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Assessing eco-efficiency with directional distance functions

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ABSTRACT. Eco-efficiency is a matter of concern at present that is receiving increasing attention in political, academic and business circles. Broadly speaking, this concept refers to the ability to create more goods and services with less impact on the environment and less consumption of natural resources, thus involving both economic and ecological issues. In this paper we propose the use of directional distance functions and Data Envelopment Analysis techniques to assess eco-efficiency. More specifically, we show how these functions can be used to compute a range of indicators representing different objectives of policymakers and/or firm managers regarding economic and ecological performance. Our methodological approach is illustrated by an empirical application to a sample of olive-growing farmers located in Southern Spain. Our foremost finding is that eco-inefficiency is a widespread managerial practice. We also suggest further avenues to explore in this burgeoning line of research.

KEYWORDS. Data Envelopment Analysis; eco-efficiency assessment; directional distance functions.

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Assessing eco-efficiency with directional distance functions

1. Introduction

The notion of economic-ecological efficiency, commonly known as eco-efficiency, emerged in the 1990s as a practical approach to the more encompassing concept of sustainability (Schaltegger, 1996). Generally speaking, eco-efficiency refers to the ability of firms, industries or economies to produce goods and services with fewer impacts on the environment and less consumption of natural resources. At the end of the 1990s, the OECD defined eco-efficiency as '*the efficiency with which ecological resources are used to meet human needs*' (OECD, 1998). Afterwards the concept was popularised by the World Business Council for Sustainable Development (WBCSD, 2000) as a way of encouraging companies to become simultaneously more competitive and more environmentally responsible.

In the last fifteen years, the concept of eco-efficiency has received growing attention from policymakers, academics and firm managers. While politicians face the challenge of upholding longer-term sustainability, academics have the task of providing them with sound information to improve the design of their environmental policies. Furthermore, most firm managers have realised that taking the lead in ecological behaviour could bring them important benefits (Elsayed and Paton, 2005). Creating better performing products with less environmental impact is nowadays an important competitive strategy for firms (Porter and van der Linde, 1995; Picazo-Tadeo and Prior, 2009). Assessing eco-efficiency emerges thus as a practice with great potential to provide policy decision-makers and firm managers with relevant information as a sound basis for strategic decision making.

Eco-efficiency can be assessed by using ratios that relate the economic value of goods and services produced to the environmental pressures or impacts involved in production processes. The assessment of eco-efficiency was initially approached using very simple indicators such as GDP over CO_2 at the macro-level, or units of output per unit of waste or environmental pressure at the micro-level. In spite of their straightforwardness, these indicators have important shortcomings, ignoring, for example, that a given economic output can be produced with different combinations of pressures or impacts on the environment. In recent years, more sophisticated approaches to assessing eco-efficiency have been developed, among them those which use benchmarking techniques and activity analysis or Data Envelopment Analysis techniques (DEA) in the framework of the neoclassical production theory.

According to Korhonen and Luptacik (2004), who propose several models to assess the eco-efficiency of European power plants, two different approaches to modelling and assessing eco-efficiency in a DEA-based framework can be followed. The first one involves making use of activity models in an initial step to obtain separate evaluations of both economic efficiency and ecological efficiency, and then joining them together in a second stage by means of a new DEA-based model. One example of this is the work by De Koeijer et al. (2002), in which scores of both environmental efficiency and profit efficiency for a sample of sugar beet farms in The Netherlands are computed in a first step, and then joined together in another model of sustainable efficiency.

The second approach to assessing eco-efficiency with DEA-based models takes into account economic and ecologic performance jointly and leads to a wide diversity of models depending on how economic product and/or wastes and environmental pressures are treated. In this line of research, one outstanding paper is that by Kuosmanen and Kortelainen (2005), which uses conventional *Shephard distance functions* to assess the eco-efficiency of road transportation in three towns in Finland. Moreover, Kortelainen and Kuosmanen (2007) analyse eco-efficiency in consumer durables with DEA techniques measuring efficiency in terms of absolute shadow prices, which have a direct economic meaning as monetary losses due to inefficiencies. Zhang et al. (2008) addresses undesirable outputs as inputs and uses several linear programming transformations of conventional activity analysis models to evaluate the eco-efficiency of thirty provincial industrial systems in China.

