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Assessing the Environmental Efficiency of Greek Dairy Sheep Farms: GHG Emissions and Mitigation Potential

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Abstract: One of the main ecological challenges that agricultural and especially livestock production systems face is the adoption of management practices that encourage the mitigation of greenhouse gas (GHG) emissions, while maintaining their production level. According to the relevant literature, the potential for GHG reduction lies mainly in greater efficiency in meat and dairy production, which suggests that the ecological modernization of livestock farms follows the efficiency/substitution pathway. This study aims to investigate the above assumption and explore the link between the technical efficiency (TE) and environmental efficiency (EE) of livestock farms using data envelopment analysis (DEA). The analysis focuses on dairy sheep farming, since the activity is important for the Greek rural economy while at the same time responsible for half of the country's agricultural methane emissions. Results indicate that the correlation between technical and environmental efficiency of sheep farms is significant. Environmental efficiency is affected by farm size, specialization and production orientation. Feeding practices, like the ratio of concentrates to forage, also appear to have a positive effect on environmental efficiency. On the other hand, experienced farmers tend to have lower environmental efficiency, which may indicate their reluctance to adopt modern farming practices.

Keywords: environmental efficiency; data envelopment analysis; greenhouse gas emissions; dairy sheep farming

1. Introduction

Agriculture is one of the main contributors of greenhouse gases (GHG) released into the atmosphere, and therefore agricultural activities are not only affected by climate change but also contribute to the phenomenon [1–3]. The main gases emitted by the sector are methane (CH_4) from livestock, nitrous oxide (N_2O) from fertilizer use and livestock and carbon dioxide (CO_2) from energy use. According to the Intergovernmental Panel on Climate Change (IPCC) [4], the most important greenhouse gas directly associated with livestock production is methane produced as a byproduct of enteric fermentation in ruminants. The amount of methane that is produced during this process depends on the type of digestive tract, age and weight of an animal, as well as the quality and quantity of feed consumed. Generally, the higher the feed intake of animals the higher the methane emissions produced during fermentation. Feed intake relates to animal size, growth rate and production. Other greenhouse gases directly linked to livestock farming are methane and nitrous oxide produced during manure management and storage or deposition on pasture. Methane is produced during the decomposition of manure under anaerobic conditions and therefore manure methane emissions are higher in intensive farming, where a large number of animals share a confined area. Nitrous oxide emissions occur during the management and storage of manure, but also from soils during deposition on pasture both directly and indirectly. Direct N_2O emissions are produced through a nitrification and denitrification process of nitrogen contained in manure [5]. A sufficient amount of oxygen is required for the nitrification process to occur, and therefore direct emissions are considered negligible when manure is stored in liquid form. Indirect emissions occur from volatile nitrogen losses in the forms of ammonia and NOx.

The contribution of agriculture to total European Union (EU) emissions is stressed in a number of studies and technical reports [6]. It has been estimated that agriculture accounts for 10.3% of total EU GHG emissions (in year 2012) [7], with methane from enteric fermentation accounting for 32% of total EU agricultural emissions and manure management contributing another 16% in these emissions. The above statistics refer to direct emissions from livestock, but the impact of livestock on climate change is even greater considering the amount of inputs and especially feed required for the production of livestock products [6].

On the other hand, livestock plays a significant economic, social and political role in rural areas. It is estimated that 1.3 billion people are occupied in the sector globally, especially in poor areas of the world [6]. Livestock provides not only occupation and income, but also contributes significantly in consumers' protein intake. Global demand for livestock products, mainly meat and milk, will continue to increase and actions have to be taken to satisfy this demand while at the same time controlling adverse effects on the environment. In this context, the EU has committed to a second phase of the Kyoto protocol and aims to reduce total emissions by 20% by 2020 compared to 1990. Further reductions are targeted by 2030 and 2050 according to the EU climate action plan (40% and 80–95% compared to 1990, respectively).

Indeed, agriculture and especially livestock have the potential to provide solutions to the climate change problem through both emission mitigation and carbon sequestration. According to Horlings and Marsden [8], there are two ecological modernization pathways for agricultural systems. Biodiversity-based agriculture aims to develop ecosystem services provided by biological diversity. This requires developing diversified, place-based farming systems and practices. For livestock systems, suggested strategies to achieve this form of ecological modernization are self-sufficiency in animal feeding, grassland and pastureland use, or even collaboration with specialized crop farms [9]. Currently, this form of modernization exists only as a niche. On the other hand, the most common form of ecological modernization is efficiency–substitution-based agriculture, which implies that sustainability and mitigation of adverse effects on the environment can be achieved mainly by increasing input use efficiency. This form is in continuity with productivist agriculture and, as Duru et al. [10] point out, "it consists of incrementally modifying practices in specialized systems to comply with environmental objectives". As far as livestock production systems are concerned, this ecological transition pathway leads to intensification through the use of high-productivity livestock capital, feed efficiency and balanced rations, precision agriculture and less pastureland.

