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Energy efficiency measurement in agriculture with imprecise energy content information [*]

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Abstract: Energy efficiency measurement is crucial when planning energy reduction policies. However, decision makers understandably are reluctant to act in the absence of solid data and results supporting a policy position. The main objective of this paper is to propose an alternative method to measure farm energy efficiency. This method is based on the Data Envelopment Analysis (DEA) approach in a cost framework introduced by Farrell (1957) and developed by Färe et al. (1985). We decompose energy efficiency measurement into two components, namely technical and allocative efficiencies. Here, input prices are replaced by their energy content. The energy efficiency model is used to explore the optimal input-mix that produces the current outputs at minimum energy-consumption. We show that this decomposition can help policy makers considerably to design accurate energy policies. The presence of uncertainty on data, and more particularly on energy content of inputs, leads us to recommend exploiting the methodologies proposed for calculating the bounds of efficiency measurement in order to produce more robust results. We expect to alert policy-makers in the fact that efficiency is not a fixed value and should be considered with caution. A 2007 database of French farms specialized in crops is used for empirical illustration.

Keywords: Data Envelopment Analysis, energy efficiency, uncertainty.

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

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1. Introduction

With Greenhouse Gas mitigation, energy reduction is a growing concern within the international community. Indeed, the European Union has adopted a series of measures to increase energy savings since 2002 and the commission adopted an "Energy Efficiency Plan" in March 2011. Also, in France, an energy efficiency plan was defined wherein a part is dedicated to the agricultural sector. The main idea is to measure farms energy efficiency. By referring to the idea of the lowest level of energy to produce output, this measurement should highlight their potential in energy savings in order to reduce the energy dependence of agriculture.

The energy efficiency is commonly defined by the ratio between outputs in physical units or converted to energy and inputs converted to energy (Patterson, 1996). Therefore, its measurement requires not only information on outputs and inputs of farms but also information on the energy content of inputs. Concerning agricultural inputs, it is possible to distinguish between renewable and non-renewable forms and also direct and indirect energy. Direct energy is the direct energy content of an input (the MJ content of diesel oil, for instance), whereas indirect energy corresponds to the energy consumed in order to produce and transport an input (e.g., fertilizer, pesticides).

Due to its construction as a single ratio between output and input converted to energy, the energy efficiency measurement does not allow us to consider all the possible ways to save energy and thus where to focus efforts. However, at least two possibilities can be listed. First, savings can be easily made if the waste of resources comes under managerial failures of farmers i.e. too much of some inputs are used with respect to what is needed in order to produce a constant amount of output. Second, savings are possible if input misallocation exists and may need the intervention of a regulator. Consequently, given their importance, we must wonder how to measure and decompose these dimensions of energy efficiency and what the implications in terms of policy design are.

Among alternative approaches to measuring and decomposing energy efficiency, we list the non parametric estimation techniques especially powerful in evaluating relative performance of different decision making units known as Data Envelopment Analysis (DEA). As stated by Zhou and Ang (2008) and Zhou et al. (2008), DEA has gained in popularity in energy efficiency analysis. Developed by Charnes et al. (1978) following the seminal paper of Farrell (1957), DEA involves the use of linear programming methods to construct a non-parametric frontier. The best practices located on the frontier form the benchmark against which the potential energy saving for those that are not on the frontier can be calculated. Therefore, by comparing the practice of different farms, we can identify the amount of energy saving likely to be possible. In this case, energy efficiency is thus defined in terms of the ratio between best practices compared with actual practice.

In agriculture, various papers deal with the topic of energy efficiency by using the DEA framework. Chauhan et al. (2006) measured farmers' efficiencies with regard to energy consumption in rice production in India. Their study helps to identify wasteful consumption of energy by inefficient farmers and to suggest reasonable savings in energy consumption. More recently, Nassiri and Singh (2009, 2010) and Houshyar et al. (2010) determined the amount and efficiency of energy consumption for wheat and paddy production in Iran by using the basic DEA method. Nevertheless, in these papers, the question of energy efficiency decomposition is absent. Hoang and Rao (2010) are the first to deal with the decomposition of energy efficiency to explore the optimal input-mix that produces the current outputs at minimum energy consumption. The authors rely on the same concepts introduced by Farrell (1957) in the cost context and developed by Färe et al. (1985). More precisely, we identify *i*) technical efficiency (TE) which measures the farm's ability to use the best practices given existing technologies and *ii*) allocative efficiency (AE) which measures the ability to make optimal decisions in terms of resource allocation. Following partly this methodology, we propose to decompose the global energy efficiency. Relatively to these studies, we also consider a short-run environment where some inputs are held quasi-fixed in order to take into account the nature of some agricultural inputs such as land or family labor rather than long-run where all inputs are variable. Furthermore, by focusing on inputs reduction in order to diminish energy consumption, we can reasonably assume that policy-makers shall exclude some inputs from the list (for instance, land, employees or family labor)[1].

To obtain an energy efficiency indicator, it is generally necessary to have information about energy content of inputs. Several techniques exist to assess these energy contents but no single best source has been found. For instance, the French Environment and Energy Management Agency (ADEME) choses the Life Cycle Assessment (LCA) perspective. Unfortunately, due to the great number of parameters entering this model, the energy input content may include uncertainty (Huijbregts, 1998). In some cases, the range of reasonable values for energy coefficients is large. These large intervals are the source of confusion, misleading conclusions and sometimes discomfort to policy-makers. As stated by some authors, even for the same crop or the same input, the coefficient found in literature may vary greatly. The variability may also be explained by the complex process involved in their elaboration or by the confidentiality mentioned by the manufacturers concerning pesticides (Zegada-Lizarazu et al., 2010). Therefore, the question is how to take this uncertainty or incomplete information into account when measuring energy efficiency of farms.

In the previous studies, the DEA technique is applied without considering any potential uncertainty. Yet, over the years, DEA literature has grown to include papers dealing with this topic. Among other authors, Kuosmanen and Post (2001, 2003), Camanho and Dyson (2005) or Mostafaee and Saljooghi (2010) showed that modified DEA models can provide robust efficiency measurement in the situation of price uncertainty. In some cases, to deal with uncertain price problems, weight restrictions are incorporated in DEA model in the manner of Thompson et al. (1986), Thompson et al. (1990) and Charnes et al. (1990)[2]. Clearly, the uses of such restrictions does not solely concern prices but can be extended to any other pertinent units. Another contribution of our paper is indeed precisely to consider the uncertainty on energy contents of inputs partly in the vein of Camanho and Dyson (2005) and Mostafaee and Saljooghi (2010). By addressing this uncertainty, we also expect to provide robust energy efficiency.