Other recent papers dealing with the issue of assessing eco-efficiency from different perspectives are Barba-Gutierrez et al. (2009), Lin et al. (2010), Picazo-Tadeo et al. (2011), Wang and Côté (2011), Wursthorn et al. (2011), Yang et al. (2011), Zhao et al. (2011).

Our paper belongs to the research stream that deals with economic and ecological performance jointly, and contributes to this burgeoning literature by using directional distance functions and Data Envelopment Analysis techniques to assess eco-efficiency. More specifically, by assuming diverse scenarios for the so-called direction vector, we calculate a range of indicators of eco-efficiency representing different objectives concerning economic performance and ecological performance. As far as we are aware, directional distance functions have not been used before to assess eco-efficiency as we do in this paper. Furthermore, we illustrate our methodological proposal with an empirical application to a sample of Spanish olive-growing farmers. Our major finding is that eco-inefficiency is a widespread managerial practice among olive farmers.

Following this Introduction, Section 2 develops the methodology and Section 3 describes the dataset and comments on the results. Finally, Section 4 concludes and suggests several avenues for further research.

2. Methodology

2.1. Eco-efficiency and directional distance functions

In this paper, we use the most common definition of eco-efficiency in the ecological literature as the ratio between economic value added and environmental pressures (Schmidheiny and Zorraquin, 1996). Eco-efficiency improves when environmental pressures decrease as value added is maintained, value added increases as environmental pressures are maintained or, also, when value added increases at the same time as pressures decrease. In this way, according to the classification in Huppes and Ishikawa (2005), we adopt a micro-level environmental-productivity ratio approach.

Let us now assume that we observe the economic value added, variable v, generated by a set of $k = 1,\ldots,K$ decision-making units (DMUs) in their production processes. Furthermore, the production process induces a set of $n = 1,\ldots,N$ damaging pressures on the environment, also observed at decision-making unit level, which are denoted by $p = (p_1,\ldots,p_n)$. Following Kuosmanen and Kortelainen (2005) (see also Picazo-Tadeo et al., 2011), the *pressure generating technology set* (PGT) representing all feasible combinations of value added and environmental pressures is defined as:

$$\mathrm{PGT} = \left[(v,p) \in R_{+}^{1+N} \;\middle|\; \text{value added } v \text{ can be generated with pressures } p \right] \qquad (1)$$

In addition, some basic properties are assumed on the pressure generating technology. These assumptions are the following: a) economic activity unavoidably entails some pressure will be exerted on the environment, such that the only way of not generating pressure is not producing; b) a lower value added can always be obtained with the same amount of pressure on the environment; c) pressure on the environment can always be increased for any given value added; and, finally, d) any convex combination of two or more feasible (observed) pairs of value added and environmental pressures is also feasible.

In accordance with earlier papers by Korhonen and Luptacik (2004), Kuosmanen and Kortelainen (2005) and Zhang et al. (2008), among others, in our characterisation of technology, environmental pressures are formally treated as conventional inputs.[1] As noted by Zhang et al. (2008; 308) '…*there are two essential classes of inputs from the nature into the economy that may be distinguished: the supply of goods/resource (such as raw materials), and nature's function as the sink for the discharge of residuals and pollutants'*. Environmental pressures could be mainly considered as inputs from the nature belonging to the second category.

Based on this technology, our concept of eco-efficiency is formalised as:

$$\text{Eco} - \text{efficiency} = \frac{\text{Economic value added}}{\text{Environmental pressure}} = \frac{v}{P(p)} \qquad (2)$$

with P being a function that aggregates the n environmental pressures into a single environmental pressure score.

In computing the single environmental pressure score we follow the most common approach in the current literature consisting of taking a linear weighted average of the particular environmental pressures as aggregating function. Formally this function is defined as:

$$P(p) = \sum_{n=1}^{N} w_n p_n \qquad (3)$$

where w_n is the weight assigned to pressure n.

