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Technical efficiency and fertilizers use in Italian farms using a machine learning approach

Nicola Galluzzo
Association of Geographical and Economic Studies in Rural Areas (ASGEAR) – Rieti, Italy
E-mail: asgear@libero.it

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Abstract: The Common Agricultural Policy has supported a less intense use of fertilizers and chemicals in agriculture in the next five years (2023 – 2027) because of the European Green Deal proposals that are environmental protection-oriented. The most common consequence of input reduction in farms was a direct effect to the technical efficiency in farm. The main purpose of this research was to assess the technical efficiency in a sample of Italian farm part of the Farm Accountancy Data Network (FADN) dataset using the Data Envelopment Analysis (DEA) input-oriented approach and by the machine learning approach such as the iterative decision tree evaluating which quantity of chemical fertilizer in terms of nitrogen (N), phosphorus (P) and potassium (K) has to be reduced to improve the technical efficiency. Results have pointed out that between a reduction of chemical fertilizers and technical efficiency there is a fundamental link and the drop in chemical fertilizers has impacted the technical efficiency in Italian farms part of FADN dataset. Based on these results emerged the need of putting into practice some actions towards farmers to compensate the reduction in technical efficiency and the produced output in the productive process as well.

Keywords: DEA; interactive decision tree; FADN; nitrogen; type of farmings

INTRODUCTION

The European Union by some regulatory and individual-incentive schemes as Nitrates Directive in 1991, Water Framework Directive in 2000, Agri-Environment Regulation 2078/92/EEC has been able to generate useful leverages addressed at reducing the environmental costs arising from the use of agro-fertilizers and the cross-compliance requirements of the Common Agricultural Policy (CAP) are good examples in environmental protection and drop in chemical input in agriculture (Expósito and Velasco, 2020). These two authors have underlined as the policy measures of the CAP have been addressed in reducing the use of mineral fertilizers and in particular since the 1980s there has been a reduction in total nitrogen inputs of 15%.

One of the main changes in the Common Agricultural Policy since the early 2020s has been a significant reduction of chemical inputs in farm as proposed by the Green Deal Strategy. The fundamental purpose of the Green Deal was to undertake actions in order to improve environmental and climate protection with significant and direct impacts to the farmers (Prandecki et al., 2021). According to these authors, the European farmers, with some excesses in labour input and in other input such as buildings or machine, have to diversify their agricultural activities paying attention to the impacts of some techniques and technologies on the environment and the challenges faced by the EU Member States in the environmental protection and sustainability. Previous studies carried out in some EU countries have argued that a drop in using some fertilizers is one of the main strategies of the Green Deal approach, and a reduction of these inputs is able to impact the technical efficiency of farms (Reinhard et al., 1999).

An improper use of chemical inputs is able to impact to the technical efficiency in farms, as argued in a recent research using the efficiency of chemical fertilizers utilization and agricultural yield by the non-parametric Data Envelopment Analysis (DEA) (Toma et al., 2017). According to these latter authors, the European countries have been experiencing increasing or decreasing returns to scale in agricultural productions and this has implied their potential in increasing their production efficiency by a different allocation in some inputs as fertilizers and irrigated areas.

Comparing new member states of the EU and old EU countries, significant differences in terms of technical efficiency due to the application of the CAP emerge (Toma et al., 2017).

Based on these differences the role of the public policy in the primary sector and the priorities in environmental protection can impact the technical and economic efficiency in farms. Hence, it is important to promote measures and techniques able to avoid an environmental resource overexploitation without depressing the production in farm (Toma et al., 2017). A drop in the high-input systems is a good strategy in environmental production that has to be adequately compensated by specific economic supports and aids allocated by the CAP. A reduction in input use considering the differences in the agricultural system in all EU countries is a tool able to impact to the technical efficiency for farmers with the serious risk that a decrease in output and in the efficiency push many farmers to quit their business and close down their farms.

The intensive use of mineral fertilizers by agriculture puts significant pressure on water resources in Europe and in the primary sector as well (Expósito and Velasco, 2020) and the economic effect in the EU countries on an intense use of nitrogen fertilizers in terms of cost of damage has been estimated in 320 thousand million euros annually while the estimated economic benefit of its use is about 80 thousand million euros (Sutton et al., 2011).

A recent study carried out in EU countries focused on exploring the environmental efficiency of the European agricultural sector in the use of mineral fertilizers has pointed out that Belgium-Luxembourg, Denmark, the Netherlands, Sweden, and the United Kingdom in the periods 2002 – 2003 and 2007 – 2008 had higher values in technology, which implies country-specific efficiency paths in the use of fertilizers (Expósito and Velasco, 2020).

The estimation of technical efficiency by DEA has used three chemical fertilizers combinations such as nitrogen (N), phosphorus (P) and potassium (K) and the findings have pointed out K has a higher possibility to decrease, followed by P and N (Yadava, 2023). The study proposed by Yadav (2023) has estimated the potential minimization of fertilizer input without compromising the agricultural yield level and the role of farm-level policies in a framework of a proper use of fertilizers aimed at reducing the chemical fertilizer intensiveness in production and at the same time increasing the farmers' income through an input saving strategy in terms of fertilizers utilization.

