From energy efficiency measurement to energy policies in the agricultural sector*

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Abstract: The main objective of this paper is to derive some policy implications for the analysis of the energy efficiency in agricultural sector. Based on Data Envelopment Analysis (DEA) models and following the procedure adopted in a cost framework by Farrell (1957) and developed by Färe et al. (1985), we propose to decompose an overall energy efficiency measure into two components, namely technical and allocative efficiencies. The presence of uncertainty on data and more particularly on energy content of different inputs leads us to recommend exploiting the methodology proposed by Camanho and Dyson (2005) in order to produce more robust results. Thus, this methodology allows deriving both upper and lower bounds for the efficiency measures. A year 2007 database of French farms specialized in crops is used for empirical illustration.

Keywords: Crop-farming, Data Envelopment Analysis, energy efficiency, uncertainty

J.E.L. classification: D24, O13, Q15, Q4

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1. Introduction

Energy and GHG (Greenhouse Gas) mitigation is a growing concern within the international community. As a consequence, the French government defined an energetic performance plan. A part of this plan is dedicated to farms. The main idea is to measure their energy efficiency and to rank farms with respect to their energy consumption in order to bring them to the fore their potential in energy savings but also to design public policies that can help them to improve their energy efficiency. In order to pursue this goal, the French national environmental and energy agency (ADEME) develops tools to measure farms energy efficiency. Nevertheless, the seminal aim of agriculture is to produce food. What about the technical efficiency of farms? Are technical and energy efficiency measurements consistent? Can we decompose energy efficiency of farms and why is important from a public policy point of view? It is the first set of questions that we want to address in this work.

When measuring the energy efficiency of farms, one needs to compute the energy content of inputs used by farms in order to produce food. ADEME chose to take a Life Cycle Assessment (LCA) perspective. LCA is a technique that allows including the energy consumed in order to produce and transport an input that is used in a production process (see EPA, 2006 for more details on the method). Nevertheless, as underlined by Huijbregts (1998), in order to achieve this aim, many parameters are used and choices are made. As a consequence, the LCA of input energy content is uncertain. How to take this uncertainty into account when measuring technical and energy efficiency of farms? It is the second question that we will address in this work.

From the best of our knowledge, the literature on energy efficiency of farms is not wide. We mainly found works applied to the US (see for instance Cleveland, 1995) and to developing countries (see for instance Karkacier et al., 2006). These papers concentrated on the effect of energy factor on agricultural productivity and production. They used parametric estimations which depend on the assumptions made on the functional form of the production function. Charnes et al. (1978) developed a non parametric estimation method especially powerful in evaluating relative efficiency of different decision making units (e.g. farms): Data Envelopment Analysis (DEA). DEA involves the use of linear programming methods to construct a non-parametric piece-wise surface (or frontier) over the data. Efficiency measures are then calculated relative to this surface. For more details, Zhou et al. (2008) recall the basic methodology and provide a thorough literature review of data envelopment analysis in energy and environmental studies. More recently, Houshyar et al. (2010) and Nassiri and Singh (2009) determine the amount and efficiency of energy consumption for wheat and paddy production in Iran, by using the basic method.

Within the framework of energy and GHG mitigation, the main extension of interest to the basic method is the incorporation of undesirable outputs, such as GHG. Generally these methods can be divided into two groups. One is based on data translation and the utilization of traditional DEA models (see Seiford and Zhu, 2002). The other uses the original data but is based on the concept of weak disposability reference technology (see Färe et al., 1989). The main idea behind these methods is that in particular cases, the reduction of undesirable outputs would be costly. Therefore, it is not appropriate to use the strong disposability reference technology. In our work, we will concentrate on crop-farming. As a consequence, GHG emissions will be related to the inputs used like direct energy (petroleum, gas...) or more indirect energy like manufacturing, packaging and transporting of fertilizer for instance. We will not incorporate undesirable outputs that are more appropriate for livestock farming.

Another environmental efficiency measurement is the one based on the materials balance condition proposed by Coelli et al. (2007) and Lauwers (2009). The materials balance condition essentially says that "what goes in must come out". These authors argued that the methods based on undesirable outputs are inconsistent with this fundamental equation and proposed to incorporate pollution into the production model in a same manner to which price is normally incorporated. They produced an environmental efficiency measure that can be decomposed into technical and allocative components in the same way as the conventional cost efficiency decomposition first formulated by Färe et al. (1985). They applied their method to nutrient pollution of pig-farming. When one wants to apply this framework to energy, the materials balance condition is related to the first law of thermodynamics. Each input must then be converted into a common energetic unit: the Joule. If one think of crop-farms, it is possible to distinguish between renewable (human power and seed) and non-renewable energy (petroleum, fertilizers and pesticides for instance). We propose to focus on the use of non-renewable energy. As a consequence, we will assume that the energy content of inputs such as land and labor is very small. Furthermore, the LCA framework adopted by ADEME allows taking into account more indirect energy consumption than the direct use of energy such as petroleum for instance. For another input like fertilizer, for instance, the LCA consists in computing all the energy consumed in order to produce and transport this input. This perspective is very similar to the cumulative exergy approach that was demonstrated as being an efficient tool for energy policy making applications by Dincer (2002). Hoang and Rao (2010) proposed a decomposition of the sustainable efficiency of agricultural production based on this approach. Nevertheless their aim is not to provide an energy efficiency measurement. Furthermore, the material balance principle applied to energy assumes that a farm is like a system. This is not obvious. It is why we prefer to refer to the interpretation in terms of preference structure.

The idea of DEA models with preference structures is that the efficient targets yielded by the envelopment models are not preferred when the farms bear an energy reduction goal in mind. Therefore, some other targets along the efficient frontier should be considered as preferred ones. Zhu (1996) developed a set of weighted non-radial DEA models in order to construct preference structure over the proportions by which the current input levels can be changed. As a consequence, if one imposes a proper set of preferences weights for each farm under consideration, then the DEA Preference-Structure model yields energy efficiency measure. Energy efficiency can then be decomposed into technical and allocative efficiency scores. For this, we rely on the same concept introduced by Farrell (1957) in the cost context and developed by Färe et al. (1985).