---

[1] Dyckhoff and Allen (2001) discuss the advantages and weaknesses of different approaches to treating the undesirable resultants of production processes in DEA-based models.

Our next theoretical block is the *directional distance function* (Färe and Grosskopf, 2000 summarise the theory of directional distance functions and Picazo-Tadeo et al., 2005 show how they can be used to assess environmental performance). The directional distance function provides a complete representation of the pressure generating technology and is defined as:

$$\vec{D}\left[v,p;\, g=\left(g_v,-g_p\right)\right]=\mathrm{Sup}\,\left[\beta\,\left|\left(v+\beta g_v,\ p-\beta g_p\right)\in PGT\right.\right], \tag{4}$$

with the *direction vector* being:

$$g=\left(g_v,-g_p\right) \tag{5}$$

The directional distance function of expression (4) models value added and environmental pressures jointly, allowing for increasing value added while simultaneously reducing environmental pressures along a path previously determined by the researcher through a given direction vector. Accordingly, it inflates value added in the g_v direction and contracts environmental pressures in the $-g_p$ direction, while staying within the pressure generating technology set. Furthermore, it can be proved that (other properties are described in Chambers et al., 1998):

$$\vec{D}\left[v,p;\, g=\left(g_v,-g_p\right)\right]\geq 0 \Leftrightarrow \left(v,p\right)\in PGT \tag{6}$$

One outstanding feature of directional distance functions is that they provide a really flexible tool for efficiency analysis. This characteristic is particularly relevant for the purpose of our research, as it allows us to compute a wide range of measures of eco-efficiency which might represent the objectives of firm managers, policymakers and/or researchers as regards economic and ecologic performance. These objectives are represented by different direction vectors.

2.2. Direction vectors and objectives on economic and ecological performance

Let us then consider, in the first place, that we are interested in assessing the extent to which pressures on the environment exerted by the DMUs in our sample could be proportionally decreased without affecting their economic performance, namely, by maintaining value added. The direction vector that represents this objective is:

$$g = (g_v, -g_p) = (0, -p), \tag{7}$$

and the directional distance function that allows us to assess eco-efficiency in this scenario becomes:

$$\text{Eco-efficiency}_A = \vec{D}\left[v, p; g = (0, -p)\right] = \text{Sup}\left\langle \beta_A \,\middle|\, \left[v, (1-\beta_A)p\right] \in PGT \right\rangle \tag{8}$$

Given the pressure generating technology, this directional distance function, namely the parameter β_A, assesses the proportion by which all environmental pressures could be reduced, while maintaining the value added at the observed level.[2] As already noted, this function is lower-bounded to zero, the score that represents eco-efficiency; furthermore, the greater the directional distance function the lower the level of eco-efficiency.

A particular case of environmental pressure reduction might arise if policymakers were interested in identifying the extent to which just one pressure could be reduced without increasing the remaining pressures and maintaining value added. For instance, environmental policymakers might plan to legislate an environmental regulation aimed at reducing a particular pressure, and be interested in previously estimating the capacity of firms within an industry or economic activity to decrease this environmental pressure while maintaining their economic performance. Denoting the environmental pressure being reduced as i and the remaining pressures as –i, under this scenario the direction vector becomes:[3]

---

[2] This assessment could have also been achieved using the following direction vector:

$$g = (g_v, -g_p) = (0, -1)$$

which would lead to the directional distance function:

$$\vec{D}\left[v, p; g = (0, -1)\right] = \text{Sup}\left\langle \beta_A^* \,\middle|\, \left[v, (p - \beta_A^*)\right] \in PGT \right\rangle$$

However, while the directional distance function of expression (8) is invariant to the units of measurement of environmental pressures, i.e., it assesses proportions, with this alternative direction vector the model becomes additive and the directional distance function unit-dependent. This difficulty can be, nonetheless, easily overcome in practice by using the transformation proposed by Picazo-Tadeo et al. (2005; 137), which consists of transforming the observed value of all the variables involved as a fraction of the maximum observed value in the sample, before computing the distance function. The original distances can then be easily retrieved from the distances computed using the transformed (normalised) variables (Macpherson et al., 2010 also use this transformation).

