# Mitigation of greenhouse gas emissions and technical efficiency of Greek dairy sheep production systems: meeting the ecological challenge

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**Abstract:** *One of the main ecological challenges that agricultural and especially livestock production systems face is the adoption of practices and management approaches that encourage the mitigation of Greenhouse Gas (GHG) Emissions, while maintaining their production level. Relevant literature suggests that the potential for GHG reduction lies mainly in greater efficiency in meat and dairy production, which suggests that the ecological modernization of livestock farms lies in the efficiency/substitution pathway. This study aims to investigate the above assumption and explore the link between the traditional concept of technical and the novel concept of environmental efficiency of livestock farms, in terms of GHG emissions, 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. In the DEA model, GHG emissions can be considered as non-desirable by-products of the farms. Furthermore, the analysis aims to investigate the main factors that affect the environmental efficiency of the farms, using multivariate analysis. The results of the analysis indicate that the correlation between technical and environmental efficiency of sheep farms is significant. Environmental efficiency scores are 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, more experienced farmers tend to have smaller environmental efficiency than young farmers, which may indicate their reluctance to adopt modern farming practices.*

***Keywords:*** *Technical Efficiency, Data Envelopment Analysis, Greenhouse gas emissions, Dairy sheep farming*

## Introduction

Agriculture is one of the main contributors of greenhouse gases released to the atmosphere and therefore agricultural activities are not only affected by climate change but also contribute to the phenomenon (Rosenzweig et al., 2008; Thornton et al., 2009; Nardone et al. 2010). 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 IPCC (2006) the most important greenhouse gas directly associated to livestock production is methane produced as a by-product of enteric fermentation in ruminants. The amount of methane that is produced during this process depends on the type of digestive tract, the age and weight of animals and 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 are in a confined area. Nitrous oxide emissions occur during the management and storage of manure but also during deposition on pasture both directly and indirectly. Direct $N_2O$

emissions are produced through a nitrification and denitrification process of nitrogen contained in the manure. For the nitrification process, sufficient amount of oxygen is required, 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 $NO_x$.

The contribution of agriculture in total EU emissions is stressed in a number of studies and technical reports (FAO, 2006). It is estimated that agriculture accounted for 10% of total EU GHG emissions in 2011 (Van Doorslaer et al., 2015). Methane from enteric fermentation accounted for 32% of these emissions and manure management contributed another 16% in total EU emissions. The above statistics refer to direct emissions from livestock. But the impact of livestock to the problem of climate change is even greater, considering the amount of inputs and especially feed required for the production of livestock products (FAO, 2006).

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 (FAO, 2006). 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 control diverse effects to the environment. In this context EU has committed to a second phase of the Kyoto protocol and aims to reduce total emissions by 20% until 2020, compared to 1990. Further reductions are targeted until 2030 and 2050 according to the EU climate action plan (40% and 80-95% compared to 1990, respectively).

Indeed, agriculture and especially livestock has the potential to provide solutions to the climate change problem, through both emission mitigation and carbon sequestration. According to Horlings and Marsden (2001), there are two ecological modernization pathways of agricultural systems. Biodiversity-based agriculture aims to develop ecosystem services provided by biological diversity. It 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 (DURU et al., 2015a). Currently, this form of modernization exists only as a niche. On the other hand, the most common form of ecological modernization is the 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. (2015b) 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 use.

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 products (Weiske et al., 2006; FAO, 2010; Shortall and Barnes, 2013). Evidence from Greece also supports the above assumption. Sintori (2012; 2015) and Sintori et al. (2013) 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 is the efficient use of inputs and the increased productivity of livestock.

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) (Coelli, 1995; Kumbhakar and Lovell, 2000). Many studies focus on the estimation of the technical efficiency (TE) in livestock farms abroad (Toro-Mujica et al., 2011; Zhu et al., 2012) and in Greece (Theodoridis at al., 2006; Theodoridis et al, 2014) using Data Envelopment Analysis (DEA) (Coelli et al., 2005; Bogetoft and Otto, 2010). 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 is then measured, resulting in an efficiency score for this particular production unit.

