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PhD Thesis

Optimizing inputs' use efficiency in agriculture: Operational, energy and environmental dimensions.

by

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Professor

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Optimizing inputs' use efficiency in agriculture: Operational, energy and environmental dimensions.

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Publications

Journal articles

1. **Kyrgiakos L.S**, Kleftodimos G., Vlontzos G, Pardalos PM. «A systematic literature review of Data Envelopment Analysis implementation in agriculture under the prism of sustainability», Operational Research, 2023; 23(1):7
2. **Kyrgiakos L.S**, Kleftodimos G., Kremantzis M.D, Vlontzos G, Pardalos PM. «Assessing efficiency differences in a common Agriculture Decision Support System - A comparative analysis between Greek and Italian durum wheat farms» Int. J. Food System Dynamics. 2023; 14 (1)
3. **Kyrgiakos L.S**, Vlontzos G, Pardalos PM. «Assessing efficiency of cotton farms considering qualitative factors under DEA TOPSIS model». Int. J. of Sustainable Agricultural Management and Informatics. 2021
4. **Kyrgiakos L.S**, Vlontzos G, Pardalos PM. «Ranking EU Agricultural Sectors under the Prism of Alternative Widths on Window DEA». Energies. 2021;14(4):1021.

Scientific Conferences

1. 14-18/2/2022 16th International European Forum (Igls-Forum) (180th EAAE Seminar), Garmisch-P, Germany, "Assessing homogeneity of durum wheat production protocol, using Data Envelopment Analysis (DEA) in Italy and Greece" **Kyrgiakos L.S**, Andrikopoulos G. and Vlontzos G.
2. 24-27/9/2020 HAICTA 2020, 9th International Conference on Information and Communication Technologies in Agriculture, Food & Environment, Thessaloniki, Greece, «Evaluating the efficiency of cotton cultivation considering climate change challenges», **Kyrgiakos L.S**, Kleisiari C., Niavis S., Vlontzos G., Moulogianni C. and Tigka E.
3. 24-26/8/2020 ESCC 2020, 7th International Conference on Energy, Sustainability and Climate Change, 24-26 August 2020, Skiathos, Greece, «Leguminous crops inputs use efficiency under climate change index», **Kyrgiakos L.S**, Kleisiari C. and Vlontzos G.

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General Comment on Graphical abstracts

The following section provides in an illustrative way the main findings of the current PhD thesis. More precisely, an overall illustration, which presents the literature review gaps as well as the contribution of this thesis per chapter, is presented. In the next pages, graphical abstracts, providing the main points of Introduction, State-of -the-art, Methodology, Application, Results and Conclusions section for each chapter, can be found.

Overall Graphical abstract

Optimizing inputs' use efficiency in agriculture: Operational, energy and environmental dimensions

Chapter 1: Introduction

Due to the increased need for providing to future generations equal access to natural and energy resources, the current Ph.D. thesis seeks to address new methodological approaches that contribute to a fairer sustainability assessment, under the scope of benchmarking and efficiency measurement in agriculture.

Chapter 2: Systematic literature review of 120 papers under PRISMA guidelines led to the following Literature Review Gaps (LRGs)

LRG1: Lack of social aspect

LRG2: Data availability

LRG3: Need for more complex methodologies.

Contribution

<u>Chapter 3</u>

DEA+TOPSIS methodology to incorporate demographic characteristics in the benchmarking process

<u>Chapter 4</u>

Cooperation with Barilla Firm; Farm data from 563 farms through GD.NET, a Decision Support System for durum wheat farmers in Italy and Greece

<u>Chapter 5</u>

Implementation of Window DEA methodology by using EUROSTAT data to highlight the influence of window width in the analysis process.

Chapter 6: Overall Conclusions

This thesis has provided the appropriate methodological tools so as to fulfil the literature review gaps presented in Chapter 2. However, agricultural research field has to deal with a great amount of variability and uncertainty, a point which can be fulfilled by collecting detailed datasets of agricultural activities and by implementing more complex methodologies than the traditional ones.

Graphical abstract: Chapter 2

A systematic literature review of Data Envelopment Analysis implementation in agriculture under the prism of sustainability

Introduction

Increasing number of DEA applications in agriculture has raised awareness about the different approaches and methodologies used. This section reviewed 120 papers so as to provide final remarks on the future goals that needs to be achieved in the agricultural operational research field as well as to underline the contribution of these papers to the three aspects of sustainability.

State-of-the-art

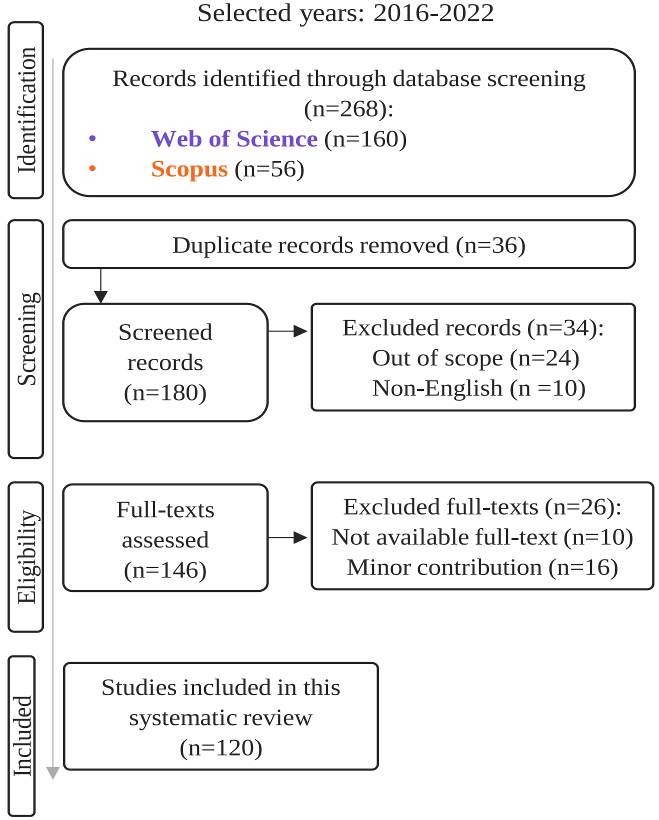
Papers were reviewed in 6 main categories and 23 sub-categories in total in an attempt to clarify the way that DEA is implemented in the agricultural field.

Categories
1. General information
2. DEA Implementation
3. DEA Extensions
4. Data Type
5. Data collection and processing
6. Sustainability Dimensions

Methodology

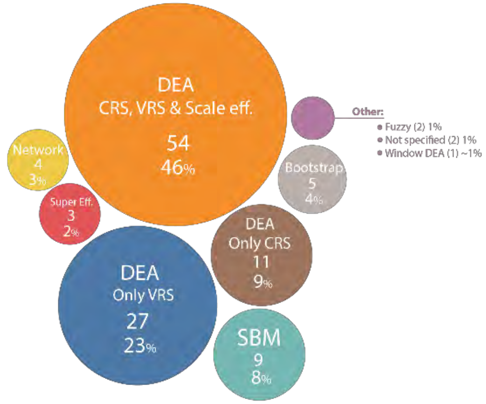
PRISMA guidelines

Terms: **DEA** + **sustainability** + **agriculture**
Selected years: 2016-2022



Results

Most of the papers are implementing basic DEA models while there is an urgent need for more complex methodologies which handle uncertainty and deal with panel data.



Conclusions

- There is a lack of a system both in national and international level that monitors agricultural expenses per farm.
- Lack of geospatial information is a limitation for acquiring more accurate final efficiency scores.
- Lack of the inclusion of the social dimension in the benchmarking process.
- Term «agriculture» should be used in keywords section.

Graphical abstract: Chapter 3

Assessing efficiency of cotton farms considering qualitative factors under DEA TOPSIS model

Introduction

Although the pillars of economy and environment are well represented when DEA is applied in agriculture, societal dimension is still the least presented

State-of-the-art

TOPSIS and DEA methodologies are combined to embody categorical variables in the overall benchmarking process.

Methodology

TOPSIS model was used to create a vector of benchmarking for societal characteristics that can be embodied in DEA data frame.

Data collection	Data processing	Outcome
Survey design	TOPSIS	Final Results
Questionnaire distribution	+	
Data validation	DEA	

Application

Data from 107 cotton farmers were collected through personal interviews with the use of a 3-part questionnaire.

Inputs

1. Area (ha)
2. Seeds (€)
3. *PPNPs (€)
4. Energy (€)
5. Irrigation (€)
6. Labor (€)

Outputs

1. Production (kg)
2. Revenue+subsidies (€)
3. Social characteristics

TOPSIS

1. Education
2. Experience

*Plant Protection and Nutrition Products

Results

Almost 65% of the examined farmers had an overall efficiency score greater than 0.9.

Ameliorations should be implemented on:

- Limitation of irrigation and labor expenses
- Differences between small, medium and large-scale producers
- Proper use of PPNPs

Conclusions

DEA-TOPSIS combination can be used to easily rank DMUs that contain both scale and ordinal variables, providing an additional handful tool for policy makers while contributing to quantification of SDGs achievement.

Graphical abstract: Chapter 4

Are there any efficiency differences between durum wheat farmers operating under a common Agriculture Decision Support System? A comparative study between Italy and Greece.

Introduction

This study assesses inputs' use efficiency of durum wheat farmers that are subscribed in GD.NET application, an Agricultural Decision Support System (ADSS) designed by Barilla and HORTA for this cultivation, in order to highlight differences between Italian and Greek farmers.

State-of-the-art

Comparing farmers of different countries operating under the suggestions of same ADSS.

Methodology

<u>Data collection:</u> **GD.NET database**

Undesirable outputs

- Seeds
- Fertilizers
- Diesel Consumption
- Plant Protection Products
- Labour
- Yield
- Carbon Footprint
- Water Footprint
- Ecological Footprint

Econ DEA

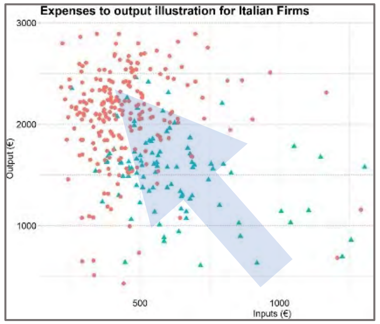
Eco DEA

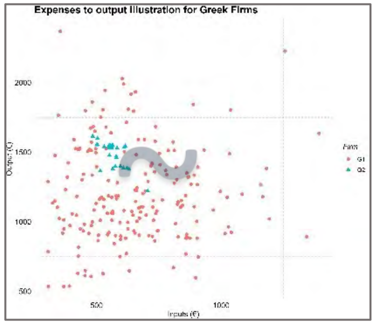
Results

Results indicate that there are differences on the implementation stage of GD.NET suggestions as well as a great potential for reduction of undesirable outputs.

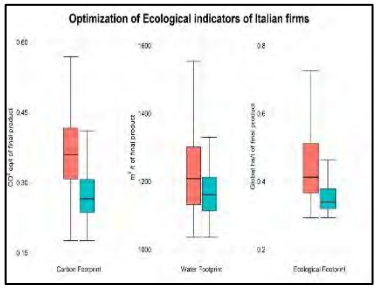
328 Farms

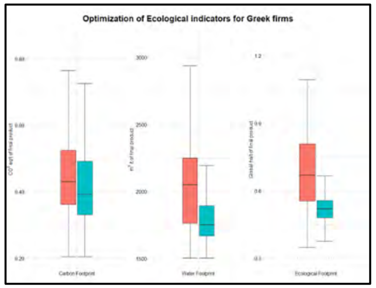
235 Farms





Potential Reductions of undesirable factors





Production Year 2020-2021

Discussion

Italian farmers are focusing to inputs' minimization. Greek farmers implement a looser production protocol.

Factors affecting the benchmarking process:

- Limited timeframe
- Durum wheat physiology
- Climate change
- Spatial characteristics
- Institutional structure

Conclusions

Increased need for appropriate land use especially at the current period of Russia-Ukraine war to ensure food security.

Graphical abstract: Chapter 5

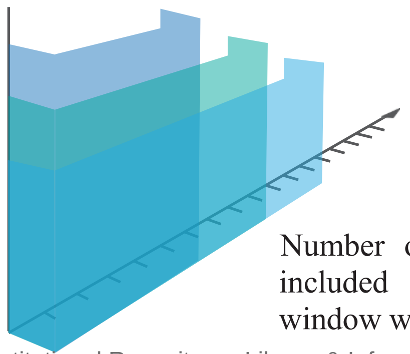
Ranking EU Agricultural Sectors Under the Prism of Alternative Widths on Window DEA

Introduction

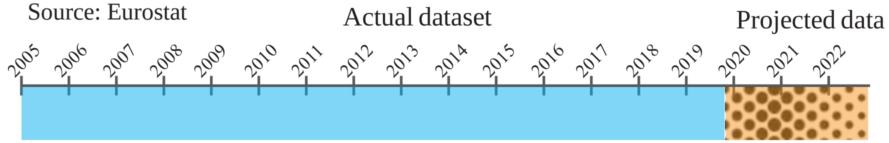
Window DEA is used for assessing the efficiency of EU agricultural sectors. Moreover 3-year-projections are estimated, as well as the influence of window width selection in final results is also presented.

State-of-the-art

Despite the fact that window width selection on Window DEA was arbitrary, in Section 5 influence of window width is assessed. Moreover, it is highlighted that when performing Window DEA analysis, there is an assumption of zero technological change.



Methodology



<u>DEA model:</u>
VRS model

Input-oriented

Country	Year	Inputs	Outputs
x1			
⋮			
x1			
⋮			
x26			
⋮			
x26			

Window 1

Reference Period: [2005, 2013]

Country	Year	Inputs	Outputs
x1	[2005, 2013]		
⋮	⋮		
x26	[2005, 2013]		

Window 2

Reference Period: [2006, 2014]

Country	Year	Inputs	Outputs
x1	[2006, 2014]		
⋮	⋮		
x26	[2006, 2014]		

•••

Window 10

Reference Period: [2014, 2022]

Country	Year	Inputs	Outputs
x1	[2014, 2022]		
⋮	⋮		
x26	[2014, 2022]		

DEA

Country	Year	Eff. score
x1	[2005, 2013]	
x26	[2005, 2013]	

DEA

Country	Year	Eff. score
x1	[2006, 2014]	
x26	[2006, 2014]	

•••

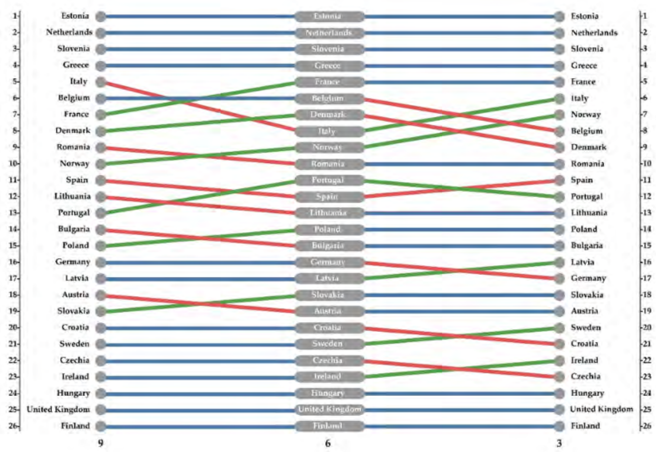
DEA

Country	Year	Eff. score
x1	[2014, 2022]	
x26	[2014, 2022]	

Country	Year	Eff. score
x1	[2005, 2022]	
x26	[2005, 2022]	
x1	[2005, 2022]	
x26	[2005, 2022]	
x1	[2005, 2022]	
x26	[2005, 2022]	

Results

Influence of window width selection was tested on final results of the benchmarking process.



Conclusions

- Ideal window width estimation has been calculated.
- Differences between alternative window widths have been highlighted.
- Estimation of ideal window width showed that significant technological change is evident every 7 years, which matches with CAP's programming period each time.
- Importance of continuous monitoring, to assure sustainable accurate measurements.

Highlights

Chapter 2

- PRISMA guidelines were used to evaluate 120 papers regarding DEA and sustainability between 2016-2022.
- Social dimension is often absent from the overall “sustainability” assessment.
- Data availability seems to be an issue for acquiring data on farm level.
- Increased need for more complex methodologies than the conventional DEA approaches is evident.
- «Agriculture» term should be used more systematically in abstract and keywords.

Chapter 3

- Inclusion of demographic characteristics in the benchmarking process.
- Field survey of 107 cotton farmers for cultivation year 2019-2020.
- Emphasis was given on the incorporation of ordinal values in the benchmarking process.

Chapter 4

- Assessment of applied practices under the same Agricultural DSS.
- Quantification of differences between Italian and Greek farmers.
- Considerable potential for minimizing undesirable outputs.
- Hints for appropriate land use management to ensure food security.

Chapter 5

- Assessment of EU agricultural sectors for time period: 2005-2019.
- Estimations for 3-year projections.
- Highlight the influence of window width selection when performing WDEA.
- Technological change is evident in a 7-year-timeframe, which coincides with the time period of CAP’s reforms.

Περίληψη

Η παρούσα πτυχιακή διατριβή έχει ως στόχο να συνεισφέρει σε νέες μεθοδολογικές προσεγγίσεις που αφορούν την αριστοποίηση χρήσης εισροών υπό το πρίσμα της βιώσιμης ανάπτυξης (οικονομία, κοινωνία, περιβάλλον) στον κλάδο της γεωργίας.

Για το λόγο αυτό, παρατίθεται μια σύντομη εισαγωγή που καθορίζει τη συλλογιστική πορεία με βάση την οποία η συγκριτική αξιολόγηση αγροτικών συστημάτων είναι επιβεβλημένη, λαμβάνοντας υπόψιν τις οδηγίες που έχουν δοθεί σε παγκόσμιο επίπεδο από τον Οργανισμό των Ηνωμένων Εθνών, ενώ υπάρχει και μια ειδικότερη περιγραφή για τη μέθοδο της Data Envelopment Analysis (DEA), που είναι και η βασική μεθοδολογία που διερευνάται στην παρούσα διατριβή.

Στο Κεφάλαιο 2 καταγράφονται τα ερευνητικά ερωτήματα που προέκυψαν από την ανάλυση 120 άρθρων στον τομέα της αριστοποίησης χρήσης εισροών στον κλάδο της γεωργίας. Πιο συγκεκριμένα, υπάρχει αναγκαιότητα για: 1) την εισαγωγή κοινωνικών παραγόντων στη συνολική διαδικασία αξιολόγησης ώστε να λαμβάνονται αποφάσεις που να καλύπτουν και τους 3 πυλώνες της βιώσιμης ανάπτυξης, 2) τη δημιουργία βάσεων δεδομένων αγρού που να παρουσιάζουν υψηλό βαθμό ακρίβειας 3) τη χρήση πιο σύνθετων μεθοδολογικών προσεγγίσεων, όπως αυτές εφαρμόζονται σε άλλους κλάδους της επιχειρησιακής έρευνας.

Στο Κεφάλαιο 3, πραγματοποιείται ένας συνδυασμός της DEA με την πολυκριτηριακή μέθοδο λήψης αποφάσεων TOPSIS, προκειμένου να εξαχθούν αποτελέσματα που εμπεριέχουν και την κοινωνική διάσταση, εστιάζοντας στο πρώτο βιβλιογραφικό κενό. Η έρευνα που πραγματοποιήθηκε αφορούσε 107 παραγωγούς βάμβακος στη Θεσσαλία και τη Μακεδονία. Τα τελικά αποτελέσματα δείχνουν ότι υπάρχει ένα καλά εγκαθιδρυμένο πρωτόκολλο παραγωγής ενώ είναι ελάχιστοι οι παραγωγοί που παρουσιάζουν χαμηλό βαθμό αποδοτικότητας. Αναφορικά με το συνδυασμό DEA και TOPSIS φαίνεται να είναι ιδιαίτερα χρήσιμος, όχι μόνο για την ενσωμάτωση κοινωνικών χαρακτηριστικών, αλλά και για περιπτώσεις που είναι δύσκολο να υπάρχουν ακριβείς μετρήσεις αγρού.

Το Κεφάλαιο 4 αναφέρεται σε μια μελέτη περίπτωσης όπου μελετάται η αποδοτικότητα χρήσης εισροών για παραγωγούς σε Ελλάδα και Ιταλία μέσα από το δίκτυο του GD.NET, ενός συστήματος λήψεων αποφάσεων για την καλλιέργεια σκληρού σίτου, το οποίο έχει προκύψει από τη συνεργασία της HORTA με την

Barilla. Στη συγκεκριμένη περίπτωση, αναδείχθηκε η διαφορά που προκύπτει από την εφαρμογή των καλλιεργητικών συμβουλών που παρέχει το GD.NET. Πιο συγκεκριμένα, αποδείχθηκε ότι οι Ιταλοί αγρότες έχουν μια ξεκάθαρη τάση για μείωση των εισροών, ενώ στην Ελληνική επικράτεια η εφαρμογή του πρωτοκόλλου δεν παρουσιάζει την ίδια συνεκτικότητα. Παρόλα αυτά, το κεφάλαιο αυτό προωθεί τον τρόπο λειτουργίας μιας σύγχρονης γεωργίας με τη συλλογή και επεξεργασία δεδομένων αγρού, μέσω συστημάτων υποβοήθησης λήψης αποφάσεων, που έχουν ως στόχο την αύξηση της αποδοτικότητας και τη μείωση των περιβαλλοντικών επιπτώσεων.

Στο Κεφάλαιο 5 παρουσιάζεται η εφαρμογή της DEA με τη χρήση δεδομένων χρονοσειράς από τους αγροτικού τομείς της Ευρωπαϊκής Ένωσης. Το μεθοδολογικό ενδιαφέρον της συγκεκριμένης έρευνας αποσκοπεί στην επίδραση της επιλογής του κατάλληλου παραθύρου (Window), το οποίο αντιστοιχεί με το χρονικό διάστημα με βάση το οποίο η μεταβολή της επίδρασης της τεχνολογίας θεωρείται μη σημαντική. Στην περίπτωση αυτή το ιδανικό χρονικό παράθυρο που προέκυψε ισοδυναμούσε με 7 έτη, που αντιστοιχούν με το χρονικό διάστημα εφαρμογής των προγραμματικών περιόδων εφαρμογής της ΚΑΠ.

Στο τελευταίο κεφάλαιο πραγματοποιείται μια σύνοψη των κεφαλαίων που έχουν προηγηθεί καθώς και οι προκλήσεις που συνοδεύουν την εφαρμογή της DEA από την πλευρά των επιχειρήσεων αλλά και τον ακαδημαϊκό κλάδο, προκειμένου να επιτευχθεί η μεγαλύτερη δυνατή συμβολή προς τις γενικές κατευθύνσεις του ΟΗΕ για επίτευξη της βιώσιμης ανάπτυξης έως το 2050.

Λέξεις-Κλειδιά: αριστοποίηση, αποδοτικότητα, Περιβάλλουσα Ανάλυση Δεδομένων, TOPSIS, Window DEA, Αγροτικό σύστημα λήψης αποφάσεων, σκληρό σιτάρι, βαμβάκι, γεωπονία

Abstract

The current PhD thesis aims to contribute to new methodological approaches concerning the optimization of inputs use efficiency, under the prism of sustainable development (economy, society, and environment) in the agricultural sector.

For this reason, a brief introduction is provided, outlining the rationale on which the benchmarking of agricultural systems is imperative, based on the guidelines given at the global level by the United Nations (UN), while there is also a more specific description of Data Envelopment Analysis (DEA), which is also the methodology assessed in this thesis.

Chapter 2 outlines the research questions that emerged from the analysis of 120 articles in the field of optimization in the agricultural sector. More specifically, there is a need: 1) to introduce social factors into the overall assessment process, so that decisions can be made that cover all 3 pillars of sustainable development, 2) to create farm specific databases that show a high degree of accuracy 3) to use more complex methodological approaches, such as those applied in other sectors of operational research.

In Chapter 3, a combination of DEA with the multi-criteria decision-making method TOPSIS is applied, to derive results that also include the social dimension, focusing on the first literature gap. The research carried out concerned 107 cotton producers in Thessaly and Central Macedonia regions. Final results show that there is a well-established production protocol, while there are few producers that perform under a low degree of efficiency. Regarding the combination of DEA and TOPSIS, it seems to be particularly useful not only for the integration of social characteristics, but also for cases where it is difficult to have accurate field data.

Chapter 4 refers to a case study where the inputs' use efficiency of producers in Greece and Italy is studied through the network of GD.NET, a decision-making system for the cultivation of durum wheat, which has derived from the collaboration of HORTA and Barilla. In this case, differences resulting from the application of the Agricultural Decision Support System (ADSS) provided by GD.NET on a local and national level, were highlighted. More specifically, it seems that Italian farmers have a clear tendency to reduce their inputs, while Greek durum wheat producers do not apply the production protocol under the same consistency. Nevertheless, this chapter

promotes the way of how modern agriculture should be applied, collecting and processing field data with the use of ADSS, aiming at increasing efficiency and mitigating negative environmental externalities.

Chapter 5 presents the application of DEA using time series data of the agricultural sectors of the European Union members. The methodological interest of this research is focusing on the impact of appropriate window width selection, which corresponds to the time interval based on which the impact of technology change is considered as insignificant. In this case, the ideal window width appeared to be of 7 years, which corresponds to programming periods of the Common Agricultural Policy (CAP).

In the last chapter, a summary of all chapters is being presented, as well as the challenges that accompany the application of DEA on a business and academic perspective, to comply with the general directions of the UN, to achieve sustainable development until the year 2050.

Keywords: optimization, efficiency, Data Envelopment Analysis, DEA, TOPSIS, Window DEA, Agricultural Decision Support System (ADSS), durum wheat, cotton, agriculture

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Table of Abbreviations

Abbreviation	Full name
CAP	Common Agricultural Policy
DEA	Data Envelopment Analysis
DMU	Decision Making Unit
ADSS	Agricultural Decision Support System
EC	European Commission
LRG	Literature Review Gap
UN	United Nations
PA	Precision Agriculture

Chapter 1

1.1. General Introduction

Common Agricultural Policy (CAP) was officially born on 14 January 1962, proposing various regulations for the productivity increase of the agricultural sector. Up to now, a gradual transition of a purely economic approach to a holistic one that considers economic, environmental, and social aspects of the agricultural sector is apparent. United Nations' Sustainable Development Goals (SDGs) (2015) , Biodiversity Plan, Farm to Fork Strategy and Green Deal's were highly influential towards the formation of a European agricultural framework capable of achieving increased competitiveness, environmental protection and development of rural societies. Promotion of the “sustainability” term is of a high importance issue for the achievement of the above objectives. This determines that the successful performance of a farmer or of a country is not based only on meeting pure economic goals, but environmental protection, as well as the level of well-being of farmers and citizens of rural areas, are equally important targets to be met.

Image 1.1 : Sustainable Development Goals, Source: United Nations, 2015

The newly introduced CAP 2023-2027 started to be implemented from 1st January 2023. It incorporates the SDGs’ principles, setting 10 Objectives that contribute to sustainability in the agricultural field (European Commission, 2022b). As shown in Image 1.22, the first three objectives are referring to the economic dimension, the following three ones to environmental protection, while the last three ones are referring to the societies of rural areas representing the social dimension. It should be noted that knowledge and innovation was added as an extra objective to highlight the importance of research and development in European agriculture.

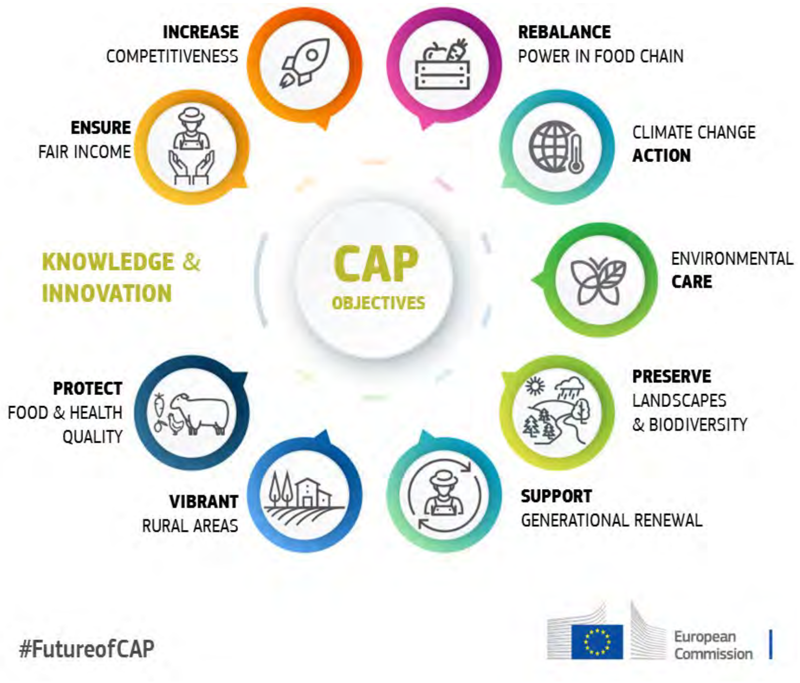

Image 1.2: The 10 CAP Objectives, Source: (European Commission, 2022b)

More precisely, the economic dimension is expressed as labour productivity and opportunity cost (Objective 1), management of conventional production factors (land, labour, and capital) towards sustainable production of agricultural products (Objective 2) and strengthening of farmers' position in the supply chain regarding their negotiating power (Objective 3). Following, the environmental dimension is considered as the actions for climate change mitigation (Objective 4), soil health (Objective 5) and biodiversity increase in farmland landscapes (Objective 6). The social dimension is consisted of objectives that support the income and living standards of young farmers (Objective 7), promote favourable treatment of isolated areas (Objective 8) and reduction of antibiotics use (Objective 9). It is evident that the future of the European agriculture is considered as a multi-objective mission, where close monitoring and continuous evaluation of the resources used are needed to ensure the success of it.

Budget allocation can elucidate the intentions of the European Commission regarding the development of the agricultural sector for the upcoming years. For instance, climate change relevant activities will be further funded compared with previous CAP periods (40% of total CAP budget). EU provides motives for farmers to be part of groups that are enabled to organic farming, low carbon farming, Precision Agriculture (PA) through eco-schemes. Knowledge and innovation goal will utilize 10 billion euros for Horizon projects dedicated to food supply chain, bioeconomic models and development of rural areas. It is also anticipated that the dissemination of research results will be done via agricultural advisors, who will then transfer this knowledge on an operational level in EU farming, strengthening by this way agricultural value chains and improve farms' competitiveness globally. It is prominent that the EU has already settled milestones that should be checked annually, with further reforms to be implemented if needed.

Figure 1.1 presents overall CAP expenses by support type for the period 1980-2021 (European Commission, 2021a). More specifically, from 1991 to 2012, there is an elimination of expenses for export subsidies, with market support subsidies following to a large extent the same path. For the 1992 -2007 time period, coupled payments are radically reduced. Decoupled payments deployed for the first time in 2005, being until nowadays the dominants means for supporting directly agricultural income, without jeopardizing market distortions. Moreover, it is evident that greening payments cover almost one third of total budget of decoupled payments, while the budget for rural development and climate change management have increased as well. A gradual transition towards a European agriculture of increased competitiveness with high environmental standards and increased support to research and innovation field is depicted (Figure 1.1). Current CAP's objectives are contributing towards this direction further promoting the above-mentioned aspects.

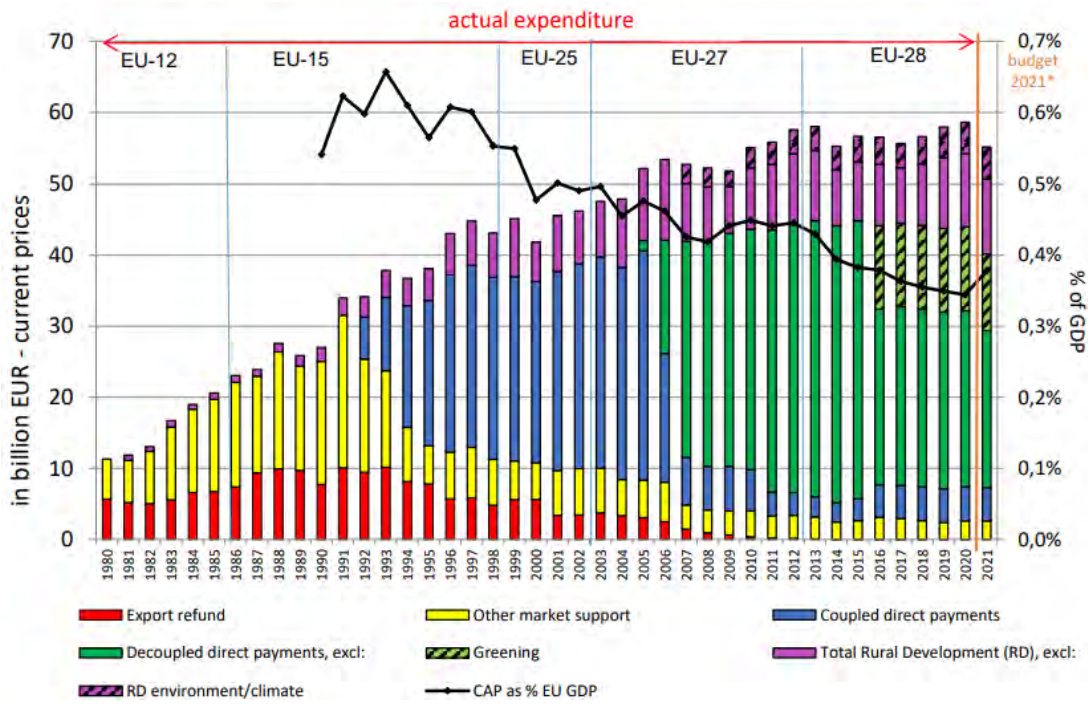

Figure 1.1: CAP Expenditures, Source: (European Commission, 2021a)

Figure 1.2 presents the €291 billion budget allocation for Pillar 1 of CAP 2023-2027, referring to the direct support of farmers' income. Additionally, €95.5 billion will be spent for the support of rural areas (Pillar 2). Next generation EU injection concerns budget allocation for farmers' relief due to COVID-19 pandemic.

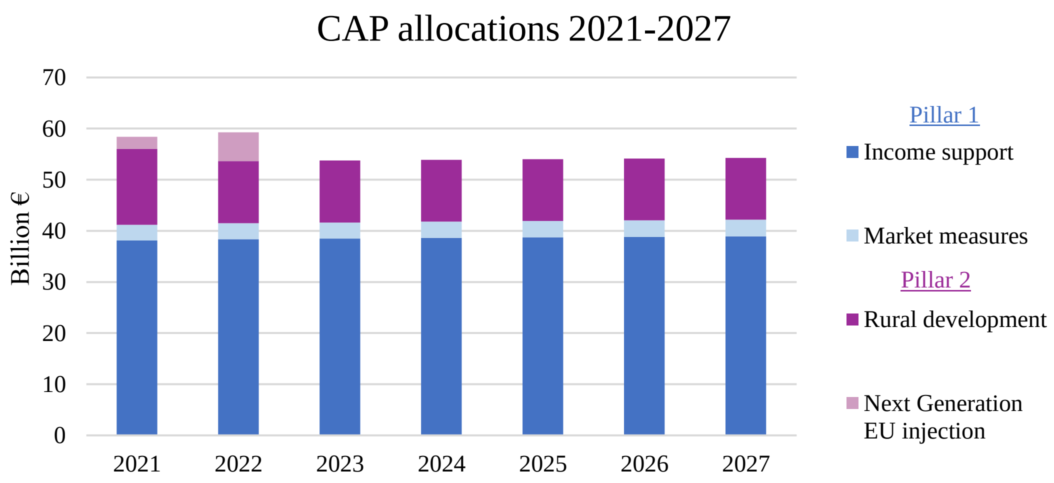

Figure 1.2: CAP Allocation 2021-2027, Source: (European Commission, 2022a), Author's elaboration

European agriculture is focusing on an integrated approach for maintaining environmental protection and social cohesion in rural areas, where agricultural activities are dominant. From an economic perspective, building consensus between producers and policy makers is more than a necessity, accepting the fact that successful farming is not defined only by economic terms but also by fulfilling a group of criteria related to environmental and social indicators (Latruffe et al., 2016). Furthermore, the concern about environmental protection has undoubtedly increased, compared to previous decades (Hoffmann et al., 2022), especially with the increase of the impact of climate change, as well as the importance of the social dimension in agriculture (Janker et al., 2019; Nowack et al., 2022).

Terms such as increasing competitiveness, productivity and efficiency are top priorities on the CAP agenda. Increasing the efficiency of a system is considered as necessary precondition to minimize the use of additional resources, which can be used in other production processes, thus leading to higher levels of productivity. From an economic point of view, which corresponds with the first three CAP's objectives, enhancement of inputs' use efficiency is crucial to achieve competitive prices, high quality standards and increased levels of environmental protection for the final products. Apart from capital, land is another significant production factor which simultaneously serves many purposes like providing space for cultivation, suppling nutrients to the plants and enhancing biodiversity. However, its value is most evident when its functionality is absent, in cases of places which face challenges of soil erosion, desertification or high concentrations of heavy metals. That is the reason why the EU Commission has set it as a separate objective to highlight its importance and its role in local economies. Agricultural labor is another aspect that is thoroughly considered by the CAP's objectives, both from the Objective 1 which supports farmers income but also generation renewal (Objective 7) which enhances the implementation of innovative technologies from young farmers and contributes to a better understanding of the supply chain requirements. Collaboration under an agricultural cooperative scheme can further increase farmers efficiency, since lower prices of agricultural agrochemicals or more favorable repayment conditions that ensure them better liquidity can be achieved. At the same time, farmers' bargaining power regarding the price and terms of sale of their final products also increases. In this way, the reduction of production costs, as well as the emergence of opportunities for better commercial agreements, are leading to agricultural systems of higher efficiency that reward the parts of the supply chain that hold the greatest risk volumes (Objective 3).

Regarding the environmental aspect, climate change mitigation (Objective 4) is considered significant from the EU Commission's side to mitigate its consequences, due to the high vulnerability of the sector to this phenomenon compared to other economic sectors. Apart from the income loss for farmers, food security issues are rising in case of extreme weather events. Additionally, an integrated approach for minimum agrochemical use is promoted to produce safe agricultural products for human consumption, which cause the least possible impact on living organisms and environment (Objective 4). Creation of resistant varieties to extreme exogenous conditions would act as a resilience factor, in terms of final production of agricultural products. Even if their productivity was lower, they could probably ensure sufficient quantities of final products, so as not to create disruptions in the supply chain. Despite productivity loss, the overall efficiency of the system could remain at the same levels, in cases where the farmers were using less inputs for these cultivars. Several actions like implication of precision agriculture (lower fertilizer applications and machinery carbon footprint), minimization of enteric fermentation and manure management are leading to an overall decreased amount of Greenhouse Gases emissions, which is another great concern of modern agriculture. Minimization of the environmental impact of agricultural activities is usually accompanied by savings in resources such as agrochemicals and energy, which brings positive changes in the economic sector as well.

Policy framework refinements, concerning the social aspect of the agricultural sector, are focusing on providing guidelines for smoothing the tendency of the arable land concentration in the hands of few people (Objective 7). Moreover, additional support is provided to young farmers to face high rents, increased cultivation costs and initial purchase costs of agricultural machinery/equipment. An effort to minimize the gender and age gap is evident in promoting similar values to those of the SDGs in rural societies. This will further support the revival of rural areas which correspond for 44% of total EU area, but they concentrate only 19% of the EU Population (Objective 8). Considering only the economic perspective, the above-mentioned approaches are not as efficient as possible, due to the fact that the involvement of several limiting factors such as multi-division of agricultural land or support of younger generation. However, it is of paramount importance for European Commission to provide appropriate guidelines for creating an agriculture that will meet sustainability goals. For this reason, it is considered necessary to optimize each dimension (economic, environmental, societal) separately to achieve maximum overall efficiency. It should be noted that all dimensions are interrelated and that the overall success of one is closely related to the success of the other. For instance, the rural population cannot be renewed without simultaneously providing economic incentives for the return of young people in rural areas. Also, reducing the carbon, water and environmental footprint is not possible without the use of new technologies produced by research organizations funded by the taxes of European citizens.

Furthermore, another aspect that is under presented through the CAP objectives is the spatial dimension. Kleinhanß et al., (2007) states that efficiency can be assessed from different spatial perspectives (farm-level, local, national, European) and under different dimensions (economical, environmental, social), highlighting the difficulty of subsidy sharing. Improving efficiency in agriculture on an international level is a challenge of growing importance, difficult though to be met. The arrival of agriculture 4.0 (Zhai et al., 2020) will contribute to collecting the necessary data for a more realistic, continuous and up-to-date assessment of the sector, justifying in a more credible way the allocation of funds supporting agricultural incomes and investments.

Multiple frameworks which contribute on the sustainability dimensions assessment have been grouped and analysed from Lacoste et al. (2017). Both qualitative and quantitative methods are used to provide further insights on this topic. Participatory approaches can be used to highlight the concerns of local communities, as well as to transfer knowledge that is difficult to be acquired elsewhere (Vaidya & Mayer, 2014). This type of analysis is ideal for an initial exploratory phase, providing the appropriate initiatives to a research team to further clarify the challenges of local communities. Thus, knowledge and information of local communities, regarding sustainability issues, can influence the final outcomes of this method.

Life Cycle Assessment (LCA) is the most well-known approach, which measures the environmental impact of the production process. Besides the fact that this methodology can quantify carbon, water and environmental footprint, as well as other environmental impacts depending on the given system each time, it does not present high flexibility in the incorporation of agricultural practices like organic farming or implication of agroecological practices (Meier et al., 2015; van der Werf et al., 2020). This is due to the fact this methodology focuses on an output-oriented approach and such variables are not taken into consideration.

Creating Key Performance Indicators (KPIs) can quantify the results derived from the above type of research. For instance, Agovino et al. (2019) have included 16 variables to assess sustainability following Wroclaw Taxonomic method, creating Index of Sustainable Agriculture (ISA). They have concluded in three different groups of high, medium and low sustainability levels for European countries. Similar approach was followed by A. K. Singh et al. (2019) by creating an environmental index for Asian countries for the 1990-2012 time-period. Although this study has included only environmental indicators, it has also embodied policy recommendations, adding another aspect in the environmental assessment.

At the same time as the publication of the 17 SDGs, the United Nations also issued a protocol for sustainability assessment in the agricultural sector (FAO, 2015). More precisely, Sustainability Assessment of Food and Agriculture (SAFA) can be described as a constructed protocol which aims to provide scores (1-5) on the end of its process for the environmental, economic, societal, and political aspects of an entity. Although this type of analysis can highlight weaknesses in an agricultural supply chain, it does not involve any comparison among different similar units, and the final outcome can be considered as subjective.

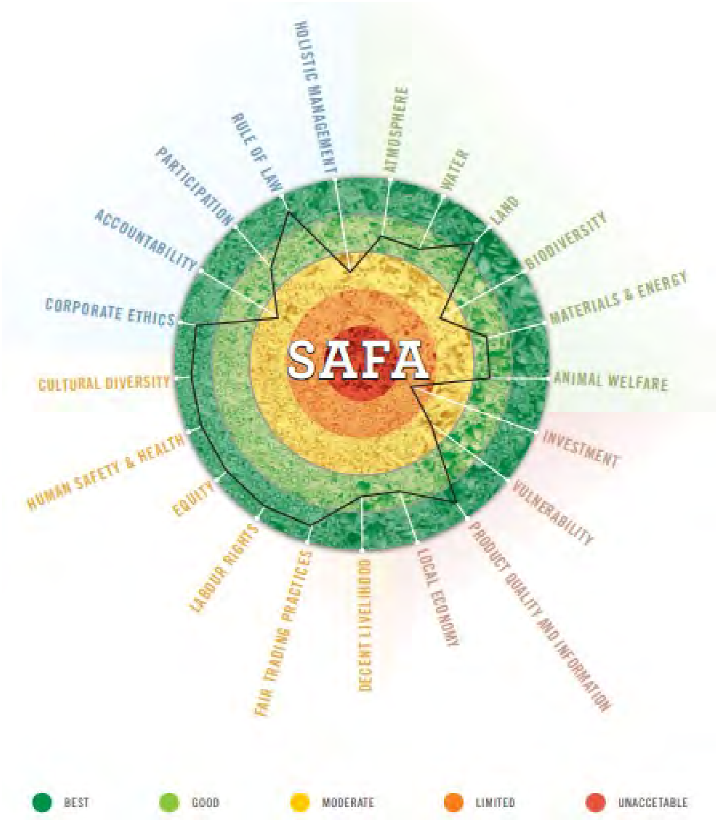

Figure 1.3: Sustainability Assessment of Food and Agriculture (SAFA) results illustration, Source: (FAO, 2015),

However, the aforementioned methodologies are not able to quantify to a large extent, the changes that should be implemented in order to achieve sustainability in the long term. It is therefore of considerable necessity the application and development of assessment and benchmarking statistical tools and models, to measure agricultural performance and efficiency, taking into consideration the group of criteria being introduced by CAP policy makers and consumers' priorities and concerns for greener and safer primary sectors.

1.2. Efficiency Measurement Techniques

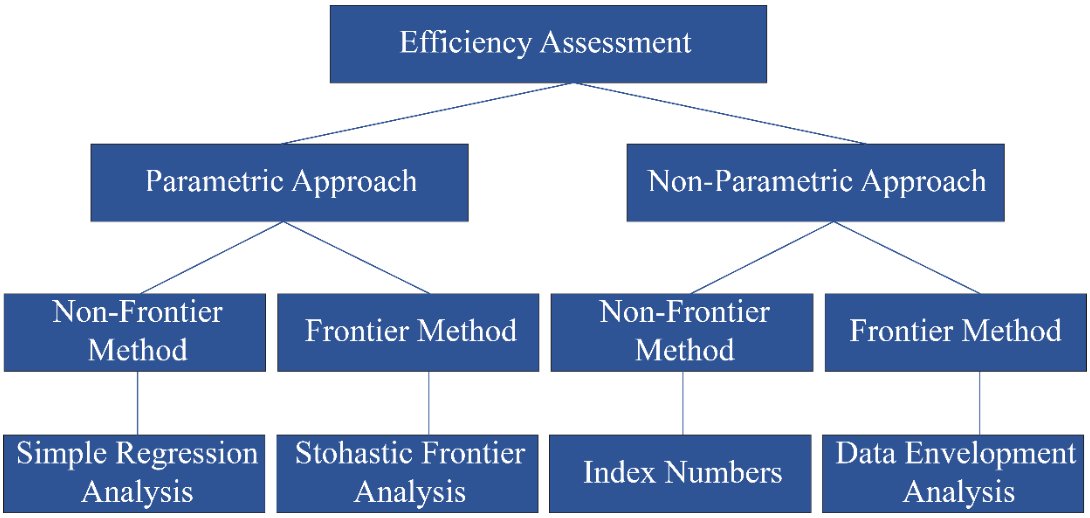

Figure 1.4: Efficiency assessment methodologies, Author's elaboration

Figure 1.4 visualizes the entire spectrum of efficiency assessment methodologies. Parametric models are used to evaluate efficiency, by computing noise and error performance. Stochastic Frontier Analysis (SFA), which was introduced by Aigner et al. (1977) and then developed by later researchers is the most renowned techniques when it comes to parametric models. The method attributes the error: 1) to the general noise of the data 2) to the technical efficiency term. Compared to DEA, SFA as a parametric model does not provide only final values but error intervals are included as well.