Many studies that use farm-level data verify that improvements in farm management practices, associated with increased productivity and efficiency, enable mitigation and are associated with fewer emissions per unit of livestock product [11–13]. Evidence from Greece also supports the above assumption. Sintori [14,15] and Sintori et al. [16] focused on selected small ruminant livestock farms and found that more intensive farming systems produce fewer emissions per kilogram of milk. The main reason for this was the efficient use of inputs and the increased productivity of livestock.

It should be emphasized that even though the production of GHGs from livestock farms has been addressed in a number of studies, these studies focus mainly on cow production systems (e.g., [13,17–19]). Additionally, studies that focus on the emission of GHGs from sheep and goat farms refer mainly to meat and wool production farming systems, which have different technical and economic characteristics from dairy farms (e.g., [20–22]). Limited studies use farm-level data to estimate GHG emissions of dairy sheep farms and assess their mitigation potential [16].

The concept of efficiency is well known in agricultural economics. It is defined as the ability of a decision-making unit (DMU) to obtain the maximum output from a given set of inputs (output orientation) or to produce an output using the lowest possible amount of inputs (input orientation) [23,24]. Many studies focus on estimating the technical efficiency (TE) of livestock farms abroad [25,26] and in Greece [27,28] using data envelopment analysis (DEA). DEA is a linear programming method that creates a "frontier" where all technically efficient production units lie. The position of all other production units relative to this frontier results in an efficiency score for each production unit.

Given the rising concern for the impact of agricultural activities on the environment, the concept of technical efficiency can be used to explore the ecological transition of agricultural systems, and to identify management practices and techniques that improve efficiency while at the same time reducing adverse effects on the environment. In this environmental efficiency (EE) context, the main idea is to incorporate undesirable outputs of the production process in the analysis. In this paper, this has been done by adding the total amount of GHG emissions of livestock farms in the DEA model as an input (i.e., as a non-desirable negative output/positive input) [11,29]. The DEA model aimed to minimize inputs, including the production of GHGs, while maintaining the same level of outputs (milk and meat).

This also reflected the interest of policymakers to lower GHG emissions without compromising productivity. Input-oriented technical efficiency is more appropriate in the case of Greek livestock farms since their management is mainly based on inputs control. This is even more apparent in the last decade, as the financial crisis has drastically affected cash flows.

Furthermore, following Simar and Wilson [30], a regression analysis was performed to investigate the main factors that affect the environmental efficiency of the farms. Specifically, the effect of structural and managerial characteristics of the farms, as well as the effect of farmer's characteristics using environmental efficiency scores, was investigated.

This study utilizes farm-level data from Greek dairy sheep farms. Sheep farming is one of the most important agricultural activities in Greece, where almost nine million sheep are bred [31]. The activity offers income to over 87,000 farms, while 43% of the total milk produced in Greece comes from sheep farming. On the other hand, agriculture accounted for 9% of total Greek GHG emissions in 2015 [32]. Though total agricultural emissions have decreased by 18% since 1990, this reduction is attributed mainly to the reduced use of synthetic fertilizers. As far as methane is concerned, no significant reduction since 1990 has been accomplished (3.26%), even though agriculture, and especially livestock, is responsible for half of total methane emissions. It is therefore important to identify appropriate mitigation options for Greek sheep farming and to investigate management systems that promote technical and environmental efficiency.

In the next section, the data and methods used in this analysis are presented. The main findings and results are then presented and discussed. The final section of this paper includes the conclusions, the limitations of the analysis and suggestions for further research.

2. Materials and Methods

For the estimation of GHG emissions and efficiency of Greek dairy sheep farms, detailed technico-economic data is required. Therefore, an available dataset from 144 sheep farms located in Western Greece (Aitoloakarnania prefecture) and Macedonia (Serres and Drama prefectures) was utilized. The data were gathered in 2008 within the framework of the EU project Search for Innovative Occupations of Tobacco Producers in the Rural Sector (Measure 9, Reg (EU) 2182/02). The project was implemented by the Agricultural Economics Research Institute under the coordination of Dr Irene Tzouramani. The initial data set contained 150 farms, 6 of which were excluded as outliers due to their extremely low level of milk yield, which was mainly self-consumed. This dataset was chosen for this study because it consists of a large number of farms, which allows for statistical analysis. Furthermore, it consists of detailed information on all crop and livestock activities of the farms, as well as their farming practices, which is necessary for the estimation of GHG emissions and other variables used in the analysis. Specifically, the data involves meat and milk production of the farms, characteristics of the livestock, variable and fixed capital, family and hired labor inputs, pasture and crop production, demographics and social characteristics of the farmer. A more extensive description of the dataset can be found in Sintori [14].