Given the rising concern for the impact of agricultural activities to the environment, the concept of technical efficiency and DEA analysis can be used to explore the ecological transition of agricultural systems and identify management practices and techniques that improve efficiency while at the same time reduce adverse effects on the environment. In this environmental efficiency (EE) context, the main idea is to incorporate in the analysis, undesirable outputs of the production process. In this paper, this is done by adding in the DEA model the total amount of GHG emissions of livestock farms as an input i.e. as a non-desirable negative output (positive inputs) (Mohammadi et al. 2013; Shortall and Barnes, 2013). The DEA model aims to minimize inputs, including the production of GHGs, while maintaining the same level of outputs (milk and meat).

This also reflects the interest of policy makers to lower GHG emissions without compromising productivity. Input oriented technical efficiency is particularly meaningful in the case of Greek livestock farms since their managerial strategy is mainly based on inputs control, especially in the recent years of financial crisis that has dramatically affected cash flows.

Furthermore, multivariate analysis is 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, the production orientation, as well as the profile of the farmer, in terms of social and demographic characteristics, on the environmental efficiency scores is investigated.

The analysis utilizes farm level data from Greek dairy sheep farms. Sheep farming is one of the most important agricultural activities in Greece, where almost 9 million sheep are bred (H.S.A.[1], 2016). 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 GHG emissions of Greece in 2015 (M.E.E.[2], 2017). Though total agricultural emissions 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 (3.26%) has been accomplished, 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 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 and limitations of the analysis and suggestions for further research.

## Data and Methods

For the estimation of GHG emissions and efficiency of Greek dairy sheep farms detailed technico-economic data are required. Therefore an available data set[3] from 144 sheep farms located in Western Greece and Macedonia is utilized. The data set is appropriate since the number of farms is considered adequate for statistical analysis while all necessary information regarding the inputs, the outputs and the characteristics of the farms and the farmer are included. Specifically, the data involves meat and milk production of the farms, characteristics of the livestock, variable and fixed capital, family and hired labour inputs,

[1] Hellenic Statistical Authority
[2] Ministry of Environment and Energy
[3]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 contain 150 farms, six of which were excluded as outliers, due to their extremely low level of milk yield, which was mainly self-consumed.

pasture and crop production, demographic and social characteristics of the farmer. A more extensive description of the data set can be found in Sintori (2012).

The first step in our methodology is the estimation of the inputs and outputs of the farms that were used in the DEA analysis. The main outputs considered in the analysis are milk and meat produced per ewe. The inputs considered in the analysis are pastureland per ewe, labour per ewe, feedstuff per ewe, other variable capital per ewe and carbon dioxide emissions per ewe. The descriptive statistics of these inputs and outputs are presented in Table 1. The variables are characterised 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.

**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 (stremmas) | 2.96 | 4.40 |
| Labour per productive ewe (€) | 19.40 | 10.68 |
| Feedstuff per productive ewe (kg) | 2936.86 | 2091.76 |
| Variable capital per productive ewe (€) | 7.11 | 4.69 |
| 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 |

## Estimation of GHG emissions

The second step of the analysis involves the estimation of the livestock GHG emissions, namely methane from enteric fermentation and manure and nitrous oxide from manure. For the estimation of these emissions the guidelines proposed by the IPCC (2006) are followed. It should be noted that $CH_4$ and $N_2O$ have been converted to $CO_2$-equivalents using the following conversion factors: 1kg of $CH_4$ = 25 $CO_2$-equivalents and 1 kg of $N_2O$=298 $CO_2$-equivalents (IPCC, 2006). The method used to estimate emissions from various sources in the sheep farms is described in more detail in the following paragraphs. Emissions from all sources estimated as $CO_2$-equivalents are added together to estimate total GHG emissions of the sheep farms.

