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Empirical comparison of pollution generating technologies in nonparametric modelling:

The case of greenhouse gas emissions in French sheep meat farming¹

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Abstract.

In this paper we consider different models that assess eco-efficiency with production frontier estimation when both desirable outputs and undesirable outputs (or residuals) are considered. These models are confronted to livestock farm data (sheep meat farms) and greenhouse gas (GHG) emissions, to discuss their suitability in eco-efficiency measurement. The application is to French sheep meat farms. Our results show that under certain conditions the existing models, except for the by-production, yield the same results as when residuals are treated as inputs. The results also reveal that the by-production model augmented with dependence constraints offer some promising opportunities. Besides, environmental inefficiency appears to be the main contributor of eco-inefficiency in the sheep meat production.

Keywords: eco-efficiency; undesirable output; multiple frontier technology; GHG emissions; sheep meat farming; France

JEL codes: C00, O13

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1. Introduction

Since the pioneering work of Pittman (1983) to account for undesirable outputs (or unwanted or detrimental outputs, or pollutants, or residuals) in production technology modelling, many models have been developed in this area for the case of nonparametric analysis. In general, pollutants are treated as an extra input that is added to the technology (Hailu and Veeman, 2001, Hailu, 2003, Mahlberg et al., 2011) or included as an output under the weak disposability and the null-jointness assumptions (Färe et al., 1989, Chung et al., 1997, Färe et al., 2005). These two approaches, largely used in empirical applications (Zhou et al., 2008), have been criticized in the literature for their inadequacy to properly model pollution generating technologies (Coelli et al., 2007, Podinovski and Kuosmanen, 2011, Murty et al., 2012, Chen, 2014). However, in this debate some recent developments have emerged to circumvent the drawbacks associated to the previous models: first, models linked to the materials balance principles (Hampf and Rødseth, 2014), and second, models relying on the estimation of separate sub-technologies (Førsund, 2009, Murty et al., 2012, Sueyoshi and Goto, 2012, Dakpo, 2015). This latter formulation assumes that a production system cannot be represented by a single equation and uses multiple independent frontier representations, where one sub-technology is related to the production of good outputs and the other one to the generation of residuals. Given this abundant literature, there has been to date no empirical discussion on these models that can give more insights on their similarities or differences.

The objective of this paper is then to carry on a systematic comparison of the aforementioned methods and discuss their suitability to real data in agriculture, with the specific case of livestock farms. The application to the livestock sector is relevant for two reasons. First, the complex interactions between agriculture and the environment can make difficult the choice of a method. Second, the last decade saw a growing attention at the international scale of the role played by livestock farming in the global greenhouse gas (GHG) emissions (Steinfeld et al., 2006, Gerber et al., 2013). Given these two issues and a projected increase in future demand of animal products, this sector is a suitable candidate to investigate the challenge of eco-efficiency computations. Besides, according to Hoang and Alauddin (2012), “for the sake of farmers” sustainability must become an important objective since the tensions on the environment might affect the ecosystem which can no longer sustain the agricultural activities. In this paper, we focus on sheep meat breeding systems located in French grassland areas. The low farm profitability in this sector – due to high competition, cost increase, low public support – and the sector’s key role in the viability of rural areas - through for instance the maintenance of rural landscapes – imply the double challenge of socio-economic and environmental performance.

The eco-efficiency computation, based on the Data Envelopment Analysis (DEA) methodology, aims at finding the maximal attainable ratio of a good output (here meat production) on a bad output. Here the latter is considered as an aggregation of the three main GHG emissions reported in livestock farming namely carbon dioxide (CO₂), methane (CH₄) and nitrous oxide (N₂O). Besides, in this empirical application we devote a particular care to the nature of methane (CH₄) generation which is largely associated to the animal physiology, and in this case this gas can be viewed as given (fixed) and removed from the technology modelling. Following Hampf and Rødseth (2014) we also propose a decomposition of performance into different potential sources of improvement given different assumptions on the flexibility available to producers in their decision making.

The paper is organized as follows. In **Section 2** we briefly explain the main assumptions, the basis and the significant features of each model. **Section 3** describes the data used and the empirical results obtained. **Section 4** discusses the appropriateness of each approach to the farm data used and points out the challenges that still remain. **Section 5** concludes.

2. Pollution-generating technologies modelling: theoretical basis and eco-efficiency computations

We begin by describing the environmental production technology which is represented by the set of good and bad outputs (y, b) that can be produced by the inputs x :

$$\Psi_{bad} = [(x, y, b) | x \in \mathbb{R}_+^K, x \geq 0, \text{ can produce } y \in \mathbb{R}_+^Q, y \geq 0 \text{ and } b \in \mathbb{R}_+^R, b \geq 0] \quad (1)$$

We shall also assume the following classic postulates: no free lunch, non-emptiness, closeness, boundness, convexity, free (strong) disposability of inputs and good outputs and variable returns to scale (VRS). One can refer to Chambers (1988) and Färe and Grosskopf (2004) for more details regarding the standard axioms of production theory. Given this framework pollution has been modelled in different ways in the literature. For our particular case study, we consider one good output and one undesirable output.

2.1. Inclusion of undesirable outputs in the production technology: literature review

Considering that pollution generates social costs, and that an input orientation is straightforwardly interpreted in terms of costs savings (minimization), some authors (e.g. Dyckhoff and Allen, 2001,

Prior, 2006) recommended to introduce unwanted outputs as extra inputs and to assume their free disposability. These authors argued that emissions of environmentally detrimental outputs can be viewed as the usage of the environment's capacity for their disposal. Hence, according to them, considering them as inputs is likely a good way to account for the consumption of natural resources. Under this assumption, the technology can be represented as the following, where N is the number of Decision Making Units (DMUs):

$$\Psi_{bad}^{inputs} = [(x, y, b) \in \mathbb{R}_+^{K+1+1} | y \leq \sum_{i=1}^N \lambda_i Y_i; b \geq \sum_{i=1}^N \lambda_i B_i; \\ x \geq \sum_{i=1}^N \lambda_i X_i; \sum_i \lambda_i = 1 \text{ and } \lambda_i \geq 0; i = 1, \dots, N] \quad (2)$$

This approach has however been criticized in the literature because it violates the physical laws of thermodynamics (Färe and Grosskopf, 2003).