The methodology used to estimate farm efficiency in this analysis was based on the construction of a model that can depict the production process/function of sheep farms. Each one of the sample farms used inputs like feedstuff and labor to produce outputs (mainly milk but also meat). Some of these farms were more efficient than others, since they could produce the same output with the use of fewer inputs (input-oriented analysis). The basic concept of the DEA methodology was to assign efficiency scores to each one of the sample farms, indicating how much they could reduce their inputs and still produce the same amount of output. During this production process, GHGs were also produced and thus considered as a non-desirable byproduct of the production process.

The first step for the implementation of the analysis was the estimation of the inputs and outputs of the farms that were used in the DEA model. The main outputs considered were milk and meat produced per ewe (wool production was considered negligible). As far as the inputs of the sheep farms were concerned, these could be divided into four categories: fixed capital inputs, land inputs, labor inputs and variable capital inputs. Fixed capital was not considered in the analysis, since it remained constant in the short-run. As far as land inputs were concerned, pastureland utilized by the farms was incorporated into the model to reflect stocking rate. Moreover, farmers could choose how much of this input (especially communal pastureland) they utilized each year. In this sense, pastureland as an input resembled variable capital inputs. Labor inputs were also included in the DEA model, and were estimated for each individual farm using detailed data on all tasks and practices performed within one year.

Regarding variable capital, two variables were used in the DEA model. The first one reflected the feedstuff used, and the second one included all other variable inputs (e.g., medicines). Feedstuff was separated from the rest of the variable inputs as it represented the most important input for sheep farms. The composition of the ration was estimated for each individual farm; however, it should be noted that the main roughage used in Greek sheep farms is alfalfa hay, and the main compound feedstuff is maize for grain. To avoid using too many variables regarding the feeding practices of the farm, all energy offered from supplementary feeding was summed up to a single variable expressed as Mj.

To summarize, the inputs considered in the analysis were pastureland per ewe, labor per ewe, feedstuff per ewe, other variable capital per ewe and GHG emissions per ewe. The descriptive statistics of inputs and outputs used in the analysis are presented in Table 1. The variables are characterized by high standard deviation, which reflects the heterogeneity of the Greece sheep farming activity. The sample used contains farms that differ in the level of intensification, their size and their production orientation. The methodology for the estimation of the GHG emissions per ewe is presented in more detail in the following paragraphs.

Table 1. Descriptive statistics of the input and output variables used in the analysis (annual basis).

	Mean Value	**St. Deviation**
Inputs		
Pastureland per productive ewe (ha)	0.296	0.440
Labor per productive ewe (€)	19.40	10.68
Feedstuff per productive ewe (Mj)	3451.20	1588.85
Variable capital per productive ewe (€)	7.11	4.69
Greenhouse gas (GHG) emissions per ewe (kg of CO_2 equivalents)	501.51	99.00
Outputs		
Milk per ewe (kg)	136.75	62.22
Lamb per ewe (kg)	10.41	4.49

2.1. Estimation of GHG Emissions

The second step of the analysis involved an estimation of the GHG emissions of the livestock farms. For the estimation of these emissions, the guidelines proposed by the IPCC [4] were followed. According to the IPCC, livestock emissions involve CH_4 from the enteric fermentation and CH_4 and N_2O, which occurs during the storage and treatment of manure (manure management). However, Greek sheep farms are mainly extensive or semi-intensive and, therefore, the majority of manure is not managed but rather deposited on soils (i.e., pastureland). Manure deposited on pasture also causes emissions, particularly N_2O, that occur directly and indirectly from the soil and are for this reason reported as "emissions from managed soils" by the IPCC. These emissions have also been included in the analysis since they are directly linked to the livestock activity. The omission of these emissions would result in an underestimation of the total GHG emissions of extensive and semi-intensive livestock farms that utilize pastures. It should be noted that other pre-chain emissions like emissions linked to the production of feedstuff and other inputs were not considered in this analysis. Furthermore, carbon sequestration is not accounted for since there is much controversy regarding the abatement that can be achieved this way in the long run [33,34]. Methane and N_2O have been converted to CO_2-equivalents using the following conversion factors: 1 kg of CH_4 = 25 CO_2-equivalents and 1 kg of N_2O = 298 CO_2-equivalents [4]. Emissions from all sources estimated as CO_2-equivalents were added together to estimate the total GHG emissions of the sheep farms.

2.1.1. Methane from Enteric Fermentation

To estimate CH_4 from enteric fermentation the following equation is used [4]:

$$EF = \left[\frac{GE \cdot \frac{Y_m}{100} \cdot 365}{55.65} \right] \quad (1)$$

where: EF = emission factor kg of CH_4/head/year, GE = gross energy intake Mj/head/day, Y_m = methane conversion factor (6.5 for mature sheep and 4.5 for lambs <1 year). The factor 55.65 (Mj/kg CH4) is the energy content of methane. Gross energy intake is estimated taking into account the net energy for maintenance, activity, lactation, pregnancy and growth as proposed by the IPCC [4] and the activity data presented in Table 2.

Table 2. Main activity data used for the estimation of GHGs (average of the sample farms).