From a policy viewpoint, in an evidence-based world, the providing of robust results is crucial. Indeed, decision makers, understandably, will be reluctant to act in the absence of solid data and results supporting a policy position. In the same sense, several scenarios should be considered in order to help policy-makers avoid the choice of just one scenario that may lead to inadequate policies (for instance, too stringent or not enough). Moreover, our

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[1] Another method is a set of weighted non-radial DEA models developed by Zhu (1996) in order to construct preference structure over the proportions by which the current input levels can be changed.
[2] For further details about weight-restricted DEA models, see Allen et al. (1997) or Pedraja-Chaparro et al. (1997).

benchmarking approach is useful because efficiency measurements are determined from the best practices located on the production frontier. This allows us to identify the most energy efficient practices. The measurement decomposition offers different ways of reducing inefficiency for policy-makers. Technical inefficiency reflects managerial failures. It can be remedied at the Decision Making Unit (DMU) level. In this case, energy use reduction is possible by learning the practices of peer or reference units. On the other hand, allocative inefficiency involves inputs reallocation towards those that are less intensive in energy and may need the intervention of a regulator.

Finally, in this paper, we propose an extended DEA-based measurement of energy efficiency with uncertain energy content of inputs partly based on Camanho and Dyson (2005) and Mostafaee and Saljooghi (2010). The methodology is applied to a sample of French crop farms observed in 2007.

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

2. Methodology for measuring energy efficiency with or without uncertainty on energy content of inputs

The notion of energy efficiency (hereafter noted EE) indicates the extent to which a production unit minimizes 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 a minimum energy level. After the seminal paper of Farrell (1957), Färe et al. (1985) formulated a programming model for EE assessment. This model requires input and output values as well as energy content of inputs at each DMU. In the next subsection, we present the DEA-like model to measure EE. In the subsection 2.2, we also present the weight-restricted DEA methodology for measuring energy efficiency when energy contents of inputs are uncertain or bounded.

2.1. The energy efficiency and its decomposition into technical and allocative efficiency within a conventional DEA model

To graphically illustrate the energy, technical and allocative efficiency concepts, suppose, in 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 technically 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 produces the same output level with the least input level.
Let us introduce information on the energy content of inputs (w_1 and w_2) and assume that these contents are fixed and known. Consider $EC = w_1 x_1 + w_2 x_2$ as the iso-energy line, that is to say, the line showing all combinations of inputs with the same energy consumption. For instance, the iso-energy line of **F** is $EC^{\mathbf{F}} = w_1 x_1^{\mathbf{F}} + w_2 x_2^{\mathbf{F}}$. Technical efficiency is equivalent to the ratio between the iso-energy line EC^T and that of observed plan $EC^{\mathbf{F}}$.
Now, suppose that DMU **F** has eliminated its technical inefficiency by moving to point **f** (linear combination of **A** and **B**). This point is not energy efficient when it is compared to

DMU **C** located at the tangency point between the iso-cost line and the isoquant. DMU **C** is the least energy-intensive production plan. Thus, given the energy contents of inputs, the composite DMU **f** and **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 content because it fails to make the substitution (or reallocation) involved in moving from **f'** to **C**. The allocative efficiency measurement 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**: $EC^{\min}/EC^{T}$. Finally, we have the relationship:

0**f'**/0**F** = (0**f**/0**F**) × (0**f'**/0**f**)

or

Energy efficiency = Technical efficiency × Allocative efficiency (1)

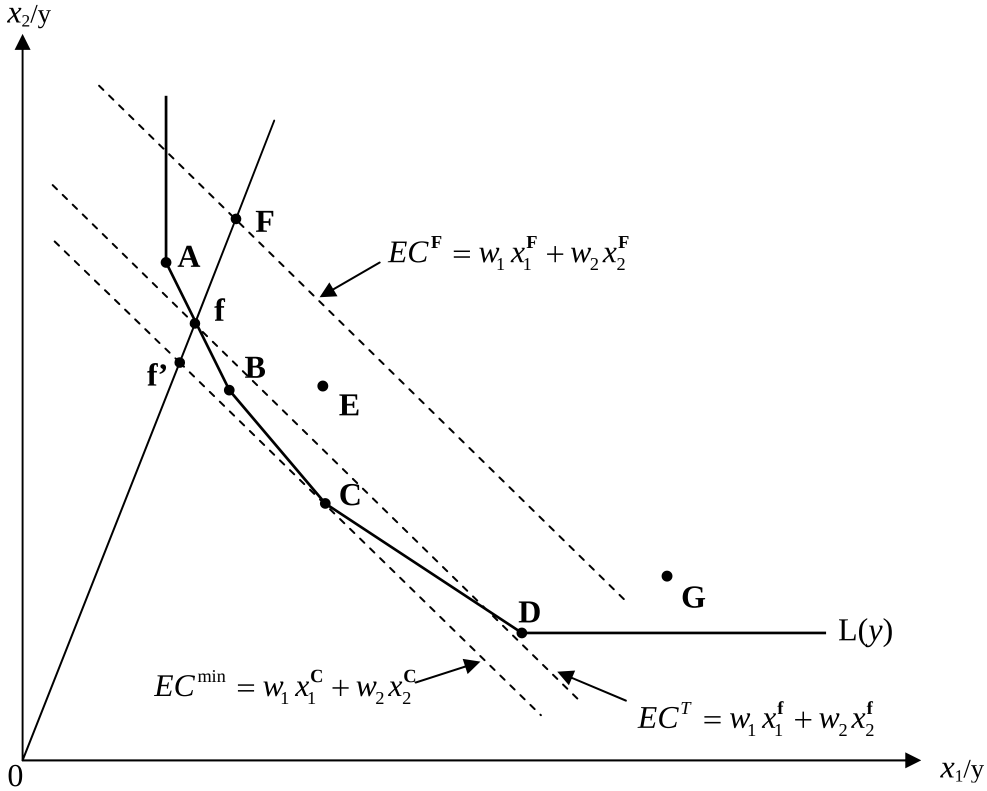

Figure 1: Energy, allocative and technical efficiency measurements in the input space

In the previous discussion, for simplicity, we do not consider the fact that some inputs may be quasi-fixed. However, in the short-term or following decision-makers' preferences, input adjustment is not possible or undesirable for all inputs. In such situations, the quasi-fixed inputs will be treated as a parameter. With this distinction, the decision-maker or policy-maker is able to distinguish what can be achieved in a relatively short time[3]. For readers interested in methodological issues, appendix A.1 details the theory and DEA models that we implement to compute the energy, allocative and technical efficiency scores.

[3] In fact, we will have an equivalent of short-run cost-minimization problem (Färe et al., 1985).

2.2. The extended DEA models to account for imprecision on energy content of inputs

Our efficiency measurements are not meaningful in the case where energy content of inputs is uncertain or imprecise. For this reason, it is desirable to develop a framework for energy efficiency measurement adapted to this topic. As suggested by Cooper et al. (1996), to compute input cost efficiency when knowledge of exact price does not exist, it is possible to introduce constraints with lower and upper bounds on the admissible values. In this way, we could use the knowledge of upper and lower bounds whose relative energy content is expected to vary. In order to exploit this information, the Assurance Region (AR) approach introduced by Thompson et al. (1986) and redefined by Thompson et al. (1990) or the Cone Ratio approach proposed by Charnes et al. (1990) can be used. Usually expressed in the form of lower and upper bounds, the assurance region or Cone Ratio methods put constraints on the ratio of inputs (outputs) weight or multipliers. Several authors propose studies built on these methodologies, for instance Camanho and Dyson (2005). In the same vein of these two authors, we adopt two perspectives viz. optimistic and pessimistic and thus assess two energy efficiency scores: 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). Note here that optimistic and pessimistic notions are relative to each unit. For instance, a pessimistic situation for an evaluated unit is not necessarily so for another unit.