Another modelling strategy considers residuals as extra outputs but impose the weak disposability assumption (WDA) and also the null-jointness of both types of outputs (good and bad) (Färe et al., 1989, Chung et al., 1997, Färe et al., 2007). The WDA can be summarized as follows:

$$(y, b) \in \Psi_{bad}, 0 \leq \theta \leq 1 \Rightarrow (\theta y, \theta b) \in \Psi_{bad} \quad (3)$$

As for the null-jointness property, it is represented by:

$$(y, b) \in \Psi \text{ and } b = 0 \text{ then } y = 0 \quad (4)$$

The WDA implies that it is not costless to reduce bad outputs. More precisely, if one wishes to reduce undesirable outputs, good outputs must also be reduced for a given level of inputs. This implies that resources must be diverted to abatement activities in order to mitigate pollution level. Under this assumption the production technology is defined as:

$$\Psi_{bad}^{weak} = [(x, y, b) \in \mathbb{R}_+^{K+1+1} | y \leq \theta \sum_{i=1}^N \lambda_i Y_i; b = \theta \sum_{i=1}^N \lambda_i B_i; \quad (5)$$

$$x \geq \sum_{i=1}^N \lambda_i X_i; \sum_i \lambda_i = 1 \text{ and } \lambda_i \geq 0; i = 1, \dots, N; 0 \leq \theta \leq 1]$$

As formulated in (5) the WDA assumes a common proportional reduction of desirable and undesirable outputs. The model thus considers that all DMUs share the same uniform abatement effort θ . Yet, as pointed out by Kuosmanen (2005) and Kuosmanen and Podinovski (2009), policies should be targeted to abatement activities where the abatement costs are lowest. The authors therefore proposed an extension of the traditional WDA modelling by assuming a specific abatement effort for each producer (firm-specific abatement factor). The new technology proposed is similar to the one in problem (5) except that θ is replaced by θ_i . Despite the interesting feature of this model, some recent studies have cast a doubt on the relevance of the WDA. For instance Murty et al. (2012), using a transformation function to estimate the different trade-offs, showed some inconsistencies linked to this assumption. Chen (2014) also revealed some empirical drawbacks related to the WDA using an illustrative example.

Since it has been discussed that the WDA does not really fit with the physical laws, Hampf and Rødseth (2014) suggested to use the weak G-disposability which is based on the materials balance principles (MBP). This approach is related to the first two laws of thermodynamics. Let the input set be divided into two different subsets: material inputs x^M which generate pollution, and non-material inputs x^{NM} which are pollution free. The technology set can be defined as:

$$\begin{aligned}
\Psi_{bad}^{weak\ G} &= [(x, y, b) \in \mathbb{R}_+^{K+1+1} | y + s_y = \sum_{i=1}^N \lambda_i Y_i ; b - s_b = \sum_{i=1}^N \lambda_i B_i ; \\
x^M - s_{x^M} &= \sum_{i=1}^N \lambda_i X_i^M ; x^{NM} - s_{x^{NM}} = \sum_{i=1}^N \lambda_i X_i^{NM} ; \\
W' s_{x^M} + H s_y - s_b &= 0 ; \sum_i \lambda_i = 1 \text{ and } \lambda_i \geq 0 ; i = 1, \dots, N]
\end{aligned} \tag{6}$$

where s_x, s_y and s_b are respectively input excesses, good output shortfall and pollution excess, that are present in the technology due to inefficiency. W is the vector of input pollution factors and H represents the recuperation factor associated to the good output. This new approach grounded on MBP differs from the one proposed by Coelli et al. (2007) which is based on the estimation of an iso-environmental line in the same vein as iso-costs lines, and which totally neglects the possibility of interaction (substitution) between material and non-material inputs. However, as pointed out in Førsund (2009), the mass conservation equation ($W' s_{x^M} + H s_y - s_b = 0$) does not explicitly show how residuals are generated; instead the equation simply puts forward how the variables are related given the MBP. In addition, the mass balance equation introduces “some limits on derivatives in the system of equations”. Furthermore, Hampf and Rødseth (2014) have also demonstrated that under some assumptions the weak G-disposability is equivalent to the weak disposability as proposed in Färe and Grosskopf (2012).

Recognizing the importance of the materials balance in modelling the technology that generates unwanted outputs, Førsund (2009) recommended the use of the by-production methodology proposed in Murty and Russell (2002) and generalized by Murty et al. (2012). This approach, which relies on the estimation of two separate frontiers, assumes the cost disposability of bad outputs. This assumption is based on the idea that given the level of consumption of some inputs, only a minimal level of pollution can be reached and the presence of inefficiency can lead to the generation of more quantity than this minimal level. The global technology is viewed in the theory as the intersection of the two sub-frontiers. Empirically, Murty et al. (2012) defined this global technology as:

$$\begin{aligned}
\Psi_{bad}^{by} &= (x^M, x^{NM}, y, b) \in \mathbb{R}_+^{K^M + K^{NM} + 1 + 1} | y \leq \sum_{i=1}^N v_i Y_i ; \\
x^M &\geq \sum_{i=1}^N v_i X_i^M ; x^{NM} \geq \sum_{i=1}^N v_i X_i^{NM} ; x^M \leq \sum_{i=1}^N \xi_i X_i^M ; \\
b &\geq \sum_{i=1}^N \xi_i B_i ; \sum_{i=1}^N v_i = 1 ; \sum_{i=1}^N \xi_i = 1 ; v_i, \xi_i \geq 0 ; i = 1, \dots, N]
\end{aligned} \tag{7}$$

