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Assessing agricultural eco-efficiency in Italian Regions

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ABSTRACT

Agriculture plays a key role in providing a wide range of ecosystem services, such as food, feed, fiber and biofuel, thus taking part in the economic development of countries. On the other hand, this sector also gives rise to negative externalities. The eco-efficiency has been considered as a meaningful index for assessing how efficient economic activities are in terms of resource-use and environmental pressures: measuring eco-efficiency provides policy makers with important information for developing policies focused on sustainable management and efficient use of natural resources in the agricultural sector. In this context, sustainable development is now one of the most important objectives of the European Union Common Agricultural Policy (CAP) that has a key role in facing the challenges of the new paradigm of sustainability of agriculture. In this direction, the aim of this paper is to evaluate the eco-efficiency of the Italian agricultural sector, as an index useful for emphasizing the differences among some national geographical areas. This paper tries to fill the lack of scientific studies on agricultural eco-efficiency in Italy, despite the strategic role played by Italy in Europe. For this purpose, the Data Envelopment Analysis (DEA) methodology was used, focusing on the integration between agricultural productivity and resource conservation, in order to develop a support tool for policy makers and managers. The analysis had shown a better orientation in saving resources for the Southern Regions and a greater orientation in productivity for the Northern Regions. Overall, Italy seems to have a good capacity for sustainable management of agricultural resources although there is still space for improvement. In this regard, the measurement of eco-efficiency provides a useful index for policy makers to achieve better performances in terms of agricultural sustainability. This means that CAP subsidies should be granted in exchange for specific environmental externalities provided by farmers as a result of more ecologically friendly management with a land use planning avoiding the depleting of Ecosystem Services rich areas, allowing for the achievement of a balance between economic growth and ecosystem protection. Although the paper has expanded the literature on agricultural eco-efficiency, this work has some limitations that could serve as a reference for future studies that can include other ecological variables such as the provision of some ecosystem services that can be enhanced or impacted by agricultural development. Finally, the challenge to realize sustainable agriculture can represent a long-term guarantee of food security as well as societal well-being.

1. Introduction

Agriculture has always performed essential environmental, economic and social functions, providing a wide range of ecosystem services (ES) (Bommarco et al., 2018). These include local food security, farmland biodiversity, enhancement of environmental quality, and so on (Glavic and Lukman, 2007; Connelly et al., 2012; Waas et al., 2011). Ecosystem services contribute to the maintenance of environmental conditions and material necessary for human survival (Costanza et al., 1997; Millennium Ecosystem Assessment, MA, 2005; TEEB, 2010). In particular, land-use supports the ecosystem services, such as biomass production, recreational activity space, water retention, environmental cleaning, carbon sequestration or climate regulation, and biodiversity conservation (Costanza et al., 1997; Ouyang et al., 2016), hence land use changes, related to productivity requirements, may be the cause of their loss (Fu and Zhang, 2014; Fu et al., 2015; Pang et al., 2019). The Millennium Ecosystem Assessment (MA, 2005) provided evidence that approximately 60% of global ecosystems faced a degradative trend during the past five decades with enormous effects on the supply of ecosystem services (de Groot et al., 2010, 2012; Chen et al., 2016; Shi

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et al., 2012). Nowadays, the challenges are even more complex than in the past, because the continuous growth of the population makes it necessary to produce large quantities of food, trying to avoid or reduce as much as possible the environmental consequences. The development, utilization and management of landscape resources by the agricultural sector will directly interest environmental security at all scales (Petrosillo et al., 2008, 2009; Bakshi and Small, 2011; Lowitt and Côte, 2013; Shi et al., 2011). Agriculture represents an economic sector which brings multiple benefits, such as food security. On the other hand, this sector also gives rise to negative externalities, such as water and land deterioration due to agrochemical pollution (Adegbeye et al., 2020), significant water resource demand and the production of pollution emissions (Maia et al., 2016). However, agriculture is a key socio-economic sector for sustainable development, and climate change mitigation (Srinivasa Rao et al., 2009), due to its contribution to GHG emissions, which represent one of the main factors to be considered in assessing the environmental sustainability of different crops (Montanaro et al., 2017). This is especially true when agriculture assumes forms of intensification and specialization, which can cause (Pendrill et al., 2019; Miglietta et al., 2017; Serio et al., 2018): deforestation due to the uncontrolled use of soil, groundwater pollution caused by the reckless use of pesticides and fertilizers, loss of biodiversity, and so on.

In this context, the concept of “eco-efficiency” was proposed by Schaltegger and Sturm (1990) as “a business link to sustainable development”, and in 1992 the term was disclosed by World Business Council as the index of economic and environmental efficiency, namely as a management strategy that links financial and environmental performance to create more value with less ecological impact (Robert et al., 2003). Later, it was defined by OECD (1998) as “the efficiency with which ecological resources are used to meet human needs” attributing to firms, industries or economies the ability to produce goods and services with less impact on the environment, while consuming fewer natural resources (Picazo-Tadeo et al., 2011). In other words, eco-efficiency increases when the maintenance or rise of the production economic value corresponds to a decrease of environmental impacts (Kharel and Charmondusit, 2008), in terms of reduced impact of economic production on ecosystem services (Moutinho et al., 2017). Therefore, it represents an important index for assessing the sustainability of specific economic sectors such as agriculture, in terms of resource-use and environmental pressure (UNESCAP, 2009). In particular, the agricultural “eco-efficiency” is increasingly attracting the interest of national and European institutions that recognize it as playing a key role in achieving many 2030 Sustainable Development Goals (Caiado et al., 2017; Toma et al., 2017). Therefore, measuring eco-efficiency in the agricultural sector provides an important index for development strategies to policy makers (Picazo-Tadeo et al., 2011).

In this framework, the aim of this paper is to evaluate the eco-efficiency index of the Italian agricultural sector, emphasizing the differences existing between different national geographical areas. This paper intends to fill the lack of scientific studies on agricultural eco-efficiency in Italy, despite its strategic role played in Europe, through the use of Data Envelopment Analysis (DEA) methodology.

The paper is organized as follows: Section 1 describes the Italian agricultural sector with its strength and weaknesses. Section 2 develops a comprehensive literature review of studies on the application of DEA to the evaluation of agricultural eco-efficiency. Section 3 describes the methodology and the environmental and economic variables used in the model. Section 4 presents and discusses the achieved results, emphasizing Italian territorial differences. Finally, Section 5 presents the main conclusions and the research needs.

1.1. The importance of the Italian agricultural sector in the European context

In the context of agriculture, sustainable development is now one of the most important objectives of the European Union Common Agricultural Policy (CAP), although assessing sustainability is difficult in principle and practice (Van Passel et al., 2006; Maia et al., 2016; AitSidhoum, 2018). The EU CAP (European Commission, 2013) aims to improve the efficiency of member Countries in terms of food production, development of rural communities and environmental sustainability farming (Niavis et al., 2018). Therefore, the EU CAP can play a key role in facing the challenges of the new paradigm of sustainability of agriculture, aimed at the conservation of biodiversity of agricultural land, the functionality of the soil, and the rural vitality of agricultural landscapes.