Activity Data	Mean
Number of days on farm (lambs)	52
Number of productive ewes	124
Number of rams	7
Number of non-productive ewes	11
Number of ewes kept for replacement	25
Weight (mature ewes) (kg)	48.7
Milk yield per ewe (kg)	136.8
Milk fat content (%)	6%
Digestibility of feed (%)	65%
Prolificacy index	1.37
Weight at birth (kg)	3.7
Weight of lambs at sale (kg)	10.8
Weight growth per day (kg/day)	0.136

2.1.2. CH_4 and N_2O from Manure Management and Deposition on Soils

Methane and direct and indirect N_2O emissions generated by manure management and deposition on pasture are included in the analysis. As already mentioned, methane is produced during the decomposition of manure under anaerobic conditions, and therefore CH_4 emissions from manure are higher in more intensive farms where animals are managed in a confined area. On the other hand, the nitrification of nitrogen, which is a prerequisite for the emission of N_2O, requires a sufficient supply of oxygen and does not occur under anaerobic conditions. Therefore, N_2O soil emissions are higher in extensive and semi-intensive farms where the annual amount of manure nitrogen deposited on pasture is significant.

Methane emissions from manure were estimated using the Tier 2 methodology proposed by the IPCC [4]:

$$EF = (VS \cdot 365) \cdot \left[B_o \cdot 0.67kg/m^3 \cdot \sum_{S,k} \frac{MCF_{S,k}}{100} \cdot MS_{(S,k)} \right] \tag{2}$$

where: EF = annual methane emissions from manure ($kgCH_4$/head/year), VS = daily volatile solids excreted (kg of dry matter/head/year), B_o = maximum methane producing capacity for manure produced (m^3CH_4/kg/VS), $MCF_{(s,k)}$ = methane conversion factors for each manure management system S and climate region k, $MS_{(s,k)}$ = fraction of manure handled using manure management system S to climate region k. VS is estimated from the gross energy intake, the digestibility of the feed and the ash content of manure, as proposed by the IPCC [4].

Direct N_2O emissions from manure management and deposition on soils were estimated using the following equation [4]:

$$N_2O_{D(mm)} = \frac{44}{28} \cdot \sum_{S} Nex \cdot MS_{(S)} \cdot EF_{(S)} \tag{3}$$

where: $N_2O_{D(mm)}$ = direct N_2O emissions from manure management kg/year/head, N_{ex} = annual N excretion (kg/head/day) estimated using the live weight of each livestock category, $EF_{(s)}$ = emission factor for direct N_2O emissions from manure management system S (kg N_2O-N/kg N). $EF_{(s)}$ equaled 0.02 kg N_2O-N/kg N when manure was managed in solid storage and 0.01 kg N_2O-N/kg N when manure was deposited on pasture [4].

Finally, for the estimation of indirect N_2O emissions, the fraction of N that volatilizes as NH_3 and NO_x is estimated according to the IPCC [4].

2.2. Efficiency Analysis

The third step of our methodology was the implementation of the efficiency analysis using data envelopment analysis (DEA). DEA is a non-parametric method to estimate efficiency, developed by Charnes et al. [35]. As previously mentioned, the main idea behind this methodology is to construct a frontier where all the DMU—in our study, the farms—that use minimum level of inputs to produce a certain output lie (input-oriented DEA). The production frontier constructed by DEA is deterministic, so each deviation from the frontier is reported as inefficiency. The main advantage of DEA is that, unlike other methodologies (e.g., stochastic frontier analysis), it does not a priori assume a specific form of production function.

Consider n DMUs producing m outputs using h inputs (the inputs and outputs considered in our analysis have already been presented in Table 1). Let, $\mathbf{Y}$ = the $m \times n$ matrix of outputs and $\mathbf{X}$ = the $h \times n$ matrix of inputs. $\mathbf{Y}$ and $\mathbf{X}$ contain data for all n DMUs. Technical efficiency scores can be estimated as:

$$\begin{gathered} \min \theta, \\ \text{subject to:} \\ -\mathbf{y}_i + \mathbf{Y}\lambda \geq 0 \\ \theta\mathbf{x}_i - \mathbf{X}\lambda \geq 0 \\ \lambda \geq 0 \end{gathered} \tag{4}$$

Model (4) is solved for each DMU. θ is the DMU's index of technical efficiency, $\mathbf{y}_i$, and $\mathbf{x}_i$, represent the output and input of DMU i, respectively, and $\mathbf{Y}\lambda$ and $\mathbf{X}\lambda$ are the projections on the constructed frontier. When $\theta_i = 1$, the DMU is technically efficient. Therefore, $1 - \theta$ measures how much the DMU i's inputs can be proportionally reduced without any loss in the level of output. Model (4) assumes that each DMU operates under the constant returns to scale (CRS) assumption. This assumption implies that all DMUs are operating at an optimal scale [36]. But this assumption can be easily violated by various factors like imperfect competition and financial constraints. In these situations, CRS specification results in measures of technical efficiencies that are confounded by scale inefficiencies. To overcome the above issues, variable returns to scale (VRS) specification can be applied, and the model is formulated as:

$$\begin{gathered} \min \theta, \\ \text{Subject to:} \\ -\mathbf{y}_{\boldsymbol{i}} + \mathbf{Y}\lambda \geq 0 \\ \theta \mathbf{x}_{\boldsymbol{i}} - \mathbf{X}\lambda \geq 0 \\ \mathbf{NI}'\lambda = 1 \\ \lambda \geq 0 \end{gathered} \tag{5}$$