As can be seen in (7), the global technology is represented with two intensity factors, each one associated to one different sub-technology. As presented in (7) the by-production approach offers the advantage of separating the operational performance and the environmental performance. However, the model empirically assumes independence between the two sub-technologies. Dakpo (2015) then developed an extension of the by-production model by augmenting (7) with some dependence constraints relative to the pollution generating inputs.

$$\sum_{i=1}^N v_i X_i^M = \sum_{i=1}^N \xi_i X_i^M \tag{8}$$

In the same line, as Murty et al. (2012), Sueyoshi et al. (2010) and Sueyoshi and Goto (2010) proposed a unification strategy that is based on the use of a single intensity factor. To this aim they separated the input slacks s_x into their positive and negative parts which are mutually exclusive ($s_x^- \cdot s_x^+ = 0$). The model is specified as follows:

$$\Psi_{bad}^{unified} = [(x, y, b) \in \mathbb{R}_+^{K+1+1} | y + s_y = \sum_{i=1}^N \lambda_i Y_i ; b - s_b = \sum_{i=1}^N \lambda_i B_i ; \tag{9}$$

$$x - s_x^- + s_x^+ = \sum_{i=1}^N \lambda_i X_i; \sum_i \lambda_i = 1 \text{ and } \lambda_i \geq 0; i = 1, \dots, N;$$

$$s_x^- \cdot s_x^+ = 0]$$

According to the authors, the different parts associated to the inputs define the possible adaptation choice made by the firm managers. The negative part s_x^- is related to the natural disposability, which reflects a negative adaptation since the manager considered chooses to reduce the levels of the consumption of inputs in order to decrease pollution. On the other side, the positive part s_x^+ is linked to the presence of managerial disposability (positive adaptation), and in this situation some managerial efforts (adoption of new technologies, substitution of clean inputs to polluting ones...) can lead the firm to increase its consumption of inputs and simultaneously reduce the volume of pollution generated. To go beyond this framework Sueyoshi and Goto (2011) proposed an input separation into energy (material) and non-energy (non-material) inputs. In this new framework, the energy inputs are associated to both disposability concepts whereas the non-energy inputs are only related to the natural disposability. As pointed out in Manello (2012), the non-linearity introduced in the unified framework may generate some dominated efficient DMUs and thus may create some identification problems of the efficient DMUs since the two technology subsets can generate contradictory results.

2.2. *Eco-efficiency assessment and decomposition*

As explained in **Section 1**, we choose in this paper to consider the maximal production intensity per unit of undesirable output as the objective for each of the above-mentioned models. We retain this approach because, first, it is in line with the definition of the eco-efficiency (Huppes and Ishikawa, 2005) and, second, the unicity of the ratio allows the comparison and the discussion of the models on the same foundation. Based on these ratios an eco-efficiency score can be computed by comparing the attainable optimal ratios to the actual observed ratio. The eco-efficiency can be measured by:

$$Eco_{eff} = \frac{ratio^{observed}}{ratio^{optimal}} \quad (10)$$

Based on the work of Hampf and Rødseth (2014) a decomposition of the performance score can be obtained relative to the possible choices available to the producers. These choices will be reflected by the number of decision variables in the objective function.

- The most restrictive assumption specifies that the producer cannot freely choose nor the inputs nor the good output; both variables are given and only the level of the bad output is free of choice. The interesting point relative to this assumption is that it can be used to assess the technical inefficiency in pollution generation. Let's denote by $r_{x,y/f}^*$ the optimal ratio obtained under this assumption.
- Under a second less restrictive assumption both outputs are free of choice and are thus endogenous in the optimization programs. But the inputs are given and the producer does not have a free choice on these variables. Let's denote by $r_{x/f}^*$ the optimal ratio obtained in this case. This ratio can be helpful to evaluate the existence of allocative inefficiency in the production of good and bad outputs.
- A third, more flexible, possibility is to allow the free choice of the amount of inputs, of the good output, and of the bad output. This means that all variables in the models are endogenously determined in the optimization program. Under this assumption (of free choice of all the variables present in the program), all DMUs yield an optimal scale (namely the most productive scale size – MPSS). We denote by $r_{./f}^*$ the optimal ratio obtained in this situation.

Based on these possibilities and the degree of adjustment offered to the producer, we can write the following relationship between the optimal ratios:

$$r_{./f}^* \geq r_{x/f}^* \geq r_{x,y/f}^* \quad (11)$$

If the eco-efficiency score is computed as $Eco_{eff} = ratio^{observed} / r_{./f}^*$, the following decomposition can be made:

$$Eco_{eff} = \frac{ratio^{observed}}{r_{./f}^*} = \frac{ratio^{observed}}{r_{x,y/f}^*} \times \frac{r_{x,y/f}^*}{r_{x/f}^*} \times \frac{r_{x/f}^*}{r_{./f}^*} \quad (12)$$

$\frac{ratio^{observed}}{r_{x,y/f}^*}$ measures the eco-efficiency level when both inputs and good outputs are held fixed.

More precisely, as previously stated, it evaluates the presence of technical inefficiencies in the generation of detrimental output. This measure was coined the ‘weak ratio efficiency’ in Hampf and

Rødseth (2014). $\frac{r_{x,y/f}^*}{r_{x/f}^*}$ refers to the possible increase in the performance score when allowing more

flexibility regarding the level of good output. This second component has been termed the

‘allocative ratio efficiency’. The last component, $\frac{r_{x/f}^*}{r_{./f}^*}$, assesses the amount by which the

performance can be improved (relative to $r_{x/f}^*$) when the manager can freely decide the amount of

inputs in addition to the amounts of both outputs. Hampf and Rødseth (2014) referred to this third

component as the ‘input ratio efficiency’. It is worth mentioning that most of the models estimated

in this paper are based on fractional programming. They can be linearized by using adequate

transformations and variables changes (Charnes and Cooper, 1962).

