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A non-parametric bootstrap-data envelopment analysis approach for environmental policy planning and management of agricultural efficiency in EU countries

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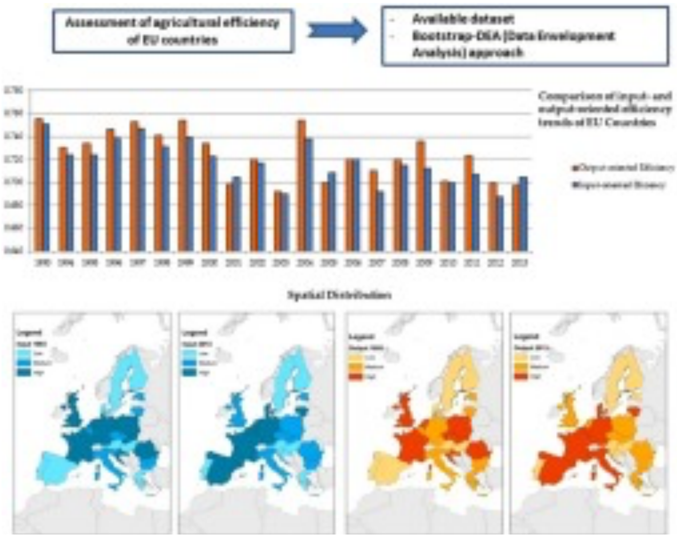
Highlights
•Bootstrap DEA method overpasses the limitation attributed to DEA methods constantly applied to the agricultural sector.
•The majority of EU countries show the potential to increase their production efficiency through decreasing their input use.
•From 1993 to 2013 some of the best input-oriented efficient countries are Belgium-Luxembourg, Estonia, France, and Germany.
•Most of the oldest EU member countries have a more efficient crop production from the resource savings point of view.
•There is an heterogeneity of countries efficiency performances and the potential for increasing agricultural production.

Abstract

Globally, agriculture is a dominant form of human use of land with agro-ecosystems covering about 40% of the terrestrial surface of the Earth. In this context, the European Union considers agriculture a key sector of the economy, recognizing, however, the related environmental implications. The aim of this paper is to examine the agricultural efficiency of EU countries, through a bootstrap-Data Envelopment Analysis (DEA) approach, an effective nonparametric method for evaluating the relative efficiency of the decision-making units. European datasets, suitable for policies and focused on the integration between agricultural productivity and ecosystem services (ESs) conservation, have been used to support planners and managers. Data related to five inputs (labor, land, capital, fertilizers, and irrigation area) and to one output connected to the economic value of agricultural production were collected from 1993 to 2013. The results show that the majority of EU countries have been experiencing increasing or decreasing returns to scale, highlighting their potential to increase their production efficiency by modifying their input use. Both for the output-oriented approach and the input-oriented approach, the majority of EU countries could better rationalize their input use obtaining more outputs and achieving production efficiency. DEA, a non-parametric methodology has been applied, using the concept of a reference group of efficient decision-making units that produce a similar output (peer group). Input-oriented and output-oriented DEA results and comparison indicate that most of the oldest EU countries have a more efficient and optimized crop production process in terms of resource savings and output maximization. This is probably due to the application of the Common Agricultural Policy. Therefore, in policy planning but also in management decisions, attention should always be paid not only to the maximization of agricultural production, but also to the environmental resource overexploitation. In this sense, best agricultural practices could represent a model to follow because they can maintain ESs without depressing production by using practices like conservation tillage, crop diversification, legume intensification and biological control perform giving the same results as intensive, high-input systems.

Graphical abstract



Keywords

Environmental planning and management

Bootstrap-DEA

Agricultural efficiency

Ecosystem services

Common agricultural policy

1. Introduction

The fundamental global role played by agriculture in terms of environmental conservation, economic development, and social support to nutrition of the ever-growing world population, has made it a field of research interest (Pang et al., 2016). Given the fact that

food accessibility represents one of the main factors supporting human welfare and quality of life (MEA, 2005), the stability of agricultural production, expressed in terms of crop yield and cultivated area, is of scientific and practical relevance (Garibaldi et al., 2011).
Agriculture is a dominant form of human land use globally, and agro-ecosystems cover about 40% of the terrestrial surface of the Earth (Power, 2010). In this context, the European Union considers agriculture a key sector of the economy, recognizing, however, the related environmental implications. Being a sector in a continuous phase of structural changes and affecting efficiency and productivity growth significantly, agriculture still draws the dominant interest of European institutions in terms of sustainable management and efficiency of natural resources use. Therefore, measuring environmental and economic efficiency provides policy-makers with valuable information for designing policies focused on regional sustainable development (Picazo-Tadeo et al., 2011).
In terms of sustainable development, it is important to recognize that ecological systems both contribute to and are affected by the production of goods and services, called ecosystem services (ESs), which are of value to people. Among the four categories of ESs, food in terms of agricultural products is part of the provisioning services with a direct economic use-value associated to human use (MEA, 2005; Krutilla and Fisher, 1975). As highlighted by Dale and Polasky (2007), agriculture can affect and be affected by ESs through synergies and trade-offs, or by services and disservices (Zhang et al., 2007).
The aim of this paper is to examine the agricultural efficiency of EU countries, through a bootstrap-Data Envelopment Analysis (DEA) approach and the use of datasets suitable for policies, focused on the integration between agricultural productivity and ESs conservation, in order to develop a support tool for planners and managers.

In this paper, firstly, the general problem of trade-off between agricultural productivity and the maintenance of ES provision is presented as well as a comprehensive literature review of studies on agricultural efficiency based on the use of DEA. Afterwards, the methodology developed in this research is described with an overview of the model variables. Finally, the results are discussed, focusing on some insights for the optimization of agricultural production in the EU Countries in the light of the conservation of ESs.

1.1. The relation between agriculture and ecosystem services: synergies and trade-offs

Modern agriculture can be seen as a Green Revolution that has simplified traditional agro-ecosystems and replaced biological functions with increased external inputs of energy and agrochemicals (Bommarco et al., 2013). Agricultural intensification usually assures that the increasing global food demands are met, because it raises the productivity per unit area. However, it can have significant negative impacts on the environment and ESs (Tilman et al., 2001, Moss, 2008, Potts et al., 2010, Matson, 1997), or even negative effects on sustained crop productivity (Matson, 1997, Dale and Polasky, 2007). As a consequence, agriculture and other environmental threats, such as climate change, pollution, and biotic invasions have eroded many ESs sustaining human well-being (MEA, 2005). Agriculture and ESs are interrelated in at least three ways (Dale and Polasky, 2007): (1) agro-ecosystems generate beneficial ESs such as fertile soil production and retention, food production, and aesthetics; (2) agro-ecosystems receive beneficial ESs from other ecosystems such as pollination from surrounding non-agricultural ecosystems; and (3) ESs from non-agricultural systems may be impacted by agricultural practices.

Although agro-ecosystems may have low ES values per unit area when compared with other ecosystems, such as estuaries and wetlands (Costanza et al., 1997), they offer the best chance of increasing global ESs via definitions of appropriate goals for agriculture and the use of land-management regimes that favor ES provision. Therefore, as highlighted by Porter et al. (2009), agriculture can be seen as the largest ecological experiment on Earth, with a large potential to damage global ESs but also to promote them via ecologically informed approaches to the design of agro-ecosystems that value both marketed and non-marketed ESs. In this context, Bommarco et al. (2013) have proposed ecological intensification as an alternative to agricultural intensification, in order to make agriculture more productive, stable, and resilient while minimizing environmental impacts (Foley et al., 2005) and consisting in integrating the management of ESs into crop production systems.

1.2. Literature review on the DEA method

1.2.1. The data envelopment analysis (DEA) method

Assessing efficiency for different levels of territoriality and economic sectors has relevant practical implications, and thus, efficiency has become an essential research field. The classic paradigm defines productivity as the ratio between an output and the inputs used to achieve it (Daraio and Simar, 2007). Similarly, according to Lovell (1993), the productivity of a unit is the ratio of its outputs to its inputs, as well as in the efficiency literature where many authors conceptualize both productivity and efficiency as the ratio between outputs and inputs, without underlying any difference between the two concepts (Sengupta, 1995, Cooper et al., 2007).