Model (5) incorporates a new constraint: $\mathbf{NI}'\lambda = 1$, where $\mathbf{NI}$ is a $n \times 1$ vector of ones. This constraint prevents the comparison of firms with an unequal size, and in this way the data is enveloped more tightly. Scale efficiency (SE) can be calculated as the ratio of the CRS TE score to the VRS TE score.

According to Simar and Wilson [37], a major drawback of the original DEA approach was that it produced efficiency scores that were upward-biased. The reason for this was that the actual frontier was placed higher than the frontier produced using sample observations. To produce the actual frontier, all the efficient DMUs of the population should be included in the sample, which is practically impossible. In other words, the technology set constructed by sample observations ($\hat{T}$) was a subset of the true but unknown technology (T). The outcome of the minimization over a smaller technology set was an estimation of a higher efficiency level than the one resulting for the minimization over the real (larger) technology set. Therefore, $\widehat{E^k} \geq E^k$, where E^k is the estimation of the true but unknown efficiency θ^k of the k DMU. The bias can be estimated as [38]:

$$bias^k = EV\left(\hat{\theta}^k\right) - \theta^k \tag{6}$$

In order to estimate the unknown θ^k, a bootstrapping method can be applied. Bootstrapping involves the repeated process of random sampling with replacement from the original dataset (resampling) to form new samples of equal size [37]. Then, the parameter of interest (i.e., θ^k) is estimated in each sample (see Simar [39]). Thus, each bootstrap process produces a replica estimation of θ^k, noted as θ^{kb}. Then, the bootstrap estimation of the bias, $bias^{*k}$, is:

$$bias^{*k} = \frac{1}{B}\sum_{b=1}^{B}\theta^{kb} - \hat{\theta}^k = \overline{\theta}^{*k} - \hat{\theta}^k \tag{7}$$

where $\overline{\theta}^{*k}$ is the mean of the replications θ^{kb}. The bias-corrected estimator of θ^k, $\widetilde{\theta}^k$ is then:

$$\widetilde{\theta}^k = \hat{\theta}^k - bias^{*k} = \hat{\theta}^k - \overline{\theta}^{*k} + \hat{\theta}^k = 2\hat{\theta}^k - \overline{\theta}^{*k} \tag{8}$$

To estimate $\widetilde{\theta}^k$, we applied the bootstrap algorithm proposed by Simar and Wilson [37,40], slightly adjusted by Badunenko and Mozharovskyi [41].

The efficiency scores of the DEA model can be further investigated and associated with certain socioeconomic characteristics of the farm and farmer. This was accomplished by performing a second-stage regression analysis. In the relevant literature, many studies have employed this two-stage approach using Tobit regression. However, Simar and Wilson [30] demonstrate that Tobit regression analysis is not appropriate in this case, as it is inconsistent and biased. They introduced a bootstrap procedure, where the bias-corrected efficiency scores yielded in the first-stage of the analysis were regressed on a set of explanatory variables. In other words, the regression analysis was complementary to the DEA analysis and aimed to identify factors that affected efficiency and were not incorporated in the DEA model as inputs. The set of explanatory variables used in this study is presented in Table 3.

Table 3. Set of socioeconomic variables used in the regression of the bias-corrected environmental efficiency (EE) scores.

Variable	Description/Explanation
No of productive ewes	Indicator of the size of the farm
Part-time farming	Binary variable that indicates the existence of other non-agricultural economic activities of the farmers (pluriactivity)
Education	Number of years spent in school and higher education
Share of family to total labor	The share of labor offered by family members
Experience	Number of years in farming
Share of milk to total income	Indicator of the specialization of the farm on milk or meat production
Gross margin per productive ewe	Revenues minus variable cost per productive ewe (€)
Non-specialized farming	Binary variable that indicate the existence of multiple agricultural activities in the farm (crops and/or livestock diversification) (usually goat farming)
Compound feedstuff to total feedstuff	The share of energy intake covered by compound feedstuff
CH_4 from enteric fermentation per ewe	CH_4 emissions from sheep enteric fermentation (in kg of CO_2 equivalents)
CH_4 from manure per ewe	CH_4 emissions from sheep manure in kg of CO_2 equivalents
Direct N_2O emissions from manure per ewe	Direct N_2O emissions from manure in kg of CO_2 equivalents
Indirect N_2O emissions from manure per ewe	Indirect N_2O emissions from manure in kg of CO_2 equivalents

