Economic-environmental efficiency of European agriculture – a generalized maximum entropy approach[1]

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Abstract: The study aims to estimate the agricultural economic-environmental efficiency (eco-efficiency) for European countries. Eco-efficiency is obtained by the data envelopment analysis (DEA) and stochastic frontier analysis (SFA) using a generalized maximum entropy (GME) approach. Agriculture gross value added (GVA) is considered as the desirable output and greenhouse gas (GHG) emissions as the undesirable output. Capital, labour, land, energy and nutrients are regarded as inputs. The GVA/GHG ratio is the measure of eco-efficiency. The estimation was made for the years 2005 and 2010, which correspond to the 1st year of commitment to the Kyoto Protocol and the most recent year with information concerning all the variables in the study, and is a period that can allow us to see some changes after the agreement. The results show that in 2005, Austria, Slovenia, Hungary, the Netherlands and Portugal revealed the higher levels of eco-efficiency; and countries such as Estonia, Germany, Ireland, Latvia and Slovakia are the group with the lowest levels of eco-efficiency. In 2010, Bulgaria, Finland, Greece, the Netherlands and Portugal are the group of countries with the higher levels of eco-efficiency, while Denmark, Germany, Latvia, Romania and the United Kingdom are the group with the lowest levels of eco-efficiency.

Keywords: agriculture, economic-environmental efficiency, European countries, stochastic frontier analysis

The World Development Report estimated an increase in cereals and meat production by 50% and 85% in 30 years (20002030) in order to meet the world demand (World Bank 2008). Intensive farming practices have been largely put into practice during recent years by using greenhouses and poly-tunnels, for example, as a response to the increasing demand for fresh

[1] **Final version of this paper is published in *Agricultural Economics – Czech*, 64(10), 423-435, 2018. (OPEN ACCESS – https://doi.org/10.17221/45/2017-AGRICECON)**

goods by the developed countries (Romero-Gámez et al. 2012). The demand for the bio- fuels and biomass through processing agriculture goods has been increasing as well, and therefore several thousand million hectares of arable land might be needed, according to Bindraban et al. (2009). The increasing agricultural production augmented the energy consumption and the usage of non-renewable products as nitrogen and phosphorus, as well as the pesticides, according to Nemecek et al. (2011), raising several environmental problems such as loss of biodiversity, deterioration of the land and pollution of the ecosystem.

Given the heterogeneity of the levels of development of European agricultural regions and the existence of gaps in productivity, there are relevant reasons leading to the analysis and evaluation of economic-environmental efficiency (eco-efficiency) in this sector. The Common Agricultural Policy (CAP), particularly with the proposed schedule for 2014-2020, tries to establish a series of recommendations to ensure the environmental conservation and whose incidence optimise the efficiency of the inputs used in the process of agricultural production and livestock.

The agriculture eco-efficiency can be seen, as defined by Schmidheiny and Zorraquin (1996), by the gross value added (GVA) by the greenhouse gases (GHG) emissions ratio (usually interpreted by the proportionality between agricultural production to gases emissions); or, according to Huppes and Ishikawa (2005), eco-efficiency is the ratio of value created per one unit of environmental impact.

In the analysed agricultural sector literature, evaluating the efficiency and assessment of the environmental consequences of the production process are found to be an important basis for the decision-making. Regarding what concerns the efficiency in agricultural production, the empirical studies are usually performed using the data envelopment analysis (DEA) or the stochastic frontier analysis (SFA), which identify the material balance as key drivers for different levels and variations in scores that rank the agricultural systems on their level of eco-efficiency.

Although not new, the methodology used in this work has not been applied at the sectoral level or in particular to the agriculture sector. A maximum entropy approach, which combines information from the DEA and the structure of composed error from the SFA without requiring distributional assumptions, is used to estimate the stochastic frontier model with a translog specification (Coelli et al. 2005; Rezek et al. 2011). The methodology was applied with the goal of estimating the agricultural eco-efficiency at the country level. The years of 2005 and 2010 will be considered, which correspond to the 1st year of commitment to the

Kyoto Protocol and the most recent year with information concerning all the variables in the study. This last year also allows us to see if some changes occurred after the agreement.

In our model, the agriculture GVA is considered as the desirable output and the GHG emissions from agriculture as the undesirable output. We use the ratio between GVA and GHG emissions as the definition of the eco-efficiency. Nutrients, energy (lubricants consumption), land, capital and labour are regarded as inputs. The GVA by GHG emissions ratio is maximised given the values of the other five variables. Eco-efficiency will be greater when the emissions decrease and the GVA is the same when agricultural production is greater for the same amount of emissions, or simultaneously when agricultural production increases and the GHG emissions shrink. The previous analyses show that the productivity of agriculture in Europe relies on the intensity of energy, capital, labour and land. Different improvements in labour productivity, land intensity and energy efficiency can effectively enhance the technical and technological efficiency. However, capital deepening has a mitigating effect on the efficiency mentioned. The Kyoto Protocol commitment implies that the technological change of the European's agricultural production biases energy use and capital saving, causing a high-energy demand, particularly in the development of the agricultural sector.

