Available online at www.centmapress.org

INTERNATIONAL JOURNAL ON FOOD SYSTEM DYNAMICS

Int. J. Food System Dynamics 14 (1), 2023, 22-45

DOI: https://dx.doi.org/10.18461/ijfsd.v14i1.E2

Assessing efficiency differences in a common Agriculture Decision Support System
- A comparative analysis between Greek and Italian durum wheat farms -

Leonidas Sotirios Kyrgiakos[*1], Georgios Kleftodimos[1,2], Marios Dominikos Kremantzis[3], George Vlontzos[1], Panos M. Pardalos[4]

[1]Department of Agriculture, Crop Production and Rural Environment, University of Thessaly, Fytoko, 38446 Volos, Greece
[2]Mediterranean Agronomic Institute of Montpellier (CIHEAM-IAMM), 34093 Montpellier, France
[3]University of Bristol Business School, University of Bristol, UK
[4]Department of Industrial and Systems Engineering, University of Florida, 401 Weil Hall, Gainesville, FL 32611-6595, USA
[*]lkyrgiakos@uth.gr; kleftodimos@iamm.fr; marios.kremantzis@bristol.ac.uk; gvlontzos@uth.gr; pardalos@ise.ufl.edu

Received September 2022, accepted December 2022, available online January 2023

ABSTRACT

This study assesses inputs use efficiency of durum wheat farmers, subscribed under a common Agricultural Decision Support System (ADSS), especially designed by Barilla and HORTA for this cultivation. Data Envelopment Analysis was the main analysis used to highlight differences in the implementation stage of ADSS's suggestions, between 4 agricultural firms (2 Italian and 2 Greek) (N= 563 farmers). By incorporating economic (variable costs) and environmental factors (Carbon, Water and Environmental footprints), performance differences between farms both on regional and national level arose. Lastly, closer monitoring for clarifying the reasoning of the obtained differences in the implementation stage is proposed.

Keywords: DEA; durum wheat; undesirable factors; optimization; efficiency; agriculture; decision support system.

1 Introduction

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

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

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

2 Literature review

2.1 Farmers relationship with ADSS

Focusing on ADSSs and their relationship with end-users, there are four concrete stages that can be assessed to clarify the factors affecting ADSS and farmers cooperation status as Figure 1 presents: (a) creation, (b) use, (c) evaluation of the acquired results, and (d) redesign. Referring to the first stage of ADSSs, many of them are designed for fulfilling one specific goal like water-saving from irrigation (Navarro-Hellín et al., 2016; Viani et al., 2017), optimum fertilization (Villalobos et al., 2020), and chemical elements' runoff (Drohan et al., 2019).

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

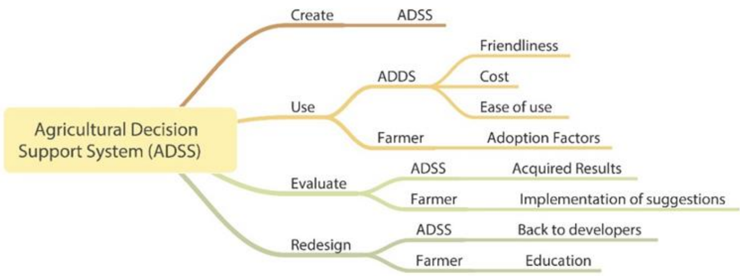

Figure 1: The four stages of ADSSs and famers interaction.

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

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

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

2.2 Efficiency assessment

Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis are the most well-established techniques when it comes to efficiency measurement in the agricultural sector (Lampe and Hilgers, 2015). For instance, Ilahi et al. (2019) have assessed wheat production in the Chinese regions, considering greenhouse gas emissions as undesirable outputs, proving that the average inefficiency gap for the examined farmers is around 30%. Similar results were obtained from Janusz Gołaszewski et al. (2014) when exploring energy efficiency differences between 6 European countries (Germany, Netherlands, Finland, Poland, Greece and Portugal) on wheat cultivation by implementing DEA methodology. Moreover, DEA has been used for the eco-efficiency assessment of wheat production in the Italian regions, signifying regional changes between 2004 and 2017 (Coluccia et al., 2020), emphasizing to the environmental impacts of agricultural activity. DEA can be combined with Malmquist index in order to highlight annual efficiency changes in a given time period (Forleo et al., 2021).

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

3 State of the art

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

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

a) if GD.NET suggestions were leading to greater input use efficiency and
b) if the suggestions of GD.NET are being followed by farmers.

4 Methodology

4.1 Data Envelopment Analysis (DEA)

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

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

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

Constant Return to Scale (CRS)

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

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

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

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

j= 1,...,n - firms index
i= 1,...,m - inputs index
r= 1,...,s - outputs index
ε= non-Archimedian value

Variable Return to Scale (VRS) Add:

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

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

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

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

4.2 Models' specification

Taking into consideration the above-mentioned methodological part, GD.NET dataset, , was used to assess input use efficiency of durum wheat farmers referring to the cultivation year of 2020-2021. Two models were created for measuring technical efficiency of all DMUs involved. The first one (EconDEA) enables only the variable costs of durum wheat cultivation (Seeds, Fertilizers, Plant Protection Products, Diesel, Labour and Yield), while the EcoDEA model, incorporates both economic and environmental factors. More accurately, Carbon Footprint, Water Footprint and Ecological Footprint, were assessed under the common name of CWEFs. CWEFs were treated as undesirable factors in the EcoDEA model, after the linear monotone decreasing transformation as proposed by Seiford and Zhu (2002). It should be mentioned that CWEFs values were provided immediately by GD.NET. Table 1 provides an overall summary of the involved variables per model. The analysis process was conducted in the RStudio using rcompanion (for Median differences), deaR (Benchmarking) and ggplot2 (Visualisation) libraries (Mangiafico, 2016; Wickham, 2016; Coll-Serrano et al., 2022).

This paper is separated in two distinct parts. The first one provides descriptive statistics of all variables involved conducting Mood's Median test in order to assess differences between the involved variables. It should be noted that both descriptive statistics and the DEA section part are referring to the functional unit of final production of Durum Wheat per Hectare (Ha) under 13% moisture level. Moving forward to the next part, the acquired results of EconDEA and EcoDEA are presented. Both CRS and VRS results were calculated for the two models to compute Scale Efficiency.

Table 1
Inputs and Outputs used per DEA function.

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

5 Results

5.1 Descriptive statistics

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

An extended version of **Fehler! Ungültiger Eigenverweis auf Textmarke.** (Table A1) containing additional information about minimum, maximum, and mean values can be found in the Appendix section as well as a boxplot for each of the involved variables in the DEA process (Figures A1-A9). Embodied letters in the boxplot figures signify median differences as indicated from Mood's median test.

Table 2 presents descriptive statistics of inputs and output per firm. More precisely, G1 uses the greatest amount of seeds between the four firms, while both Greek firms have higher median values than I1, I2. Fertilizers use indicates that I1 is again the best performer while G1 displays the largest consumption. Regarding Plant Protection Products use, it is evident that I2 has the largest median value, considerably higher than the ones of other firms. Examining Plant Protection Products in national level, it appears that Italian firms are presenting higher median values compared to the Greek ones. It should be stated that G2 has a very small value of Standard Deviation, which is under consideration for data quality. Apart from G1, which has the greatest value and the largest interquartile range, all the other firms display almost similar median values regarding diesel consumption. G1& G2 present similar median values, while G2 and I1 have lower medians. Labour variable presents similar characteristics for G1 and I2 which have the higher medians between the four samples. A smaller standard deviation is observed again for G2 firm. In terms of yield, I1 has the largest median score, considerably higher than the other firms. G2 and I2 display similar median scores and G1 ranks fourth in this comparison.

Considering CWEFs, median score of Carbon Footprint is similar for G1 and I2, I1 displays the lowest median value, while G2 displays a great volatility despite the small number of included farms. G2 has a considerably higher median value regarding Water footprint and I1 displays the lowest median value followed by the smallest standard deviation between the four firms. Environmental footprint expresses the numbers of affected hectares for the production of one tonne of final product. I1 seems to have the least impact, while the rest of the variables present similar median scores. Lastly, although the cultivated area was not inserted in the DEA models, it considered appropriate to be further analyzed. The average cultivated area of the sample is 9.25 ha and apart from I2 which presents a larger standard deviation and some extreme outliers (n=8, >50ha), all the other firms present similar variances.

An extended version of **Fehler! Ungültiger Eigenverweis auf Textmarke.** (Table A1) containing additional information about minimum, maximum, and mean values can be found in the Appendix section as well as a boxplot for each of the involved variables in the DEA process (Figures A1-A9). Embodied letters in the boxplot figures signify median differences as indicated from Mood's median test.

Table 2
Descriptive statistics of GD.NET dataset per country and per firm.

