemes like RES portfolio standards, special technology mandates, and building codes
	The absence of certification procedures and standards	In many countries, there is a lack of standards and certification procedures to ensure that RES equipment and spare parts that are produced in other countries satisfy the standards desired by importers.	There are the following standards: vehicle standards, low-carbon standards, etc.

Source: Compiled by the author

the production and sale of excess energy generated by renewable energy-based microgeneration technologies. This has a significant impact, enhancing the energy supply security inside the agricultural sector. Therefore, the positive impacts of renewable energy sources in agriculture are linked to new income and job opportunities for farmers, distributed and independent energy generation and supply, a reduced negative environmental impact, diversification of the energy supply, and increased energy security. The main RES sources that have a wide application in agriculture are wind, solar, geothermal, and biomass.

Solar energy can be applied in various ways in the agricultural sector, by enabling maximization of self-reliance, cost savings, and a reduction of pollution. Although with solar panels the power source fluctuates during the day and on a daily basis, the use of solar energy reduces the electricity demand and leads to significant cost savings for farmers. Solar energy can provide the following benefits for rural communities and farmers (Chel and Kaushik 2011):

- cost reduction for farms through reducing diesel and other fuel consumption;
- low requirements for maintenance of solar panels as there are no moving parts;
- increase in energy supply reliability and security leading to higher efficiency of agricultural operations;
- provision of clean energy and mitigation of climate change.

Photovoltaics (PV) is a cheap electricity source for farm operations. The use of solar panels provides a cheaper energy source for all applications necessary for agricultural operations linked to agricultural lands, including lighting, water pumping, irrigation and watering of livestock, wastewater treatment, and the use of electric fencing (Carbone et al. 2011). It is very simple to use PV for water pumping. Water pumping in the agricultural sector is associated with intensive use of electricity; therefore, water pumping systems powered by PV can lead to big cost savings. PV can be applied for the water pumping required for many watering purposes necessary in the agricultural sector, such as watering of stocks, irrigation of crops, and domestic use of water on farms (Schwarz 2006). In addition, solar systems have the ability to store water on cloudy days, thus avoiding the need for batteries, increasing the simplicity of the system, and reducing the costs of agricultural operations. PV systems can also be applied (Xue 2017) for refrigeration purposes; provision of energy for grinding; for egg collection and egg handling; in fishery for water pumps and compressors; livestock feeding equipment; and electric fences to protect livestock.

Also, PV systems can be applied for heat production, which has many applications in agricultural operations, such as solar water heaters applied for cleaning domestic animals necessary for livestock farms, drying crops through exposure to the sun, and solar-powered driers applied for drying crops (Chikaire et al. 2010). Solar energy can be widely applied for heating greenhouses. Solar energy can be applied just for lighting in usual greenhouses (Carbone et al. 2011); however, in solar greenhouses, the solar energy can be used for lighting and heating as well (Bellows and Adam 2008). Conventional greenhouses are dependent on oil- or gas-based heaters to maintain the necessary temperatures to ensure a comfortable environment for plants in cold seasons (von Zabeltitz 1986). A modern solar greenhouse uses storage equipment and insulation chambers to prevent the loss of heat and for storing solar heat during cold seasons (Taki et al. 2017). Therefore, solar greenhouses are very useful for reducing the usage of fossil fuels for heating. There are modern greenhouses that have an integrated filter applied as a delivery system and for reflecting near-infrared radiation (Sonneveld et al. 2009).

Mechanical energy and power generated by wind energy technologies can also be widely applied in the agricultural sector. Wind power plant or windmill technology is identified by scholars as the quickest penetrating RES technology, overtaking solar PV, bioenergy, etc. The improvements in wind energy generation technologies through the application of hybrid systems will enable further growth of economically efficient windmills. This trend makes producers in the agricultural sector maximize investments in the development of wind power infrastructure. The application of windmills is a reliable and cost-effective way of satisfying various energy needs encountered by agricultural operations. Wind energy can be applied for the water pumping necessary for crops irrigation and for electricity generation, minimizing power supply costs due to the absence of costs for installing transformers, electric poles, and power lines. Wind energy can also be applied for grinding legumes and grains (Halliday and Lipman 1982). Windmills provide environmentally friendly energy and allow the usage of fossil fuels like diesel for agricultural operations to be avoided. The use of wind energy allows the reduction of environmental pollution and acid rain formation because of the reduction of oxide compounds, as well as the reduction of GHG emissions, prevention of noise, and avoidance of toxic and radioactive waste formation (Kondili and Kaldellis 2012). It is necessary to stress that wind-powered farms are also economically very efficient due to the decrease of operation and maintenance costs of agricultural operations, avoidance of fossil fuel use, and the reduction of fuel import dependency (Leung and Yang 2012).

In addition, the application of small wind generators can supply power of 400 W to 40 kW or even more, which is enough for all agricultural operations at farms (Ali et al. 2012). Farmers can be prosumers or producers of wind energy as such small wind generators require quite small areas of land. The usage of net metering can provide farmers with multiple benefits from the use of wind turbines as electricity produced by a turbine exceeds the energy requirements of farmers, and the surplus of power flows back to supply energy for other farms through the triggering of a backward movement by the electric meter. If a wind turbine produces insufficient electricity for the farm at any particular time, a forward spin is applied by the meter (Poullikkas et al. 2013).

Biomass resources can be obtained from various organic wastes resulting from agricultural operations and from plants like trees, crops, manure, and crop residues. There are usually large quantities of waste that have accumulated from crops production that can be applied for producing energy. The converted energy from biomass can be applied for producing the fuel for vehicles, and electricity supply for households, businesses, and commercial purposes. The use of biomass for energy generation has a lot of benefits, including reducing GHG emission, and provides additional revenues for farmers and rural communities. Though the highest shares of crops and livestock waste are applied for land erosion mitigation, soil nutrient recycling, and disposal cost reduction, large quantities of such waste can be applied for energy generation as well (Solé et al. 2018). Biomass energy is very useful for small-scale farming as the application of bioenergy in agriculture enables farms' sustainability growth in terms of economic, social, and environmental dimensions. Economic dimensions include cost savings in farm operations and income diversification opportunities. The social dimension is linked with the creation of new jobs and social development of rural areas. Environmental dimensions are linked to ecological farming opportunities, as well as the reduction of pollution and GHG emissions due to the avoidance of fossil fuels.

Biomass energy can be applied in biorefineries, which are widely applied for various purposes in all sectors. A biorefinery is a widely applied technology for the conversion of biomass to energy and generation of electricity, heat, ethanol, steam, biodiesel, etc. These energy carriers are good replacements for fossil fuels in chemical feedstock and vehicle fuels and enable security of energy supply and climate change mitigation. Biorefinery technology enables the conversion of corn to animal feed, corn syrup, and ethanol. By applying biorefinery technology, wood can be transformed into various wood products, electricity, and heat.

Geothermal energy based on heat and water can be widely applied in agricultural operations. There are three types of geothermal power plants: dry-steam, binary-cycle, and flash-steam plants. It is worth mentioning that geothermal energy can be applied for power generation and the production of hot fluids. These fluids can be utilized in fisheries and farm operations like the dehydration of alliums, heating of buildings, milk pasteurization, and for operating greenhouses (Lund 2010). Geothermal fluids at temperatures of over 149 °C are usually applied for power generation in the agricultural sector. Geothermal energy also has a lot of benefits for the agricultural sector, including for increasing its economic efficiency. The cascade can be applied simultaneously for various purposes, indicating that geothermal energy can be a very secure and reliable source of energy generation in the agricultural sector (Lund 2010). Replacing fossil fuels with geothermal energy also provides costs savings and allows the mitigation of climate change and the negative environmental impact of fossil fuel usage.

Hence, the application of renewable energy sources in agricultural sectors has a lot of benefits and contributes to the sustainable development of agriculture, pollution reduction, climate change mitigation, and better water and land management and food processing practices. As energy consumption has a negative impact on climate change and threatens food security, the use of renewable energy can allow many of the important challenges of the climate–water–land–energy–food nexus to be addressed, such as resource savings, and increasing green agricultural productivity and efficiency, and enables the development of sustainable agriculture.

2.5 Implications of the Climate–Water–Land–Energy–Food Nexus for the Common Agricultural Policy

As previously mentioned, the water–land–energy–food nexus concept was introduced in 2011 by the German government during the Bonn Nexus Conference. This concept was elaborated in response to climate change as well as globalization, urbanization, and population growth challenges (Hoff 2011). As water, land, energy, and food are the main resources required for the survival of humans, it is expected that the demand for water, land, energy, and food resources will constantly grow because of the growing population and the negative influence of climate change on these resources.

This concept is useful for developing a systematic approach to maintaining sustainable human future prospects. Exceptionally, the interlinked theoretical, practical, and policy approaches are inevitable for covering climate–water–land–energy–food nexus issues. The development of optimum policy packages dealing with climate, water, land, energy, and food is necessary (Qadir et al. 2007; Karimi et al. 2012; Akangbe et al. 2011).

The issue linked to the climate–water–land–energy–food nexus has been present for many years. However, the synergy of the climate–water–land–energy–food nexus has not been addressed in an integrated way before. Taking into account the fact that agriculture is characterized as the sector of the economy linked first of all with land use, agriculture can also be considered a sector of the economy that has huge technical and economic potential for the usage of renewable energy sources as well for replacing fossil fuel-based processes with renewables. The vast land surfaces available in rural areas can be used for developing large wind and solar energy parks owned or leased by local communities. Furthermore, the agriculture sector is the key supplier of bioenergy resources and biomass, including crop residues and livestock breeding, and growing crops dedicated to bioenergy or biofuel production. As previously mentioned, various types of renewables are produced in vast rural areas, including biomass, biogas, solar, wind, and geothermal energy resources.

In addition, climate–water–land–energy–food nexus issues are closely interlinked with the European Green Deal policy initiative started by the US government and followed by the European Commission. The main aim of this initiative is to achieve a carbon-neutral society in Europe by 2050 (EC 2018). Boosting all branches of the economy through new advanced green and sustainable energy technologies, such as hydrogen and fuel cells, creating sustainable industrial, and agricultural systems and clusters, together with mitigating climate change and reducing pollution, is the central aim in this Green Deal policy, thereby also opening up wide opportunities for business. Besides the target of low-carbon energy transition by 2050, the Green Deal is aiming for a 50–55% GHG emission reduction compared with the 1990 level by 2030. In the EU MS national climate plans finalized in 2020, the target for GHG emission reduction was 40% compared with the 1990 level. Therefore, the Green Deal has raised EU ambitions regarding climate change mitigation and placed a heavy burden on energy sector transformation towards 100% renewables. It is clear that a fast shift to renewable energy sources creates a lot of challenges for all sectors of the economy, including agriculture. As the battery-based energy storage option has limited storage time, long-duration storage options like hydrogen are necessary; however, these technologies require upscaling and commercial testing (EC 2015, 2018, 2019).

The Green Deal also aims to be an example to other countries around the world in terms of a transition to a green, circular, and digital economy, and it foresees important actions for the coming decades and outlines a path for new investment opportunities. There are four main areas of the Green Deal providing investment opportunities for agriculture: decarbonization, circular economy, preserving ecological systems, and digitalization (EC 2019).

Decarbonization is closely linked with all EU energy and climate targets and policies as well as with the climate–water–land–energy–food nexus. The decarbonization of the EU economy is a policy priority focused on branches of the economy responsible for the uppermost shares of greenhouse gas (GHG) emissions, such as using wherever possible renewable energy sources, advanced storage systems, and smart metering and smart energy networks; decarbonization of the transport sector and heavy industries; supporting sustainable, resource-efficient, and high-quality food supply systems and agricultural operations; and inspiring EU MSs to initiate a "renovation wave" in buildings to ensure energy use efficiency and a reduction of GHG emissions.

The circular economy concept is directly linked to the climate–water–land–energy–food nexus and also allows the achievement of decarbonization targets such as the adoption of a "circular" economy model, the decoupling of economic growth from resource use, and decoupling of resource use from emissions of pollutants, and this can be achieved by increasing the efficient use of energy and other resources like water, land, and materials as well as food production and use efficiency. The EU foresees the production of durable, repairable, reusable, and recyclable goods. To achieve this, the enhancement of waste collection, processing, and recycling is crucial. The Green Deal enables the development of an internal market for secondary raw materials.

Preserving and restoring ecosystems and biodiversity are at the centre of the Green Deal concept and are also closely related to the climate–water–land–energy–food nexus. The most important Green Deal principle is that all policies should contribute to the preservation and restoration of natural capital in the EU. The main focus areas in Green Deal policy are sectors linked to agriculture or rural areas such as forestry, fishery, and sustainable agriculture systems. The new concept for fishery was developed with the term sustainable "blue economy", which opens up the potential of EU aquatic and marine resources while ensuring healthy and resilient seas and oceans (EC 2019).

Digitalization can enable the targets described above to be achieved. Digital tools are indispensable for implementing the Green Deal concept. Digital technology empowers such functions as monitoring progress towards set targets to facilitate new policies and decision-making, information dissemination and awareness raising, and empowering consumers due to the increase in transparency of goods' characteristics. Digitalization allows the increase of energy as well as resource efficiency and automation of processes. The development of 5G infrastructure is necessary for the digital transformation of the EU economy.

Although the Green Deal started as environmental policy, now it covers much bigger areas and sets of policies tied to major funding and trade initiatives. Though the COVID-19 pandemic imposes many problems for the implementation of the Green Deal's goals, the European Recovery Fund was established in July 2020 to respond to the COVID-19 pandemic and to provide further funding for Green Deal initiatives. Therefore, the Green Deal is getting about 1 trillion euros based on the Sustainable Europe Investment Plan. This is split into financing from the EU budget and by the InvestEU programme, designed to attract financial support from private investments, banks, and EU MS budgets (EC 2019).

The Green Deal is also important for the EU's foreign relations and international trade strategies as it is interlinked with the UN Sustainable Development Goals (SDGs) and the Paris Agreement. The Green Deal can inspire other regions to move towards sustainability, and therefore, strategic partnerships are necessary, and it is expected that this initiative will have a huge impact on the future trade agreements necessary to implement the Paris Agreement as well.

The Green Deal will have significant implications for all EU citizens and creates many opportunities for businesses to contribute towards a sustainable and carbon-neutral future. Among the most important challenges of the Green deal for agriculture are increasing climate ambition and cross-sectoral tasks; climate-neutral and socially innovative communities; clean, affordable, and secure energy; closing the industrial carbon cycle and implementing universal solutions for the territorial deployment of the circular economy; energy- and resource-efficient buildings by fostering a wave of renovation; promotion of sustainable and smart mobility modes; restoration of biodiversity and ecosystem services; innovative, universal zero-pollution solutions in all economic activities to protect health, the environment, and natural resources from chemicals and other hazards; developing end-user products supporting climate adaptation and mitigation; implementation of systemic innovations for sustainable food from farm to fork; strengthening knowledge and empowering EU citizens through education, citizen science, observation initiatives, and civic involvement for transition towards a climate-neutral and sustainable Europe and support of the European Green Deal (EC 2019).

The implementation of the Green Deal and climate–water–land–energy–food nexus should also be addressed by the Common Agricultural Policy (CAP), which has been a foundation of EU agricultural and rural policy for more than 50 years. The CAP was developed by the European Commission (EC) in 1960 with the aim of creating a balanced policy framework that would ensure adequate supply of agricultural products, safeguarding the increase of agricultural productivity and just transactions for producers and customers alike. These urgencies have transformed over time as new issues like environmental safety and public health were evolving. As a result, the CAP has progressively shifted from a market-oriented to a production-oriented subsidized framework by integrating food safety, environmental, biodiversity, and animal welfare standards (Balaceanu 2013).

The CAP is the oldest and most cohesive of the common EU policies based on the Treaty of Rome, which was established in 1961. The origins of this policy were a response to the food supply difficulties that emerged after the Second World War. Hence, due to the vivid decline in agricultural production in post-war Europe, followed by a surge in American imports, the policy to mitigate negative effects on the trade balance of Europe was urgent.

So far, the CAP has made a significant contribution to the process of economic integration, as European trade in agricultural products has been unified both through the elimination of customs duties and through the application of a common external customs duty. The CAP has significantly contributed to the expansion of production and exports of agriculture products, as well as improving agricultural productivity and farmers' incomes resulting from mechanization and technical progress (Balaceanu 2013).

However, given the growing significance of the manufacturing sector and the rigid demand for agricultural commodities due to price inelasticity, income from agriculture is usually lower than that from industry. Therefore, governments have taken measures to protect agricultural goods and promote specific agricultural products, which vary among countries.

Consequently, due to the protectionist policies, production in the agricultural sector saw a fall in demand and this led to a surplus of wheat production, particularly in France, which needed to export it. The resolution to sign several bilateral agreements came in order to safeguard the realization of wheat. An additional problem was linked to the insurance of labour supply balances in agriculture as being due to the mechanization in this area of the economy. Labour force was absorbed by other branches due to mechanization of agriculture and reduced net agricultural income. All these difficulties end with the idea of developing common agricultural regulation for the EU, which was initiated in the Netherlands. It was supposed that such a policy framework is able to provide the necessary stability, to ensure the continuity of agricultural product exports, and guarantee farmers' incomes.

During initiation of the CAP, various reforms of the CAP were initiated, which were closely linked to the financial resources that were made available for this framework. During the reforms, several tasks were accomplished: reviewing direct support schemes; matching subsidies and aid for rural communities' development; integration of environmental issues; and addressing the improvement of European agriculture competitiveness. In such circumstances, the interests of the various stakeholders need to be addressed in turn to obtain a better picture of stakeholders' and various players' preferences at the European level.

Summing up, the Common Agricultural Policy is an EU common policy delivering financial support to rural communities and farmers in the member states. The CAP is one of the initial policies of the European market, linking national intervention programmes into one specific scheme to ensure the ability to compete for farmers on a level playing field by also providing protection from agricultural fluctuations, and thus income fluctuations, and ensuring the security of the food supply in Europe.

Article 39 of the Treaty on the EU establishes the following specific CAP goals:

- to raise the supply of agricultural products;
- to increase the productivity and efficiency of the agriculture sector by encouraging technological advancement and the optimal use of production factors, especially labour;
- to ensure stabilization of the market by purchasing production surplus at guaranteed prices;
- to build agriculture product stock;
- to guarantee fair prices for customers;
- to raise farmers' incomes.

These objectives were pursued based on the framework of the common organization of the European agricultural market with regard to private placement of a product and/or group of products. The CAP throughout its existence has delivered support to farmers by subsidizing the prices of their production. Following the major reform of the CAP conducted in 2005, the two main axes of CAP payments were established: direct support of farmers' income (pillar 1) and rural development support (pillar 2). It is necessary to point out that direct income support is a much larger programme than rural development.

Pillar 1 payments are direct payments to farmers. These payments aim to eliminate the incentive for agricultural product overproduction. Pillar 1 payments are built taking into account the land owned by the farmer and are not related to their earnings. The money for pillar 1 is allocated from the EU budget and national governments are responsible for its administration. Farmers must meet certain requirements and standards of environmental management, animal welfare, and traceability in order to receive the payment; these conditions are referred to as "cross-compliance". Member states may also, under certain conditions, apply some market support measures.

Pillar 2 requires co-financing by member state governments. The EU describes the objectives of this activity as follows:

- promoting agricultural competitiveness;
- ensuring the sustainable management of natural resources;
- mitigating climate change;
- achieving sustainable territorial development of rural communities and economic viability, including the creation of new job places and maintenance of existing jobs in the agricultural sector.

The most important factors for shaping the CAP are directly linked to the climate–water–land–energy–food nexus: improving the welfare of the rural countryside; safeguarding food security and safety; environmental protection; saving natural resources; climate change mitigation and adaptation; and preservation of animal health and welfare. The CAP evolves and responds to the demands of EU citizens based on the EU budget financed mainly by taxpayers, i.e. ordinary citizens. Therefore, all EU policy priorities discussed above like the Green Deal, low-carbon transition, and energy and climate targets and policies need to be addressed by the CAP in pillar 1 and pillar 2.

Several historical CAP reforms have been implemented:

- In 1984, the productivity of farms had increased significantly and a production surplus had emerged; therefore, several important measures were developed to adjust agricultural production levels to the market needs.
- In 1992, a major shift of the CAP from market support to producer support was initiated by the EC. Therefore, price support was replaced by direct payments to farmers. Also, measures to promote environmentally friendly production practices were initiated in line with the Sustainable Development Goals. This CAP reform with its environmental focus was driven by the Rio Earth Summit on sustainable development carried out by the UN in 1992 and followed by the Johannesburg Summit in 2002 and the Rio + 20 Summit in 2012.
- In 2003, income support was initiated in the CAP. This new CAP reform provided interruption of relationship among subsidies and agricultural production. New conditions to support farmers' income were created. The income support was provided based on the requirements for farmers to look after the farmland and fulfil environmental standards, ensure animal health and welfare conditions, and guarantee food safety and security.
- In 2013, the CAP was reformed again in order to strengthen the competitiveness of European agriculture. Measures to support sustainable farming practices and innovative management were initiated in order to create and maintain jobs for rural communities and to ensure economic growth and social development in rural areas. Also, the shift of financial assistance towards the productive use of land was initiated during this CAP reform.
- The new CAP reform was initiated in 2019, and the main aim was to address climate change issues better.
- Therefore, a clear understanding of the need to link climate change mitigation and adaptation with the CAP was shown by the EC. It is necessary to stress that this linking of climate issues to CAP goals needs to address the broader climate–water–land–energy–food nexus.

Therefore, as previously stressed, the sustainable management and protection of natural resources and integration of climate policy is one of the three main objectives of the CAP. It is expected that greater sustainability will be achieved through a combination of various measures in the post-2020 financing period (EURACTIVE 2019).

Firstly, a better targeted cross-compliance framework was established in the CAP during the 2019 CAP reform. It reflects the most important environmental requirements that must be fulfilled to receive full CAP funding in a new financing period. Second, in 2015, a novel policy instrument—green direct payments—was introduced in the CAP. These "green payments" are aimed at addressing three obligatory agricultural operation practices, namely the diversification of crops, the development of ecological focus areas, and the establishment of permanent grassland in order to achieve several important environmental benefits linked to the climate–water–land–

energy–food nexus, including the protection of biodiversity, water, and land, and ensuring carbon sequestration and better landscaping. These areas represent around 30% of the direct payments from the total CAP budget.

Because green direct payments are obligatory, they have an impact on the spread of environmentally and climate-friendly agricultural practices to a large proportion of the utilized agricultural land. Thirdly, based on the main binding elements mentioned above, the rural development is also able to provide implementation of the CAP's environmental and climate change challenges.

Therefore, the main objectives of the rural development policy addressed in the CAP are closely related to the environment and climate change goals of the EU that are in line with the climate–water–land–energy–food nexus (European Commission 2020):

- Restoration, conservation, and enhancement of natural resources and ecosystems reliant on agriculture and forestry and fisheries;
- Promotion of productivity and resource efficiency and supporting the transition to low-carbon and climate-resilient agriculture, food, and forestry systems.

Furthermore, innovation, climate change mitigation, and environmental protection are at the heart of the EU's rural development policy. These three objectives (innovation, climate change mitigation, and environmental sustainability) should be incorporated in agricultural strategies and policy instruments established in EU MSs. The importance of sustainability issues in EU rural development policy is reflected by the requirement that at least 30% of every rural development programme budget must be dedicated to targeted and voluntary measures providing clear benefits in terms of environmental and natural resource protection and climate change mitigation and adaptation (European Environmental Bureau 2019).

The whole complementary set of CAP policies is supplemented by foreseen training programmes and initiatives available in the Farm Advisory System. In addition, the findings and results attained via the Innovation Partnership and R&D are channelled to support farmers in finding the right decisions and actions based on their specific situation. As previously mentioned, it was foreseen that the CAP will provide significant input to the sustainability of agriculture in the EU via all measures established in pillar 1 and pillar 2.

It is necessary to mention that in 2019 the EC issued an assessment of the climate impact of the CAP for the period 2014–2020. The main conclusion of this report was that though climate actions were among the most important CAP objectives, the main problem was the voluntary nature of foreseen measures. As there was room to maintain the status quo, most voluntary climate change mitigation and environmental measures were not implemented.

The report also pointed out other weaknesses, such as the lack of CAP measures to address the methane and nitrogen oxide emissions of ruminants through soil management. As already mentioned, methane and nitrogen oxide emissions are the two largest sources of GHG emissions from agricultural operations (European Commission 2020).

In 2016, the European Court of Auditors also issued an important report on the evaluation of the climate action of the EU and the budget allocated for this purpose. The evaluation by the European Court of Auditors stated that "the agricultural sector was not able to make a significant achievement in climate policy". The report also highlighted that the agriculture sector is one of the biggest hurdles for the EU to implementing its overall GHG emission reduction target by 2020, i.e. to reduce GHG emissions by 20% compared to the 1990 level.

As previously elaborated, the first pillar of the CAP, which is aimed at "income support" or providing direct payments to farmers, covers the biggest share of the budget under the CAP. In 2018, it covered about 70% (44.44 billion euros) of total support for agriculture in the framework of the CAP. Over 30% of these direct payments are earmarked for greening measures such as diversification of crops and maintaining ecological areas and everlasting pastures. These measures are designed to achieve the following environmental goals: climate change mitigation and adaptation, sustainable management of natural resources, and biodiversity protection. Under these measures, farmers receive direct payments and are obliged to conform with the main requirements for cross-compliance with the best agricultural and environmental conditions (GAEC). Then, the EU, on the basis of this rule, established that 19.5% of direct payments should enable the EU GHG emission mitigation objectives to be achieved (European Environmental Bureau 2019).

The European Court of Auditors (ECA) in a published report stressed that the greening measures were applied in MSs to achieve the consolidation of already existing agricultural practices rather than initiating new environmental and climate change mitigation initiatives and advanced innovative agricultural practices. The assessment found that environmental protection was rarely a priority for MSs in designing and implementing greening measures. Besides that, it was found that the CAP still provides funding for agricultural practices that contribute directly to climate change and therefore has negative environmental impacts. In addition, the worst thing is that most of the support that is channelled according to the level of production is allocated to dairy and meat sectors, which are responsible for GHG emissions, linked to ruminants. It was found that large per hectare payments go to drained peatlands or carbon emission hot spots (European Environmental Bureau 2019).

Pillar 2, which is aimed at supporting sustainable rural development, covered the remaining 24% (14.37 billion euros) of the CAP budget allocated for the year 2018. The national rural development programmes (RDPs) by EU MSs were restructured to address the reformed CAP's six priorities including environmental protection and climate change mitigation. Therefore, the national rural development programmes changed to become more oriented towards results and more focused on delivering the CAP priorities.

In pillar 2, the key environmental measure is the agri-environment-climate measure (AECM). These payments under the agri-environment-climate measure aim to support environmentally friendly agricultural practices of farmers that ensure environmental protection and improvement of the landscape, saving and protection of natural resources, soil, and genetic resources as well as climate change mitigation and adaptation. It was found and stressed in the report by the ECA that GHG emissions in the agricultural sector are expected to increase progressively by 2030 and that the current climate mitigation measures foreseen in the national RDP will have a significant impact on climate change mitigation.

The ECA report identifies the following main shortcomings of RDPs in EU member states:

1. There are no clear objectives and quantifiable results for specific measures.
2. There is a lack of impartial scientific evaluation of measures implemented during the set period of time or no obligation to report their impact.
3. There is a lack of strategic planning to ensure the coherence of objective and specific RDP measures with other policies.
4. The voluntary nature of the measures and their limited resources is also a weakness.

Also, much of this criticism reiterates that RDPs lack clear objectives and solid indicators for guiding climate change mitigation policies in agriculture and evaluating the effects of climate change mitigation and environmental measures. Therefore, the ECA report concluded that the CAP must be significantly improved to provide concrete input to the climate change mitigation and adaptation and environmental and natural resource management in the agricultural sector (European Environmental Bureau 2019). The same is applicable for addressing the climate–water–land–energy–food nexus.

Though there is no precise GHG emission target set for the agricultural sector, which should be addressed by EU MSs during preparation of the National Energy and Climate Plan (NECP), the role of agriculture is very important for shaping EU climate change mitigation policies and moving towards a climate-neutral society by 2050. The crucial issue is how the agricultural and LULUCF sectors will enable the GHG emission reduction set by the national targets of EU MSs. So, harmonization of NECP and national RDP is necessary to associate EU MS Strategic Plans with the future of the CAP in the content of their NECP. Also, the EU food security issues should be integrated and made consistent with the EU climate change mitigation objectives. Therefore, the climate–water–land–energy–food nexus should be addressed in shaping the future CAP.

Overall, the new results-based approach that redefines the accountability of the EU and the MSs in designing and implementing the CAP is necessary, moving from full compliance with EU rules to joint strategic planning. The CAP Strategic Plans (CSPs) of each MS will be accepted by the European Commission and the progress of the programming objectives will be monitored annually.

The most recent reform proposed for the CAP enables broader incorporation of environmental and climate concerns into the CAP as a whole. All interventions are aligned with the overall EU objectives, but they are designed and will be implemented according to member states' national and regional needs and their CSP priorities in mind.

In addition, member states would be legally required to (European Environmental Bureau 2019):

- address national climate change mitigation plans stemming from specific EU legislation and demonstrate how the CAP's green architecture will be used to achieve national climate change mitigation goals;
- set out a strategy outlining how interventions in their CSPs will be tailored to their specific national needs through specific CAP objectives;
- show a greater level of climate change mitigation and environmental protection determination than the current CAP requires (known as the so-called "no back-sliding" clause).

The tools and means by which member states can support more sustainable land management solutions between farmers and land managers are commonly known as the "green architecture" of the CAP. Initially encompassing voluntary agri-environmental measures, supported by a combination of EU and national funding, new measures have been incorporated into the CAP over several decades. Over time, both pillars of the CAP have developed a "green" structure for compulsory, voluntary, and instrumental measures. Green architecture after 2020 enables the reorganization of existing CAP measures and instruments known as the "ecosystem". It aims to promote more sustainable farm and land management practices through intensification of direct payments (pillar 1).

As proposed, the ecosystem could be provided to farmers on a voluntary basis and it would be compulsory for member states. The new instrument will complement existing agri-environment and climate commitments and will be provided on a voluntary basis to farmers through CAP rural development programmes (pillar 2). The Ecological Scheme and existing agri-environment and climate measure (AECM) commitments under pillar 2 will be based on conditions setting out the basic requirements and standards that beneficiaries of the CAP must meet.

The set of tools that make up the new green architecture and their ability to affect practices of land use and management in beneficial ways for sustainable land management and soil protection under the CAP conditionality approach are described below.

Farmers getting direct payments under pillar 1 and under pillar 2 linked to area- and animal-based payments must satisfy two types of conditionality across their entire farm set in Statutory Management Requirements (SMR). These requirements originated from EU legislation and affect all farmers. SMR sets standards of Good Agricultural and Environmental Conditions (GAECs) that must be fulfilled by farmers. In Table 2.4, updated GAEC standards on soil are given. These standards are also very important for the climate–water–land–energy–food nexus.

Under the European Commission's proposals (EC 2019), member states must define the ten specific GAEC standards by addressing "the certain characteristics of the areas of concern. The GAECs include the overarching principles for all EU MSs, but EU MSs must provide the detailed requirements according to the GAECs.

The GAEC standards need to be reviewed and validated by the Commission as part of the CSP approval process. Conditionality sets the legal requirements for the design of the eco-scheme and the environment-climate commitments.

Table 2.4 EU framework on CAP conditionality—soil-relevant aspects

Main issue	New GAEC standards	Soil threat addressed	
	GAEC 1	Maintenance of permanent grassland as a general safeguard against conversion to preserve carbon stock	Erosion of soil, damage to organic matter/soil carbon, damage to soil biodiversity
Climate change	GAEC 2	Conservation of soils rich in carbon such as peatlands and wetlands (new)	Damage to organic matter/soil carbon, loss of soil biodiversity, soil erosion
	GAEC 3	Prohibition of burning stubble on arable lands to maintain soil organic matter, except for plant health reasons	Loss of soil organic matter/ soil carbon
Water	GAEC 4	Formation of buffers along with watercourses	Contamination (diffuse), soil erosion, loss of organic matter, compaction
	GAEC 5	Application of Farm Sustainability Tool for Nutrients (new)	Contamination (diffuse)
	GAEC 6	Management of tillage to reduce soil degradation risks, incorporating slope concern in order to ensure minimum land management reflecting site-specific conditions to limit erosion	Soil erosion, damage to soil organic matter/soil carbon, etc.
Soil	GAEC 7	No uncovered soil in the most sensitive period(s) to protect during winter	Soil erosion, loss of soil organic matter/soil carbon, soil biodiversity
	GAEC 8	Rotation of crops to ensure necessary soil potential (new)	Loss of soil organic matter/ soil carbon, soil biodiversity, compaction
Biodiversity and landscapes	GAEC 9	To improve farm biodiversity by maintaining non-productive areas	Loss of soil organic matter/ soil carbon, soil erosion, soil biodiversity, compaction
	GAEC 10	Prohibition of permanent grassland in Natūra 2000 sites, conversion to protect habitats and species (new)	Loss of organic matter/soil carbon, loss of soil biodiversity, soil erosion

Source: Meredith (2019), European Environmental Bureau (2019), EC (2020)

The eco-schemes, implemented according to the measures envisaged in pillar 1, and pillar 2 agri-environment-climate measure (AECM) commitments, are built on the basic standards and requirements of conditionality to incentivize farmers to take further environmental protection and climate change mitigation action. They are supposed to encourage the uptake of environmentally and climate-friendly practices and management systems by farmers. In Table 2.5, a comparison of the requirements for eco-schemes and other agri-environmental climate requirements is provided.

Both the eco-schemes under pillar 1 and pillar 2 AECM commitments initiated in the reformed CAP would allow member states to tailor them specifically to address

Table 2.5 Comparison of programming requirements for eco-schemes and other agri-environmental-climate requirements

Main issue	Instrument	
	Eco-scheme covering climate and the environment schemes—(Art. 28)	AECM: Environment, climate, and other management commitments—Art. 65)
Intervention logic	Support the uptake of environmentally and climate-friendly practices and systems based on meeting one or several relevant CAP goals	
Beneficiaries (including eligibility criteria	Farmers fulfilling the genuine farmer, eligible hectares criteria established by the member states, additional selection criteria are also established by the member states	Farmers and land managers accomplishing the objectives of the scheme or operation, other selection criteria could be defined by the member states
Duration of contract	Annual or multiannual	Up to 5–7 years or even more
Type of payment and computation	Annual per hectare payment. Complete or fractional reimbursement for cost incurred, covering opportunity costs, or fixed top-up payment to support basic income created according to EU MS justification	Multiannual per hectare payment, one flat rate or as a one-off payment per unit. Full or limited reimbursement to cover cost acquired and/or income lost including opportunity costs
Funding	EAGF (100% EU financed)	EAFRD (EU and nationally co-financed)

Source: Meredith (2019), European Environmental Bureau (2019), EC (2020)

national and regional soil threats and other land management needs. In addition, other rural development interventions can be used to complement the implementation of the CAP agri-environmental climate instruments, for example, investments in environmentally friendly equipment for soil management, and "soft" measures incorporating training, information dissemination, and advice for farmers.

The eco-efficiency objectives under pillar 1 and AECM under pillar 2 can be further extended to better address, in an integrated systematic way, the climate–water–land–energy–food nexus. Therefore, based on current advances, a more harmonized approach to sustainable agriculture development is necessary for the EU and EU MSs as too many interlinked policies have been developed and a systematic approach that enables the monitoring of achieved progress in all interlinked objectives of the EU in terms of the environment, energy, climate, and agriculture is still lacking. The centre of such a systematic approach to sustainable agriculture development as well as sustainable energy development and shaping the CAP's future should be the climate–water–land–energy–food nexus.

2.6 Conclusions

Agriculture accounted for 12% of the overall greenhouse gas emissions of the EU, including from land use and land use change (LULUC) of grassland and cropland, in 2018. Since 1990, GHG emissions in agriculture have fallen by 24% due to improved agricultural management, modern technologies, advanced knowledge, and specific climate change practices implemented in the agriculture sector.

EU agriculture has a key role to play in order for the EU to fulfil its Paris Agreement commitments, and it is more vulnerable to climate change than other economic sectors. The strength of negative climate change impacts also depends also on human and natural systems' vulnerability and exposure to these impacts.

The main actions for mitigating climate change in the agriculture sector include use of carbon sink by ensuring better soil management practices; use of advanced and innovative farm management practices in growing livestock to reduce GHG emissions linked to ruminants; reduction of waste and other agricultural production losses; decrease in fossil fuel intensity of farm production, etc.

Climate actions are an important issue in the EU's rural development policy, which supports the modernization of farms to reduce energy consumption, produce renewable energy, improve cost efficiency, and reduce GHG emissions. $104 billion was allocated to this issue or 25% of all Common Agricultural Policy (CAP) support for the period 2014–2020. The appropriations for the Common Agricultural Policy in future will be even more climate-related, though the original aim of the CAP was to ensure the sufficiency and stability of agri-food markets and to establish a decent standard of living in the agri-food sector.

Renewable energy provides clean energy for farms by ensuring the protection of natural resources and the environment, and the use of renewables enhances energy efficiency and leads to energy and income savings for farmers; therefore, it is necessary to ensure that renewables are applied in all agricultural operations. To this end, business-friendly regulations to overcome renewable energy penetration barriers are necessary. It is possible to create innovative financing measures to attract private investment in renewable energy projects in the agricultural sector. These actions would bring multiple benefits, such as climate change mitigation, environmental protection, natural resource savings, and the improvement of business viability in the agricultural sector.

An important challenge for the CAP is achieving long-term sustainable development of agriculture and ensuring food security as bioenergetic plants and some biomass and other renewables compete with crops for land. Thus, it is essential to ensure the development of the market for organic products and promote skills and practices of eco-efficient behaviour. Currently, as the main goals of the CAP are not limited to setting certain prices and incomes that are sufficient for farmers, new issues linked to the conservation of natural resources and climate change mitigation need to be addressed.

However, the Common Agricultural Policy (CAP) is still clearly lacking ambition in terms of climate and the National Energy and Climate Plans (NECPs) do not take sufficient account of agriculture. Many climate mitigation tools are too weak and lack a reliable monitoring and assessment system based on robust objectives and indicators. There are indicated and documented discrepancies between requested climate change mitigation action driven by the CAP and the actual situation.

In order to overcome these gaps, close cooperation between environmental, climate, and agricultural authorities is essential for the development of reasoned and effective policies and measures and ensuring the involvement of various stakeholders. Policymakers should strive to empower public actors such as farmers, landowners, environmental experts, and scholars working in interlinked climate–water–land–energy–food areas, to make a significant contribution to viable CAP development.

Though climate action in the agricultural sector can suffer from carbon leakage, which means that GHG emissions are being offset by increased GHG emissions in third countries, this cannot prevent GHG emission reduction efforts linked to reducing the production of agricultural products with a carbon footprint. Therefore, clear rules in terms of regulation of EU trade policy are also necessary. EU international trade policies must enable increased use of low-carbon footprint products. To do so, the export orientation of livestock and dairy farming must first be stopped. In addition, the EU should set stringent monitoring standards for greenhouse gas emissions from agricultural imports and then make sure that they do not influence the growth of the carbon footprint in comparison to EU agricultural production.

In addition, private investment should be attracted to support climate action in all sectors of the economy as well as in agriculture. It is necessary to develop an evidence-based taxonomy by setting more stringent standards for "green activities" in agriculture and other sectors, thereby attracting private investments in programmes and projects that have a positive impact on climate change mitigation and environmental protection.

The CAP, since 2020, has provided new opportunities for member states to tailor CAP interventions to their specific needs and priorities, while maintaining specific climate policy objectives. Strategic planning should give member states scope to retreat and rethink how they use CAP support to tackle their environmental and climate problems, along with the socio-economic challenges facing the agricultural and forestry sectors. For example, given the multifunctional role of soil management and the important contribution of soil ecosystems, such an integrated approach should provide significant opportunities for additional action across green architecture.

The most important factors for shaping the CAP's future should be directly linked to the climate–water–land–energy–food nexus: improving the welfare of the rural countryside; safeguarding food security and safety; environmental protection; natural resource saving; climate change mitigation and adaptation; preservation of animal health and welfare. The main EU policy priorities provided in the Green Deal for the creation of a carbon-neutral society and low-carbon transition by 2050 need to be addressed by both pillars of the CAP. For this reason, a clear understanding of the need to link climate change mitigation and adaptation with the CAP was shown by the EC; however, it is necessary to point out that the linking of climate issues to CAP goals needs to address the broader climate–water–land–energy–food nexus, and this has not been achieved so far in the recent reform of the CAP aimed at climate-smart agriculture development.

There are important incentives that can be taken to address climate change issues, namely growing bioenergy plant products and biofuels or burning wood to produce bioenergy. It is also necessary to apply definite biodiversity safeguards to implemented climate change mitigation measures to address the trade-off between biodiversity and climate change mitigation goals. Therefore, land use change policy, like afforestation, must incorporate biodiversity into its goals. The frameworks are necessary not only to monitor the reduction of GHG emissions but also for their impact on other environmental issues. Monitoring is one of the main issues in harmonizing climate, energy, and agriculture policies, and therefore to achieve the best results, indicator systems for addressing sustainable agriculture, energy, and climate issues need to be developed and applied.

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Chapter 3
Modelling Production Technology for Development of Agricultural Sector

Tomas Baležentis

3.1 Introduction

Agricultural production can be modelled in the same manner as any other economic sector. The basic technology includes factor and intermediate inputs along with outputs. The representations of production technology (among which, the production function is the best known) can be used to formally relate these variables. Implicit aggregation without price data occurs when the primal representations are used.

Production technology is intrinsically related to the notion of total factor productivity (or multifactor productivity if we acknowledge that it is impossible to include all the production factors in the modelling). Basically, (total factor) productivity is the ratio of the (aggregate) output quantity to the (aggregate) input quantity. The representations of production technology allow for estimating the maximum attainable level of the (aggregate) output or the minimum level of the (aggregate) input. This gives rise to yet another measure—the maximum attainable (total factor) productivity. The ratio of the actual to the maximum (total factor) productivity is the measure of efficiency (Ramanathan 2003). However, there exist different measures of efficiency that can be adapted to the empirical analysis.

This chapter presents the theoretical preliminaries of the efficiency measurement in Sect. 3.2. These include the properties and representations of the production technology, measures of efficiency, and the corresponding quantitative models. The empirical models can be implemented in parametric and nonparametric settings. This chapter discusses both cases. These principles can be applied for production analysis in any economic activity.

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T. Baležentis et al., *Structural Change, Productivity, and Climate Nexus in Agriculture*, https://doi.org/10.1007/978-3-030-76802-7_3

The agricultural sector features certain issues that require dedicated analysis and analytical tools. For instance, the effects of public support may be assessed from the viewpoint of productivity. In order to identify the key issues, Sect. 3.3 embarks on a citation-based literature review. The major topics, models, and outlets for issues related to the analysis of agricultural productivity are identified as a result.

The empirical analysis focuses on the case of agriculture in the European Union (EU). Section 3.4 discusses the data for the selected EU countries on the agricultural production. The results are then presented in Sect. 3.5. The analysis relies on the production frontier approach. Both parametric and nonparametric approaches are applied. Restricted models are also used to impose regularity conditions on the production frontier.

3.2 Preliminaries

3.2.1 Production Technology

The modelling of production technology allows the relationships between the inputs and outputs to be identified. Let the quantities of inputs be denoted by the vector $x = (x_1, x_2, \ldots, x_m) \in \mathfrak{R}_+^m$ and the quantities of outputs by the vector $y = (y_1, y_2, \ldots, y_n) \in \mathfrak{R}_+^n$. The production technology (graph) relates these quantities:

$$T = \{(x, y) : x \text{ can produce } y\}. \tag{3.1}$$

The technology, T, is assumed to satisfy the conventional axioms (Chambers 1988). The technology is assumed to be non-empty, a closed, and convex set. In addition, free disposability of inputs, x, and outputs, y, is assumed, which implies that production can be inefficient (may fall below the production surface). For any finite input level x, the technology T is bounded from above, and inactivity is possible (but a “free lunch” is impossible).

In the most general case, the transformation function, $F(\cdot)$, can be used to relate the multiple inputs to multiple outputs (Chambers 1988):

$$F(x, y) = 0. \tag{3.2}$$

The production function is a special case of the transformation function. In this case, the single output is considered and the following relationship is established:

$$F(x, y) = y - f(x) = 0, \tag{3.3}$$

where $f(\cdot)$ is the production function relating a set of inputs to a single output. The transformation function in Eq. (3.3) defines the efficient production plans (as indicated by the equality). This is more obvious by considering the following definition of the production function (Färe and Primont 2012):

$$f(x) = \max\{y : (x, y) \in T\}. \tag{3.4}$$

Note that the vector and scalar notations are misused in the equations above in order to avoid cumbersome presentation. However, one should note that appropriate dimensions of the underlying vectors are assumed.

The feasible production plans defined in Eq. (3.1) can also be defined in terms of Eq. (3.3). The feasible production plans are those located on or below the production frontier (surface):

$$T = \{(x, y) : \mathrm{F}(x, y) \leq 0\}. \tag{3.5}$$

The technology can be described in terms of the input correspondence or output correspondence (Färe 1988; Färe and Primont 2012). The input correspondence is defined as a mapping of output quantities to the subsets of the input quantities

$$L : \mathfrak{R}^n_+ \to 2^{\mathfrak{R}^m_+}, \tag{3.6}$$

where $2^{\mathfrak{R}^m_+}$ denotes a subset of $\mathfrak{R}^m_+$, i.e. $2^{\mathfrak{R}^m_+} = \left\{A : A \subseteq \mathfrak{R}^m_+\right\}$ (Färe 1988). Similarly, the output correspondence is defined as a mapping of input quantities to the subsets of the output quantities:

$$V : \mathfrak{R}^m_+ \to 2^{\mathfrak{R}^n_+}. \tag{3.7}$$

The correspondences outlined in Eqs. (3.6) and (3.7) provide the basis for establishing the input set, $L(y)$, and the output set, $V(x)$, that correspond to the given level of outputs or inputs, respectively:

$$L(y) = \{x : (x, y) \in T\}, \tag{3.8}$$

$$V(x) = \{y : (x, y) \in T\}. \tag{3.9}$$

The feasible production plans do not indicate the degree of (technical) inefficiency potentially existing in the production. In order to identify the optimal decisions to produce, one needs to consider the boundary production plans. Such production plans comprise the boundaries of the input and output sets defined in Eqs. (3.8) and (3.9). The input and output isoquants are defined as follows:

$$\mathrm{Isoq}L(y) = \{x : x \in L(y), \lambda x \notin L(y), \lambda \in [0, 1)\}, \tag{3.10}$$

$$\mathrm{Isoq}V(x) = \{y : y \in V(x), \lambda y \notin V(x), \lambda > 1\}. \tag{3.11}$$

Thus, Isoq$L(y)$ contains all the production plans whose input levels cannot be scaled down any further for the given levels of outputs, whereas Isoq$V(x)$ contains the production plans whose output levels cannot be expanded any further for the given levels of inputs. The input or output isoquants should have a negative slope, implying substitution among inputs or outputs. However, the empirical data and definitions provided in Eqs. (3.10) and (3.11) do not guarantee that the resulting isoquants have a negative slope globally. Thus, the efficient parts of the isoquants can be identified as subsets thereof that are negatively sloped (Färe 1988):

$$\mathrm{Eff}L(y) = \{x : x \in L(y), x' \leq x, x' \notin L(y)\}, \tag{3.12}$$

$$\mathrm{Eff}V(x) = \{y : y \in V(x), y' \geq y, y' \notin V(x)\}, \tag{3.13}$$

where inequalities are read element-wise ensuring that $x \neq x'$ and $y \neq y'$.

3.2.2 Distance Functions and Measures of Efficiency

The efficiency can be measured by the output and input distance functions. For the two representations of the production technology in Eqs. (3.12) and (3.13), the corresponding distance functions can be defined to identify the efficient production plans (Shephard 1953, 1970). The output distance function seeks to expand the output for a given observation (x, y) subject to the production technology:

$$D_{\mathrm{o}}(x, y) = \min\left\{\theta : \left(x, \frac{y}{\theta}\right) \in T\right\}. \tag{3.14}$$

Thus, function $D_{\mathrm{o}}(\cdot)$ is a mapping $D_{\mathrm{o}} : \mathfrak{R}_+^m \times \mathfrak{R}_+^n \rightarrow \mathfrak{R}_+ \cup +\infty$. Inefficient production plans show $D_{\mathrm{o}}(x, y) < 1$. The production function $f(x)$ is related to the output distance function as follows (Färe and Primont 2012):

$$\begin{aligned} D_{\mathrm{o}}(x, y) = \min\left\{\theta : f(x) \geq \frac{y}{\theta}\right\} \\ = y/f(x). \end{aligned} \tag{3.15}$$

Therefore, the output distance function directly shows the technical efficiency: unity indicates the full efficiency, whereas lower values indicate inefficiency.

The input distance function seeks to find the minimum input quantity for a given level of outputs and production technology. This problem can be stated as follows:

$$D_{\mathrm{i}}(x, y) = \max\left\{\phi : \left(\frac{x}{\phi}, y\right) \in T\right\}. \tag{3.16}$$

The input distance function $D_{\mathrm{i}}(\cdot)$ is a mapping $D_{\mathrm{o}} : \mathfrak{R}_+^m \times \mathfrak{R}_+^n \rightarrow \mathfrak{R}_+ \cup +\infty$.

The distance functions serve as measures of technical efficiency. However, economic agents adjust their decisions based on the price data (which may not always be available to the analysts). The optimal economic decisions can also be described in terms of the cost and revenue functions that assume cost minimization and revenue maximization, respectively.

The inverses of Shephard's measures are known as the Farrell measures of efficiency. The output- and input-oriented Farrell measures of efficiency are defined as:

$$E_{\mathrm{o}}(x,y) = \max\{\phi : (x,\phi y) \in T\} = (D_{\mathrm{o}}(x,y))^{-1}, \tag{3.17}$$

$$E_{\mathrm{i}}(x,y) = \min\{\phi : (\phi x,y) \in T\} = (D_{\mathrm{i}}(x,y))^{-1}. \tag{3.18}$$

Note that the input- and output-oriented measures are reciprocal in case the constant returns to scale technology is maintained (Chambers et al. 1998). These functions also fully characterize the underlying technology.

The cost function minimizes cost by adjusting the input quantities subject to the production technology and input prices (Färe and Primont 2012):

$$C(y,p) = \min_x \{px : x \in L(y)\}, y \in \mathrm{Dom}L, p > 0, \tag{3.19}$$

where p is the input price vector and $\mathrm{Dom}L = \left\{y \in \mathfrak{R}^n_+ : L(y) \neq \varnothing\right\}$ is the effective domain of the input correspondence resulting in non-empty input sets. The revenue function defines the maximum revenue by changing the output quantities for a given technology and output price vector:

$$R(x,w) = \min_y \{wy : y \in V(x)\}, \tag{3.20}$$

where w is the output price vector. Färe and Primont (2012) proved the duality existing between the input (respectively output) distance and cost (respectively revenue) functions. As regards cost minimization, the following result holds:

$$\begin{aligned} &C(y,p) = \min_x \{px : D_{\mathrm{i}}(x,y) \geq 1\}, p > 0 \\ &\Updownarrow \\ &D_{\mathrm{i}}(x,y) = \inf_p \{px : C(y,p) \geq 1\}, x \in \mathfrak{R}^m_+. \end{aligned} \tag{3.21}$$

Similarly, the duality related to revenue maximization is described as:

$$
\begin{aligned}
&R(x,w) = \max_{y}\{wy : D_{\mathrm{o}}(x,y) \leq 1\}, w \in \Re_{+}^{n} \\
&\Updownarrow \\
&D_{\mathrm{o}}(x,y) = \sup_{w}\{wy : R(x,w) \leq 1\}, y \in \Re_{+}^{n}.
\end{aligned}
\tag{3.22}
$$

Thus, the distance functions can be recovered from the cost/revenue functions and vice versa. This provides an economic interpretation over choosing input or output orientation in the efficiency analysis.

Up until now, we have considered the two extreme cases of the optimization given by the input and output distance functions (Eqs. 3.14 and 3.16). They allow adjustment in either inputs or outputs (moreover, their proportions are kept fixed). However, economic decisions and analysis are often related to a non-radial context where the proportions in the input or output vectors cannot be maintained (e.g. negative or zero values are present) and/or directed optimization is not the only option (i.e. both inputs and outputs can be adjusted simultaneously assuming non-oriented optimization) (see, for instance, Zhang and Choi 2014).

A measure that generalizes the input and output distance function is known as the "directional distance function". The directional distance function originated from the directional input distance function. The directional input distance function (Chambers et al. 1996) was built on the concept of the benefit function (Luenberger 1992) and defined the non-radial adjustment in the inputs, thus generalizing the input distance function defined by Shephard. The directional distance function is defined as follows (Chambers et al. 1998; Färe and Grosskopf 2000):

$$
D\left(x,y;g_x,g_y\right) = \max\left\{\beta \in \Re : \left(x - \beta g_x, y + \beta g_y\right) \in T\right\},
\tag{3.23}
$$

where the direction of optimization is given by the directional vector $\left(g_x, g_y\right) \in \Re_{+}^{m} \times \Re_{+}^{n}$. Note that $D(\cdot)$ is equal to zero for efficient observation and increases as the inefficiency increases. The coefficient β indicates inefficiency and scales the inputs and outputs to the same extent for a given directional vector. This property resembles the radial movement towards the efficiency frontier. If the elements of the directional vector ensure that inputs and outputs are adjusted simultaneously, the directional distance function can be considered a non-oriented measure of efficiency.

As is the case with the input and output distance functions, duality can be established with the price-based measures of efficiency. Obviously, the input and output distance functions can be generalized by considering the cost and revenue functions simultaneously due to the discussed duality. Thus, the profit function that adjusts input and output quantities for a given technology and input/output prices needs to be considered:

$$
\pi(p,w) = \sup_{(x,y)\geq 0}\{wy - px : D(x,y) \geq 0\}.
\tag{3.24}
$$

Then, the duality between the directional distance function and the profit function can be established (Chambers et al. 1998):

$$\begin{aligned}
&\pi(p,w) = \sup_{(x,y)\geq 0}\left\{wy - px + D\left(x,y;g_x,g_y\right)\left(wg_y + pg_x\right)\right\} \\
&\Updownarrow \\
&D\left(x,y;g_x,g_y\right) = \inf_{(p,w)\geq 0}\left\{\frac{\pi(p,w)-(wy-px)}{wg_y+pg_x}\right\}.
\end{aligned} \tag{3.25}$$

Therefore, the directional distance function corresponds to generalization of the primal measures of the technical efficiency (distance functions) and dual ones (profit function comprising the cost and revenue functions).

The directional distance function can further be generalized by allowing for the variable-specific measures of inefficiency, i.e. $\beta \in \mathfrak{R}_{+}^{m+n}$. This allows for a non-oriented and non-radial optimization. The non-radial directional distance function was formalized by Zhou et al. (2012) as follows:

$$D\left(x,y;g_x,g_y\right) = \max\left\{\omega\beta : ((x,y) + g\cdot \mathrm{diag}(\beta)) \in T\right\}, \tag{3.26}$$

where $\omega \in \mathfrak{R}_{+}^{m+n}$ is the normalized weight vector and $g = (-g_x, g_y)$ is the directional vector defining input reduction and output expansion at the same time. Note that appropriate dimensions are assumed for β, ω, and g without using the transposition operator for the sake of brevity.

A slack-based measure was developed by Tone (2001) in order to facilitate non-oriented non-radial optimization. Later on, Färe and Grosskopf (2010) showed that the directional distance function can be extended into a non-oriented directional distance function and perform in the same manner as the slack-based measure of technical efficiency.

The directional distance function allows for simultaneous change in the input and output quantities when projecting a production plan onto the efficiency frontier. There is yet another measure that is capable of generalizing the input and output orientations (i.e. using a non-oriented approach) and ensuring proportional change in the input and output quantities. The hyperbolic distance function devised by Färe et al. (1985) defines a simultaneous adjustment of both input and output vectors along a hyperbolic path (rather than a ray). The hyperbolic (graph) measure seeks to simultaneously optimize input and output quantities subject to the underlying production technology:

$$D_{\mathrm{h}}(x,y) = \max\left\{\lambda : \left(\lambda x, \lambda^{-1}y\right) \in T\right\}, \lambda \geq 0, \tag{3.27}$$

where $\lambda \in [0,1]$ is the measure of efficiency. In general case, $D_{\mathrm{h}} : \mathfrak{R}_{+}^{m} \times \mathfrak{R}_{+}^{n} \to \mathfrak{R}_{+} \cup \{+\infty\}$. Note that Färe et al. (1985) referred to the hyperbolic measure the Farrell one as the input quantities are multiplied in the fashion of the Farrell efficiency measures and the resulting measure follows the same interpretation.

Färe et al. (2016) discussed the linear programming models for estimation of D_{h}. The econometric estimation of the hyperbolic measures was discussed by Cuesta and Zofío (2005).

3.2.3 Production Function

The representations of the technology allow one to assess the contribution of each input towards the generation of the outputs (and input requirements for the generation of each output). If the panel data are available, one can introduce the technical progress and assess the productivity change due to different effects. The technology can be described in a parametric or nonparametric manner. The parametric representations follow predefined functional forms, and estimation or optimization is used to identify the associated parameters. In a nonparametric approach, there are no assumptions regarding the functional form of a representation; however, certain economic axioms can be imposed.

Among the primal representations of the production technologies, perhaps the most widely applied and most intuitive is the production function (which can be derived from the transformation function or output distance function; cf. Eqs. (3.3) and (3.15)). The Cobb–Douglas function (Cobb and Douglas 1928; Douglas 1976) and constant elasticity of substitution (CES; McFadden 1963) were the two earliest production functions. Moreover, the Leontief production function (Walras 1954) was often applied. Färe (1988) related these production functions (as special cases) to a McCarthy-type production function (as a general case), whereas Csontos and Ray (1992) discussed the linkages among the CES as a general case and Cobb–Douglas and CES as special (limiting) cases thereof.

Perhaps, one of the earliest attempts to apply the production theory in the agricultural sector was made by Heady (1946, 1957) and Heady et al. (1960). Farrell (1957) also focused on agriculture when devising a nonparametric framework. Heady (1946) used the Cobb–Douglas production function on a sample of farms, whereas the generalized linear production function was applied by Heady (1957).

Let there be multiple inputs represented by the input quantity vector, $x = (x_1, x_2, \ldots, x_m)$, and a single output represented by a scalar quantity, y. The CES production function is given as (Ferguson 1969):

$$\begin{aligned} &y = a_0 \left(\sum_{i=1}^{m} a_i {x_i}^{-\rho} \right)^{-v/\rho}, \\ &\sum_{i=1}^{m} a_i = 1, a_i > 0, a_o > 0, \\ &\rho \in [-1, +\infty), v > 0. \end{aligned} \tag{3.28}$$

The function provided in Eq. (3.28) can be logged as follows:

$$\ln y = \ln a_0 - (v/\rho) \ln \left(\sum_{i=1}^{m} a_i x_i^{-\rho} \right). \tag{3.29}$$

The Leontief production function can be written as (Chambers 1988):

$$y = f(x) = \min_{i=1,2,\ldots,m} \{a_i x_i\}, \alpha_i > 0. \tag{3.30}$$

This production function is increasing in x_i until input quantity y/α_1 is achieved and then is a flat line further on (if there are only two inputs and $x_2 = y/\alpha_2$).

As one can see, neither the Leontief nor the CES functions are linear in their parameters. Therefore, they are cumbersome to estimate via the conventional techniques. Thus, the Cobb–Douglas and other functions are more often applied for the efficiency and productivity analysis.

The generalized linear production function is presented as (Diewert 1971):

$$y = h\left(\sum_{i=1}^{m} \sum_{j=1}^{m} a_{ij} x_i^{0.5} x_j^{0.5} \right). \tag{3.31}$$

where $h(\cdot)$ is a continuous monotonically increasing function with $h(0) = 0$ and $a_{ij} = a_{ji} \geq 0$.

The Cobb–Douglas production function is defined as

$$y = A \prod_{i=1}^{m} x_i^{\alpha_i}, \alpha_i > 0. \tag{3.32}$$

The function provided in Eq. (3.32) is nonlinear in its parameters. Therefore, the logarithmic form of Eq. (3.32) is often considered:

$$\ln y = \ln A + \sum_{i=1}^{m} \alpha_i \ln x_i. \tag{3.33}$$

The coefficients in Eq. (3.33) can be interpreted as the output elasticities with regard to inputs. Note that these elasticities are constant across the observations.

The quadratic production function is flexible as it includes the products of input quantities and hence exhibits nonzero second-order derivatives. Its original form is defined as follows (Coelli et al. 2005):

$$y = a_0 + \sum_{i=1}^{m} \alpha_i x_i + \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} \alpha_{ij} x_i x_j. \tag{3.34}$$

The translog (transcendental logarithmic) production function was defined by Christensen et al. (1972, 1973). The translog function is also flexible and is defined as follows (Boisvert 1982):

$$y = f(x) = a_0 \prod_{i=1}^{m} x_i^{\alpha_i} \prod_{i=1}^{m} x_i^{0.5\left(\sum_{j=1}^{m} \beta_{ij} \ln x_j\right)}. \tag{3.35}$$

Taking logs of both sides of Eq. (3.35) renders the estimable translog production function:

$$\ln y = \ln a_0 + \sum_{i=1}^{m} \alpha_i \ln x_i + \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{m} \beta_{ij} \ln x_i \ln x_j. \tag{3.36}$$

The translog function can also be appended by the time trend, which affects the production in a Hicks-neutral or non-neutral manner. One may consult, for example, Orea and Zofío (2017) or Coelli et al. (2005), for a more detailed exposition.

The production functions can be estimated in a number of ways. The parametric estimation can follow either a stochastic approach or the deterministic one. The stochastic approach can be facilitated via ordinary least squares (OLS), corrected OLS, or SFA. In addition, such estimators as generalized least squares or the Bayesian approach can be employed. The deterministic approach relies on mathematical programming. The nonparametric approach relies on mathematical programming as well, but no functional form is implied in such a case. The semi-parametric approach, which is a combination of nonparametric and parametric approaches, fits parametric regression locally. These approaches are discussed in this chapter.

3.2.4 Estimation of the Distance Functions

3.2.4.1 Deterministic Parametric Approach

The most general setting is that of the multiple inputs multiple outputs. In this case, one considers simultaneous reduction in the inputs (i.e. input distance function) or expansion of the outputs (i.e. output distance function). The distance functions can be estimated (note that "estimation" is not used sensu stricto here) in three ways: via parametric deterministic estimation (Aigner and Chu 1968), via econometric estimation (Coelli and Perelman 1999), and via nonparametric estimation (Thanassoulis et al. 2008). Some methods have also been proposed combining nonparametric and stochastic estimation (Kuosmanen and Johnson 2017).

The deterministic parametric programming approach can be implemented by directly defining the distance functions and minimizing their value in order to ensure the minimum extrapolation. The choice of the functional form of the distance function (translog, quadratic) allows the production possibilities to be identified. Further on, the measurement of distance (mapping) is facilitated via imposition of the (almost-)homogeneity conditions that are adapted to the specific case of the distance function (input/output, hyperbolic, directional). The corresponding linear programming problems can be established.

Almost-homogeneity is a crucial notion in the estimation of the parametric distance functions. Aczel (1966) proposed the following definition of almost-homogeneity:

$$F\left(\mu^{k_1}x, \mu^{k_2}y\right) = \mu^{k_3}F(x, y), \mu > 0. \tag{3.37}$$

According to Lau (1972), the following relationship holds for $F(x, y)$ that is homogeneous of degrees (k_1, k_2, k_3):

$$k_1 \sum_{i=1}^{m} \frac{\partial F(x, y)}{\partial x_i} x_i + k_2 \sum_{j=1}^{n} \frac{\partial F(x, y)}{\partial y_j} y_j = k_3 F, \tag{3.38}$$

where the fact that $\frac{\partial F(x,y)}{\partial x} \frac{F}{x} = \frac{\partial \ln F(x,y)}{\partial \ln x}$ is exploited for the translog case (Cuesta and Zofío 2005). The condition provided in Eq. (3.37) can be used to impose the desired degree of homogeneity on the distance functions.

The translog functional form is preferred when approximating the distance functions due to its flexibility, yet the quadratic function is used for the directional distance functions due to its translation property. The output distance function in translog form is defined as follows (Coelli and Perelman 1999):

$$\begin{aligned} \ln D_o^k = \alpha_0 &+ \sum_{i=1}^{m} \alpha_i \ln x_{ki} + \frac{1}{2} \sum_{i=1}^{m} \sum_{i'=1}^{m} \alpha_{ii'} \ln x_{ki} \ln x_{ki'} \\ &+ \sum_{j=1}^{n} \beta_j \ln y_{kj} + \frac{1}{2} \sum_{j=1}^{n} \sum_{j'=1}^{n} \beta_{jj'} \ln y_{kj} \ln y_{kj'} \\ &+ \sum_{i=1}^{m} \sum_{j=1}^{n} \delta_{ij} \ln x_{ki} \ln y_{kj}, \end{aligned} \tag{3.39}$$

where $k = 1, 2, \ldots, K$ is the index of the observations (decision-making units). The translog output distance function is accompanied by restrictions on its first- and second-order coefficients in order to ensure homogeneity of degree +1 in outputs:

$$\sum_{j=1}^{n} \beta_j = 1,$$
$$\sum_{j'=1}^{n} \beta_{jj'} = 0, j = 1, 2, \ldots, n, \tag{3.40}$$
$$\sum_{j=1}^{n} \delta_{ij} = 0, i = 1, 2, \ldots, m.$$

Also, the symmetry conditions are imposed by setting

$$\begin{aligned} \alpha_{ii'} &= \alpha_{i'i}, i, i' = 1, 2, \ldots, m \\ \beta_{jj'} &= \beta_{j'j}, j, j' = 1, 2, \ldots, n. \end{aligned} \tag{3.41}$$

The representation is ensured by restricting the values of the distance function:

$$\ln D_o^k \leq 0. \tag{3.42}$$

Then, the objective function is to minimize the distances to the frontier (subject to restrictions in Eqs. 3.40–3.42):

$$\max_{\alpha, \beta, \delta} \sum_{k=1}^{K} \ln D_o^k. \tag{3.43}$$

The translog input distance function follows the same structure as in Eq. (3.39) (Coelli and Perelman 1999):

$$\begin{aligned} \ln D_i^k = \alpha_0 &+ \sum_{i=1}^{m} \alpha_i \ln x_{ki} + \frac{1}{2} \sum_{i=1}^{m} \sum_{i'=1}^{m} \alpha_{ii'} \ln x_{ki} \ln x_{ki'} \\ &+ \sum_{j=1}^{n} \beta_j \ln y_{kj} + \frac{1}{2} \sum_{j=1}^{n} \sum_{j'=1}^{n} \beta_{jj'} \ln y_{kj} \ln y_{kj'} \\ &+ \sum_{i=1}^{m} \sum_{j=1}^{n} \delta_{ij} \ln x_{ki} \ln y_{kj}. \end{aligned} \tag{3.44}$$

The homogeneity of degree +1 in inputs needs to be imposed by setting the following restrictions for the coefficients in Eq. (3.44):

$$\begin{aligned} &\sum_{i=1}^{m} \alpha_i = 1, \\ &\sum_{i'=1}^{m} \alpha_{ii'} = 0, i = 1, 2, \ldots, m, \\ &\sum_{i=1}^{m} \delta_{ij} = 0, j = 1, 2, \ldots, m. \end{aligned} \tag{3.45}$$

The symmetry requirements from Eq. (3.41) are maintained. In addition, the representation property is satisfied by restricting the values of the input distance function:

$$\ln D_i^k \geq 0. \tag{3.46}$$

The objective function minimizes the distance to the frontier as follows:

$$\min_{\alpha, \beta, \delta} \sum_{k=1}^{K} \ln D_i^k. \tag{3.47}$$

The hyperbolic distance function (Eq. 3.27) can be estimated by considering the constraints and objective function for the output distance function (cf. Eqs. 3.39, 3.41–3.43; note that D_o is replaced with D_h) imposing additional homogeneity requirements in lieu of Eq. (3.40) as follows (Cuesta and Zofío 2005; Vardanyan and Noh 2006):

$$\begin{aligned} &\sum_{j=1}^{n} \beta_j - \sum_{i=1}^{m} \alpha_i = 1, \\ &\sum_{j'=1}^{n} \beta_{jj'} - \sum_{i=1}^{m} \delta_{ij} = 0, j = 1, 2, \ldots, n, \\ &\sum_{j=1}^{n} \delta_{ij} - \sum_{i'=1}^{m} \alpha_{ii'} = 0, i = 1, 2, \ldots, m. \end{aligned} \tag{3.48}$$

3.2.4.2 Stochastic Approach

Coelli and Perelman (1999) also presented the derivation of the econometric models for estimation of the translog input and output distance functions. In order to present the estimable models, one needs to obtain variation on both sides of the econometric equation. Therefore, the homogeneity of the distance functions is exploited.