We present figures showing the evolution between 2005 and 2010 of the GVA/GHG ratio, as well as of the inputs considered in our study. Figure 1-2 show that some countries that stand out for the GVA/GHG ratio as Finland (+ 109%), Germany (+ 25%) and Portugal (+ 9%). Slovakia, Ireland, the Czech Republic and Denmark have significant adverse developments for the production by the pollution emitted in agriculture. We also found in Figure 3 that countries with greater intensity in the use of nutrients are Bulgaria, Ireland and Slovakia, and those with bigger energy intensity are Ireland, Slovakia and the Czech Republic. The best-performing countries, that is, with significant negative changes, are Finland, Greece and Malta for nutrients and Finland, Luxembourg, Germany and Portugal for energy. Joining these observations with the ones about the GVA/GHG ratio, we see that the intensity in the use of nutrients and energy can be strongly related to eco-efficiency of the sector.

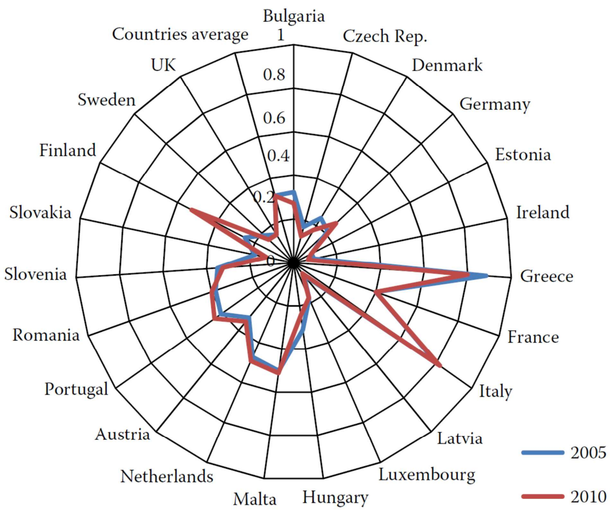

Figure 1. Gross value added divided by greenhouse gases in 2005 and 2010 for agriculture in European countries (in million EUR/gigagram CO_2 eq.)

Source: own elaboration based on data from the Eurostat (more information in Data)

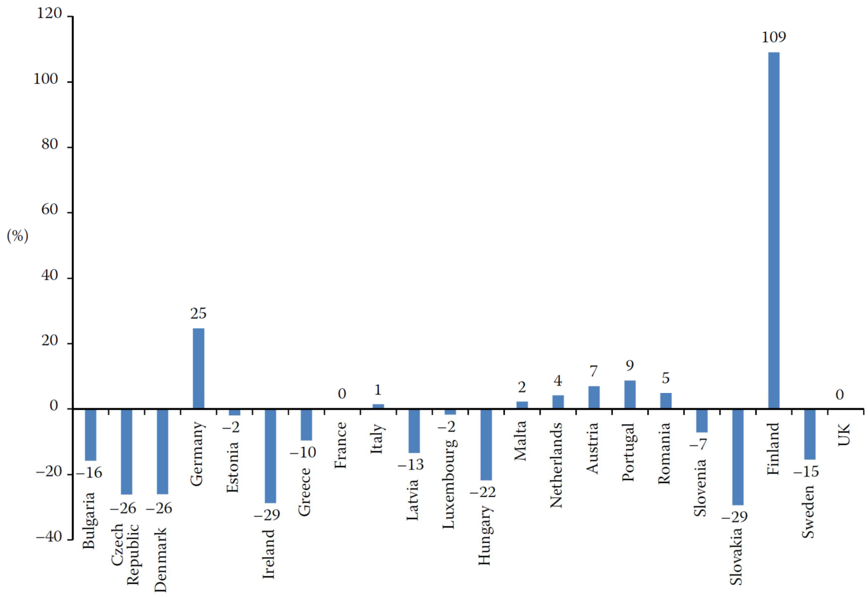

Figure 2. Variation of gross value added divided by greenhouse gases between 2005 and 2010 for agriculture in European countries

Source: own elaboration based on data from the Eurostat (more information in Data)

If we look at the productivity of agricultural production factors (capital, labour and land) in Figure 4, we can also establish some relationships with the economic and environmental efficiency. We have for example countries like Finland, Estonia and Latvia with a very satisfactory overall performance, while countries like Malta, Hungary or Ireland show a decrease in the factors productivity.

Following this preliminary analysis, it is clear that there are differentiating levels in the cross-country dispersion in agriculture in Europe on the relationship between the measure of eco-efficiency and its determinants.