		Greece N=235		Italy N=328	
Characteristic	Overall, N = 563[1]	G1, N = 202[1]	G2, N = 33[1]	I1, N = 229[1]	I2, N = 99[1]
Seeds (kg/t of final product)	41.50, (19.70), [32.50-55.90]	56.65, (18.38), [45.42-67.97]	44.50, (3.77), [42.80-46.90]	31.40, (16.18), [27.20-36.40]	43.30, (15.95), [38.35-51.55]
Fertilizers (kg/t of final product)	78.90, (36.37), [59.90-101.40]	94.00, (35.96), [67.12-118.83]	87.80, (7.24), [86.20-92.70]	64.40, (31.37), [53.10-78.00]	89.70, (39.78), [73.95-108.75]
Plant Protection Products (kg/t of final product)	0.39, (0.39), [0.17-0.65]	0.18, (0.15), [0.11-0.33]	0.10, (0.02), [0.09-0.10]	0.51, (0.39), [0.38-0.74]	0.77, (0.37), [0.57-0.97]
Diesel (L/t of final product)	23.00, (10.73), [20.00-29.00]	31.00, (9.73), [25.00-37.75]	23.00, (4.53), [21.00-25.00]	21.00, (10.85), [19.00-24.00]	19.00, (5.91), [17.00-21.00]
Labour (€/t of final product)	18.00, (8.83), [14.08-23.00]	22.16, (8.20), [17.70-28.06]	17.97, (2.83), [15.39-19.83]	14.26, (8.56), [12.26-16.93]	20.18, (8.26), [16.33-24.90]
Yield (t/ha)	5.24, (1.83), [3.92-6.96]	3.84, (1.13), [3.16-4.71]	5.11, (0.29), [4.66-5.14]	7.07, (1.52), [6.20-7.89]	5.25, (1.32), [4.31-5.73]
Carbon Footprint (CO_2eq/t of final product)	0.39, (0.15), [0.33-0.48]	0.43, (0.13), [0.37-0.52]	0.39, (0.16), [0.35-0.67]	0.34, (0.14), [0.29-0.39]	0.44, (0.16), [0.39-0.51]
Water Footprint (m^3/t of final product)	1,394 (457.52), [1,201-1,950]	2,099, (307.10), [1,827-2,271]	1,539, (204.76), [1,517-1,882]	1,169, (94.62), [1,110-1,229]	1,356, (219.58), [1,318-1,563]
Ecological Footprint (Global ha/t of final product)	0.53, (0.24), [0.40-0.70]	0.72, (0.22), [0.58-0.86]	0.56, (0.03), [0.54-0.58]	0.39, (0.19), [0.35-0.45]	0.53, (0.20), [0.49-0.63]
Area (ha)	5.00, (13.25), [3.00-10.00]	4.59, (8.88), [2.86-7.50]	2.30, (4.03), [1.00-5.00]	5.00, (6.15), [3.00-8.00]	13.00, (23.90), [7.00-25.50]

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

5.2 DEA Results

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

5.2.1 Italy

Figure 2 presents the results of EconDEA in a bar plot, revealing that the greatest part of farmers (63,1%) acquired efficiency scores between 0.7-0.9, meaning that they should reduce their inputs by 10-30% accordingly. Additionally, considering only economic dimension, scale efficiency scores indicate that farmers should adjust their farms size in order to operate at optimum scale. However, EcoDEA model results for scale efficiency suggest that the majority of the farmers (71%) are operating at optimum farm size when environmental factors are enabled. Moreover, a positive image is depicted for VRS efficiency scores as well, where farmers are achieving higher efficiency scores. In other words, the inclusion of are ameliorating farmers' performance providing an intergrated approach regarding the agricultural activities of Italian durum wheat farmers.

Figure 3 illustrates I1 and I2 differences in a density plot. It is apparent that I1 utilizes in a more efficient way used inputs since it dominates over I2 at efficiency scores higher than 0.85. It should be noted that there is an ongoing assumption that external factors (climate, weather conditions, etc.) affect the production process in the same way for every farm participating in this assessment. Moreover, in Table , median scores for I1 and I2 are presented, corresponding to 0.86 and 0.77 respectively. It is very promising that I2 farms achieved an efficiency score of 1.00, considering that this score arose after its comparison with farms of I1, meaning that in both samples there are efficient producers (efficiency score=1).

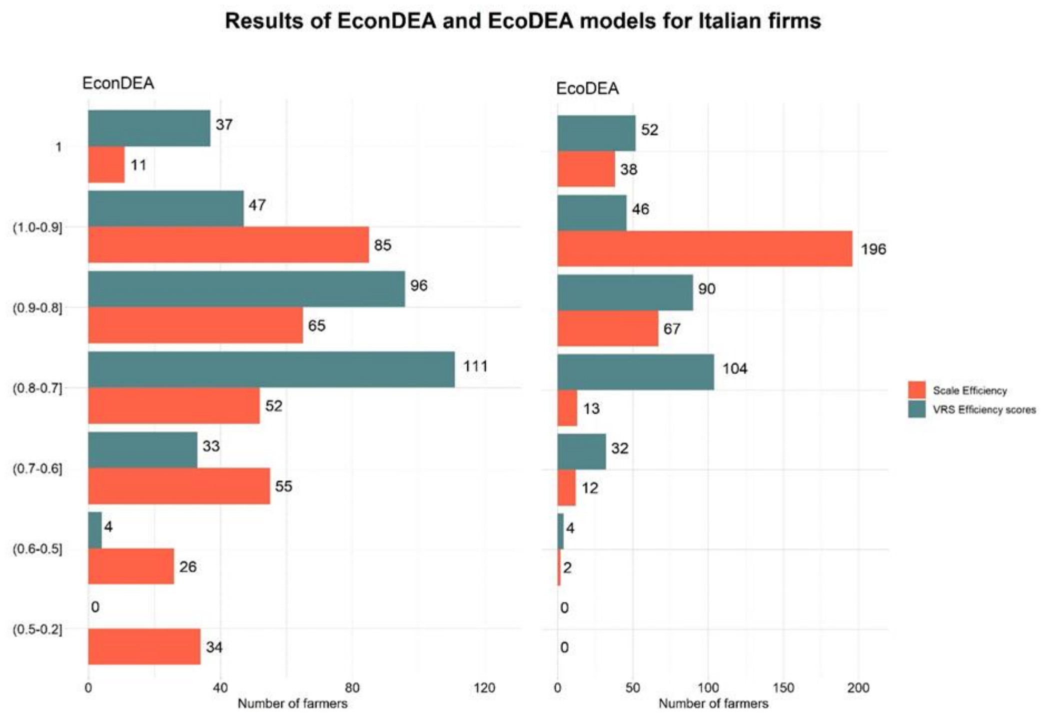

Figure 2. VRS and Scale Efficiency scores for the Italian sample (EconDEA & EcoDEA).

From another perspective, I2 has a greater need for inputs without achieving the same output as I1. Figure 4 presents the used inputs to output in monetary values through a scatterplot. The majority of I2 farms need more Inputs to achieve the same or smaller outcome in most cases. However, it is apparent that there is a tendency for inputs minimization in the Italian sample.

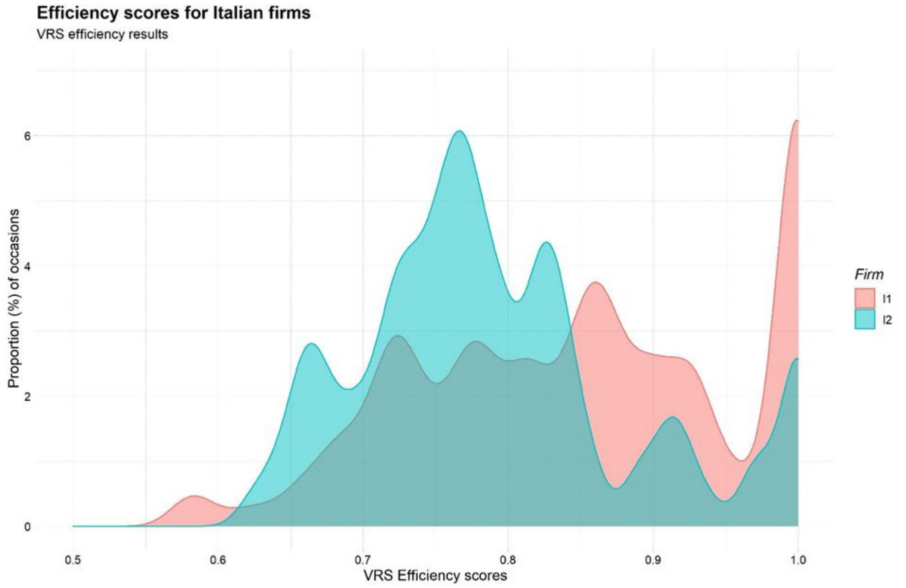

Figure 3. VRS Efficiency scores distribution for Italian firms (EcoDEA).

Table 3
Descriptive statistics of VRS efficiency scores per Italian firm

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

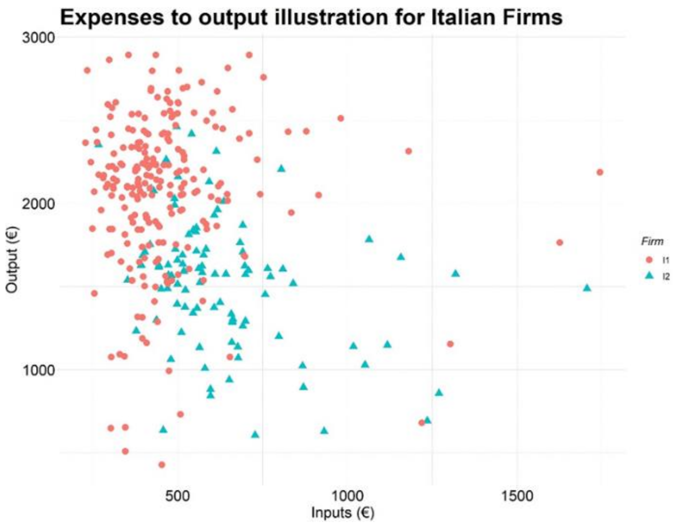

Figure 4. Monetary values of inputs used to final output for the Italian firms.