3. Empirical application

3.1. Data description and environmental impacts’ computations

The empirical application of the models described in the previous section is conducted on a sample of 1,302 farm-year observations between the period 1987 and 2013. The panel consists of 124

different farms specialized in sheep meat production and located in the centre of France in grassland areas. Several bookkeeping and production process characteristics are available in the database.

Following the literature on farms’ technical efficiency, we have retained three inputs, namely

utilized land, farm labour and production-related costs. It is worth noting that we do not include the

herd size in the input variables contrary to some studies on livestock farms’ technical efficiency

(Karagiannis and Tzouvelekas, 2005, Ludena et al., 2005, Alvarez and del Corral, 2010). One

reason is the evident and strong correlation of the herd size with some input variables. The idea is to

keep a sort of ‘independence’ between input variables. Another reason is that we performed two

regressions with the dependent variable being the total amount of meat production, and the

independent variables being the inputs. In one regression we included the herd size and in the

second one we omitted it. When introducing herd size in the estimation, surprisingly the utilised

land displays a significant and negative sign which is counterintuitive since this variable can be

viewed as an important (positive) input in grazing livestock systems. Also, when looking at the

Variance Inflation Factor (VIF), the herd size appears to be the source of some multicollinearity

which might lead to some serious bias in the estimation. When excluding the herd size variable we

obtained more reasonable results, with all the inputs presenting a positive and significant impact on

the meat production. Based on this, we believe that the herd size should be set aside, and possibly used in a second stage as a determinant or an environmental factor (Latruffe et al., 2008) to assess for instance the effect of farm size on the eco-efficiency score (but this is out of the scope of this paper). The production-related costs variable consists of operating expenses and structural costs. Operating expenses, also called proportional costs, comprise all costs related to animal feeding, crop fertilizers, pesticides and all the other costs directly associated to the presence of livestock (veterinary costs, mortality insurance, litter straw costs, marketing costs, animal purchase expenses...). Regarding structural costs, they are mainly made of mechanization and building costs (depreciation, maintenance costs, expenses for fuels and lubricants, costs of related insurances) as well as overheads (electricity costs, water costs, costs for miscellaneous insurances, financial charges, capital opportunity cost...). The choice of these two types of costs relies on regressions that we performed, where specification tests (Ramsey, 1969) showed that the model with combined costs performs better. All costs are expressed in constant currency (2005 Euros) to keep relative quantity based information. Utilized land represents the total number of hectares available to the producer for the sheep farming activity. This is essentially the main fodder area associated to the sheep livestock. Labour measures the quantity of full-time workers devoted to sheep meat production.

As for the outputs, the good output is measured by the quantity of meat production expressed in kilograms of carcass, and the bad output relate to GHG. The computations of the latter are based on the Life Cycle Assessment (LCA) methodology (Guinée et al., 2002), which was used for the estimation of the three main GHG generally considered in livestock farming (carbon dioxide, methane and nitrous oxide). Since our primary interest is on global warming the three gases were aggregated based on their Global Warming Potential (GWP) relative to carbon dioxide. The bad output is thus computed as the total GHG emissions expressed in carbon dioxide equivalent. However, given the fact that some gases like methane are in some sense “incompressible” because associated to animal biology (namely enteric fermentation, see (Martin et al., 2010) we split the GHG emissions into two categories: on the one hand, variable GHG emissions, including carbon dioxide and nitrous oxide; on the other hand, fixed GHG emissions, consisting of methane only. In this case where we consider that methane emissions are fixed, we simply discard the methane emissions from the technology constraints. Actually, not including methane emissions in the production technology makes more sense since herd size is not included in the analysis while this gas is related to the animal bodily processes. A last note on the methodology is that, when applying the LCA we have restrained the system boundary (the perimeter of analysis) from the cradle to the farm gate i.e. all upstream processes are considered up to the point where the meat production

leaves the farm. It means that we did not take into account the flows associated with the processing (slaughtering and transformation) and marketing chains of the meat products. More, we adapted the GES'TIM (Gac et al., 2011) and the Dia' terre® (ADEME, 2011) tools to our sample of meat sheep farms. These tools provide us the great majority of emissions factors required for the estimation of the global warming impact. The main characteristics of the sample are summarized in **Table 1**.

On average, over the period of study, farms in our sample produced around 10 thousand kilograms carcass of meat on a land area of 74 hectares. The pollution intensity, which is measured as the ratio of the total GHG emissions on meat production, is about 38 kg of carbon dioxide equivalent per kg of carcass on average. However when excluding methane from the analysis this pollution intensity falls to 14.5 kg carbon dioxide equivalent. Methane is by far the most important GHG and contributes to more than 60% of the total emissions. Not shown in the table, the herd size is about 77 livestock units on average per farm. A look to the relative standard deviation shows some high variability in all the data, since the coefficients of variation are all greater than 25% (Tufféry, 2011). It can also be seen in **Figure 1** showing the relation between the pollution intensity (computed with the total GHG emissions) and other Key Performance Indicators (KPIs, see (Bogetoft, 2013)). On the left panel one can see the negative relation between pollution intensity and the stocking rate (calculated as the number of livestock units per hectare of utilized land), suggesting that animal intensification (per hectare of land) might be a solution of eco-efficiency improvement. On the other hand, labour productivity (calculated as the number of livestock units per full-time equivalent worker) exhibits, on the right panel, a positive correlation with pollution intensity. However, these correlations should not be taken to generalization conclusions to efficiency, given the partial character of the indicators used. We thus need to assess the eco-efficiency in a more global way and provide more insights about these preliminary findings.