In other non-EU countries some farmers have been encouraged to use an optimum combination in fertilizer with the purpose to improve their production even if this action has been tightly linked to some exogenous variables such as an adequate education for farmers and fertilizer price subsidies (Abu, 2011).

The policy of improving income of farmers by specific subsidies has been a good tool in increasing technical efficiency of fertilizer and a decrease pollution in other extra EU nations (Yang and Han, 2011). Yang and Han (2011) have argued as the low efficiency in fertilizers impacts the output technical efficiency even if other variables as fertilizer price, income of farmers and skills and knowledge for farmers are important in affecting technical efficiency of fertilizer. Furthermore, subsidies policies can reduce the pollution stimulating a different use of fertilizers as well. As mentioned before, by a study of the technical efficiency carried out in other countries, results have pointed out results have pointed out some rice farmers should be encouraged to adopt optimum fertilizer rate in order to achieve an increase in rice production and an optimal level of technical efficiency hence, some fertilizer price subsidies and a due allocation of distribution of fertilizers to farmers can positively act to the technical efficiency in farms (Abu, 2017). On the contrary, an overuse of fertilizers has pointed out some effects in the technical efficiency in farms with significant differences between all investigated areas (Huang and Jiang, 2019).

Because agriculture is an environmental impacting activity, it is a very minefield to assess, with particular attention, its environmental efficiency using quantitative approaches such as the DEA, which can be a synthetic indicator of agricultural sustainability, and a CAP evaluation as proposed in some Italian regions (Fusco et al., 2023).

Drawing some conclusions after the literature review, it emerges that lots of efforts have been made to improve eco-efficiency through the efficient use of productive factors as fertilizers within each Italian and European region and encouraging place-based policies by the CAP with the purpose of understanding the multidimensional linkages between agriculture, socio-economic aspects, and the environment (Bianchi et al., 2020).

Aim of the research

In literature the analysis of regional eco-efficiency by quantitative approach is useful to compare different performances between regions, investigating in depth territorial differences (Bianchi et al., 2020). At this stage, in Italian literature there are not studies that have assessed the technical efficiency in a sample of Italian farm part of the FADN dataset using the DEA input-oriented approach and the machine learning approach such as the iterative decision tree with the purpose to evaluate which quantity of chemical fertilizer in terms of nitrogen (N), phosphorus (P) and potassium (K) has to be reduced to improve the technical efficiency. The aim of this paper is to assess and to compare the regional eco-efficiency of all Italian regions, focusing attention on chemical fertilizers and the effect of some changes in chemical fertilizer impacts the technical efficiency. The results estimated by the DEA will allow to answer to the following questions: in which regions farms showed a higher level of efficiency and if the chemical fertilizer has impacted efficiently the investigated farms.

METHODOLOGY

The DEA approach has been most commonly applied in literature to assess eco-efficiency and farming eco-efficiency (Korhonen and Luptacik, 2004; Kuosmanen and Kortelainen, 2005; Zhang et al., 2008; De Koeijer et al., 2002; Picazo-Tadeo et al., 2011). Furthermore, the DEA incorporating economic and environmental input and output is useful in the performance assessment comparing different regions or countries estimating the best Decision Making Unit (Galluzzo, 2023; 2021a; 2021b; Bianchi et al., 2020; Fusco et al., 2023). 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 in other studies the overall efficiency and consequently the performance of States with different agricultural policies (Kočišová, 2015; Toma et al., 2017).

In literature, the technical efficiency is a specific and direct measure of the ability of a farm in obtaining the best quantity of output given a set of inputs (output-oriented model) or an assessment of the farm in producing an optimal level of output using the minimum amount of input in case of input-oriented model (Charnes et al., 1978; Farrell, 1957).

Technical efficiency can be estimated through two different quantitative approaches: a parametric or stochastic modelling called Stochastic Frontier Analysis (SFA) or a non-parametric modelling using the Data Envelopment Analysis or DEA (Farrell, 1957; Lovell, 1993; Coelli et al., 2005; Battese and Coelli, 1992; Galluzzo, 2019). The DEA, compared to the SFA, does not need of a well-defined model of estimation of the function of production, such as Cobb-Douglas function or a translog one, and it is able to use more input and output in the estimation of the technical efficiency (Farrell, 1957; Lovell, 1993; Coelli et al., 2005; Battese and Coelli, 1992; Galluzzo, 2021a).