*Methane from enteric fermentation*

To estimate $CH_4$ from enteric fermentation the following equation is used (IPCC, 2006):

$$EF = \left[ \frac{GE \bullet \frac{Y_m}{100} \bullet 365}{55{,}65} \right] \qquad (1)$$

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)[4]. Gross energy intake is estimated taking into account the net energy for maintenance, activity, lactation, work, pregnancy, growth and wool using the following equation:

[4]The factor 55.65 (Mj/kg $CH_4$) is the energy content of methane

$$GE = \left[ \frac{\left( \frac{NE_m + NE_a + NE_l + NE_{work} + NE_p}{REM} \right) + \left( \frac{NE_g + NE_{wool}}{REG} \right)}{\frac{DE\%}{100}} \right] \qquad (2)$$

where *REM* is the ratio of net energy available in diet for maintenance to digestible energy consumed, and *REG* is the ratio of net energy available in diet for growth to digestible energy consumed.

To estimate net energy, data from the sample farms is used, such as weight of each animal category, weight gain per day, weight until weaning, milk production and prolificacy index. To estimate $REM$ and $REG$ equations 3 and 4 are used, respectively, where DE% is digestible energy expressed as a percentage of gross energy (IPCC, 2006):

$$REM = \left[ 1{,}123 - \left( 4{,}092 * 10^{-3} * DE\% \right) + \left( 1{,}126 * 10^{-5} * (DE\%)^2 \right) - \left( \frac{25{,}4}{DE\%} \right) \right] \qquad (3)$$

$$REG = \left[ 1{,}164 - \left( 5{,}160 * 10^{-3} * DE\% \right) + \left( 1{,}308 * 10^{-5} * (DE\%)^2 \right) - \left( \frac{37{,}4}{DE\%} \right) \right] \qquad (4)$$

*$CH_4$ and $N_2O$ from manure*

Methane and direct and indirect $N_2O$ emissions from livestock during manure management and grazing are included in the analysis. Methane emissions from livestock are estimated using the Tier 2 methodology proposed by the IPCC (2006), which takes into account the management system of manure and the energy consumption of livestock (Equation 5).

$$EF = (VS \cdot 365) \cdot \left[ B_o \cdot 0{,}67 kg/m^3 \cdot \sum_{S,k} \frac{MCF_{S,k}}{100} \cdot MS_{(S,k)} \right] \qquad (5)$$

where: *EF*=annual methane emissions from manure (kg $CH_4$/head/year), *VS*=daily volatile solid excreted (kg of dry matter/head/year), $B_o$=maximum methane producing capacity for manure produced ($m^3$ $CH_4$/kg VS), $MCF_{(s,k)}$=methane conversion factors for each manure management system and climate region, $MS_{(s,k)}$=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, using equation 6.

$$VS = GE/18{,}45 \cdot (1 - DE/100) \cdot (1 - ASH/100) \qquad (6)$$

Direct $N_2O$ emissions from manure management and pastureland are estimated according to the Tier 1 methodology proposed by the IPCC (2006), using the live weight of each livestock category (equations 7)[5]:

$$N_2O_{D(mm)} = \frac{44}{28} \cdot \sum_S Nex \cdot MS_{(S)} \cdot EF_{(S)} \qquad (7)$$

where: $N_2O_{D(mm)}$=direct $N_2O$ emissions from manure management kg/year/head, $N_{ex}$=annual N excretion (kg/head/day), $EF_{(s)}$=emission factor for direct $N_2O$ emissions from manure management system *S* (kg $N_2O$-N/kg N). $EF_{(s)}$ equals 0,02 kg $N_2O$-N/kg N when manure is

[5] It should be noted that according to the IPCC guidelines $N_2O$ emissions generated by manure deposited on pastures is reported under *Emissions form managed soils*. In this analysis, However, these emissions have been considered, so that comparison between grazing and housed animals can be made.

managed in solid storage and 0,01 kg $N_2O$-N/kg N when manure is deposited on pasture (IPCC, 2006).