Furthermore, optimization of CWEFs proved that there is a great potential for minimizing the environmental impact of durum wheat production. More precisely, Figure 5 presents the distributional characteristics of CWEFs as initial values on the left side of each graph and the distribution of target values after the optimization process in the right side. As shown in the following boxplot, Carbon and Ecological footprints can be decreased by 38% and 23% accordingly, while water footprint has a little potential of 4.6% reduction based on median values.

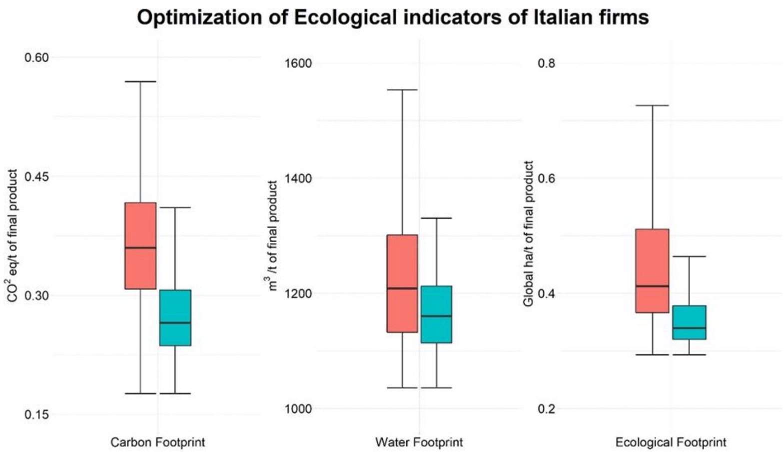

Figure 5. Reduction potential of CWEFs after the optimization process for the Italian farms.

5.2.2 Greece

Figure 6 illustrates the distribution of VRS and scale efficiency results for Greek Firms in a bar plot. Although the distribution of the acquired efficiency scores seems closely to Figure 2, it should be stated that efficiency scores are calculated based on the best performer of each region. Most of the farmers (57%) have acquired an efficiency score between 0.7-0.9, however greater scale inefficiency is presented in the lower bound of the distribution, where 35% of the examined farms have obtained scores lower than 0.6. The inclusion of the CWEFs has again a positive impact in the overall assessment for both pure technical and scale efficiency.

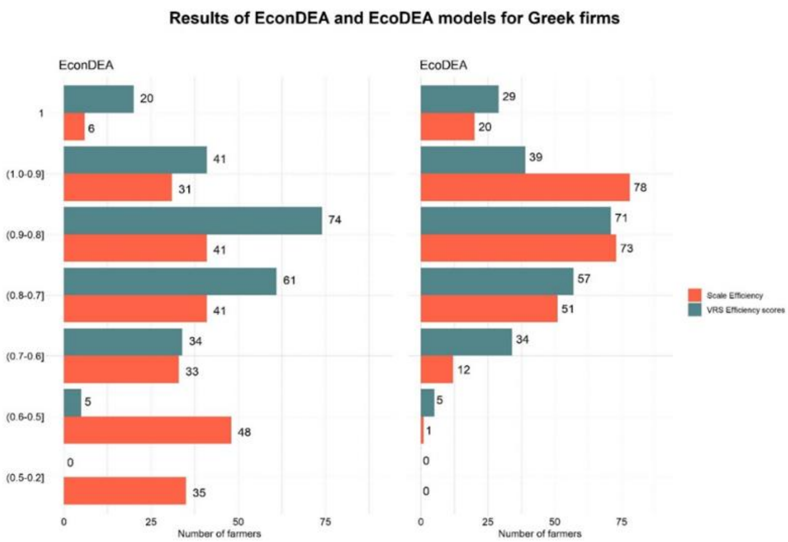

Figure 6. VRS and Scale Efficiency scores for the Greek sample (EconDEA & EcoDEA).

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

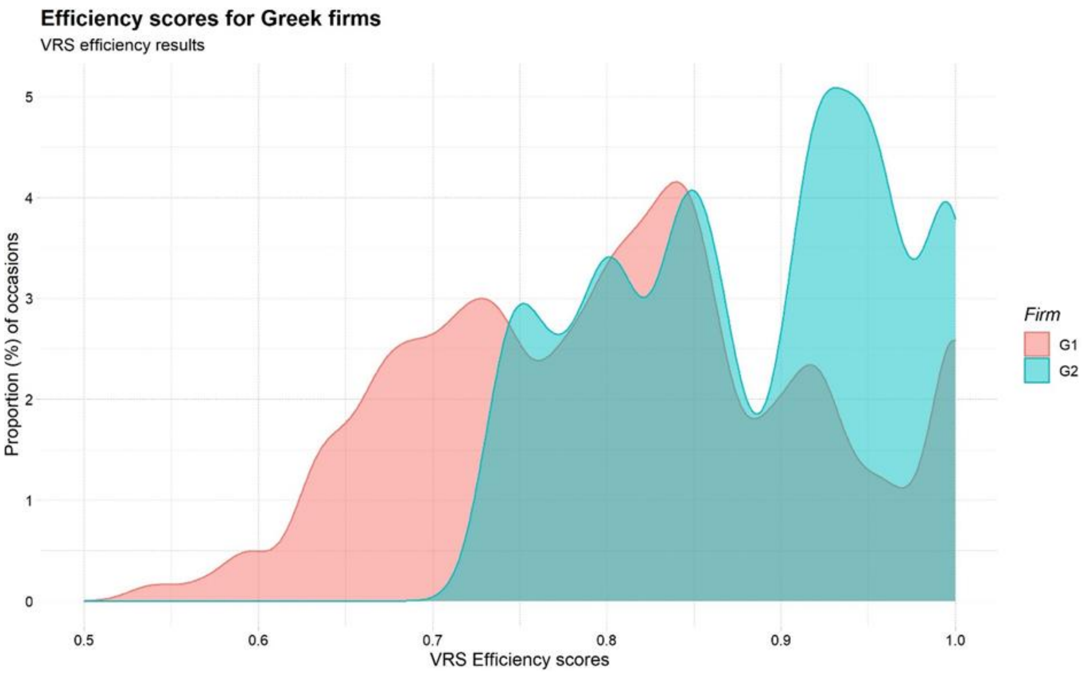

Figure 7. VRS Efficiency scores distribution for Greek firms (EcoDEA).

Table 4

Descriptive statistics of VRS efficiency scores per Greek firm.

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

Following the same rationale of the Italian sample, Figure 8 illustrates the acquired output per farm given its variable costs in a scatter plot. Compared to figure 4, a more disperse distribution of the Greek DMUs is revealed, which is of particular interest in terms of management practices. In other words, in the Italian sample there is a clear strategy for inputs minimization, however in the Greek territory there is no tendency neither for inputs minimization nor for outputs maximization.

Results of EcoDEA model for the Greek model reveal that both water and ecological footprints can be reduced by 17% and 30% accordingly while carbon footprint can be decreased by 9.7% as seen in Figure 9. Compared with the Italian farms, Greek farms present a smaller potential for reduction on carbon footprint (IT: -38 %), but they should decrease in higher rates their ecological and water footprint (IT: -23 % & -4.5% accordingly).

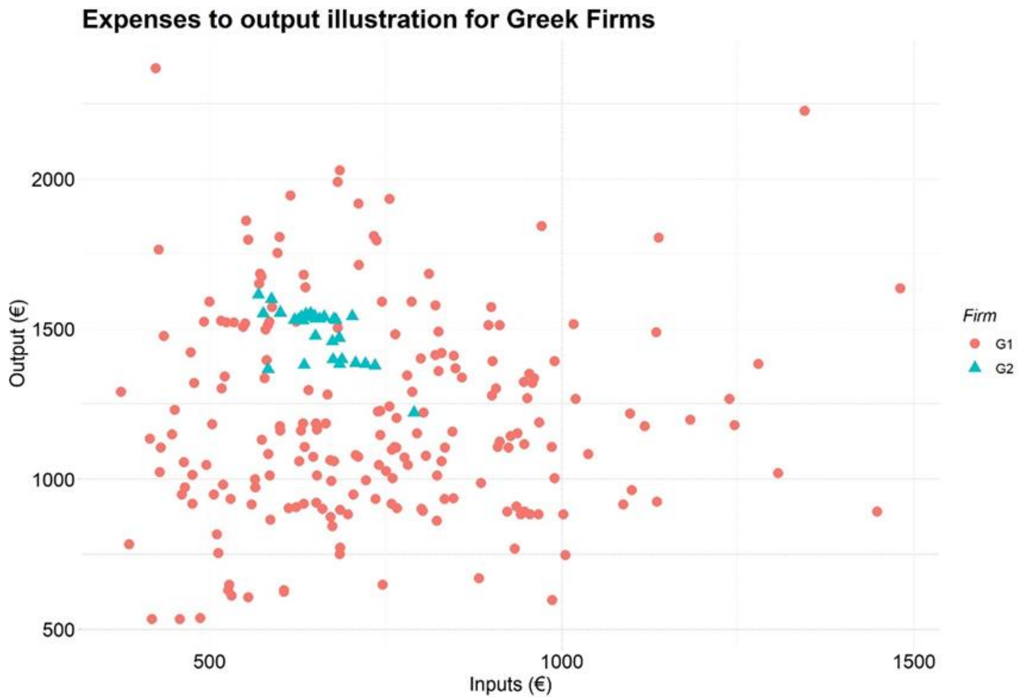

Figure 8. Monetary values of inputs used to final output for Greek firms.