To graphically illustrate these notions (for methodological details, see the appendix A.2.), consider the case where only the maximal and the minimal energy content for all DMUs can be identified, e.g. for two inputs 1 and 2 we have $w_1^{\min}, w_2^{\min}, w_1^{\max}$ and $w_2^{\max}$. The energy content (or weight) ratios underlying the energy efficiency evaluation would be restricted to the following range: $\frac{w_1^{\min}}{w_2^{\max}} \leq \frac{v_1}{v_2} \leq \frac{w_1^{\max}}{w_2^{\min}}$.

The slope of the iso-energy underlying the evaluation of CE could vary between the slope of $E_\beta E_{\beta'}$ i.e. $-\frac{w_1^{\max}}{w_2^{\min}}$ and the slope $E_\alpha E_{\alpha'}$ i.e. $-\frac{w_1^{\min}}{w_2^{\max}}$. The optimistic EE measurement 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 energy content ratio of the iso-energy line is as close as possible to the marginal rate of substitution between the inputs). Conversely, the pessimistic frontier measurement 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**. Intuitively, **F** which has adopted a more x_2-intensive input mix is seen as a farm with a more significant cost reduction potential if $w_1^{\min}$ and $w_2^{\max}$ are retained rather than $w_1^{\max}$ and $w_2^{\min}$.

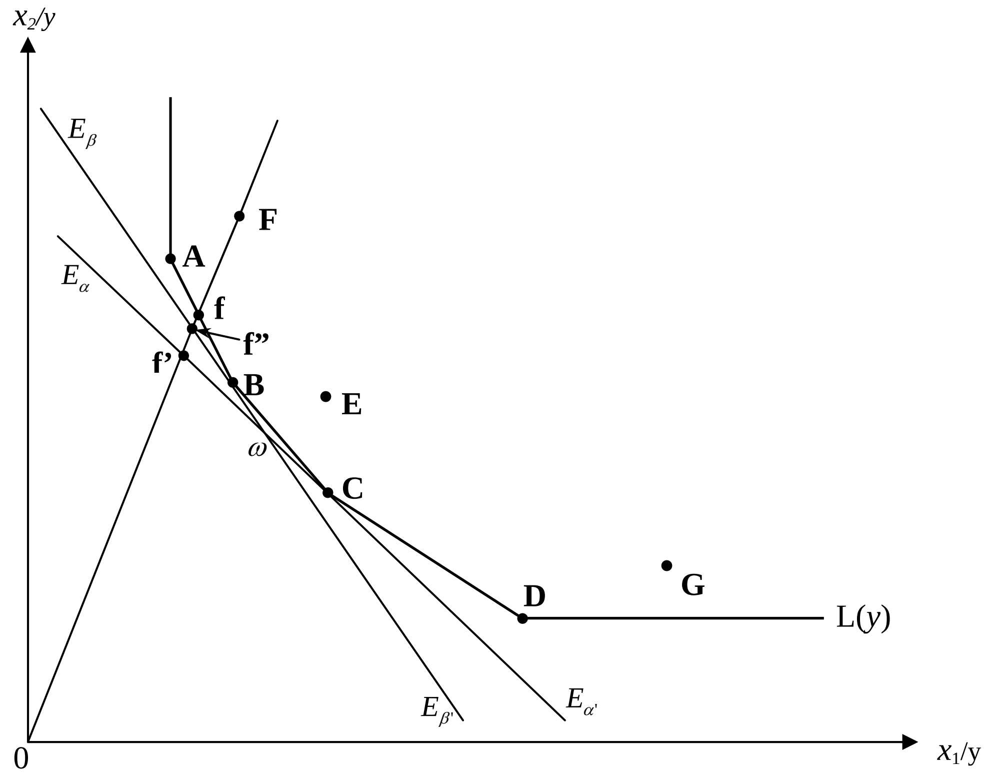

Figure 2: Optimistic and pessimistic energy efficiency measurements in the input space

3. Data and variables

This study is based on data provided by SOLAGRO, a French non-profit organization which promotes sustainable energy and agriculture, and respect for the environment. With the financial support of the French Environment and Energy Management Agency (ADEME), SOLAGRO and other partners proposed a tool, namely PLANETE, used to analyze the energy efficiency of farms. Energy efficiency measurement is expressed as the ratio between outputs and inputs converted to common energy units (the joule). The final data set concerns 133 crop farms[4] investigated during the year 2007. The sample presents homogenous characteristics i.e. *i*) the same production (cereals), *ii*) the quasi similar pedo-climatic conditions by being all located in the same geographical area (center-west of France) and *iii*) the identical production system (conventional). Even if this sample of farms is not representative, the results can help to explore the different ways that can be used to reduce energy consumption on the basis of the decomposition of energy efficiency. The results can also incite caution to policy-makers before taking decisions.

Concerning output, we retain cereals expressed in tons. For the agricultural inputs, we selected chemical fertilizers, pesticides, petroleum, land, labor and machinery. Fertilizers and petroleum are the major inputs contributing to the total energy requirements of the crop cultivation (Bochu, 2002). Note that fertilizer which encompasses nitrogen, phosphorus and potassium represents 49% of total energy consumption. Petroleum, which means petroleum-based fuels such as diesel, gasoline, liquefied petroleum gas, and natural gas, represents 21 %

[4] As DEA is an empirically based estimation technique, it is sensitive to outliers. Outlying observations may be attributed to measurement errors. To detect and remove them, we have used the Wilson (1993, 2010) procedure included in the software package FEAR proposed by Wilson (2008).

of total energy consumption. In our study, we first restricted ourselves to nitrogen-based fertilizer since 90% of the energy consumed in fertilizer is due to this input. However, we then extended to diesel fuel mainly consumed for land preparation, cultural practices and transportation[5]. We also decided to focus on non-renewable energy and to investigate its potential reduction. As a consequence, we will assume that the reduction of land, labor but also machinery is not a priority contrary to the most energy consuming inputs. These three inputs are considered as fixed. It also becomes useless to convert it into energy, except for machinery[6]. Table 1 provides some descriptive statistics of these variables.

Table 1: Descriptive statistics of inputs and output for the 133 farms

	Mean	Standard deviation	Min	Max
Variable inputs				
- Nitrogen (kg)	26 952	18 556	1 992	91 919
- Petroleum (liter)	18 561	14 931	2 193	91 279
- Pesticides (kg of active ingredient)	662	518	16	3 500
Fixed inputs				
- Land (hectare)	196	113	34	568
- Labor (unit)	1.72	1.11	0.50	6.50
- Machinery (MJ)	7 595	6 520	125	33 949
Output				
- Cereals (Quintal)	10 538	6 720	585	33 529

In a first step, nitrogen, petroleum and pesticides were converted from physical to energy units by using the coefficients provided by ADEME (2011)[7]. However, to account for the uncertainty, minimum and maximum reasonable values are also given for these coefficients in order to compute the upper and lower bounds for energy efficiency. These bounds are based on coefficient information reported in the literature. The coefficients reported here are those found in Dalgaard et al. (2001) and Zegada-Lizarazu et al. (2010). The various coefficient values and the reference in brackets are listed in Table 2.