$N_{ex}$ is estimated taking into account the typical animal mass (TAM) and N excretion rate using the equation:

$$Nex = N_{rate} \cdot \frac{TAM}{1000} \cdot 365 \tag{8}$$

According to the IPCC (2006), for the estimation of indirect $N_2O$ emissions, the amount of manure nitrogen that is lost due to volatilization of NH3 and NOx and the fraction of N that volatilizes as $NH_3$ and $NO_x$ are used (equations 9 and 10).

$$N_2O_{G(mm)} = \left(N_{volatilization-MMS} \cdot EF_4\right) \cdot \frac{44}{28} \tag{9}$$

$$N_{volatilization-MMS} = \sum_S Nex \cdot MS_{(S)} \cdot Frac_{GasMS,(s)} \tag{10}$$

where: $EF_4$ =emissions factor for $N_2O$ from N that volatilizes

**Efficiency Analysis**

The third step of our analysis is 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. (1978).The main idea is to construct a frontier where all efficient DMUs lie. The production frontier constructed by DEA is deterministic, so each deviation from the frontier is reported as inefficiency.

The orientation (input or output orientation) depends on the scope of the analysis. In this paper, we implement the input-oriented DEA as we are interested in the minimization of GHG emissions, keeping the same level of outputs.

Consider $n$ DMUs producing $m$ different outputs using $h$ different inputs. **Y,** is an $m \times n$ matrix of outputs and **X** is an $h \times n$ matrix of inputs. Both matrices contain data for all $n$ DMUs. The technical efficiency measure can be formulated as follows:

$$\begin{gathered} \min \theta, \\ \text{subject to:} \\ -\mathbf{y}_i + \mathbf{Y}\lambda \geq 0 \\ \theta\mathbf{x}_i - \mathbf{X}\lambda \geq 0 \\ \lambda \geq 0 \end{gathered} \tag{11}$$

and solved for each DMU in the sample. $\theta$, 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 efficient projections on the frontier. A measure of $\theta_i = 1$ indicates that the DMU is technically efficient. Thus, $1-\theta$, measures how much the DMU $i$'s inputs can be proportionally reduced without any loss in output.

Model (11) implies that all DMUs operate under constant returns to scale (CRS). However, the CRS assumption is only appropriate when all DMUs are operating at an optimal scale (i.e., one corresponding to the flat portion of the LRAC curve) (Coelli et al., 2002). Several factors like imperfect competition and constraints on finance may cause a DMU not to operate at optimal scale. The use of the CRS specification when not all DMUs are operating at the optimal scale results in measures of TE which are confounded by scale inefficiencies.

The application of the Variable Returns to Scale (VRS) specification permits the calculation of pure TE, thus eliminates these scale inefficiencies. The model formulated is as follows:

$$\begin{gathered} \min \theta, \\ \text{Subject to:} \\ -\mathbf{y}_i + \mathbf{Y}\lambda \geq 0 \end{gathered} \tag{12}$$

$$\theta \mathbf{x}_i - \mathbf{X}\lambda \geq 0$$
$$\mathbf{NI}'\lambda = 1$$
$$\lambda \geq 0$$

The new constraint is $\mathbf{NI}'\lambda = 1$ where **NI** is a $n \times 1$ vector of ones. This constraint allows only the comparison of firms of similar size, by forming a convex hull of intersecting planes, so that the data is enveloped more tightly. Scale efficiency can be calculated by conducting both a CRS and a VRS DEA upon the same data. If there is a difference in the two TE scores for a particular DMU, then this indicates scale inefficiency, and the SE score is equal to the ratio of the CRS TE score to the VRS TE score.

A major criticism of the traditional DEA approach is that it produces point estimates of efficiency that are upward biased and lack statistical properties (Simar and Wilson, 1998). The upward bias is the outcome of the fact that DEA constructs an inner approximation of the underlying actual production possibility set. Assuming no measurement errors, all of the observations in the sample are from the technology set $\hat{T} \subset T$ where $T$ is the true but unknown technology. Then: $\widehat{E^k} \geq E^k$, where $E^k$ is the estimation of the true but unknown efficiency $\theta^k$ of the *k* DMU. This is the outcome of the minimization over a smaller technology set and thus the estimated efficiency may be larger than the real efficiency. The size of $\hat{T}$ depends on the sample, and therefore, $E^k$ is sensitive to sampling variations in the obtained frontier. This bias is particularly large in those parts of the production space where there are few observations, and can be estimated as (Bogetoft and Otto, 2011):

$$bias^k = EV(\hat{\theta}^k) - \theta^k \tag{13}$$

As the distribution of $\theta^k$ is unkown, there is no direct way to calculate $EV(\hat{\theta}^k)$, and a bootstrapping method can be used. Bootstrapping allows the assessment of whether the distribution has been influenced by stochastic effects and can be used to build confidence intervals for point estimates. Random samples are obtained by sampling with replacement from the original data set, which provides an estimator of the parameter of interest (Gocht and Balcombe, 2006).