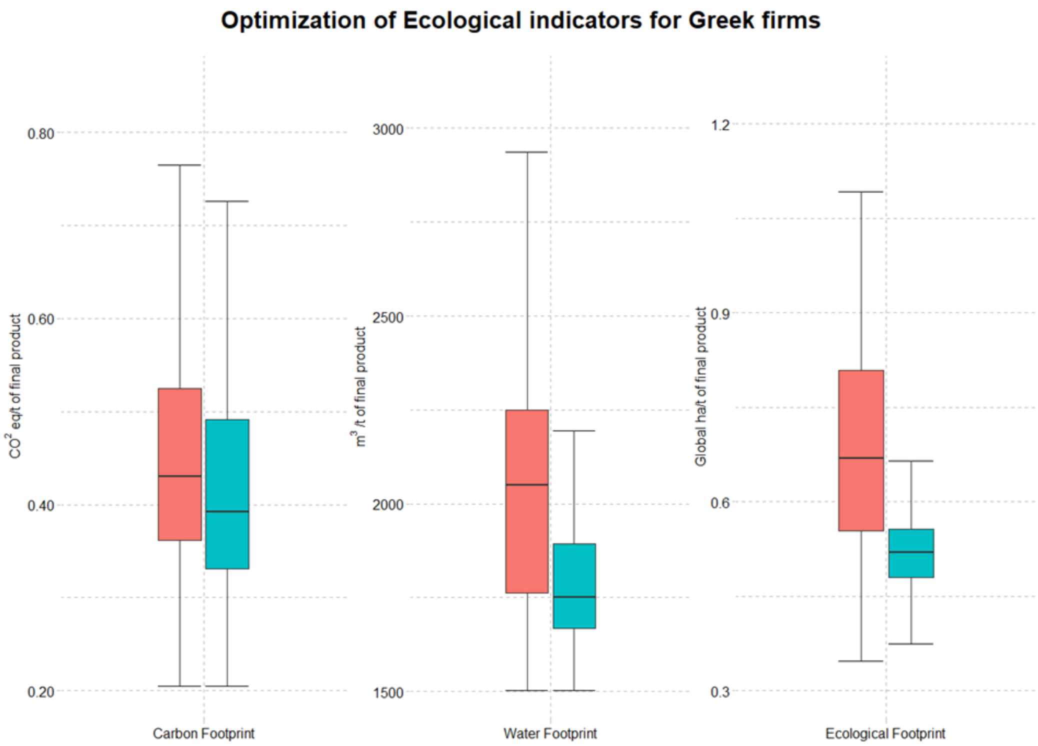

Figure 9. Reduction potential of CWEFs after the optimization process for the Greek farms.

6 Discussion and study limitations

By evaluating the acquired results, several remarks were arisen. Firstly, it is positive that both countries have representative farms at a proportion of around 10% for the EconDEA model, that is there are several examples of efficient producers in each sample . Moreover, it is prominent that the inclusion of CWEFs did not decrease the overall number of farms that have previously achieved high efficiency scores through the EconDEA model. On the contrary the number of the efficient farms has increased both for the Italian and Greek sample when implementing the EcoDEA model (Figure 2, Figure 6). Through the previous stated remarks, it is evident that there in a holistic approach in the overall GD.NET management system, due to the fact that the inclusion of CWEFs would normally lead to lower efficiency scores, since it would be more difficult for producers to be both economically and environmentally efficient. Another remark is that scale efficiency has improved, a result that validates the prior point of guidelines that promotes both economic and environmental aspect of durum wheat cultivation. Regarding the acquired scores per firm, G2 acquires the highest median value of 0.9; however the sample of this firm was small (N=33). According to authors' experience in the Greek territory, the acquired efficiency results are higher than expected and this may lay to the fact that these farms were part of agricultural cooperatives. Moreover, a more stretched distribution was anticipated; However considering the fact that each sample is evaluated through each best performer, this was not feasible.

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

Figure 2 and Figure 6 provide strong evidence that there are external factors affecting the performance of durum wheat farmers in the Greek sample, compared to the Italian ones, where there is a clear tendency for inputs minimization from the Italian part while in the Greek territory a more scattered distribution is illustrated. In this section, sustainability, agricultural, institutional and data collection issues are discussed, to further clarify the arisen differences between the two countries.

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

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

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

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

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

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

7 Conclusions

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

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

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

Acknowledgment

This study was funded by Barilla under the project entitled: «Assessing inputs' use efficiency of durum wheat cultivation» [Grant number: 6679 - Special Account for Research Grants, University of Thessaly).

References

Ahado, S., Hejkrlík, J., Enkhtur, A., Tseren, T., Ratinger, T. (2021). Does cooperative membership impact the yield and efficiency of smallholder farmers? Evidence from potato farmers in Mongolia. *China Agricultural Economic Review*, **13** (4): 736–755.

Ait Sidhoum, A., Serra, T., Latruffe, L. (2019). Measuring sustainability efficiency at farm level: a data envelopment analysis approach. *European Review of Agricultural Economics*, **47** (1): 200–225.

Alletto, L., Vandewalle, A., Debaeke, P. (2022). Crop diversification improves cropping system sustainability: An 8-year on-farm experiment in South-Western France. *Agricultural Systems*, **200**: 103433-103447.

Anderies, J. M., Folke, C., Walker, B., Ostrom, E. (2013). Aligning Key Concepts for Global Change Policy: Robustness, Resilience, and Sustainability. *Ecology and Society*, **18** (2): 8–16.

Bao, B., Jiang, A., Jin, S., Zhang, R. (2021). The Evolution and Influencing Factors of Total Factor Productivity of Grain Production Environment: Evidence from Poyang Lake Basin, China. *Land*, **10** (6): 606–627.

Bonfante, A., Monaco, E., Manna, P., de Mascellis, R., Basile, A., Buonanno, M., Cantilena, G., Esposito, A., Tedeschi, A., de Michele, C., Belfiore, O., Catapano, I., Ludeno, G., Salinas, K., Brook, A. (2019). LCIS DSS—An irrigation supporting system for water use efficiency improvement in precision agriculture: A maize case study. *Agricultural Systems*, **176**: 102646–102660.

Bournaris, T., Vlontzos, G., Moulogianni, C. (2019). Efficiency of vegetables produced in Glasshouses: The Impact of Data Envelopment Analysis (DEA) in land management decision making. *Land*, **8** (1): 17–28.

Boyd, T., Docken, G., Ruggiero, J. (2016). Outliers in data envelopment analysis. *Journal of Centrum Cathedra*, **9** (2): 168–183.

Bux, C., Lombardi, M., Varese, E., Amicarelli, V. (2022). Economic and Environmental Assessment of Conventional versus Organic Durum Wheat Production in Southern Italy. *Sustainability*, **14** (15): 9143–9157.

Capalbo, S. M., Antle, J. M., Seavert, C. (2017). Next generation data systems and knowledge products to support agricultural producers and science-based policy decision making. *Agricultural Systems*, **155**: 191–199.

Cerf, M., Jeuffroy, M. H., Prost, L., Meynard, J. M. (2012). Participatory design of agricultural decision support tools: Taking account of the use situations. *Agronomy for Sustainable Development*, **32** (4): 899–910.

Charnes, A., Cooper, W. W., Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, **2** (6): 429–444.

Chemak, F., Chenoune, R., Belhouchette, H., Mazhoud, H. (2020). A Crop Model for Improvement Water Use Efficiency and Durum Wheat Pro-duction in the Siliana Region. *Selcuk Journal of Agricultural and Food Sciences*, **34** (1): 24–30.

Coble, K. H., Mishra, A. K., Ferrell, S., Griffin, T. (2018). Big Data in Agriculture: A Challenge for the Future. *Applied Economic Perspectives and Policy*, **40** (1): 79–96.

Coll-Serrano, V., Bolos, V., Benitez Suarez, R. (2022). Conventional and Fuzzy Data Envelopment Analysis - deaR library. Available at: https://cran.r-project.org/web/packages/deaR/deaR.pdf (accessed on July 7, 2022).

Coluccia, B., Valente, D., Fusco, G., de Leo, F., Porrini, D. (2020). Assessing agricultural eco-efficiency in Italian Regions. *Ecological Indicators*, **116**: 106483–106495.

Dettori, M., Cesaraccio, C., Duce, P., Mereu, V. (2022). Performance Prediction of Durum Wheat Genotypes in Response to Drought and Heat in Climate Change Conditions. *Genes*, **13** (3): 488–513.

Devkota, M., Yigezu, Y. A. (2020). Explaining yield and gross margin gaps for sustainable intensification of the wheat-based systems in a Mediterranean climate. *Agricultural Systems*, **185**: 102946–102962.

Drohan, P. J., Bechmann, M., Buda, A., Djodjic, F., Doody, D., Duncan, J. M., Iho, A., Jordan, P., Kleinman, P. J., McDowell, R., Mellander, P.-E., Thomas, I. A., Withers, P. J. A. (2019). A Global Perspective on Phosphorus Management Decision Support in Agriculture: Lessons Learned and Future Directions. *Journal of Environmental Quality*, **48** (5): 1218–1233.