[3] Likewise, these objectives could be modelled with a direction vector:

$$g=\left[g_v,-\left(g_{p_i},g_{p_{-i}}\right)\right]=\left[0,(-p_i,0)\right], \tag{9}$$

and the directional distance function:

$$\begin{aligned}\text{Eco-efficiency}_{Ai} &= \vec{D}\left\langle v,p;\, g=\left[0,(-p_i,0)\right]\right\rangle \\ &= \operatorname{Sup}\left\{\beta_{Ai}\,\middle|\,\left\langle v,\left[\left(1-\beta_{A_i}\right)p_i,p_{-i}\right]\right\rangle \in PGT\right\}\end{aligned} \tag{10}$$

The parameter β_{Ai} assesses, in this case, the maximum attainable reduction in environmental pressure i without increasing the remaining –i pressures and maintaining value added at the observed value.

Instead of reducing environmental pressures, policymakers and/or firm managers might be interested, in the third place, in assessing the extent to which economic performance could be improved, i.e., increasing value added, without generating additional pressures on the environment. This objective can be formalised using the following direction vector:[4]

$$g=\left(g_v,-g_p\right)=\left(v,0\right) \tag{11}$$

and the directional distance function:

$$\text{Eco-efficiency}_B=\vec{D}\left[v,p;\, g=(v,0)\right]=\operatorname{Sup}\left\langle\beta_B\,\middle|\,\left[\left(1+\beta_B\right)v,p\right]\in PGT\right\rangle \tag{12}$$

$$g=\left(g_v,-g_p\right)=\left[g_v,-\left(g_{p_i},g_{p_{-i}}\right)\right]=\left[0,(-1,0)\right]$$

and the directional distance function:

$$\vec{D}\left\langle v,p;\, g=\left[0,(-1,0)\right]\right\rangle=\operatorname{Sup}\left\{\beta^*_{A_i}\,\middle|\,\left\langle v,\left[\left(p_i-\beta^*_{A_i}\right),p_{-i}\right]\right\rangle\in PGT\right\}$$

In this case, the model also becomes additive and the directional distance function unit-dependent, such that it needs to be interpreted as the potential reduction of environmental pressure i, assessed in the same measurement units as this pressure is measured.

[4] In accordance with comments made on alternative directions to assess eco-efficiency in previous scenarios, these preferences could also be modelled with the direction vector:

$$g=\left(g_v,-g_p\right)=(1,0)$$

and the directional distance function:

$$\vec{D}\left[v,p;\, g=(1,0)\right]=\operatorname{Sup}\left\langle\beta^*_B\,\middle|\,\left[\left(v+\beta^*_B\right),p\right]\in PGT\right\rangle$$

Once more, the model becomes additive and the directional distance functions need to be interpreted as potential increases in value added in the same units as this variable is measured.

The directional distance function of expression (12), that is, the parameter β_B, also has a lower bound of zero and measures the proportion by which value added could be increased without increasing environmental pressures and staying within the pressure generating technology set.

Finally, let us consider a further scenario in which our interest lies in how firms could achieve better economic performance, i.e., increasing value added, and simultaneously improve their environmental performance, i.e., decreasing environmental pressures. This schedule of objectives is modelled by means of the direction vector:[5]

$$g = (g_v, -g_p) = (v, -p), \tag{13}$$

which leads to the following directional distance function:

$$\begin{aligned} \text{Eco}-\text{efficiency}_C &= \vec{D}\left[v, p; g = (v, -p)\right] \\ &= \text{Sup}\left\langle \beta_C \;\middle|\; \left[(1+\beta_C)v, (1-\beta_C)p\right] \in PGT \right\rangle \end{aligned} \tag{14}$$

The directional distance function of expression (14), namely, the parameter β_C, measures the proportion by which value added could be increased while environmental pressures are reduced in the same proportion.