When $\theta^{kb}$ is a bootstrap replica estimate of $\theta^k$, the bootstrap estimation of the bias is:

$$bias^{*k} = \frac{1}{B}\sum_{b=1}^{B} \theta^{kb} - \hat{\theta}^k = \bar{\theta}^{*k} - \hat{\theta}^k \tag{14}$$

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

$$\tilde{\theta}^k = \hat{\theta}^k - bias^{*k} = \hat{\theta}^k - \bar{\theta}^{*k} + \hat{\theta}^k = 2\hat{\theta}^k - \bar{\theta}^{*k} \tag{15}$$

To estimate $\tilde{\theta}^k$, we applied the bootstrap algorithm proposed by Simar and Wilson (1998; 2000), slightly adjusted by Badunenko and Mozharovskyi, (2016). The approach replicates sampling uncertainty by creating repeated samples of the original sample.

After the estimation of the above efficiency measures, a second-stage statistical analysis can be performed to associate efficiency scores with several socio-economic variables. In this paper, we follow Simar and Wilson (2007) who performed truncated regression analysis of DEA efficiency scores and calculate bootstrap standard errors and confidence intervals (Badunenko and Mozharovskyi, 2016).

The set of socioeconomic variables used in the truncated regression analysis are presented in Table 2.

**Table 2.** Set of socioeconomic variables used in the truncated Regression of the biased corrected Environmental Efficiency 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 spend in school and higher education |
| Share of family to total labour | The share of labour covered by the 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) |
| $CH_4$ 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 |
| Compound feedstuff to total feedstuff | The share of energy intake covered by compound feedstuff |

## Application and Results

Table 3 presents the mean and standard deviation of the total GHG emissions estimated for the sheep farms. Apart from the aggregated GHG emissions, the descriptive statistics are also presented for the four sources of GHGs that were taken under consideration in the analysis.

**Table 3.** Descriptive statistics of Greenhouse Gas Emissions

| Variable | Mean | Standard Deviation |
| --- | --- | --- |
| $CH_4$ from enteric fermentation per ewe (in kg of $CO_2$-equivalents) | 347.69 | 69.49 |
| $CH_4$ from manure per ewe (in kg of $CO_2$-equivalents) | 10.23 | 1.67 |
| Direct $N_2O$ emissions from manure per ewe (in kg of $CO_2$-equivalents) | 130.12 | 47.71 |
| Indirect $N_2O$ emissions from manure per ewe (in kg of $CO_2$-equivalents) | 13.48 | 3.94 |
| Total livestock GHG emissions per ewe (in kg of $CO_2$-equivalents) | 501,51 | 99,00 |

As mentioned in the previous section, both the technical and environmental efficiency of the dairy sheep farms were estimated. The two DEA models differ only in the inclusion of GHG emissions as an input. Table 4 presents the results of the DEA application. The average environmental efficiency is equal to 0.84 while the technical efficiency is much lower (0.61) (see also Fig. 1). The DEA analysis estimates the maximum equiproportionate reduction of inputs given the level of outputs. In the case of TE, the average score indicates that all inputs can be reduced by 39%. In the case of the EE, the feasible equiproportionate reduction is 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 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 reduction a reduction in livestock output is necessary (e.g. De Cara and Jayet, 2000; Sintori, 2012). This is also emphasized by the fact that GHG emissions are characterized by less variability compared to other inputs (see Table 1). A Wilcoxon sign-rank test was also performed to compare the EE and TE scores. The results verify that EE scores are higher (z=10.05, P>|z|=0). However, the Spearman correlation coefficient, estimated at 0.43, indicates that there is a positive and statistically significant correlation between TE and EE (at 99% of significance level).