As mentioned by Theodoridis & Psychoudakis (2008) the above two efficiency analysis methods, namely DEA and SFA, are the ones that are used most often but the research goal should always be to create a database for the substantial improvement of the agri -food sector. It is also worth noting that in the early 2000s most articles referring to SFA analysis were mainly implemented for economic efficiency at the farm level (Ören & Alemdar, 2006), while in recent years there has been a swift of articles referring to sustainability and environmental aspects of agricultural activity (Deng & Gibson, 2018; Ho et al., 2018)

Data Envelopment Analysis (DEA) is the mostly used methodology when it comes to efficiency assessment, as well as the estimation of target values that should be accomplished after the benchmarking process. Figure 1.5 presents the wide applicability of DEA on multiple fields such as engineering, computer science, business management and accounting etc. as well as environmental science.

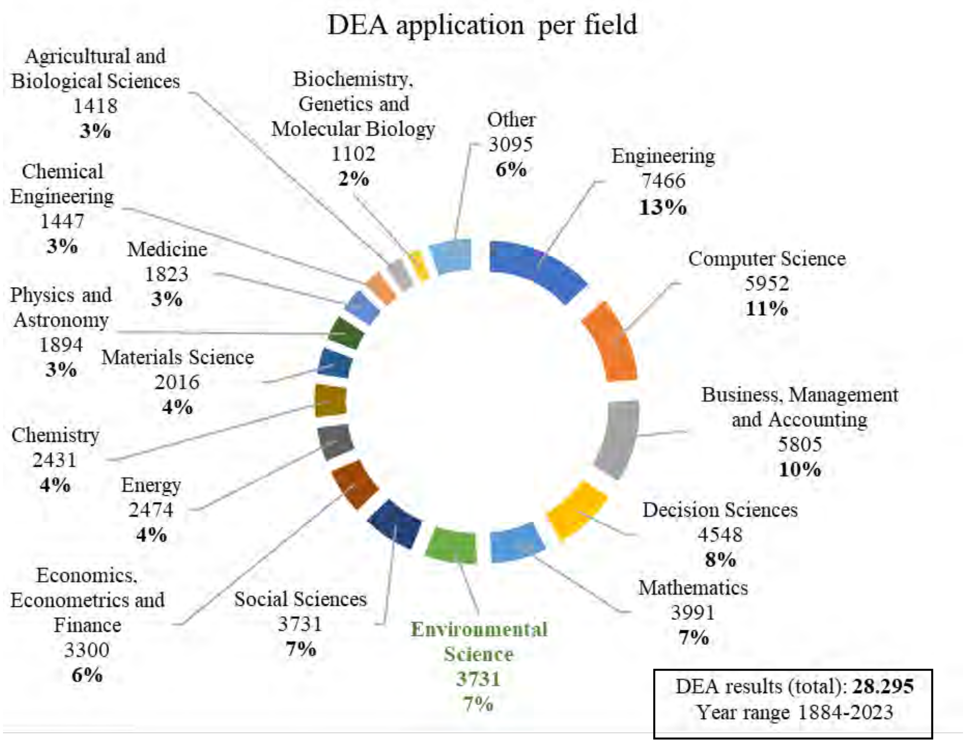

Figure 1.5: DEA publications from 1884-2022, Source: Scopus database, Author's elaboration

More precisely DEA applicability in the agricultural field is also proved through the increasing number of annual publications (Figure 1.6). However, as it can be seen in Chapter 2, there is a need to implement more complex DEA methodologies to obtain results of greater explanatory power.

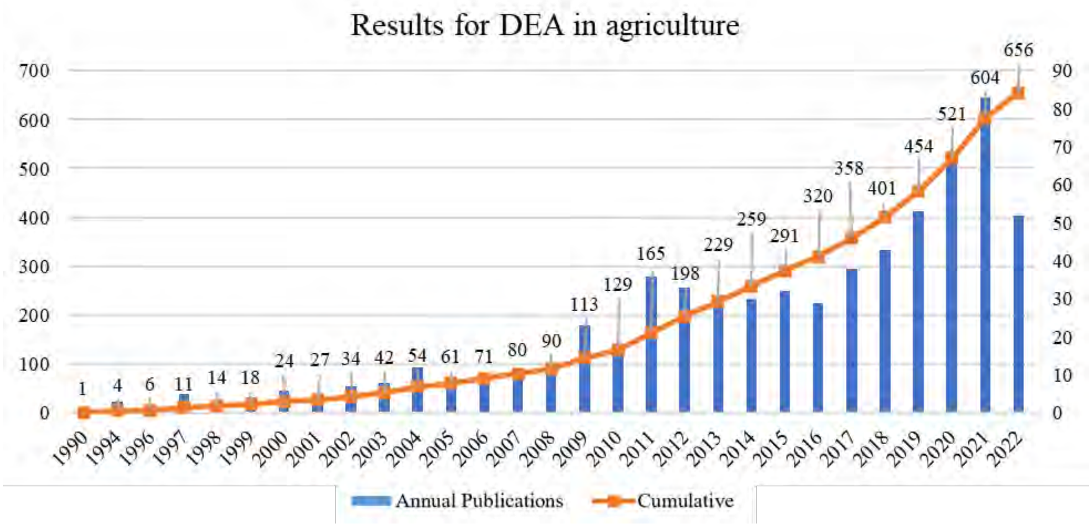

Figure 1.6: DEA publications from 1990-2022, Source: Scopus database, Author's elaboration

1.3. DEA interpretation

Focusing on the objectives of this thesis, a short introduction about the basic structure of DEA should be analysed. DEA is a non-parametric technique, which uses linear programming principles to estimate measures of technical efficiency of different units. Given the fact that every production process has the need of *n* inputs (I) to produce *k* outputs (O), there are two approaches of improving the efficiency of a given system. The first one includes the inputs minimisation, maintaining the same number of outputs (input oriented), while the second one maintains the used inputs in same levels, increasing the output (output oriented). In general, an input-oriented approach is selected for most DEA applications in agriculture, for minimising production costs and the environmental impact of every agricultural activity. Moreover, final yield cannot be reassured, being this another reason for focusing on inputs' use minimisation. In the following figures both approaches are being presented. (Figure 1.7, Figure 1.8).

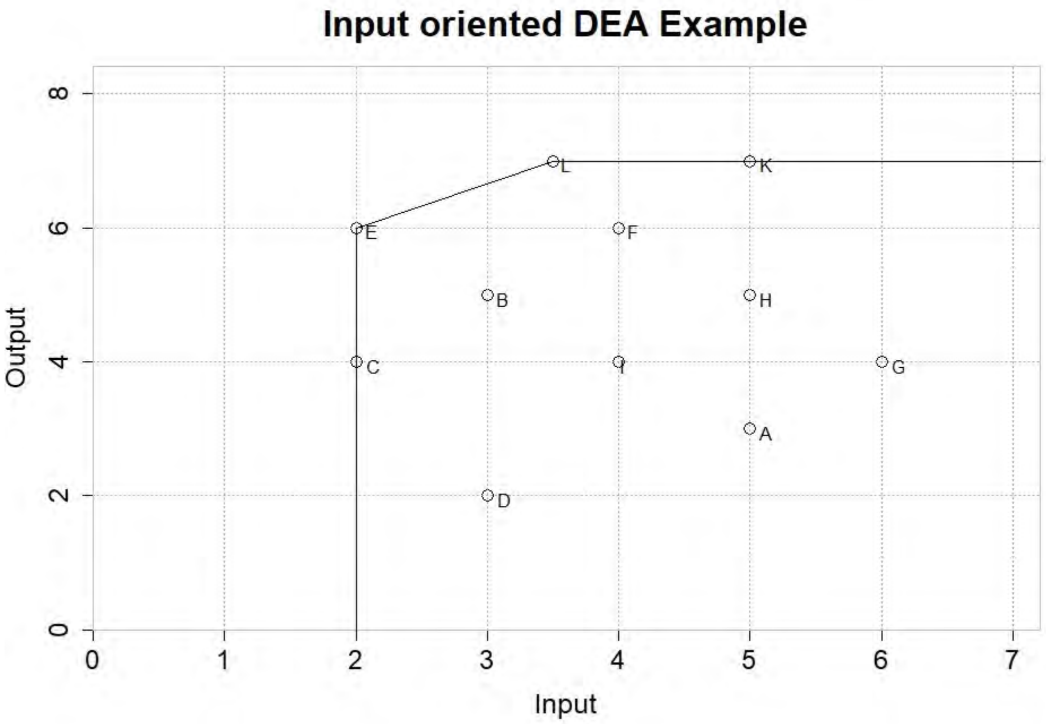

Figure 1.7: Input oriented DEA Example, Author's elaboration

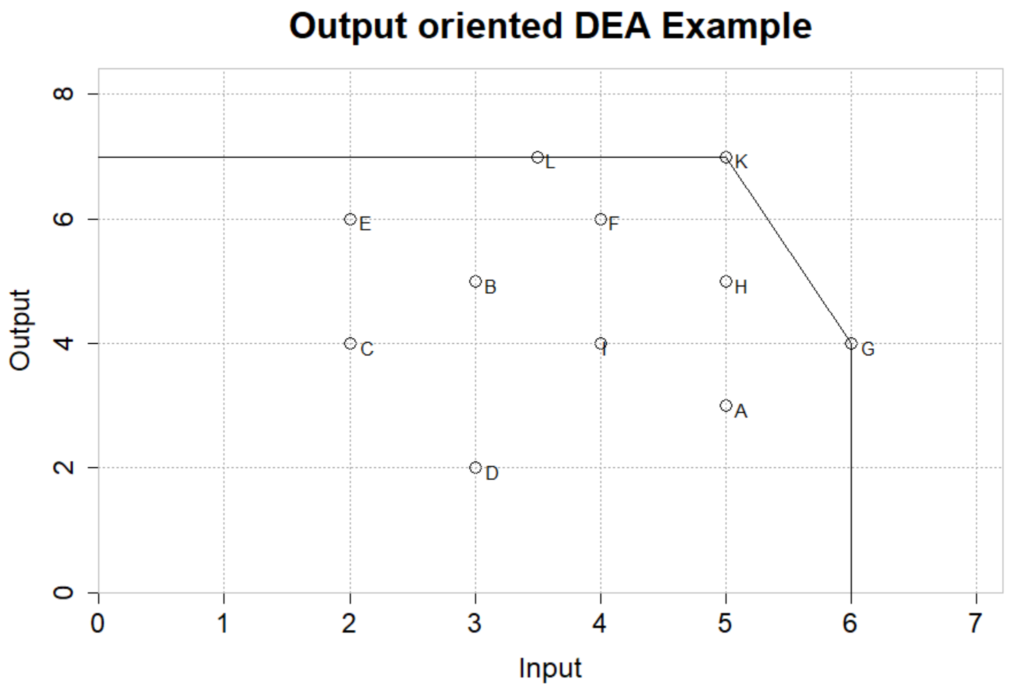

Figure 1.8: Output oriented DEA Example, Author's elaboration

Explaining DEA methodology in further details, it should be mentioned that there are two main models. The first one is Constant Returns to Scale (CRS) which assumes that the increase of one unit of input is increasing the output at the same way. Additionally, Variable Returns to Scale assumes that the relationship between Inputs and Outputs is not constant, but it can be either increasing or decreasing. Every unit which makes decisions about Inputs use and achieved Outputs is called Decision Making Unit (DMU). When performing DEA in agriculture, every farm is a different DMU. The most efficient DMUs are receiving a score of 1, formulating the efficient frontier. On the contrary, the least efficient DMUs score from 0.99-0. Technical inefficiencies formulate the operational changes that a DMU should implement, in order to be efficient. Scale inefficiency can be easily explained from the Figure 1.9. DMU (C) can produce 4 outputs by using 2 inputs. In comparison with all DMUs involved, it is the most efficient one, apart from its comparison with DMUs (E,L,K). DMU (C) should mitigate its slacks too and achieve the same productivity levels as DMU E to be fully efficient.

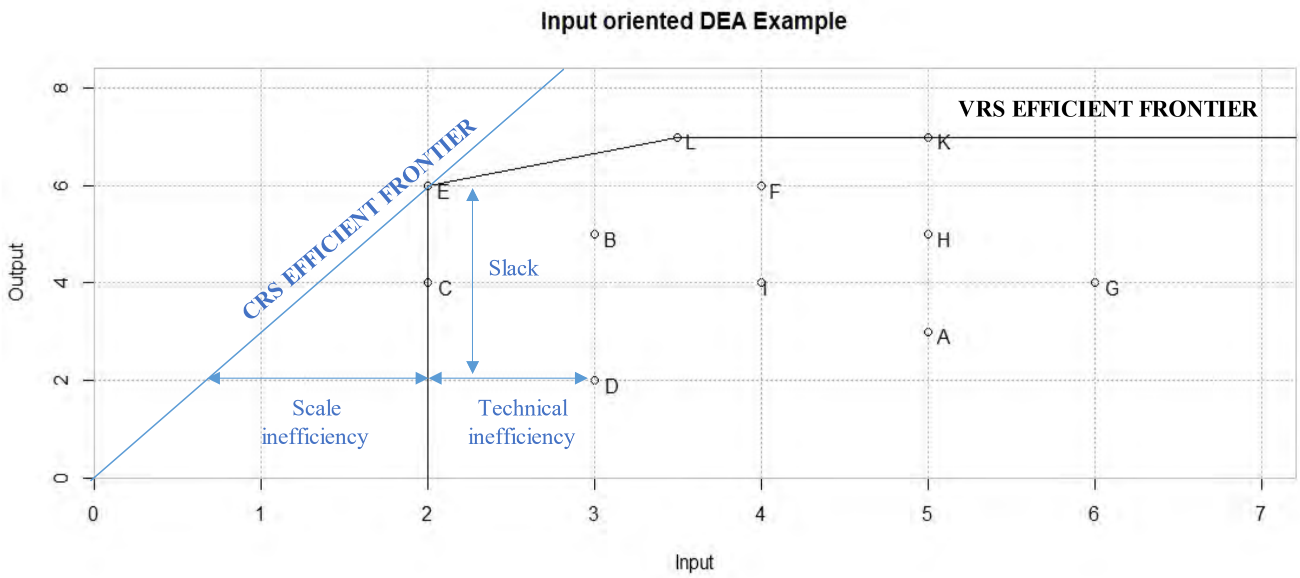

Figure 1.9: Graphical explanation of input-oriented DEA Example, Author’s elaboration

From a mathematical perspective, the above-mentioned problem can be used both for input-oriented CRS and VRS DEA models by using the following formulas:

Constant Return to Scale (CRS)

$$z = \min \theta - \varepsilon(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+) \qquad (1)$$

$$s.t. \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{io} \; i = 1, \dots, m \qquad (2)$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro} \; r = 1, \dots, s \qquad (3)$$

$$\lambda_j, s_i^-, s_r^+ \geq 0 \; \forall i, r, j. \qquad (4)$$

Variable Return to Scale (VRS) Add:

$$\sum_{j-1}^{n} \lambda_j = 1 \qquad (5)$$

Where: n DMU_j (j= 1,…,n) use x_{ij} as inputs (e.g. seeds, fertilizers etc) producing y_{rj} as outputs (e.g. durum wheat yield), λj is a non-negative constant while s_i^- and s_r^+ are the input and output slacks accordingly. The absence of the non-Archimedean value (ε) would lead to the infeasibility of identifying the most efficient DMUs (Toloo, 2014). In order to characterize a DMU as efficient, both z should be equal to 1 and slacks should be equal to zero. As a final step, Scale Efficiency (SE) can be computed by

$$SE_i = \frac{CRS_i}{VRS_i} \qquad (6)$$

Where CRS_i and VRS_i are the efficient scores obtained for each DMU with the use of the aforementioned models (eq. (1)-(5)).

1.4. Overall contribution

Following the Introduction section rationale, it is evident that the new CAP 2023-2027 will further support the environmental and social aspect of agricultural activity, shaping a smooth transition towards sustainable agriculture. The use of optimization measurement techniques can be valuable for evaluating the current status of each region or country, as well as designing future steps by following EU guidelines. Under this scope, the development of methodological approaches that can assess the performance of decision-making units in different application levels, is considered as a necessity for the EU. By this means, the provision of clear instructions to the EU members as well as the ability to modify the CAP strategy, based on real time results, can be feasible. It should be underlined that the efficiency assessment should not only include economic parameters, but environmental and social dimensions can be taken into consideration.

Although there is a constantly increasing effort from the agricultural operational research society's side (Figure 1.6) on implementing DEA for increasing the efficiency of different agricultural systems, development of new techniques that will further support EU directives are considered necessary. For this reason, the current thesis is aiming to provide new methodological approaches to the following research questions:

- What are the main methodological gaps when implementing DEA in the agricultural sector considering sustainability?
- Is the current infrastructure enough to support decision making on a national and local level?
- Which are the methodologies that can be combined with DEA, so as to provide sufficient indicators for CAP 2023-2027 performance?
- What was the long-term effect of the CAP implementation regarding the inputs' use efficiency of the EU members?

The contribution of the current thesis lies on the highlighting of the methodological deficiencies, considering the agricultural sector's special needs and challenges, as well as to provide solutions for a holistic efficiency assessment, including all sustainability dimensions in a multi-year panel.

1.5. Structure of thesis

In this thesis, critical literature review and new methodological approaches on the use of DEA in the agricultural field are presented. More precisely:

Chapter 2 presents an integrated literature review of DEA application in agriculture. While there is an increase of published papers in Energy and Environmental fields using DEA, Chapter 2 seeks to address the special requirements of this methodology when applied in the agricultural sector. More specifically, 120 papers were included in this review, and they were tested in the following groups i) General information, ii) DEA implementation, iii) DEA extensions, iv) Data type, v) Data collection and processing, and vi) Sustainability dimensions. Results indicate that there is a great need for weights used when performing DEA in the agricultural sector, to acquire results with greater explanatory power. Moreover, systematic data collection of multiple factors could lead to the implementation of complex methodologies, providing feasible solutions to involved stakeholders. Lastly, the social aspect is the least represented dimension out of the three aspects of sustainability (economy, environment, society), indicating the need for the integration of social factors in such analyses, especially when DEA is used to create a policy framework in a specific area.

Chapter 2 Contribution: Highlight the Literature Review Gaps (LRG):

a) Under represented social dimension (1st LRG)

b) Data availability (2nd LRG)

c) Need for more complex methodologies (3rd LRG)

Chapter 3 incorporates social factors in the benchmarking process, as an attempt to provide means for fulfilling the 1st LRG presented in Chapter 2. In this chapter, input use efficiency of cotton growers was assessed with a view to minimize exploitation of natural resources and promote incorporation of qualitative attributes in DEA. Cotton cultivation has been selected due to its diachronic significance for the Greek territory. More specifically, Greece is producing 80% of the European cotton, which corresponds in a cultivation land of around 320 thousand hectares per year. It should be also stated that cotton cultivation is followed by a unique subsidy phenomenon since Greece’s accession to the European Economic Community (EEC).

Cotton farmers are receiving coupled payments for their agricultural activity, which is related to the total cultivated area limits, established by the European Union (250 thousand hectares for Greece), and under the precondition that minimum quality standards of the final product are met.

Considering that the EU focuses on a holistic approach about the economic, environmental and social aspect of agricultural activity, Greek cotton cultivation is considered appropriate due to the fact that it fulfills all the three aspects of sustainability. In a more explicit way, cotton is an arable crop of increased needs of fertilizers and irrigation. This combination increases the risk of nitrate pollution in the cultivation regions. By optimizing the amount of fertilizers used, farmers need to invest less on their resources, environmental benefits due to reduction of nitrate contamination also arise, as well as there is an increase of local communities' living standards. As the first LRG of the systematic literature review highlighted, there was a lack of representation of the social aspect. Education and experience were added as the main variables to represent the social aspect of cotton cultivation and this selection is further explained in Chapter 3. However, the European Union has defined more accurately the framework of the social dimension of the agricultural sector, since the beginning of this thesis, providing additional data that could be embodied in the optimization process in future research. For instance, the European Union seems to focus on supporting young farmers and more specifically on their initial investment costs, rent coverage as well as the ease of capital acquisition. The above variables, from the one hand ensure sufficient quantities of cotton production, while on the other hand the foundations for the revival of rural areas are laid. The above statements prove the dynamics presented in the agricultural economics research field and the necessity for creation of appropriate methodologies that can provide handful results to agricultural experts and policy makers. Nevertheless, even today the available data regarding social variables through Eurostat are referring to the national level (NUTS1) of EU agricultural sector and not the local one (NUTS2 or NUTS3), underlying the difficulty of collecting this specific data.

Consequently, a three-part questionnaire was created, containing 1) demographics 2) used inputs (land, seeds, agrochemicals, energy, irrigation, and labour) and 3) extracted outputs (production, revenue). TOPSIS model was used7, to transform categorical variables of demographics (education and experience), as an input to the following DEA for benchmarking the input use efficiency. Out of 107 examined cotton farms 42 (39.3%) of them are operating efficiently, while the average obtained score is 0.915, meaning that there is a well-established production protocol which is followed by the majority of cotton farmers. Apart from providing quantitative targets for cotton farmers, this chapter seeks to address DEA-TOPSIS combination, as a useful tool for efficiency assessment, contributing to a holistic sustainability evaluation.

Chapter 3 Contribution: Covering 1st LRG by inclusion of demographic characteristics in DEA

Additionally:

a) Combination of DEA with TOPSIS

b) Inclusion of any ordinal values in the benchmarking process

Chapter 4 assesses inputs use efficiency of durum wheat farmers that are subscribed in Grano Duro Net (GD.NET) application, an appropriate Agricultural Decision Support System (ADSS) designed by Barilla and HORTA for this cultivation, aiming to highlight differences on the implementation of the suggested production protocol between 4 agricultural firms (2 Italian and 2 Greek) (N= 563 farmers, IT: 328, GR: 235).

Durum wheat has been strategically selected and subsidised from the EC as one of the cultivars that can achieve sustainability within the EU area, among rice, wheat, dried fodder and nuts. By this means the dependency of durum wheat imports decreases, assuring adequate amounts of locally produced raw material for pasta production, which is an essential commodity for everyday life. On top of that, Barilla company already applies a strategy for inputs minimization through the establishment of GD.NET and its implementation from producers' side. This proves that Barilla aims to produce competitive products, ensuring environmental protection through the integrated management of durum wheat cultivation, while influencing local communities for achieving sustainability. From farmers perspective, the operation of GD.NET system leads to more accurate and precise applications, minimizing the risk of a final product that does not meet economic and environmental criteria. Moreover, it contributes to the production of a homogenized product for the entire company.

Another point that should be highlighted is that this survey assesses the interaction between the farmers and the ADSS, focusing on the implementation stage. In other words, this study examines the degree of implementation of the proposed actions by producers that cultivate durum wheat for Barilla. The novelty of the above-mentioned assessment lies on the fact that there are no other surveys having access to such dataset of farmers that operate under similar guidelines on a local and national level, as well as farmers' acceptance to the ADSS consultancy services.

For this purpose, the GD.NET database was analysed to check for significant statistical differences of the input variables (seeds, fertilizers, plant protection products and diesel) and the final output (yield) among the 4 firms. Incorporating the sustainability strategy of Barilla enterprise in the analysis process, two input-oriented DEA models were developed: i) DEA: using only the aforementioned inputs and output, and ii) EcoDEA: an extension of the first model by incorporating additional factors as undesirable outputs (Water Footprint, Carbon Footprint, Ecological Footprint). Results indicate that there are efficiency differences between farms both on regional and national level. Even though there are several factors (e.g., agricultural, environmental, institutional) affecting the benchmarking process, it is evident that in the Italian sample there is a tendency for input minimization, while in the Greek firms apply the production protocol in a loosen way. Moreover, proper visualization of undesirable factors distribution before and after optimization was also plotted. This chapter presents and quantifies the differences derived from the implementation of a common and dynamic ADSS on a comparative basis (operational and spatial), providing new insights for improving the effectiveness of such or similar tools.

Chapter 4 Contribution: Covering 2nd LRG by analysing farm-level data from 563 durum wheat farms in international level (Italy, Greece) that operate under the same ADSS and policy framework

Additionally:

a) Inclusion of environmental indicators as undesirable factors
b) Visualization of target efficiency scores for undesirable factors

Chapter 5 aims to cover another point highlighted in the conclusions section of Chapter 2, which concerns the lack of more complex methodological approaches. For this purpose, Window Data Envelopment Analysis (WDEA) was selected as a benchmarking technique, to assess input use efficiency of agricultural sectors of EU countries for the 2005–2019 period. Moreover, three-year projections (until 2022) were calculated to acquire future efficiency scores. Window DEA has been selected as the appropriate methodology to assess the long-term influence of a common policy in the EU region. Particularly, assessing differences in a national level considering environmental factors, can highlight the points that should be further ameliorated resulting in a European agricultural sector of greater performance with fewer inequalities.

Emphasis was given on the selection of alternative window widths, examining their influence on calculating efficiency scores for both projected and actual dataset. From a methodological point of view, this paper aims to highlight the assumption of zero technological change within WDEA frames and present their differences. At the same time, results indicate that Estonia (1.000), the Netherlands (0.999) and Slovenia (0.999) are the most efficient countries in terms of input use efficiency, while Finland, UK, and Hungary (0.670, 0.755 and 0.771) score the least. Countries of central Europe (Hungary, Czech Rep., Croatia, Slovakia, and Austria) should redesign their agricultural strategies, to achieve the nine objectives of the CAP (2021–2027). Lastly, it should be underlined that the methodology for acquiring ideal window width is presented and, in this case, the ideal window width with the initial dataset was equal to 7, meaning that in our study we assume that there is a significant change in the implemented technology every 7 years, which matches with the application timeframe of CAP.

<u>Chapter 5 Contribution</u>: Covering 3rd LRG by highlighting the influence of window width selection when performing Window DEA. Technological level changes significantly every 7 years, which coincides with the implementation of the programming period of each CAP.

<u>Additionally:</u>

a) Three-year projections.
b) Estimation of ideal window width.
c) Applying multiple window widths to assess their influence on final

Chapter 2

A systematic literature review of Data Envelopment Analysis implementation in agriculture under the prism of sustainability

2.1. Introduction

Food security, overpopulation, and conservation of natural resources are the biggest challenges for today's agriculture (Calicioglu et al., 2019). In addition, the global trend towards adopting Sustainable Development Goals (SDGs) (United Nations, 2015) has not left the agricultural sector unaffected, as the same principles will have to be integrated into this sector for sustainable agriculture (European Commission, 2015).

Although the search for «sustainability» term shows a slight increase from 2014 to 2021 for general Google users, there is a rapid increase in searching for the term in the academic community of 160% for the same period, verifying the effort of researchers to find solutions or methodologies to achieve the globally accepted sustainable development goals (Google Trends, 2021). Taking into consideration the need to provide food for an ever-growing population with an inexhaustible number of available resources, leads humanity to the establishment of new systems or the invention of new technologies which can produce the same amount of output using the least possible energy and resources. In other words, for ensuring sustainability in agriculture, the efficiency of existing systems needs to be increased. On operational terms, this means that either production levels should remain at the same levels, with the need for inputs to be decreased, or output should be increased, given the inputs used. With this goal reassurances can be provided that future generations will have equal opportunities to access energy and natural resources.

Following the above line of reasoning, efficiency analyses can contribute to quantifying losses and highlight weak points on production processes in the agricultural sector, to minimize the exploitation of natural resources while producing adequate amounts of feed and food. Efficiency measurement can be achieved by using either parametric (e.g. Stochastic Frontier Approach -SFA (Aigner et al., 1977)) or non-parametric approaches such as DEA (Charnes et al., 1978). SFA is capable of distinguishing noise from inefficiency, however, DEA includes noise in its final results (Lampe & Hilgers, 2015). Moreover, SFA is not so sensitive to outliers as DEA, due to the fact that SFA is based on regression models, while DEA computations are based on linear programming principles. Removal of outliers is a crucial stage for data preparation when performing DEA, which may end up in a false interpretation of the results if neglected (Sarkis, 2007). On the other hand, DEA is mostly used in the agricultural sector, due to the fact that it can handle multiple inputs and outputs, in contrast with conventional SFA models which can handle single input or output and multiple inputs or outputs, respectively. DEA also does not need any prior assumption about inputs and outputs relationship, compared with SFA, a decision that may lead to uncertain results (Watto & Mugera, 2019).

In order to assess the way that efficiency measurement is applied in the agricultural sector, VOSViewer software (Waltman & van Ecken, 2010) was used. More precisely, Figure 2.1 presents efficiency and agriculture results from the most cited papers of Scopus (first 2,000) and Web of Science (WoS) (first 1,000) databases. Three distinct clusters were formed. The first one (red) is referring to operational/technological aspect of agricultural activity, the second (blue) is concerning the environmental impact of either greenhouse gases or agro-chemicals, while the third one (green) is concerning waste water management. DEA and Life Cycle Assessment (LCA) are the only two represented methodologies out of the whole sample. Considering the advantages and disadvantages presented in the previous paragraph as well as the results of Figure 1, DEA is selected to be further analyzed in this literature review.

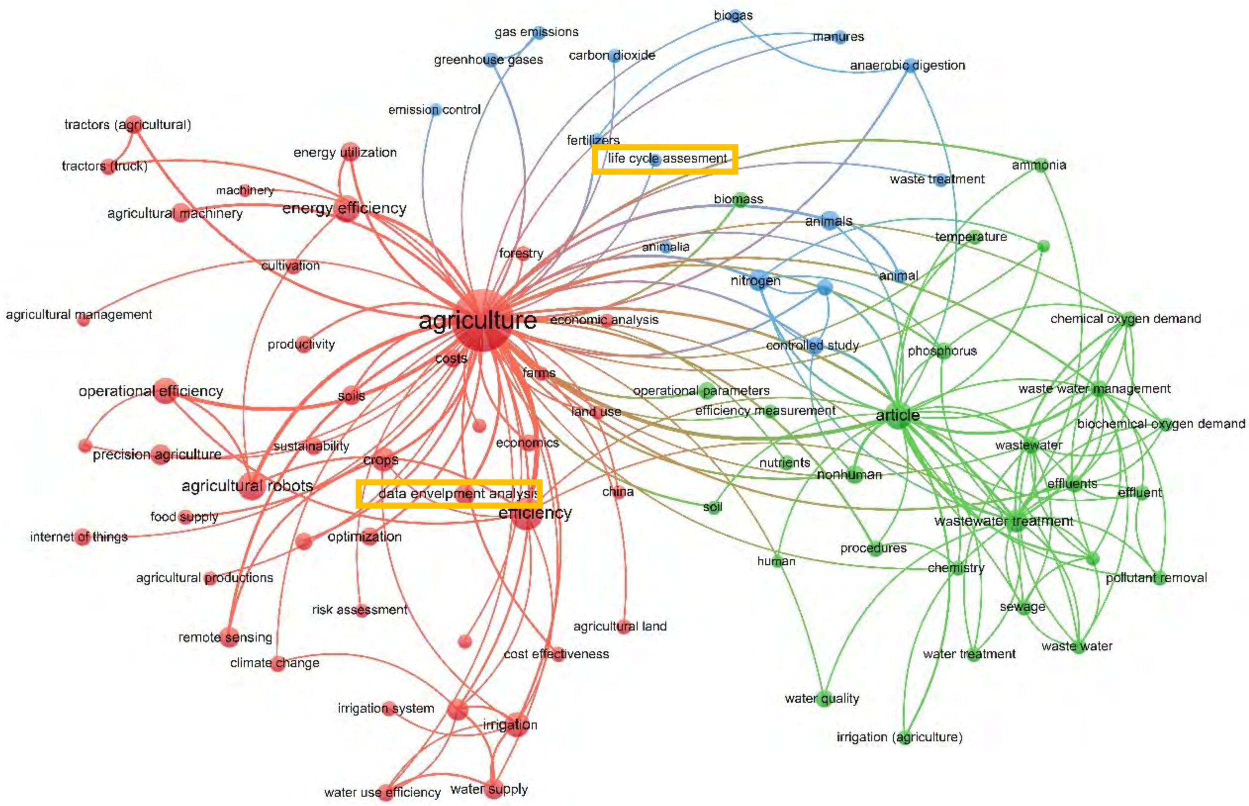

Figure 2.1: Keywords' relationship for agriculture & efficiency terms

Focusing on DEA implementation, there are two ways of increasing the overall efficiency of Decision Making Units (DMUs) of the examining system each time, either by reducing the involved inputs (input-oriented) or by increasing the final outputs (output-oriented). Moreover, Constant-Returns-to Scale (CRS) and Variable-Returns-to Scale (VRS) are the most used DEA models, permitting researchers to calculate scale efficiencies as well.

Apart from the conventional DEA models, slack-based models (SBM) can compute further reductions or surpluses, after the initial optimization process. More precisely, slacks are described as technical efficiency remainings, meaning that after the first stage of efficiency computations, further decreases for some variables can be implemented not horizontally, but on a DMU basis. Application of different weights between inputs and outputs is feasible by using assurance region models (Thompson et al., 1996), leading to a fairer benchmarking.

Additionally, newer approaches such as super efficiency models are excluding the examining DMU each time from the reference set, acting as a sensitivity analysis for DEA models (Seiford & Zhu, 1999; Thrall1996). Another model is Network DEA, which can perform efficiency evaluation in different stages of a production process, rather than considering only the initial inputs and final outputs. For instance, production and distribution are two main processes until the products will reach to final stores. By using Network DEA it is possible to optimize the procedure in each stage, without considering the whole system as a black box (Färe et al., 2007; Sarkhosh-Sara et al., 2020). Bootstrap DEA can create replicate datasets in order to check the standard error of their final outcomes (Bogetoft & Otto, 2011), a meaningful technique for agriculture which deals with high variability of the involved factors or small samples (Tetteh Anang et al., 2020). Fuzzy DEA model is another approach where the integrated values are not constant, but they are varying within a range, quantifying the risk of the final decisions. Hatami-Marbini et al. (2011) in their literature review paper are presenting different approaches on how imprecise data can be handled under fuzzy concept, while Houshyar et al. (2012) have performed a Fuzzy DEA model so as to assess the sustainability performance of corn farmers. Lastly, Window DEA can be used for measuring efficiency through the use of time-series data. For instance, Pishgar-Komleh et al. (2021) assessed the eco-efficiency of the agricultural sector of European countries for 2008-2017 time period by using the Window DEA method. It should be stated that all the afore-mentioned approaches can handle undesirable outputs (e.g. greenhouse gas emissions) when estimating efficiency scores (Halkos & Petrou, 2019), a significant characteristic for considering negative externalities to the environment or human health in the optimization process. Taking all the above mentioned into consideration, this study seeks to address the ways that DEA methodologies are implemented under the prism of sustainability in the agricultural sector.

This study proceeds as follows. The first section provides an overview of similar literature reviews in the energy and agricultural sector, clarifying the contribution of this paper through the research questions. Furthermore, it presents the overall process of paper collection and screening. The next section presents general information of the included papers; DEA model implementation; DEA extensions; Data types used in DEA model; Data collection and processing and sustainability dimensions represented through DEA implementation. There is also provision for further insights into the acquired results, proposing possible combinations with already existing papers, while in the last part of it proposals for future surveys are being made.

2.2 State of the art

The literature review of Zhou et al. (2018) is a crucial reference point, regarding DEA implementation under the sustainability term, indicating the chronological connection of published papers and the key points of DEA evolution from 1996-2016, reviewing 320 publications in total. The main conclusions of this study can be summarized as followed 1) Integration of undesirable or bad output in DEA, 2) Interaction of all three aspects of sustainability and the lack of social factor inclusion, 3) Implementation strategies from enterprises and policymakers' side. Another literature review of Mardani et al. (2018), having reviewed 145 articles on the environmental and energy field, concludes that there is a need for further assessment of methodological aspects relative to DEA. Big data, uncertainty, and heterogeneity of the involved DMUs are the main areas that DEA methodology should be further expanded to deal with the complex environment of the energy sector (T. Xu et al., 2020). Tsaples and Papathanasiou (2021) underline also the need for social inclusion, when performing DEA for sustainability. Moreover, on the same survey, it is highlighted that there is a misconception between eco-efficiency and sustainability term, while some authors use more dimensions, apart from economic, environmental, and social, like innovativeness or technology adoption.

The above-mentioned surveys have assessed DEA implementation in Energy and Environmental sectors in total. Considering the idiosyncrasies of the agricultural sector, due to the interaction of multiple factors such as biotic and abiotic environment, cultivation protocols, and applied agricultural practices, including the incorporation of sustainability principles, a literature review of 120 papers was conducted, considering the year after SDGs' release as a reference point for further promoting sustainability principles in the agricultural operational research society. Although Streimikis and Saraji (2021) have recently published a literature review for DEA in agriculture, focusing on the research gaps and main conclusions of each survey of undesirable outputs, the present review aims to contribute on the following questions:

1) What are the methodological gaps and the future research proposals?

2) How are the data collected and analyzed?

3) What are the methodologies combined or compared with DEA results?

4) Which of the three pillars of sustainability are covered through published papers or conference proceedings for application of DEA in agriculture?

2.3 Material and Methods

To achieve the aim of this paper, a systematic literature review has been performed through the Scopus and Web of Science (WoS) database, using PRISMA guidelines (Page et al., 2021). More precisely, for this survey terms of «efficiency», «agriculture» and «sustainability» were used. Title, summary, or keywords were the main areas in which the above terms should be present to be included in this research. Due to a large number of acquired results (n=6,960- Scopus and n=7,237-WoS) and the fact that this paper focuses on DEA implementation, the «efficiency» term was replaced with «DEA» term, leading to 75 results from Scopus and 203 from WoS. Given the fact that this literature review assesses the ways in which DEA is applied in agriculture, under the prism of sustainability, this term was highly promoted after the SDGs' release in 2015 (United Nations, 2015). Having this as a reference point the period 2016-2022 was selected to be further analysed, leading to a number of 180 unique articles or conference proceedings (Figure 2). Significant academic efforts prior to the selected years have been made in this field (Gerdessen & Pascucci, 2013; Reig-Martínez et al., 2011; Zahm et al., 2008), thus this review seeks to capture the contribution of agricultural operational research to sustainability aspects after the year 2016, where there was a rapid increase of publications as Figure 2.2 presents.

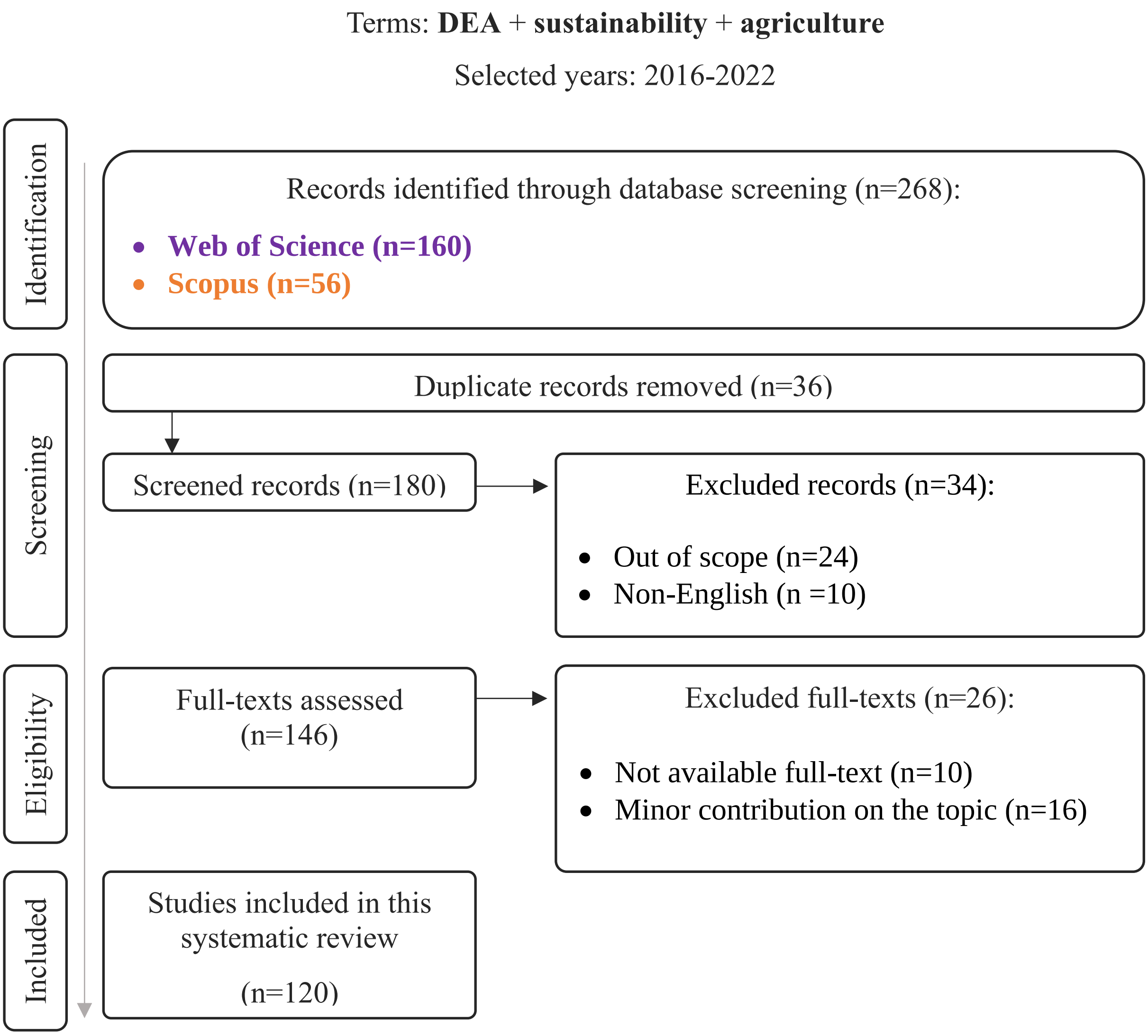

Figure 2.2: Literature review methodology under PRISMA guidelines

References were exported on September 9th, 2022. Further screening was performed for removing duplicates and clarifying the content of the included papers. Out of 180 unique records, 34 of them were removed from the first stage, due to the fact that 24 paper were not relevant to this literature review (mainly because they were referring in their abstract to the term «agriculture» as a part of an example or as a future implementation) and 10 of them were non-English papers. On the eligibility phase, 26 papers were excluded, 10 of them due to unavailability of full text and 16 of them due to minor contribution on the topic, meaning that in most cases agricultural sector was compared with other sectors mostly in national level but without deepening on agriculture. Based on the above-mentioned process, 120 papers were included in this systematic literature review. Out of the entire set of examined for this review, 116 were journal articles, accounting for 97% of the total, while the remaining 3% were conference papers.

Moreover, a detailed table of criteria, prior to the detailed review of each paper, was constructed based on the authors' experience in the field. As shown in Table 2.1, 23 variables were evaluated in each paper. More specifically, the selection of the variables was made to capture the overall picture of the DEA applicability in agriculture under the prism of sustainability, but also to highlight the points that need further amelioration, or better integration of new methodologies from other scientific fields.

Table 2.1: Examined data through the literature review process

Category	No.	Element	Description
1. General information	1.	Author(s)	(-)
	2.	Year	Year of publication
	3.	Level	Application-level: International, National, Prefecture, Local
	4.	Document Type	Journal article, Conference paper, Proceedings, etc
	5.	Source Type	Journal name
	6.	Inputs	Type of variables used as inputs
	7.	Outputs	Type of variables used as outputs
	8.	Application system	Description of application system
2. DEA Implementation	9.	Approach	Input-oriented, Output-oriented
	10.	DEA Model	Used DEA Models (VRS, CRS, SBM, Window etc.)
	11.	Undesirable Output	Use and Type of undesirable output
	12.	Homogeneity/Weights	If all DMUs have been treated as homogenous
3. DEA Extensions	13.	Combination	Use and Type of any combined methodology with DEA
	14.	Comparison	Use and Type of any methodology used to compare DEA results
4. Data Type	15.	Qualitative data	Use of qualitative data
	16.	Timeseries	Use of data for a longer period than one year
	17.	Geographic information system (GIS) Incorporation	Incorporation of GIS information in DEA model

5. Data collection and processing	18.	Source of Dataset	Personal interviews, Pubic or Private Datasets,
	19.	Total Sample	Number of DMUs
	20.	Sample equation	Followed methodology for defining sample size
	21.	Software	Which software has been used for DEA implementation
6. Sustainability Dimensions	22.	Sustainability Dimensions (in the DEA process)	Which of the 3 aspects of sustainability are assessed in the DEA model
	23.	Sustainability Dimensions (in the total paper)	Which of the 3 aspects of sustainability are assessed in the whole paper's contribution

The above-mentioned data provide further insights on the given dataset of references, leading to the fulfilment of the goals set in the State-of-the-Art section.

2.4 Results

All categories of variables listed in Table 2.1are presented in the same order in this section.

2.4.1 General information

Regarding publication year, Figure 2.3 presents that there is a noteworthy increase from 2016 to 2022. Apart from year 2020, which was the first year of COVID-19 pandemic, there is an additional amount of publications each year leading to an almost quadrupling of annual publications between 2016 and 2022, signifying there is a great deal of academic interest in this topic.

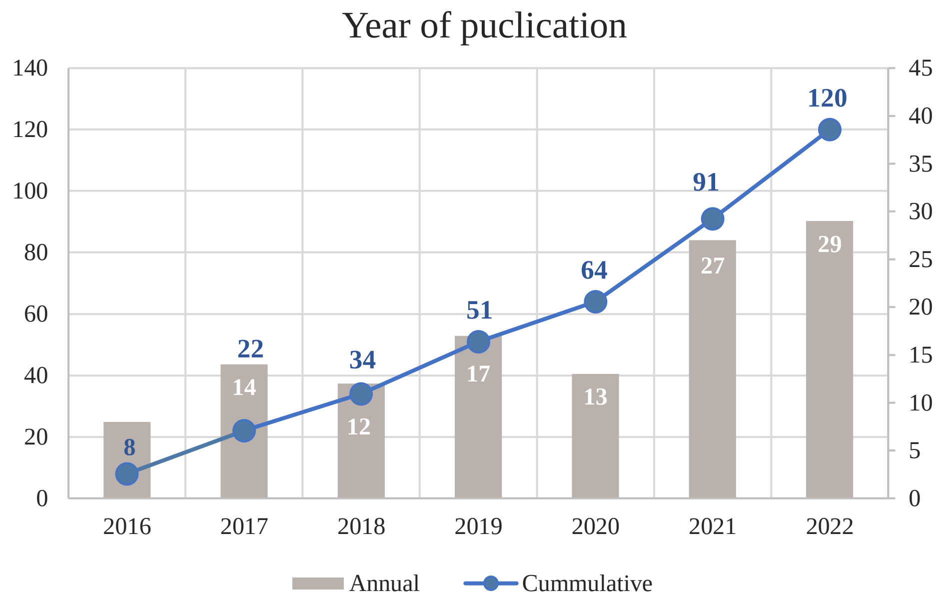

Figure 2.3: Year of publication

Table 2.2 contains the number of reviewed papers by source type, referring to 65 out of 120 papers (54%). *Sustainability*, *Journal of Cleaner Production*, *Science of the Total Environment* and *Agriculture* were the sources out of which the most papers were extracted for this review.