For the output distance function, the homogeneity of degree +1 in outputs results in the following relationship (Lovell et al. 1994):

$$D_{\mathrm{o}}(x, \omega y) = \omega D_{\mathrm{o}}(x, y), \omega > 0. \tag{3.49}$$

While Eq. (3.49) presents a general case with the arbitrary multiplier ω, one can pick a specific value for the coefficient. A certain output can be used as the numéraire in order to benefit from the homogeneity of the output distance function. Without loss of generality, let us assume y_n is used as the normalizing output; i.e., we set $\omega = 1/y_n$. In this setting, Eq. (3.49) is written as

$$D_{\mathrm{o}}^k(x_k, y_k/y_{kn}) = D_{\mathrm{o}}(x_k, y_k)/y_{kn}, k = 1, 2, \ldots, K. \tag{3.50}$$

Let the normalized output vector be $y_k^* = (y_{k1}/y_{kn}, y_{k2}/y_{kn}, \ldots, y_{kn-1}/y_{kn}, 1)$. Thus, $D_{\mathrm{o}}^k(x_k, y_k/y_{kn}) = D_{\mathrm{o}}^k\left(x_k, y_k^*\right)$. The translog output distance function in Eq. (3.38) can be exploited to parametrize $D_{\mathrm{o}}^k\left(x_k, y_k^*\right)$ as follows:

$$\begin{aligned} \ln D_{\mathrm{o}}^k\left(x_k, y_k^*\right) = \alpha_0 &+ \sum_{i=1}^{m} \alpha_i \ln x_{ki} + \frac{1}{2} \sum_{i=1}^{m} \sum_{i'=1}^{m} \alpha_{ii'} \ln x_{ki} \ln x_{ki'} \\ &+ \sum_{j=1}^{n-1} \beta_j \ln y_{kj}^* + \frac{1}{2} \sum_{j=1}^{n-1} \sum_{j'=1}^{n-1} \beta_{jj'} \ln y_{kj}^* \ln y_{kj'}^* \\ &+ \sum_{i=1}^{m} \sum_{j=1}^{n-1} \delta_{ij} \ln x_{ki} \ln y_{kj}^*. \end{aligned} \tag{3.51}$$

Let us denote the expression in Eq. (3.51) by $\ln D_{\mathrm{o}}^k\left(x_k, y_k^*\right) = TL\left(x_k, y_k^*; \alpha, \beta, \delta\right)$. Taking logs of both sides of Eq. (3.50) and rearranging gives

$$\ln D_{\mathrm{o}}^k\left(x_k, y_k^*\right) = \ln D_{\mathrm{o}}^k(x_k, y_k) - \ln y_{kn}, \tag{3.52}$$

which can be further written as

$$-\ln y_{kn} = TL\left(x_k, y_k^*; \alpha, \beta, \delta\right) - \ln D_{\mathrm{o}}^k(x_k, y_k). \tag{3.53}$$

Thus, the left- and right-hand sides of Eq. (3.53) show variation across the observations and render an estimable model. The second term on the right-hand side of Eq. (3.53), $\ln D_{\mathrm{o}}^k$, can be treated as a random error and then processed by means of corrected ordinary least squares or as an inefficiency term obtained via stochastic frontier analysis (see, e.g., Kumbhakar and Lovell (2003) for details on these procedures).

The same reasoning can be followed for the input distance function. Assuming input (cost) minimization, the homogeneity in inputs is exploited for the case of the input distance function. Following Coelli and Perelman (1999), one can relate the two distance functions:

$$D_{\mathrm{i}}^{k}(x_k/x_{km}, y_k) = D_{\mathrm{i}}(x_k, y_k)/x_{km}, k = 1, 2, \ldots, K. \tag{3.54}$$

Then, we denote $x_k^* = (x_{k1}/x_{km}, x_{k2}/x_{km}, \ldots, x_{km-1}/x_{km}, 1)$. The translog form of the homogeneity-imposed input distance function is given as

$$\begin{aligned} \ln D_{\mathrm{i}}^{k}\left(x_k^*, y_k\right) = \alpha_0 &+ \sum_{i=1}^{m-1} \alpha_i \ln x_{ki}^* + \frac{1}{2} \sum_{i=1}^{m-1} \sum_{i'=1}^{m-1} \alpha_{ii'} \ln x_{ki}^* \ln x_{ki'}^* \\ &+ \sum_{j=1}^{n} \beta_j \ln y_{kj} + \frac{1}{2} \sum_{j=1}^{n} \sum_{j'=1}^{n} \beta_{jj'} \ln y_{kj} \ln y_{kj'} \\ &+ \sum_{i=1}^{m-1} \sum_{j=1}^{n} \delta_{ij} \ln x_{ki}^* \ln y_{kj}. \end{aligned} \tag{3.55}$$

A shorthand notation can be introduced for the translog input distance function: $\ln D_{\mathrm{o}}^{k}\left(x_k^*, y_k\right) = TL\left(x_k^*, y_k; \alpha, \beta, \delta\right)$. By taking logs of both sides of Eq. (3.54), we have:

$$-\ln x_{km} = TL\left(x_k^*, y_k; \alpha, \beta, \delta\right) - \ln D_{\mathrm{i}}(x_k, y_k). \tag{3.56}$$

Again, we observe variation on both sides of Eq. (3.56) and can use econometric techniques to obtain the coefficients of the translog distance function.

Note that constant returns to scale can be assumed for the input and output distance functions. According to Coelli and Perelman (1999), one needs to impose homogeneity of degree -1 in outputs (resp. inputs) in the case of the input (resp. output) distance function.

Besides the input and output distance functions, the hyperbolic distance function (Eq. 3.27) can be used for efficiency analysis in order to take into account the simultaneous adjustments in the input and output quantities. Cuesta and Zofío (2005) discussed the parametric formulation of the hyperbolic distance function (based on the translog functional form) using the homogeneity condition as in Lovell et al. (1994). In the case of the hyperbolic distance function, homogeneity in both inputs and outputs is ensured. The almost-homogeneity conditions (Eq. 3.37) are imposed with $(k_1, k_2, k_3) = (-1, 1, 1)$. This can be achieved by adjusting the input and output quantities with respect to either the numéraire input or output. If one picks the normalization by output, y_n, then the homogeneity is imposed in the following manner:

$$D_{\mathrm{h}}^{k}(x_k y_{kn}, y_k/y_{kn}) = D_{\mathrm{h}}^{k}(x_k, y_k)/y_{kn}. \tag{3.57}$$

Let the normalized input and output vectors be denoted as $x_k^{**} = (x_{k1}y_{kn}, x_{k2}y_{kn}, \ldots, x_{km}y_{kn})$ and $y_k^{*} = (y_{k1}/y_{kn}, y_{k2}/y_{kn}, \ldots, y_{kn-1}/y_{kn}, 1)$. Note that $y*$ contains one element normalized to unity, whereas this is not the case for the normalized input vector, $x**$, as the output quantity is used for normalization. The translog form of the hyperbolic distance function for the normalized production plan ensuring the homogeneity conditions is

$$\begin{aligned} \ln D_{\mathrm{h}}^{k}\left(x_k^{**}, y_k^{*}\right) = \alpha_0 &+ \sum_{i=1}^{m} \alpha_i \ln x_{ki}^{**} + \frac{1}{2}\sum_{i=1}^{m}\sum_{i'=1}^{m} \alpha_{ii'} \ln x_{ki}^{**} \ln x_{ki'}^{**} \\ &+ \sum_{j=1}^{n-1} \beta_j \ln y_{kj}^{*} + \frac{1}{2}\sum_{j=1}^{n-1}\sum_{j'=1}^{n-1} \beta_{jj'} \ln y_{kj}^{*} \ln y_{kj'}^{*} \\ &+ \sum_{i=1}^{m}\sum_{j=1}^{n-1} \delta_{ij} \ln x_{ki}^{**} \ln y_{kj}^{*}. \end{aligned} \tag{3.58}$$

We further denote $\ln D_{\mathrm{h}}^{k}\left(x_k^{**}, y_k^{*}\right) = TL\left(x_k^{**}, y_k^{*}; \alpha, \beta, \delta\right)$ and rewrite the logged form of Eq. (3.57) as

$$-\ln y_{kn} = TL\left(x_k^{**}, y_k^{*}; \alpha, \beta, \delta\right) - \ln D_h^{k}(x_k, y_k). \tag{3.59}$$

Here, $\ln D_{\mathrm{h}}$ is an inefficiency term that can be estimated econometrically as discussed above. In its essence, this term indicates the contraction in inputs and expansion of outputs that ensures a certain production plan is projected on the efficiency frontier along with the hyperbolic path. The CRS can also be imposed by ensuring that D_{h} is homogeneous of degree $-1/2$ in inputs (Cuesta and Zofío 2005).

The distance functions (and production technologies) can also be extended to take into account the externalities related to the production process. The estimation is then adjusted by assuming additional (terms in the) constraints on homogeneity. A discussion on this issue can be found in Vardanyan and Noh (2006) and Zhou et al. (2014). Note that these models can also be boiled down to the conventional production technology.

3.2.4.3 Nonparametric Approach

The nonparametric analysis of efficiency and productivity requires modelling the production possibilities (without parametric specification of the underlying representation of the production technology) and applying the measures of efficiency discussed in Sect. 3.2.2. The theoretical foundations of nonparametric efficiency analysis were provided by Farrell (1957) and Afriat (1972). The nonparametric analysis can also rely on both primal and dual representations of the technology and measures of efficiency. The nonparametric technologies can be approximated by assuming axioms of convexity, returns to scale, and disposability.

Free disposability of inputs and outputs implies that a decision-making unit (DMU) is able to operate within a "box" in the input–output space dominated by a certain production plan (x_0, y_0). This provides the basis for modelling the production possibilities as an infinite number of feasible production plans appear for a given (observed) production plan. Using more inputs and/or producing fewer outputs is thus feasible if compared to a certain plan (x_0, y_0) under the free disposability technology:

$$\widehat{T}_{\mathrm{FD}} = \{(x, y) : x_0 \leq x, y \leq y_0\}, \tag{3.60}$$

where (x, y) are the feasible production plans. Note that the multidimensional vectors x and y can be used with inequalities read element-wise.

A basic delineation can be made between convex and non-convex technologies. Indeed, assuming convexity renders a set of an infinite number of feasible production plans. First, we discuss the convex case without assuming free disposability. Let there be K production plans observed indexed over $k = 1, 2, \ldots, K$. Then, the technology is formally established as a convex polyhedral cone:

$$\widehat{T}_{\mathrm{PC}} = \left\{ (x, y) : \sum_{k=1}^{K} \lambda_k x_k = x, y = \sum_{k=1}^{K} \lambda_k y_k, \lambda_k \geq 0 \right\}, \tag{3.61}$$

where λ_k is the intensity variable, or weight, associated with DMU k. Thus, each observation can be scaled up or down along the ray going through it from the point of origin, and combinations of such vectors are all feasible. This is a constant returns to scale (CRS) technology (i.e. the maximum productivity DMU is used as a yardstick for shaping the technology and hence adjusting the efficiency scores).

A stricter approach is to constrain $\widehat{T}_{\mathrm{PC}}$ to the convex polyhedron by imposing restrictions on the intensity variables. The resulting technology is a variable returns to scale (VRS) one:

$$\widehat{T}_{\mathrm{PV}} = \left\{ (x, y) : \sum_{k=1}^{K} \lambda_k x_k = x, y = \sum_{k=1}^{K} \lambda_k y_k, \sum_{k=1}^{K} \lambda_k = 1, \lambda_k \geq 0 \right\}. \tag{3.62}$$

Note that the convexity constraint decreases the volume of the technology (if compared to the CRS case and the pure technical efficiency may increase as a result).

One can further combine the assumptions of free disposability (Eq. 3.60) and convexity. This results in DEA technologies that are CRS or VRS depending on the presence of the convexity constraint. One can refer to Hackman (2007) for a detailed description of the DEA technologies. The corresponding DEA technologies are defined in the following manner:

$$\widehat{T}_{\mathrm{CRS}}^{\mathrm{DEA}} = \left\{ (x, y) : \sum_{k=1}^{K} \lambda_k x_k \leq x, y \leq \sum_{k=1}^{K} \lambda_k y_k, \lambda_k \geq 0 \right\}, \tag{3.63}$$

$$\widehat{T}_{\mathrm{VRS}}^{\mathrm{DEA}} = \left\{ (x, y) : \sum_{k=1}^{K} \lambda_k x_k \leq x, y \leq \sum_{k=1}^{K} \lambda_k y_k, \sum_{k=1}^{K} \lambda_k = 1, \lambda_k \geq 0 \right\}. \tag{3.64}$$

Thus, the DEA-like technology allows production anywhere in the convex set of the observed production plans and allows for resource wasting due to free disposability. Note that hypothetical benchmarks may occur due to these assumptions.

The assumption of convexity can be relaxed in order to avoid hypothetical benchmarking. Free Disposability Hull (FDH) technology assumes free disposability without convexity (Tulkens 1993). The VRS FDH technology is defined as

$$\widehat{T}_{\mathrm{VRS}}^{\mathrm{FDH}} = \left\{ (x, y) : \sum_{k=1}^{K} \lambda_k x_k \leq x, y \leq \sum_{k=1}^{K} \lambda_k y_k, \sum_{k=1}^{K} \lambda_k = 1, \lambda_k = \{0, 1\} \right\}. \tag{3.65}$$

As one can see, the intensity variables are restricted to being the binary variables, and convexity constraint in this case implies that a single observation is chosen as a benchmark (it cannot be scaled up or down). Kerstens and Eeckaut (1999) discussed the CRS case of the FDH technology, which is given by

$$\widehat{T}_{\mathrm{CRS}}^{\mathrm{FDH}} = \left\{ (x, y) : \begin{array}{l} \sum_{k=1}^{K} \lambda_k^* x_k \leq x, y \leq \sum_{k=1}^{K} \lambda_k^* y_k, \\ \sum_{k=1}^{K} \lambda_k = 1, \lambda_k = \{0, 1\}, \lambda_k^* = \delta \lambda_k \end{array} \right\}. \tag{3.66}$$

Note that the convexity constraint can be modified in to inequality to impose non-increasing or non-decreasing returns to scale in the nonparametric technologies. Thus, the CRS FDH technology picks a single DMU as a benchmark for any feasible production plan (which is also the case in the VRS FDH technology) and scales it up or down with respect to the point of origin (which is impossible in the VRS FDH case) in order to define the production possibilities.

As shown in Eqs. (3.65) and (3.66), the production possibilities and benchmarking are defined with respect to the observed production plans. This assumption may be relaxed without abandoning the non-convexity. Even though such technologies are not frequently used in the empirical applications, they are illustrative of the possible modifications of the underlying economic axioms. Bogetoft and Otto (2010) discussed the additive technologies (Free Replicability

Hull) where feasible production plans can be combined, thus defining semi-real production possibilities:

$$\widehat{T}^{\mathrm{FRH}} = \left\{ (x,y) : \begin{array}{c} \sum_{k=1}^{K} \lambda_k x_k \leq x, y \leq \sum_{k=1}^{K} \lambda_k y_k, \\ \sum_{k=1}^{K} \lambda_k \leq U, \lambda_k = \{\text{integer}\} \end{array} \right\}. \tag{3.67}$$

Here, U is the upper bound of the sum of integer intensity variables that restricts the degree to which the observations can be replicated. The individual λ_k can also be restricted in this fashion.

Green and Cook (2004) discussed the Free Coordination Hull that allows combinations (addition) of the observed production plans. Again, the intensity variables are restricted to the integer set, thus implying non-divisibility of the production plans observed. Let the power set of the DMU set, K, be denoted by $P(K)$. Then, the aggregate production plans can be established for each possible combination of the DMUs that comprise the power set, i.e. $(x_q, y_q) = \left(\sum_{p \in q} x_p, \sum_{p \in q} y_p \right)$, $q \in P(K)$. The Free Coordination Hull technology is defined as follows:

$$\widehat{T}^{\mathrm{FCH}} = \left\{ (x,y) : \begin{array}{c} \sum_{q \in P(K)} \lambda_q x_q \leq x, y \leq \sum_{q \in P(K)} \lambda_q y_q, \\ \sum_{q \in P(K)} \lambda_q = 1, \lambda_q = \{0,1\}, q \in P(K) \end{array} \right\}. \tag{3.68}$$

The technical efficiency can be measured by plugging the measures described in Sect. 3.2.2 into the nonparametric technologies described in this section. The resulting mathematical programs render the efficiency scores. More details on the underlying calculations can be found in studies by, for example, Charles et al. (2020) and Lotfi et al. (2020).

The discussed primal representations of the production technology can be replaced by dual ones. This requires knowledge of the price data (and the assumption that the prices are variable across the observations). The profit, revenue, and cost functions can be established. In general, the cost functions are often employed in the productivity analysis literature as the other dual representations are data-intensive and require an additional assumption in regard to the economic behaviour and market structure (Greene 2008). The cost function can be derived following the ideas of Diewert (1971) and Caves et al. (1980). The translog functional form is often assumed. Thanassoulis et al. (2008) presented a survey on the nonparametric estimation of the dual measures of efficiency.

Nonparametric analysis can be supplemented by measures of statistical precision. Bootstrapping techniques are available to handle the effects of the underlying sampling distribution (Simar and Wilson 1998, 1999). The partial frontiers (Daraio and Simar 2007) and quantile approach (Jradi and Ruggiero 2019) can be applied to mitigate the impact of outlying observations.

3.3 Scientometric Review

In order to identify the major approaches and models for measurement of agricultural productivity, scientometric analysis was carried out. The analysis relied on the Clarivate Analytics Web of Science database. The query used for the analysis included the terms related to the area of application (agriculture) and methods used (frontier methods for efficiency or productivity analysis). Thus, the following string was applied: "agriculture and frontier and (efficiency or productivity)". The query rendered 589 results (as of November 2020).

Clearly, increasing attention has been paid to the analysis of agricultural productivity and efficiency over time (Fig. 3.1). This indicates that agricultural productivity has attracted more attention in academia over time. This can be attributed to the need to assess the performance of agricultural support programmes as a demand factor and increase computational capacities as a supply factor.

In order to provide an overall picture of the problematique underlying the research on agricultural productivity based on the frontier techniques, the VOSviewer package was applied (Van Eck and Waltman 2010). Three issues were addressed: keyword analysis, cited paper analysis, and outlet analysis. Such an approach allows one to identify the major areas of research along with the key publications and journals.

The citation-based analysis of the keywords appearing in the papers on agricultural productivity is presented in Fig. 3.2. The keywords were clustered based on their appearance in the documents. The major clusters of keywords can be identified as follows: (1) agricultural context; (2) economic model; (3) estimators; and (4) post-estimation analysis. However, some of the keywords appear in different clusters with

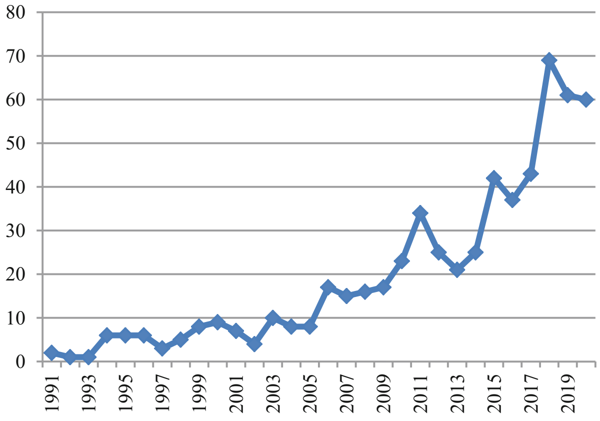

Fig. 3.1 Number of publications on agricultural productivity and efficiency applying frontier techniques in the Web of Science database (1991–2020)

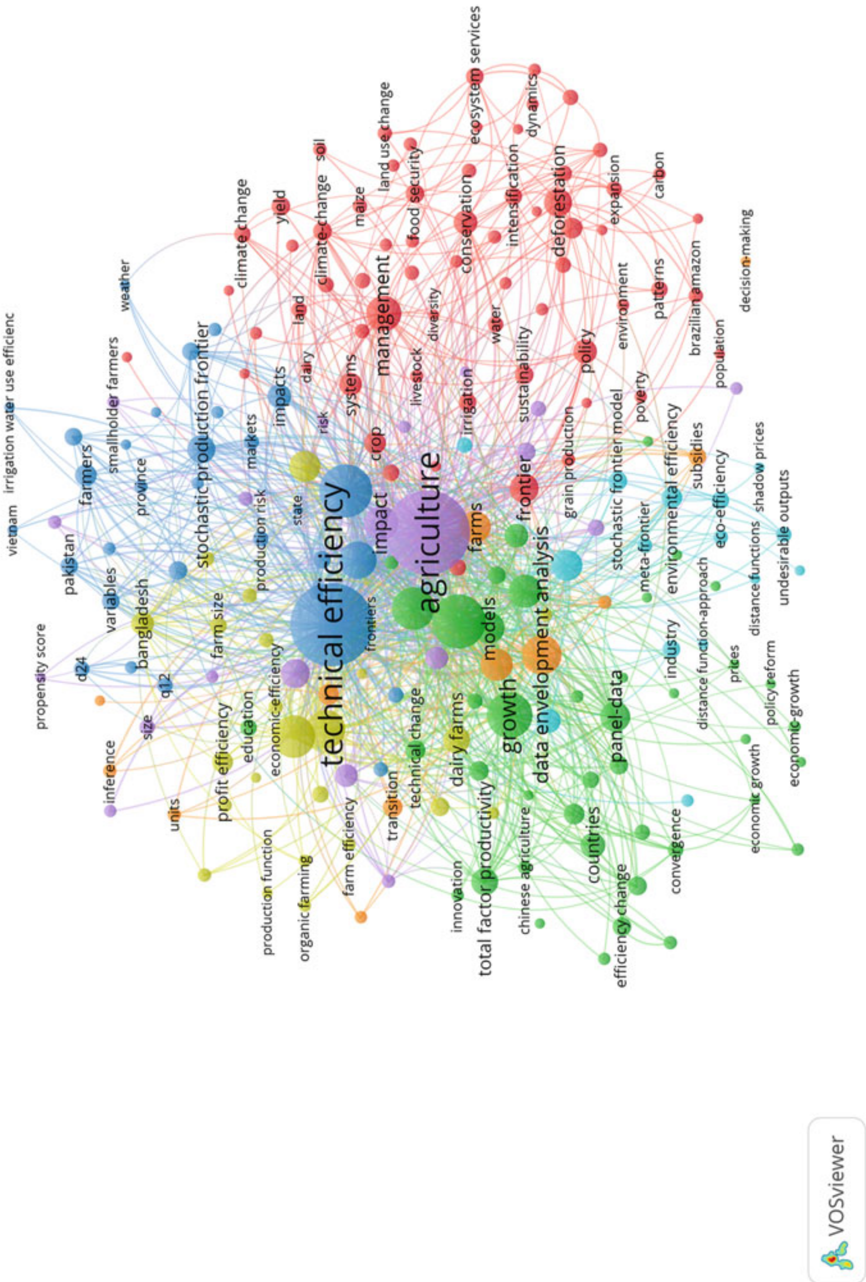

Fig. 3.2 Citation-based map of keywords appearing in the papers on agricultural productivity and efficiency

slight modifications (e.g. stochastic production frontier and stochastic frontier model).

The agricultural context is manifested by keywords related to such overarching issues as food security, sustainability, policy, management, climate change, and ecosystem services. Also, keywords indicating the importance of the management practices associated with the factor inputs are relevant in this cluster: deforestation, conservation, intensification, land use change, yield. The types of products are included as well: maize, dairy, crop. This pattern suggests that more attention has been given to the conservation of the resources and increase in the sustainability of farming. Indeed, the use of the frontier techniques is promising in this regard as the multiple-input multiple-output setting can be specified, leading to estimation of the integrated indicators of performance (e.g. efficiency, total factor productivity change).

The economic model is based on behavioural assumptions. Generally, farms seek to maximize their profits. The frontier techniques can be used to calculate profit efficiency, revenue efficiency, cost efficiency, and technical efficiency. Technical efficiency requires data on the input and output quantities, whereas the other types of efficiency also require data on the input and/or output prices. Accordingly, different representations (primal or dual ones) are used to describe the production technology. These keywords appear in the corresponding cluster.

The estimators include parametric (stochastic frontier analysis) and nonparametric (data envelopment analysis) methods. Parametric estimation relies on the representations of the production technology. Distance functions are used in the multiple-input multiple-output cases (e.g. input distance functions are used in the cost-minimizing settings). The frontier models can assume different technologies during the optimization. Thus, such keywords as eco-efficiency, undesirable outputs, and meta-frontier indicate the assumption underpinning the production technologies defining the production possibilities. Again, the presence of keywords related to environmental pressures indicates the increasing importance of sustainability.

The measures of efficiency and productivity change are important themselves, yet the assessment of the context requires relating the aforementioned measures to the explanatory variables or some descriptive indicators. The keywords suggest that the key measures of interest include efficiency change and technical change that comprise the total factor productivity change. The convergence is also mentioned. This indicates that the convergence in the total factor productivity change and its sources has become an important topic for agricultural policy analysis.

The key approaches involving handling the theoretical assumptions and empirical data during the efficiency and productivity analysis are represented by the seminal papers that have been cited in the relevant papers. Figure 3.3 presents a co-citation-based map of the papers that have been cited in the relevant literature. This allows the major strands of the efficiency and productivity research to be identified. In addition, Fig. 3.4 presents a citation-based map of the seminal papers. These two maps differ in that the co-citation map tends to display the theoretical fundaments of the research on agricultural productivity, whereas the citation map relates the surveyed papers among themselves and thus identifies the most recent papers that received more

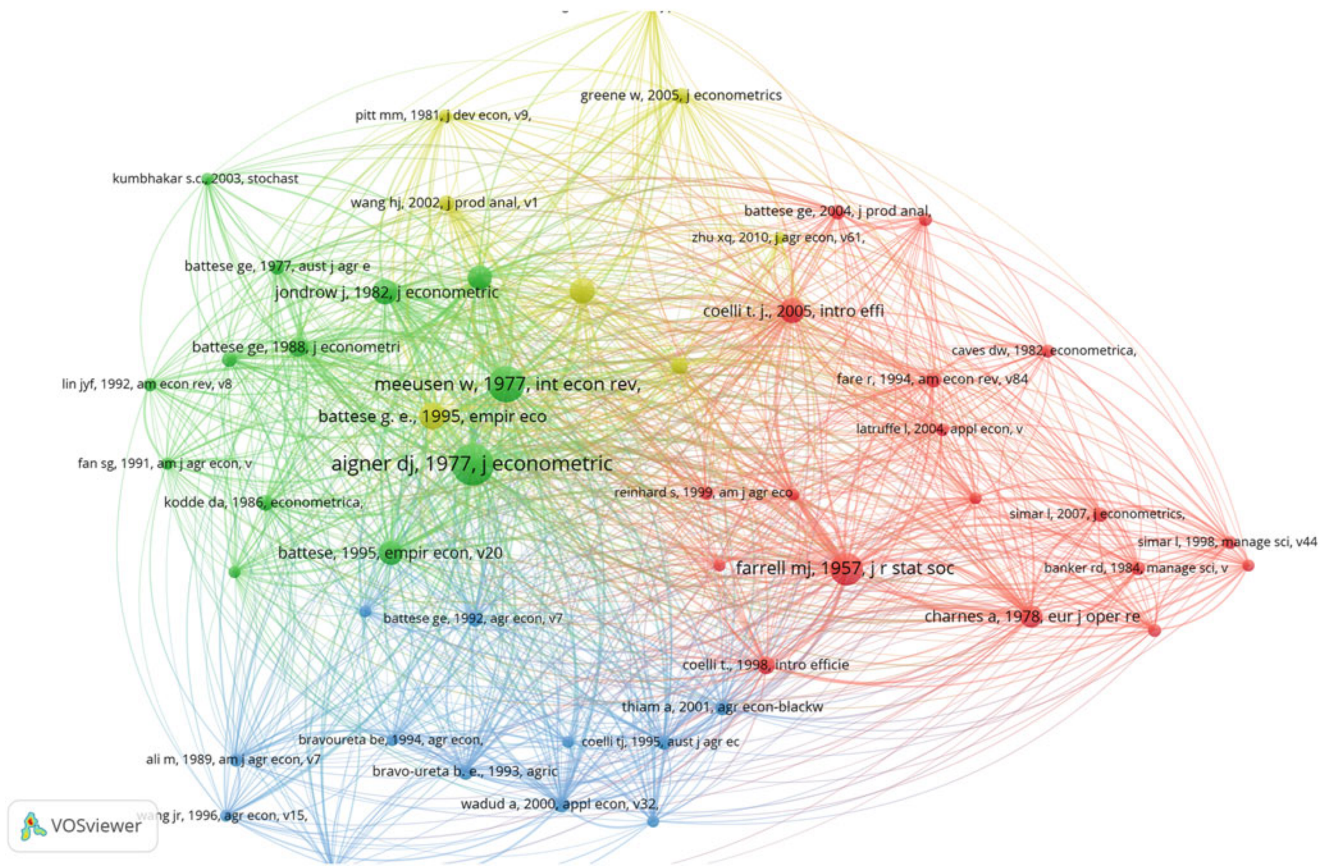

Fig. 3.3 Co-citation map of the seminal papers cited in the literature on agricultural productivity analysis

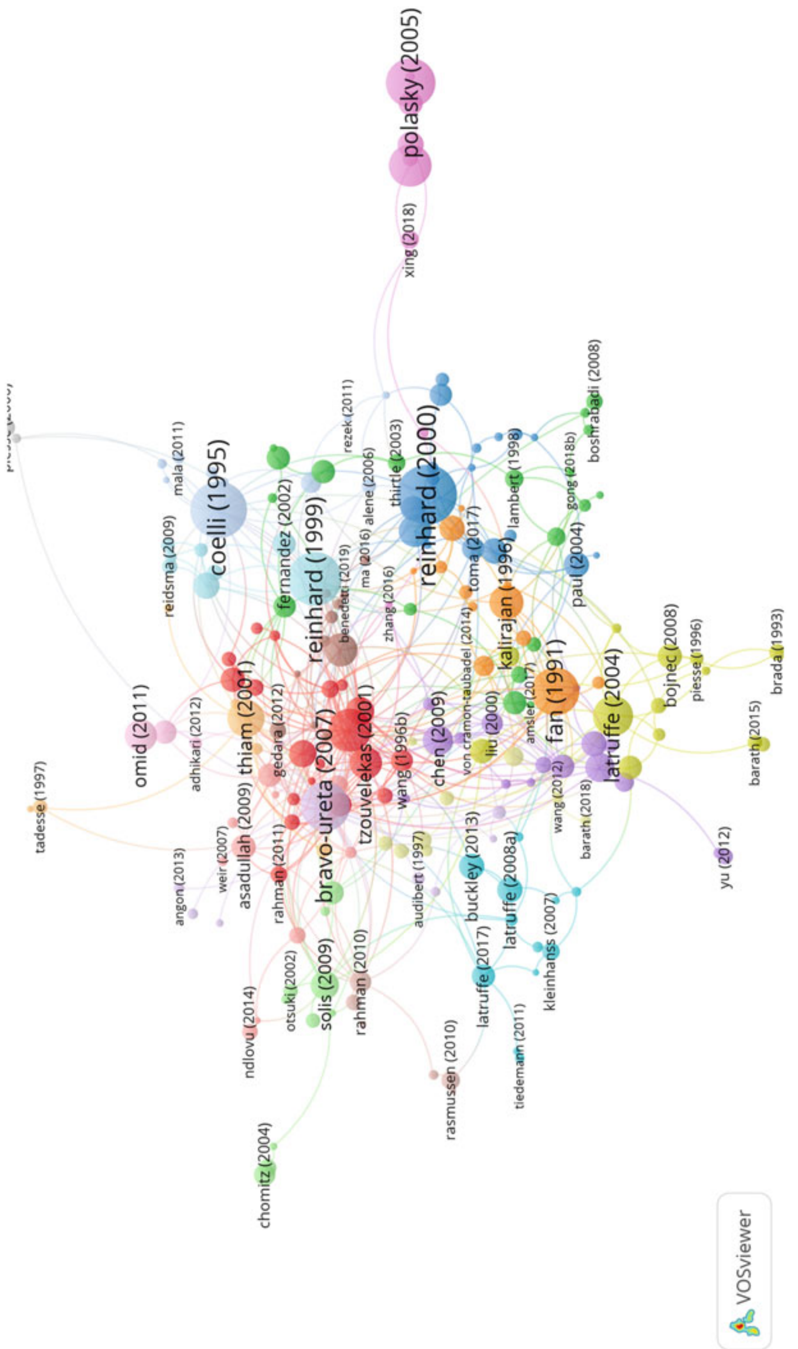

Fig. 3.4 Citation map of the seminal papers cited in the literature on agricultural productivity analysis

attention in the related literature. In general, the latter map mostly focuses on the empirical papers along with recent extensions of the frontier methods.

The co-citation map indicates the presence of the two major groups of papers most cited in the research on agricultural efficiency and productivity. These include (1) parametric methods and (2) nonparametric methods. Furthermore, there are two groups of papers, (3) meta-reviews and (4) specific models for parametric analysis. Among the nonparametric papers, DEA occupies the central position with papers by Farrell (1957), Charnes et al. (1978), and Banker et al. (1984) discussing the theoretical preliminaries of DEA. The study by Färe et al. (1994) discussed the computations and decomposition of the Malmquist productivity index that was widely applied for the agricultural sector. The statistical approach towards the calculation of the bias-corrected efficiency scores (bootstrapped DEA) was proposed by Simar and Wilson (1998, 2007). Battese et al. (2004) discussed the use of the meta-frontier to compare the production technologies among themselves. Latruffe et al. (2004) provided an empirical case of farm efficiency analysis in Poland.

The parametric papers are mostly based on the SFA proposed by Meeusen and van Den Broeck (1977) and Aigner et al. (1977). Jondrow et al. (1982) proposed the estimator of efficiency term. Battese and Coelli (1995) proposed the efficiency effects model that allows the effects of the correlates of the efficiency scores to be assessed in a single-step approach. The use of SFA models for analysis of agricultural efficiency is often related to considerations over farm heterogeneity. This is indicated by the presence of the studies by Wang (2002) and Greene (2005) in the co-citation map. Random- and fixed-effects models (as well as extensions thereof) are adapted to the case of the SFA and, in particular, agricultural sector analysis in order to identify the heterogeneity effects and inefficiency effects (including transient and persistent parts of inefficiency). Wadud and White (2000) compared the results from DEA and SFA when assessing the agricultural efficiency of Bangladeshi farms.

The papers related to environmental pollution in the productivity analysis can be seen in the co-citation map. Pittman (1981) presented an econometric model involving undesirable outputs in the translog production function. Reinhard et al. (1999) proposed an SFA-based approach for analysis of environmental efficiency, yet this paper appears to be cited often by papers focused on nonparametric analysis. Therefore, undesirable outputs (mostly pollutant emissions) have been involved in the analysis of agricultural efficiency.

The citation map indicates the papers most frequently cited (rather than co-cited) in the literature on agricultural efficiency and productivity change. The focus of the papers on agricultural efficiency is often placed on the developing or transition countries. These countries face distortions in terms of factor markets and institutional environment that require the policy priorities to be identified in the sense of farming types and farm size groups. Chavas et al. (2005) developed a theoretical model explaining the behaviour of farm households (rather than farms) that is more relevant for small-scale farms in transition economies.

Fan (1991) used province-level panel data to analyse the performance of the Chinese agricultural sector. A quasi-translog production function (Karagiannis and

Tzouvelekas 2001) was applied to avoid the multicollinearity issue inherent in the translog production and function and ensure flexibility (which is impossible with the Cobb–Douglas functional form). Kalirajan et al. (1996) utilized the random coefficients model (Griffiths 1972; Hildreth and Houck 1968) to estimate the production frontier for the agricultural sector in China at the province level. The random coefficients allowed the differences in the output elasticities across the provinces to be identified. The efficiency was also estimated by adjusting the coefficients to their maximum observed values and obtaining the expected output level.

Chen et al. (2009) applied the translog stochastic production frontier to a sample of China's rural households (farms) for the period 1995–1996. Four regions were considered (North, North-East, East, and South-West China). Solís et al. (2009) applied the translog stochastic input distance function for a sample of Central American farms (households). The latter study applied the approach of Battese and Coelli (1995) and included efficiency effects in the model. As some of the explanatory factors may be endogenous, the generalized least squares model was also applied to implement the instrumental variables approach. In the discussed case, soil conservation practices might be induced by farm performance and also affect it.

Bravo-Ureta and Pinheiro (1993) and Coelli (1995) presented a survey of the early papers using DEA and SFA for analysis of agricultural efficiency. The meta-analysis of the literature on agricultural efficiency and productivity growth has become an important topic for research and the studies by Thiam et al. (2001), Bravo-Ureta et al. (2007), and Gorton and Davidova (2004). Such factors as the representation of the production technology (primal or dual), functional form (translog, Cobb–Douglas), number of inputs and outputs, and stochastic or deterministic estimation are usually considered in the meta-analysis as explanatory factors for variation in the technical efficiency or (total) factor productivity growth. Gorton and Davidova (2004) focused on the Central and Eastern European countries, where agriculture has faced decollectivization. Henningsen (2009) provided insights into the underlying causes of inefficiency in such economies. A more recent study by Latruffe et al. (2017) discussed the linkages between subsidies and technical efficiency in dairy farms. This is yet another crucial question in shaping agricultural support policies. Minviel and Latruffe (2017) argued that public subsidies tend to negatively affect the technical efficiency of farms.

The outlets for papers on agricultural efficiency and productivity are analysed in two ways. A citation map (Fig. 3.5) is used to indicate the hierarchical relationships among the journals based on the citations. Then, a co-citation map (Fig. 3.6) is designed in order to reveal the linkages among the journals that are cited simultaneously. In the former case, the strength of linkages corresponds to the citations received, whereas the co-citation map represents the number of appearances in the citations.

The citation map for journals implies that the two most cited journals are related to agricultural economics in general (*Agricultural Economics* and *Journal of Agricultural Economics*) and productivity analysis (*Journal of Productivity Analysis*). Journals related to agricultural economics and agricultural science that have published papers related to agricultural efficiency include *American Journal of*

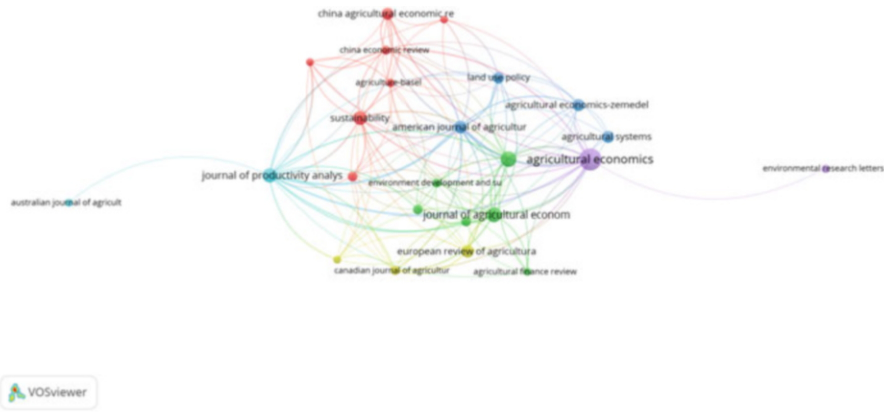

Fig. 3.5 Citation map for journals cited in papers related to agricultural efficiency and productivity

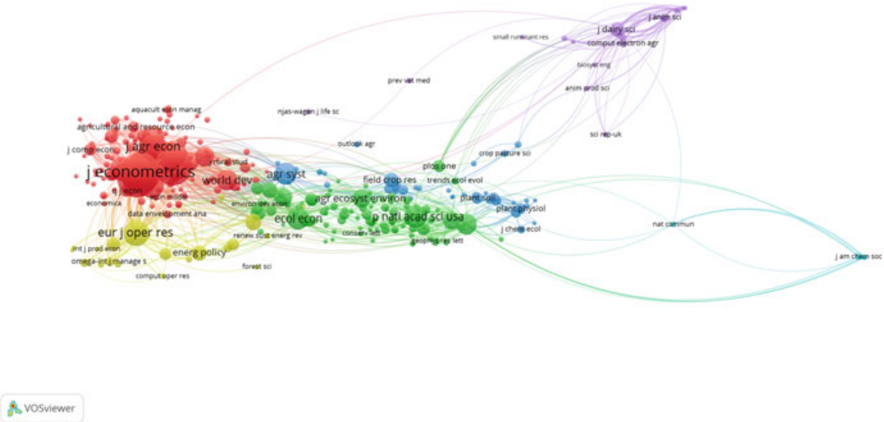

Fig. 3.6 Co-citation map for journals cited in papers related to agricultural efficiency and productivity

Agricultural Economics, *Land Use Policy*, and *Agricultural Systems*. There are two clusters of journals related to particular regions and associated development issues. *European Review of Agricultural Economics* and *Canadian Journal of Agricultural Economics* are more related to the mainstream agricultural economic journals. *China Agricultural Economic Review* and *China Economic Review* form a separate cluster around them.

The co-citation map for journals is helpful in identifying the theoretical and empirical preliminaries for the papers on agricultural efficiency. Five major clusters of journals can be identified based on the co-citation analysis. First, the mainstream (*Empirical Economics*, *Applied Economics*, *International Economic Review*, *American Economic Review*), agricultural (*Agricultural Economics*, *Journal of*

Agricultural Economics, *American Journal of Agricultural Economics* along with the region-specific *European Review of Agricultural Economics*, *Canadian Journal of Agricultural Economics*, and *China Economic Review*), and development economics journals (*Food Policy*, *World Development*) are closely interrelated with econometrics (*Journal of Econometrics*, *Econometrica*) journals. Second, there is a cluster of operations research journals that focus on optimization techniques (*European Journal of Operational Research*, *Management Science*, *Omega*) that are related to journals linked to energy and environment issues (*Energy Economics*, *Energy Policy*, *Energy*, *Journal of Cleaner Production*). The third cluster is related to agricultural resource use. Specifically, journals related to land resources include *Land Use Policy*; journals related to water use include *Water Resources Research* and *Agricultural Water Management*. A more holistic approach is manifested by the presence of such versatile outlets as *Journal of Environmental Management*, *Ecological Economics*, *Nature*, *Science*, *Proceedings of the National Academy of Sciences of the USA*, *Agricultural Ecosystems and Environment*, and *Global Environment Change*. The last two clusters that can be identified based on the co-citation map represent the areas of application, namely crop and livestock farming. The journals related to crop farming and soil science include *Agricultural Systems*, *Field Crops Research*, *Plant and Soil*, *Plant Physiology*, *Crop Science*, and *European Journal of Agronomy*. As regards livestock farming, journals such as *Journal of Dairy Science*, *Livestock Science*, and *Journal of Animal Science* are present.

The scientometric analysis carried out identified several traits of the research on agricultural efficiency and productivity. First, there are methodological strands in regard to the underlying models for the measurement of efficiency (statistical approach vs optimization). Second, the efficiency analysis focuses on regional or sectoral issues and can include environmental considerations. Third, the efficiency analysis relies on, and relates to, the technological issues covered, for example, by the field of agricultural science.

3.4 Data

Annual data describing the performance of the agricultural sectors of the selected European countries are used. The data come from the Eurostat database. Agricultural statistics and energy balance data are used to derive the input and output indicators.

The output is the total agricultural output of the agricultural "industry" from the Agricultural Accounts (in Purchasing Power Standards of 2010). Five inputs are used in the analysis. The intermediate consumption (in PPS) less the energy expenses is taken from the Agricultural Accounts. Land (in hectares) is taken from the agricultural statistics (the main cropping area). Energy consumption (in tonnes of oil equivalent) is taken from the energy balance. Capital consumption is measured by depreciation (in PPS), which is taken from the Agricultural Accounts. The labour input is taken from agricultural statistics provided by Eurostat (in Annual Working Units).

The period covered is 1995–2017. This time frame includes accession to the EU of the new member states, which provides insights into the effects of the operation of the Common Agricultural Policy. The data are mean-adjusted in order to ensure the convergence and improve the interpretability.

3.5 Empirical Analysis

3.5.1 Deterministic Parametric Modelling

The agricultural performance of the EU member states was analysed by applying the deterministic parametric frontier (Aigner and Chu 1968). This setting allows the properties of the production function (e.g. elasticities) to be recovered and the desirable axioms of the production technology to be ensured. The underlying assumption is that the observations lie on or below the production frontier due to technical inefficiency. Therefore, the approach is deterministic as the distance to the frontier is assumed to be solely attributed to inefficiency. The data are mean-scaled to ensure convergence.

We assume the translog production frontier, which allows the elasticities for each observation to be assessed. The first-order coefficients of the translog production frontier indicate the elasticities at mean of the data. All the elasticities are assumed to be non-negative, so monotonicity is fulfilled (this constraint is not applied for the time trend). The resulting programming problem is as follows:

$$
\begin{aligned}
&\min \sum_{k,t} \varepsilon_{kt} \\
&\text{s.t.} \\
&\ln y_{kt} = \beta_0 + \sum_{i=1}^{m} \beta_i \ln x_{ikt} \\
&+\frac{1}{2}\sum_{i=1}^{m}\sum_{i'=1}^{m}\beta_{ii'} \ln x_{ikt}x_{i'kt} + \beta_t t + \frac{1}{2}\beta_{tt}t^2 + \varepsilon_{kt}, \\
&\frac{\partial \ln y_{kt}}{\partial \ln x_{ikt}} = \beta_i + \sum_{i'=1}^{m}\beta_{ii'} \ln x_{i'kt} \geq 0, \\
&\beta_{ii'} = \beta_{i'i}, i, i' = 1, 2, \ldots, m, i \neq i', \\
&\varepsilon_{kt} \leq 0,
\end{aligned}
\tag{3.69}
$$

where the first constraint imposes the functional form of the production technology (i.e. translog), the second one imposes monotonicity, and the third one assumes symmetry in the second-order coefficients. The last constraint in Eq. (3.69) implies that the error terms are non-positive. Therefore, the resulting production frontier envelopes the observations and the output-oriented technical efficiency (TE) can be obtained as

$$\mathrm{TE}_{kt} = \exp\left(\varepsilon_{kt}\right). \tag{3.70}$$

Note that $\epsilon_{kt} \leq 0$ and thus $0 \leq \mathrm{TE}_{kt} \leq 1$. In this case, TE $= 1$ implies full efficiency and values below unity show that the output should be increased by 1/TE times in order to reach full efficiency. Thus, we can identify the relative performance gaps for each country and time period.

The estimates of the coefficients of the production frontier are provided in Table 3.1. The first-order coefficients indicate the input elasticities of output at the sample mean (as the data are mean-scaled). The highest elasticity is observed for the intermediate consumption. The regression coefficient implies that a 1% increase in the material consumption renders a 0.423% increase in the agricultural output on average. The coefficients associated with energy and labour were quite similar (0.171 and 0.168, respectively). Therefore, energy and labour units play a relatively important role in the agricultural production of the EU member states. The elasticity associated with capital input is lower (0.129) and implies that the use of capital inputs could be further improved. The lowest elasticity is observed for the land input (0.098). Indeed, the expansion of farms appears to be less important than the

Table 3.1 Estimates of the coefficients of the translog production function

Coefficient	Variable	Estimate	Coefficient	Variable	Estimate
β_0	Intercept	0.256	β_{t1}	t ln$M$	0.007
			β_{t2}	t ln$Land$	−8.02E-04
β_1	ln$M$	0.423	β_{t3}	t ln$E$	−0.004
β_2	ln$Land$	0.098	β_{t4}	t ln$L$	−0.003
β_3	ln$E$	0.171	β_{t5}	t ln$K$	−0.003
β_4	ln$L$	0.168			
β_5	ln$K$	0.129	β_t	t	0.016
			β_{tt}	t^2	8.04E-04
β_{11}	$\ln^2 M$	−0.059			
β_{12}	ln$Land$ ln$M$	0.04	β_{33}	$\ln^2 E$	−0.008
β_{13}	ln$E$ ln$M$	0.053	β_{34}	ln$L$ ln$E$	−0.092
β_{14}	ln$L$ ln$M$	0.017	β_{35}	ln$K$ ln$E$	0.012
β_{15}	ln$K$ ln$M$	−0.042			
			β_{44}	$\ln^2 L$	−0.014
β_{22}	$\ln^2 Land$	−0.034	β_{45}	ln$K$ ln$L$	0.006
β_{23}	ln$E$ ln$Land$	−0.069			
β_{24}	ln$L$ ln$Land$	0.041	β_{55}	$\ln^2 K$	0.038
β_{25}	ln$K$ ln$Land$	0.03			

Note: M indicates intermediate consumption; *Land*—utilized agricultural area; E—energy; L—labour force; K—capital consumption; t—time trend intensification of the agricultural practices. The elasticities add up to 0.989, indicating that the technology is an almost constant returns to scale one. The time trend is positive, implying a 1.6% annual growth in productivity. As we apply the translog production function, the observation-specific elasticities can also be recovered due to its flexibility.

The coefficients on input and trend interactions identify the technical bias associated with different inputs. Specifically, a positive value is observed for materials (intermediate consumption) and trend interaction, which indicates materials-using technical change. Therefore, biochemical-based development is possible for EU agriculture. All the other interactions of inputs and trend show negative signs.

Technical efficiency is estimated following Eq. (3.70). The results are depicted in Fig. 3.7. The distribution of the efficiency scores in 1995 was wider than that in 2017. Also, the mean value shifted to the left during 1995–2017, indicating a decline in the technical efficiency level. Therefore, it is important to identify the trends in efficiency and possible sources of growth in EU agriculture.

Besides the distributions for the fixed time points, one can consider the evolution of the coefficient of variation for the efficiency scores. This allows the intertemporal dynamics in the cross-country patterns of efficiency to be described. Specifically, this type of measure allows it to be ascertained whether there has been σ-convergence. The dynamics in the coefficient of variation for the TE scores of the EU member states is depicted in Fig. 3.8.

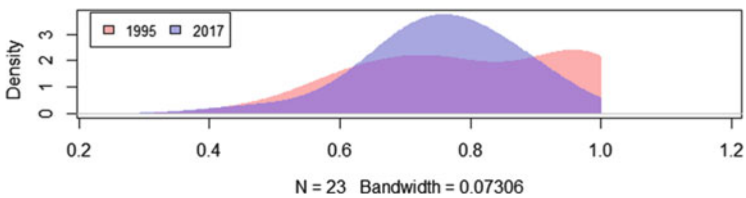

Fig. 3.7 Density plots for TE scores for 1995 and 2017

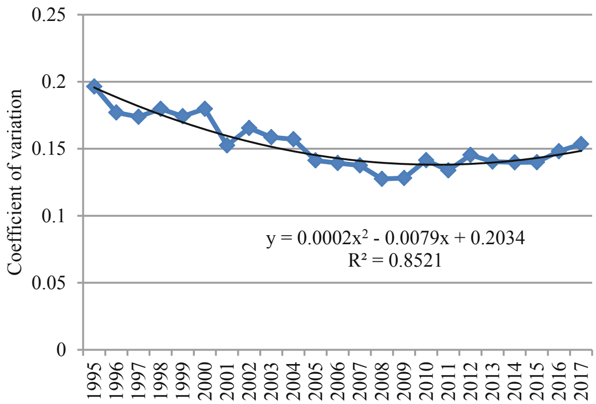

Fig. 3.8 Coefficient of variation for the TE scores, 1995–2017

The coefficient of variation followed a U-shaped trend, which indicates that there had been convergence in terms of the efficiency scores, yet this trend was reversed in recent years. The period of convergence is 1995–2009, whereas the years 2010–2017 mark a slight increase in the coefficient of variation. This may be the result of economic crisis and changes in the international markets that made certain countries less competitive and agricultural markets. Also, the investments have intensified (especially in the new EU member states), which can also reduce the TE if the investments are not fully exploited. Anyway, the coefficient of variation had not reached the initial value of 1995 as of 2017. Thus, convergence has been achieved, but a certain rebound effect is also evident for the agricultural sectors of the EU member states.

The dynamics in the average TE for the EU member states is exhibited in Fig. 3.9. The trend in the average TE follows an inverse U shape. Thus, the average efficiency tended to increase during 1995–2008 and declined thereafter. The level of 2017 is lower than that of 1995. This confirms the findings presented in Fig. 3.7. Given that the coefficient of variation tended to increase during the period of decline in the TE, one can assume that a certain group of countries were responsible for the decline in the average TE.

The country-specific TE levels are presented in Table 3.2. Spain and the UK exhibit average efficiency scores exceeding 90%. Both of these countries also show negative trends in their efficiency scores. The next group of countries include those exhibiting efficiency scores belonging to the interval of 80–90%: France, Greece, Italy, Slovenia, Denmark, Lithuania, Belgium, Estonia, Slovakia, and Ireland. Most of these countries also show negative trend coefficients for their efficiency scores. This can explain the decline in the average efficiency scores for the EU member states over the period 1995–2017. The lowest efficiency scores were observed for Sweden, Latvia, and Finland. The case of Finland can be explained by the high land, materials (intermediate consumption), and energy intensity prevailing in the agricultural production there.

Fig. 3.9 Dynamics in the average TE, 1995–2017

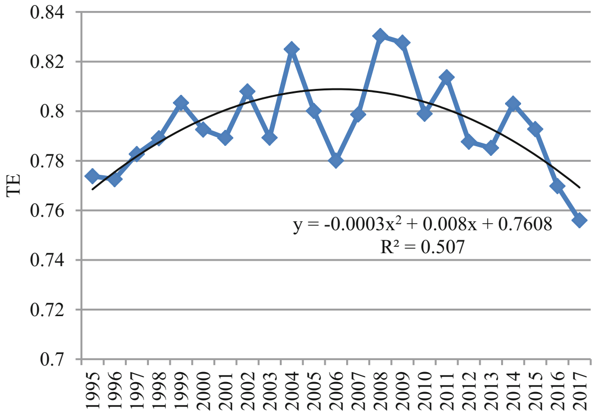

Table 3.2 Average efficiency scores for 1995–2017

Country	Average	Trend
Spain	0.939	−0.0015
UK	0.927	−0.0094
France	0.887	−0.0055
Greece	0.883	−0.0021
Italy	0.877	0.0019
Slovenia	0.862	−0.0072
Denmark	0.855	−0.0020
Lithuania	0.846	0.0022
Belgium	0.830	0.0097
Estonia	0.826	−0.0042
Slovakia	0.824	0.0118
Ireland	0.820	−0.0075
Bulgaria	0.799	0.0062
Average	0.794	0.0000
Portugal	0.788	−0.0048
Netherlands	0.779	−0.0039
Poland	0.765	0.0047
Romania	0.765	0.0050
Hungary	0.738	0.0019
Austria	0.732	−0.0015
Czechia	0.715	0.0018
Sweden	0.667	0.0074
Latvia	0.665	−0.0015
Finland	0.482	−0.0007

Note that the measure of the technical efficiency does not provide enough information to identify the trends in the profitability. Specifically, the technical efficiency addresses the conversion of inputs into outputs. In our case, the total agricultural output is considered the sole output of the productive technology. Therefore, even inefficient countries may face higher profitability levels in the case of favourable price patterns.

As previously mentioned, the translog production function is a flexible one. Therefore, one can analyse the patterns of the elasticities. Figure 3.10 presents the dynamics in the average elasticities for inputs throughout 1995–2017. The materials elasticity of output was the highest one throughout the whole period covered and showed a positive trend. This indicates that the use of materials (including biochemical ones) is gaining more importance in the agricultural process. Therefore, the development of agricultural practices involving reasonable use of biochemicals and fertilizers remains an important topic for research and development in agriculture. In this regard, precision agriculture should be further promoted to meet the goals of economic growth and sustainability.

The second-highest elasticity is observed for energy. It showed a positive trend with a slight decline after the year 2010. Labour elasticity declined over time even

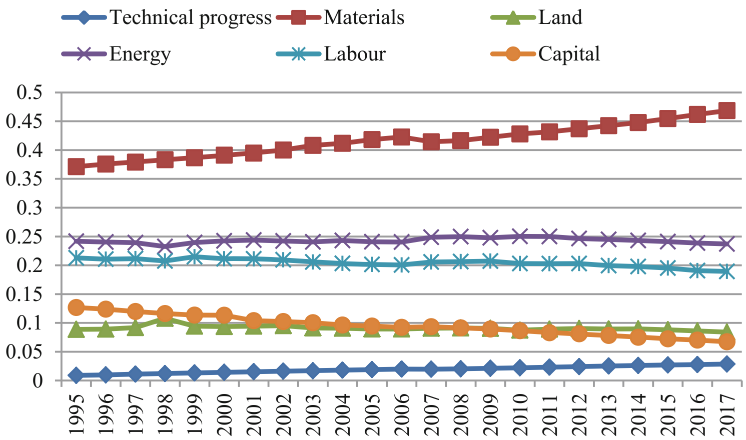

Fig. 3.10 Dynamics in the average elasticities in the EU member states, 1995–2017

though the rate of change was rather meagre. The capital elasticity of output showed the steepest decline, indicating that overinvestment may pose a problem for further development of the agricultural sectors in the EU. Therefore, these findings can shed light on the limits for growth of agriculture and possible solutions to these challenges.

The average elasticities were also calculated across the countries. The resulting estimates are presented in Fig. 3.11. In this figure, the countries are arranged in increasing order of the elasticity of scale. Therefore, Poland, France, the Netherlands, Spain, and Italy show decreasing returns to scale, whereas the other countries exhibit increasing returns to scale. The highest values of scale elasticity are observed for Estonia, Slovakia, and Slovenia. In general, countries with increasing returns to scale face restrictions on input use and could expand their production to the highest extent by intensifying input use. The countries with low values of scale elasticity could reduce their input consumption in general.

The output elasticities can also be compared to the relevant first-order coefficients. For instance, the first-order coefficient for materials use is 0.42. As one can see in Fig. 3.10, the average materials consumption elasticity of output goes up from 0.37 to 0.47. Therefore, from 2011 onwards, the materials use elasticity of output exceeded the value of the first-order coefficient. Thus, the technological knowledge and input endowments contributed to increasing productivity of materials use, and the overall effect (input elasticity of output) exceeded the direct effect represented by the first-order coefficient.

The contributions of input elasticities towards scale elasticity in Fig. 3.11 indicate which inputs are the most important ones in expanding the agricultural output. In general, one can see that land and materials elasticities are basically uniform across the countries. The energy elasticity and labour elasticity of output increase with the scale elasticity. In contrast, the capital elasticity of output declines with the increasing scale elasticity. These findings suggest that the EU member states vary in their

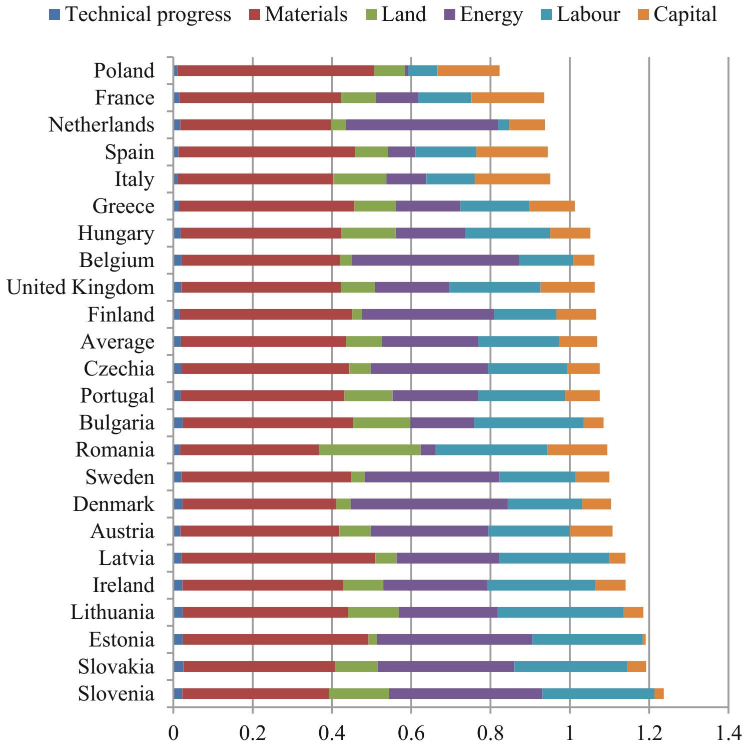

Fig. 3.11 Average input elasticities of output across the EU member states, 1995–2017

access to energy, labour, and capital inputs. The countries with the highest capital elasticity (mostly the old EU member states) face relatively low energy and labour elasticities of output, thus suggesting that the new member states have benefited from investment support payments under the CAP to a substantial effect. The misalignments in the input elasticities existing among the EU member states are likely to result in changes in the input prices and, eventually, reallocation of certain inputs. However, the labour input may be related to the inflow of labour force from third countries and no significant changes in the labour input price in the short run.

Convergence in technologies can be measured by considering the coefficient of variation (CV) for the elasticities associated with the production factors. Figure 3.12 presents the trends in the CVs for inputs that show the σ-convergence across the EU member states. The steepest increase in the CV was observed for the capital input. This suggests that the EU member states tended to increase their differences in terms of the capital elasticity over the period 1995–2017. These differences can be partially attributed to the differences in the investment support measures as the new member states were subject to such support, whereas the old ones did not benefit from such measures. The expanding gap in the capital elasticities of output suggests that the

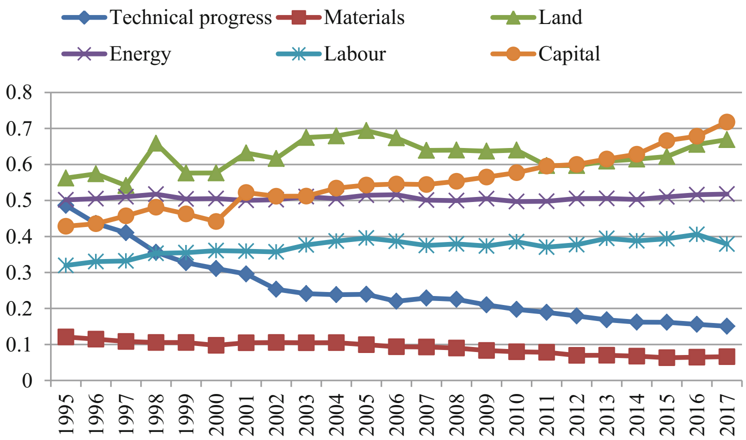

Fig. 3.12 Coefficients of variation for input elasticities of output, 1995–2017

investment support measures and CAP in general require revision in order to ensure proper resource allocation.

Land and labour also showed increasing divergence in terms of the output elasticities. However, this resulted in less pronounced changes than was the case with the capital input. Therefore, labour is becoming a limiting factor for some countries, which calls for reasonable changes in the production technology (e.g. mechanization or automatization). However, this is currently a problematic issue as the capital elasticity of output seems to be lower in countries with high labour elasticity of output (cf. Fig. 3.11).

The estimation of the parametric deterministic production function for the selected EU member states showed that the countries differ in terms of the technical efficiency levels and the input elasticities of the outputs. The trend of the average efficiency was also not desirable as a decline was observed for the period 2009–2017. The divergence in terms of elasticities related to certain inputs (especially capital) further confirms that the countries face resource misallocation.

3.5.2 *The OLS-Based Production Frontier*

Production technology can be represented by different production functions. They can differ in terms of the functional form and the estimators. Therefore, we further compare the deterministic translog production function based on linear programming (Table 3.3) to the simple ordinary least squares (OLS) estimators of both Cobb–Douglas and translog production functions. The ridge regression is applied for the translog production function to check the effects of multicollinearity. In addition, nonparametric regression is invoked to allow for a fully flexible production frontier.

Table 3.3 OLS estimates of the Cobb–Douglas production function

Variable	Estimate	Std error	*t* value	Pr(>|*t*|)	Sig.
(Intercept)	0.019959	0.010252	1.947	0.0521	.
ln*M*	0.696382	0.020562	33.868	<0.0001	***
ln*Land*	0.009536	0.014361	0.664	0.507	
ln*E*	0.094742	0.011152	8.496	<0.0001	***
ln*L*	0.155827	0.010298	15.132	<0.0001	***
ln*K*	0.112265	0.01361	8.248	<0.0001	***
t	0.012662	0.00123	10.291	<0.0001	***
t^2	0.000203	0.000199	1.021	0.3078	

Note: *** indicates significance at the 0.1% level of significance; . indicates significance at the 10% level of significance; *M* indicates intermediate consumption; *Land*—utilized agricultural area; *E*—energy; *L*—labour force; *K*—capital consumption; *t*—time trend

The OLS models involve random error in estimation as the dependent variable is assumed to be a random variable. This implies that the resulting estimates of the production function are stochastic (e.g. the statistical hypotheses can be tested in regard to regression coefficients). However, from the viewpoint of efficiency analysis, OLS can be regarded as an instance of the deterministic efficiency analysis methods as the whole error term in the regression model corresponds to the random error. In this context, one can recall the stochastic frontier analysis (Aigner et al. 1977) that decomposes the error term into statistical noise and an inefficiency term. At the other end of the spectrum, the modified OLS fully attributes the (modified) error term to inefficiency.

The data are pooled across time periods. The resulting estimates of the Cobb–Douglas production frontier (based on OLS) are given in Table 3.3. The Cobb–Douglas functional form entails sample-specific (rather than observation-specific) elasticities; i.e., this functional form is not flexible. As one can see, the highest output elasticity is observed with respect to the intermediate consumption (almost 0.7), which is consistent with Fig. 3.10 where intermediate consumption is also attached to the highest importance in terms of the generation of the agricultural output. Labour, capital, and energy inputs show lower output elasticities ranging between 0.09 and 0.15. These inputs are not ranked in the same order among themselves as in the case of the deterministic translog function. This can be explained by the differences in the two functional forms and constraints on the regularity of the translog function in the deterministic setting. Still, the coefficient for the land input is not significantly different from zero in the case of the Cobb–Douglas OLS model, which corresponds to the low elasticity observed in Fig. 3.10. The OLS model suggests linear technical progress occurring at the rate of 1.27% per year. This indicates that the output increases by this margin each year if the input level remains fixed. Note that the second-order coefficient for the time trend is not significant.