In this research we used the DEA because it does not need of *a priori* specification about the production function assessing at the same time multiple inputs and multiple outputs (Coelli et al., 2005; Bravo-Ureta and Pinheiro, 1993; Galluzzo, 2019). DEA estimates the technical efficiency by comparing each Decision Making Unit (DMU) that in our case is each farm against all other units (Galluzzo, 2019). The optimal level of efficiency is represented by all the DMUs placed on the frontier of technical efficiency, which represents the optimal combination of input to produce a well-defined level of output, while all the DMUs placed under this frontier can be considered as inefficient, having a value lower than the optimal threshold that is equal to 1 (Coelli et al., 2005; Galluzzo, 2019; Chavas and Aliber, 1993; Bravo-Ureta and Pinheiro, 1993). One of the main advantages of the technical efficiency estimated by the DEA is to get a value of efficiency that is invariant to technology and this can be easily used in a small sample of farms (Arru et al., 2019). In our case the sample is made by Italian farms part of the Farm Accountancy Data Network (FADN) dataset investigated from 2014 to 2021. The variables used in the model are: labour in terms of total hours of work per year, land capital in hectares of usable agricultural areas, total assets in euro, total specific costs and farming overhead costs in euro as well. The output is made by the produced output from farm in euro.

The technical efficiency estimated in the input-oriented model by the DEA for a single output is derived by solving a linear programming model (Galluzzo, 2019; Coelli et al., 2005) aimed at estimating θ_i. The value of θ_i is the proportional increase in output possible for the *i*-th DMU (Battese and Coelli, 1992). Summing up some conclusions, a farm has efficient results when the values of θ are equal to 1; on the contrary, a DMU is inefficient when $\theta > 1$ hence, the technical efficiency is the distance between the observed and optimal input used for a certain function of production.

The machine learning (ML) approach has been proposed by Samuel (1959) and it is the ability of a machine to learn without any actions of programming. ML is a branch of artificial intelligence that, employing different statistical methods, is able to improve the performance of an algorithm using a large number of information and other data expanding consequently the results through a process of independent learning (De Mauro, 2019; Bishop, 2006; Samuel, 1959). In literature and in particular in the primary sector, the concept of machine learning has been introduced as a consequence of the elaboration of huge amounts of data, and ML offers an opportunity to understand the relevance of the data without having to perform any programming actions (Liakos et al., 2018). These latter authors have done a wide review of the literature focused both in analysing different approaches and opportunities of machine learning in agriculture and also in identifying some different fields of application of ML but only in 2019 has been published a study focussing on the challenges and opportunities in using machine learning in applied economics in agricultural economics (Storm et al., 2019). This study has tried to fill the gap in literature where there are not studies addressed at using machine learning to investigate the technical efficiency and the use of chemical fertilizers in farms. This study was therefore conceived to make an use of this innovative quantitative approach, considering that analysing big data in agriculture represents a new, vast, and important challenge for investigations in the primary sector (Coble et al., 2018; Liakos et al., 2018; Storm et al., 2020; Galluzzo, 2022). Despite there are many different models, methodologies, and algorithms used in machine learning, in this study it has been fundamental to define the learning phase aimed at learning from the training data, which represent the experience in a specific field of investigation with the purpose to reach a well-defined task (Liakos et al., 2018; Storm et al., 2020). In this paper, a supervised approach such as the interactive decision tree has been used through which it has been possible to predict the output, or rather the technical efficiency based on the quantity in chemical fertilizers used in farms part of the Italian FADN dataset considering two clusters of farms stratified, using a dummy variable, in two groups of farms in function of a percentage of incidence of cost in crop protection on the total specific costs above or below the 25% since 2014 to 2021. In order to assess whether there were farms that used a high amount of on-farm chemicals input, the dummy variable was introduced. In fact, farms that had an incidence of chemical use had crop protection costs out of the total specific costs greater than 25%. A threshold of 25% implied that farms made heavy use of chemicals in their production processes. The estimation of technical efficiency using the DEA approaches has been made using the RStudio software package Benchmarking (Bogetoft and Otto, 2011; Galluzzo, 2023) while by packagings Rpart, Rpart.plot and Cubist (Therneau et al., 2015; Milborrow and Milborrow, 2022; Kuhn et al., 2023) it has been possible to assess the machine learning and the interactive decision tree. By the interactive decision tree it is possible to predict the technical efficiency that will come next using some specific input in the productive process hence, considering a well-defined level of technical efficiency it is possible to define which is the best allocation in some input in the productive process.

The further and last stage of this research has been addressed in comparing if the type of farming has impacted the technical efficiency in all Italian farms hence, it has clustered the Italian farms part of the FADN dataset in 15 type of farming.

RESULTS AND DISCUSSION

The main results on the sample of 1,400 Italian farms part of the FADN dataset have been showed in Table 1. The descriptive statistics have pointed out the average value of labor input has been above 3,300 hours per farm that has had a significant amount of land capital endowment, close to 24 hectares.