Duan, S. X., Wibowo, S., Chong, J. (2021). A Multicriteria Analysis Approach for Evaluating the Performance of Agriculture Decision Support Systems for Sustainable Agribusiness. *Mathematics*, **9** (8): 884–900.

Fellmann, T., Witzke, P., Weiss, F., van Doorslaer, B., Drabik, D., Huck, I., Salputra, G., Jansson, T., Leip, A. (2018). Major challenges of integrating agriculture into climate change mitigation policy frameworks. *Mitigation and Adaptation Strategies for Global Change*, **23** (3): 451–468.

Forleo, M. B., Giaccio, V., Mastronardi, L., Romagnoli, L. (2021). Analysing the efficiency of diversified farms: Evidences from Italian FADN data. *Journal of Rural Studies*, **82**: 262–270.

Galanopoulos, K., Aggelopoulos, S., Kamenidou, I., Mattas, K. (2006). Assessing the effects of managerial and production practices on the efficiency of commercial pig farming. *Agricultural Systems*, **88** (2): 125–141.

Gao, S., Li, D. (2014). Spatial-temporal analysis of agricultural production technical efficiency: Through DEA in Mianyang city. *International Journal of Technology, Policy and Management*, **14** (2): 193–203.

Glauben, T., Svanidze, M., Götz, L., Prehn, S., Jamali Jaghdani, T., Đurić, I., Kuhn, L. (2022). The War in Ukraine, Agricultural Trade and Risks to Global Food Security. *Intereconomics*, **57** (3): 157–163.

HORTA (2012). Grannoduro.net. Available at: https://www.horta-srl.it/en/granoduro-net/ (accessed on July 5, 2022).

Ilahi, S., Wu, Y., Raza, M.A.A., Wei, W., Imran, M., Bayasgalankhuu, L. (2019). Optimization Approach for Improving Energy Efficiency and Evaluation of Greenhouse Gas Emission of Wheat Crop using Data Envelopment Analysis. *Sustainability*, **11** (12): 3409–3426.

Iyer, P., Bozzola, M., Hirsch, S., Meraner, M., Finger, R. (2020). Measuring Farmer Risk Preferences in Europe: A Systematic Review. *Journal of Agricultural Economics*, **71** (1): 3–26.

Jakku, E., Taylor, B., Fleming, A., Mason, C., Fielke, S., Sounness, C., Thorburn, P. (2019). "If they don't tell us what they do with it, why would we trust them?" Trust, transparency and benefit-sharing in Smart Farming. *NJAS: Wageningen Journal of Life Sciences*, **90–91** (1): 100285–100298.

Jakku, E., Thorburn, P. J. (2010). A conceptual framework for guiding the participatory development of agricultural decision support systems. *Agricultural Systems*, **103** (9): 675–682.

Gołaszewski, J., van der Voort, M., Meyer-Aurich, A., Baptista, F., Balafoutis, A., Mikkola, H.J. (2014). Comparative Analysis of Energy Efficiency in Wheat Production in Different Climate Conditions of Europe. *Journal of Agricultural Science and Technology B*, **4** (8): 632–640.

Jiang, H., Hua, M., Zhang, J., Cheng, P., Ye, Z., Huang, M., Jin, Q. (2020). Sustainability efficiency assessment of wastewater treatment plants in China: A data envelopment analysis based on cluster benchmarking. *Journal of Cleaner Production*, **244** (6): 118729–118739.

Lacoste, M., Powles, S. (2016). Beyond modelling: considering user-centred and post-development aspects to ensure the success of a decision support system. *Computers and Electronics in Agriculture*, **121**: 260–268.

Lampe, H. W., Hilgers, D. (2015). Trajectories of efficiency measurement: A bibliometric analysis of DEA and SFA. *European Journal of Operational Research*, **240** (1): 1–21.

Li, C., Shi, Y., Khan, S. U., Zhao, M. (2021). Research on the impact of agricultural green production on farmers' technical efficiency: evidence from China. *Environmental Science and Pollution Research*, **28** (29): 38535–38551.

Lin, B., Wang, X., Jin, S., Yang, W., Li, H. (2022). Impacts of cooperative membership on rice productivity: Evidence from China. *World Development*, **150**: 105669–105682.

Mangiafico, S. (2016). Summary and Analysis of Extension Program Evaluation in R. Available at: https://cran.r-project.org/web/packages/rcompanion/rcompanion.pdf (accessed on July 7, 2022).

Masuda, K. (2019). Eco-Efficiency Assessment of Intensive Rice Production in Japan: Joint Application of Life Cycle Assessment and Data Envelopment Analysis. *Sustainability*, **11** (19): 5368–5382.

Meuwissen, M. P. M., Feindt, P. H., Spiegel, A., Termeer, C. J. A. M., Mathijs, E., Mey, Y. de, Finger, R., Balmann, A., Wauters, E., Urquhart, J., Vigani, M., Zawalińska, K., Herrera, H., Nicholas-Davies, P., Hansson, H., Paas, W., Slijper, T., Coopmans, I., Vroege, W., Ciechomska, A., Accatino, F., Kopainsky, B., Poortvliet, P. M., Candel, J.J.L., Maye, D., Severini, S., Senni, S., Soriano, B, Lagerkvist, C-J., Peneva, M., Gavrilescu, C., Reidsma, P. (2019). A framework to assess the resilience of farming systems. *Agricultural Systems*, **176**: 102656–102666.

Mir, S. A., Qasim, M., Mubarak, T., Bhat, Z. A., Bhat, J. A., Bangroo, S. A., Sofi, T. A. (2015). Decision support systems in a global agricultural perspective - a comprehensive review. *International Journal of Agriculture Sciences*, **7** (1): 403–415.

Moutinho, V., Robaina, M., Macedo, P. (2018). Economic-environmental efficiency of European agriculture – A generalized maximum entropy approach. *Agricultural Economics (Czech Republic)*, **64** (10): 423–435.

Navarro-Hellín, H., Martínez-del-Rincon, J., Domingo-Miguel, R., Soto-Valles, F., Torres-Sánchez, R. (2016). A decision support system for managing irrigation in agriculture. *Computers and Electronics in Agriculture*, **124**: 121–131.

Olakojo, S. A., Onanuga, O. T. (2020). Effects of Climate Change on the Long-run Crops' Yields in Nigeria. *International Journal on Food System Dynamics*, **11** (3): 270–296.

Paltasingh, K. R., Goyari, P. (2018). Impact of farmer education on farm productivity under varying technologies: case of paddy growers in India. *Agricultural and Food Economics*, **6** (1): 1–19.

Pan, W.-T., Zhuang, M.-E., Zhou, Y.-Y., Yang, J.-J. (2021). Research on sustainable development and efficiency of China's E-Agriculture based on a data envelopment analysis-Malmquist model. *Technological Forecasting and Social Change*, **162**: 120298–120304.

Partel, V., Charan Kakarla, S., Ampatzidis, Y. (2019). Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence. *Computers and Electronics in Agriculture*, **157**: 339–350.

Pignatti, E., Carli, G., Canavari, M. (2015). What really matters? A qualitative analysis on the adoption of innovations in agriculture. *Journal of Agricultural Informatics*, **6** (4): 73–84.

Pooniya, V., Jat, S. L., Choudhary, A. K., Singh, A. K., Parihar, C. M., Bana, R. S., Swarnalakshmi, K., Rana, K. S. (2015). Nutrient Expert assisted site-specific-nutrient-management: An alternative precision fertilization technology for maize-wheat cropping system in South-Asian Indo-Gangetic Plains. *Indian Journal of Agricultural Sciences*, **85** (8): 996–1002.

Rakshit, I., Mandal, S. K. (2020). A global level analysis of environmental energy efficiency: an application of data envelopment analysis. *Energy Efficiency*, **13** (5): 889–909.

Reziti, I. (2020). Total factor productivity change in Greek crop production using a Fare-Primont index analysis. *International Journal of Food and Agricultural Economics*, **8** (2): 167–178.

Reziti, I., Zangelidis, L. (2019). Regional Productivity and Efficiency Growth in Greek Agriculture. *Journal of Economics and Business*, **69** (4): 3–20.

Rose, D. C., Sutherland, W. J., Parker, C., Lobley, M., Winter, M., Morris, C., Twining, S., Ffoulkes, C., Amano, T., Dicks, L.V. (2016). Decision support tools for agriculture: Towards effective design and delivery. *Agricultural Systems*, **149**: 165–174.

Rossi, V., Sperandio, G., Caffi, T., Simonetto, A., Gilioli, G. (2019). Critical Success Factors for the Adoption of Decision Tools in IPM. *Agronomy*, **9** (11): 710.

Rossi, V., Manstretta, V., Ruggeri, M. (2015). A multicomponent decision support system to manage *Fusarium* head blight and mycotoxins in durum wheat. *World Mycotoxin Journal*, **8** (5): 629–640.

Rossi, V., Meriggi, P., Caffi, T., Giosue, S., Bettati, T. (2010). A Web-based Decision Support System for Managing Durum Wheat Crops. In: Devlin, G. (2010) (Ed.), *Decision Support Systems*. InTech, pp. 1–28.

