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The environmental impact of agriculture: An instrument to support public policy

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ABSTRACT

Agriculture is a key activity in guarantying food security, one of the Sustainable Development Goals set by the UN Agenda 2030 for sustainable development. However, agriculture can be an environmental impacting activity when it is managed without attention towards its environmental efficiency. Thus, the assessment of eco-efficiency in agriculture is a crucial tool to evaluate this economic activity in terms of both natural resources exploitation and revenue generation. To address the complex issues associated with this problematic trade-off, the application of a Data Envelopment Analysis (DEA) has been to assess the environmental and economic performance of agriculture in terms of eco-efficiency. DEA has been applied the Italian case study at regional level, to provide policy-makers with a synthetic indicator of agricultural sustainability, when implementing funding policies. In particular, the analysis of the case study has taken into account the implementation of the European Common Agricultural Policy (CAP), as implemented through the Rural Development Plans. Our approach is a first step in the direction of assessing the long-lasting issue of developing benchmarking policies between the different Italian regions. This works paves the way to future and more in-depth studies needed to determine the eco-efficiency at local scale and, thus, the possibility to identify specific forms of agriculture as nature-based solutions.

1. Introduction

Agriculture is the productive sector that secures the largest portion of food supply, a crucial ecosystem service for the human well-being.. In addition, agriculture is important to guarantee food security, therefore, it underpins Sustainable Development Goal (SDG) 2 (SDG 2 - Zero Hunger) but also other SDGs set in the UN Agenda 2030 for Sustainable Development. Agricultural systems can be seen as social-ecological systems, providing vital ecosystem services (Mace et al., 2012). In addition, they are strongly influenced both by natural processes and by human dynamics, being complex semi-natural systems, (Garbach et al., 2014; Swinton et al., 2007). They also provide a wide range of ecosystem services, such as (Power, 2010; Naumann et al., 2013; Smith et al., 2013; Liu et al., 2019, Marinelli et al., 2021): maintenance of soil health, CO_2 absorption, regulation of water flow, enhancement of biodiversity. If well-managed, agricultural systems can increase the resilience of landscapes to adapt to climate change and environmental disturbances, maintaining food production, and improving human health and well-being (Felipe-Lucia et al., 2020).

So that, sustainable management of agroecosystems can conserve and promote key ecosystem functions and services that can ensure the delivery of multiple benefits to society and the natural environment, as well as reducing the environmental footprint of agricultural production activities (Doswald et al., 2014; MEA, 2005).

It has long been recognized that sustainable agriculture is based on the integration of natural capital into the dynamics of food production (Pretty, 2008). While considering this integration, an economic process, nonetheless, recognizes environmental costs as negative externalities,

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consequently not integrating them as part of market prices (Jauker and Diekötter, 2022).

In the years, many ways have been paved toward the clarification of the relationship between economic performance and environmental sustainability, aiming at the preservation of natural resources, objectives of a correct land management and a fair level of food security. In this way, the agricultural sector is closely associated with the concept of eco-efficiency. According to the World Business Council for Sustainable Development (WBCSD, 2006) the main objective of eco-efficiency is to provide goods and services at competitive prices by improving people's lifestyle and reducing environmental impacts.

In a context of intense economic and demographic development with a consequent increase in human activities, agroecosystems have been affected by profound changes (Shen et al., 2020; Xu et al., 2021), to increase their agricultural productivity. In fact, it is believed that the fast production of food and fibres is one of the main causes of environmental degradation (Kopittke et al., 2019). However, assuring such increase under highly changing environmental conditions and without affecting environmental resources is a key challenge (Islam et al., 2022).

The agricultural sector, having the duty of providing subsistence to the population with the production of essential goods, must try to minimize the damage that feeding the world can cause to the environment. Indeed, Caiado et al. (2017) shows that the concept of eco-efficiency is more frequently applied in the agricultural sector than any other. Agricultural eco-efficiency is promoted as a means of increasing primary production and improving food security (Jansen, 2003). Although profits have always motivated the agricultural industry's pursuit of efficiency (Keating et al., 2010), the combination of dramatic growth of the world population and the negative externalities associated with industrialization have made sustainability and environmental preservation a central emergency for the entire world. To address the complex issues associated with this problematic trade off, a Data Envelopment analysis (DEA) is the most commonly approach to investigate the eco-efficiency (Lahouel, 2016; Zhou et al., 2018). In a context of "scarce" resources such as that of government resources, it is necessary to provide a set of parameters capable of allocating resources efficiently, thanks to the score provided by the DEA methodology (Zhang et al., 2019). Therefore, in the perspective of the European Common Agricultural Policy (CAP) implementation, aimed at pursuing the integration of environmental concerns into agricultural practices (Rybaczewska-Błażejowska and Gierulski, 2018), the aim of the present study is to assess the environmental and economic performance of agriculture in terms of eco-efficiency at regional level in Italy. As an active promoter of European Common Agricultural Policy, Italy deems agriculture a vital sector for the national economic backbone, while recognizing its environmental consequences. Italy's economy is known as one of the most relevant contributors to the agricultural system of the EU, producing nearly 20 % of the added value generated (ISTAT, 2019). Italy's efforts in improving its own environmental performance can be collated into different indicators. This includes the presence of a considerable number of products endowed with quality marks (PDOs, TGIs, or TGS – eAmbrosia, 2021), an increasing number of organic farming producers (FiBL, 2021) and a growing interest of consumers toward the purchase of sustainable agriculture products (Nomisma, 2021).