Bearing this interpretation that is more adapted to our work in mind, we can nevertheless compare the cumulative exergy content provided by Hoang and Rao (2010) for their OECD empirical study to the energy content provided by ADEME (2011) for French farms. If we look at the nitrogen input, for instance, Hoang and Rao propose to apply 32.8 MJ/kg of nitrogen and ADEME 55.57 MJ/kg. The difference is quite important. The difference is lower for oil energy: 42.8 MJ/kg in Hoang and Rao and 46.4 MJ/kg in ADEME. The main implication of this comparison is that the energy content of input, when using a LCA framework, is uncertain. As a consequence, the energy efficiency measurement provided when applying the cost efficiency framework must be adapted. Camanho and Dyson (2005) showed that DEA models can provide robust estimates of cost efficiency even in situation of price uncertainty. Following Kuosmanen and Post (2001), they developed a method for the estimation of upper and lower bounds for the cost efficiency measurement in situation of price uncertainty. This method incorporates weight restrictions of the form of input cone assurance regions that was first developed by Thompson et al (1996). Following Camanho and Dyson

(2005), we will apply this method to the case of the uncertainty of energy content of input. More recently, Mostafaee and Saljooghi (2010) proposed to go further into the analysis by also considering some uncertainty on the data on inputs and outputs. Fortunately, our data were obtained from precautious surveys. It is why we will not consider this kind of uncertainty.

The remainder of the paper is structured as follows. In the following section, we describe the methodology. The section 3 provides a description of data set and retained variables. Section 4 is devoted to our results that will be presented as policy implications. Finally, section 5 concludes.

2. Methods: Energy efficiency measurement with uncertainty on energy content of input

The notion of Energy efficiency (EE) indicates the extent to which a production unit minimizes the energy to produce a given output vector, given the energy content of input it faces. In other words, it assesses the ability to produce current outputs at minimal energy. After Farrell (1957) who introduced this concept, Färe et al. (1985) formulated a programming model for EE assessment. This model requires input and output quantity as well as input prices at each DMU. In next subsection, we recall the basic model DEA-like to measure EE. In the subsection 2.2, we also presented the weight-restricted DEA model for measuring energy efficiency when input price are uncertain that can be adopted in line of Camanho and Dyson (2005).

2.1. The decomposition of energy efficiency into technical and allocative efficiency within a basic envelopment model

2.1.1. Graphical illustration

To graphically illustrate the energy, technical and allocative efficiency concepts, suppose in the Figure 1, seven DMUs (**A** to **G**) which produce y with two inputs x_1 and x_2. The segments linking DMUs **A**, **B**, **C** and **D** form the efficient frontier. We use DMU **F** to illustrate the efficiency concepts. The ratio 0**f**/0**F** gives the technical efficiency. This means that it is possible to find another DMU or to build a composite DMU (**f** in our case) which produce the same output level with the less input level. Note that the value is equivalent to the ratio between the technically efficient plan (E^T) and the observed plan ($E^{\mathbf{F}}$) i.e. $E^T / E^{\mathbf{F}}$. Let us introduce some information on the energy content of input (w_1 and w_2). Assume now that DMU **F** has eliminated its technical inefficiency by moving to point **f**. However, this point is not energy efficient when compared to DMU **C** which is less energy-intensive production plan. Thus, given the prices, the composite DMU **f** and thus **F** appears allocatively inefficient contrary to **C**. The ratio 0**f'**/0**f** gives the allocative inefficiency which measures the extent to which a technically efficient point falls short of achieving minimum energy contents because it fails to make the substitutions (or reallocations) involved in moving from **f'** to **C**. The allocative efficiency measure can also be expressed in terms of a ratio between the minimum energy at point **C** and the used energy at the technically efficient point **f**: $E^{\min} / E^T$. Finally, we have the relationship:

0**f'**/0**F** = (0**f**/0**F)** × (0**f'**/0**f)**
or
Energy efficiency = Technical efficiency × Allocative efficiency

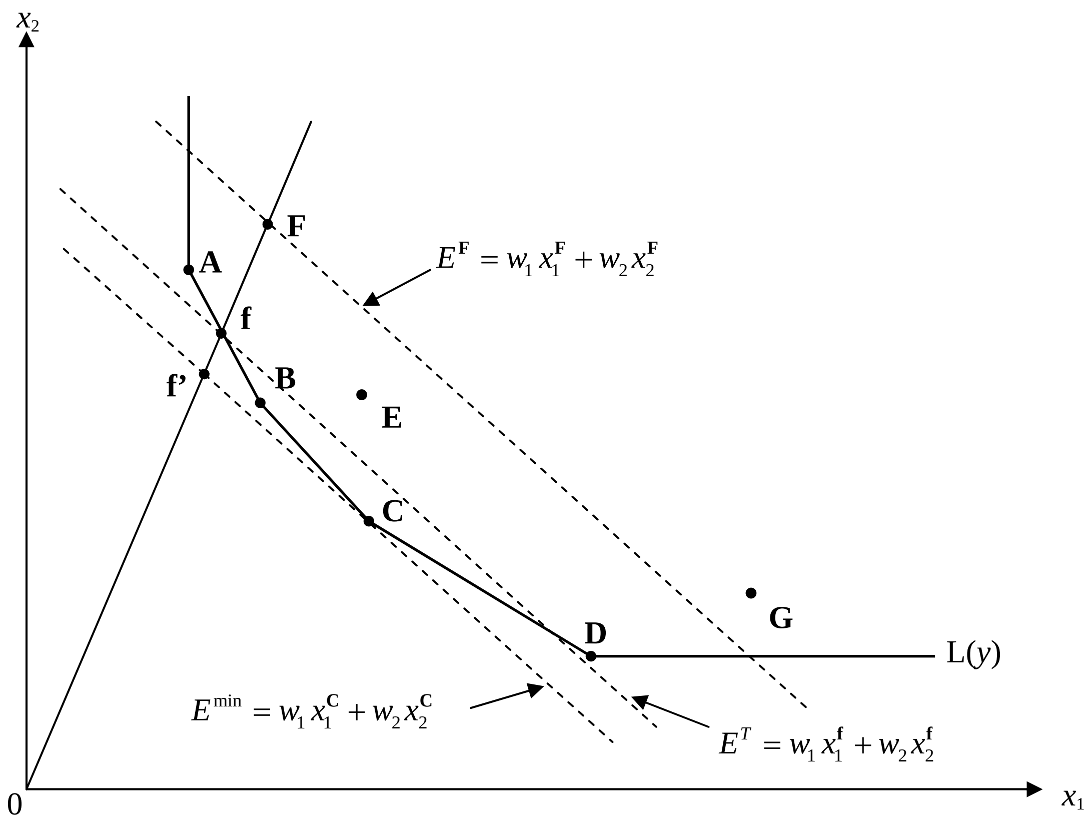

Figure 1: Energy, allocative and technical efficiency measurement in the input space