Efficiency can be better defined as a distance between a certain quantity of input and output, and the quantity of input and output that defines the best possible frontier for a unit in its cluster. However, efficiency and productivity are complementary concepts. Measures of efficiency are more accurate than measures of productivity, because the former are

compared with the most efficient frontier, by integrating the information included in productivity measures (Daraio and Simar, 2007).
The theme of productive efficiency has been analyzed since Adam Smith's pin factory and even before. However, a rigorous analytical approach applied to the measurement of efficiency in production originated only with the theoretical approach of Koopmans (1951) and Debreu (1951), empirically applied by Farrell (1957). International literature contains a large number of surveys and case studies dealing with efficiency, which represents the key factor to reach the global target of sustainable development (Song et al., 2012).
The two main approaches to measure efficiency are parametric and non-parametric, and in most cases, both methods achieve highly correlated results (Wadud and White, 2000, Thiam et al., 2001, Alene and Zeller, 2005). In this context, DEA is an effective non-parametric method for evaluating the relative efficiency of the decision-making units (DMUs), which does not need the exact functional form between inputs and outputs, overcoming some disadvantages of the parametric approach.
Due to their advantages DEA methods have been constantly applied to the agricultural sector. The first model proposed in scientific literature considered an input orientation and constant returns to scale (CRS) assumption (Charnes et al., 1978). In order to account for variable returns to scale (VRS) conditions, Banker et al. (1984) went beyond the CRS DEA model. In fact, biased technical efficiency (TE) values can be generated by adopting the CRS assumption, due to scale efficiencies (SE) that occur when not all DMUs are operating on the optimal scale (Coelli et al., 2005). The main limitation is that, since it is based on a deterministic model, it does not take into account the uncertainty characterizing the real world (so-called stochastic error). In fact, the classical DEA technique does not allow for the construction of confidence intervals, nor for the carrying out of tests on the estimated values (Seiford and Thrall, 1990). In order to overcome the limitation of the construction of confidence intervals, Simar and Wilson, 2000a, Simar and Wilson, 2000b suggested to adopt a bootstrap DEA method, which allows to validate the results by obtaining confidence intervals and adjusted efficiency scores.

1.2.2. DEA applied to agricultural studies

As highlighted by the literature review of DEA application to agriculture (Table 1), there is a lack of studies evaluating agricultural efficiency at a regional or national level since scientific research addressing the efficiency evaluation of European agricultural sector is lacking.

Table 1. Literature review of DEA application to agricultural sector.

Author(s) (Year)	Country(ies)	Input variables	Output variables	Aim(s) of the study
Atici and Podinovski (2015)	Turkey	Agricultural area; Labor costs; Crop production costs; Capital expenditures.	Individual crop productions	This paper estimates efficiency scores using data envelopment analysis (DEA) for the evaluation of units with output profiles exhibiting specialization. An application of this methodology is conducted considering agricultural farms in different areas of Turkey.
Chebil et al. (2015)	Tunisia	Applied water; Seeds; Chemical fertilizer; Labor; Machinery.	Output value	This paper, through a DEA method, aims to measure the technical, scale and economic efficiencies for a sample of 170 farms producing cereals in a Central area of Tunisia.
Kočišová (2015)	EU Countries	Annual Work Units; Total Utilized Agricultural Area; Total Assets.	Total Output Crops and Crop Production; Total Output Livestock and Livestock Products	This study, using Data Envelopment Analysis (DEA), analyzes the technical efficiency of the agricultural sector in the European Union (EU) during the period 2007–2011.
Liu et al. (2015)	China	Capital; Labor; Land; Machinery; Fertilizer.	Gross value of agricultural output	The paper is an application of Data Envelopment Analysis (DEA) to observe the efficiency and efficiency change of prefecture-level cities in the North-East China from 2000 to 2012.
Toma et al. (2015)	Romania	Land area (ha); Work (hours); Number of mechanical assets.	Production value (thou RON)	In this article DEA is applied at a regional level, under input orientation, CRS and VRS technical assumptions, to analyze the performance of agricultural practices in plain, hill and mountain areas of the Romanian territory.
Bojnec et al. (2014)	Bulgaria, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, and Slovenia	Total labor force (in working units); Number of agricultural tractors; Agricultural area in hectares; Total fertilizers use;	Gross value added	This paper, using Data Envelopment Analysis and econometric panel data analysis, analyzes the agricultural technical efficiency of 10 new EU member states.

Author(s) (Year)	Country(ies)	Input variables	Output variables	Aim(s) of the study
		Number of animal livestock units		
Hoang and Alauddin (2012)	30 OECD Countries	Fertilizers; Land; Feed; Seed; Labor; Machinery	Fisher quantity index (using price data as weights)	In this study, an input-oriented data envelopment analysis (DEA) framework is implemented to assess agricultural efficiency for a sample of 30 OECD countries.
Yu et al. (2011)	Asia-Pacific Economic Cooperation	Arable land area; Agricultural population; Share of irrigated land; Total fertilizer consumption; Number of tractors and threshers	Grain production output	In this paper, an evaluation of land use efficiency in the APEC is conducted, through Data Envelopment Analysis, to test which agricultural sector could produce the same amount with less resource input.
Moreira and Gomes (2011)	The 40 countries with the largest value added by agricultural sector in 2005	Agricultural area; Agricultural labor force; Fertilizer consumption; Capital stock in agriculture	Value added by the agricultural sector	This paper estimates an agricultural process function using DEA efficiency scores output-oriented and with variable returns to scale.
Armagan (2008)	Turkey	Labor (man power); Capital; Value of variable inputs; Value of production units.	Gross production value.	In this paper, efficiency scores of agricultural enterprises are calculated by using data envelopment analysis, as a first stage, and then some determinants of efficiency are investigated.
Balcombe et al. (2008)	Bangladesh	Bullock Labor; Human Labor; Seed; Fertilizer; Rice area.	Rice production	In this article, the DEA double bootstrap is used to measure and evaluate the technical efficiency of rice farming in Bangladesh, overcoming severe limitations of the efficiency techniques traditionally used in the literature.
Lilienfeld and Asmild (2007)	USA	Irrigation water; Labor; Capital; Seed; Fertilizer; Precipitation; AWS	Production output per crop	The aim of this article is to estimate irrigation water use efficiency, assessing the impacts of irrigation system types for a sample of 43 operators in Kansas between 1992 and 1999.
Gocht and Balcombe (2006)	Slovenia	Purchased seed, home grown seed; Purchased fertilizer,	Wheat production output	This paper demonstrates how data envelopment analysis (DEA), adjusted

Author(s) (Year)	Country(ies)	Input variables	Output variables	Aim(s) of the study
		manure; Chemicals, other direct costs, wages; Services and other costs.		with a smoothed bootstrap method, is more effective in obtaining consistent efficiency rankings for farms.
Latruffe et al. (2005)	Poland	Utilized agricultural area; Annual work units; Capital factor (depreciation plus interest); Intermediate consumption.	Total output value.	This study aims at measuring farm efficiency in Poland using a DEA method and assessing differences caused by farm specialization, in crop or livestock, in 1996 and 2000.
Dhungana et al. (2004)	Nepal	Land; Seed; Labor; Mechanical labor; Fertilizers; Other inputs.	Rice yield.	The aim of this article is to measure inefficiencies from an economic, technical and scale points of view using data envelopment analysis for a sample of 76 Nepalese rice farmers.
Paul et al. (2004)	USA	Labor; fuel; Fertilizer; seed; Feed; Animal inputs; Crop inputs; Capital Machinery; Land; other. These input variables are annual per-farm expenditures.	Total value of sales for each type of farm product.	This study, through DEA estimation, explores the potential of small U.S. farms compared with larger U.S. enterprises in terms of economic efficiency.
Iraizoz et al. (2003)	Spain	Labor (number of hours worked); Land (utilized agricultural area); Capital (average annual inventory of machinery and buildings); Cultivation costs.	Sales of asparagus and gross tomato production.	The aim of this study consists of the efficiency estimation of the tomato and asparagus production in Navarra, using both non-parametric and parametric techniques.
Mao and Koo (1997)	China	Land; Labor; Machinery; Fertilizers; Draft animals.	Added value of agricultural output.	This article analyzes the Chinese agricultural sector from 1984 to 1993 in order to estimate technology and efficiency differences using DEA and TFP analysis.
Piot-Lepetit et al. (1997)	France	Cereal acreage; Other acreage; Annual worker units; Equipment; Fertilizers;	Cereal output; Other product output	Potential input and environmental impact reductions in the agricultural production are the focus of this study, which demonstrates the

Author(s) (Year)	Country(ies)	Input variables	Output variables	Aim(s) of the study
		Pesticides; Seeds; Others.		benefit of DEA methods for this type of estimations.