OLS is also applied to estimate the translog production function (Table 3.4). As this is a flexible functional form, we will not embark on a detailed analysis of the observation-specific elasticity. Instead, we consider the first-order coefficients that indicate output elasticity with respect to inputs at the sample mean (as all the

Table 3.4 OLS estimates of the translog production function

Variable	Estimate	Std error	t value	Pr(>|t|)	
(Intercept)	−0.0248	0.012303	−2.015	0.044411	*
ln$M$	0.509383	0.036116	14.104	<2e-16	***
lnLand	0.091697	0.024116	3.802	0.000161	***
ln$E$	0.020347	0.019022	1.07	0.285293	
ln$L$	0.205256	0.016666	12.316	<2e-16	***
ln$K$	0.222693	0.018733	11.888	<2e-16	***
I(0.5 * ln$M$^2)	−0.21485	0.093738	−2.292	0.022328	*
I(0.5 * ln$Land$^2)	0.216692	0.067447	3.213	0.001401	**
I(0.5 * ln$E$^2)	−0.0934	0.032441	−2.879	0.004163	**
I(0.5 * ln$L$^2)	0.172334	0.03658	4.711	3.21E-06	***
I(0.5 * ln$K$^2)	0.010827	0.051211	0.211	0.832642	
I(ln$M$ * ln$Land$)	−0.1426	0.075109	−1.899	0.058217	.
I(ln$M$ * ln$E$)	0.166276	0.058315	2.851	0.004537	**
I(ln$M$ * ln$L$)	−0.05729	0.047183	−1.214	0.225283	
I(ln$M$ * ln$K$)	0.02207	0.053489	0.413	0.680076	
I(lnM * Yr)	−0.00104	0.004368	−0.238	0.811934	
I(ln$Land$ * ln$E$)	−0.19897	0.038994	−5.102	4.81E-07	***
I(ln$Land$ * ln$L$)	−0.07957	0.042812	−1.858	0.063702	.
I(ln$Land$ * ln$K$)	0.334064	0.065023	5.138	4.03E-07	***
I(ln$Land$ * Yr)	−0.00565	0.002642	−2.138	0.032973	*
I(ln$E$ * ln$L$)	0.064703	0.020833	3.106	0.002008	**
I(ln$E$ * ln$K$)	−0.02328	0.038185	−0.61	0.542351	
I(ln$E$ * Yr)	−0.00238	0.002243	−1.059	0.290075	
I(ln$L$ * ln$K$)	−0.13351	0.037537	−3.557	0.000412	***
I(ln$L$ * Yr)	0.006132	0.001913	3.205	0.00144	**
I(ln$K$ * Yr)	0.000421	0.002437	0.173	0.863039	
Yr	0.016087	0.001322	12.167	<2e-16	***
I(0.5 * Yr2)	0.000439	0.000361	1.217	0.224177	

Note: significance codes: *** 0.001, ** 0.01, * 0.05, . 0.1; M indicates intermediate consumption; $Land$—utilized agricultural area; E—energy; L—labour force; K—capital consumption; Yr—time trend

variables are mean-scaled). Again, the output elasticity of intermediate consumption is the highest among those for the other inputs. Specifically, the estimates indicate that an increase in the intermediate consumption of 1% renders a 0.51% increase in the agricultural output at the sample mean. The second-highest elasticity is observed for the capital input (0.22). Then, labour input shows elasticity of 0.21 (at the sample mean). Output elasticity with respect to land is 0.09 in the translog OLS model. Finally, the first-order coefficient for energy input is not significantly different from zero. In general, 19 out of 28 coefficients estimated are significant. Thus, the translog model indicates a higher impact of the land input in the agricultural production process if compared to the case of the Cobb–Douglas production function, yet the role of the energy consumption declines when switching from the Cobb–Douglas to the translog production function.

3.5.3 Nonparametric Production Frontier

The production function can be estimated by means of nonparametric regression. Nonparametric regression is a locally weighted (usually linear) regression as proposed by Racine and Li (2004). It does not require specification of the underlying functional form for the estimation (Li and Racine 2007). In practice, nonparametric regression can be implemented by such packages as np (Hayfield and Racine 2008).

Nonparametric regression has been used for the analysis of production frontiers by, among others, Martins-Filho and Yao (2007). Furthermore, Lee et al. (2014) proposed imposing monotonicity conditions on the representation of the productive technology estimated via nonparametric regression. This makes nonparametric regression similar to the deterministic approaches that easily impose the desirable economic axioms onto the frontier models. Fan et al. (1996) suggested using nonparametric regression to estimate the deterministic part of the production frontier and invoked stochastic frontier analysis to decompose the resulting error term. Such an approach allowed for both the inefficiency term and the random error in the nonparametric setting. In order to further improve the approach of Fan et al. (1996) by adopting the virtues of the deterministic approaches while ensuring stochastic handling of the inefficiency term, Martins-Filho and Yao (2015) proposed employing the profile likelihood approach. Czekaj and Henningsen (2013) applied panel nonparametric regression models for Polish farm data in order to estimate production frontiers. For a more detailed study on the use of nonparametric regression for productivity analysis, one can refer to Henderson and Parmeter (2015).

Nonparametric regression entails a flexible production frontier with a gradient that may vary across observations. The kernels are used for weighting the observations. The kernels can be Gaussian, Epanechnikov, uniform, or in other forms. Kernels can also accommodate ordered or discrete data. In order to construct the production frontier, a continuous Gaussian kernel for the input data can be applied, whereas the time trend can be handled by the Li-Racine kernel for the ordered discrete data (Li and Racine 2007). The generalized kernel (De Witte and Kortelainen 2013) is formed as a product of the different kernels. The values of the kernel function depend on the distance between two data points and the bandwidth parameter that scales the distance. The bandwidth parameter can be estimated by the means of the least squares cross-validation procedure (Li and Racine 2008; Li et al. 2013). In general, smaller values of the bandwidth imply that the regression is estimated in the vicinity of an observation (which leads to an increasing curvature), and larger values suggest that the whole sample is taken into account (which implies a decreasing curvature and approaching OLS). The regression coefficients for observation x are estimated by considering its neighbourhood via the locally linear estimator:

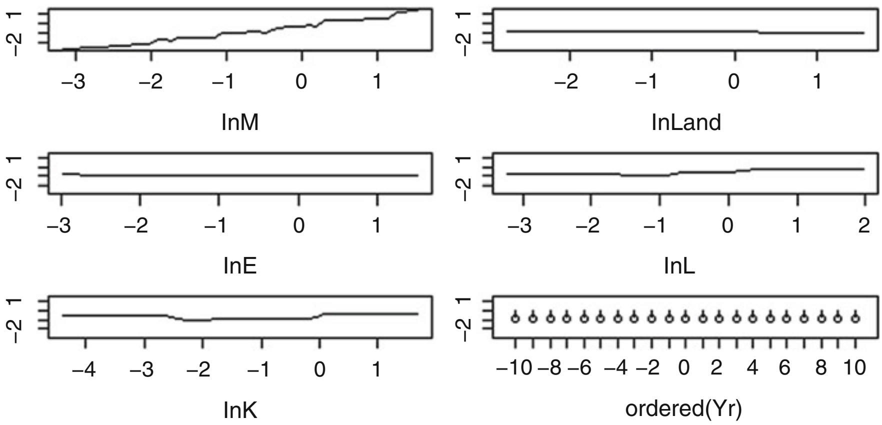

Fig. 3.13 Partial means of the nonparametric production function

$$\min_{a,b} \sum_{k,t} \left(y_{kt} - a - (x_{ikt} - x_i)'b\right)^2 K\left(\frac{x_{kt} - x}{h}\right), \tag{3.71}$$

where a is the observation-specific intercept and b is the observation-specific vector of the regression coefficients, $K(\cdot)$ is the generalized kernel, and h is the bandwidth parameter. Nonparametric regression is further applied to the sample of European countries (k and t are indexes for countries and time periods, respectively). The inputs considered in the deterministic and OLS models are used in the nonparametric model as well.

The results of the nonparametric regression cannot be given in the same way as in the case of the parametric analysis as the nonparametric regression's coefficients vary across the observations. Figure 3.13 presents the partial means of the nonparametric production frontier. Note that the partial means for each input variable and output combination are depicted by keeping the rest of the inputs at their median/modal values. Therefore, the plots in Fig. 3.13 are combinations of a certain input quantity and the estimated value of the nonparametric production function, $\left(x_i, \widehat{f}\left(x_i, \overline{x}_{(-i)}\right)\right)$. The agricultural output increases with the values of the intermediate input. This suggests an almost linear relationship between intermediate consumption and agricultural output. Land and energy consumption show no clear contribution towards the agricultural production. Labour seems to make a positive contribution to the level of agricultural output. The relationship between capital input and agricultural output follows a U-shaped function. Finally, the time trend shows an increasing contribution towards agricultural output over time. Indeed, this partly confirms the results rendered by the OLS models where either land or energy input appeared to be insignificant depending on the functional form of the production function.

The significance of the regression coefficients resulting from the locally linear estimation can be tested using the bootstrap approach (Racine et al. 2006). This

Table 3.5 Bootstrap-based test of the significance for the nonparametric production function

Variable	*P* value	Sig.
ln*M*	<2.22e-16	***
ln*Land*	0.345865	
ln*E*	0.12782	
ln*L*	0.002506	**
ln*K*	<2.22e-16	***
ordered(*Yr*)	<2.22e-16	***

Signif. codes: *** 0.001, ** 0.01

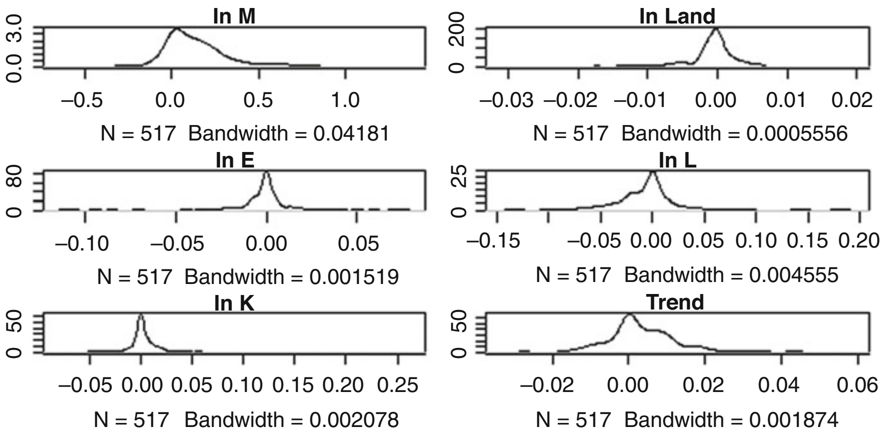

Fig. 3.14 Kernel density plots for the gradients of the nonparametric production function

allows the partial mean plots to be supplemented with probabilities that more extreme estimates of the gradients (coefficients) can be observed. The results of the nonparametric significance test are provided in Table 3.5. As previously suggested by the partial mean plots, the land and energy inputs are not significant at any acceptable level of significance. Intermediate consumption, labour, capital, and time trend are all significant at the 1% level of significance.

The gradients of the nonparametric regression correspond to the local coefficients of the slope in Eq. (3.71), i.e. $\partial\widehat{f}\left(x_i, \overline{x}_{(-i)}\right) / \partial \ln x_i$. The kernel density plots for gradients associated with the inputs in the nonparametric production frontier for the agricultural sectors of the selected European countries are depicted in Fig. 3.14. As one can see, partial mean plots and gradient distributions need to be considered simultaneously in order to assess the significance of the relationship between a certain input and output. For instance, the case of the capital input is related to a U-shaped relationship with the output level, yet the gradient plot would just indicate a distribution around zero value (the bootstrap-based test of significance confirms this as a significant relationship).

3.5.4 Production Frontier Based on the Ridge Regression

The production functions typically include a number of inputs as explanatory (independent) variables. The number of independent variables increases in the case of flexible functional forms, e.g. the translog function. In the translog specification, one considers products of input quantities among other variables. This may render a multicollinearity problem and inflate the coefficients. In order to circumvent this issue, the penalization approach can be utilized to control for the magnitude of the regression coefficients.

Zou and Hastie (2005) presented the elastic net that allows the linear regressions' coefficients to be adjusted with respect to the penalty factor. As reported by Friedman et al. (2010), the following problem is solved to obtain the elastic net coefficients (assuming the data are standardized):

$$\min_{\beta_0,\beta}\left(\frac{1}{KT}\sum_{k,t}\left(y_{kt}-\beta_0-x'_{kt}\beta\right)^2+\lambda P_\alpha(\beta)\right), \tag{3.72}$$

where K and T are the number of countries and time periods in the analysis, (x_{kt}, y_{kt}) are the observed data, $P_\alpha(\beta)$ is the penalization term that renders either lasso or ridge regression, and λ is the coefficient for the penalization term. The penalization term is defined as follows (Friedman et al. 2010):

$$\begin{aligned} P_\alpha(\beta) &= (1-\alpha)\|\beta\|_{\ell_2}^2+\alpha\|\beta\|_{\ell_1} \\ &= \sum_{i=1}^{m}\left(\frac{1}{2}(1-\alpha)\beta_i^2+\alpha|\beta_i|\right). \end{aligned} \tag{3.73}$$

The coefficient, α, picks either lasso regression ($\alpha = 0$) or ridge regression ($\alpha = 1$). Note that the Euclidean norm penalizes the largest values, whereas the city block norm treats all the values equally. As a result, the ridge regression tends to affect the coefficients that are correlated by keeping them equal, whereas the lasso regression scales down as many coefficients as possible. The ridge regression was used by Lin and Liu (2017) and Lin and Ahmad (2016) when analysing the energy and economic performance.

Ridge regression is applied to estimate the translog production frontier, which is more likely to suffer from multicollinearity than the Cobb–Douglas one. The estimation of the ridge regression requires choosing the value of parameter λ that indicates the importance of penalization. The changes in the coefficients of regression with the values of λ are given in Fig. 3.15. The numbers at the top of the figure suggest that the number of nonzero coefficients remains constant with the values of the tuning parameter (this is the outcome of the ridge regression, which does not push coefficients to zero as happens in the lasso regression).

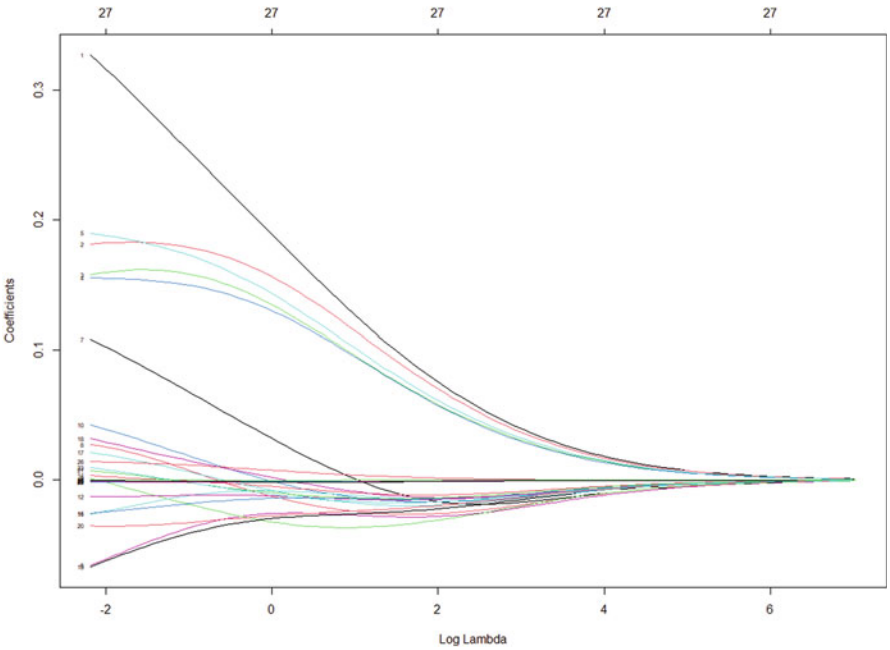

Fig. 3.15 Ridge regression coefficients across the values of the tuning parameter

The tuning parameter is related to the cross-validated error in Fig. 3.16. Obviously, the error increases with the values of the tuning parameter. Therefore, the optimal value of the parameter that minimizes the error is chosen around the value of $\exp(-2)$. Thus, this value is imputed into Eq. (3.72) when estimating the ridge regression.

The resulting estimates of the ridge regression are provided in Table 3.6. As one can see, the first-order coefficients representing elasticities at the sample mean become much more similar to each other if compared to the case of the OLS estimation (Table 3.4). The coefficient for intermediate consumption remains the highest one, indicating that the use of the intermediate inputs provides the major source of growth in the agricultural output. If compared to the case of the OLS estimates, the ridge regression first-order coefficient for the intermediate inputs drops from 0.51 to 0.33. The highest increases in the values of the first-order coefficients are observed for land and energy, which increase more than twofold when switching from the OLS regression to the ridge regression. The capital input appears to be the least affected in terms of the magnitude of the associated first-order coefficient. In general, the ridge regression suggests that energy and labour inputs play less important roles than the other inputs in the generation of agricultural output (at the sample mean). Thus, the changes in the regression coefficients due to penalization implied by the ridge regression are more of a quantitative nature rather

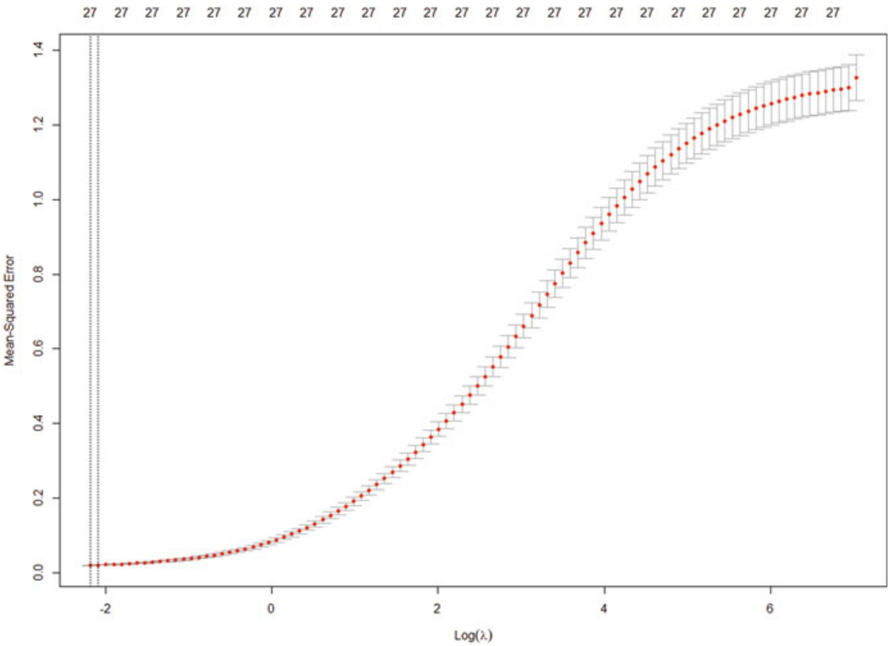

Fig. 3.16 Cross-validation error across the values of the tuning parameter

Table 3.6 Estimates of the ridge regression

Coefficient	Variable	Estimate	Coefficient	Variable	Estimate
β_0	Intercept	0.027313	β_{t1}	t ln$M$	−0.00071
			β_{t2}	t ln*Land*	−0.00055
β_1	ln$M$	0.327936	β_{t3}	t ln$E$	−0.00164
β_2	ln*Land*	0.1807	β_{t4}	t ln$L$	−0.00087
β_3	ln$E$	0.157875	β_{t5}	t ln$K$	−0.00045
β_4	ln$L$	0.155093			
β_5	ln$K$	0.190048	β_t	t	0.014311
			β_{tt}	t^2	0.000122
β_{11}	ln^2M	−0.07246			
β_{12}	ln*Land* ln$M$	−0.02422	β_{33}	ln^2E	0.025416
β_{13}	ln$E$ ln$M$	−0.00952	β_{34}	ln$L$ ln$E$	−0.03635
β_{14}	ln$L$ ln$M$	−0.06424	β_{35}	ln$K$ ln$E$	0.006788
β_{15}	ln$K$ ln$M$	0.004849			
			β_{44}	ln^2L	0.001057
β_{22}	ln^2*Land*	0.104543	β_{45}	ln$K$ ln$L$	0.008559
β_{23}	ln$E$ ln*Land*	−0.02524			
β_{24}	ln$L$ ln*Land*	0.021815	β_{55}	ln^2K	0.042874
β_{25}	lnK ln*Land*	0.031285			

Note: M indicates intermediate consumption; *Land*—utilized agricultural area; E—energy; L—labour force; K—capital consumption; t—time trend than inducing qualitative shifts. In this model, the trend is ignored as it does not necessarily follow the regularity conditions.

3.5.5 Restricted Regression-Based Production Function

Section 3.5.1 presented the deterministic parametric production frontier. The linear programme corresponding to the calculation of the coefficients for the production function (Eq. 3.69) can easily accommodate assumptions of monotonicity, etc. However, these assumptions may not hold when econometric techniques (e.g. OLS) are used. Different approaches have been suggested for imposing regularity on the parametric and nonparametric regression. The nonparametric regression and its extensions were discussed in Sect. 3.5.3. As regards the parametric regression, the procedure suggested by Henningsen and Henning (2009) can impose the regularity conditions while preserving the stochastic nature of the underlying production function.

The study by Henningsen and Henning (2009) proposed using quadratic programming in order to retrieve the restricted stochastic production frontier (based on the SFA) along with efficiency scores. However, one can also apply this approach without invoking the inefficiency term. In the case of the SFA, the proposed procedure comprises three steps: (1) estimation of the stochastic production frontier without regularity restrictions; (2) running a quadratic programming problem to obtain the restricted production function coefficients that are similar to the regression-based ones; and (3) re-estimation of the stochastic frontier by using the estimates from (2) for the deterministic part of the frontier. The adjustment of the OLS model with regard to the monotonicity constraints does not require step (3).

The procedure for the restricted production frontier fulfilling the regularity conditions begins with estimation of the OLS model:

$$y_{kt} = f(x_{kt}; \beta) + \varepsilon_{kt}. \tag{3.74}$$

Then, the estimates of the regression coefficients, $\widehat{\beta}$, and the covariance matrix, $\widehat{\Sigma}_{\beta}$, are used in the next stage when imposing the regularity conditions. A quadratic programming problem then finds a new vector of coefficients that minimizes the distance from the econometric estimates, $\widehat{\beta}$. The optimization is carried out by incorporating a set of monotonicity restrictions, i.e. letting the first-order derivatives of the production functions be non-negative. Thus, the quadratic programming problem is established as follows:

Table 3.7 Estimates of the ridge regression

Coefficient	Variable	Estimate	Coefficient	Variable	Estimate
β_0	Intercept	−0.0040	β_{33}	$\ln^2 E$	−0.0151
			β_{34}	$\ln L \ln E$	0.0109
β_1	$\ln M$	0.6918	β_{35}	$\ln K \ln E$	−0.0159
β_2	$\ln Land$	0.0442			
β_3	$\ln E$	0.0369	β_{44}	$\ln^2 L$	0.0496
β_4	$\ln L$	0.1238	β_{45}	$\ln K \ln L$	0.0131
β_5	$\ln K$	0.1794			
			β_{55}	$\ln^2 K$	−0.0145
β_{11}	$\ln^2 M$	−0.0592			
β_{12}	$\ln Land \ln M$	−0.0076	β_{22}	$\ln^2 Land$	−0.0136
β_{13}	$\ln E \ln M$	0.0490	β_{23}	$\ln E \ln Land$	−0.0305
β_{14}	$\ln L \ln M$	−0.0998	β_{24}	$\ln L \ln Land$	0.0217
β_{15}	$\ln K \ln M$	0.0593	β_{25}	$\ln K \ln Land$	0.0293

Note: *M* indicates intermediate consumption; *Land*—utilized agricultural area; *E*—energy; *L*—labour force; *K*—capital consumption; *t*—time trend

$$\begin{aligned}
&\widehat{\beta}_0 = \arg\min_{\beta_0} \left(\beta_0 - \widehat{\beta}\right)^T \widehat{\Sigma}_\beta \left(\beta_0 - \widehat{\beta}\right) \\
&\text{s.t.} \\
&f_i(x_{kt}; \beta_0) \geq 0, \forall i, k, t,
\end{aligned} \tag{3.75}$$

where $f_i(\cdot)$ is the first-order derivative of the production function with respect to the ith input. Henningsen and Henning (2009) also argue that this problem is superior to a single-step maximum likelihood exercise in that it avoids issues related to obtaining a consistent covariance matrix for $\widehat{\beta}_0$. Thus, the parameter vector resulting from optimization in Eq. (3.75) features both the stochastic nature of the regression-based estimation and the economically sound restrictions imposed in the programming problem.

The results of the procedure outlined above are given in Table 3.7. As one can see, the output elasticity of intermediate consumption at the sample mean is rather high (0.69). However, this value may be inflated due to the omission of the time trend in the model. Capital input appears as the second-most important in the sense of the output elasticity at the sample mean (0.18), whereas labour, land, and energy show lower levels of elasticity.

Kernel density plots are used to depict the distributions of the output elasticities (Fig. 3.17). Land and labour show distributions that are closer to the normal distributions if compared to those for intermediate consumption, energy, and capital. Capital and intermediate inputs show the most pronounced bi-modal distribution. This indicates that the European countries covered in the analysis tend to differ in the utilization of the factor inputs (i.e. the marginal productivity and, in turn, output elasticity differ across countries).

The average output elasticities for the countries analysed are provided in Table 3.8. As regards intermediate consumption, the lowest output elasticity is

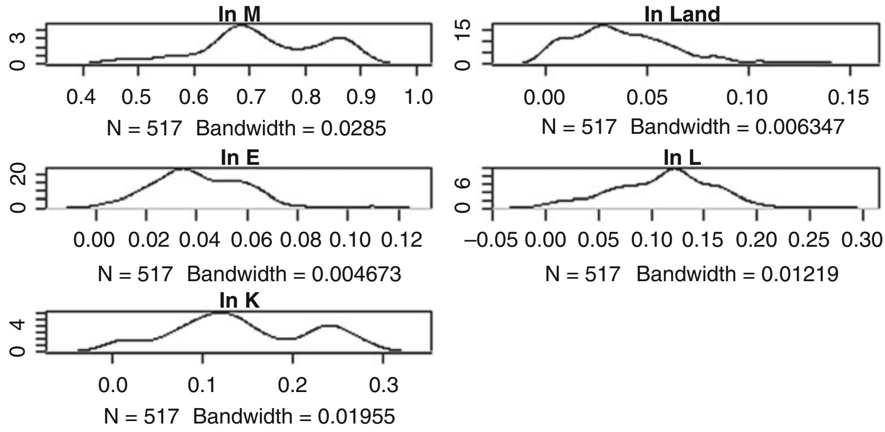

Fig. 3.17 Distributions of the output elasticities based on the restricted production function

Table 3.8 Output elasticities across countries (average values for 1995–2017) based on the restricted translog frontier

Country	Intermediate consumption	Land	Energy	Labour	Capital
Austria	0.874	0.007	0.050	0.046	0.079
Belgium	0.537	0.046	0.079	0.117	0.197
Bulgaria	0.776	0.019	0.037	0.088	0.129
Czechia	0.867	0.009	0.039	0.036	0.112
Denmark	0.813	0.012	0.029	0.149	0.011
Estonia	0.711	0.040	0.043	0.102	0.145
Finland	0.673	0.053	0.037	0.165	0.145
France	0.659	0.036	0.019	0.125	0.246
Greece	0.683	0.029	0.031	0.067	0.275
Hungary	0.684	0.068	0.031	0.125	0.226
Ireland	0.711	0.029	0.026	0.192	0.059
Italy	0.654	0.055	0.051	0.142	0.120
Latvia	0.633	0.057	0.057	0.119	0.185
Lithuania	0.863	0.005	0.064	0.014	0.127
Netherlands	0.814	0.046	0.023	0.121	0.103
Poland	0.569	0.028	0.041	0.163	0.241
Portugal	0.671	0.053	0.051	0.131	0.147
Romania	0.496	0.118	0.067	0.150	0.261
Slovakia	0.766	0.084	0.059	0.159	0.012
Slovenia	0.751	0.045	0.052	0.092	0.104
Spain	0.872	0.023	0.012	0.127	0.067
Sweden	0.861	0.009	0.018	0.091	0.093
UK	0.707	0.028	0.030	0.067	0.229

observed for Romania and Belgium, whereas countries such as Austria, Czechia, Lithuania, and Sweden show the highest output elasticity. Indeed, higher values of the output elasticity imply a shortage of a particular input. For land, the highest output elasticity is observed for Romania and Slovakia. Belgium shows the highest output elasticity with respect to energy. Poland and Slovakia are the countries with the highest output elasticity of labour. Romania, Poland, and Greece are the three countries with the highest output elasticity of capital. Therefore, different countries require improvements in different input levels.

3.5.6 Random Coefficients Model

The random coefficients model was proposed by Hildreth and Houck (1968) and Griffiths (1972). The empirical application to the agricultural sector is provided by Kalirajan et al. (1996). The random coefficients model assumes that the intercept and slope coefficients are distributed according to normal distribution with its parameters to be estimated. Essentially, this implies that the coefficients vary across the panels. In the case of this research, one can assume that the coefficients of the production function may vary across the countries.

Let there be indexes k and t for countries and time periods. The production function can be fitted for a certain country in an isolated manner. Thus, the country index is dropped from the notations used. Then, the pooled regression assumes the uniform slope and intercept coefficients across the observations:

$$\ln y_t = \alpha + \sum_{i=1}^{m} \beta_i \ln x_{it} + \varepsilon_t. \tag{3.76}$$

The random coefficient regression model can be defined by establishing the panel-specific slopes and intercepts and taking all the countries into consideration:

$$\ln y_{kt} = \alpha_k + \sum_{i=1}^{m} \beta_{ik} \ln x_{ikt} + \varepsilon_{kt}, \tag{3.77}$$

where α_k and β_k are the intercept and slope coefficients for country k, respectively. The coefficients are assumed to be distributed normally, i.e. $\alpha_k \tilde{N}\left(\alpha, \sigma_\alpha^2\right)$ and $\beta_k \tilde{N}\left(\beta, \sigma_\beta^2\right)$. The regression equation can be rewritten by separating the "systematic" parts of the coefficients and the random deviations:

$$\ln y_{kt} = \alpha + a_k + \sum_{i=1}^{m} \beta_i \ln x_{ikt} + \sum_{i=1}^{m} b_{ik} \ln x_{ikt} + \varepsilon_{kt}. \tag{3.78}$$

In this case, a_k and b_k denote the random effects associated with each panel that are distributed as $a_k\tilde{N}\left(0,\sigma_\alpha^2\right)$ and $b_k\tilde{N}\left(0,\sigma_\beta^2\right)$. The maximum likelihood approach is applied to estimate the parameters in Eq. (3.78). The R package lme4 implements the random coefficients model (Bates et al. 2007). The resulting estimates are presented in Tables 3.9 and 3.10.

The random coefficients model estimates the variances of the random coefficients along with the mean values for the fixed effects. The setting used for analysis of the agricultural production function assumes that all the coefficients in the model are random ones. The point estimates of the coefficients on the inputs suggest that output elasticity for material inputs is the highest among the inputs included in the production function. This corresponds to results obtained by other parametric models in this study. Labour and capital inputs also play an important role in the production process. The lowest importance is attached to the land and energy inputs. In general, positive technical progress is observed (1% per year).

As the mixed model involves both random and fixed coefficients, the expected posterior modes can be obtained for each coefficient. As we assume the coefficients

Table 3.9 Estimates of the random coefficients model (random effects)

REML criterion at convergence: −1586.9						
Scaled residuals:						
Min	1Q	Median	3Q	Max		
−3.9925	−0.4548	0.0455	0.5406	3.9983		
Random effects:						
Groups	Name	Variance	Std Dev.			
Country	(Intercept)	0.069131	0.26293			
	ln*M*	0.06482	0.2546			
	ln*Land*	0.023082	0.15193			
	ln*E*	0.012127	0.11012			
	ln*L*	0.02222	0.14906			
	ln*K*	0.021116	0.14531			
	Yr	0.000162	0.01273			
Residual		0.001414	0.0376			
Number of obs: 517, groups: c, 23						
Corr						
	(Intercept)	ln*M*	ln*Land*	ln*E*	ln*L*	ln*K*
ln*M*	0.48					
ln*Land*	−0.81	0.12				
ln*E*	−0.59	−0.07	0.63			
ln*L*	0.24	−0.73	−0.76	−0.44		
ln*K*	0.49	−0.43	−0.84	−0.33	0.81	
Yr	0.06	−0.64	−0.49	0.07	0.77	0.49

Table 3.10 Estimates of the random coefficients model (fixed effects)

Fixed effects						
	Estimate	Std error	*t* value			
(Intercept)	−0.04222	0.061908	−0.682			
ln*M*	0.482264	0.061955	7.784			
ln*Land*	0.070274	0.044733	1.571			
ln*E*	0.026642	0.028315	0.941			
ln*L*	0.158755	0.038524	4.121			
ln*K*	0.164042	0.040394	4.061			
Yr	0.010443	0.002826	3.695			
Correlation of fixed effects						
	(Intr)	ln*M*	ln*Land*	ln*E*	ln*L*	ln*K*
ln*M*	0.352					
ln*Land*	−0.474	0.03				
ln*E*	−0.442	−0.093	0.346			
ln*L*	0.305	−0.608	−0.577	−0.33		
ln*K*	0.416	−0.415	−0.586	−0.246	0.567	
Yr	0.104	−0.57	−0.323	0.098	0.721	0.33

vary across countries, Table 3.11 presents the expected mode for each country. As one can see, regularity conditions are not satisfied for all the countries. For instance, six countries show negative coefficients for land input, eight countries for energy input, one country for labour input, and two countries for capital input. The coefficients may indicate the possible presence of input congestion.

Looking at the coefficient of variation (CV), the highest variability is observed for the intercept and output elasticity of energy. The output elasticity of intermediate inputs is the only coefficient that does not get negative values across the countries. This coefficient shows the lowest CV. A relatively low CV is also observed for the output elasticity of labour. The trend coefficient is negative for three countries, namely Finland, Portugal, and Romania. However, the elasticities obtained from the random coefficients model differ from those based on the deterministic frontier (Fig. 3.11) or restricted model (Table 3.8). Therefore, the choice of the estimator needs to be made with caution in order to ensure robust results.

3.6 Conclusions

Analysis of the technical efficiency of the European agricultural sector suggests that there has been technical progress observed, yet the efficiency scores have declined. This indicates that a spillover of advanced farming technologies is needed in the EU. This can be achieved through the promotion of R&D activities within and among countries. The declining output elasticity with respect to capital suggests the need for further optimization of the levels of investment in European agriculture.

Table 3.11 Posterior mode estimates of the random coefficients for the production function

Country	(Intercept)	ln*M*	ln*Land*	ln*E*	ln*L*	ln*K*	*Yr*
Austria	0.3714	0.0962	−0.3544	−0.1555	0.6018	0.5147	0.0419
Belgium	−0.4299	0.1287	0.1840	−0.1137	0.2346	0.1029	0.0011
Bulgaria	−0.0813	0.3078	0.0266	0.0489	0.2474	0.2537	0.0176
Czechia	0.1328	0.4454	−0.0592	−0.0889	0.2743	0.2182	0.0168
Denmark	−0.4159	0.3072	0.2457	0.1177	0.0905	0.1332	0.0010
Estonia	−0.0343	0.3801	0.0245	0.0553	0.2055	0.3058	0.0090
Finland	0.3436	0.9271	−0.0060	−0.0990	0.0333	0.1815	−0.0115
France	0.3345	0.6992	−0.0906	−0.1073	0.1931	0.2170	0.0087
Greece	−0.0020	0.6728	0.1196	0.0430	0.0488	0.1087	0.0013
Hungary	0.1420	0.6905	0.0322	−0.0034	0.1006	0.1735	0.0032
Ireland	−0.1484	0.4734	0.1364	0.1417	0.1014	0.1698	0.0100
Italy	−0.0445	0.2335	−0.0271	0.0988	0.3026	0.3349	0.0254
Latvia	−0.1137	0.5157	0.1304	0.0837	0.1227	0.0362	0.0193
Lithuania	0.1395	0.7127	0.0427	0.0205	0.0840	0.1626	0.0040
Netherlands	−0.1367	0.4765	0.1299	0.0956	0.1204	0.1152	0.0130
Poland	0.0892	0.4776	−0.0178	−0.0616	0.2398	0.1559	0.0182
Portugal	−0.1255	0.5235	0.1413	−0.0281	0.0958	0.1145	−0.0031
Romania	0.1203	0.9316	0.1423	0.0120	−0.0515	−0.0078	−0.0038
Slovakia	−0.0265	0.6491	0.1263	0.1008	0.0554	0.0909	0.0089
Slovenia	−0.2030	0.2833	0.0967	0.1536	0.2243	0.1327	0.0312
Spain	−0.6324	0.2961	0.3834	0.2169	0.0180	−0.0404	0.0082
Sweden	−0.2016	0.2191	0.0702	0.0536	0.2583	0.2133	0.0195
UK	−0.0486	0.6450	0.1391	0.0282	0.0503	0.0861	0.0005
Average	−0.0422	0.4823	0.0703	0.0266	0.1588	0.1640	0.0104
Max	0.371	0.932	0.383	0.217	0.602	0.515	0.042
Min	−0.632	0.096	−0.354	−0.155	−0.052	−0.040	−0.011
StD	0.246	0.232	0.139	0.097	0.136	0.117	0.012
CV	−5.820	0.482	1.982	3.639	0.856	0.714	1.172

Indeed, the investment support available in the new EU member states needs to be streamlined in order to avoid excessive investments that do not contribute to increasing productivity. The deterministic frontier rendered results suggesting that Spain, the United Kingdom, France, Greece and Italy were the most efficient agricultural producers in 1995–2017. However, these countries also showed negative trends in the efficiency scores. As regards the underperforming cases, Austria, Czechia, Sweden, Latvia and Finland were identified. These countries feature relatively high energy intensity. Therefore, energy-intensive agricultural systems require further measures to increase their competitiveness and sustainability. Also, technological heterogeneity should be taken into account (by means of, e.g., latent class frontier models).

In this chapter, the panel data were pooled and treated as cross-sectional data. In such a setting, we were not able to isolate efficiency change and technical progress as the two key terms of productivity growth and assess their overall effect. This can be left for future studies employing (total factor) productivity indices and indicators. Yet another direction for research is identification of the determinants of efficiency. These could include output mix, subsidy rates, market integration, farm size, demographic characteristics of farmers, and macroeconomic conditions. Further studies are also required to check the environmental performance of the European agricultural sector. The present study only took into account the conventional output (agricultural output). The inclusion of the agricultural greenhouse gas emission, nutrient balance, biodiversity and similar agrienvironmental indicators provides yet another avenue for efficiency analysis. This can be implemented in a parametric or nonparametric manner. Multiple models are available that assume different directional functions and relationships between the desirable and undesirable outputs. These models need to be tested on an extended dataset describing performance of the European agriculture.

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Chapter 4
Structural Dynamics in Agriculture

Nelė Jurkėnaitė

4.1 Introduction

Structural changes contribute to the future course of economic growth and the well-being of society. Such changes are a complex phenomenon that fuels multidisciplinary academic research and contributes useful fragments of knowledge to the mosaic explaining evolutionary changes in economic systems. This chapter brings into the focus the changing role of agriculture in the EU economic system and investigates the ongoing evolution of the EU agricultural system for the years after the EU's 2004 enlargement.

This chapter follows the following structure. In Sect. 4.2, a review of the main methodological approaches towards the investigation of structural change is provided. The findings suggest that methodological frameworks vary greatly in terms of sophistication, applied data aggregation, and other important aspects. Thus, the selection of the method is highly dependent on the research objectives. Section 4.3 identifies two research objectives, explains the origin of the research data, describes the main principles of data aggregation, and provides a methodological research framework.

Section 4.4 focuses on an analysis of the changing role of agriculture, forestry, and fishing economic activity in the EU economy. Economic developments are observed, applying such measures of structural change as gross value added and employment. The main findings rely on several complementary methods, namely the monitoring of structural change indices; the analysis of changes in the shares of economic activities in the overall economy over the investigated period; and the outcome of shift-share analysis for agriculture, forestry, and fishing economic

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T. Baležentis et al., *Structural Change, Productivity, and Climate Nexus in Agriculture*, https://doi.org/10.1007/978-3-030-76802-7_4

activity in member states. The structural change dynamics of the main economic activities is examined both at the EU level and in individual member states.

Section 4.5 examines structural changes within the EU agricultural system, applying an original index decomposition analysis identity that allows the changes in the average farm size to be decomposed into contributions of structural components and pure farm size. The changes in the EU agricultural system are investigated, applying such measures of farm size as the utilized agricultural area, the standard output, and the directly employed labour force. The proposed research framework allows us to monitor structural changes at the EU, member state, and farming type levels.

The empirical results from Sects. 4.4 and 4.5 evidence that the pace and directions of structural changes in individual member states vary significantly. Although many member states demonstrate similar development trends that fall in line with the key directions at the EU level, some deviations from the general rule often take place. For this reason, Sect. 4.6 presents a discussion on the key driving forces of change in the EU agricultural system during the investigated period. Section 4.7 summarizes the most important findings and discusses applications of the research results.

4.2 Review of Structural Change Research in Agriculture

4.2.1 Measuring Structural Change

Evolutions of economic systems and the ongoing structural changes attracted academic interest around the world. The complexity of the structural change phenomenon has encouraged the emergence of multiple research questions and resulted in a wide-ranging choice of methodological research frameworks. In fact, many of those frameworks continue to develop into more sophisticated techniques and models. Although the following review provides a non-exhaustive list of the previous studies on structural changes, the brief outline gives guidelines on the important directions of the methodological developments in this academic research niche.

Structural changes are explained as changes in economic systems in terms of the total size, and the redistribution of economic activities and resources. Although the list of indicators enabling structural changes to be investigated is long (Lankauskienė and Tvaronavičienė 2013), different types of measures related to change in value added and employment are the most frequently applied (van Neuss 2019). Consequently, a considerable number of studies have developed and employed indices to measure structural change. In most academic studies, these structural change indices (SCIs) do not deal with change agents and such methodological frameworks are classified as ex post techniques. In this respect, it is worth noting that some academics go beyond and provide the forecasted values.

The reviewed studies show that structural changes are measured by applying various SCIs that quantify the pace of changes between reference years. The sophistication of applied indices, the level of data aggregation, and other important aspects of the selected methodological frameworks result in different research limitations; thus, the selection of such indices depends on the aims of the research. Examples of indices allowing structural change to be examined are provided in Moore (1978), Lilien (1982), the Productivity Commission (1998, 2013), Bessonov (2002), Wolff (2002), Pannell and Schmidt (2006), the OECD (2007), Dietrich (2009, 2012), Connolly and Lewis (2010), Brakman et al. (2013), etc.

It should be noted that the research objectives and applied methodological frameworks of the aforementioned studies differ. Moore (1978) suggests a SCI to measure the composition of the output. Lilien (1982) proposes a model for the analysis of shifts in employment demand, while Dietrich (2009, 2012) introduces a modified Lilien index allowing the measurement of structural change. Wolff (2002) proposes three measures of structural change complementing each other: (1) an index that monitors structural changes in occupation; (2) an index that observes changes in interindustry technical coefficients; (3) an index that demonstrates the changes in capital coefficients of the investigated industries. Brakman et al. (2013) propose using the Harmonic Mass Index in order to map periods of structural changes. Pannell and Schmidt (2006) investigate structural changes by reconciling labour in agriculture with the tertiary-to-secondary ratio.

Different variations of simple but informative SCIs, allowing the pace of change in the overall economy to be measured, are applied in the Productivity Commission (1998, 2013), Bessonov (2002), the OECD (2007), Connolly and Lewis (2010), and Dietrich (2009, 2012). These indices could be applied to monitor reallocation changes in both output and input structures. However, the aggregated indices that observe changes in the entire economic system often hide the leading and stagnating individual economic activities that determine growth or recession with their heterogeneous contributions. Furthermore, these SCIs are sensitive to the level of aggregation and the selected investigation period (Productivity Commission 2013). Thus, the subsequent disaggregated analysis provides more detailed knowledge about the role of economic activities in the overall economic performance and growth. According to van Neuss (2019), the analysis of the evolution often relies on changes in shares of sectors in the entire economic system.

Another important academic research niche is the application of index decomposition analysis (IDA) to observe structural transformations. This technique is relatively new as it emerged in the early 1980s and was used to investigate electricity consumption (Ang 2015). Since then, this niche has attracted considerable contributions to methodological developments, while the scientific area of the application has expanded. The IDA approach allows relative impacts of structural changes on the entire system and the structural components to be studied. Although numerous studies use IDA models for ex post analysis, some attempts to employ these models for forecasting purposes were made in recent studies.

In most of the academic studies, the IDA model investigates structural changes of the entire economic system, whereas agriculture is treated as a component of this system. For example, Zhou et al. (2017) apply production decomposition analysis to investigate changes in energy consumption. Wier (1998), Hatzigeorgiou et al. (2010), and Chang and Lahr (2016) develop IDA models allowing an in-depth analysis of structural changes related to CO_2 emissions in different economic sectors. Carrascal Incera (2017) employs the IDA model to map structural changes in youth employment and identify the determinants of these changes. The IDA methodological framework offers major potential in terms of its application in studies with a specific focus on agriculture. For instance, Junsong and Canfei (2009) use the IDA model to link CO_2 emissions and energy consumption with such agricultural indicators as export of raw materials, labour, and land productivity. Compared to the simple SCIs, this approach is more advanced as it allows including into the model important interrelated indicators and estimating their contribution to the overall structural change.

Another relevant niche covers academic research that uses shift-share analysis to investigate structural changes and regional developments. This type of analysis is classified as ex post and allows the results of change to be measured (Knudsen 2000); however, some researchers go beyond and combine the shift-share with other models to forecast the possible development (e.g. Mayor et al. (2007)). The traditional shift-share analysis model identifies three components that measure structural changes in (1) national growth, (2) economic activities growth (referred to as “industry-mix”), and (3) local conditions (referred to as “competitive”). Since the first application, the shift-share model has been an object of the ongoing improvements and modifications. Loveridge and Selting (1998) and Brox and Carvalho (2008) provide a comprehensive review on critics of this technique and explain the main strengths that encourage academics to employ this model and continue its development.

The shift-share analysis framework was introduced by Dunn (1960), who used the technique to investigate changes in employment growth. Since then, the method has been widely used to measure changes in the structure of employment, productivity, production, and gross value added, etc. For example, Herath et al. (2013) employ a dynamic spatial shift-share model to analyse changes in employment, Andersson and Lindmark (2008) examine labour productivity growth, while Brox and Carvalho (2008) expand the traditional model by including different age and sex cohorts to analyse the structural changes. Mayor et al. (2007) combine a dynamic shift-share and ARIMA models in order to forecast regional employment. O’Leary and Webber (2015) use the shift-share model to investigate the nexus between structural change and productivity growth, Le Gallo and Kamarianakis (2011) combine the shift-share and space-time econometric models to investigate differences in regional productivity, while Liu and Yao (1999) focus on the issues of economic growth.

Although in most of the shift-share analysis studies agriculture is treated as a sector of the economy, some researchers adapt this method for in-depth analysis of structural changes in agriculture. For example, Nengli et al. (2009) employ this method to identify the role of agriculture in the structure of the agricultural region. Xia et al. (2011) use the shift-share model for the analysis of changes in crop production and trade. Nevertheless, it should be noted that shift-share analysis traditionally investigates only one selected indicator, while the nexus between indicators and their contributions to the structural change of the entire system is not covered.

Another key research niche covers studies that use input–output analysis to investigate structural changes. Although this method rooted in the economic tables introduced in the second half of the eighteenth century, the technique has regained popularity with the appraisal of the Leontief model enabling the analysis of national or regional economies employing matrices. Later, input–output analysis became an important tool for general and partial equilibrium analysis. Furthermore, this tool empowered forecasting and a better understanding of the driving factors behind change. A comprehensive review of the wide application of input–output analysis in economics is provided in ten Raa (2006).

The input–output models show the relationships between economic activities in the economic system, explaining how output from a particular economic activity contributes as an input to another economic activity. According to Andréosso-O'Callaghan and Yue (2000), this type of analysis assists in identifying industries that contribute most to the interindustrial structural change in the country.

Input–output analysis is widely applied and has attracted much criticism and many improvements, as well as the development of new research frameworks merging different methods. In most of these studies, agriculture is considered an element of the economic system, and research focuses on structural changes in the whole economic system. For instance, Shishido et al. (2000) use the input–output model and rely on Leontief input–output coefficients to examine the changes in the production structure of 20 countries. Okuyama et al. (2006) use a temporal Leontief inverse analysis to understand the structural changes in Chicago. Andréosso-O'Callaghan and Yue (2000) use a biproportional filter to study structural changes in China, while de Mesnard (2004) discusses the use of biproportional methods for the estimation of structural change considering the case of France. Vaninsky (2009) combines the modified input–output model with the objective function and introduces the efficiency of structural change in order to analyse and forecast structural changes in gross output. Jacob (2005) decomposes economic growth, applying the input–output framework in order to identify the driving forces of growth and the links between them.

However, some academics apply input–output analysis with a specific interest in agriculture. Ciobanu et al. (2004) stress the importance of this sector in the region of Greece and propose the disaggregation of main agricultural activities, while the input–output analysis is focused on structural changes in employment, income, and output. Bruckner et al. (2019) propose an extended input–output model for food and agriculture biomass that assists in explaining multiregional links and movements of food and agricultural products in the global economy. Stadler et al. (2018) introduce the multiregional input–output extended model enriched by social and environmental components that link structural changes in economic systems with environmental pressure. Zhang and Diao (2020) decompose economic growth by combining input–output and general equilibrium analysis to estimate the structural changes in agriculture. Pattnaik and Shah (2015) decompose agricultural growth and crop output in order to analyse the explanatory factors of the growth in agriculture.

To conclude, the reviewed methodological frameworks for the analysis of structural changes in economic systems vary in their level of sophistication and the application of results. Researchers apply structural change indices or different models that vary in terms of aggregation: they can be static or dynamic, apply equilibrium or disequilibrium approaches, etc. The aforementioned research niches are widely applied; however, neither the list of niches nor the coverage of topics within the niches is exhaustive. At the same time, the studies on structural changes in agricultural systems also vary in terms of methodological developments and research aims. The following review provides academic contributions to the scientific discussion focusing on the most common measure of the structural change in agriculture, namely farm size.

4.2.2 Farm Size as a Measure of Structural Change

Over the last few centuries, agricultural systems around the world have survived dramatic transformations. This determined the emergence of a considerable amount of academic studies with a particular focus on structural changes in agriculture, because the methodological frameworks dealing with the changes within economic systems were often insufficient to explain the evolution. On the other hand, the focus on different aspects of structural changes in agricultural systems and the huge diversity of methodological approaches, as well as research objectives, contributed to a better understanding of changes in the overall economic systems.

According to the reviewed literature, farm size is the key indicator describing structural changes in agricultural systems. It is important to note that the changes can be investigated by selecting different measures of farm size. The size of a farm could assist in measuring assets or invested capital, real land and building value, standard output, gross margins or sales, real cash receipts or real cash receipts including government payments, number of livestock, land area, and labour force (Bowler 1992/2014; Gorton and Davidova 2004; Yee and Ahearn 2005; Lowder et al. 2016). In order to provide an in-depth analysis of structural changes in agricultural systems, some studies combine results for different measures of farm size (Guiomar et al. 2018).

In academic studies, the most widespread measure of the farm size is land area (Bowler 1992/2014; Lowder et al. 2016; Guiomar et al. 2018), because this indicator allows cross-comparable data to be obtained that follow similar methodological developments. Nevertheless, in the long term, even this measure of farm size is not available for all countries worldwide (Lowder et al. 2016). Methodological differences in statistics and the unique nature of structural changes in individual countries support an extraordinarily large number of studies at the level of individual countries [e.g., Weiss (1998, 1999), Jackson-Smith (1999), Rizov and Mathijs (2003), Key and Roberts (2007), Dannenberg and Kuemmerle (2010), Unay Gailhard and Bojnec (2015), Kirchweger and Kantelhardt (2015), Bachev et al. (2017)] or focus on groups of countries [e.g., Gorton and Davidova (2004), Breustedt and Glauben (2007), Błażejczyk-Majka et al. (2011), Zimmermann and Heckelei (2012), Bakucs et al. (2013), Bartolini and Viaggi (2013), Kazukauskas et al. (2013), Bański (2018), Guiomar et al. (2018)] with comparable statistical methodologies. As a result, the findings of these studies are fragmented and country-specific.

A considerable number of studies have investigated the link between farm size and its contribution to the sustainable development of agricultural systems. Most of these studies bring individual dimensions of sustainability into focus and demonstrate the evolution of agricultural systems and changes in farm structure relying on different issues. Examples of studies covering the economic dimension include the research on the nexus between farm size and different aspects of productivity or efficiency (Deolalikar 1981; Gorton and Davidova 2004; Błażejczyk-Majka et al. 2011; Chen et al. 2011; Adamopolous and Restuccia 2014; Novotná and Volek 2016). The environmental dimension covers studies that explain the impact of farm size on participation in agri-environmental measures (Unay Gailhard and Bojnec 2015; Defrancesco et al. 2018), biodiversity (Belfrage et al. 2015), crop diversity and landscape (Uthes et al. 2020), sustainable intensification and environmental issues (Areal et al. 2018; Pan et al. 2019), organic production and financial outcomes (Khanal et al. 2018), etc. It is worth noting that some academics have investigated the nexus between farm size and sustainable performance (Bachev et al. 2017; Lewandowska-Czarnecka et al. 2019). Although the findings of such studies are conflicting and based on fundamentally different methodological approaches, small farms are recognized as a viable and sustainable form of business development in many studies. Thus, the evolution of the average farm size is an important aspect in forecasting the path of development of agricultural systems.

Numerous studies focus on the driving forces of structural transformation and their contributions to changes in farms, agriculture, and the entire economic system. A mapping of the main change-driving forces is provided in studies by Strauss (2001), Zimmermann et al. (2009), Ryschawy et al. (2013), Neuenfeldt et al. (2019), and van Neuss (2019). Hence, studies about the impact of government policy and interventional measures on the development of structural changes have a distinct role in the academic discussion about the change-driving forces. Studies by Yee and Ahearn (2005), Breustedt and Glaubem (2007), Douarin and Latruffe (2011), Bartolini and Viaggi (2013), Kirchweger and Kantelhardt (2015), Brenes-Muñoz et al. (2016), and Neuenfeldt et al. (2019) can be highlighted as examples of the aforementioned academic contributions. In accordance with literature review, the following factors also play a key role in structural changes in agricultural systems, namely path dependency (Balmann 1997; Neuenfeldt et al. 2019), agricultural income (Neuenfeldt et al. 2019; van Neuss 2019), non-farm economy and employment opportunities (Breustedt and Glaubem 2007; Möllers and Fritzsch 2010), the development of an institutional framework (Bakucs et al. 2013; Kazukauskas et al. 2013), human capital-related issues (Strauss 2001; Zimmermann et al. 2009; Offermann and Margarian 2014; Neuenfeldt et al. 2019), input and output prices (Neuenfeldt et al. 2019), natural conditions (Neuenfeldt et al. 2019), technology (Strauss 2001; Zimmermann et al. 2009; Kazukauskas et al. 2013; Neuenfeldt et al. 2019; van Neuss 2019), scale size (Hallam 1991; Kazukauskas et al. 2013), competition for resources with non-agricultural sectors (Neuenfeldt et al. 2019), the evolution of input–output relations (van Neuss 2019), and globalization (Strauss 2001; Ryschawy et al. 2013; van Neuss 2019).

One important research direction discusses the driving forces of change and their contribution to the structural transformations of individual farming activities and entire agricultural systems (Zimmermann et al. 2009; Ryschawy et al. 2013; Neuenfeldt et al. 2019). Another research niche covers studies that examine the nexus between driving forces and their impact on structural changes in the farm structure (Happe 2004; Huettel and Margarian 2009; Sahrbacher 2012; Knight and Newman 2013; Offermann and Margarian 2014; Storm et al. 2015; Mann et al. 2017). Academics have developed a considerable number of models that allow the forecasting of developments in farm structure; the methodological frameworks differ fundamentally and rely on regression, the cellular automata approach, agent-based models, multiplicative competitive interaction models, various Markov chain frameworks, highly sophisticated multimodel approaches (for instance, combining farm and regional models), etc. Structural changes in agricultural systems depend on the life cycle situation; as a result, some attention is given to research on farm enrolment and growth (including Gibrat's law), exit and survival aspects (Weiss 1998, 1999; Pagano and Schivardi 2003; Lotti et al. 2003; Rizov and Mathijs 2003; Huettel and Margarian 2009; Möllers and Fritzsch 2010; Bakucs et al. 2013; Kazukauskas et al. 2013; Knight and Newman 2013; Petrick and Götz 2019; Bojnec and Fertő 2020), and path dependence in agriculture (Balmann 1997). The improved knowledge about the changes in farm structure allows the main change-driving forces to be identified and more reliable forecasting models to be developed.

In conclusion, the academic research on the link between farm size and different aspects of structural changes in agriculture varies in terms of research aims and methodological developments. This study applies the structural change index and shift-share analysis in order to demonstrate the changing role of agriculture in the entire economic system over the investigated period. Although the aforementioned methods have some limitations, they can be successfully used to give an idea of the pace and directions of structural changes in the economic system and the role of agricultural economic activity in this context. The structural changes in the overall economic system are examined, employing the most common measures of structural change in academic studies, namely employment and gross value added.

Furthermore, the literature review shows that in-depth analysis of structural changes in agriculture often relies on specific measures of structural change. As a result, this study selects the average farm size as a measure of structural change in agricultural systems. This empirical study expands the application of IDA models and proposes employing the aforementioned approach to describe structural changes in agricultural systems. The developed original IDA model shows the impact of structural components on the change in the average farm size between the reference years. The reviewed research demonstrates that selecting one measure of farm size could result in misleading conclusions. Thus, the following empirical research covers different farm size measures to investigate both input- and output-related changes in agricultural systems.

4.3 Data and Research Methodology

The empirical study on structural changes in EU agriculture covers two objectives and employs a research framework combining different methodological approaches. The first objective investigates structural changes in the overall economic system and places the main focus on the changing role of agriculture. The key changes in the economic system are analysed by applying measures of employment and gross value added. Section 4.4 integrates the results of the shift-share analysis and structural change indices and examines changes in shares of economic activities.

The second objective investigates structural changes in the EU agricultural system and member states, focusing on the evolution of the average farm size. In order to achieve this objective, the original IDA model is developed. This model enables identification of pure changes in farm size and the structural components that determine changes. The evolution of agricultural systems is investigated, applying three different measures of farm size that demonstrate both input- and output-related dynamics of structural changes. In Sect. 4.5, the main findings show changes at the EU level and in member states, and the reallocation of resources between farming types.

Research data and applied classifications The analysis of structural changes in both the overall EU economic system and agriculture relies on Eurostat data. In Sect. 4.4, the empirical study employs indicators of total employment (domestic concept), measured in number of persons, and gross value added in current prices, measured in euro. These fundamental structural change measures show changes in the economic system linked to the situation of income generation or well-being and labour resource mobilization. The annual statistics show a breakdown into ten economic activities according to statistical classification of economic activities in the EC (NACE Rev. 2). Consequently, the analysis of structural changes focuses on the reallocation of gross value added and labour between ten economic activities. As the results of the structural changes in the EU economic system complement the following research on the changes in the EU agricultural system, the empirical study uses annual indicators starting from the year 2005.

The existing data on employment do not cover statistics from Greece and Sweden for some economic activities in 2018. Thus, for these countries, the study relies on data for 2017 to calculate the long-term SCI values. It is worth noting that data for wholesale and retail trade, transport, accommodation, and food service activities in Denmark are not available, and it is assumed that the change in this economic activity is equal to zero. This study does not introduce SCI values for the UK, because the Eurostat database does not provide data in accordance with the selected classification by economic activities.

Van Neuss (2019) argues that the interpretation of structural change results strongly depends on the selected research measures. In that regard, the study introduces several measures of farm size allowing the main characteristics of the evolution of the average farm size in EU agriculture to be monitored. In Sect. 4.5, the measures of the average farm size are calculated using the indicators of utilized agricultural area (ha), standard output (euro), labour force directly employed (annual working unit), and the corresponding number of farms. The analysis relies on the recent available data from the Eurostat database, which provides statistics for the reference years 2005, 2007, 2010, 2013, and 2016. CAP reforms and the remarkable enlargement of the EU took place over the selected research period under consideration. Hence, the cross-comparison of the changes in agricultural systems of countries that have acceded to the EU post-2003 (hereinafter EU-13) with the 15 countries of the EU that joined before 2004 (hereinafter EU-15) becomes an interesting research topic.

Eurostat classification describes the EU agricultural system, distinguishing 21 farming types; however, some of these types are less relevant in the investigated member states. This study excludes from the research farming types with data gaps for more than three countries, namely specialist olive, various permanent crops combined, specialist vineyard, various granivores combined, and non-classified farms. The remaining farming types are aggregated into seven farming types as described below:

1. Specialist field crops:
   (a) general field cropping,
   (b) specialist cereals, oilseed, and protein crops.
2. Specialist horticulture, fruit, and citrus fruit:
   (a) specialist horticulture indoor,
   (b) specialist horticulture outdoor,
   (c) other horticulture,
   (d) specialist fruit and citrus fruit.
3. Specialist grazing livestock:
   (a) specialist dairying,
   (b) specialist cattle-rearing and fattening,
   (c) cattle-dairying, rearing, and fattening combined,
   (d) sheep, goats, and other grazing livestock.
4. Specialist granivores:
   (a) specialist pigs,
   (b) specialist poultry.
5. Mixed cropping.
6. Mixed livestock:
   (a) mixed livestock, mainly grazing livestock,
   (b) mixed livestock, mainly granivores.

7. Mixed combined:
   (a) field crops-grazing livestock combined,
   (b) various crops and livestock combined.

It should be noted that in some member states data for the selected indicators are not available. The problem of missing data is solved by applying the next set of assumptions. First, the Eurostat database does not provide data on Croatian indices for the year 2005. Therefore, the study presumes that the changes in the selected indicators were minor and, in 2005, applied a set of data for the year 2007 to extend the cross-comparison of the situation in all member states. Second, data for specialist cereals, oilseed, and protein crops farming type in Malta are missing for the entire analysed period. Thus, the contribution of time series is treated as being equal to zero.

Third, for the year 2016, some member states (the Estonian specialist pig farms and the Maltese field crops-grazing livestock combined farms) had gaps in time series of the particular indices (labour force and utilized agricultural area). The missing data were filled, extrapolating the ratio between the selected indicator and number of farms for the previous year values to the year with missing data. Fourth, specialist horticulture outdoor farms in Luxembourg and specialist cattle-rearing and fattening farms in Malta had data gaps for all selected years in the middle of the time series, which were filled by applying the average for the nearest 2 years. The missing data for specialist horticulture indoor, rearing and fattening combined, cattle-dairying, rearing and fattening combined, specialist poultry, and mixed cropping farming types in some member states (Czech Republic, Luxembourg, Malta, and Cyprus) were filled, extrapolating the value of the nearest year.

Methodological research framework The direction and the significance of the structural transformation in the EU economic system are analysed, investigating changes in relative sizes of economic activities and structural change index. The study applies NACE (Rev. 2) classification in order to identify the shares of ten economic activities in the total structure and calculate the SCIs between the reference years. The index is calculated by dividing by two the sum of the shares of the structural change measure of the investigated economic activities expressed as the absolute values of the percentage change over the reference period. The SCI formula applied is explained in Productivity Commission (1998, 2013).

Section 4.4 also employs the logic of the traditional shift-share analysis to evaluate the performance of agriculture, forestry, and fishing economic activity in selected member states in relation to the EU economy over the reference period. This study applies a model that is similar to the standard shift-share model used by Herath et al. (2013). The following specification of the shift-share analysis is used:

$$\Delta \mathrm{SCM}_{ij} = \mathrm{SCM}_{ij,a} - \mathrm{SCM}_{ij,b} = E_{ij} + A_{ij} + M_{ij} \tag{4.1}$$

$$\Delta\mathrm{SCM}_{ij} = \mathrm{SCM}_{ij,b} \times r + \mathrm{SCM}_{ij,b} \times (r_i - r) + \mathrm{SCM}_{ij,b} \times \left(r_{ij} - r_i\right) \tag{4.2}$$

where $\Delta\mathrm{SCM}_{ij}$ is the change in the selected structural change measure, namely employment or gross value added, in the ith economic activity of the jth member state, while a and b correspond to the years of the investigated period. E_{ij} is a change in the ith economic activity of the jth member state that corresponds to the same growth as the EU economy. A_{ij} shows the change due to the effect of economic activities' mix; i.e., member states with a more favourable mix of economic activities demonstrate a higher growth rate than other EU countries. M_{ij} shows the competitiveness of the selected economic activities in individual member states. The growth rate of the EU economy is r, while r_i and r_{ij} correspond, respectively, to the growth rate of the ith economic activity in the EU economy and the growth rate of the ith economic activity in the jth member state.

The main components of the shift-share model are described in Eqs. (4.3)–(4.5):

$$E_{ij} = \mathrm{SCM}_{ij,b} \times r = \mathrm{SCM}_{ij,b} \times \frac{\mathrm{SCM}_a - \mathrm{SCM}_b}{\mathrm{SCM}_b} \tag{4.3}$$

$$\begin{aligned} A_{ij} &= \mathrm{SCM}_{ij,b} \times (r_i - r) \\ &= \mathrm{SCM}_{ij,b} \times \left(\frac{\mathrm{SCM}_{i,a} - \mathrm{SCM}_{i,b}}{\mathrm{SCM}_{i,b}} - \frac{\mathrm{SCM}_a - \mathrm{SCM}_b}{\mathrm{SCM}_b}\right) \end{aligned} \tag{4.4}$$

$$\begin{aligned} M_{ij} &= \mathrm{SCM}_{ij,b} \times \left(r_{ij} - r_i\right) \\ &= \mathrm{SCM}_{ij,b} \times \left(\frac{\mathrm{SCM}_{ij,a} - \mathrm{SCM}_{ij,b}}{\mathrm{SCM}_{ij,b}} - \frac{\mathrm{SCM}_{i,a} - \mathrm{SCM}_{i,b}}{\mathrm{SCM}_{i,b}}\right) \end{aligned} \tag{4.5}$$

where $\mathrm{SCM}_{ij,a}$ and $\mathrm{SCM}_{ij,b}$ are the values of the selected structural change measure in the ith economic activity of the jth member state for the end and base years of the investigated period, and SCM_a and SCM_b are the total values of the selected structural change measure in the EU economy for the end and base years of the investigated period. $\mathrm{SCM}_{i,a}$ and $\mathrm{SCM}_{i,b}$ correspond to the values of the selected structural change measure in the ith economic activity for the end and base years of the investigated period.