3.2. Comparison of eco-efficiency between various models: empirical results

For the estimation, we consider here one single frontier which is estimated for the whole period (by pooling all observations together), that is to say we assume no technological change. In addition we consider land and labour as non-material inputs that are assumed to generate no GHG emissions. Besides, in light of the LCA methodology undertaken for this paper, no emission factors are associated to labour. However for the case of land, it is possible to take into account carbon sequestration in soils (which is a good output that comes in deduction to the gross GHG emissions), but this has not been considered in the current paper. By contrast, still based on the LCA, we assume that the production-related costs are pollution generating.

The average eco-efficiencies and their components, calculated with all methods described in the previous section, are summarized in **Table 2**. For comparison purposes, we have also estimated a classic production technology where pollution is not an issue to the producers who can freely choose both the levels of input consumption and also the level of the good output. This pollution free technology can shed light on the potential operational efficiency of the DMUs under evaluation, independently of the pollution generated. We then evaluate the eco-efficiency for each farm given their unchanged pollution emissions. For the sake of simplicity we present the pollution intensity instead of the ratio of meat production per unit of GHG emission. As explained above, for the approaches that include pollution in the production technology, the eco-efficiency score is based on the flexible assumption of free choice of inputs, good output and bad output. We also display, in addition to the results for the cases where all the GHG are treated as one variable undesirable output, the results where methane emissions are not included in the technology constraints.

The results in **Table 2** show that all pollution generating models except the by-production approaches, yield the same eco-efficiency scores (respectively 0.540 and 0.390 on average depending on the specification of methane emissions) and the same pollution intensity (respectively 19.19 and 5.13 kg CO₂-eq/kg meat on average), similarly to when residuals are considered as inputs. Hence these models suggest that in the case methane emissions are considered as variable bad outputs, farmers could reduce about 46% of their actual pollution intensity on average. In the situation of ignoring methane generation in the technology and only focus on variable GHG emissions (CO₂+N₂O), this reduction potential increases to 61%. This result suggests that there is more inefficiency in variable GHG generation than in methane emissions. This is quite understandable given what has been said earlier that mainly methane emissions are intrinsic to animal biology. Another feature of these aforementioned methodologies (pollution as input, weak disposability assumption, weak G-disposability, unified model under natural and managerial disposability) is that they mainly underline the same source of inefficiency, namely the weak inefficiency ratio (the weak ratio efficiency is the lowest of all three ratios). As explained earlier, this ratio accounts for the presence of technical inefficiencies in the pollution generation process since both inputs and good output are held fixed. However, some small differences can be found for the cases of the models of weak G-disposability and unified efficiency under natural and managerial disposability, which give more importance to the other sources of inefficiencies.

The most pessimistic model is the by-production modelling with independence between the two sub-technologies. In fact this model leads to seemingly unrealistic results in terms of eco-efficiency since more than 97% of inefficiency is found to be present in the sample. These questionable results

can be explained by the fact that the model separately optimizes the operational efficiency (with the good output frontier) and the environmental efficiency (with the bad output frontier). According to these independent estimations, the operational efficiency is 0.300 and the environmental efficiency 0.123 in the case total GHG emissions are considered, methane included (results not shown in the table). When methane is excluded from the analysis, the operational efficiency is still 0.300, but the environmental efficiency falls to 0.085. Again this observation confirms what has been said earlier that there is more inefficiency in variable GHG emissions. However, when an interdependence constraint is imposed along the suggestion of Dakpo (2015), the by-production model yields more acceptable results such as an average eco-efficiency score of 26.7% (respectively 21.7% for the case of methane exclusion). Besides, by introducing the dependence constraints in the by-production model, the three sources of inefficiency seem to play an equal role in the explanation of the estimated eco-inefficiency. A closer look at the efficiency scores under each sub-technology given the interdependence constraints indicates that in the case where all GHG are treated as one variable bad output, the operational efficiency is 0.831 and the environmental efficiency 0.389. In the case of methane exclusion, the operational efficiency significantly rises to 1.367 and the environmental efficiency falls to 0.197. Actually, as explained in **Section 2** under the flexible assumption of free choice of all variables (good and bad outputs, inputs), all the DMUs reach an optimal scale, and this does not preclude the presence of over-efficient (efficiency greater than one) observations in one or the other of the sub-frontier. For instance, in the case where a DMU is above this optimal scale and produces more meat, then its operational efficiency is higher than one. In the opposite, in the situation where a DMU uses less polluting inputs and generates a lower pollution level than the optimal scale, its environmental efficiency is higher than one. Given all these aspects, we can say that the efficiency scores obtained (operational and environmental) above also embed some scale components.

A general finding is that in all the situations considered, it appears that environmental inefficiency is the major contributor of eco-inefficiency. Another remark is that the inclusion of the dependence constraints in the by-production model introduces some kind of trade-offs between the operational and the environmental performance. Actually, the presence of super-efficient DMUs (374 farm-year observations) in the case of operational efficiency, means that these units could give up some operational performance to improve their environmental efficiency. The situation of these super-efficient DMUs describes the common view of economists that environment comes at a cost (Palmer et al., 1995). We also have a few super-efficient farms (22 farm-year observations) in terms of environmental performance; these farms could give up a part of this environmental efficiency to improve their operational performance. However, a large part of the DMUs (906 farm-year

observations) may experience a win-win situation by simultaneously improving their operational and environmental performance. These results are related to the case where all GHG are considered as one variable bad output. In the case where methane emissions are excluded from the analysis, the results are quite different: the number of super-efficient DMUs regarding the operational performance is 920, and it is 6 regarding the environmental performance. The DMUs that may evidence a win-win situation are 376 in total.

As explained earlier from the GHG emissions, these models that yield the same results as when bad outputs are treated as inputs, show some increase in the non-material inputs like land and labour, while the polluting input level is decreased, all this in comparison to the sample average. In this case, we can conclude that in these models non-material inputs are substituted to material ones. In light of managerial and natural disposability, farmers might exhibit some managerial effort in terms of non-material inputs in order to mitigate pollution.