To this end, we propose different efficiency scores in order to capture the multi-faceted aspects of the case study at hand. Specifically, we perform a two-steps investigation. In the first step, we assess the level of eco-efficiency of each region in a comprehensive sense, i.e. by accounting for all environmental factors at once. The purpose of the second step, instead, is to evaluate separately the effect of each single environmental factor on the overall efficiency score of each region. A quantitative analysis applying a DEA methodology is used to assess the impact of economic performance using the inputs and outputs on of the agricultural regions of Italy in 2017.

The unique contribution of this paper is in identifying possible eco-efficiency mismatches across the Italian Regions, including measures of eco-efficiency and environmental pressures such as Water pressure, Fertilizer pressure and Energy pressure. The results are used to create a parameter to be used as a landmark in the implementation of public policies in the agricultural sector.

The remainder of the paper is as follows: the theoretical framework follows this introductory section. A methodological section appears next, followed by an empirical analysis, the report of empirical results, and a brief contemporary analysis of the Italian agricultural system. A final section concludes the study, with a focus on the implications, limits and ways forward for the future research.

2. Defining the framework

The concept of "eco-efficiency" was initially developed as a measure reflecting the sustainability of the economic activities (Bleischwitz, 2003). Over time this concept has received remarkable attention in the sustainable agriculture literature, because it was considered an effective indicator to provide scientifically based directives for policy development, program, public finance management, and decision making (Huppes and Ishikawa, 2005). It has been applied within the literature at three different levels: the macro-economic level (national economy), the *meso*-economic level (region), and the micro-economic level (company) (Mickwitz et al., 2006). Also, different methodologies have been deployed for measuring these levels. Firstly, in the ratio approach eco-efficiency is expressed relating either the product system value to either its environmental impacts or the environmental impacts of a product system to the value of a product system (Huppes et al., 2007; WBCSD, 2000).

This approach has some limitations, however, as it can be applied only in one of two ways: either as a partial approach where the performances are evaluated using a single input, or as an integrated approach where the eco-efficiency assessment accounts for all the inputs used simultaneously, including their links and combinations. The aggregation of different inputs is based, however, on a subjective weighting scheme (Zhang et al., 2008). Even specialists are unable to reach a consensus about the proper weights to use. This lack of consensus motivated an alternative frontier approach using Data Envelopment Analysis (DEA), which has gained support as an appropriate instrument for quantifying eco-efficiency (Zhang et al., 2008; Rybaczewska-Błażejowska and Masternak-Janus, 2018).

The DEA approach has been most commonly applied in literature to assess eco-efficiency (Korhonen and Luptacik, 2004; Kuosmanen and Kortelainen, 2005; Zhang et al., 2008). Relatively few of these studies have approached the analysis of farming eco-efficiency using DEA analysis (De Koeijer et al., 2002; Picazo-Tadeo et al., 2011; Masuda, 2016), despite the ability of this model to incorporate input and output of both an economic and environmental nature. These characteristics makes the DEA approach particularly useful in the field of study of performance assessment, where the focus is not on the estimation of an average technology production function used by all units analyzed, but on the identification of the best practicing units. The DEA method can be used to construct a best practice production frontier, where all units of analysis are related to this frontier (Cooper et al., 2007).

The DEA methodology has been used to evaluate the overall efficiency across agricultural sectors and across geographical areas (Gocht and Balcombe, 2006; Lemonakis, 2015), with most studies focused on China (He et al., 2018; Li et al., 2018; Deng et al., 2016). Most of these studies have been carried out on single crops or production processes and performed at the farm level (Bournaris et al., 2019; Oluwatayo and Adedeji, 2019; Gatimbu et al., 2020). Furthermore, recent empirical studies have used the DEA to compare the performance of states with different agricultural policies (Kocisova, 2015; Toma et al., 2017). In a recent article, Coluccia et al. (2020) evaluate the eco-efficiency index of the Italian agricultural sector using both economic and environmental input variables, emphasizing the differences that exist between different geographical areas. The aim of this paper is to calculate the regional eco-efficiency of Italian agricultural enterprises, focusing attention on water and energy overuse, as well as the use of chemical fertilizers. Starting from the development of environmental indicators and the subsequent use of Data Envelopment Analysis (DEA), our results will allow to answer to the following questions:

- In which regions do agricultural enterprises show a higher level of eco-efficiency?
- What is the resource used least efficiently in Italian agriculture?