In order to eliminate the impact of inflation on the results of the shift-share analysis, the study provides an alternative calculation of the shift-share components applying gross value added in real prices for the base year 2005. For this reason, the study uses Eurostat's implicit deflator for agriculture, forestry, and fishing activity and total economic activities. This study applies the EU-28 average for agriculture, forestry, and fishing activity in Malta, because the implicit deflator for this economic activity is not available.

Section 4.5 covers the second objective and reports on the results of the index decomposition analysis, investigating changes in the average farm size in EU agriculture. Although IDA models are widely applied in energy intensity decomposition studies (e.g. Jenne and Cattell (1983), Li et al. (1990), Huang (1993)), the application of decomposition analysis to estimate changes in the agricultural system is a promising research niche.

The decomposition of the average EU farm size follows the following IDA specification:

$$\frac{\mathrm{FS}}{f} = \sum_{mn} \frac{\mathrm{FS}_{mn}}{f_{mn}} = \sum_{mn} \frac{f_n}{f} \times \frac{f_{mn}}{f_n} \times \frac{\mathrm{FS}_{mn}}{f_{mn}} \tag{4.6}$$

where f is the total number of farms in the EU, f_n shows the total number of EU farms in the nth farming type, f_{mn} corresponds to the number of farms in the nth farming type of the mth member state, FS_{mn} is the investigated measure of farm size in the mth member state for the nth farming type, while FS corresponds to the total investigated measure of farm size in EU agriculture.

The empirical study runs three IDA equations to investigate the changes in the average farm size in EU agriculture:

1. FS corresponds to utilized agricultural area,
2. FS corresponds to standard output,
3. FS corresponds to labour force directly employed.

The average farm size in EU agriculture is decomposed into two structural subindices and an indicator of pure average farm size change (see Eq. 4.6). Ang (2015) suggests the logarithmic mean Divisia index I (LMDI-I) method as an efficient instrument to deal with aggregation and multiple subcategories in similar cases. Consequently, the multiplicative decomposition of the average farm size change at the level of the EU agricultural system is described as Eq. (4.7):

$$C_T = \frac{\left(\frac{\mathrm{FS}^a}{f^a}\right)}{\left(\frac{\mathrm{FS}^b}{f^b}\right)} = S_{\mathrm{EU}} \times S_{\mathrm{M}} \times I_I \tag{4.7}$$

where C_T is the change in the selected average farm size indicator at the EU level over the investigated period, S_{EU} denotes the switch between farming types at the EU level (applying the change in farm numbers), S_{M} describes the changes in the structure of the farming types due to EU member states, I_I demonstrates the pure change in the measure of the average farm size in EU countries selected for the analysis, and a and b identify the years of the investigated period.

To estimate the subindices of structural change, the multiplicative decomposition of the average farm size change employs the LMDI-I model (see Choi and Ang (2003) and Ang (2015) for more details):

$$S_{\mathrm{EU}} = \exp\left(\sum_{mn} \frac{\frac{\frac{\mathrm{FS}_{mn}^a}{f^a} - \frac{\mathrm{FS}_{mn}^b}{f^b}}{\ln\left(\frac{\mathrm{FS}_{mn}^a}{f^a}\right) - \ln\left(\frac{\mathrm{FS}_{mn}^b}{f^b}\right)}}{\frac{\frac{\mathrm{FS}^a}{f^a} - \frac{\mathrm{FS}^b}{f^b}}{\ln\left(\frac{\mathrm{FS}^a}{f^a}\right) - \ln\left(\frac{\mathrm{FS}^b}{f^b}\right)}} \times \ln\left(\frac{\frac{f_n^a}{f^a}}{\frac{f_n^b}{f^b}}\right)\right) \tag{4.8}$$

$$S_{\mathrm{M}} = \exp\left(\sum_{mn} \frac{\frac{\frac{\mathrm{FS}_{mn}^a}{f^a} - \frac{\mathrm{FS}_{mn}^b}{f^b}}{\ln\left(\frac{\mathrm{FS}_{mn}^a}{f^a}\right) - \ln\left(\frac{\mathrm{FS}_{mn}^b}{f^b}\right)}}{\frac{\frac{\mathrm{FS}^a}{f^a} - \frac{\mathrm{FS}^b}{f^b}}{\ln\left(\frac{\mathrm{FS}^a}{f^a}\right) - \ln\left(\frac{\mathrm{FS}^b}{f^b}\right)}} \times \ln\left(\frac{\frac{f_{mn}^a}{f_n^a}}{\frac{f_{mn}^b}{f_n^b}}\right)\right) \tag{4.9}$$

$$I_I = \exp\left(\sum_{mn} \frac{\frac{\frac{\mathrm{FS}_{mn}^a}{f^a} - \frac{\mathrm{FS}_{mn}^b}{f^b}}{\ln\left(\frac{\mathrm{FS}_{mn}^a}{f^a}\right) - \ln\left(\frac{\mathrm{FS}_{mn}^b}{f^b}\right)}}{\frac{\frac{\mathrm{FS}^a}{f^a} - \frac{\mathrm{FS}^b}{f^b}}{\ln\left(\frac{\mathrm{FS}^a}{f^a}\right) - \ln\left(\frac{\mathrm{FS}^b}{f^b}\right)}} \times \ln\left(\frac{\frac{\mathrm{FS}_{mn}^a}{f_{mn}^a}}{\frac{\mathrm{FS}_{mn}^b}{f_{mn}^b}}\right)\right) \tag{4.10}$$

The empirical study investigates structural changes in the EU agricultural system applying three measures of the structural change that allow three aspects of the average farm size transformation to be monitored. Thus, the individual calculations of Eqs. (4.6)–(4.10) for each measure of farm size are applied.

The analysis is carried out by applying chain-linked and entire period estimation of the average farm size change. The chain-linked calculations rely on Eurostat reference years and allow the values for the four interim periods (2005–2007, 2007–2010, 2010–2013, and 2013–2016) to be included in the analysis. The aforementioned period-specific indices of the average farm size change evidence gradual changes and assist in identifying the most important turning points of the EU agricultural system. The change indices for the entire period of 2005–2016 introduce the overall transformations of the EU agriculture, and structural changes in member states and between farming types.

It should be noted that this empirical study also faces some limitations that must be taken into account. The first challenge deals with the level of aggregation that often hides the directions and amplitudes of changes within the aggregated indicator. For example, the SCI could hide the directions of changes in individual economic activities and member states, while the aggregated structural change components of IDA conceal the directions and paces of change in disaggregated measures by farming types. The methodological developments of the selected structural change measures in member states could also contribute to changes in results. Nevertheless, the investigation of the chain-linked periods allows such data to be considered with caution.

Another important issue addresses the interpretation of IDA results for the standard output of agricultural product. In the Eurostat database, the calculation of this measure relies on the average value for the reference period of 5 years, with the exception of results for 2005. The transition from standard gross margin to standard output concept during the investigated period could also have an impact on data. It is worth noting that standard output is a monetary value, which means that inflation can introduce some changes in development trends at the EU level and in individual member states. The analysis of changes in Eurostat's implicit deflator values for agriculture, forestry, and fishing activity shows that in some member states the inflation rate is high. However, the IDA model uses standard output for farming types; thus, the application of the implicit deflator for agriculture, forestry, and fishing could significantly distort the results for particular farming types. For the aforementioned reasons, this study does not provide alternative calculations for the average standard outcome; however, the empirical results for the standard output must be interpreted with caution, especially in the case of countries with high inflation rates during the investigated period. Furthermore, it should not be forgotten that standard output does not estimate production costs in the individual member states.

4.4 Dynamics of Structural Changes in the EU Economic System: Focus on Agriculture

4.4.1 Pace of Structural Change in the EU Economy

According to the world population prospects of the United Nations, the size of the world population will increase from 7.8 billion in 2020 to 9.7 billion in 2050 (United Nations 2019). This development trend makes well-functioning agricultural systems vital to prosperity. At the same time, previous studies report on the diminishing role of agriculture in the overall economic system. Bah (2011) argues that developed and developing countries often face different scenarios of structural changes in agriculture. In developed countries, the pace of structural change differs, but the increase in the gross domestic product is led by the decreasing share of agriculture in the structure of output and the increase in the share of service-related economic activities, while in developing countries the role of agriculture differs.

In that context, structural changes in agriculture have an impact on agriculture-related economic activities and overall economic performance. These changes can be determined by the resource reallocation between the economic activities, differences in the input–output growth pace of economic activities or changes in spatial distribution within the EU economic system. The following empirical research contributes to the understanding of the most important structural change patterns in the EU economy and focuses on the role of agriculture, forestry, and fishing activity in this context.

A single glance at the dynamics of structural changes in the EU economy is provided in Fig. 4.1. SCI is a measure reflecting the numerous changes in all

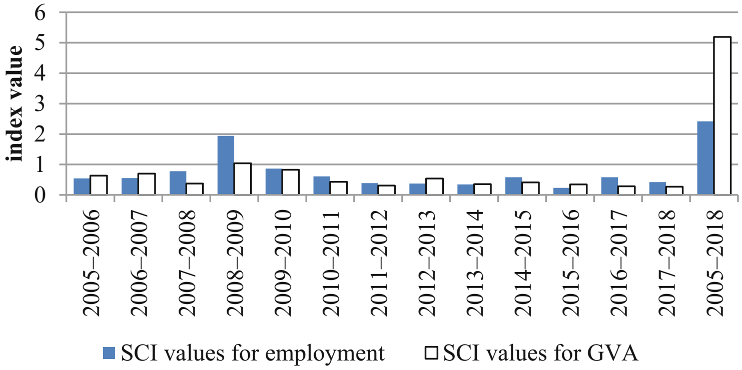


Fig. 4.1 Short-term and long-term developments of SCIs in the EU-28 group over the period 2005–2018. Source: Own calculations based on Eurostat data

economic activities and enabling awareness of the significance of structural changes that took place in the economy over the investigated period. Figure 4.1 combines the short-term and long-term changes in SCIs for the EU economy during the period 2005–2018. The results suggest that the overall structural change of the EU economic system is not significant as the SCI for gross value added accounts for 2.42, while the value of SCI for employment is 5.19. Given that the values of SCI vary from 0.00 to 100.00, the results show that for the EU-28 group, on average, the reallocation of gross value added and labour is minor. In this regard, it is important to note that structural changes in employment are more dynamic than in the case of the gross value added reallocation between economic activities.

The short-term SCI values show that structural changes have a permanent character at a slow pace. However, in the case of gross value added, a slightly higher reallocation of resources between economic activities is observed during the period from 2007 to 2010. SCI values for employment demonstrate similar behaviour, although the period with higher values is shorter. Both structural change measures demonstrate the peak of SCI values from 2008 to 2009, but the magnitude of the reallocation for gross value added is higher. These results allow the presumption that the financial and economic crisis of 2008 could have an impact on a more remarkable resource reallocation in the EU economic system. During the period from 2005 to 2018, the SCI values for both structural change measures, with the exception of the aforementioned crisis-related peak, demonstrate the signs of a slight cyclical development, which could be explained by the influence of different temporary factors.

The minor importance of the reallocation at the EU level does not mean the same slow pace of structural change in the economic systems of the individual member states. Figure 4.2 demonstrates that in Ireland, Malta, and Romania the SCI values for gross value added exceed 10.00. SCI values for gross value added range from 5.00 to 10.00 in 14 member states, namely Spain, Finland, Estonia, Latvia, Portugal, Cyprus, Luxembourg, Bulgaria, Belgium, Lithuania, Greece, Sweden, Croatia, and the Czech Republic. The remaining countries experience less dramatic structural changes in the structure of gross value added, and the SCI values are less than 5.00.

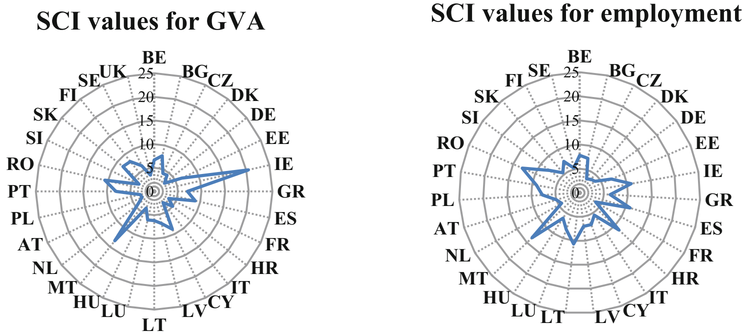


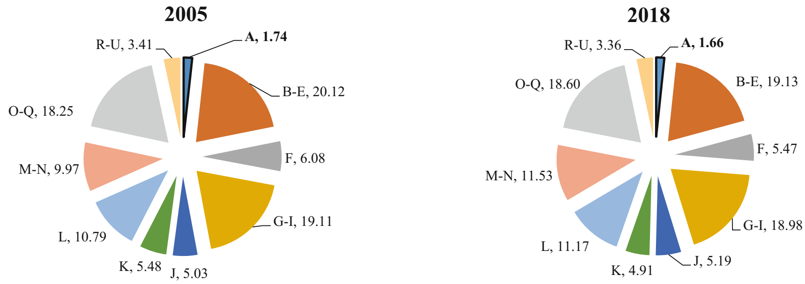
Fig. 4.2 SCI values in individual member states for the period 2005–2018. Source: Own calculations based on Eurostat data

The SCI values for employment in individual member states are outlined in Fig. 4.2. The most spectacular employment reallocations, ranging from 10.00 to 15.00, involve Malta, Romania, Croatia, Spain, Ireland, and Lithuania. Only the Netherlands, the Czech Republic, Germany, and France have the slowest overall pace of change, and the SCI values are lower than 5.00. In Denmark, the situation is similar; however, the SCI does not cover real change in wholesale and retail trade, transport, accommodation, and food service activities. In most of the member states, the SCIs for employment vary between 5.00 and 10.00.

According to the SCIs introduced in Fig. 4.2, the pace of structural change is country-specific rather than being dependent on accession to the EU, although in some countries the change in the business environment has accelerated the evolution of national economies. Results suggest that Malta, Ireland, and Romania experienced the most dramatic structural change during the period 2005–2018, while the pace of structural change in Germany, France, the Netherlands, and the Czech Republic is among the lowest values. The chain-linked SCI values for member states do not allow a clear period of structural change for the EU economic system to be identified either. Although most of the countries experience the steepest growth pace during the period related to crisis, in some countries, the highest SCI values are recorded before a crisis or lag.

4.4.2 Directions of Structural Changes in the EU Economy

SCI shows the net impact of changes on the structure of the investigated structural change measure, while the directions of structural change in the reallocation among the individual economic activities remain a limitation of the selected method. However, the direction of structural changes could be explained by the redistribution of structural change measures in the overall structure of the EU economy. According to Eurostat, over the investigated period, the share of agriculture, forestry, and



Economic activities: A – agriculture, forestry, and fishing; B–E – industry (except construction); F – construction; G–I – wholesale and retail trade, transport, accommodation and food service activities; J – information and communication; K – financial and insurance activities; L – real estate activities; M–N – professional, scientific and technical activities; administrative and support service activities; O–Q – public administration, defence, education, human health and social work activities; R–U – arts, entertainment and recreation; other service activities; activities of household and extra-territorial organizations and bodies.

Fig. 4.3 Structure of gross value added by economic activities (%), 2005 and 2018. Source: Own calculations based on Eurostat data

fishing (A) in the total gross value added of all economic activities in the EU economy slightly reduced and in 2018 accounted for 1.66%, compared to 1.74% in 2005.

Figure 4.3 demonstrates that in the shares of industry (including construction) (B–F), financial and insurance activities (K) also declined during 2005–2018, while the increase in the share of such economic activities as professional, scientific, and technical activities, administrative and support service activities (M–N), public administration, defence, education, human health, and social work activities (O–Q), and real estate activities (L) was remarkable.

Figure 4.4 demonstrates the diminishing role of agriculture, forestry, and fishing (A) in the overall structure of employment by economic activities. According to Eurostat, the share of this economic activity in the structure of the EU employment reduced from 6.02% in 2005 to 4.24% in 2018, and the change in pace is slightly higher than in the case of gross value added. It should be noted that the overall change trends in employment structure almost correspond to the development of gross value added reallocation directions. However, an opposite change in direction is reported for wholesale and retail trade, transport, accommodation, and food service activities (G–I) and arts, entertainment and recreation; other service activities; and activities of household and extraterritorial organizations and bodies (R–U). In this regard, results suggest that industry and construction (B–F) are less important in the overall employment structure at the EU level, while the share of service-related economic activities expands to a significant extent.

The cross-comparison of gross value added and employment structures in 2005 and 2018 allows it to be stated that the development of the EU economy is in line with the previous studies that confirm the growing role of the service sector in economic systems (Pannell and Schmidt 2006; Bah 2011) and the switch from

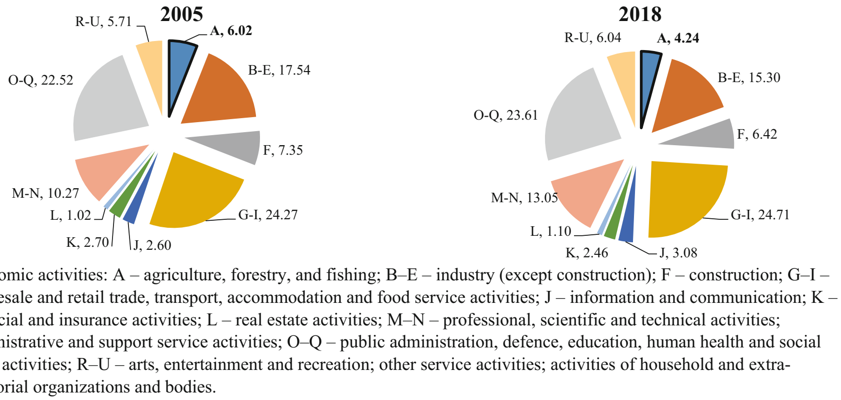


Fig. 4.4 Structure of employment by economic activities (%), 2005 and 2018. Source: Own calculations based on Eurostat data

agriculture to manufacturing and service sectors (Ciobanu et al. 2004). For example, Brakman et al. (2013) argue that countries traditionally pass through three stages of evolution with a corresponding shift in the dominance of primary production, manufacturing, and service activities. Bah (2011) also highlights the growing importance of service activities in economic systems around the world and points out the acceleration of that trend over several centuries. It is worth noting that in the study by Bah (2011) the structural transformation of industry does not demonstrate a clear development trend over the long period of investigation. In fact, the empirical findings outlined in Figs. 4.3 and 4.4 contribute to the aforementioned studies and suggest that the process of labour outflow from agriculture to other sectors is not finished, while the reallocation of gross value added in the overall EU structure is an ongoing process too. Results also suggest that structural changes in the EU economy were of an evolutionary rather than revolutionary nature over the period 2005–2018.

However, the analysis of structural changes at the EU level hides rather heterogeneous structures of economic activities and the pace of changes in member states due to the aggregation procedure. In order to get a clear picture, Tables 4.1 and 4.2 show the developments of gross value added and employment by economic activities in member states during the period from 2005 to 2018. The tables indicate the changes in shares of the individual economic activities from 2005 to 2018. The negative values show the decreasing role of the economic activity in member states during the investigated period, while the positive numbers demonstrate the growing importance of the selected economic activity over the investigated period.

The results in Table 4.1 confirm that the changes in shares of gross value added by economic activities in the EU countries differ significantly; i.e., the driving economic activities behind the change and the pace of development vary across member states. In most countries, the importance of industry and construction (B–F) diminished during the investigated period, while the service sector expanded. According to Table 4.1, the share of agriculture, forestry, and fishing economic activity

Table 4.1 Changes in the shares of gross value added by economic activities in member states for the period 2005–2018, %

	A	B–E	F	G–I	J	K	L	M–N	O–Q	R–U
BE	−0.38	−4.19	0.33	−2.01	0.25	0.67	1.00	3.36	1.14	−0.16
BG	−4.67	−0.83	−1.95	1.39	2.99	0.84	0.17	2.20	−0.41	0.26
CZ	−0.38	−0.83	−1.09	−1.84	0.99	1.15	1.08	0.68	0.39	−0.17
DK	−0.17	−2.56	0.77	−0.65	0.28	0.47	0.65	2.25	−0.95	−0.09
DE	0.05	0.17	1.19	−0.29	−0.06	−1.60	−0.53	0.67	1.01	−0.59
EE	−0.66	−0.67	−1.24	−3.64	1.56	−0.10	1.19	1.57	2.42	−0.43
IE	−0.23	12.09	−7.19	−4.20	5.89	−3.73	−0.17	2.86	−4.54	−0.78
GR	−0.50	1.57	−3.87	−0.74	−0.42	−1.12	4.65	−0.33	0.85	−0.08
ES	0.00	−2.51	−5.67	1.23	−0.64	−0.48	3.32	2.18	1.85	0.70
FR	−0.01	−2.80	0.16	−0.44	−0.05	0.30	0.65	1.55	0.83	−0.19
HR	−1.17	−1.61	−2.58	1.07	−0.11	0.20	0.72	1.80	0.79	0.90
IT	−0.06	−0.31	−1.65	0.78	−0.70	−0.30	1.84	0.19	−0.20	0.41
CY	−0.79	−2.22	−4.15	0.71	2.25	1.35	2.15	2.19	−1.92	0.43
LV	0.01	−0.48	−0.09	−5.69	1.13	−0.75	2.93	1.82	0.98	0.15
LT	−1.54	−3.49	−0.83	3.70	−0.29	0.06	0.15	2.08	0.20	−0.04
LU	−0.15	−3.78	0.23	−0.04	1.45	−0.02	−2.05	3.65	1.02	−0.31
HU	−0.12	−1.00	−0.44	1.80	−0.19	−0.70	−0.04	2.11	−1.42	0.01
MT	−1.24	−6.04	−3.66	−2.65	1.31	−1.67	−1.45	7.06	−1.62	9.99
NL	−0.24	−2.94	−0.74	0.86	0.00	−0.51	0.10	2.23	1.28	−0.04
AT	−0.13	−1.32	−0.32	−0.17	−0.05	−0.83	0.75	1.84	0.31	−0.08
PL	−0.74	−0.16	−0.02	0.62	−0.13	0.33	−1.15	2.12	−0.75	−0.12
PT	−0.29	0.23	−2.73	2.44	−0.38	−1.66	3.85	1.35	−3.23	0.42
RO	−4.75	−3.26	−1.85	−1.17	1.44	0.43	−0.23	5.12	3.11	1.15
SI	−0.34	−0.53	−0.74	1.87	−0.11	−0.72	−0.19	1.95	−0.67	−0.51
SK	0.82	−4.92	1.47	−2.53	0.41	−0.63	1.83	3.44	0.83	−0.72
FI	0.16	−6.62	1.00	−1.62	0.89	0.35	2.62	2.39	0.50	0.33
SE	0.16	−5.09	1.79	−0.36	0.91	−0.56	−0.09	2.61	0.55	0.09
UK	0.07	−2.59	−0.21	−0.33	0.66	−0.41	−0.19	2.57	0.09	0.34
EU-28	−0.08	−0.99	−0.62	−0.13	0.15	−0.57	0.38	1.56	0.35	−0.04

Economic activities: A—agriculture, forestry, and fishing; B–E—industry (except construction); F—construction; G–I—wholesale and retail trade, transport, accommodation, and food service activities; J—information and communication; K—financial and insurance activities; L—real estate activities; M–N—professional, scientific, and technical activities; administrative and support service activities; O–Q—public administration, defence, education, human health, and social work activities; R–U—arts, entertainment, and recreation; other service activities; activities of household and extraterritorial organizations and bodies

Source: Own calculations based on Eurostat data

Table 4.2 Change in the shares of employment by economic activities in member states for the period 2005–2018, %

	A	B–E	F	G–I	J	K	L	M–N	O–Q	R–U
BE	−0.53	−3.42	0.05	−2.47	0.35	−0.74	0.09	5.32	1.95	−0.61
BG	−3.51	−2.28	0.34	2.65	1.00	0.67	0.25	1.94	−1.57	0.51
CZ	−0.63	−0.93	−1.47	−0.20	0.79	0.08	0.10	1.07	0.53	0.66
DK	−0.44	−2.78	−0.30	NA	0.31	−0.06	0.18	2.09	−0.81	0.26
DE	−0.37	−1.36	−0.17	−0.70	0.03	−0.73	−0.12	2.85	1.11	−0.54
EE	−1.88	−4.33	−0.67	0.45	2.46	0.69	−0.04	3.13	−0.27	0.45
IE	−0.80	−3.99	−5.01	3.47	0.50	−0.49	0.22	2.54	4.11	−0.54
GR[a]	−0.69	−2.26	−2.97	2.28	0.23	−0.41	0.07	1.52	1.54	0.69
ES	−0.66	−3.91	−6.25	1.83	0.42	−0.11	0.21	3.39	4.33	0.74
FR	−0.64	−2.81	−0.09	−0.09	0.41	−0.03	−0.15	2.62	0.34	0.45
HR	−7.94	−1.84	−1.44	1.37	1.28	0.65	0.25	2.73	4.16	0.79
IT	−0.41	−2.88	−1.54	1.64	0.09	−0.21	0.11	2.32	−0.48	1.36
CY	−1.48	−2.26	−1.97	−1.29	0.43	0.34	0.21	4.48	0.69	0.86
LV	−2.28	−3.16	0.55	−1.15	1.90	−0.18	0.50	3.78	−0.24	0.28
LT	−6.92	−2.19	−1.50	3.03	0.96	0.23	0.37	4.29	−0.08	1.80
LU	−0.49	−4.00	−0.96	−2.30	1.09	−0.32	0.28	4.54	2.17	−0.01
HU	−1.01	−3.54	−0.28	−1.14	0.99	−0.29	−0.02	4.13	0.72	0.45
MT	−0.84	−8.94	−1.52	−2.12	1.61	0.52	0.23	7.83	−0.16	3.39
NL	−0.49	−1.78	−1.02	0.29	0.38	−0.93	−0.10	2.98	0.24	0.43
AT	−2.08	−1.57	0.03	−0.71	0.29	−0.56	−0.13	2.91	1.57	0.25
PL	−7.71	0.59	1.33	1.52	1.02	0.42	−0.04	1.93	0.43	0.50
PT	−3.26	−1.55	−4.27	2.52	0.83	0.03	0.27	3.70	1.38	0.34
RO	−11.08	−1.86	2.24	6.64	0.97	0.38	0.01	1.79	0.28	0.64
SI	−2.54	−4.16	−0.72	1.04	0.95	−0.38	0.22	3.32	1.46	0.81
SK	−1.57	−2.41	−0.10	1.00	0.89	0.28	0.27	2.74	−1.33	0.21
FI	−1.67	−3.92	1.08	−1.66	0.38	−0.05	0.10	4.09	0.80	0.86
SE[a]	−0.11	−3.97	1.86	0.09	0.11	−0.25	0.20	2.72	−0.62	−0.10
UK	−0.09	NA	−0.27	NA	0.70	−0.54	0.48	NA	NA	NA
EU-28	−1.78	−2.24	−0.93	0.44	0.48	−0.24	0.08	2.78	1.08	0.33

Economic activities: A—agriculture, forestry, and fishing; B–E—industry (except construction); F—construction; G–I—wholesale and retail trade, transport, accommodation, and food service activities; J—information and communication; K—financial and insurance activities; L—real estate activities; M–N—professional, scientific, and technical activities; administrative and support service activities; O–Q—public administration, defence, education, human health, and social work activities; R–U—arts, entertainment, and recreation; other service activities; activities of household and extraterritorial organizations and bodies

Source: Own calculations based on Eurostat data

NA not available

[a]Change for 2005–2017

(A) declined in 21 countries, but this economic activity was not among the three economic activities with the highest drop in percentage, with the exception of Belgium, Bulgaria, Greece, Croatia, Lithuania, Poland, and Romania. Although six member states demonstrated positive dynamics in the share of agriculture, forestry, and fishing economic activity (A) over the investigated period, none of these countries belonged to the group of states with the highest growth rates. Nevertheless, the most dramatic drops in the share of agriculture, forestry, and fishing economic activity (A) were typical of the countries that joined the EU in 2004 and later. The situation in the EU-15 was more stable, and these member States demonstrated fluctuations raging from −0.50% to 0.16%. Table 4.1 shows that the reallocation of gross value added between ten economic activities in member states was country-specific; however, in most countries, the greatest growth rates in the share of economic activities took place in the service-related area.

For employment, the changing role of agriculture, forestry, and fishing economic activity (A) in the overall structure of economic activities is less favourable, because in 20 Member States this economic activity is nominated among the top three with the steepest decrease in the share from 2005 to 2018 (Table 4.2). In case of employment, as in the case of gross value added, findings imply that countries that have joined the EU post-2003 deal with the worst situation due to higher rates of decline and more dramatic reallocation of labour force. However, the changes in EU-15 take place at a higher magnitude, compared to the reallocation of gross value added, and range from −3.26% to −0.09%.

The results suggest that the role of agriculture and industry in employment and job creation is diminishing in most member states. Taking into consideration the ongoing growth in demand for food, the results reflect deep structural changes within agricultural systems that allow the reduction of labour input and increasing productivity. As a result, the service-related economic activities must deal with the surplus of labour force switching from agriculture and industry. The EU countries have quite a diverse pace of growth of service-related activities. Indeed, professional, scientific and technical activities, administrative and support service activities (M–N) are among the top three activities with the highest growth in share of employment over the period considered.

To conclude, the directions of structural changes in individual member states mainly follow the widely recognized trends and correspond to the findings for the aggregated economic activities at the EU level: the role of agriculture, forestry, and fishing economic activity (A) in the overall economy is diminishing. Most member states face a switch from agriculture and industry to service-related economic activities; however, a few countries demonstrate quite unique development paths for the aforementioned vulnerable economic activities. Hence, the nature of this behaviour could depend on local competitive advantages or a successful mix of economic activities.

4.4.3 The Changing Role of Agriculture, Forestry, and Fishing Activity in Member States

The findings of the previous sections show that the share of agriculture, forestry, and fishing economic activity (A) in the overall structure of the EU economy is modest. According to Eurostat, gross value added reduced from 1.74% in 2005 to 1.66% in 2018, while the share of employment dropped from 6.02% to 4.24% for the same reference period. However, the role of agriculture, forestry, and fishing economic activity (A) in the economic system of the individual member states differs significantly. As illustrated by Fig. 4.5, in most countries, the role of agriculture, forestry, and fishing in the overall structure of economic activities is diminishing. The most dramatic structural changes are reported for Romania and Bulgaria, where agriculture, forestry, and fishing activity (A) used to have a significant role in domestic

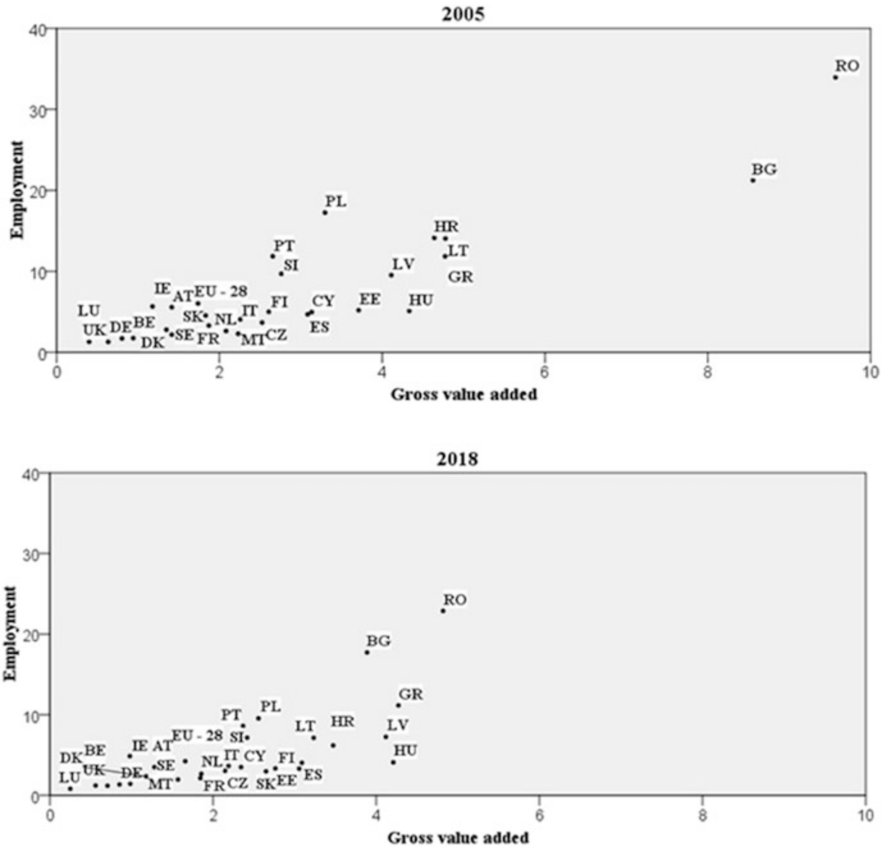


Fig. 4.5 Agriculture, forestry, and fishing activity by member states in 2005 and 2018, % of the overall structure. Source: Own calculations based on Eurostat data

Table 4.3 Changes in shares of gross value added for agriculture, forestry, and fishing activity, %

Country	2005–2007	2007–2010	2010–2013	2013–2016	2016–2018	2005–2018
BE	0.05	−0.14	−0.09	−0.06	−0.15	−0.38
BG	−3.07	−0.87	0.59	−0.53	−0.79	−4.67
CZ	−0.22	−0.60	0.94	−0.32	−0.17	−0.38
DK	0.04	0.01	0.11	−0.40	0.07	−0.17
DE	0.06	0.03	0.15	−0.27	0.08	0.05
EE	0.76	−0.88	−0.09	−1.11	0.67	−0.66
IE	0.00	−0.13	0.14	−0.17	−0.07	−0.23
GR	−1.33	−0.18	0.35	0.48	0.17	−0.50
ES	−0.30	−0.14	0.22	0.24	−0.02	0.00
FR	−0.07	−0.02	−0.15	−0.02	0.25	−0.01
HR	−0.23	−0.06	−0.16	−0.45	−0.28	−1.17
IT	−0.14	−0.14	0.41	−0.24	0.04	−0.06
CY	−0.79	0.00	−0.04	0.15	−0.10	−0.79
LV	−0.53	0.91	−0.97	0.01	0.58	0.01
LT	−0.91	−0.49	0.54	−0.46	−0.22	−1.54
LU	0.06	−0.18	0.04	−0.07	0.01	−0.15
HU	−0.27	−0.45	1.04	−0.02	−0.42	−0.12
MT	−0.25	−0.32	−0.30	0.01	−0.39	−1.24
NL	−0.05	−0.06	0.01	−0.01	−0.13	−0.24
AT	0.17	−0.16	−0.01	−0.16	0.04	−0.13
PL	0.15	−0.53	0.32	−0.54	−0.14	−0.74
PT	−0.35	−0.10	0.18	−0.01	−0.01	−0.29
RO	−3.40	−0.57	0.50	−1.57	0.29	−4.75
SI	−0.42	−0.16	0.11	0.03	0.11	−0.34
SK	0.73	−0.72	1.18	−0.03	−0.34	0.82
FI	0.11	0.05	−0.02	−0.07	0.08	0.16
SE	0.36	0.09	−0.22	−0.07	−0.01	0.16
UK	−0.01	0.06	0.06	−0.07	0.03	0.07
EU-28	−0.05	−0.03	0.10	−0.15	0.06	−0.08

Source: Own calculations based on Eurostat data

employment and the creation of gross value added before countries joined the EU. The sudden change in the business environment in the countries that joined the EU in 2004 and after encouraged similar behaviour; however, in some member states, the pace of change was less dramatic. In the EU-15, the changes in the shares of agriculture, forestry, and fishing economic activity (A) were less pronounced than in other member states.

Tables 4.3 and 4.4 show the chain-linked and period-specific changes in the share of agriculture, forestry, and fishing activity (A) for the identified reference years. It is important to note that the peak periods with the steepest changes in gross value added and employment often differ for the same country. The distribution of minimum and maximum change rates does not allow the time period with similar

Table 4.4 Changes in shares of employment for agriculture, forestry, and fishing activity, %

Country	2005–2007	2007–2010	2010–2013	2013–2016	2016–2018	2005–2018
BE	−0.13	−0.19	−0.11	−0.04	−0.05	−0.53
BG	−1.81	0.29	−0.54	−1.13	−0.31	−3.51
CZ	−0.34	−0.27	0.27	−0.26	−0.03	−0.63
DK	−0.30	0.04	−0.05	−0.03	−0.11	−0.44
DE	−0.08	−0.07	−0.06	−0.09	−0.07	−0.37
EE	−0.75	−0.29	−0.04	−0.35	−0.45	−1.88
IE	−0.47	0.68	0.04	−0.46	−0.59	−0.80
GR	−0.76	0.28	0.85	−0.91	−0.15[a]	−0.69[a]
ES	−0.66	0.05	0.07	−0.03	−0.10	−0.66
FR	−0.26	−0.21	−0.05	−0.05	−0.06	−0.64
HR	−0.99	1.02	−3.46	−3.16	−1.35	−7.94
IT	−0.18	−0.02	−0.18	0.08	−0.11	−0.41
CY	−0.54	−0.19	−0.09	−0.18	−0.48	−1.48
LV	−1.39	−0.29	−0.22	−0.02	−0.35	−2.28
LT	−3.92	−1.33	−0.43	−0.48	−0.76	−6.92
LU	−0.10	−0.09	−0.13	−0.10	−0.06	−0.49
HU	−0.39	−0.57	0.11	−0.04	−0.13	−1.01
MT	−0.07	−0.06	−0.38	−0.27	−0.06	−0.84
NL	−0.20	−0.12	−0.07	−0.05	−0.05	−0.49
AT	−0.41	−0.31	−0.53	−0.37	−0.45	−2.08
PL	−2.62	−1.60	−1.06	−1.42	−1.01	−7.71
PT	−0.29	−0.43	0.28	−2.01	−0.82	−3.26
RO	−2.28	0.65	−2.07	−6.40	−0.97	−11.08
SI	−0.99	−0.40	0.02	−0.60	−0.56	−2.54
SK	−0.75	−0.43	0.01	−0.25	−0.14	−1.57
FI	−0.39	−0.25	−0.26	−0.42	−0.36	−1.67
SE	−0.15	0.15	0.15	−0.21	−0.16	−0.22
UK	−0.06	0.20	−0.18	0.02	−0.07	−0.09
EU-28	−0.53	−0.16	−0.33	−0.53	−0.23	−1.78

Source: Own calculations based on Eurostat data
[a]Applies 2017 instead of 2018

changes in all member states to be identified. Thus, the structural changes in agriculture, forestry, and fishing activity (A) in member states have unique development features and different paces of change.

The chain-linked changes in gross value added by member states—with the exception of Croatia—demonstrate both increases and decreases in the share of agriculture, forestry, and fishing economic activity (A). However, the dynamics of chain-linked changes in employment is substantially different from the development of gross value added. In fact, as many as 13 member states challenge the ongoing decline in employment, while the period-specific paces of changes in the shares of employment by countries often appear to be substantially higher than the relevant developments in share values of gross value added. In contrast to the situation of gross value added, almost all period-specific values show a shrinking of the employment share in the total employment structure, and the steepest decrease in shares is typical for countries that joined the EU in 2004 and later. The rational basis for this situation is the switch towards higher productivity and modern technologies due to the higher level of competition introduced in countries that have acceded to the EU since 2004.

The aforementioned results report on changes in shares of agriculture, forestry, and fishing activity (A) in member states and the EU economy. The shift-share analysis expands this horizon and shows the possible performance of structural change measures in this economic activity by member states under different assumptions. Tables 4.5 and 4.6 provide the main components of the shift-share analysis (Eqs. 4.3–4.5) and the total change of the structural change measure for agriculture, forestry, and fishing activity (A) from 2005 to 2018.

The shift-share results for gross value added should be interpreted with caution (Table 4.5). During the investigated period, some member states faced a dramatic increase in the values of the price index and the results for gross value added in current and real prices differ substantially. According to Eurostat, in Luxembourg, the Czech Republic, Latvia, Poland, and Estonia, the price index values for agriculture, forestry, and fishing activity (A) skyrocketed and exceeded 150, while other member states demonstrated remarkable fluctuations in price index values over the period 2005–2018. Consequently, the growth rates for the estimations in real and current prices alter significantly. In fact, the real prices make the number of countries with negative change in gross value added five times higher.

The component E_{ij} shows the change in agriculture, forestry, and fishing activity (A) for the selected member state that corresponds to the growth rate at the level of the EU economy. If the value of the component E_{ij} rises above the value of the total change, the development pace of gross value added for agriculture, forestry, and fishing activity (A) in the selected member state exceeds the growth rate of the EU economy. According to Table 4.5, in 12 member states, the development of gross value added in current prices for agriculture, forestry, and fishing activity (A) is above the growth rate of the EU economy. However, the application of price indices reduces the number of countries with favourable development twice, and the new list of countries with favourable development includes Romania and Slovenia, which demonstrate a higher growth rate in agriculture, forestry, and fishing activity (A) in real terms.

The component A_{ij} shows the changes due to the effect of the mix of economic activities in member states. In the EU countries, this component demonstrates only negative development directions. The component M_{ij} refers to the competitiveness of the agriculture, forestry, and fishing activity (A) in the investigated member state. Although Table 4.5 shows both positive and negative developments of this component, results imply that the effects of inflation can drastically alter the interpretation of the local advantage. Nevertheless, the component of local competitiveness plays an important role in many member states.

A decomposition of the total change in employment for agriculture, forestry, and fishing activity (A) is provided in Table 4.6. In all member states, with the exception

Table 4.5 Shift-share results for gross value added in agriculture, forestry, and fishing activity, 2005–2018

	E_{ij}	A_{ij}	M_{ij}	Total change	E_{ij}	A_{ij}	M_{ij}	Total change
	Gross value added (million euro, current prices)				Gross value added (million euro, 2005 = 100)			
BE	957.87	−163.01	−1103.95	−309.10	494.21	−181.50	−726.55	−413.83
BG	643.53	−109.52	−394.21	139.80	332.03	−121.94	−483.34	−273.25
CZ	926.30	−157.64	794.55	1563.20	477.93	−175.51	−587.72	−285.31
DK	896.12	−152.51	−93.72	649.90	462.36	−169.78	−601.64	−309.08
DE	6113.68	−1040.45	3997.77	9071.00	3154.38	−1158.42	−729.10	1266.86
EE	137.05	−23.32	206.08	319.80	70.71	−25.97	13.57	58.31
IE	646.91	−110.09	609.49	1146.30	333.77	−122.58	313.12	524.32
GR	3137.14	−533.89	−4269.35	−1666.10	1618.62	−594.426	−1288.79	−264.59
ES	9437.52	−1606.11	103.59	7935.00	4869.33	−1788.22	5740.21	8821.31
FR	10,903.93	−1855.67	260.74	9309.00	5625.92	−2066.08	423.06	3982.91
HR	523.42	−89.08	−384.34	50.00	270.06	−99.18	−501.29	−330.40
IT	11,163.21	−1899.80	−4911.02	4352.40	5759.70	−2115.20	−2929.84	714.66
CY	151.38	−25.76	−109.52	16.10	78.11	−28.68	−154.48	−105.06
LV	184.24	−31.35	384.52	537.40	95.058	−34.91	29.40	89.55
LT	333.74	−56.80	130.75	407.70	172.20	−63.24	−58.08	50.88
LU	39.21	−6.67	−2.84	29.70	20.23	−7.43	−53.85	−41.04
HU	1245.82	−212.02	330.60	1364.40	642.78	−236.06	−226.05	180.68
MT	36.60	−6.23	−22.18	8.20	18.89	−6.94	−19.03	−7.08
NL	3761.56	−640.16	−580.40	2541.00	1940.79	−712.74	577.17	1805.22
AT	1175.99	−200.13	245.65	1221.50	606.76	−222.83	357.98	741.91
PL	2622.14	−446.25	1828.91	4004.80	1352.90	−496.84	−1641.44	−785.38
PT	1342.29	−228.44	−581.85	532.00	692.56	−254.34	−147.79	290.43
RO	2470.83	−420.50	142.46	2192.80	1274.84	−468.17	497.53	1304.19

(continued)

Table 4.5 (continued)

	E_{ij}	A_{ij}	M_{ij}	Total change	E_{ij}	A_{ij}	M_{ij}	Total change
	Gross value added (million euro, current prices)				Gross value added (million euro, 2005 = 100)			
SI	259.58	−44.18	41.50	256.90	133.93	−49.19	79.01	163.76
SK	234.44	−39.90	1297.56	1492.10	120.96	−44.42	1089.94	1166.48
FI	1378.93	−234.67	678.74	1823.00	711.47	−261.28	722.33	1172.52
SE	1455.05	−247.62	1388.48	2595.90	750.74	−275.70	47.89	522.92
UK	4285.75	−729.36	85.61	3642.00	2211.25	−812.06	−905.27	493.92

Sources: Own calculations based on Eurostat data

Table 4.6 Shift-share results for employment in agriculture, forestry, and fishing activity, 2005–2018 (thousand persons)

Country	E_{ij}	A_{ij}	M_{ij}	Total change	Country	E_{ij}	A_{ij}	M_{ij}	Total change
BE	6.21	−23.87	1.76	−15.90	LT	16.62	−63.90	−53.85	−101.13
BG	61.76	−237.49	57.89	−117.84	LU	0.33	−1.28	0.60	−0.35
CZ	15.08	−57.98	27.23	−15.67	HU	17.51	−67.34	30.43	−19.40
DK	6.49	−24.96	10.47	−8.00	MT	0.29	−1.11	0.77	−0.05
DE	56.50	−217.25	89.75	−71.00	NL	18.22	−70.07	33.85	−18.00
EE	2.67	−10.27	−3.03	−10.63	AT	17.99	−69.17	−7.60	−58.78
IE	9.25	−35.57	22.71	−3.61	PL	201.91	−776.40	−284.90	−859.40
GR[a]	45.81	−176.16	42.38	−87.97	PT	49.77	−191.39	−33.78	−175.40
ES	76.95	−295.89	93.25	−125.70	RO	258.70	−994.80	−394.70	−1130.80
FR	72.55	−279.00	86.45	−120.00	SI	7.50	−28.86	4.25	−17.10
HR	19.27	−74.09	−73.54	−128.36	SK	7.91	−30.41	−0.38	−22.88
IT	82.97	−319.06	166.49	−69.60	FI	10.09	−38.81	−4.78	−33.50
CY	1.52	−5.84	0.90	−3.42	SE	7.90	−30.40	27.49	5.00
LV	7.69	−29.56	−5.20	−27.07	UK	30.95	−119.00	104.42	16.37

Sources: Own calculations based on Eurostat data
[a]Change for 2005–2017

of the UK and Sweden, the number of persons employed in agriculture, forestry, and fishing activity decreases, while applying the EU economy growth rate a positive higher number of employed persons is expected. The component E_{ij} demonstrates that in agriculture, forestry, and fishing activity (A), on average, the employment rate is lower than at the level of the EU economy. As in the case of gross value added, the component A_{ij} for employment is negative in all member states, but in some countries the real situation is more favourable than the projected A_{ij} values. According to the values of the component M_{ij}, only ten member states have a negative development of employment due to local competitive advantages, namely Estonia, Croatia, Latvia, Lithuania, Austria, Poland, Portugal, Romania, Slovakia, and Finland. Nevertheless, in most of those countries, the projected M_{ij} values showed a more favourable development situation than the real change over the investigated period.

To conclude, Sect. 4.4 reports on the diminishing role of agriculture in the EU economic system during the period 2005–2018. At the EU level, the structural change indices do not demonstrate dramatic reallocations of structural change measures within ten economic activities. However, it must be recognized that the structural changes in the reallocation of labour are remarkably higher than in the case of gross value added. Another important issue is that economic systems often survive more significant structural changes at the level of individual member states, and their structural change indices demonstrate a wider magnitude of alterations.

The results of the empirical study are in line with previous research and confirm the ongoing process of switching from agriculture, forestry, and fishing activity to service-related activities at the EU level. Structural changes in member states vary in terms of the development pace and directions. Some member states maintain a similar share of gross value added in the national structure of economic activities both in 2005 and in 2018, but the role of agriculture, forestry, and fishing activity in total employment is diminishing in the vast majority of countries.

According to the shift-share analysis, the values of the total change in employment show that the development direction is opposite to the overall growth rate of the EU economy, while in the case of gross value added the results are country-specific and highly sensitive to the selected methodological assumptions. Findings for economic activity mix and local competitiveness components are highly dependent on the national economic system.

4.5 Dynamics of Structural Changes in the EU Agricultural System

4.5.1 Changes in the Average Farm Size at the EU Level

This section introduces the most important empirical results of the decomposition that quantifies the contribution of structural and pure changes to the evolution of the average utilized agricultural area, the average standard output, and the average directly employed labour force (in annual working units) on farms in EU agriculture. The decomposition carried out (see Eqs. 4.7–4.10) provides a threefold focus on the changes in agriculture, namely changes at the EU level; the transformation of structural change measures by type of farming; and the evolution of agriculture in member states.

During the investigated period of 2005–2016, the EU agricultural system survived a remarkable transformation. The overall change (C_T) in the average utilized agricultural area on farms at the EU level accounted for 1.42 (i.e. it corresponded to the increase of 41.55%), while the growth of the average standard output at the EU level was even more impressive and the overall change (C_T) amounted to 1.80 (79.65%). Nevertheless, the substantial increase in factors related to land use and output in EU agriculture was not followed by similar changes in labour input. According to empirical results, the overall change (C_T) in the average directly employed labour force on farms in EU agriculture was 1.01 (1.34%).

The main driving component of the structural change in the EU agricultural system was the pure change in the selected structural change measures (I_I). The highest growth of the subindex I_I—1.84 (84.45%)—was observed for the average standard output, while the change in the aforementioned subindex for the average utilized agricultural area and the average directly employed labour force amounted to 1.31 (31.04%) and 1.09 (9.46%), respectively.

Over the period from 2005 to 2016, the development of the structural subindices S_{EU} and S_{M} depended on the selected measures of farm size. At the EU level, all measures demonstrated a negative development of the structural subindex S_{M} linked to the changes in the structure of the farming types due to member states [the average utilized agricultural area—0.99 (decreased by 0.41%), the average standard output—0.97 (fell by 2.72%), the average directly employed labour force—0.96 (dropped by 4.08%)].

The structural subindex S_{EU}, showing the switch between farming types at the EU level, in the case of the average utilized agricultural area, demonstrated growth of 8.47% (1.08). However, during 2005–2016, the same structural subindex S_{EU} for the average standard output was almost stable and accounted for 1.00 (an increase of 0.12%). In the case of the average directly employed labour force, this subindex dropped by 3.48% (0.97).

The chain-linked results of the decomposition for the investigated measures of structural change are demonstrated in Fig. 4.6. It is interesting to note that time intervals with the most rapid growth rates depend on the selected measure of farm size. According to Fig. 4.6, in the EU agricultural system, indicators of the average utilized agricultural area and the average standard output demonstrated the highest increase during the period 2007–2010, while the changes in the average directly employed labour force per farm lagged and reached the peak in 2010–2013. Period-specific growth rates also differed remarkably and the development was not uniform. As illustrated by Fig. 4.6, the period-specific overall changes (C_T) in the average directly employed labour force were moderate and fluctuated around the situation of the initial period. Growth of the average utilized agricultural area was noticed during

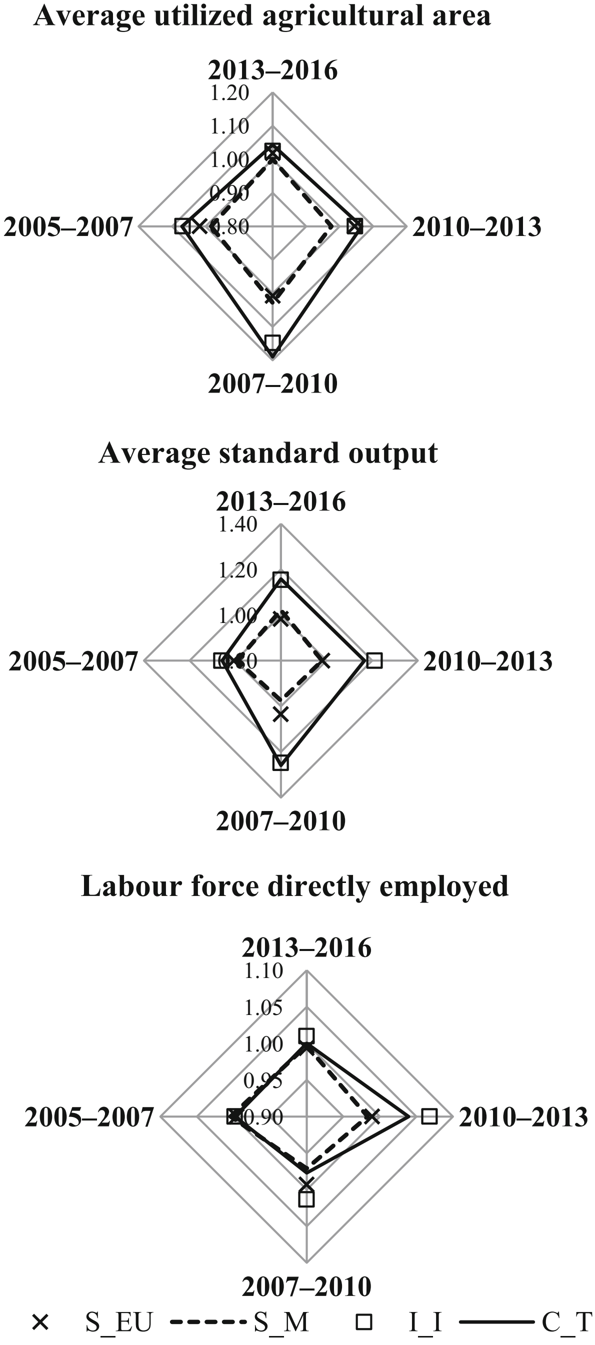


Fig. 4.6 Chain-linked decomposition of the investigated structural change measures at the EU level. Source: Own calculations based on Eurostat data

all investigated periods; however, it had one period with a significant increase in the index C_T, compared to the growth rate of other periods. The development of the average standard output in EU agriculture reflected the sustained growth during the investigated period from 2005 to 2016.

4.5.2 Changes in the Average Farm Size by Type of Farming at the EU Level

The decomposition of the index C_T by type of farming allows it to be stated that the overall changes in the EU agricultural system are determined by substantial changes in reallocation patterns among the various farming types. Hence, the situation of the investigated farm size measures differs too (see Fig. 4.7). Over the analysed period of 2005–2016, the significant growth of the index C_T for all selected measures of structural change is a common characteristic for specialist field crops (I) and specialist grazing livestock (III) farms; i.e., those farming types, on average, used more agricultural area on farms, improved the employment position, and generated a higher standard output, while the changes on farms with other specializations were less dramatic and differed in their directions of development.

The detailed empirical results, outlined in Fig. 4.7, allow period-specific changes of the index C_T by type of farming to be explored. A value of the index C_T that is equal to unity means that the situation remains without changes over the investigated period, while a value above/below unity shows a growth/decline in the analysed index. Consequently, the decomposition of the average utilized agricultural area by farming type shows that the highest chain-linked indices C_T were at specialist field crops (I) and specialist grazing livestock (III) farms, while contributions of the index C_T to the change for the period from 2005 to 2016 amounted to 1.27 and 1.11, respectively. It is important to note that the index C_T for the average utilized agricultural area remained almost stable at specialist horticulture, fruit, and citrus fruit (II), specialist granivore (IV), and mixed cropping (V) farms. The remaining farming types demonstrated moderate period-specific fluctuations of the indices C_T on mixed livestock (VI) and mixed combined (VII) farms amounting to 0.98 and 1.01, respectively.

The highest increase in values of the index C_T is recorded for the measure of the average standard output. During the period from 2005 to 2016, the biggest increase in the average standard output took place on specialist field crop (I)—1.20, specialist grazing livestock (III)—1.21, and specialist granivore (IV)—1.12 farms. At the same time, the index C_T for mixed livestock (VI) farms showed a negligible decline in the average standard output and amounted to 1.00. The overall growth of the index C_T for the average standard output on mixed cropping (V), specialist horticulture, fruit, and citrus fruit (II), and mixed combined (VII) farms was rather modest and period-specific indices did not demonstrate significant fluctuations.

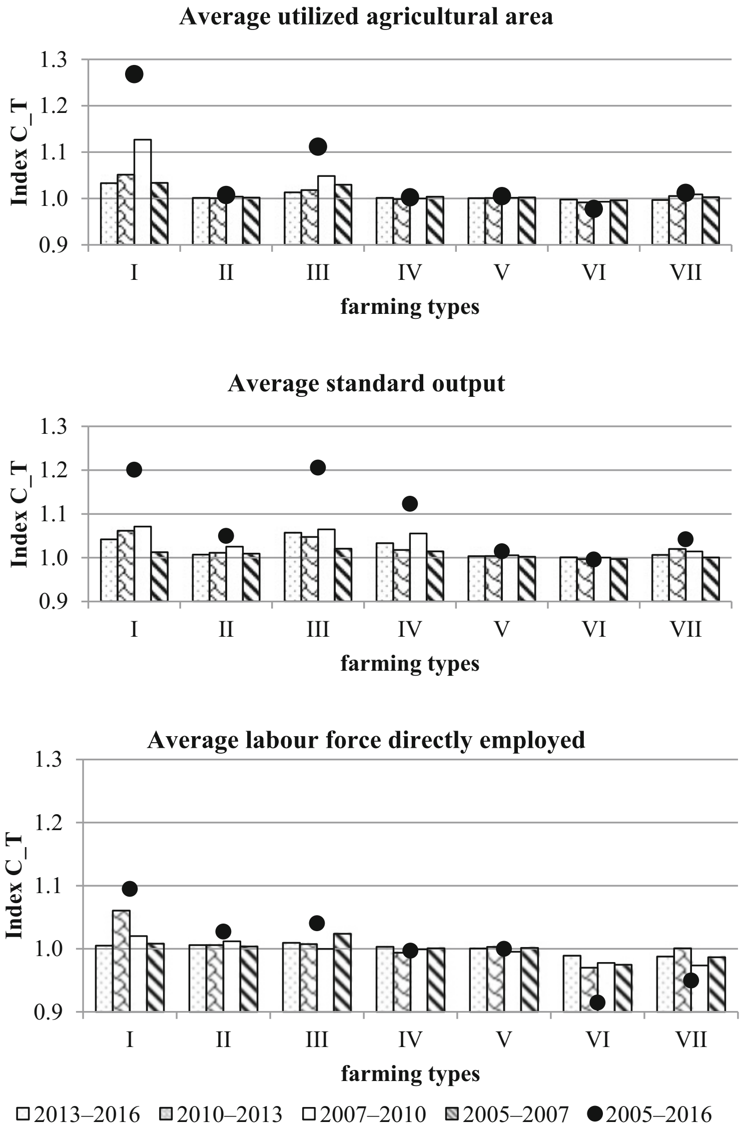


Fig. 4.7 Chain-linked decomposition of the index C_T by type of farming at the EU level. Source: Own calculations based on Eurostat data

However, the development of the index C_T for the average directly employed labour force differed from the indices for the average utilized agricultural area and the average standard output. As in the case of two other measures of farm size, the most significant contributions to the EU growth came from specialist field crop (I) and specialist grazing livestock (III) farms, but the growth rate of the index C_T

Table 4.7 Contributions of subindices to the overall change index C_T for the average utilized agricultural area by type of farming at the EU level

Type of farming	Subindex	2013–2016	2010–2013	2007–2010	2005–2007	2005–2016
I	S_{EU}	1.0387	1.0515	1.0210	1.0120	1.1240
	S_M	0.9914	0.9828	1.0326	0.9937	1.0055
	I_I	1.0031	1.0171	1.0686	1.0278	1.1220
II	S_{EU}	1.0007	0.9982	1.0017	1.0004	1.0010
	S_M	0.9996	1.0003	0.9991	0.9997	0.9988
	I_I	1.0009	1.0022	1.0031	1.0017	1.0077
III	S_{EU}	0.9941	1.0085	1.0079	1.0164	1.0265
	S_M	1.0080	0.9909	1.0092	0.9906	0.9992
	I_I	1.0108	1.0186	1.0307	1.0226	1.0839
IV	S_{EU}	0.9970	0.9964	1.0045	0.9988	0.9959
	S_M	1.0029	1.0005	0.9918	1.0012	0.9972
	I_I	1.0014	1.0013	1.0036	1.0035	1.0094
V	S_{EU}	1.0001	1.0013	0.9973	1.0023	1.0008
	S_M	0.9993	0.9992	1.0012	0.9985	0.9983
	I_I	1.0013	1.0002	1.0031	1.0013	1.0058
VI	S_{EU}	0.9949	0.9869	0.9977	0.9904	0.9693
	S_M	1.0010	1.0042	0.9900	1.0023	0.9988
	I_I	1.0015	1.0004	1.0053	1.0033	1.0097
VII	S_{EU}	0.9935	1.0021	0.9781	0.9981	0.9722
	S_M	0.9978	0.9975	1.0044	0.9976	0.9981
	I_I	1.0052	1.0054	1.0267	1.0069	1.0431
Total	S_{EU}	1.0183	1.0446	1.0078	1.0182	1.0847
	S_M	1.0000	0.9755	1.0282	0.9836	0.9958
	I_I	1.0244	1.0459	1.1481	1.0688	1.3104

Source: Own calculations based on Eurostat data

was significantly lower, i.e. 1.09 and 1.04, respectively. Over the investigated period, an almost stable directly employed labour force was found on specialist horticulture, fruit, and citrus fruit (II), specialist granivore (IV), and mixed cropping (V) farms. At the same time, the indices related to direct employment on mixed livestock (VI) and mixed combined (VII) farms reported a decline in the values and amounted to 0.93 and 0.96, while these farming types demonstrated a consistent chain-linked decline in the values associated with the index C_T.

Table 4.7 explains the contributions of structural (S_{EU} and S_M) and pure change (I_I) subindices to the fluctuations of the index C_T for the average utilized agricultural area by type of farming at the EU level. The decomposition allows it to be stated that the change on farms with different specializations at the EU level was driven by both structural and pure change subindices, but the role of these components depends on the selected type of farming and the investigated period. Although the subindex of pure average utilized agricultural area change (I_I) could be mentioned as the most important contributor to period-specific changes on specialist horticulture, fruit, and citrus fruit (II), specialist grazing livestock (III), and mixed combined (VII) farms, the remaining farming types are characterized by period-specific changes in decisive subindices with shifts from structural to pure change components (Table 4.7).

During the period 2005–2016, specialist field crop (I) was the sole farming type where the overall C_T changes were driven by the structural subindex S_{EU}. However, the subindex S_{EU}, denoting the switch between farming types at the EU level, had gained the role of the driving contributor only after the year 2010, while over the previous periods the overall increase in the value of C_T was determined by pure growth of the average utilized agricultural area. According to the results in Table 4.7, specialist granivore (IV), mixed cropping (V), and mixed livestock (VI) farms had the periods with the highest contributions of structural subindices, but the overall change in the index C_T was mainly caused by the subindex I_I.

The development trajectories of the subindices for the average standard output also vary by type of farming (Table 4.8). The chain-linked comparison of subindices demonstrates that the increase in pure average standard output (I_I) was the most

Table 4.8 Contributions of subindices to the overall change index C_T for the average standard output by type of farming at the EU level

Type of farming	Subindex	2013–2016	2010–2013	2007–2010	2005–2007	2005–2016
I	S_{EU}	1.0194	1.0247	1.0097	1.0055	1.0588
	S_{M}	0.9982	0.9886	1.0107	0.9967	0.9965
	I_I	1.0239	1.0478	1.0496	1.0103	1.1381
II	S_{EU}	1.0039	0.9894	1.0105	1.0023	1.0054
	S_{M}	0.9935	0.9971	0.9936	0.9960	0.9804
	I_I	1.0096	1.0247	1.0210	1.0108	1.0651
III	S_{EU}	0.9946	1.0076	1.0070	1.0144	1.0241
	S_{M}	1.0012	0.9885	1.0097	0.9953	0.9947
	I_I	1.0613	1.0513	1.0472	1.0109	1.1836
IV	S_{EU}	0.9769	0.9740	1.0291	0.9931	0.9725
	S_{M}	1.0273	1.0047	0.9646	1.0037	0.9993
	I_I	1.0293	1.0398	1.0631	1.0177	1.1557
V	S_{EU}	1.0001	1.0013	0.9974	1.0021	1.0008
	S_{M}	1.0003	0.9979	1.0013	0.9981	0.9979
	I_I	1.0031	1.0044	1.0069	1.0018	1.0158
VI	S_{EU}	0.9931	0.9837	0.9974	0.9901	0.9644
	S_{M}	1.0021	1.0061	0.9907	1.0028	1.0030
	I_I	1.0057	1.0071	1.0125	1.0041	1.0293
VII	S_{EU}	0.9947	1.0017	0.9836	0.9986	0.9785
	S_{M}	0.9986	0.9977	1.0048	0.9991	1.0009
	I_I	1.0131	1.0204	1.0262	1.0026	1.0639
Total	S_{EU}	0.9823	0.9817	1.0347	1.0059	1.0012
	S_{M}	1.0210	0.9807	0.9750	0.9916	0.9728
	I_I	1.1542	1.2113	1.2483	1.0595	1.8445

Source: Own calculations based on Eurostat data

Table 4.9 Contributions of subindices to the overall change index C_T for the average directly employed labour force by type of farming at the EU level

Type of farming	Subindex	2013–2016	2010–2013	2007–2010	2005–2007	2005–2016
I	S_{EU}	1.0229	1.0284	1.0107	1.0061	1.0654
	S_M	1.0007	0.9986	1.0049	1.0001	1.0032
	I_I	0.9818	1.0327	1.0045	1.0019	1.0245
II	S_{EU}	1.0039	0.9908	1.0080	1.0016	1.0045
	S_M	0.9972	1.0006	0.9960	0.9990	0.9921
	I_I	1.0049	1.0145	1.0079	1.0030	1.0307
III	S_{EU}	0.9950	1.0071	1.0064	1.0124	1.0210
	S_M	1.0011	0.9964	0.9985	1.0006	0.9960
	I_I	1.0133	1.0038	0.9950	1.0105	1.0231
IV	S_{EU}	0.9932	0.9921	1.0092	0.9977	0.9913
	S_M	1.0043	0.9968	0.9837	1.0031	0.9889
	I_I	1.0056	1.0049	1.0065	1.0000	1.0169
V	S_{EU}	1.0001	1.0022	0.9956	1.0036	1.0014
	S_M	0.9989	0.9967	1.0013	0.9986	0.9964
	I_I	1.0014	1.0041	0.9984	0.9991	1.0020
VI	S_{EU}	0.9878	0.9669	0.9943	0.9773	0.9259
	S_M	0.9990	1.0029	0.9850	1.0031	0.9909
	I_I	1.0022	1.0002	0.9982	0.9941	0.9970
VII	S_{EU}	0.9910	1.0030	0.9694	0.9972	0.9609
	S_M	0.9957	0.9913	1.0016	0.9994	0.9910
	I_I	1.0009	1.0064	1.0029	0.9898	0.9974
Total	S_{EU}	0.9935	0.9895	0.9930	0.9956	0.9652
	S_M	0.9968	0.9833	0.9710	1.0040	0.9592
	I_I	1.0098	1.0682	1.0134	0.9983	1.0946

Source: Own calculations based on Eurostat data

important contributor on specialist field crop (I), specialist horticulture, fruit, and citrus fruit (II), specialist granivore (IV), mixed livestock (VI), and mixed combined (VII) farms, while over the period from 2005 to 2007, specialist grazing livestock (III) and mixed cropping (V) farming had the highest structural subindex S_{EU}.