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

Inputs	Unit	ADEME	Min	Max
Nitrogen	kilogram	55.57 (ADEME)	32.2 (Zegada-Lizarazu et al., 2010)	78.2 (Zegada-Lizarazu et al., 2010)
Petroleum	liter	46.4 (ADEME)	35.9 (Zegada-Lizarazu et al., 2010)	51.5 (Zegada-Lizarazu et al. , 2010)
Pesticides	kilogram	282 (ADEME)	76 (Dalgaard et al., 2001)	455 (Dalgaard et al., 2001)

[5] The seeds are not retained in this study. Fortunately, they represent generally an insignificant part of energy expenditure.
[6] This aggregated variable was provided directly by SOLAGRO.
[7] For further details about data, see Bochu (2002).

4. Results and policy implications

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

4.1. The energy efficiency measurement and decomposition in the deterministic case

To examine energy efficiency and its components (technical and allocative efficiency) in the deterministic case (i.e. when the energy content is known), we first run the linear programming models [P1] and [P2a][8] in appendix A.1. At this stage we use the energy content of inputs provided by ADEME (2011) and presented in Table 2. Table 3 provides the scores obtained with these equivalents.

Table 3: Energy, technical and allocative efficiency scores

	Mean	Standard Deviation	Min	Max	Number of efficient farms
Energy Efficiency	0.626	0.175	0.277	1	12
Technical Efficiency	0.696	0.171	0.409	1	21
Allocative Efficiency	0.898	0.097	0.447	1	12
ADEME score	0.579	0.123	0.277	1	1

Energy efficiency varied across farms from 0.28 to 1. The average overall EE is 0.63 indicating that, on average, the farms could reduce all the inputs and thus minimize their energy consumption by 37%. DEA-based energy efficiency scores are higher than the scores computed by ADEME[9]. This may be due to the fact that ADEME do not consider fixed inputs such as land and labor. With respect to the single ratio proposed by ADEME, one of our contributions is to propose an energy efficiency decomposition into technical and allocative efficiency. According to Table 3, we can identify the two sources of inefficiency. Technical efficiency ranged from 0.41 to 1 with an average score of 0.70. Thus, the energy use could potentially be decreased by 30% if each farm were technically efficient. Even after eliminating mismanagement of resources, most farms have a second means by which to reduce their energy consumption that consists in reallocating inputs or changing the input-mix. Indeed, allocative efficiency ranged from 0.45 to 1 with an average efficiency of 0.90. More precisely, through input reallocation, farms can still reduce their energy consumption to 10% relative to their costs on the production frontier.

As stated above, this methodology allows us to identify the best performers. Twenty one farms are technically efficient but only twelve are both technically and allocatively efficient.

From a policy perspective, an energy policy based on basic energy efficiency scores will consist in helping farms with low scores to moderate energy-consuming input. In other words, energy efficiency improving policies may need to be designed targeting the most energy inefficient farms.

[8] The programs were implemented by using GAMS software.

[9] For non-specialists, the score currently used by ADEME is obtained by dividing the sum of the energy consumed (through variable input use) in Mega Joule by the output (cereals) in quintal. We then normalized the minimum to one (representing the efficient farm) in order to obtain an efficiency score that can be compared with the DEA score.

To illustrate the insights gained from a decomposition of the energy efficiency scores into technical and allocative efficiency scores, we propose to consider the cases of three farms (**1**, **43** and **80**). Table 4 lists their input and output levels whereas Table 5 provides the potential reduction of energy used on each component of these three farms.

Table 4: Input and output data for three illustrative farms

	Farm 1	**Farm 43**	**Farm 80**
Variable inputs			
- Chemical fertilizers (kg)	10 511	5 625	22 686
- Petroleum (liter)	9 562	11 273	29 648
- Pesticides (kg of active ingredient)	216	1 525	321
Fixed inputs			
- Land (hectare)	160	160	184
- Labor (unit)	1	1	1
- Machinery (MJ)	4 590	6 972	6 883
Energy consumption	**1 088 685**	**1 265 698**	**2 726 850**
Output			
- Cereals (quintal)	5 184	8 046	14 450

Note: Energy consumption is obtained by summing the variable input converted in energy thanks to energy equivalent provided by ADEME (2011).

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

	Farm 1	**Farm 43**	**Farm 80**
Energy Efficiency	0.653	0.872	1
Potential reduction in energy	*377 774*	*162 009*	*0*
Technical Efficiency	0.771	1	1
Potential reduction in energy	*249 309*	*0*	*0*
Allocative Efficiency	0.848	0.872	1
Potential reduction in energy	*128 465*	*162 009*	*0*

For example, farm **43** can benefit from energy saving by eliminating only allocative inefficiency that corresponds to 12.8% of energy observed i.e. 162 009 MJ. Compared to farm **43**, farm **1** suffers both from an input mismanagement and from an input misallocation: it can reduce its energy spent by two means. Its total potential energy saving is equal to 377 774 MJ. The energy gains would come from mainly the elimination of technical inefficiency. We also have the case of farm **80** that cannot benefit from energy saving. The decomposition proposed helps to go further into the design of an energy policy.

For instance, a more precise energy policy designed towards farm **43** would consist in giving it incentives to reallocate its inputs in a way corresponding more to the allocation chosen by energy-extensive farms. Such a policy aim is to induce an evolution of farms towards more energy-extensive systems. Consequently, our method helps to identify both farms characterized by an energy-extensive system (like farm **80**) and farms characterized by an energy-intensive system (like farms **1** and **43**). Studying the differences between both will help the policy-maker to design an appropriate energy policy.

An energy policy designed towards farm **1** would be more complex than one designed towards farm **43** since it would consist in, both, giving incentives to reallocate inputs like energy-extensive farms but also to reduce the use of input. The interesting point 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, hence, at a lower cost. As a consequence, a policy specifically designed in order to induce this reduction will not have to go through the price system but rather through agricultural consulting.

Finally, note that in our sample we do not find the case of farms that only suffer from an input misallocation. Within the framework of our sample, this means that this is more important for the policy-maker to put money into policies aiming at increasing allocative performance score, i.e. policies based on incentives rather than on advice.

From all of this, a first result emerges. The consideration of only the energy efficiency 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 energy policies towards farmers. For example, energy policies should help to move towards energy-friendly agricultural systems by input reallocation.