The insights gained by answering these questions may contribute to improve the design and implementation of public policies aimed at improving governance in the agricultural sector.

3. The empirical analysis

3.1. Methodology

In this study we adopt a DEA methodology to evaluate the eco-efficiency level for all Italian regions. Estimation of eco-efficiency can be obtained using appropriate ratios, such as dividing specified outputs by relevant inputs. Recently, different combinations of environmental pressures were considered as inputs to determine the possible effects that input substitutions that may have on business performance, using the value added as the output (Godoy-Durán et al., 2017). Therefore, according to Kortelainen and Kousmanen (2007) the eco-efficiency level improves when the environmental pressures decrease and the economic output remains constant, or when the economic output increases as environmental pressures decrease.

The computation of this indicator could be obtained through different methodologies (Tyteca, 1996), but in general, all methodologies consider the existence of an eco-efficient frontier that represents the best possible practice for a given level of technology. Briefly, we can subdivide these approaches in two groups, namely (i) parametric approaches characterized by the assumption of a specific functional form for the level of technology (Karagiannis and Sarris, 2005; Cuesta et al., 2009; Yang et al., 2017), and (ii) non parametric approaches using a data envelopment analysis (DEA) (Cooper et al. 2007; Picazo- Tadeo et al.,2011; Villanueva et al., 2014; Robaina-Alves et al., 2015; Liu et al. 2020).

In this study, we adopt the DEA non-parametric approach to estimate eco-efficiency through different scores. Through a multifactor productivity analysis, this methodology can provide the relative efficiency of a homogeneous set of Decision Making Unit (DMU) (Tone, 2004). Using this methodology, it is possible to calculate the relative distance from the eco-efficient frontier for each Decision Making Unit (DMU) in the considered sample. In the following analysis, the obtained efficiency scores are in the interval [0,1] by definition. In fact, the DEA method does not provide a measure of absolute efficiency, but a relative efficiency in the given sample. As mentioned previously, the eco-efficiency level improves on decreasing environmental pressures and constant or increasing economic output, where the efficiency score of each DMU is determined by following this criterion. For this reason, each Decision-Making unit (DMU) can be evaluated as efficient or inefficient by measuring its distance from a technological frontier estimated from the best practices observed.

This study adopts an economic-environmental score at the Italian regional level (Costantini et al., 2013, Zeng et al., 2017) to determine which regions are the most eco-efficient. Assuming that the economic indicator in the analysis is the value added v_k for each region $k = 1, \cdots, K$, which generates a series $p_k = (p_{1k}, \cdots, p_{Nk})$ of N environmental pressures for each Region $k = 1, \cdots, K$, we can define the PGT (pressure generating technology) as the set of all attainable pairs of value added and corresponding environmental pressures.

$$PGT = \left\{(v,p) \in R^{1+N} \,|addedvaluev \in \mathbb{R}canbegeneratedwithapressurep \in \mathbb{R}^N\right\}$$

Having defined the technology, the next step is to determine a formula for the eco-efficiency level for each DMU (region):

$$Eco - Efficiency_k = v_k / P_{(pk)}$$

where $P_{(pk)}$ is a function that aggregates the n environmental pressures of the k-th region in one single value. The most common choice for $P_{(pk)}$ is the following:

$$P_{(pk)} = \sum_{n=1}^{N} w_n p_{nk}$$

i.e. a convex linear combination of individual environmental pressures, where the w_n are suitable non-negative weights to be determined via a constrained linear program, described as follows. By applying the DEA methodology in constant returns to scale (CRS) form (Charnes et al., 1978), the Eco-efficiency level for the k-th Region is computed as follows:

$$Eco - Efficiency_k = \max_{w_1,\cdots,w_N} \frac{v_k}{\sum_{n=1}^{N} w_n p_{nk}}$$

subject to:

$$\frac{v_j}{\sum_{n=1}^{N} w_n p_{nj}} \le 1 \;\; \forall j = 1, \cdots, K$$

$$w_n \ge 0 \forall n = 1, \cdots, N$$

If $Eco - Efficiency_k = 1$, the k-th region is a frontier point, in this case it is eco-efficient.

If $Eco - Efficiency_k < 1$, the k-th region is eco-inefficient.