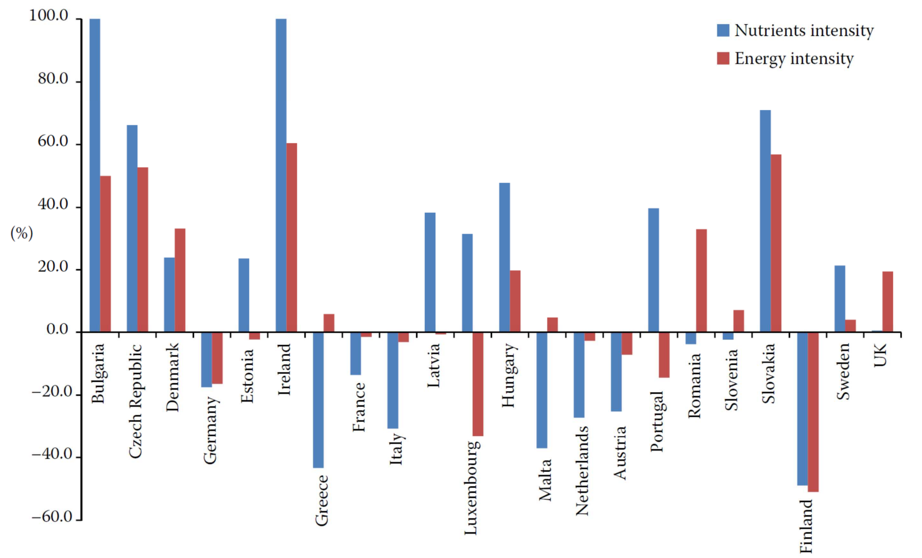

Figure 3. Variation of nutrients intensity and energy intensity between 2005 and 2010 for agriculture in European countries

Source: own elaboration based on data from the Eurostat (more information in Data)

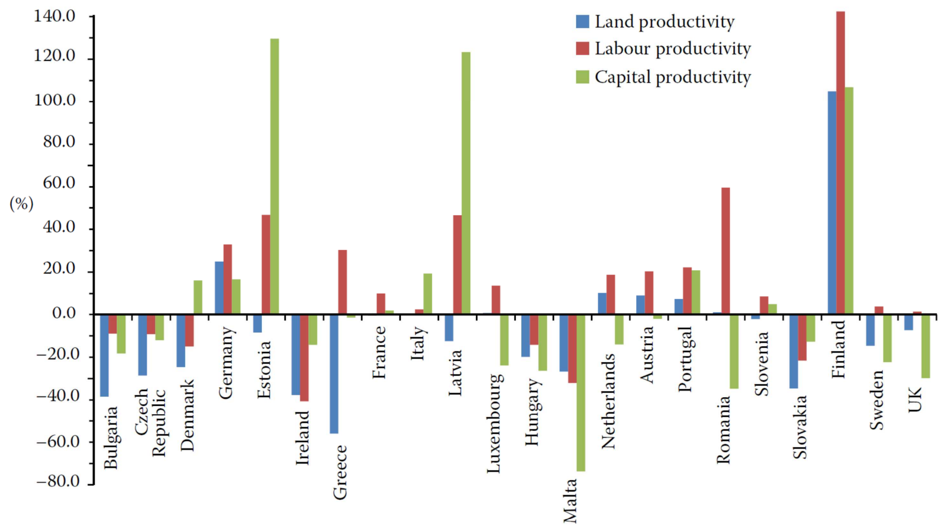

Figure 4. Variation of land, labour and capital productivities between 2005 and 2010 for agriculture in European countries

Source: own elaboration based on data from the Eurostat (more information in Data)

LITERATURE REVIEW: EFFICIENCY AGRICULTURAL STUDIES

Among the analysed agricultural sector literature, evaluating the efficiency and assessment of the environmental consequences of the production process is found to be an important decision making basis.

The identification of natural resources as explanatory to justify the variability of levels of environmental efficiency in the context of agricultural production, justified the need for analytical frameworks, as suggested for example in empirical studies by Reinhard et al. (2002), Battese and Coelli (1995), Greene (2005), Coelli et al. (2005), Simar and Wilson (2007), Lauwers (2009). All these studies covered the three most referenced models usually used to measure economic efficiency versus environmental efficiency, such as the environmental efficiency of production, the frontier of environmental efficiency and adjusted based on material balance models.

A particular innovation in the eco-efficiency analysis with adjusted production models is the use of a production frontier to analyse the relationship between input(s) and output(s), under the assumption that pollutant emissions are seen as undesirable inputs and/or outputs. This efficiency boundary is used for modelling the relationships between economic and ecological results to derive the environmental efficiency measures, such as supported by Callens and Tyteca (1999), Tyteca (1999), Kortelainen (2008), Kuosmanen and Kortelainen (2005), Lauwers (2009), Wursthorn et al. (2011), Picazo-Tadeo et al. (2011) and Picazo-Tadeo et al. (2012). To these authors, the measures of eco-efficiency are related to the economic value of outputs involved in production processes, under the assumption of the existence of environmental pressures.