Rossi, V., Salinari, F., Poni, S., Caffi, T., Bettati, T. (2014). Addressing the implementation problem in agricultural decision support systems: the example of vite.net®. *Computers and Electronics in Agriculture*, **100**: 88–99.

Sabella, E., Aprile, A., Negro, C., Nicolì, F., Nutricati, E., Vergine, M., Luvisi, A., De Bellis, L. (2020). Impact of Climate Change on Durum Wheat Yield. *Agronomy*, **10** (6): 793–806.

Saiz-Rubio, V., Rovira-Más, F. (2020). From Smart Farming towards Agriculture 5.0: A Review on Crop Data Management. *Agronomy*, **10** (2): 207–228.

Seiford, L. M., Zhu, J. (2002). Modelling undesirable factors in efficiency evaluation. *European Journal of Operational Research*, **142** (1): 16–20.

Skevas, T., Stefanou, S. E., Oude Lansink, A. (2014). Pesticide use, environmental spillovers and efficiency: A DEA risk-adjusted efficiency approach applied to Dutch arable farming. *European Journal of Operational Research*, **237** (2): 658–664.

Sridhar, A., Balakrishnan, A., Jacob, M. M., Sillanpää, M., Dayanandan, N. (2022). Global impact of COVID-19 on agriculture: role of sustainable agriculture and digital farming. *Environmental Science and Pollution Research,* 1-17.

Tang, X., Lu, C., Meng, P., Cheng, W. (2022). Spatiotemporal Evolution of the Environmental Adaptability Efficiency of the Agricultural System in China. *Sustainability*, **14** (6): 3685–3700.

Theodoridis, A. M., Psychoudakis, A. (2008). Efficiency Measurement in Greek Dairy Farms: Stochastic Frontier vs. Data Envelopment Analysis. *International Journal of Economic Sciences and Applied Research*, **1** (2): 53–67.

Theodoridis, A., Ragkos, A., Roustemis, D., Galanopoulos, K., Abas, Z., Sinapis, E. (2012). Assessing technical efficiency of Chios sheep farms with data envelopment analysis. *Small Ruminant Research*, **107** (2–3): 85–91.

Toloo, M. (2014). The role of non-Archimedean epsilon in finding the most efficient unit: With an application of professional tennis players. *Applied Mathematical Modelling*, **38** (21–22): 5334–5346.

Veflen, N., Scholderer, J., Elvekrok, I. (2019). Composition of Collaborative Innovation Networks: An Investigation of Process Characteristics and Outcomes. *International Journal on Food System Dynamics*, **10** (1): 1–20.

Viani, F., Bertolli, M., Salucci, M., Polo, A. (2017). Low-Cost Wireless Monitoring and Decision Support for Water Saving in Agriculture. *IEEE Sensors Journal*, **17** (13): 4299–4309.

Viergutz, T., Schulze-Ehlers, B. (2018). Exploring the Spatiotemporal Dynamics of Cooperative Members' Switching Decisions. *International Journal on Food System Dynamics*, **9** (5): 438–452.

Villalobos, F. J., Delgado, A., López-Bernal, Á., Quemada, M. (2020). FertiliCalc: A Decision Support System for Fertilizer Management. *International Journal of Plant Production*, **14** (2): 299–308.

Vivek, S., Jesma, V. (2019). The changing phase of agriculture: Artificial intelligence. *AgricINTERNATIONAL*, **6** (1): 33–38.

Weber, R., Braun, J., Frank, M. (2022). How does the Adoption of Digital Technologies Affect the Social Sustainability of Small-scale Agriculture in South-West Germany? *International Journal on Food System Dynamics*, **13** (3): 275–293.

Wickham, H. (2016). ggplot2: Elegant Graphics for Data Analysis. Available at: https://cran.r-project.org/web/packages/ggplot2/citation.html (accessed on July 6, 2022).

Xiu-Shuang, L., Kang, Y. (2021). Contributions of Productivity and Relative Price Changes to Wheat Profitability Changes in China. *International Journal of Engineering and Management Research*, **11** (4): 263–272.

Yang, L., Zhou, Y., Meng, B., Li, H., Zhan, J., Xiong, H., Zhao, H., Cong, W., Wang, X., Zhang, W., Lakshmanan, P., Deng, Y., Shi, X., Chen, X., Zhang, F. (2022). Reconciling productivity, profitability and sustainability of small-holder sugarcane farms: A combined life cycle and data envelopment analysis. *Agricultural Systems*, **199**: 103392–110403.

Yigezu, Y. A., Mugera, A., El-Shater, T., Aw-Hassan, A., Piggin, C., Haddad, A., Khalil, Y., Loss, S. (2018). Enhancing adoption of agricultural technologies requiring high initial investment among smallholders. *Technological Forecasting and Social Change*, **134**: 199–206.

Zhai, Z., Martínez, J. F., Beltran, V., Martínez, N. L. (2020). Decision support systems for agriculture 4.0: Survey and challenges. *Computers and Electronics in Agriculture*, **170**: 105256–105272.

Appendix

Table A1

Extended descriptive statistics of the assessed sample

Characteristic	Overall, N = 563[1]	G1, N = 202[1]	G2, N = 33[1]	I1, N = 229[1]	I2, N = 99[1]
Seeds (kg/t of final product)	15.00, 46.35, 41.50, 157.70, (19.70), [32.50-55.90]	27.00, 59.30, 56.65, 127.50, (18.38), [45.42-67.97]	37.20, 44.30, 44.50, 56.50, (3.77), [42.80-46.90]	15.00, 34.71, 31.40, 157.70, (16.18), [27.20-36.40]	23.30, 47.52, 43.30, 123.90, (15.95), [38.35-51.55]
Fertilizers (kg/t of final product)	26.50, 85.91, 78.90, 272.50, (36.37), [59.90-101.40]	37.70, 97.00, 94.00, 218.30, (35.96), [67.12-118.83]	76.90, 89.21, 87.80, 110.60, (7.24), [86.20-92.70]	26.50, 69.85, 64.40, 266.10, (31.37), [53.10-78.00]	38.20, 99.35, 89.70, 272.50, (39.78), [73.95-108.75]
Plant Protection Products (kg/t of final product)	0.02, 0.48, 0.39, 2.41, (0.39), [0.17-0.65]	0.02, 0.23, 0.18, 0.81, (0.15), [0.11-0.33]	0.08, 0.10, 0.10, 0.19, (0.02), [0.09-0.10]	0.02, 0.62, 0.51, 2.41, (0.39), [0.38-0.74]	0.14, 0.79, 0.77, 2.33, (0.37), [0.57-0.97]
Diesel (L/t of final product)	10.00, 25.89, 23.00, 121.00, (10.73), [20.00-29.00]	12.00, 32.52, 31.00, 73.00, (9.73), [25.00-37.75]	13.00, 21.55, 23.00, 29.00, (4.53), [21.00-25.00]	14.00, 23.30, 21.00, 121.00, (10.85), [19.00-24.00]	10.00, 19.83, 19.00, 52.00, (5.91), [17.00-21.00]
Labour (€/t of final product)	7.93, 20.02, 18.00, 92.66, (8.83), [14.08-23.00]	8.83, 23.83, 22.16, 62.82, (8.20), [17.70-28.06]	12.13, 17.65, 17.97, 22.77, (2.83), [15.39-19.83]	7.93, 16.24, 14.26, 92.66, (8.56), [12.26-16.93]	9.29, 21.78, 20.18, 57.61, (8.26), [16.33-24.90]
Yield (t of final product/ha)	1.43, 5.43, 5.24, 9.64, (1.83), [3.92-6.96]	1.78, 4.00, 3.84, 7.89, (1.13), [3.16-4.71]	4.07, 4.97, 5.11, 5.38, (0.29), [4.66-5.14]	1.43, 6.90, 7.07, 9.64, (1.52), [6.20-7.89]	2.02, 5.10, 5.25, 8.20, (1.32), [4.31-5.73]
Area (ha)	0.20, 9.25, 5.00, 142.00, (13.25), [3.00-10.00]	0.50, 7.13, 4.59, 62.20, (8.88), [2.86-7.50]	0.20, 3.91, 2.30, 14.00, (4.03), [1.00-5.00]	0.38, 6.69, 5.00, 48.33, (6.15), [3.00-8.00]	2.00, 21.31, 13.00, 142.00, (23.90), [7.00-25.50]
Carbon Footprint (CO_2eq/t of final product)	0.18, 0.42, 0.39, 1.32, (0.15), [0.33-0.48]	0.21, 0.46, 0.43, 0.95, (0.13), [0.37-0.52]	0.31, 0.47, 0.39, 0.77, (0.16), [0.35-0.67]	0.18, 0.36, 0.34, 1.32, (0.14), [0.29-0.39]	0.24, 0.48, 0.44, 1.17, (0.16), [0.39-0.51]
Water Footprint (m^3/t of final product)	1,036, 1,585, 1,394, 3,113, (457.52), [1,201-1,950]	1,556, 2,089, 2,099, 3,113, (307.10), [1,826-2,271]	1,502, 1,678, 1,539, 2,051, (204.76), [1,517-1,882]	1,036, 1,181, 1,169, 1,738, (94.62), [1,110-1,229]	1,235, 1,460, 1,356, 2,279, (219.58), [1,317-1,563]
Ecological Footprint (Global ha/t of final product)	0.29, 0.58, 0.53, 1.94, (0.24), [0.40-0.70]	0.35, 0.74, 0.72, 1.51, (0.22), [0.58-0.86]	0.50, 0.56, 0.56, 0.67, (0.03), [0.54-0.58]	0.29, 0.44, 0.39, 1.94, (0.19), [0.35-0.45]	0.34, 0.59, 0.53, 1.38, (0.20), [0.49-0.63]