2.1.2. The energy, allocative and technical efficiency models

Let us consider that K DMUs are observed and we denote $\mathfrak{K} = \{1,\ldots,K\}$ by the associated index set. We assume that DMUs face a production process with M outputs and N inputs where $y = \left(y_1,\ldots,y_M\right) \in R_+^M$ is the vector of outputs and $x = \left(x_1,\ldots,x_N\right) \in R_+^N$ is the vector of inputs. We also define the respective index sets of outputs and inputs as $\mathfrak{M} = \{1,\ldots,M\}$ and $\mathfrak{N} = \{1,\ldots,N\}$. Following Färe et al. (1985), the model is defined by the production possibility set:

$$T = \left\{ (x,y) : \sum_{k\in\mathfrak{K}} \lambda^k y_m^k \geq y_m \ \ \forall m \in \mathfrak{M}, \sum_{k\in\mathfrak{K}} \lambda^k x_i^k \leq x_i \ \ \forall i \in \mathfrak{N}, \sum_{k\in\mathfrak{K}} \lambda^k = 1, \ \lambda^k \geq 0 \ \ \forall k \in \mathfrak{K} \right\} \qquad (1)$$

For a DMU j with a production plan (x^j, y^j), the minimum energy E is computed via the following program:

$$E = \min \sum_{i \in \mathfrak{N}} w_i \, x_i$$

subject to:

$$\begin{aligned}
&\sum_{k \in \mathfrak{K}} \lambda^k y_m^k \geq y_m^j \quad \forall m \in \mathfrak{M} \\
&\sum_{k \in \mathfrak{K}} \lambda^k x_i^k \leq x_i \quad \forall i \in \mathfrak{N} \\
&\sum_{k \in \mathfrak{K}} \lambda^k = 1 \\
&\lambda^k \geq 0 \quad \forall k \in \mathfrak{K}
\end{aligned} \tag{2}$$

where w_i is the weight (here, the energy content) of input *i* faced by DMU *j* and therefore *E* corresponds to the minimum energy required to produce output vector *y* at input prices *w*. If we denote E^j the total energy content of the current input levels of DMU *j*, then its energy efficiency is measured as the ratio of minimum energy to the current energy: $\dfrac{E}{E^j} = \dfrac{\sum_{i \in \mathfrak{N}} w_i \, x_i^{j*}}{\sum_{i \in \mathfrak{N}} w_i \, x_i^j}$, in which "*" indicates the optimality. $\left[\left(1 - \text{energy efficiency}\right) \times 100\right]$ indicates the percentage of total wasting energy.

In the same spirit of cost efficiency developed by Färe et al. (1985), the energy efficiency incorporates two sources of inefficiency viz. technical efficiency and allocative efficiency. Technical inefficiency reflects managerial failures that can be remedied in the short term while allocative inefficiency reflects an input misallocation and can be remedied in the long term. Consequently, a DMU will only be energy efficient if it is both technically and allocatively efficient.

In order to obtain a decomposition of energy efficiency, we need to measure technical efficiency by the traditional input-oriented DEA model. Since our work is based on the dual linear programming problems to the envelopment models (called multiplier models), we propose here to recall this form of the traditional input-oriented DEA model:

$$\max \sum_{m \in \mathfrak{M}} u_m y_m^j$$

subject to:

$$\begin{aligned}
&\sum_{i \in \mathfrak{N}} v_i \, x_i^j = 1 \\
&\sum_{m \in \mathfrak{M}} u_m y_m^k - \sum_{i \in \mathfrak{N}} v_i \, x_i^k \leq 0 \quad \forall k \in \mathfrak{K} \\
&u_m \geq \varepsilon \quad \forall m \in \mathfrak{M} \\
&v_i \geq \varepsilon \quad \forall i \in \mathfrak{N}
\end{aligned} \tag{3}$$

As demonstrated by Schaffnit et al. (1997) and reemphasized by Camanho and Dyson (2005) in cost context, we can also demonstrate that the measure of energy efficiency (EE) can be alternatively obtained with the inclusion of weight restrictions in the standard DEA models. They also noted the relevance of the relative input prices for the EE measurement. Also, the restrictions imposed to the weights underlying the assessment are that the relative value of the energy content of input observed at each DMU, such that: $\frac{v_{i^a}}{v_{i^b}} = \frac{E_{i^a}}{E_{i^b}}, \quad i^a, i^b = 1, \ldots, N$ where a and b are for example two inputs among the set $\mathfrak{N}$.

For the DMU j, the resulting energy efficiency model based on the DEA model with the addition of weights restrictions is as follows:

$$
\begin{aligned}
& \max \sum_{m \in \mathfrak{M}} u_m y_m^j \\
& \text{subject to:} \\
& \sum_{i \in \mathfrak{N}} v_i\, x_i^j = 1 \\
& \sum_{m \in \mathfrak{M}} u_m y_m^k - \sum_{i \in \mathfrak{N}} v_i\, x_i^k \leq 0 \quad \forall k \in \mathfrak{K} \\
& v_{i^a} - \frac{E_{i^a}}{E_{i^b}} v_{i^b} = 0 \\
& i^a < i^b, \quad i^a, i^b = 1, \ldots, m \\
& u_m \geq \varepsilon \quad \forall m \in \mathfrak{M}
\end{aligned}
\tag{4}
$$

2.2. An extension with uncertainty on energy content of inputs

With uncertainty on energy content of input, we can adopt two perspectives viz. optimistic and pessimistic and thus assess two EE: one with the most favorable energy content scenario (the energy content is minimal) and one other with the least favorable energy content (the energy content is maximal).