Table 2.2. Number of included papers by source type

No.	Source Type	Number of included papers
1.	Sustainability	29
2.	Journal of Cleaner Production	9
3.	Science of the Total Environment	4
4.	Agriculture	4
5.	Energies	3
6.	Agricultural systems	3
7.	Land Use Policy	3
8.	Environmental Science and Pollution Research	2
9.	Energy	2
10.	Information Processing in Agriculture	2
11.	Applied Energy	2
12.	Energy for Sustainable Development	2

Due to the fact that DEA considers all the involved DMUs as homogenous, it was important to focus more on the geographical aspect of these applications. It is assumed that increased locality of application fits better to the characteristics of the model, mitigating the influence of different external factors. Figure 2.4 presents that the greatest part of papers (51%) is performed on a local, or regional level. Local level refers to surveys held inside the boundaries of a prefecture, prefecture label refers to the implementation of the survey between neighbouring prefectures, national label refers to the inclusion of the majority of prefecture inside a country and lastly, international label refers to the comparison of agricultural sectors between different countries. It should be noted that in this figure 118 papers are included, because the remaining two are review papers.

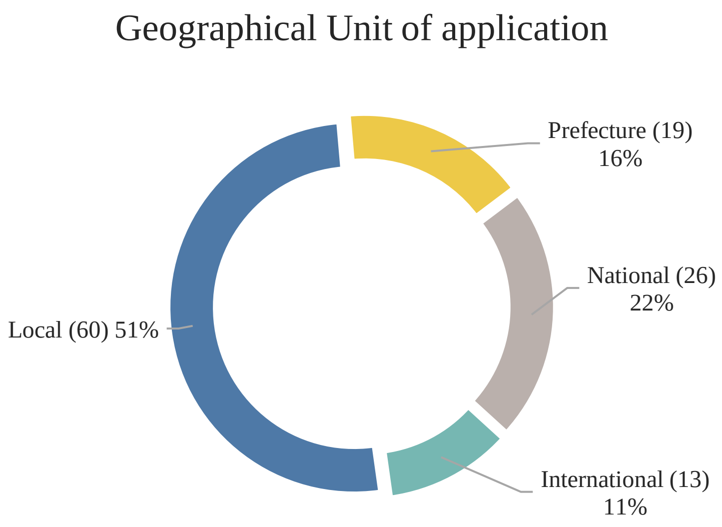

Figure 2.4: Geographical unit of application

Regarding the application system, Figure 2.5 presents that a great part of the examined papers are referring to the agricultural sector in general, 38% implements optimization models for arable crops and a small part is referring to livestock, greenhouse products, fruits, timber and vegetables.

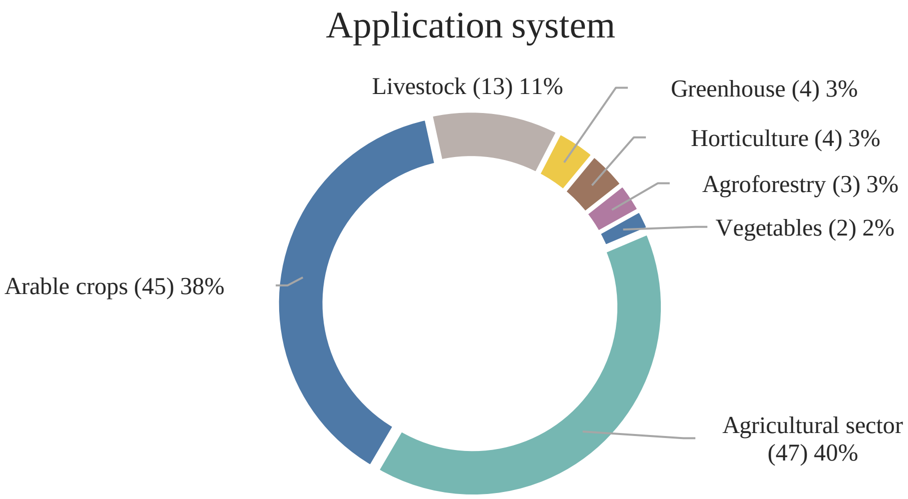

Figure 2.5: Application system

Table A1 of the Appendix section provides an overall view of included papers in this review. More particularly, author, year, application level, type of inputs and outputs as well as the specification of the application are presented.

2.4.2 DEA implemantation

Regarding the selected approach, 76% used an input-oriented approach, 20% used an output-oriented approach, 2% compared the approaches of both results, and 2% did not specify the approach used.

Examining the use of DEA models in agriculture, it is evident that most of the obtained results were acquired using typical DEA models like CCR (CRS) and BCC (VRS). Particularly, as shown in Figure 2.6, almost half of the examined papers (46%) are using both CRS, VRS and Scale efficiency, 23% used only VRS model (27 papers) and 9% used only CRS model (11 papers. Although the selection of the CRS or VRS approach is problem specific, in agricultural sector VRS assumption is preferred, due to the fact that the increase of inputs does not mean necessarily that this will lead to a proportional increase of outputs. In other words, doubling inputs (e.g. fertilizer) does not ensure double production in the end of the cultivation year. CRS scores are mainly extracted for scale efficiency calculations.

Additionally, Slack-based model (SBM) was used from 9 papers. As mentioned in the Introduction section, SBM models are used to provide accurate estimations of target values of each variable enabled in the DEA model. Debbarma et al. (2021b) used SBM model to elucidate Iranian farmers' efficiency under the consideration of GHG emissions as undesirable output, while same model was used from Tian et al. (2016) for open-field grape production. Bootstrap DEA was used in 5 cases with a view to minimize the stochastic errors by producing replicate datasets. For instance, Nodin et al. (2022) have created 3,000 replicate datasets of rice producers to assure the reliability of acquired results. Super efficiency was performed by 3 papers or 2% of total sample. Cecchini et al. (2021) used this approach for minimizing the influence of extreme values to their final results when implementing an efficiency assessment on Italian sheep farms.

Network DEA was also implemented from 5 papers in order to reveal causes of inefficiency in different sub-systems of an overall process. Saputri et al. (2019) performed this methodology to assess the efficiency between the three distinct stages of agri-food supply chain (agricultural production, processing, transportation) for Indonesian rice producers. Kord et al. (2022) presented agricultural activity as two different stages (environmental and economic) and by using shared inputs between the two stages they performed a sustainability assessment for Iranian regions. Lu et al. (2022) have created a three stage Network model for assessing agricultural food production systems of EU countries under circular economy principles, meaning that the final output was acting as a carry over the next period.

Fuzzy DEA and Window DEA were the least presented methodologies of this sample referring to only 3% cumulatively. Mu et al. (2018) have assessed 55 dairy farms setting a range of -20 to +20 of their given values, so as to incorporate the uncertainty in their Fuzzy DEA model. Window DEA was used from Masuda (2019) to minimize the effects of global warming and eutrophication in rice production for 2005-2011 time period. Lastly, it should be mentioned that the followed methodology was not specified in 2 papers and the review papers (2) are excluded from this review process.

Regarding the comparison of the acquired results, only two surveys have proceeded to this step. W Kamal & Ilmas (2017) have compared their DEA results with SFA, concluding that SFA technical efficiency results were higher than the ones of DEA, attributing this to bias correction of the SFA model. Khanjarpanah et al.

(2017) implemented 2 types of cross-efficiency DEA models (aggressive and benevolent) to assess switchgrass cultivation in Iran and they proposed a third one additional model which contributes to a fairer optimization process.

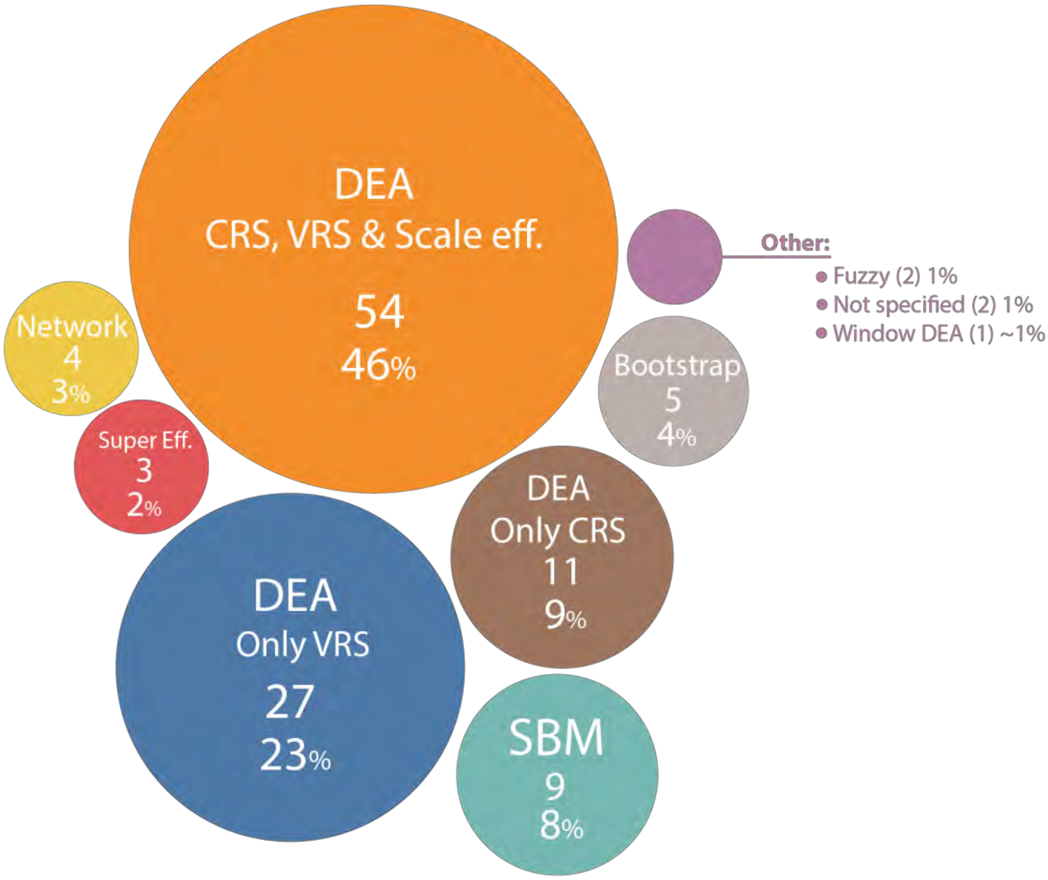

Figure 2.6: Results of DEA Models used

Undesirable outputs impact assessment is another significant factor towards the achievement of sustainable development in agriculture, mainly by focusing on reducing their impacts on the environment, or trying to create a circular path. For these reasons, 25% (30 papers) used undesirable outputs in total. Most of them were using either Greenhouse Gas Emissions (GHG) as a total or applying CO_2 emissions only and this may be due to easy data accessibility. Lamkowsky et al. (2021) has also used N surplus indicator as undesirable output in Dutch dairy farms, a variable which has not been detected in crop production systems at all (e.g N leaching). Additionally, Tang et al. (2022) included farm-specific undesirable variables such as soil erosion rate and grey water footprint in their DEA model, a characteristic that was absent from the other surveys. It should be noted that Grassauer et al. (2021) and

Rybaczewska-Błazejowska & Gierulski (2018) included LCA results as inputs in their DEA models to minimize the environmental effects of agricultural productivity.

As stated in the general information section, there is an assumption of homogenous examined units when performing DEA. Especially in the agricultural sector, which has a great variability both of abiotic (temperature, humidity, precipitation, type of soil etc.) and biotic environment (cultivar, variety, pests etc.) as well as the interaction between them, use of different weights is essential for setting an equal starting point for all DMUs involved. None of the included references has implemented any methodology that would make a fairer evaluation, a crucial point when considering equality on the agricultural sector. Such issue is partially delivered from Molinos-Senante et al. (2016) where an attempt of highlighting efficiency differences between farmers, with immediate access to water or not is being made, underlying the need for policy framework modifications. In this line of reasoning, other agronomic factors such as access to land with high levels of organic matter, or vulnerability from specific pests should be considered in the evaluation process.

2.4.3 DEA Extensions

DEA has not been combined with any other model or methodology for 30% of the examined references, proving that most researchers are implementing additional steps after the calculation efficiency scores. From the remaining 82 papers, regression models was the most frequent option such Tobit (10), Truncated (4), Ordinary Least Squares (OLS) (4) and other not specified linear regression models (6). Tobit model was used for checking which socio-economic variables are affecting the extracted efficiency scores (Hassen et al., 2017; W Kamal & Ilmas, 2017). As mentioned from (Chang et al., 2022) the use of OLS model can be biased due to the potential inclusion of zero values extracted from the DEA implementation process. Martinsson & Hansson (2021) have used OLS to assess the effect of subsidies in the performance of dairy farms and their overall productivity. Frangu et al. (2018) incorporated in their linear regression model aspects like farmers training on crop nutrition or type of power source used (e.g electricity, fuel) fulfilling also other dimensions than the typical social characteristics (e.g age, education, income, years of experience)

Apart from the regression models Malmquist index was used in 10 cases in order to check efficiency differences between years. Pan et al. (2021) used Malmquist index to assess differences of total factor productivity between the years 2015-2018, proving that there was a significant increase in productivity of various Chinese regions. Ren et al. (2017) applied the same index to depict the water use efficiency per year, in order to propose regional changes to policymakers. Another least explored index used in combination with the DEA is Theil index, which was used for exploring economic inequalities between different Chinese regions regarding their eco-efficiency (Pang et al., 2016).

LCA is another commonly combined analysis with the DEA for assessing the environmental impacts of agricultural activities. In the examined sample, 14 papers (11%) implemented the afore-mentioned methodology. When LCA is applied there are two approaches of either implementing DEA in the initial stage and then target values are used (Grados et al., 2017), or LCA is performed first and its results are proceeding to further analysis with the DEA (Rybaczewska-Błazejowska & Gierulski, 2018). For instance, Mohammadi et al. (2022) have assessed the impacts of agricultural activity to air, water and soil, clarifying the differences between current and target values for Iranian wheat farms.

Principal component Analysis (PCA) and Factor Analysis (FA) were used from a small number of papers (4). After the collection of economic, social and environmental data, Sánchez-Zamora & Gallardo-Cobos (2019) have applied PCA for grouping Spanish regions with common characteristics to measure and compare their resilience scores, extracted from DEA. Ramos de Oliveira et al. (2022) implemented PCA in order to elucidate the interactions among the sustainability factors, proving that social and environmental dimensions should not be neglected when transportation routes of agricultural products are being assessed for their efficiency levels.

Kord et al. (2021) have incorporated a sensitivity analysis in their approach, to assess the allocation of human resources in a 2 stage Network DEA model. More precisely, this paper seeks to address the optimal value of human resources intervention in the plantation/maintenance of the cultivar (first stage) and harvesting (second stage). Abbas et al. (2022) used the aforementioned analysis, so as to indicate the change of crop output under the condition of different number of inputs each time.

Grey relational analysis was applied to check the influence of the included variables on the environmental performance of China's families (Y. Yang et al., 2019).

Lastly, special attention was paid to the incorporation of spatial characteristics in the reviewed papers. Tian et al. (2016) have implemented spatial analysis, after estimating the efficiency scores for Chinese grape farms. Spatial Durbin Model was implemented from the following researchers to identify technological spillovers through different regions (J. Li et al., 2021; Wu et al., 2022; P. Xu et al., 2022). Examining the spatial relationship of the acquired results is a necessity for agricultural operational research to reveal potential patterns that may have been neglected in the analysis process.

2.4.4 Data Type

A similar pattern of used inputs Pesticides, Diesel, Electricity, Fertilizers, Labour, Machinery, Seeds, and Yield as used output is revealed through this process. However, it is should be underlined that irrigation has been used only from 24 surveys, raising awareness about data collection and data availability of such a valuable natural source. As it was also mentioned in the data analysis section, farm data regarding agronomic characteristics are missing. This situation does not permit researchers to perform a fairer assessment, treating all the involved DMUs as homogenous.

Apart from the quantitative variables, none of the papers used qualitative variables (e.g Likert scale) when performing DEA, a valuable characteristic for assessing agronomic characteristics which cannot be easily or precisely measured or quantified. Cook (2004) provides the appropriate methodology on how the incorporation of qualitative data can be implemented. Considering time-series data, 34 out of 118 included references have analyzed data of more than one year. Authors selected to include this variable, in order to check the validity of acquired results that may present high variations, due to external factors. For instance, bad weather conditions can result in small yield for one region, perceiving it as inefficient compared with another one in the same year. Seasonal differences should be carefully considered when DEA is applied in agriculture. It should be also highlighted that only one survey has applied Window DEA to treat time-series data (Gatimbu et al., 2020), which is the most appropriate methodology for this type of data. Moreover, only none of the studies has incorporated any information from GIS system, highlighting the need for acquiring up-to-date data in an easier and more precise way. In this way, farms or regions can be better characterized, setting on the optimisation process all their unique features that may influence the validity of acquired results.

2.4.5 Data Collection and Processing

Although there is a detailed record of all the included sources, in this review four larger groups were created. Data were collected through; public databases (EUROSTAT, FADN, FAOSTAT, China Statistical Yearbook, other sources) by 49% (58 papers); personal interviews by 45% (53 papers); funded project collaboration by 3% (3 papers); private sector by 3% (2 papers) and not specified in one of them. It should be mentioned that Seo & Umeda (2021) used data from field experiments, an aspect which was absent from this literature review process and should be further promoted for acquiring accurate results. Total sample size has been added as a variable to check the rule of thumb for the ratio of DMUs involved compared to the number of examined variables. None of the examined papers appeared to be problematic on that.

Focusing on data collection through personal interviews, a small part of them (12 papers) had a reference on how they collected their samples. More precisely, 4 referred to Random sampling technique formula (Raheli et al., 2017; Ramezani et al., 2022; Sherzod et al., 2018; Sui et al., 2022); another 4 to Cochran technique (Ashraf et al., 2020; Esfahani et al., 2017; Molinos-Senante et al., 2016; Payandeh et al., 2021); 2 to Yamane technique (Haq & Boz, 2019; Ul Haq et al., 2020); 1 to Stratified Sampling formula (Godoy-Durán et al., 2017) and one to snowball sampling method (Mwambo et al., 2021).

To authors’ surprise, the greatest part of the papers (51%) did not specify which DEA software they used to acquire DEA results, which would be helpful for results reproducibility. DEA Solver, DEAP, and STATA were the most used as shown in Figure 2.7. Regarding the Rstudio software, Benchmarking library was used in 4 papers while 62ver library in another 2.

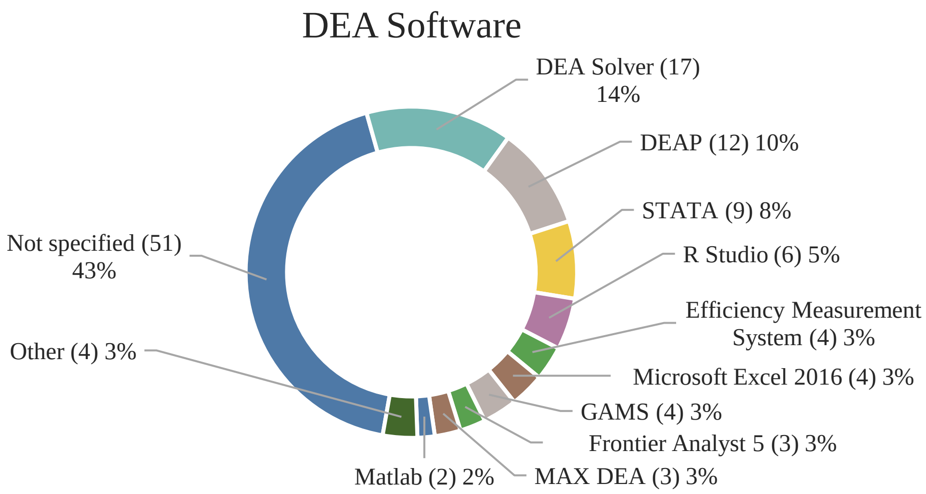

Figure 2.7: DEA Software

2.4.6 Sustainability dimension

Lastly, all papers were grouped by the sustainability dimension that they represent. Although there is a large discussion about how we can define sustainability and which aspects should be included (Purvis et al., 2019), for the scope of this review sustainability is represented by the three aspects of economic development, environmental protection, and social inclusion. It should be mentioned that categorization was made based on two stages. The first stage was referring to the variables inserted immediately in the DEA model, while the second stage was examining the overall contribution to sustainability assessment. For instance, if a paper was using typical inputs and outputs (e.g. labour, fertilizers, land, energy and overall production), it was perceived as solely economic. When a paper has included in the above stated variables an undesirable output (e.g GHG emissions) or LCA results, it was classified in the economic and environmental category. There were also 2 cases in which Human Development Index (HDI) (Babazadeh et al., 2018; Khanjarpanah et al., 2017) was used in the optimization process, meaning that at the DEA stage the social aspect was represented. As Figure 2.8 shows, at the DEA stage half of the papers are contributing only to the economic aspect, 35% concerns both economic and environmental aspect, while only in 11% of the examined papers are representing all sustainability dimensions. For instance, Tang et al. (2022) have incorporated land cost, HDI, annual precipitation and amount of water resources covering all three aspects of sustainability. Sánchez-Zamora & Gallardo-Cobos

(2020) have embodied 22 indicators covering economic, environmental, social, institutional and spatial development characteristics.

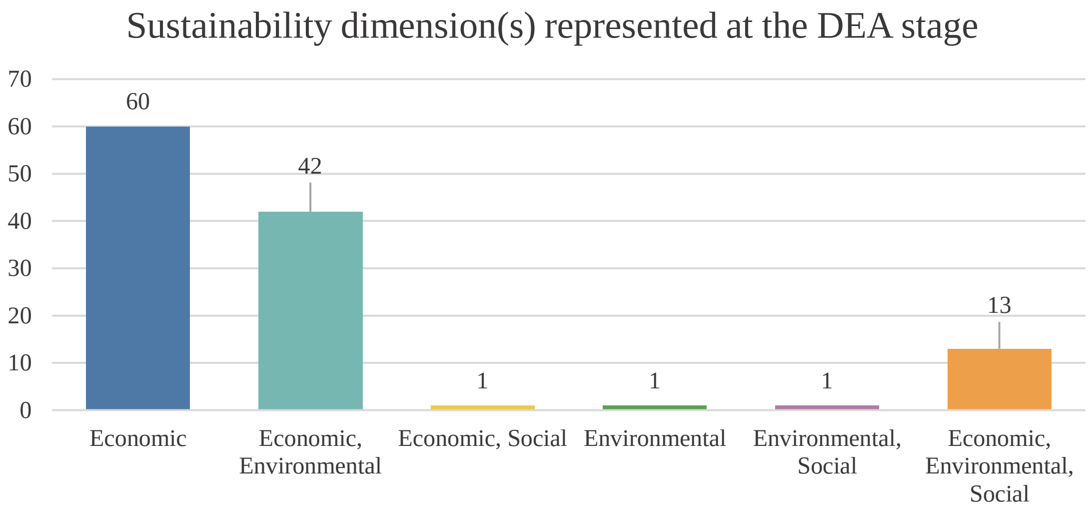

Figure 2.8: Sustainability dimension(s) represented at the DEA stage

Following the same rationale as at the first stage, the examined papers were categorised by the total combination of variables and methods that they implemented in their approaches of sustainability. Figure 2.9 shows that there is a shift only from the economic perspective of Figure 2.8 to a combined economic and environmental approach. In other words, in many cases where only economic pillar was represented in a DEA methodological approach, authors embodied methodologies such as LCA (Beltrán-Esteve et al., 2017; Gamboa et al., 2020) or functions for the calculation of CO_2 emissions (Ashraf et al., 2020; Basavalingaiah et al., 2020; Ilahi et al., 2019) or environmental cost benefit analysis (Mwambo et al., 2020). Economic and social aspect increased as well, due to the fact that DEA outcomes were used as dependent variables in regression models such as Tobit (Haq & Boz, 2019; Sherzod et al., 2018) or truncated regression (L. Liu & Sun, 2019; Martino et al., 2016), to identify significant relations of socioeconomic variables to them. It is really positive the fact that the number of DEA papers contributing to all sustainability pillars increased from 13 to 24, representing almost 20% of the sample, thus the percentage remains low given the fact that examined papers have been retrieved through a structured search for sustainability in agriculture.

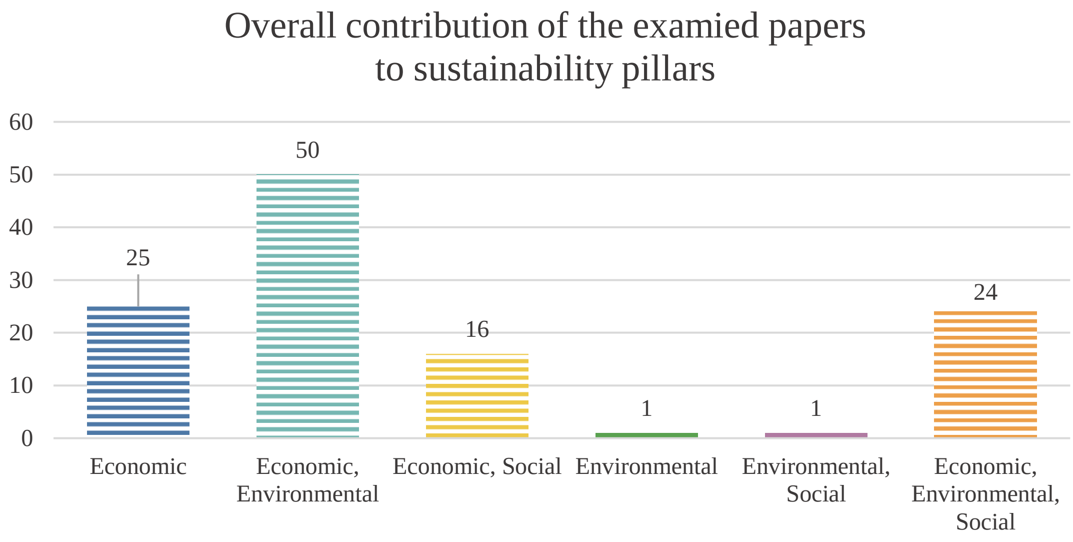

Figure 2.9: Overall contribution of examined papers to sustainability pillars

As a final part of this review, obtained results were visualized to provide a clear image to the reader. As expected, "sustainability" term is closely related to DEA. LCA term is also present, meaning that authors either refer to the applicability of this method in their papers, or they implement it in combination with DEA, a result which was extracted from Subsection 4.3. In the lower left corner of Figure 2.10, there is the label "human" which indicates that even if the number of documents including social features remains small, this term is under authors' consideration.

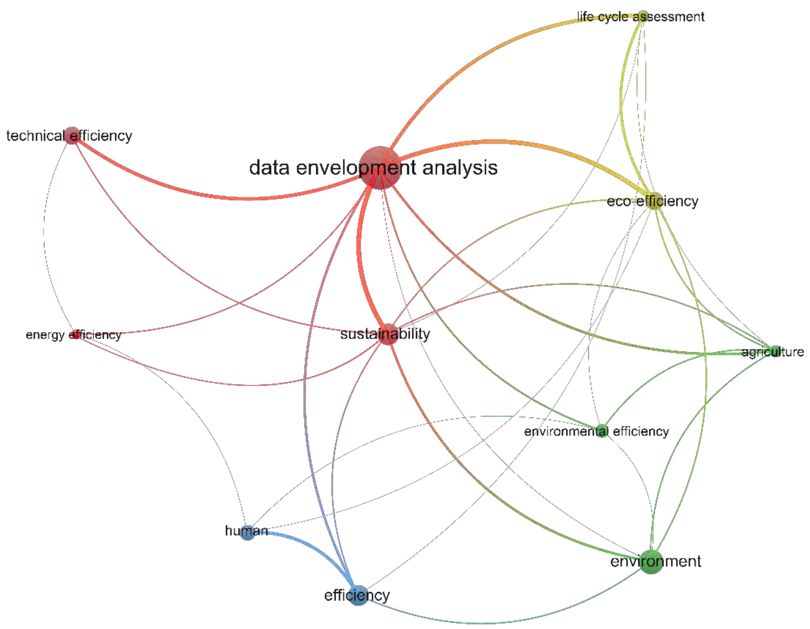

Figure 2.10: Keywords' relationship of the included papers

2.5 Discussion

The main objective of this study is to identify methodological gaps and propose future directions for the operational research field of agriculture, considering sustainability as a driving force. Additionally, the contribution of the reviewed papers to the fulfilment of the 3 aspects of sustainable development was evaluated. The significance of this literature review does not stem from its findings but from highlighting missing aspects or points that needs to be improved.

Over the years there is a clear approach of constantly finding new methodologies to better integrate the concepts of reduced resource availability and environmental protection in DEA methodology. As Galanopoulos et al. (2006) stated, farmers can only control their inputs and they have less impact on the final output, due to a series of external factors. This is the reason why the input-oriented approach is selected, to minimize the risk of the invested capital from the farmer's side as well as promote environmental protection through reduced use of agrochemicals. Although fertilizers skyrocketed the production potential on a global scale, high amounts of energy are needed for their production and distribution (Dimitrijević et al., 2020). This is another reason why the input-oriented approach is selected, leading to production systems with lower energy requirements.

Results indicate that the greatest part of surveys was held out on a local level, thus DEA remains a handful tool for measuring the performance on a greater scale. However, none of the examined papers have assessed the infrastructure of agricultural domains for each country. For example, how the funds of EU agricultural sectors are distributed in subsections like crop production, livestock production and mixed systems, through hierarchical network models (Kremantzis et al., 2022) . It should be also underlined that the implementation of weights would lead to more reliable results (Mosbah et al., 2020; Thompson et al., 1994, 1995). This is a point of great importance for the agricultural field, where multiple external factors affect the interactions of the used inputs, also influencing the final output. For example, temperature affects nitrogen release rates depending on fertilizer type or soil type (Ransom et al., 2020), soil pH plays an important role in plant growth (Xiao et al., 2017), salinity (Hessini et al., 2019), and a series of factors that affect the final output can be inserted in DEA model as weights. That is the reason why the incorporation of GIS information in DEA methodology is essential, but there is a limited number of papers available online with this combination (Liang et al., 2019).

Estimation of undesirable outputs is another point of interest for agricultural productivity. Literature review shows that most researchers use CO_2 or GHG emissions to align their papers with the global effort for GHG emissions reduction. These outcomes are in accordance with Streimikis and Saraji's (2021) review results. However, there is an increasing need for creating circular flows to eliminate the wasted energy, supporting this transition by an appropriate policy framework (Guo et al., 2021).

Moreover, it should be stated that data availability remains an issue in the agricultural field. Almost half of the surveys used data acquired through personal interviews, proving that data collection is a time-demanding process that also involves an increased risk of imprecise data. On top of that, researchers have limited access only to basic information as shown in Table A1, mainly because additional data collection requires an establishment of greater infrastructure e.g. agro-related applications where farmers insert either manually or automatically their data, local agro-managers provide a first stage data screening and lastly, researchers provide further insights and results from visualization. Further assessment is needed regarding qualitative data, like the quality of sowing, quality of spraying or quality characteristics of the final product. TOPSIS Model, which can handle both scale and categorical data, can be easily combined with DEA methodology in the agricultural sector, embodying a wider range of involved variables in the benchmarking process (Kyrgiakos et al., 2021; Wang et al., 2021).

Additionally, out of the 34 papers that used time-series data, 31 extracted them from public datasets, 1 from project collaboration, and another 1 from the private sector. By this statement a lack of constant monitoring by cultivar type and by specific region is highlighted, as the remaining papers performed an annual analysis, indicating the need for incorporating a greater part of variability, derived from multiple years analyses.

The social dimension is the least represented aspect, when measuring efficiency in agriculture under the sustainability framework, a conclusion that derives both from the present review, but also has been highlighted in literature reviews of energy and environmental fields (Tsaples & Papathanasiou, 2021; H. Zhou et al., 2018). Although most surveys include demographic characteristics (age, education, family labor, experience) to represent the social aspect of agriculture, social welfare, government support, social protection and access to non-financial support should be considered as well (Dania et al., 2022). It is not still clear both from the policy makers' side as well as from the academic community which social aspects serve as the best performing KPIs, when assessing sustainability in the agricultural field.

Moreover, even though the economic dimension is the most highlighted one in Figure 2.8, it should be considered that when estimating the potential reduction of the amount of fertilizer per land unit, it is apparent that this act enhances environmental protection. Though, the main outcome of this survey is that the social aspect is still underrepresented, as highlighted in Figure 2.9.

The limitation of this research lies in the fact that the sources were extracted only by using a firm approach of paper selection, searching for DEA and sustainability and agriculture «terms» on their title, abstract, or keywords. Although authors are aware of the existence of a higher number of papers with DEA implementation in the agricultural sector with great potential, e.g application of DEA in agriculture at the EU level (Kočišová, 2015; Madau et al., 2017), local level (Işgın et al., 2020), comparisons of DEA results with SFA (Theodoridis & Psychoudakis, 2008) or newer approaches like 2-stage DEA (F. Ren et al., 2021), engagement of spatial characteristics (Z. Li et al., 2021), DEA with Artificial Neural Networks (ANNs) (Vlontzos & Pardalos, 2017) or Window DEA approaches (Kyrgiakos et al., 2021; Shahraki et al., 2019), thus they were excluded because they did not fulfil the previously stated limitation. Moreover, prominent journals like American Journal of Agricultural Economics or Journal of Agricultural Economics are missing from the two databases, a fact that should be seriously considered by researchers when using these search engines.

Eco-efficiency was another serious consideration when designing this survey due to the fact that there is a considerable effort of several researchers under this term as well (Gómez-Limón et al., 2012; Kiani Mavi et al., 2019; Rebolledo-Leiva et al., 2019). However, using this specific term the pillar of environmental protection would be overestimated and this may lead to non-objective results. Taking the above-mentioned limitations into consideration, authors agreed to proceed with this approach, assuming that the sample size is representative and can provide a simple and realistic overview to the reader. As a final remark, the «agriculture» term should be placed in title, abstract, or keywords section from the future authors, to easily distinguish their papers from closely related ones.

2.6 Conclusions

In this literature review, 120 papers were included referring to the use of DEA in the agricultural sector considering sustainability. Results indicate that there is a need for a more systematic data collection that will incorporate data of agricultural practices (both quantitative and categorized), weather data, as well as an effort of combining DEA methodology with information extracted from GIS databases. Also, it is a necessity to perform optimization methods on a multiple-year basis, to engage all the involved variability. Such applications will permit the implementation of more complex DEA models with greater adaptability in real-case scenarios. The integration of weights in DEA models can contribute to achieving the above goal, ensuring the same baseline before the benchmarking process. Additionally, it is necessary to integrate social factors, especially in cases where the aim of the research is to provide information to policymakers. Concluding, data availability and implementation of more complex methodologies are needed to acquire results with greater explanatory power, contributing to the achievement of sustainable development principles in the agricultural sector.

Chapter 3

Assessing efficiency of cotton farms considering qualitative factors under DEA TOPSIS model

3.1. Introduction

Modern agriculture focuses on increased use efficiency of available resources, while producing the same amount of output with the least environmental externalities (Zulfiqar & Thapa, 2016). Cotton production is an input intensive cultivation, thus a series of different studies have contributed to the elimination of redundant resources through precision agriculture (Theodoridis, Hasanov and Abruev, 2014; Watcharaanantapong et al., 2014), and the assurance of qualitative and quantitative characteristics under genotypic and environmental variation (Shahzad et al., 2019). At the same time, environmental protection should be further promoted through non-chemical alternatives of pesticides (Luo, Naranjo and Wu, 2014). Taking into consideration average production quantities of the last decade (2009-2020) from (FAOSTAT, 2021) data, China, India and USA are holding the first places. In terms of productivity, Australia, Turkey and Mexico have the highest yields of 44K hg/ha or more. The only European representative on the top 10 countries is Greece, with an average annual production of 800K Tones. Cotton production is strongly connected with Greek agriculture, while its cultivation has been motivated under a tailored made European subsidy scheme, immediately after the country’s accession to the EU (Vlontzos, 2007). Since then, several modifications of this scheme have taken place, with the most radical ones to be related with the implementation of the Agenda 2000. More specifically, since the year 2005 there is a partial decoupling of payments on a ratio of 65%-35% decoupling and coupling payments. Taking into account that limitation of natural resources will be further extended due to climate change with unpredicted results, (Ahmad et al., 2017; Chen et al., 2015) for cotton production, a rising interest of saving useful resources is apparent.

In general, cotton (*Gossypium hirsutum L.)* is a highly demanding crop in terms of irrigation and energy use (Imran, Özçatalbaş and Bashir, 2020). According to Anapali et al. (Anapalli et al., 2016) irrigation is one of the crucial factors regarding cotton cultivation, resulting in large differences in final yields between rain fed and irrigated cotton fields. Furthermore, practices followed by farmers can contribute to a higher water use efficiency. For instance, late planting of a month period can be a feasible solution, given the fact that irrigation systems ensure increased water use efficiency (Q. Luo et al., 2016). The aforementioned technique is confirmed for Australian cotton growers, while an increased overall cotton production is expected for the following decades, due to climate change, as their results indicate (Anwar et al., 2020).

Moreover, energy demands of cotton production are mostly derived from the excess amount of fertilizers. Indeed, synthetic fertilizers are the greatest contributors of GHG emissions in cotton cultivation (46%), from seeding to port, underlying the importance of farmers being cautious with their use (Hedayati et al., 2019). In their literature review Khan *et al*. (2017), present a series of suggestions (partially substitution of synthetic with biological fertilizers, slow release fertilizers, legume-based crop rotation) for minimizing GHG emission of N-fertilizers, concluding that future surveys should focus on organic substances with low melting points and moderate water solubility. Additionally, in an effort of minimizing the fertilizers use, a long term survey of 29 consecutive years in Tennessee (X. V. Zhou et al., 2017) has proven that systems with no cover crops have the maximum profit for farmers' side, while if the aforementioned practice is beneficial for environment and society, it should be subsidized by the government.

However, apart from the aforementioned factors, the ongoing climate change is another important factor to be considered, especially for arable land farmers. Climate change will affect irrigation and increase the existence of extreme weather events (Voloudakis et al., 2015). For this reason, European Union through the new Common Agricultural Policy (CAP 2021-2027) enabled the support of farmers in case of extreme weather events (European Commission, 2018). Moreover, CAP 2021-2027 promotes sustainable development, creating the 9 CAP objectives, giving equal importance to the economy, environment and local communities. It should be underlined that constant increase of sustainability awareness from every societal group (farmers and non-farmers) can pinpoint the future for a greener cotton production (Mohapatra & Saha, 2019).

For the above-mentioned reasons, this study has focused on the assessment of input use efficiency of Greek cotton production, especially irrigation and fertilizers, given the fact that the involved inputs will be less available in the future due to climate change. As it was above mentioned, cotton production in Greece is a cultivation of major economic importance because 16% of arable land is cultivated with cotton, resulting to a Gross Production Value of approximately 424M US$ (FAOSTAT, 2021). Hence, it is of paramount importance to examine the input use efficiency of Greek cotton farms, in order to safeguard their resilience towards climate change. In order to achieve this goal, DEA has been used for measuring technical and scale efficiency of Greek Cotton Farms, while on the same time social characteristics have been taken into consideration with the use of TOPSIS model. Social characteristics have been included in the overall benchmarking through the TOPSIS model and have been considered as outputs in order to remain at same levels, since the suggested model is input-oriented. In other words, the goal of this study is to assess the efficiency levels of Greek cotton farmers, considering social factors.

In the first section, applicability of DEA and TOPSIS model are presented, ensuring the validity of the used analysis. In the Methodology section, data collection, descriptive statistics of the sample and computations used for further data analysis are presented, providing useful insights about the conduction of this study. In the Results section, main findings of input use efficiency of the sample are presented. Discussion section highlights the best and worst performers, indicating the need for further assessment regarding irrigation. Last but not least, Conclusion section contains information about limitations of this study and future uses of the applied methodology.

3.2. Background

Although more than 60 years have passed since the conception of DEA, its undoubted usefulness is proven through its use in evaluating the efficiency of various production sectors of the economy (Charnes, Cooper and Rhodes, 1978; Cooper, Seiford and Zhu, 2011). Banks use DEA to a large extent as a useful tool for evaluating, monitoring and developing the performance of stocks and companies (Titko, Stankevičienė and Lāce, 2014). In addition, DEA has been used to identify specific sections inside industries that can be optimized, maximizing their overall efficiency (Baran et al., 2016). It is crucial that suggested solutions regarding DEA methodology are immediately applicable, due to the fact that they have arisen through the assessment of similar units.

While DEA has been used to evaluate the efficiency of a number of productive sectors of the economy, its use in agricultural economics field is relatively recent. As Scopus research reveals, there is an increased interest of "DEA agriculture" term, especially the last decade, probably due to its advantages of ranking DMUs of a given system, while proposing improvements for the ones of lower efficiency (Scopus, 2021). For example, EU agricultural sectors have been assessed through DEA, delivering changes for ameliorating their performance on energy use and negative environmental impacts mitigation (Vlontzos, Niavis and Manos, 2014).

Furthermore, DEA methodology has been also used to assess production protocols of greenhouses, determining efficiency scores among different cultivars. For example, the study of Bournaris et al. (2019) examined the efficiency score of 4 cultivars, (eggplant, cucumber, pepper, tomato) to identify which one has the greatest input use efficiency in a greenhouse. The results highlighted that eggplant greenhouse cultivation was the most efficient out of four, while tomato was the least efficient. Alternatively, Atici and Podinovski (2015) have incorporated specialization parameters when estimating scale efficiency, proving that a combination of different crops can outperform monocultures in some cases. The above-mentioned surveys prove that DEA can assess different production systems and incorporate a significant amount of parameters. Among these parameters it can be easily integrated the use and provision of natural resources. For instance, Watto and Mugera (2014) used DEA in order to assess water use efficiency in cotton production areas of Pakistan, between farmers with immediate access to water (tube well owners) and water buyers. Results indicate significant differences on the overall production between the two groups of farmers of the same area, due to different levels of water efficiency. More specifically, the farmers with immediate access to water had higher water efficiency, due to the 73ulfilment of cotton water needs at the right timing. Therefore, DEA results can be used in multiple dimensions, such as promoting the strategies of the most efficient farmers, supporting those with lowest input use efficiency scores or regional framework implementation, achieving greater land use management.

Additionally, many studies use DEA to optimize energy efficiency, so as to reduce operational cost and minimize environmental effects at the same time. More specifically, Nabavi-Pelesaraei and Amid (2014) used the Constant Return to Scale (CRS) model and the Variable Return to Scale (VRS) model in order to identify the optimal requirements for energy in eggplant production in Iran. The authors evaluated farmers based on their technical, pure technical and scale efficiency. Similarly, Powar et al. (2020) also used the CRS and VRS models to evaluate the efficiency in energy use and identify the optimal energy resources in sugarcane production, while also focusing on technical, pure technical and scale efficiency to categorize farmers as efficient or inefficient. Furthermore, undesirable outputs, like GHG can be identified and eliminated or diminished with the use of DEA, leading to a sustainable agriculture and achieving SDGs. For example, Khoshnevisan et al. (2013) have identified GHG surplus, after analyzing data of 260 French wheat farmers via personal interviews.

Another methodology that can be combined with DEA, is the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) in order to employ qualitative data in the benchmarking process. TOPSIS has been developed by (Hwang and Yoon, 1981) based on the Euclidean distance between DMUs. DEA-TOPSIS combination has been used in order to find the optimal solution, given the fact that both numerical and categorical values are taken into account. For instance, Zeydan and Çolpan (2009) have used this methodology to assess the efficiency of different job shops, taking into account not only quantitative variables like number of personnel, operational unit cost, quality adequacy score and number of personnel, but also TOPSIS results as an outcome of multiple questions about the satisfaction level from these shops. In the agricultural area this technique has been merely used to evaluate the agricultural mechanization in 30 Chinese regions (Y. Yang, 2012).

However, according to the literature review of H. Zhou et al. (2018) there is a rather limited number of studies combining DEA with socio-economic characteristics, proving that agricultural production should have a holistic approach, assessing all three pillars of sustainability. It should be mentioned that the above statement has been exported out of 212 papers in which 63 were referring to the use of DEA in agricultural sector. Additionally, previous surveys indicate the positive relationship between education, as a socio-economic characteristic, and minimized agrochemical products, with increased productivity (Das & Sahoo, 2012; Shetty et al., 2010).

Taking into consideration the above-mentioned studies, it is evident that optimization of agricultural systems has been widely assessed, thus there are several factors, such as social or agronomical characteristics, affecting inputs' use efficiency that is unable be included properly in DEA methodology. The major concern is the fact that their precise quantification is very challenging. TOPSIS methodology can be used as an extra step, in order to convert both scale and ordinal data to a continuous variable that can be included in DEA afterwards. Considering that the upcoming CAP 2021-2027 will focus on the main pillars of sustainable development (economy, environment, society), a proposed methodology is needed to benchmark the involved DMUs and clarify inefficiency differences of a given system, combining both quantitative and qualitative data.

3.3. Methodology

To assess the efficiency of all inputs and outputs used in cotton cultivation, a three-section- questionnaire has been created and distributed to Greek cotton growers. The first part was referring to demographic characteristics of the interviewee like (age, gender, education, class of income, experience). The second part was focusing on a detailed recording of all involved inputs (seeds, pesticides, fertilizers, irrigation, energy use and labour) for the cultivation year 2019-2020. The last part contained questions about the overall cotton production of each farm, and annual amount of money gained from subsidies. Image 3.1 indicates the places where interviews have taken place and Table 3.1 describes the number of farms per prefecture of the overall sample.