In order to delve deeper into the intuition of our indicators of eco-efficiency, let us provide a graphic illustration. In the first place, we consider a pressure generating technology (PGT) involving value added v and two environmental pressures, namely p_1 and p_2 (figure 1). Decision-making unit K is unmistakeably eco-inefficient because it is located inside the PGT. Projecting decision-making unit K onto the eco-efficient frontier, which is represented by the lower bound of the PGT, with a direction that proportionally reduces both pressures while maintaining value added, i.e., a Southwest direction g=(0,-p), yields point K', showing that by behaving eco-

[5] Maximum feasible increase in value added while simultaneously reducing environmental pressures could also be assessed using the direction vector:

$$g = (g_v, -g_p) = (1, -1)$$

and directional distance function:

$$\vec{D}\left[v, p; g = (1, -1)\right] = \text{Sup}\left\langle \beta_C^* \;\middle|\; \left[(v + \beta_C^*), (p - \beta_C^*)\right] \in PGT \right\rangle$$

In this case, the transformation proposed by Picazo-Tadeo et al. (2005; 137) also needs to be implemented in order to obtain meaningful estimates from the directional distance function.

efficiently unit K could reduce environmental pressures by a proportion β_A while maintaining value added. The eco-efficient level of environmental pressures p_1 and p_2 at the efficient point K' would be $(1-\beta_A)p_1$ and $(1-\beta_A)p_2$, respectively. Furthermore, projecting South with a direction vector $g=[0,(-p_1,0)]$ would locate decision-making unit K at point K'' on the eco-efficient frontier, showing that environmental pressure p_1 could be reduced by a proportion β_{A1} without decreasing value added and maintaining pressure p_2 at its observed level.

Please, insert figure 1 around here

Let now consider the pressure generating technology depicted in figure 2, with a value added v and just one environmental pressure p. Projection onto the eco-efficient frontier North, i.e., with the direction vector g=(v,0), locates decision-making unit K at point K''', where the value added is increased by a proportion β_B while the observed level of pressure p is maintained. Finally, projecting Northwest with a direction vector g=(v,-p) would locate decision-making unit K on the eco-efficient frontier at point K'''', where value added is increased by a proportion β_c, exactly the same proportion by which pressure p is decreased.

Please, insert figure 2 around here

2.3. Computing directional distance functions with Data Envelopment Analysis

The choice we make to deal with the computation of the indicators of eco-efficiency defined in Section 2.2 is, as noted in the introduction, to use Data Envelopment Analysis (DEA) techniques. These techniques are a well known non-parametric approach to efficiency measurement pioneered by Charnes et al. (1978) that use a variety of mathematical programming models to evaluate the relative performance of comparable decision-making units (see Cooper et al., 2007 and Cook and Seiford, 2009 for an appraisal of the foundations of DEA).[6]

DEA has several advantages over the econometric approach to efficiency measurement. One of these advantages is that no prior assumptions regarding the

[6] DEA has been widely used in the study of environmental performance (see Zhou et al., 2008 for a recent review of these techniques in energy and environmental studies). Furthermore, Van Meensel et al., 2010 compare different frontier methods for economic-environmental trade-off analysis.

specific functional form of the technology are required. In their place, a piecewise linear technological frontier representing best practices is constructed on the basis of empirical observations. Deviations of particular decision making-units' observed behaviours from the efficient frontier are used to compute measures of their relative performance. Furthermore, this approach allows the possibility of substitution between inputs or outputs in conventional efficiency analysis, and between environmental pressures in the case of eco-efficiency analysis. Accordingly, when using DEA, the weights with which individual pressures enter into the computation of the single environmental pressure score involved in the denominator of the ratio of eco-efficiency, namely variables w_n in expression (3), are determined endogenously at decision-making level.[7] In particular, the set of weights for individual pressures is chosen so that it maximises the relative eco-efficiency score of each decision-making unit when it is compared to the other units in the sample.[8]