The EU CAP contributes to the achievement of several 2030 Sustainable Development Goals (SDGs): SDG 1 (no poverty) since the rural population is part of the world’s extreme poor and agriculture can contribute by reducing poverty more than any other sector; SDG 2 (zero hunger) since agriculture can contribute to food security; SDG 6 (clean water and sanitation) considering the sustainable use of mineral fertilizers required by the EU CAP; SDG 8 (decent work and economic growth) by guaranteeing rural development; SDG 12 (responsible consumption and production) related to the PAC sustainable requirement in terms of use of water and other natural resources; SDG 13 (climate action) for the role of different crops of acting as sink of GHG emission; and SDG 15 (life on land) since agriculture can contribute to the conservation of landscape biodiversity.

In this context, Italy considers agriculture a key economic sector, while acknowledging its environmental implications. Almost one fifth of the added value of the EU’s agricultural system is generated in Italy that is considered as the leading European country in terms of the number of Protected Denomination of Origin (PDO), Protected Geographical Indication (PGI) and Traditional Specialities Guaranteed (TSG) acknowledgements. In 2018, agriculture contributed with 2.1% to the Italian added value, making Italy the top country in the EU in terms of added value derived from agriculture, and if the food industry is also included, the agri-food sector corresponds to the 3.9% of the added value of the national economy (ISTAT, 2018).

However, there are important imbalances between the different geographical areas: although the farms in the North of Italy are about half of those in the South, they produce more than 50% of the national agricultural value. In fact, the Italian Regions have different endemic crops as a result of a strong value of cultural identity associated with certain agricultural products (Brundu et al., 2017).

Italian agriculture has shown a progressive advance that can be partly attributed to the application of corporate restructuring strategies, the process of motorization and mechanization, and the use of massive fertilizers and pesticides to support extensive production.

In particular, about 47.5 million quintals of fertilizers for agricultural use are actually distributed on Italian soil (ISTAT, 2018). However, in recent years, the use of fertilizers and pesticides for agricultural purposes has decreased significantly (ISTAT, 2017), with positive effects on agroecosystem biodiversity (Tong et al., 2019).

Moreover, agriculture is the main user of water with 49% of the national consumption for irrigation use, plus the consumption of farms themselves (ISTAT, 2014). Finally, one of the main weaknesses of the Italian agricultural sector is the constant decrease in the land to be cultivated. In particular, since 1990, almost 20% of the utilized agricultural area (UAA) has been lost, mainly due to the expansion of urbanized areas (ISPRA, 2018).

2. Literature review on eco-efficiency applied to the agricultural sector

Numerous studies have established the environmental impacts that agriculture has on the ecosystem and the consequent need to control the inputs used to ensure continuity of production over time (Foley et al., 2011). For example, agriculture contributes to 25–33% of the greenhouse gas emissions (Tilman et al., 2011); it occupies 40% of the Earth's surface (Zhang et al., 2019); it is responsible for 70% of freshwater withdrawal (Molden et al., 2007); it contributes to deforestation; and, by requiring the use of fertilizers and pesticides, it causes groundwater and marine pollution (Ramankutty and Foley, 1999).

The literature on the environmental impact of agriculture considers the concept of *eco-efficiency*, using it as an index to analyze agricultural sustainability and to relate the economic value of a production activity with its environmental impact (Müller et al., 2015). Eco-efficiency has been paid remarkable attention in the sustainable development literature, as it was considered an effective index for sustainability analysis (Zhang et al., 2008) on three different scales: the macro-economic (national economy), the *meso*-economic (Region) and the micro-economic (company) (Mickwitz et al., 2006). In the literature different methodologies have been identified for its measurement and, among the most widely used, there are: the ratio approach, the material flow analysis and the frontier approach (Yang and Zhang, 2018). The first approach defines eco-efficiency as the relationship between the economic value of some goods and their environmental impact, but it is used only if numerator and denominator can be integrated into a certain value (Zhang et al., 2008). As regards material flow analysis, however, the Life Cycle Assessment (LCA) methodology is widely used in literature to assess the potential environmental impact that occurred throughout the life cycle of a product, from the acquisition of raw materials to the end of its life (Roy et al., 2009). However, this approach requires large amounts of hard-to-find data with consequent approximations (Yang and Zhang, 2018). Finally, the frontier approach, and in particular the Data Envelopment Analysis (DEA) methodology that integrates economic and environmental inputs and outputs and appears to be the most applied methodology in literature (Kuosmanen and Kortelainen, 2005; Huang et al., 2014; Mavi et al., 2019).

These characteristics make DEA particularly useful in research on performance assessment where the focus is not on the estimation of an average technology production function used by all units analyzed, but to identify the best practicing units, a best practice production frontier is constructed, and all units of analysis are related to this frontier (Cooper et al., 2007). In other words, the DEA does not provide an absolute efficiency index, but provides a measure of relative efficiency, which identifies, among the observed units, the efficient and inefficient ones. This is assumed to lead to a better understanding of the conditions under which the units of analysis operate (Dyckhoff and Allen, 2001; Huang et al., 2014). This method is widely used by researchers to analyze the performance of the agricultural sector starting from different inputs and outputs (Kuosmanen and Kortelainen, 2005; Kharel and Charmondusit, 2008; Yin et al., 2014). However, in agriculture, the selection process of environmental inputs is very important because the outputs (production value, work productivity, etc.) depend upon these input consumptions. If an area can obtain the current level of outputs with lower level of inputs, this can be assumed to be an implementation of sustainable development goals for agriculture (Caiado et al., 2017).

Table 1 shows how, over the years, the use of DEA methodology for assessing the eco-efficiency in agricultural sector has grown significantly, thanks to its potential to provide results on agricultural production models, and useful to policy makers in sustainable planning .

Indeed, it has been widely applied at a national level, with a prevalence of studies focused on China, but more recent studies have analyzed the performances comparing countries with different agricultural policies (Kočišová, 2015; Madau et al., 2017; Toma et al., 2017).

Moreover, a certain heterogeneity can be also found in terms of the objectives pursued by the authors. In fact, while some studies evaluate the overall efficiency of the agricultural sector in the considered geographical area, others carry out more detailed investigations, aimed at calculating the efficiency of individual productions or of different types of crops.

As highlighted in Table 1 there is a lack of studies that evaluate the eco-efficiency of the entire Italian agricultural sector, despite its importance in the context of European agriculture. Moreover, there are not many studies able to integrate ecosystem services and socio-economic elements at regional scale into a joined context for sustainability analysis, and this knowledge gap prevents the enforcement of proper policy making (Lauransa et al., 2013).