4.2. Extension with energy content uncertainty

Although this decomposition can help policy-makers, it can be of limited value because it assumes exact knowledge of energy contents. This exact knowledge may be difficult to have. Solutions to the latter problem involve using averages or specific values. As proposed by Cooper et al. (1996), another possibility is to introduce constraints with lower and upper bounds on the admissible values of energy contents. We propose to follow this idea and therefore to extend the previous analysis to a framework in which the energy content of inputs is uncertain. In order to do so, 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. In addition to model [P1], we used the programming models [P3] and [P4] in appendix A.2 in order to obtain EE in the pessimistic case and in the optimistic one. Optimistic and pessimistic AE are obtained by respectively calculating optimistic EE/TE and pessimistic EE/TE. In the uncertain case, only AE and EE varied whereas TE was unchanged (i.e. 0.696). The results are summed up in Table 6. We recall some statistics from the deterministic case in order to compare with the uncertain case.

Table 6: Efficiency Scores with and without uncertainty

	Mean	Standard deviation	Min	Max	Number of Efficient farms
Optimistic EE	0.665	0.170	0.360	1	15
EE	0.626	0.175	0.277	1	12
Pessimistic EE	0.549	0.190	0.198	1	11
Optimistic AE	0.957	0.069	0.621	1	19
AE	0.898	0.097	0.447	1	12
Pessimistic AE	0.780	0.132	0.302	1	11

A first and direct implication is that AE and EE scores in the deterministic case are upper and lower bounded respectively by the optimistic and pessimistic scores. Even in the optimistic scenario, inefficiency persists. These findings confirm and justify the interest of potential policy intervention. In a perspective of reducing energy consumption, some caution must be taken. Four energy efficient farms in the optimistic case become inefficient in the pessimistic case. To avoid errors and controversy, an energy policy should appoint the eleven farms efficient in both cases like energy-saving target units.

This is illustrated by Table 7 that relates the specific results for our three illustrative farms.

Table 7: Efficiency results for illustrative farms under uncertainty

	Farm 1	**Farm 43**	**Farm 80**
EE Optimistic	0.721	1	1
TE	0.771	1	1
AE Optimistic	0.936	1	1
EE Pessimistic	0.524	0.561	1
TE	0.771	1	1
AE Pessimistic	0.680	0.561	1

In Table 7, we note that the potential reduction in energy of farm **1** increases by 20% from the optimistic case to the pessimistic case. This is different for farm **43** for whom it increases from 0 to 44%. Furthermore, we see that, for farm **43**, the uncertainty relies only on the effect of input reallocation contrary to farm **1** that can also reduce the inputs used thanks to better management. Policy-makers should beware of farm **43**. Indeed, it appears as a target in the optimistic case but can still be an energy-saving target unit for inefficient farms in a pessimistic one. Finally, farm **80** is among those which stay energy efficient in all cases and therefore constitutes an ideal (i.e. well-identified) target for the others.

A second result is note worthy. When the energy content of inputs is considered as uncertain but the minimal and maximal admissible values are available, policy-makers cannot base their policies solely on average or specific values. The derivation of upper and lower bounds for the energy efficiency and allocative efficiency through the incorporation of weight restrictions allows the possibility to rely on the bound values with full knowledge of the consequences. Policy-makers can thus design their energy policies according to their risk preferences. A risk-neutral policy-maker will base its energy policy on the results obtained from an average or specific value of energy input content. Inversely, a risk-averse policy-maker will use the pessimistic results whereas a risk-lover will use the optimistic results.

4.3. Energy efficiency and economic efficiency

When target units are identified, the question that arises is how to make the farms converge towards these targets. In other words, how can we eliminate technical and allocative inefficiency to achieve energy efficiency?
Reducing technical inefficiency does not need input mix change and constitutes a win-win strategy for both the farmers and society. Indeed, this reduces simultaneously energy consumption and input expenditures. By contrast, allocative efficiency improvement can be necessary to achieve energy efficiency but can be inefficient from farmers' viewpoint due to reorganization costs. This modification can lead to deviations relative to the cost minimization

objective. Hence, changing input mix needs a policy intervention which may be designed to modify the price system. More specifically, the slope of iso-cost lines may be different from the slope of the iso-energy lines since the price ratio has no reason to be identical to the ratio of energy content of inputs. The tangency point between iso-cost line and the isoquant gives the equilibrium which will be spontaneously chosen by a cost-efficient farm without energy policy. As a consequence, an energy policy aiming at reducing the energy consumption of cost-efficient farms must be designed in order to induce the farmers to choose the equilibrium corresponding to a lower energy consumption. From an operational viewpoint, such an energy policy will consist in subsidizing or taxing the most energy-consuming inputs in such a way that the slope of the iso-cost lines coincides with the slope of iso-energy lines.

5. Conclusion and extensions

In this paper, we highlighted how the Data Envelopment Analysis (DEA) approach could be used in order to design more accurate energy policies in the agricultural sector than the policies designed with current indicators. Firstly, DEA methods provide information on energy efficiency of farms that can help policy-makers to target energy policy towards specific farms. Secondly, results indicate that energy inefficiency in the agricultural sector can be driven either by mismanagement of input or by misallocation of input mix. DEA methods allow policy-makers to design the policies differently depending on the kind of inefficiencies that characterizes a farm. If a farm is technically inefficiency, the energy policy will consist in giving farms advice in order to reduce the input levels used, given output levels. If it is characterized by allocative inefficiency, it will be helpful to study energy-extensive agricultural systems in more detail and to compare them to energy-intensive agricultural systems in order to implement the most accurate energy policy. Thirdly, an extended DEA approach allows us to carry out a robust sensitivity analysis of the basic results given the uncertainty of energy content of inputs, and thus to test the need for policy intervention in different contexts[10].

Within the framework of our sample, on average, a policy designed in order to induce farms to move towards the less intensive-energy farms will save up to 37% of energy. In this case, we consider the specific value of energy content of inputs retained by ADEME. Nevertheless, the data used to build the technology are sometimes uncertain. In this paper, we also proposed to tackle the problems of imprecise data by combining several procedures to derive both upper and lower bounds for energy efficiency by considering low and high values for some energy coefficients. Hence, energy savings can be included between 33% and 45%. These findings help to justify the interest of policy intervention since potential savings exist even in an optimistic case.

The reduction of energy consumption through simple policies is not an easy matter. In order to be acceptable, energy policies must economically satisfy the producers who undertake them. Farmers cannot afford to jeopardize their year's income in an attempt to refine the energy efficiency of their practices. A comparison between a cost minimization and an energy consumption minimization should also be made by policy-makers in order to check the cost of the policies to be implemented.

[10] Some additional analysis could be relevant to achieve more robust results. Bootstrap procedure as proposed by Simar and Wilson (1998, 2008) could help. Some other approaches like robust alternatives to DEA models (Cazals et al., 2002; Daraio and Simar, 2006) could also be considered.

In the energy analysis process, the measurement of efficiency is the first step. The next step consists in highlighting the factors which explain efficiency. In order to do so, the policy-maker needs more data than the one used in our work. This would allow it to distinguish more precisely the part of inefficiency due to the exogenous factors beyond the farmers' control from the part reasonably solvable by better management.