After many applications aiming to support the best management practices at a micro-level, since 2010 scientific interest has begun to rise in relation to the comparison of different agricultural policy visions among countries and their results in terms of efficiency (Table 1). In particular, Hoang and Rao (2010) adopted for the first time a country-based analysis to evaluate the sustainability efficiency of the agriculture sector of 29 OECD countries. In 2011 Moreira and Gomes analyzed, globally, the 40 countries with the largest value added by agricultural sector in 2005, by using output-oriented DEA efficiency measures with variable returns to scale assumption. Their analysis has highlighted that the total agricultural added value could be increased by at least 53.9% without increasing input usage and with the prevailing technology.

The potentials of DEA estimations for policy-makers in obtaining significant results referring to the agricultural productive patterns and, consequently, to sustainable development planning, have also been recently confirmed in the EU context by some studies based on country performance comparisons (Bojnec et al., 2014, Kočišová, 2015).

2. Materials and methods

The research design adopted is a secondary data analysis. Existing quantitative datasets have been used as data sources to realize a DEA analysis and to verify two supposed determinants of efficiency scores.

The methodology consists of the non-parametric evaluation of a best practice frontier for the best possible productions, resulting from the observed sample, in relation to which we need to calculate the distance to be transformed into a measure of efficiency normalized in the interval [0,1], for each unit observed.

The DEA method allows for the calculation of the relative efficiency of the data, and does not provide any information on the absolute efficiency. The most efficient DMUs are those situated on the frontier, the others can reach this allocation if:

•they reduce the inputs, while maintaining a constant output;
•they increase the outputs, while maintaining the inputs constant;
•they perform a combination of the two previous solutions.

The distance between each DMU and its related best point is a measure of the inefficiency, that is, how much it is possible to expand the output given the input (or how much it is possible to reduce the input given the output). Through DEA, therefore, the relative efficiency is measured, given by the ratio between the length of the segment joining the origin with the point representing the DMU and the length of the segment joining the origin with the best point associated with the same DMU. In DEA, we use the concept of “reference set”, which is useful to identify the best production unit with which to compare all the other observations concerning the sample.

The DEA method is applied by adopting two different approaches that are both based on the concept of technical efficiency, defined as the ability of the DMU (the decision-making unit of production), given the existing technology, to produce the highest level of outputs from a given combination of inputs (output model – oriented), or alternatively, to use the least possible amount of inputs to obtain a given output (model input – oriented) (Reinhard et al., 2000). Therefore, this non-parametric methodology provides guidance on how the inefficient production units could become efficient, using the concept of reference group of efficient decision-making units that produce a similar output (peer group) (Simar and Wilson, 2008).

The panel data used for the DEA efficiency evaluation of EU countries has been acquired from the FAOSTAT database, used for the dissemination of statistics by the Statistics Division of the FAO (FAOSTAT, 2016). However, the data concerning labor have been extracted from the Eurostat database (EUROSTAT, 2016).

For the purpose of this study, a sample of Countries was selected among European Countries whose indicators chosen for this research have been previously computed and are annually available for the analyzed period of time. For this reason, Ireland and Latvia are the only EU countries that are not considered in the analysis, due to the lack of data. Data availability, and consequently, the choice of the analyzed period of time are conditioned also by the years of independence obtained by some eastern countries.

In particular, the time series included in this research goes up to 2013 and it does not go further because the year 2013 is the last year when complete and reliable data for the variables used in our framework could be found. The approach is similar to the stochastic production frontier model of Tonini (2012) that tried to illustrate important differences among the levels and trends of agricultural productivity of European countries, using a Bayesian approach and a smaller time range.

The definitions of both input and output variables are described below. In particular, the analysis is based on five input variables: labor, land, capital, fertilizers and irrigation area. These variables have been selected as the most important variables affecting agricultural productivity, according to the literature indicated in Table 1. For what concerns the main output related to the agricultural sector, it is represented by the value of agricultural production. Table 2 reports the descriptive statistics of these variables. The estimation of efficiency scores through DEA models was conducted using the R software.

Table 2. Descriptive statistics of the variables used for the DEA.

Empty Cell	Empty Cell	**Inputs**					**Outputs**
Empty Cell	Empty Cell	**Labor (1,000 AWU)**	**Land (1,000 ha)**	**Gross capital stock* (millions of USD $)**	**Fertilizers (tonnes)**	**Irrigation area (1,000 ha)**	**Agricultural production value (1,000 I $)**
1993	Mean	700.66	5,223	68,905	4,32,106	732	91,57,083
	Std. Dev.	976.72	5,822	98,487	5,57,932	1,145	1,07,42,056
	Min	4.75	13	178	1,000	1	66,836
	Max	4,039.69	19,657	3,95,544	22,22,000	3,648	3,81,12,085
1994	Mean	679.68	5,184	69,086	4,48,661	731	88,83,165
	Std. Dev.	950.19	5,812	98,856	5,93,927	1,167	1,05,28,746
	Min	4.56	13	189	1,000	1	70,601
	Max	3,912.86	19,496	3,99,695	23,08,300	3,657	3,77,04,490
1995	Mean	660.35	5,141	69,264	4,40,638	723	89,44,877
	Std. Dev.	924.92	5,736	99,153	6,03,886	1,157	1,05,72,537
	Min	4.57	11	194	1,000	1	71,953
	Max	3,786.04	19,348	3,99,522	23,91,700	3,642	3,86,46,092
1996	Mean	645.52	5,153	70,132	4,72,856	732	93,33,556
	Std. Dev.	893.79	5,771	1,00,608	6,35,017	1,169	1,12,54,206
	Min	4.47	11	207	1,000	2	88,345
	Max	3,368.80	19,368	4,07,335	25,23,900	3,639	4,07,20,575
1997	Mean	644.19	5,159	70,862	4,64,057	737	93,49,418
	Std. Dev.	901.57	5,769	1,01,477	6,29,687	1,178	1,13,28,372
	Min	4.48	10	221	1,000	1.5	80,530
	Max	3,473.00	19,421	4,11,718	25,13,100	3,639	4,07,75,963
1998	Mean	622.34	5,123	71,191	4,61,033	741	93,19,371
	Std. Dev.	864.2	5,730	1,02,148	6,35,669	1,185	1,13,38,007

Empty Cell	Empty Cell	**Inputs**					**Outputs**
Empty Cell	Empty Cell	**Labor (1,000 AWU)**	**Land (1,000 ha)**	**Gross capital stock* (millions of USD $)**	**Fertilizers (tonnes)**	**Irrigation area (1,000 ha)**	**Agricultural production value (1,000 I $)**
	Min	4.65	9	235	1,159	1.5	87,975
	Max	3,460.00	19,462	4,14,187	24,88,100	3,710	4,08,89,585
	Mean	604.34	5,102	71,680	4,63,219	742	95,49,262
1999	Std. Dev.	853.25	5,730	1,02,980	6,58,664	1,197	1,16,64,610
	Min	4.66	9	249	451	1.5	87,159
	Max	3,648.00	19,497	4,17,333	25,71,400	3,780	4,13,09,252
	Mean	591.45	5,063	71,874	4,41,705	747	94,66,573
2000	Std. Dev.	851.57	5,729	1,03,286	5,95,383	1,207	1,16,71,126
	Min	4.74	9	257	450	1.5	84,316
	Max	3,645.00	19,495	4,16,806	23,16,300	3,856	4,04,37,977
	Mean	564.67	4,954	72,411	4,44,103	751	93,53,551
2001	Std. Dev.	779.82	5,700	1,04,405	6,02,050	1,221	1,13,89,096
	Min	4.47	10	266	300	1.5	84,082
	Max	3,121.00	19,481	4,21,398	23,97,000	3,896	3,85,70,813
	Mean	535.19	4,909	73,235	4,32,141	755	93,17,811
2002	Std. Dev.	702.5	5,642	1,05,353	5,72,990	1,234	1,14,57,189
	Min	4.3	10	275	598	1.5	82,450
	Max	2,765.00	19500	4,26,525	22,03,200	3,936	4,06,93,640
	Mean	523.69	4,864	74,195	4,55,564	741	91,70,131
2003	Std. Dev.	691.77	5,613	1,06,512	6,03,607	1,246	1,12,86,273
	Min	4.3	10	286	521	1.5	81,631
	Max	2,696.00	19,471	4,31,763	23,75,400	3,977	3,78,54,779
	Mean	499.36	4,860	74,321	4,33,182	740	96,90,184
2004	Std. Dev.	646.79	5,596	1,07,428	5,87,858	1,251	1,17,65,137
	Min	4.3	10	289	643	1.5	79,495
	Max	2,336.00	19,479	4,38,012	23,24,000	3,975	4,04,04,652
2005	Mean	499.59	4,837	75,235	4,15,785	743	93,08,871