3. Materials and methods

In this research we adopt the DEA methodology, considering the available data from 2004 to 2017 in twenty-one Italian Regions, that is, 19 Regions and two different sub regions, Alto Adige and Trentino.

The main source of data is the FADN (Farm Accountancy Data Network) database by the Directorate-General Agricultural and Rural Development of the European Commission, which provides all the economic and accounting data for the agricultural holdings (Table 2). The latter are individual units, both technically and economically, operating under single management and which undertake agricultural activities within the economic territory of the European Union.

The data considered were selected as the most important input variables that influence agriculture, according to the literature indicated in Table 1. We have two economic variables i.e. Labor and Gross Capital, which are the traditional economic production factors and three environmental variables i.e. Land, Fertilizer and Irrigation Area. The latter were selected to provide a measure of the main environmental impacts generated by agricultural activities (Stoate et al., 2009), namely: water expenditure, groundwater pollution from the use of fertilizers, the increasing use of soils which has led to increased deforestation and greenhouse gas emissions. Finally, agricultural production is the output variable used in the empirical estimation model.

In particular, the variable *Labor* corresponds to the Annual Working Units (1,000 AWU), fulltime person equivalents, employed on average in the agricultural holding for each Region.

The *Gross Capital* variable expressed in Euro (€) indicates the total fixed assets, which are i.e. agricultural land, farm building and forest capital, on average for each Italian Region.

The *Land* variable measures the average hectares (1,000 ha) and represents the area dedicated to the cultivation of different types of crops, excluding areas used for mushrooms, land rented for less than one year, woodland and the other farm areas.

The *Agricultural Production* represents the total outputs on average in the agricultural holdings for each Italian Region, which corresponds to the sum of the outputs of crops and crop products, livestock and livestock product and other output, expressed in Euro (€).

The data regarding *Irrigation Area* measure the area (in 1,000 ha) equipped for irrigation; these data were extracted from RICA database (Rete di Informazione Contabile Agricola-Italian Farm Accountancy Data Network).

Finally, the *Fertilizer* variable refers to the quantities expressed in tons (t) of active substances or active ingredients distributed during the cultivation process; these data were collected from a database provided by the Italian National Statistical Institute.

The methodology used in the study is DEA analysis, which consists of a non-parametric approach to estimating the efficiency through different scores. DEA provides for a multifactor productivity analysis for measuring the relative efficiency of a homogenous set of Decision-Making Units (DMU).

Using this methodology, we computed the distance between the best practice frontier for the best possible production, for each unit (DMU), in the considered sample. Then we transformed the obtained value into a measure of efficiency normalized in the interval [0, 1]. In fact, the DEA method does not provide a measure of absolute efficiency, but it allows us to know the relative efficiency of the data.

Each DMU can reach this position in different ways i.e. reducing the input, maintaining constant output or increasing the outputs, maintaining the inputs constants. Moreover, another strategy could be a

Table 1
Literature review on DEA method applied to agricultural sector.

Author(s) (Year)	Title	Area of study	Input Variables	Output Variables	Aims of the study
Piot-Lepetit et al., 1997	Agriculture's environmental externalities: DEA evidence for French agriculture	France	Cereal acreage; Other acreage; Annual worker units; Equipment; Fertilizers; Pesticides; Seeds; Others.	Cereal output; Other product output	This study adopts the DEA method focusing on potential input and environmental impact reductions in French agricultural production.
Binam et al., 2003	Factors Affecting Technical Efficiency among Coffee Farmers in Cô te d'Ivoire: Evidence from the Centre West Region	Cote d'Ivoire	Land; Age; Labours; Fertilizer; Tools	Production (Annual quantity of coffee produced)	In this paper, DEA techniques are used to measure technical efficiency for a sample of 81 peasant farmers. In a second step analysis, two-limit Tobit regression techniques were used to examine the relationship between TE and various farm/ farmer characteristics.
Nkamleu, 2004	Productivity Growth, Technical Progress and Efficiency Change in African Agriculture	African countries	Labours; Land; Fertilizer; Tractor.	Agricultural Production	In this paper, the relative performance of the agricultural sector was gauged using DEA from a panel data set of 16 countries, from 1970 to 2001. In addition, mathematical programming methods were used to measure Malmquist indexes of total factor productivity.
Lilienfeld and Asmild, 2007	Estimation of excess water use in irrigated agriculture: a data envelopment analysis approach	USA	Irrigation water; Labor; Capital; Seed; Fertilizer; Precipitation; AWS	Production output per crop	The purpose of this paper is to assess the impacts of irrigation system type on irrigation water use efficiency considering a sample of 43 irrigators in western Kansas, between 1992 and 1999.
Armagan, 2008	Determining the factors affecting efficiency scores in agriculture	Turkey	Labor; Capital; Value of variable input; Value of production units.	Gross production value	In this paper DEA is used to calculate the efficiency scores of agricultural enterprises in Turkey and then some determinants of efficiency are investigated.
Mihci and Mollaveligiu, 2011	An Assessment of Sustainable Agriculture In The OECD Countries With Special Reference To Turkey	Turkey	Labours; Land; Ferilizer; Machinery	Value of agricultural production; Food Security; Greenhouse Gas Emission.	The purpose of the paper is to measure and assess, in a comparative way, using DEA analysis, the efficiency of the Turkish agricultural sector with the OECD countries in the context of sustainability for the 1990–2005 periods.
Picazo-Tadeo et al., 2011	Assessing farming eco-efficiency: A Data Envelopment Analysis approach	Spain	Seeds, Nitrogen, Pesticides, Energy, Phosphorus	Sales, Coupled subsidies, Agri-environmental payments	This paper assesses farming eco-efficiency scores for a sample of Spanish farmers operating in the rain-fed agricultural system of Campos County, using Data Envelopment Analysis (DEA) techniques.
Lemonakis, 2015.	Application of data envelopment analysis and key characteristics of Greek agro-firms	Greece	Leverage; Capital; Fixed Assets	Total Sales; Gross Profit	The purpose of this study is to investigate key characteristics for the competitiveness in Greek agro-firms during the time period 2004 to 2011: at the first stage of analysis, DEA analysis is used to measure the efficiency score of the three separate types of Greek agricultural firms; at the second stage, EGLS regression is run to examine the relationships between Market Share (a proxy for firms' competitiveness) and DEA method's efficiency scores.
Kočišová, 2015	Application of the DEA on the measurement of efficiency in the EU countries	EU countries	Annual Work Units; Total Utilized Agricultural Area; Total Assets	Gross Output Crops and Crop Production; Total Output Livestock and Livestock Products	In this study the DEA model is used to analyze the technical efficiency of the agricultural sector in the European Union (EU) in the period 2007–2011.
Deng et al 2016	Provincial water use efficiency measurement and factor analysis in China: Based on SBM-DEA model	China	Labor; Capital; Water	GDP (desiderable); Sewage (undesiderable)	This paper adopts the undesirable slack based measure-data envelopment analysis (SBM-DEA) model to calculate water use efficiency of each province in China.
Masuda, 2016	Measuring eco-efficiency of wheat production in Japan: a combined application of life cycle assessment and data envelopment analysis	Japan	Global warming potential (GWP); Acquatic eutrophication potential (AEP)	Wheat yield	In this study, a combined methodology of LCA and DEA was used to measure eco-efficiency, which was defined as wheat yield per single environmental impact index.
He et al, 2018	The comprehensive environmental efficiency of socioeconomic sectors in China: An analysis based on a non-separable bad output SBM	China	Labour; Capital; Fertilizer; Energy use	Value Added (Desirable outputs); CO2 (Undesirable outputs)	The paper presents a comprehensive environmental efficiency index based on evaluating the environmental efficiency of major socioeconomic