**Table 4.** 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 | | DMUs | | | |
| IRS | | 114 farms (79.17%) | | | |
| CRS | | 29(20.14%) | | | |
| DRS | | 1 farm (0.69%) | | | |

The results for SE indicate that the majority of farms are not operating at the optimum level of production i.e. their size in not optimal. There are 114 farms that operate at Increasing Returns to Scale (IRS) and therefore they should increase in size (production level). On the other hand, only one farm operates at Decreasing Returns to Scale (DRS). Finally, 29 farms operate under Constant Returns to Scale (CRS) i.e. have the optimal farm size.

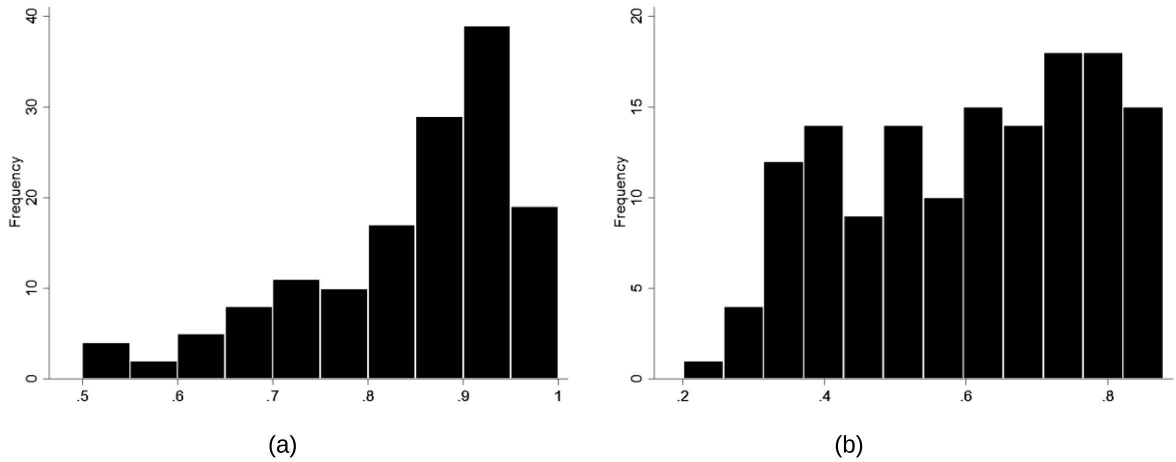


**Figure 1.** Histograms of (a) Environmental Efficiency (EE) and (b) Technical Efficiency (TE)

The sources of environment inefficiency were examined using the truncated regression analysis, as mentioned in the Data and Methods section. The results are presented in Table 5. The number of productive ewes has a positive and statistically significant effect in the EE score. This indicates that bigger farms are more efficient than smaller farms and produce less GHG emissions per output. This corresponds to the fact that the majority of farms operates at increasing returns to scale. This is in accordance with the relative literature. Shortall and Barnes (2013) come to the same conclusion in their study on technical and environmental efficiency of Scottish dairy farming.

It is also important to mention that specialization has significant and positive impact on EE scores. Non-specialized farms are less efficient than farms that focus on sheep farming. Moreover, the production orientation towards milk positively affects EE (at 10% level of significance).

Another management practice that seems to positively affect EE is the use of compound feed, which increases productivity. On the other hand the utilization of family labour does not seem to significantly affect EE.

Furthermore, the achieved gross margin per ewe also positively affects EE. However, the farms that achieve higher gross margin per ewe are either characterized by high productivity - and therefore higher revenues - or lower inputs-costs. High productivity is generally achieved by more modern and intensive farms, while low input farming is usually performed in less favoured areas, where it utilizes low productivity livestock and pastureland (extensive farming). The results of our analysis indicate that both of these production systems can achieve high EE scores, in terms of GHG emissions.

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 agro-ecological transition of livestock systems in intensive, lowland agricultural zones of Greece. However, this may not be the appropriate path to support ecological modernization of livestock farms in less favoured areas of the country. The analysis indicates that, low input, pasture-based farming systems that 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 resemble more the biodiversity-based modernization pathway, and should be further investigated and considered in agricultural policy planning.