Specific costs have been higher than farming overhead costs which represent almost one third of the specific cost. The total output in average value has been above 90,000 euro with significant fluctuations among farms over the time of inves-

Table 1. Main descriptive statistics in the Italian FADN farms since 2014 to 2021

Variable	Unit	Obs.	Mean	Std. dev.	Min	Max
Labour	Hour	1,400	3,367.123	1,291.041	1,263.22	12,969.63
Land Capital	Hectares	1,400	24.36	16.76	1	105.09
Assets	Euro	1,400	415,401.2	337,873.2	75,737	6,692,804
Farming overhead costs	Euro	1,400	12,745.83	12,019.72	2,629	160,028
Specific costs	Euro	1,400	31,989.99	54,967.18	2,092	591,959
Total Output	Euro	1,400	93,961.09	115,489.7	12,039	1,075,998
Total CAP subsidies	Euro	1,400	10,517.26	7,923.158	62	69,673
RDP subsidies	Euro	1,400	2,799.792	2,941.097	0	29,251
Environmental subsidies	Euro	1,400	1,530.396	1,713.926	0	16,922

Source: Author's elaboration on data https://agridata.ec.europa.eu/extensions/FADNPublicDatabase/FADNPublicDatabase.html.

tigation 2014 – 2021. Addressing the attention to the financial subsidies allocated by the CAP, the total amount of them has been equal to 15,517 euro per farm and only 2,799 euro have been the payments and other financial supports disbursed by the second pillar of the CAP. Environmental subsidies to farmers have been approximately close to 1,530 euro. In terms of chemical fertilizers Italian farms part of the FADN have used in average more than 11 kilograms of nitrogen fertilizers per year and less than 6 and 5 kilograms per year of phosphorus and potassium (Table 2).

The technical efficiency estimated by the DEA in an input oriented approach has been in average value equal to 0,762 or rather under the optimal threshold equal to 1 (Table 3). The further stage of this research has generated two clusters in function of the percentage of incidence of chemical input which have been partially explained in terms of crop protection cost on the total specific costs for crops in each farm of the FADN dataset above or below a threshold of 25% of the total specific cost. In this case we have used in the model a dummy variable 1 if the percentage has been above the threshold of 25%, 0 otherwise.

Comparing the technical efficiency using this dummy variable significant differences in technical efficiency emerge. In fact, farms in the cluster where the incidence of cost of crop protection has been above 25%, have been more technical efficient than farms with an incidence of cost in crop protection under 25% of the specific costs. Farms stratified in the cluster with dummy variable 1 have had a technical efficiency equal to 0,813, on the contrary farms in the cluster with a dummy variable of 0 have had a technical efficiency equal to 0,744.

The best results of technical efficiency estimated by the DEA input oriented approach have been found in a north-west Italian regions as Liguria, Lombardy and Trentino-Alto Adige (Table 4). On the contrary, the lowest values of technical efficiency have been found in many central Italian regions as Tuscany, Marche and Umbria.

Table 2. Main Descriptive statistics in the Italian FADN farms since 2014 to 2021 of chemical fertilizers

Variable	Unit	Obs.	Mean	Std. dev.	Min	Max
Nitrogen	kg	1,400	11.305	11.911	0	80.37
Phosphorous	kg	1,400	5.871	5.772	0	42.40
Potassium	kg	1,400	4.674	5.832	0	44.02

Source: Author's elaboration on data https://agridata.ec.europa.eu/extensions/FADNPublicDatabase/FADNPublicDatabase.html.

Table 3. Average value of technical efficiency in the Italian FADN farms sample

Variable	Obs.	Mean	Std. dev.	Min	Max
Technical efficiency	1,400	0,762	0,118	0	1,00
Technical efficiency with dummy equal to 1	165	0,813	0,120	0	1,00
Technical efficiency with dummy equal to 0	1,235	0,744	0,103	0	1,00

Source: Author's elaboration on data https://agridata.ec.europa.eu/extensions/FADNPublicDatabase/FADNPublicDatabase.html.

Drawing some conclusions, a dichotomy in the technical efficiency distribution between Italian regions does not exist while significant unbalances among regions occur due to a different allocation of input and produced output.

Comparing the different type of farming investigated in FADN Italian farms, the highest value of technical efficiency estimated by the DEA input oriented approach has been assessed in horticulture farms and the lowest have been assessed in cattle and sheep and goats farms (Table 5).

Over the time of investigation 2014 – 2021 in all Italian farms part of the FADN dataset there has been a significant use of nitrogen that has had some fluctuations over the time and a stable use of phosphorous and potassium that have been lower 5,5 kilograms (Fig. 1). Focusing the attention in two clusters significant different quantity use of chemical fertilizers emerge (Fig. 2).

Farms in the cluster 1 have underlined an intense use of chemical fertilizers and in particular nitrogen and potassium (Fig. 2).

Table 4. Comparing technical efficiency in all Italian regions

Region	**n**	**Mean**	**St. dev.**
Valle d'Aosta	23	0.680	0.211
Piedmont	77	0.718	0.088
Lombardy	65	0.808	0.106
Trentino	32	0.817	0.122
Alto-Adige	37	0.797	0.144
Veneto	80	0.786	0.091
Friuli-Venezia-Giulia	64	0.754	0.107
Liguria	57	0.869	0.110
Emilia-Romagna	73	0.782	0.093
Tuscany	85	0.672	0.122
Marche	64	0.696	0.097
Umbria	77	0.738	0.086
Latium	91	0.778	0.112
Abruzzo	73	0.752	0.109
Molise	71	0.730	0.102
Campania	88	0.808	0.106
Calabria	39	0.813	0.087
Apulia	75	0.739	0.132
Basilicata	75	0.711	0.106
Sicily	91	0.825	0.111
Sardinia	63	0.750	0.094
Total FADN Italian sample	*1,400*	*0.762*	*0.118*

Source: Author's elaboration on data https://agridata.ec.europa.eu/extensions/FADNPublicDatabase/FADNPublicDatabase.html.