There are several studies that use the DEA and SFA to identify different levels of eco-efficiency of agricultural systems, where the inputs are nutrients, nitrogen and phosphorus, since they have been found significant in explaining emissions, particularly for farms and livestock. As examples, we can point out the following studies: Callens and Tyteca (1999), Reinhard and Thijssen (2000), Reinhard et al. (2002), Van der Werf and Petit (2002), Pacini et al. (2003), Abay et al. (2004), Payraudeau and Van der Werf (2005), Alene et al. (2006), Asmild and Hougaard (2006), Rao and Rogers (2006), Hoang and Coelli (2011) and Hoang and Alauddin (2012). Coelli et al. (2007) investigated the environmental performance of 117 pig farms in Belgium using a DEA non-parametric technical analysis. Lauwers (2009) and Van Meensel et al. (2010) used the DEA and SFA to recognise the existing trade-off between environmental effectiveness and economic efficiency using the same data of Coelli et al. (2007).

Other authors advocate that agriculture eco-efficiency should be evaluated considering the principle of the balance of materials, as the cost allocative efficiency, the fertiliser consumption intensity, the size of land and the share of owned land out of the total land. Some examples are the studies of Coelli et al. (2007), Van Passel and Van Huylenbroeck (2007), Cherche and Puyenbroeck (2007), Bell and Morse (2008), Lauwers (2009), Barba-Gutiérrez et al. (2009), Van Meensel et al. (2010), Hoang and Coelli (2011), Picazo-Tadeo et al. (2011), Hoang and Alauddin (2012), Picazo-Tadeo et al. (2012), Khoshnevisan et al. (2013). Nguyen et al. (2012) investigated the environmental performance of 196 rice farms in South Korea based on the material balance theory, revealing a high variability in the coefficients associated with the explanatory drivers of eco-efficiency in all farms.

Hoang and Rao (2010) evaluated the efficiency of the agricultural sector of 29 OECD countries, decomposing it into the technical efficiency and the cumulative exergy allocative efficiency, and defining new efficiency sustainable measures that ensure the capacity for the sustainability of crop and livestock production. In the reviewed studies, the environmental assessment was mainly focused on the efficient use of natural resources and nutrients, but we must consider, particularly in Africa, that there is a credible support that the systems of agricultural production are limited by the existing restriction of the low topsoil fertility (due to scarcity of water and nutrients), as reported in the studies of Robertson et al. (2007), Giller et al. (2006), Bindraban et al. (2008), Twomlow et al. (2008) and Sanginga and Woomer (2009).

DATA AND METHODOLOGY

Data

In our model, we considered the GVA/GHG ratio for agriculture as the output and energy (lubricants), land (agricultural area), labour, capital and nutrients are considered as inputs by using a translog agricultural production function.

GVA is the gross value added of agriculture at basic and constant prices, in millions of EUR, available on the Economic Accounts for Agriculture of the Eurostat. GHG emissions (CO_2 eq.) in Gigagrams were obtained from the FAOSTAT. Energy (lubricants) consumption in millions of EUR at constant prices was obtained from the Economic Accounts for Agriculture in the Eurostat. Agricultural area in % of the land area was obtained from the FAOSTAT. Agricultural labour in absolute figures (1 000 annual work units) was obtained from the Agricultural Labour Input Statistics, Eurostat. For the variable capital, we considered the gross fixed capital formation in millions of EUR at basic and constant prices available on the Economic Accounts for Agriculture of the Eurostat. Nutrients are the sum of nitrogen and phosphate fertilizers in tonnes of nutrients per 1000 ha obtained from the FAOSTAT.

We considered data for the two distinct years 2005 and 2010 for the following European countries: Austria, Bulgaria, the Czech Republic, Denmark, Estonia, Finland, Germany, Greece, France, Hungary, Ireland, Italy, Latvia, Luxembourg, Malta, the Netherlands, Portugal, Romania, Slovenia, Slovakia, Sweden and the United Kingdom.

Although this study initially intended to include in its analysis the first year of the Kyoto Protocol (2005) and the year reflecting the end of the second phase (2012), this goal could not be achieved, as 2010 is the last year for which there is valid information for all countries considered. Also, notice that we had to exclude Belgium, Norway and Switzerland for missing data on some variables, and Cyprus, Lithuania, Poland and Spain were eliminated for the lack of data on capital invested in agriculture in 2010.

Table 1 reports descriptive statistics of the variables used for the full sample of the agriculture sector (22 countries). On average, in 2010 in relation to 2005, the countries values show practically a maintenance of the ratio for the eco-efficiency measure (GVA/GHG). The mean values for labour and capital decreased while the mean values for land, energy and nutrients increased.