To graphically illustrate these notions, consider the case where only the maximal and the minimal energy content for all DMUs can be identified, e.g. for two inputs we have $E_1^{\min}, E_2^{\min}, E_1^{\max}$ and $E_2^{\max}$. The price (or weight) ratios underlying the energy efficiency evaluation would be restricted to the following range: $\frac{E_1^{\min}}{E_2^{\max}} \leq \frac{v_{i^a}}{v_{i^b}} \leq \frac{E_1^{\max}}{E_2^{\min}}$.

The slope of the iso-energy underlying the evaluation of CE could vary between the slope of $E_\beta E_{\beta'}$ i.e., $-\frac{E_1^{\max}}{E_2^{\min}}$ and the slope $E_\alpha E_{\alpha'}$ i.e., $-\frac{E_1^{\min}}{E_2^{\max}}$. The optimistic EE measure assesses each DMU by comparison to the most favorable iso-energy line. In Figure 2, the optimistic EE frontier corresponds to the segments linking $E_\beta, \mathbf{B}, \mathbf{C}$ and $E_{\alpha'}$ (the price ratio of the iso-energy line is as close as possible to the marginal rate of substitution between the inputs). Conversely, the pessimistic frontier measure assesses each DMU by comparison to the least favorable energy content scenario. It corresponds to the segment linking E_α, ω and $E_{\beta'}$ for the pessimistic frontier. In the case of DMU **F** the optimistic EE is measured by 0**f''**/0**F** whereas pessimistic EE is measured by 0**f'**/0**F**.

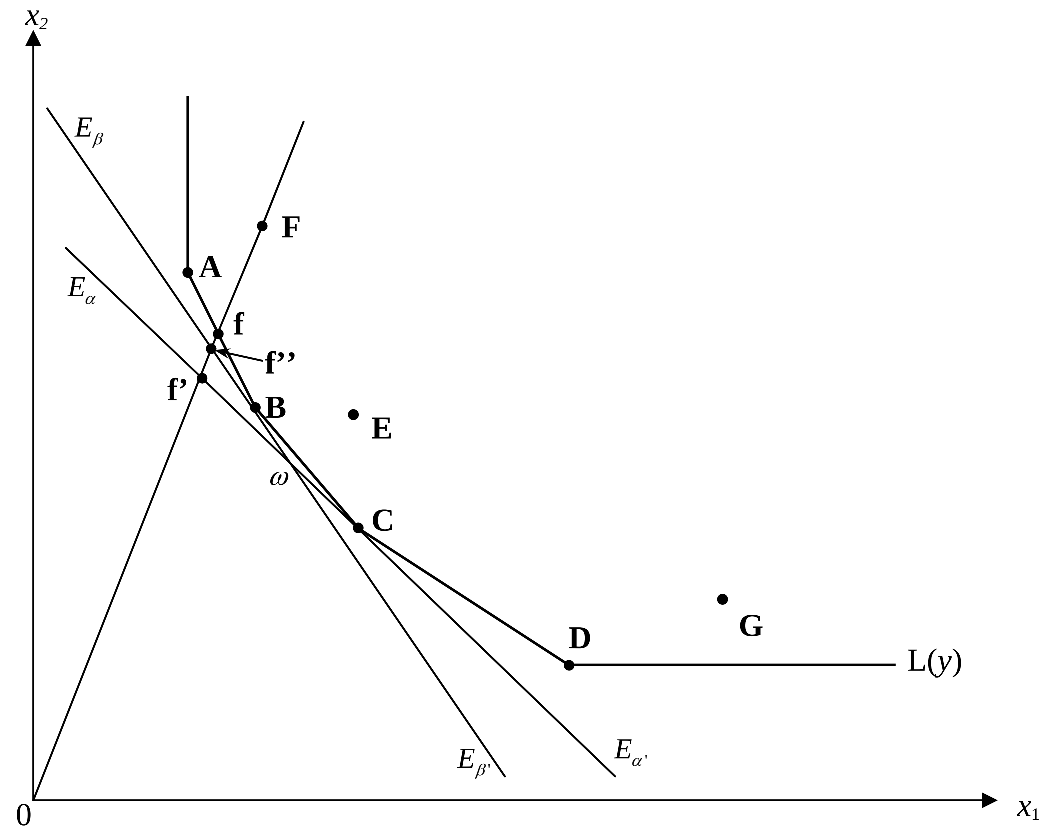

Figure 2: Optimistic and Pessimistic EE measurement in the input space

As mentioned above, for the optimistic EE model, we focus our attention on the most favorable price scenario. Optimistic EE model can be written as follows:

$$
\begin{aligned}
&\max \sum_{m \in \mathfrak{M}} u_m y_m^j \\
&\text{subject to:} \\
&\sum_{i \in \mathfrak{N}} v_i x_i^j = 1 \\
&\sum_{m \in \mathfrak{M}} u_m y_m^k - \sum_{i \in \mathfrak{N}} v_i x_i^k \leq 0 \ \forall k \in \mathfrak{K} \qquad (5) \\
&\frac{E_{i^a}^{\min}}{E_{i^b}^{\max}} \leq \frac{v_{i^a}}{v_{i^b}} \leq \frac{E_{i^a}^{\max}}{E_{i^b}^{\min}} \\
&i^a < i^b, i^a, i^b = 1, \ldots, N \\
&u_m \geq \varepsilon \ \ \forall m \in \mathfrak{M}
\end{aligned}
$$