Empty Cell	Empty Cell	Inputs					Outputs
Empty Cell	Empty Cell	Labor (1,000 AWU)	Land (1,000 ha)	Gross capital stock* (millions of USD $)	Fertilizers (tonnes)	Irrigation area (1,000 ha)	Agricultural production value (1,000 I $)
	Std. Dev.	675.84	5,551	1,08,945	5,68,534	1,256	1,13,01,430
	Min	4.06	9	305	578	1.4	76,285
	Max	2,596.00	19,488	4,45,839	22,05,000	3,973	3,86,94,420
2006	Mean	489.08	4,816	75,277	4,10,555	737	92,22,995
	Std. Dev.	667.47	5,519	1,09,916	5,56,566	1,251	1,11,51,778
	Min	4.06	9	321	926	1	80,543
	Max	2,527.00	19,436	4,51,732	22,04,665	3,960	3,74,23,955
2007	Mean	464.78	4,750	76,438	4,35,229	763	90,88,097
	Std. Dev.	626.92	5,450	1,11,432	6,05,676	1,266	1,11,43,816
	Min	4.2	9	338	571	1	77,457
	Max	2,299.30	19,358	4,58,112	24,02,000	3,951	3,70,31,114
2008	Mean	453.77	4,774	77,181	3,99,220	731	94,24,729
	Std. Dev.	619.8	5,460	1,12,802	5,20,091	1,238	1,13,27,868
	Min	4.2	9	357	339	1	83,461
	Max	2,299.30	19,320	4,62,237	20,99,000	3,879	3,74,62,189
2009	Mean	439.33	4,765	77,746	3,75,357	719	95,32,377
	Std. Dev.	604.71	5,432	1,13,480	5,01,149	1,212	1,12,63,473
	Min	4.2	9	362	415	1	76,208
	Max	2,213.80	19,283	4,65,403	19,00,820	3,807	3,85,61,296
2010	Mean	403.73	4,862	78,142	4,08,064	711	94,17,847
	Std. Dev.	515.07	5,447	1,13,712	5,46,270	1,209	1,15,57,204
	Min	4.9	10	372	410	0.5	77,668
	Max	1,914.80	19,312	4,65,904	20,43,000	3,753	3,83,49,063
2011	Mean	392.75	4,848	78,940	3,99,937	721	95,94,521
	Std. Dev.	499.54	5,416	1,15,091	5,13,859	1,223	1,16,94,261
	Min	4.9	10	388	460	0.5	74,905
	Max	1,914.80	19,282	4,71,865	19,44,450	3,825	3,91,27,358

Empty Cell	Empty Cell	Inputs					Outputs
Empty Cell	Empty Cell	**Labor (1,000 AWU)**	**Land (1,000 ha)**	**Gross capital stock* (millions of USD $)**	**Fertilizers (tonnes)**	**Irrigation area (1,000 ha)**	**Agricultural production value (1,000 I $)**
2012	Mean	391.09	4,874	79,497	4,06,636	738	92,55,189
	Std. Dev.	500.9	5,467	1,15,470	5,19,045	1,262	1,13,55,394
	Min	4.9	10	403	2038	0.5	71,617
	Max	1,914.80	19,286	4,71,260	19,14,915	3,923	3,90,08,782
2013	Mean	386.87	4,781	79,845	4,20,681	747	95,61,086
	Std. Dev.	500.34	5,515	1,14,841	5,31,597	1,274	1,16,68,428
	Min	5	10	409	3458	0.4	72,123
	Max	1,937.10	19,302	4,65,401	20,04,605	4,005	3,82,77,824

*It includes land development, machinery and equipment, farm structures and orchards.

The first input, *labor*, has been measured by the "Employment in agriculture" data, expressed as the number of workers (1000 annual working units). Employment is defined as the number of people of working age engaged in agricultural activities. The second input, *land*, has been measured by the extension (in 1000 ha) of the land-use class "Arable Land and permanent crops". The third input variable, *capital*, has been measured by the "Gross Capital stock" expressed in millions of US dollars at constant 2005 prices. It includes land development, machinery and equipment, farm structures and orchards, where the number of machines is a proxy of fuel and energy inputs. In order to quantify the forth input, *fertilizers*, a proxy given by the nitrogenous fertilizer consumption (in tonnes) has been used. *Irrigation area* is instead the input value used to measure the area (in 1000 ha) equipped for irrigation. Finally, the output given by the *agricultural production value* has been expressed as the net production value at constant 2004–2006 International dollars. In this study, we adopt input and output oriented DEA models where the efficiency estimates measure how much a country could reduce the use of its inputs as compared to the best DMUs in the first specification, and how much a country could increase the production of its output as compared to the best DMUs in the second specification.

Nevertheless, conventional point estimates are not enough to consider DEA a consistent efficiency estimator. Relevant scientific efforts have been addressed to the study of the statistical property of DEA estimators. In this context, Simar and Wilson (1998) have proposed a general methodology for bootstrapping in frontier models to construct

confidence intervals, clarifying and developing this method in subsequent articles (Simar and Wilson, 2000a; 2000b). In particular, when the Data Generating Process (DGP) is unknown, as in this analysis, a non-parametric DEA approach shows distinct advantages, such as less severe constraints on the technology than parametric methods. Through bootstrapping a pseudo-replicate dataset is created to test the reliability of the original dataset. This method indicates if the distribution has been influenced by stochastic errors and, thus, it can be used to construct confidence intervals for point estimates, which cannot be derived analytically.
Using Monte Carlo approximation, the bootstrap method can simulate the DGP and provide a reasonable estimator of the original unknown sampling distribution.

Suppose that the DGP *P* generates a random sample $\chi=\{(x_k,y_k|k=1,\ldots,n)\}$. Using the data χ with a nonparametric method $\hat{\theta}_k=\min\{\theta|y_k\leq\sum_{i=1}^{n}\gamma_i y_i|\theta x_k\geq\sum_{i=1}^{n}\gamma_i x_i|\sum_{i=1}^{n}\gamma_i=1,\gamma_i\geq0|\theta\geq0|i=1,\ldots,n\}$
To obtain $\hat{X}(y),\alpha\hat{X}(y)$, it is possible to estimate its efficiency $\hat{\theta}_k=\min\{\theta|\theta x_k\in\hat{X}(y_k)\}$. The bootstrap procedure is used to determine $\hat{P}$ as a reasonable estimator of the true unknown DGP generated through the data χ. The efficiency estimates represent a new population, from which it is possible to build a new dataset $\chi^*=\{(x_i^*,y_i^*)|i=1,\ldots,n\}$. This pseudo-sample defines the corresponding quantities $\hat{X}^*(y)$ and $\alpha\hat{X}^*(y)$, whose distributions, conditionally on χ, are known, since $\hat{P}$ is known. Monte Carlo approximation is employed to overcome difficulty in the analytical computation of $\hat{P}$ and to obtain the sampling distributions, generating *B* pseudo-samples χ_b^*, where *b* = 1, ..., *B* and pseudo-estimates of the efficiency scores. The empirical distribution of these pseudo-estimates gives an approximation of the unknown sampling distribution of the efficiency scores, but unfortunately generates inconsistent estimates.
Following Simar and Wilson (1998), a homogeneous smoothed bootstrap procedure is applied in this study. An algorithm for generating the bootstrap consistent values $\hat{\theta}_b^*$ from a kernel density estimate is implemented.
For each Country *k* given the input–output data $(x_k,y_k)_{k=1,\ldots,n}$, $\hat{\theta}_k$ is computed by the linear program to get the efficiency estimators.
The smoothed bootstrap sample θ_1^*, ..., θ_n^* for *i* = 1, ..., *n* is generated by letting β_1^*, ..., β_n^*, a simple bootstrap sample obtained by drawing uniformly with replacement. Define sequence $\tilde{\theta}_i^*=\{\beta_i^*+h\varepsilon_i^* \text{ if } \beta_i^*+h\varepsilon_i^*\leq1, 2-\beta_i^*-h\varepsilon_i^* \text{ otherwise}\}$ and obtain the corrected bootstrap sample by $\theta_i^*=\bar{\beta}^*+1/(1+h^2/\hat{\sigma}^2)(\tilde{\theta}_i^*-\bar{\beta}^*)$ with $\bar{\beta}^*=1/n\sum_{i=1}^{n}\beta_i^*$ and $\hat{\sigma}_{\hat{\theta}}^2$ is the sample variance of $\hat{\theta}_1^*$, ..., $\hat{\theta}_n^*$.