In the case of employment, the investigation of the chain-linked contributions of structural and pure change subindices to the overall fluctuation of the index C_T indicates an entirely different situation to the previous two measures of farm size (Table 4.9). The results for the specialist field crop (I) farming type, except for the period 2010–2013, are driven by the contribution of the subindex S_{EU}. Outcomes warn about the redistribution of the directly employed labour between the EU farming types (S_{EU}) and within member states (S_M). Hence, the subindex of pure average directly employed labour force (I_I) declines from the year 2013. The results for specialist grazing livestock (III) farms also confirm the importance of structural changes in the EU farming system. Mixed livestock (VI) and mixed combined (VII) farms demonstrate the declining role of these farming types in direct employment at the EU level (S_{EU}) and within member states (S_{M}) for most of the estimated periods. Specialist horticulture, fruit, and citrus fruit (II) and mixed cropping (V) farming types do not demonstrate dramatic changes in direct employment.

To conclude, the empirical results confirm that over the period 2005–2016 the EU agricultural system evolved. The decomposition of the average utilized agricultural area, the average standard output, and the average directly employed labour force by type of farming shows a significant increase in farm size on specialist field crop (I) and specialist grazing livestock (III) farms, while, according to the overall change index C_T, the developments on mixed livestock (VI) farms are unfavourable.

4.5.3 Changes in the Average Farm Size by Member States

A decomposition of the indices C_T by member states is provided in Fig. 4.8. The visualization of empirical results allows us to conclude that the contribution of member states to the overall changes at the EU level differs significantly. Another important point to make is that the indices C_T for the average utilized agricultural area, the average standard output, and the average directly employed labour force demonstrate various growth rates even for the same member states.

For the period from 2005 to 2016, the decomposed values of the index C_T for the average utilized agricultural area in member states range from 1.00 to 1.06 (Fig. 4.8). The major contributors to the index C_T change at the EU level are France (1.06), the UK (1.04), Spain (1.03), Germany, (1.03), and Poland (1.03), while the contribution of other member states is less important. The chain-linked decomposition of the average utilized agricultural area by member states allows the peak periods and the leading subindices that determine the evolution of the national agricultural systems to be identified (Table 4.10). This decomposition level also assists in comparing the development patterns in member states.

The decomposition of the index C_T by member states leads to similar results to the decomposition at the EU level. The most remarkable period-specific increase in the average utilized agricultural area occurred from 2007 to 2010. However, two member states became exemptions from this rule. In Poland, the highest value of the index C_T was observed during the period 2005–2007, while in Cyprus the major change was in 2013–2016. The subindices for the entire period show that in most of the EU member states the driving component of transformations is the subindex of pure change (I_I) of the utilized agricultural area per farm, but in eight member states the contributions of the structural subindices have the greatest weight. Thus, in Ireland, Cyprus, Austria, and Romania, the values of the index C_T are largely influenced by the subindex S_{EU}, while in Spain, Malta, Portugal, and Slovenia, the most important contributor is the subindex S_{M}.

The range of decomposed indices C_T for the average standard output is larger than the interval for the average utilized agricultural area, and the values fluctuate between 1.00 and 1.10 (Fig. 4.8). The greatest contributions to the overall change at the EU level are made by France (1.10), Italy (1.08), Germany (1.07), Poland

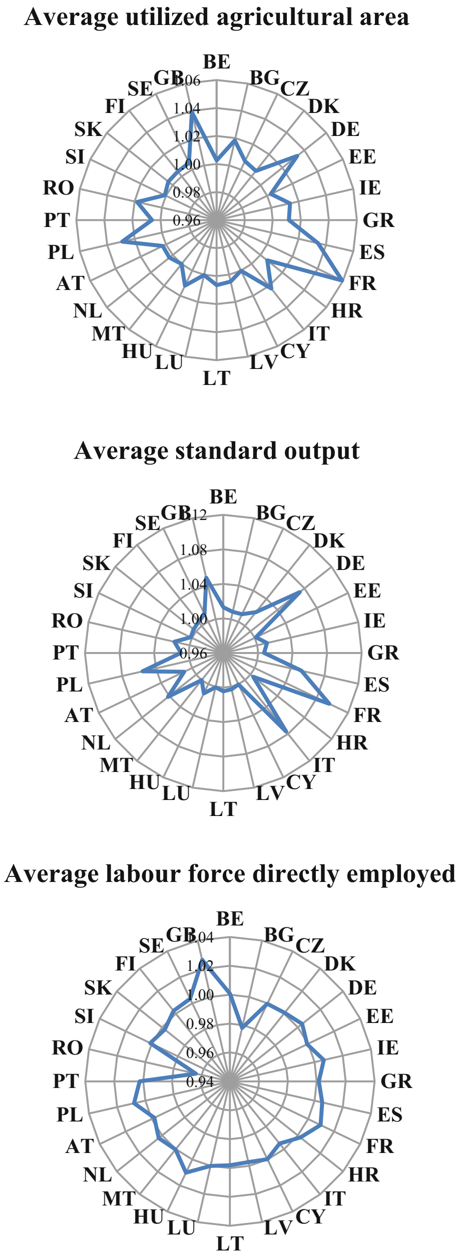


Fig. 4.8 Decomposition of the index C_T by member states for the period 2005–2016. Source: Own calculations based on Eurostat data

(1.06), and Spain (1.05). Table 4.11 shows that the development of the average standard output is mainly determined by the subindex of pure change (I_I). Over the period 2005–2016, Malta and Cyprus were the only exceptions to this general development direction, because their change was driven by the structural subindex S_{M}.

Table 4.10 Chain-linked decomposition of the average utilized agricultural area indices

	2005–2016				2013–2016				2010–2013				2007–2010				2005–2007			
	C_T	S_{EU}	S_M	I_I	C_T	S_{EU}	S_M	I_I	C_T	S_{EU}	S_M	I_I	C_T	S_{EU}	S_M	I_I	C_T	S_{EU}	S_M	I_I
BE	1.0027	1.0001	1.0002	1.0023	1.0007	0.9999	1.0002	1.0005	1.0002	1.0001	0.9997	1.0004	1.0013	1.0000	1.0004	1.0009	1.0005	1.0001	0.9998	1.0005
BG	1.0183	1.0045	0.9973	1.0165	1.0004	1.0018	0.9959	1.0026	1.0029	1.0026	0.9943	1.0060	1.0123	1.0007	1.0057	1.0059	1.0031	1.0004	0.9997	1.0030
CZ	1.0067	0.9989	0.9978	1.0100	1.0008	0.9999	1.0011	0.9998	1.0014	1.0005	1.0040	0.9970	1.0033	0.9989	0.9927	1.0118	1.0011	0.9998	0.9993	1.0019
DK	1.0049	1.0013	0.9970	1.0065	1.0010	1.0001	0.9997	1.0012	1.0008	1.0004	0.9992	1.0012	1.0022	1.0005	0.9997	1.0019	1.0008	1.0002	0.9984	1.0022
DE	1.0334	1.0035	0.9976	1.0323	1.0050	1.0000	1.0022	1.0029	1.0065	1.0025	1.0010	1.0030	1.0152	0.9998	0.9946	1.0209	1.0061	1.0013	1.0000	1.0048
EE	1.0029	1.0006	0.9980	1.0043	1.0008	1.0001	1.0006	1.0000	1.0004	1.0003	0.9995	1.0006	1.0008	1.0001	0.9987	1.0020	1.0008	1.0001	0.9992	1.0015
IE	1.0136	1.0024	1.0090	1.0022	1.0010	0.9999	1.0009	1.0001	1.0018	1.0012	1.0006	1.0000	1.0098	1.0006	1.0070	1.0021	1.0012	1.0011	0.9997	1.0003
GR	1.0116	1.0031	0.9986	1.0099	0.9993	1.0012	0.9984	0.9998	1.0001	1.0019	1.0009	0.9973	1.0112	1.0003	0.9979	1.0131	1.0014	1.0005	1.0009	1.0000
ES	1.0342	1.0152	1.0154	1.0032	1.0057	1.0034	1.0008	1.0014	1.0059	1.0062	1.0009	0.9987	1.0143	1.0027	1.0156	0.9961	1.0078	1.0031	0.9975	1.0072
FR	1.0593	1.0128	1.0115	1.0340	1.0085	1.0018	1.0012	1.0054	1.0100	1.0066	0.9903	1.0132	1.0295	1.0013	1.0233	1.0048	1.0099	1.0040	0.9959	1.0100
HR	1.0061	1.0003	1.0015	1.0043	1.0004	1.0002	0.9987	1.0015	1.0020	1.0003	0.9972	1.0046	1.0031	0.9999	1.0036	0.9997	1.0004	1.0000	1.0004	1.0000
IT	1.0225	1.0085	0.9906	1.0236	1.0055	1.0017	1.0027	1.0011	1.0018	1.0034	0.9873	1.0113	1.0106	1.0013	0.9987	1.0106	1.0041	1.0021	1.0022	0.9999
CY	1.0001	1.0001	0.9999	1.0001	1.0001	1.0000	1.0000	1.0000	1.0000	1.0000	0.9999	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9999	1.0001
LV	1.0051	1.0007	0.9970	1.0075	1.0009	1.0003	0.9986	1.0020	1.0015	1.0006	1.0003	1.0006	1.0015	1.0000	0.9990	1.0026	1.0011	1.0001	0.9988	1.0022
LT	1.0064	1.0005	1.0008	1.0051	1.0010	1.0004	0.9970	1.0035	1.0018	1.0008	0.9993	1.0017	1.0031	0.9997	1.0015	1.0019	1.0002	1.0000	1.0013	0.9989
LU	1.0003	1.0000	1.0001	1.0002	1.0000	1.0000	1.0000	1.0000	1.0001	1.0000	1.0000	1.0000	1.0001	1.0000	1.0001	1.0000	1.0001	1.0000	0.9999	1.0001
HU	1.0119	1.0028	1.0034	1.0057	1.0014	1.0010	0.9981	1.0023	1.0017	1.0017	0.9998	1.0002	1.0072	1.0001	1.0080	0.9992	1.0015	1.0003	0.9974	1.0038
MT	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
NL	1.0029	1.0010	0.9989	1.0031	1.0002	1.0000	0.9983	1.0018	1.0006	1.0003	0.9998	1.0004	1.0016	1.0003	1.0011	1.0003	1.0005	1.0004	0.9997	1.0005
AT	1.0026	1.0017	1.0004	1.0006	1.0004	1.0001	0.9997	1.0005	1.0004	1.0006	0.9997	1.0001	1.0011	1.0005	1.0007	0.9999	1.0008	1.0005	1.0003	1.0000
PL	1.0290	0.9997	0.9847	1.0453	1.0045	1.0013	1.0015	1.0017	1.0056	1.0018	0.9995	1.0043	1.0086	0.9987	0.9772	1.0335	1.0104	0.9983	1.0063	1.0058
PT	1.0061	1.0005	1.0031	1.0025	1.0009	0.9998	1.0013	0.9998	1.0011	1.0003	0.9985	1.0022	1.0039	0.9999	1.0049	0.9991	1.0001	1.0005	0.9982	1.0014
RO	1.0181	1.0068	1.0063	1.0049	1.0012	1.0026	0.9998	0.9989	1.0049	1.0034	1.0074	0.9941	1.0075	1.0001	1.0005	1.0069	1.0045	1.0006	0.9989	1.0050
SI	1.0010	1.0000	1.0005	1.0005	1.0001	1.0000	1.0000	1.0002	1.0002	1.0000	1.0001	1.0001	1.0004	1.0000	1.0003	1.0001	1.0002	1.0001	1.0001	1.0001
SK	1.0040	1.0003	0.9966	1.0070	1.0005	1.0001	1.0012	0.9991	1.0008	1.0005	1.0001	1.0002	1.0016	0.9997	0.9937	1.0084	1.0011	1.0001	1.0015	0.9995
FI	1.0043	1.0021	0.9974	1.0049	1.0004	1.0004	0.9989	1.0011	1.0009	1.0008	0.9981	1.0020	1.0020	1.0005	1.0006	1.0010	1.0011	1.0004	0.9998	1.0008
SE	1.0053	1.0020	1.0005	1.0027	1.0007	1.0003	0.9995	1.0010	1.0010	1.0009	0.9990	1.0011	1.0027	1.0003	1.0023	1.0001	1.0007	1.0006	0.9998	1.0004
GB	1.0390	1.0121	0.9921	1.0348	1.0011	1.0017	1.0036	0.9958	1.0094	1.0057	0.9990	1.0047	1.0198	1.0021	1.0009	1.0167	1.0088	1.0035	0.9885	1.0171
Π	1.4155	1.0847	0.9958	1.3104	1.0431	1.0183	1.0000	1.0244	1.0658	1.0446	0.9755	1.0459	1.1897	1.0078	1.0282	1.1481	1.0704	1.0182	0.9836	1.0688

Table 4.11 Chain-linked decomposition of the average standard output indices

	2005–2016				2013–2016				2010–2013				2007–2010				2005–2007			
	C_T	S_{EU}	S_M	I_I	C_T	S_{EU}	S_M	I_I	C_T	S_{EU}	S_M	I_I	C_T	S_{EU}	S_M	I_I	C_T	S_{EU}	S_M	I_I
BE	1.0128	0.9985	0.9991	1.0153	1.0000	0.9992	1.0015	0.9994	1.0063	0.9989	0.9977	1.0097	1.0060	1.0009	1.0001	1.0049	1.0012	0.9999	0.9997	1.0016
BG	1.0088	1.0009	0.9967	1.0112	1.0021	1.0004	0.9986	1.0032	1.0034	1.0004	0.9969	1.0061	1.0023	1.0002	1.0000	1.0021	1.0005	1.0000	1.0005	1.0000
CZ	1.0098	0.9985	0.9972	1.0142	1.0027	0.9996	1.0009	1.0022	1.0031	0.9998	1.0027	1.0005	1.0031	0.9995	0.9940	1.0097	1.0006	0.9997	0.9995	1.0014
DK	1.0204	0.9992	0.9943	1.0270	1.0047	0.9985	0.9998	1.0064	1.0054	0.9987	0.9991	1.0076	1.0086	1.0019	0.9971	1.0096	1.0016	0.9999	0.9985	1.0032
DE	1.0730	0.9970	0.9962	1.0804	1.0165	0.9962	1.0042	1.0161	1.0261	0.9971	1.0030	1.0260	1.0181	1.0033	0.9884	1.0266	1.0098	1.0006	1.0008	1.0084
EE	1.0018	1.0001	0.9993	1.0024	1.0005	1.0000	0.9999	1.0006	1.0004	1.0000	1.0000	1.0004	1.0007	1.0001	0.9997	1.0010	1.0002	1.0000	0.9998	1.0003
IE	1.0118	1.0010	1.0052	1.0055	1.0050	0.9997	1.0009	1.0045	1.0035	1.0002	1.0005	1.0028	1.0017	1.0006	1.0031	0.9980	1.0004	1.0006	0.9998	1.0001
GR	1.0072	1.0013	1.0005	1.0054	0.9993	1.0002	0.9994	0.9997	1.0054	1.0003	1.0018	1.0033	1.0007	1.0004	0.9980	1.0023	1.0022	1.0005	1.0014	1.0003
ES	1.0526	1.0000	1.0176	1.0344	1.0110	0.9976	1.0065	1.0070	1.0147	0.9960	1.0043	1.0144	1.0207	1.0069	1.0049	1.0087	1.0059	1.0006	1.0010	1.0042
FR	1.0958	1.0019	1.0187	1.0737	1.0173	0.9980	1.0030	1.0163	1.0284	0.9987	0.9994	1.0304	1.0406	1.0037	1.0186	1.0179	1.0080	1.0015	0.9974	1.0091
HR	1.0041	0.9997	1.0003	1.0041	1.0004	0.9999	0.9995	1.0010	1.0002	1.0000	0.9972	1.0031	1.0035	0.9999	1.0027	1.0009	1.0003	1.0000	1.0004	1.0000
IT	1.0765	1.0039	0.9868	1.0866	1.0300	0.9980	1.0092	1.0227	0.9944	0.9976	0.9794	1.0178	1.0428	1.0072	0.9930	1.0426	1.0088	1.0017	1.0048	1.0023
CY	1.0004	1.0001	1.0005	0.9998	1.0005	1.0000	1.0006	0.9999	1.0002	1.0000	0.9998	1.0004	0.9999	1.0001	1.0000	0.9997	0.9997	1.0000	0.9999	0.9997
LV	1.0031	1.0001	0.9998	1.0032	1.0009	1.0000	1.0000	1.0008	1.0009	1.0001	1.0000	1.0008	1.0012	1.0000	0.9999	1.0012	1.0001	1.0000	0.9999	1.0002
LT	1.0045	0.9999	1.0005	1.0040	1.0013	1.0000	0.9993	1.0019	1.0017	1.0001	1.0001	1.0016	1.0016	1.0000	1.0002	1.0015	0.9995	0.9999	1.0001	0.9994
LU	1.0008	1.0000	1.0001	1.0007	1.0002	1.0000	1.0000	1.0002	1.0002	1.0000	1.0000	1.0002	1.0003	1.0000	1.0001	1.0002	1.0001	1.0000	0.9999	1.0001
HU	1.0121	0.9997	1.0010	1.0114	1.0038	0.9998	0.9995	1.0045	1.0024	0.9999	0.9992	1.0033	1.0053	1.0005	1.0029	1.0018	1.0002	0.9999	0.9989	1.0015
MT	1.0001	1.0000	1.0002	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0001	1.0000	1.0001	1.0000	1.0000	1.0000	1.0001	0.9999
NL	1.0418	1.0005	0.9926	1.0490	1.0115	0.9987	0.9926	1.0204	1.0100	0.9969	1.0002	1.0128	1.0147	1.0040	1.0012	1.0095	1.0047	1.0008	0.9982	1.0057
AT	1.0103	1.0001	1.0006	1.0095	1.0020	0.9996	1.0001	1.0023	1.0017	0.9997	0.9996	1.0024	1.0055	1.0009	1.0003	1.0044	1.0014	1.0001	1.0003	1.0010
PL	1.0558	0.9952	0.9728	1.0907	1.0140	0.9985	1.0005	1.0150	1.0144	0.9977	0.9967	1.0200	1.0187	1.0006	0.9713	1.0481	1.0078	0.9982	1.0039	1.0057
PT	1.0090	1.0001	1.0022	1.0066	1.0024	0.9998	1.0014	1.0012	1.0008	0.9998	0.9990	1.0021	1.0058	1.0004	1.0029	1.0025	1.0000	1.0002	0.9987	1.0012
RO	1.0180	0.9982	1.0054	1.0144	1.0020	0.9996	0.9999	1.0026	1.0107	0.9989	1.0036	1.0083	1.0035	0.9996	1.0025	1.0014	1.0013	0.9996	0.9998	1.0019
SI	1.0019	0.9999	1.0004	1.0016	1.0004	0.9999	1.0000	1.0005	1.0006	1.0000	1.0000	1.0006	1.0006	1.0000	1.0002	1.0003	1.0004	1.0000	1.0002	1.0002
SK	1.0039	0.9999	0.9968	1.0073	1.0006	1.0000	1.0005	1.0002	1.0007	1.0000	0.9997	1.0009	1.0027	0.9999	0.9957	1.0071	1.0001	1.0000	1.0006	0.9996
FI	1.0060	1.0007	0.9972	1.0082	1.0009	0.9999	0.9990	1.0020	1.0019	1.0000	0.9989	1.0030	1.0029	1.0005	0.9996	1.0029	1.0004	1.0003	0.9996	1.0006
SE	1.0100	1.0007	1.0011	1.0082	1.0022	0.9998	0.9996	1.0028	1.0042	1.0001	0.9999	1.0042	1.0024	1.0004	1.0011	1.0009	1.0009	1.0004	1.0006	1.0000
GB	1.0491	1.0041	0.9906	1.0547	1.0149	0.9993	1.0043	1.0112	1.0131	1.0007	1.0019	1.0105	1.0192	1.0026	0.9977	1.0189	0.9991	1.0014	0.9875	1.0103
Π	1.7965	1.0012	0.9728	1.8445	1.1575	0.9823	1.0210	1.1542	1.1661	0.9817	0.9807	1.2113	1.2592	1.0347	0.9750	1.2483	1.0569	1.0059	0.9916	1.0595

Contrary to the chain-linked decomposed results of the average utilized agricultural area with a clear common period of the highest increase in the index C_T, the average standard output peaks in the indices C_T depend on the selected member state. Yet, in most member states, the peak values of the index C_T are observed during the period 2007–2010. In Belgium, Bulgaria, the Czech Republic, Germany, Greece, Lithuania, Romania, and Sweden, the peak lags and the sharpest increase is noticed between 2010 and 2013, while in Ireland and Cyprus the delay is longer and the highest growth rate corresponds to the period from 2013 to 2016.

The values of the index C_T for the average directly employed labour force range from 0.96 to 1.03. As illustrated in Fig. 4.8, the employment situation in member states remained almost stable over 2005–2016, though some exceptions with extreme values can be mentioned. For example, Romania (0.96) and Bulgaria (0.98) show the most remarkable drop in the index C_T, while the UK (1.03) and Hungary (1.01) demonstrate the highest contribution of the aforementioned index related to employment on farms.

According to Table 4.12, over the period 2005–2016, only in 16 member states are the changes in the average directly employed labour force driven by the highest contribution from the subindex of pure change (I_I). In other countries, the contributions of structural subindices are critical explanatory components of structural changes in employment. The highest values of the subindex S_{EU} are reported for Estonia, Greece, and Italy, while the greatest contributions of the subindex S_{M} are observed in Ireland, Spain, France, Cyprus, Malta, Austria, Portugal, Romania, and Slovenia. Thus, the results imply that the role of structural subindices in member states is important, and the reallocation of directly employed labour force between farming types contributes to the evolution of the EU's agricultural system.

Compared to the results of the average utilized agricultural area and the average standard output, the peak values for the average directly employed labour force in member states are spread over a longer time period. Austria, Slovakia, Sweden, and the UK made the highest period-specific contributions to the overall national change in 2005–2007. Only 11 member states demonstrated peak values of the index C_T during the period 2007–2010. The Czech Republic, Denmark, Greece, Latvia, Lithuania, Poland, Romania, and Slovenia have one period lag and reached the maximum values of the national index C_T in 2010–2013, while Estonia, Italy, Cyprus, Malta, and Finland observed the greatest contributions in 2013–2016.

To conclude, the decomposition of the change indices C_T for the average utilized agricultural area, the average standard output, and the average directly employed labour force on farms by member states shows that the behaviour of the analysed index depends on the selected measure of farm size. According to research results, the change in the index C_T for the average utilized agricultural area and the average standard output is often determined by pure change in the aforementioned measures (subindex I_I), but in many EU countries the change in the average directly employed labour force is driven by structural subindices. The results also confirm country-specific differences in the pace of development and peak values during the investigated periods.

Table 4.12 Chain-linked decomposition of the average directly employed labour force indices

	2005–2016				2013–2016				2010–2013				2007–2010				2005–2007			
	C_T	S_{EU}	S_M	I_I	C_T	S_{EU}	S_M	I_I	C_T	S_{EU}	S_M	I_I	C_T	S_{EU}	S_M	I_I	C_T	S_{EU}	S_M	I_I
BE	1.0007	1.0000	0.9994	1.0014	1.0001	0.9999	1.0001	1.0001	0.9999	0.9999	0.9993	1.0007	1.0007	1.0002	1.0001	1.0004	1.0000	1.0001	0.9999	1.0001
BG	0.9779	0.9972	0.9830	0.9976	0.9933	0.9999	0.9953	0.9981	0.9938	0.9995	0.9896	1.0047	0.9993	0.9993	0.9990	1.0010	0.9913	0.9991	0.9990	0.9932
CZ	0.9996	0.9987	0.9982	1.0027	1.0004	0.9997	1.0009	0.9998	1.0005	0.9999	1.0025	0.9981	0.9993	0.9994	0.9948	1.0050	0.9995	0.9998	0.9996	1.0001
DK	1.0007	1.0002	0.9989	1.0016	1.0000	0.9999	0.9999	1.0002	1.0006	1.0000	0.9996	1.0010	1.0002	1.0002	0.9998	1.0002	0.9999	1.0001	0.9996	1.0003
DE	1.0039	1.0011	0.9967	1.0061	0.9992	0.9996	1.0010	0.9987	1.0014	1.0002	1.0001	1.0012	1.0029	1.0007	0.9960	1.0063	1.0004	1.0008	0.9998	0.9998
EE	0.9992	1.0002	0.9989	1.0001	0.9999	1.0000	0.9999	1.0000	0.9999	1.0000	0.9999	0.9999	0.9996	1.0000	0.9995	1.0001	0.9998	1.0001	0.9996	1.0002
IE	1.0066	1.0013	1.0048	1.0005	1.0006	0.9998	1.0009	0.9999	1.0011	1.0006	1.0007	0.9998	1.0046	1.0004	1.0036	1.0006	1.0004	1.0006	0.9998	1.0001
GR	1.0014	1.0020	1.0008	0.9986	0.9997	1.0004	0.9985	1.0007	1.0069	1.0006	1.0033	1.0029	0.9952	0.9999	0.9971	0.9982	0.9998	1.0008	1.0020	0.9969
ES	1.0054	1.0031	1.0058	0.9966	1.0010	1.0009	1.0010	0.9991	0.9997	0.9994	1.0028	0.9975	1.0038	1.0020	1.0032	0.9985	1.0010	1.0012	0.9987	1.0011
FR	1.0095	1.0027	1.0055	1.0013	1.0015	0.9999	1.0002	1.0013	0.9989	1.0004	0.9985	1.0000	1.0094	1.0012	1.0085	0.9997	0.9999	1.0013	0.9983	1.0004
HR	1.0023	0.9980	1.0019	1.0024	0.9992	0.9996	0.9983	1.0013	0.9999	0.9997	0.9939	1.0063	1.0023	0.9993	1.0075	0.9955	1.0010	0.9997	1.0013	1.0000
IT	0.9951	1.0065	0.9873	1.0013	1.0087	1.0014	1.0025	1.0049	0.9980	1.0012	0.9841	1.0129	0.9858	1.0013	0.9989	0.9856	1.0023	1.0023	1.0036	0.9965
CY	0.9997	1.0001	1.0001	0.9995	1.0001	1.0000	1.0002	0.9999	0.9999	1.0000	0.9999	1.0000	0.9997	1.0000	1.0001	0.9996	1.0000	1.0000	0.9999	1.0000
LV	0.9973	0.9994	0.9974	1.0005	1.0000	1.0000	0.9996	1.0004	1.0003	1.0001	1.0001	1.0001	0.9993	0.9998	0.9983	1.0011	0.9977	0.9998	0.9992	0.9987
LT	0.9981	0.9983	0.9973	1.0025	1.0006	0.9999	0.9979	1.0028	1.0009	0.9999	0.9990	1.0019	0.9992	0.9994	1.0000	0.9997	0.9974	0.9996	0.9991	0.9986
LU	1.0001	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
HU	1.0101	0.9984	1.0017	1.0100	0.9994	0.9994	0.9989	1.0011	1.0040	0.9992	0.9982	1.0065	1.0090	1.0006	1.0058	1.0026	0.9979	0.9997	0.9978	1.0004
MT	1.0003	1.0000	1.0002	1.0001	1.0001	1.0000	1.0001	1.0001	1.0000	1.0000	1.0000	1.0001	1.0001	1.0000	1.0001	1.0000	1.0000	1.0000	1.0001	1.0000
NL	1.0030	1.0007	0.9978	1.0044	1.0001	1.0001	0.9975	1.0026	1.0002	0.9995	1.0000	1.0007	1.0026	1.0008	1.0006	1.0011	1.0001	1.0003	0.9995	1.0003
AT	0.9980	1.0006	1.0007	0.9967	0.9994	0.9999	0.9999	0.9995	1.0006	1.0001	1.0000	1.0005	0.9974	1.0004	1.0007	0.9964	1.0006	1.0003	1.0001	1.0002
PL	1.0081	0.9845	0.9504	1.0775	0.9800	1.0007	1.0001	0.9793	1.0171	0.9992	0.9966	1.0214	0.9990	0.9942	0.9417	1.0669	1.0128	0.9934	1.0128	1.0065
PT	1.0024	0.9981	1.0048	0.9995	1.0007	0.9995	1.0017	0.9996	0.9987	0.9994	0.9984	1.0009	1.0062	0.9991	1.0075	0.9996	0.9970	1.0001	0.9971	0.9997
RO	0.9642	0.9719	1.0350	0.9586	1.0108	0.9934	1.0012	1.0163	1.0116	0.9893	1.0172	1.0052	0.9625	0.9940	1.0136	0.9554	0.9789	0.9955	0.9992	0.9841
SI	1.0012	0.9996	1.0017	0.9999	0.9999	0.9998	1.0001	1.0000	1.0013	0.9999	1.0003	1.0011	1.0005	0.9999	1.0009	0.9997	0.9995	1.0001	1.0002	0.9992
SK	0.9977	0.9996	0.9964	1.0016	0.9998	0.9999	1.0004	0.9995	0.9998	1.0000	1.0000	0.9997	0.9980	0.9997	0.9951	1.0032	1.0000	0.9999	1.0008	0.9993
FI	1.0025	1.0008	0.9979	1.0038	1.0030	1.0001	0.9993	1.0037	1.0002	1.0002	0.9992	1.0008	0.9998	1.0002	1.0000	0.9995	0.9994	1.0002	0.9998	0.9995
SE	1.0034	1.0004	1.0004	1.0027	0.9999	1.0000	0.9997	1.0002	1.0007	1.0002	0.9998	1.0007	1.0002	1.0002	1.0007	0.9993	1.0026	1.0001	1.0001	1.0024
GB	1.0262	1.0017	0.9974	1.0271	1.0029	1.0001	1.0015	1.0012	1.0031	1.0008	1.0007	1.0017	1.0011	1.0007	0.9993	1.0011	1.0191	1.0005	0.9973	1.0213
Π	1.0134	0.9652	0.9592	1.0946	1.0001	0.9935	0.9968	1.0098	1.0393	0.9895	0.9833	1.0682	0.9770	0.9930	0.9710	1.0134	0.9979	0.9956	1.0040	0.9983

Source: Own calculations based on Eurostat data

4.5.4 Changes in the Average Farm Size by Type of Farming in Member States

An important research question is how the structural changes in the national agriculture of member states contribute to the overall change in the EU agricultural system. As shown in Fig. 4.9, the development of the index C_T for the average utilized agricultural area in member states depends on the farming type. During the period 2005–2016, the values of the index C_T for specialist horticulture, fruit, and citrus fruit (II), specialist granivore (IV), and mixed cropping (V) farms remain almost stable and fluctuate around a unity in most member states, whereas on mixed livestock farms (VI) the situation is similar with the exception of the index C_T decrease in Poland. The situation on mixed combined (VII) farms depends on the country, and in several member states, values of the index C_T have larger deviations from unity. General field cropping (I) and specialist grazing livestock (III) farms demonstrated extreme fluctuations in the period 2005–2016. These changes in the index C_T are the main cause of the average utilized agricultural area growth at the EU level.

Table 4.13 reports on the major contributing subindices that determine the change in the average utilized agricultural area over the period 2005–2016. It is important to note that the evolution of the average farm size is driven by both structural subindices and the pure change of land use on farms. Furthermore, the most contributing subindex depends on the farming type and the member state. General field cropping (I) is the only farming type where the structural and pure change subindices are distributed equally among member states; i.e., the index C_T in 11 countries is driven by the subindex S_{EU}, in 3 by the subindex S_{M}, and in 14 by the subindex of pure change I_I. Thus, the empirical results evidence important structural changes in land use on general field cropping (I) farms in the EU agricultural system.

According to Table 4.13, other types of farming face changes in the average utilized agricultural area mainly due to the highest contribution of the pure change subindex I_I, but for some member states the role of the structural components is crucial. Findings suggest that the changes in the index C_T are driven by the structural subindex S_{M} on mixed livestock (VI) farms (in 11 countries), on mixed combined (VII) farms (in 10 countries), on specialist granivore (IV) farms (in 9 countries), on specialist horticulture, fruit, and citrus fruit (II) farms (in 7 countries), on mixed cropping (V) farms (in 7 countries), and on specialist grazing livestock (III) farms (in 6 countries). Consequently, the contribution of member states to the overall change at the EU level and the transformations within the national farming systems plays an important role. The contribution of the structural subindex S_{EU} for the farming types that do not include general field cropping (I) to the index C_T has the highest values only in four countries covering specialist grazing livestock (III), mixed cropping (V), and specialist horticulture, fruit, and citrus fruit (II) farms.

The cross-comparison of the index C_T for the average utilized agricultural area and the average standard output allows differences in development patterns to be

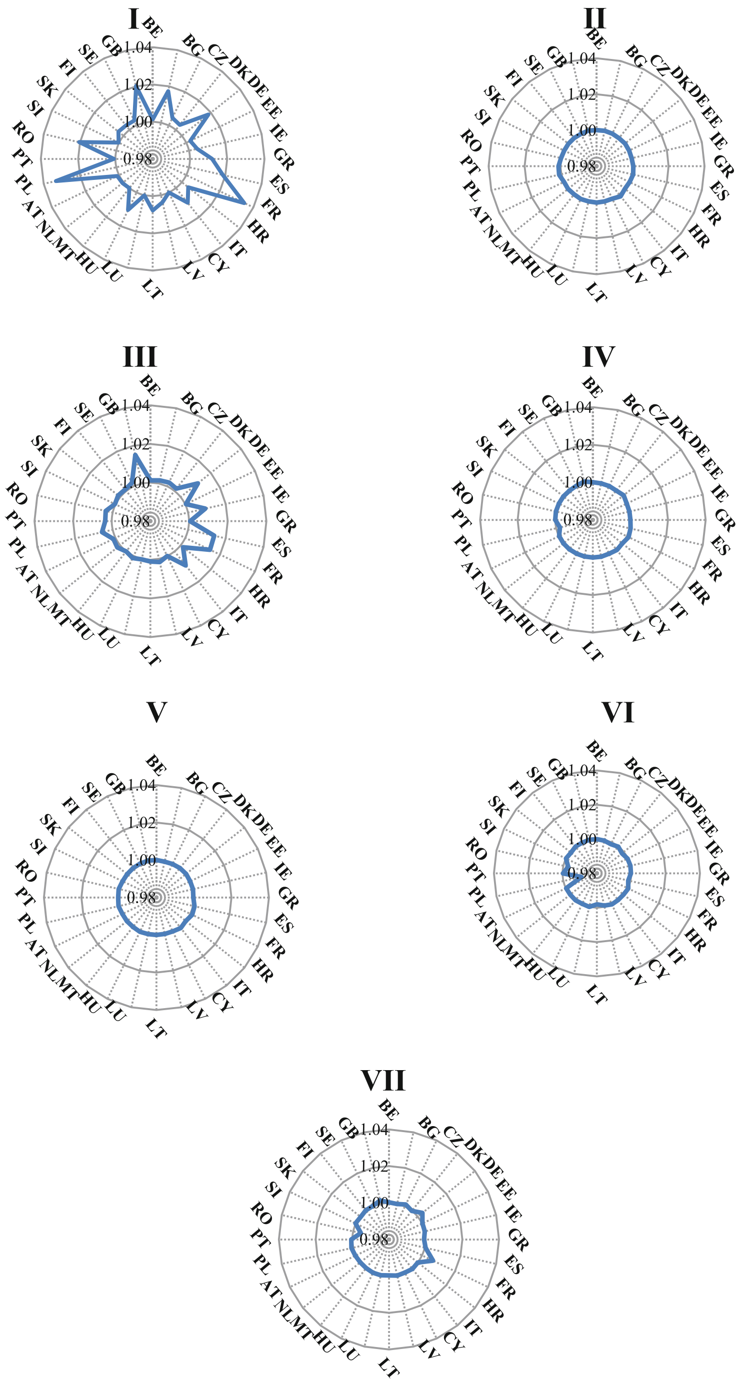


Fig. 4.9 Decomposition of the index C_T for the average utilized agricultural area change by type of farming in member states. Source: Own calculations based on Eurostat data

Table 4.13 Decomposition of the average utilized agricultural area by type of farming for the period 2005–2016

	S_{EU}							S_M							I_I						
	I	II	III	IV	V	VI	VII	I	II	III	IV	V	VI	VII	I	II	III	IV	V	VI	VII
BE	1.0005	1.0000	1.0003	0.9999	1.0000	0.9996	0.9997	1.0004	0.9999	0.9994	1.0000	1.0000	1.0002	1.0003	1.0003	1.0002	1.0014	1.0001	1.0000	1.0001	1.0003
BG	1.0049	1.0000	1.0001	1.0000	1.0000	0.9998	0.9997	0.9995	1.0001	0.9993	0.9998	0.9998	0.9998	0.9990	1.0129	1.0001	1.0022	1.0001	0.9999	1.0000	1.0012
CZ	1.0017	1.0000	1.0004	1.0000	1.0000	0.9986	0.9982	0.9989	1.0000	1.0007	0.9999	0.9996	0.9999	0.9990	1.0039	1.0000	1.0012	1.0001	1.0003	1.0004	1.0040
DK	1.0020	1.0000	1.0003	0.9996	1.0000	0.9998	0.9996	0.9980	0.9999	0.9999	0.9992	1.0002	1.0000	0.9999	1.0034	1.0000	1.0014	1.0012	1.0000	1.0001	1.0004
DE	1.0095	1.0000	1.0029	0.9992	1.0000	0.9963	0.9956	0.9981	0.9997	0.9968	1.0008	0.9999	1.0005	1.0017	1.0106	1.0004	1.0118	1.0010	1.0003	1.0018	1.0060
EE	1.0007	1.0000	1.0002	1.0000	1.0000	0.9999	0.9999	0.9995	1.0000	0.9988	1.0000	1.0000	0.9999	0.9998	1.0022	1.0000	1.0015	1.0000	1.0000	1.0000	1.0006
IE	1.0009	1.0000	1.0018	1.0000	1.0000	1.0000	0.9998	1.0027	0.9999	1.0061	1.0000	1.0000	1.0000	1.0002	1.0010	1.0000	1.0011	0.9999	1.0000	1.0000	1.0001
GR	1.0033	1.0000	1.0003	1.0000	1.0000	0.9998	0.9996	0.9974	1.0001	1.0016	1.0000	0.9995	1.0001	0.9999	1.0113	1.0002	0.9986	1.0000	1.0002	0.9999	0.9997
ES	1.0177	1.0003	1.0026	0.9995	1.0002	0.9966	0.9983	1.0106	1.0000	1.0026	1.0014	1.0005	1.0005	0.9998	0.9904	1.0005	1.0086	0.9997	1.0001	1.0016	1.0025
FR	1.0169	1.0001	1.0053	0.9994	1.0001	0.9958	0.9954	1.0089	1.0003	0.9940	1.0016	1.0003	1.0017	1.0047	1.0085	0.9999	1.0149	1.0001	1.0008	1.0028	1.0066
HR	1.0008	1.0000	1.0002	1.0000	1.0000	0.9996	0.9997	1.0017	1.0001	0.9996	0.9999	0.9999	1.0001	1.0003	1.0019	1.0001	1.0019	1.0001	1.0001	1.0001	1.0001
IT	1.0083	1.0001	1.0016	0.9998	1.0002	0.9993	0.9992	0.9929	0.9992	1.0010	1.0000	0.9990	1.0000	0.9985	1.0090	1.0020	1.0066	1.0007	1.0016	1.0004	1.0029
CY	1.0001	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9999	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0001	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
LV	1.0014	1.0000	1.0002	1.0000	1.0000	0.9995	0.9996	0.9983	0.9999	1.0002	1.0002	0.9997	0.9996	0.9991	1.0042	1.0001	1.0013	1.0000	1.0002	1.0002	1.0016
LT	1.0020	1.0000	1.0003	1.0000	1.0000	0.9991	0.9992	1.0044	1.0001	0.9989	1.0001	0.9998	0.9990	0.9986	1.0014	1.0001	1.0017	0.9999	1.0001	1.0000	1.0019
LU	1.0000	1.0000	1.0001	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0002	1.0000	1.0000	1.0000	1.0000
HU	1.0045	1.0000	1.0002	0.9999	1.0000	0.9992	0.9990	1.0025	1.0000	1.0008	0.9999	1.0000	1.0006	0.9997	1.0035	1.0002	1.0001	1.0002	1.0003	0.9999	1.0015
MT	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
NL	1.0008	1.0000	1.0005	0.9999	1.0000	0.9998	0.9999	0.9996	0.9999	0.9993	1.0000	1.0000	1.0000	1.0000	1.0003	1.0004	1.0020	1.0001	1.0001	1.0000	1.0001
AT	1.0018	1.0000	1.0006	0.9998	1.0000	0.9997	0.9998	0.9996	1.0000	1.0005	0.9998	1.0001	1.0001	1.0002	0.9997	1.0000	1.0002	1.0002	1.0000	1.0001	1.0004
PL	1.0101	1.0001	1.0012	0.9994	1.0000	0.9929	0.9961	1.0031	0.9986	0.9971	0.9952	0.9994	0.9944	0.9967	1.0198	1.0026	1.0074	1.0034	1.0012	1.0020	1.0083
PT	1.0009	1.0000	1.0008	1.0000	1.0000	0.9994	0.9993	1.0000	1.0005	1.0022	1.0000	0.9999	1.0004	1.0002	0.9999	1.0007	1.0004	1.0001	1.0004	1.0000	1.0011
RO	1.0131	1.0000	1.0008	0.9999	1.0001	0.9956	0.9973	0.9998	1.0006	1.0010	1.0001	1.0012	1.0017	1.0018	1.0075	0.9996	1.0019	1.0001	0.9994	0.9998	0.9966
SI	1.0001	1.0000	1.0001	1.0000	1.0000	0.9999	0.9999	1.0002	1.0000	0.9999	1.0000	1.0000	1.0001	1.0002	1.0000	1.0000	1.0003	1.0000	1.0000	1.0000	1.0001
SK	1.0012	1.0000	1.0002	1.0000	1.0000	0.9996	0.9993	1.0011	1.0000	0.9997	0.9998	0.9997	0.9997	0.9967	1.0012	1.0000	1.0015	1.0003	1.0002	1.0000	1.0038
FI	1.0020	1.0000	1.0004	0.9999	1.0000	1.0000	0.9998	0.9993	1.0000	0.9984	0.9997	0.9999	1.0000	1.0002	1.0018	1.0001	1.0022	1.0004	1.0001	1.0000	1.0003
SE	1.0019	1.0000	1.0007	0.9999	1.0000	0.9998	0.9996	0.9991	1.0001	1.0009	1.0000	1.0001	1.0000	1.0004	1.0018	1.0000	1.0003	1.0002	1.0000	1.0000	1.0003
GB	1.0104	1.0000	1.0041	0.9998	1.0000	0.9994	0.9984	0.9905	0.9997	1.0006	0.9997	0.9999	1.0003	1.0013	1.0193	1.0006	1.0103	1.0015	1.0003	1.0004	1.0021
Π	1.1240	1.0010	1.0265	0.9959	1.0008	0.9693	0.9722	1.0055	0.9988	0.9992	0.9972	0.9983	0.9988	0.9981	1.1220	1.0077	1.0839	1.0094	1.0058	1.0097	1.0431

Source: Own calculations based on Eurostat data

noticed (Fig. 4.10). As in the case of the average utilized agricultural area, mixed cropping (V) and mixed livestock (VI) farms do not demonstrate significant changes in the average standard output, and the values of the index C_T fluctuate around unity. In some member states, specialist horticulture, fruit, and citrus fruit (II) and mixed combined (VII) farms have an increase in the average standard output; however, the gap between the situation in 2005 and 2016 is not large. Hence, it is mainly the situation in general field cropping (I), specialist grazing livestock (III), and specialist granivore (IV) farms that explains the growth of the average standard output at the EU level. The aforementioned farming types demonstrate the largest growth in values and cover a greater number of EU countries with remarkable change compared to the remaining four farming types.

The decomposition of the index C_T into structural and pure change subindices confirms that the driving forces behind the overall change in the average utilized agricultural area on farms and the evolution of the average standard output per farm differ. Despite the fact that the change in the average utilized agricultural area per farm is strongly driven by structural components, the major contributor to changes in the index C_T for the average standard output is the subindex of pure change I_I (Table 4.14).

Thus, contrary to the situation of the average utilized agricultural area on general field cropping (I) farms, in the case of the average standard output decomposition, only in Greece and Cyprus is the main contributor the subindex S_{EU}, while the subindex S_{M} is important in Ireland, Croatia, Malta, and Slovenia, i.e. structural subindices relevant mostly in countries that belong to the EU-13 group. The changes in specialist grazing livestock (III), mixed cropping (V), and mixed combined (VII) farming types are mostly determined by the increase in pure standard output, while only in three member states (in the case of each farming type) is the index C_T driven by the structural subindex S_{M}. The contributions from the EU countries where the role of the subindex S_{M} is important come from specialist granivores (IV) and specialist horticulture, fruit, and citrus fruit (II), i.e. in seven countries for each farming type, respectively. In eight member states, the highest contribution of the subindex S_{M} to the values of the national index C_T is from mixed livestock (VI) farms.

As shown in Fig. 4.11, the development of the average directly employed labour force takes the opposite direction to the aforementioned measures of farm size. Depending on the farming type and the investigated member state, the index C_T takes both positive and negative development directions. Specialist horticulture, fruit, and citrus fruit (II), specialist granivore (IV), and mixed cropping (V) farms demonstrate minor changes in the values of the index C_T for direct employment on farms. Other farming types are characterized by similar behaviour patterns, but for several member states the gap between the number of directly employed labour force in 2005 and 2016 is larger. For example, Poland shows more remarkable fluctuations for general field cropping (I) and mixed livestock (VI) farming types, Romania for mixed livestock (VI) and mixed combined (VII) farms, and the UK for the specialist grazing livestock (III) farming type. However, the changes in the index C_T are minor compared to the other investigated measures of farm size.

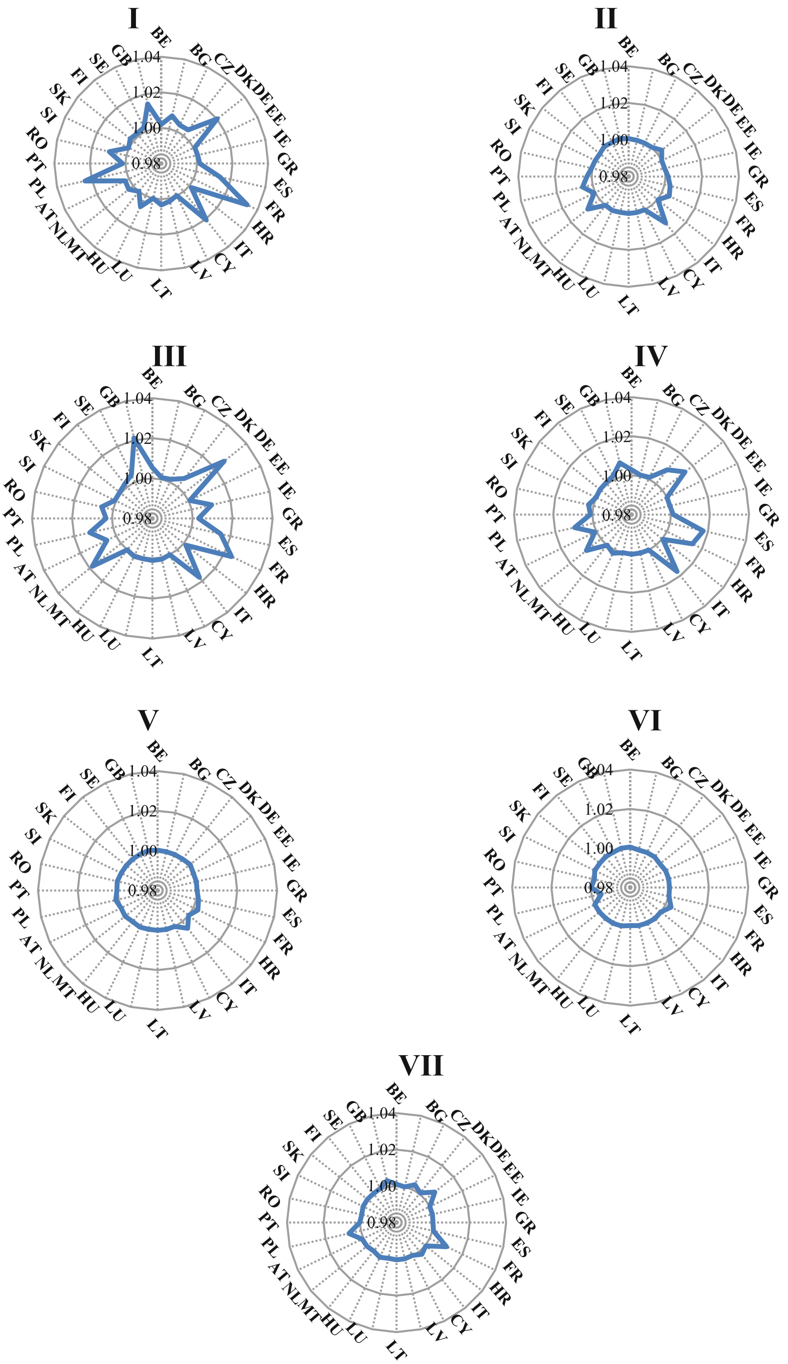


Fig. 4.10 Decomposition of the index C_T for the average standard output change by type of farming in member states. Source: Own calculations based on Eurostat data

Table 4.14 Decomposition of the average standard output by type of farming for the period 2005–2016

	S_{EU}							S_M							I_I						
	I	II	III	IV	V	VI	VII	I	II	III	IV	V	VI	VII	I	II	III	IV	V	VI	VII
BE	1.0006	1.0002	1.0006	0.9992	1.0000	0.9984	0.9995	1.0004	0.9978	0.9988	1.0005	1.0000	1.0011	1.0005	1.0010	1.0027	1.0060	1.0032	1.0001	1.0012	1.0010
BG	1.0014	1.0000	1.0001	0.9998	1.0000	0.9997	0.9998	0.9998	1.0003	0.9992	0.9984	0.9999	0.9997	0.9993	1.0063	0.9999	1.0015	1.0024	1.0001	1.0001	1.0010
CZ	1.0009	1.0000	1.0002	0.9998	1.0000	0.9989	0.9988	0.9994	1.0000	1.0003	0.9986	0.9996	0.9999	0.9993	1.0037	1.0002	1.0012	1.0028	1.0004	1.0010	1.0049
DK	1.0012	1.0001	1.0006	0.9981	1.0000	0.9996	0.9996	0.9988	0.9991	0.9997	0.9966	1.0002	1.0000	0.9999	1.0041	1.0012	1.0052	1.0147	1.0000	1.0003	1.0013
DE	1.0081	1.0006	1.0039	0.9961	1.0001	0.9930	0.9952	0.9984	0.9957	0.9956	1.0038	0.9997	1.0010	1.0019	1.0137	1.0068	1.0263	1.0150	1.0012	1.0053	1.0097
EE	1.0002	1.0000	1.0001	1.0000	1.0000	1.0000	1.0000	0.9999	1.0000	0.9995	1.0001	1.0000	1.0000	0.9999	1.0008	1.0000	1.0012	1.0001	1.0000	1.0000	1.0003
IE	1.0004	1.0000	1.0011	0.9997	1.0000	0.9999	0.9999	1.0011	0.9995	1.0038	1.0006	1.0000	1.0001	1.0001	0.9996	1.0006	1.0053	0.9997	1.0000	1.0001	1.0002
GR	1.0016	1.0002	1.0003	0.9998	1.0000	0.9998	0.9996	0.9987	1.0005	1.0016	1.0002	0.9994	1.0001	0.9999	1.0013	1.0008	1.0011	1.0012	1.0003	1.0001	1.0004
ES	1.0046	1.0010	1.0020	0.9956	1.0001	0.9976	0.9992	1.0028	1.0000	1.0019	1.0123	1.0002	1.0003	0.9999	1.0063	1.0022	1.0110	1.0096	1.0008	1.0023	1.0017
FR	1.0109	1.0005	1.0035	0.9969	1.0001	0.9936	0.9964	1.0057	1.0020	0.9960	1.0082	1.0004	1.0026	1.0037	1.0166	1.0020	1.0243	1.0095	1.0020	1.0069	1.0103
HR	1.0003	1.0000	1.0001	0.9999	1.0000	0.9995	0.9998	1.0006	1.0001	0.9996	0.9997	0.9999	1.0001	1.0002	1.0006	1.0002	1.0017	1.0007	1.0002	1.0003	1.0004
IT	1.0076	1.0009	1.0027	0.9954	1.0002	0.9985	0.9987	0.9935	0.9951	1.0016	1.0001	0.9986	1.0001	0.9977	1.0194	1.0164	1.0133	1.0218	1.0055	1.0016	1.0058
CY	1.0001	1.0000	1.0001	0.9999	1.0000	1.0000	1.0000	0.9999	1.0000	0.9999	1.0007	1.0000	1.0000	1.0000	1.0000	1.0000	1.0002	0.9995	1.0000	1.0000	1.0000
LV	1.0003	1.0000	1.0001	0.9999	1.0000	0.9999	0.9999	0.9996	1.0000	1.0001	1.0006	0.9999	0.9999	0.9998	1.0017	1.0001	1.0008	0.9997	1.0001	1.0001	1.0007
LT	1.0005	1.0000	1.0001	0.9999	1.0000	0.9997	0.9997	1.0012	1.0001	0.9996	1.0006	1.0000	0.9996	0.9995	1.0015	1.0000	1.0013	0.9998	1.0000	1.0001	1.0012
LU	1.0000	1.0000	1.0001	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0006	1.0000	1.0000	1.0000	1.0000
HU	1.0017	1.0001	1.0001	0.9994	1.0000	0.9991	0.9993	1.0009	1.0001	1.0005	0.9990	1.0000	1.0006	0.9998	1.0042	1.0004	1.0004	1.0036	1.0004	1.0004	1.0019
MT	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0001	1.0001	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
NL	1.0013	1.0010	1.0018	0.9981	1.0000	0.9987	0.9996	0.9994	0.9949	0.9976	1.0004	1.0000	1.0002	1.0001	1.0026	1.0127	1.0190	1.0111	1.0007	1.0011	1.0011
AT	1.0007	1.0000	1.0006	0.9994	1.0000	0.9996	0.9998	0.9998	1.0004	1.0005	0.9995	1.0001	1.0001	1.0003	1.0019	1.0004	1.0041	1.0019	1.0002	1.0003	1.0009
PL	1.0042	1.0003	1.0010	0.9981	1.0000	0.9941	0.9975	1.0013	0.9963	0.9976	0.9844	0.9996	0.9954	0.9979	1.0184	1.0091	1.0134	1.0278	1.0019	1.0056	1.0114
PT	1.0004	1.0001	1.0004	0.9997	1.0000	0.9997	0.9997	1.0000	1.0010	1.0012	0.9998	0.9999	1.0002	1.0001	1.0013	1.0015	1.0015	1.0015	1.0004	1.0000	1.0004
RO	1.0035	1.0000	1.0006	0.9996	1.0000	0.9961	0.9984	1.0000	1.0008	1.0008	1.0006	1.0006	1.0015	1.0011	1.0065	0.9997	1.0046	1.0023	1.0001	1.0010	1.0001
SI	1.0001	1.0000	1.0001	1.0000	1.0000	0.9998	0.9999	1.0001	1.0001	0.9999	0.9999	1.0000	1.0001	1.0002	1.0001	1.0000	1.0007	1.0003	1.0001	1.0000	1.0002
SK	1.0004	1.0000	1.0001	0.9999	1.0000	0.9998	0.9996	1.0004	0.9999	0.9999	0.9985	0.9998	0.9999	0.9984	1.0014	1.0001	1.0009	1.0022	1.0002	1.0001	1.0024
FI	1.0006	1.0001	1.0004	0.9998	1.0000	1.0000	0.9999	0.9998	0.9997	0.9983	0.9993	0.9999	1.0000	1.0001	1.0013	1.0013	1.0034	1.0016	1.0002	1.0000	1.0003
SE	1.0008	1.0000	1.0006	0.9997	1.0000	0.9998	0.9998	0.9997	1.0003	1.0008	0.9999	1.0001	1.0000	1.0003	1.0021	1.0002	1.0028	1.0023	1.0001	1.0001	1.0007
GB	1.0053	1.0002	1.0024	0.9983	1.0000	0.9991	0.9988	0.9952	0.9964	1.0004	0.9972	0.9999	1.0005	1.0010	1.0138	1.0047	1.0182	1.0116	1.0006	1.0009	1.0038
Π	1.0588	1.0054	1.0241	0.9725	1.0008	0.9644	0.9785	0.9965	0.9804	0.9947	0.9993	0.9979	1.0030	1.0009	1.1381	1.0651	1.1836	1.1557	1.0158	1.0293	1.0639

Source: Own calculations based on Eurostat data

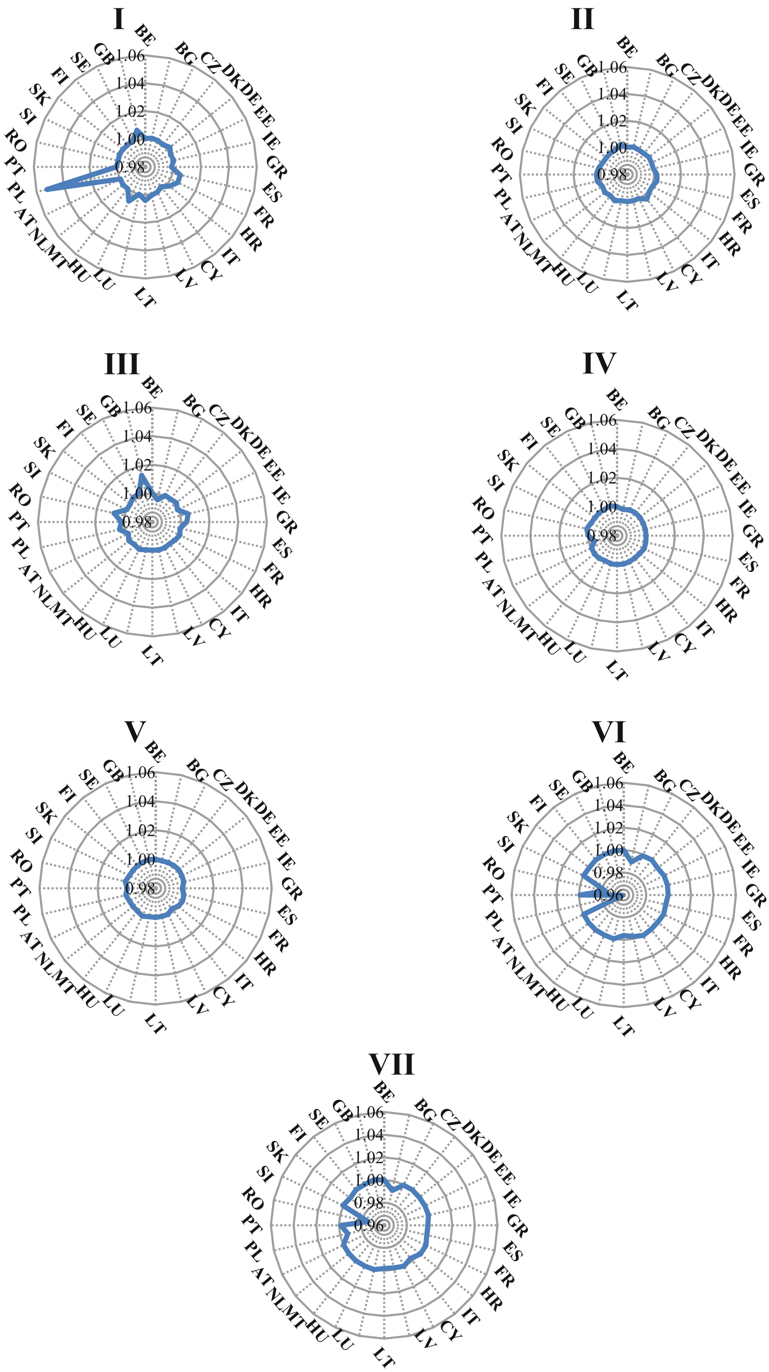


Fig. 4.11 Decomposition of the index C_T for directly employed labour force change by type of farming in member states. Source: Own calculations based on Eurostat data

According to Table 4.15, the analysis of structural and pure change subindices of the average directly employed labour force shows that the development of the index C_T is characterized by structural changes in EU agriculture. Furthermore, the share of countries with the leading role of structural subindices is higher than in the case of the average utilized agricultural area. Results for general field cropping (I) and specialist grazing livestock (III) farming types show that the major contributor is the subindex S_{EU}, which covers 17 and 11 countries, respectively, while for the same farming types, the subindex S_{M} is of critical importance only in 4 and 8 member states.

The decomposition confirms the significance of structural changes at the EU level in direct employment on general field cropping (I) and specialist grazing livestock (III) farms; however, the results for specialist granivore (IV), mixed combined (VII), and mixed livestock (VI) farms show that in many member states the major contributor to change is the subindex S_{M}. The situation in the mixed cropping (V) farming type demonstrates the balance between the leading role of structural and pure change subindices; i.e., in 14 member states, the driving subindex is the pure change subindex I_I, in 8 the subindex S_{EU}, and in 6 the subindex S_{M}. Nevertheless, the specialist horticulture, fruit, and citrus fruit (II) farming type is the only specialization where the overall changes are driven by the subindex of pure change I_I, while in ten member states the main contributor is the subindex S_{M}.

In conclusion, Sect. 4.5 provides the key findings for the decomposition of the average utilized agricultural area, the average standard output, and the average directly employed labour force on farms over the investigated period. The results suggest that important structural changes took place in the EU and national agricultural systems from 2005 to 2016.

According to the empirical study, at the EU level, the average farm size in terms of the utilized agricultural area and standard output increased, while the average directly employed labour force on farms remained almost without changes. Findings imply the significant role of the reallocation among farming types over 2005–2016. Although the pace of change of the index C_T depends on the selected farm size measure, the highest contributions to the changes in the average farm size are reported for specialist field crop (I) and specialist grazing livestock (III) farms, while mixed livestock (VI) farms demonstrate the largest decrease in the index C_T values.

Nevertheless, the decomposition by member states shows that structural changes in national agricultural systems vary in terms of development pace, directions of reallocation, and peaks over the investigated period. Thus, changes in land use, standard output evolution, and direct employment on farms are country-specific. In fact, this aspect is explained in academic research by differences in combinations of change-driving factors in member states. Section 4.6 presents a discussion on the most important determinants of structural changes in EU agriculture.

Table 4.15 Decomposition of the average directly employed labour force by type of farming for the period 2005–2016

	S_{EU}							S_M							I_I						
	I	II	III	IV	V	VI	VII	I	II	III	IV	V	VI	VII	I	II	III	IV	V	VI	VII
BE	1.0002	1.0001	1.0002	0.9999	1.0000	0.9997	0.9999	1.0002	0.9992	0.9996	1.0001	1.0000	1.0002	1.0001	1.0000	1.0009	1.0004	1.0000	1.0000	1.0000	1.0000
BG	1.0026	1.0001	1.0009	0.9998	1.0000	0.9955	0.9984	0.9997	1.0013	0.9949	0.9978	0.9994	0.9954	0.9945	0.9989	0.9996	1.0001	1.0010	1.0000	0.9994	0.9987
CZ	1.0007	1.0000	1.0002	0.9999	1.0000	0.9989	0.9990	0.9996	1.0000	1.0004	0.9994	0.9996	0.9999	0.9994	1.0008	1.0000	1.0001	1.0005	1.0002	1.0001	1.0010
DK	1.0005	1.0000	1.0001	0.9998	1.0000	0.9999	0.9999	0.9995	0.9997	0.9999	0.9996	1.0001	1.0000	1.0000	1.0004	1.0001	1.0004	1.0007	1.0000	1.0000	1.0001
DE	1.0033	1.0003	1.0018	0.9994	1.0000	0.9979	0.9984	0.9993	0.9980	0.9980	1.0006	0.9999	1.0003	1.0006	1.0000	1.0024	1.0018	1.0003	1.0006	1.0004	1.0006
EE	1.0002	1.0000	1.0001	1.0000	1.0000	0.9999	0.9999	0.9998	1.0000	0.9993	1.0000	1.0000	0.9999	0.9999	1.0000	1.0000	1.0001	1.0000	1.0000	1.0000	1.0000
IE	1.0003	1.0000	1.0012	1.0000	1.0000	1.0000	0.9999	1.0008	0.9999	1.0039	1.0001	1.0000	1.0000	1.0001	0.9999	1.0000	1.0006	1.0000	1.0000	1.0000	1.0000
GR	1.0028	1.0003	1.0007	0.9999	1.0001	0.9994	0.9988	0.9977	1.0009	1.0034	1.0001	0.9987	1.0002	0.9998	0.9982	1.0010	1.0000	1.0000	0.9996	1.0000	0.9999
ES	1.0040	1.0009	1.0014	0.9994	1.0001	0.9982	0.9990	1.0024	1.0000	1.0014	1.0016	1.0003	1.0003	0.9999	0.9993	1.0017	0.9970	0.9994	0.9996	0.9999	0.9997
FR	1.0043	1.0004	1.0021	0.9994	1.0001	0.9980	0.9985	1.0022	1.0015	0.9976	1.0015	1.0003	1.0008	1.0016	0.9993	0.9988	1.0016	0.9999	1.0002	1.0007	1.0007
HR	1.0008	1.0000	1.0003	0.9999	1.0000	0.9981	0.9989	1.0015	1.0005	0.9992	0.9996	0.9995	1.0004	1.0012	0.9999	1.0003	1.0008	1.0003	1.0004	1.0002	1.0006
IT	1.0065	1.0008	1.0015	0.9997	1.0003	0.9990	0.9988	0.9944	0.9958	1.0009	1.0000	0.9983	1.0001	0.9978	0.9972	1.0070	0.9970	1.0001	0.9993	0.9999	1.0007
CY	1.0001	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9999	1.0001	0.9999	1.0001	1.0000	1.0000	1.0001	1.0000	0.9998	1.0000	0.9999	0.9999	1.0000	0.9999
LV	1.0008	1.0000	1.0002	0.9999	1.0000	0.9989	0.9995	0.9990	0.9998	1.0003	1.0006	0.9996	0.9992	0.9989	1.0009	1.0002	0.9997	0.9996	1.0001	0.9999	1.0002
LT	1.0010	1.0000	1.0004	0.9999	1.0000	0.9980	0.9989	1.0022	1.0003	0.9986	1.0007	0.9996	0.9978	0.9982	1.0009	0.9999	1.0007	0.9995	1.0004	1.0002	1.0009
LU	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
HU	1.0028	1.0002	1.0003	0.9988	1.0001	0.9980	0.9983	1.0015	1.0002	1.0010	0.9983	0.9999	1.0013	0.9994	1.0030	1.0013	1.0001	1.0020	1.0013	1.0002	1.0021
MT	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0001	1.0001	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
NL	1.0005	1.0003	1.0005	0.9998	1.0000	0.9998	0.9999	0.9998	0.9986	0.9994	1.0000	1.0000	1.0000	1.0000	1.0003	1.0026	1.0012	1.0003	1.0000	1.0000	1.0001
AT	1.0006	1.0000	1.0006	0.9999	1.0000	0.9996	0.9998	0.9999	1.0003	1.0005	0.9999	1.0000	1.0001	1.0002	0.9993	1.0001	0.9976	0.9999	1.0000	0.9999	0.9999
PL	1.0156	1.0006	1.0027	0.9984	1.0002	0.9772	0.9900	1.0047	0.9925	0.9934	0.9870	0.9980	0.9822	0.9917	1.0313	1.0099	1.0076	1.0107	1.0030	1.0014	1.0113
PT	1.0008	1.0002	1.0006	0.9999	1.0001	0.9980	0.9985	1.0000	1.0020	1.0017	0.9999	0.9996	1.0014	1.0003	1.0001	1.0010	0.9993	1.0002	0.9998	0.9997	0.9994
RO	1.0122	1.0002	1.0032	0.9979	1.0003	0.9710	0.9873	0.9999	1.0028	1.0042	1.0035	1.0042	1.0114	1.0086	0.9880	0.9989	1.0002	1.0002	0.9970	0.9947	0.9790
SI	1.0002	1.0000	1.0003	1.0000	1.0000	0.9994	0.9997	1.0004	1.0002	0.9998	0.9999	1.0001	1.0005	1.0008	1.0000	1.0000	0.9998	1.0000	1.0001	1.0000	1.0001
SK	1.0004	1.0000	1.0001	0.9999	1.0000	0.9996	0.9995	1.0004	1.0000	0.9998	0.9991	0.9997	0.9997	0.9978	0.9996	1.0001	1.0000	1.0006	1.0002	0.9999	1.0012
FI	1.0006	1.0000	1.0004	0.9999	1.0000	1.0000	0.9999	0.9998	0.9998	0.9985	0.9998	0.9999	1.0000	1.0001	0.9999	1.0003	1.0030	1.0003	1.0001	1.0000	1.0001
SE	1.0003	1.0000	1.0002	1.0000	1.0000	0.9999	0.9999	0.9998	1.0001	1.0003	1.0000	1.0000	1.0000	1.0001	1.0009	1.0002	1.0013	1.0001	1.0000	1.0000	1.0001
GB	1.0015	1.0001	1.0008	0.9999	1.0000	0.9998	0.9997	0.9986	0.9986	1.0001	0.9998	1.0000	1.0001	1.0002	1.0067	1.0041	1.0125	1.0015	1.0004	1.0004	1.0012
Π	1.0654	1.0045	1.0210	0.9913	1.0014	0.9259	0.9609	1.0032	0.9921	0.9960	0.9889	0.9964	0.9909	0.9910	1.0245	1.0307	1.0231	1.0169	1.0020	0.9970	0.9974

Source: Own calculations based on Eurostat data

4.6 Discussion on Drivers of Recent Changes in the EU Agricultural System

The main empirical findings of this study suggest that the role of agriculture in the structure of the EU economy continues to diminish, while the EU agricultural system has survived significant structural changes since the largest EU expansion in 2004. Section 4.6 contributes to the discussion on the key driving forces behind the structural changes in agricultural systems. For this reason, the study identifies the main drivers of structural change based on a review of academic research and considers the relevance of these factors for the development of the EU agricultural system over the investigated period. This study supports the position that structural changes in agriculture are the aftermaths of multiple interrelated driving forces.