The constraints $\frac{E_{i^a}^{\min}}{E_{i^b}^{\max}} \le \frac{v_{i^a}}{v_{i^b}} \le \frac{E_{i^a}^{\max}}{E_{i^b}^{\min}}, \quad i^a < i^b, i^a, i^b = 1, \ldots, N$ provide inequality bounds for multipliers that are reasonable from an energetic point of view (see Thompson et al., 1990 for economically reasonable bounds). Thus, the assurance region is specified by this input cone. Finally, optimistic CE model can be rewritten in linear form as follows:

$$
\begin{aligned}
&\max \sum_{m \in \mathfrak{M}} u_m y_m^j \\
&\text{subject to:} \\
&\sum_{i \in \mathfrak{N}} v_i x_i^j = 1 \\
&\sum_{m \in \mathfrak{M}} u_m y_m^k - \sum_{i \in \mathfrak{N}} v_i x_i^k \le 0 \quad \forall k \in \mathfrak{K} \\
&v_{i^a} - \frac{E_{i^a}^{\max}}{E_{i^b}^{\min}} v_{i^b} \le 0 \\
&v_{i^a} - \frac{E_{i^a}^{\min}}{E_{i^b}^{\max}} v_{i^b} \le 0 \\
&i^a < i^b, \quad i^a, i^b = 1, \ldots, N \\
&u_m \ge \varepsilon \quad \forall m \in \mathfrak{M}
\end{aligned}
\tag{6}
$$

Since the DMU's evaluation is based on n inputs, there are C_2^N different ratios between two inputs, which give a total of $2 \times C_2^N$ linear inequality constraints.

To obtain the EE model under a pessimistic perspective, as noted by Camanho and Dyson (2005), it is necessary to develop an alternative method. It requires solving more than one linear program. The assessment consists of running a set of linear programming models, where each DMU in the set is considered in turn as a potential peer for evaluated DMU. This kind of models has the following structure:

$$
\begin{aligned}
&\max \psi_j^p = \sum_{m \in \mathfrak{M}} u_m y_m^j \\
&\text{subject to:} \\
&\sum_{i \in \mathfrak{N}} v_i x_i^j = 1 \\
&\sum_{m \in \mathfrak{M}} u_m y_m^p - \sum_{i \in \mathfrak{N}} v_i x_i^p = 0 \\
&\sum_{m \in \mathfrak{M}} v_m y_m^k - \sum_{i \in \mathfrak{N}} v_i x_i^k \le 0 \quad \forall k \in \mathfrak{K} \\
&v_i \ge \varepsilon \quad \forall i \in \mathfrak{N} \\
&u_\mathrm{m} \ge \varepsilon \quad \forall m \in \mathfrak{M}
\end{aligned}
\tag{7}
$$

where the index p represents the peer DMU underlying the efficiency assessment of DMU j. The second constraint forces the efficiency of the peer p to be equal to one in the assessment of DMU j. If not, model (7) has no solution which indicates that DMU p is not suitable as a peer of DMU j. Moreover, model (7) is only feasible if the peer used for DMU j is located on the frontier. For large problems, the set of peer DMUs can be reduced to efficient DMUs (belonging to the frontier) By introducing the constraints of model (5) i.e. $\frac{E_{i^a}^{\min}}{E_{i^b}^{\max}} \le \frac{v_{i^a}}{v_{i^b}} \le \frac{E_{i^a}^{\max}}{E_{i^b}^{\min}}, \quad i^a < i^b, i^a, i^b = 1,\ldots,N$ in (7) we have the Farrell CE.

Finally, to obtain the pessimistic EE model, we replace the restrictions of model (5) in model (7) and change the objective function of (7) from maximization to minimization (the pessimistic CE measure is obtained choosing the minimal score ψ_j^p). The model is written as follows:

$$
\begin{aligned}
&\min \ \psi_j^p = \sum_{m \in \mathfrak{M}} u_m y_m^j \\
&\text{subject to:} \\
&\sum_{i \in \mathfrak{N}} v_i x_i^j = 1 \\
&\sum_{m \in \mathfrak{M}} u_m y_m^p - \sum_{i \in \mathfrak{N}} v_i x_i^p = 0 \\
&\sum_{m \in \mathfrak{M}} u_m y_m^k - \sum_{i \in \mathfrak{N}} v_i x_i^k \le 0 \quad \forall k \in \mathfrak{K} \\
&\frac{E_{i^a}^{\min}}{E_{i^b}^{\max}} \le \frac{v_{i^a}}{v_{i^b}} \le \frac{E_{i^a}^{\max}}{E_{i^b}^{\min}} \\
&i^a < i^b, \quad i^a, i^b = 1,\ldots,N \\
&u_m \ge \varepsilon \quad \forall m \in \mathfrak{M}
\end{aligned}
\tag{8}
$$

3. Data and variables

This study is based on data collected by a French group of agronomists (named PLANETE and created in the 90s) and centralized by SOLAGRO, a French non-governmental organization established to promote sustainable energy and agriculture, and respect for the natural environment. The members of PLANETE worked for ADEME in order to supply software computing an energy assessment of farms. Bochu (2002) summarized the results of this study. A consequence is that, for each farm, we have at our disposal the details on both all the outputs produced but also all the inputs used for this production. Entering these data for each farm, the software is able to calculate the energy efficiency of each one, basically computing the ratio between outputs and inputs. In order to do so, it applies coefficients that convert carefully inputs and outputs into a common energetic unit: the joule. Currently, the software has evolved to a more modern one named DIATERRE that does not consider the energy content of output anymore because of the difficulties of leading a LCA related to them. The conversion coefficients have been actualized and are summarized in a guide available upon request. We will use those coefficients.

SOLAGRO provided us a data set of 151 farms investigated during the year 2007. Our main request was to have homogeneous farms. As a consequence,

- they all grow the same culture: cereals;
- they are all facing the same pedo-climatic conditions by being located in the same area: west-center of France;
- they are characterized by the same production system: there is no organic farm.

This sample of farms cannot be a representative one since the energy assessment made by PLANETE was not an obligation and only voluntary farms made it. Our aim is not to provide a general analysis of the energy efficiency of some farms. It is to investigate the measurement to be used in order to decompose farms energy efficiency.