(*continued on next page*)

Table 1 (*continued*)

Author(s) (Year)	Title	Area of study	Input Variables	Output Variables	Aims of the study
					sectors (agriculture, power, industry, residential and transportation) at a province level in China in 2010, based on a slack-based measure DEA model with non-separable bad output and weights determined by the coefficient of variation method.
Madau et al., 2017	Technical efficiency and total factor productivity changes in European dairy farm sectors	EU countries	Land area; Cows; Labour; Capital; Variable costs; Other fixed costs	Production (Annual quantity of milk produced)	This paper aims to evaluate, using the DEA model, the technical efficiency and the total factor productivity change of dairy farms in EU countries.
Toma et al., 2017	A non-parametric bootstrap-data envelopment analysis approach for environmental policy planning and management of agricultural efficiency in EU countries	EU countries	Labor; Land; Gross capital stock; Fertilizers; Irrigation area	Agricultural production value	The aim of this paper is to examine the agricultural efficiency of EU countries, through a bootstrap-Data Envelopment Analysis (DEA) approach.
Khoshroo et al., 2018	Improving energy efficiency considering reduction of CO2 emission of turnip production: A novel data envelopment analysis model with undesirable output approach	Iran	Human labor; Machinery; Diesel fuel; Feed; Fertilizer; Water for irrigation	Turnip Emissions	In this paper, the DEA model is designed to investigate the efficiency of turnip farms.
Li et al., 2018	Efficiency evaluation and improvement potential for the Chinese agricultural sector at the provincial level based on data envelopment analysis (DEA)	China	Chemical energy; Heat energy; Mechanical energy; Biological energy	Gross output value of Agriculture, forestry; Animal husbandry and fishery	In this study, indices for the overall technical efficiency (OTE) and energy-saving target ratio (ESTR) were developed, using data envelopment analysis (DEA) to calculate the relative efficiency and energy-saving potential of 30 provinces in China from 1997 to 2014.
Yang and Zhang, 2018	Assessing regional eco-efficiency from perspective of resources environmental and economic performance in China: A bootstrapping approach in global data envelopment analysis	China	Capital stock; Labor; Construction land area; Water consumption; Energy consumption	GDP; Solid waste emission; Household refuse; SO2 emission; Soot and industrial dust emission; Waste water emission	In this paper, using an extended DEA model, eco-efficiency from the perspective of resources, environmental and economic performance is estimated in China.
Bournaris et al., 2019	Efficiency of Vegetables Produced in Glasshouses: The Impact of Data Envelopment Analysis (DEA) in Land Management Decision Making	Peloponnese and Crete (Greece)	Acreage; crop protection costs; Fertilizers; Labor; Energy and Other costs	Turn over of each crop (€)	This paper, using Data Envelopment Analysis, measures operational efficiency of glasshouse farming, evaluating four different vegetables (cucumber, eggplant, pepper, and tomato).
Gatimbu et al., 2019	Environmental efficiency of small–scale tea processors in Kenya: an inverse data envelopment analysis (DEA) approach	Kenya	Green Leaf; Electricity; Firewood; Depreciation; Number of employees	Process waste; Level of GHG emission and wastewater	The study, adopting the DEA approach on panel data and Tobit regression, analyzed the environmental efficiency and its determinants of the small-scale tea processors in Kenya.
Ma et al., 2019	Technical efficiency analysis of the conversion of cropland to forestland program in Jiangxi, Shaanxi, and Sichuan	China	Land, Labor, Capital	Farmer Income	This study uses an input-oriented DEA model to examine farming operations following the implementation of the CCFP, by observing the technical efficiency of affected farmers in Jiangxi, Shaanxi, and Sichuan.

Table 2
Data used as Input and Output, their source, the time period, and the study area of this research (FADN stands for Farm Accountancy Data Network, RICA stands for Italian Farm Accountancy Data Network, ISTAT stands for Italian National Institute of Statistics).

Source of data	Code	Type	Data acquired	Time period	Study area
FADN	SE010	Input	Labor (1,000 Annual Working Unit – AWU)	From 2004 to 2017	Italian Regions
	SE441	Input	Gross Capital (€)		
	SE025	Input	Land (1,000 ha)		
	SE131	Output	Agricultural Production (€)		
RICA	–	Input	Total Irrigation Area (1,000 ha)		
ISTAT	–	Input	Fertilizer (tons)		

Table 3
Descriptive statistics.