The above model, proposed by Charnes et al. (1978), is widely used in the literature and is comparable to the work of others (Kuosmanen and Kortelainen, 2005; Galdeano-Gómez et al., 2006; Rodríguez-Rodríguez et al., 2012). These studies are deemed optimal for the computation of eco-efficiency levels in the present work. In fact, the main feature of Charnes's model is that of being of CRS type, as opposed to variable returns to scale (VRS) models. The difference is that, in CRS models the total amount of attainable outputs will change proportionally with the inputs. Thanks to the input-oriented approach, we can estimate the ability of each DMU to obtain a certain quantity of output, using the lowest possible amount of inputs (Reinhard et al., 2000). It is worth remarking that in a non-parametric approach it is necessary to specify a minimal set of axioms to uniquely determine the estimated attainable set from the observed DMUs without any specified functional form. For instance, in (Kuosmanen and Kortelainen, 2005), such minimal set of assumptions includes convexity and disposability of inputs and outputs. Here, the uniqueness of the estimated attainable set is ensured by the CRS assumption. Such a minimal set of assumptions must be chosen carefully to mirror the economic features of the case study at hand. It is worth remarking that, for the special case of single input ($N = 1$), the considered efficiency score boils down to the ratio $\frac{v_k}{p_k}$ between the output v_k and the input (pressure) p_k. We close this section by noting that, in the adopted measure of eco efficiency, the heterogeneity in units in environmental pressures is taken care of by the weights p_{nj}, resulting in a non-dimensional eco-efficiency score.

3.2. Case study: Agricultural sector in Italian regions

Italy represents the first European country for added value generated by agriculture which is considered a key economic sector (Coluccia et al., 2020). However, there are significant imbalances in the level of value-added agricultural output across the different geographical areas of Italy. For example, although the number of farms in the North of Italy are about half of those in the South, the northern farms produce more than half of the national agricultural value. Moreover, Italy is characterized by a great variety of food crops as a result of the highly varied morphology across the territory, the variety of climatic situations, and a strong value of local cultural identity associated with certain agricultural products (Brundu et al., 2017).

Italian agriculture has progressively advanced over time. This can be partly attributed to the application of corporate restructuring strategies and to the use of intensive cultivation techniques, which have caused significant damage to the environment. For example, 47.5 million quintals of fertilizers are distributed on Italian soil yearly. Nearly half of all freshwater consumption of agriculture depends on irrigation, and the agricultural sector represents around 7 % of national greenhouse gas emissions (ISTAT, 2019).

The latter phenomenon refers to land take which is linked to settlement and infrastructural dynamics and is mainly due to the construction of new buildings and settlements, to the expansion of cities, and, in general, to the infrastructure of the territory. Intensive agriculture is then closely linked to soil degradation, which is a phenomenon of alteration of soil conditions due to the reduction or loss of biological or economic productivity mainly due to human activity (Oldeman et al., 1990). Potential processes underlying land degradation include intensification of croplands, leading to soil erosion and salinization (Gisladottir and Stocking, 2005; Cowie et al., 2018).

Therefore, considering the strategic importance of the Italian agriculture in the international scene, as well as the environmental impacts that its activities are causing on the territory, there is the need to use scientific and institutional information to identify an optimal political strategy that can combine environmental and economic performance of Italy's agricultural production.

3.3. Variables selection

As explained in the methodology section, the study of eco-efficiency requires the elaboration of ratios which relate economic output to various environmental pressure indicators. The variables needed to compute the eco-efficiency scores have been acquired from the Farm Accountancy Data Network (FADN) database by the Agricultural and Rural General Directorate (ARGD) (Table 1). The latter data appear as individual units, both technically and economically, operating under single management and which undertake agricultural activities within the economic territory of the European Union. This study is based on the available data from the year 2017 for the Italian regions, however Valle D'Aosta and Liguria are the only Italian regions not included in the analysis, due to the lack of data. The values of the variables are averages between the local farmers within each region, weighted according to firm size. Consequently, the computed region-wise efficiency scores coincide with the values that would be obtained by aggregating all firms. Large sized farms are included in the FADN sample, as they can be considered commercial operations and are required to keep specific accounting data. The FADN Public Database provides this value at the regional level.

As economic component, a net income per hectare at regional level (i_k), has been considered and calculated using the following formula:

$$i_k = \frac{Net\,farm\,value\ added_k}{Land\,area_k} \tag{1}$$

Table 1
Source of Data.

Source of data	Type	Data acquired	Area of study
FADN	Output	Net Farm value added	Italian regions
	Input	Fertilizers	
	Input	Energy	
ARGD	Input	Total Irrigation Area	

where *Net farm added values* have been measured in Euros and are obtained by deducting total intermediate consumption (farm-specific costs and overheads) and depreciation from total farm receipts (including both total output and public support). For each region, the resulting operating income is measured per unit of surface area and is expressed in Eur/ha.