4.6.1 Historical Legacy

The EU agricultural system started a long evolutionary path in 1951, when six countries launched economic cooperation. Since then, the EU has survived seven enlargements and one withdrawal from the union. Each of these events had an impact on the functioning of the EU agricultural system, with the introduction of a more diverse and complex structure. Today, the EU agricultural system covers national agricultures that are the aftermaths of different historical legacies and institutional environments. Thus, academic studies often refer to the concept of path dependence and suggest that the evolution of the EU's agriculture could be explained by farm structure in the past. According to Djelic and Quack (2007), path dependence introduces mechanisms that enable the stabilization and anchoring of the development trajectories rather than the focus on change.

Neuenfeldt et al. (2019) argue that structural changes in the EU agriculture can be explained to a large extent by shares of farm groups in the past and their historic specialization. In this regard, it is worth noting that Neuenfeldt et al. (2019) recognize substantial differences between member states and define countries that joined the EU in 2004 and after as a distinct group. The key feature of this group is the higher pace of structural changes compared to member states that joined the EU before 2004.

This phenomenon is often explained by the historic legacy of agricultural systems in member states. Most of the countries that acceded in 2004 and after survived dramatic structural changes due to multiple reforms after the collapse of the Soviet Union and membership of the EU became a new challenge. In new member states, the important role of small farms in the farm structure was a historical legacy in most of the countries. During the first years of independence, land restitution was introduced in most of these countries, while in some member states small farms survived during Soviet times. Meanwhile, in many countries that acceded to the EU before 2004 large-scale farms occupied a considerable share in the overall national farm structure. Such countries as Denmark, France, Germany, the Netherlands, some regions of Ireland, and Scotland represent large-scale farming (Guiomar et al. 2018), and these member states have overcome the process of land consolidation and farming specialization that considerably reduced the number of vulnerable small farms.

Indeed, in some EU-15 countries, institutional arrangements (such as succession laws, land reforms, and historical patterns) favour the dominant position of semi-subsistence farms. These small farms often contribute to poverty alleviation goals and their holders are senior farmers who neither invest nor apply profit maximization strategies. Salvioni et al. (2014) argue that Italy, Greece, and Portugal are examples of such structures where the recent agricultural policy was aimed at enlarging the average farm size and managing land abandonment. As a result, the disappearance of a significant share of small farms became a characteristic feature of these countries. Furthermore, even the analysis of farm exit rates during the 1990s in Western Europe confirms that exit rates are higher in regions that have smaller farms (Breustedt and Glauben 2007).

However, in the EU-15, a longer period of a more stable and predictable environment allowed investment and the pursuit of a coherent development of farming business. Błażejczyk-Majka et al. (2011) argue that long-term relative stability in agriculture contributes to higher efficiency in farming. Moreover, path dependency contributes to better efficiency in small farms (Gorton and Davidova 2004) too. On the one hand, the farming structures in the EU-15 have a stronger path dependence due to accumulated competitive advantage. On the other hand, large-scale farms are less flexible in switching to other farming types, while viable small farms often benefit from the inverse hypothesis of productivity. According to Salvioni et al. (2014), semi-subsistence farms apply pluriactivity or outsourcing in order to survive.

Guiomar et al. (2018) provide a sophisticated small-farm distribution typology at the EU level and identify as many as eight clusters in accordance with the corresponding role of small farms in agriculture. Academics show that member states have individual farming structures and even in the same country the role of small farms could depend on the region. Guiomar et al. (2018) demonstrate that the role of small farms differs if one considers the coverage of the agricultural land area by small farms and focuses on the level of income and the average utilized agricultural area of small farms in the particular regions. In fact, the aforementioned diversity could result in different development directions of farming structures in the EU agricultural system. For example, Bakucs et al. (2013) investigate the validity of Gibrat's law on field crop and dairy farms in Slovenia, Hungary, and France. Academics conclude that the growth of small farms has different patterns not only between France and countries that joined the EU post-2003 but also between transition agricultures. Thus, results imply that the patterns of structural change depend on the member state, the farming type, and the selected time period.

Research on structural changes in the EU farm structure with a particular focus on the situation of small farms in member states is presented in numerous academic studies (Gorton and Davidova 2004; Dannenberg and Kuemmerle 2010; Hubbard et al. 2014; Salvioni et al. 2014; Aceleanu et al. 2015; Popescu et al. 2016; Bański

2018). Aceleanu et al. (2015) and Popescu et al. (2016) focus on the unique situation of agriculture in Romania. Academics evidence the slow change of the average farm size in the country with the highest share of small farms. Aceleanu et al. (2015) argue that Romania must move from the dominance of a subsistence economy towards commercially viable family farms and underline the importance of agricultural land consolidation and a further increase in the average farm size in order to compete on the market, while Popescu et al. (2016) ascertain the ongoing process of small farms' exit. In contrast, the second-most important country with the highest number of small farms, Poland, has adapted to changes in a new competitive environment by enlarging farm size, while a certain share of small farms sold their land (Dannenberg and Kuemmerle 2010). This country survived the disappearance of medium-sized farms and the establishment of bipolarity, reacting to the changes in the agricultural value chain (Dannenberg and Kuemmerle 2010) introduced by the collapse of the Soviet Union.

Bański (2018) and Gorton and Davidova (2004) have a particular interest in the development patterns of countries that joined the EU in 2004 and after. For example, Gorton and Davidova (2004) focus on farm productivity and efficiency issues in selected countries of Central and Eastern Europe. The latter study provides arguments explaining the survival of small farms in agriculture. In contrast, Bański (2018) underlines the growing importance of large-scale and specialized farms in Central Europe and points out the bipolarity issue in some member states where small farms coexist with large farms, while the medium-sized farm layer is weak.

The aforementioned academic research shows that the historic legacy and country-specific institutional arrangements of individual member states result in significant differences in structural change patterns. The reviewed contributions often select individual farming types and a limited number of EU countries for the analysis, while this study is aiming to provide a holistic picture of important resource reallocation in the EU agricultural system. Section 4.5 contributes to the discussion on structural changes by introducing two structural subindices—S_{EU} and S_{M}—that employ a number of farms to monitor changes in farming structures at the EU level and in member states. Results suggest that member states demonstrate growing contributions of the subindex S_{EU} for specialist field crop (I) and specialist grazing livestock (III) farms that result in an increase in the average farm size at the EU level. In the case of specialist horticulture, fruit, and citrus fruit (II) and mixed cropping (V) farms, the component S_{EU} depends on the selected measure of farm size and member state, but in most cases the situation remains without changes or contributions have positive developments. Other farming types, namely specialist granivore (IV), mixed livestock (VI), and mixed combined (VII) farms, often demonstrate negative development trends. In this regard, the reallocation of resources in the EU farming structure goes from mixed farming to specialized farming types.

However, the behaviour of the structural subindex S_{M}, reporting on the changes in member states, demonstrates significant variations for individual member states by type of farming and the selected measures of farm size. In the case of the average utilized agricultural area and the average directly employed labour force, the growth of the subindex S_{M} at the EU level occurs only for specialist field crop (I) farms, while other farming types show a decline in S_M value for these size measures at the EU level. Thus, the contributions of individual countries differ significantly and do not necessarily demonstrate development trends corresponding to the changes at the EU level. For the average standard output, a positive development of the subindex S_M at the EU level is reported for mixed livestock (VI) and mixed combined (VII) farms, while other farming types show a fall in structural subindex value below unity. Again, country-specific developments of this subindex show rather different results by type of farming.

Despite the dramatic fall in the number of small farms over the investigated period, the current situation in agriculture shows that small farms represent a significant part of the EU farm structure. This fact, combined with the knowledge about the demographic viability of these farms, allows us to assume that the further evolution of the EU agricultural system will be led by the exit of a certain share of small farms and the enlargement of the average farm size in terms of the utilized agricultural area. This process will contribute to further resource reallocation.

4.6.2 Technology in Agriculture

In agriculture, technology is recognized as one of the most important drivers of change (Zimmermann et al. 2009; Bakucs et al. 2013; Kazukauskas et al. 2013; Neuenfeldt et al. 2019), allowing productivity to be increased and production cost reduced. According to the Neo-Schumpeterian approach, the world technology frontier becomes an important guidance (Berglof 2015) empowering structural changes. Thus, technological revolutions are an important driving force that changes the structures in the long run. Reati (2014) identifies as many as five periods with development growth surges due to technological revolutions. These periods are linked to the spread of radical and incremental innovations, as well as heavy investments in the replacement of equipment and plants (Reati 2014).

In the case of agriculture, technological revolutions played the most dramatic role and determined the ongoing diminishing of the agricultural share in the structure of the economy. Over the last few centuries, agriculture also lost its importance in the structure of total employment. Technological innovations had a major impact on agriculture in terms of reducing the dependence on labour force and improving the control over the production process. Capital replaced labour force, increased productivity, and provided substantial cost savings on farms. Haugen and Brandth (1994) argue that technologies pushed females out of agriculture, because this economic activity relied heavily on so-called men's technologies. In fact, technological revolutions contributed to the evolution of gender structure in agriculture.

According to Reati (2014), the fifth period of the development is empowered by the progress in computer and information technologies. During this period, the replacement of important production factors with capital continues. Indeed, the diminishing role of agriculture in employment remains a sensitive issue. The situation is exacerbated by new challenges pushing towards reducing dependence on cheap labour force and replacing it with technologies. Many EU farms that relied on migrants were not able to ensure the relevant labour force on time during the COVID-19 outbreak. This situation provided additional arguments for academics advocating the application of robots in agriculture.

Technological innovations allow output cost per unit to be reduced. Thus, there is an important nexus between technology and economies of scale. According to Zimmermann et al. (2009), early adopters of technological innovations benefit from reduced costs and push other farmers to follow the same path of innovation in order to survive after the spread of technology leading to a fall in market prices. Farm size is often linked to capital availability and the possibility of investing in such innovations; i.e., larger farms are more likely to adopt new technologies than small farms. This problem is often stressed, explaining the challenges of individual member states that joined the EU in 2004 and later [e.g., Dannenberg and Kuemmerle (2010), Błażejczyk-Majka et al. (2011), Aceleanu et al. (2015)]. These countries face difficulties competing on the EU market, because the development level of the technology employed has a significant gap compared to the situation in EU-15 countries. In the long run, the moving towards the world technology frontier determines the evolution of the optimal farm size in the individual farming types and results in structural changes at the EU level.

The academic research on the nexus of economies of scale and farm productivity or efficiency issues provides contradicting results [e.g., Latruffe et al. (2004), Gorton and Davidova (2004), Błażejczyk-Majka et al. (2011)]. In regard to this research niche, findings suggest that the alteration of such patterns as the selection of the member state, farming type, and time periods could result in different outcomes. A widely shared view that large-scale farming is characterized by higher productivity is denied by some studies on inverse productivity. For example, the study by Błażejczyk-Majka et al. (2011) investigates the link between economies of scale and efficiency on field crop and mixed farms in selected EU-15 countries and new regions, namely the Czech Republic, Poland, Hungary, and Slovakia. Findings suggest that the stable business environment in the EU-15 gave a competitive advantage and allowed large-scale farms to select technology and organizational models, thereby improving efficiency, while small farms have a higher pure technical efficiency than large farms. According to Błażejczyk-Majka et al. (2011), the application of technology leaves space for improving efficiency in both groups of member states; however, in countries that joined the EU in 2004 and later the situation is worse. Gorton and Davidova (2004) investigate the link between economies of scale and farm efficiency in Central and Eastern Europe countries that joined the EU in 2004 and later. They do not find evidence that small farms are less efficient than corporate structures and argue that human capital and support could make small farms a competitive business form.

It is worth noting that some member states that joined the EU in 2004 and after launched special programmes to foster modernization and help farmers to compete on the EU market. However, these measures often contributed to an increased gap of inequity within the country, because small farms had no access to support allowing them to invest in technologies, while large farms improved their good position.

Nevertheless, the low productivity in agriculture remained the main concern in most of those member states and resulted in structural transformations and the exit of small farms. Today, at the EU level, many different measures are aimed at assisting in the spread of innovations in agriculture. Special measures are funded from the rural development budget of the CAP, while other funds contribute with research and development activities, improvement of human skills, start-up initiatives, and the dissemination of information about available innovative technologies. Policy that encourages movement towards the world technology frontier will introduce further structural changes in the average farm size and result in resource reallocation at the level of the EU economy.

4.6.3 Agricultural Policy

One of the most powerful drivers of structural change is agricultural policy that shapes the national support model. The study by Neuenfeldt et al. (2019) show that subsidies are a useful factor in explaining the variation in the EU farm structure, but the nexus between changes in the support model and structural changes in agriculture depends on the country. According to Neuenfeldt et al. (2019), the impact of subsidies is remarkably stronger in countries that joined the EU in 2004 and after. As a result, changes in the CAP support model can make significant corrections in the farming structures of those countries. In fact, the study by Breustedt and Glauben (2007) demonstrates that high subsidies can reduce farm exit rates.

In member states, the evolution of national agricultural systems is influenced by the combined effect of the CAP and national agricultural policy. The CAP is managed at the EU level and redistributes a significant share of the EU budget. The policy measures address three main actions: income support, market measures, and rural development. Given that income support in the CAP represents a significant share of the budget, this support measure, namely direct payments, has a strong impact on the structural changes of agricultural systems. Furthermore, some academics argue that the abolishment of direct payment could go beyond the agricultural system and have negative effects on the economy (Křístková and Habrychová 2011). However, the consequences of the abolishment will strongly depend on national farm structures and regional conditions (Uthes et al. 2011).

It is worth noting that in the EU-15 the CAP was an important factor contributing to the establishment of the current farm structure. During the early years, the CAP widely applied market measures that allowed the food security problem to be solved and resulted in overproduction at the EU level. Later, the policy introduced coupled direct payments that helped in adjusting to support loss due to the reduction of funding from market measures. According to von Witzke and Noleppa (2007), this type of support secured income for large-scale production and landowners, while small farms and land operators were not among the real beneficiaries of this reform. Thus, the policy contributed to the survival of large-scale farms and encouraged relevant structural changes in the EU agricultural system. Nevertheless, the switch in support measures did not change the behaviour of farmers, who heavily relied on direct payments and often ignored market demand and profitability issues.

In 2003, a new reform was launched, and payments for production were replaced by area-based payments. This reform introduced decoupled direct payments to reduce overproduction and encourage a higher market orientation on farms. According to academic research, the effect of coupled and decoupled direct payment determined different consequences (Sahrbacher et al. 2009). Member states started gradually replacing coupled payments with decoupled payments. As a result, after 2007 the share of decoupled payments was dominant in the CAP budget. However, the reform did not solve persistent problems and direct payments were criticized due to unequal distribution and a high concentration of the CAP budget in large farms.

Many studies confirmed that direct payments contributed to inequality within countries (von Witzke and Noleppa 2007; Beluhova-Uzunova et al. 2017). Ciaian et al. (2018) and Sahrbacher et al. (2009) argue that direct payments lead to land price capitalization. Low access of small farms to support resulted in land redistribution and the growth of the average farm size. Furthermore, this structural change contributed to rural vitality problems and demographic changes. The average direct payments in member states also differed, and this situation determined unequal farming conditions within the EU agricultural system, creating less favourable support conditions for countries that joined the EU post-2003. Thus, convergence and regionalization remained a serious concern of the direct payments model (Sollazo et al. 2014). On the other hand, payments were criticized because they supported inefficient farms and delayed structural changes towards higher social welfare (Iraizoz et al. 2007; von Witzke and Noleppa 2007).

In 2014, the new fundamental reform of the CAP was introduced in order to address the aforementioned problems and react to new challenges. The direct payments moved from decoupled to target-oriented measures, helping to achieve the specific objectives and overcome the main challenges of the EU agricultural system. Area-based direct payments were replaced by multipurpose payments that contributed to income support, a more sustainable farm land use, generational renewal, fostering of small farms, and compensation for the excessive farming cost in areas with specific natural constraints, and provided a coupled support for problematic sectors. The overall CAP support system became holistic, and direct payments were used to complement rural development measures. In member states, the fundamental changes in direct payment redistribution were fully implemented after transitional periods. As a result, the effects of this reform on the structural changes of the EU agricultural system are not covered by this study. However, according to Zimmermann et al. (2009), social settings that shape policy are an important driving force of structural change. In this regard, the aforementioned revolutionary changes in the support model must lead to corresponding further development of the farm structure.

The results of this empirical study are consistent with academic research forecasting the impact of direct payments on the changes in the agricultural system. At the EU level, the surge in the average utilized agricultural area on farms coincided with the transition to decoupled direct payments that link the support to the farm size in terms of land area. This transformation of the CAP support model and food price crises strongly contributed to the growth in the average standard output on farms. In some member states, the surge in crop prices and support measures encouraged a switch of small farms from livestock or mixed farms with decreasing margins to less labour-intensive farming activities, while other small farms made decisions resulting in the growth of the average farm size. However, the capital of large-scale farms and better access to support measures allow them to invest in innovations and modernize farms in order to reduce the dependence on labour force. As a result, changes in directly employed labour force do not demonstrate the same pace of development as other measures of farm size. Hence, the rural development measures become a critical element of policy allowing the lower employment in agriculture to be dealt with.

Nevertheless, the decomposition of farm size by member state shows that countries demonstrate different patterns of development. The specific combinations of driving forces and natural conditions of those countries to some extent explain differences in structural changes. Furthermore, the differences in support models—such as specific combinations of national and CAP measures, inequities within countries and between member states—contribute to the better understanding of differences in development.

4.6.4 Crises and Natural Disasters

Farming activities are related to multiple crises that must be overcome by farmers during their farming cycle. Such crises in agriculture could be a result of natural disasters or disease outbreaks; they could also have economic, political, or other origins. The nexus between crisis and structural changes in agriculture is a widely discussed topic, and studies introduce two opposing academic viewpoints on the role of crisis in structural change of agricultural systems.

According to the first viewpoint, crises and natural disasters do not have a critical impact on structural changes in agriculture. Farmers are aware that their activity is riskier than alternative businesses and they can wisely plan their high profits after good years. The main goal of such farms is to maintain and transfer a viable farm to the next generation rather than profit maximization in the short run.

Numerous studies, mainly focusing on the agricultural systems in the EU and USA, estimate farming attractiveness from an economic point of view proposing a link between non-viability and financial well-being (Zeddies 1991; Morehart 2000; Hennesy et al. 2008; Argilés 2010; Developments... 2010; Vrolijk et al. 2010; Agrosynergie 2011; Coppola et al. 2013). Some researchers report on the limitations of such estimations and underline the importance of non-financial indicators (Argilés 2010), off-farm income (Fritzsch et al. 2010), and support measures (Breustedt and Glauben 2007; Vrolijk et al. 2010; Agrosynergie 2011; Coppola et al. 2013) in family budgets. Hence, the advocates of generational family farm transfers argue that the forecasting of real farm exits remains problematic. In fact, in some agricultural systems, farm exits are more often determined by retirement and failures in farm succession than by financial viability (Argilés 2010).

Consequently, attempts to predict farm exit applying financial ratios and traditional bankruptcy prediction models often fail, explaining the real structural changes in agriculture after the crisis. In that case, the decision of the farmer concerning the status of the farm (exit, switching to another farming activity, or staying) depends on many important factors, namely (Jurkėnaitė 2015): expectations for the following years, including the link between expected income and family needs, level of off-farm income in family budget, and farmer's knowledge and skills that could be sold on the market to earn for living or initial capital that could be used to start a new business. In the light of the aforementioned aspects, single episodes of crisis do not determine dramatic structural changes in agriculture.

The advocates of the second viewpoint state that the main goal of the farm is profit maximization. This point of view suggests that the reactions of farmers and entrepreneurs to crisis or natural disaster are similar. Mann et al. (2017) argue that the role of crises in highly protected agricultural systems with small-scale farming differs from liberalized large-scale agricultural systems. Mann et al. (2017) investigate the impact of crises on structural changes in the Australian large-scale agricultural system and conclude that external shocks (such as economic downtowns and natural disasters) contribute to the structural changes in farming activity. Results imply that crises reduce profitability and work satisfaction and therefore contribute to the structural changes, because farmers switch to another activity. Furthermore, Mann et al. (2017) assume that higher price volatility and climate change will increase the role of crises in the agricultural systems of the EU in the context of globalized trade.

The results of this empirical study support the nexus between crisis and structural changes. In Sect. 4.4, structural change indices demonstrated a strong surge in values for gross value added and employment during the economic crisis of 2008. In agriculture, the periods from 2007 to 2008 and from 2010 to 2012 are widely recognized as world food price crises. During these periods, the food price spikes were dramatic due to the mix of poor harvests in important exporting countries and the ongoing growth of input prices. According to Neuenfeldt et al. (2019), agricultural prices can be used to explain the changes in the EU farm structure, while macroeconomic variables (for instance, interest rate, GDP growth, and unemployment rate) also contribute to a better understanding of structural changes.

The effects of food price crises to some extent can be seen in graphs that introduce period-specific changes in the EU agricultural system. In Sect. 4.5, the change indices C_T for the period 2007–2010 demonstrate the largest increase in values for the utilized agricultural area and standard output, while changes in directly employed labour force lag and the peak comes for the period 2010–2013. For example, during this period, the Romanian agriculture became an activity employing after the economic crisis (Aceleanu et al. 2015); similar behaviour was noticeable in some other member states. However, in the case of the EU agricultural system, the aforementioned crises coincide with the important reform of the CAP that aimed to change farmers' behaviour and could have an impact on the evolution of the average farm size.

The impact of crises on the switch in farming activities can be illustrated by the Lithuanian case of pig farming. The country faced a dramatic decrease in the pig population and structural changes in this sector due to the combination of several crises. First, the food price crisis had resulted in skyrocketing feed costs, and this business option lost its attractiveness on small farms. Later, African swine fever and the corresponding response of the Ministry of Agriculture encouraged the switchover of small farms to other farming types. This case is an example that demonstrates the growing importance of crises for the development of the national farming structure. Nevertheless, member states have similar experiences, because crises often contribute to exacerbation of the overall situation in individual agricultural sectors and accelerate structural changes.

4.6.5 Demographics and Human Capital in Agriculture

Structural changes in agricultural systems are closely related to demographic farm viability and the *farm generational renewal* situation in the country. It is widely recognized that EU agriculture faces farmers' ageing problem, but the scale of this problem often depends on the definition of the young farmer. As a general rule, demographically viable farms have young operators or at least one family farm member below the indicated maximum young farmer age threshold, ranging in different studies from 35 to 45 years (Dillon et al. 2010; Jurkėnaitė 2013, 2015).

Indeed, current statistics in member states focuses on the age of farm operators rather than on the concept of demographic farm viability. However, even this indicator is very useful in providing a pessimistic picture of the generational renewal situation on farms. Figure 4.12 demonstrates that in 2016 only Austria, Germany, France, and Poland had a favourable generational renewal situation characterized by the fact that the number of young farmers exceeds the senior population. Countries such as Luxembourg, Finland, and Slovakia have an almost balanced situation with a

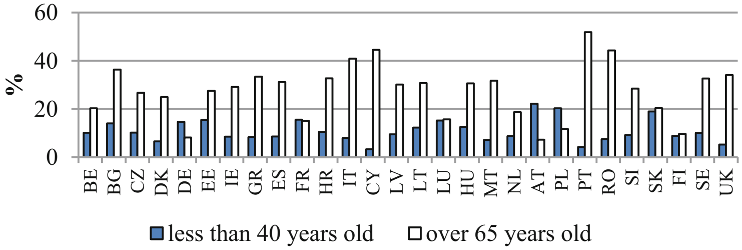


Fig. 4.12 Shares of young and senior farmers in national agriculture by member states in 2016. Source: Calculated based on Eurostat data

sign of slight shrinking of the farmers' population, while the remaining member states demonstrate a dramatic generational renewal situation.

In many countries, demographic farm viability is one of the most important indicators explaining the continuation of the farming activity in the long term. Furthermore, this knowledge also allows assumptions to be made about possible structural changes, because the previous academic contributions show the nexus between demographic patterns and business development. For example, the study by Neuenfeldt et al. (2019) demonstrates that the age of the farm holder is an important variable explaining structural changes in agricultural systems. The ageing process in agricultural systems is an important indicator of expected structural changes for several reasons.

First, age is linked to the farming cycle and the willingness to expand the farm and apply different risk management strategies. According to Viira (2014), farm growth is unlikely during the entrance stage of young farmers as well as the exit stage of senior farmers. During the exit stage, senior farmers reduce their work on the farm, their behaviour becomes risk averse, and they maintaining the well-known farm business as usual. A cardinal switch to other farming activity is unlikely. Nevertheless, Viira (2014) and Neuenfeldt et al. (2019) argue that the behaviour of older farmers depends on the succession situation; i.e., farms with successors attract more investments and have better management. For this reason, the concept of demographic farm viability could be important in explaining performance differences on farms operated by senior operators.

A key demographic issue related to structural changes is the nexus between age, human capital, and technological development. Zimmermann et al. (2009) highlight the *human capital* factor, including such variables as managerial skills and education-related characteristics, as being critical for farm management and the adoption of new technologies. The disproportionate over-representation of senior farm operators in the farm structure could be linked to a lower level of education and limited farm development prospects (Danilowska 2008), while young farmers support innovations and adapt to changes faster (Trisorio 2004). As a result, the competitiveness of the national agricultural system and expectations of structural change depend on the generational renewal situation.

Second, in most cases, the high share of aged operators is linked to uncertainty and a greater possibility of structural change, because often farms with senior operators are not demographically viable. Even demographically viable farms with young family members could be sold, because a successor is not willing to operate a farm. In such cases, the exit of the senior farmer means that the land will either be sold to a new operator or abandoned. In fact, this process often contributes to structural changes such as a switch of farming activities or changes in the average farm size.

Third, in some member states, the dramatic situation of the generational renewal on farms is critical due to peculiarities of the evolutionary changes in the national agricultural system. For example, in some countries that joined the EU post-2003, the reforms after the collapse of the Soviet Union determined the entrance of the new generation of farmers at the same time. For this reason, a large proportion of farms

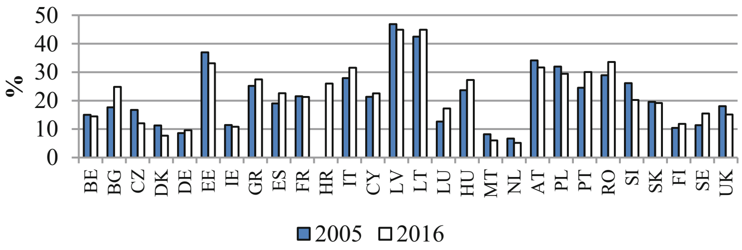


Fig. 4.13 Share of female operators in national agricultural systems by member states, 2005 and 2016. Data for Croatia for 2005 are not available. Source: Calculated based on Eurostat data

faced the ageing challenge simultaneously, and a faster pace of structural changes is likely, because generational renewal issues coincide with other important driving forces of change in those countries.

Another important demographic issue is related to the gender of the farm operator and the *gender balance challenge* in national agricultural systems. In most of the EU countries, the share of male-operated farms is dominant, while the number of female-operated farms is decreasing. The research on gender differences in agriculture shows that in some countries farming is traditionally seen as a male occupation (Haugen and Brandth 1994; Brandth and Haugen 2010; Quendler et al. 2017). Quendler et al. (2017) argue that the diminishing role of females in agriculture and work classification into "male" and "female" are the aftermaths of agricultural modernization. However, the return of female operators becomes possible due to the agricultural multifunctionality approach, because females successfully develop new businesses and find viable farm operating niches.

Multiple studies find evidence that the operating strategies and goals of female farmers differ from those of male farmers. For example, Coppola et al. (2013) argue that in Italy female operators have smaller farms that attract less capital and require less labour force. According to the aforementioned study, these farms are less economically efficient than the farms operated by males; however, female farmers contribute to the diversification of family income and help to solve poverty problems in rural areas. Nevertheless, the modest role of female operators in family income could be explained by women's multiple roles (Ayoola et al. 2011; Quendler et al. 2017) in families and society, because female farmers have responsibilities that are not typical for male operators.

Hence, the share of female farm operators and the generational renewal of those farms are important aspects determining the state of the national agricultural system and explaining structural changes. In this regard, the gender balance in national agriculture can be useful for explaining the main trends of the average farm size or farm income development and other important issues. According to Eurostat, female operators have a different significance in EU member states (Fig. 4.13). Female farm operators are more common in countries that joined the EU post-2003, while in many EU-15 countries large-scale farming remains a male occupation.

During the period from 2005 to 2016, some EU member states managed to increase the share of female operators, while in other countries the decreasing trend was obvious. Furthermore, even structures with a high number of female operators often hide the problem of generational renewal, because senior female operators are often replaced by young male operators. This female operators' generational renewal gap could contribute to structural changes in the agricultural system in the immediate future.

To conclude, structural changes in the EU agricultural system are a complex phenomenon driven by the interaction of different factors. It is worth noting that the situation in each member state is unique; however, some general patterns could be useful in predicting the expected evolutionary paths of EU agriculture. The starting point that assists in explaining the possible pace and directions of structural change is national farm structures resulting from different historical legacies. Farm structure and agricultural policy could accelerate changes or result in stronger path dependence. Another critical aspect that could be linked to expectations for the development of the national agricultural system is the demographic situation on farms. Research suggests that age structure, gender balance issues, and human capital patterns are important explanatory variables of structural changes in agriculture. In fact, these characteristics of national agricultural systems could be linked with technological developments and attitudes towards innovations that change farming structures. An important factor shaping the latest development of the EU agricultural system is the growing significance of crises. The aforementioned driving forces play an important role in agricultural structural change and in the long run influence the development of the overall structure of the EU's economic activities; however, this list of driving forces is not exhaustive and other country- or region-specific factors could make an important contribution to the evolutionary processes.

4.7 Conclusion

Given the widely recognized importance of the EU agricultural system for societal well-being, an academic interest in structural changes is critical for the successful management and prevention of undesirable aftermaths. The literature review stresses the complexity of the structural change phenomenon, resulting in multiple research focuses, structural change measures, and methodological research frameworks. These contributions shed more light on the nature of structural changes, but the selection of methods must correspond to the research goals and take into consideration research limitations introduced by different methodologies.

This study brings into focus the most recent structural transformations in the EU agricultural system and the changing role of agriculture in the EU economy. The selected research framework combines methods that deal with different aspects of structural change. The evolution of the EU economic structure is investigated by employing the structural change index, analysis of changes in the structure of economic activities, and the shift-share method, while structural changes in agriculture are analysed by applying index decomposition analysis.

Findings suggest that the role of agriculture, forestry, and fishing activity in the overall structure of the economic activities is diminishing in terms of contributions to the creation of gross value added and employment vacancies. In most of the EU countries, this process is accompanied by the growing role of service-related activities in the national economic structures. The analysis of structural change indices suggests that individual member states often survive more dramatic changes in national economic systems, while at the EU level the pace of change is less significant. It is important to note that the pace and directions of structural change in member states differ significantly, and countries that joined the EU in 2004 and later often face the steepest structural changes. Although multiple academic studies have confirmed the relevance of these processes, results imply that the evolution is not over, and this ongoing process is driven by new challenges in agriculture. For example, the COVID-19 crisis has shown the vulnerability of the EU agricultural system and encouraged consideration of the potential of technologies in order to reduce the reliance on cheap labour force, the climate challenge has underlined the importance of dietary changes resulting in lower demand for meat and dairy products with a corresponding shift in farming structure.

The shift-share analysis for gross value added suggests that in member states results are strongly influenced by inflation. In most of the member states, the pace of change in gross value added in agriculture, forestry, and fishing activity is lower than the growth rate of the EU economy. The mix of economic activities demonstrates only negative developments for agriculture, forestry, and fishing activity, while the competitiveness component is negative in many countries. The shift-share analysis for employment shows that in all member states except Sweden and the UK, the total change in the number of employed people demonstrates negative values, while application of the EU economy growth rate suggests that the change must be positive. Results demonstrate negative developments for the mix of economic activities; however, the competitiveness component shows a positive development in most countries.

The empirical study of structural changes in agriculture relies on the original IDA identity allowing the change in the average farm size to be decomposed into two structural components and pure change of the selected farm size measure. This method empowers the analysis of structural changes at the EU level, in member states, and individual farming types. The application of the IDA model for the EU agricultural system shows the most important changes in the average farm size in terms of utilized agricultural area, standard output, and directly employed labour force.

Findings indicate significant structural changes in EU agriculture. During the period from 2005 to 2016, the average farm size demonstrates a remarkable growth in terms of the use of utilized agricultural area and the generation of standard output. However, these transformations of the average farm size at the EU level are not accompanied by a corresponding growth of the average directly employed labour force. The changes in the EU agricultural system are determined by the significant growth of the average farm size on specialist field crop and grazing livestock farms, while some mixed farming types demonstrate negative developments of the average farm size. Changes in national agricultural systems often follow the aforementioned patterns, but member states demonstrate quite significant differences in the pace of change, peak periods, and even development directions. The substantial disparities in evolution could be explained by significant differences in historic development that resulted in individual farm structures, institutional environments and agricultural policy, demographics, and the level of technological developments in national agricultures. The unique situation of these factors determines different starting points of the evolution and individual initial conditions to cope with crises and react to other important driving forces of change.

The proposed decomposition model allows a quick mapping of the main development trends in the EU agricultural system and warns about undesirable structural change directions introduced by multiple driving forces. The identification of similar structural change patterns at the EU level or in groups of member states demonstrates the problem areas and challenges for in-depth academic research on driving forces of transformations. The application of the model makes it possible to show the nature of structural change relying on the importance of contributions from structural and pure change subindices. Furthermore, the model assists in the investigation of resource reallocations in input and output structures. In this regard, the results could be important for policymakers involved in the development of agricultural policy. However, the level of aggregation plays an important role, because aggregated indicators hide changes of different origin within one value and result in research limitations. Although the model allows different measures of farm size to be selected and important aspects of sustainable development to be monitored, the availability of long series of reliable and comparable data for the environmental dimension remains a challenge.

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Chapter 5
Footprint of Agriculture

Vida Dabkienė

5.1 Introduction

The Farm Accountancy Data Network (FADN) is already widely used for assessing farms' economic performance, but analysts still face methodological issues in evaluating the environmental impacts of farms. The targets set in the EU strategies like The European Green Deal (EC 2019b), Farm to fork strategy (EC 2020c), EU 2030 Biodiversity strategy (EC 2020a), and European Climate Law (EC 2020b) influence the EU CAP design. To monitor the policy interventions and the situation on farms, FADN data are one of the main data sources (EC 2020d). In response to policy needs, FADN database is revised in terms to collect additional data needed for the decision-makers (EC DG Agriculture and Rural Development 2020), and therefore, new possibilities arise for the development of new indicators and frameworks. Agriculture's role is crucial, both in adapting climate change and contributing to mitigation. The strengthened relevance of environmental issues in the Strategic Plan for the next long-term EU budget 2021–2027 requires additional analysis to provide justifications and an evidence-based rationale for the strategic choices and interventions, providing the background against which the interventions can be justified, relevant, and adequate in terms of the optimal use of the CAP. The aim of this research was to develop a tool for agri-environmental performance assessment at farm level using simple, sound, and transparent Agri-environmental Footprint Index (AFI) construction procedures.

The AFI development method involved three major stages: selection of indicators, data elaboration, and score analysis. Twelve indicators were developed to quantify environmental pressures of farming activities. The min–max method was applied to produce normalized values of indicators from 0 to 1. Principal component

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T. Baležentis et al., *Structural Change, Productivity, and Climate Nexus in Agriculture*, https://doi.org/10.1007/978-3-030-76802-7_5

analysis (PCA) and equal weighting (EW) were applied to determine weights for the indicators and to yield AFI_{PCA} and AFI_{EW}, respectively. The threshold values of AFI were graded as low, medium, and high. Lithuanian FADN of family farms data for the years 2016 and 2017 were taken to measure the environmental impact of different farming types and economic size classes.

The assessment results indicate a good level of Lithuanian family farm agri-environmental performance as over 70% of the sample farms were defined by a medium AFI_{PCA} and AFI_{EW} level. The highest AFI values within farm groups in terms of their economic size were found for the medium farms in SO classes II–IV and SO classes III–IV, using the PCA and EW indicators weighting method, respectively. In contrast, the lowest values were observed for the largest farms (SO class VII). With respect to type of farming, the highest AFI values were found for permanent crop and field crop farms, using PCA and EW, respectively. At the other end of the spectrum, the lowest AFI values were obtained for farms specialized in granivores irrespective of the weighting method applied. The index structure is flexible and can be used for diverse local policy needs and in particular for monitoring and planning policy interventions. The results of the AFI provide new knowledge about farms' environmental performance, disclose problem areas within farm groups, and can be the basis for political assumptions that contribute to sustainable development of the agricultural sector in Lithuania.

The aim of this chapter is to develop a tool for agri-environmental performance assessment at the farm level using simple, sound, and transparent index construction procedures. Lithuanian FADN primary data were applied to measure and compare the environmental impacts of different farming types and economic size classes. The rest of the chapter is structured as follows: Sect. 5.2 presents a literature review; Sect. 5.3 describes the data used and methods applied to calculate the AFI at farm level that were used for empirical research; Sect. 5.4 presents the results of agri-environmental performance indicators and the AFI calculated on the basis of the weighting for Lithuanian family farms and discusses the results; and finally, the chapter concludes with Sect. 5.5.

5.2 Rationale for the Agri-environmental Footprint Index Construction

Lithuania's ecological footprint exceeds the country's biocapacity; consequently Lithuania is losing the image of being a "green country". Although the ecological deficit is only estimated at 0.8 gha in 2017, Lithuania is the only one of the Baltic States to run an ecological deficit (Global Footprint Network 2021). According to Lithuanian strategic documents (LAEI 2016), the agriculture sector remains one of the priority sectors and performs an important economic, environmental, and social role. However, the Lithuanian agricultural sector experiences numerous challenges in achieving environmental sustainability. Several negative environmental impacts are briefly described below. Lithuanian agriculture between 2005 and 2018 saw a 3.3% increase in greenhouse gas (GHG) emissions and this sector was indicated as being responsible for 21.1% of the total national GHG emission in 2018 (LNIR 2020). The production of renewable energy from agriculture per ha of utilized agricultural area (UAA) was 2.8 times lower than in the EU-28 on average in 2018 (EC 2019a). The use of inorganic nitrogen fertilizers increased by 34.8% in 2018 as compared to 2008 (Eurostat 2020). Consequently, the fertilizers used in agriculture have an impact upon diffuse pollution to the surface and ground water bodies. During the period 2010–2018, the Curonian Lagoon and the coastal waters of the Baltic Sea did not meet the criteria of a good ecological state (Environmental Protection Agency 2020). The sales of fungicides and insecticides increased in 2018, as compared to 2011, by 87.2% and 114.8%, respectively. Furthermore, the agricultural biodiversity is declining in Lithuania. This is demonstrated by the common farmland bird index decreasing by 15 percentage points in 2018, as compared to 2008 (Eurostat 2020). The low environmental performance of the Lithuanian agricultural sector is also proved in the research conducted by Kasztelan and Nowak (2021): the Lithuanian agricultural sector ranked second to last among 20 EU countries in terms of the green performance of agriculture over the period 2008–2017.

The environmental performance of agriculture is manifold (Hřebíček et al. 2013; Migliorini et al. 2018); therefore, a variety of criteria and indicators have been proposed by researchers (Hani et al. 2003; Van Cauwenbergh et al. 2007; Zahm et al. 2008; Gómez-Limón and Sanchez-Fernandez 2010; Westbury et al. 2011; Gerrard et al. 2012). However, using many indicators, there is a problem in providing a concise account of the environmental situation and in tracking the environmental changes on farms influenced by policy interventions. The aggregated information is argued to provide oversimplistic messages, and in order to overcome, this limitation index decomposition analysis can be used as a possible solution (Stylianou et al. 2020). Composite indicators that aggregate different environmental issues into one index on farms were developed in previous studies (Purvis et al. 2009; Vesterager et al. 2012). Purvis et al. (2009) proposed a common methodology to assess the farm-scale effects of rural development interventions using the Agri-environmental Footprint Index (AFI). The authors integrated the evaluation of multiple and complex environmental issues concerning such themes as natural resources, biodiversity, and landscape quality. Vesterager et al. (2012) designed the Agri-Environmental Footprint Index and demonstrated the results for Danish farms. Twenty indicators were applied involving natural resources, biodiversity, and landscape.

The investment intervention possibilities proposed in the EU's CAP encourage farmers to apply new technologies and management practices to cope with climate change, and protect and maintain the environment. Consequently, it is essential to measure agricultural impacts on the environment at farm level and to evaluate how and how well farmers cope with the issues of climate warming and to track their achievements. The need for the agricultural sector's sustainability issues to be assessed at farm level is widely acknowledged by scholars (Galdeano-Gómez et al.

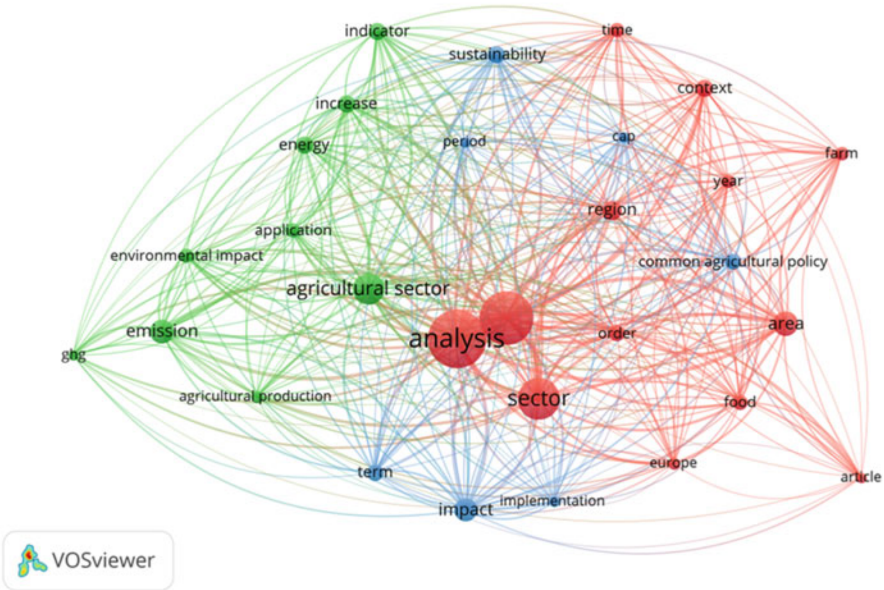

Fig. 5.1 Keywords co-occurrence map

2017; Kelly et al. 2018; Migliorini et al. 2018; Tzouramani et al. 2020). Most of the proposed assessment methods use an aggregate or macroeconomic approach (Galdeano-Gómez et al. 2017), and this leads to limit analysis within farm groups that is necessary for strategic planning. As the acquisition of farm-scale data is costly and time-consuming, annually collected by the EU Member States FADN database has been widely used in research (Westbury et al. 2011; Gerrard et al. 2012; Lynch et al. 2018; Czyżewski et al. 2019; Uthes and Herrera 2019) to account for environmental issues. The FADN is the only standardized and harmonized farm accountancy system in the EU that provides up-to-date information to policymakers for future decisions. Notwithstanding the potential of FADN data in terms of providing answers to complex emerging policy questions, Kelly et al. (2018) pointed out that this system still lacks sufficient data to address environmental concerns. The strengthened relevance of environmental issues in the EU Common Agricultural Policy 2021–2027 (EC 2020d) requires additional analysis to provide justifications and an evidence-based rationale for strategic choices and interventions, providing the background against which the interventions can be justified, relevant, and adequate in terms of the optimal use of the CAP. Furthermore, in the national CAP strategic plans, each member state of the EU can design mandatory sector-specific financial support measures. Consequently, analysis is required to direct the interventions towards various sectors' needs.

In order to present the main topics related to the agricultural sector's environment issues in the EU, the VOSviewer software tool was used. Figure 5.1 presents the scientometric analysis obtained through the VOSviewer software with scientific publications (articles, proceeding papers, and reviews) extracted from the Web of Science (all databases) and Scopus scientific platforms over 1990–2021. The query was performed on 24 February 2021, using the following string: TOPIC (agricultural sector) AND TOPIC (environmental analysis) AND TOPIC (European Union). The query identified 83 publications. Duplicated keywords were eliminated before the data were loaded into VOSviewer. The VOSviewer software showed three clusters of the most relevant issues addressed in the papers: agricultural production, agricultural policy, and sustainability.

Recently, in Lithuania, a few studies were conducted to examine farms' environmental issues, developing a set of indicators or composite indices on the basis of FADN system data (Koloszko-Chomentowska et al. 2015; Volkov and Melnikienė 2017; Dabkienė 2018). Koloszko-Chomentowska et al. (2015) assessed the environmental and economic sustainability aspects of Lithuanian and Polish specialist milk and granivore farms, taking into account the share of cereals in crops, stocking density (LU/ha), total intermediate consumption (EUR/ha), mineral fertilizers (EUR/ha), plant protection products (EUR/ha), the value of purchased feed (EUR/ha), and energy consumption (EUR/ha). Volkov and Melnikienė (2017) examined the linkages between the direct payment system and environmental sustainability indicators in Lithuania and Italy (Puglia region). The list of environmental indicators included: costs for inorganic fertilizers (EUR/ha), livestock density (LU/ha), the ratio between temporary and permanent grassland and UAA, and the Shannon Diversity Index, which was calculated for cereals, other field crops, vegetables and flowers, orchards, other permanent crops, and forage crops.

The research of the Farm Relative Sustainability Index (Dabkienė 2018) analyses the sustainability of Lithuanian agriculture and simultaneously considers economic, environmental, and social dimensions, developing for each a set of indicators. To measure the environmental dimension, eight indicators were constructed, namely use of inorganic fertilizers (kg/ha UAA); use of pesticides (EUR/ha UAA); GHG emissions per farm; energy intensity; Simpson Diversity Index; meadows and pastures share in UAA; livestock density (LU/ha UAA); and environment-friendly farming (score). The indicators were aggregated into an index (FRSI) using three weighting approaches: PCA, EW, and expert questionnaire. The results of environmental sustainability across types of farming were presented.

To assess farms' environmental performance, FADN data were exploited in international studies conducted by Westbury et al. (2011), Gerrard et al. (2012), Lynch et al. (2018), Sulewski and Kłoczko-Gajewska (2018), Czyżewski et al. (2019), and Tzouramani et al. (2020). Westbury et al. (2011) measured the environmental impacts for arable, lowland livestock, and upland livestock English farms in 1995, 2000, and 2005 constructing the Agri-environmental Footprint Index (AFI). Two assessment criteria matrices were designed to evaluate differences in the AFI according to farm participation in agri-environmental schemes. The indicators used in the assessment included fertilizer use (t/ha UAA), energy consumption (EUR/ha UAA), Shannon indices related to crop diversity and land use diversity, the woodland and uncropped land share on farms, livestock density (LU/ha UAA), and the rough grazing area in UAA. Equal weights were given to the calculated indicators. Gerrard et al. (2012) investigated the environmental performance differences between organic and conventional English farms participating in the FADN survey. The following indicators were developed for the analysis: costs of fertilizer and pesticide per ha of UAA and total output; purchased feed costs per ha of UAA and per livestock unit (LU); an intensification indicator (developed as costs of fertilizers, pesticides, and purchased concentrates per ha of UAA); support payments under agri-environmental schemes per ha of UAA; LU density units per ha of forage area; and the Shannon Crop Diversity Index considering areas for barley, wheat, oilseed rape, beans, peas, sugar beet, horticulture, potatoes, and permanent grassland. The findings are presented at the indicator level. Lynch et al. (2018) developed a decision support tool to estimate current farm performance named "Farmscoper" and tested it empirically on cereal and dairy farms using Farm Business Survey (English FADN system) data for 2012. The environmental negative impacts of agricultural activity related to greenhouse gas emissions were addressed in the research. The Farm Sustainability Index designed by Sulewski and Kłoczko-Gajewska (2018) is based on Polish FADN system data enriched with data collected through farmers' interviews. The obtained data were beneficial in the development of 12 agro-environmental, 22 economic and production, and 11 social indicators. Sulewski and Kłoczko-Gajewska (2018) emphasized the costs of farm-level data and assumed that there is a direct relationship between the number of farm-scale variables incorporated in the assessment and the research costs. Czyżewski et al. (2019) evaluated the environmental sustainability of 130 EU FADN regions in 2015, and the research framework included the following indicators based on EU standardized FADN data: livestock density per ha of UAA; mineral fertilizers and plant protection products; energy consumption per ha of UAA; and the share of woodland area in UAA. One more example is currently being developed in Greece (Tzouramani et al. 2020) where the sustainability performance of Greek sample farm specialists in permanent crop, olive production, arable crop, and livestock (sheep) farms has been assessed. The indicators selected to provide a picture of environmental performance included GHG emissions and pesticide use per hectare, the share of UAA with nitrate risk, water consumption, and farm gate N-balance per kg of product.

On the one hand, these previous researches have demonstrated that FADN data are a valuable source of information regarding farms' environmental performance, while on the other hand, the different multiple indicator sets used by researchers limit the comparison between studies. Compared to the aforementioned studies, this paper presents some innovative elements. In this paper, the emphasis was put on the agri-environmental performance of family farms. The developed set of 12 indicators covers the main environmental components used in previous studies and is in line with the environmental objectives set at the EU level for the CAP 2021–2027. The detailed methodology for calculating GHG emissions using FADN data based on the previous article of the authors (Dabkienė et al. 2020) and empirical research results are presented for two reasons: first, the assessment of GHGs on farms is often excluded from analysis because of its calculation complexity; second, in the present research, the results of GHGs in 2016 and 2017 are compared. As highlighted by Hřebíček et al. (2013), the results of GHG assessment of farms are provided in the original values in order to provide knowledge for the improvement of farming systems. In addition, the agri-environmental indicators and AFI values are weighted to be representative of the Lithuanian agricultural sector and the obtained results can be jointly analysed with the other Lithuanian family farm results presented in the Lithuanian FADN survey results (LAEI 2020).

5.3 Methodological Research Framework

The AFI, constructed on an FADN data basis, follows the index construction steps presented in OECD-JRC (2008). The sequence of the AFI construction stages and the relationship among data, indicators, and indices and their end-users and producers are provided in Fig. 5.2. In the case of the AFI, specialists and researchers identify the acquisition of the primary data necessary for the calculation of selected indicators. In the next stage, researchers and specialists provide insights into how data could be elaborated in terms of providing the information required for decision-making. The aggregated data presented as an index are better understood by decision-makers, farmers, and the public. Moreover, the constructed AFI facilitates the comparison of results within analysed farm groups, and this information may support policy decisions regarding the identification of needs, prioritization, and ranking in the process of preparing a national CAP Strategic Plan. In order to present a detailed analysis of the results, a decomposition analysis of the AFI is presented: results of individual indicators and indices are provided in graphs and tables. The AFI construction method is based on three main stages as presented by Gaviglio et al. (2017): selection of indicators, data elaboration, and score analysis.

Lithuanian FADN system data for the year 2016 and 2017 were used and the research involved sets of 1300 and 1301 family farms, respectively. The results of agri-environmental performance indicators and the AFI were examined by types of farming and economic farm size classes. In line with the EU FADN typology classification, the following farming types were examined:

- specialist cereals, oilseeds, and protein crops (COP) (Type of farming, TF 15);
- general field cropping and mixed cropping (TF 16);
- horticulture (TF 20);
- various permanent crops combined (TF 36);

Fig. 5.2 AFI construction stages

- specialist dairying (TF 45);
- grazing livestock (TF 49);
- specialist granivores (TF 50);
- field crops-grazing livestock combined (TF 80);
- various crops and livestock combined.

The research results were reported for the economic size classes (expressed in standard output (SO) value, thousand EUR) as rendered in Lithuanian FADN:

- $4 \leq \text{EUR} < 8$;
- $8 \leq \text{EUR} < 15$;
- $15 \leq \text{EUR} < 25$;
- $25 \leq \text{EUR} < 50$;
- $50 \leq \text{EUR} < 100$;
- $100 \leq \text{EUR} < 250$;
- $\text{EUR} \geq 250$.

The main size characteristics of the family farms according to their farming types and economic sizes are provided in Table 5.1.

The primary data of FADN surveys (individual family farm records) were employed. It should be noted that the presented analysis covers only family farms; i.e., agricultural companies are not included in the research. A family farm is characterized as a business where the family owns, manages, and supplies most of the labour, land, and capital. In Lithuania, family farms make up 99.4% of all farms and own 86.6% of agricultural land (Statistics Lithuania 2018). It should also be emphasized that the FADN is not suitable for providing results on the farm structure of all farms, because it does not include the whole agricultural population and applies thresholds (SO of 4000 EUR is the threshold for farm participation in the Lithuanian FADN survey). Moreover, the FADN does not present the results in totals but in average values per farm.

Based on the Shapiro–Wilk test, the normality of environmental performance indicators and AFIs was evaluated. The analysis of variance and Kruskal–Wallis one-way analysis of variance test were performed for comparing agri-environmental performance indicators and AFIs between farm groups in terms of farming types and farm sizes using SPSS software. The variability level of agri-environmental performance indicators and AFI values within economic farm sizes and types of farming were evaluated using the coefficient of variation (CV% = (standard deviation/mean) *100)—a greater value of the CV indicates greater variability. The threshold values for CV adopted according Araro et al. (2019) are as follows: CV < 20% (low); 20 < CV < 30 (moderate); 30 < CV < 40 (high); 40 < CV < 70 (extremely high); and CV > 70% (severe).

Stage 1—Selection of agri-environmental performance indicators

On the basis of scientific literature, the selection and development of indicators were specified in four steps:

Step 1. The composition of the initial list of indicators concerning farm-level agri-environmental performance assessment based on literature review.

Table 5.1 Main size characteristics of family farms according to their farming type and economic size in 2016 and 2017

	Number of sample farms	Number of representative farms	Economic size of farm (thousand EUR) Mean ± SD Min/Max	UAA (ha) Mean ± SD Min/Max	AWU Mean ± SD Min/Max	FWU Mean ± SD Min/Max	LU Mean ± SD Min/Max	Total output (thousand EUR) Mean ± SD Min/Max
In 2016								
Farming type								
COP	449	17,024	43.8 ± 80.2 [4.9;1396.7]	72 ± 117 [6.2/ 1823.5]	1.6 ± 1.0 [1.0/ 30.5]	1.3 ± 0.4 [0.4/3.2]	1.7 ± 5.0 [0.0/107.0]	41.6 ± 91.2 [2.7/1486.9]
Field crops	114	3825	22.6 ± 64.4 [5.7/1274.3]	33 ± 62 [2.6/ 1250.3]	1.5 ± 1.2 [1.0/ 31.7]	1.2 ± 0.3 [0.5/3.0]	1.5 ± 3.3 [0.0/55.9]	24.0 ± 80.9 [1.2/1687.9]
Horticulture	37	924	21.1 ± 72.7 [4.5/1015.8]	9 ± 15 [0.2/ 176.6]	1.8 ± 2.8 [1.0/ 56.7]	1.2 ± 0.6 [0.2/2.7]	0.3 ± 0.5 [0.0/1.4]	24.2 ± 133.4 [1.7/1837.7]
Permanent crops	36	316	27.8 ± 29.5 [6.4/126.2]	35 ± 33 [10.0/ 127.3]	1.5 ± 1.0 [0.4/7.0]	1.1 ± 0.5 [0.2/2.2]	0.2 ± 0.7 [0.0/5.3]	20.0 ± 23.6 [0.5/111.0]
Dairy	322	18,030	22.7 ± 43.0 [4.5/1460.2]	29 ± 41 [2.3/ 956.8]	1.6 ± 0.9 [1.0/ 27.8]	1.5 ± 0.4 [0.5/4.0]	15.0 ± 29.3 [2.5/800.8]	19.9 ± 50.8 [2.6/2298.3]
Grazing livestock	120	3678	15.6 ± 19.5 [4.7/223.6]	43 ± 41 [4.7/ 309.2]	1.5 ± 0.6 [1.0/6.8]	1.4 ± 0.4 [0.6/4.0]	19.0 ± 25.6 [1.1/260.1]	18.8 ± 25.8 [2.0/322.5]
Specialist granivores	15	167	36.2 ± 102.1 [6.8/676.1]	12 ± 38 [0.0/ 350.1]	2.1 ± 1.2 [1.2/9.9]	1.7 ± 0.4 [0.6/2.0]	31.7 ± 97.2 [1.9/737.4]	52.8 ± 150.6 [4.7/1264.0]
Field crops-grazing livestock combined	162	5993	27.8 ± 56.3 [4.8/993.7]	48 ± 64 [6.5/ 941.9]	1.6 ± 1.0 [1.0/ 21.8]	1.4 ± 0.4 [0.4/4.5]	15.2 ± 24.9 [1.0/394.4]	25.1 ± 57.0 [4.2/895.7]

(continued)

Table 5.1 (continued)

	Number of sample farms	Number of representative farms	Economic size of farm (thousand EUR) Mean ± SD Min/Max	UAA (ha) Mean ± SD Min/Max	AWU Mean ± SD Min/Max	FWU Mean ± SD Min/Max	LU Mean ± SD Min/Max	Total output (thousand EUR) Mean ± SD Min/Max
Various mixed farms	46	6807	9.3 ± 7.3 [4.0/103.8]	11 ± 13 [0.0/ 124.0]	1.4 ± 0.4 [1.0/2.7]	1.3 ± 0.4 [1.0/2.0]	3.0 ± 6.0 [0.0/92.8]	11.7 ± 14.5 [2.0/106.4]
Economic size class (thousand EUR SO)								
4 ≤ 8	85	22,468	6.4 ± 1.0 [4.4/8.0]	13 ± 13 [1.3/96.8]	1.4 ± 0.3 [1.0/2.4]	1.3 ± 0.3 [0.5/2.3]	2.8 ± 2.7 [0.0/19.6]	6.3 ± 4.3 [1.7/51.6]
8 ≤ 15	161	15,294	11.2 ± 2.0 [8.0/15.0]	22 ± 14 [0.0/ 115.6]	1.4 ± 0.5 [0.4/4.2]	1.4 ± 0.4 [0.2/3.0]	5.0 ± 4.9 [0.0/35.6]	11.2 ± 9.9 [1.2/113.7]
15 ≤ 25	139	6177	19.5 ± 3.0 [15.0/25.0]	37 ± 18 [2.2/ 117.3]	1.4 ± 0.5 [1.0/5.1]	1.3 ± 0.3 [0.4/2.1]	9.6 ± 9.1 [0.0/49.3]	16.4 ± 8.2 [0.5/54.1]
25 ≤ 50	241	5991	36.2 ± 7.1 [25.1/50.0]	58 ± 26 [11.1/ 204.4]	1.6 ± 0.5 [1.0/4.7]	1.4 ± 0.5 [0.3/4.0]	14.0 ± 15.4 [0.0/99.0]	30.2 ± 14.6 [7.2/135.6]
50 ≤ 100	242	3893	72.0 ± 14.8 [50.0/100.0]	104 ± 41 [4.5/ 268.4]	1.8 ± 0.6 [1.0/4.3]	1.4 ± 0.5 [0.4/4.0]	21.1 ± 26.8 [0.0/153.2]	61.8 ± 26.1 [9.5/171.3]
100 ≤ 250	272	2341	156.7 ± 40.3 [100.2/249.6]	216 ± 88 [0.0/ 596.1]	2.9 ± 1.8 [1.0/ 56.7]	1.4 ± 0.6 [0.2/3.8]	35.6 ± 51.9 [0.0/260.1]	154.9 ± 77.9 [25.4/1837.7]
≥250	161	600	439.5 ± 206.8 [251.2/1460.2]	527 ± 277 [3.2/ 1823.5]	6.8 ± 4.9 [1.4/31.7	1.4 ± 0.6 [0.4/4.5]	73.6 ± 123.3 [0.0/800.8]	498.6 ± 295.0 [86.4/2298.3]
Total	1301	56,764	27.6 ± 58.5 [4.4/1460.2]			1.4 ± 0.4 [0.2/4.5]	8.7 ± 21.7 [0.0/800.8]	26.4 ± 68.1 [0.5/2298.3]

				43 ± 77 [0.0/1823.0]	1.6 ± 1.0 [0.4/56.7]			
In 2017								
Farming type								
COP	490	17,070	44.3 ± 80.8 [4.0;1451.3]	75 ± 118 [7.5/1807.0]	1.5 ± 1.1 [1.0/30.1]	1.2 ± 0.3 [0.5/3.0]	1.5 ± 4.4 [0.0/79.8]	52.6 ± 117.2 [2.8/2328.2]
Field crops	100	3452	22.9 ± 60.8 [4.0/1245.0]	30 ± 62 [2.6/1206.7]	1.5 ± 1.1 [0.4/18.3]	1.2 ± 0.4 [0.4/3.0]	1.1 ± 3.1 [0.0/29.3]	28.8 ± 81.0 [1.0/1743.8]
Horticulture	31	740	27.3 ± 84.7 [5.4/1016.5]	11 ± 26 [0.2/324.8]	1.9 ± 2.5 [0.7/22.9]	1.2 ± 0.5 [0.2/2.4]	0.3 ± 0.5 [0.0/1.4]	28.9 ± 139.7 [3.0/1727.1]
Permanent crops	30	320	25.9 ± 29.4 [4.0/145.2]	34 ± 32 [3.1/161.8]	1.7 ± 0.6 [0.4/2.8]	1.2 ± 0.4 [0.2/2.0]	0.1 ± 0.5 [0.0/2.1]	27.9 ± 21.2 [1.9/89.5]
Dairy	313	18,042	23.1 ± 42.5 [4.7/1619.6]	28 ± 40 [2.3/978.1]	1.6 ± 0.8 [1.0/32.2]	1.4 ± 0.4 [0.4/3.8]	15.2 ± 28.9 [1.9/879.1]	24.8 ± 61.8 [1.9/3133.1]
Grazing livestock	102	4461	14.0 ± 15.4 [4.0/229.8]	34 ± 34 [5.9/332.9]	1.5 ± 0.5 [1.0/5.4]	1.5 ± 0.4 [0.6/3.9]	17.6 ± 22.3 [2.2/288.7]	17.2 ± 21.5 [4.0/405.3]
Specialist granivores	15	45	130.9 ± 227.3 [9.0/823.9]	32 ± 63 [0.0/333.0]	2.6 ± 2.2 [1.0/11.9]	0.9 ± 0.3 [0.1/1.8]	129.0 ± 220.6 [4.4/796.4]	207.8 ± 489.5 [9.0/2792.9]
Field crops-grazing livestock combined	162	7669	22.0 ± 48.5 [4.2/983.2]	43 ± 58 [4.0/1000.6]	1.4 ± 0.9 [1.0/20.1]	1.2 ± 0.3 [0.5/3.2]	11.8 ± 21.8 [1.0/356.6]	23.6 ± 59.5 [3.2/1026.1]
Various mixed farms	57	6819	9.3 ± 8.9 [4.0/255.9]	13 ± 15 [0.0/345.4]	1.3 ± 0.4 [0.4/6.7]	1.3 ± 0.3 [0.4/2.0]	4.4 ± 6.2 [0.0/103.6]	10.9 ± 12.9 [0.0/338.0]

(continued)

Table 5.1 (continued)

	Number of sample farms	Number of representative farms	Economic size of farm (thousand EUR) Mean ± SD Min/Max	UAA (ha) Mean ± SD Min/Max	AWU Mean ± SD Min/Max	FWU Mean ± SD Min/Max	LU Mean ± SD Min/Max	Total output (thousand EUR) Mean ± SD Min/Max
Economic size class (thousand EUR SO)								
4 ≤ 8	99	24,289	6.5 ± 1.2 [4.0/8.0]	12 ± 10 [0.2/81.0]	1.3 ± 0.3 [0.4/2.8]	1.2 ± 0.3 [0.4/2.0]	3.1 ± 2.9 [0.0/16.2]	7.6 ± 6.5 [1.9/56.7]
8 ≤ 15	151	15,345	11.7 ± 2.1 [8.0/15.0]	24 ± 14 [0.0/ 117.2]	1.4 ± 0.5 [0.4/4.2]	1.3 ± 0.4 [0.2/3.0]	5.3 ± 5.2 [0.0/38.9]	12.5 ± 9.0 [1.0/73.8]
15 ≤ 25	126	6142	19.5 ± 3.0 [15.0/25.0]	37 ± 17 [2.2/ 103.7]	1.4 ± 0.5 [1.0/5.1]	1.3 ± 0.3 [0.4/2.1]	10.0 ± 8.7 [0.0/39.6]	19.5 ± 9.4 [3.3/64.8]
25 ≤ 50	222	5990	36.5 ± 6.7 [25.0/49.7]	62 ± 33 [2.1/ 292.5]	1.5 ± 0.5 [1.0/3.7]	1.4 ± 0.4 [0.6/3.2]	14.3 ± 16.2 [0.0/109.3]	35.8 ± 16.4 [0.0/102.6]
50 ≤ 100	252	3793	70.8 ± 14.9 [50.0/99.9]	105 ± 42 [6.9/ 300.1]	1.8 ± 0.6 [1.0/4.4]	1.4 ± 0.5 [0.5/3.9]	20.2 ± 25.4 [0.0/139.0]	74.8 ± 36.3 [10.6/243.5]
100 ≤ 250	279	2434	151.5 ± 38.1 [100.0/249.0]	209 ± 81 [2.5/ 529.1]	2.8 ± 1.4 [1.0/9.6]	1.4 ± 0.6 [0.2/3.8]	34.5 ± 51.6 [0.0/288.7]	182.1 ± 83.5 [32.4/413.0]
≥250	171	625	431.0 ± 207.0 [252.6/1619.6]	523 ± 284 [0.0/ 1807.0]	6.7 ± 4.4 [1.1/32.2	1.4 ± 0.6 [0.1/3.1]	68.9 ± 124.8 [0.0/879.1]	604.7 ± 360.4 [100.4/3133.1]
Total	1300	58,618	27.0 ± 57.4 [4.0/1619.6]	42 ± 77 [0.0/ 1807.0]	1.5 ± 0.9 [0.4/ 32.2]	1.3 ± 0.4 [0.1/3.9]	8.7 ± 21.4 [0.0/879.1]	31.0 ± 82.1 [0.0/3133.1]

UAA utilized agricultural area, *AWU* agricultural work unit, *COP* specialist cereals, oilseeds, and protein crop

Step 2. The analysis of data availability in Lithuanian FADN regarding the calculation of the initial indicators.
Step 3. The correlation analysis between indicators.
Step 4. The validity examination of the final list of indicators.