		Inputs					Output
		Labor (AWU)	Land (1,000 ha)	Gross capital (1,000€)	Fetilizer (Ton)	Irrigation area (1,000 ha)	AgrProd Value (1,000€)
2004	Mean	1,367.14	16,964.76	280,175.67	2,004,593.57	5,293.67	49,363.52
	Std. Dev.	257.04	9,927.99	136,222.03	1,863,068.55	4,592.69	29,580.19
	Min	820.00	3,360.00	132,552.00	2,334.00	940.00	18,804.00
	Max	1,770.00	43,260.00	584,445.00	6,019,580.00	20,150.00	143,462.00
2005	Mean	1,354.29	18,191.90	307,065.38	1,857,798.29	5,623.81	49,119.62
	Std. Dev.	258.47	11,267.33	151,231.88	1,796,266.13	5,466.39	28,374.69
	Min	830.00	4,400.00	138,280.00	2,421.00	610.00	20,699.00
	Max	1,790.00	44,850.00	707,690.00	5,694,617.00	21,450.00	142,605.00
2006	Mean	1,377.14	18,770.48	310,439.38	1,820,394.05	5,364.48	50,489.43
	Std. Dev.	282.28	11,405.93	146,474.03	1,727,670.14	5,058.45	28,471.77
	Min	870.00	4,280.00	131,346.00	1,944.00	700.00	20,539.00
	Max	2,010.00	46,790.00	686,703.00	5,513,664.00	22,800.00	148,692.00
2007	Mean	1,355.71	16,114.29	306,959.38	1,916,068.52	5,282.43	57,357.57
	Std. Dev.	223.10	8,074.93	147,123.82	1,935,319.68	4,590.07	36,219.93
	Min	920.00	3,460.00	143,948.00	1,505.00	940.00	27,777.00
	Max	1,850.00	31,470.00	650,719.00	6,070,215.00	20,160.00	167,256.00
2008	Mean	1,351.90	16,063.33	283,242.81	1,620,353.00	5,540.48	50,234.76
	Std. Dev.	211.89	8,376.89	127,439.02	1,629,504.08	5,503.71	27,786.55
	Min	1,050.00	3,240.00	102,929.00	1,809.00	610.00	23,128.00
	Max	1,940.00	32,530.00	543,950.00	4,871,223.00	21,460.00	140,118.00
2009	Mean	1,307.62	17,866 19	295,949.43	1,242,734.00	5,401.90	50,808.81
	Std. Dev.	259.13	9,772.79	132,586.02	1,242,640.01	5,084.46	26,113.61
	Min	930.00	3,530.00	100,490.00	1,548.00	700.00	25,294.00
	Max	1,950.00	43,510.00	523,729.00	3,789,534.00	22,810.00	134,117.00
2010	Mean	1,277.62	16,953.81	296,386.57	1,263,331.52	5,334.76	50,735.00
	Std. Dev.	204.99	9,305.03	125,616.16	1,343,367.00	4,565.02	26,006.80
	Min	960.00	3,190.00	98,694.00	1,256.00	940.00	25,988.00
	Max	1,920.00	40,580.00	527,086.00	4,181,783.00	20,170.00	136,991.00
2011	Mean	1,299.52	16,980.95	316,101.00	1,331,536.90	5,337.14	53,585.86
	Std. Dev.	202.87	9,298.00	163,249.55	1,597,118.42	4,606.86	28,670.69
	Min	1,040.00	3,380.00	103,578.00	1,522.00	940.00	26,830.00
	Max	1,920.00	40,430.00	769,176.00	5,784,131.00	18,960.00	149,995.00
2012	Mean	1,341.90	17,468.10	332,197.90	1,465,855.90	5,337.14	60,351.95
	Std. Dev.	225.42	9,379.82	169,378.09	1,782,166.63	4,203.08	34,060.97
	Min	1,010.00	5,350.00	111,507.00	1,374.00	1,210.00	29,536.00
	Max	1,800.00	40,010.00	717,824.00	6,143,634.00	17,170.00	180,224.00
2013	Mean	1,330.48	17,682.86	327,501.90	1,115,819.67	5,370.95	58,617.00
	Std. Dev.	192.47	9,183.50	169,571.28	1,177,485.27	4,380.92	31,000.30
	Min	1,010.00	5,140.00	112,792.00	1,221.00	1,180.00	32,609.00
	Max	1,730.00	40,240.00	709,489.00	3,960,944.00	18,210.00	164,514.00
2014	Mean	1.350.00	21,114.76	313,575.81	1,132,653.57	7,445.24	71,459.90
	Std. Dev.	210.19	11,085.67	148,467.25	1,165,585.51	5,900.81	36,342.09
	Min	1,040.00	6,350.00	134,740.00	1,640.00	1,280.00	41,329.00
	Max	1,870.00	49,350.00	616,706.00	4,056,470.00	25,100.00	185,738.00
2015	Mean	1,336.19	21,219.52	302,265.57	1,146,450.90	7,693.81	68,068.00
	Std. Dev.	228.55	11,313.44	154,323.61	1,158,258.46	6,204.70	35,446.23
	Min	1,050.00	6,000.00	119,157.00	2,650.00	1,170.00	35,622.00
	Max	1,900.00	50,690.00	701,253.00	3,945,650.00	26,000.00	186,445.00
2016	Mean	1,300.48	21,497.14	304,424.43	1,270,209.67	6,896.67	68,902.62
	Std. Dev.	201.80	11,447.35	163,695.03	1,402,747.05	5,383.80	34,548.47
	Min	1,000.00	5,920.00	123,536.00	1,950.00	980.00	32,696.00
	Max	1,680.00	52,930.00	757,232.00	5,107,510.00	21,000.00	172,912.00
2017	Mean	1,363.33	21,421.90	299,629.38	1,249,108.43	6,904.29	68,561.81
	Std. Dev.	215.55	11,587.85	168,053.34	1,359,668.16	5,446.37	33,562.75
	Min	1,070.00	5,770.00	114,357.00	2,170.00	1,030.00	36,020.00
	Max	1,940.00	53,290.00	726,498.00	4,692,070.00	21,330.00	169,232.00

combination of the previous solutions.

The first DEA model was published in 1978 (Charnes et al., 1978) and it measured the efficiency of DMUs, in conditions of Constant Returns of Scale (CRS). Only around the 1980s a model able to consider in its formulation also the scale effects was introduced, which allowed for the evaluation of Variables Returns to Scale (VRS) (Banker et al., 1984).

Currently, DEA can be applied choosing between two different approaches: the output-oriented model or the input-oriented model. The first defines the ability of the DMU to reach the highest level of outputs from a given combination of inputs; the second, instead, defines the ability of DMU to use the least possible amount of inputs to obtain a given output (Reinhard et al., 2000).

In this paper both models (output-oriented/input-oriented) were applied assuming VRS.

For the calculation of the efficiency score we use the following Variable Return of Scale model (VRS):

$$\sum_{j-1}^{n} \lambda_j = 1$$

Where j is the number of observations of the DMUs. Each DMUj ($j = 1, 2, \ldots n$) uses m input $x_{i,j}$ ($i = 1, 2, \ldots m$) to produces s outputs $y_{r,j}$ ($r = 1, 2, \ldots s$). These n observations determined the efficient frontier. Where θ is the efficiency score for each DMU. Two properties guarantee that a piecewise linear approximation was developed to the efficient frontier and the area dominated by the frontier.

$$\sum_{j-1}^{n} \lambda_j xij \ \mathrm{i} = (1, 2, \cdots \mathrm{m}) \tag{1}$$

$$\sum_{j-1}^{n} \lambda_j \mathrm{yrj} \ \mathrm{r} = (1, 2, \cdots \mathrm{s}) \tag{2}$$

1) and 2) are the possible inputs and outputs achievable by the DMUj where $\lambda_j (j = 1, 2, ..n)$ are non-negative scalars that $\sum_j^n \lambda_j = 1$. The same $y_{r,j}$ can be obtained by using $\widehat{x_{ij}}$, where $\widehat{x_{ij}} \geq x_{i,j}$, and the same $x_{i,j}$ can be used to obtained $\widehat{y_{ij}}$, where $\widehat{y_{ij}} \geq y_{i,j}$. Moreover s_i^- and s_j^+ indicate input and output slacks. The efficiency target is:

$$\widehat{\mathrm{x}_{ij}} = \theta * \mathrm{x}_{io} - s_i^{-*} \ i = 1, 2, \cdots m$$

$$\widehat{\mathrm{y}_{ij}} = \mathrm{y}_{io} + s_j^{+*} \ r = 1, 2, \cdots s$$

If $\theta^* = 1$ then the DMU under evaluation is a frontier point.