Image 3.1 : Locations of the interviews

Table 3.1: Number of farms per prefecture

Prefecture	Number of cotton farms
Larisa	76
Trikala	2
Katerini	25
Thessaloniki	4
Total	**107**

Focusing on the objectives of this survey, DEA methodology has been applied, in order to benchmark inputs use efficiency of cotton growers, a cultivation of major importance not only for the development of local communities, but also for global agriculture, as the Introduction section has suggested. More precisely, an input-oriented approach has been selected, so as to minimize the environmental impact of the cultivar and the amount of money spent by farmers. For this reason, input oriented CRS and VRS DEA model have been selected in order to estimate the technical efficiency scores of different cotton farms:

$$z = \min \theta - \varepsilon\left(\sum_{i=1}^{m} s_i^{-} + \sum_{r=1}^{s} s_r^{+}\right) \qquad (1)$$

$$s.t.\sum_{j=1}^{n}\lambda_j x_{ij} + s_i^- = \theta x_{io}\ i = 1, \dots, m \quad (2)$$

$$\sum_{j=1}^{n}\lambda_j y_{rj} - s_r^+ = y_{ro}\ r = 1, \dots, s \quad (3)$$

$$\lambda_j, s_i^-, s_r^+ \geq 0\ \forall i, r, j. \quad (4)$$

Variable return to Scale (VRS) Add

$$\sum_{j-1}^{n}\lambda_j = 1 \quad (5)$$

Where: n DMU_j= j= 1,…,n use x_{ij} as inputs (e.g. fertilizers, irrigation) producing y_{rj} as outputs (e.g. cotton production), λ_j is a non-negative constant while s_i^- and s_r^+ are the input and output slacks accordingly. In order to characterize a DMU as efficient, both z should be equal to 1 and slacks should be equal to zero. The inclusion of non-Archimedean value (ε) ensures the identification of the most efficient DMUs (Toloo, 2014). As a final step, Scale Efficiency (SE) has been computed by

$$SE_i = \frac{CRS_i}{VRS_i} \quad (6)$$

Where CRS_i and VRS_i are the efficient scores obtained for each DMU with the use of the aforementioned models (eq. (1)-(5)).

Furthermore, education and experience of cotton growers have been selected as key qualitative characteristics to be included in DEA model. Considering that both education level and experience has been collected as categorical values, TOPSIS model was used to transform them into meaningful results, so as to be embodied in the DEA model. In order to achieve this, the following calculations have been made.

For implementing the TOPSIS model, a normalized matrix should be created, using eq (7), where ι represents the number of alternatives (or in this case the number of farmers), j is the number of the involved criteria.

Step 1: $\overline{x_{ij}} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{n} {x_{ij}}^2}}$ (7)

Equal weights have been given to each variable and then Euclidean distance from ideal best and worst is computed.

Step 2: $s_i^+ = \left[\sum_{j=1}^{m} \left(v_{ij} - {v_j}^+\right)^2\right]^{0.5}$, $s_i^- = \left[\sum_{j=1}^{m} \left(v_{ij} - {v_j}^-\right)^2\right]^{0.5}$ (8)

where: ${v_j}^+, {v_j}^-$ represent the best and worst alternative from the ideal solution.

Step 3: $P_i = \frac{s_i^+}{s_i^+ + s_i^-}$ (9)

where P_i is the final score achieved for each unit.

Due to the fact that the agricultural sector has incorporated a series of technological innovation, thus it is crucial to have the appropriate knowledge so as to operate a farm as efficient as possible (Marinoudi et al., 2019). Moreover, well educated people are more willing to adopt precision farming techniques and technology, achieving higher input use efficiency scores (Paustian & Theuvsen, 2017). On the other hand, gaining experience year by year is another important factor, for ameliorating farmers' performance as a result of a consecutive trial and error process (Gul et al., 2009). In this study highly educated people with experience have been selected as the optimal ones.

Figure 3.1 displays the methodology followed in this paper, as a 3-stage approach. Results have been obtained using base and Benchmarking library of R studio.

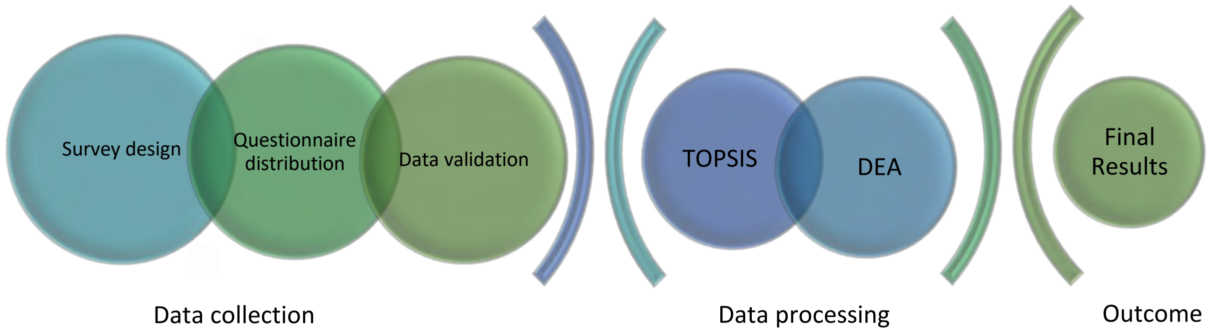

Figure 3.1: Analysis flowchart

3.3.1. Descriptive statistics

An overall sample of 128 questionnaires has been collected but only 107 of them have been further processed after validity check of information given. Analyzing the demographic characteristics of the sample, it can be noted that the average age is 48.5 years old (Figure 3.2) and the greatest part of the respondents were males (86%). Most of the respondents were high school graduates (55%), while only 17% of them had a university degree and the rest 28% were farmers of lower education.

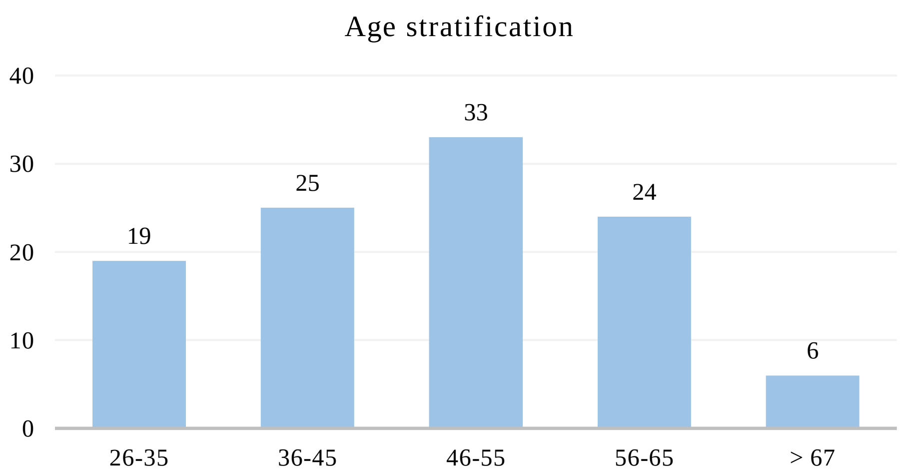

Figure 3.2: Age stratification of cotton growers of the sample

Figure 3.3 illustrates the harvested area of the interviewees. It is evident that cultivated land per farm is really small, compared to the 495Ha average farm size of

Australian cotton growers (Cotton Australia, 2016), but similar surveys in the Mediterranean region present same size characteristics (Gul et al., 2009; Işgın et al., 2020). Furthermore, 69% of the farmers were producing less than 30K Euros as gross annual income, including subsidies.

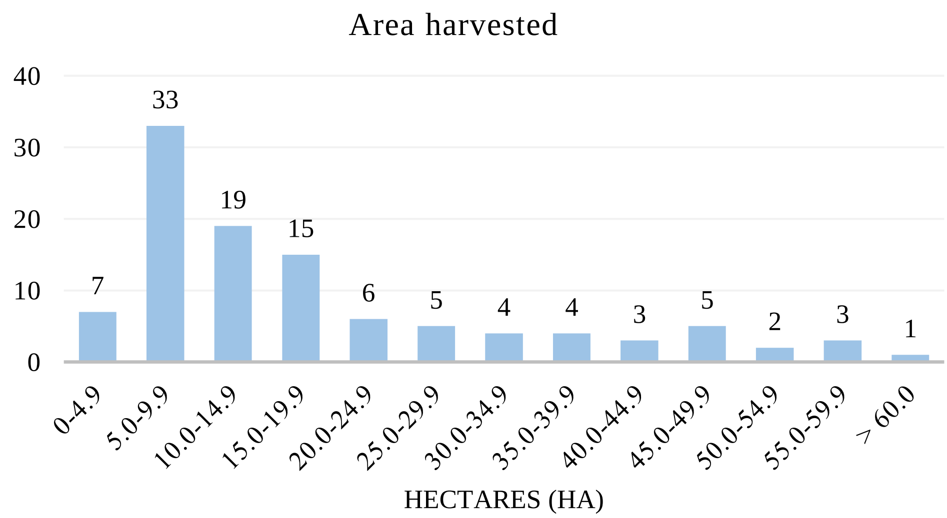

Figure 3.3: Area harvested of cotton growers of the sample

On Figure 3.4 and Figure 3.5 educational level and experience of farmers are presented accordingly. More precisely, it can be observed that the majority of cotton farmers of the sample (55%) have completed compulsory education and they started their professional career as cotton farmer, with 40% of them to have an experience of more than 15 years.

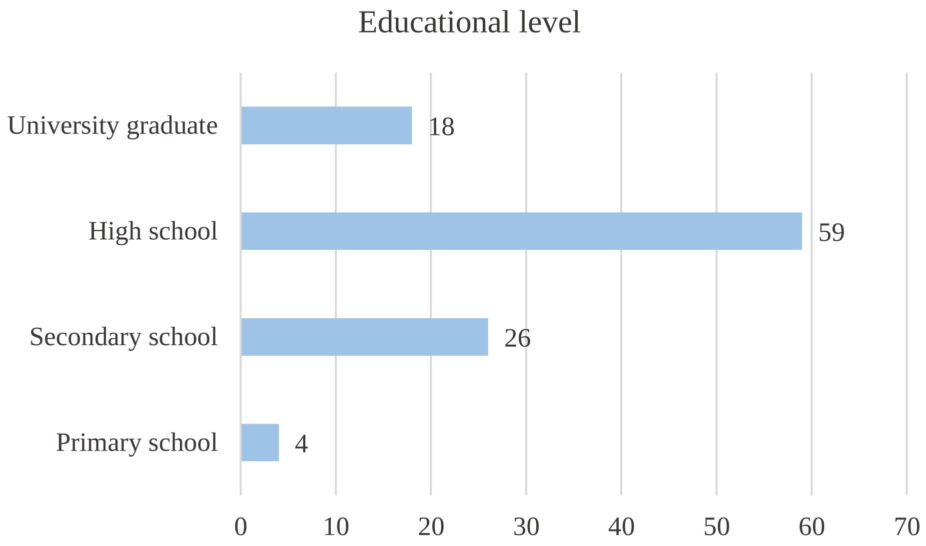

Figure 3.4: Educational level of cotton growers of the sample

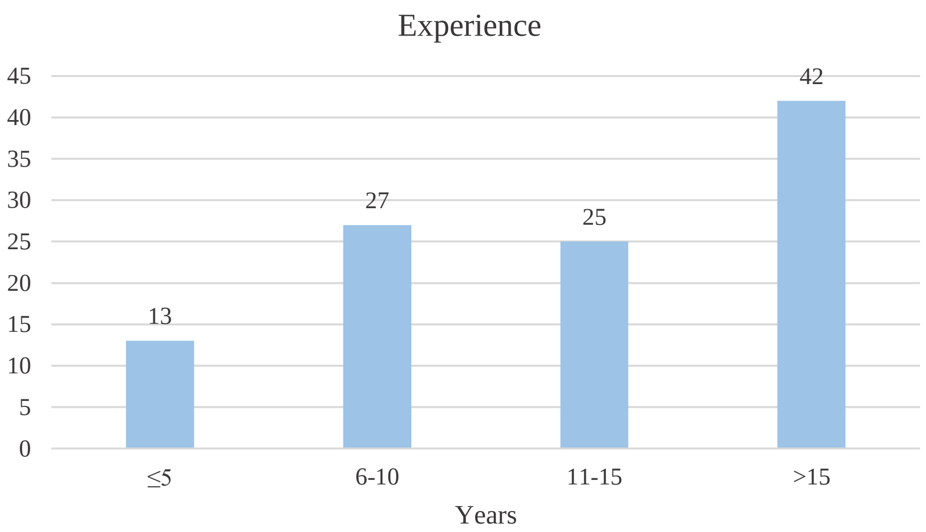

Figure 3.5: Experience of cotton growers of the sample

Table 3.2: Descriptive statistics of the sample

Variables	Mean±SD	Min	Max
Area (ha)	18.6±15.2	2.8	70.0
Seeds (€)	2,298±1,968	300	9,660
Fungicides (€)	53±136	40	1,000
Herbicides (€)	1,675±1.738	50	8,900
Insecticides (€)	2,155±2,081	50	8,400
Fertilizers (€)	3,560±2,707	400	12,000
Diesel (€)	4,775±4,061	485	24,288
Electricity (€)	3,245±3,304	130	14,225
Irrigation (m^3)	73,749±61,502	9,000	290,000
Labour (€)	1,408±1,617	10	6,400
Output (kg)	82,626±70,516	12,000	322,000
Revenue + subsidies (€)	50,720±45,441	6,450	209,340

It has to be clarified that variables of Table 3.2 were grouped and used for further analysis with the DEA model, while education and experience have been taken into consideration using TOPSIS model, following the calculations (7)-(9). The exported vector of TOPSIS model was considered as an output for the DEA model, to maintain social characteristics at the same levels, while optimising inputs' use efficiency. The above-mentioned grouping refers to expenses for fungicides, herbicides, insecticides, fertilizers that have been summed up in a new variable of Plant Protection and Nutrition Products (PPNPs) and diesel, electricity have been also summed, creating the Energy variable.

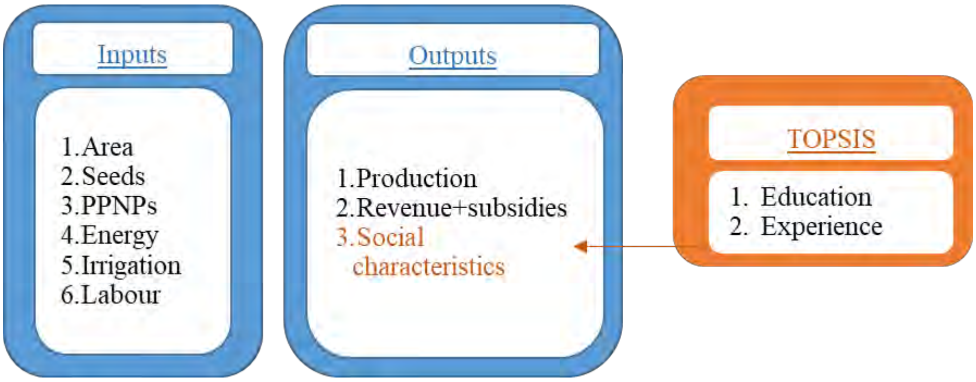

Figure 3.6: Inputs and Outputs of DEA model

3.4. DEA & TOPSIS results

Taking advantage of TOPSIS model to convert categorical variables into scale ones, education and experience have been included in DEA methodology, being extra criteria for the efficiency assessment. By this combination it is feasible to extract results under a series of multiple criteria, conceptualizing efficiency on a wider range. Final DEA results of input CRS and VRS model are presented in Table 3.3 and Table 3.4. Moreover, Scale Efficiency (SE) has been also computed for defining whether or not cotton farmers should adjust their inputs regarding to their size, with a view to have higher profit.

Table 3.3: Descriptive statistics of CRS, VRS and Scale Efficiency (SE) results

	Min	1st Quartile	Median	Mean	3rd Quartile	Max
CRS	0.513	0.812	0.926	0.888	1.000	1.000
VRS	0.529	0.844	0.975	0.915	1.000	1.000
SE	0.793	0.957	0.995	0.970	1.000	1.000

Table 3.4: Input oriented CRS, VRS and Scale Efficiency results by efficiency range

Efficiency range	CRS	VRS	SE
	N of DMUs, (%)	N of DMUs, (%)	N of DMUs
0.5-0.59	2, (1.9)	2, (1.9)	-
0.6-0.69	6, (5.6)	2, (1.9)	-
0.7-0.79	16, (15.0)	12, (11.2)	1
0.8-0.89	22, (20.6)	21 (19.6)	7
0.9-0.99	32, (29.9)	28 (26.2)	70
1	29, (27.1)	42 (39.3)	29

Results indicate that there is not a large variability in the obtained efficiency scores. Average VRS score is equal to 0.915, meaning that there is a well-established production protocol followed by most farmers. Thus, there is a potential of almost 10% or more for the majority of cotton farms included in this sample. Also, it is apparent that 16% of selected cotton farms demonstrate low efficiency scores, meaning that their cultivation protocols should be re-examined, or their owners should seek for other income alternatives. It is very prominent that 39.3% of the total sample achieves maximum efficiency scores, confirming that there is the appropriate knowledge and equipment for efficient cotton production.

3.5. Discussion

In general, this survey assesses input use efficiency in the main cotton cultivation areas of Greece. Structural characteristics of best performers are not clear, regarding their farm size, because as it has been already mentioned, both the largest and the smallest farms are able to operate in the most efficient ways. Worst performers have medium size farms, overusing both irrigation and labour variables. It should be noted that only variable costs were considered in this study due to data availability reasons, which is another factor that may influence the final results. Assessing inefficiency causes of the given sample, there are three major findings that can be extracted. The first one, signifies the urgency of both farmers and policy makers to find new ways of limiting the excess amount of water used for irrigation (Manos et al., 2007). Despite the fact that in this survey the type of mechanical equipment used in the production process has not been recorded, there is a great variability on the irrigation slacks that probably derives from various irrigation system being used. This fact should really concern local communities, because water availability becomes more and more limited, with simultaneous losses in water quality. Through personal interviews, farmers which use pumping system for irrigation confirm that year by year the whole process becomes more energy demanding, due to the fall of underground water level.

Another interesting fact is that there is some evidence of a U-shape regarding VRS scores and farm size (Figure 3.7). More precisely, it seems that the small and large scale farmers achieve maximum efficiency scores, while on the other hand medium scale farmers tend to have lower efficiency scores. A logical explanation of this phenomenon is that the small scale farmers need to save enough from their expenditures so as to survive, and large scale farmers need to be as effective as possible, otherwise they will have huge loses. However, medium scale farmer gain enough for ensuring a good life quality and they may be less interested on their everyday actions. The same result has been also presented from (Işgın et al., 2020), conducting a survey on the neighbouring Turkey, thus more data are needed in order to validate the above mentioned statement in Greece.

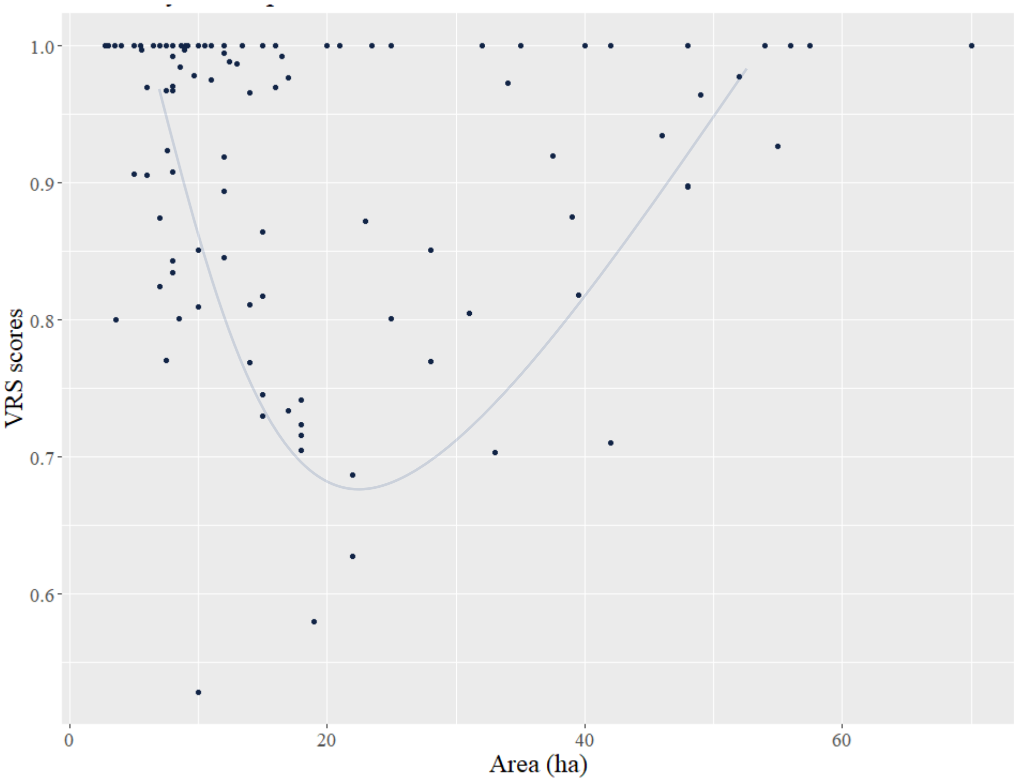

Figure 3.7: Efficiency scores per Cotton farm regarding their cultivated area.

The last finding validates the limited excess use of PPNPs, an issue of major importance on these areas, because farmers were used to spend more than needed especially in crops that were not intended for human consumption (Pantzios, Rozakis and Tzouvelekas, 2002). As results indicate, the majority of cotton farms perform at optimal size, meaning that there is no need for increasing or decreasing their sizes in order to achieve higher productivity. Furthermore, qualitative characteristics inclusion in DEA model provides the opportunity to consider demographic characteristics of the sample on the overall assessment. Previous surveys have proved that both education and experience can affect input use efficiency (Hashmi et al., 2016; Işgın et al., 2020). For this reason, highly educated cotton farmers with high levels of experience have been chosen as an ideal solution for TOPSIS model. The inclusion of TOPSIS results in DEA model provides the opportunity of giving an extra promotion to farmers that fulfil the above-mentioned criteria. In this way they can be easily distinguished from farmers with less experience, meaning that are less susceptible of following less efficient practices or practices that have failed in the past, and also less educated farmers may have a lower understanding of all factors involved in the agricultural production. This approach can contribute on the same holistic direction as Manos et al. (2011).

3.6. Conclusions

Results indicate that there is not large variability in the obtained efficiency scores, meaning that there a well-established production protocol. Almost 70% of cotton growers are operating efficiently. Even though cotton cultivation has a limited amount of profit per land unit, lower efficiency scores indicate further economic losses for cotton farmers. Additionally, exploitation of natural resources due to overuse should be minimized, promoting environmental protection and biodiversity. To a further extent, this approach should be followed to identify if lower efficiency scores were occurring in a specific region, or the production protocol of individual farmers in this region should be redesigned by experts. Constrains of this survey are referring to the difficulty of gaining access to data sources, due to the fact that personal interviews was a time-demanding process. Additionally, a time extension of the research period is required, so as to eliminate the influence of random factors affecting the final production, such as environmental conditions. Taking into consideration the lack of surveys combining both qualitative and quantitative characteristics in terms of efficiency assessment, it can be stated that TOPSIS-DEA mixture can substantially contribute to a greater overview of the agricultural sector. It is also important to mention that this approach enables the analysis of a series of additional factors affecting both operational and environmental performance, such as toxicity of agrochemicals, scarcity of water resources and labour intensity. The proposed approach can be implemented in cases where multiple factors affect agricultural production and it is very challenging to record them precisely, e.g. quality of plowing.

Future surveys should focus either on incorporating additional social characteristics, such as familiarity with new technologies or willingness on participating in cooperatives or national schemes, or focus on agronomical characteristics, as the ones mentioned before. Moreover, the proposed methodology can be implemented for incorporating regional features and benchmarking regions that can be more or less appropriate for a specific cultivation. On the other hand, it can lead to a number of criteria for evaluating the “sustainability” term, by quantifying the impact of social, economic and environmental factors. This is the main feature that can be utilized by policy makers' side to benchmark farmers' hard and soft skills, deciding at the same time the strategy that will follow, either by supporting the weak ones or by ameliorating the best performers.

DEA – TOPSIS model has an added value due to its easiness of results interpretation and practical implementation of them. Although some of the cotton farms are fully efficient, the greatest part of the sample needs to adopt minor or major changes on their production protocol. The proposed analysis can contribute to the sustainability assessment, especially in the era of increasing interest for SDGs, in cases where precise measurements of a value is not easy to be met. Considering the above statement, this methodology could be a useful tool to rank the various DMUs but also to indicate practices of best performers and apply changes accordingly in the given production system. Tailored made strategies for policy makers and stakeholders involved is a key element for accomplishing SDGs and achieving sustainability.

Chapter 4

Are there any efficiency differences in a common Agriculture Decision Support System? A comparative analysis between Greek and Italian durum wheat farms.

4.1. Introduction

The modern agricultural sector faces important and urgent challenges such as food security, climate change, and increased prices in all inputs (mainly in electricity, diesel, and fertilizers) (Fellmann et al., 2018). The COVID-19 pandemic intensified the effects of the above-mentioned issues, while as Sridhar et al. (2022) stated, the adoption of new technologies, which contribute to the collection, processing and transmission of information both in farm and off-farm operations, is the on-going revolution after the mechanization of the agricultural sector. This leads to food systems of increased resilience. Moreover, there is a global demand for enhanced environmental protection, agricultural products with high quality standards, as well as action plans for preserving improved welfare for rural communities. Considering that agriculture is dependent on a series of exogenous factors (type of cultivation, pests, temperature, precipitation, soil type etc.), there is a need for collecting and analysing all available information to make decisions leading to risk mitigation. This has led to the escalation of Agricultural Decision Support Systems (ADSSs), a trend that confirms the necessity of their existence. ADSSs are applications that provide cultivating directives, based on given data related to specific agricultural practices (application of agrochemicals, irrigation, fertilization, and timing of each one) and climatic data like temperature, wind speed or moisture level (Jakku and Thorburn, 2010).

Mir et al. (2015) provide an extended classification of ADSSs based on their contribution for solving farm-related issues, such as nutrient balance, pest management, irrigation, and crop planning. Precise identification of target values of each of the above-mentioned aspects, leads to the minimization of exploited resources (both economic and environmental), resulting in agricultural systems of higher efficiency (Saiz-Rubio and Rovira-Más, 2020). In particular, ADSSs specialized in wheat and durum wheat cultivation are dealing with managing fungi infections (Rossi et al., 2015) irrigation (Chemak et al., 2020) or fertilization (Pooniya et al., 2015). Rossi et al. (2010) proposed an integrated durum wheat ADSS which includes weather, soil, planting and harvesting parameters. However, the economic and environmental dimension was merely explored.

The objective of this study is to clarify efficiency differences between Greek and Italian farmers that operate under a common ADSS specialized in durum wheat cultivation, considering both economic and environmental factors. The suggestions of an ADSS are not immediately applicable and it is under the farmer's discretion whether they will be implemented or not. For this reason, it was considered appropriate to assess the stages in which this relationship between technology and the human factor is formed in the Literature review (Section 2), also embodying an overview of efficiency assessment methodologies. State-of-art (Section 3) clarifies the contribution of this empirical research, compared to similar surveys. The Methodology part (Section 4) presents the Data Envelopment Analysis (DEA) and its applications in this case study, regarding the economic and environmental performance of Italian and Greek durum wheat farmers. In the Results section (Section 5), descriptive statistics of the involved variables and obtained efficiency scores for the two countries are also analysed. Discussion and study limitations section (Section 6) assesses the peculiarities of DEA implementation in the agricultural sector. Lastly, in the Conclusions section (Section 7) final remarks regarding the use of ADSS in the agricultural sector are being made.

4.2. Literature review

4.2.1. Farmers relationship with ADSS

Focusing on ADSSs and their relationship with end-users, there are four concrete stages that can be assessed to clarify the factors affecting ADSS and farmers' cooperation status as Figure 4.1 presents: (a) creation, (b) use, (c) evaluation of the acquired results, and (d) redesign. Referring to the first stage of ADSSs, many of them are designed for fulfilling one specific goal like water-saving from irrigation (Navarro-Hellín et al., 2016; Viani et al., 2017), optimum fertilization (Villalobos et al., 2020), and chemical elements' runoff (Drohan et al., 2019).

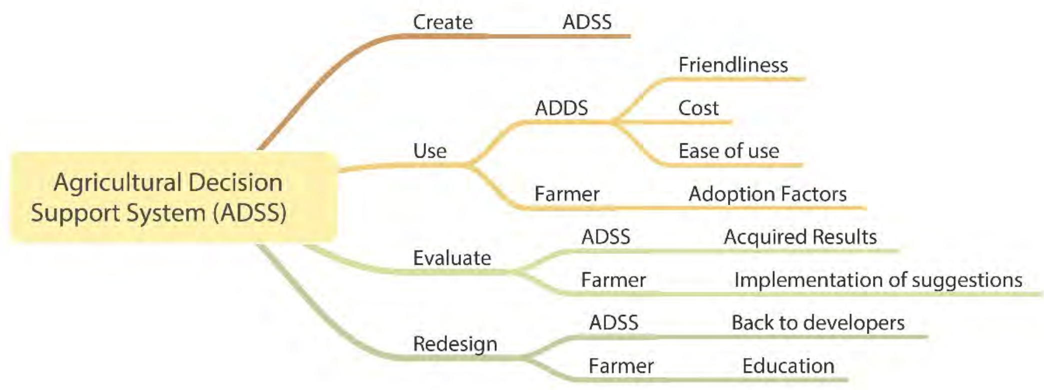

Figure 4.1: The four stages of ADSSs and famers interaction.

Due to the increasing number of ADSSs, different methodologies were developed on selecting the most appropriate one, based on farmers' needs, providing answers on a) Which ADSS should be used, and b) Why it should be adopted by farmers. Duan et al. (2021) proposed a multiple criteria system, under a sustainability context, meaning that a) economic b) environmental and c) social dimensions were assessed, taking under consideration the d) technology and e) structural characteristics of the farm. Applying the previously stated methodology, ADSSs which promote sustainable development and provide clear and feasible goals for the farmers, can be easily distinguished, indicating a step-by-step process for reaching sustainability goals in agricultural production.

Furthermore, the second stage of use, the interaction of both sides (ADSSs and farmers) should be assessed. From the ADSS aspect, ease of use, friendliness to the end-user, cost, and trust in the achieving results are critical factors for ADSS to be adopted, but as Rose et al. (2016) state, the adoption rate is still very low. After reviewing 13 ADSSs, Zhai et al. (2020) concluded that a simplified version of the interface is essential for increased understanding of the results from the farmers' side, while an interdisciplinary approach (data analysts – agro-managers – farmers) is needed for a concrete ADSSs' outcome evaluation. The aforementioned results are validated by Rossi et al. (2019), highlighting two factors: a) user-friendliness in ADSSs and b) the necessity of synergies-making for sharing knowledge and experience.

On the farmers' perspective, many factors have been identified, influencing them for adopting an ADSS. Management of uncertainty and risk are significant motives for adoption. There is evidence that farmers are risk-averse, meaning that they choose options with less risk, even though their potential income is lower (Iyer et al., 2020). The same review states that there is an increasing trend for surveys that assess risk measurement in the last decade, especially nowadays that the occurrence of unexpected extreme weather events is more frequent due to climate change. Moreover, decisions are being affected from the space and time as Viergutz and Schulze-Ehlers (2018) indicate. It should also be stated that the cost of using these systems, particularly the return-on-investment proportion, is a restricting factor (Yigezu et al., 2018).

The evaluation of the acquired results is necessary for the acceptance or not of the proposals of the ADSS by a larger group of people. For instance, Chen et al. (2020) evaluated an ADSS for cotton irrigation, proving that its use increased the final yield by 32%. Moreover, due to the increased number of ADSSs, researchers often implement more than one at a time to evaluate their results (Bonfante et al., 2019). This stage is of particular importance, especially for systems where Artificial Intelligence is used, for further model training and greater results assurance (Vivek and Jesma, 2019; Partel et al., 2019).

Last step concerns the implementation of major or minor redesign, both for the ADSS and farmers. Participatory approaches are requested to demonstrate the weak spots of such systems and help on increasing the utility of ADSS (Cerf et al., 2012). The educational level of farmers increases their productivity and their understanding about the current needs of the food supply chain, but field schools could help on further familiarize with ADSS (Paltasingh and Goyari, 2018). In other words, a coordinated effort is needed from both sides (ADSS and farmers) to achieve higher levels of cooperation.

4.2.2. Efficiency assesment

Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis are the most well-established techniques when it comes to efficiency measurement in the agricultural sector (Lampe and Hilgers, 2015). For instance, Ilahi et al. (2019) have assessed wheat production in the Chinese regions, considering greenhouse gas emissions as undesirable outputs, proving that the average inefficiency gap for the examined farmers is around 30%. Similar results were obtained from Janusz

Gołaszewski et al. (2014) when exploring energy efficiency differences between 6 European countries (Germany, Netherlands, Finland, Poland, Greece and Portugal) on wheat cultivation, by implementing DEA methodology. Moreover, DEA has been used for the eco-efficiency assessment of wheat production in the Italian regions, signifying regional changes between 2004 and 2017 (Coluccia et al., 2020), emphasizing to the environmental impacts of agricultural activity. DEA can be combined with Malmquist index in order to highlight annual efficiency changes in a given time period (Forleo et al., 2021).

Significant effort was also made by the implementation of similar techniques such as Material Flow Analysis, to evaluate the economic and environmental dimension of durum wheat production in Italy (Bux et al., 2022). The total factor productivity can also be assessed by using Färe-Primont productivity index (Reziti and Zangelidis, 2019). For instance, Xiu-Shuang and Kang (2021) have used the above-mentioned index to clarify efficiency differences in Chinese wheat production. Although results indicate that there is a slight increase (~10%) regarding the total factor productivity, farmers' profitability was decreased by 25%, raising awareness about the food security issues and the future of rural areas.

4.3. State of the art

Combining the aforementioned surveys regarding the relationship of farmers with ADSS and efficiency assessment, it appears that a small number of surveys have been carried out on evaluating the acquired results after the implementation of the ADSSs suggestions. For instance, vite.net which is a holistic ADSS for viticulture was set into action on multiple vineyards in Italy, testing not only the suggestion of the system, but also researchers monitored the implementation level of suggested actions and level of overall satisfaction of the end-user (Rossi et al., 2014). In comparison to the latter paper, which focuses on the interaction between farmers and ADSS, our article additionally assesses the economic and environmental performance of farmers supported by the same ADSS. More precisely, data collected through granoduro.net (GD.NET), which is a holistic ADSS specialized in durum wheat production co-designed by Barilla and HORTA in 2009, were used for the performance evaluation of the farmers (HORTA, 2012). GD.NET integrates and processes data from different sources to produce simple and effective alarms for durum wheat farmers. Collected data are referring to four different firms, two Italian and two Greek ones for the cultivation period 2020-2021. It should be underlined that all firms are operating under the suggestions of the above-mentioned ADSS, creating a common environment for all the involved farmers.

Taking into account the current status of ADSS adoption and the increased need to ensure an adequate amount of food, due to the ongoing Russian-Ukrainian war, a specific type of wheat was selected for this study. Durum wheat is raw material for pasta making due to its high protein concentration, thus only a few areas around the globe satisfy its climatic needs. Italy and Greece are neighboring countries that both 93veral durum wheat needs, operating under the same ADSS. Minimizing the influence of external factors and ensuring that farmers are provided with suggestions from the same system, this study focuses on the evaluation stage of GD.NET aiming to explain:

a) if GD.NET suggestions were leading to greater input use efficiency and

b) if the suggestions of GD.NET are being followed by farmers.

4.4. Methodology

4.4.1. Data Envelopment Analysis (DEA)

Focusing on the objectives of this study, DEA has been applied, to assess inputs use efficiency of durum wheat producers. DEA is a well-established non-parametric benchmarking technique, which takes advantage of linear programming principles to estimate measures of technical efficiency of different units (Charnes et al., 1978) . The optimization method can be either input-oriented, minimizing the used inputs or output-oriented, maximizing the produced outputs (Moutinho et al., 2018; Bournaris et al., 2019). Input-oriented approach was selected, for minimizing the environmental impact of durum wheat cultivation and the amount of money spent by farmers (Skevas et al., 2014). Moreover, the amount of final yield is not secured every year, and this is another reason why the risk should be mitigated by using the least inputs needed (Galanopoulos et al., 2006). It should be noted that the same dataset can be treated by applying both approaches.

Explaining DEA methodology in further details, it should be mentioned that there are two main models. The first one is the Constant Returns to Scale (CRS), which assumes that the increase of one unit of input is increasing the output at the same way. Additionally, Variable Returns to Scale (VRS) assumes that the relationship between Inputs and Outputs is not constant but it can be either increasing or decreasing. Every unit, which makes decisions about inputs use and achieved outputs, is called Decision Making Unit (DMU). Each durum wheat farm is considered as a DMU that decides for the used amount of inputs. The most efficient DMUs are receiving a score of 1, formulating the efficient frontier. On the contrary, the least efficient DMUs score from 0.99 to 0.

From a mathematical perspective, the above-mentioned problem can be used both for input-oriented CRS and VRS DEA model by using the following formulas:

Constant Return to Scale (CRS)

$$\min \theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \qquad (1)$$

$$s.t. \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{io} \qquad i = 1, \dots, m \qquad (2)$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro} \qquad r = 1, \dots, s \qquad (3)$$

$$\lambda_j, s_i^-, s_r^+ \geq 0 \ \forall i, r, j. \qquad (4)$$

j= 1,…–n - firms index

i= 1,...–m - inputs index

r= 1,...–s - outputs index

ε= non-Archimedian value

Variable Return to Scale (VRS) Add:

$$\sum_{j=1}^{n} \lambda_j = 1 \qquad (5)$$

Where: n DMU_j (j= 1,…,n) use x_{ij} as inputs (e.g. seeds, fertilizers etc) producing y_{rj} as outputs (e.g. durum wheat yield), λj is a non-negative constant while s_i^- and s_r^+ are the input and output slacks accordingly. To characterize a DMU as fully efficient, both conditions should be met: the efficiency score θ should be equal to 1 and slacks should be equal to zero. The absence of the non-Archimedean value (ε) would lead to the infeasibility of identifying the most efficient DMUs (Toloo, 2014). As a final step, Scale Efficiency (SE) has been computed by equation (6)

4.4.2. Models' specification

Taking into consideration the above-mentioned methodological part, GD.NET dataset, was used to assess input use efficiency of durum wheat farmers, referring to the cultivation year of 2020-2021. Due to data availability reasons only variable costs have been included in this study. Two models were created for measuring technical efficiency of all DMUs involved. The first one (EconDEA) enables only the variable costs of durum wheat cultivation (Seeds, Fertilizers, Plant Protection Products, Diesel, Labour and Yield), while the EcoDEA model, incorporates both economic and environmental factors. More accurately, Carbon Footprint, Water Footprint and Ecological Footprint, were assessed under the common name of CWEFs. CWEFs were treated as undesirable factors in the EcoDEA model, after the linear monotone decreasing transformation as proposed by Seiford and Zhu (2002). It should be mentioned that CWEFs values were provided immediately by GD.NET. Table 4.1 provides an overall summary of the involved variables per model. The analysis process was conducted in the RStudio using rcompanion (for Median differences95vereaR (Benchmarking) and ggplot2 (Visualisation) libraries (Mangiafico, 2016; Wickham, 2016; Coll-Serrano et al., 2022).

Table 4.1: Inputs and Outputs used per DEA function

	EconDEA	**EcoDEA**
Inputs	Seeds Fertilizers Plant Protection Products Diesel Labour	Seeds Fertilizers Plant Protection Products Diesel Labour
Outputs	Yield	Yield Carbon Footprint Water Footprint Ecological Footprint

This study is separated into two distinct parts. The first one provides descriptive statistics of all variables involved, conducting Mood's Median test, in order to assess differences between the involved variables. It should be noted that both descriptive statistics and the DEA section part are referring to the functional unit of final production of Durum Wheat per Hectare (ha) under 13% moisture level. Moving forward to the next part, the acquired results of EconDEA and EcoDEA are presented. Both models have been applied at a national level, as the involved DMUs are subject to different external factors, which are likely to influence the final efficiency scores. Both CRS and VRS results were calculated for the two models to compute Scale Efficiency.

4.5. Results

4.5.1. Descriptive statistics

As presented in the Methodology section, the first part of the results was referring to descriptive statistics of all variables involved in the analysis, highlighting differences between their medians. In total, 563 durum wheat farms have been assessed, 328 (58%) for the Italian sample and 235 (42%) for the Greek sample. Since the data presented are highly confidential, the names of participating firms in the analysis were changed to I1 229 (41%), I2 99 (18%) and G1 202 (36%), G2 33 (6%) for the Italian and Greek firms respectively. Table 4.2 presents descriptive statistics of inputs and output per firm.

Table 4.2: Descriptive statistics of GD.NET dataset per country and per firm

		Greece N=235		Italy N=328	
Characteristic	Overall, N = 563[1]	G1, N = 202[1]	G2, N = 33[1]	I1, N = 229[1]	I2, N = 99[1]
Seeds (kg/t of final product)	41.50, (19.70), [32.50-55.90]	56.65, (18.38), [45.42-67.97]	44.50, (3.77), [42.80-46.90]	31.40, (16.18), [27.20-36.40]	43.30, (15.95), [38.35-51.55]
Fertilizers (kg/t of final product)	78.90, (36.37), [59.90-101.40]	94.00, (35.96), [67.12-118.83]	87.80, (7.24), [86.20-92.70]	64.40, (31.37), [53.10-78.00]	89.70, (39.78), [73.95-108.75]
Plant Protection Products (kg/t of final product)	0.39, (0.39), [0.17-0.65]	0.18, (0.15), [0.11-0.33]	0.10, (0.02), [0.09-0.10]	0.51, (0.39), [0.38-0.74]	0.77, (0.37), [0.57-0.97]

		Greece N=235		Italy N=328	
Characteristic	Overall, N = 563[1]	G1, N = 202[1]	G2, N = 33[1]	I1, N = 229[1]	I2, N = 99[1]
Diesel (L/t of final product)	23.00, (10.73), [20.00-29.00]	31.00, (9.73), [25.00-37.75]	23.00, (4.53), [21.00-25.00]	21.00, (10.85), [19.00-24.00]	19.00, (5.91), [17.00-21.00]
Labour (€/t of final product)	18.00, (8.83), [14.08-23.00]	22.16, (8.20), [17.70-28.06]	17.97, (2.83), [15.39-19.83]	14.26, (8.56), [12.26-16.93]	20.18, (8.26), [16.33-24.90]
Yield (t/ha)	5.24, (1.83), [3.92-6.96]	3.84, (1.13), [3.16-4.71]	5.11, (0.29), [4.66-5.14]	7.07, (1.52), [6.20-7.89]	5.25, (1.32), [4.31-5.73]
Carbon Footprint (CO_2eq/t of final product)	0.39, (0.15), [0.33-0.48]	0.43, (0.13), [0.37-0.52]	0.39, (0.16), [0.35-0.67]	0.34, (0.14), [0.29-0.39]	0.44, (0.16), [0.39-0.51]
Water Footprint (m^3/t of final product)	1,394 (457.52), [1,201-1,950]	2,099, (307.10), [1,827-2,271]	1,539, (204.76), [1,517-1,882]	1,169, (94.62), [1,110-1,229]	1,356, (219.58), [1,318-1,563]
Ecological Footprint (Global ha/t of final product)	0.53, (0.24), [0.40-0.70]	0.72, (0.22), [0.58-0.86]	0.56, (0.03), [0.54-0.58]	0.39, (0.19), [0.35-0.45]	0.53, (0.20), [0.49-0.63]
Area (ha)	5.00, (13.25), [3.00-10.00]	4.59, (8.88), [2.86-7.50]	2.30, (4.03), [1.00-5.00]	5.00, (6.15), [3.00-8.00]	13.00, (23.90), [7.00-25.50]

[1]Median, (SD), IQR[25%-75%]

An extended version of Table 4.2 (Table A2.1) containing additional information about minimum, maximum, and mean values can be found in the Appendix section as well as a boxplot for each of the involved variables in the DEA process (Figures A4.1-A4.9). Embodied letters in the boxplot figures signify median differences as indicated from Mood's median test.

4.5.2. DEA Results

Considering the increased number of factors affecting durum wheat production, like weather conditions, seed quality, agrochemical active ingredients, soil type etc, and input use efficiency was tested on a national level, so as to provide a clear description of best and worst practices. For both countries, an overall illustration of inputs to outputs in monetary values is presented, followed by efficiency scores for EconDEA and EcoDEA models in national and firm level. Moreover, target values of CWEFs were compared with the initial values to indicate potential reductions after the optimization process, according to the acquired data from best performers. Given the fact that VRS model has greater adaptability to the dataset under consideration, incorporating in a better way the existing variability, it was selected as the main model for results visualization. However, CRS efficiency scores were also calculated to estimate the Scale Efficiency. In the following section, there is a detailed description for both countries and firms.

4.5.2.1. Italy

Figure 4.2 presents the results of EconDEA in a bar plot, revealing that the greatest part of farmers (63.1%) acquired efficiency scores between 0.7-0.9, meaning that they should reduce their inputs by 10-30% accordingly. Additionally, considering only the economic dimension, scale efficiency scores indicate that farmers should adjust their farms size, in order to operate at an optimum scale. However, EcoDEA model results for scale efficiency suggest that the majority of the farmers (71%) are operating at an optimum farm size when environmental factors are enabled. Moreover, a positive image is depicted for VRS efficiency scores as well, where farmers are achieving higher efficiency scores. In other words, the inclusion of environmental indicators in the empirical model are ameliorating farmers' performance, providing an integrated approach regarding the agricultural activities of Italian durum wheat farmers.