Table 5. Different technical efficiency in the main type of farming in Italian farms

Type of farming	**n**	**Mean**	**St. dev.**	**min**	**max**
Cereals Oil seeds and protein	117	0.755	0.097	0.566	1.000
Other field crops	146	0.738	0.094	0.557	1.000
Horticulture	61	0.914	0.086	0.690	1.000
Wine	154	0.877	0.098	0.634	1.000
Orchards-fruit	98	0.799	0.086	0.632	1.000
Olives	59	0.810	0.097	0.651	1.000
Permanent crops combined	84	0.833	0.099	0.616	1.000
Milk	130	0.708	0.086	0.502	0.916
Sheep and goats	92	0.678	0.116	0.503	1.000
Specialised cattle	113	0.676	0.088	0.460	0.924
Granivores	85	0.832	0.101	0.610	1.000
Mixed crops	133	0.728	0.080	0.577	1.000
Mixed livestock	5	0.771	0.114	0.674	0.961
Mixed crops and livestock	123	0.664	0.074	0.520	0.944
Total	*1,400*	*0.762*	*0.118*	*0.460*	*1.000*

Source: Author's elaboration on data https://agridata.ec.europa.eu/extensions/FADNPublicDatabase/FADNPublicDatabase.html.

Figure 3 showed the different use of nitrogen chemical fertilizers in all Italian regions and the findings have pointed out as in the North-eastern and in North-western regions there have been the highest level of nitrogen use in FADN farms over the time of investigation. In regions located in mountainous areas the consumption of nitrogen fertilizers has had the highest level. A significant dichotomy in the use of other chemical fertilizers as phosphorous and potassium has been underlined in other Italian regions compared to the others located in the central and southern Italian peninsula (Fig. 4 – 5). The higher is the fertilizers consumption the higher is the level of output in some specialised Italian regions and this is one of the main explanation of an intense use of chemical fertilizers adoption in some regions.

With the purpose to assess if there was a link between the quantity of chemical fertilizers and the output produced in farms part of the FADN dataset it has used a simple analysis of correlation in order to assess the link and direction in some variables such as quantity of fertilizers (N, P and K) and total produced output in Italian FADN farms. Results have pointed out a weak link between the nitrogen, phosphorus and potassium used and the total output produced with a significance of 1% in a range between 0.39 – 0.42 and this link is increased in the cluster of farms classified as farms with a cost of crop protection below the threshold below 25% of the total specific cost. Furthermore, between the variable quantity of chemical fertilizers input used in farms and the total subsidies allocated by the measures of environmental protection by the Common Agricultural Policy, research's findings have pointed out a weak and indirect link with negative values in a range between -0.0839 and -0.2024.

The distribution of frequency of the technical efficiency estimated by the DEA input oriented

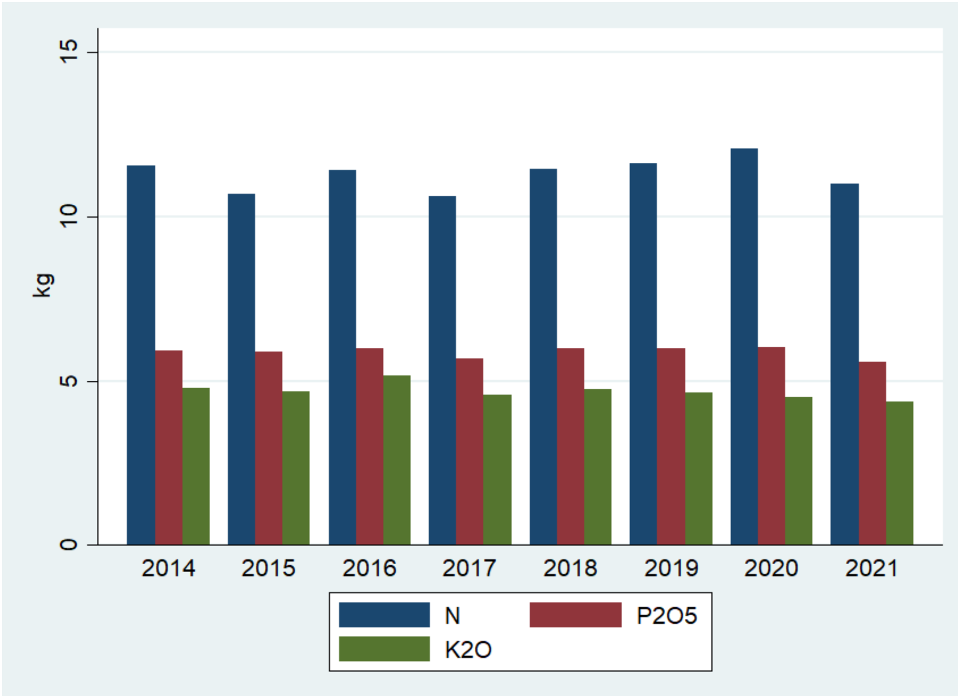

Fig. 1. Different use of chemical fertilizer in all Italian farms over the time of study

Source: Author's elaboration on data https://agridata.ec.europa.eu/extensions/FADNPublicDatabase/FADNPublicDatabase.html.