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

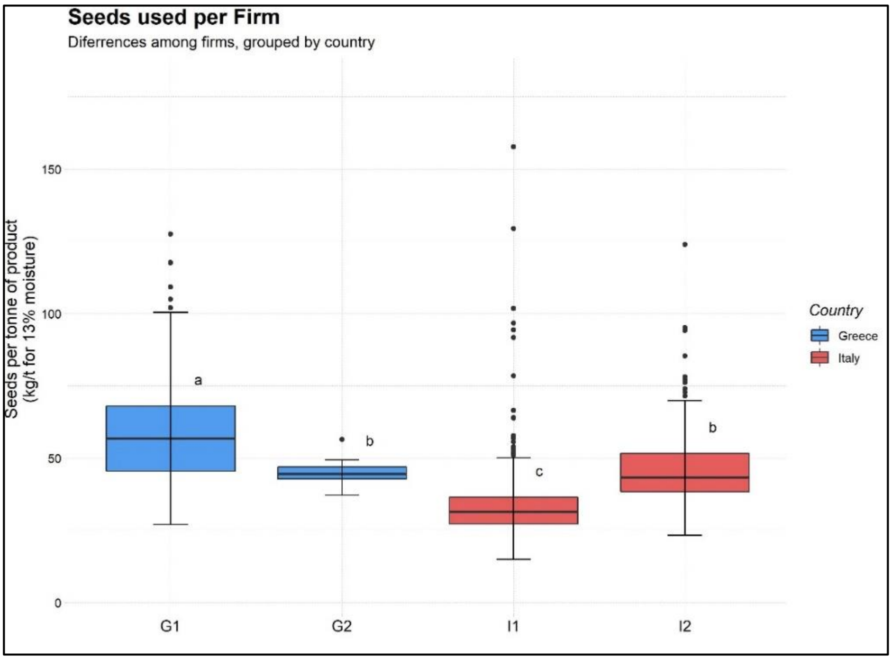

Figure A1: Seeds used per firm.

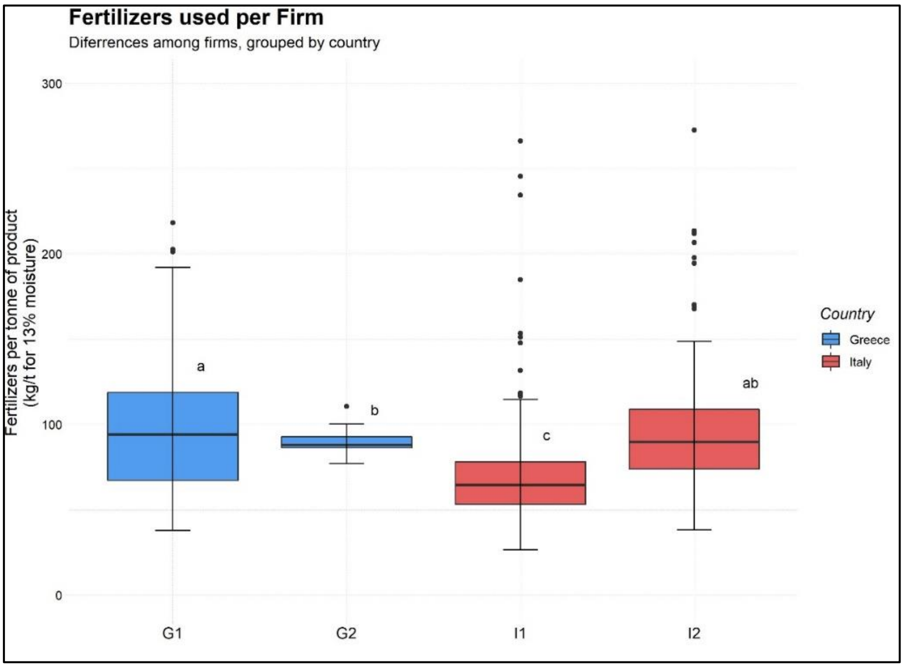

Figure A2: Fertilizers used per firm.

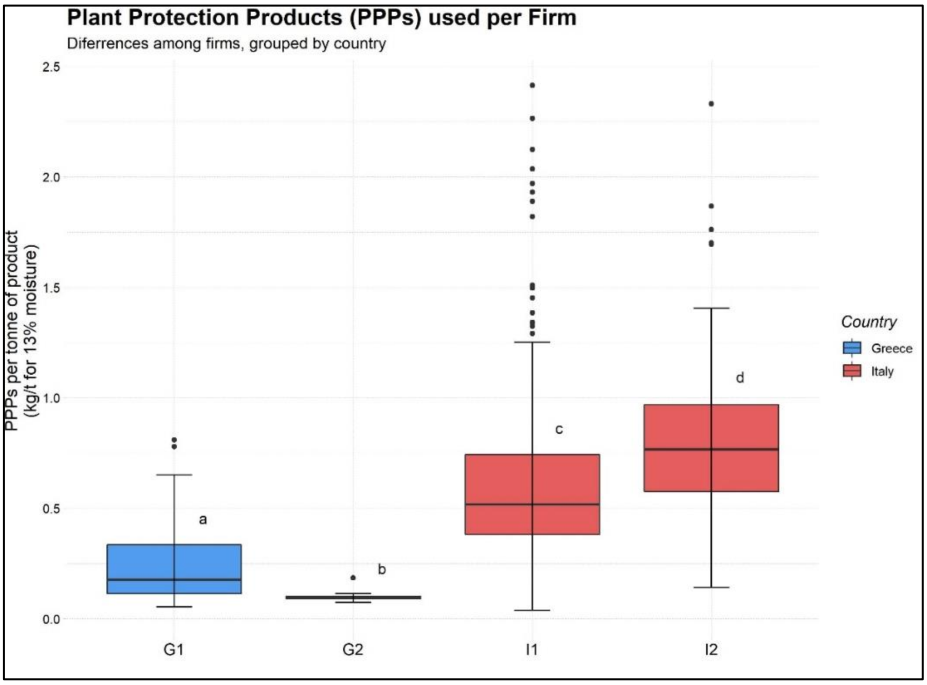

Figure A3: Plant Protection Products used per firm.

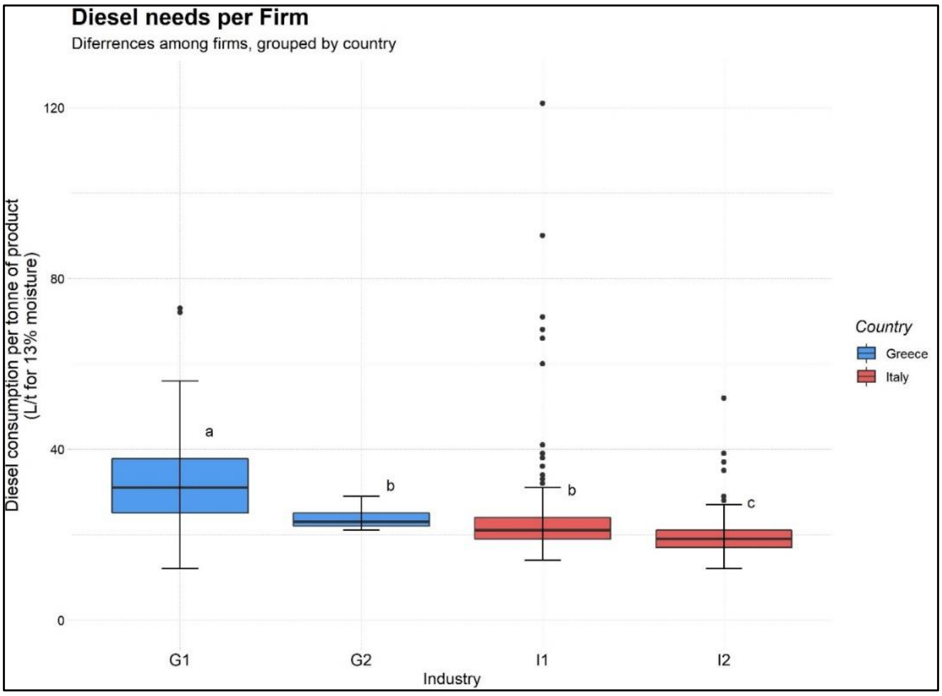

Figure A4: Diesel needs per firm.