Appendix

A.1. The energy, allocative and technical efficiency models

Let us consider that K DMUs are observed and we denote $\mathfrak{K} = \{1,\dots,K\}$ by the associated index set. We assume that DMUs face a production process with M outputs, N energy inputs and Z non-energy or fixed inputs where $y = (y_1,\dots,y_M) \in R_+^M$ is the vector of outputs, $x = (x_1,\dots,x_N) \in R_+^N$ is the vector of energy inputs and $r = (r_1,\dots,r_Z) \in R_+^Z$ is the vector of fixed inputs. We also define the respective index sets of outputs and inputs as $\mathfrak{M} = \{1,\dots,M\}$, $\mathfrak{N} = \{1,\dots,N\}$ and $\mathfrak{Q} = \{1,\dots,Q\}$. Following Färe et al. (1985), under constant returns to scale, convexity and strong disposability on input and output assumptions, the model is defined by the production possibility set T:

$$T = \Big\{(x,r,y) : y \le \sum_{k\in\mathfrak{K}} \lambda^k y_m^k \ \ \forall m \in \mathfrak{M}, x \ge \sum_{k\in\mathfrak{K}} \lambda^k x_i^k \ \ \forall i \in \mathfrak{N}, \quad r \ge \sum_{k\in\mathfrak{K}} \lambda^k r_q^k \ \ \forall q \in \mathfrak{Q}, \lambda^k \ge 0 \ \forall k \in \mathfrak{K}\Big\} \tag{2}$$

where λ is an intensity vector which ensures that all convex combinations of the observed inputs and outputs belong to the production technology set T. This later may be equivalently defined using the corresponding input requirement set that represents the set of all variable input required to produce a specific output level y for a given level of quasi-fixed input r. That is:

$$V(y\,|\,r) = \Big\{x : y \le \sum_{k\in\mathfrak{K}} \lambda^k y_m^k \ \ \forall m \in \mathfrak{M}, x \ge \sum_{k\in\mathfrak{K}} \lambda^k x_i^k \ \ \forall i \in \mathfrak{N}, \quad r \ge \sum_{k\in\mathfrak{K}} \lambda^k r_q^k \ \ \forall q \in \mathfrak{Q}, \lambda^k \ge 0 \ \forall k \in \mathfrak{K}\Big\} \tag{3}$$

To measure and decompose energy efficiency we need a functional representation of the production technology. An input distance function introduced by Shephard (1953) is used for this purpose. The input distance function is defined on the input set $V(y\,|\,r)$ as:

$$D_i(x,r,y) = \min\{\theta : \theta x \in V(y\,|\,r)\} \tag{4}$$

Now, suppose that variable inputs are converted into energy thanks to energy equivalents $w=\left(w_1,\ldots,w_N\right)\in R_+^N$ and policy-makers seek to minimize the energy consumption of each DMU. Therefore, we can define the energy function as:

$$EC\left(x,r,w\right)=\min\left\{wx:\left(x,r,y\right)\in T\right\} \tag{5}$$

The energy function is interpreted as the minimal energy consumption given an output vector (*y*), fixed input vector (*r*) and an energy equivalents vector (*w*) attributed to input variables.

From these operational definitions of the production set (2) and energy function (5), the energy efficiency for a DMU *j* with a production plan $\left(x^j,r^j,y^j\right)$ is computed via the following linear program [P1]:

$$\begin{aligned}
& EC^{*}=\min\sum_{i\in\mathfrak{N}} w_i^j x_i \\
& \text{s.t.}\ \sum_{k\in\mathfrak{K}}\lambda^k y_m^k\geq y_m^j \quad \forall m\in\mathfrak{M} \\
& \qquad \sum_{k\in\mathfrak{K}}\lambda^k x_i^k\leq x_i \quad \forall i\in\mathfrak{N} \\
& \qquad \sum_{k\in\mathfrak{K}}\lambda^k r_q^k\leq r_q^j \quad \forall q\in\mathfrak{Q} \\
& \qquad \lambda^k\geq 0 \quad \forall k\in\mathfrak{K}
\end{aligned} \tag{P1}$$

where w_i^j is the weight (here, the energy content) of variable input *i* faced by DMU *j*. The non-zero elements of λ identify the reference set of DMU j. Due to the possible existence of positive slack variables to the optimum, some reductions in fixed inputs are possible even if there are not variables to optimize. x_i corresponds to each variable input i determined by the model which allows the production of each *y* for DMU j. Therefore, EC^* corresponds to the minimum energy consumption required to produce output vector *y* at input fixed and variable input weight *w*.

If we denote EC^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 consumption to the current energy:

$$\frac{EC^*}{EC^j}=\frac{\sum_{i\in\mathfrak{N}} w_i^j x_i}{\sum_{i\in\mathfrak{N}} w_i^j x_i^j} \tag{6}$$

in which "*" indicates the optimality. $\left[\left(1-\text{energy efficiency}\right)\times 100\right]$ is the percentage of total wasted energy.

In the same spirit of cost efficiency developed by Färe et al. (1985), the energy efficiency (EE) incorporates two sources of inefficiency viz. technical efficiency (TE) and allocative efficiency (AE). Technical inefficiency reflects managerial failures or a form of wasteful use of inputs that can be reduced for instance by a better nutrient and fertilizer management whereas allocative inefficiency reflects an input misallocation or an inappropriate input mix. 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 start from operational definitions of the production set (3) and input distance function (4). Thus, we measure technical efficiency by the basic input-oriented DEA model [P2a]. This model does not require *a priori* specification of input and output weights. Hence, the multipliers may take on unreasonable values (Schaffnit et al., 1997). Fortunately as we will see below, the multipliers may be easily bounded by using the dual programming problems (called multiplier models). When the multipliers involve solely input (respectively output) multipliers, it is called an input (respectively output) cone. The dual program to the envelopment models is given by [P2b][11]. Finally we have:

$$
\begin{aligned}
& D_i^j(x,r,y) = \min \theta \\
\text{s.t.}\quad & \sum_{k\in\mathfrak{K}} \lambda^k y_m^k \geq y_m^j \quad \forall m \in \mathfrak{M} \\
& \sum_{k\in\mathfrak{K}} \lambda^k x_i^k \leq \theta x_i \quad \forall i \in \mathfrak{N} \qquad \text{[P2a]} \\
& \sum_{k\in\mathfrak{K}} \lambda^k r_q^k \leq r_q^j \quad \forall q \in \mathfrak{Q} \\
& \lambda^k \geq 0 \quad \forall k \in \mathfrak{K}
\end{aligned}
$$

$$
\begin{aligned}
& \max \sum_{m\in\mathfrak{M}} u_m y_m^j - \sum_{q\in\mathfrak{Q}} z_q r_q^j \\
\text{s.t.}\quad & \sum_{m\in\mathfrak{M}} u_m y_m^k - \sum_{i\in\mathfrak{N}} v_i x_i^k - \sum_{q\in\mathfrak{Q}} z_q r_q^k \leq 0 \quad \forall k \in \mathfrak{K} \qquad (7) \\
& \sum_{i\in\mathfrak{N}} v_i x_i^j = 1 \qquad \text{[P2b]} \\
& u_m \geq \varepsilon \quad \forall m \in \mathfrak{M} \\
& v_i \geq \varepsilon \quad \forall i \in \mathfrak{N} \\
& z_q \geq \varepsilon \quad \forall q \in \mathfrak{Q}
\end{aligned}
$$

where ε is a small positive number.