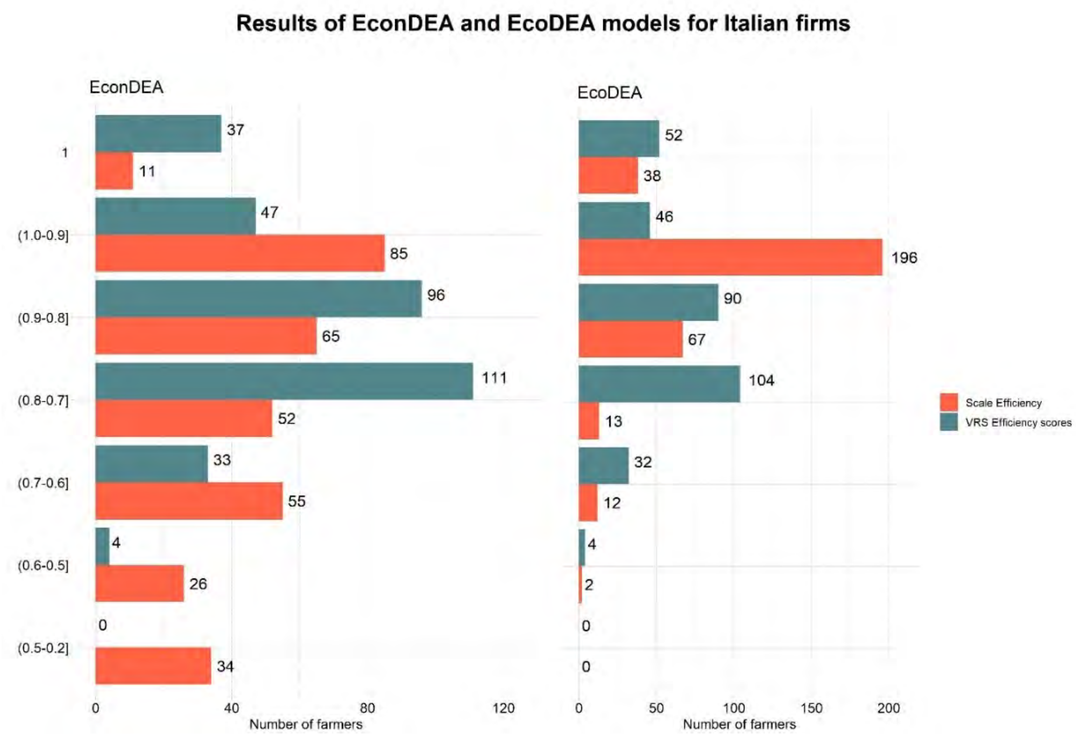

Figure 4.2: VRS and Scale Efficiency scores for the Italian sample (EconDEA & EcoDEA)

Figure 4.3 illustrates I1 and I2 differences in a density plot. It is apparent that I1 utilizes in a more efficient way used inputs, since it dominates over I2 at efficiency scores higher than 0.85. It should be noted that there is an ongoing assumption that external factors (climate, weather conditions, etc.) affect the production process in the same way for every farm participating in this assessment. Moreover, in Table 4.3, median scores for I1 and I2 are presented, corresponding to 0.86 and 0.77 respectively. It is very promising that I2 farms achieved an efficiency score of 1.00, considering that this score arose after its comparison with farms of I1, meaning that in both samples there are efficient producers (efficiency score=1).

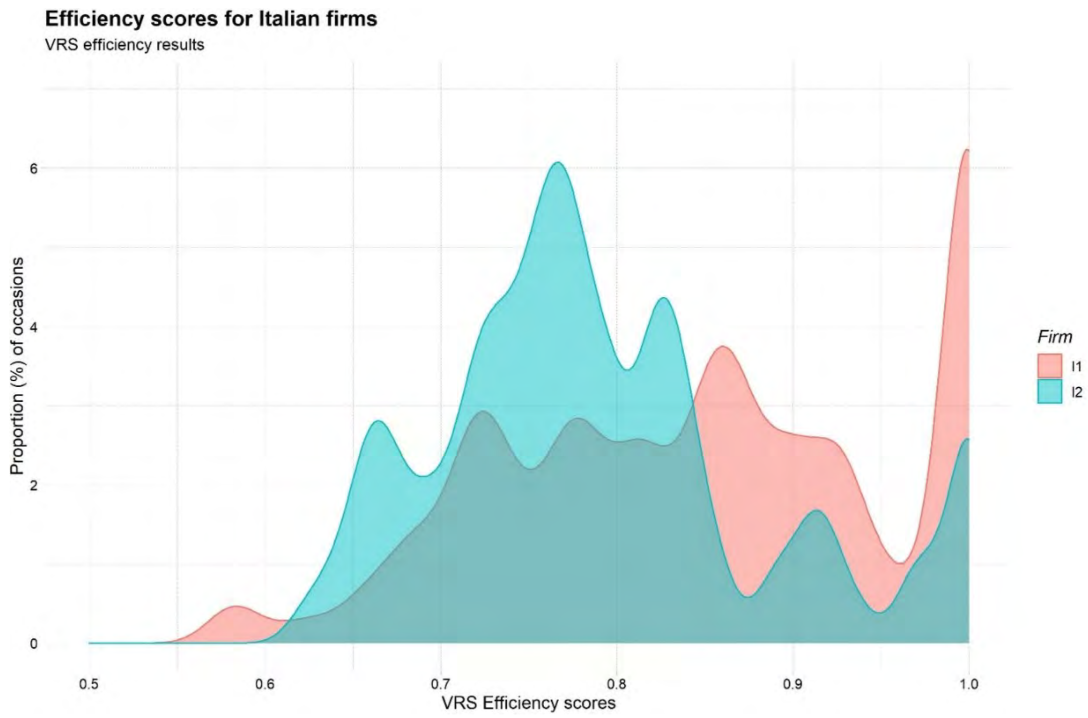

Figure 4.3: VRS Efficiency scores distribution for Italian firms (EcoDEA)

Table 4.3: Descriptive statistics of VRS efficiency scores per Italian firm

		I1, N = 229	I2, N = 99
EcoDEA *VRS efficiency scores*	Min.	0.58,	0.62,
	Median	0.86,	0.77,
	Mean	0.85,	0.79,
	Max.	1.00,	1.00,
	(SD)	(0.11),	(0.10),
	IQR [25%-75%]	[0.76-0.94]	[0.73-0.83]

From another perspective, I2 has a greater need for inputs without achieving the same output as I1. Figure 4.4 presents the used inputs to output in monetary values through a scatterplot. The majority of I2 farms need more Inputs to achieve the same or smaller outcome in most cases. However, it is apparent that there is a tendency for inputs minimization in the Italian sample.

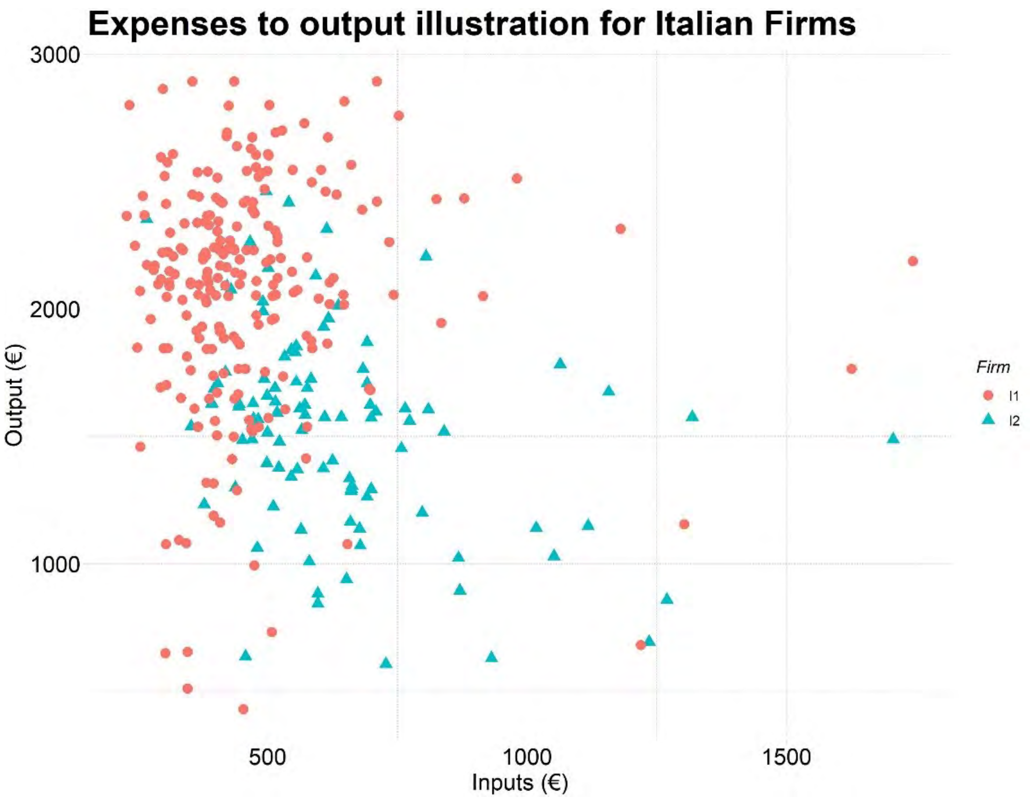

Figure 4.4: Monetary values of inputs used to final output for the Italian firms.

Furthermore, optimization of CWEFs proved that there is a great potential for minimizing the environmental impact of durum wheat production. More precisely, Figure 4.5 presents the distributional characteristics of CWEFs as initial values on the left side of each graph and the distribution of target values after the optimization process in the right side. As shown in the following boxplot, Carbon and Ecological footprints can be decreased by 38% and 23% respectively, while water footprint has a little potential of 4.6% reduction, based on median values.

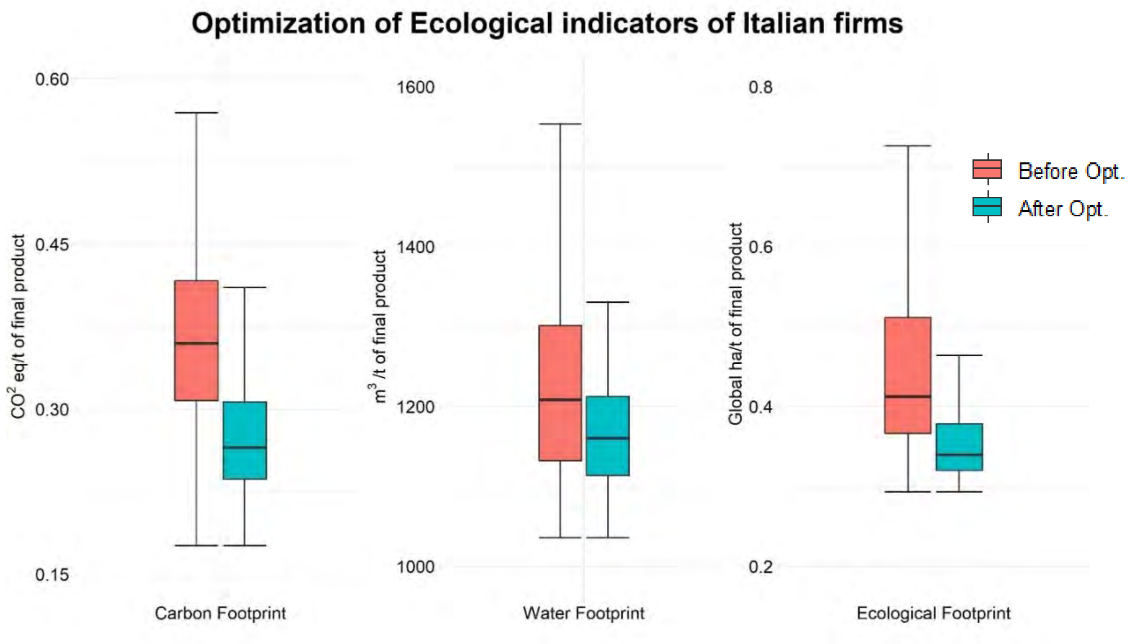

Figure 4.5: Reduction potential of CWEFs after the optimization process
for the Italian farms

4.5.2.2. Greece

Figure 4.6 illustrates the distribution of VRS and scale efficiency results for Greek Firms in a bar plot. Although the distribution of the acquired efficiency scores appears with similarity to Figure 4.2, it should be stated that efficiency scores are calculated based on the best performer of each region. Most of the farmers (57%) have acquired an efficiency score between 0.7-0.9, however greater scale inefficiency is presented in the lower bound of the distribution, where 35% of the examined farms have obtained scores lower than 0.6. The inclusion of the CWEFs has again a positive impact in the overall assessment for both pure technical and scale efficiency.

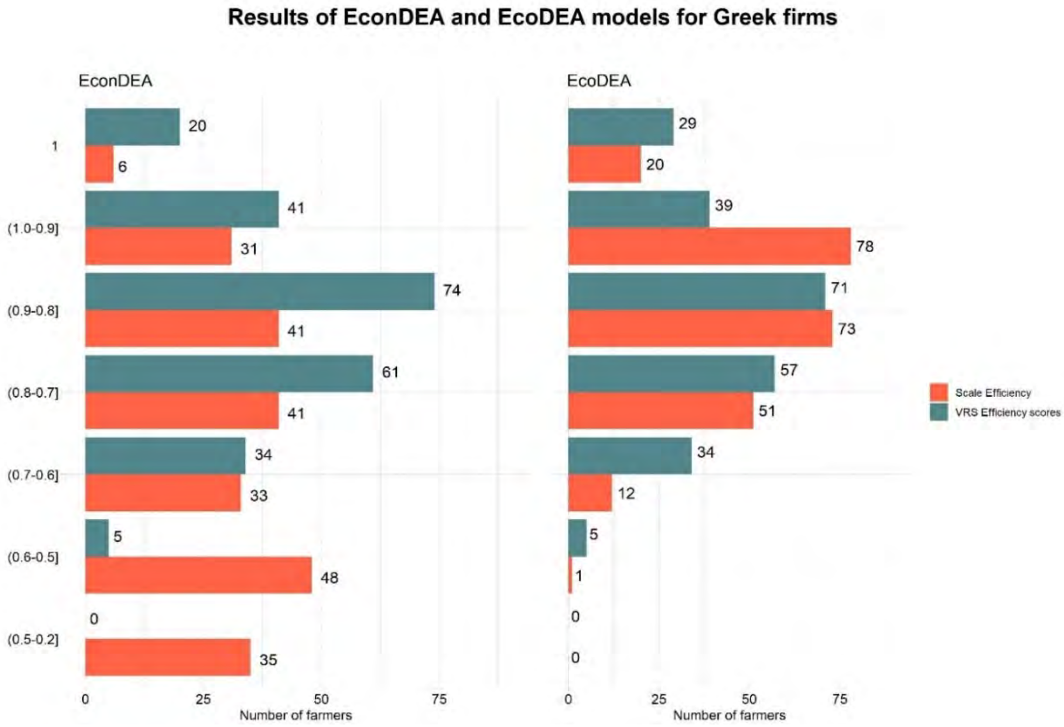

Figure 4.6*:* VRS and Scale Efficiency scores for the Greek sample (EconDEA & EcoDEA)

Figure 4.7 presents the acquired VRS efficiency scores through a density graph. It is evident that G2 has a greater performance than G1, since it is presented with higher proportions for efficiency scores greater than 0.9. Table 4.4 displays the descriptive statistics of the acquired efficiency scores per firm. Although their median values are differing by 0.1, this result is of limited credibility due to the smaller sample of Greek firms (N=33).

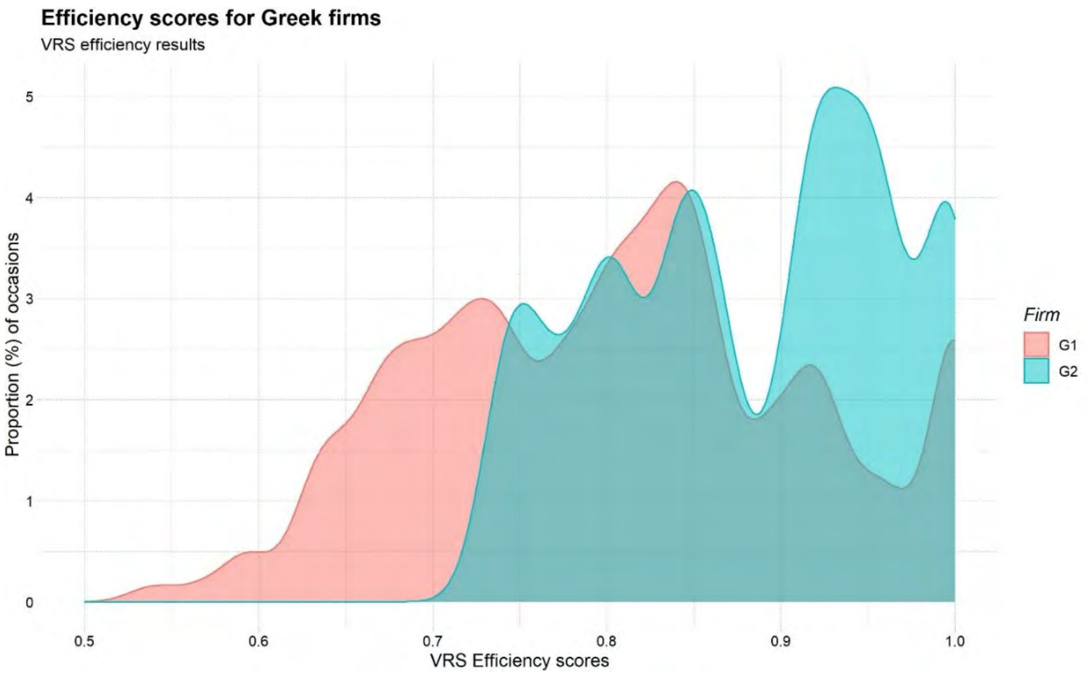

Figure 4.7: VRS Efficiency scores distribution for Greek firms (EcoDEA)

Table 4.4: Descriptive statistics of VRS efficiency scores per Greek firm.

Characteristic		G1, N = 202[1]	G2, N = 33[1]
EcoDEA *VRS efficiency scores*	Min. Median Mean Max. (SD) IQR [25%-75%]	0.54, 0.79, 0.81, 1.00, (0.11), [0.72-0.89]	0.74, 0.90, 0.92, 1.00, (0.08), [0.87-1.00]

Following the same rationale of the Italian sample, Figure 4.8 illustrates the acquired output per farm given its variable costs in a scatter plot. Compared to Figure 4.4, a more disperse distribution of the Greek DMUs is revealed, which is of particular interest in terms of management practices. In other words, in the Italian sample there is a clear strategy for inputs minimization, however in the Greek territory there is no tendency neither for inputs minimization nor for outputs maximization.

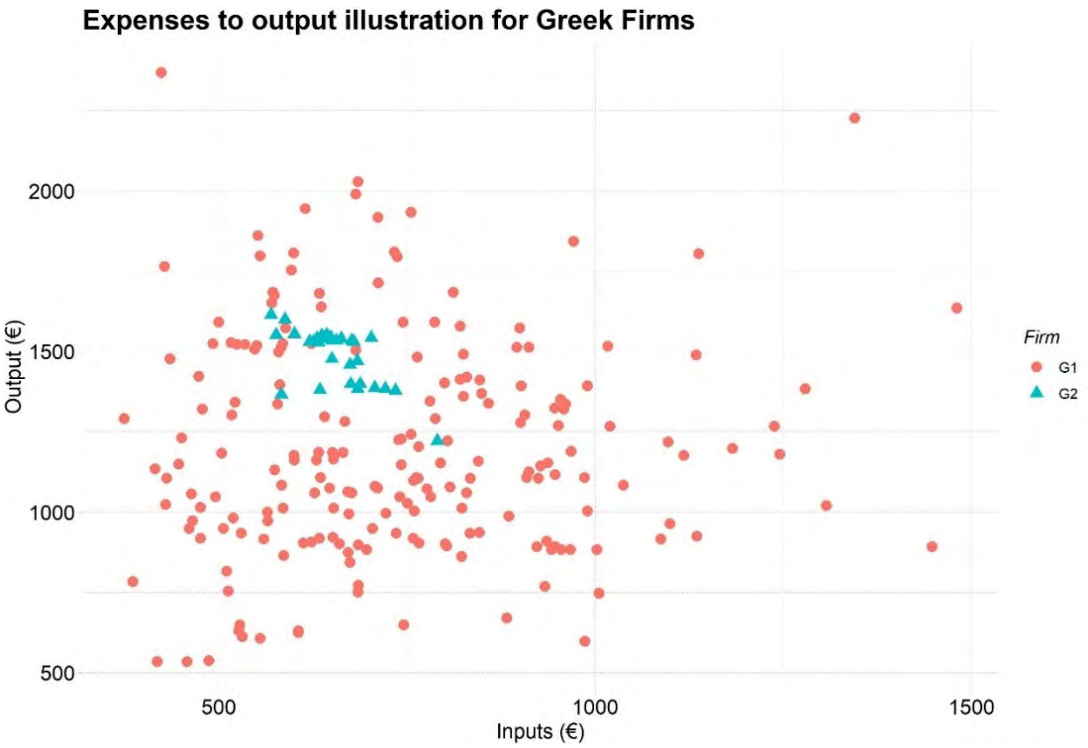

Figure 4.8: Monetary values of inputs used to final output for Greek firms.

Results of EcoDEA model for the Greek model reveal that both water and ecological footprints can be reduced by 17% and 30% respectively, while carbon footprint can be decreased by 9.7% as seen in Figure 4.9. Compared with the Italian farms, Greek farms present a smaller potential for reduction on carbon footprint (IT: -38 %), but they should decrease in higher rates their ecological and water footprint (IT: -23 % & -4.5% respectively).

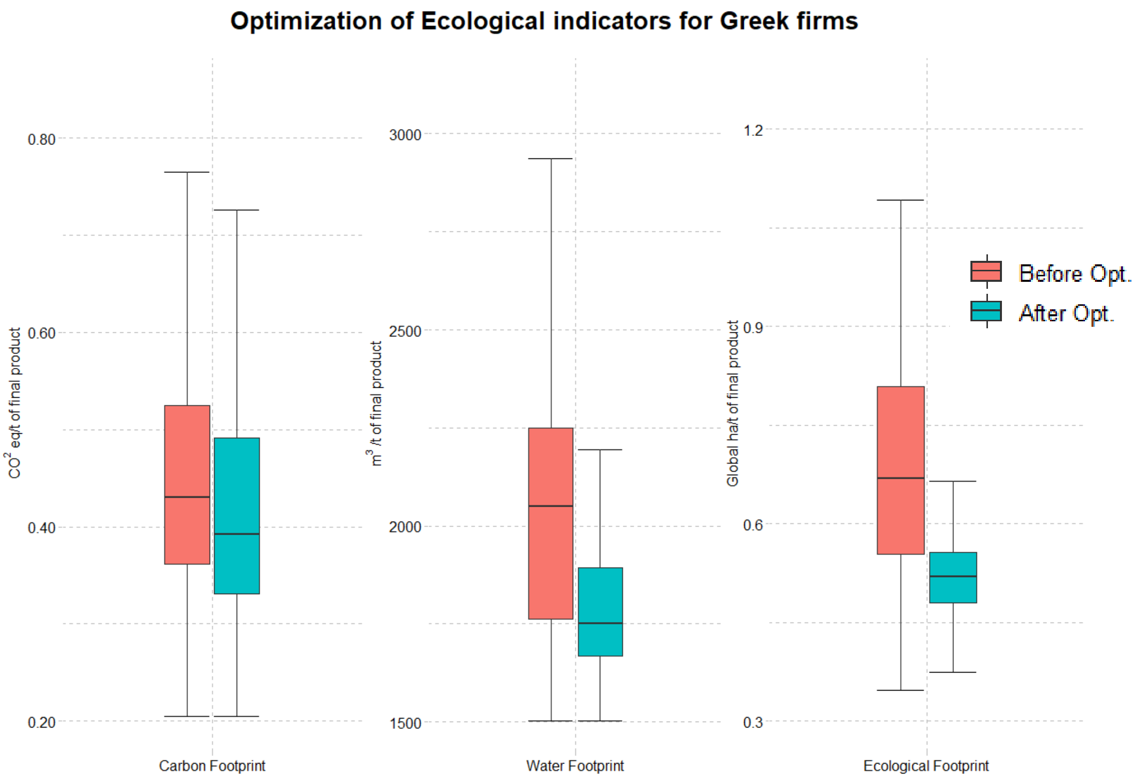

Figure 4.9: Reduction potential of CWEFs after the optimization process for the Greek farms

4.6. Discussion

By evaluating the acquired results, several remarks were arisen. Firstly, it is positive that both countries have representative farms at a proportion of around 10% for the EconDEA model, confirming that there are several examples of efficient producers in each sample. Moreover, it is prominent that the inclusion of CWEFs did not decrease the overall number of farms that have previously achieved high efficiency scores through the EconDEA model. On the contrary, the number of the efficient farms has increased both for the Italian and Greek sample when implementing the EcoDEA model (Figure 4.2, Figure 4.6). Through the previous stated remarks, it is evident that the adoption of the overall GD.NET management system, in a holistic approach, verifies the better performance of farmers on an operational level, despite the anticipation that it would be more difficult for producers to be both economically and environmentally efficient. Another remark is that scale efficiency has improved, a result that validates the prior point of guidelines that promotes both economic and environmental aspect of durum wheat cultivation. Regarding the acquired scores per firm, G2 acquires the highest median value of 0.9;

however the sample of this firm was small (N=33). According to authors' experience in the Greek primary sector, the acquired efficiency results are higher than expected, and this may lay to the fact that these farms were part of agricultural cooperatives. Moreover, a more stretched distribution was anticipated. However, considering the fact that each sample is evaluated through each best performer, this was not feasible.

Considering solely CWEFs, a greater potential for decreasing Water and Ecological footprint was revealed for the Greek firms. Proportional reduction of Carbon footprint seems to be greater for the Italian firms. Apart from the proportional differences, Greek firms have considerably higher Water footprint than the Italian ones, an outcome which should be further explored for minimizing the exploitation of natural resources.

Figure 4.4 and Figure 4.8 provide strong evidence that there are external factors affecting the performance of durum wheat farmers in the Greek sample, compared to the Italian ones, where there is a clear tendency for inputs minimization. Greek firms have a more scattered distribution. In this section, sustainability, agricultural, institutional and data collection issues are discussed, to further clarify the arisen differences between the two countries.

Enabling sustainability principles on the farm level is a necessity for achieving SDGs, providing clear instructions to agro-managers and farmers. Although economic and environmental dimensions are embodied in the analysis process, demographic characteristics of farmers are missing. For instance inefficiency causes could have been arisen due to lower educational level of Greek farmers or their unwillingness to participate in agricultural training programs, which are significant factors according to Li's et al. (2021) recent results . However, it should be stated that new technologies adoption also enhances the social dimension, contributing to sustainability achievement in rural areas (Weber et al., 2022).

Assessing the agricultural dimension of the DEA benchmarking, it is crucial to acquire more insights, by using specific data for each farm. It seems that the tillage method and application timing of fertilizers are significant for durum wheat output (Devkota and Yigezu, 2020). Consequently, detailed monitoring of each individual agricultural activity is a necessity. Moreover, additional information is needed to assess the impact of previous crops in the final outputs of durum wheat, ameliorating both the economic and environmental performance (Alletto et al., 2022).

The selection of durum wheat cultivars is another factor that should be explored, since focusing only on efficiency improvement leads to a narrow approach of cultivars, which may not be the essential ones under extreme weather conditions (such as extended drought or heat) (Dettori et al., 2022). It should be also stated that effects of climate change should be measured in the long run (Olakojo and Onanuga, 2020), meaning that appropriate data should be collected towards this direction. Resilience, or otherwise the ability of agricultural systems to be adopted in new situations, can be evaluated quantitatively and qualitatively in a local region (Meuwissen et al., 2019) on an annual basis by a composite indicator and thus lead to a tailored made national and worldwide policy making (Anderies et al., 2013). Additionally, different cultivation practices can be assessed with the implementation of DEA to achieve the production of a given quality with the least use of inputs (Giannoulis et al., 2014).

Furthermore, acquiring a multiple-year dataset would contribute to a clearer benchmarking process for the farmers, also indicating efficiency changes year by year (Pan et al., 2021). Malmquist productivity index calculates the annual productivity changes of efficiency of each DMU, contributing to further clarification of external factors' influence (Forleo et al., 2021). The inclusion of similar factors would further clarify reasons of inefficiency between Greek and Italian firms.

An additional stIp in the analysis process would be the incorporation of spatial characteristics of each farm which were absent in our case. Only few surveys have embodied spatial information (Gao and Li, 2014; Tang et al., 2022), as a part of the benchmarking process, assessing efficiency on a larger scale (regional level) and not on farm level. Depicting efficiency scores on the map, in conjunction with their interactions with other factors, such as those mentioned above (temperature, humidity, and rainfall) can reveal more information about best farming practices and the environmental impact of farmers' actions. It is also possible to create thematic maps where the spatial boundaries that allow the cultivation of the specific crop in an efficient way are perceived, and therefore lead to the reduction of natural resources waste. Additionally, DEA results validity could have been increased by comparing them with acquired results of other similar methodologies, as the ones mentioned in the introduction section, such as SFA (Theodoridis & Psychoudakis, 2008) or Färe-Primont productivity index (Reziti, 2020).

It should be underlined that all firms participating in this analysis are of high entrepreneurial standards, meaning that farmers are part of a cooperative or they are acting under certain guidelines apart from those ones provided from GD.net. Far’ers' participation in collective schemes seems to increase their efficiency (Ahado et al., 2021; Lin et al., 2022). Additionally, Veflen et al. (2019) highlight the importance of management and clear guidelines provision for increasing efficiency, especially in heterogenous collaborative networks, which can be a strong influence in this case. On the other hand, as it was stated in the Introduction section, trust is a significant aspect between the ADSS and the farmer, a statement whIch is also supported from Jakku et al. (2019). Although both Italian and Greek farmers are expressing skepticism towards the benefits of new technology adoption, there is no clear evidence for differences in the implementation stage (Pignatti et al., 2015). Lacoste and Powles (2016) state that building an ADSS is a continuous process of receiving farmers’ feedback and ameliorating the easiness of use to achieve the maximum degree of implementation rate.

4.7. Conclusons

In this paper, GD.NET dataset for the cultivation year 2020-2021 was analyzed to assess the economic and environmental performance of subscribed farmers in this ADSS. Following Barilla’s strategy for sustainability principles adoption at farm level, the factors that affect the relationship between farmers and the ADSS in all four stages (creation – use – evalua–ion - redesign) and the actual results of the implementation process were examined. Results indicate that there is a tendency in the Italian sample for inputs minimization, while on the Greek sample it seems that the production protocol is not well defined for the examined year. However, it should be stated that environmental and institutional factors can contribute to this, as described in the Discussion section. To the best of our knowledge, no other survey has paid attention to assessing the inputs’ use efficiency results of farmers that cultivate under a common ADSS, presenting differences in the implementation stage of the ADSS suggestions. As it was proved, in the Results section, GD.NET provides an integrated approach of durum wheat cultivation (both economically and environmentally). However, differences arisen during the implementation stage, where Italian farmers are aiming to inputs minimization, while for the Greek ones there is not a clear strategy.

This phenomenon should be further evaluated on the following years for clarifying the reasons that have affected the Greek sample, or if it was an unexpected event in the Greek durum wheat cultivation timeline. That is the reason why in this survey the importance of close data monitoring in multiple layers (expenses, application time, environmental and spatial data) is highlighted, a remark that is a general requirement in the agricultural economics research field (Capalbo et al., 2017; Coble et al., 2018).

Results of this paper should be also considered under the scope of the Ukrainian war and post COVID-19 era (Glauben et al., 2022). Their domino effect in the European and global agri-food sector can disrupt food security and cause famine, especially in regions with low purchasing power. That is the reason why, both on the entrepreneurial and national level, saving resources should be a priority, not only to reduce production costs and environmental impact from the farmers' side, but also to reduce the potential loss of agricultural production, due to misuse of cultivated land or resources.

Chapter 5

Ranking EU Agricultural Sectors Under the Prism of Alternative Widths on Window DEA

Existence and evolution of humanity is strongly linked within the development of agriculture. It was no later than the end of World War II when the EU decided to support the primary sectors of member states by establishing the first mutually agreed policy tool, the Common Agricultural Policy (CAP). Price support and export refund systems had a significant negative impact on global agricultural trade, suppressing at the same time natural resources and the environment in rural areas (Bellmann & Hepburn, 2017). CAP strategic goals have been customized periodically since then, so as to meet global food security and safety standards, promoting at the same time fairer trade, and increased competitiveness. European Commission (EC) has set nine key objectives through the CAP (2021–2027) period, which can be grouped in three basic categories: 1) economy 2) environmental protection and 3) rural communities support, in order to promote sustainable development and achieve SDGs until 2030 (European Commission, 2020).

The assessment of policy interventions, on both operational and environmental level, is very crucial. The policy framework developed under the Agenda 2000 reform is more market oriented, introducing schemes such as decoupled payments, requiring robust approaches for evaluating their suitability, applicability, and effectiveness (Petit, 2011). This study introduces such an assessment tool, taking into consideration both the diversified structural characteristics of EU member states primary sectors and the influence of the market on them. DEA is used for assessing efficiency of multiple DMUs in various sectors. DEA can be a useful tool, indicating the inputs or outputs that are not used efficiently, leading to the point solutions for the optimization of a given system. The wide applicability of DEA is based on the fact that efficiency scores are calculated, based on the existing DMUs, without the need for predefined optimum values. For this reason, DEA has been used for the improvement of various sectors such as banking systems (Ouenniche & Carrales, 2018), healthcare systems (Kohl et al., 2019), tourism (Niavis & Tsiotas, 2019), logistics (Martí et al., 2017) and agriculture both in crop and livestock production (Siafakas et al., 2019; P. Singh et al., 2019; A. Theodoridis et al., 2012).

5.1. Literature Review

On the line of SDGs, EU agriculture should succeed on assuring food security and environmental protection, while on the same time on securing fair income for farmers.

5.1.1. Land

In the case of agricultural sector efficiency assessment, DEA methodology has been used in order to evaluate total factor productivity (TFP) (Le et al., 2019), revealing the need for improvement between countries with similar structural profiles. Under the scope of energy usage and natural environment protection, X. Zhou et al (2019) have assessed changes of environmental efficiency between years 2006–2015, revealing geographical patterns that should be further supported from governments, connecting efficiency scores with regional characteristics. Feasible solutions for crop management can be provided through DEA results, has led to improved management of available agricultural land as a whole, in the most efficient way, combining crops' productive needs with regional structural characteristics (Atici & Podinovski, 2015). On the same approach, Toma et al. (2015) have classified 36 countries according to their geographical characteristics, clustering them in three distinct groups (plain, hill, mountainous), using as inputs the three production factors (land, labour and level of mechanization) and production value as the output. Efficient land use can be achieved by examining Greenhouse Gas (GHG) emissions of different crop types, leading to agriculture with lower emissions. As suggested, DEA can provide meaningful results about crop selection in greenhouse farming, optimizing the use of all inputs involved (Searchinger et al., 2018).

5.1.2. Energy

As FAO suggests, agriculture consumes 30% of total energy spent, while the greatest share of this energy is referring to in-farm procedures (FAO, 2016). On a global scale, constant population growth and increased food demand had led to intensification of production. Despite the urge for covering the previous mentioned needs, agricultural land has remained in similar levels from 1961 to 2014, resulting in higher energy inputs, agrochemicals, and fertilizers, per land unit. It should be mentioned that Pellegrini & Fernández (2018) confirm the existence of Jevons paradox in agriculture, claiming that technology evolution was not accompanied by input minimization, due to the extended use of these innovations for achieving higher yields.

Energy consumption affects famers' income, having frequently a negative impact on natural resources. That is the reason why conventional agriculture systems are gradually transforming to sustainable ones, using minimum energy resources and producing a fair output as yield (Moradi et al., 2018). Literature review of Smith et al., 2015) indicates higher energy efficiency scores for organic agriculture, but mainly in the crop production domain, while conventional livestock farms achieve higher efficiency scores than the organic ones. According to FADN database, Guth & Smędzik-Ambroży (2020) analyzed EU agricultural sectors, concluding that countries with the highest amounts of labour, land and capital achieve the higher efficiency scores, underlying the need for restricting measures in order to promote environmental and societal development. Efficiency differences can also arise due to different economic size of farms as well (Rezitis et al., 2010). DEA results can contribute to sustainable intensification ameliorating in-farm operations (energy consumption, integrated pest management, greener logistics) and policies promoting environmental protection on a national and EU level (Gadanakis et al., 2015).

Another advantage of DEA methodology, apart from calculating efficiency scores of all DMUs of a given system and ranking them from the most to the least efficient ones, is the slacks calculation. Slacks are used to quantify the changes that should occur in each variable, in order for a DMU to be efficient. Their interpretation is meaningful both for stakeholders and policy makers, in order to take final decisions, while from analyst's perspective, it can be signified which slacks have major or minor importance. Assessment of French diary sector according to their energy use, has resulted in a positive relation between subsidies and energy use slacks, meaning that larger farms have higher amounts of exploited energy, than the smaller ones proportionally (Ghali et al., 2016). This is an applicable example of slacks contribution in energy use minimization on the farm level, but also indicates potential policy reformation for French livestock sector. Significance of slacks has been also highlighted in the Greek livestock sector from Vlontzos & Theodoridis (2013). Adjustment of slacks has resulted in improved efficiency scores, providing optimal solutions for both developed and developing countries, regarding their energy consumption and CO_2 emissions (X. Lin et al., 2020). Slack-Based-Model (SBM) implementation from Apergis et al. (2015) raises concern about the decreasing energy efficiency of OECD countries, proving the feasibility of methodology in real case problem solving.

5.1.3. GHG Emissions

DEA methodology has also been used to assess the energy efficiency of national agricultural sectors, in relation to GHG emissions as an undesirable output. According to the Window DEA methodology of Pishgar-Komleh et al. (2019) , Spain, Greece, Italy and Malta achieved the highest efficiency scores, presenting outcomes both using or neglecting CO_2eq as an output. Similar results have been obtained using DEA for 2005 and 2010 for agricultural sectors of European countries with the use of Gross Value Added (GVA) from agriculture to GHG (GVA/GHG) as an eco-efficiency index (Victor et al., 2018). High improvement potential of up to 56% has been identified, applying DEA for the reduction of CO_2 emissions in Chinese provinces (Fei & Lin, 2017). The authors underline the need for incentives from government's side to farmers, for higher rates of technology acceptance that will reduce GHG emissions, and align Chinese agricultural undesirable output with global standards. Moreover, DEA results have revealed 70% space for improvement in energy saving for the Spanish supply chain of agricultural products (Laso et al., 2018). Focusing on agricultural inputs and especially fertilizers, slight improvements have been observed in Latvian agricultural sector, providing at the same time the appropriate methodology for continuous monitoring (Gancone et al., 2017). On a farm level, DEA can also be applicable, while an overall reduction in carbon footprint could be achieved with the implementation of proposed actions, leading to a cleaner production protocol (Rebolledo-Leiva et al., 2017). Despite the constant need for minimizing GHG emissions in global scale, data availability remains an issue (Amani & Schiefer, 2011).

Literature review of Mardani et al. (2018), reveals the extensive applicability of DEA methodology for optimization of energy consumption and environmental protection under operational terms. DEA results can provide meaningful insights for efficiency assessment of multi-sectorial industries, while providing feasible solutions for energy optimization, accentuating the importance for green technology alternatives (Sueyoshi & Goto, 2019b). Another remark from the previous survey, is the calculation of efficiency scores depending on the given objective every time, proposing methodology for managerial or environmental-based results. New approaches provide the appropriate tools for mathematical expression of limiting factors that cannot be controlled both for inputs or outputs (e.g., reduced efficiency of solar panels due to environmental conditions), depicting reality more sufficiently (Sueyoshi & Goto, 2019a). Combining the above-mentioned surveys, Mo & Wang (2019) have estimated environmental sustainability of road transport for OECD countries, an approach that can be applied in the agricultural logistics, or in the whole agricultural supply chain as a whole. At the same direction it should be also noticed that sustainability assessment has been assessed from a sample of 206 livestock farmers in 7 different countries, concluding to different strategies for each country to increase their efficiency (Paraskevopoulou et al., 2020)

Focusing on agriculture, the number of publications per year combination of DEA + Life Cycle assessment (LCA) have been increased during the 2003–2018 time period, due to the increased interest for cleaner production systems and eco-friendly products (Suzigan et al., 2020). Farm specialization is very crucial, in order to achieve improved management status and efficient resources handling. Examining all inputs involved in winter wheat production in Poland, researchers realized excessive use of fertilizers, seeds and fuel, providing to local farmers additional information for inputs minimization (Pishgar-Komleh et al., 2020). Another survey highlights the resource saving on energy and water, by decreasing cotton seed on optimum levels (Ullah et al., 2016). It should be underlined that no statistical differences have been pointed out between large and small scale farms, regarding eco-efficiency.

Introduction of uncertainty to DEA approach for measuring eco-efficiency can alter the final outcome, thus it is essential to be taken into consideration especially in systems that are affected from various factors (Ewertowska et al., 2017). Statistical significance can be assessed for multiple DMUs over frames of a certain period of time, checking results validity (Lorenzo-Toja et al., 2018). Defining weights in DEA model is another approach of assuring results implementation in real case scenarios, especially when dealing with small samples (Theodoridis et al., 2020). Even though there are several studies examining environmental and economic aspects of agricultural production, only few of them are connecting their results with society, due to lack of the appropriate data or methodology (H. Zhou et al., 2018).

5.1.4. Labour

Labour, expressed as Annual Working Units (AWU), is one of the three main production factors in agriculture (Centre for European Policy Studies, 2013). Differences in labour productivity have been observed among EU countries, something which expected to be, because of differences of the structural characteristics of their holdings and value chains (Giannakis & Bruggeman, 2018). Additionally, soil erosion, local economic prosperity and population density seem to be the most crucial factors affecting labor productivity. Results are correlated with educational level of farmers, highlighting the need for training, which will lead to a better communication between producers and agricultural consultants. It should be mentioned though, that the EU is in a transitional period of full digitalization. Automation and robotics will totally reform agriculture globally, creating opportunities and negative externalities for labour (Marinoudi et al., 2019).

5.1.5. Policy

Policy assessment can rely on DEA results. (Rybaczewska-Błazejowska & Gierulski, 2018) have concluded to two large groups (efficient (10) and inefficient (18)) of EU-28 countries according to their eco-efficiency status, examining both for environmental and operational performance. Greatest factor that limits eco-friendliness in EU agriculture is the excessive use of fuels and fertilizers, contributing to larger releases of GHG emissions. A controversial issue that has emerged with overpopulation is the land use for food or fuel. DEA methodology can be used to assess the crops with high input-efficiencies in certain regions and provide the appropriate answers, given the fact that there is a clear managerial strategy (Forleo et al., 2018). It should be mentioned that planning of agricultural production can be achieved through the use of ADSS (Bournaris & Papathanasiou, 2012). Depending on the approach needed in the policy creation procedure, Vázquez-Rowe and Iribarren have proposed a five stage Boolean tree of DEA + LCA approach, so as to facilitate the above-mentioned procedure (Ng et al., 2019). Risk management can also be minimized by the usage of DEA. Proposed methodo115verall115lyzes all different risks as inputs, while all innovations are considered to be outputs (Arabshahi & Fazlollahtabar, 2017). It should be underlined, that in the paper of Petsakos et al. (2009) there is evidence about the fact that 2 producers with same amount of available resources may end up with different decisions due to different approaches of risk handling.

DEA has been used in combination with Artificial Neural Networks (ANNs), giving meaningful results for national agricultural sectors' performance (Vlontzos & Pardalos, 2017). The greatest advantage of the previous application is the creation of emissions forecast, a handful tool for policy makers and stakeholders involved, for making valid decisions in advance and achieve zero emissions goals by 2030. Another survey assesses the applicability of DEA + ANNs of ranking "green suppliers" providing future perspectives (Shabanpour et al., 2017). Overall, forecasts provide the opportunity to quantify future situations with high accuracy, facilitating the creation of multiple scenarios for easier risk management. Sueyoshi & Goto (2020) have proposed a methodology on handling imprecise data when performing DEA for computing projected efficiency scores, calculating upper and lower hyperplanes for values replacement when needed. In this survey, an alternative methodology of future projections regarding benchmarking and efficiency scores is introduced, combining DEA with time series forecast, focusing on assessing input use efficiency of the EU agricultural sector, providing valid future results.

5.2. State of the Art

Mardani et al. (2018) mentioned in their extended literature review about different types of DEA models that only 5 out of 163 papers referred to the implications of the Window DEA model, proving the need for further deepening on the specific methodology. This approach provides the ability for efficiency assessment of multiple years and DMUs, being the reason it should be further assessed. Evolution of technology has permitted the construction and manipulation of large datasets, while future projections with high accuracy can be obtained, enhancing the applicability of Window DEA. Estimating efficiency scores for the period of 2012–2018 for Iranian ports, Zarbi et al. (2019) chose arbitrary window width equal to 4. Changing window width would not lead to radical changes, because of the relative short period of time analyzed. Another study that has implemented Window DEA methodology for energy efficiency in the Spanish electricity sector, used an arbitrary window width of five years for an overall 9-year-period (2006–2015) (Sánchez-Ortiz et al., 2020). A similar approach with this paper has been followed for the assessment of dairy farming system in Iran, exploring differences between different window widths when using Window DEA (Sefeedpari et al., 2020). Differences indicate a decreasing average score for all DMUs involved, due to the enlargement of window width. Thus, it should be underlined that the ideal window length has not been estimated, so that the ranking differences can become apparent between the ideal and other window widths. Window DEA regarding energy use and social characteristics has been perform for Chinese provinces, revealing efficiency gaps between them (A. Zhang et al., 2018). In that survey, a 2-year-window length has been selected for the energy use assessment for the years 2005–2014. Taking into consideration all the above-mentioned papers, and given the fact that window DEA is not widely explored, assessment of window width influence has been made in an extended period (with actual and projected dataset), so as to indicate the resulting differences.

5.2.1. Structure and Scope

This survey consists of the following sections. The Introduction and Literature review highlight the contribution of DEA methodology regarding efficiency of production factors in agriculture and environmental performance, as well as its use in combination with other well stated methodologies such as LCA and ANNs. The State of the Art section signifies the impact of this study, in comparison with other similar articles. The Methodology section presents briefly the DEA Analysis and focuses on Window DEA Analysis methodology and selection of appropriate window width. Moreover, the Data section provides a detailed description about data source, type of variables and overall data handling. In the Results section, descriptive statistics of the sample provide a clear image to the reader for all inputs and outputs involved. Moreover, estimations of ideal window width and final rankings for actual (2005–2019) and projected (2005–2022) data set are presented, emphasizing on differences between different window widths. The Discussion section addresses the main findings in an applicable way for EU-members, compares findings with related surveys, and connects findings with specific SDGs. Main findings, referring to the methodological approach and possible implementation of actual results, are included in the Conclusion section. Last but not least, this section includes limitations of this study and potential future contribution in the field.

The scope of this study is to introduce a methodological approach for assessing the efficiency of the primary sectors of EU member states after the implementation, on an operational level, of the AGENDA 2000 CAP. This is quite important due to the radical characteristics of this reform, which is the reduction of intervention on the decision making process of agricultural holdings, and the increase of market forces' influence on the value chains of agricultural products. The chosen methodological approach allows us to present a prognosis of efficiency performance of member states, following similar approaches of other economic sectors, where institutional intervention is either minimized or absent. The examination of the reliability of alternative widths of Window DEA model, improves the suitability of this model for this assessment. The contribution of this paper to academic literature is to highlight differences in final rankings between ideal and arbitrary chosen window widths, due to the existence of zero technological change assumption within window when performing Window DEA, as it is described in the Methodology section.