Step 1. A primary list of variables and indicators for compiling a comprehensive list of agri-environmental performance indicators was drawn up via a literature review regarding farm-level environmental, sustainability, sustainable intensification, and landscape diversity assessment (Table 5.2).

Step 2. The data availability was evaluated in the primary data set of the Lithuanian FADN of the year 2017 to calculate selected variables. Different indicators were used by researchers to assess certain variables related to farms' agri-environmental performance. Consequently, when choosing the indicators for the AFI, the set of criteria proposed by Wieck and Hausmann (2019) denoted by the acronym RACER, which stands for Relevant, Accepted, Credible, Easy, and Robust, was taken into account. The developed indicators are cost-effective as readily available farm-scale FADN data are employed. In addition, following the idea stressed by Purvis et al. (2009), special care has been taken when developing indicators in order to avoid the construction of the binary (yes/no) indicators, which produce strongly polarized "black-and-white" results.

Step 3. Correlations between agri-environmental indicators were analysed using two-tailed Spearman tests. A strong relationship ($r = 0.881$; $n = 1300$, $p < \alpha$ and $r = 0.856$; $n = 1301$, $p < \alpha$ for 2016 and 2017, respectively) was identified between the indicators related to the use of inorganic fertilizers and pesticide use on farms (Table 5.3).

Nonetheless, both indicators were added into the final list of indicators to assess the agri-environmental performance of family farms within the framework of this research, as these indicators represent different sources of pollution and are usually both included by academia (Westbury et al. 2011; Czyżewski et al. 2019; Tzouramani et al. 2020) (Table 5.2).

Step 4. The selected farm environmental performance indicators were examined by validating the coverage of environmental components and environmental objectives of the EU CAP. Aiming to construct a scientifically sound set of indicators, the selected indicators were tested as to whether they cover environmental components used in previous studies (Purvis et al. 2009; Vesterager et al. 2012; Gaviglio et al. 2017). As pointed out by Wu and Wu (2012), theme- or issue-based frameworks give a flexible conceptual structure that arranges indicators around the key issues. In this study, the set of indicators is comprised of six themes/components, namely agricultural practices, energy, diversity, organization of spaces, natural resources, and farmers' agricultural skills. The constructed AFI is attempting to be a useful tool for tracking agri-environmental performance changes on family farms and to provide information to facilitate agricultural policy design. Consequently, it was important that developed indicators were in line with the sector's strategic documents. The developed indicators reflect four out of nine specific objectives of the future Common Agricultural Policy (CAP) for 2021–2027 (EC 2020d) that contribute to the

Table 5.2 Farm environmental performance indicators used in previous studies

Variable	Source of inspiration	Examples of indicators used by researchers
Use of fertilizers	Hani et al. (2003); Van Cauwenbergh et al. (2007); Meul et al. (2008); Zahm et al. (2008); Purvis et al. (2009); Westbury et al. (2011); Gerrard et al. (2012); Vesterager et al. (2012); Frater and Franks (2013); Koloszko-Chomentowska et al. (2015); Peano et al. (2015); Paracchini et al. (2015); Ryan et al. (2016); Sabiha et al. (2016); Bachev (2017); Gaviglio et al. (2017); Sulewski and Kłoczko-Gajewska (2018); Lynch et al. (2018); Uthes and Herrera (2019); Czyżewski et al. (2019); Tzouramani et al. (2020)	Amount of mineral fertilizers per hectare of UAA (kg/ha UAA); Farm gate N, P, K-balance; Proportion of applied amount of nitrogen fertilizer to that of the recommended dose; Fertilizer units per ha UAA
Use of crop protection	Hani et al. (2003); Van Cauwenbergh et al. (2007); Meul et al. (2008); Zahm et al. (2008); Purvis et al. (2009); Westbury et al. (2011); Vesterager et al. (2012); Gerrard et al. (2012); Peano et al. (2015); Paracchini et al. (2015); Sulewski and Kłoczko-Gajewska (2018); Gaviglio et al. (2017); Uthes and Herrera (2019); Czyżewski et al. (2019); Tzouramani et al. (2020)	Crop protection costs per ha UAA; Cost of pesticide per output; Pesticide treatment index; Pesticide usage
GHG emissions	Van Cauwenbergh et al. (2007); Ryan et al. (2016); Lynch et al. (2018); Uthes and Herrera (2019); Tzouramani et al. (2020)	GHG per farm; GHG per output; Efficient use of resources; GHG balance; GHGs per kg product
Energy intensity	Hani et al. (2003); Van Cauwenbergh et al. (2007); Zahm et al. (2008); Westbury et al. (2011); Vesterager et al. (2012); Paracchini et al. (2015); Peano et al. (2015); Gaviglio et al. (2017); Czyżewski et al. (2019)	Electricity costs and machinery, heating and vehicle fuels and oil per hectare of UAA; Tillage intensity and timing per ha of farmed area; Degree of self-sufficiency for energy consumption; Use of renewable energy sources; Energy dependence; Energy input per unit of agricultural land; Energy input per unit of workforce
Biodiversity	Hani et al. (2003); Van Cauwenbergh et al. (2007); Meul et al. (2008); Zahm et al. (2008); Purvis et al. (2009); Westbury et al. (2011); Gerrard et al. (2012); Frater and Franks (2013); Barnes and Thomson (2014);	Shannon Equitability Index (crop variation on arable land); Deviations from an equal distribution of four crop groups all important to biodiversity on the farm; Land use diversity;

(continued)

Table 5.2 (continued)

Variable	Source of inspiration	Examples of indicators used by researchers
	Koloszko-Chomentowska et al. (2015); Sabiha et al. (2016); Bachev (2017); Goswami et al. (2017); Gaviglio et al. (2017); Areal et al. (2018); Uthes and Herrera (2019)	Proportion of intensely used agricultural land; Herfindahl Index of crop concentration; Number of crops with a share of >5% in arable farm area; Number of cultural species; Use of local and improved crop varieties and livestock breeds; Average field size; Enhancement and conservation of genetic heritage; Ratio of livestock output to total output; Share of cereals in crops; Tree crops diversity
Meadows and pastures	Westbury et al. (2011); Vesterager et al. (2012); Barnes and Thomson (2014); Koloszko-Chomentowska et al. (2015); Areal et al. (2018)	Percentage of grassland area that is temporary grassland; Percentage of UAA that is classified as rough grazing; Extensively managed grassland areas as a share of the whole farm area; Permanent grassland, proportion of UAA
Livestock density	Zahm et al. (2008); Westbury et al. (2011); Gerrard et al. (2012); Koloszko-Chomentowska et al. (2015); Bachev (2017); Sulewski and Kłoczko-Gajewska (2018); Czyżewski et al. (2019)	Average number of grazing livestock units per hectare of forage; stocking rate; Number of livestock per ha
Environment-friendly farming	Goswami et al. (2017); Sulewski and Kłoczko-Gajewska (2018); Areal et al. (2018); Uthes and Herrera (2019)	Agri-environmental monetary receipts from agri-environmental schemes per ha UAA; Ecological focus area; Follow agro-ecological principles and processes
Wooded area	Purvis et al. (2009); Westbury et al. (2011); Vesterager et al. (2012); Barnes and Thomson (2014); Migliorini et al. (2018)	Wooded area of total agricultural area
Water use	Hani et al. (2003); Van Cauwenbergh et al. (2007); Zahm et al. (2008); Meul et al. (2008); Westbury et al. (2011); Peano et al. (2015); Paracchini et al. (2015); Gaviglio et al. (2017); Tzouramani et al. (2020)	Water units per hectare of UAA; Water consumption per kg of product; Water conservation and an efficient use of resources; Water resource protection; Adequate amount of surface water is supplied; Flooding and run-off regulation are

(continued)

Table 5.2 (continued)

Variable	Source of inspiration	Examples of indicators used by researchers
		maintained/enhanced; Share of alternative water resources (rainwater, surface water, and shallow groundwater) used on the farm;
Accessibility	Purvis et al. (2009); Vesterager et al. (2012); Peano et al. (2015); Diti et al. (2015); Goswami et al. (2017)	Intensity of recreational visitors; Recognition and conservation of agricultural heritage systems; Preservation of traditional production/processing methods
Education	Purvis et al. (2009); Sulewski and Kłoczko-Gajewska (2018)	Knowledge of the concept of sustainable agriculture; Knowledge of plant needs

climate mitigation objective, environmental care, halt the loss of biodiversity, improve the response of EU agriculture considering the societal demands on food and health, and cover cross-cutting EU policy objective related to fostering and sharing knowledge and innovation in agriculture and rural areas (Table 5.4).

Two components were addressed, namely agricultural practices and energy, in order to evaluate the energy use efficiency and family farms' situation in terms of their contribution to climate change mitigation and adaption.

Amount of inorganic fertilizers per ha of UAA: consumption of inorganic fertilizers in Lithuania increased by 42% between 2008 and 2018 (Fig. 5.3). This finding could be linked mainly to the increase of the cereals production area by 23% in 2018 as compared to 2008. The application of precise fertilization techniques and sustainable agricultural practices in the agricultural sector should be extended in order to reduce the use of fertilizers by at least 20% compared to the reference period of 2012–2014 by 2030 (EC 2019b).

Information on the use of fertilizers in quantities has been provided by the Lithuanian FADN since 2014. Inorganic fertilizers dominate in the fertilizer use structure, as evidenced by the fertilizer cost structure on farms: according to Lithuanian FADN data for 2017, the costs for inorganic fertilizers made up 96.7% of the total fertilizer costs on family farms (LAEI 2020). To ascertain inorganic fertilizer use on farms within types of farms and economic farm sizes, the results of original values in terms of quantities and costs per ha of UAA were computed (Table 5.5).

The application rates of inorganic fertilizers were 65.6 and 69.6 kg per UAA and 51.4 and 50.0 EUR/ha per farm, on average, in Lithuanian farms in 2016 and 2017, respectively. In both years, the highest inorganic fertilizer intensity in terms of used kg per ha across types of farming and economic size classes was achieved on COP farms and in the largest farm size class (25,000 EUR SO and over). The highest use of fertilizer intensity in terms of cost per hectare was obtained on horticulture farms and in the largest farm size class (with 250,000 EUR SO and over) in considered years.

Crop protection costs per ha of UAA: In Lithuania, pesticide use per hectare of cropland over 2010–2018 was relatively low compared to the EU-28 level.

Table 5.3 Spearman's correlation coefficient within AFI indicators

	Use of fertilizers	Use of crop protection	GHG emissions	Energy intensity	Biodiversity	Meadows and pastures	Livestock density	Wooded area	Accessibility	Environment-friendly farming	Water use	Education
Data of 2016												
Use of fertilizers	1											
Use of crop protection	0.856**	1										
GHG emissions	0.434**	0.393**	1									
Energy intensity	−0.284**	−0.285**	−0.294**	1								
Biodiversity	−0.240**	−0.226**	0.019	0.022	1							
Meadows and pastures	0.468**	0.478**	0.089**	−0.166**	−0.064*	1						
Livestock density	−0.464**	−0.510**	0.146**	0.007	0.180**	−0.480**	1					
Wooded area	0.022	0.002	−0.149**	−0.014	−0.046	0.029	0.011	1				
Accessibility	0.050	0.060*	0.070*	0.049	0.039	0.027	−0.011	0.029	1			
Environment-friendly farming	0.423**	0.400**	0.126**	−0.124**	−0.079**	0.117**	−0.077**	0.099**	0.051	1		
Water use	−0.203**	−0.211**	−0.305**	0.153**	0.040	−0.168**	0.187**	0.083**	−0.002	−0.041	1	
Education	−0.229**	−0.229**	−0.277**	0.096**	0.029	−0.098**	0.097**	0.066*	−0.056*	−0.002	0.081**	1
Data of 2017												
Use of fertilizers	1											
Use of crop protection	0.881**	1										

(continued)

Table 5.3 (continued)

	Use of fertilizers	Use of crop protection	GHG emissions	Energy intensity	Biodiversity	Meadows and pastures	Livestock density	Wooded area	Accessibility	Environment-friendly farming	Water use	Education
GHG emissions	0.451**	0.412**	1									
Energy intensity	−0.316**	−0.295**	−0.290**	1								
Biodiversity	−0.177**	−0.167**	0.034	−0.020	1							
Meadows and pastures	0.299**	0.338**	−0.102**	0.004	−0.124**	1						
Livestock density	−0.458**	−0.517**	0.123**	−0.038	0.110**	−0.594**	1					
Wooded area	−0.022	−0.016	−0.192**	0.057*	−0.056*	0.056*	0.015	1				
Accessibility	0.062*	0.063*	0.072**	0.044	−0.019	−0.016	0.016	0.038	1			
Environment-friendly farming	0.431**	0.421**	0.115**	−0.152**	−0.028	0.097**	−0.091**	0.079**	0.072**	1		
Water use	−0.264**	−0.264**	−0.301**	0.187**	0.026	−0.156**	0.181**	0.076**	0.010	−0.065*	1	
Education	−0.211**	−0.229**	−0.289**	0.127**	0.025	−0.080**	0.120**	0.084**	−0.041	−0.010	0.147**	1

Correlation is significant (**) at the 0.01 level and (*) at the 0.05 level

Table 5.4 Computation of the final set of selected indicators and their scope within the main agri-environmental components

Component	Variable	Indicator	Variables (corresponding EU FADN code, Table)
Agricultural practices	Use of fertilizers	$\frac{\text{Amount of inorganic fertilizers}}{\text{Hectares of UAA}}$	SE296; SE297; SE298; SE025
	Use of crop protection	$\frac{\text{Crop protection costs}}{\text{Hectares of UAA}}$	SE300; SE025
	GHG emissions	GHG emissions per farm	Lithuanian FADN 2016 and 2017 variables, IPCC guidelines (2006), and LNIR (2019)
Energy	Energy intensity	$\frac{\text{Energy costs}}{\text{Total output}}$	SE345; SE131
Diversity	Biodiversity	Shannon Evenness Index	Lithuanian FADN 2016 and 2017 primary data on area of land use elements
Organization of spaces	Meadows and pastures	$\frac{\text{Hectare of meadows and pastures}}{\text{Hectares of UAA}}$	Table 1 in Lithuanian FADN 2016 and 2017
	Livestock density	$\frac{\text{Livestock units}}{\text{Hectares of UAA}}$	SE080; SE025
	Wooded area	$\frac{\text{Hectares of wooded area}}{\text{Farm size in hectares}}$	Table 1 in Lithuanian FADN 2016 and 2017
	Accessibility	Output from agro-tourism and processed products	Lithuanian FADN 2016 and 2017 primary data on output from agro-tourism and processed products
Natural resources	Environment-friendly farming	$\frac{\text{Organic farming subsidies and Natura 2000 payments}}{\text{Total subsidies, excluding on investments}}$	Table 9 in Lithuanian FADN 2016 and 2017; Lithuanian FADN 2016 and 2017 primary data on payments related to Natura 2000; SE605
	Water use	$\frac{\text{Water costs}}{\text{Total output}}$	Lithuanian FADN 2016 and 2017 primary data on water costs, SE131
Farmers' agricultural skills	Education	Farmers' level of education	Lithuanian FADN 2016 and 2017 primary data

Note: Lithuanian family farms' FADN data are presented in LAEI (2020)

However, the use of pesticides increased slowly from the year 2010 until 2018, and then, it started to decrease. As compared with neighbouring countries, namely Latvia and Poland, in Lithuania the use of pesticides showed a similar pattern to that in Latvia and was 1.8 times lower than in Poland (Fig. 5.4).

In the EU countries, the increasing public awareness of the harmful effects of pesticides on human health and the environment has prompted pesticide action plans to reduce the usage of pesticides (Kudsk et al. 2018). In 2009, the EU adopted Directive 128/2009EC establishing a framework for EU actions to promote a sustainable use of pesticides and to estimate trends in risks from pesticide use

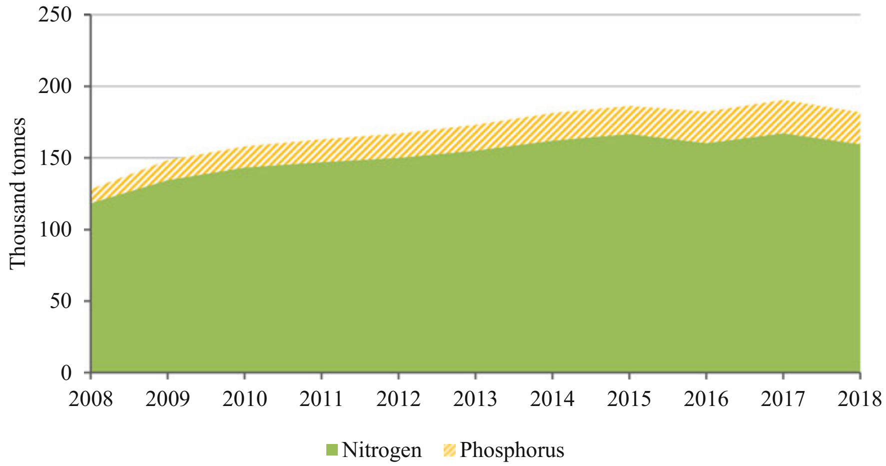

Fig. 5.3 Inorganic fertilizer consumption by agriculture in Lithuania, 2008–2018. Source: Eurostat (2020)

(EC 2009). Eurostat presents Harmonized Risk Indicator 1 (HRI1), which evaluates the quantities of active pesticide substances that are placed on the market, with a weighting applied regarding the classification of the active substance, in regard to Regulation EC No. 1107/2009. In Lithuania, HRI1 increased gradually from 2011 to 2016, and then, it started to decrease, reflecting the overall reductions in quantities of pesticides placed on the market. The decrease of pesticide sales in 2018 narrowed the gap between the EU-28 and the Lithuanian index (Fig. 5.5).

The figure below shows the total sales of pesticides for active substances in Groups 2–4 for the years 2011–2018 in Lithuania. Group 2 sales of pesticides were relatively stable over the period, with a downward tendency observed in the last 2 years. The sales of pesticides attributed to Group 3 increased steadily until 2016, followed by a gradual decline in subsequent years. The sales of Group 4 showed an increase in 2012 and 2013 but then decreased in 2014 followed by an increase in 2015–2017 before decreasing again in 2018 reaching the 2011 year level (Fig. 5.6).

On Lithuanian farms, the crop protection costs per hectare of UAA amounted to 37.2 EUR per ha UAA per farm in 2010–2018, on average. Although in 2018, as compared to 2008, pesticide use intensity increased by 65%, it was approximately two times lower than the EU average (Fig. 5.7).

The FADN provides only the aggregated data considering the costs of all types of crop protection products, and it is a simplified approach in terms of crop protection products' toxicity and impact on the environment. The EU Commission set a target to reduce the use of chemical and more hazardous pesticides by 50% by 2030 (EC 2019b). Therefore, in future, the results of crop protection products used on farms could be provided following the methodology presented by Eurostat according to the categorization of active pesticide substances.

Table 5.5 Use of inorganic fertilizers across types of farming and economic farm size classes in Lithuanian family farms, 2016 and 2017

	Fertilizer use on farm kg/ha UAA			Cost of fertilizer EUR/ha UAA		
	Mean	SD	Max	Mean	SD	Max
In 2016						
Type of farming						
COP	134.3	145.0	793.7	94.7	99.1	604.9
Field crops	79.8	121.0	941.7	62.9	80.6	489.3
Horticulture	79.1	160.3	996.9	182.1	430.8	5377.2
Permanent crops	21.9	45.0	180.2	22.1	35.7	149.9
Dairy	27.9	47.0	416.2	25.2	38.6	407.5
Grazing livestock	15.5	38.5	158.4	16.4	39.4	167.1
Specialist granivores	20.8	70.1	356.4	13.3	43.5	277.1
Field crops-grazing livestock combined	46.0	73.5	503.6	34.5	57.0	326.3
Various mixed farms	31.2	54.9	362.3	24.5	43.7	309.8
Economic farm size class (thousand EUR SO)						
$4 \leq 8$	41.2	80.2	517.7	30.2	43.0	204.4
$8 \leq 15$	54.1	98.3	466.7	46.0	117.3	1333.3
$15 \leq 25$	42.5	93.3	657.1	32.3	66.8	423.2
$25 \leq 50$	95.3	113.4	441.0	71.8	88.4	407.5
$50 \leq 100$	144.3	147.2	793.7	112.0	107.6	588.7
$100 \leq 250$	182.3	138.2	996.9	149.6	155.1	5377.2
≥ 250	245.0	149.5	941.7	200.7	116.9	1102.7
Total	65.6	108.2	996.9	51.4	94.0	5377.2
In 2017						
Type of farming						
COP	145.7	148.4	706.0	93.9	91.6	465.1
Field crops	71.7	96.5	571.2	68.4	78.7	545.3
Horticulture	135.1	181.7	781.7	233.5	393.4	1166.7
Permanent crops	119.3	237.4	681.6	77.5	156.6	450.1
Dairy	33.3	50.0	354.9	24.5	34.0	249.1
Grazing livestock	24.5	42.5	146.8	24.5	46.5	168.2
Specialist granivores	58.9	84.4	409.0	43.9	64.4	307.1
Field crops-grazing livestock combined	37.7	67.4	734.7	27.1	42.9	264.0
Various mixed farms	30.5	64.7	380.2	19.5	40.2	289.8
Economic farm size class (thousand EUR SO)						
$4 \leq 8$	55.8	89.1	681.6	47.7	95.6	1166.7
$8 \leq 15$	41.6	86.8	671.2	26.1	46.2	212.8
$15 \leq 25$	57.9	110.6	574.3	36.7	66.6	258.6
$25 \leq 50$	83.6	109.2	645.0	53.3	66.9	378.2
$50 \leq 100$	154.8	150.0	781.7	102.1	100.6	578.2
$100 \leq 250$	202.1	154.5	706.0	132.5	98.9	642.9
≥ 250	248.3	150.1	734.7	183.2	110.9	660.9
Total	69.6	110.9	781.7	50.0	85.3	1166.7

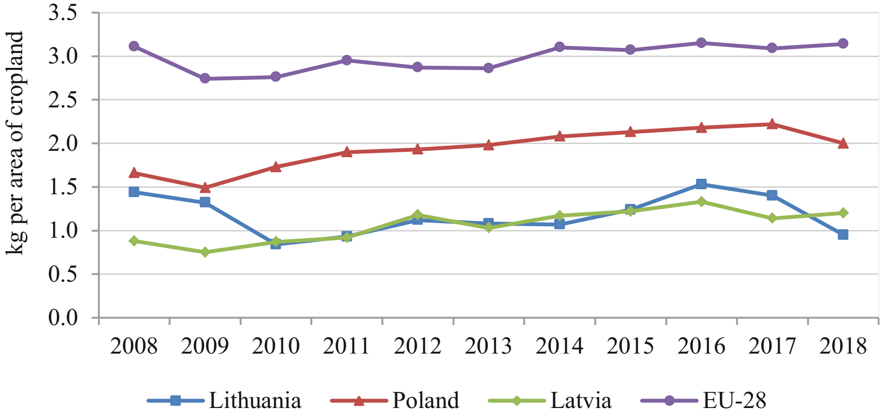

Fig. 5.4 Use of pesticides per area of cropland in Lithuania, Latvia, Poland, and the EU-28, 2008–2018. Source: FAOSTAT (2020)

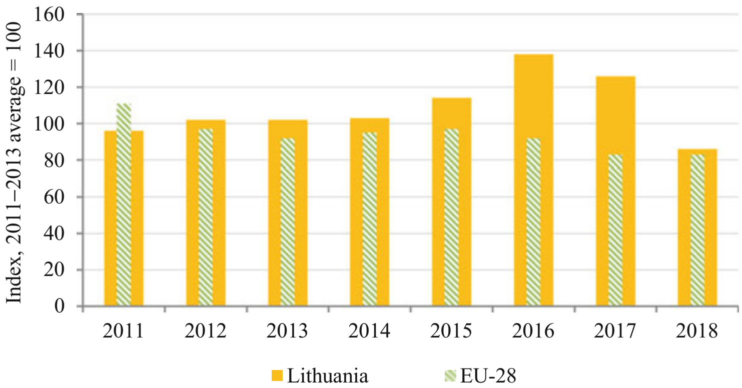

Fig. 5.5 Evolution of harmonized risk indicator 1 in Lithuania and EU-28, 2011–2018. Source: EC (2020e)

GHG emissions: The environmental pressures related to family farming were measured as the total amount of GHG produced by farming activities on farms. In this study, special attention was paid to disclosing methodology issues and results across farming types and economic farm size classes for the GHG emissions assessment at farm level. The environmental pressures related to family farming were measured in terms of the total amount of GHG emissions per farm produced by farming activities and GHG emissions intensity using a range of metrics including GHG emissions intensity per ha of UAA, total output, and livestock unit (LU). The measurement of the GHG emission is important for the agricultural sector, which is responsible for a substantial share of the GHG emission and is impacted by different support schemes across the world. As regards the European Union, the CAP aims to improve the competitiveness and sustainability of the agricultural sector (EC 2020d).

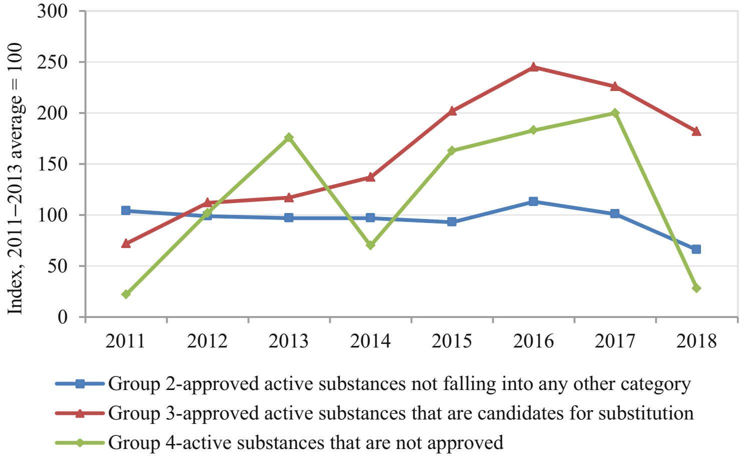

Fig. 5.6 Sales of pesticides for active substances in Lithuania, 2011–2018. Note: No/insufficient data available to calculate values for one group—low-risk active substances. Source: EC (2020b)

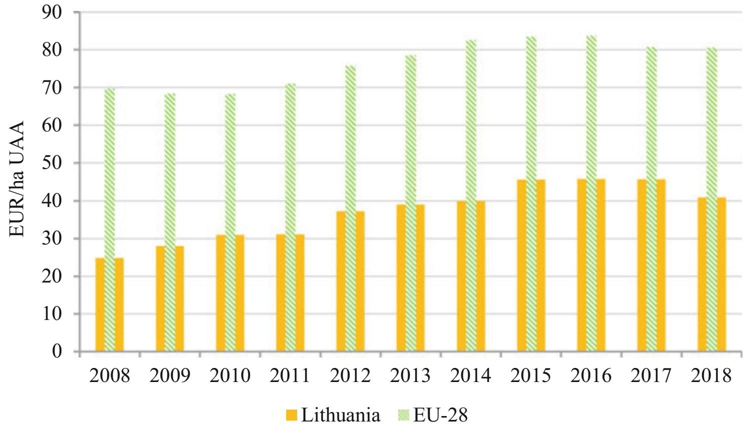

Fig. 5.7 Costs of pesticides in Lithuania and EU-28, on average per farm in 2008–2018. Source: EU FADN (2020)

The CAP supporting the Green Deal (EC 2019b), Biodiversity strategy (EC 2020a), Farm to Fork (EC 2020c), and others put an emphasis on the environmental performance of the agricultural sector, and consequently, the new farm management practices will need to be adopted by farmers to lower GHG emissions on farms.

The GHG emissions on farms are quantified according to IPCC (2006) guidelines. These guidelines present internationally agreed methodologies for calculating and reporting GHG emissions by signatories to the United Nations Framework Convention on Climate Change (Yona et al. 2020). The IPCC guidelines are often employed in studies related to environmental performance of farms by academia:

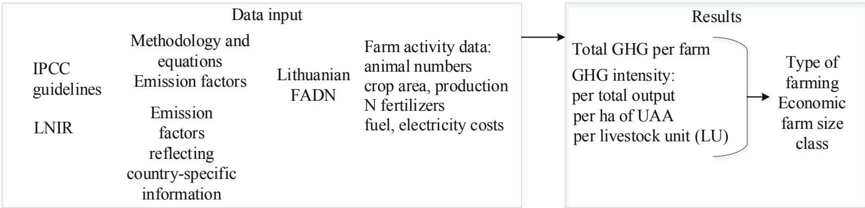

Fig. 5.8 GHG emission assessment framework

Browne et al. (2011) presented GHG emissions analysis in Australian enterprises; Riaño and García-González (2015) analysed the changes in GHG emissions in the swine manure treatment plant located in Spain due to the installation of anaerobic tank of manure; Lynch et al. (2018) estimated GHG emissions of Anglian cereal and dairy farms; and Schueler et al. (2018) investigated the differences in GHG emissions within 20 Norwegian dairy organic and non-organic farms.

Using the framework previously described by Dabkienė et al. (2020), the present research methodology is based on IPCC guidelines (IPCC 2006) and LNIR (2019) as LNIR contains some developed emission factors reflecting country-specific information (Fig. 5.8). Considering the main GHG emission sources of the agricultural sector and the availability of farms' activity data in the FADN, the emissions from enteric fermentation of domestic livestock, direct and indirect emissions from manure management, direct and indirect N_2O emissions from managed soils, and combustion of energy in the research were inventoried.

The GHG emissions inventoried in the study were distinguished into the three main subcategories for presenting results across farm farming types, economic and physical farm size classes: (1) "GHG enteric fermentation and manure management", which includes CH_4 emissions from enteric fermentation and CH_4 from manure management, and N_2O direct and indirect emissions related to manure management; (2) "GHG agricultural soils"—N_2O direct and indirect emissions related to agricultural soils fell into this subcategory; and (3) "GHG energy", which includes emissions from fuel and electricity combustion.

GHG emissions (in CO_{2eq}) were calculated by summing up CO_2, CH_4, and N_2O emissions based on their equivalence factor in terms of CO_2 (100-year time horizon): 1 for CO_2, 25 for CH_4, and 298 for N_2O.

On Lithuanian family farms, on average, the key source categories of on-farm emissions were CH_4 from enteric fermentation and N_2O direct emissions from agricultural soils, as together they constituted 69.3% and 68.3% of the total farm emissions in 2016 and 2017, respectively. The emissions from fuel combustion ranked third in importance behind CH_4 from enteric fermentation and N_2O direct emissions from agricultural soils, indicating the importance of reporting and monitoring these emissions in farms (Fig. 5.9).

Descriptive statistics related to farm size of Lithuanian family farms across different types of farming are reported in Table 5.1. The economic size of family farms averaged 27,600 EUR and 27,000 EUR in 2016 and 2017, respectively. The

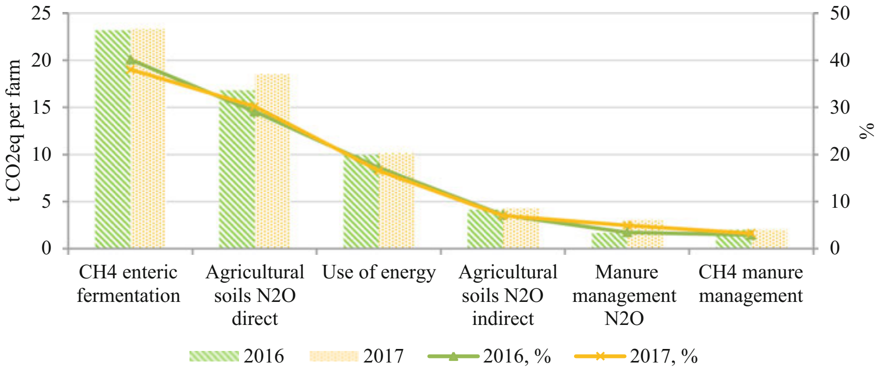

Fig. 5.9 GHG emissions by sources in 2016 and 2017

biggest economic size was registered for farms specialized in COP and granivores, which was 59% and 4.9 times higher than the average in 2016 and 2017, respectively. COP farms were largest in terms of physical farm size and averaged 72.5 and 75.1 ha of UAA in 2016 and 2017, respectively. The highest output value was observed in farms specialized in granivores, and their output was twofold and sixfold higher than for the whole Lithuanian sample on average in 2016 and 2017, respectively. The farms specialized in granivores were the largest in terms of the number of raised livestock for both years considered for analysis.

In 2016, the total GHG per farm value varies considerably across farm types (CV 75.1%), though the differences were not that large in 2017 (CV 59.7%). In 2016, the field crops-grazing livestock combined farms had the highest total GHG per farm as the emissions amounted to 75.1 t CO_{2eq}/farm. On these farms, the largest share (63%) of GHG emissions was attributed to enteric fermentation and manure management (Table 5.6).

In 2017, the farms specialized in granivores had the highest total GHG emissions per farm and the emissions amounted to 92.8 t CO_{2eq}/farm (Fig. 5.10). Comparing this result with the previous year, it was 3.2 times higher due to a 4.1-fold increase in the number of raised animals on these farms. On these farms, the largest share (66%) of GHG emissions was attributed to enteric fermentation and manure management. The lowest value of total GHG emission per farm was observed on horticulture farms for both years considered for analysis. The GHG emissions generated from the use of fuel and electricity were the most significant contributors and amounted to 70% and 53% and 57% and 41% on permanent crops and on horticulture farms, respectively.

A variation of GHG emissions intensity per ha of UAA across farming types was apparent, as evidenced by extremely high (CV 50.2%) and severe (CV 103.4%) CV values in 2016 and 2017, respectively. Permanent crop farms showed the lowest intensity in both considered years, whereas farms specialized in horticulture and granivores recorded the highest intensity in 2016 and 2017, respectively (Fig. 5.11).

The GHG emissions intensity in terms of total farm output averaged 2.7 kg CO_{2eq}/EUR for both research years (Fig. 5.12). In both years, the highest intensities

Table 5.6 Structure of total GHG emissions per farm by emission sources by types of farming

Type of farming	GHG per farm structure in 2017, %			Change in 2017 compared to 2016, percentage points		
	Energy	Enteric fermentation and manure management	Agricultural soils	Energy	Enteric fermentation and manure management	Agricultural soils
COP	23	8	69	0	1	−1
Field crops	25	15	60	−2	−1	3
Horticulture	41	20	39	−13	−6	19
Permanent crops	57	10	33	−13	6	7
Dairy	10	75	15	−1	−1	2
Grazing livestock	10	81	9	−1	3	−2
Granivores	19	66	15	−6	10	−5
Field crops-grazing livestock combined	15	62	23	1	−1	0
Various mixed farms	18	66	16	−11	11	0
Total	17	46	37	−1	0	1

Note: The results for 2016 can be found in Dabkienė et al. (2020)

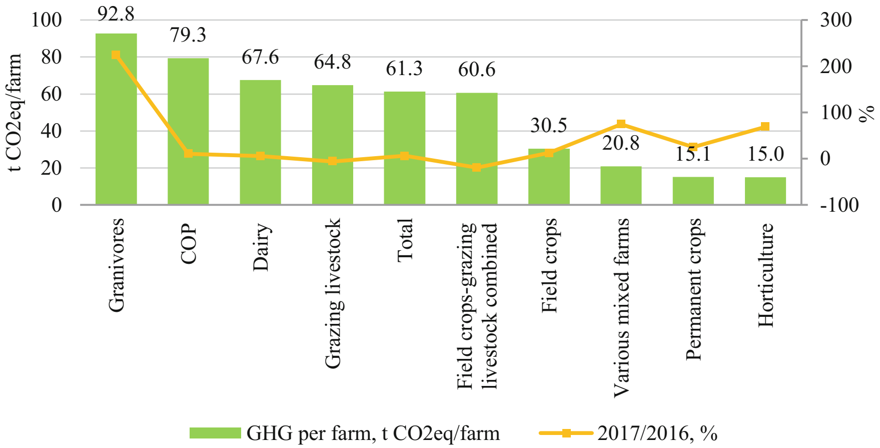

Fig. 5.10 Total GHG emissions per farm by types of farming. Note: The results for 2016 can be found in Dabkienė et al. (2020)

were found on dairy and grazing livestock farms. In contrast, the lowest GHG emissions intensity per total output was observed on farms specialized in granivores and horticulture in 2016 and 2017, respectively. The largest variability across farm

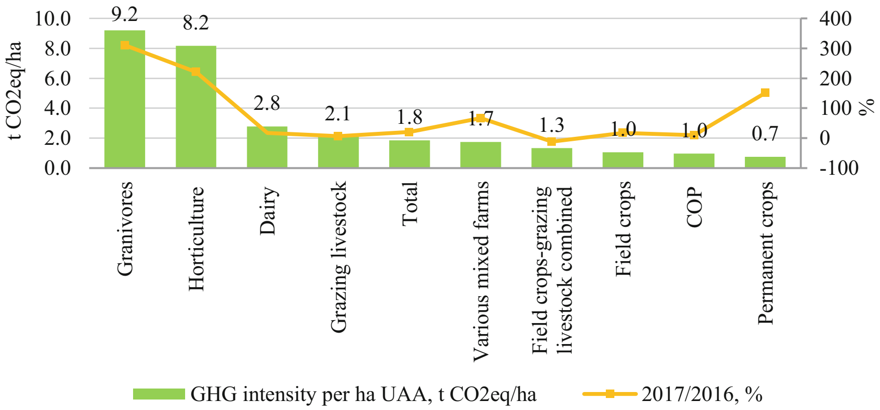

Fig. 5.11 GHG emissions intensity per ha of UAA by types of farming. Note: The results for 2016 can be found in Dabkienė et al. (2020)

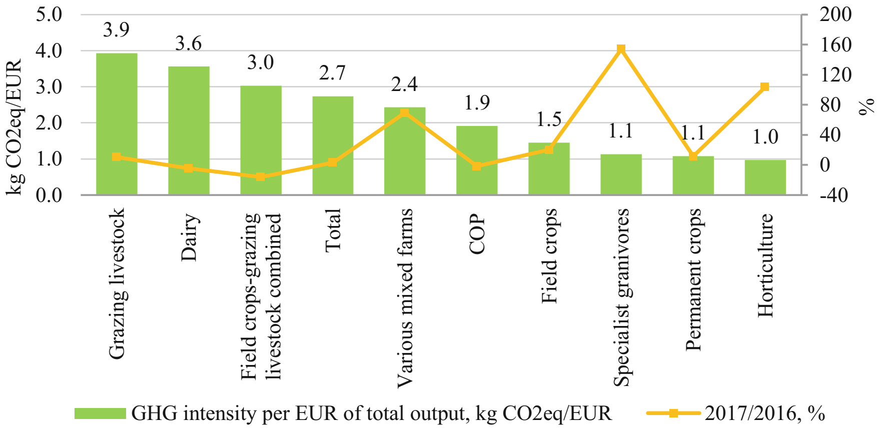

Fig. 5.12 GHG emissions intensity per total output by types of farming. Note: The results for 2016 can be found in Dabkienė et al. (2020)

types was estimated for GHG emissions intensity per total output (CV value equalled 75.5%) and for GHG emissions intensity per ha of UAA (CV 103.4%) in 2016 and 2017, respectively.

A greater variation was observed in terms of GHG emissions intensity per LU across farming types in 2017 (CV 72.4%) than in 2016 (CV 59.9%). The GHG emissions intensity per LU varied from 0.9 in permanent crop farms to 10.6 t CO_{2eq}/LU in COP farms and from 1.2 in permanent crop farms to 9.7 t CO_2eq/LU in specialist granivores farms, in 2016 and 2017, respectively (Fig. 5.13).

The differences in total GHG emissions per farm, GHG emissions intensities per ha of UAA, LU, and total output were statistically significant ($p < 0.001$) across types of farming.

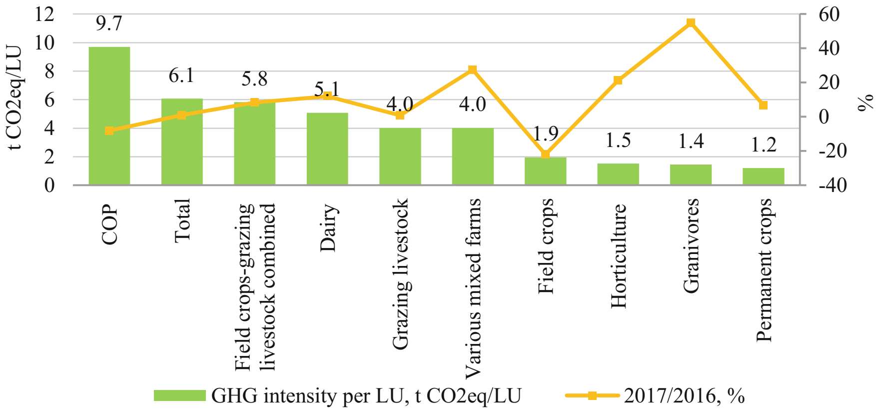

Fig. 5.13 GHG emissions intensity per LU by types of farming. Note: The results for 2016 can be found in Dabkienė et al. (2020)

Table 5.7 Structure of total GHG emissions per farm by emission sources by economic farm size classes

Economic farm size class	GHG per farm structure in 2017, %			Change in 2017 compared to 2016, percentage points		
	Energy	Enteric fermentation and manure management	Agricultural soils	Energy	Enteric fermentation and manure management	Agricultural soils
$4 \leq 8$	17.1	59.0	23.8	−6	−2	8
$8 \leq 15$	17.5	63.3	19.2	−3	2	1
$15 \leq 25$	14.9	64.7	20.4	−1	−1	3
$25 \leq 50$	15.7	57.9	26.4	0	2	−2
$50 \leq 100$	15.7	42.3	41.9	1	−3	2
$100 \leq 250$	16.6	34.0	49.4	0	−1	1
≥ 250	17.8	23.0	59.1	1	−3	1
Total	16.6	46.3	37.2	−1	0	1

In 2016, the main component of emissions in the case of farms in SO classes I–V was emissions from enteric fermentation and manure management, whereas in classes VI–VII, the GHGs from agricultural soils led the way (Table 5.7). Almost the same tendency is observed for the year 2017, except in SO class V, where the share of GHG emissions related to enteric fermentation and manure management and agricultural soils equally.

The economic size of a farm is assessed using the SO of the farm defined as the standard value of gross production. In Lithuania, the physical farm size generated output value, and LU increases with the economic size of a family farm (Table 5.1). The calculated total GHG per farm shows the same tendency (Fig. 5.14). The lowest value of GHG per farm was found on farms in SO class I and the highest in SO class

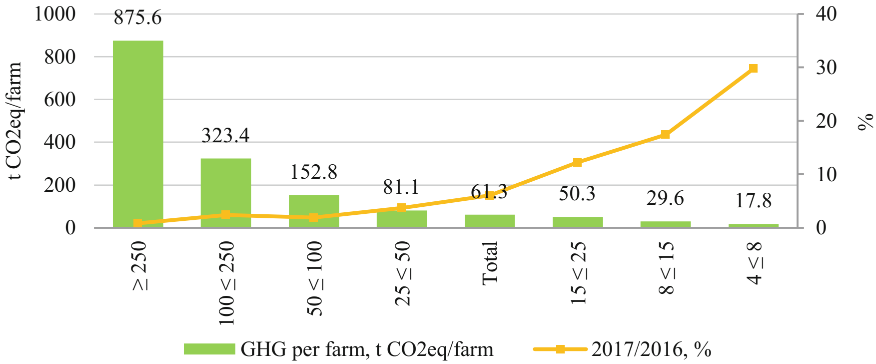

Fig. 5.14 Total GHG emissions per farm by economic size classes

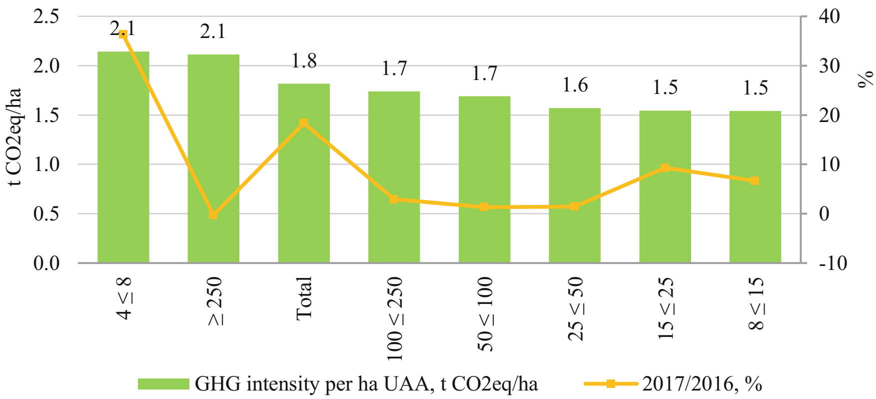

Fig. 5.15 GHG emissions intensity per ha of UAA by economic size classes

VII, in both years of the research. The economic size of a farm reflects the farm specialization in relation to the physical farm size tendency in Lithuanian agriculture: the COP farms represent the largest share at 61.8% and 62.1% of farms in SO class VII in the Lithuanian FADN sample of 2016 and 2017, respectively. The specialist COP farms made up 54.8% of farms, producing 250,000 EUR or more of SO (Statistics Lithuania 2018).

The GHG emissions intensity per ha of UAA was fairly different, as evidenced by the low CV values: CV 14.4% and CV 14.7% in 2016 and 2017, respectively (Fig. 5.15).

The highest GHG emissions intensity per output was observed in SO class III and in SO classes II–III, in 2016 and 2017, respectively (Fig. 5.16). The low and moderate variation of the GHG intensity per output across the economic farm size classes was determined and made up 15.2% and 21.2% in 2016 and 2017, respectively.

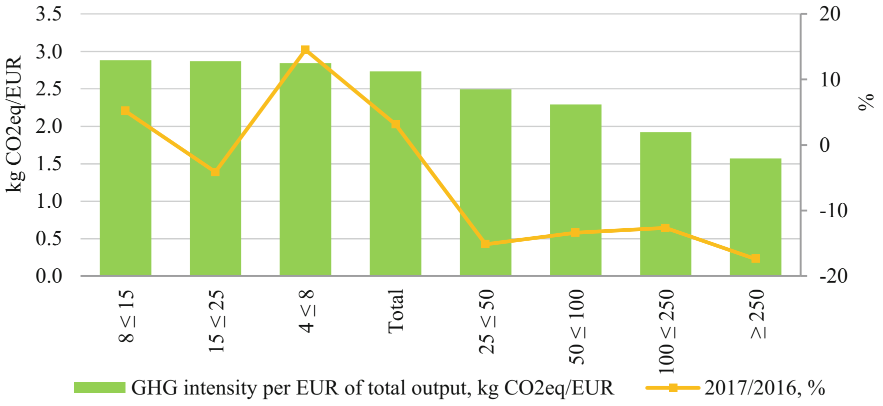

Fig. 5.16 GHG emissions intensity per total output by economic size classes

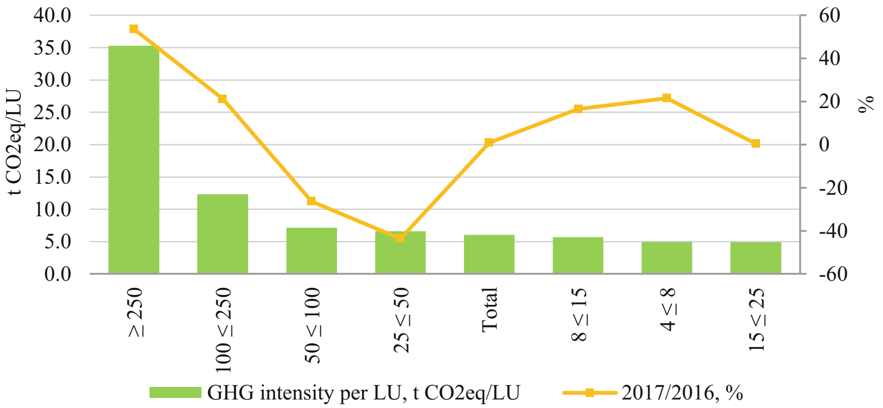

Fig. 5.17 GHG emissions intensity per LU by economic size classes

A greater variation was observed in terms of GHG emissions intensity per LU across SO classes in 2017 (CV 100.5%) than in 2016 (CV 67.1%). The GHG intensity per LU varied from 4.1 to 23.0 t CO_{2eq}/LU and 4.9 to 35.3 t CO_2eq/LU in 2016 and 2017, respectively (Fig. 5.17). The differences in total GHG emission per farm, GHG emissions intensities per ha of UAA, LU, and total output were statistically significant ($p < 0.001$) across economic farm size classes.

This subsection presents a detailed methodology for appraisal of the carbon factor for Lithuanian family farms using farm-level data from the FADN. Research results make it possible to identify the relative contribution of different farms by type of farming and size to the total carbon budget of the agricultural sector. The resulting data can be integrated into different decision-making frameworks. Therefore, the obtained CF is used as an environmental performance indicator for developing the AFI.

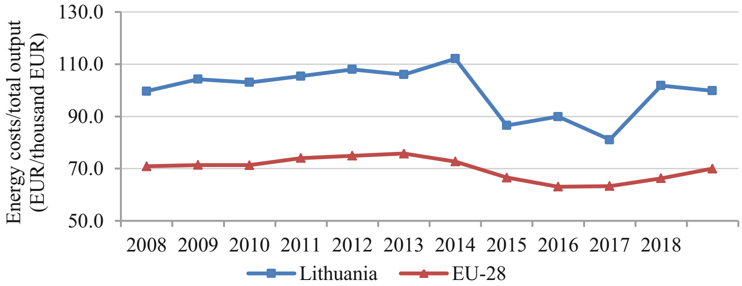

Fig. 5.18 Energy intensity in Lithuania and EU-28, on average per farm in 2008–2018. Source: EU FADN (2020)

Energy costs per total output: Energy intensity on Lithuanian farms, measured as the ratio of energy costs (EUR) to total output (thousand EUR), amounted to 99.8 per farm in 2008–2018, on average. Lithuanian farms were less energy efficient than the EU-28 average (Fig. 5.18).

On Lithuanian farms, the use of energy (EUR) per ha of UAA over 2008–2018 averaged 76 EUR per farm, and it was 1.9 lower than the EU-28 average. The lower intensity of energy use per ha of UAA in Lithuania can be attributed to the structure of farms: cereal, oil, and leguminous crops constituted 49% of the total UAA (Statistics Lithuania 2018).

The use of renewable energy is considered an important issue in regard to farm autonomy and environmental sustainability (Peano et al. 2015; Gaviglio et al. 2017). The renewable energy generated from the Lithuanian agricultural sector made up 10.3% of the total production of renewable energy (EC 2019a). In order to assess farms' involvement in on-farm renewable energy production, a future FADN database could be supplemented by such data.

The contribution of family farms to the protection of biodiversity, improving ecosystem services, and preserving habitats and landscapes was assessed via two components, namely diversity and organization of spaces.

Shannon Evenness Index: Changes in structure of agriculture and in management practices have caused the number of birds to dwindle in agricultural areas in Lithuania. The farmland bird indicator has declined by 41.5% since 2000 (Fig. 5.19).

The Shannon Evenness Index, which represents land use diversity, was chosen to measure the biodiversity of farms. Although as many as 28 land use elements were provided in the primary data set, the most detailed data are provided for specialist COP farms, and the least for various permanent crop combined farms as data for tree composition in orchards are not recorded. Guiomar et al. (2018) emphasized the role of small farms in biodiversity, saying that they "support high levels of biodiversity". In line with that, farms up to 5 ha of UAA, in this study, were considered as having the most beneficial effect on the conservation of agricultural biodiversity. Small farms dominated in farm structure in terms of physical size (ha UAA): farms up to 5 ha of UAA constituted 50.0% of all farms in Lithuania (Statistics Lithuania 2018).

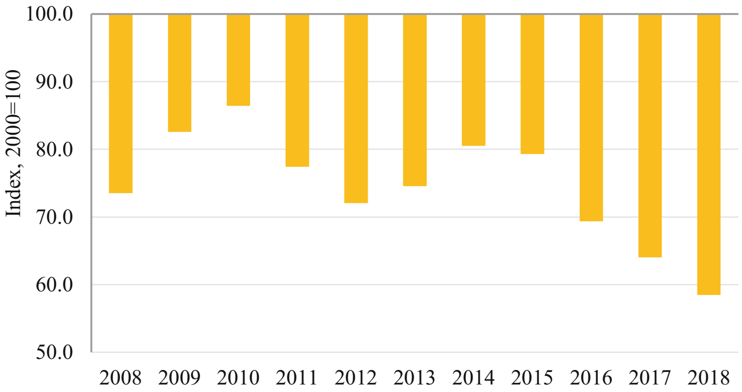

Fig. 5.19 Common Farmland Bird Index in Lithuania, 2008–2018. Source: Eurostat (2020)

The Shannon Diversity and Evenness Indices were calculated as follows (Eurostat 2011):

$$\mathrm{SDI} = -\sum_{i}^{m} (P_i * \ln (P_i)), \tag{5.1}$$

where

SDI = Shannon Diversity Index;
P_i = surface proportion of land use element i;
m = number of different land use elements.

The Shannon Diversity Index was standardized to a measure of evenness by calculating the Shannon Evenness Index, i.e. calculating the ratio of the observed diversity to the maximum diversity:

$$\mathrm{SEI} = \frac{-\sum_{i}^{m} (P_i * \ln (P_i))}{\ln_m}, \tag{5.2}$$

where

SEI = Shannon Evenness Index;
$\ln_m = \mathrm{SDI}_{\max}$.

The SEI measure is constrained between 0 and 1 with 1 indicating that the proportions of each land use element are nearly equal.

Share of meadows and pastures in UAA: In Lithuania, the area of meadows and pastures is increasing: the meadows and pastures share in UAA rose by 14.6 percentage points in 2018, as compared to 2008 (Fig. 5.20).

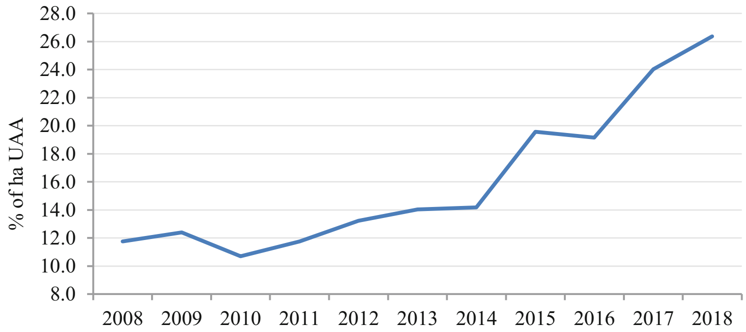

Fig. 5.20 Proportion of meadows and pastures in UAA in Lithuania, 2008–2018. Source: LAEI (2020)

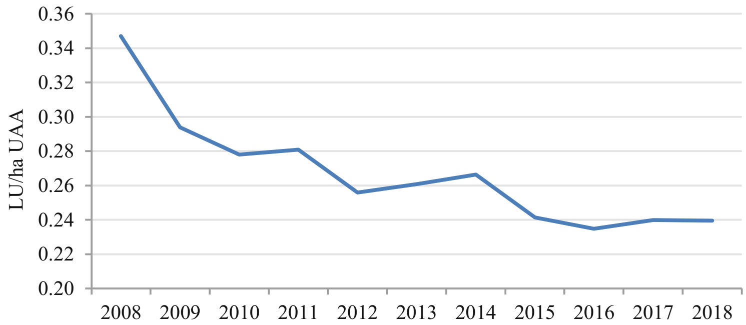

Fig. 5.21 Livestock density per farm in Lithuania, 2008–2018. Source: EU FADN (2020)

Livestock units per ha of UAA: Svanbäck et al. (2019) found that large nitrogen and phosphorus surpluses often occurred in areas with high livestock density. In Lithuania, during 2008–2018, the total number of livestock units per UAA decreased by 31% (Fig. 5.21). The decrease was mainly attributed to a decline in the number of cattle by 14.1% in 2018 compared to 2008 (Statistics Lithuania 2020).

Note that livestock unit (LU) is an index defined using the coefficients related to the weight of an animal (the ratios are provided in FADN 2018).

Share of wooded area in farm size: In a recent 10-year period (2008–2018), the proportion of wooded area in the total farm area per farm was quite stable and fluctuated at around 2.7% (LAEI 2020).

Accessibility. This indicator was evaluated qualitatively with a binary scale denoting the presence or absence of output from agro-tourism and processed products on farms. The potential of agro-tourism in contributing to the recognition and conservation of agricultural heritage systems and the preservation of traditional production is not being exploited by Lithuanian family farms, as output from agro-tourism per farm was about eight times lower than the EU-28 average in 2018 (Fig. 5.22).

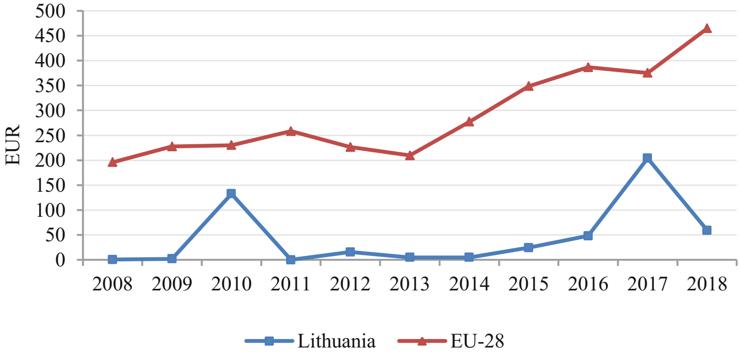

Fig. 5.22 Output from agro-tourism per farm in Lithuania and EU-28, 2008–2018. Source: EU FADN (2020)

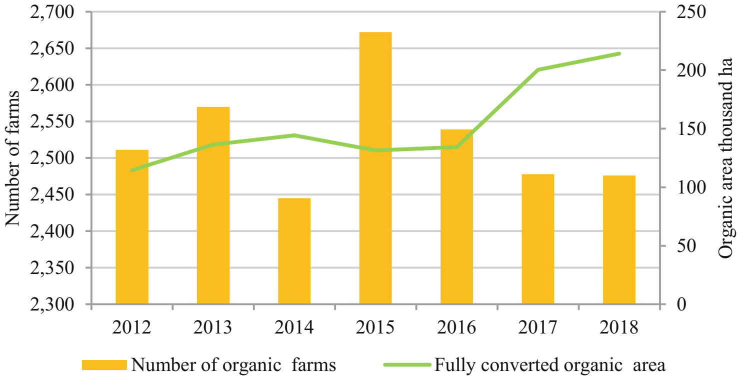

Fig. 5.23 Evolution of the area and number of holdings involved in the organic sector in Lithuania, 2012–2018. Source: Eurostat (2020)

In order to investigate the achievements of family farms with respect to farms' sustainable management of natural resources, like water, soil, and air, the research framework encompasses two components, namely natural resources and farmers' agricultural skills.

Share of organic farming subsidies and Natura 2000 payments in total subsidies, excluding on investments: This is a proxy indicator to assess farmers' participation in agri-environmental programmes. Goewie et al. (2006) stated that agro-ecological farming places an emphasis on sustainability with profitability as a side product. In Lithuania, the number of organic farms (agricultural producers) represented only 1.7% of all farms in 2016 (Statistics Lithuania 2018; Eurostat 2020). In Lithuania, the total organic area amounted to an estimated 7.3% of the total UAA in 2018. Structural change is occurring in the organic farming sector, as reflected by the decrease in the number of farms and the increase in organic farming area. As a result, active farms tend to get larger (Fig. 5.23). It should be underlined that the European

Commission's Farm to Fork and Biodiversity Strategies (EC 2020a, c) include the target of increasing the agricultural land under organic farming in the EU to 25% by 2030 compared to the reference year of 2018.

Water costs per total output: Recently, Lithuanian farmers faced challenges in water availability due to droughts in 2018 and 2019, which increased demand for water use. This experience impelled farmers to improve water management practices on farms. The Lithuanian FADN takes into account water costs for water purchased from common water supply networks. The data on water use in volume on farms from different sources of water, such as on-farm groundwater, on-farm surface water, and others, would be more valuable regarding water use in a sustainable way.

Farmers' level of education: As regards the professional background of Lithuanian farmers in agriculture, only 16.4% had a completely agricultural background (Statistics Lithuania 2018). The level of farmers' education was evaluated qualitatively, following a three values scale, where the maximum value equalled 1 when the farm was managed by a farmer with full agricultural training; the average value equalled 0.5 when the farm was managed by a farmer with basic training; and the minimum value equalled 0 when the farm was managed by a farmer with practical experience only. Previous studies (Dantsis et al. 2010; Gómez-Limón and Sanchez-Fernandez 2010) have shown that the education level of farmers has a positive impact on farms' environmental performance. The EU's CAP during the next 2021–2027 programming period emphasizes the importance of farmers' knowledge, innovation, and digitalization of farms (EC 2020d). The highest percentage of farms with full agricultural training across types of farms was within specialized COP and permanent crop farms in 2016 and 2017, respectively. As regards economic farm size classes, it can be stated that the percentage of farmers with full agricultural training increases in line with farms' economic size (Table 5.8).

Descriptions of the variables employed for AFI construction with their summary statistics are shown in Table 5.9.

Stage 2—Data elaboration

The data elaboration was accomplished in four steps:

Step 1. The calculation and normalization of indicators.
Step 2. The assignment of weights to indicators.
Step 3. The aggregation of indicators.
Step 4. The estimation of AFI levels.

Step 1. Since the environmental performance indicators are expressed in different units, the normalization min–max method, which has been adopted in many studies (Trivino-Tarradas et al. 2019; ul Haq and Boz 2020), was employed. This benchmark activity allows indicators to be rescaled into a range of values between 0 (worst performing) and 1 (best performing) and thus indicators to be aggregated into the index. The following two normalization equations were used (Krajnc and Glavič 2005). Equation (5.3) is applied for indicators where an increase in values acts positively in terms of environmental performance, and Eq. (5.4) is employed for indicators whose increasing values have a negative impact on farm agri-environmental performance:

Table 5.8 Farmers' education by farming type and economic farm size class, % of farms

	2016			2017		
	Farmers with practical experience only	Farmers with basic training	Farmers with full agricultural training	Farmers with practical experience only	Farmers with basic training	Farmers with full agricultural training
Type of farming						
COP	42.6	30.0	27.4	44.9	26.4	28.7
Field crops	53.0	28.3	18.7	63.7	15.4	20.9
Horticulture	41.1	46.3	12.6	43.5	40.3	16.2
Permanent crops	38.9	34.8	26.3	55.3	12.2	32.5
Dairy	52.2	29.1	18.7	65.0	23.4	11.6
Grazing livestock	54.9	19.3	25.7	38.1	31.7	30.2
Specialist granivores	86.2	11.2	2.4	60.0	28.9	11.1
Field crops-grazing live-stock combined	55.4	27.8	16.8	72.0	10.5	17.5
Various mixed farms	53.9	35.8	10.3	64.2	23.4	12.4
Economic farm size class (thousand EUR SO)						
$4 \leq 8$	52.9	33.7	13.4	62.2	25.9	11.9
$8 \leq 15$	53.4	29.5	17.1	67.3	16.0	16.7
$15 \leq 25$	54.7	27.1	18.2	53.3	26.1	20.7
$25 \leq 50$	39.6	25.5	34.9	44.7	25.1	30.3
$50 \leq 100$	45.4	22.8	31.8	38.1	25.2	36.8
$100 \leq 250$	29.4	23.0	47.5	31.7	21.2	47.1
≥ 250	16.3	14.7	69.0	21.0	16.3	62.7
Total	49.9	29.6	20.5	57.5	22.9	19.6

$$I^{+}_{N,it} = \frac{I^{+}_{A,it} - I^{+}_{\min,\ t}}{I^{+}_{\max,\ t} - I^{+}_{\min,\ t}}, \tag{5.3}$$

$$I^{-}_{N,it} = \frac{I^{-}_{\max,t} - I^{-}_{A,\ it}}{I^{-}_{\max,t} - I^{-}_{\min,\ t}}, \tag{5.4}$$

where

$I^{+}_{N,it}/I^{-}_{N,it}$—normalized value of positive/negative indicators whose increasing value has a positive/negative impact on farms' agri-environmental performance;

$I^{+}_{A,it}/I^{-}_{A,it}$—indicator whose increasing value has a positive/negative impact on farm agri-environmental performance;

Table 5.9 Description and summary statistics of agri-environmental performance indicators

Variables	Unit	Qualitative/ quantitative	Impact of indicator	Min	Max	Mean	SD
In 2016							
Use of fertilizers	kg/ha UAA	Quantitative	Negative	0.0	996.9	65.6	108.2
Use of crop protection	EUR/ha UAA	Quantitative	Negative	0.0	750.0	20.8	46.4
GHG emissions	t CO2eq/ farm	Quantitative	Negative	0.0	4369.7	57.8	126.9
Energy intensity	EUR/thousand EUR	Quantitative	Negative	0.4	1359.8	137.8	93.2
Biodiversity	index	Quantitative	Positive	0.0	1.0	0.7	0.3
Meadows and pastures	%	Quantitative	Positive	0.0	100.0	28.1	34.2
Livestock density	units/ha UAA	Quantitative	Negative	0.0	116.4	0.3	0.9
Wooded area	%	Quantitative	Positive	0.0	63.4	2.8	10.0
Accessibility	score	Qualitative	Positive	0.0	1.0	0.0	0.2
Environment-friendly farming	%	Quantitative	Positive	0.0	83.1	5.1	14.7
Water use	EUR/thousand EUR	Quantitative	Negative	0.0	149.6	10.1	14.1
Education	score	Qualitative	Positive	0.0	1.0	0.4	0.4
In 2017							
Use of fertilizers	kg/ha UAA	Quantitative	Negative	0.0	781.7	69.6	110.9
Use of crop protection	EUR/ha UAA	Quantitative	Negative	0.0	875.0	21.6	51.2
GHG emissions	t CO2eq/ farm	Quantitative	Negative	0.5	5047.8	61.3	126.2
Energy intensity	EUR/thousand EUR	Quantitative	Negative	−494.6	1073.5	130.9	103.1
Biodiversity	index	Quantitative	Positive	0.0	1.0	0.7	0.3
Meadows and pastures	%	Quantitative	Positive	0.0	100.0	12.7	21.8
Livestock density	units/ha UAA	Quantitative	Negative	0.0	394.9	0.3	1.8
Wooded area	%	Quantitative	Positive	0.0	84.4	2.1	7.7
Accessibility	score	Qualitative	Positive	0.0	1.0	0.1	0.2
Environment-friendly farming	%	Quantitative	Positive	0.0	60.5	4.7	12.9
Water use	EUR/thousand EUR	Quantitative	Negative	0.0	87.4	9.1	10.9
Education	score	Qualitative	Positive	0.0	1.0	0.3	0.4

Table 5.10 KMO and Bartlett's test

		2016	2017
Kaiser–Meyer–Olkin measure of sampling adequacy		0.740	0.709
Bartlett's Test of Sphericity	Approx. Chi-Square	3356	3812
	df	66	66
	Sig.	0	0

$I^{+}_{\min,\ t}/I^{-}_{\min,\ t}$—indicator with minimum value and positive/negative impact on farm agri-environmental performance;

$I^{+}_{\max,\ t}/I^{-}_{\max,\ t}$—indicator with maximum value and positive/negative impact on farm agri-environmental performance; *i*—agri-environmental performance indicator, *t*—time in years.