As for environmental aspects, these have been estimated using three environmental pressures: the use of water resources, the use of fertilizers, and energy consumption (Rennes et al., 2020; Zhang et al., 2021).

The use of water resources has been measured using a proxy given by Water used per unit of irrigation area (p_1), measured in m^3/ha.

$$p_1 = Irrigation\,area = \frac{Water\ used_k}{Land\,area_k}. \tag{2}$$

The use of fertilizers (p_2) has been estimated by considering the total quantity of fertilizers purchased by each farm per hectare of crop (ton/ha).

$$p_2 = Use\,of\,fertilizers = \frac{Fertilizers_k}{Land\,area_k}. \tag{3}$$

Finally, Energy consumption per hectare of crop (p_3) has been used as a proxy of greenhouse gases (GHG) emissions (Gómez-Limón et al., 2012).

$$p_3 = Energy\,consumption = \frac{Energy_k}{Land\,area_k}. \tag{4}$$

This variable, as expressed in €/ha, includes not only electricity consumption but also motor fuels, lubricant, and heating fuels costs per hectare of cropland.

The framework has been divided in a two-step DEA analysis specifically devised to assess the impact of each natural resource on the eco-efficiency scores.

1) The eco-efficiency measure has been computed as introduced in Section 3.1 with $N = 3$, by including all three environmental pressures.

Second, three different eco-efficiency scores with $N = 1$ have been computed, by separately considering each of the three environmental pressures for each score. The descriptive statistics of the sample are summarized in Table 2.

4. Results and discussion

The nationally aggregated scores for eco-efficiency are reported in Table 3 The first column shows the comprehensive eco-efficiency scores that account for all three environmental pressures together (N = 3, Step 1 of the analysis), while in the other columns the eco-efficiencies based on each of the three singular pressure scores are reported (N = 1, Step 2 of the analysis).

From the results we can affirm that the Italian regions produce with an average eco-inefficiency margin equal to 42 %, as the average eco-efficiency score is 0.58. This value indicates that the environmental pressures could be reduced to 0.42 while maintaining the same level of value added. The other columns of Table 3 report the average score of eco-efficiency for each environmental pressure, which underlines the

Table 2
Estimate values of the economic output and environmental pressures.

	Economic output	Irrigation area	Use of fertilizers	Energy ratio
Mean	2,392.39	6,904.29	198.33	241.31
Std. Dev.	1,632.82	5,446.37	239.50	130.56
Min	5,79.63	1,030.00	3.30	67.39
Max	7,575.04	21,330.00	1,178.68	696.01

Table 3
Nationally aggregated scores of eco-efficiency.

	Eco-efficiency(p_1, p_2,p_3)	*Eco-efficiency* (p_1)	*Eco-efficiency* (p_2)	*Eco-efficiency* (p_3)
Mean	0.58	0.31	0.35	0.53
Std. Dev.	0.202	0.273	0.174	0.144
Min	0.39	0.06	0.21	0.39
Max	1.00	1.00	1.0	1.00

gross margin of improvement in the use of natural resources to preserve the environment and ensure a sustainable production. The results are in lines with other studies, which show an important overuse of water resources in the agricultural sectors of other countries (Garcia-Herrero et al., 2018). In the agricultural production process, the ability to use water resources in a sustainable manner can certainly represent a fundamental factor in the balance of water resources globally, as well as in food security (Lu et al., 2022).

The environmental pressure related to phytosanitary products reveals that strong margins of improvement exist, while avoiding a reduction in economic input. The average eco-efficiency score at national level is low (0.35), underling the need to better focus the research towards the identification of alternative fertilizations systems more sustainable. In general, the increasing agricultural intensification, with the consequent increase in the use of fertilizers and pesticides, for example, but also the progressive reduction of crop diversity, can determine serious consequences at the landscape level in terms of loss of the ecosystem services provided, such as the reduction of pollinator diversity and therefore related pollination services in a wide range of agricultural crops (Kennedy et al., 2013; Bartomeus et al., 2014; Connelly et al., 2015; Marinelli et al., 2021; Marinelli et al., 2023).

Finally, the third environmental pressure of energy consumption, used as a proxy for GHG emissions, shows an average level of eco-efficiency equal to 0.53. Energy consumption has increased due to the wide-spread adoption of technology in the Italian agricultural sector, increasing the demand for energy. This highlights the importance of saving energy and reducing GHG emissions as in other economic sectors such as transport and manufacturing (Chen et al., 2020). These results underline the key role played by agriculture in environmental sustainability, also in terms of climate change mitigation, as it contributes significantly to greenhouse gas emissions (Blandford et al., 2014).