In the model [P2b] the constraints (7) guarantee that such a set of weights yield efficiency scores less than or equal to one for all DMUs. As suggested by Cooper et al. (1996) and as in Schaffnit et al. (1997) in the cost context, we can also demonstrate that the measurement of energy efficiency can be alternatively obtained with the inclusion of weight restrictions in the multiplier DEA model [P2b]. More precisely, the restrictions imposed on the weights underlying the assessment are the relative values of the energy input content observed at each DMU, such that: $\frac{v_{i^a}}{v_{i^b}} = \frac{w_{i^a}}{w_{i^b}}, \quad i^a, i^b = 1,\ldots,N$ where a and b are for example two inputs among the set $\mathfrak{N}$.

[11] The dual programming with variable and fixed inputs was initially proposed by Banker and Morey (1986) in the form of a linear fractional program.

Following the decomposition (1) in page 5, we can now compute allocative efficiency as the ratio between energy efficiency $\sum_{i\in\mathfrak{N}} w_i^j x_i / \sum_{i\in\mathfrak{N}} w_i^j x_i^j$ and technical efficiency $D_i^j\left(x,r,y\right)$. Formally, we have:

$$\text{Allocative efficiency} = \frac{\sum_{i\in\mathfrak{N}} w_i^j x_i}{D_i^j\left(x,r,y\right)\sum_{i\in\mathfrak{N}} w_i^j x_i^j} \tag{8}$$

A.2. Optimistic and pessimistic energy efficiency models

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

$$\begin{aligned}
&\max \sum_{m\in\mathfrak{M}} u_m y_m^j - \sum_{q\in\mathfrak{Q}} z_q r_q^j \\
&\text{s.t. } \sum_{m\in\mathfrak{M}} u_m y_m^k - \sum_{i\in\mathfrak{N}} v_i x_i^k - \sum_{q\in\mathfrak{Q}} z_q r_q^k \le 0 \quad \forall k\in\mathfrak{K} \\
&\qquad \sum_{i\in\mathfrak{N}} v_i x_i^j = 1 && \text{[P3]} \\
&\qquad \frac{w_{i^a}^{\min}}{w_{i^b}^{\max}} \le \frac{v_{i^a}}{v_{i^b}} \le \frac{w_{i^a}^{\max}}{w_{i^b}^{\min}} && (9) \\
&\qquad i^a < i^b, i^a, i^b = 1,\ldots,N \\
&\qquad u_m \ge \varepsilon \quad \forall m\in\mathfrak{M},\ z_q \ge \varepsilon \quad \forall q\in\mathfrak{Q}
\end{aligned}$$

The constraints $\frac{w_{i^a}^{\min}}{w_{i^b}^{\max}} \le \frac{v_{i^a}}{v_{i^b}} \le \frac{w_{i^a}^{\max}}{w_{i^b}^{\min}}$ denoted (9) provide bounds for variable input multipliers. They follow the Cone Ratio/Assurance Region approach first developed in Thompson et al. (1986) and defined more precisely in Thompson et al. (1990). Cone Ratio/Assurance Region is specified as a set of homogenous inequalities which define an acceptable input weight to underline the efficiency assessment. Program [P3] is nonlinear due to constraints (9). Fortunately, to obtain an optimistic EE linear model, constraints (9) can be easily rewritten in linear form, given by following constraints:

$$\begin{cases} v_{i^a} - \dfrac{w_{i^a}^{\max}}{w_{i^b}^{\min}} v_{i^b} \le 0 \\[2ex] v_{i^a} - \dfrac{w_{i^a}^{\min}}{w_{i^b}^{\max}} v_{i^b} \ge 0 \end{cases} \tag{10}$$

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, Camanho and Dyson (2005) also propose a method. However, as stated by the authors themselves their model is computationally expensive and may not be feasible (p. 441). Therefore, we deviate from their methodology and propose another algorithm for the estimation of pessimistic CE which tends towards the Mostafaee and Saljooghi (2012) methodology[12]. Contrary to these latter, we confine our attention to the dual program and hence propose to solve for each DMU the following two-level program:

$$\min \left\{ \max \sum_{m \in \mathfrak{M}} u_m y_m^j - \sum_{q \in \mathfrak{Q}} z_q r_q^j \right.$$

$$\text{s.t.} \quad \sum_{m \in \mathfrak{M}} u_m y_m^k - \sum_{i \in \mathfrak{N}} v_i x_i^k - \sum_{q \in \mathfrak{Q}} z_q r_q^k \leq 0 \quad \forall k \in \mathfrak{K} \qquad \text{[P4]}$$

$$\sum_{i \in \mathfrak{N}} v_i x_i^j = 1$$

$$\frac{v_{i^a}}{v_{i^b}} \in \mathfrak{F}, \; i^a = 1 \text{ and } i^b = 2, \ldots, N \qquad (11)$$

$$\left. u_m \geq \varepsilon \quad \forall m \in \mathfrak{M}, \; z_q \geq \varepsilon \quad \forall q \in \mathfrak{Q} \right\}$$

where $\mathfrak{F}$ is a family of 2^N sets composed of $(N-1)$ relative input energy contents obtained from the extreme points $w_i^{\min}$ and $w_i^{\max}$ where $i = 1, \ldots, N$.

For instance, let us consider two inputs *a* and *b* and their upper and lower bounds of the energy content i.e. $w_{i^a}^{\min}, w_{i^b}^{\min}, w_{i^a}^{\max}, w_{i^b}^{\max}$. So we have a family of four singleton sets which can be written formally: $\mathfrak{F} = \left\{ \left\{ \frac{w_{i^a}^{\min}}{w_{i^b}^{\max}} \right\}, \left\{ \frac{w_{i^a}^{\max}}{w_{i^b}^{\min}} \right\}, \left\{ \frac{w_{i^a}^{\min}}{w_{i^b}^{\min}} \right\}, \left\{ \frac{w_{i^a}^{\max}}{w_{i^b}^{\max}} \right\} \right\}$.

This inner program i.e. the second-level program is performed for each set of the family $\mathfrak{F}$. Therefore, it allows us to obtain cost efficiency measurements for each set. The outer program determines the set of relative energy input content that produces the lowest cost efficiency measurement for each DMU. Hence, we adopt for the estimation the least favorable scenario within the range of energy input content considered.
Let us finish by noting that the program [P4] is nonlinear like program [P3]. In the same manner, we rewrite constraints (11) in linear form.

References

ADEME (2011). Guide des valeurs Dia'terre. Version du référentiel 1.13, 187 pages.

Allen, R., Athanassopoulos, A., Dyson, R.G. and Thanassoulis, E. (1997). Weights restrictions and value judgements in Data Envelopment Analysis: Evolution, development and future directions. *Annals of Operations Research* **73(0)**: 13-34.