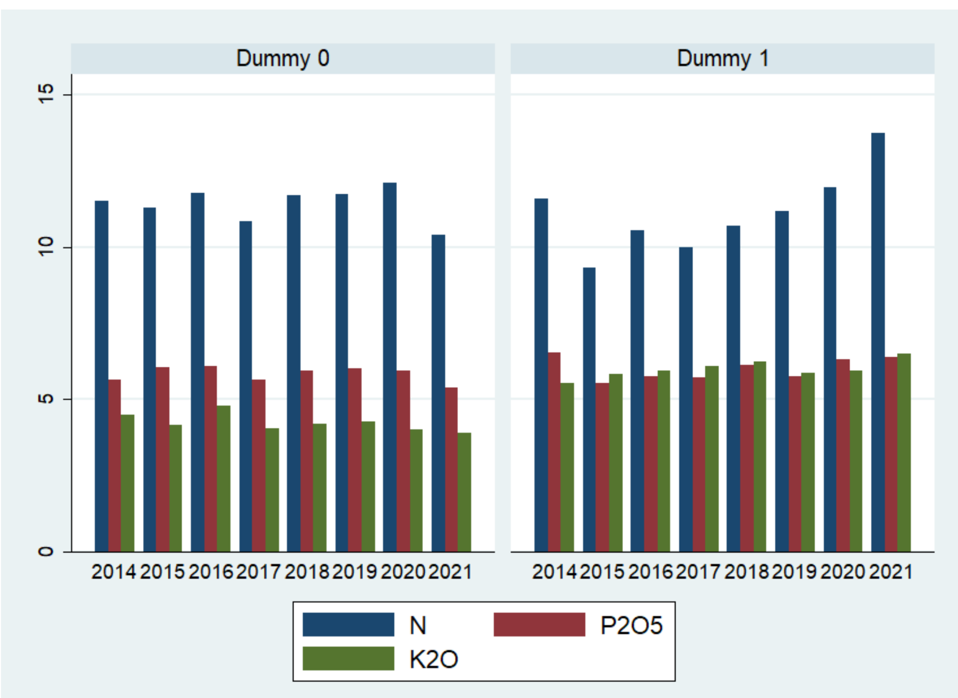

Fig. 2. Different use of chemical fertilizer in two clusters (dummy variables 1 and 0) of farms in function of the percentage of cost in crop protection

Source: Author's elaboration on data https://agridata.ec.europa.eu/extensions/FADNPublicDatabase/FADNPublicDatabase.html.

Fig. 3. Different use of nitrogen chemical fertilizer in all Italian regions

Source: Author's elaboration on data https://agridata.ec.europa.eu/extensions/FADNPublicDatabase/FADNPublicDatabase.html.

Fig. 4. Different use of phosphorous chemical fertilizer in all Italian regions

Source: Author's elaboration on data https://agridata.ec.europa.eu/extensions/FADNPublicDatabase/FADNPublicDatabase.html.