The results about eco-efficiency scores at regional scale are shown in Table 4 for both steps of the analysis (i.e. N = 3 and N = 1, respectively).

These results, obtained with the application of constant return of scale model (CRS), provide some information about the eco-efficiency performances, making it possible to (i) compare the regions, as well as (ii) to determine which environmental pressures are more critical for each region.

The eco-efficiency condition, which is attained when a DMU (Decision-Making Unit) has an eco-efficient score equal to 1, implies that the DMU under evaluation is a frontier point. On the other hand, if the DMU's eco-efficiency score is lower than 1, then the DMU is eco-inefficient.

Table 4 reveals that the best eco-efficient Italian Regions are Alto Adige, Trentino, and Calabria when all the three pressures are analyzed together (eco-efficiency score equal to 1). On the other hand, the worst Italian Region with an eco-efficiency score lower than 0.46 are Umbria, Puglia, Molise, Marche, and Lazio.

For what concerns the average eco-efficiency score for each environmental pressure, it is possible to notice that most regions register low eco-efficiency scores related to water consumption with the exception of Trentino and Calabria, probably for their high availability of water at regional level. This confirms the relevance of the management of water resources in the agricultural sector (Laureti et al., 2021). It is important to notice, however, that water consumption is strongly dependent on

Table 4
Region-wise scores of eco-efficiency.

	Eco-efficiency (p_1,p_2,p_3)	*Eco-efficiency* (p_1)	*Eco-efficiency* (p_2)	*Eco-efficiency* (p_3)
Abruzzo	0.529	0.375	0.316	0.453
Alto Adige	1	0.624	1	1
Basilicata	0.471	0.146	0.255	0.471
Calabria	1	0.913	0.369	0.662
Campania	0.693	0.512	0.377	0.492
Emilia-Romagna	0.524	0.091	0.210	0.524
Friuli-Venezia Giulia	0.538	0.147	0.243	0.538
Lazio	0.420	0.200	0.345	0.420
Lombardia	0.523	0.091	0.445	0.523
Marche	0.398	0.234	0.223	0.398
Molise	0.387	0.176	0.257	0.387
Piemonte	0.529	0.111	0.251	0.529
Puglia	0.448	0.219	0.264	0.442
Sardegna	0.464	0.063	0.412	0.464
Sicilia	0.486	0.298	0.247	0.486
Toscana	0.540	0.388	0.300	0.477
Trentino	1	1	0.270	0.705
Umbria	0.393	0.088	0.370	0.395
Veneto	0.632	0.208	0.455	0.632
Italy	0.58	0.31	0.35	0.53

climate conditions, so that southern regions with a Mediterranean climate, characterized by long dry seasons and short rainy seasons, can affect this indicator (Giuditta et al., 2018).The use of fertilizers deserves the same attention of the use of water, given that all regions show low values with the exception of Alto Adige. This result is in line with previous studies which emphasize that there are strong linkages between the use of water and fertilizers. Fortunately, innovative methods for fertigation are now available that guarantee less overuse of water and fertilizations but at the same time a greater yield (Forleo et al., 2018; Expósito and Velasco, 2020; Liao et al., 2021).

Finally, the energy consumption has shown a better performance at national and at regional level with the exception of Umbria, Molise, and Marche. The variable reflects energy expenditure and includes electricity consumption and all the costs for the fuels of agricultural vehicles. Therefore, part of these observed results can be attributed to the higher gasoline costs encountered in southern Italy in recent years (ISTAT, 2019). However, these regions show significantly higher consumption than the northern regions with consequent low efficiency performances. Furthermore, the results obtained are in line with Yzquierdo and Sánchez-Bayón (2019), who found that in Trentino Alto Adige, only 17 % of gross energy production comes from thermoelectric sources, representing the leading region in Italy in terms of renewable energies.

The graphical representation of these results represents the last step of this empirical analysis. Fig. 1 shows the spatial distribution of eco-efficiency across the agricultural enterprises located in the Italian Regions. The graphic illustrates that in line with previous studies (Coluccia et al., 2020), in general, the northern regions appear to be more efficient than the southern regions (Fig. 1a). This result probably indicates a better productive capacity of agricultural enterprises locates in the northern regions as well as a greater resistance to environmental pressures. However, the analysis of the three single indicators notices that the result at national level is mainly determined by the energy consumption efficiency with higher scores in the North than in the South of Italy. The only exception among the southern regions is Calabria that, with the integration of the three indicators, has shown good results in terms of eco-efficiency.