5.3. Methodology

5.3.1. DEA Analysis

DEA focuses on measuring productivity of the same and comparable values or groups that can be defined as DMUs. The first attempt to evaluate the efficiency of DMUs was made by Farrell (1957). Based on his work, (Charnes et al., 1978) introduced a newer evaluation method for different DMUs with multiple inputs and outputs. More specifically, DEA is a non-parametric method, which uses linear programming techniques to evaluate the effectiveness of DMUs. Efficiency is defined as the ratio of inputs to outputs. Efficiency has been calculated according to the following formula (J. Zhu, 2014):

$$\begin{aligned} &\varphi^* = \min \varphi \\ &s.t \sum_{j=1}^{n} x_{ij}\lambda_j \leq x_{io} && i = 1,2,\ldots m \\ &\sum_{j=1}^{n} y_{rj}\lambda_j \geq \varphi y_{ro} && r = 1,2,\ldots m \qquad (1) \\ &\lambda_j \geq 0 && j = 1,2,\ldots n \end{aligned}$$

where φ^* represents the relative technical efficiency of x_{ij} and λ_j the weights in order to define the set of DMUs where $\varphi^*=1$ and calculate the efficiency scores for the rest DMUs afterwards ($\varphi^*<1$). It should be noted that DEA can increase efficiency of

DMUs either by minimizing inputs (input-oriented) or maximizing outputs (output-oriented) given the same amount of all factors involved. Input-oriented DEA is preferable in most cases in agriculture, due to the fact that limited exploitation of natural resources and reduced cash flows for inputs from farmers' side are preferred (Suzigan et al., 2020). That is the reason input-oriented approach has been selected for this analysis.

Furthermore, as seen in the literature review, undesirable factors can be handled with DEA. You and Yan present four ways of treating undesirable factors: 1) complete ignorance, 2) consider undesirable outputs as inputs, 3) non-linear monotonic decreasing approach, 4) linear monotonic decreasing approach (You & Yan, 2011). For the purpose of this survey option 3 has been selected in order to handle the amounts of emitted emissions by transposing the CO_2 amount. The same methodology was proposed by Scheel (2001) when dealing with both desirable and undesirable factors in DEA model. Data normalization can also be used to deal with undesirable factors, thus it should be noted that some of the available information is lost in the process of data manipulation, as well as results interpretation, to people who are not familiar with the above methodology (Jahanshahloo et al., 2005).

5.3.2. Window DEA Analysis

Although the aforementioned approach of DEA can be used in order to assess the efficiency of different DMUs in a given period of time, thus a new approach was needed for time series due to the fact that every unit is considered to be independent even if it is the same DMU in another period of time. For this purpose, a window DEA has been proposed, based on the principles of moving average (Charnes et al., 1984). Applying Window DEA, a reference period should be defined and then data are grouped in distinct groups (windows). This framework permits the comparison of different DMUs within the given window and an overall average score can be retrieved in the end of this procedure as the mean of all years involved. It should be clarified that efficiency scores for a given period and same DMU are different, due to the fact that it is compared with a different dataset.

Window DEA implementation is summarized in Table 5.1. Subsets of initial dataset are constructed in accordance with the chosen window length. Average scores per Year and per Country (*ASYC*) are obtained in order to calculate mean efficiency scores for every country in the predefined period of time.

Table 5.1: Window DEA analysis.

Country (x)	**t**	**t+1**	**t+2**	**t+3**	**t+4**	**t+5**	**⋯**	**t+k−5**	**t+k−4**	**t+k−3**	**t+k−2**	**t+k−1**	**t+k**
Window 1													
Window 2													
Window 3													
⋮				⋮	⋮	⋮	⋮						
Window n−2													
Window n−1													
Window n													
*ASYC**	(1)	(2)	(3)	(4)	(5)	(6)	(…)	(n−2)	(n−1)	(n)	(n+1)	(n+2)	(n+3)
	Mean of *ASYC* of Each country												

**ASYC* = Average Efficiency Score/Year/Country.

5.3.3. Window Width

The selection of the DEA window width is very crucial for the result extraction. As Asmild et al. (2004) stated, window width should be short enough so as to permit the comparison between different windows and contain enough elements for accurate efficiency measurement. Although width in many papers selection is arbitrary, it is essential to use the appropriate methodology (Hao et al., 2013; S. Lin et al., 2018). For this purpose, the ideal window width has been calculated, performing DEA model for each year (*i*) for the reference period (*1-T*) and by window (*j*c. The construction of a new matrix (*A*) is following, calculating Equation (2), where $Mean^i$ is the average value of year (*i*) for every *j*.

$$v_{ij} = \frac{M_{ij} - Mean^i}{Mean^i} * 100\% \qquad (2)$$

For every year in matrix *A*, $Absmin_{ij} = |\min(v_{ij})|$ are selected. The window width which acquires the greater number of $Absmin_{ij}$ is the appropriate one. Thus, it should be underlined that window DEA imposes an assumption of zero technological change within the window and this should be taken into consideration when performing Window DEA Analysis (Asmild et al., 2004).

5.3.4. Data

For data selection, variables that compose production factors in agriculture (land, labour, and capital) were selected for efficiency estimation of EU countries (Table 5.2). Selected variables are Total Used Agriculture Area (*UAA*), Labour force

(*L*) and Fixed Capital Consumption (*FCC*) which express the previous mentioned aspects. Data for standard inputs such as Seeds and Planting Stock (*SPS*), Plant Protection Products (*PPP*), and N, P fertilization (*NFert*, *PFert*) were taken into consideration due to the high amounts of energy consumed for their production, especially for fertilizers. Moreover, Energy (*EN*) has also been included as a separate variable due to the need for emphasizing in energy consumption minimization, following the EU guidelines for the benchmarking process. As outputs, monetary values of Total agriculture output (*TO*) and $CO2_{eq}$ emissions (*EM*) have been taken into consideration. All data have been acquired through EUROSTAT database and more precisely: [aact_eaa07], [nrg_bal_s], [aei_fm_usefert], [env_air_gge], [apro_cpshr] (EUROSTAT, 2023).

Table 5.2: Data selection Inputs and Outputs for reference period 2005–2019.

Reference period: 2005–2019	
Variable	**Measurement Units**
Inputs	
Total Used Agriculture Area (*UAA*)	1000 Hectare (ha)
Labour (*L*)	1000 Annual Working Units (AWU)
Fixed Capital Consumption (*FCC*)	Million Euro (€)
Energy (*EN*)	Thousand Tonnes of oil equivalent (TOE)
Seeds and Planting Stock (*SPS*)	Million Euro (€)
Plant Protection Products (*PPP*)	Million Euro (€)
Consumption of N-Fertilizers (*NFert*)	Tonnes
Consumption of P Fertilizers (*PFert*)	Tonnes
Outputs	
Crop output (*TO*)	Production value at basic price, Million Euro (€)
Emissions (*EM*)	Th. Tonnes of Greenhouse gases (CO2eq)

Data source: Eurostat, 2020.

The data set selected refers to the time period after the implementation of AGENDA 2000 in operational terms. Cyprus, Malta, and Luxembourg were excluded due to their relatively small agricultural sector size, when compared with the other EU countries. On the other hand, data from the Norwegian agricultural sector was added, due to the strong trade relationship of the country with the EU and the fact that its agricultural sector presents similar characteristics with the rest of the Scandinavian countries. Considering that all available data were referring to 2005 until 2019, 3-year data projection has been made with a view to provide an up to date information, extending the reference period until 2022. It should be underlined that EUROSTAT had already made estimations for 2020 for some of the above-mentioned data. To avoid the confusion of projection data methodologies, 2019 has been set as the ending year of the dataset and forecasts have been equally generated. Data projections have been obtained using Double Exponential Smoothing for Time Series in Minitab 17 Statistical Software. DEA and window DEA results have been acquired using Benchmarking library in R Studio.

Providing a better understanding of all procedures involved, a panel of 26 EU countries, 10 different variables and a time period of 18 consecutive years has been constructed, using EUROSTAT's data. Figure 5.1 demonstrates all steps followed until the extraction of final efficiency scores and rankings per country. Further explaining the above-mentioned methodology and taking as an example the whole panel (actual and projected data), a subset of initial dataset has been constructed for each reference period of window width (9). The next step includes DEA implementation for each subset, so as to acquire efficiency scores for every window. As mentioned in the Methodology section, different efficiency scores are obtained for the same country and year among windows. For instance, efficiency scores for Austria 2015 differ in Window 1 and Window 2, due to the fact that it is compared with a new dataset. Following steps include the construction of a new data frame, in which all efficiency scores per window frame are collected and average scores per year and per country are calculated. Computation of mean efficiency scores is the last step, providing at the same time the corresponding rankings for every country after sorting the data.

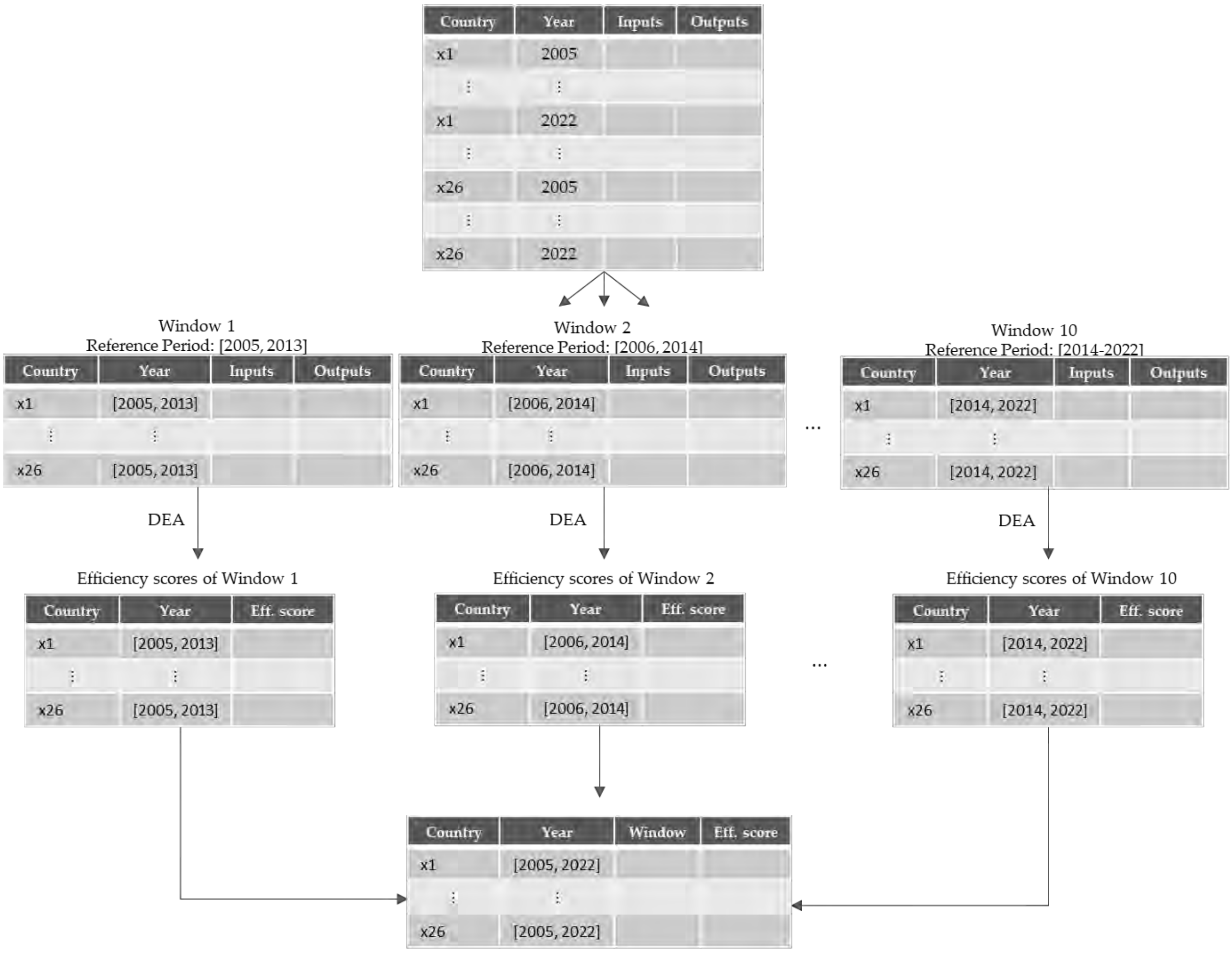

Figure 5.1: Step by step representation of the applied methodology.

A summarized viewpoint of Window DEA analysis is presented in

Table 5.3. Diamond-shaped data structures are built, so as to provide average scores per year for every country. Mean of *ASYC* is the final score for each country but it should be stated that assessment of final rankings is more valuable than changes in the actual values of efficiency scores.

Table 5.3: Window DEA analysis representation for actual and projected dataset.

Window DEA Analysis																		
	Actual Data															Projections		
Country(x)	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Window1																		
Window2																		
Window3																		
Window4																		
Window5																		
Window6																		
Window7																		
Window8																		
Window9																		
Window10																		
ASYC *	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Mean of *ASYC* = Final Score of each Country (x)																	

**ASYC* = Average Efficiency Score/Year/Country.

5.4. Results

5.4.1. Descriptive Statistics

Descriptive statistics of both inputs and outputs were examined before proceeding to the main analysis (Table A.5.1 -Appendix section). According to the *UAA* for the period 2005–2019, the greatest negative differences have been identified for Austria, Italy, and Poland (-18.7%, -10.6%, -9.7%) while the agricultural area increased in the following countries: Latvia, Croatia, and Greece (13.0%, 24.2%, and 26.6%). A slight decrease of 3.2% of *UAA* was calculated for all countries involve124verallverall drop of 29.0% for Labour input is being depicted, with Ireland being the only country presenting an 8% increase. On the other hand, the great decreases are highlighted for Estonia (-50.1%), Slovakia (-55.0%), and Bulgaria (-69.6%). It should be underlined that even if Labour has been decreased, annual wage per *AWU* increased by approximately 20% (base year = 2010) (European Commission, 2019).

Capital consumption from national agricultural sectors increased by 8.8%, meaning that the EU agricultural sector is becoming more challenging, demanding higher financial resources from all stakeholders involved. European Commission report signifies that intermediate costs will keep increasing until 2030, leading to a more capital intensive agricultural domain (European Commission, 2017). The energy sector presents great differences among countries analyzed. Greece, Bulgaria and Ireland are the three countries achieved highest rates of energy minimization, thus Latvia, Romania, and Germany presented increases of more than 60%. Considering Plant Protection Products, a total increase of 17.0% is being depicted, despite the EU's intense effort for agricultural chemicals reduction. The Netherlands has achieved an overall reduction of (-20.4%) and (-77.4%) in *NFert*, *PFert* fertilizers respectively, which is the best performance from all countries involved. Crop output has increased by 10.2% for the period 2005–2019, with Latvia, Estonia, and Lithuania presenting the highest rates of improvement, while Italy, Germany and Finland have reduced rates (-12.6%, -10.4%, -4.7%). Analysis of $eqCO_2$ indicates that there is only a slight decrease of -1.6% for the last 15 years, a not so overwhelming result, given the fact of technological progress and global pressures for zero emissions.

Figure 5.2 and Figure 5.3 illustrate the above-mentioned results, which have been obtained during the initial stages of the analysis and provide a general picture of agricultural sectors of EU countries. In Figure 2, the Netherlands is an exceptional remark with very high needs in *EN* and *SPS*, but very low needs in *L* and *UAA*, achieving the fifth highest agricultural output. This can be easily explained, based on the great number of greenhouses which can be described as intense input production method, especially in energy demands for heating. Another remark that should be highlighted, is referring to the cases of Estonia and Slovenia. Both of them have the least inputs and least outputs of all EU agricultural sectors but they present great differences in terms of inputs use efficiency as it will be presented in the Window DEA results section. It should be underlined that the two countries have significant differences in their climate conditions, which has an immediate effect on the overall production.

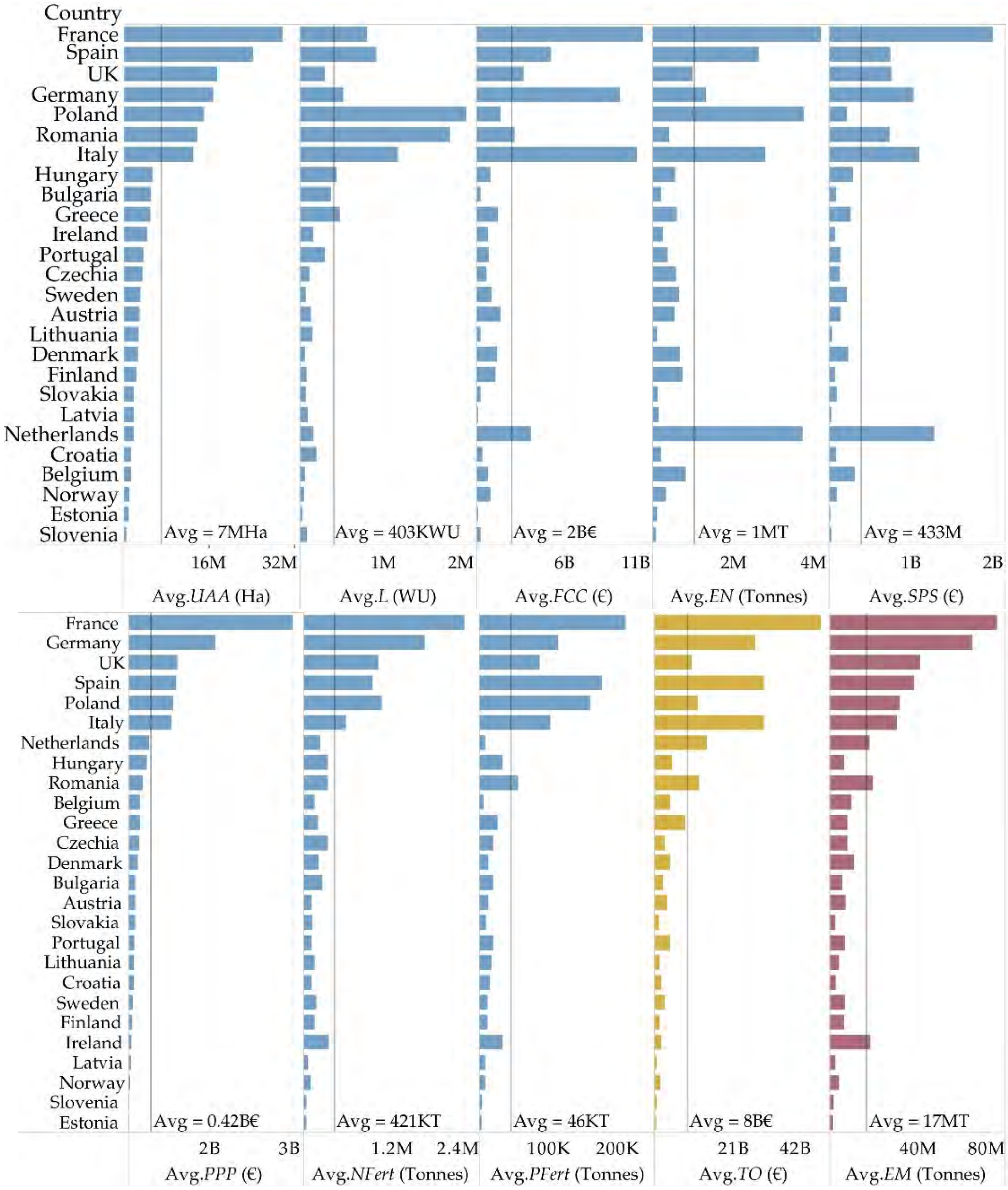

Figure 5.2: Descriptive statistics of Average Inputs and Outputs per country for reference period 2005–2019.

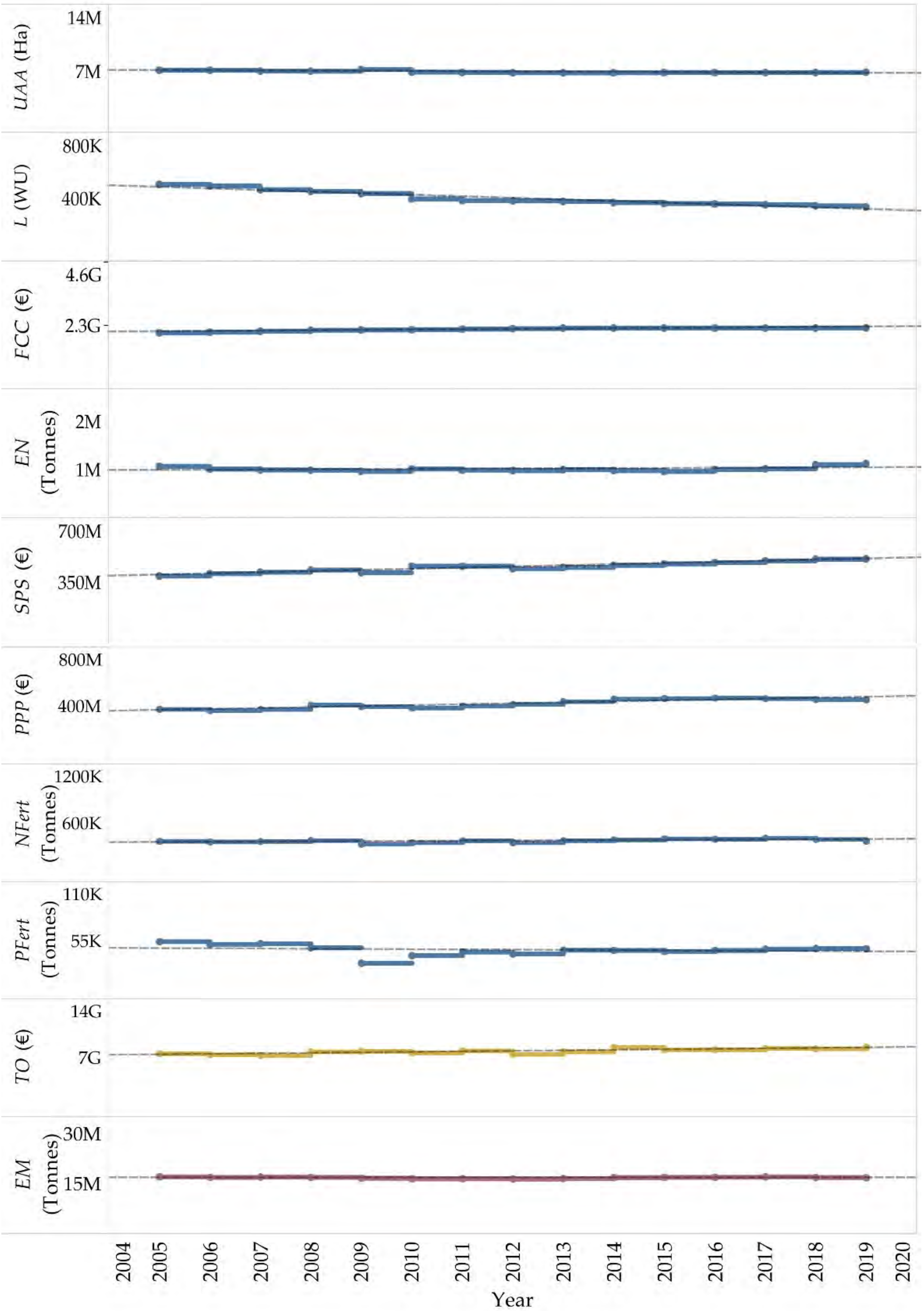

Figure 5.3:Average values of Inputs and Outputs for reference period 2005–2022.

Total *UAA* and *EN* were plotted together so as to examine Pellegrini's et al. statement about energy use in the EU agriculture (Pellegrini & Fernández, 2018) (Figure 5.4). Despite the fact that total *UAA* decreased by 3% from 2005 to 2019, *EN* seems to have a significant increase of 16.9% from 2015 to 2019. This can be partially explained from the recovery of EU countries after a long period of economic recession in EU countries. Moreover, it should be mentioned that the share of renewable energies in agriculture has remained on the same levels for the last two decades, signifying the need for finding more sustainable solutions for agricultural energy consumption.

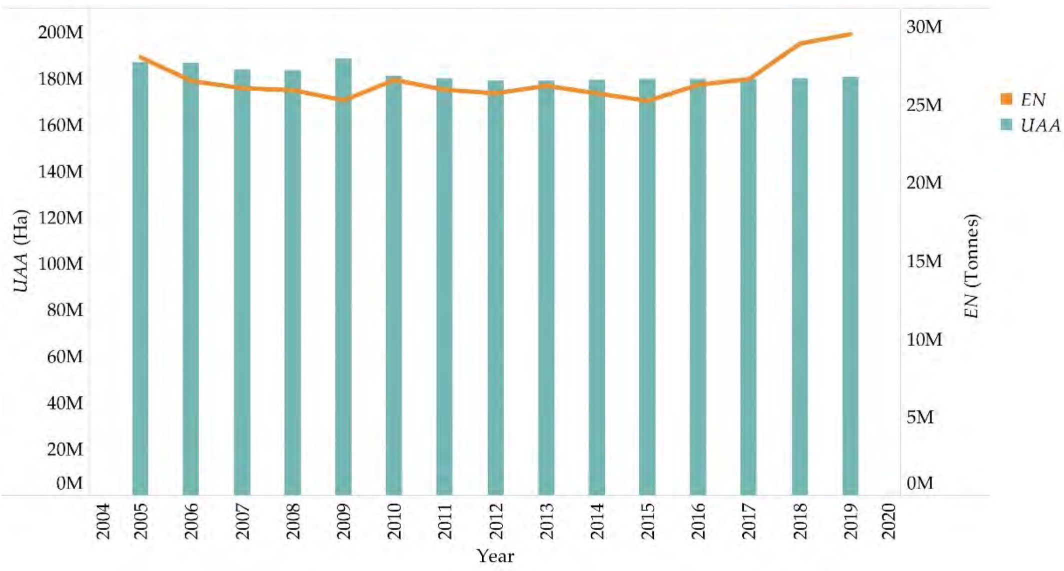

Figure 5.4: Total Used Agricultural Area (*UAA*) and Energy consumption in agriculture (*EN)* for the period 2005–2019.

In Figure 5.5, it is pointed out that there is not a great variance among examined countries, apart from Germany and Greece regarding Annual Energy consumption. Despite the fact that Germany has a large variance through the reference period of this study, other countries such as France, Portugal and the Netherlands appear with higher energy demands. That is the reason the two outliers identified in Germany were accepted, before proceeding to the main analysis.

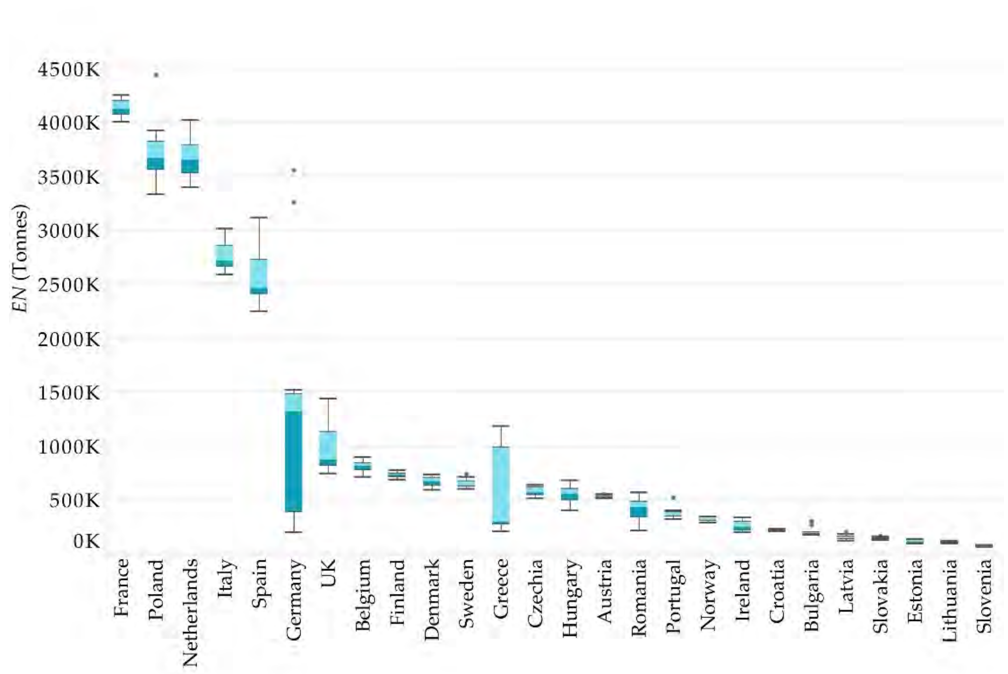

Figure 5.5: Annual Energy Consumption (*EN*) per country for the period 2005–2019.

5.4.2. Window DEA Results

As already described, before proceeding to Window DEA, it is essential to identify the ideal window width for this data set. For this purpose, Window DEA was performed for all possible window widths and then results were grouped by year. Using Equation (2) results, Table 5.4 was constructed. The window width with the least difference from the average score for all possible window widths for a given year was selected. Window Width equals to 7 was selected as the ideal one, due to the fact that it contained the highest amount of absolute minimum difference.

Table 5.4: Equation (2) results (absolute values) for all possible window lengths for the reference period 2005–2019.

	Possible Window Widths														
Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
2005	4.9	4.4	3.8	2.7	1.7	1.3	**0.3**	0.4	0.7	1.6	2.1	2.8	3.0	4.0	4.5
2006	7.0	5.2	3.8	2.4	1.6	0.8	**0.0**	0.4	1.1	1.9	2.5	2.8	3.3	4.0	4.7
2007	8.4	6.0	4.5	2.9	1.7	0.8	**0.0**	0.7	1.4	2.2	2.7	3.3	3.9	4.7	5.6
2008	5.5	4.3	3.7	3.0	2.1	1.3	0.5	**0.4**	1.1	1.8	2.4	3.0	3.4	3.9	4.5
2009	2.7	2.6	2.2	1.7	1.4	0.9	0.3	**0.2**	0.5	0.9	1.3	1.6	2.0	2.3	2.9
2010	6.2	4.3	3.1	2.3	1.7	1.1	0.3	**0.3**	0.9	1.6	2.3	2.7	3.2	3.7	4.4
2011	4.8	4.0	3.0	2.3	1.5	1.0	0.5	**0.2**	0.7	1.4	2.0	2.5	2.9	3.3	3.9
2012	6.5	4.1	3.0	1.9	1.2	0.6	**0.1**	0.4	1.0	1.6	2.2	2.5	2.9	3.2	3.7
2013	4.7	3.5	2.6	2.0	1.4	0.8	**0.2**	0.2	0.6	1.3	1.8	2.2	2.6	3.0	3.5
2014	3.1	2.3	1.7	1.3	0.8	0.4	0.2	**0.1**	0.3	0.6	1.1	1.4	1.7	2.1	2.5
2015	4.2	2.4	1.8	1.1	0.5	0.3	**0.0**	0.3	0.6	0.8	1.0	1.4	1.7	2.1	2.4
2016	4.1	2.5	1.5	1.0	0.5	0.2	**0.0**	0.4	0.7	0.9	1.1	1.2	1.5	1.8	2.2
2017	3.5	2.0	1.2	0.7	0.4	0.2	**0.1**	0.1	0.4	0.7	1.0	1.1	1.2	1.6	2.0
2018	3.6	2.2	1.5	0.9	0.5	0.2	**0.0**	0.3	0.4	0.8	1.1	1.3	1.4	1.5	2.1
2019	2.0	1.4	1.0	0.9	0.4	0.1	**0.1**	0.1	0.1	0.2	0.9	1.0	1.1	1.1	1.2
N(MIN)	0	0	0	0	0	0	**10**	5	0	0	0	0	0	0	0

Setting window width equal to 7, Window DEA model was applied. The results of the analysis for 26 EU agricultural sectors are presented in Figure 5.6 and Table A5.2 (Appendix section). An assumption of zero technology evolution within frames is made when performing Window DEA. To check the interference of this assumption to the proposed results, a narrower window width has been selected. In this case, an arbitrary window length equals to 4 was chosen in order to identify differences between the widths. Rankings are presenting slightly different results, concluding that technology evolution had a positive impact for the following countries: Greece, Belgium, France, Spain, Portugal, Slovakia, and Ireland. All previous countries confronted serious issues with the financial crisis (2008–2014) and a narrower window frame can highlight their recovery through technological adaptation. Although differences in the climatic conditions which largely affect primary production, Estonia ranks first, in comparison with Slovenia which ranks third. The scores of these countries present three points of interest: 1) apart from their relative small size, in comparison with the other EU agricultural sectors, they achieve scores placing them in the top-3 countries, 2) despite their climatic differences Estonia scores higher than Slovenia 3) placement of the Netherlands in the second position assures results validity even in the presence of large scale differences.

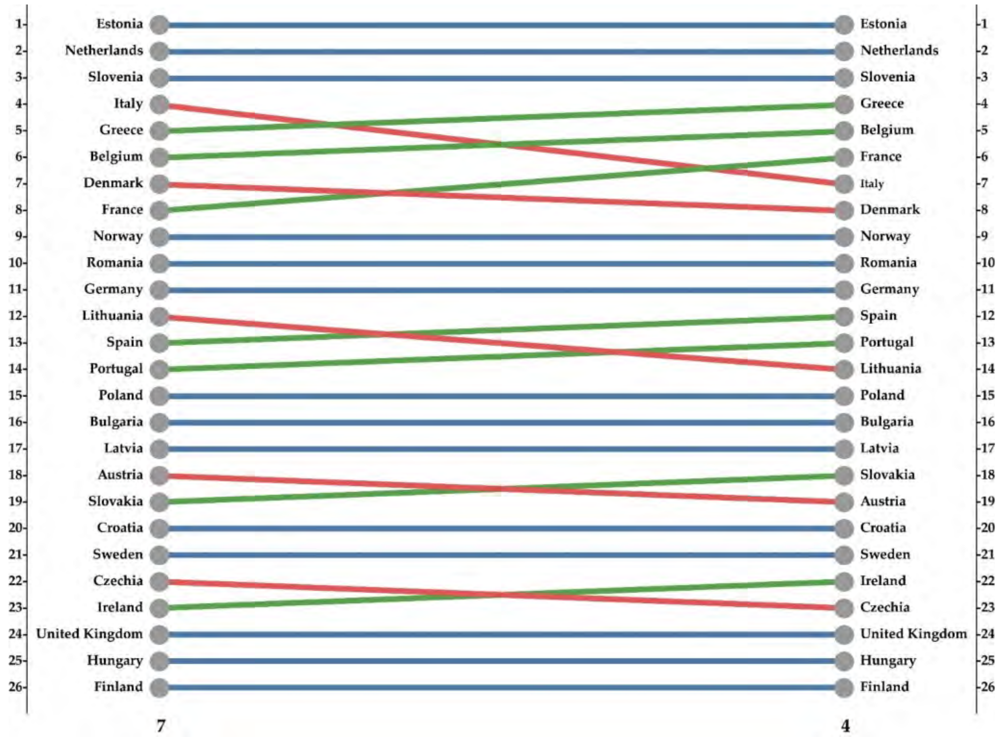

Figure 5.6: Differences in ranking between Window Width equals to 7 (left) and 4 (right).

5.4.3. Projected Efficiency Scores

Data from 2005 to 2019 for all variables involved were projected to 2022, in order to acquire projected efficiencies. The above-mentioned procedure was followed, estimating the ideal window width and performing DEA Window model. Table 5.5 indicates that ideal window equals to 9.

Table 5.5: Equation (2) results (absolute values) for all possible window lengths for the reference period 2005–2022.

	Possible Window Widths																	
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
2005	5.9	5.4	4.8	3.7	2.8	2.3	1.3	0.6	**0.3**	0.7	1.1	1.8	2.0	3.0	3.6	4.0	4.9	6.1
2006	8.0	6.3	4.8	3.4	2.6	1.8	1.0	0.5	**0.1**	0.9	1.5	1.9	2.4	3.1	3.6	4.2	5.0	5.9
2007	9.6	7.2	5.7	4.1	2.8	1.9	1.1	0.4	**0.3**	1.1	1.6	2.2	2.8	3.5	4.1	4.9	5.7	6.6
2008	6.6	5.4	4.8	4.1	3.1	2.4	1.5	0.7	**0.0**	0.7	1.4	1.9	2.5	3.2	3.9	4.4	5.0	5.6
2009	3.4	3.3	2.9	2.5	2.1	1.6	1.0	0.5	**0.2**	0.2	0.6	1.0	1.4	2.0	2.4	2.8	3.2	3.7
2010	7.2	5.3	4.1	3.3	2.7	2.0	1.3	0.7	**0.1**	0.6	1.2	1.8	2.4	3.1	3.6	4.1	4.6	5.3
2011	5.7	4.7	3.9	3.1	2.4	1.8	1.3	0.7	**0.1**	0.4	1.0	1.7	2.1	2.7	3.2	3.7	4.1	4.8
2012	7.4	4.8	3.9	2.7	2.0	1.4	1.0	0.5	**0.1**	0.7	1.3	1.8	2.2	2.7	3.1	3.5	3.9	4.5
2013	5.6	4.4	3.8	2.9	2.2	1.6	1.1	0.6	**0.1**	0.6	1.2	1.6	2.0	2.5	2.9	3.3	3.8	4.5
2014	4.1	3.2	2.6	2.3	1.8	1.3	0.9	0.4	**0.0**	0.3	0.7	1.0	1.4	1.8	2.1	2.6	3.0	3.7
2015	5.1	3.3	2.7	2.0	1.6	1.1	0.6	**0.1**	0.2	0.4	0.7	1.0	1.4	1.8	2.1	2.4	2.9	3.5
2016	5.0	3.4	2.4	1.8	1.3	1.0	0.5	**0.0**	0.4	0.6	0.8	0.9	1.3	1.7	2.0	2.2	2.5	3.0
2017	4.4	2.9	2.0	1.5	1.0	0.6	0.5	0.2	**0.1**	0.3	0.6	0.7	0.9	1.4	1.7	2.0	2.4	3.0
2018	4.5	3.1	2.2	1.6	1.1	0.7	0.3	**0.2**	0.2	0.5	0.8	1.0	1.1	1.3	1.7	2.0	2.3	2.9
2019	3.0	2.3	1.7	1.2	0.8	0.6	0.3	**0.0**	0.1	0.1	0.5	0.7	0.8	1.0	1.1	1.4	1.9	2.5
2020	3.2	2.1	1.3	1.0	0.7	0.4	**0.0**	0.2	0.4	0.2	0.5	0.6	0.7	0.8	0.9	1.0	1.5	2.1
2021	2.4	1.8	1.3	0.8	0.6	0.4	**0.0**	0.3	0.3	0.4	0.3	0.5	0.6	0.7	0.8	0.8	0.9	1.6
2022	1.6	1.5	1.3	0.7	0.5	0.3	**0.1**	0.2	0.3	0.3	0.4	0.5	0.5	0.6	0.7	0.8	0.8	1.0
Total MINs	0	0	0	0	0	0	3	4	**11**	0	0	0	0	0	0	0	0	0

Analysis was performed with window width 9 and another two sub groups of 3 and 6 have been tested in order to minimize the effect of zero technological improvement (Figure 5.7 and Table A.5.3). The four highest ranking countries remained the same for all widths examined. The same situation is depicted for Finland, the UK, and Hungary, which achieved the lowest efficiency scores in all estimated widths. A very interesting case in the following benchmarking is this of Italy, in which position is downgraded (5 -> 8) in window width 9 compared to 6 and upgraded from 8 -> 6 when window is being shorten to three years. Constant technological improvement seems to affect Norway’s performance, due to the fact that its rankings are higher and higher between nine and three-year frame.

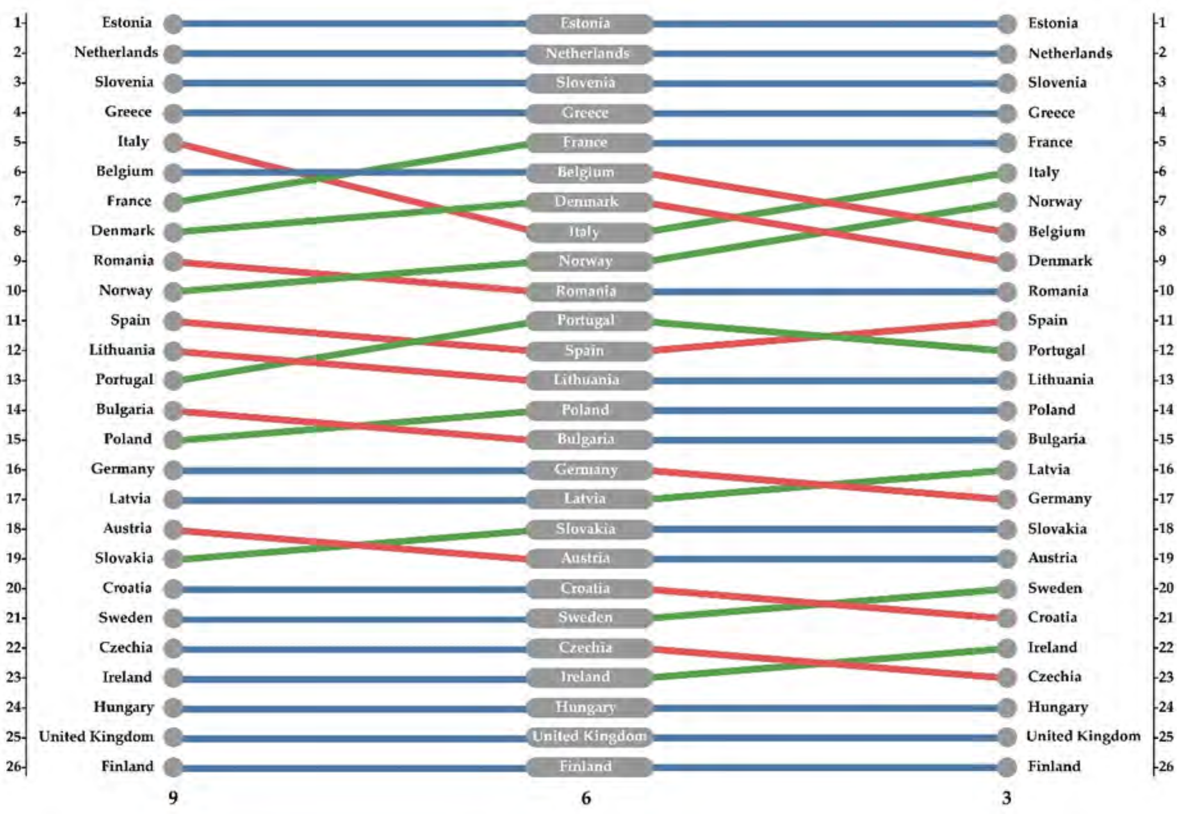

Figure 5.7: Differences in ranking between Window Width equals to 9 (left), 6 (center) and 3 (right) for projected data.

For visualization purposes, Figure 5.8 and Figure 5.9 were created so as to depict the efficiency scores achieved for each country from DEA Window analysis ideal window widths 7 and 9 for periods 2005–2019 and 2005–2022, respectively. Lower efficiency scores can be observed on central EU countries (Austria, Czech Rep., Hungary, and Croatia) and Finland presents the lower performance. Only few changes occurred between projected and non-projected efficiency scores. Projected data reveal higher efficiency scores for Greece, France, Romania, Spain, Portugal, Bulgaria, and Hungary for the next three years. Italy, Denmark, Norway, Germany, and UK obtained lower efficiency scores, underlying the urge for changes in their agricultural sectors, regarding all inputs involved in agricultural production. The greatest difference in the ranking system is for the agricultural domain of Germany, which falls from place 11 for actual data to place 16 for the projected data.

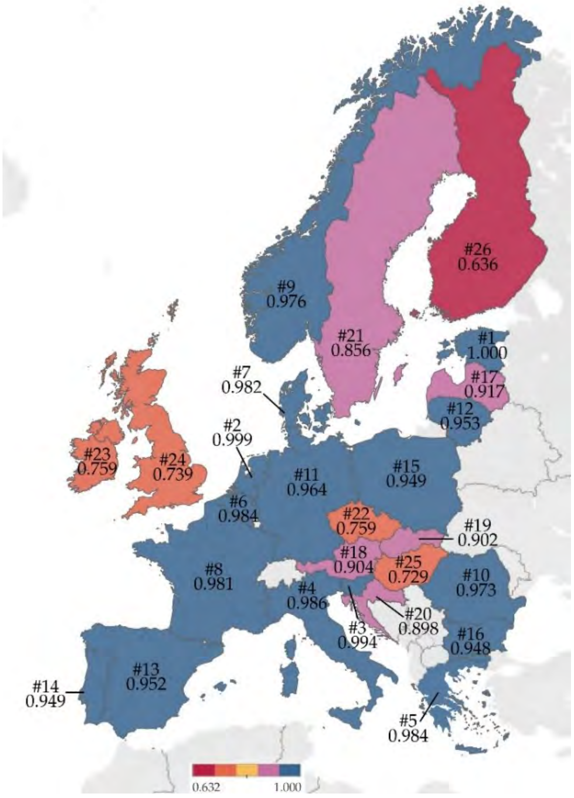

Figure 5.8: Efficiency scores map, Window Width (7) (2005–2019).

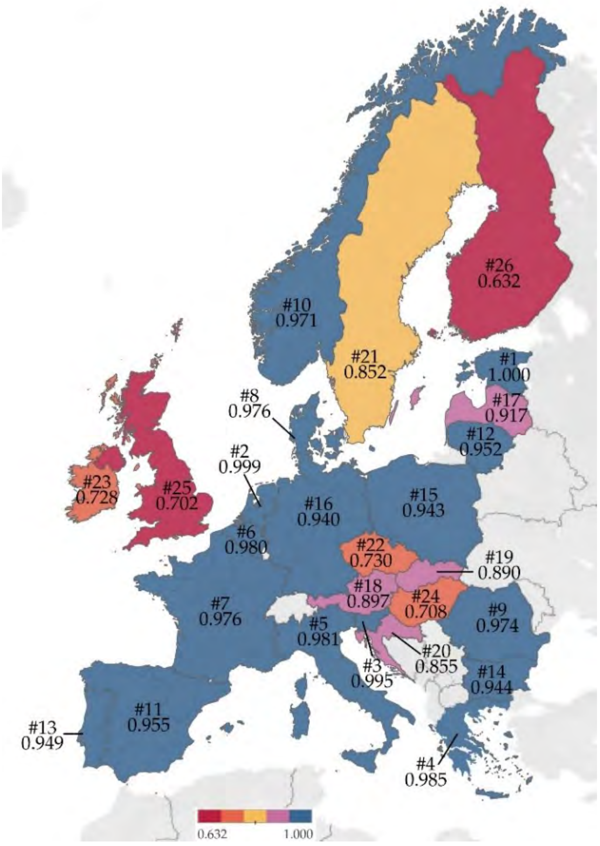

Figure 5.9: Efficiency scores map, Window Width (9) (2005–2022).