For the same reason, we decided to concentrate on major inputs. The output under consideration will be an aggregated value of the mass of cereals produced. Concerning the inputs, we first selected the following one: area, units of labor, petroleum, nitrogen, seeds and pesticides. We then ran some correlation tests in order to check that the selected inputs are correlated to the output. Unsurprisingly, we found no correlation between pesticides and the amount of cereals produced: the contribution of damage control agents to production differs fundamentally from that of standard inputs. We did not find any correlation between seeds and the output also. The explanation relies on the fact that only seeds bought are considered[1]. We do not know the amount of seeds produce by the farm. As a consequence, we decided not to consider those inputs in our analysis. This choice does not change our main results.

Once these choices were made, we deleted the observations with missing values on the crucial variables of interest and we computed the productivity of each input in order to check consistency of data. Finally, 145 observations were left. Table 1 provides some descriptive statistics of these variables.

[1] This choice is consistent with the seminal aim of the data set that is to lead a LCA on all inputs used by the farms.

Table 1: Descriptive statistics of inputs and output

	Mean	Standard deviation	Min	Max
Area (hectare)	193	111	33	568
Labor (unit of labor)	1.7	1.1	0.5	6.5
Nitrogen (kg)	27 247	18 723	2 103	95 705
Petroleum (Liter)	18 143	14 619	2 193	91 279
Cereals (Quintal)	10 282	6 606	585	33 528

In order to compute the energy content of inputs, we used the same conversation coefficients as ADEME (2011). These coefficients are based on the LCA guidance provided by ECOINVENT, a Non-Profit Swiss Centre for Life Cycle Inventories and were adapted to the French case by ADEME. As explained in the introduction, we decided to focus on non-renewable energy. It is why area and labor have a small (10^{-6}) and determinist conversion coefficient. We also explained that conversion coefficients based on a LCA are characterized by a high level of uncertainty. We do not have access to the minima and the maxima provided by ECOINVENT since ADEME only based its adaptation to the French case on mean data. As a consequence, in order to illustrate our view, we propose to base our analysis on the coefficient provided by Hoang and Rao (2010). We will use these coefficients as the minimum value and we will derive the potential maximum by applying the same difference to the mean. All the coefficients used are summarized in Table 2. We again remind here that our aim is not to provide a careful empirical analysis of farms energy efficiency. It is to formulate some policy implications for the measurement of farms energy efficiency when the energy content of input is uncertain.

Table 2: Energy contents of inputs (in MJ/unit)

	Mean	Min	Max
Nitrogen	55.57	32.8	78.34
Petroleum	46.4	42.8	50

4. Results and policy implications

The subsection 4.1 will be dedicated to the results and policy implication in the deterministic setting and the subsection 4.2 to the one in the uncertain case.

4.1. The decomposition of energy efficiency in the deterministic case

To examine energy efficiency (EE) and its components (technical and allocative efficiency) in the deterministic case, we first run the linear programming models (3) and (4)[2]. At this stage we applied the mean of the energy content of inputs (see table 2). The allocative efficiency (AE) scores were directly deduced from the other efficiency scores. Table 3 provides the scores obtained.

[2] The linear programs previously described were implemented by using the solver function of Excel. All files are available upon request to the authors.

Table 3: Energy, technical and allocative efficiency scores

	Mean	Standard Deviation	Min	Max	Number of efficient farms
Energy Efficiency	0.4756	0.1080	0.2282	1	1
Technical Efficiency	0.7181	0.1535	0.2953	1	9
Allocative Efficiency	0.6721	0.1135	0.3318	1	1
ADEME	0.4756	0.1080	0.2282	1	1

The results for EE indicate us that, on average, farms could reduce all the inputs used and thus minimize their energy use by 53% (i.e. 1-EE). We also computed what we named an ADEME score that corresponds to the score actually used by ADEME through the implementation of the French energetic performance plan. It is simply obtained by dividing the sum of the energy consumed (through input use) in Joule by the output (cereals) in quintal. We then normalized the minimum to one (it will be the efficient farm) in order to obtain an efficiency score that can be compared with the DEA one. We can observe that, on average, the efficiency scores obtained with the ADEME methods are very close to the EE scores. Checking more precisely, we can observe that the rankings are exactly the same one. A remark follows.

Remark: *When the energy content of inputs is known, the DEA method confirms the results obtained by the ADEME method.*

An energy policy based on EE (or equivalently ADEME) scores will consist in helping farms with low scores to moderate input use where the energy content is high and, as a consequence, in reducing energy use, explicit energy efficiency policies may need to be designed toward farms whose efficiency is low.

Furthermore, table 3, shows that, some farms could minimize their energy use by reducing technical and allocative inefficiency. By only eliminating mismanagement of resources (TE), farms could reduce all the inputs used by 29% without reducing the amount of output produced. Finally, by making reallocation on input or changing input-mix, farms can reduce their energy use to 33%.

To illustrate the insights gained from a decomposition of the EE scores into TE and AE scores, we propose to consider three cases of three farms (**39**, **43** and **107**) as shown in Table 4.

Table 4: Input and output data for three illustrative farms

	Farm 39	Farm 43	Farm 107
Area (hectare)	152	160	222
Labor (unit of labor)	0.8	1	2
Nitrogen (kg)	15 844	5 940	20 237
Petroleum (liter)	11 460	11 273	22 774
Cereals (quintal)	10 542	8 046	6 182

Table 5 provides the potential reduction of energy used on each component of these three farms.

Table 5: Efficiency results and potential reduction of energy in MJ for illustrative farms

	Farm 39	**Farm 43**	**Farm 107**
Energy Efficiency	0.7916	1	0.3005
Potential reduction in energy	*294 322*	*0*	*1 525 747*
Technical Efficiency	1	1	0.4063
Potential reduction in energy	*0*	0	*1 295 060*
Allocative Efficiency	0.7916	1	0.7397
Potential reduction in energy	*294 322*	0	*230 687*

For example, farm **39** can benefit from energy saving by eliminating only allocative inefficiency that corresponds to 21% of observed energy i.e. 294 322 MJ. Compared to farm **39**, farm **107** suffers both an input mismanagement and misallocation and can reduce its energy used by two ways. The potential energy saving is about to 1.526 millions of MJ. The energy gains would come from mainly the elimination of technical inefficiency. Finally, we have the case of farm **43** which cannot benefit from energy saving. Finally, note that the case of farms which only suffer of input misallocation is not found in our sample. The decomposition proposed helps to go further into the design of an energy policy.