3. Results

3.1. GHG Emissions

Table 4 presents the mean and standard deviation of the total GHG emissions estimated for the sheep farms. Apart from the aggregated GHG emissions, descriptive statistics are also presented for all the GHG-related variables. Enteric fermentation is the main source of GHGs, as it accounts for almost 70% of total GHG emissions. Direct N_2O emissions are also significant since they account for 26% of total emissions. As mentioned in the Materials and Methods section, these emissions refer mainly to soil emissions caused by the deposition of manure on pastures by grazing animals, and are particularly high since the majority of the sample farms are extensive or semi-intensive (93%). In more intensive farms, soil N_2O emissions are lower because animals are mainly kept indoors. Methane emissions from manure management and soil are lower and represent only 3% of total emissions.

Table 4. Descriptive statistics of greenhouse gas emissions.

Variable	Source	Mean	Standard Deviation
		(in kg of CO_2-equivalents)	
CH_4 from enteric fermentation per ewe	Enteric fermentation	347.69	69.49
CH_4 from manure per ewe	Manure management and soil	10.23	1.67
Direct N_2O emissions from manure per ewe	Manure management and soil	130.12	47.71
Indirect N_2O emissions from manure per ewe	Manure management and soil	13.48	3.94
Total livestock GHG emissions per ewe		501.51	99.00

3.2. DEA Scores of Technical and Environmental Efficiency

As mentioned in the previous section, both the technical and environmental efficiency of the dairy sheep farms were estimated. The two DEA models differed only in the inclusion of GHG emissions as an input. Table 5 presents the results of the DEA application. The average environmental efficiency was equal to 0.84, while the technical efficiency was much lower (0.61) (see also Figure 1). The DEA analysis estimated the maximum feasible equiproportionate reduction of inputs given the level of outputs. In the case of TE, the average score indicates that all inputs could be reduced by 39%. In the case of the EE, the feasible equiproportionate reduction was only 16%, indicating that there is less room for improvement when GHG emissions are incorporated in the model. In other words, a further reduction of GHG emissions per ewe would require a reduction in output. This outcome is particularly important not only for agriculturalists but also for policymakers. It implies that mitigation measures have to be carefully designed and have realistic goals regarding the abatement potential of livestock farms, otherwise they may lead to the reduction of output, which in view of the increasing demand for livestock products and the significance of the activity in remote areas (where it is mainly located) is undesirable. This finding is in accordance with other studies that use alternative methodologies to explore mitigation options of livestock farms. These studies suggest that managerial practices can only reduce GHG emissions up to a specific level, while for further mitigation a reduction in livestock output is necessary (e.g., [14,42]). It should be emphasized that the methodology used in this analysis allowed for the precise estimation of the amount of emissions that could be reduced, without compromising the output of the farms.

Table 5. Descriptive statistics of environmental efficiency (EE), technical efficiency (TE), scale efficiency (SE) and scale of operation.

Variable	Mean	Standard Deviation	CV	Min	Max
EE	0.84	0.11	13.4%	0.5	0.98
TE	0.61	0.17	28.6%	0.2	0.88
SE	0.71	0.16	22.8%	0.4	1
Scale of operation	Decision Making Units (DMUs)				
Increasing Returns to Scale (IRS)	114 farms (79.17%)				
Constant Returns to Scale (CRS)	29 (20.14%)				
Decreasing Returns to Scale (DRS)	1 farm (0.69%)				

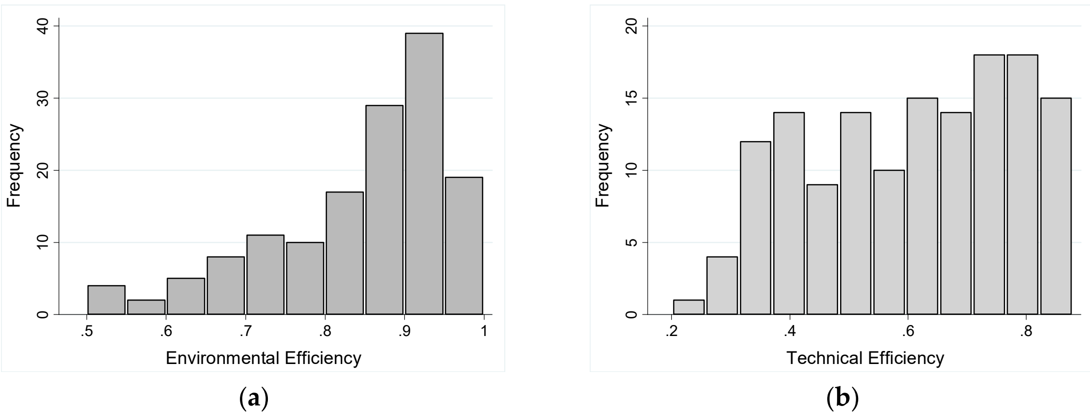

Figure 1. Histograms of (**a**) environmental efficiency (EE) and (**b**) technical efficiency (TE).