Interestingly, pluriactive farmers tend to achieve higher EE scores. One possible explanation for this may be the fact they tend to better allocate their resources e.g. family labour and capital, among their alternative activities. Nevertheless, further research is required to better understand this finding.

Another important finding of the analysis is that the level of education has no significant relationship with EE, while experience has a negative effect on efficiency (at 10% significance level). This means that neither experience nor education can ensure better farm management in terms of productivity and GHG emissions. Especially, the negative relation of experience with EE indicates that the years spend in farming may in fact be an obstacle in achieving environmental efficiency. 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 have a negative effect on environmental efficiency.

**Table 5.** Truncated Regression of the biased corrected Environmental Efficiency scores

| | Coef. | Std. Err. | z | P>z | [95% Conf. Interval] | |
|---|---|---|---|---|---|---|
| No of productive ewes | 0.000198 | 0.000053 | 3.74 | 0 | 0.0000928 | 0.0003 |
| Education | -0.00202 | 0.001826 | -1.11 | 0.269 | -0.0055567 | 0.001714 |
| Experience | -0.00073 | 0.00039 | -1.87 | 0.061 | -0.0014856 | 0.000032 |
| Share of family to total labour | 0.034783 | 0.026958 | 1.29 | 0.197 | -0.0134491 | 0.089928 |
| Share of milk to total income | 0.088787 | 0.050128 | 1.77 | 0.077 | -0.0109018 | 0.182699 |
| Compound feedstuff to total feedstuff | 0.00285 | 0.00166 | 1.72 | 0.086 | 0.0005866 | 0.006914 |
| Gross margin per productive ewe | 0.000439 | 0.000113 | 3.88 | 0 | 0.0002192 | 0.00066 |
| Part-time farming | 0.083933 | 0.024949 | 3.36 | 0.001 | 0.0366141 | 0.135906 |
| Non specialized farming | -0.03447 | 0.014305 | -2.41 | 0.016 | -0.0630919 | -0.0064 |
| $CH_4$ from enteric fermentation per ewe | -0.00096 | 0.000167 | -5.71 | 0 | -0.0012789 | -0.00063 |
| $CH_4$ from manure per ewe | 0.000167 | 0.008104 | 0.02 | 0.984 | -0.0158972 | 0.015903 |
| Direct $N_2O$ emissions from manure per ewe | -0.00089 | 0.000149 | -5.97 | 0 | -0.0011626 | -0.00058 |
| Indirect $N_2O$ emissions from manure per ewe | -0.00501 | 0.001908 | -2.63 | 0.009 | -0.0089387 | -0.00129 |
| Constant | 1.23604 | 0.058814 | 21.02 | 0 | 1.11924 | 1.349679 |

## Conclusions

The main objectives of agricultural policy focus on meeting the rising demand for agricultural and especially livestock products and 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 (DEFRA, 2007; FAO, 2010), 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. Olesen et al., 2006; Weiske et al., 2006).

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

For the estimation of GHGs the IPCC (2006) guidelines were followed. All sources of GHG emissions directly linked to the livestock activity were taken under consideration, namely methane emissions from enteric fermentation and manure management and deposition on pasture and nitrous oxide direct and indirect emissions from manure management and deposition on pasture.

However, the inclusion of other sources of emissions related to the livestock activity is 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 emissions associated with the production and transportation of these feedstuffs, as well as carbon dioxide emissions from electricity and fuel use should also be accounted. This 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 or the reduction of tillage. Furthermore, carbon sequestration has to be considered, as it may affect the environmental efficiency of mainly the extensive farms that utilize pastures. Finally, it should be noted that other impacts of the livestock activity to the environment, like pasture degradation, have not been 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 of the TE of the sheep farms, since they can reduce their inputs by 39% and maintain the same level of output. On the other hand, their EE is much higher and 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 that are characterised by high productivity, or low inputs 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 (labour and capital) among their alternative economic activities in a rational way, ensuring that they will be used efficiently. This finding should be considered by policy makers, since pluriactivity is common in some parts of the country.

Finally, the analysis also highlighted that the level of education and the 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 the farm to increase its EE. This could be explained by the reluctance or perhaps inability 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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