If $\theta^* < 1$ in this condition the DMU is inefficient and must decrease its input level.

λ_j^* the non-zero optimal indicates the benchmark for a specific DMU under evaluation. The efficiency target shows how input can be decreased to make efficient the DMU under evaluation.

The VRS model is considered a common applied version of radial measure that is slack based (Tone, 2001, 2011). The directional distance function model provides the ability to project the DMU evaluated by appointing a vector in the Euclidean space. The principal advantage of this method is to highlight the direction of decreasing inputs and increasing outputs, besides including the undesirable outputs that are generated during the production process (Chambers et al., 1998).

In this study, we decided to use VRS for both input and output oriented model, because it results more appropriate in the agricultural sector (Toma et al., 2017, Bournaris et al., 2019). Table 3 reports the descriptive statistics of the variables used in the analysis. The estimation of the efficiency scores through DEA models was carried out using STATA 15 software (StataCorp, 2017 www.stata.com).

4. Results and discussion

The complexity of socio-ecological-economic systems needs to be captured by ecological-economic models, as complexity is an essential part of those systems (e.g. Levin et al., 1998; Limburg et al., 2002); else, political strategies failures can occur (Costanza, 1987). The input–output (IO) models are interesting because they can assess not only direct but also indirect results of policy tools (or ecosystem modifications) (Cordier et al., 2017).

Input-output modelling has often been used for the issue faced for a long time (Heijman and Schipper, 2010). The asset of the model is that in doing so it is possible to assess in a reliable way the impact of even relatively small sectors on the whole regional economy. Furthermore, it provides us with a standard way of computing that will allow for future evaluation of the socioeconomic development of agriculture.

The analysis starts with the calculation of the input-oriented efficiency scores of the Italian Regions. The closer the value of Efficiency Score to 1, the more efficient the Region is, which means that the Region is making the best use of resources to reach the fixed output level (input-oriented model) and at the same time is minimizing the environmental impact (Madaleno et al., 2016). The input orientation approach keeps the output fixed and investigates the possible average proportional reduction in the use of inputs. Therefore, this method can be considered more environmentally compatible (Reinhard et al., 2000). It is called the *resource saving approach* (Toma et al., 2017). Moreover, the results obtained with the application of variable return of scale model (VRS) show which Regions are more efficient than others. Any producing a DEA efficiency score lower than 1 indicates that the Region uses inputs inefficiently (Madaleno et al., 2016). In particular, we consider the following conditions of efficiency:

if $\theta^* = 1$ the Region under evaluation is a frontier point, so it is eco-efficient.

if $\theta^* < 1$ the Region is eco-inefficient.

The results of the input-oriented analysis summarized in Table 4 outline that during the period 2004–2017 the average score of the sample of the Italian Regions is around 0.97 under VRS assumption and this value indicates that the current value of outputs can be reached using approximately 0.03 fewer inputs.

Moreover, in the Table 4, we can see that Trentino Alto Adige, Valle d'Aosta, Calabria, Friuli, Liguria, Molise and Lombardia are the most efficient Italian Regions in term of natural and economic resource management, with a score equal to 1; on the other hand, the worst Italian Regions are Basilicata, Umbria, Toscana, Emilia Romagna, Lazio, Piemonte and Sardegna, which register a value less than 0.95 in terms of average input-oriented efficiency score. The latter denotes a lower ability to manage resources.

Table 4
Descriptive statistics of eco-efficiency: input-oriented scores (VRS model) for Italian Regions.

	Mean	SD	Change (%) (2004–2017)
Abruzzo	0.985	0.030	0.006
Alto Adige	1.000	0.000	0.000
Basilicata	0.937	0.068	0.002
Calabria	1.000	0.000	0.000
Campania	0.960	0.046	0.003
Emilia Romagna	0.884	0.055	0.005
Friuli	1.000	0.000	0.000
Lazio	0.916	0.045	0.001
Liguria	1.000	0.000	0.000
Lombardia	1.000	0.000	0.000
Marche	0.977	0.036	−0.002
Molise	1.000	0.000	0.000
Piemonte	0.913	0.058	0.000
Puglia	0.982	0.025	−0.001
Sardegna	0.946	0.072	0.002
Sicilia	0.998	0.008	0.000
Toscana	0.943	0.077	−0.004
Trentino	1.000	0.000	0.000
Umbria	0.944	0.042	0.003
Valle d'Aosta	1.000	0.000	0.000
Veneto	0.959	0.042	0.003
Italy	**0.969**	**0.015**	**0.002**

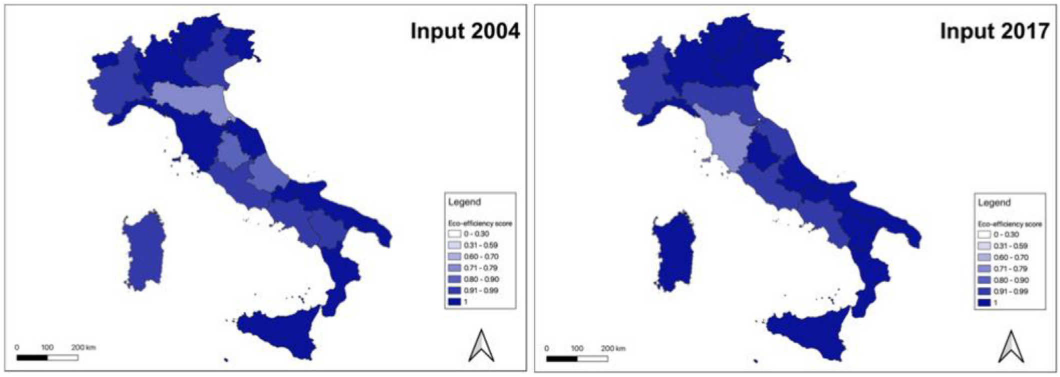

Fig. 1. Spatial distribution of eco-efficiency in Italian Regions in 2004 and in 2017: input-oriented perspective (if "Eco-efficiency score" = 1 the Region under evaluation is eco-efficient, if "Eco-efficiency score" < 1 the Region under evaluation is eco-inefficient).

The third column of Table 4 shows the change in the input-oriented efficiency score, calculated as the geometrical mean between the annual change rate in the period 2004–2017. This value indicates that during this period, the Italian agricultural sector performance remained mainly constant, indicating 0.002 value on average. In fact, the annual change of the input-oriented efficiency score for the majority of the Italian Regions shows a positive value with an annual average change value between 0 and 0.006; while there are only three exceptions with a negative value: Marche, Puglia and Toscana.