Fig. 1 is the spatial distribution of eco-efficiency results for each type of environmental pressure (water, fertilizers, energy), as well as the total eco-efficiency score. Those regions capable of obtaining the best results, in terms of added value and moderate energy expenditure, are those in the Northern regions, particularly Trentino Alto Adige. The only

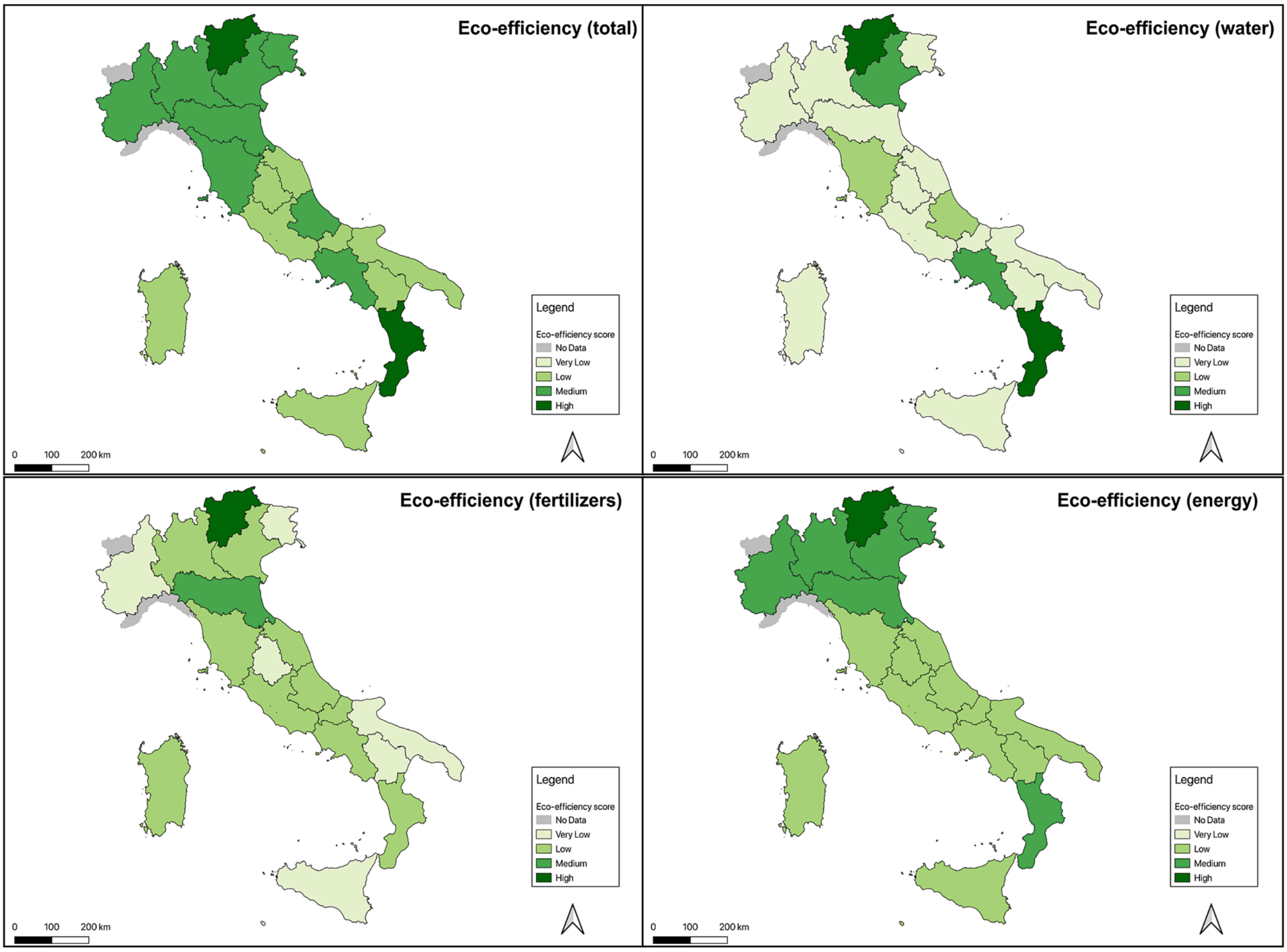

Fig. 1. Spatial distribution of eco-efficiency in Italian regions: (a) Eco-efficiency score based on the inclusion af all pressure indicators; (b) Eco-efficiency based only on the pressure indicator "Water consumption" (p_1); (c) Eco-efficiency based only on the pressure indicator "Use of fertilizers" (p_2); (d) Eco-efficiency based only on the pressure indicator "Energy consumption" (p_3).

Southern region with an "intermediate" level of eco-efficiency energy is Calabria.

Finally, our analysis reveals that the Italian agricultural sector overall is extremely eco-inefficient in terms of water consumption and fertilizers use, with some positive notes for energy consumption.