Through these procedures, the sample values assume the same mean and variance as the original values. The bandwidth factor *h* is calculated following a methodological procedure that has been discussed in detail by Simar and Wilson (2011).

The smoothed bootstrap sample sequence is used to compute new data $\chi b^*=\{(xib^*,yi)|i=1,\ldots,n\}$, where, $xib^*=(\theta i/\theta ib^*)xi,\{i=1,\ldots,n\}$and obtain the bootstrap efficiency estimates $\{\hat{\theta}ki|i=1,\ldots,n\}$ by solving the DEA model for each χb^*. Country using the data

In this paper 2000 iterations (*B*) of these two last steps have been carried out in order to ensure adequate coverage of the confidence intervals. The bootstrap efficiency scores $\hat{\theta}k^*$ represent approximations to the $\hat{\theta}k$, just as the DEA efficiency scores $\hat{\theta}k$ represent approximations to θ_k.

Since the bootstrap estimates $\{\hat{\theta}k,b^*=1,\ldots,B\}$ are biased by definition (Simar and Wilson, 2000a) and $BIAS(\hat{\theta}k=E(\hat{\theta}k)-\theta$, the empirical bootstrap bias for the original estimator $\hat{\theta}k$ can be calculated as $BIASB(\hat{\theta}k)=B-1(\sum b=1B\hat{\theta}k,b^*)-\hat{\theta}k$. The adjusted DEA scores are obtained by subtracting the bias from the original efficiency estimates. Since the bias correction introduces additional noise and could have a higher mean square error than the original point estimates, the analysis provides corrections to find interval estimations.

The percentile method modified by Simar and Wilson (2000a) has been carried out to obtain confidence intervals, correcting automatically for bias without the use of a noisy biased estimator. Using the bootstrap score, we construct confidence intervals for each Country *k*. If we knew the distribution of $(\hat{\theta}^*(x,y)-\theta(x,y))$, it would be possible to find a_α, b_α such that $Pr(-b\alpha\leq\hat{\theta}k(xo,yo)-\theta(xo,yo)\leq-a\alpha=1-\alpha$. Because a_α, b_α are unknown, we use $\{\hat{\theta}k,b^*=1,\ldots,B\}$ to find values $\hat{b}\alpha,\hat{a}\alpha$ such that $Pr(-\hat{b}\alpha\leq\hat{\theta}k(xo,yo)-\theta(xo,yo)\leq-\hat{a}\alpha|\hat{P}(\chi n))=1-\alpha$.

Finding $\hat{b}\alpha,\hat{a}\alpha$ implies arranging the values $\hat{\theta}k,b^*(xo,yo)-\hat{\theta}k(xo,yo),b=1,\ldots,B$ in increasing order and then eliminating a number of rows equal to $[(\alpha/2)\times100]\%$ at either end of the list and setting $-\hat{b}\alpha,-\hat{a}\alpha$ to the endpoints of the array with $\hat{a}\alpha\leq\hat{b}\alpha$. The $1-\alpha$ percent confidence interval is then:$\hat{\theta}k(xo,yo)+\hat{a}\alpha\leq\theta(xo,yo)\leq\hat{\theta}k(xo,yo)+\hat{b}\alpha$

This procedure is repeated *n* times to obtain *n* confidence intervals, one for each Country obtaining $\hat{a}\alpha\leq0,\hat{b}\alpha\leq0$ and $\hat{\theta}k$ values above the confidence interval.

3. Results and discussion

Input oriented efficiency scores of EU countries analyzed in this paper are summarized in Table 3.

Table 3. Summary statistics of input-oriented efficiency scores (VRS model) for 25 EU member Countries over 1993–2013 (average over time).

Empty Cell	**Mean**	**SD**	**Change (%) 1993–2013**
AUT	0.391	0.025	0.009
BEL-LUX	0.924	0.037	0.001
BGR	0.859	0.059	0.002
CYP	0.415	0.026	0.001
DNK	0.771	0.140	0.027
EST	0.902	0.036	0.000
FIN	0.224	0.044	0.033
FRA	0.923	0.035	−0.001
DEU	0.920	0.024	0.000
GRC	0.685	0.129	−0.023
HUN	0.470	0.069	−0.013
HRV	0.574	0.214	−0.048
ITA	0.888	0.028	0.001
LTU	0.769	0.124	0.003
MLT	0.911	0.038	−0.002
NLD	0.913	0.026	−0.001
CZE	0.721	0.070	−0.021
POL	0.914	0.039	−0.001
PRT	0.384	0.027	0.011
ROU	0.832	0.093	−0.006
SVN	0.663	0.210	−0.027
SVK	0.710	0.118	−0.024
ESP	0.856	0.089	0.011
SWE	0.397	0.042	0.017
GBR	0.928	0.028	−0.002
EU	**0.676**	**0.055**	**−0.002**

The results obtained considering variable returns to scale (VRS) assumption have been analyzed, because the ratios between CRS and VRS estimates assumed values of scale efficiency (SE) different from 1, highlighting decreasing or increasing returns to scale.

The CRS assumption, in fact, is only appropriate when all DMUs are operating at an optimal scale. The use of the CRS specification when all DMUs are not operating at the optimal scale results in measures of efficiency, which are confounded by scale efficiencies (SE). The use of the VRS specification allows for the calculation of efficiency devoid of these SE effects.

The input-oriented analysis, summarized in Table 3, shows that the average efficiency score of the whole sample of EU countries over the period 1993–2013 is about 71.8% under the VRS assumption, meaning that the current level of output can be achieved using 28.2% fewer inputs on average.

In particular, the average efficiency scores vary between a minimum of about 68.8% to a maximum of 75.1% (Fig. 1). Therefore, the majority of EU countries are experiencing increasing or decreasing returns to scale, highlighting their potential to increase their production efficiency through modifying their input use.

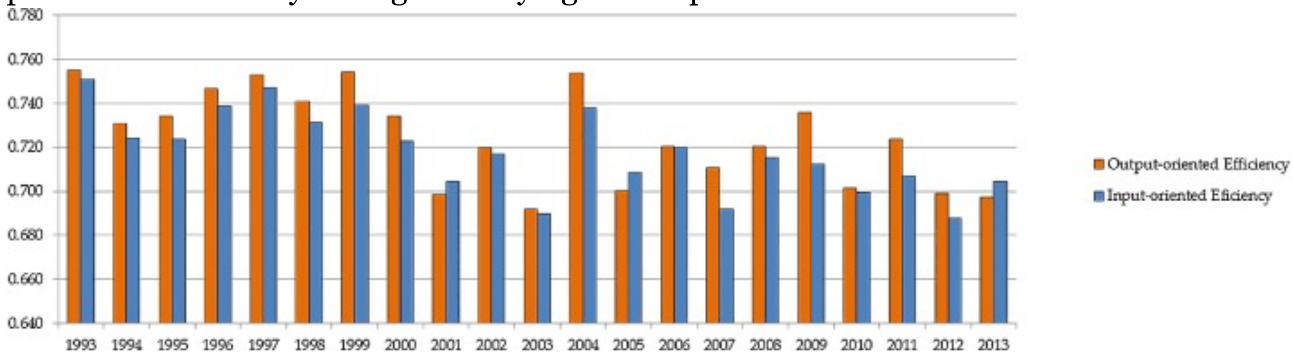


Fig. 1. Comparison of input- and output-oriented efficiency trends of EU Countries.

As shown in Table 3, the best efficient countries in the analyzed time period are Belgium and Luxembourg, Estonia, France, Germany, Malta, the Netherlands, Poland, and the United Kingdom, registering an average input-oriented efficiency score greater than 0.9. The worst countries are, instead, Finland, Austria, Cyprus, Hungary, Portugal, and Sweden, which do not even achieve the value of 0.5 in terms of average input-oriented efficiency score.

Input-oriented efficiency score change, calculated as a geometrical mean of the annual change rate between 1993 and 2013, shows that the EU agricultural sector has generally stagnated over time, indicating a −0.2% value on average. The average annual change of the input-oriented efficiency scores, in fact, marks an overall decrease in EU countries with some significant exceptions represented by Finland, Denmark, Portugal, Spain, and Sweden, which register positive rates in a range between 1.1% and 3.3%. On the other hand, the above-mentioned most efficient countries highlight an almost steady average of change rates in the period of analysis, in line with the general trend. Among the less efficient ones, Hungary registers a rate of −1.3% in terms of an average decrease in the input-oriented efficiency score, while the others have positive average annual change rates varying between 0.1% and 3.3%.