The aforementioned input substitution in some of the models discussed is also visible in the case of by-production modelling under dependent technologies, where the consumption of the non-material input land is increased whether methane is included or excluded (by respectively almost 26% and 4%, in line with the observed sample average of utilised land), while the pollution generating inputs are reduced. This leads to lower levels of GHG emissions. In terms of meat production, the difference between the two tables is that in **Table 3** where all GHG are considered, the optimal scale is higher than the sample average, while in **Table 4** it is smaller. Thereby, the way methane is considered in the modelling of the production technology provides different implications essentially in terms of the optimal farm size.

The highest meat production is obtained under the pollution free technology where all inputs are increased to produce more than twice amount of meat (compared to the sample average).

Nevertheless, this situation creates larger levels of absolute GHG emissions (ten times more than in the by-production and five times more than the other pollution technologies in the case where all GHG are considered²). The difference between pollution free technology and by-production approach seems to be a matter of trade-off: to produce more good output to compensate for the pollution emissions (pollution free technology), or to pollute less by reorganizing inputs and take advantage of the possible substitution between material and non-material inputs (by-production technology), and try to produce good output as much as possible given the new inputs. This trade-

² In the other case where methane is excluded, this pollution free technology generates a level of pollution 27 times greater than the level obtained under the by-production and 7 times for the other technologies.

off might imply, for the case of sheep meat producers, a choice between intensification and extensification strategies.

The specification of methane emissions significantly affects the time trend of the eco-efficiency measures. In **Figure 2**, showing the results of the by-production model with dependence constraints, there is a clear evidence of eco-efficiency decrease when all GHG emissions are considered as one variable bad output (right panel), but this evolution becomes quite steady when methane is excluded from the analysis (left panel). Another observation from these plots is the erratic distribution of the eco-efficiency during the period of study. This evolution can be correlated to some external factors (climate events, diseases, policy reforms, price chocks...) showing the high sensitivity of the eco-efficiency in the sheep meat sector to these exogenous variables.

4. Methodologies similarities or differences: a discussion

Although many of the presented models reach the same average optimal eco-efficiency score, they differ in their assumptions. From a theoretical perspective, models that consider pollution as input or as output under the WDA produce arbitrary wrong trade-offs and do not capture the real nature of undesirable outputs. Murty et al. (2012) estimated these trade-offs and found a negative relation between pollution generating inputs and the pollution level, which is definitely in opposition to the idea that these inputs are pollution generators. More, they also proved that under some conditions, for a fixed level of inputs, there exist large possibilities of good/bad output combinations that are efficient. This violates the idea behind by-production that there is only one minimal amount of undesirable outputs given the levels of inputs. Other shortcomings of the WDA have been reported by Hailu and Veeman (2001).

To overcome the drawbacks of the previous two models (namely pollution as inputs and WDA), Murty et al. (2012) developed the by-production modelling by assuming that the production process is made of different sub-technologies, and the global technology is the intersection of the good and the bad outputs sub-technologies. However, in the operationalization of the approach the authors assumed independence between both frontiers. We have seen here that under this assumption inconsistent results are generated. For this reason we prefer the recent by-production modelling proposed in Dakpo (2015) which introduces some interdependence constraints linking the usage of material inputs in both sub-frontiers. Also, in relation to this multiple frontier framework, Sueyoshi and Goto (2011) proposed a unification of the operational and environmental efficiency based on the use of one single intensity factor and also by allowing two possible opposite directions for the

inputs. However, in light of the previous results, it seems that this interesting approach collapses into the model where pollution is considered as an additional input.

The model assuming the weak G-disposability and the materials balance conditions is supposed to reflect the real production process by accounting for the laws of thermodynamics. However, in terms of results, this model also reaches the same results as the one in which GHG emissions are treated as input.

Finally, it is worth mentioning that, despite the fact that models which consider pollution under the WDA, or under the weak G-disposability, or in the unified model under natural and managerial disposability, yield the same results in terms of eco-efficiency as the one where pollution is simply an extra input, some small differences can be found in the sources of improvements.

5. Conclusion

In this paper we have empirically compared eco-efficiency obtained using the main models developed in the literature, for the specific case of sheep meat farms and GHG emissions. Eco-efficiency is computed as the ratio of good output on bad output and is aimed at providing easily interpretable results. To our knowledge this is the first paper that undertakes eco-efficiency models comparison in the agricultural case.

In light of the obtained results, all the models come to the same conclusion of the presence of large inefficiencies in sheep meat farms. The results also showed that there is a trade-off between intensification and extensification as response to the emissions of GHG in sheep meat production. Besides, different implications have been suggested depending on the specification of methane emissions. One limitation of this study is that we did not account for carbon sequestration in soils which is a specific feature of livestock farming as a potential abatement option. This aspect could be explicitly modelled in the by-production technology. Also, a robust estimation is required to check the consistency of the results.

Tables and Figures

Table 1: Summary statistics of the sample (period 1987-2013)

Variables	Mean	Standard deviation	Relative standard deviation	Minimum	Maximum
Utilized land (hectares)	74.1	35.10	0.47	12.40	257.02
Labour (full-time equivalents)	1.38	0.48	0.35	0.14	3.50
Production-related costs (2005 Euros)	51, 429	21, 297	0.41	33, 65	179, 169
Meat (kg of carcass)	9, 913	4, 614	0.47	565	33, 028
Total GHG emissions (kg CO ₂ -eq)	353, 141	149, 533	0.42	35, 777	1, 153, 434
Variable GHG emissions [CO ₂ +N ₂ O] (kg CO ₂ -eq)	136, 940	67, 203	0.49	8949	561, 580
Fixed GHG emissions [CH ₄] (kg CO ₂ -eq)	216, 201	90, 560	0.42	26, 473	602, 287
Pollution intensity (kg CO ₂ -eq/kg meat carcass)	37.8	10.6	0.28	19.2	104.9
Pollution intensity with variables GHG (kg CO ₂ -eq/kg meat carcass)	14.5	4.67	0.32	5.1	48.4
Herd size (livestock units)	76.65	31.46	0.41	10.89	200.00
Number of farm-year observations	1,302	-	-	-	-

Notes: CO₂-eq: carbon dioxide equivalent. The gases are carbon dioxide (CO₂), methane (CH₄) and nitrous oxide (N₂O). The relative standard deviation is computed as the ratio of the standard deviation on the mean and can be seen as the coefficient of variation.