5.5. Discussion

The main objective of this study was to assess input use efficiency for all EU countries involved after the implementation of the AGENDA 2000, assuring the validity of Window DEA methodology and clarifying the influence of window width in the results obtained. Major goal of Agenda 2000 was to set the base for increased efficiencies of small and medium enterprises (SMEs) in agriculture, leading to more competitive EU primary sectors (European Commission, 1997). According to the Agenda 2000, new technologies engagement was the key factor for improving performance of European agriculture. Following the upcoming evolution of the Agenda 2000 and CAP (2014–2020), in the new CAP programming period (2021–2027) the main strategy is based on the same objectives, focusing even more on applying specific environmental indicators for assessing performance of agricultural holdings. This is the rationale for the Integrated Farm Management (IFM) approach, defining the equilibrium between economy, environment and society (Rose et al., 2019). On operational terms, IFM proposes the minimum use of every input, reducing the overall cost and enhancing environmental protection. Taking into consideration the above-mentioned approach, the DEA model was used with an input orientation, aiming to assess in a quantified manner the efficiency distances among EU countries, while the use of Window DEA presented in a graphical manner the evolution of efficiencies for this specific time period. However, it should be clarified that through the assessment of alternative window lengths, technology influence has been revealed as an important factor for achieving efficient use of both energy and non-energy related inputs in agriculture.

Ideal window width estimation has been calculated for creating a reference point where, according to methodology, technological change is apparent. Further limiting of window widths leads to the emergence of countries that have adopted new changes in a shorter period of time and these changes had an impact on the overall way they use their inputs. For this reason, even ideal window frame has been calculated for 7 and 9 years respectively, smaller window frames have been appointed also, pinpointing differences due to the aforementioned assumption.

Window DEA has the unique feature of using the same DMU multiple times in the same window, being considered to be a different one. Benchmarking of agricultural sectors highlighted that Estonia, the Netherlands, Slovenia, Greece, and

Italy have the best performance, while Finland, UK and Hungary should reconsider their inputs' usage. The results of this analysis have been compared with previous survey examining eco-efficiency in agricultural sectors of EU countries with as base year 2015 (Rybaczewska-Błazejowska & Gierulski, 2018). Similar results have been exported, despite the fact that previous stages of LCA have been performed. A point of particular interest is that Bulgaria and Romania were characterized as environmentally friendly, but presented decreased economic performance. In this study, where both environmental and economic factors consist this model, Romania and Bulgaria achieve moderate scores. Another great remark is the difference in ranks between agricultural sectors of common input and output characteristics (Estonia (1) and Slovenia (3)), despite the negative impact of climatic conditions for the first one. Validity of the results between agricultural sectors with moderate scale differences is proven, due to the fact that the Netherlands, which handles much greater amounts of inputs and outputs from Slovenia and Estonia, ranks second.

Both the literature review (Apergis et al., 2015; Pellegrini & Fernández, 2018) and descriptive statistics revealing the need for further training and dissemination activities for farmers, regarding energy minimization. Despite the efforts of the EU to mitigate energy consumption in agriculture, it seems that only very few changes have occurred in recent decades. As Eurostat's data reveal, there is a 5% increase in energy, while total used agricultural area has a slight decrease of 3%. Overall energy consumption should have been dropped, due to the increased energy efficiency of technological equipment and the need for minimizing agricultural expenditures and environmental impact. It should be also pointed out that share of renewable energy sources has not changed for the last two decades, while amounts of fertilizers have remained stable for the examined period. This fact should be severely considered by the policy makers' side, linking payments with energy efficiency for farmers, leading to minimized production needs for fertilizer industry. Skjærseth (2016) states that European Commission should gain a higher level of control from member states, in order to achieve sustainable goals by 2050, leading to minimized energy exploitation and limited GHG emissions.

Figure 4 indicates a geographical pattern, where neighboring countries of central Europe achieve lower scores than the others. The comparison of results obtained from past studies (Toma et al., 2015; H. Zhou et al., 2018), with the results of this one, lead to the need for further studies to clarify the reasons behind the achievement of lower efficiency use of inputs involved in agricultural production. Factors such as climate conditions, support on a national level, by providing sufficient financial and administrational aid, and farm structure characteristics should be taken into consideration.

Risk management, in case of extreme weather conditions and environmental protection, are highly considered in the CAP (2021–2027). Thus, there is lack of data regarding the quality and quantity of the equipment used on a national level for agricultural production, and R&D support. Emphasis should be given on the amounts of water used for irrigation. Although the existence of data referring to irrigated agricultural area and water exploitation index is confirmed, monitoring of quantities consumed remains insufficient on an EU level, taking also into consideration that agriculture is the greater water consumer (World Bank, 2020). All the above-mentioned factors are crucial for effective benchmarking and targeted decision making for each EU country.

It is very prominent that European Commission has just released a dedicated webpage to energy consumption indicating the enhanced importance for energy monitoring. It referred that the overall energy dependency of EU is around 60% (2018) (EUROSTAT, 2021), while 1 out of 3 crude oil barrels used to come from Russia. Moreover, energy efficiency results are displayed for every EU country, but the results are not linked to the agricultural domain. An addition of energy use efficiency per sector is proposed, both for providing information to the general public, but also for immediate comparisons among EU countries.

SDGs and especially those referring to food security, sustainable production, and climate change mitigation (SDG2, 12, 13) have to be adopted from all EU countries. Climate change already has various effects on agricultural production (Nastis et al., 2012), creating new geographical pattern both for productive species and their pests. Assuring that every EU country can produce with high efficiency input use rates, resilience can be built up for all member states, especially under the existence of unpredictable phenomena such as prolonged drought, very low temperatures, or a potential increase in prices of imported inputs from non-EU countries.

5.6. Conclusions

To conclude, an alternative method for prognosticate future efficiency scores is proposed. Window DEA has been performed multiple times, assessing differences between various window widths and reference periods. From an academic point of view, this study provides multiple nested comparisons between actual and projected data. Differences between optimal window width and arbitrary chosen window length have been highlighted. Due to the fact that DEA is a benchmarking technique, emphasis has been given on the final rank of each EU agricultural sector and not on the actual values of efficiency scores. It has been notified several times that researchers should be aware of the assumption of zero technological change within frames, when performing Window DEA; for this reason, window width should be resized accordingly. This need becomes more apparent when dealing with large time series, when window width selection can influence final rankings. A possible limitation of this survey, regarding future projections, is its actual dataset. For instance, EUROSTAT database had a panel of full data from 2005 until 2019. To assure projections' validity, only a 3-year period time data have been forecasted. With a larger dataset, a projection of an elongated period would have been possible and maybe a larger variation in the rankings between actual and projected data would be apparent.

Implication of the results signify differences between alternative window widths, meaning that external factors within frame had influence on input use efficiency of the examined countries. Moreover, projected data have been calculated, by identifying 2019 as the ending year of the dataset. Few changes occurred between projected and non-projected efficiency scores, underlying the need for the following countries: Czech Republic, Finland, Ireland, Hungary, and the UK should reconsider their production protocols and the usage of their production factors. Despite the fact that this survey has pointed out the above-mentioned countries as the least efficient, a following analysis is needed in order to highlight the inefficiencies of each variable leading to more applicable results. Thus, it should be stated that the major goal of this study was mostly to identify differences among several window widths, rather than focusing on DEA slacks. Results indicate the importance of continuous monitoring, so as to assure sustainable exploitation of the involved inputs, mainly regarding energy consumption. Figure 5.8 and Figure 5.9 pinpoint lower efficiency scores for countries of central Europe Austria, Czech Republic, Hungary, and Croatia, meaning that they should be supported accordingly. It should not be neglected that the above-mentioned countries will have to restrain climate change effects, partially replacing the production of Mediterranean countries such as Italy, Spain, and Greece. For this reason, emphasis should be given on the development of their agricultural sectors, maintaining low emission levels at the same time. Moreover, ranking differences for Germany, between actual and projected data, should act as a warning notification. Projected data are referring to an extra 3-year period time, which can be considered to be a short one for large changes in this agricultural sector.

Future studies can focus on the infrastructures of EU agricultural sectors, defining the variables that mostly affect the extracted results. Furthermore, they should provide insights for every agricultural sector, in order to clarify the reasons which affect most efficiency shortage (e.g., lack of information, aged population, soil of decreased productivity, climatic conditions etc.). In addition, this study focuses on farm activities, while future studies can implement Window DEA methodology in whole supply chains. Energy use in packaging, storage and transportation will largely affect the extracted results, providing an overall inputs use efficiency from farm to fork. Additionally, technological evolution will bring more changes for arable land crops and greenhouse farming, gradually decreasing the need for human labour, but increasing the need for energy use.

The energy use factor affected the extracted results both directly as an input, but also indirectly with the use of fertilizers and GHG emissions. Energy prices influence immediately the primary production by increasing the cost of all inputs involved. A combination of the results with Skjærseth's (2016) statements (Discussion section) will enhance the argument of augmented control from national sectors, in order to deal with their challenges on a local level. Benefits for improved input use efficiencies can be provided, to motivate more individuals or groups towards this direction. Given the fact that energy dependency of EU is high (EUROSTAT, 2021), measures that assure energy security in the agricultural sector should be taken, in order to prevent future energy instability situations, such as the case of Russia–Ukraine gas disputes. Extensive on-farm use of sensors technology will permit the accurate data recording and monitoring, leading in optimized decisions for everyday tasks, and it will also provide insights for policy making both on a national and European level, in order to achieve greater energy use efficiency.

Moreover, Perpiña Castillo et al. (2016) survey states the remarkable dynamic for establishment of large scale photovoltaic systems in Southern European countries taking into consideration sunlight, population distance, land use, morphological characteristics and policy. It should be underlined that implementation of solar power generation could be a great alternative for covering EU countries energy needs, while preserving natural resources from exploitation.

Cost parameter, regarding energy use, is very crucial due to the fact that it affects both in a direct (oil, electricity, gasoline), or in an indirect way inputs such as fertilizers, agro-chemicals, or transportation costs. As it is stated in the latest European Report about energy prices, share of energy costs in fertilizers' industry is of 71% (European Commission, 2020). Furthermore, it can immediately influence supply and demand curves, leading to either increased or decreased consumption. However, pricing strategies applied by agrochemical industries are not usually based on production costs, but in a close relation with the upcoming benefits derived from their use. Therefore, we assume that energy cost is still an important parameter for the overall production cost in every European country, being at the same time a top priority target for the significant reduction of it for both operational and environmental purposes.

Furthermore, agricultural inputs have to be limited, preventing degradation of natural resources and mitigating environmental consequences. To conclude, all the above-mentioned parameters should be taken into consideration from EU countries for the CAP (2021–2027), to adjust their national strategies and achieve SDGs.

Chapter 6

6.1. Summary

In this thesis, methodological approaches for ameliorating the performance of DEA in the agricultural field are presented. More precisely:

Chapter 2 indicates that DEA is the most frequently applied methodology when it comes to efficiency estimation. However, in agriculture usually complex methodologies are not being met, as this is the case for other economic sectors. Having in mind the new operational status of primary sectors and their increased association to risks related to the markets and the continuously negative impact of climate change, require the development and application of more integrated assessment tools, incorporating parameters such as environment, societal structure, and marketing. Robust DEA models are able of quantifying this risk, providing accurate measurements of uncertainty level to the data analyst. Window DEA is another approach that should be further implemented in agriculture, in order to assess inputs' use efficiency in a timeline. The combination of the above-mentioned approaches of robust and window DEA models can lead to high impact optimization models such as the recently published approach of Peykani et al. (2022), thus agriculture domain does not provide enough open access data that can be used for this purpose. Moreover, it is highlighted that the term "agriculture" is often neglected, leading to decreased access to relative research findings, when the major searching tool for allocating relative papers is enabled, focusing on information being published with the use of more general keywords in operational research. Inserting "agriculture" term either on abstract or keywords contributes to the creation of a clearly defined sector of operational research directly related with agricultural activity.

Another point is the lack of the incorporation of GIS information in the benchmarking process, underestimating the spatial dimension of agriculture. The new satellite technology, in collaboration with PA technology, can overcome the usual difficulties of obtaining data on a small scale, which until recently was the main obstacle for applying such modelling. Incorporation of external factors in the analysis process can be achieved of either embodying environmental factors directly to DEA model, or checking for dependencies of efficiency scores with such factors after the benchmarking process. Application of complex datasets for efficiency assessment purposes can lead to greater insights and tailored future policy measures on a smaller scale, improving by this way the effectiveness of them and increasing the efficiency of budget allocation and decreasing production costs in a feasible and realistic way.

Furthermore, there is space for incorporating the social dimension in the benchmarking process. This can be really useful in cases of policy implementation, where policy-makers want to assess the efficiency level of farms, while at the same time certain demographic goals should be met. Such case studies are in accordance to the main trend of the CAP, as societal characteristics of rural communities are of great importance for monitoring and evaluation. Chapter 3 provides a discrete methodology about embodying ordinal data, classifying information like educational level or annual income, to be utilized when using DEA, contributing to 1st LRG of Chapter 2. By applying this methodology either demographics or other characteristics that are difficult to be quantified, can be taken into consideration. In this case, quality of spraying or quality of plowing can be inserted as variables, for acquiring final efficiency scores. In another perspective, data quantifying the adaptation status of climate change mitigation actions, or the resistance of a cultivation to an external factor, e.g salinity or high temperatures, can be used as well. To this extend, policy makers could have a tool for objectively assessing the contribution of farmers towards sustainability.

Chapter 4 provides a case study of durum wheat farmers both in Italy and Greece that operate under the suggestions of common ADSS. As it is clearly displayed on Figure 4.4 and Figure 4.8 there is a clear difference between the two countries, where Italian farmers are focusing on minimising inputs' usage to decrease production costs, while in Greece there is not clear trend towards inputs' minimization usage. Apart from the above-mentioned conclusion, this case study underlines a proper way of data management and utilisation in the agricultural sector, where farmers are keeping regular records for spending and agricultural applications under a unified system. To this extent, amelioration points can be easier highlighted, setting future goals and design the cultivation for the next year. Chapter 4 analyses all the interactions between farmers – ADSS, highlighting a great importance of further adoption of similar synergistic protocols focusing on improving the operational status of farms.

The proposed methodological approach verified that despite the fact that participating farms operate under the same regulatory policy framework, achieved significantly different efficiency scores. So, there are considerable hints that modelling can identify factors creating obstacles for achieving homogenous efficiency levels, providing by this way new roles and new utilities derived from similar applications. Factors like farm size, influence from family and local community (Weltin et al., 2017), and the level of ICT adoption are the main aspects under which decision-making process of farmers is attempted to be explained (Edwards-Jones, 2006). Theory of Planned behaviour is often used to describe this process conceptualizing that farmers of certain attitudes can display similar behaviours, being though the decision-making process still an unidentified process (Bartkowski & Bartke, 2018). Agent-based models is another approach for modelling farmers' decisions, thus this type of analysis is focusing on one specific aspect each time, such as land-use management, biodiversity, or transition to organic farming (Huber et al., 2018). DEA can be applied towards this direction, in order to create composite indicators that will provide more dimensions to the above-mentioned models (Blancard et al., 2021). Moreover, DEA can be used as a supportive tool for selecting the optimum cultivation strategy, in the existence of alternatives (Giannoulis et al., 2013). Assessing the decision-making process of farmers is a very significant issue for creating effective policies for the achievement of EU goals and promotion of sustainable rural economy (Bonisoli et al., 2018; Chrysafo-Anna et al., 2021).

Chapter 5 contributes on the 3rd LRG of complex methodologies as Chapter 2 indicates. More precisely, it highlights the importance of window width selection when performing Window DEA and provides an appropriate methodology to estimate the time period in which technological level does not remain constant, but it has significantly increased. It is worth noticing that the ideal window width in this case is estimated on 7 years, which matches with the timeframe the programming period of CAP. This is first evidence that the policy measures being applied in every programming period might have a considerable impact on technological change, affecting positively the improvement of EU agricultural productivity. The proposed sensitivity analysis, when performed, can optimize further the width of time frames being applied in such cases. An alternative way to analyse similar cases is the application of Malmquist productivity index, combined with Window DEA methodology, for identifying efficiency changes for each DMU on an annual basis (Sardar Shahraki & Aliahmadi, 2021). Window DEA is a suitable tool for assessing efficiency with the use of panel data, being this a common and useful tool in agricultural cases, where variability of the factors being involved is high. The proposed methodological approach follows, to a large extent, the same rational with the recently proposed methodology from Peykani et al. (2022) about Robust Window DEA. Although their case study is assessing the stock market, it can be transferred into the agricultural sector, as far as the Variable returns to Scale model is applied.

6.2. Overall conclusions

DEA has been evolved over the years in the context of agriculture, with new developments and applications emerging, in response to the changing needs and demands of the agricultural sector. As mentioned in the Introduction section, CAP underwent a series of reforms to reduce production costs and to promote competitiveness on an EU level. Market-oriented policies, as well as the elimination of price supports, mitigated production surpluses. Moreover, 2000s’ reform has introduced measures of rural support and cross compliance, indicating the need for a holistic approach that considers both social and environmental aspects, other than the economic outcome of the production process itself. Furthermore, reforms have been made to ensure environmental protection and rural development, while the introduction of knowledge and innovation in the current CAP’s programming period adds a new dimension in the overall assessment of agricultural performance. Overall, CAP’s evolution reflects the changing needs and demands of the agricultural sector and the wider society, as well as the ongoing efforts to create a more sustainable and competitive agricultural sector in the EU.

Considering the above points, from an operational research perspective, it is evident that the Key Performance Indicators (KPIs) of the agricultural sector were considered solely economic for many decades prior to Agenda 2000. For instance, some of the most common KPIs were the overall production in monetary values and the contribution of agricultural sector to the national Gross Domestic Product. However, the next reforms added multiple dimensions in the overall optimization problem, paying attention to the environmental footprint (carbon, water and ecological footprints) of agricultural activity, as well as the wellbeing of farmers, utilizing for this as indicators the produced income per Agricultural Working Unit or gender gap in rural areas. DEA has been extended to a multi-objective analysis, allowing the evaluation of multiple conflicting objectives, such as maximizing yield and minimizing environmental impacts, in agricultural production. Due to the fact that some of the above-mentioned societal characteristics are difficult to be accurately measured or quantified, Chapter 3 introduces a combination of DEA+TOPSIS methodology that could be considered as appropriate in such cases. To a further extend, this methodology could contribute on the assessment of more complex scenarios, where the implementation of a series of agro-ecological practices would be considered in the overall optimization process.

Furthermore, another point that should be discussed is the environmental protection aspect. In all Chapters of this thesis (apart from Chapter 3), environmental dimension is assessed, either by the way it is presented in the relevant literature review, or by the inclusion of environmental variables in the form of undesirable outputs. Energy efficiency, water use, and greenhouse gas emissions are considered as top priority issues for the EU and through this thesis the applicability of DEA on mitigating the negative effects of agricultural activities is verified. It is really prominent that DEA can identify the best practices for reducing the environmental impact of a particular process and provide solutions extracted from the examined sample each time.

Taking into consideration the last statement, DEA can be used to further promote innovative agro-ecological practices on a farm level. Providing farm specific instructions is considered as a complex task for agricultural experts, due to the fact that there are several factors affecting the overall production of a given quality. However, the application of DEA in the agricultural field provides two benefits that are often neglected or less discussed. The first one is that DEA can provide applicable solutions by enabling only basic variables relevant to the agricultural activity of each farm, assuming that the influence of external factors is equal for all farms. This can be considered advantageous in cases where there is lack of data regarding the climatic, spatial, or agricultural data of a region -which is often the case; but the embodiment of such data could lead to more accurate results.

The second one stands on the fact that farmers can learn from their colleagues by the example-demonstration method and not by a theoretical optimum value. In other words, best performers of a region can act as the best-case examples and can contribute to the evolution of agriculture in local systems. Cristofari et al. (2018), Kalule et al. (2019) and Ranjan et al. (2019) agree that farmers can change their practices or the way that perceive a situation, when these practices are implemented by someone in their region.

This technique can find application through the Living Labs approach, a user-centered ecosystem that aims to provide solutions for a common problem among all involved stakeholders. More precisely, the combination of DEA application and Living Labs can be used in order to optimize a given production process, taking into account the perspectives of multiple actors such as organizations, public authorities or entrepreneurs. This process can provide methodological benefits for DEA as well, based on the evaluation of suggested solutions in practice.

Identification of regional disparities can be also achieved by using DEA, comparing the efficiency scores among regions, and assessing the additional inputs used. The projection of the acquired results in a geospatial information system would lead to a clearer overview for agricultural experts and policy makers. Chapter 4 contains all the above-mentioned principles referring to environmental inclusion, data availability, identification of best performers and differences on both national and local level when performing DEA. However, due to the increased complexity of the involved factors in agricultural production, a multi-year assessment is preferred.

Monitoring changes of agricultural performance for an extended time period can be achieved with the use of Window DEA, by identifying efficiency differences among farms or agricultural sectors. A proposed methodological approach for the assessment of the impact of CAP on technological change has been presented in Chapter 5. This could be further developed during the upcoming years, where multiple objectives, being introduced from SDGs' principles, could be embodied in the overall optimisation process. In Chapter 5 it was pointed out that technological change is evident within seven years. Using the same technique, the subsequent impact of this CAP on the EU agricultural sectors can be assessed and potential differences between the two periods (before and after) of the last CAP reform can be highlighted.

To a further extent, the combination of all chapters highlights the need of a multi-year assessment, where environmental and societal variables will be considered, apart from the solely economic ones, in order for the EU to reach its goals for achieving sustainability until 2050. Preliminary results show that this combination can lead to the creation of a multi-objective tool that can be used in multiple application levels. For instance, this tool could be used from farmers to check their performance and to be exemplified by their colleagues of the same region, or agricultural experts that could provide tailored made solutions, considering all sustainability aspects. Policy makers is another potential target group that could have a clearer overview, and thus a more detailed and accurate design capability.

Furthermore, as the analysis of GD.NET dataset indicated, even in cases where there is a close monitoring system, there is still place of improvement. Particularly, it was prominent that in each country there was at least 10% of efficient farmers that can act as good examples for the other durum wheat growers of the region. However, the key-points of this process are that a) durum wheat farmers can further ameliorate their performance by reducing the amount of the resources that they use, being guided by DEA results and b) by combining Window DEA, agricultural managers of Barilla company have the chance to monitor durum wheat cultivation in a longer time period than one cultivation year, providing more accurate guidance to the farmers. This leads to the creation of a new product that serves all three sustainability aspects. Relative information about the holistic strategy of the Barilla company can be displayed on the products packaging, to gain consumers attention.

Considering the above-mentioned points this thesis achieved to provide new methodological approaches that can support a holistic assessment (economic, environmental, and social) of the new CAP, either on an annual or in a multiyear context. Even though there was a need to reduce the inputs used in the agricultural sector in previous years, both COVID-19 pandemic and the Russian-Ukrainian war have disrupted both production and distribution of agricultural products, setting as a priority the increased efficiency of resources used. Current structures that provide data regarding the agricultural activity should be amplified, with a bottom-up approach, meaning that focus should be given on acquiring farm specific data that will permit a fairer assessment for region and countries. In this way, policy makers will have more accurate data to propose agricultural policy modifications.

In the last part of the conclusion section, it is considered appropriate to answer point by point the research questions that has been set in the Overall contribution section.

- *What are the main methodological gaps when implementing DEA in the agricultural sector considering sustainability?*

Although the number of publications, the last decade has been increased (Figure **1**.**6**), 78% of the studies are using the conventional DEA models (Figure 2.6). This highlights the need for implementation of more complex methodologies that are taking into consideration, time-series data, structural characteristics of the agricultural activity or handling uncertainty. Moreover, the social aspect is underrepresented since the overall contribution of papers, that have been retrieved with the keywords. DEA, sustainability and agriculture, are considering all 3 sustainability dimensions in only 24 papers out of 120 (Figure 2.9). This is the reason why new methodological approaches that can incorporate social variables into the overall optimisation process are needed. Furthermore, DEA is mostly combined with linear regression models, while researchers have combined with life-cycle assessment methodology underlying the need for the combination of DEA with geospatial information systems to acquire more accurate results.

- *Is the current infrastructure enough to support decision making on a national and local level?*

The enactment of SDGs from the UN in 2015 has been largely influential towards the main principles that have been adopted through the 10 objectives of the current CAP 2023-2027. Besides the fact that Eurostat was providing summarised information about multiple production factors per country (production, cultivated land, fertilisers use, labour etc.), it has recently added indicators about European countries performance regarding SDGs. This underlines the significance that the EC is giving priority to other dimensions related to the agricultural activity like the living standards of people in rural areas, young farmers support as well as the increase environmental protection standards. However, there is still lack of data regarding the activities that are performed in farm level, leading to less accurate data when it comes to national level. For this reason, the new CAP is subsidising precision agriculture practices to collect all the appropriate information from each country in farm level. By this means all the involved stakeholders (farmers, agricultural managers, enterprises, and policymakers) will have the chance to better organise their activities and active higher performance. That was the main reason why in this PhD thesis an extended analysis of an ADSS was embodied a) to highlight the fact that the accurate data collection is leading to handful results and b) to showcase how a modern agricultural system including field sensors data, agricultural experts guidance as well as an additional step of analysis in the end of cultivation year should operate.

- *Which are the methodologies that can be combined with DEA, so as to provide sufficient indicators for CAP 2023-2027 performance?*

Both the introduction section and the systematic literature review process have indicated that DEA can be combined with several methodologies, such as linear regression, life-cycle assessment, sensitivity analysis, as well as the creation of index numbers, similar to the tool of the SAFA (Figure 1.3). However, these methodologies can be applied prior or after the DEA implementation stage, meaning that the researcher cannot acquire an overall benchmarking by including ordinal values in the optimisation process. Additionally, if the ordinal variables are not included in the benchmarking process, there is no clue about the final target values and the final ranking of the involved DMUs. This is the contribution of the DEA and TOPSIS combination, where ordinal values representing either the social aspect, or other variables that are difficult to be measured (e.g. quality of spraying, quality of tillage, hazardous level of agrochemicals used etc.) can be considered from the early beginning in the optimisation process. In this way, this combination can be implemented to assess the performance of all three dimensions of the current CAP 2023-2027, as well as to indicate the points that should be further ameliorated.

- *What was the long-term effect of the CAP implementation regarding the inputs' use efficiency of the EU members?*

CAP has been set into action from 1962, and it is one of the most significant frameworks for the EU region. Several CAP revisions have been made to ensure the economic development and the environmental protection of the the EU countries. Although the EC has made a series of changes to balance regional disparities, it is still evident that there are efficiency differences among the different EU agricultural sectors, operating under the same policy. Window DEA implementation is considered as an appropriate methodology to analyse time-series data for assessing efficiency changes within a certain time-period. Technological influence seems to be crucial for the agricultural sector. The sensitivity analysis highlighted the differences in ranking when different window widths are selected, indicating the influence of technology at shorter periods of time. Considering that the EU is aiming to achieve sustainability in the agricultural sector, meaning that additional dimensions should be evaluated, Window DEA and TOPSIS combination has a great potential for providing further insights in this holistic assessment.

6.3. Future guidelines

In general, the greatest peculiarities of agricultural operational research, in comparison with other branches of operational research, are the variability of involved factors and uncertainty handling (Anderies et al., 2013; Mardani Najafabadi & Taki, 2020; Varas et al., 2021). In other words, a farm operates under the influence of numerous exogenous factors that have significant impact on the quantity and quality of the final product. All these impacts are difficult to be accurately measured and embodied in a DEA model, thus it is appropriate to be considered under confidence intervals.

Moreover, it should be stated that as Chapter 2 concludes, there is a necessity for the implementation of more complex methodologies. Apart from the ones mentioned in the conclusion section of Chapter 2 (Network DEA, Window DEA, DEA and AI combination), another approach, that is less explored in agriculture, is the parallel hierarchical structures where the whole production procedure is set into the benchmarking process rather than a single inputs-outputs approach. Even though this methodology has been implemented in other fields like banks or energy sector (Azadeh et al., 2014; S. K. Lee et al., 2013; J. Liu et al., 2020) it has not been applied in agriculture yet. For instance, the structure of EU agricultural sectors can be assessed taking into consideration that each agricultural sector has a defined structure, like crop production, livestock production and mixed systems (Figure 6.1). In other words, this analysis will not only lead to efficiency estimations of each country (Level 1) but also to the assessment of their subdivisions as well (Level 2-Level 4). In this way, the excess use of resources can be identified in each level, while providing feasible solutions for the amelioration of inefficient points. This methodology could be used in the policy making process for an improved resources allocation and the provision of specific guidelines to each country. Similar approaches can be used on farms that are dedicated to the production of more than one product, to assess the profitability or the environmental impact of the production process of each product.

Ideally data flow in the EU will be similar to the one proposed in Figure 6.1, from farm-level, to local communities, to national level, and finally to the hands of data analysts and policy-makers on a European level. However, adaptation of new agricultural technology related to the recording of agronomical and weather data on a farm-level, farmers' training, data storage facilities and lack of appropriate policy-framework, are some of the restrictions which has not been managed yet. Approaches that use machine learning algorithms, in combination with DEA will further decrease the computation time of efficiency scores with increased accuracy (up to 94%) (N. Zhu et al., 2021).

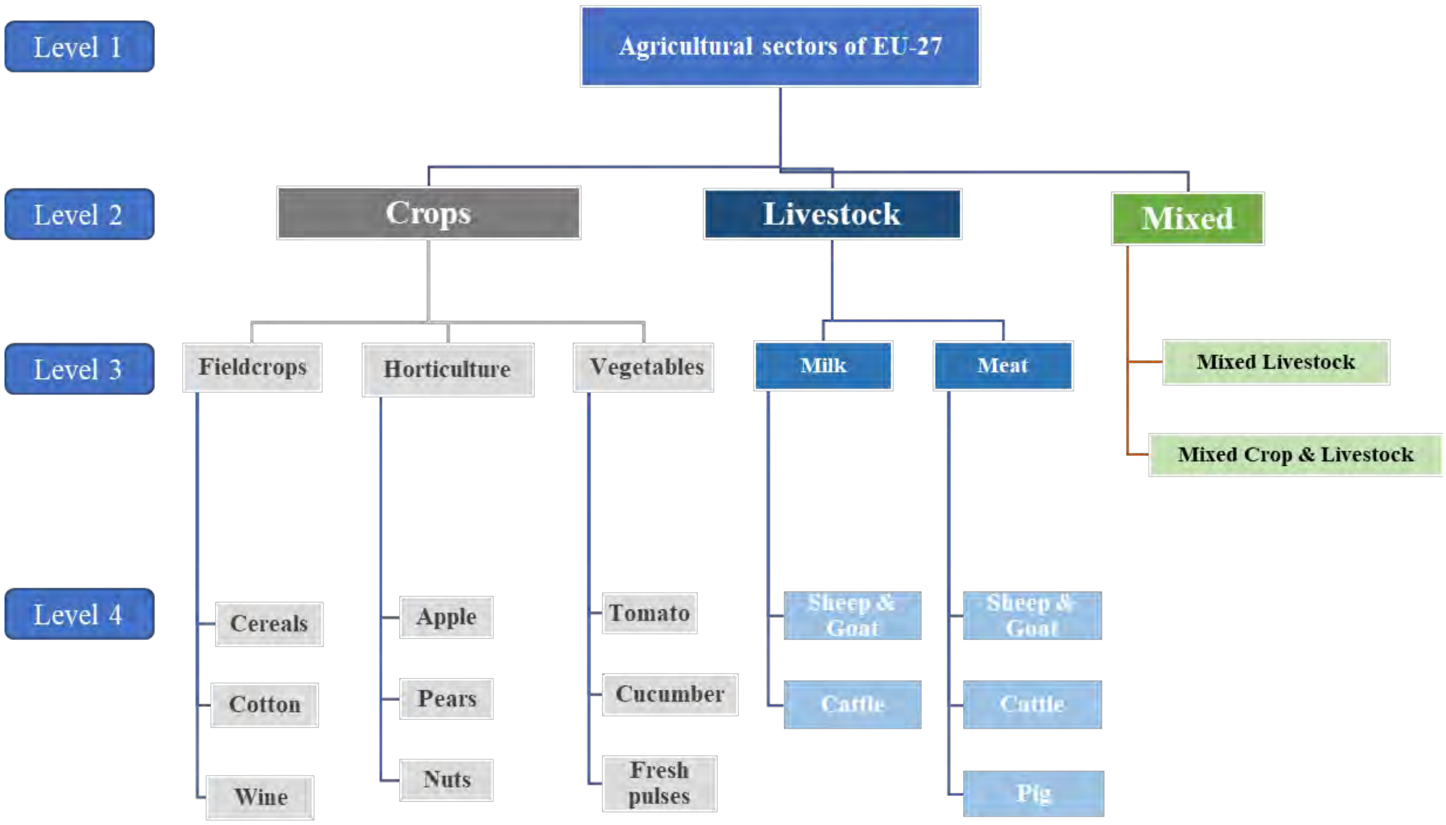

Figure 6.1: Graphical example of hierarchical structure in the agricultural sector

Last but not least, as mentioned in the beginning of this chapter, variability and uncertainty handling can only be confronted with the existence of appropriate datasets for multiple years. Specialized ADSS for each cultivation and the upcoming agriculture 4.0 will contribute on this direction. It is prominent that FAO has included the term “efficiency” in its recently published report for transitioning to a sustainable agriculture, meaning that agricultural operational research field has a great potential for the near future (Image 6.1).

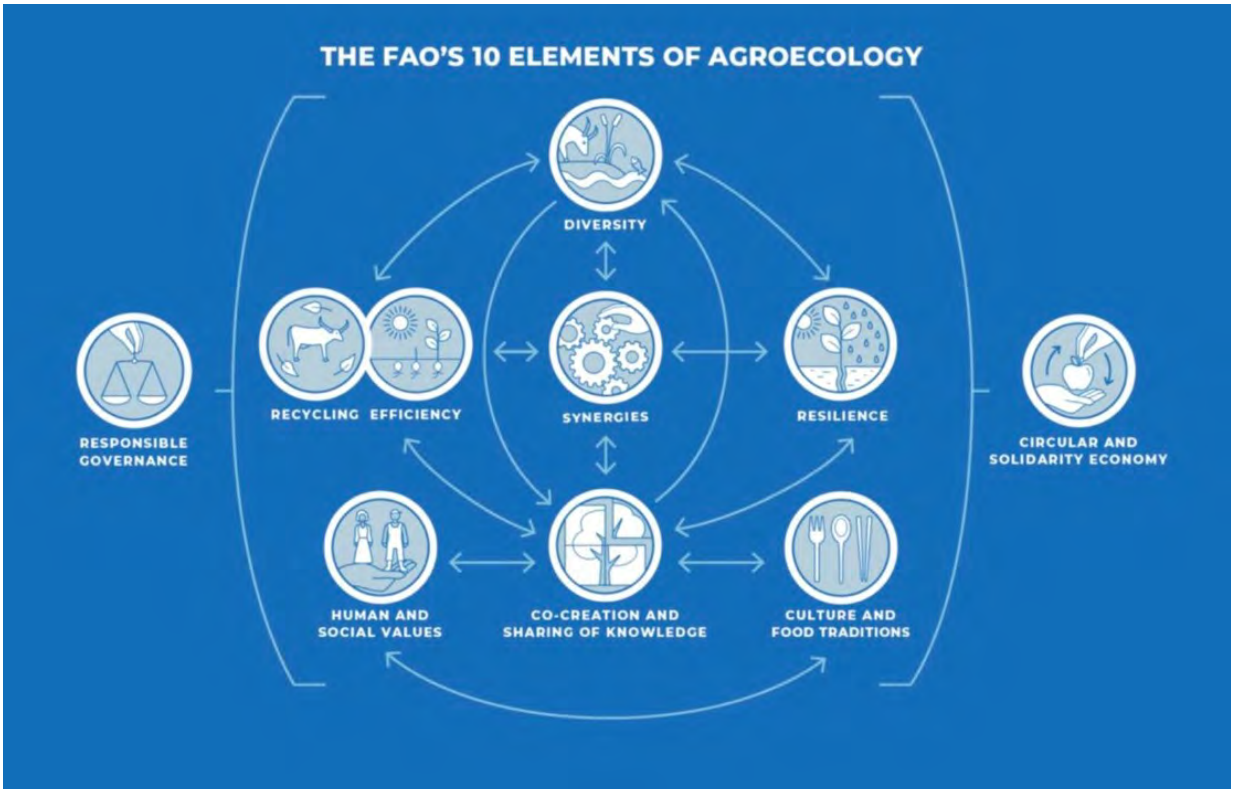

Image 6.1: 10 Elements of Agroecology, Source: FAO

6.4. Contribution to SDGs

As a final point of this doctoral thesis, a brief report on its contribution to the SDGs should be provided, so that it is in full compliance with the global guidelines for achieving sustainability until 2050.

Target 6.3 Improve water quality by reducing pollution, eliminating dumping, and minimizing release of hazardous chemicals and materials.

- Minimizing the excess use of agrochemicals
- Minimizing leaching

Target 7 Ensure access to affordable, reliable, sustainable and modern energy for all

- Minimizing energy use in agricultural systems
- Increasing energy efficiency
- Promote sustainable production of energy

Target 11a Support positive economic, social and environmental links between urban, peri-urban and rural areas by strengthening national and regional development planning

- Ensure income for people in rural areas
- Reduce additional expenses

Target 12 Ensure sustainable consumption and production patterns

- Efficient use of natural resources
- Reducing waste of the different production processes
- Support companies for close monitoring on their sustainable indicators

Target 13.1 & Target 13.2

13.1 Strengthen resilience

13.2 Integrate climate change measures into national policies, strategies, and planning

- Proposing resilience strategies to local municipalities
- Promote SDGs implementation in local and national level

Target 15.1 Ensure the conservation, restoration and sustainable use of terrestrial and inland freshwater ecosystems and their services

- Proper land use management

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Appendix

Table A.2.1: All the included references of the reviewed papers

Authors	Ap. Lvl	Inputs	Outputs	Application System
(Skevas & Serra, 2016)	L	Capital, Labour, Land, Other costs, Pesticides, Fertilizers	Production (Euro)	Arable farms
(Pang et al., 2016)	N	Agricultural Machinery, Agricultural film input, Fertilizers	Added Value	Agricultural sector
(Tian et al., 2016)	N	Agricultural film input, Agro-chemicals, Diesel, Electricity, Irrigation, Labour, Organic Fertilizers	Production	Grapes
(Baležentis et al., 2016)	N	Energy, Labour, Real Fixed Capital Stock	Added Value	Agricultural sector
(Molinos-Senante et al., 2016)	L	Energy, Labour, Pesticides, Fertilizers	Production	Agricultural sector
(Ghali et al., 2016)	L	Capital, Intermediate consumption, Labour, Land	Crop output, Livestock output, Other Output	Agricultural sector
(C. N. Wang et al., 2016)	L	Equity, Liabilities, total assets	Gross Profit, Net Revenue	Agroforestry
(Martino et al., 2016)	L	Capital, Labour, Land, Other costs	Gross Product	Agricultural sector
(Vlontzos et al., 2017)	I	Agro-chemicals, Capital, Energy, Labour, Land	Production (Euro)	Agricultural sector
(C. Ren et al., 2017)	L	External hidden flow, Import water resources, Local water resources	Local waste output, Local waste system	Agricultural sector
(Grados et al., 2017)	P	Agro-chemicals, Labour, Machinery, Seeds, Fertilizers	Production	Potato
(Raheli et al., 2017)	L	Agro-chemicals, Diesel, Irrigation, Labour, Machinery, Manure, Seeds, Fertilizers	Yield	Tomato
(Godoy-Durán et al., 2017)	L	Economic, Environmental, Social	Yield	Horticulture

(Esfahani et al., 2017)	L	Electricity, Land, Manure, Fertilizers	Yield	Corn
(Beltrán-Esteve et al., 2017)	L	Income	Ecotoxicity, Eutrophication potential, Global Warming Potential, Human toxicity, Lentil, Ozone	Citrus
(Rebolledo-Leiva et al., 2017)	P	Energy, Land, Machinery, Pesticides, Raw materials, Fertilizers	Packaging residues, Production	Blueberry
(P. Lee & Park, 2017)	L	Agro-chemicals, Diesel, Electricity, Irrigation, Labour, Machinery, Seed, Fertilizers	Production, straw	Soybeans
(Y. Wang et al., 2017)	P	Agro-chemicals, Irrigation, Machinery, agricultural population, blue water, green water, irrigated area	Production, Production (Euro)	Agricultural sector
(Hassen et al., 2017)	L	Agro-chemicals, Ferilizers, Labour, Land, Machinery, Seeds	Production	Wheat
(Martinho, 2017)	I	Agro-chemicals, Labour, Labour wages, Fertilizers, total assets	Total Output	Countries
(Khanjarpanah et al., 2017)	P	Annual percipitation, Human Development Index, Irrigation, Land, Population, percipitation, temprature, unemployment index	Production	Switchgrass
(W Kamal & Ilmas, 2017)	N	Feed, Labour, Medication, Number of animals, Utilities	Production (Euro)	Broiler
(Varela-Candamio et al., 2018)	P	Capital, Labour, Land, Shadow price	Production, Subsidies	Agricultural sector
(Rybaczewska-Błazejowska & Gierulski, 2018)	I	Agricultural Land Occupation, Climate Change, Freshwater Eutrophication, Freshwater ecotoxicity, Human toxicity, Ionizing radiation, Marine Ecotoxicity, Marine Eutrophication, Ozone depletion, Terrestial acidification, Urban Land Occupation, fossil depletion, metal depletion, natural land transformation, photochemical oxidant formation, terrestrial ecotoxicity, water depletion	Gross ouput value	Agricultural sector

(Sherzod et al., 2018)	L	Labour, Seeds, Fertilizers	Production	Wheat
(He & Zhang, 2018)	L	Quality management system, Quality improvement plan, Relative price level per employee, Training time, Equipment Environmental amelioration Cost input rate of research funding	Product qualification rate, Rate of return on total assets, Quick ratio, Profit growth rateon-time delivery, Rate order completion Rate enterprise reputation, Information level, Strategic objective compatibility, carbon dioxide emission, "three wastes" recycling rate	Agricultural sector (Supply Chain)
(Babazadeh et al., 2018)	N	Annual percipitation, Cost of cultivation, Human Development Index, Land, Number of oil extraction, Population, Sunlight, Water resources	Production	Rapeseed, Soybeans
(Dong et al., 2018)	P	Area, Labour, Machinery, Nitrogen	Added Value, CO2 emissions	Agricultural sector
Mutyasira 2018	L	Farm Sustainability Index	Economic, Environmental, Social variables	Agricultural sector
(Izadikhah & Khoshroo, 2018)	L	Labour, Machinery, Seed, Fertilizers	Total Production	Maize
(Mu et al., 2018)	L	Land, Livestock units, Milk costs, fat content, protein content	Energy use, Gross Margin, Land use, N Surplus, P Surplus	Dairy farms
(Frangu et al., 2018)	P	Labour, Land, insecticides	Production	Greenhouse Vegetables
(Xing et al., 2018)	N	CO2 Emissions, Energy Usage, Exhaust emission, Hazardous Waste Generation, Waste water discharge, Water withdrawl	Economic output	Multiple Production Sectors
(Abbas et al., 2018)	L	Chemicals, Diesel, Electricity, Human Labour, Irrigation, Machinery, Seed, Fertilizers	Yield	Wheat

(Masuda, 2019)	L	Agro-chemicals, Buildings, Electricity, Land, Machinery, Production costs, Seeds, Fertilizers	Yield, Yield (Straw)	Rice
(Rodrigues et al., 2019)	P	Economic, Environmental, Social	Production (Euro)	Fisheries
(Sintori et al., 2019)	L	Feed, Labour, Land, variable capital cost	Meat, Milk	Sheep Farms
(Dania et al., 2019)	T.M	Economic, Environmental, Social	System Requirments	Agricultural sector (Supply Chain)
(Saputri et al., 2019)	L	Capital, Energy, Labour, Material and Service, Services	Production	GMO & non-GMO Products
(Tan et al., 2019)	N	Equity financing cost, Interest expenses, Investment in innovation, Main business cost, Total debt	Economic value added, Return on asset ratio, Weighted average return	Agricultural businesses
(Liang et al., 2019)	P	Agro-chemicals, Labour, Land, Manure, Material and Service, Seeds, Fertilizers	Gross ouput value	Greenhouse Vegetables
(Bournaris et al., 2019)	P	Agro-chemicals, Area, Labour, Other costs, Seeds, Fertilizers	Gross Returns	Greenhouse Vegetables
(Elhag & Boteva, 2019)	L	Agro-chemicals, Diesel, Electricity, Irrigation, Labour, Seeds, Fertilizers	Yield	Greenhouse Vegetables
(Grados & Schrevens, 2019)	L	Labour, Machiner, Ferilizers, Pesticides, Fungicides	Production	Potato
(Sánchez-Zamora & Gallardo-Cobos, 2019)	P	Economic, Environmental, Social	Composite indicator	Agricultural sector
(Ilahi et al., 2019)	P	Chemicals, Diesel, Electricity, Labour, Machinery, Seeds, Water, Fertilizers	Yield (Wheat grain)	Wheat
(Ozden & Ozer, 2019)	N	Capital, Labour, Land, Pesticides, Population, cattle stock, Fertilizers	Production (Euro)	Agricultural sector
(Haq & Boz, 2019)	L	Labour, Fertilizers	Production	Tea
(Y. Yang et al., 2019)	L	2 models, Ferilizers, Fertilizer per Ha, Labour, Land, Machinery, Pesticide per Ha, Pesticides, Seeds	Crop output	Crop Farms

(L. Liu & Sun, 2019)	L	Land, Other costs, Fertilizers	Bamboo roots, Bamboo wood, Production, Production (Euro)	Timber
(M. Watto & Mugera, 2019)	L	Agro-chemicals, Farm size, Irrigation, Labour, Seed, Fertilizers	Yield	Wheat
(Gatimbu et al., 2020)	L	Capital, Energy, Labour, Land, Material and Service	Only undesirable outputs	Tea
(Gamboa et al., 2020)	L	Labour, Machinery, Pesticides, Fertilizers	Production	Quinoa
(Coluccia et al., 2020)	N	Gross Capital, Irrigation, Labour, Land, Fertilizers	Production	Agricultural sector
(Ul Haq et al., 2020)	L	Labour, Fertilizers	Production	Tea
(Pereira Domingues Martinho, 2020)	I	Energy costs, Fixed assets, Labour	Total Output	Agricultural sector
(Mwambo et al., 2020)	L	Agricultural Services, Evapotranspiration, Human Labour, Seeds, animal Labour, Fertilizers, topsoil loss	Yield	Wheat
(Ayouba & Vigeant, 2020)	L	Capital, Labour, Land, Pesticides, Raw materials	Production	Wheat
(Bartova & Fandel, 2020)	L	Energy, Fixed assets, Labour, Land	Production	Wheat
(Ashraf et al., 2020)	L	Agro-chemicals, Diesel, Electricity, Irrigation, Labour, Machinery, Seed	Yield (Cereals), Yield (Straw)	Wheat
(Basavalingaiah et al., 2020)	L	Agro-chemicals, Diesel, Energy, Farmyard manure, Irrigation, Labour, Machinery, Seeds, Fertilizers	Grain Yield, Yield (Straw)	Rice
(Nguyen et al., 2020)	L	Crop production cost, Labour, Land, Other costs, Pesticides	Production	Orange
(García-Cornejo et al., 2020)	L	Depreciation expenses, Labour, fixed capital cost, variable capital cost	Production (Euro)	Dairy farms
(Nguyen et al., 2020)	N	Land, Family Labour, Outsourced Labour cost, Crop Production cost, Other expenditures	Production	Oranges