The average input-oriented efficiency score at the beginning of the period was 75.1%, indicating that efficiency could be improved on average by 24.9%. This efficiency consistently varied over years and in 2012 reaches 68.8%, highlighting a positive peak in the room for efficiency improvement equal to 21.1%.

Input-oriented DEA results and comparison between efficiency levels in 1993 and in 2013, indicate that older EU member countries, Germany, France, Belgium-Luxembourg and the Netherlands, have a more efficient and optimized crop production process from the resource savings point of view (Fig. 2, Fig. 3), obtaining a certain level of agricultural value added with fewer inputs compared to the other Countries. As clearly evident from Fig. 2, the above-mentioned countries reveal a high median value and a relatively little inter-quartile range where the 50% of the efficiency scores are concentrated. The upper whisker coincides, in fact, with the maximum value 1, while the lower one, for these countries, is very close to the box, highlighting that 25% of the efficiency scores fall in a small range.

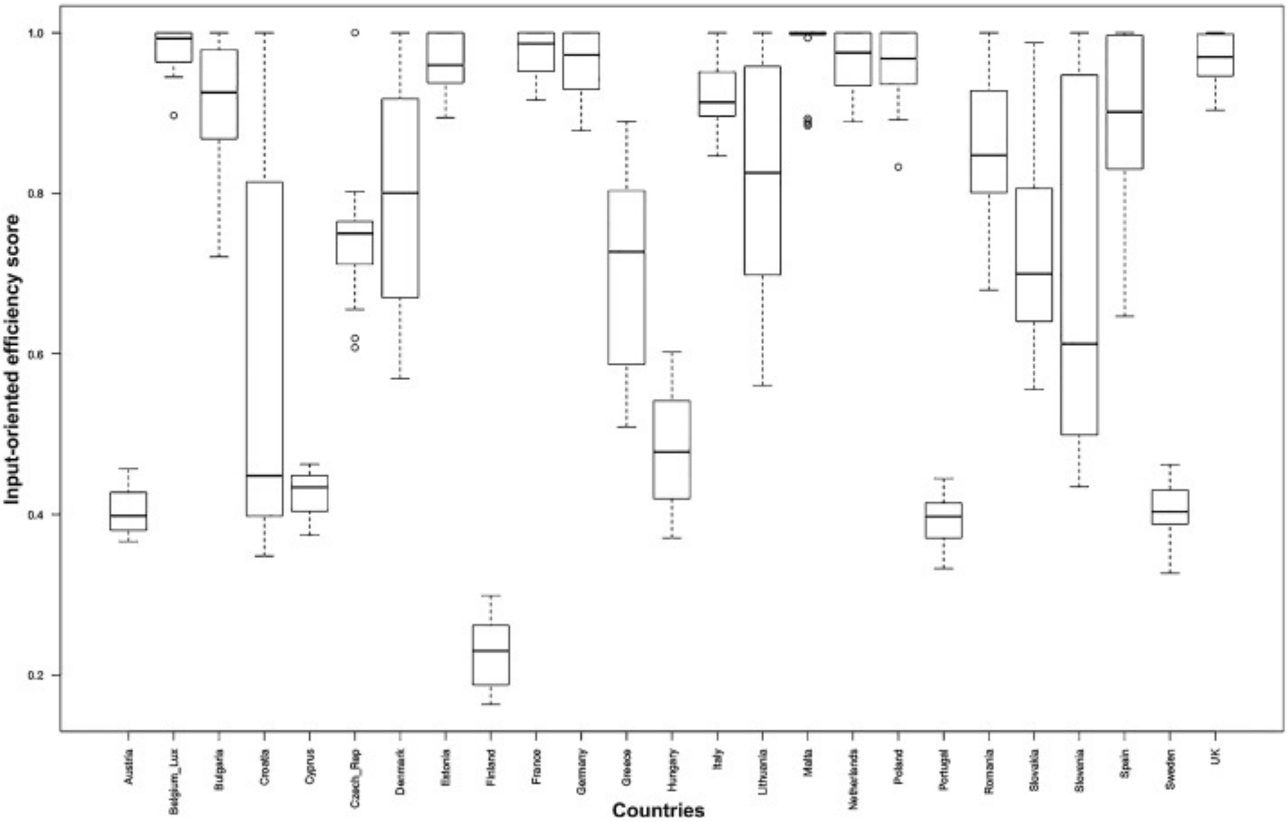


Fig. 2. Boxplot distribution of agricultural input-oriented efficiency (VRS model) by Country between 1993 and 2013.

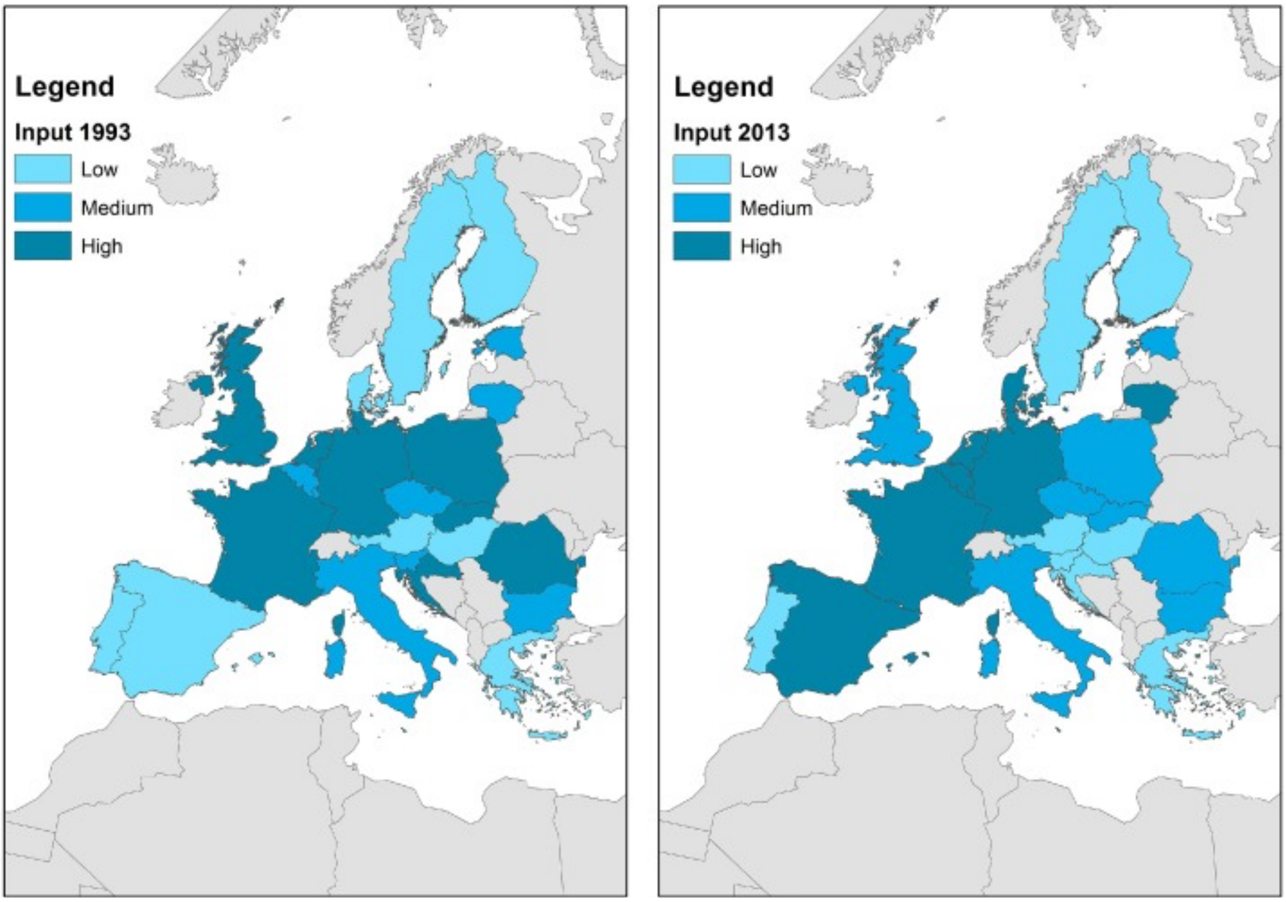


Fig. 3. EU agricultural input-oriented efficiency spatial distribution patterns in 1993 and in 2013. Low = Efficiency ≤ 0.5; Medium = 0.5 < Efficiency ≤ 0.8; High = Efficiency > 0.8.