From these results it is possible to affirm that the eco-efficiency score in the input-oriented analysis does not show relevant changes during this period, but it is possible to notice that seven Regions have a value lower than 0.95, five of which are located in the North.

The spatial distribution of input-oriented efficiency score in the Italian Regions, shows that between 2004 and 2017 the Central Regions register the greatest relative improvements in terms of efficiency level (Fig. 1). Noteworthy is the variation regarding the Toscana score; in fact, although there has been a general progressive improvement in Italy, in Toscana, the level of eco-efficiency shows a significant decrease. Considering the long agricultural tradition and the importance that Toscana has in Italy in terms of quality agriculture (it is the fourth Region by number of DOP and IGP products), the result was unexpected.

From the results of the input-oriented analysis it is possible to underline that the number of eco-efficient Regions rose from 2004 to 2017, denoting a general improvement in resource saving ability, and therefore, a general reduction of environmental impact, denoting a more environmentally compatible behavior. The fact that it is possible to observe higher Eco-efficiency scores in the input-oriented model may be due to the fact that they are more "willing" to accept the environmental targets and make a greater engagement in advancing the economic and environmental goals (Madaleno et al., 2016).

As outlined above, the output-oriented model defines the ability of the different Regions to produce the highest level of outputs from a given combination of inputs. It is called *increasing productivity approach* (Toma et al., 2017).

Output-oriented scores of Italian Regions are summarized in Table 5. It shows an average value equal to 0.831 for the sample under VRS assumption, indicating that the current level of input serves to achieve on average the 0.831 of the output.

For the period considered we can see that the annual average eco-efficiency scores vary between a minimum of 0.745 to a maximum of 0.888. This result shows that most of the Italian Regions could make a better use of inputs, obtaining greater results and achieving production efficiency.

Alto Adige, Friuli Venezia Giulia, Liguria, Lombardia, Toscana, Trentino, Valle d'Aosta and Veneto are the most efficient Italian Regions in terms of maximizing profit, registering an average output-oriented score greater than 0.9. On the other hand, the Regions that have a lowest output-oriented efficiency scores are Umbria, Sardegna, Puglia, Molise and Basilicata that present values lower than 0.7.

Table 5
Descriptive statistics of eco-efficiency: output-oriented scores (VRS model) for Italian Regions.

	Mean	SD	Change (%) 2004–2017
Abruzzo	0.763	0.177	0.013
Alto Adige	1.000	0.000	0.000
Basilicata	0.604	0.085	0.005
Calabria	0.880	0.167	0.020
Campania	0.836	0.093	0.014
Emilia Romagna	0.790	0.089	−0.001
Friuli	0.988	0.044	−0.001
Lazio	0.748	0.098	0.013
Liguria	1.000	0.000	0.000
Lombardia	1.000	0.000	0.000
Marche	0.861	0.134	−0.008
Molise	0.690	0.129	0.011
Piemonte	0.818	0.106	−0.003
Puglia	0.546	0.058	0.010
Sardegna	0.655	0.121	−0.004
Sicilia	0.811	0.147	0.002
Toscana	0.960	0.057	−0.003
Trentino	0.990	0.035	−0.001
Umbria	0.599	0.167	−0.005
Valle d'Aosta	1.000	0.000	0.000
Veneto	0.914	0.054	0.004
Italy	**0.831**	**0.037**	**0.002**

Looking at the third column, the output–oriented score change, calculated as a geometrical means of the annual change rate between 2004 and 2017, remains quite constant. The average annual change of the output-oriented scores for the Italian Regions presents an overall positive trend 0.002. Noteworthy is the output-oriented score change for some Regions: Lazio, Calabria, Campania and Molise improved their eco-efficiency score during this period, registering a positive rate between 0.011 and 0.020. Moreover, we note some exceptions as Marche and Sardegna with a negative rate equal to 0.008 and 0.004 respectively.

Looking at Fig. 2, the eco-efficiency gap between North and South is evident from the output perspective. These results, showing a greater ability of the northern Regions to obtain higher level of outputs given a certain level of inputs, underline the strong *productivity orientation* that characterizes northern Italian companies. Thanks to their larger size, they can optimize the available resources leveraging economies of scale. In fact, as specified in the second paragraph, the farms in the North of Italy produce more than 50% of the national agricultural value although they are about half of those in the South.

However, comparing 2004 to 2017 there is a significant general improvement that ends up reducing the gap between the northern and

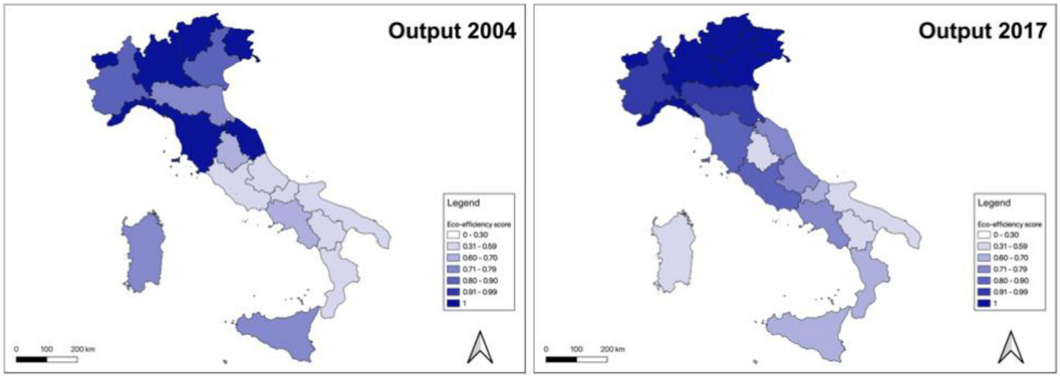

Fig. 2. Spatial distribution of eco-efficiency in Italian Regions in 2004 and in 2017: output-oriented perspective (if "Eco-efficiency score"= 1 the Region under evaluation is eco-efficient, if "Eco-efficiency score"<1 the Region under evaluation is eco-inefficient).

southern Regions. Only Marche, Sardegna, Sicilia and Toscana worsened their score in 2017.

From the output perspective, the most eco-efficient Regions (Alto Adige, Friuli Venezia Giulia, Liguria, Lombardia, Toscana, Trentino, Valle d'Aosta and Veneto) are characterized by almost constant average rates of change over the considered period, in line with the general trend.

The results obtained comparing input and output oriented eco-efficiency trends (Fig. 3), allow us to make different remarks considering the optimal management capacity of resources to obtain a given profit (input-oriented perspective) or considering the capacity to maximize profits, given a certain level of available resources (output-oriented perspective) (Fig. 3). Considering the input-oriented model, there was an overall improvement in the conscious use of natural resources, which results in a reduction in environmental impacts, an increase of the value of ecosystem services and the maintenance of economic results. The trendline (Input) shows this positive trend for the period analyzed. However, the highest value recorded in 2017 was equal to 0.981.