(Grausser et al., 2021)	N	Aquatic ecotoxixity, Cumulative energy demand, Global warming potential, Normalized eutrophication	FNI, HNVf, net food production-protein	Agricultural sector
(Lucas et al., 2021)	I	Acidification, Eutrophication, Fresh water withdrawls, GHG emissions, Land Use	Calories, Qualifying index	food sector
(Domagała, 2021)	I	Energy, Labour, Land, Fertilizers	Production, net value added	Agricultural sector
(Papadopoulou et al., 2021)	L	Labour, Number of animals, fixed capital cost, variable capital cost	Net income	Small ruminant farms
(Kord et al., 2021)	P	Area, Irrigation, Labour	Production, Production (Euro)	Agricultural sector
(Khoshroo et al., 2021)	N	Biocides, Electricity, Energy, Machinery, Fertilizers	Production (Euro)	Tomato
(G. Singh et al., 2021)	L	Agro-chemicals, Biocides, Electricity, Fuel, Irrigation, Labour, Machinery, Seeds	Grain Yield	Wheat
(Cecchini et al., 2021)	L	Area, Feed, Labour, Livestock units	Meat, wool	Sheep Farms
(Debbarma et al., 2021)	L	Capital, Energy, Labour	Production (Euro)	Agricultural sector
(P. Singh, Singh, Sodhi, & Benbi, 2021)	L	Biocides, Energy, Machinery, Seed, Fertilizers	Production, Production (Euro)	Rice, Wheat, rotation
(M. Zhang et al., 2021)	I	Ferilizers, Irrigation, Land, Machinery	Agricultural Output, CO_2 emissions	Agricultural sector
(Streimikis et al., 2021)	I	Energy consumption, Labour, Land, fixed consumption	Purchasing Power Parity	Agricultural sector
(Payandeh et al., 2021)	L	Agro-chemicals, Diesel fuel, Human Labour, Machinery, Oil, Seeds, Fertilizers	Grain Yield, Yield (Straw)	barley
(Güney, 2021)	L	Fuel, Labour, Machinery, Pesticides, Seed, Fertilizers	Production	Wheat
(Kyrgiakos et al., 2021)	L	Energy, Irrigation, Labour, Land, PNPs, Seeds	Production, Production (Euro), Social characteristics	Cotton

(Basavalingaiah et al., 2022)	L	Agro-chemicals, Diesel, Ferilizers, Labour, Lime, Machinery, Manure	Coffee, Yield	Coffee
(Pan et al., 2021)	N	Energy, Land, Technolgy, funds, resources	Production	Agricultural sector
(Lamkowsky et al., 2021)	L	Capital, Feed, Labour, Land, Machinery, Number of animals, Pesticides, Seeds, Veterinary costs, Fertilizers	Dairy Sales, Other Sales	Dairy farms
(P. Singh, Singh, Sodhi, & Sharma, 2021)	L	Biocides, Diesel, Electricity, Fuel, Irrigation, Labour, Seed, Fertilizers	Production	Wheat
(Banaś et al., 2021)	L	Area, Labour, Land, Logging costs, Other costs, Protection costs, Silviculture, Standing volume	Production	Timber
(Martinsson & Hansson, 2021)	N	Energy expenditures	Contribution to global warming	Dairy farms
(Y. Zhang et al., 2021)	I	CO_2 Emissions, Land, Yield, food loses, protein supply	Agricultural added value, import dependency ratio, irrigated area	Agricultural sector
(Nirmal Ravi Kumar & Babu, 2021)	L	Manure, Seeds, gypsum	Production	Groundnut
(Mwambo et al., 2021)	L	Agricultural Services, Evapotranspiration, Human Labour, Seeds, animal Labour, Fertilizers, topsoil loss	Yield	Maize
(J. Li et al., 2021)	N	Labour, Land, Machinery, Fertilizers	Agricultural added value	Agricultural sector
(Bagheri, 2021)	I	Electricity, Labour	CO_2 emissions, GDP	Agricultural sector
(Seo & Umeda, 2021)	L	Pest control cost	Gross farm income, Surplus of working hours	Rice
(Tang et al., 2022)	N	Irrigation, Labour, Land, Machinery, Pesticides, Plastic film, Fertilizers	Economic output, Environmental output, Social output	Agricultural sector
(P. Xu et al., 2022)	N	Agro-chemicals, Area, Electricity, Irrigation, Labour, Machinery	Output value	Agricultural sector

(Guth et al., 2022)	N	Capital, Labour, Land	Production	Agricultural sector
(Bernard et al., 2022)	I	Capital, Labour, Land	Agricultural added value	Agricultural sector
(Ramos de Oliveira et al., 2022)	N	Diesel, Fleet condition, Fuel consumption, Gini index, Production costs, Warehouse capacity, photochemical oxidant formation, transportation matrix	GHG emissions, Wheat, logistic cost	Logistics
(Streimikis et al., 2022)	I	Capital, Energy, Labour, Land	Net income	Agricultural sector
(S. Wang et al., 2022)	P	Labour, Land, Blue Footprint, Green Footprint	Yield	Agricultural sector
(Sharma, 2022)	I	Land, Seeds, Fertilizers	Production	Rice
(Yan et al., 2022)	L	Agro-chemicals, Irrigation, Labour, Land, Machinery	Production	Grain
(Kord et al., 2022)	N	Irrigation, Labour, Land	Net income, Yield	Agricultural sector
(Ziętek-Kwaśniewska et al., 2022)	P	Depreciation expenses, Electricity, Labour, Other costs, Raw materials	Net sales revenue	Dairy farms
(Chaubey et al., 2022)	P	Area, GDP, Labour, Population, percipitation	Production	Agricultural sector
(W. Li et al., 2022)	N	Capital, Labour, Land	Net income	Agricultural farms
(L. Gao et al., 2022)	N	FamilyLabor, Hired Labour, Irrigation, Machinery, Manure, Pesticides, Seeds, Fertilizers	Yield	Rice
(Chang et al., 2022)	N	Hired Labour, Irrigation, Machinery, Pesticides, Seed, Seeds, Fertilizers	Production	Agricultural sector
(Ramezani et al., 2022)	L	Agro-chemicals, Irrigation, Labour, Land, Manure, Nitrogen balance	Yield	Saffron
(Mohammadi et al., 2022)	L	Agro-chemicals, Biosides, Diesel, Electricity, Irrigation, Labour, Machinery, Seeds, Urea	Yield	Wheat
(Abbas et al., 2022)	L	Biocides, Diesel, Irrigation, Labour, Machinery, Manure, Pesticide risk,	Yield	Cotton

		Pesticides, Phosphorus balance, Seed, Fertilizers		
(Turner et al., 2022)	L	Feed, pullets	Eggs	egg farms
(L. Yang et al., 2022)	P	Diesel, Ferilizers, Pesticides	Income, Yield	Sugarcane
(Khan & Ali, 2022)	N	Land	Yield	Clover
(Nyamuhirwa et al., 2022)	L	Capital, Labour	Added Value	Agricultural sector
(Sui et al., 2022)	P	Capital, Labour, Land	Yield	Garlic
(Wu et al., 2022)	N	Agricultural film input, Expected output, Irrigation, Labour, Land, Machinery, Pesticides, Fertilizers	Carbon emissions, Net income, Non point sources, Output value	Agricultural sector
(Nodin et al., 2022)	P	Agro-chemicals, Capital, Labour, Land	Yield	Rice
(Dania et al., 2022)	L	Collabotation Factors	Economic, Environmental, Social	Agricultural sector (Supply chain)
(Lu et al., 2022)	N	(3 Stage NDEA model with circular flows)		Agricultural sector

*Applicability level: Local (L), Province (P), National (N), International (I), Theoretical Model (T.M)
** Output section does not include undesirable outputs

Table A4.1: Extended descriptive statistics of the assessed sample

Characteristic	Overall, N = 563[1]	G1, N = 202[1]	G2, N = 33[1]	I1, N = 229[1]	I2, N = 99[1]
Seeds (kg/t of final product)	15.00, 46.35, 41.50, 157.70, (19.70), [32.50-55.90]	27.00, 59.30, 56.65, 127.50, (18.38), [45.42-67.97]	37.20, 44.30, 44.50, 56.50, (3.77), [42.80-46.90]	15.00, 34.71, 31.40, 157.70, (16.18), [27.20-36.40]	23.30, 47.52, 43.30, 123.90, (15.95), [38.35-51.55]
Fertilizers (kg/t of final product)	26.50, 85.91, 78.90, 272.50, (36.37), [59.90-101.40]	37.70, 97.00, 94.00, 218.30, (35.96), [67.12-118.83]	76.90, 89.21, 87.80, 110.60, (7.24), [86.20-92.70]	26.50, 69.85, 64.40, 266.10, (31.37), [53.10-78.00]	38.20, 99.35, 89.70, 272.50, (39.78), [73.95-108.75]

Characteristic	Overall, N = 563[1]	G1, N = 202[1]	G2, N = 33[1]	I1, N = 229[1]	I2, N = 99[1]
Plant Protection Products (kg/t of final product)	0.02, 0.48, 0.39, 2.41, (0.39), [0.17-0.65]	0.02, 0.23, 0.18, 0.81, (0.15), [0.11-0.33]	0.08, 0.10, 0.10, 0.19, (0.02), [0.09-0.10]	0.02, 0.62, 0.51, 2.41, (0.39), [0.38-0.74]	0.14, 0.79, 0.77, 2.33, (0.37), [0.57-0.97]
Diesel (L/t of final product)	10.00, 25.89, 23.00, 121.00, (10.73), [20.00-29.00]	12.00, 32.52, 31.00, 73.00, (9.73), [25.00-37.75]	13.00, 21.55, 23.00, 29.00, (4.53), [21.00-25.00]	14.00, 23.30, 21.00, 121.00, (10.85), [19.00-24.00]	10.00, 19.83, 19.00, 52.00, (5.91), [17.00-21.00]
Labour (€/t of final product)	7.93, 20.02, 18.00, 92.66, (8.83), [14.08-23.00]	8.83, 23.83, 22.16, 62.82, (8.20), [17.70-28.06]	12.13, 17.65, 17.97, 22.77, (2.83), [15.39-19.83]	7.93, 16.24, 14.26, 92.66, (8.56), [12.26-16.93]	9.29, 21.78, 20.18, 57.61, (8.26), [16.33-24.90]
Yield (t of final product/ha)	1.43, 5.43, 5.24, 9.64, (1.83), [3.92-6.96]	1.78, 4.00, 3.84, 7.89, (1.13), [3.16-4.71]	4.07, 4.97, 5.11, 5.38, (0.29), [4.66-5.14]	1.43, 6.90, 7.07, 9.64, (1.52), [6.20-7.89]	2.02, 5.10, 5.25, 8.20, (1.32), [4.31-5.73]
Area (ha)	0.20, 9.25, 5.00, 142.00, (13.25), [3.00-10.00]	0.50, 7.13, 4.59, 62.20, (8.88), [2.86-7.50]	0.20, 3.91, 2.30, 14.00, (4.03), [1.00-5.00]	0.38, 6.69, 5.00, 48.33, (6.15), [3.00-8.00]	2.00, 21.31, 13.00, 142.00, (23.90), [7.00-25.50]
Carbon Footprint (CO_2eq/t of final product)	0.18, 0.42, 0.39, 1.32,	0.21, 0.46, 0.43, 0.95,	0.31, 0.47, 0.39, 0.77,	0.18, 0.36, 0.34, 1.32,	0.24, 0.48, 0.44, 1.17,

Characteristic	Overall, N = 563[1]	G1, N = 202[1]	G2, N = 33[1]	I1, N = 229[1]	I2, N = 99[1]
	(0.15), [0.33-0.48]	(0.13), [0.37-0.52]	(0.16), [0.35-0.67]	(0.14), [0.29-0.39]	(0.16), [0.39-0.51]
Water Footprint (m^3/t of final product)	1,036, 1,585, 1,394, 3,113, (457.52), [1,201-1,950]	1,556, 2,089, 2,099, 3,113, (307.10), [1,826-2,271]	1,502, 1,678, 1,539, 2,051, (204.76), [1,517-1,882]	1,036, 1,181, 1,169, 1,738, (94.62), [1,110-1,229]	1,235, 1,460, 1,356, 2,279, (219.58), [1,317-1,563]
Ecological Footprint (Global ha/t of final product)	0.29, 0.58, 0.53, 1.94, (0.24), [0.40-0.70]	0.35, 0.74, 0.72, 1.51, (0.22), [0.58-0.86]	0.50, 0.56, 0.56, 0.67, (0.03), [0.54-0.58]	0.29, 0.44, 0.39, 1.94, (0.19), [0.35-0.45]	0.34, 0.59, 0.53, 1.38, (0.20), [0.49-0.63]

[1] Minimum, Mean, Median, Maximum, (SD), IQR [25%-75%]

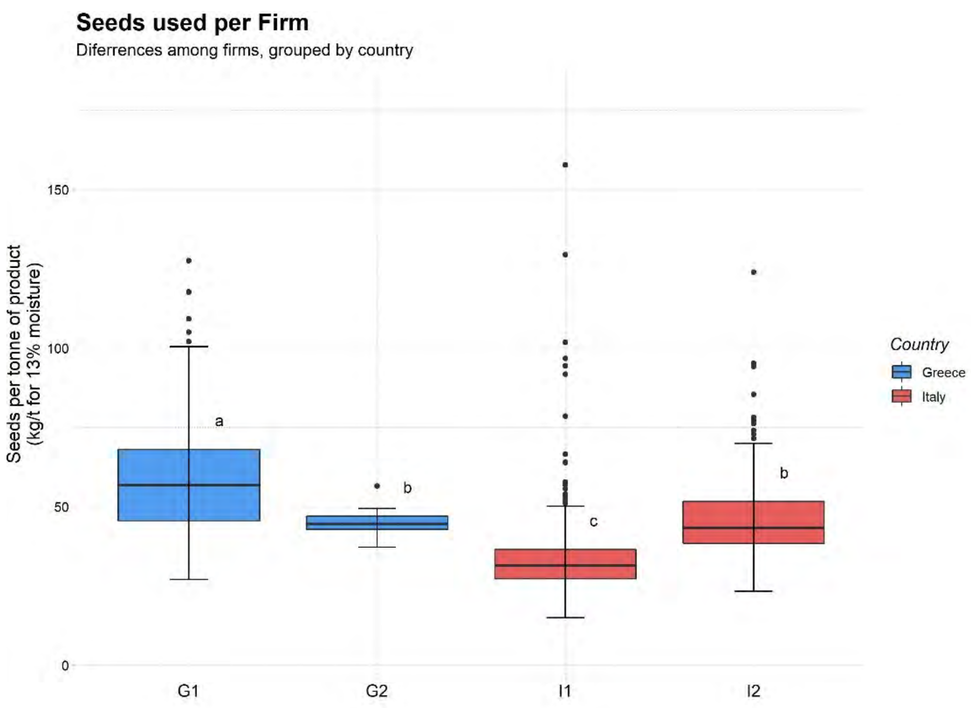

Figure A4.1: Seeds used per firm.

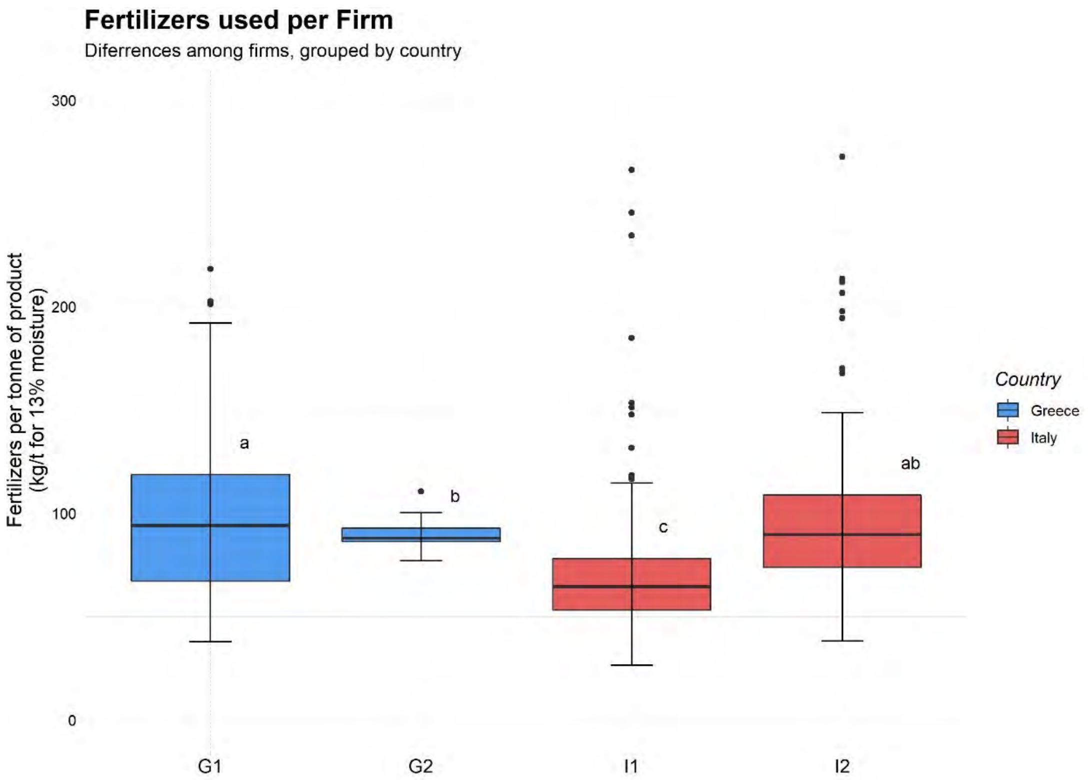

Figure A4.2: Fertilizers used per firm.

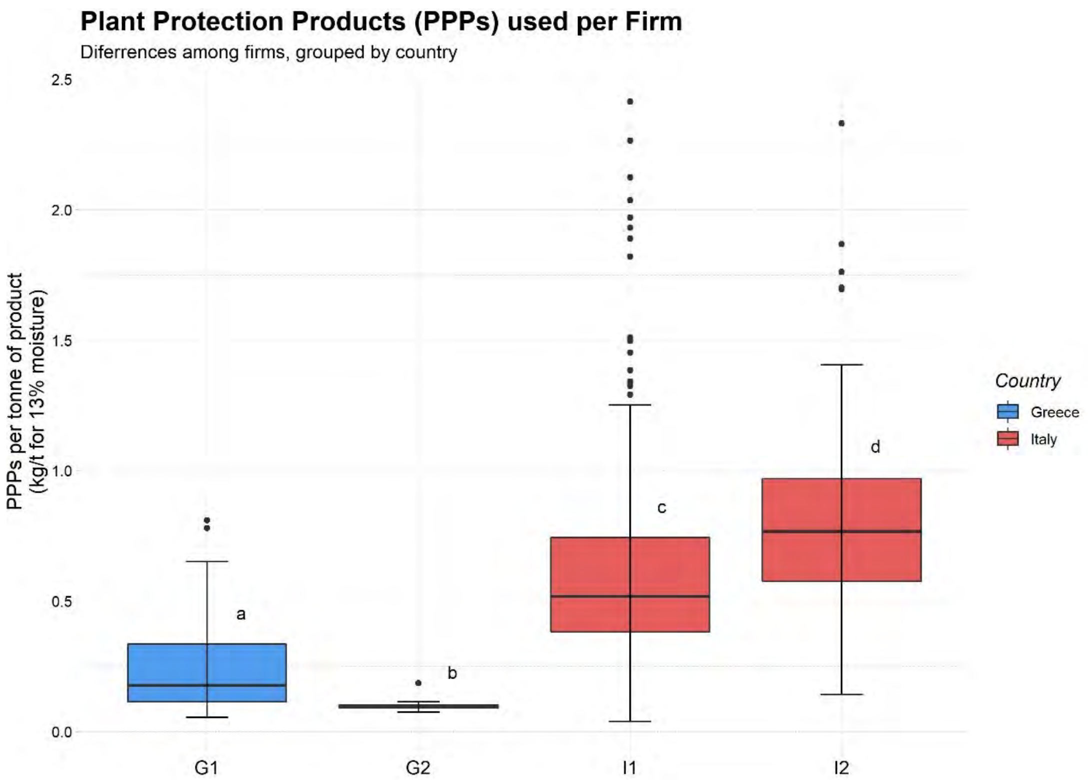

Figure A4.3: Plant Protection Products used per firm.

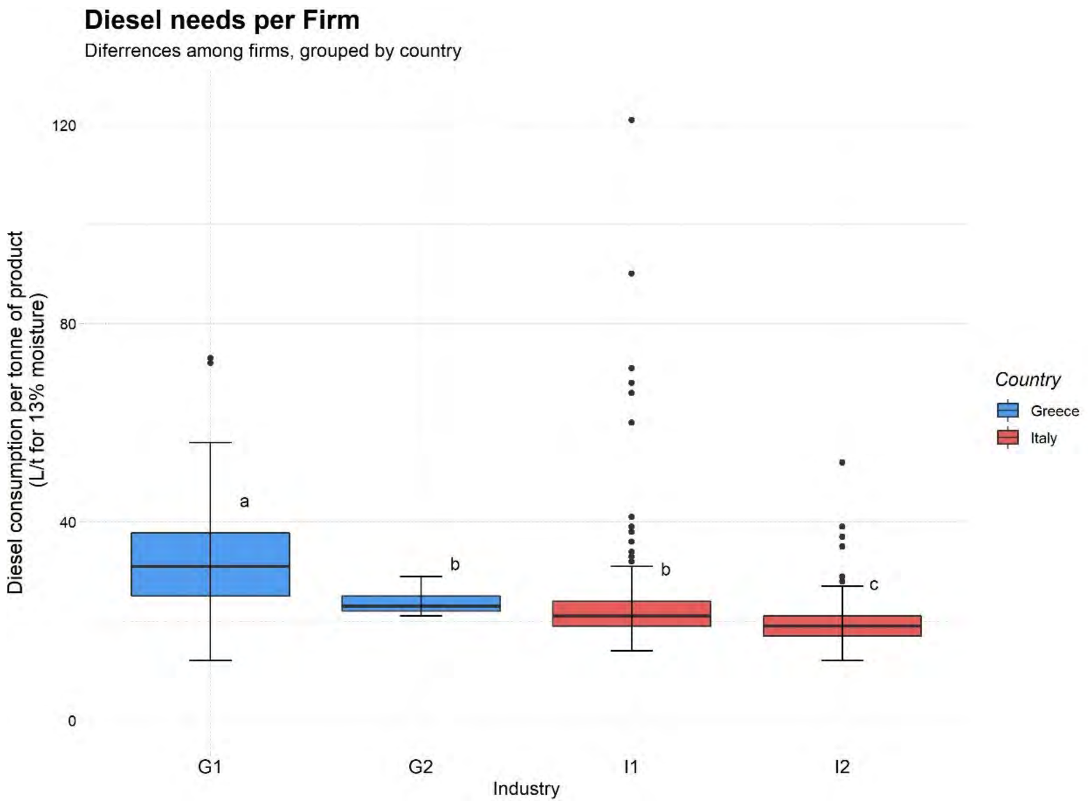

Figure A4.4: Diesel needs per firm.

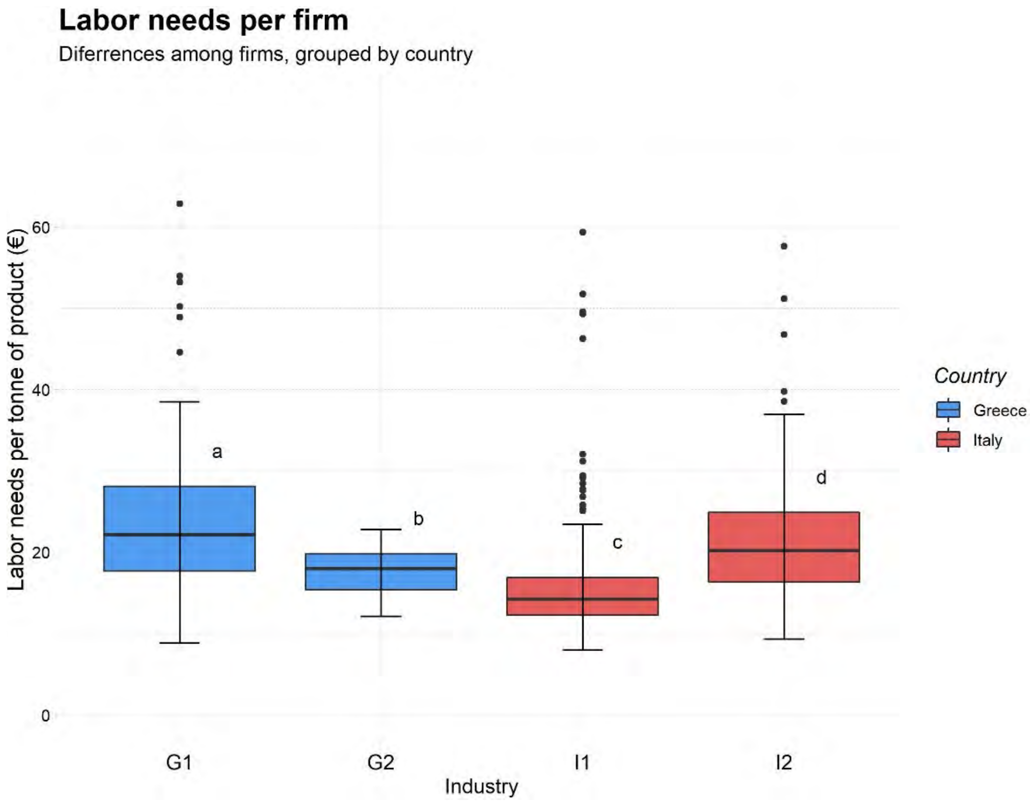

Figure A4.5: Labour needs per firm

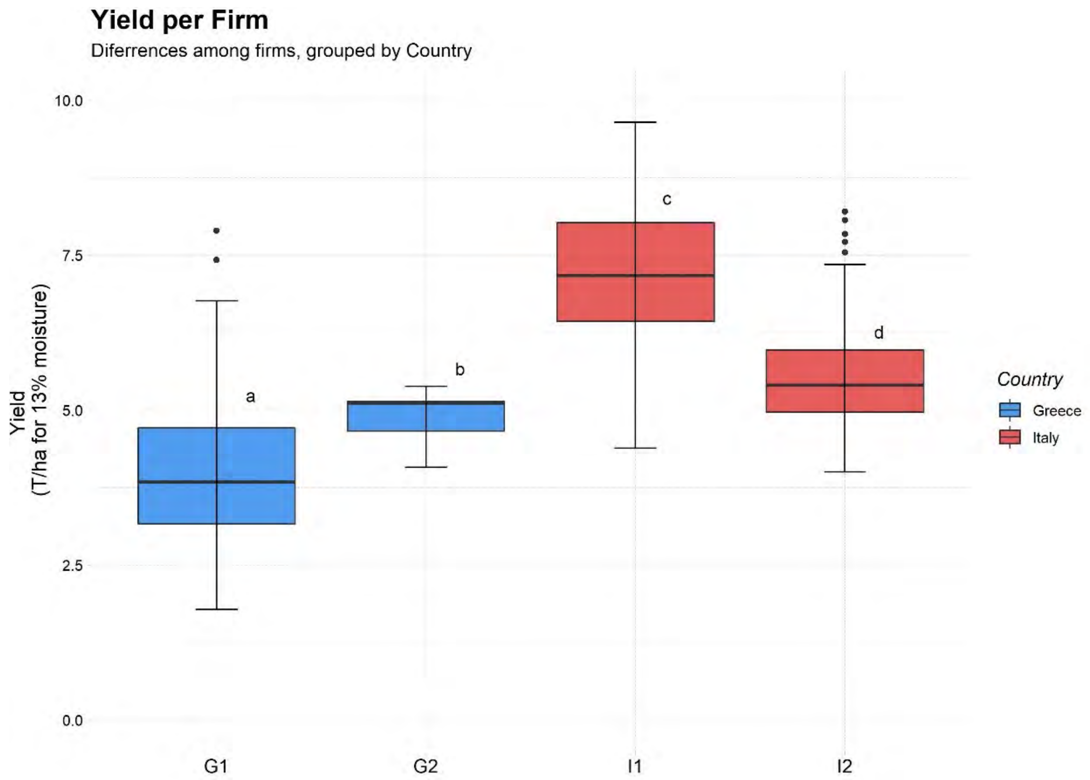

Figure A4.6: Yield per firm

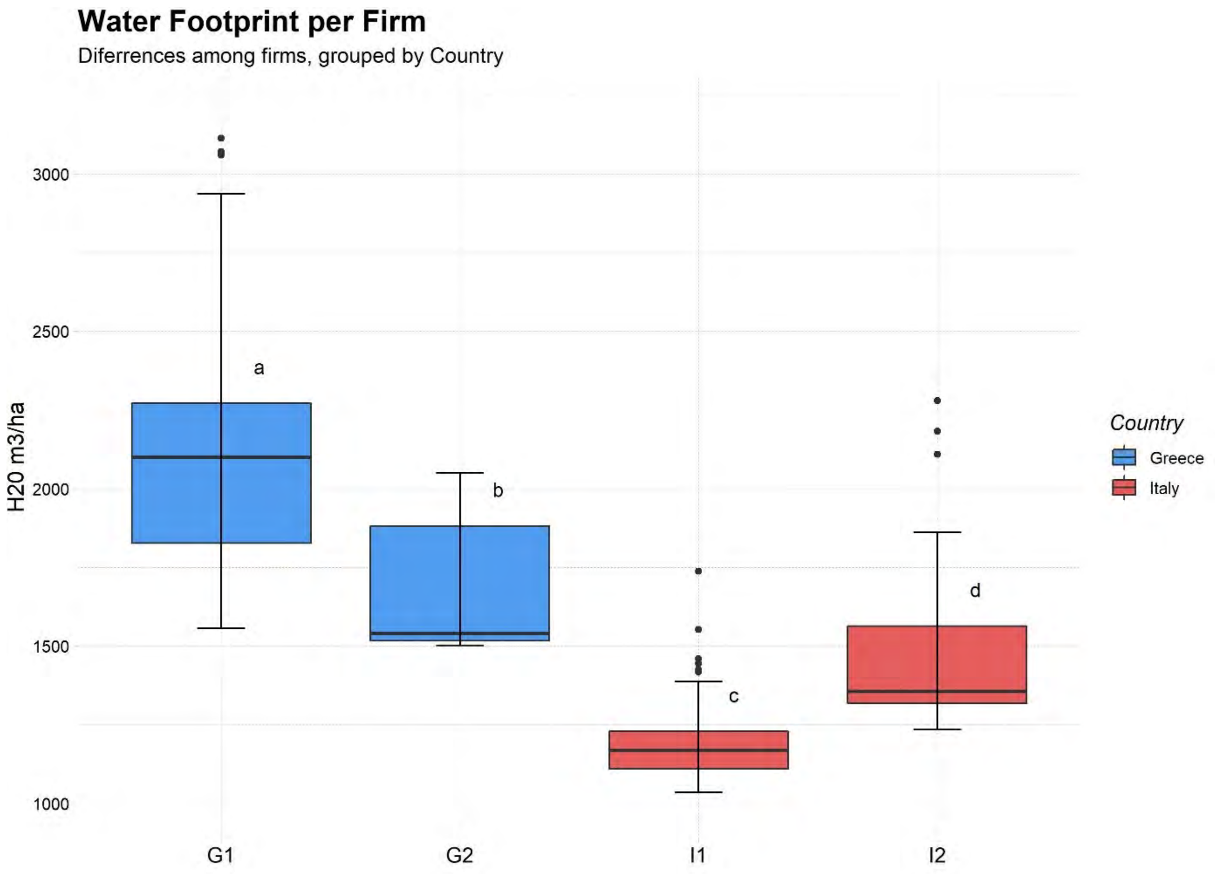

Figure A4.7: Water Footprint per firm

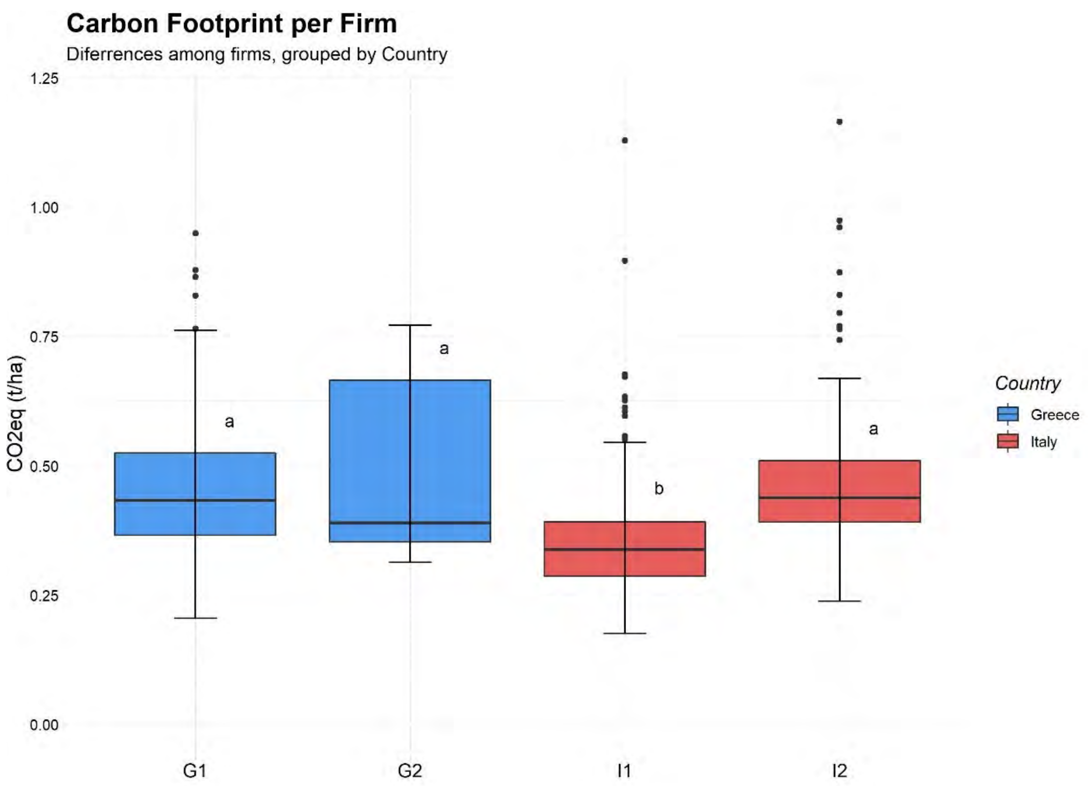

Figure A4.8: Carbon Footprint per firm

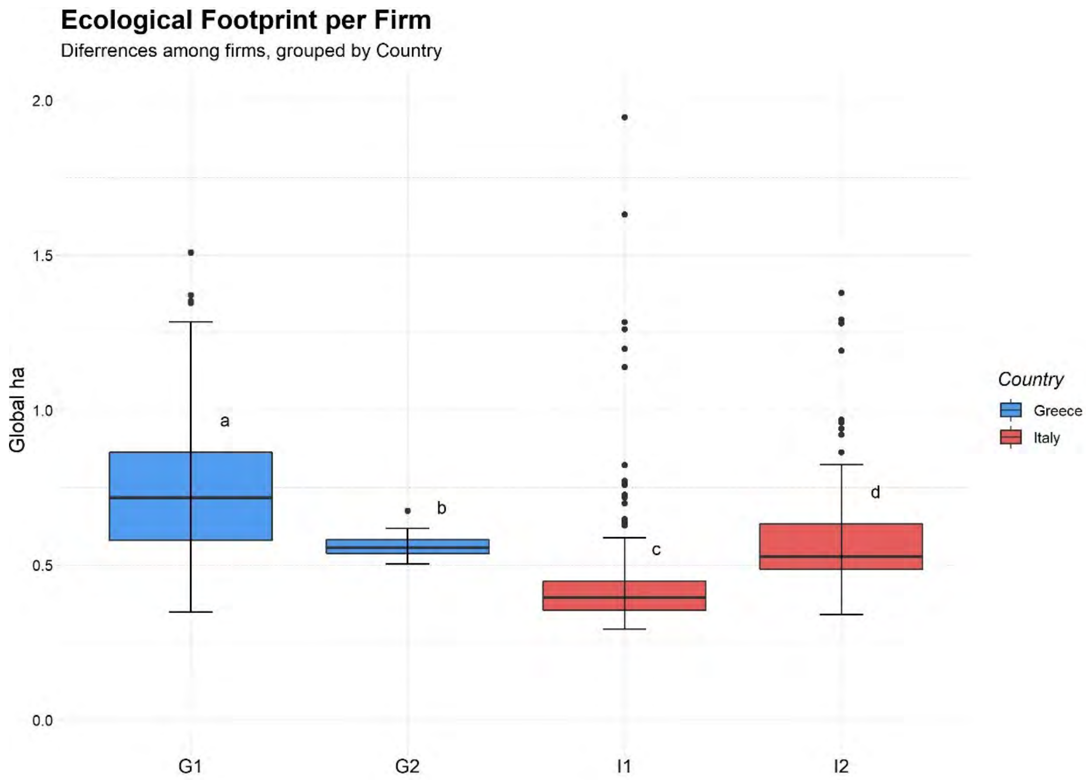

Figure A4.9: Ecological Footprint per firm

Table A.5.1: Descriptive statistics of Inputs and Outputs for reference period 2005–2022.

Year		*UAA*	*L*	*CC*	*EN*	*SPS*	*PPP*	*NFert*	*PFert*	*TO*	*EM*
2005	Min	511	37.8	49.3	75.1	5.7	6.9	20,083	2743	272	1194
	Max	29,588	2596	10,189	4438	1952	2742	2,346,289	300,652	39,435	77,314
	Avg.	7182	492	2050	1077	383	377	417,244	54,076	7521	17,074
2006	Min	491	37.4	58.2	75.4	5.7	7.1	22,610	3536	229	1193
	Max	32,346	2527	32,345	4130	1929	2676	2,163,040	258,427	38,280	76,913
	Avg.	7175	482.3	482.3	1019.7	396.0	368.2	411,693	51,577	7393	16,912
2007	Min	498	32.9	67.4	74.4	7.4	10.1	24,982	3520	316	1251
	Max	29,414	2299	29,413	4032	2005	2821	2,198,141	243,318	38,810	77,811
	Avg.	7070	458	458	1002	404	375	415,116	52,235	7305	17,019
2008	Min	492	31.2	77.0	76.4	10.6	13.2	25,039	4187	289	1309
	Max	29,385	2299	10,320	4119	2076	3148	2,425,221	282,425	40,125	78,496
	Avg.	7,060	447	2143	997	416	406	425,737	48,340	7743	16,916
2009	Min	469	29.3	82.2	66.3	11.2	10.6	27,328	2471	299	1252
	Max	35,178	2213	10,305	4206	1992	2997	2,098,801	163,851	41,119	77,674
	Avg.	7258	433	2156	972	401	395	388,395	33,785	7798	16,664
2010	Min	483	25.4	82.4	69.5	14.7	15.6	27,486	2671	275	1278

	Max	29,311	1914	10,270	4121	2016	2755	2,080,333	177,025	39,164	76,456
	Avg.	6957	399	2165	1022	437	386	402,166	40,991	7611	16,488
2011	Min	458	24.4	85.2	67.5	16.4	16.3	27,134	2680	311	1294
	Max	28,853	1914	10,449	4141	2220	2754	2,332,390	218,428	40,235	75,763
	Avg.	6927	389	2186	998	437	399	421,528	44,329	7844	16,507
2012	Min	480	23.2	92.0	71.0	17.3	18.3	26,300	2955	348	1375
	Max	29,001	1914	10,648	4014	2236	2951	2,024,929	189,633	39,632	75,656
	Avg.	6882	387	2206	989	423	410	402,175	42,477	7448	16,435
2013	Min	479	22.3	101.0	70.0	20.9	19.0	27,263	3129	352	1407
	Max	28,976	1937	10,653	4247	2084	3125	2,143,821	217,184	39,185	75,170
	Avg.	6878	383	2222	1008	430	430	422,080	46,067	7,745	16,568
2014	Min	482	22.0	100.9	75.3	21.8	19.7	28,612	3775	375	1446
	Max	28,930	1937	10,508	4185	2262	3222	2,190,930	206,798	43,218	77,204
	Avg.	6890	376	2223	989	441	448	431,685	45,887	8264	16,860
2015	Min	477	20.3	100.9	74.2	26.2	19.7	28,319	3522	451	1446
	Max	29,115	1937	10,493	4211	2460	3235	2,208,168	187,054	41,554	76,992
	Avg.	6912	369	2226	971	450	451	442,059	44,896	7997	16,927
2016	Min	478	20.3	107.4	73.4	24.4	21.1	27,095	3444	323	1402
	Max	29,089	1675	10,417	4086	2433	3308	2,221,231	191,677	37,653	75,753
	Avg.	6903	367	2224	1010	456	454	438,584	45,836	7989	16,942
2017	Min	481	20.3	111.0	72.9	29.5	21.5	27,084	3988	383	1443
	Max	29,101	1675	10,352	4003	2357	3063	2,248,277	190,414	40,501	76,190
	Avg.	6905	362	2223	1024	466	449	448,763	47,084	8144	17,080
2018	Min	478	20.1	113.1	74.5	28.1	20.8	27,293	4062	315	1438
	Max	29,020	1675	10,312	4082	2392	3093	2,141,553	190,597	40,967	74,774
	Avg.	6918	355	2226	1111	475	443	435,668	47,694	8092	16,865
2019	Min	480	18.9	127.8	73.8	26.7	19.4	28,048	3538	483	1457
	Max	29,024	1675	10296	4050	2486	3092	2,130,800	185,252	40,637	74,573
	Avg.	6946	347	2231	1134	477	442	418,517	47,456	8292	16,804
2020	Min	482	18.8	122.1	73.2	25.2	17.7	27,219	3421	427	1472
	Max	28,678	1643	10,240	4069	2511	3076	2,167,584	335,222	40,804	74,284
	Avg.	6940	340	2235	1143	484.5	441.8	420,848	54,225	8334	16,779
2021	Min	482	18.0	125.4	72.8	23.5	15.3	27,174	2602	439	1486
	Max	28,556	1610	10,253	41,22	2535.1	3077	2,167,076	389,930	40,875	73,995
	Avg.	6939	331.9	2242	1162	488.8	442.6	420,572	56,972	8414	16,755

2022	Min	482	17.2	128.7	49.3	21.8	12.9	27130	1783	451	1500
	Max	28,434	1577	10,266	4417	2559	3078	2,166,569	444,639	40,947	73,707
	Avg.	6938	323	2248	1180	493	443	42,0296	59,720	8494	16,730

Table A.5.2: Window analysis results with different window width for the reference period 2005–2019.

	Win(4)		**Win(7)**	
	Country	**Value**	**Country**	**Value**
1.	Estonia	0.9999	Estonia	0.9998
2.	Netherlands	0.9999	Netherlands	0.9995
3.	Slovenia	0.9989	Slovenia	0.9944
4.	Greece	0.9934	Italy	0.9861
5.	Belgium	0.9887	Greece	0.9842
6.	France	0.9886	Belgium	0.9841
7.	Italy	0.9874	Denmark	0.9820
8.	Denmark	0.9873	France	0.9812
9.	Norway	0.9842	Norway	0.9759
10.	Romania	0.9792	Romania	0.9730
11.	Germany	0.9756	Germany	0.9641
12.	Spain	0.9736	Lithuania	0.9526
13.	Portugal	0.9723	Spain	0.9518
14.	Lithuania	0.9641	Portugal	0.9495
15.	Poland	0.9627	Poland	0.9494
16.	Bulgaria	0.9579	Bulgaria	0.9479
17.	Latvia	0.9425	Latvia	0.9171
18.	Slovakia	0.9325	Austria	0.9037
19.	Austria	0.9226	Slovakia	0.9020
20.	Croatia	0.9101	Croatia	0.8984
21.	Sweden	0.8750	Sweden	0.8562
22.	Ireland	0.7947	Czechia	0.7591
23.	Czechia	0.7847	Ireland	0.7589
24.	UK	0.7696	UK	0.7394
25.	Hungary	0.7629	Hungary	0.7295
26.	Finland	0.6551	Finland	0.6364
	M(4)	0.9255	M(7)	0.9106

[1] M(x) is the mean value of acquired results for window width 4 or 7.

Table A.5.3: Window analysis results with different window width for the reference period 2005–2022.

	Win(3)		Win(6)		Win(9)	
	Country	**Efficiency**	**Country**	**Efficiency**	**Country**	**Efficiency**
1.	Estonia	1.0000	Estonia	0.9999	Estonia	0.9998
2.	Netherlands	0.9999	Netherlands	0.9996	Netherlands	0.9993
3.	Slovenia	0.9994	Slovenia	0.9968	Slovenia	0.9948
4.	Greece	0.9969	Greece	0.9894	Greece	0.9851
5.	France	0.9925	France	0.9866	Italy	0.9806
6.	Italy	0.9914	Belgium	0.9846	Belgium	0.9799
7.	Norway	0.9912	Denmark	0.9830	France	0.9762
8.	Belgium	0.9909	Italy	0.9821	Denmark	0.9760
9.	Denmark	0.9902	Norway	0.9800	Romania	0.9737
10.	Romania	0.9857	Romania	0.9778	Norway	0.9711
11.	Spain	0.9841	Portugal	0.9645	Spain	0.9547
12.	Portugal	0.9819	Spain	0.9635	Lithuania	0.9525
13.	Lithuania	0.9793	Lithuania	0.9635	Portugal	0.9486
14.	Poland	0.9746	Poland	0.9562	Bulgaria	0.9441
15.	Bulgaria	0.9704	Bulgaria	0.9556	Poland	0.9427
16.	Latvia	0.9662	Germany	0.9519	Germany	0.9402
17.	Germany	0.9655	Latvia	0.9397	Latvia	0.9168
18.	Slovakia	0.9488	Slovakia	0.9216	Austria	0.8973
19.	Austria	0.9306	Austria	0.9128	Slovakia	0.8903
20.	Sweden	0.8918	Croatia	0.8696	Croatia	0.8548
21.	Croatia	0.8884	Sweden	0.8683	Sweden	0.8521
22.	Ireland	0.7830	Czechia	0.7552	Czechia	0.7297
23.	Czechia	0.7799	Ireland	0.7445	Ireland	0.7280
24.	Hungary	0.7714	Hungary	0.7341	Hungary	0.7076
25.	UK	0.7552	UK	0.7274	UK	0.7017
26.	Finland	0.6703	Finland	0.6464	Finland	0.6320
	M(3)	0.9300	M(6)	0,9136	M(9)	0.9011

[1] M(x) is the mean value of acquired results for window width 3,6 or 9.