This condition could be due to the earliest application of the Common Agricultural Policy (CAP) in the oldest EU member countries, which set some conditions such as the increase in the environmental efficiency of inputs used during the agricultural production process that had to be achieved in order to receive subsidies.

Output oriented efficiency scores of EU countries analyzed in this paper are summarized in Table 4. The output-oriented analysis shows that the average efficiency score for the whole sample of EU countries is about 72.5% under VRS assumption. This reflects that the current level of input serves to achieve on average about 72.5% of the output. Annual average efficiency scores for the whole sample of EU countries varies between a minimum of about 69.2% to a maximum of 75.5%. In the case of the output-oriented approach, as well as the input-oriented approach, the majority of EU countries could better rationalize their input use obtaining more outputs and achieving production efficiency.

Table 4. Summary statistics of output-oriented efficiency scores (VRS model) for 25 EU member Countries over 1993–2013 (average over time).

Empty Cell	**Mean**	**SD**	**Change (%) 1993–2013**
AUT	0.516	0.024	0.004
BEL-LUX	0.915	0.097	0.001

Empty Cell	**Mean**	**SD**	**Change (%) 1993–2013**
BGR	0.864	0.057	0.001
CYP	0.436	0.026	0.001
DNK	0.788	0.122	0.023
EST	0.845	0.135	−0.032
FIN	0.237	0.020	0.011
FRA	0.950	0.020	−0.001
DEU	0.938	0.023	0.000
GRC	0.740	0.099	−0.018
HUN	0.565	0.059	−0.009
HRV	0.597	0.227	−0.047
ITA	0.921	0.023	0.001
LTU	0.780	0.122	0.003
MLT	0.578	0.137	0.017
NLD	0.924	0.024	−0.001
CZE	0.727	0.073	−0.022
POL	0.927	0.036	−0.002
PRT	0.447	0.035	0.013
ROU	0.868	0.072	−0.004
SVN	0.643	0.208	−0.029
SVK	0.719	0.119	−0.024
ESP	0.870	0.089	0.011
SWE	0.386	0.028	0.008
GBR	0.939	0.023	−0.002
EU	**0.689**	**0.056**	**−0.004**

Belgium-Luxembourg, France, Germany, Italy, the Netherlands, Poland and the United Kingdom are the most efficient countries, registering an average output-oriented efficiency score greater than 0.9 (Table 4), meaning less production maintaining constant inputs, and confirming in part some input-oriented efficiency results. Finland, Portugal, Cyprus and Sweden, which are the worst using the input-oriented approach, confirm an average efficiency score less than 0.5 also in the case of output-oriented analysis.

Output-oriented efficiency score change, calculated as the geometrical mean of the annual change rate between 1993 and 2013, highlights a general stagnation in the efficiency of the EU agricultural output over time. The average annual change of the output-oriented efficiency scores, in fact, shows an overall negative trend in EU countries (−0.4%) with some significant exceptions represented by Denmark, Malta, Portugal, Finland and Spain, which register positive rates in a range between 1.1% and 2.3%.

The above-mentioned most efficient countries highlight almost steady average change rates in the period of analysis, in line with the general trend. Among the worst efficient countries, Portugal shows a rate of 1.3% in terms of average increase in the output-oriented efficiency score, confirming a general growth in the level of efficiency both from an input- and an output-oriented approach, followed by Finland.

The average output-oriented efficiency score at the beginning of the period was 75.5%, indicating that outputs could be increased on average by 24.5%. In 2003, the average output-oriented efficiency score reached 69.2%, highlighting the positive peak in the room for efficiency improvement equal to 30.8% (Fig. 1). In fact, the EU countries' efficiency levels in 1993 and in 2013, as illustrated in Fig. 4, Fig. 5, confirm that the oldest EU member countries have a more efficient and optimized crop production process also from the output maximization point of view.

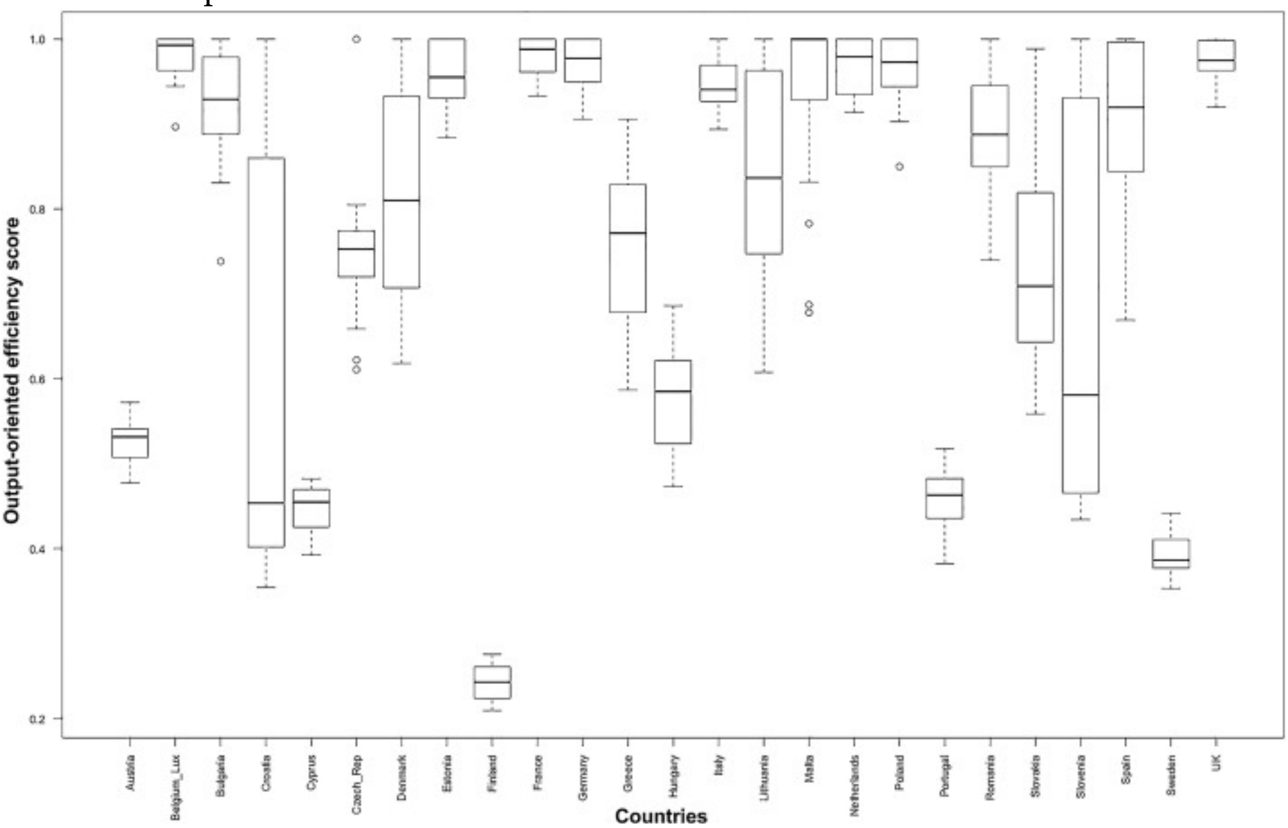


Fig. 4. Boxplot distribution of agricultural output-oriented efficiency (VRS model) by Country between 1993 and 2013.