Considering the output-oriented model, the results are very different. Although there was a general improvement in the ability to maximize production with available resources, as represented from trendline (output), the output-oriented score was characterized by a great variability. In particular, at the beginning of the analysis period the score was 0.778, indicating that output could be increased on average by the 0.221. In 2008 it presents the lowest value, in fact, is being equal to 0.745 representing the year where is maximized the distance from the frontier, equal to 0.255. In addition, in 2017 there was a score equal to 0.80 indicating that Italian Regions still have great margins for improving their output score.

The results show that the Italian Regions still have great margins for improving their output eco-efficiency score compared to their input score.

The most relevant result of the analysis is summarized in Table 6. Considering the average of the input-oriented score for Italian geographical areas, the situation appears to be homogeneous, denoting a general orientation towards the protection of resources with a view to the preservation of resources. The Regions of southern Italy, despite having significantly lower production than in central and northern Italy, show a better orientation towards sustainability and the efficient use of economic and environmental resources.

These results are of interest to policymakers for detecting the most environmental friendly practices in order to allow for the optimization

Table 6
Average of output- and input- oriented score for Italian geographical areas.[1]

	INPUT-ORIENTED	OUTPUT-ORIENTED
NORTH	0.973	0.849
CENTER	0.946	0.793
SOUTH	0.975	0.706

[1]According to the ISTAT classification, the North includes: Liguria, Lombardia, Piemonte, Valle d'Aosta, Emilia-Romagna, Friuli-Venezia Giulia, Trentino-Alto Adige, Veneto. The Center includes: Lazio, Marche, Toscana, Umbria. The South includes: Abruzzo, Basilicata, Calabria, Campania, Molise, Puglia, Sardegna, Sicilia.

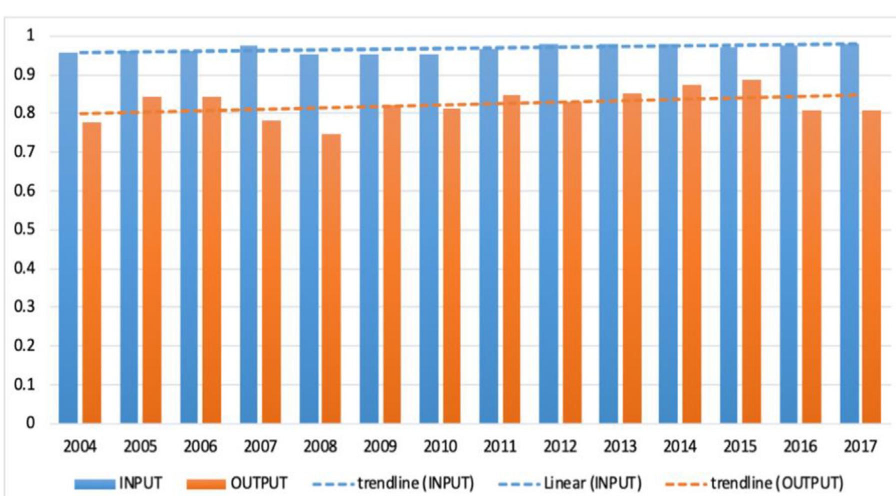

Fig. 3. Comparison of input and output-oriented eco-efficiency trends in Italy.

of agricultural resources. In this context, the southern and the northern Regions, show a good attitude of saving resources and for this they are environmental-friendly.

On the other hand, considering the average of the output-oriented score for Italian geographical areas, the Italian situation is very fragmented. The Regions of northern Italy, being able to take advantage of economies of scale, are, on average, closer to the frontier of eco-efficiency, denoting a good ability to maximize production given a certain level of input. On the other hand, the Regions of southern Italy, also due to the smaller size of the farms, which does not allow for the exploitation of economies of scale, still have important margins for improvement in performance.

In northern Italy there is a strong focus on productivity and a good attitude of saving resources; in the South there is a good capacity for sustainable resource management, but a lack of productivity orientation; in central Italy there is less orientation towards sustainability, with the possibility of further improving productivity.

5. Conclusions

Taking into account that ecosystem degradation represents one of the three principal environmental pressures due to economic development, in addition to resource consumption and pollution (Pang et al., 2019), agricultural eco-efficiency is a useful index in achieving sustainable development that combines the increase in economic results with the reduction of the consumption of natural resources and environmental impacts. The ecological and economic evaluations seen in this paper provide a basis for the improvement of agricultural ecological environmental function, helping decision makers formulate land planning and sustainable land use. The results show a better orientation towards saving resources for the southern Regions and a greater orientation towards productivity for the northern Regions, so that, if an area can reach a given level of output with lower input then there can be supposed to be achieve a sustainable development of agriculture sector (Caiado et al., 2017). These results reflect the more general socio-economic trend of the Italian areas studied: the South has always shown a tendency to save, having to face a certain scarcity of economic and natural resources, while the “rich” northern Italy was able to focus more on maximizing production (Lagravinese, 2015).

Overall, the Italian situation appears to be in line with the objectives of sustainability and efficient management of resources set by the CAP, although there is still room for improvement. In this regard, the measurement of eco-efficiency provides a useful index for policy makers to develop policies focused on achieving better performance (Kuosmanen and Kortelainen, 2005). Currently, the allocation of CAP funds takes place based on the utilized agricultural area (UAA) of each state, favoring states with large agricultural surfaces, albeit with little economic value, and leaving states, including Italy, characterized by Mediterranean agriculture at a disadvantage Therefore, although Italy represents the richest showcase in Europe in the agricultural sector, with production attentive to the quality of the product and its relationship with the territory, it is at an economic disadvantage due to the criteria used for allocating funds.

One conservative alternative to achieving more eco-efficient performance could be to condition payments to the implementation of more ecologically friendly practices or technologies or to reassign agricultural subsidies to farmers so that they are directly dependent on the provision of environmental public goods (Cooper et al., 2009). This means that CAP subsidies should be granted in exchange for specific environmental externalities provided by farmers as a result of more ecologically friendly management (Gómez-Limón et al., 2012). This because efficient land use, as well as rational land use, planning avoiding depleting ES rich areas, allows for the achievement of a balance between economic growth and ecosystem protection. The ES loss should not be neglected when pursuing true ecological sustainability, as this is an essential factor to consider in order to quantify the overall ecological costs of agricultural activities throughout the whole economic life cycle.

Although the paper has expanded the literature on agricultural eco-efficiency, this work has some limitations that could serve as a reference for future studies that could include other ecological variables such as the provision of some ecosystem services that can be enhanced or impacted by agricultural development. In addition, the DEA methodology, which provides relative eco-efficiency scores, could be associated with the Life Cycle (LC) method for sectorial intra and inter-assessment within any specific crop (Lozano et al., 2010). Finally, the challenge to realize a sustainable agriculture can represent a long-term guarantee of food security as well as societal well-being.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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