Table 1. Descriptive statistics for the full sample (22 countries) in years 2005 and 2010

Variables	2005				2010			
	minimum	maximum	mean	standard deviation	minimum	maximum	mean	standard deviation
GVA/GHG	0.07	0.88	0.32	0.21	0.06	0.82	0.32	0.22
Land	7.47	70.09	43.54	18.16	7.52	71.19	44.69	18.06
Labour	4.00	2596.00	411.62	585.1	3.60	1639.00	324.00	411.93
Capital	9.81	10895.13	1993.13	3044.51	30.26	9273.35	1946.54	2834.64
Energy	7.83	3007.30	740.99	890.66	6.66	3080.30	747.44	897.03
Nutrients	43.73	297.47	124.50	74.46	38.83	464.44	130.56	105.74

Agriculture gross value added (GVA) is considered as the desirable output and greenhouse gas (GHG) emissions as the undesirable output. The GVA/GHG ratio is the measure of eco-efficiency.

Source: authors' own elaboration

Methodology

The DEA and SFA are briefly discussed for completeness and reader's convenience. The DEA method (Charnes et al. 1978) uses linear programming to construct a non-parametric piece-wise linear production frontier using different return to scales, and the possibility of multiple inputs and multiple outputs. Some well-known DEA models are illustrated in Coelli et al. (2005). It is important to note that all deviations from the production frontier are estimated as technical inefficiency because the DEA does not account for noise.

Two DEA models are tested in this work: a constant return to scale (CRS) model and a non-increasing return to scale (NIRS) model. The NIRS output-orientated DEA model provides higher values of the technical efficiency and it is considered in this work, namely for the definition of supports in the SFA methodology.

Aigner et al. (1977), Battese and Corra (1977) and Meeusen and van den Broeck (1977) were the pioneers of the SFA methodology. The general stochastic frontier model is given by

$$\ln y_n = f(\boldsymbol{x}_n, \boldsymbol{\beta}) + v_n - u_n, \tag{1}$$

where n represents a producer (n = 1, 2, ..., N); f (.) is the production frontier; y_n is the scalar output for producer n; $\boldsymbol{x}_n$ is a row vector with logarithms of inputs; $\boldsymbol{\beta}$ is a column vector of parameters to estimate; v is a random variable representing noise (measurement errors and/or random shocks) and $u \geq 0$ is a one-sided random variable representing technical inefficiency. The random variable v is usually assumed to be normally distributed, $N(0, \sigma_v^2)$, and u is defined through different distributions such as exponential, non-negative half-normal, truncated normal or gamma. The choice of the distribution for the u error component represents the main criticism on the SFA, since different distributional assumptions can lead to different estimates of technical efficiency. However, the main advantage of the SFA is the structure of the composed error, which separates the impacts on production outside the producer's control from technical efficiency.

The output-oriented measure of technical efficiency is defined by

$$\mathrm{TE}_n = \frac{y_n}{\exp\left(f\left(\boldsymbol{x}_n, \boldsymbol{\beta}\right) + v_n \right)} = \frac{\exp\left(f\left(\boldsymbol{x}_n, \boldsymbol{\beta}\right) + v_n - u_n \right)}{\exp\left(f\left(\boldsymbol{x}_n, \boldsymbol{\beta}\right) + v_n \right)} = \exp\left(-u_n\right). \tag{2}$$

This measure represents the ratio of the observed output to the potential output for the n^{th} producer. Naturally, TE_n assumes values between zero and one.

The parameters of the model (1) are usually estimated through maximum likelihood (ML). Kumbhakar and Lovell (2000) presented all the estimation procedures with the ML estimator for different distributional assumptions required for the two-error components. However, in this work, with only 22 countries (N = 22) in the sample and assuming a translog functional form for the production frontier (Coelli et al. 2005; Rezek et al. 2011), the model (1) became ill-posed, namely affected by severe collinearity and with more parameters to estimate than observations, in both estimated models (2005 and 2010). Thus, an alternative to the ML estimation is needed.

The maximum entropy (ME) formalism was first established by Jaynes (1957a, b) based on physics (the Shannon entropy and statistical mechanics) and the statistical inference. Golan et al. (1996) generalized the ME formalism and developed the generalized maximum entropy

(GME) estimator, which can be used in models exhibiting collinearity, in models with small sample sizes (micronumerosity) and non-normal errors, as well as in models where the number of parameters to be estimated exceeds the number of observations available (under-determined models).

Recently, an increasing interest with these estimators in the technical efficiency analysis has emerged in the literature (Campbell et al. 2008; Rezek et al. 2011; Macedo et al. 2014; Macedo and Scotto 2014; Robaina-Alves et al. 2015). The main motivation comes from the advantages of the ME estimation that avoids criticisms and difficulties of the DEA and SFA. For instance, with the ME estimation, the DEA method is used only to define an upper bound for the supports, and thus the main criticism of the DEA is used as an advantage. Furthermore, the composed error structure in the SFA is used without distributional assumptions, which means that the main criticism on the SFA is avoided with the ME estimation. Thus, by avoiding the criticisms and difficulties of the DEA and SFA, the ME estimators appear to be a promising approach in the efficiency analysis.