A Wilcoxon sign-rank test was also performed to compare EE and TE scores. Wilcoxon sign-rank test is a non-parametric test that is used to compare two different estimates for the same set of observations (matched pairs of observations). It is based on the comparison of the ranking of the observations produced by these two different measures. The more similar the two rankings are, the more equal the two different estimates are (for more details, see [43]). The results verified that EE scores were significantly higher than the TE scores of the farms ($z = 10.05$, $P > |z| = 0$). However, the Spearman correlation coefficient [44], estimated at 0.43, indicates that there was a positive and statistically significant correlation between TE and EE (at 99% of significance level).

The results for scale efficiency (SE) indicate that the majority of farms are not operating at the optimum level of production (i.e., their sizes are not optimal). There are 114 farms that operated at increasing returns to scale (IRS), and therefore should increase in size (production level). On the other hand, only one farm operated at decreasing returns to scale (DRS). Finally, 29 farms operated under constant returns to scale (CRS) (i.e., had the optimal farm size).

3.3. Socioeconomic Factors that Affect Environmental Efficiency

The reasons for environmental inefficiency were further examined using truncated regression analysis, as mentioned in the Materials and Methods section. The results are presented in Table 6. The number of productive ewes had a positive and statistically significant effect on the EE score (based on the coefficient and the p-value of this variable). This indicated that bigger farms were more efficient than smaller farms and produced less GHG emissions per output, which is related to the fact that the majority of farms operated at increasing returns to scale. Apart from the effect of scale economies, another reason for this finding was that sometimes smaller farms used excessive feedstuff and/or labor inputs, while larger farms allocated their resources in a more efficient way. This outcome is in accordance with the relative literature. Shortall and Barnes [11] came to the same conclusion in their study on technical and environmental efficiency of Scottish dairy farming.

Table 6. Results of the Truncated Regression.

Variables	Coefficient	Std. Err.	z	P > z	[95% Conf. Interval]	
No. of productive ewes	0.0002	0.0001	3.74	0.000	0.0001	0.0003
Education	−0.0020	0.0018	−1.11	0.269	−0.0056	0.0017
Experience	−0.0007	0.0004	−1.87	0.061	−0.0015	0.0000
Share of family to total labor	0.0348	0.0270	1.29	0.197	−0.0134	0.0899
Share of milk to total income	0.0888	0.0501	1.77	0.077	−0.0109	0.1827
Compound feedstuff to total feedstuff	0.0029	0.0017	1.72	0.086	0.0006	0.0069
Gross margin per productive ewe	0.0004	0.0001	3.88	0.000	0.0002	0.0007
Part-time farming	0.0839	0.0249	3.36	0.001	0.0366	0.1359
Non-specialized farming	−0.0345	0.0143	−2.41	0.016	−0.0631	−0.0064
CH_4 from enteric fermentation per ewe	−0.0010	0.0002	−5.71	0.000	−0.0013	−0.0006
CH_4 from manure per ewe	0.0002	0.0081	0.02	0.984	−0.0159	0.0159
Direct N_2O emissions from manure per ewe	−0.0009	0.0001	−5.97	0.000	−0.0012	−0.0006
Indirect N_2O emissions from manure per ewe	−0.0050	0.0019	−2.63	0.009	−0.0089	−0.0013
Constant	1.2360	0.0588	21.02	0.000	1.1192	1.3497

It is also important to mention that specialization had a significant and positive impact on EE scores. Non-specialized farms were less efficient than farms that focused on sheep farming. Moreover, the production orientation towards milk positively affected EE (at a 10% level of significance). In other words, farms that focused mainly on sheep milk were more efficient than those that aimed for both milk and meat production. In the latter farm group, suckling is prolonged and lambs are kept on the farm for a longer period (fattened). It appears that these practices that reduce milk yield and increase meat production do not correspond to optimal input use.

Another management practice that seemed to positively affect EE is the use of compound feed, which increased productivity. On the other hand, the utilization of family labor did not seem to significantly affect EE.

Furthermore, the achieved gross margin per ewe also positively affected EE. The farms that achieved higher gross margin per ewe were either characterized by high productivity (and therefore higher revenues) or lower input costs. High productivity was generally achieved by the more modern and intensive farms, while low input farming was usually performed in less-favoured areas utilizing low-productivity livestock and pastureland (extensive farming). Thus, the results of our analysis indicated that both extensive and intensive production systems can achieve high EE scores, in terms of GHG emissions, for different reasons.