Figure 1: Pollution intensity vs. stocking rate and labour productivity

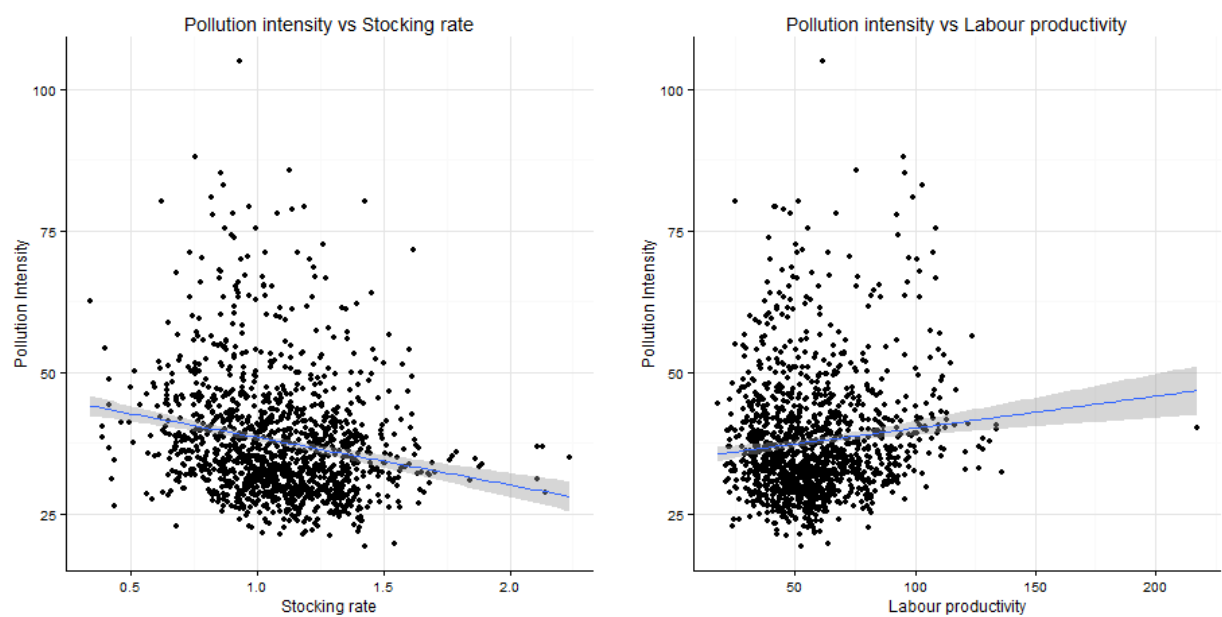


Table 2: Eco-efficiencies for different pollution generating technologies models: sample's average over the period 1987-2013

Models	Treatment of the bad outputs	Minimum pollution intensity (kg CO2-eq /kg meat carcass)	Eco-efficiency score	Three sources of efficiency (equation 12)		
				Weak ratio efficiency $\frac{ratio^{observed}}{r_{x,y/f}^*}$	Allocative ratio efficiency $\frac{r_{x,y/f}^*}{r_{x/f}^*}$	Input ratio efficiency $\frac{y}{\frac{r_{x/f}^*}{r_{.f}^*}}$
No pollution in the technology: free choice of good output and inputs	All GHG as one variable bad output	10.69	0.300	-	-	-
	Methane excluded from the constraints	4.15	0.300	-	-	-
Pollution as input (model in 2)	All GHG as one variable bad output	19.19	0.540	<u>0.585</u>	0.947	0.981
	Methane excluded from the constraints	5.13	0.390	<u>0.454</u>	0.915	0.965
WDA with uniform abatement factor (model in 5)	All GHG as one variable bad output	19.19	0.540	<u>0.574</u>	0.971	0.981
	Methane excluded from the constraints	5.13	0.390	<u>0.449</u>	0.929	0.965
WDA with non-uniform abatement factor	All GHG as one variable bad output	19.19	0.540	<u>0.566</u>	0.969	0.998
	Methane excluded from the constraints	5.13	0.390	<u>0.442</u>	0.917	0.998
Weak G-disposability (model in 6)	All GHG as one variable bad output	19.19	0.540	<u>0.708</u>	0.854	0.899
	Methane excluded from the constraints	5.13	0.390	<u>0.616</u>	0.877	0.737
By-production modelling with independent technologies (model in 7)	All GHG as one variable bad output	1.08	0.030	0.610	0.615	0.085
	Methane excluded from the constraints	0.27	0.021	0.511	0.615	0.069
By-production with an interdependence constraint across technologies (constraint 8)	All GHG as one variable bad output	9.50	0.267	0.610	0.616	0.748
	Methane excluded from the constraints	2.86	0.217	0.511	0.615	0.728
Unified model under natural and managerial disposability without input separation (model in 9)	All GHG as one variable bad output	19.19	0.540	<u>0.789</u>	0.857	0.805
	Methane excluded from the constraints	5.13	0.390	<u>0.695</u>	0.843	0.687
Unified model under natural and managerial disposability with input separation	All GHG as one variable bad output	19.19	0.540	<u>0.711</u>	0.853	0.899
	Methane excluded from the constraints	5.13	0.390	<u>0.626</u>	0.870	0.735