In this work, the supports for the parameters of the model are defined through [100, 50, 0, 50, 100] for the constant, and [5, 2.5, 0, 2.5, 5] for the remaining parameters of the model. The supports for the noise component are defined symmetrically and centred on zero with five points, using the three-sigma rule with the empirical standard deviation of the noisy observations.

An important advantage of the ME estimation is that the distributional assumptions are not necessary, although the same beliefs can be expressed in the model through the error supports. In this work, three approaches are considered: GME1 is following Campbell et al. (2008), where the prior means are chosen according to the range of the mean efficiency of the DEA and SFA (in this work, the prior mean is close to the DEA mean efficiency: 58.2% in 2005 and 52.5% in 2010); GME2 is following Rezek et al. (2011) and GME3 is following Macedo et al. (2014), in which the upper bound is given by $-\ln\left(\mathrm{DEA}_n\right)$, where DEA_n represents the lower technical efficiency estimate obtained by the DEA in the 22 observations in the sample. The supports are presented in Table 2. Note that, as mentioned by Rezek et al. (2011), the selection “of these vectors sets a prior expectation of mean efficiency; however, it does not preordain that result.” This is an important feature of the ME estimation.

Table 2. Supports for the inefficiency error component with the generalized maximum entropy (GME) estimator

	2005	2010
GME1	[0, 0.005, 0.01, 0.015, 2.68]	[0, 0.005, 0.01, 0.015, 3.19]
GME2	[0, 0.01, 0.05, 0.1, 1]	[0, 0.01, 0.05, 0.1, 1]
GME3	[0, 0.01, 0.02, 0.03, 1.84]	[0, 0.01, 0.02, 0.03, 2.19]

GME1 – supports accordingly to Campbell et al. (2008);

GME2 – supports accordingly to Rezek et al. (2011);

GME3 – supports accordingly to Macedo et al. (2014)
Source: authors' own elaboration

In the SFA with ML estimation, Kumbhakar and Lovell (2000) answering to the question "Do Distributional Assumptions Matter?" argued that the "sample mean efficiencies are no doubt apt to be sensitive to the distribution assigned to the one-sided error component (…). What is not so clear is whether a ranking of producers by their individual efficiency scores (…) is sensitive to distributional assumptions." Naturally, the same concern applies to the ME estimation: Do different supports for the inefficiency error component matter? This work provides some highlights on this discussion. If the sample mean efficiencies are clearly sensitive to the supports assigned to the inefficiency error component, the same does not happen to the classification of producers since the rankings established by GME1, GME2 and GME3 are almost identical. For example, the rank correlation coefficient between the pairs of efficiency estimates is always greater than 0.976 (p-value approximately zero). Certainly, this issue deserves a further investigation in the future.

RESULTS

According to Table 3, the eco-efficiency in European agriculture has values between, approximately, 16% and 100% in 2005, and between, approximately, 11% and 100% in 2010, with DEA. In turn, the SFA with the GME provides scores of eco-efficiency between 35% and 88%, approximately, in 2005, and between 31% and 90%, approximately, in 2010, depending on the version of the GME estimator considered in Table 1.

Table 3. Eco-efficiency in the European agriculture through the data envelopment analysis (DEA) and stochastic frontier analysis (SFA) with generalized maximum entropy (GME) in years 2005 and 2010

Country	2005				2010			
	DEA	GME1	GME2	GME3	DEA	GME1	GME2	GME3
Bulgaria	0.687	0.630	0.816	0.727	0.514	0.643	0.830	0.732
Czech Republic	0.304	0.542	0.776	0.649	0.216	0.459	0.763	0.575
Denmark	0.445	0.563	0.777	0.659	0.325	0.379	0.730	0.496
Germany	0.245	0.428	0.724	0.553	0.356	0.329	0.689	0.439
Estonia	0.310	0.447	0.732	0.565	0.241	0.401	0.765	0.541
Ireland	0.159	0.350	0.685	0.478	0.112	0.419	0.752	0.539
Greece	1.000	0.638	0.803	0.714	1.000	0.781	0.876	0.840
France	0.453	0.568	0.801	0.687	0.501	0.443	0.794	0.589
Italy	0.915	0.543	0.763	0.637	1.000	0.600	0.809	0.695
Latvia	0.212	0.421	0.739	0.560	0.133	0.311	0.713	0.448
Luxembourg	0.365	0.576	0.793	0.683	0.466	0.516	0.796	0.637
Hungary	0.592	0.710	0.847	0.790	0.381	0.484	0.787	0.610
Malta	1.000	0.648	0.820	0.738	1.000	0.641	0.820	0.721
Netherlands	0.759	0.728	0.845	0.795	0.779	0.832	0.896	0.881
Austria	0.548	0.802	0.876	0.855	0.585	0.545	0.792	0.650
Portugal	0.616	0.763	0.872	0.837	0.722	0.657	0.849	0.758
Romania	1.000	0.504	0.755	0.613	0.623	0.396	0.735	0.513
Slovenia	0.751	0.682	0.825	0.756	0.728	0.617	0.807	0.697
Slovakia	0.391	0.496	0.742	0.597	0.241	0.601	0.826	0.712
Finland	1.000	0.555	0.779	0.659	1.000	0.645	0.826	0.730
Sweden	0.830	0.572	0.799	0.686	0.403	0.380	0.749	0.516
United Kingdom	0.221	0.508	0.781	0.640	0.217	0.342	0.723	0.472