For instance, an energy policy designed toward farm **39** will more precisely consist in giving it incentives to reallocate its inputs in a way corresponding more to energy-extensive farms. Such a policy aim is to induce an evolution of farms towards more energy-extensive systems. As a consequence, our method helps to identify both farms characterized by an energy-extensive system (like farm **43**) and farms characterized by an energy-intensive system. Studying the differences between both will help the policy maker to design an appropriate energy policy.

We know from the environmental economics theory that a policy aiming to reduce the energy used by farmers must be designed in order to modify the price system if the farm is cost-efficient. More specifically, if one adds classical iso-cost lines in Figure 1, they will certainly have a different slope from the iso-energy one since the price ratio must be different from the energy content of inputs one. The intersection of the lowest iso-cost line with the isoquant curve gives the equilibrium spontaneously chosen by a cost-efficient farm without any energy policy. As a consequence, an energy policy aiming at reducing the energy use of cost-efficient farms must be designed in order to induce that the farmers choose the equilibrium corresponding to a lower energy use, exogenously chosen by the policy maker. More operationally, such energy policy will consist in subsidizing or taxing the input use in such a way that the slope of the iso-cost lines equals the one of the iso-energy one.

If we now turn back to our examples (Table 5), an energy policy designed toward farm **107** will be more complex than one designed toward farm **39** since it will consist both in giving incentives to reallocate inputs like energy-extensive farms but also to reduce the use of input. The interesting thing here is that this reduction will generate some gains for the farm since it will allow it to produce the same amount of output with less input and hence at a lower cost. As a consequence, a policy specifically designed in order to induce this reduction will not have to pass throw the price system but more throw agricultural consulting.

As a consequence, the decomposition of energy efficiency into technical and allocative efficiency offers different ways of reducing inefficiency for unit managers or policy makers.

To go further, we propose to compute some correlation tests between EE, TE and AE rankings using the Spearman's procedure. The results are summarized in Table 6.

Table 6: Spearman rank correlation tests between the different efficiency scores.

	Energy Efficiency	Technical Efficiency	Allocative Efficiency
Energy Efficiency	1.0000*		
Technical Efficiency	0.6797*	1.0000*	
Allocative Efficiency	0.3045*	-0.3837*	1.0000*

*: statistically significant test at 5% level.

The relatively high correlation between EE and TE means that EE can be a good approximation of TE and that technical and energy goals are quite consistent in our sample. As a consequence, public policies designed in order to help farms with a low rank with respect to EE (resp. TE) can also help them to improve their TE (resp. EE). In a different perspective, public policies designed in order to reward farms with a high rank with respect to EE (resp. TE) can also reward farms with a high TE score (resp. EE). From an even more general point of view, we can conclude that energy and food production goals can be consistent in the short-run in our sample.

In contrast, the low rank correlation coefficient between EE and AE rankings reveals the relevance of decomposition. For instance, in our sample, public policies designed in order to help only farms with a low EE could reduce the amount of output produced and would not be directed towards farms able to reallocate inputs in the long-run, that can only be the case if AE is also used in order to design an energy policy.

From all of this, a first policy implication follows.

Policy implication 1: *Considering only the EE can hide the existing disparities on each component (technical and allocative). Therefore, by dissociating the energy efficiency scores into each component, policy makers can better target their policies toward farmers. For example, policies should help to move towards less intensive-energy farm systems by a reallocation of inputs.*

4.2. Extension with energy content uncertainty

We then extended the previous analysis to a framework in which the energy content of inputs is uncertain. In order to do so, following Camanho and Dyson (2005), we consider two scenarios: an optimistic and a pessimistic one. The optimistic scenario corresponds to the most favorable scenario: the energy contents of inputs are minimal (see Table 2). In the pessimistic scenario, they are maximal. We used the linear programming models (6) and (8) in order to obtain EE in the pessimistic case and in the optimistic one. Optimistic and pessimistic AE are directly obtained by respectively calculating optimistic EE/TE and pessimistic EE/TE. In the uncertain case, only AE and thus EE varied (TE was unchanged). The results are summed up in Table 7. We recall some statistics from the deterministic case in order to compare with the uncertain case.

Table 7: Efficiency Scores with and without uncertainty

	Mean	**Standard deviation**	**Min**	**Max**	**Number of Efficient farms**
Optimistic EE	0.5565	0.1294	0.2381	1	1
Farrell EE	0.4756	0.1080	0.2282	1	1
Pessimistic EE	0.2873	0.0956	0.0917	1	1
Optimistic AE	0.7858	0.1372	0.3535	1	1
Farrell AE	0.6721	0.1135	0.3318	1	1
Pessimistic AE	0.4032	0.0971	0.1506	1	1

A first and direct implication is that the deterministic or Farrell AE and EE scores are upper and lower bounded respectively by the optimistic and pessimistic scores. Even in the optimistic scenario, the inefficiency exists. This confirms the interest of policy intervention. This can be checked once more with Table 8 that relates the specific results for our three illustrative farms.