As the minimum and maximum values of indicators can be outliers, similarly to Meul et al. (2008), 5% and 95% percentiles were used as minimum and maximum values of benchmarking, respectively.

Step 2. Prior to the composition of the AFI, the weights for the indicators were assigned. The weights for indicators can be derived either through equal weighting, statistic-based weighting, or public/expert opinion-based weighting (Gan et al. 2017; OECD-JRC 2008). Unlike EW and statistic-based weighting methods, public/expert opinion-based weighting requires the participation of experts. The judgements depend on expert group size, experts' composition in the group, experts' qualification and competence. Moreover, as stated by Gan et al. (2017), the weights assigned by experts can be "obscure or misleading, as weighting may measure the urgency or need for political intervention instead of importance". Due to time constraints on survey experts, two methods of weighting were chosen, namely EW and principal component analysis (PCA). The weight assignment steps for the PCA method documented in OECD-JRC (2008) were followed. The Kaiser–Meyer–Olkin (KMO) test and Bartlett's Test of Sphericity were performed to evaluate the data's suitability for PCA (Table 5.10).

In this study, the KMO values of 0.740 and 0.709 are above the acceptable limit of 0.5 (Field 2009) and the Bartlett's tests are significant at 99% ($p < 0.0001$) for 2016 and 2017 data, respectively. Four principal components with eigenvalues greater than 1.0 were retained for both data sets, explaining some 56.59% and 57.89% of the overall variance for 2016 and 2017 data, respectively (Table 5.11).

The PCA weights are obtained by considering the loadings and eigenvalues of the factors. The factors with the highest discriminatory power are used in the construction of the weights. Specifically, the minimum eigenvalue is set to unity as per suggestion of OECD-JRC (2008). The Varimax rotation matrix is applied. Then, the squared loadings are compared to the eigenvalues of the resulting factors. The normalized values are maximized across factors; i.e., one identifies the maximum normalized squared loading for each criterion. These maximum values are multiplied by the contributions of the factors associated with the maximum loadings to the overall variance (i.e. eigenvalue is compared to the sum of eigenvalues). The

Table 5.11 Principal components for the AFI indicators

Variables	Principal component			
	1	2	3	4
In 2016				
Use of fertilizers	**0.674**	0.439	0.335	0.166
Use of crop protection	**0.685**	0.406	0.323	0.171
GHG emissions	0.045	**0.759**	0.075	0.236
Energy intensity	–0.013	**–0.683**	–0.174	0.110
Biodiversity	**–0.489**	–0.087	0.123	0.097
Meadows and pastures	**0.681**	0.152	0.022	0.014
Livestock density	**–0.803**	0.264	0.029	–0.053
Wooded area	–0.078	–0.032	**0.712**	0.032
Accessibility	–0.026	–0.184	0.144	**0.778**
Environment-friendly farming	0.112	0.127	**0.702**	–0.020
Water use	–0.224	**–0.547**	0.120	0.077
Education	–0.089	–0.362	0.185	**–0.608**
% of variance	26.2	12.0	9.8	8.7
In 2017				
Use of fertilizers	**0.612**	0.556	0.332	0.033
Use of crop protection	0.589	**0.597**	0.322	0.016
GHG emissions	**0.728**	–0.053	0.066	0.091
Energy intensity	**–0.696**	0.169	–0.091	0.121
Biodiversity	–0.089	**–0.507**	0.239	–0.215
Meadows and pastures	–0.056	**0.740**	0.035	–0.041
Livestock density	0.050	**–0.833**	–0.050	0.078
Wooded area	–0.113	–0.038	**0.710**	0.061
Accessibility	–0.040	–0.012	0.124	**0.930**
Environment-friendly farming	0.205	0.078	**0.661**	0.027
Water use	**–0.589**	–0.123	0.040	0.084
Education	**–0.486**	–0.077	0.236	–0.277
% of variance	25.7	14.0	9.8	8.5

Note: Values in bold show in which factor the indicator reaches the highest loadings

resulting products are normalized to add up to unity. The resulting values serve as the weights of the criteria. The structure of AFIs using weights estimated by PCA (AFI_{PCA}) is presented in Fig. 5.24.

Step 3. A variety of EW modification techniques are available in index construction studies (e.g. Hudrlíková et al. 2013; Paracchini et al. 2015). Because of its transparency and simplicity, the EW method was employed, which implies that the weights for each indicator in the set are equal, namely each AFI indicator got a weight of 0.08 (1/12).

The AFI scores were obtained through the equation (Krajnc and Glavič 2005):

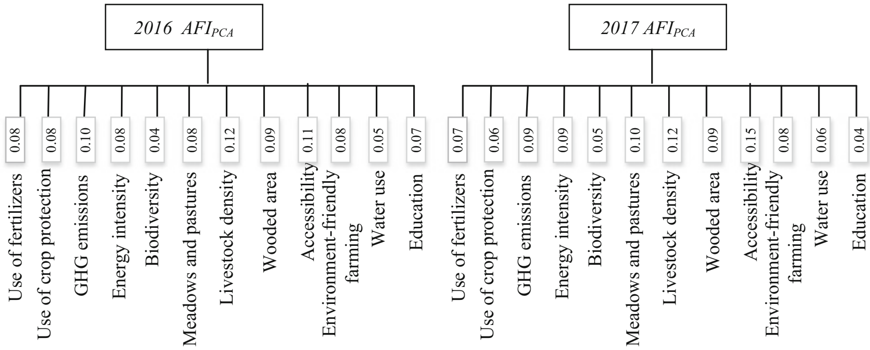

Fig. 5.24 Weights assigned to agri-environmental indicators based on PCA

$$\mathrm{AFI} = \sum_{i=1}^{n} W_i \times I^{+}_{N,it} + \sum_{i=1}^{n} W_i \times I^{-}_{N,it}. \tag{5.5}$$

Step 4. In order to give qualitative meaning to the numerical results of the AFI, the estimated index values were classified into three intervals: low, medium, and high. The threshold values of intervals were estimated according to Savickienė (2016) approach. The upper threshold value of a low agri-environmental performance interval was calculated as follows:

$$B_{\mathrm{L}} = \overline{X} - \mathrm{SD}, \tag{5.6}$$

where

B_{L}—an upper threshold value of low-performance interval;
$\overline{X}$—mean of AFI;
SD—standard deviation of AFI.

The upper threshold value of the medium-performance interval was computed according to Eq. (5.7):

$$B_{\mathrm{M}} = \mathrm{SD} + \overline{X}, \tag{5.7}$$

where

B_{M}—an upper threshold value of medium-performance interval.

The farms' sample distribution according to the farms' agri-environmental performance levels is given in Table 5.12.

Table 5.12 AFI intervals and farms' sample distribution according to the AFI level

	Descriptive statistics				AFI intervals/agri-environmental performance level (% of farms)		
	Min	Max	Mean	SD	Low	Medium	High
In 2016							
AFI_{PCA}	0.26	0.85	0.52	0.07	≤0.45 (15.9)	0.451–≤0.59 (67.5)	0.591–≤1 (16.5)
AFI_{EW}	0.28	0.84	0.53	0.08	≤0.45 (14.1)	0.451–≤0.60 (72.0)	0.601–≤1 (14.0)
In 2017							
AFI_{PCA}	0.26	0.83	0.46	0.08	≤0.38 (12.4)	0.381–≤0.54 (73.4)	0.541–≤1 (14.2)
AFI_{EW}	0.29	0.80	0.50	0.08	≤0.42 (13.7)	0.421–≤0.58 (71.7)	0.581–≤1 (15.2)

5.4 Agri-environmental Footprint Index for Lithuanian Family Farms

Stage 3—Score analysis

The score analysis consists of four steps:

Step 1. AFI decomposition analysis: the comparison of means for agri-environmental indicators in family farms on average.
Step 2. AFI decomposition analysis: the comparison of means and standard deviation of indicator values by groups of farms in terms of economic farm size class and farming type.
Step 3. The comparison of AFI values across economic farm size classes and farming types.
Step 4. The comparison of AFI values across economic farm size classes and farming types with low AFI_{EW} and AFI_{PCA} levels.

Step 1. The derived indicators attributed to agri-environmental performance at farm-level disclose problem areas on an individual farm or in a certain farm group that should be taken into account supporting policymakers' decisions towards the sustainable development of the agricultural sector. The lowest values for the whole sample of farms were recorded for indicators associated with the farms' accessibility, environment-friendly farming, wooded area, and meadows and pastures area (Fig. 5.25). The findings regarding index decomposition, namely for indicators related to the meadows and pastures area in UAA and farmers' enrolment into environment-friendly farming practices, are consistent with Dabkienė's (2018) research and thus address long-standing problems for Lithuanian farms.

Step 2. The average normalized values of the agri-environmental indicators across observed farming types are illustrated in Fig. 5.26 (for detailed descriptive statistics, see Annex 1). The analysis carried out across farming types showed that the usage of inorganic fertilizers was the most environmentally unfavourable on

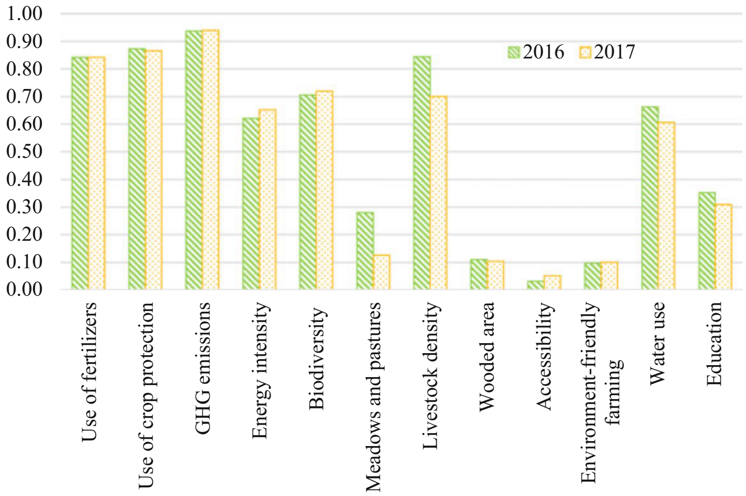

Fig. 5.25 Normalized values of AFI indicators for Lithuanian family farms in 2016 and 2017, average per farm

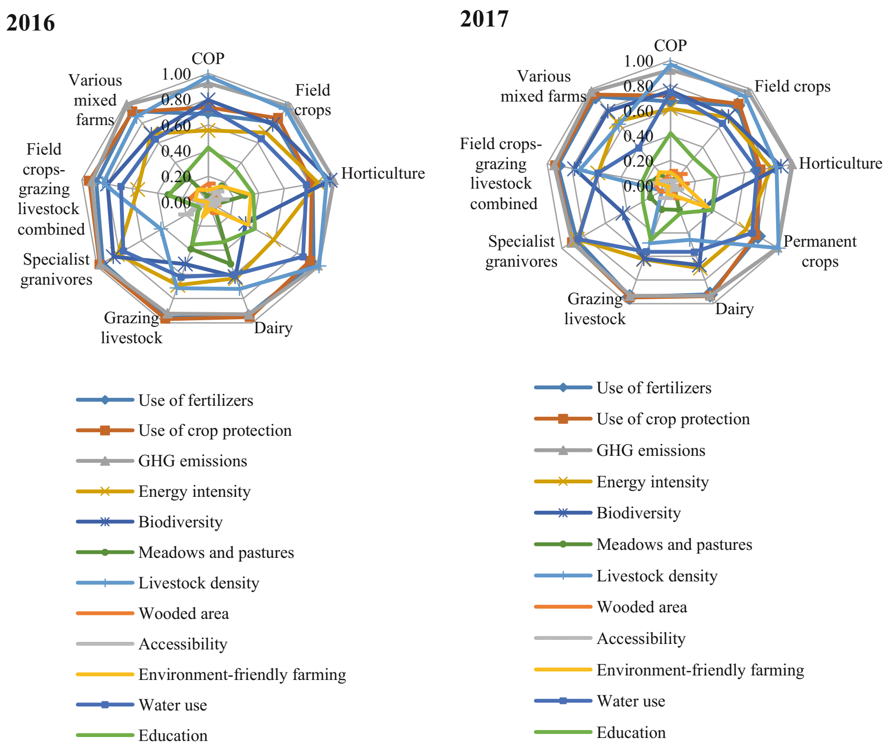

Fig. 5.26 Normalized values of AFI indicators by type of farming in 2016 and 2017

specialist COP farms, whereas the lowest level and the most environmentally favourable use of inorganic fertilizers were determined on grazing livestock farms in both considered years. The lowest intensity of crop protection products use was found on farms specialized in granivores in 2016, while in 2017 it was on grazing livestock and various mixed farms. A low variation value of GHG emissions on farms was defined, indicating small differences across types of farming. The obtained normalized lowest values for GHG emissions are in line with the CF values across types of farming. The COP, grazing livestock, and field crops-grazing livestock combined farms in 2016 and farms specialized in COP and granivores in 2017 contributed the most to thermal air pollution. The highest energy intensity level was found on COP and field crops-grazing livestock combined farms, while the lowest energy costs per total output were obtained for horticulture farms in the considered years.

The highest level of land use biodiversity, as measured by Shannon's Evenness Index, was achieved on horticulture farms, whereas the lowest level was established on permanent crop farms in 2016 and 2017. The low level of biodiversity on permanent crop farms could be addressed to the methodological limitation presented in Stage 1. This is in line with results obtained by Dabkienė (2018), where the lowest biodiversity measured by the Simpson Diversity Index was found on permanent crop farms. In addition, Gerrard et al. (2012) stated that in terms of farms' environmental assessment, the major limitation of the FADN was in measuring crop diversity as FADN data did not reflect the full range of on-farm crop varieties. The average normalized values of the meadows and pastures and livestock density are in line with farms' specialization. A great variation was observed in terms of the share of meadows and pastures in UAA across farming types (CV 69.3% and 70.2% in 2016 and 2017, respectively). The highest share of meadows and pastures in UAA was registered on dairy and grazing livestock farms in both considered years, and, at the other end of the scale, the lowest was on COP and horticulture farms in 2016 and 2017, respectively. In both the research years, the lowest normalized values of livestock density were observed on farms specialized in granivores and the highest on permanent crop farms, and this finding is consistent with farms' specialization. There is a low share of wooded area in the total farm area in family farms as normalized values varied from 0.0 (on granivore farms) to 0.14 (on COP farms) and ranged from 0.06 (on grazing livestock farms) to 0.12 (on COP and field crop farms) in 2016 and 2017, respectively. The obtained low average normalized values for accessibility revealed that there were a small number of farms generating income from agro-tourism. However, the variation of average normalized values was distinct and evidenced by severe values of CV 101.4% and 73.1% in 2016 and 2017, respectively. The farms specialized in granivores were the most accessible and open for recreational visitors in 2016, though in 2017 granivore farms showed the least accessibility. The variation in the average normalized values of environment-friendly farming across farming types was apparent (CV 78.1% and 80.9% in 2016 and 2017, respectively): permanent crop farms were most engaged, whereas the granivore farms were the least engaged in participation in agri-environmental schemes compared to other types of farming in both years of the research. The

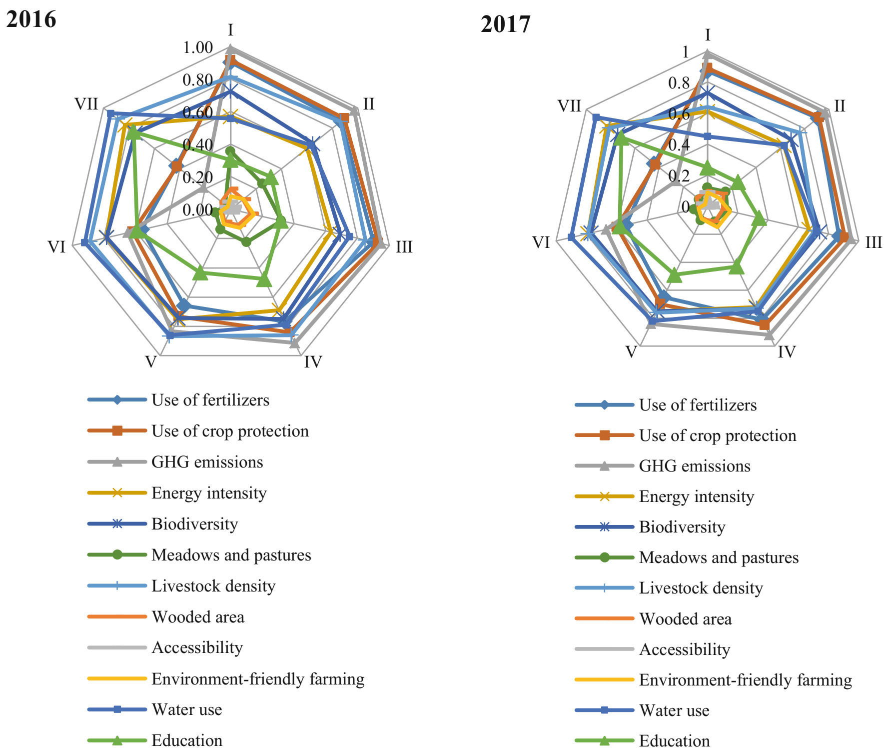

Fig. 5.27 Normalized values of AFI indicators by economic farm size classes in 2016 and 2017

highest water use efficiency measured as the ratio of water use from common water supply networks to total output was observed on permanent crop and granivore farms in 2016 and 2017, respectively. The COP and permanent crop farms (in 2016) and grazing livestock farms (in 2017), as compared to other farming types, were managed by better-educated farmers.

The agri-environmental performance results of family farms classified into the seven economic farm size classes is illustrated in Fig. 5.27 (for detailed descriptive statistics, see Annex 2). The average normalized values of the use of inorganic fertilizers, crop protection products, and GHG emissions per farm decrease with the economic size of the family farm: the lowest values of these indicators were found on farms in SO class VII (with SO of more than 250,000) and the highest in SO classes I–III (corresponding to 4000–25,000 EUR SO) in both years of the research. Due to economies of scale, large family farms used less energy per total output as energy intensity decreased with the economic farm size class in 2016 and 2017. A low variation of biodiversity across the economic farm size classes was recorded. The lowest level of biodiversity was found on farms in SO class II (farms from 8000 to 15,000 EUR SO), and the highest in SO class VI (25,000–50,000 EUR SO), in 2016 and 2017, respectively. The family farms in SO classes I and III and SO class II led the way in terms of average normalized values of the meadows and pastures in 2016 and 2017, respectively. At the other end of the scale, the lowest share of meadows and pastures in UAA was determined in the largest SO class of farms (with SO of more than 250,000) in both considered years. The number of livestock in relation to UAA did not vary much across economic farm size classes, with SO class I (4000–8000 EUR SO) having the highest livestock density compared to other classes in both research years. The most favourable ratio of wooded area to the total farm area was reported for farms in SO classes I and III (in 2016) and in SO class II (in 2017), and the least was in SO class VI in both considered years of the research. A great variation was observed in terms of farms' accessibility across SO classes as evidenced by an extremely high CV value (60.4%) and severe CV value (94.3%) in 2016 and 2017, respectively. Farmers running small farms (in SO class I producing an output of 4000–8000 EUR) were most engaged in agro-tourism and product processing. A variation in environment-friendly farming across economic farm size classes was apparent, as evidenced by extremely high CV values (47.4 and 50.0%), and medium family farms (in SO classes III–IV, farms producing an output of 15,000–50,000 EUR) were more likely to adopt environment-friendly practices on farms in both considered years. The intensity of water use on farms decreases with the economic size of family farms: the highest intensity was recorded in SO class I and the lowest intensity in SO class VII in both years of analysis. In both years of the research, the largest family farms (in SO class VII) were managed by farmers who had the highest level of agricultural education; in contrast, the smallest family farms (in SO classes I–II) had the lowest levels of agricultural education.

Step 3. Figure 5.28 shows average values of AFI_{PCA} and AFI_{EW} computed for types of farming and farm economic size classes in 2016 and 2017 (for detailed descriptive statistics, see Annex 3). Notwithstanding the method used to assign weights to the developed agri-environmental performance indicators, the obtained AFIs demonstrated almost the same tendencies across economic farm size classes. The highest AFI values across the economic farm size classes were found for medium-sized farms, namely AFI_{PCA} in SO classes III–IV and II–IV in 2016 and in 2017, respectively, and AFI_{EW} in SO classes III–IV in both considered years. In both years of the research, the lowest AFI values within economic farm size classes were observed for the largest farms (in SO class VII). These findings, to some extent, are in line with Czyżewski et al. (2019), who emphasized that small farms are hardly capable of attaining environmental sustainability. Sulewski et al. (2018) noticed that a negative relationship between farm size and environment is most often assumed. The results of research carried out by Westbury et al. (2011) revealed that farm size had no significant effect on the AFI for arable and upland livestock holdings, concluding that no relationship exists between farming intensity and farm size, whereas a significant effect of farm size on environmental performance was found for lowland livestock holdings as the AFI increased with farm size.

Looking at the results across types of farming, the highest AFI_{PCA} and AFI_{EW} values were found for horticulture farms in 2016, whereas in 2017 they were found for permanent crop and field crop farms using PCA and EW, respectively. At the other end of the scale, the lowest values of AFI_{PCA} were obtained for farms specialized in granivores in both years of the analysis, and the lowest values of AFI_{EW} were for granivore and COP farms in 2016 and for farms specialized in

Fig. 5.28 AFI_{PCA} and AFI_{EW} values concerning farming types and economic farm size classes in 2016 and 2017

granivores in 2017. The results are congruent with the findings of previous studies reported in Lithuania (Koloszko-Chomentowska et al. 2015; Dabkienė 2018).

The distribution of farms within the level of agri-environmental performance by farming types and economic farm size classes differed noticeably between AFI_{PCA} and AFI_{EW}, indicating the results of AFIs' sensitivity to the chosen indicators weighting method being employed (Table 5.13). For example, in 2016, 25.5% and 47.7% of farms in SO class VII and in 2017 76.6% and 59.1% of permanent crop farms fell within the medium AFI_{PCA} and AFI_{EW} level, respectively.

The obtained AFI intervals indicate a good level of Lithuanian family farms in terms of agri-environmental performance as 67.5% and 73.4% of AFI_{PCA}, and

Table 5.13 Farm distribution within the level of AFI by type of farming and economic farm size class, % of farms

	2016						2017					
	AFI_{PCA}			AFI_{EW}			AFI_{PCA}			AFI_{EW}		
	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High
Type of farming												
COP	23.3	65.7	10.9	18.3	72.7	9.0	4.7	77.6	17.7	11.9	69.1	19.0
Field crops	28.9	48.7	22.4	28.8	49.9	21.3	6.3	68.4	25.3	8.8	70.5	20.7
Horticulture	12.1	45.5	42.4	12.4	45.3	42.2	15.5	74.5	10.0	21.4	42.4	36.2
Permanent crops	7.9	64.9	27.2	11.7	72.8	15.5	–	76.6	23.4	19.1	59.1	21.9
Dairy	13.3	69.2	17.5	13.8	68.9	17.4	18.8	73.1	8.0	16.2	73.3	10.6
Grazing livestock	9.4	79.5	11.1	12.2	78.8	9.1	17.9	67.9	14.2	21.0	68.4	10.7
Specialist granivores	16.8	62.3	21.0	16.8	62.3	21.0	37.8	62.2	–	33.3	66.7	–
Field crops-grazing livestock combined	5.4	71.9	22.7	4.4	80.0	15.6	6.6	75.7	17.7	8.8	69.7	21.4
Various mixed farms	10.7	71.2	18.1	5.9	83.9	10.3	20.7	67.3	12.0	13.3	78.2	8.5
Economic farm size class												
$4 \leq 8$	14.2	70.3	15.5	12.8	76.9	10.3	20.7	66.1	13.2	19.9	67.5	12.6
$8 \leq 15$	14.8	66.6	18.6	16.4	68.9	14.6	4.5	78.2	17.3	7.9	75.7	16.4
$15 \leq 25$	9.5	68.8	21.7	8.7	68.4	22.8	5.2	78.5	16.3	7.0	69.1	23.9
$25 \leq 50$	10.8	70.6	18.6	8.1	71.3	20.6	5.9	78.4	15.8	8.7	71.6	19.6
$50 \leq 100$	25.6	63.3	11.1	17.7	69.7	12.5	6.0	84.6	9.5	10.0	76.4	13.6
$100 \leq 250$	39.3	53.3	7.4	25.3	65.0	9.7	14.2	80.7	5.1	16.1	77.0	6.9
≥ 250	73.8	25.5	0.7	51.0	47.7	1.3	48.3	50.1	1.6	37.6	60.0	2.4

COP specialist cereals, oilseeds, and protein crops

72.0% and 71.1% of AFI_{EW} for the whole sample of family farms were defined as medium level in 2016 and 2017, respectively. The results are in line with the findings of a previous study reported for Lithuanian farms (Dabkienė 2018) and to some extent for Bulgarian farms (Bachev 2017).

With respect to type of farming, the largest share of farms whose average normalized values of AFI fell within the high level of agri-environmental performance was found for horticulture farms using both index construction methods in 2016, while in 2017 it was for field crop farms using PCA and for horticulture farms EW. As regards the economic size of farms, the largest share of farms whose average normalized values of AFI_{PCA} and AFI_{EW} fell within the low level of agri-environmental performance was obtained for farms in SO class VII in both considered years of the analysis.

Step 4. As the environmental issues in the Lithuanian agricultural sector are of high importance, special attention is paid to farms with a low level of AFI_{EW} and AFI_{PCA}. The normalized values of agri-environmental indicators of family farms across farming types with low AFI_{EW} and AFI_{PCA} levels in 2017 are illustrated in Fig. 5.29 (for detailed descriptive statistics, see Annex 4). When taking into account the low AFI level using the EW method, permanent crop, horticulture, and COP farms showed the highest intensity in inorganic fertilizer use and crop protection costs per ha of UAA as compared with other farm types. The COP farms obtained the highest GHG emissions per farm due to the use of high rates of inorganic fertilizers on farms. The highest energy intensity was found for field crop, field crops-grazing livestock combined, and various mixed farms. Field crop farms also obtained the lowest values in terms of biodiversity on farms measured by the Shannon's Evenness Index. Farms with a low level of AFI_{EW} of all types, except those specialized in grazing livestock, had the lowest portion of meadows and pastures area in UAA. The highest level of LU per ha of UAA was obtained in farms specialized in granivores. All farms with a low level of AFI_{EW} achieved the lowest share of wooded area in a total farm area and generated the lowest output from agro-tourism and processed products. Moreover, all farm types except various mixed farms were least engaged in environment-friendly farming. Various mixed and horticulture farms had the highest water use intensity. Farms with a low level of AFI_{EW} were mostly managed by farmers with practical experience only (except horticulture farms).

In comparing results between AFI_{EW} and AFI_{PCA}, the main difference occurs for permanent crop farms as there were no permanent crop farms with a low level of AFI_{PCA}. As regards a low level of AFI_{PCA}, the highest intensity of inorganic fertilizers and crop protection products used per ha of UAA was found for horticulture farms. The results in terms of GHG emissions, energy intensity, biodiversity, meadows and pastures area share in UAA, livestock density, wooded area, accessibility, and environment-friendly farming are in line with AFI_{EW}. The highest water use intensity across farms with a low level of AFI_{PCA} was found for horticulture farms. Field crop, granivore, and field crops-grazing livestock combined farms were mostly managed by farmers with practical experience only.

The normalized values of agri-environmental indicators of family farms across economic farm size classes (as measured by the standard output) with low AFI_{EW} and AFI_{PCA} levels in 2017 are illustrated in Fig. 5.30 (for detailed descriptive statistics, see Annex 5). Regardless of the weighting method applied to obtain

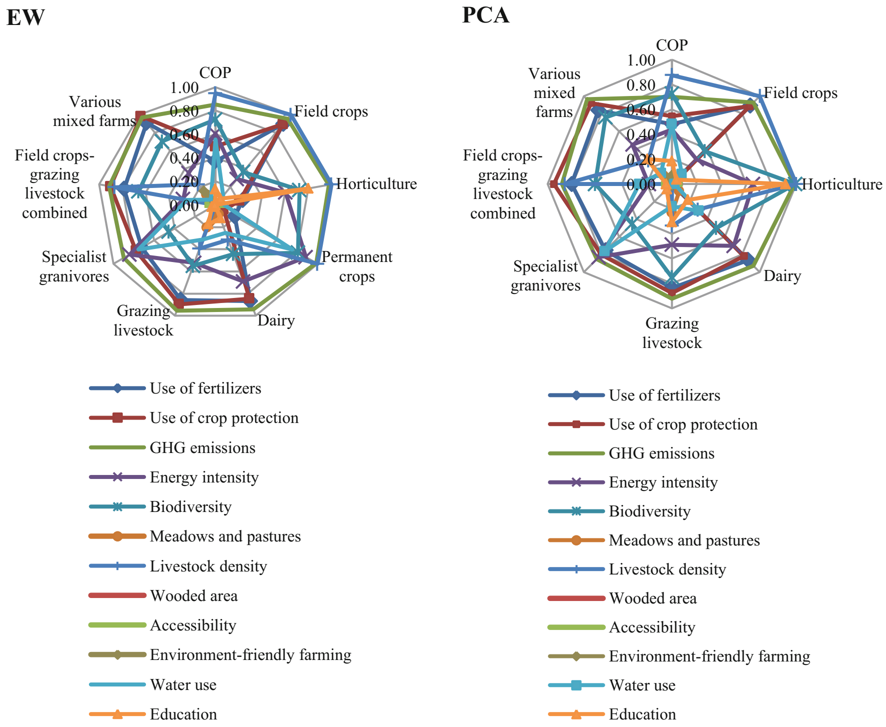

Fig. 5.29 Normalized values of AFI indicators of farms with a low AFI level by type of farming in 2017

weights for indicators, a similar pattern across farm size classes was found for indicators such as inorganic fertilizers and crop protection products use per ha of UAA, GHG emissions per farm, biodiversity on farms, meadows and pastures area share in UAA, wooded area, accessibility, environment-friendly farming, and water use intensity. The highest intensity of inorganic fertilizers and crop protection products used per ha of UAA was on farms in SO classes VI and VII. The highest GHG emissions per farm were found in the largest farm size group (SO class VII). The lowest level of biodiversity was reported on farms in SO class II (between 8000 and 15,000 EUR SO group). Farm groups II and III, corresponding to 8000–25,000 EUR SO, had the lowest share of meadows and pastures in UAA. Farms with a low AFI value had the lowest share of wooded area and were not engaged in activities related to agro-tourism and processing products. Moreover, farms with a low level of AFI did not participate in environment-friendly farming except for farms within SO class III (15,000–25,000 EUR). The highest water use intensity was reported for the smallest farms in SO class I (4000–8000 EUR SO). The highest energy intensity was found in farms in SO class III (15,000–25,000 EUR SO) using the EW method, whereas using PCA, the highest energy intensity was observed in the smallest SO class farms producing an output of 4000–8000 EUR.

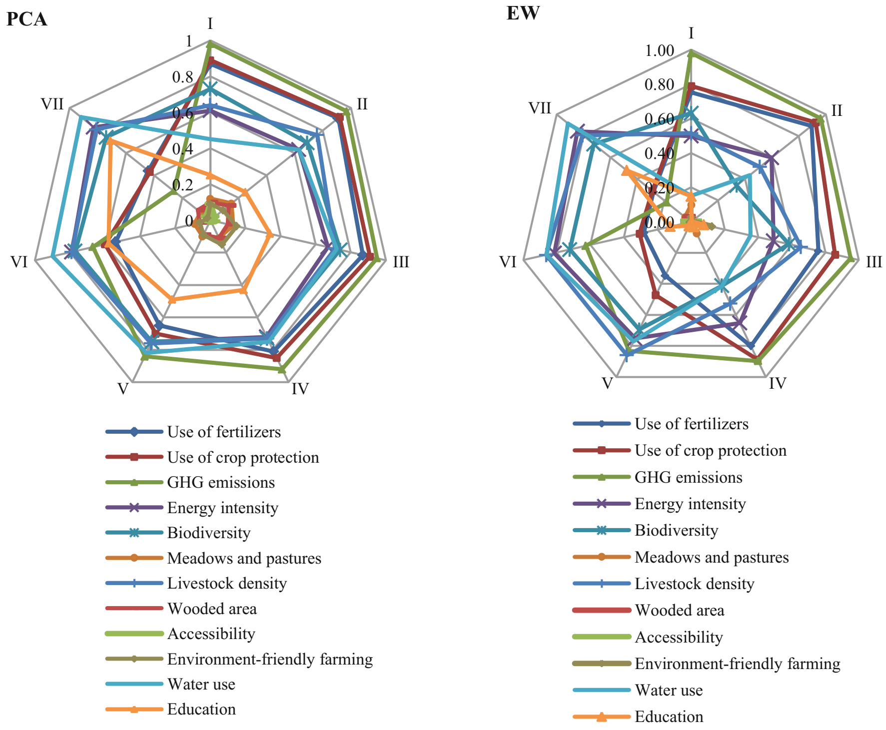

Fig. 5.30 Normalized values of AFI indicators of farms with a low AFI level by economic farm size class in 2017

When the EW method was applied, the lowest education level was achieved by farmers managing farms in SO classes II–V and in SO classes II and IV, using EW and PCA methods, respectively.

5.5 Conclusions

This paper presents the AFI methodology for assessing agri-environmental performance in agriculture at farm level. The AFI is based on 12 developed indicators that are customized to FADN data. The proposed methodology can be used to compare the agri-environmental performance of family farms within farming types, economic size classes, or other farm groups. Furthermore, the problem areas can be identified for each farm group and, accordingly, the policy measures and interventions can be targeted to their needs.

Moreover, the GHG assessment empirical research is provided in original indicator values across economic farm size classes and types of farming. GHG measured on the basis of FADN data is connected to farm activity data, and that expands the scope of the analysis of GHG emissions on farms (e.g. CAP expenditure effects on on-farm GHG; relationship between productivity and GHG; synergies between the different CAP instruments) identifying low CF development solutions.

The results showed that the major sources of GHG emissions on Lithuanian farms were related to enteric fermentation from livestock and direct N_2O emissions from agricultural soils. This suggests that the implementation of new management and nutrition technologies, livestock breeding, and methane capture technologies should be considered a priority in Lithuania.

The average GHG values of 61.3 and 57.8 t CO_{2eq}/farm were obtained for 2016 and 2017, respectively. In 2016, the GHG values ranged from 8.9 t CO_{2eq}/farm for horticultural farms to 75.1 t CO_{2eq}/farm for field crops-grazing livestock combined farms, whereas in 2017, GHG values ranged from 15.0 CO_{2eq}/farm for horticulture farms to 92.8 CO_{2eq}/farm for farms specialized in granivores. In relation to economic farm size, the GHG values increased with the economic farm size: from 13.7 t CO_{2eq}/farm up to 868.4 t CO_{2eq}/farm and from 17.8 CO_{2eq}/farm up to 875.6 CO_{2eq}/farm in 2016 and 2017, respectively.

The assessment findings indicate a good level of Lithuanian family farms' agri-environmental performance as 67.5% and 73.4% of AFI_{PCA}, and 72.0% and 71.1% of AFI_{EW} for the whole sample of family farms were defined as medium level in 2016 and 2017, respectively.

The proposed approach permits a standardized comparison between different farm groups. The highest AFI values within farm groups regarding their economic size were found for the medium farms, namely AFI_{PCA} in SO classes III–IV and II–IV, in 2016 and in 2017, respectively, and AFI_{EW} in SO classes III–IV in both considered years. The AFI across types of farming revealed that the highest AFI_{PCA} and AFI_{EW} values were found for horticulture farms in 2016, whereas in 2017 they were found for permanent crop and field crop farms using PCA and EW, respectively. At the other end of the scale, the lowest values of AFI_{PCA} were obtained for farms specialized in granivores in both years of the analysis, and the lowest values of AFI_{EW} were found for farms specialized in granivores and COP in 2016, and for farms specialized in granivores in 2017.

Additionally, this paper addresses the issue of weighting indicators using PCA and EW methods. The distribution of farms within the level of agri-environmental performance by type of farming and economic farm size classes differed noticeably between AFI_{PCA} and AFI_{EW}. In terms of the use of the AFI as a policy decision support tool, in future the weights could be assigned according to the results of prioritization and ranking needs for the national CAP Strategic Plan.

The index structure is flexible and can respond to diverse local policy needs. The results of the AFI provide new knowledge about farms' environmental performance, disclose problems across farm groups, and can be the basis for political decisions that lead to sustainable development of the agricultural sector in Lithuania.

Annexes

Annex 1: Normalized Values of AFI Indicators by Type of Farming

Variables	COP	Field crops	Horticulture	Permanent crops	Dairy	Grazing livestock	Specialist granivores	Field crops-grazing livestock combined	Various mixed farms	Total	Significance	CV, %
In 2016												
Use of fertilizers	0.68	0.81	0.83	0.95	0.93	0.96	0.95	0.89	0.82	0.84	*	10.5
	(0.32)	(0.29)	(0.34)	(0.11)	(0.12)	(0.10)	(0.17)	(0.18)	(0.14)	(0.25)		
Use of crop protection	0.74	0.85	0.82	0.92	0.95	0.97	0.98	0.94	0.92	0.87	*	8.9
	(0.30)	(0.24)	(0.35)	(0.23)	(0.11)	(0.07)	(0.10)	(0.13)	(0.13)	(0.22)		
GHG emissions	0.92	0.97	0.99	0.99	0.93	0.92	0.97	0.92	0.99	0.94	*	3.4
	(0.14)	(0.08)	(0.03)	(0.02)	(0.12)	(0.10)	(0.11)	(0.13)	(0.02)	(0.12)		
Energy intensity	0.56	0.70	0.86	0.59	0.63	0.69	0.81	0.56	0.69	0.62	*	15.6
	(0.30)	(0.31)	(0.16)	(0.35)	(0.27)	(0.25)	(0.29)	(0.24)	(0.24)	(0.28)		
Biodiversity	0.79	0.79	0.96	0.34	0.62	0.51	0.85	0.80	0.69	0.71	*	26.9
	(0.18)	(0.21)	(0.11)	(0.42)	(0.34)	(0.38)	(0.30)	(0.17)	(0.32)	(0.29)		
Meadows and pastures	0.04	0.16	0.29	0.05	0.51	0.39	0.09	0.32	0.25	0.28	*	69.3
	(0.09)	(0.21)	(0.36)	(0.14)	(0.37)	(0.35)	(0.24)	(0.28)	(0.33)	(0.34)		
Livestock density	0.98	0.94	0.94	1.00	0.72	0.71	0.42	0.83	0.87	0.84	*	22.4
	(0.05)	(0.08)	(0.10)	(0.01)	(0.18)	(0.19)	(0.23)	(0.11)	(0.13)	(0.17)		
Wooded area	0.14	0.06	0.04	0.05	0.09	0.05	0.00	0.15	0.12	0.11	*	64.9
	(0.28)	(0.15)	(0.32)	(0.28)	(0.29)	(0.37)	(0.07)	(0.24)	(0.37)	(0.30)		
Accessibility	0.01	0.10	0.11	0.04	0.04	0.00	0.20	0.06	0.01	0.03	*	101.4
	(0.10)	(0.31)	(0.31)	(0.21)	(0.19)	(0.04)	(0.40)	(0.24)	(0.08)	(0.18)		
Environment-friendly farming	0.09	0.16	0.34	0.36	0.06	0.13	0.01	0.10	0.13	0.10	*	78.1
	(0.27)	(0.35)	(0.46)	(0.43)	(0.18)	(0.28)	(0.07)	(0.26)	(0.33)	(0.27)		

Water use	0.73 (0.31)	0.64 (0.36)	0.78 (0.33)	0.85 (0.28)	0.60 (0.33)	0.62 (0.30)	0.76 (0.13)	0.69 (0.31)	0.64 (0.29)	0.66 (0.32)	*	12.0
Education	0.42 (0.41)	0.33 (0.39)	0.36 (0.34)	0.42 (0.40)	0.33 (0.39)	0.35 (0.42)	0.08 (0.21)	0.31 (0.38)	0.28 (0.34)	0.35 (0.39)	*	31.6
In 2017												
Use of fertilizers	0.67 (0.32)	0.83 (0.22)	0.71 (0.38)	0.81 (0.36)	0.92 (0.12)	0.94 (0.10)	0.86 (0.20)	0.91 (0.15)	0.93 (0.15)	0.84 (0.24)	*	11.6
Use of crop protection	0.72 (0.31)	0.85 (0.29)	0.73 (0.39)	0.79 (0.37)	0.94 (0.13)	0.95 (0.11)	0.90 (0.15)	0.93 (0.11)	0.95 (0.12)	0.87 (0.24)	*	10.9
GHG emissions	0.92 (0.14)	0.97 (0.08)	0.98 (0.04)	0.99 (0.01)	0.93 (0.11)	0.93 (0.08)	0.91 (0.17)	0.94 (0.11)	0.98 (0.03)	0.94 (0.11)	*	3.2
Energy intensity	0.61 (0.31)	0.71 (0.30)	0.81 (0.18)	0.70 (0.31)	0.70 (0.24)	0.63 (0.26)	0.86 (0.14)	0.59 (0.27)	0.67 (0.23)	0.65 (0.27)	*	12.8
Biodiversity	0.76 (0.22)	0.72 (0.27)	0.90 (0.24)	0.32 (0.40)	0.67 (0.32)	0.62 (0.33)	0.44 (0.43)	0.78 (0.22)	0.78 (0.27)	0.72 (0.28)	*	27.4
Meadows and pastures	0.03 (0.08)	0.07 (0.23)	0.00 (0.03)	0.04 (0.13)	0.20 (0.27)	0.20 (0.12)	0.18 (0.39)	0.16 (0.17)	0.12 (0.21)	0.13 (0.22)	*	70.2
Livestock density	0.97 (0.08)	0.93 (0.15)	0.86 (0.25)	1.00 (0.01)	0.46 (0.26)	0.49 (0.25)	0.08 (0.21)	0.73 (0.18)	0.64 (0.30)	0.70 (0.30)	*	44.1
Wooded area	0.12 (0.31)	0.12 (0.32)	0.09 (0.29)	0.04 (0.18)	0.11 (0.30)	0.03 (0.15)	0.10 (0.29)	0.13 (0.34)	0.07 (0.25)	0.10 (0.30)	*	40.1
Accessibility	0.04 (0.19)	0.05 (0.22)	0.01 (0.07)	0.06 (0.23)	0.03 (0.18)	0.10 (0.31)	0.00 (0.00)	0.10 (0.30)	0.04 (0.21)	0.05 (0.22)	*	73.1

(continued)

Variables	COP	Field crops	Horticulture	Permanent crops	Dairy	Grazing livestock	Specialist granivores	Field crops-grazing livestock combined	Various mixed farms	Total	Significance	CV, %
Environment-friendly farming	0.10 (0.30)	0.09 (0.26)	0.10 (0.24)	0.35 (0.42)	0.08 (0.24)	0.07 (0.21)	0.01 (0.10)	0.11 (0.27)	0.14 (0.31)	0.10 (0.27)	*	80.9
Water use	0.74 (0.29)	0.65 (0.35)	0.70 (0.40)	0.75 (0.35)	0.56 (0.35)	0.56 (0.38)	0.85 (0.22)	0.59 (0.36)	0.39 (0.36)	0.61 (0.36)	*	21.1
Education	0.42 (0.42)	0.29 (0.41)	0.36 (0.36)	0.39 (0.46)	0.23 (0.35)	0.46 (0.41)	0.26 (0.35)	0.23 (0.39)	0.24 (0.35)	0.31 (0.40)	*	27.8

Notes: Numbers in parentheses are standard deviations; *COP* specialist cereals, oilseeds, and protein crops; *Significance at $p < 0.001$

Annex 2: Normalized Values of AFI Indicators by Economic Farm Size Classes

Variables	(I) 4 ≤ 8	(II) 8 ≤ 15	(III) 15 ≤ 25	(IV) 25 ≤ 50	(V) 50 ≤ 100	(VI) 100 ≤ 250	(VII) ≥250	Total	Significance	CV, %
In 2016										
Use of fertilizers	0.90 (0.17)	0.87 (0.23)	0.90 (0.19)	0.77 (0.28)	0.66 (0.32)	0.56 (0.32)	0.43 (0.30)	0.84 (0.25)	*	25.3
Use of crop protection	0.92 (0.16)	0.90 (0.21)	0.93 (0.16)	0.84 (0.23)	0.73 (0.30)	0.62 (0.32)	0.42 (0.34)	0.87 (0.22)	*	24.8
GHG emissions	0.98 (0.01)	0.97 (0.02)	0.95 (0.03)	0.91 (0.05)	0.83 (0.09)	0.65 (0.18)	0.21 (0.25)	0.94 (0.12)	*	35.5
Energy intensity	0.57 (0.30)	0.60 (0.29)	0.63 (0.25)	0.69 (0.23)	0.75 (0.18)	0.78 (0.15)	0.83 (0.09)	0.62 (0.28)	*	14.1
Biodiversity	0.73 (0.32)	0.65 (0.30)	0.69 (0.29)	0.75 (0.22)	0.74 (0.20)	0.78 (0.16)	0.75 (0.16)	0.71 (0.29)	*	6.0
Meadows and pastures	0.36 (0.37)	0.25 (0.32)	0.32 (0.35)	0.23 (0.30)	0.14 (0.25)	0.10 (0.20)	0.04 (0.11)	0.28 (0.34)	*	57.0
Livestock density	0.82 (0.20)	0.86 (0.14)	0.85 (0.15)	0.86 (0.16)	0.87 (0.18)	0.89 (0.18)	0.89 (0.20)	0.84 (0.17)	*	2.8
Wooded area	0.13 (0.32)	0.10 (0.26)	0.13 (0.27)	0.11 (0.25)	0.09 (0.20)	0.06 (0.13)	0.07 (0.13)	0.11 (0.27)	*	27.7
Accessibility	0.05 (0.21)	0.03 (0.16)	0.02 (0.13)	0.02 (0.15)	0.01 (0.12)	0.01 (0.11)	0.02 (0.15)	0.03 (0.18)	*	60.4
Environment-friendly farming	0.08 (0.25)	0.10 (0.27)	0.15 (0.31)	0.13 (0.31)	0.10 (0.27)	0.06 (0.23)	0.02 (0.13)	0.10 (0.27)	*	47.4
Water use	0.56 (0.35)	0.63 (0.32)	0.75 (0.25)	0.79 (0.23)	0.86 (0.17)	0.92 (0.10)	0.94 (0.08)	0.66 (0.32)	*	18.4
Education	0.30 (0.36)	0.32 (0.38)	0.32 (0.39)	0.48 (0.43)	0.43 (0.43)	0.59 (0.43)	0.76 (0.42)	0.35 (0.39)	*	37.1
In 2017										
Use of fertilizers	0.87 (0.20)	0.91 (0.17)	0.87 (0.25)	0.81 (0.24)	0.65 (0.32)	0.54 (0.33)	0.44 (0.31)	0.84 (0.24)	*	25.4

(continued)

Variables	(I) 4 ≤ 8	(II) 8 ≤ 15	(III) 15 ≤ 25	(IV) 25 ≤ 50	(V) 50 ≤ 100	(VI) 100 ≤ 250	(VII) ≥250	Total	Significance	CV, %
Use of crop protection	0.89 (0.21)	0.92 (0.16)	0.91 (0.20)	0.85 (0.23)	0.70 (0.32)	0.60 (0.33)	0.43 (0.35)	0.87 (0.24)	*	24.8
GHG emissions	0.98 (0.01)	0.97 (0.02)	0.95 (0.03)	0.92 (0.05)	0.84 (0.07)	0.67 (0.16)	0.26 (0.25)	0.94 (0.11)	*	32.7
Energy intensity	0.61 (0.29)	0.63 (0.29)	0.67 (0.24)	0.72 (0.21)	0.75 (0.22)	0.79 (0.19)	0.83 (0.12)	0.65 (0.27)	*	11.5
Biodiversity	0.73 (0.31)	0.69 (0.29)	0.74 (0.25)	0.73 (0.25)	0.75 (0.21)	0.77 (0.16)	0.74 (0.16)	0.72 (0.30)	*	3.3
Meadows and pastures	0.12 (0.19)	0.15 (0.27)	0.13 (0.22)	0.11 (0.19)	0.10 (0.21)	0.09 (0.18)	0.07 (0.15)	0.13 (0.22)	*	24.1
Livestock density	0.64 (0.33)	0.76 (0.25)	0.71 (0.27)	0.73 (0.31)	0.76 (0.30)	0.79 (0.32)	0.81 (0.32)	0.70 (0.30)	*	7.6
Wooded area	0.10 (0.28)	0.13 (0.28)	0.10 (0.25)	0.11 (0.24)	0.09 (0.21)	0.06 (0.14)	0.09 (0.16)	0.10 (0.26)	*	22.0
Accessibility	0.09 (0.28)	0.03 (0.18)	0.01 (0.17)	0.01 (0.10)	0.01 (0.10)	0.01 (0.10)	0.03 (0.16)	0.05 (0.22)	*	94.3
Environment-friendly farming	0.09 (0.26)	0.09 (0.26)	0.15 (0.31)	0.15 (0.33)	0.09 (0.27)	0.06 (0.23)	0.02 (0.13)	0.10 (0.27)	*	50.0
Water use	0.45 (0.39)	0.63 (0.31)	0.72 (0.26)	0.75 (0.26)	0.82 (0.20)	0.90 (0.14)	0.92 (0.11)	0.61 (0.36)	*	22.1
Education	0.25 (0.35)	0.25 (0.38)	0.34 (0.40)	0.43 (0.43)	0.49 (0.43)	0.58 (0.44)	0.71 (0.41)	0.31 (0.40)	*	39.4

Notes: Numbers in parentheses are standard deviations; *Significance at $p < 0.001$

Annex 3: AFI_{PCA} and AFI_{EW} Values Concerning Farming Types and Economic Farm Size Classes

	AFI_{PCA}				AFI_{EW}			
	Mean	SD	Min	Max	Mean	SD	Min	Max
In 2016								
Type of farming								
COP	0.50	0.07	0.26	0.85	0.51	0.07	0.28	0.84
Field crops	0.53	0.11	0.28	0.78	0.54	0.11	0.29	0.78
Horticulture	0.57	0.10	0.34	0.73	0.57	0.10	0.31	0.71
Permanent crops	0.55	0.07	0.36	0.71	0.53	0.07	0.33	0.74
Dairy	0.53	0.07	0.28	0.74	0.53	0.07	0.33	0.77
Grazing livestock	0.52	0.06	0.38	0.73	0.53	0.07	0.39	0.77
Specialist granivores	0.49	0.08	0.30	0.62	0.51	0.07	0.35	0.64
Field crops-grazing livestock combined	0.54	0.07	0.30	0.77	0.55	0.07	0.34	0.80
Various mixed farms	0.53	0.06	0.35	0.67	0.53	0.07	0.37	0.65
Economic farm size class								
$4 \leq 8$	0.52	0.07	0.38	0.78	0.52	0.07	0.37	0.78
$8 \leq 15$	0.52	0.07	0.34	0.77	0.52	0.08	0.31	0.80
$15 \leq 25$	0.54	0.07	0.35	0.74	0.55	0.08	0.36	0.75
$25 \leq 50$	0.53	0.08	0.37	0.85	0.55	0.08	0.40	0.84
$50 \leq 100$	0.50	0.07	0.34	0.72	0.52	0.07	0.33	0.73
$100 \leq 250$	0.47	0.07	0.28	0.70	0.50	0.07	0.29	0.73
≥ 250	0.41	0.06	0.26	0.61	0.45	0.06	0.28	0.66
Total	0.52	0.07	0.26	0.85	0.53	0.08	0.28	0.84
In 2017								
Type of farming								
COP	0.47	0.07	0.30	0.72	0.51	0.08	0.30	0.80
Field crops	0.49	0.07	0.31	0.83	0.53	0.08	0.32	0.80
Horticulture	0.48	0.07	0.35	0.71	0.52	0.08	0.34	0.67
Permanent crops	0.50	0.08	0.39	0.72	0.52	0.09	0.38	0.70
Dairy	0.44	0.07	0.26	0.73	0.49	0.07	0.32	0.74
Grazing livestock	0.45	0.08	0.31	0.65	0.50	0.07	0.34	0.75
Specialist granivores	0.39	0.07	0.26	0.51	0.45	0.07	0.29	0.56
Field crops-grazing livestock combined	0.48	0.10	0.28	0.82	0.52	0.10	0.30	0.78
Various mixed farms	0.45	0.08	0.30	0.70	0.49	0.07	0.36	0.69
Economic farm size class								
$4 \leq 8$	0.45	0.09	0.30	0.82	0.48	0.08	0.35	0.78
$8 \leq 15$	0.48	0.07	0.31	0.68	0.51	0.07	0.34	0.73

(continued)

	AFI_{PCA}				AFI_{EW}			
	Mean	SD	Min	Max	Mean	SD	Min	Max
$15 \leq 25$	0.48	0.07	0.33	0.70	0.53	0.08	0.39	0.73
$25 \leq 50$	0.48	0.07	0.27	0.83	0.53	0.08	0.29	0.80
$50 \leq 100$	0.46	0.06	0.26	0.71	0.51	0.07	0.31	0.75
$100 \leq 250$	0.44	0.06	0.30	0.71	0.49	0.07	0.32	0.73
≥ 250	0.39	0.06	0.26	0.62	0.45	0.07	0.30	0.70
Total	0.46	0.08	0.26	0.83	0.50	0.08	0.29	0.80

Annex 4: Normalized Values of AFI Indicators of Farms with a Low AFI Level by Type of Farming in 2017

Variables	COP	Field crops	Horticulture	Permanent crops	Dairy	Grazing livestock	Specialist granivores	Field crops-grazing livestock combined	Various mixed farms	Total	Significance	CV, %
In 2017 EW												
Use of fertilizers	0.37 (0.31)	0.90 (0.28)	0.24 (0.42)	0.19 (0.35)	0.87 (0.14)	0.86 (0.14)	0.72 (0.29)	0.79 (0.20)	0.91 (0.20)	0.72 (0.32)	*	45.7
Use of crop protection	0.50 (0.38)	0.89 (0.29)	0.21 (0.36)	0.08 (0.28)	0.85 (0.13)	0.90 (0.06)	0.78 (0.16)	0.90 (0.19)	0.98 (0.04)	0.77 (0.16)	*	49.2
GHG emissions	0.85 (0.23)	0.95 (0.15)	0.98 (0.06)	0.99 (0.00)	0.94 (0.16)	0.96 (0.12)	0.90 (0.24)	0.92 (0.26)	0.97 (0.03)	0.92 (0.20)	*	4.7
Energy intensity	0.61 (0.38)	0.29 (0.23)	0.60 (0.16)	0.89 (0.27)	0.69 (0.26)	0.52 (0.24)	0.84 (0.19)	0.28 (0.30)	0.35 (0.19)	0.56 (0.32)	*	40.0
Biodiversity	0.72 (0.17)	0.37 (0.18)	0.73 (0.44)	0.81 (0.37)	0.44 (0.44)	0.55 (0.41)	0.46 (0.45)	0.66 (0.28)	0.70 (0.25)	0.58 (0.37)	*	25.6
Meadows and pastures	0.00 (0.01)	0.00 (0.00)	0.00 (0.00)	0.01 (0.05)	0.09 (0.14)	0.21 (0.15)	0.00 (0.00)	0.02 (0.07)	0.11 (0.15)	0.07 (0.13)	*	147.3
Livestock density	0.95 (0.11)	1.00 (0.01)	1.00 (0.00)	1.00 (0.00)	0.31 (0.30)	0.39 (0.15)	0.00 (0.00)	0.87 (0.10)	0.23 (0.24)	0.57 (0.38)	*	62.6
Wooded area	0.01 (0.04)	0.00 (0.01)	0.00 (0.02)	0.00 (0.00)	0.00 (0.02)	0.00 (0.01)	0.02 (0.01)	0.01 (0.02)	0.00 (0.00)	0.00 (0.02)	*	113.5
Accessibility	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.10)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	–	–
Environment-friendly farming	0.03 (0.16)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.01 (0.08)	0.04 (0.16)	0.00 (0.00)	0.10 (0.24)	0.03 (0.13)	*	232.1
Water use											*	81.1

(continued)

Variables	COP	Field crops	Horticulture	Permanent crops	Dairy	Grazing livestock	Specialist granivores	Field crops-grazing livestock combined	Various mixed farms	Total	Significance	CV, %
	0.55 (0.42)	0.10 (0.28)	0.06 (0.20)	0.75 (0.24)	0.25 (0.26)	0.31 (0.45)	0.75 (0.29)	0.25 (0.26)	0.06 (0.21)	0.31 (0.37)		
Education	0.14 (0.26)	0.07 (0.19)	0.80 (0.31)	0.00 (0.00)	0.12 (0.30)	0.17 (0.15)	0.03 (0.00)	0.01 (0.10)	0.00 (0.24)	0.12 (0.38)	*	169.1
In 2017 PCA												
Use of fertilizers	0.48 (0.35)	0.89 (0.29)	0.00 (0.00)	–	0.86 (0.13)	0.84 (0.14)	0.75 (0.28)	0.81 (0.17)	0.84 (0.23)	0.80 (0.25)	*	44.6
Use of crop protection	0.54 (0.44)	0.88 (0.31)	0.01 (0.03)	–	0.82 (0.20)	0.88 (0.11)	0.80 (0.21)	0.95 (0.15)	0.92 (0.15)	0.81 (0.27)	*	43.6
GHG emissions	0.70 (0.35)	0.93 (0.21)	0.99 (0.01)	–	0.93 (0.16)	0.92 (0.12)	0.85 (0.24)	0.88 (0.26)	0.96 (0.03)	0.91 (0.20)	*	10.0
Energy intensity	0.44 (0.41)	0.28 (0.21)	0.65 (0.10)	–	0.70 (0.25)	0.49 (0.24)	0.83 (0.19)	0.19 (0.29)	0.45 (0.21)	0.55 (0.31)	*	43.0
Biodiversity	0.73 (0.21)	0.37 (0.18)	0.99 (0.03)	–	0.50 (0.44)	0.75 (0.26)	0.45 (0.45)	0.62 (0.31)	0.76 (0.19)	0.62 (0.37)	*	31.1
Meadows and pastures	0.00 (0.01)	0.00 (0.00)	0.00 (0.00)	–	0.08 (0.14)	0.23 (0.11)	0.02 (0.07)	0.01 (0.05)	0.09 (0.12)	0.08 (0.13)	*	147.4
Livestock density	0.88 (0.14)	1.00 (0.00)	1.00 (0.00)	–	0.29 (0.28)	0.34 (0.18)	0.00 (0.00)	0.86 (0.12)	0.27 (0.26)	0.43 (0.35)	*	68.3
Wooded area	0.02 (0.05)	0.00 (0.01)	0.00 (0.00)	–	0.00 (0.02)	0.00 (0.01)	0.02 (0.06)	0.01 (0.03)	0.00 (0.00)	0.00 (0.02)	*	131.5
Accessibility				–							–	–

	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)		0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)		
Environment-friendly farming	0.07 (0.25)	0.00 (0.00)	0.00 (0.00)	–	0.00 (0.00)	0.01 (0.08)	0.04 (0.16)	0.00 (0.00)	0.10 (0.20)	0.03 (0.13)	*	140.3
Water use	0.48 (0.45)	0.11 (0.30)	0.02 (0.10)	–	0.31 (0.27)	0.18 (0.33)	0.76 (0.28)	0.26 (0.24)	0.12 (0.23)	0.26 (0.32)	*	85.6
Education	0.18 (0.36)	0.05 (0.21)	0.91 (0.27)	–	0.18 (0.27)	0.31 (0.31)	0.06 (0.17)	0.05 (0.19)	0.28 (0.39)	0.21 (0.33)	*	113.1

Notes: Numbers in parentheses are standard deviations; *Significance at $p < 0.001$

Annex 5: Normalized Values of AFI Indicators of Farms with a Low AFI Level by Economic Farm Size Classes in 2017

Variables	(I) 4 ≤ 8	(II) 8 ≤ 15	(III) 15 ≤ 25	(IV) 25 ≤ 50	(V) 50 ≤ 100	(VI) 100 ≤ 250	(VII) ≥250	Total	Significance	CV, %
In 2017 EW										
Use of fertilizers	0.75 (0.29)	0.89 (0.13)	0.76 (0.31)	0.80 (0.29)	0.35 (0.33)	0.28 (0.30)	0.28 (0.27)	0.72 (0.32)	*	46.3
Use of crop protection	0.79 (0.30)	0.93 (0.14)	0.86 (0.14)	0.89 (0.17)	0.47 (0.35)	0.31 (0.32)	0.29 (0.34)	0.77 (0.32)	*	43.5
GHG emissions	0.98 (0.01)	0.96 (0.01)	0.95 (0.03)	0.90 (0.05)	0.83 (0.06)	0.63 (0.14)	0.18 (0.23)	0.92 (0.16)	*	37.3
Energy intensity	0.50 (0.34)	0.60 (0.27)	0.49 (0.29)	0.65 (0.23)	0.75 (0.29)	0.81 (0.18)	0.84 (0.12)	0.56 (0.32)	*	21.7
Biodiversity	0.63 (0.36)	0.34 (0.39)	0.58 (0.33)	0.41 (0.37)	0.69 (0.24)	0.72 (0.17)	0.72 (0.17)	0.58 (0.37)	*	26.3
Meadows and pastures	0.10 (0.15)	0.01 (0.05)	0.02 (0.05)	0.07 (0.12)	0.03 (0.09)	0.02 (0.06)	0.05 (0.11)	0.07 (0.13)	*	78.0
Livestock density	0.52 (0.38)	0.51 (0.31)	0.65 (0.35)	0.53 (0.37)	0.86 (0.28)	0.86 (0.29)	0.81 (0.34)	0.57 (0.38)	*	24.2
Wooded area	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.03 (0.08)	0.04 (0.07)	0.00 (0.02)	*	174.7
Accessibility	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	–	–
Environment-friendly farming	0.03 (0.12)	0.00 (0.05)	0.12 (0.33)	0.01 (0.09)	0.00 (0.00)	0.01 (0.08)	0.00 (0.00)	0.03 (0.13)	*	178.2
Water use	0.15 (0.27)	0.44 (0.37)	0.35 (0.27)	0.41 (0.37)	0.77 (0.22)	0.86 (0.16)	0.92 (0.14)	0.31 (0.37)	*	52.2
Education	0.15 (0.25)	0.00 (0.05)	0.08 (0.18)	0.03 (0.13)	0.02 (0.11)	0.13 (0.25)	0.48 (0.45)	0.12 (0.24)	*	128.8
In 2017 PCA										
Use of fertilizers	0.83 (0.19)	0.89 (0.13)	0.84 (0.29)	0.93 (0.10)	0.66 (0.38)	0.41 (0.37)	0.34 (0.31)	0.80 (0.28)	*	34.3
Use of crop protection	0.84 (0.23)	0.91 (0.12)	0.95 (0.06)	0.96 (0.08)	0.74 (0.38)	0.44 (0.41)	0.35 (0.35)	0.81 (0.27)	*	33.4

(continued)

Variables	(I) 4 ≤ 8	(II) 8 ≤ 15	(III) 15 ≤ 25	(IV) 25 ≤ 50	(V) 50 ≤ 100	(VI) 100 ≤ 250	(VII) ≥250	Total	Significance	CV, %
GHG emissions	0.98 (0.01)	0.96 (0.01)	0.95 (0.03)	0.87 (0.06)	0.78 (0.07)	0.55 (0.17)	0.11 (0.18)	0.91 (0.20)	*	32.7
Energy intensity	0.48 (0.31)	0.69 (0.21)	0.63 (0.31)	0.70 (0.21)	0.70 (0.21)	0.77 (0.19)	0.84 (0.12)	0.55 (0.31)	*	16.7
Biodiversity	0.66 (0.36)	0.32 (0.40)	0.53 (0.41)	0.46 (0.34)	0.66 (0.30)	0.70 (0.24)	0.75 (0.14)	0.62 (0.37)	*	26.0
Meadows and pastures	0.10 (0.14)	0.01 (0.07)	0.04 (0.05)	0.07 (0.10)	0.07 (0.14)	0.07 (0.18)	0.05 (0.11)	0.08 (0.13)	*	45.2
Livestock density	0.43 (0.34)	0.37 (0.26)	0.20 (0.22)	0.27 (0.29)	0.41 (0.39)	0.68 (0.40)	0.75 (0.37)	0.43 (0.35)	*	46.1
Wooded area	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.02)	0.02 (0.07)	0.05 (0.07)	0.00 (0.02)	*	173.0
Accessibility	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	*	–
Environment-friendly farming	0.03 (0.12)	0.01 (0.07)	0.17 (0.38)	0.00 (0.01)	0.00 (0.00)	0.01 (0.08)	0.00 (0.04)	0.03 (0.13)	*	197.2
Water use	0.14 (0.19)	0.30 (0.26)	0.48 (0.25)	0.41 (0.33)	0.71 (0.28)	0.85 (0.17)	0.91 (0.14)	0.26 (0.32)	*	53.3
Education	0.22 (0.31)	0.01 (0.06)	0.19 (0.39)	0.07 (0.21)	0.28 (0.40)	0.22 (0.34)	0.62 (0.44)	0.21 (0.33)	*	86.3

Notes: Numbers in parentheses are standard deviations; *Significance at $p < 0.001$

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