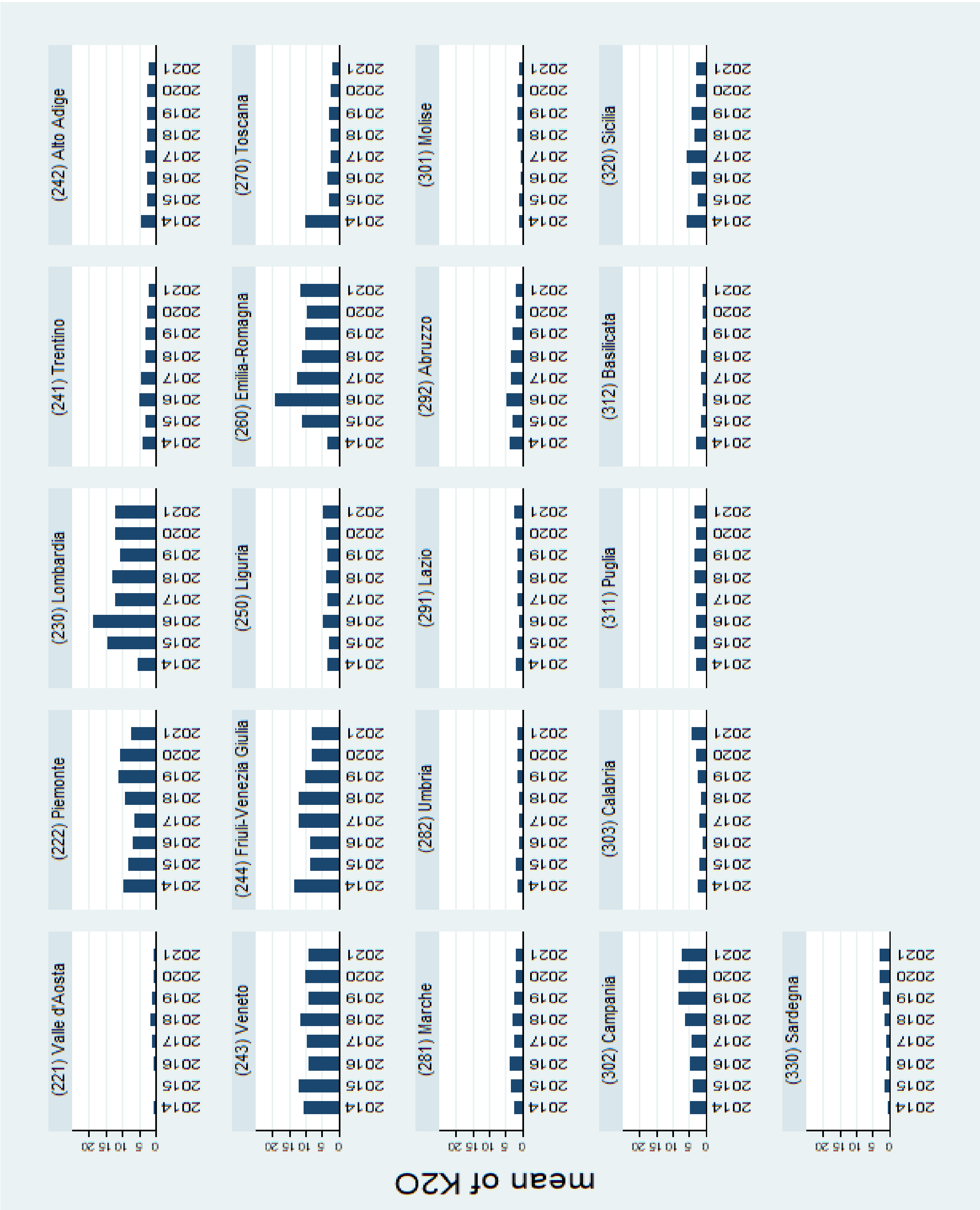

Fig. 5. Different use of potassium chemical fertilizer in all Italian regions

Source: Author's elaboration on data https://agridata.ec.europa.eu/extensions/FADNPublicDatabase/FADNPublicDatabase.html.

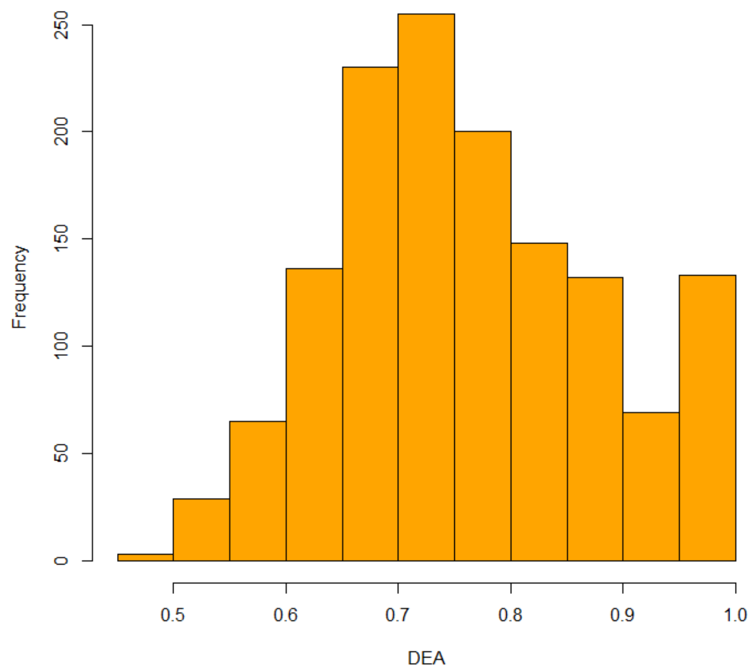

Fig. 6. Histogram of technical efficiency estimated by the DEA in all Italian FADN sample

Source: Author's elaboration on data https://agridata.ec.europa.eu/extensions/FADNPublicDatabase/FADNPublicDatabase.html.

has pointed out as an almost normal distribution of efficiency in the sample even if almost 120 farms have had the optimal level of technical efficiency (Fig. 6).

The application of the machine learning algorithm to the interactive regression tree has pointed out as farms in the cluster 1 have had the highest level of technical efficiency using a low level of chemical input (Fig. 7). On the contrary, farms stratified in the cluster using less chemical inputs such as 1,45 kilograms of phosphorus per year and very poor quantity of nitrogen chemical fertilizers have had the lowest level of technical efficiency close to 0,60. The correlation between predicted value and true value has been acceptable equal to 0,44. On average the difference between the used model and the real value of the technical efficiency estimated by the DEA input oriented has been very poor and close to 0,081 and this implies a total error in the model very modest and drawing some conclusions the machine learning approach has underlined as two variables as nitrogen and phosphorous chemical fertilizers can impact on the technical efficiency in farms.