Table 8: Efficiency results and potential reduction of energy in MJ for illustrative farms with and without uncertainty

	Farm 39	**Farm 43**	**Farm 107**
Optimistic EE	0.9095	1	0.3233
Potential reduction in energy	*91 389*	*0*	*1 108 725*
Farrell EE	0.7916	1	0.3005
Potential reduction in energy	*294 322*	*0*	*1 525 747*
Pessimistic EE	0.4912	1	0.2255
Potential reduction in energy	*923 026*	0	*2 109 701*
Optimistic TE	1	1	0.4063
Potential reduction in energy	*0*	*0*	*972 804*
Farrell TE	1	1	0.4063
Potential reduction in energy	*0*	*0*	*1 295 060*
Pessimistic TE	1	1	0.4063
Potential reduction in energy	*0*	*0*	*1 617 316*
Optimistic AE	0.9095	1	0.7958
Potential reduction in energy	*91 389*	*0*	*135 922*
Farrell AE	0.7916	1	0.7397
Potential reduction in energy	*294 322*	*0*	*230 687*
Pessimistic AE	0.4912	1	0.5551
Potential reduction in energy	*923 026*	0	*492 384*

In Table 8, we see that the potential reduction in energy of farm **39** can be multiplied by ten from the optimistic case to the pessimistic case. This is quite different for farm **107** for whom it is multiplied by less than two. Nevertheless, the difference in MJ between the optimistic case and the pessimistic case is higher for farm **107** than for farm **39**: 1.001 millions of MJ with respect to 831 637 MJ. In both cases, the difference is quite high. As a consequence, it is important to bear these boundaries in mind when designing a public policy. We furthermore see in Table 8 that, for farm **39**, the uncertainty relies only on the effect of input reallocation. It is not the case for farm **107** that can also reduce the inputs used: the uncertainty of the potential reduction in energy of this farm is equal to 644 512 MJ for the potential due to the reduction of input use and it is equal to 356 462 MJ for the potential due to the reallocation of inputs.

As a consequence, this extension of the basic energy efficiency decomposition allows policy makers to design their policies according to their risk preferences. Indeed, a risk-neutral policy-maker will base its policy on the Farrell rankings. But a risk-averse policy maker will use the pessimistic rankings and a risk-lover one, the optimistic one.

Furthermore, the extension proposed allows leading a robust sensibility analysis of the Farrell EE scores. We ran some rank correlation tests in order to check the consistency between the rankings obtained in the Farrell setting and the one obtained when the energy content of inputs is uncertain in our sample. Again, we cannot accept the null hypothesis of independence. Table 9 summarizes the correlation coefficients calculated for EE rankings.[3]

Table 9: Rank correlation coefficients of energy efficiency and allocative efficiency rankings

	EE rankings	optimistic EE rankings	pessimistic EE rankings
Farrell EE rankings	1.0000*		
optimistic EE rankings	0.9729*	1.0000*	
pessimistic EE rankings	0.7662*	0.6298*	1.0000*

*: statistically significant test at 5% level.

	AE rankings	optimistic AE rankings	pessimistic AE rankings
Farrell AE rankings	1.0000*		
optimistic AE rankings	0.9534*	1.0000*	
pessimistic AE rankings	0.6637*	0.4679*	1.0000*

*: statistically significant test at 5% level.

From Table 9, we see that, in our sample, the Farrell method is a good approximation of the EE rankings in the most favorable scenario with respect to the energy content of inputs (optimistic case): the correlation coefficient is close to one. It is not so obvious for the least favorable scenario: the correlation coefficient is lower. This means that an energy policy designed with respect to the Farell rankings of farms is more appropriate if the energy content of inputs is lower than the mean than if the energy content of inputs is higher than the mean. As a consequence an energy policy designed towards particular firms can not have the expected effects if the energy content of inputs is lower than the mean. Concerning the correlation coefficients calculated for AE rankings, one can observe that the correlation coefficients are lower than for the EE rankings. As a consequence, in our sample, an energy policy based on input reallocation will be more sensible to the uncertainty of the energy content of inputs.

A second policy implication follows.

Policy implication 2: *When the energy content of inputs is considered as uncertain but the min and the max are available, policy makers cannot based their policies on an average. DEA methods allow deriving upper and lower bounds for the energy efficiency and allocative efficiency through the incorporation of weight restrictions. And the regulator can choose to base its policy on the rankings corresponding to its risk preferences.*

[3] We ran the same tests with AE rankings and the results are the same one.

5. Conclusion and extensions

To conclude, within the framework of our sample, on average, a policy designed in order to induce farms moving towards the less intensive-energy farms will save up to 52% of energy. We showed how DEA methods could be used in order to design more accurate energy policies in the agricultural sector than the one designed with current indicators. First, DEA methods provide information on energy efficiency of farms that can help policy makers to target energy policy toward specific farms that need it. Secondly, results indicate that energy inefficiency in the agricultural sector can be driven either by mismanagement of input or by a bad choice of input mix. DEA methods allow policy makers to design the policies differently depending on the type of inefficiencies that characterizes a farm. If a farm is characterized by technical inefficiency, the energy policy will consist in giving farms some advices in order to reduce the amount of inputs used in order to produce the same amount of outputs; if it is characterized by allocative inefficiency, it will be helpful to study energy-extensive agricultural systems in more details and to compare them to energy-intensive agricultural system in order to implement the accurate energy policy. Thirdly, we showed that DEA methods allow to lead a robust sensibility analysis of the basic results other the uncertainty of energy content of inputs, and thus to test the need for policy intervention in different contexts.

Nevertheless, the data used to build the technology can be subjected to uncertainty. Indeed, the 52% of energy savings can be included between 44% and 71%. In this paper, we proposed to remove the problems of imprecise data by adopting the Camanho and Dyson (2005) procedure to derive both upper and lower bounds for energy efficiency. Other problems remain to be solved as the fact that our results are based on estimated technology and not on true technology. Therefore, some additional analysis could be relevant to achieve more robust results. Bootstrap procedure as proposed by Simar and Wilson (1998, 2008) and detecting outlier methods (Wilson, 1993; Simar, 2003) could help. Some other approaches like robust alternatives to DEA models (Cazals et al, 2002; Daraio and Simar, 2006) could also be considered.

Furthermore, in order to check the cost of the policies discussed, it would be interesting to compute the difference between the costs of energy-optimal and cost-optimal input use. In the certain case, the cost-optimal input use can be obtained in the same way as the energy-optimal input use with primal programs, the only difference being that one need to use the inputs price system. In order to follow Camanho and Dyson (2005) methods, we chose a dual approach. It does not allow computing the cost of the policies in the uncertain case. Mostafaee and Saljooghi (2010) method would be more appropriate. It would also be interesting to compare the results obtained with each methodology. Nevertheless this would consist in a new and different work from this one. It is why it is left for a future work.

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