The results obtained in this research may be important, above all, in consideration of the fact that reliable international statistical estimates report that the agricultural sector, especially the intensive one, determines 30 % of global energy consumption, 92 % of the consumption of water resources and more than 20 % of global greenhouse gas emissions (Alexandratos and Bruinsma, 2012). These are useful indications for policymakers for detecting the sustainability of the agricultural practices within the framework of CAP (Common Agricultural Policy), which is targeted to produce food while protecting the environment (Yan et al., 2018; Liu et al., 2020).

5. Conclusions

The research presented can represent a fundamental contribution to the achievement of many of the 17 goals for sustainable development of the United Nations Agenda 2030. First of all, this work provides useful indications for SDG 2, i.e. the achievement of Zero Hunger by 2030, with particular reference to the methods for achieving it, i.e. through greater attention to agricultural development for food security and nutrition (Bizikova et al., 2020).

In particular, the index of eco-efficiency, by providing useful information to decision makers, improving sustainability performance, resource management, and environmental performance, can support the achievement of:

(1) Sustainable Development Goal 6 "Clean water and sanitation"-indicator 6.4.1 "Change in water use efficiency over time", defined as the change in water use efficiency over time (Hellegers and van Halsema, 2021);
(2) SDG 7 "Affordable and clean energy", which supports sustainable development assuring energy sustainability, reliability, and convenience (Elavarasan, et al., 2021); and
(3) SDG 13 "Climate Action" taking urgent action to combat climate and its impacts (Olabi et al., 2022).

In general, an "eco-efficient" agriculture can represent a nature-based solution (NBS) capable to buffer the degradation of water quality, to improve energy sustainability and to combat climate change. In this study we assess agricultural eco-efficiency in the Italian agricultural sector, it represents a useful index in order to achieve sustainable development combining the increase in economic results with the reduction of environmental impacts. This methodology not only considers the level of total eco-efficiency, but also the impact of individual environmental resources. The results are used to establish an indicator designed for each environmental resource, with the advantage of reflecting simultaneously the impact of environmental and economic variables in one metric.

Ultimately, the total eco-efficiency score reveals an important territorial difference among the regions of the country. While the northern regions have shown a good ability to obtain positive eco-efficiency scores, thereby minimizing the use of environmental resources, the southern regions have relatively more room for improvement of their efficiency performance. In particular, the analysis revealed a generalized problem of water inefficiency, attributable to the poor adoption of effective measures to reduce its overuse in agriculture. Recently, farmers have implemented more advanced agricultural practices with the aim to raise the level of efficiency in water collection, supplementary irrigation, shortfall irrigation, precision irrigation techniques, and soil water conservation (Boutraa et al., 2010; Xue et al., 2017). In fact, the adoption of adequate water saving measures would allow an increase in food production and, subsequently, in income, thereby mitigating the financial risk, and keeping the supply of ecosystem services at a low environmental cost per water unit (Morison et al., 2017; Attwater and Derry, 2017).

In this light, it would be desirable for national and local governments to closely consider encouraging the entire agricultural sector to adopt more efficient use and management of water-saving irrigation inputs, perhaps by establishing an appropriate mix of incentive and restraint mechanisms to strengthen the efficiency of their financial investments, such as small farmland water conservancy, research and development, and promotion of agricultural water-saving technologies (Khastagir and Jayasuriya, 2011). Therefore, proper policies designed to promote sustainability objectives must be based on quantitative assessment indicators that are derived from appropriate methodologies that integrate both the economic and environmental performance of agriculture production. In this way, policy makers can design suitable economic tools that align with both environmental and economic objectives of society. This is the most effective way to achieve sustainability and resource protection objectives, as compared to more drastic measures that simply limit the level of agricultural activity (Kuosmanen and Kortelainen, 2005).

From a practical point of view, this indicator can be used by policy makers as a parameter for the efficient allocation of available resources in the Italian agriculture sector to implement precise policies aimed at reducing environmental waste and to address the greater fragility of the economy's natural resources (Bonifiglio et al., 2017). Further, the implementation of these policies must consider the diversified composition of regional economies, devoting greater attention to those that have a predominantly a rural economy and have an inefficient use of material resources on per capital level (Bianchi et al., 2020). Although this study expands the scientific literature regarding the application of each region's eco-efficiency performances and its possible implications, these results are still limited by the quality and extent of available data, in both the spatial and time dimension. Overcoming these limitations should form the basis for further empirical investigations.

CRediT authorship contribution statement

Giulio Fusco: Conceptualization, Formal analysis, Methodology, Supervision. **Francesco Campobasso:** Conceptualization. **Lucio Laureti:** Investigation. **Massimo Frittelli:** Data curation, Investigation, Methodology. **Donatella Valente:** Validation, Writing – review & editing. **Irene Petrosillo:** Supervision, Writing – review & editing.

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.

Data availability

Data will be made available on request.

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