CONCLUSIONS

This study has filled the gap in Italian literature about the use of chemical fertilizers and the technical efficiency in farms. Research's findings in this study have pointed out as an improper use of chemical input impacts the technical efficiency in Italian farms as argued by other recent studies carried out by Toma et al. in 2017 in other countries. In general, the link between fertiliser use and output produced was modest even if a correlation analysis has underlined significant relationships between total output produced and the use of nitrogen, phosphorus and potassium. An indirect and negative link in terms of correlation has been found between the variables total pro-

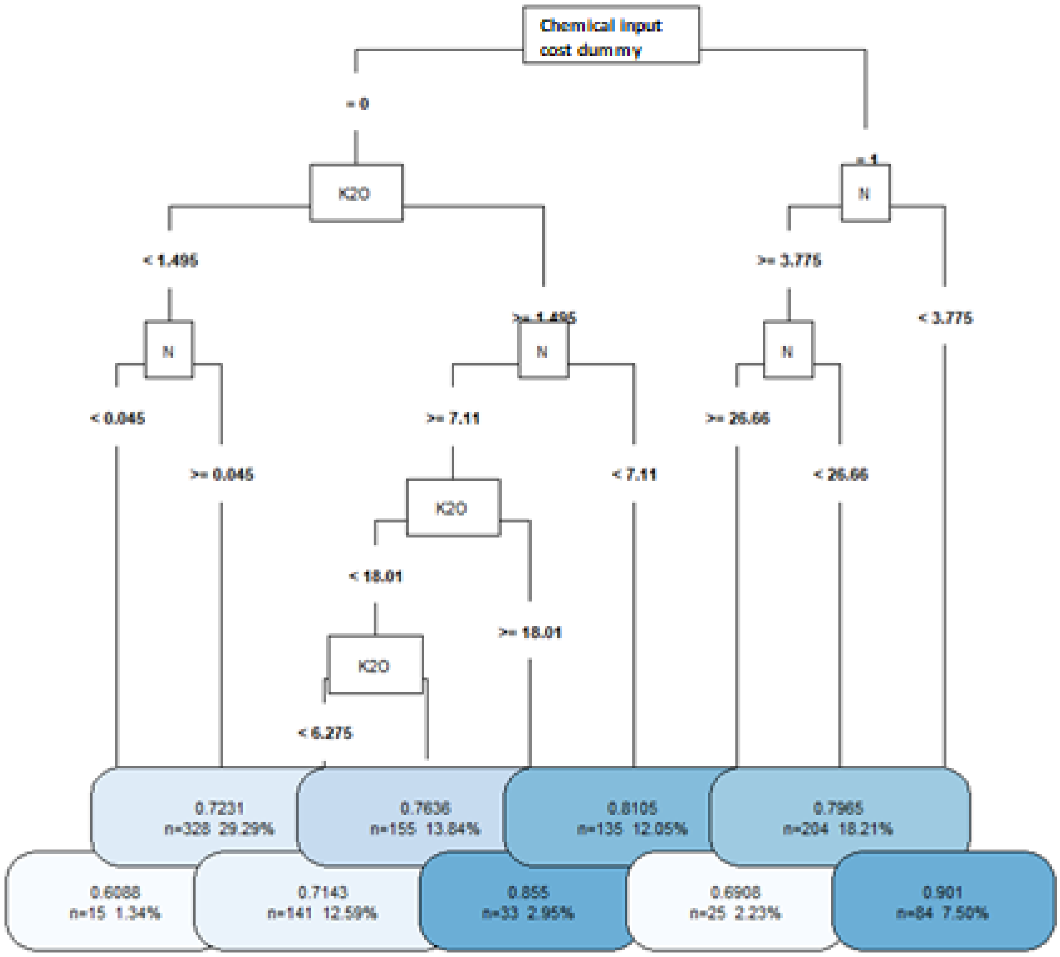

Fig. 7. Interactive regression tree estimated by the algorithm of machine learning
Source: Author's elaboration on data https://agridata.ec.europa.eu/extensions/FADNPublicDatabase/FADNPublicDatabase.html.

duced output and environmental subsides allocated by the Common Agricultural Policy. Hence, an increase in payments to the environmental measures is not positive in stimulating the total output production in Italian farms.

The use of chemical fertilisers has been lower in Italy than in other EU countries and also the use of fertilizers has been indirectly linked to the subsidies allocated by the Common Agricultural Policy in the framework of environmental subsidies and payments.

The technical efficiency has been in line with previous recent studies carried out by Expósito and Velasco (2020). It is fundamental to reduce chemical inputs in farms and by the machine learning approach it will be possible using a wide sample of data to define the role of exogenous variables such as CAP subsidies in all EU farms. Drawing some final remarks, a drop in some chemical input as proposed by the Green Deal has a fundamental impact to the technical efficiency in farms even if the type of chemical fertilisers and the use of other chemical products in the crops protection have direct and significant relationships to the technical efficiency in farms.

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