Notes: CO2-eq: carbon dioxide equivalent

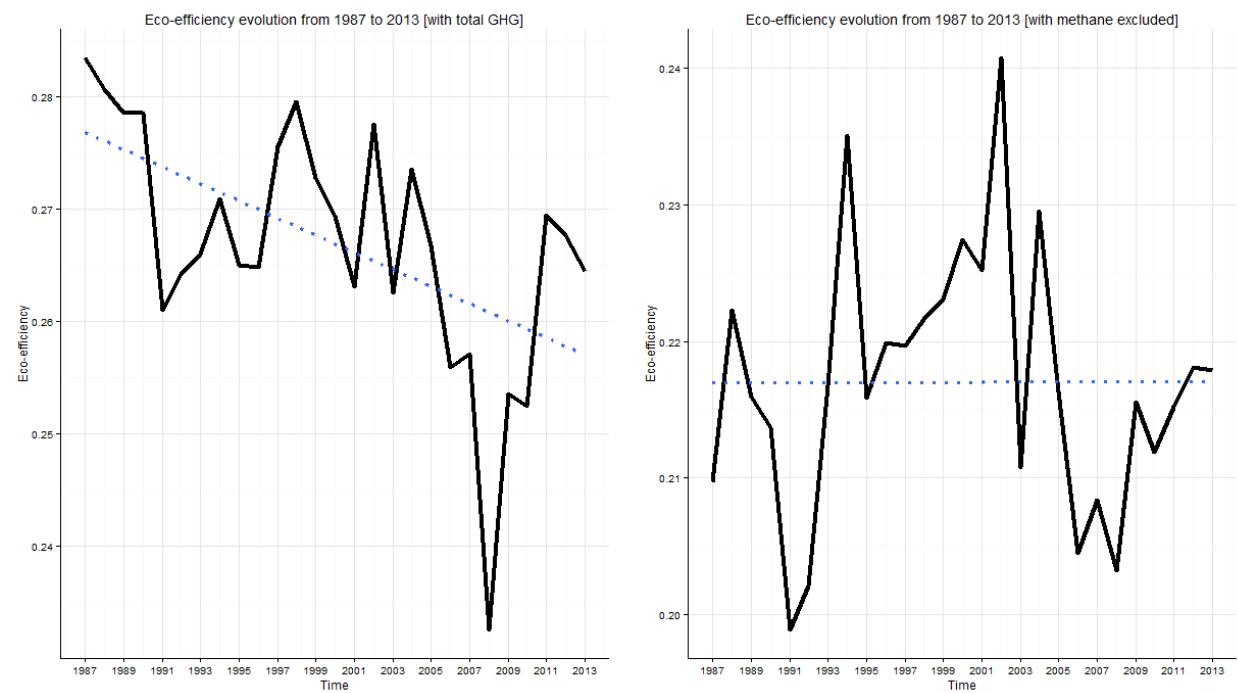
Table 3: Optimal scale for eco-efficient DMUs when the three GHG are variable

	Utilized land (hectares)	Labour (full-time equivalents)	Production-related costs (2005 Euros)	Meat production (kg)	GHG emissions (kg CO ₂ -eq)
Sample average (actual observed levels)	74.1	1.38	51, 429	9, 913	353, 141
Models					
No pollution in the technology: free choice of good output and inputs	87.1	2.17	179, 169	33, 028	1, 153, 434
Pollution as input (model in 2)	36.1	0.98	46, 040	12, 124	232, 701
WDA with uniform abatement factor (model in 5)	36.1	0.98	46, 040	12, 124	232, 701
WDA with non-uniform abatement factor	36.1	0.98	46, 040	12, 124	232, 701
Weak G-disposability (model in 6)	36.1	0.98	46, 040	12, 124	232, 701
By-production modelling with independent technologies (model in 7)	Good output technology	87.1	2.17	179, 169	33, 028
	Bad output technology	-	-	3, 544	-
By-production with an interdependence constraint across technologies (constraint 8)	93.6	1.32	29, 426	11, 937	113, 342
Unified model under natural and managerial disposability without input separation (model in 9)	36.1	0.98	46, 040	12, 124	232, 701
Unified model under natural and managerial disposability with input separation	36.1	0.98	46, 040	12, 124	232, 701

Table 4: Optimal scale for eco-efficient DMUs when methane is excluded from the GHG emissions

		Utilized land (hectares)	Labour (full-time equivalents)	Production-related costs (2005 Euros)	Meat production (kg)	Variable GHG emissions (kg CO ₂ -eq)
Sample average (actual levels)	observed	74.1	1.38	51, 429	9, 913	136, 940
Models						
No pollution in the technology: free choice of good output and inputs		87.1	2.17	179, 169	33, 028	561, 580
Pollution as input (model in 2)		85.3	1.50	43, 502	14, 960	76, 778
WDA with uniform abatement factor (model in 5)		85.3	1.50	43, 502	14, 960	76, 778
WDA with non-uniform abatement factor		85.3	1.50	43, 502	14, 960	76, 778
Weak G-disposability (model in 6)		85.3	1.50	43, 502	14, 960	76, 778
By-production modelling with independent technologies (model in 7)	Good output technology	87.1	2.17	179, 169	33, 028	-
	Bad output technology	-	-	3, 365	-	8, 949
By-production with an interdependence constraint across technologies (constraint 8)		77.0	1.00	15, 412	7, 247	20, 708
Unified model under natural and managerial disposability without input separation (model in 9)		85.3	1.50	43, 502	14, 960	76, 778
Unified model under natural and managerial disposability with input separation		85.3	1.50	43, 502	14, 960	76, 778

Figure 2: Eco-efficiency evolution depending on the specification of methane emissions



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