[12] In a recent paper about Mostafaee and Saljooghi (2010) methodology, Fang and Li (2012) have demonstrated that only the lower bound of the cost efficiency obtained for extreme points is correct. This demonstration partly explains our choice to combine methodologies (Camanho and Dyson, 2005 and Mostafaee and Saljooghi, 2010) rather than use exclusively one methodology.

Banker, R.D. and Morey, R.C. (1986). Efficiency analysis for exogenously fixed inputs and outputs. *Operations Research* **34(4)**: 513-521.

Bochu, J.-L. (2002). PLANETE : méthode pour l'analyse énergétique de l'exploitation agricole et l'évaluation des émissions de gaz à effet de serre. Mimeo available online at http://www.solagro.org/site/im_user/0286_$_014planeteooct02.pdf

Camanho, A.S. and Dyson, R.G. (2005). Cost performance measurement with price uncertainty: a DEA application to bank branch assessments. *European Journal of Operational Research* **161(2)**: 432-446.

Cazals, C., Florens, J.P. and Simar, L. (2002). Nonparametric frontier estimation: A robust approach. *Journal of Econometrics* **106(1)**: 1-25.

Charnes, A., Cooper, W.W. and Rhodes, E. (1978). Measuring the performance of decision making units. *European Journal of Operational Research* **2(6)**: 429-444.

Charnes, A., Cooper, W.W., Sun, D.B. and Huang, Z.M. (1990). Polyhedral cone-ratio DEA models with an illustrative application to large commercial banks. *Journal of Econometrics* **46(1-2)**: 73-91.

Chauhan, N.S., Mohapatra, P.K.J. and Pandey, K.P. (2006). Improving energy productivity in paddy production through benchmarking - An application of data envelopment analysis. *Energy Conversion and Management* **47(9-10)**: 1063-1085.

Cooper, W.W., Thompson, R.G. and Thrall, R.M. (1996). Introduction: Extensions and new developments in DEA. *Annals of Operations Research* **66(1)**: 1-45.

Dalgaard, T., Halberg, N. and Porter, J.R. (2001). A model for fossil energy use in Danish agriculture used to compare organic and conventional farming. *Agriculture, Ecosystems and Environment* **87(1)**: 51-65.

Daraio, C. and Simar, L. (2006). A robust nonparametric approach to evaluate and explain the performance of mutual funds. *European Journal of Operational Research* **175(1)**: 516-542.

Fang, L. and Li, H. (2012). A comment on “cost efficiency in data envelopment analysis with data uncertainty”. *European Journal of Operational Research* **220(2)**: 588-590.

Färe, R., Grosskopf, S. and Lovell, C.A.K. (1985). The measurement of performance of production, Kluwer-Nijhoff, Boston.

Farrell, M.J. (1957). The measurement of productive performance. *Journal of the Royal Statistical Society, Series A* **120(3)**: 253-282.

Hoang, V.N. and Prasada Rao, D.S. (2010). Measuring and decomposing sustainable performance in agricultural production: A cumulative exergy. *Ecological Economics* **69(9)**: 1765-1776.

Houshyar, E., Sheikh Davoodi, M.J. and Nassiri, S.M. (2010). Energy performance for wheat production using data envelopment analysis (DEA) technique. *Journal of Agricultural Technology* **6(4)**: 663-672.

Huijbregts, M.A.J. (1998). A general framework for the analysis of uncertainty and variability in life cycle assessment. *International Journal of Life Cycle Assessment* **3(5)**: 273-280.

Kuosmanen, T. and Post, T. (2001). Measuring economic efficiency with incomplete price information: With an application to European commercial banks. *European Journal of Operational Research* **134(1)**: 43-58.

Kuosmanen, T. and Post, T. (2003). Measuring economic efficiency with incomplete price information. *European Journal of Operational Research* **144(2)**: 454-457.

Mostafaee, A. and Saljooghi, F.H. (2010). Cost efficiency measures in data envelopment analysis with data uncertainty. *European Journal of Operational Research* **202(2)**: 595-603.

Nassiri, S.M. and Singh, S. (2009). Study on energy use performance for paddy crop using data envelopment analysis (DEA) technique. *Applied Energy* **86(7-8)**: 1320-1325.

Nassiri, S.M. and Singh, S. (2010). Energy efficiency for wheat production using data envelopment analysis (DEA) technique. *Applied Energy* **6(7-8)**: 1320-1325.

Patterson, M.G. (1996). What is energy efficiency? Concepts, indicators and methodological issues. *Energy Policy* **24(5)**: 377-390.

Pedraja-Chaparro, F., Salinas-Jimenez, J. and Smith, P. (1997). On the Role of Weight Restrictions in Data Envelopment Analysis. *Journal of Productivity Analysis* **8(2)**: 215-230.

Schaffnit, C., Rosen, D. and Paradi, J.C. (1997). Best practice analysis of bank branches: an application of DEA in a large Canadian bank. *European Journal of Operational Research* **98(2)**: 269-289.

Shephard, R.W. (1953). Cost and Production Functions. Princeton: Princeton University Press.

Simar, L. and Wilson, P. (1998). Sensitivity analysis of performance scores. How to bootstrap in nonparametric frontier models. *Management Science* **44(1)**: 49-61.

Simar, L. and Wilson, P. (2008). Statistical inference in nonparametric frontier models: Recent developments and perspectives. In: Fried, H.O., Lovell, C.A.K. and Schmidt, S.S. (eds). The Measurement of Productive Performance and Productivity Growth. Oxford University Press: Oxford, pp 421-521.

Thompson, R.G., Langemeier, L.N., Lee, C., Lee, E. and Thrall, R.M. (1990). The role of multiplier bounds in performance analysis with application to Kansas farming. *Journal of Econometrics* **46(1-2)**: 93-108.

Thompson, R.G., Singleton Jr., F.D., Thrall, R.M. and Smith, B.A. (1986). Comparative Site Evaluations for Locating a High-Energy Physics Lab in Texas. *Interfaces* **16(6)**: 35-49.

Wilson, P.W. (1993). Detecting outliers in deterministic nonparametric frontier models with multiple outputs. *Journal of Business and Economic Statistics* **11(3)**: 319-323.

Wilson, P.W. (2008). FEAR: A software package for frontier efficiency analysis with R. *Socio-Economic Planning Sciences* **42(4)**: 247-254.

Wilson, P.W. (2010). Detecting outliers in deterministic nonparametric frontier models with multiple outputs: Correction. Working paper. Department of Economics. Clemson University. 5 pages.

Zegada-Lizarazu, W., Matteucci, D. and Monti, A. (2010). Critical review on energy balance of agricultural systems. *Biofuels, Bioproducts and Biorefining* **4(4)**: 423-446.

Zhou, P. and Ang, B.W. (2008). Linear programming models for measuring economy-wide energy efficiency performance. *Energy Policy* **36(8)**: 2911-2916.

Zhou, P., Ang, B.W. and Poh, K.L. (2008). A survey of data envelopment analysis in energy and environmental studies. *European Journal of Operational Research* **189(1)**: 1-18.

Zhu, J. (1996). Data envelopment analysis with preference structure. *The Journal of Operational Research Society* **47(1)**: 136-150.