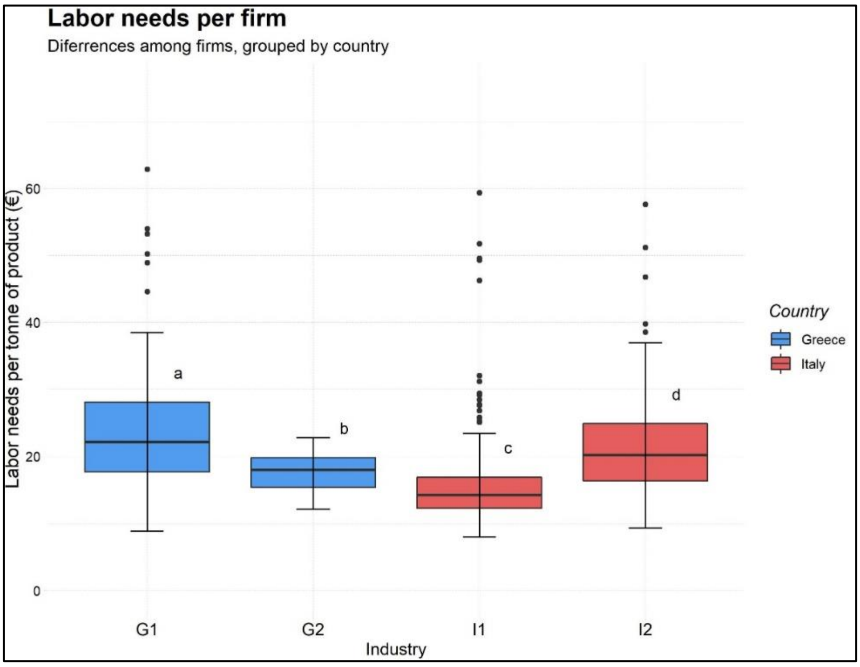

Figure A5: Labour needs per firm

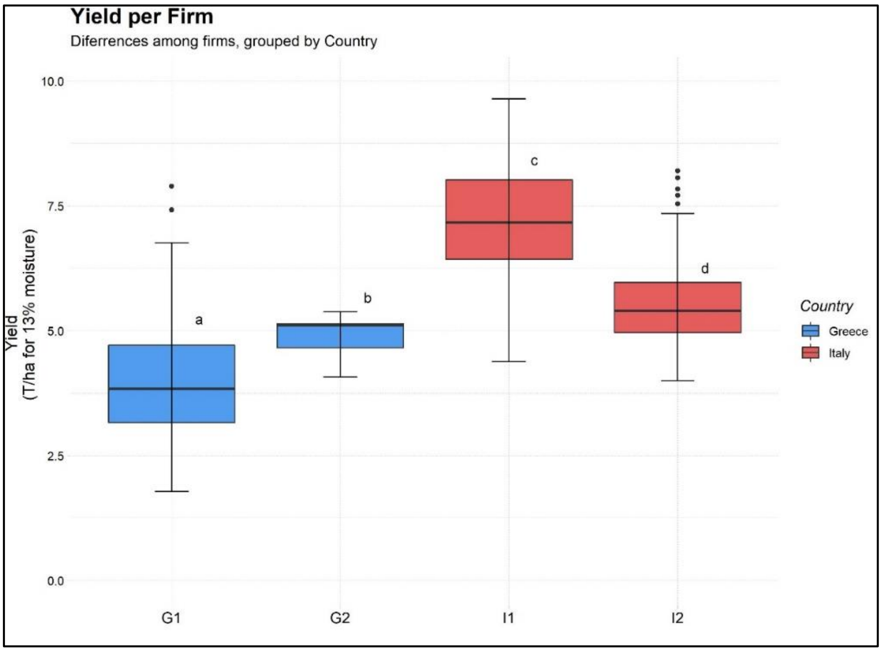

Figure A6: Yield per firm

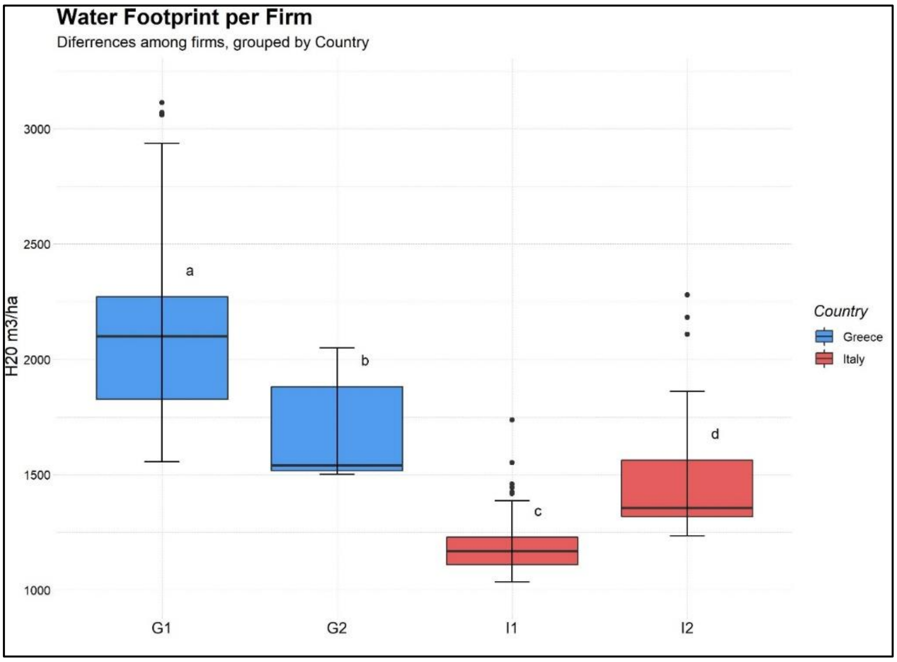

Figure A7: Water Footprint per firm

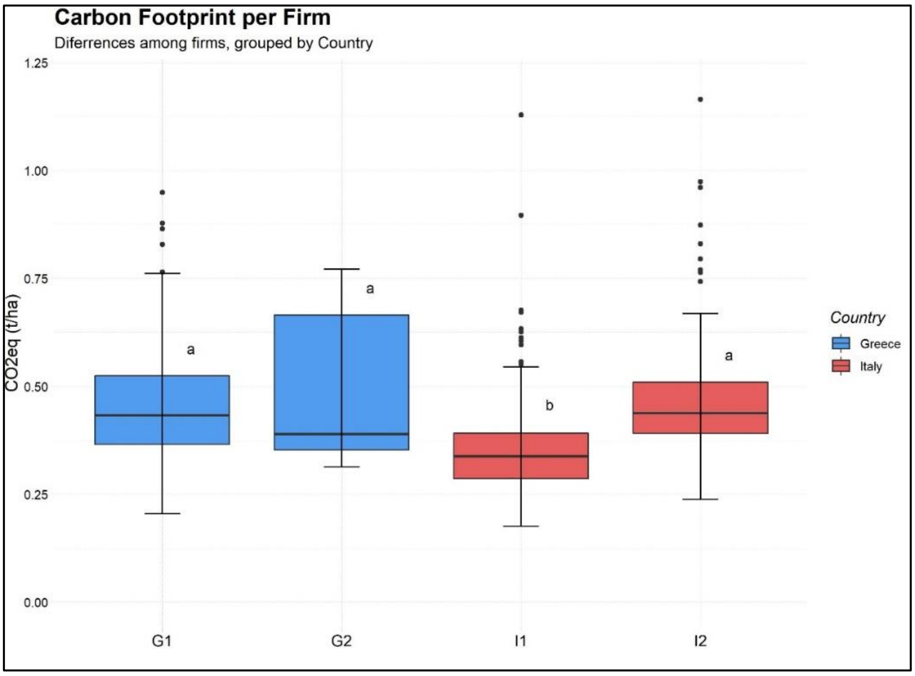

Figure A8: Carbon Footprint per firm

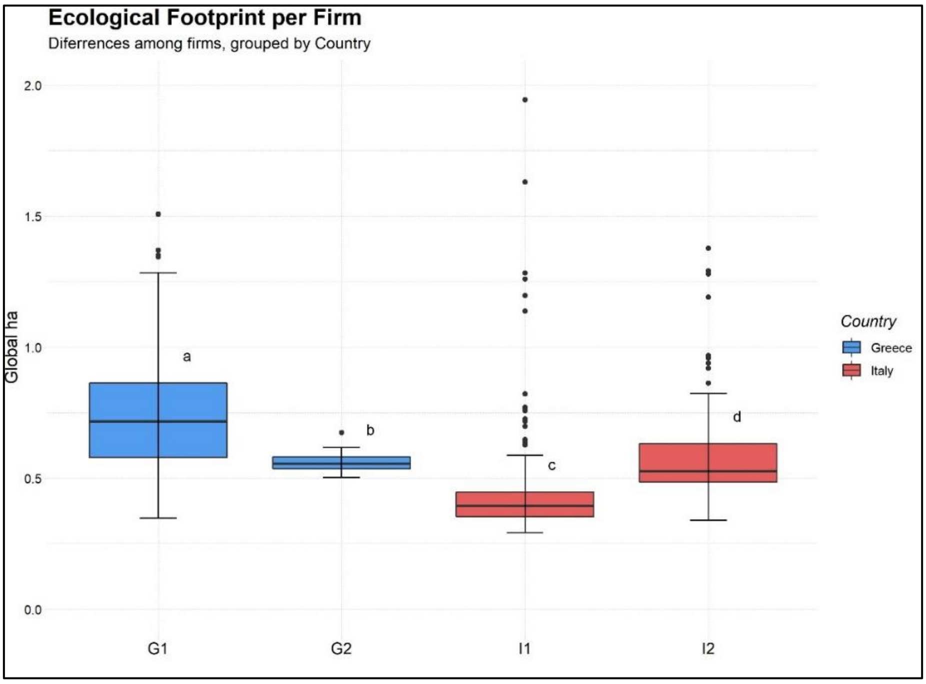

Figure A9: Ecological Footprint per firm