GME1 – supports accordingly to Campbell et al. (2008); GME2 – supports accordingly to Rezek et al. (2011); GME3 – supports accordingly to Macedo et al. (2014)

Source: authors' own elaboration.

The three GME approaches used in this study produce similar efficiency rankings. However, GME3 provides intermediate values, between GME1 providing the worst case (lowest average efficiency) and GME2 the most optimistic (higher average efficiency). All the estimation procedures were computed with a MATLAB code developed by the authors.

For the year 2005, the group defined by Austria, Hungary, the Netherlands, Portugal and Slovenia show the highest levels of eco-efficiency (between 76% and 86%). On the other hand, countries as Estonia, Germany, Ireland, Latvia, and Slovakia are the group with the worst eco-efficiency levels (between 48% and 60%).

For the year 2010, Bulgaria, Finland, Greece, the Netherlands and Portugal are the group with better eco-efficiency levels (between 73% and 88%) while Denmark, Germany, Latvia, Romania, and the United Kingdom are the group with worse eco-efficiency levels (between 44% and 51%).

Next, we will comment in particular one of the best, and one of the worst performances in the countries analysed. For instance, the results for Finland are not surprising, as we have seen in the introduction, that this country had a good performance in

GVA/GHG ratio and the consumption of energy and nutrients. Moreover, Finland improved as well as the factor productivity, having all the necessary ingredients to raise its eco efficiency level in this period.

Finland has many good examples of productive, carbon-wise and sustainable agriculture systems and innovations. For instance, Finland has a network of nutrient and energy-effective colleges and school farms, where the main themes are biogas, energy efficiency, composting, solid biofuel, manure logistic, organic fertilisers and protein self-sufficiency. Kimmo Tiilikainen, the Finish Ministry of Environment, reported that their government had the priority of increasing the Finish nutrient recycling and developing a resource efficient food system based on the circular economy, through research, innovations, dissemination of information and investment support (COP22 United Nations Climate Change Conference and UNEP 2016).

Finish farmers are pointed out as innovative, and they are encouraged to take climate actions, as good management of soil, improving its productivity and capacity of adapting, thanks to the better water retention capacity. Good growth potential of the land also supports the carbon objectives as more carbon is sequestered into the soil. Appropriate use of plant nutrients improves productivity and contributes to mitigation, while diverse crop rotations reduce the risks to farmers and enhance their adaptation capacity. Healthy and well-cared-for animals as a part of carbon- rich production systems produce valuable food with a minimised carbon footprint.

On the other hand, Ireland was among countries with the worst levels of the GVA/GHG in the period analysed, also with high levels of energy and nutrients intensity. Moreover, Ireland verified a decrease in factors productivity and had an overall bad performance in the agriculture eco-efficiency.

Ireland had the biggest net gain per citizen of any EU country under the CAP and the highest CAP direct payments per farm worker and per hectare of farmland. The Irish farm sector not only benefits from cash payments from the EU, but also from a high level of tariff protection on its key sectors of beef and dairy (OECD 2016). Despite these, the bad performance could be related with some factors as pointed out in (European Commission 2016), as the average age of Irish farmers (57) and the fact that only 6.8% of Irish farmers are under 35 years (7.5% in EU-28). Moreover, (Irish Cattle and Sheep Farmers Association 2010), points out some factors that could justify the Irish eco-efficiency performance: (i) the average farm size of 32 hectares, and the propensity towards fragmented holdings makes many farms unviable and almost no farms do have the necessary economies of scale; (ii) extremely poor products prices combined with high investment on farm facilities, which means that many farmers are carrying heavy borrowings; (iii) high costs in the Irish economy – energy, electricity, labour, the carbon tax on green diesel, the regulatory compliance; (iv) too much tendency by some farmers to over-invest in machinery and buildings without adequate assessment of the economic returns; (v) the lack of tradition of machinery sharing and the consequent under-utilisation of costly equipment; (vi) the over-dependence on the EU subsidies.

Confronting the significant evidence found with the referenced in the study of Vlontzos et al. (2014) on the energy and environmental efficiency in Europe, despite the estimated models are different, there is a confirmation that only Germany and Sweden display low levels of efficiency and confirming that to the countries showing the highest levels, belong Denmark, France or Ireland. The results from Hoang and Rao (2010) and Hoang and Coelli (2011) show that the most sustainable systems in the European agriculture were the Belgium-Luxembourg, Denmark and the Netherlands, although our study only confirms this evidence for the Netherlands.