The above findings are in line with the efficiency–substitution redesign framework and pinpoint the practices that farms should adopt to evolve within this pathway. Size increase, specialization, improved animal capital and substitution of grazing with compound feed seem to reduce emissions and support the agroecological transition of livestock systems in the intensive, lowland agricultural zones of Greece. However, this may not be the appropriate path to support the ecological modernization of livestock farms in less-favoured areas of the country. Our analysis indicates that low input, pasture-based farming systems which utilize low productivity but highly adaptive to the local environment, indigenous animal capital present another dynamic in the agroecological transition of livestock farms. These characteristics more-closely resemble the biodiversity-based modernization pathway and should be further investigated and considered in agricultural policy planning.

Interestingly, pluriactive farmers tended to achieve higher EE scores (part-time farming variable in Table 5). One possible explanation for this may be the fact that they tended to better allocate their resources (e.g., family labor) and capital among their alternative activities. Nevertheless, further research is required to better understand this finding.

Another important finding of the analysis was that the level of education had no significant correlation with EE, while experience had a negative effect on efficiency (a 10% significance level). This means that neither experience nor education ensured better farm management in terms of efficiency and GHG emissions. Especially, the negative relation of experience with EE indicates that years spent in farming may in fact be an obstacle in achieving environmental efficiency. One reason for this may be the fact that farmers tend to stick to well-known practices and are less eager to adopt new farming techniques. These findings also emphasize the crucial role of training as a policy tool to enhance productivity and reduce GHG emissions.

Finally, as can be expected, methane emissions from enteric fermentation and nitrous oxide emissions had a negative effect on overall environmental efficiency.

4. Discussion and Conclusions

The main objectives of agricultural policy focus on meeting the rising demand for agricultural and especially livestock products, while at the same time mitigating adverse effects on the environment. According to the literature there are two main pathways to achieve sustainability of agricultural production systems, the efficiency–substitution-based ecological modernization and the biodiversity-based ecological modernization of these systems. Many studies suggest that GHG mitigation can be achieved by increasing productivity and efficiency in input use [12,45], which corresponds to the former modernization pathway. The majority of these studies focus on livestock farms and especially dairy cow farming, employing alternative methodologies to investigate the above assumption (e.g., [13,17]).

This study aimed to estimate the environmental efficiency of Greek dairy sheep farms and identify good management practices that promote their agroecological modernization. Environmental efficiency is defined in terms of produced GHGs and for their estimation DEA analysis was implemented. Multivariate analysis was also performed to test the attribute of socioeconomic variables in EE scores and identify the characteristics of efficient farms.

For the estimation of GHGs, IPCC [4] guidelines were followed. All sources of GHG emissions directly linked to livestock activity were taken under consideration. Specifically, CH_4 emissions from enteric fermentation and CH_4 and N_2O emissions from manure management were included in the analysis. The main soil emissions in livestock farms (i.e., emissions) caused by the deposition of manure on pastures were also accounted for.

However, the inclusion of other sources of emissions not directly related to livestock activity was required to fully explore the concept of environmental efficiency as defined in this analysis. Livestock uses inputs and especially feedstuff produced on or off the farm. The inclusion of emissions associated with the production and transportation of these feedstuffs, as well as carbon dioxide emissions from electricity and fuel will enable the exploration of other mitigation options for the livestock farms not necessarily related to livestock, like the use of manure instead of synthetic fertilizers, the reduction of tillage or the use of on-produced forage and grains. Furthermore, carbon sequestration had to be considered, as it may affect the environmental efficiency of mainly the extensive farms that utilize pasture. However, previous research on Greek sheep farms indicated that the carbon footprint of milk produced in intensive farms was lower than the carbon footprint of milk in extensive farms, even when carbon sequestration was taken under consideration [16]. Finally, it should be noted that other impacts of livestock activity on the environment, such as pasture degradation, were not taken under consideration in the estimation of the EE of the sheep farms.

The results of the analysis indicate that there is significant room for improvement in the TE of the sheep farms, as they can reduce their inputs by 39% and maintain the same level of output. On the other hand, their EE is much higher and therefore the possibility of reducing emissions directly related to livestock through management improvements, while maintaining the same level of output, is limited. As indicated by the truncated regression analysis performed, increased EE is associated with high specialization to sheep farming and milk production, high use of compound feedstuff and increased gross margin per ewe. The latter can be achieved either from intensive farms characterized by high productivity, or low input, extensive farms that utilize low cost pastureland. In other words, alternative ecological modernization scenarios can be proposed for intensive lowland and extensive highland livestock systems.

Another interesting finding of the analysis that should be further investigated is that part-time farmers, identified by the existence of other sources of income, tend to have higher EE. One explanation for this is the need of these farmers to allocate their resources (labor and capital) among their alternative economic activities in a rational and efficient way. This finding should be considered by policymakers, since pluriactivity is common in some parts of the country.

Finally, the analysis also highlighted that level of education and experience in farming do not ensure the efficient use of inputs and the environmental efficiency of farms. In fact, experience seems to have a negative effect on the ability of farms to increase their EE. This could be explained by the reluctance or perhaps limited ability of experienced farmers to adopt new technologies or practices. Either way, high-quality, carefully planned and implemented extension services are required alongside policy measures to promote EE.

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