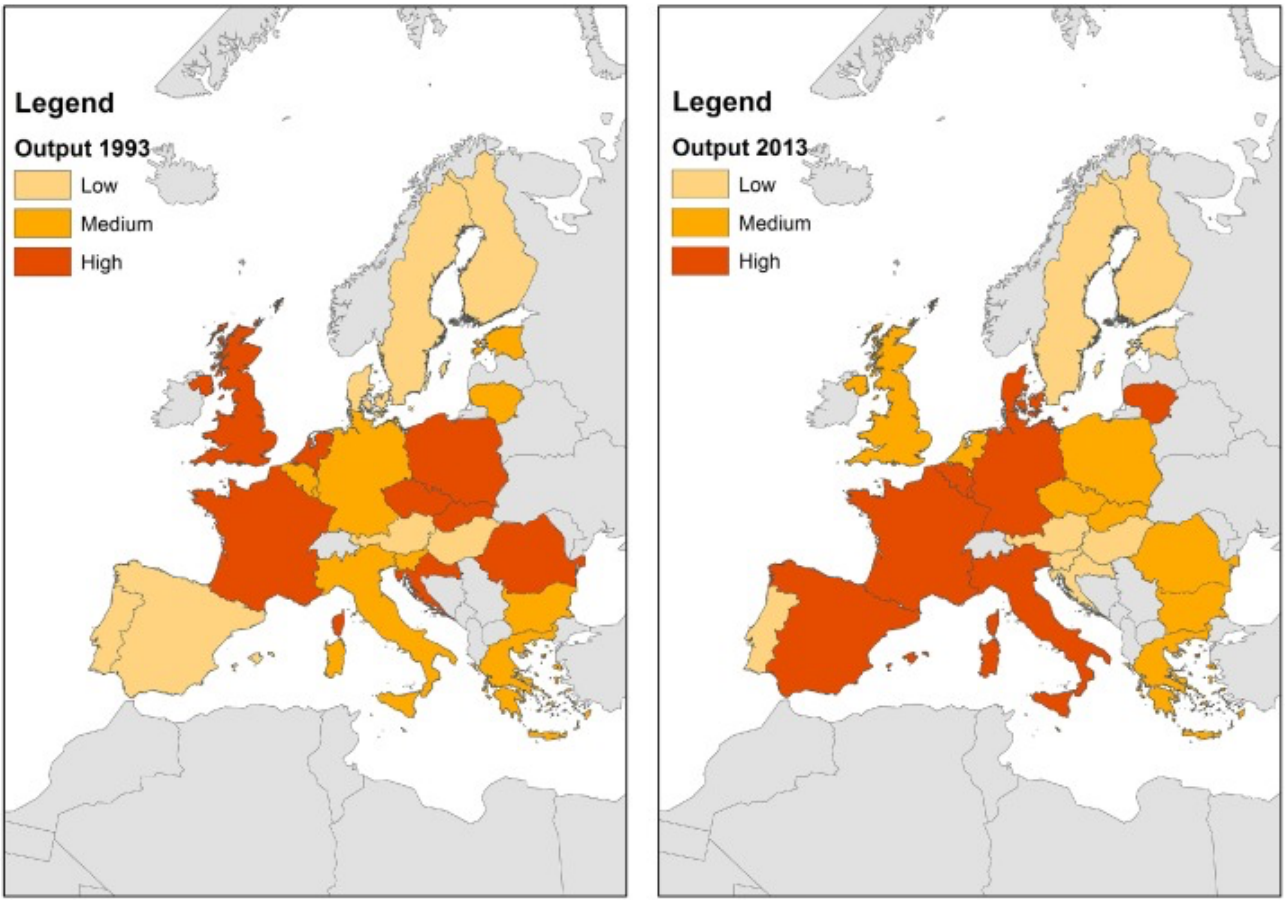


Fig. 5. EU agricultural output-oriented efficiency spatial distribution patterns in 1993 and in 2013. Low = Efficiency ≤ 0.5; Medium = 0.5 < Efficiency ≤ 0.8; High = Efficiency > 0.8.

Fig. 4 illustrates that Germany, France, Belgium-Luxembourg, and the Netherlands confirm high median values and a limited inter-quartile range of efficiency scores, also analyzing the output-oriented approach. The upper whisker of the boxplot coincides, in fact, with the maximum value 1, while the lower one, for these countries, is very close to the inter-quartile range, highlighting limited variations in the efficiency scores around the high median value. The comparison of input- and output-oriented efficiency trends of the overall EU Countries (Fig. 1) points out a general decrease in efficiency over the analyzed period, with a trend reversal in the last year, which registers a level of efficiency higher for the input than the output perspective.

A general consideration about the output-oriented framework from an agricultural policy perspective highlights a greater attitude towards intensive production, and an approach aimed at the generation of agricultural production value from given environmental resource inputs. This puts in evidence an interest more oriented towards the sectorial economic return that is accentuated in the agricultural oriented economy.

4. Conclusions

The results of this study provide information on the heterogeneity of countries' efficiency performances and the potential for increasing agricultural production in the EU, balancing environmental resource savings with economic return. A consistent variation of agricultural efficiency scores among countries both for the output-oriented and the input-oriented approaches is observed. These differences demonstrate the existence of a competitive context in which efficient and non-efficient countries must develop their agricultural practices in a substantially open global market with low barriers.

Even if the DEA approach is mainly used in economic analysis, from our perspective it can capture some relevant environmental aspects. Furthermore, the bootstrap version of DEA makes results statistically more consistent than the traditional approach, allowing us to obtain corrected efficiency measures and confidence intervals. Given that, the bootstrap-DEA is a very promising approach as a policy and management assessment tool, providing measurable evidence of efficiency levels, also when investigating the most important factors for modeling a socio-economic and environmental competitive advantage.

This paper ultimately contributes to a wider practical implementation of environmental planning and management programs based on the production process and bootstrap-DEA methodology, which represents an effective monitoring tool useful for decreasing human pressure, like agriculture, on environmental resources. Clearly, some of the input variables, such as fertilizer use, extension of irrigated area, but also the "capital" variable in terms of fuel and energy use can have some environmental effects. However, assessing resource use efficiency through input- and output-oriented DEA approaches helps planners and managers to understand if agricultural policy should be aimed at minimizing input (resource savings approach) or maximizing output using the current quantity of inputs (increasing productivity approach) (Toma et al., 2016).

Ecological intensification in the place of agricultural intensification requires a substantial change of the target from the maximum attainable food production (high output-oriented approach) to the minimum agriculture-induced environmental impact (low input-oriented approach) in order to safeguard food security and human well-being (Baulcombe et al., 2009).

The largest agricultural support system worldwide, the Common Agricultural Policy (CAP) of the European Union, has now come to a critical point, given the recent change of funding priorities in a context of global economic crisis. This changed approach includes the conservation of farmland biodiversity, soil functionality, agricultural landscapes and rural vitality (Plieninger et al., 2012).

The efficient expansion of the agricultural sector will be completely possible after the full implementation of the EU CAP for the period 2014–2020, which identifies rural and sustainable development as key factors and offers a unique opportunity to trigger a transition from commodity-based subsidy policies to policies based on the efficient provision of ESs from agricultural land in Europe (Tankosic and Stojsavljevic, 2014, Plieninger et al., 2012).

The inclusion of ESs into crop production can have the potential to ensure both productive and environmentally friendly agriculture globally, although management decisions often focus on the immediate provision of a commodity or service, at the expense of the same or another ES at a distant location or in the future (Power, 2010). Measuring tradeoffs between agricultural added value and its natural resource pressures can contribute to building policy instruments for an improved agricultural resource management (Azad and Ancev, 2014).

Suitable unambiguous management objectives set in the context of agricultural policy allow a country to achieve outcomes more effectively (Cary and Roberts, 2011), and the measurement of agricultural performance can be a crucial aspect in the improvement of policy planning and management, allowing for the identification of important best practices in sustainability evaluation (Dong et al., 2015).

When investigating the ability of agricultural production processes in combining inputs and outputs, the knowledge of the level of efficiency is relevant, not only to policy makers, but also to agricultural farmers, which can benefit and base their decisions on the efficiency results. In this context, some examples of paying farmers for ESs have already been debated (Plieninger et al., 2012). However, further research could be addressed to better our framework to enhance the management of agro-ecosystems in order to support many ESs while still maintaining the provisioning services that agro-ecosystems were designed to produce. In such a framework, the output-oriented approach will be something more enlarged where the output variable given by the "Agricultural production value" will be modified as the "Agricultural ESs production value" output variable. In this novel and more inclusive output variable, the payments for ESs can increase the agricultural efficiency and ensure that the targeted public ES is actually provided. This in accordance with the EU Biodiversity Strategy 2020 that is moving through the enhancement of direct payments for environmental public ESs in the EU Common Agricultural Policy, and by better targeting rural development towards biodiversity conservation.

Although this work has already widened the approach to environmental indicators linked to the agricultural process, future studies could also update the results of this paper, extending the assessment to other geographical and agriculturally relevant regions, analyzing the impact of other contextual variables on efficiency using non-parametric models (Bădin et al., 2012), assessing the technological convergence using Mastromarco et al. (2013) methodology, and including the assessment of ecosystem services in the productivity analysis. This could improve the economic concept of productivity in an ecological context, by also including the production of ecosystem services.

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