This mix of evidence found in the three referred studies can be explained by its connection to the considerable changes in the energy and environmental efficiency after the implementation of the new CAP (Bartolini and Viaggi 2013). The subsidy policy had effects on the energy and environmental efficiency levels of the new Member States compared to the older Member States, as admitted by Hoang and Rao (2010) and Vlontzos et al. (2014). On the other hand, these differences are also owed to the low level of technology implemented in the production process in agriculture more evident in the countries of Central and Eastern Europe (Vlontzos et al. 2014). In fact, the differences in productivity and farm income between countries and/or agricultural regions are associated with different government support schemes for the economically weaker regions, on the other hand, the strengthening of specific sectors of the economy where agriculture is a central focus, as admitted by Gorton and Davidova (2004). However, we should note that the structure of agriculture in the EU varies not only from country to country, but also between agricultural regions, so the decisions on where and how to produce a given agricultural crop or animal production may depend heavily on local conditions, such as the type of soil, climate and infrastructure.

In general, we can see that there has been maintenance of the overall eco-efficiency of the agriculture sector in Europe, although it has improved in some countries and worsened in others (Table 3).

CONCLUSION

A maximum entropy approach, which combines the information from the DEA and the structure of composed error from the SFA without requiring distributional assumptions, was used to estimate an ill-posed stochastic frontier model with a translog specification. The methodology was applied with the goal of estimating the agricultural eco-efficiency at the country level for 22 European countries, considering data for 2005 and 2010.

Our results show that, in 2005, the group defined by Austria, Hungary, the Netherlands, Portugal and Slovenia reveals higher levels of the eco-efficiency; and countries as Estonia, Germany, Ireland, Latvia and Slovakia are the group with the lowest levels of eco-efficiency. However, in 2010, Bulgaria, Finland, Greece, the Netherlands and Portugal are the group of countries with higher levels of eco-efficiency, while Denmark, Germany, Latvia, Romania and the United Kingdom are the group with the lowest levels of eco-efficiency.

In general, we can see that there has been maintenance of the overall eco-efficiency of the agriculture sector in Europe, although it has improved in some countries and worsened in others. From the aggregate point of view, there was almost no economic growth in this period, and the GHG emissions did not grow.

This period suffered from an economic crisis starting in 2008. Given that the Kyoto Protocol imposed its first targets to be met between 2008 and 2012, the period under study (2005–2010) is precisely a period of adaptation and adjustments of the various sectors to meet national emissions goals.

At the CAP level, the successive reforms that have been approved had the objective of promoting the sustainable development of agricultural activity, Changes in the production systems and practices aimed, in particular, at the extensification and the reduction of the use of nitrogen fertilisers. In this context, countries encouraged the practices and production systems that promote the sequestration of carbon in agricultural soil, such as the direct seeding and biodiverse pastures, decreasing the concentration of CO2 in the atmosphere. Moreover, they also contribute to the soil protection against the water erosion and to improve fertility through the increased soil organic matter content.

Furthermore, the whole policy of supporting renewables developed after the Kyoto, including the support for farmers, in particular for the renewable energy production projects, as well as the increasing demand of consumers for the organic products, has reduced the consumption of fossil fuels as well as pollutant fertilisers of the sector.

Given that in some countries, there has been an improvement in the eco-efficiency in this period, we can associate it with these the Kyoto-related measures. In other countries, the GHG reduction may be "camouflaged" by the economic crisis, but we are not sure that the changes are only cyclical or structural, that can improve the eco-efficiency after the crisis.

The topics of future research include a detailed econometric analysis to better study the specific determinants of the eco-efficiency indicators, including the variables considered in this work and others such as taxes, subsidies or information at the time of the country's entry into the EU. Another useful approach could be the use of the decomposition analysis to identify the most relevant factors in the eco-efficiency assessment.

The authors also propose a complementary analysis using decoupling indicators, according to Tapio (2005), which investigates the elasticity of the GVA relative to the consumption of resources or the production of some pollutants using the dissociation indicator. Diakoulaki and Mandaraka (2007), De Freitas and Kaneko (2011), combine the dissociation index with the decomposition analysis, while Jorgenson and Clark (2012), Wang (2013) combines the dissociation analysis with econometric methods.

Acknowledgements

Supported by the Portuguese Foundation for Science and Technology (FCT – Fundação para a Ciência e a Tecnologia), CIDMA – Center for Research and Development in Mathematics and Applications (UID/MAT/04106/2013), the research unit on Governance, Competitiveness and Public Policy (POCI-01-0145-FEDER-006939) and FEDER funds (COMPETE2020 – Programa Operacional Competitividade e Internacionalização (POCI)).

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