That said, using DEA techniques on our observed set of DMUs allows us to compute the first of our indicators of eco-efficiency for unit k', namely eco-efficiency$_A$, from the solution to the following mathematical program:

$$\begin{aligned}
&\text{Maximize}_{\beta_A^{k'},\, z^k}\ \text{Eco}-\text{efficiency}_A^{k'} = \beta_A^{k'} \\
&\text{subject to:} \\
&\qquad v^{k'} \le \sum_{k=1}^{K} z^k v^k && && \text{(i)} \\
&\qquad \left(1-\beta_A^{k'}\right) p_n^{k'} \ge \sum_{k=1}^{K} z^k p_n^k && n = 1,\dots,N && \text{(ii)} \\
&\qquad z^k \ge 0 && k = 1,\dots,K && \text{(iii)}
\end{aligned} \qquad (15)$$

z^k being a variable that represents the weighting of decision-making unit k in the composition of the eco-efficient frontier decision making unit k' is compared to.

---

[7] A frequent practice in the literature on the construction of composite indicators of environmental performance is, however, to rely on weights which are determined exogenously on the basis of expert opinions. Moreover, these weights are the same for all decisions-making units under analysis (see Gómez-Limón and Sanchez-Fernandez, 2010 and Reig-Martínez et al., 2011).

[8] While the endogeneity of weights in DEA can be seen as one of the strengths of this technique, in some cases the optimal set of weights can take values that make little sense, for example assigning great importance (weights) to pressures that are scarcely relevant. In order to tackle this potential problem, as proposed by Kuosmanen and Kortelainen (2005), additional *a priori* restrictions on the relative importance of different environmental pressures can be incorporated into DEA-based models (Allen and Thanassoulis, 2004 reviews diverse techniques to introduce restrictions on weights in DEA).

The parameter computed as the solution to program (15) assesses, as already noted, the proportion by which decision-making unit k' could reduce all the pressures it exerts on the environment while at the same time maintaining its value added at the observed level. While a computed score of zero would point to eco-efficiency, i.e., no peer has been found that generates lesser pressures with the same value added, a score of, say, 0.3 would mean environmental pressures could be decreased by 30 per cent without decreasing value added.

In the scenario where our interest is assessing how much a given environmental pressure, namely pressure i, could be reduced without increasing the remaining pressures –i, and still maintaining value added at the observed level, the program for decision-making unit k' is:

$$
\begin{aligned}
&\text{Maximize}_{\beta^{k'}_{Ai},\, z^k}\ \text{Eco-efficiency}^{k'}_{Ai} = \beta^{k'}_{Ai} \\
&\text{subject to:} \\
&\qquad v^{k'} \le \textstyle\sum_{k=1}^{K} z^k v^k && && \text{(i)} \\
&\qquad \left(1-\beta^{k'}_{Ai}\right) p^{k'}_i \ge \textstyle\sum_{k=1}^{K} z^k p^k_i && i \in n \text{ and } i \notin -i && \text{(ii)} \\
&\qquad p^{k'}_{-i} \ge \textstyle\sum_{k=1}^{K} z^k p^k_{-i} && -i \in n && \text{(iii)} \\
&\qquad z^k \ge 0 && k = 1,\ldots,K && \text{(iv)}
\end{aligned}
\tag{16}
$$

In the third place, the maximum feasible increase in value added attainable by decision-making unit k' without generating additional pressures on the environment, namely our indicator eco-efficiency$_B$, is assessed by solving the following program:

$$
\begin{aligned}
&\text{Maximize}_{\beta^{k'}_{B},\, z^k}\ \text{Eco-efficiency}^{k'}_{B} = \beta^{k'}_{B} \\
&\text{subject to:} \\
&\qquad \left(1+\beta^{k'}_{B}\right) v^{k'} \le \textstyle\sum_{k=1}^{K} z^k v^k && && \text{(i)} \\
&\qquad p^{k'}_n \ge \textstyle\sum_{k=1}^{K} z^k p^k_n && n = 1,\ldots,N && \text{(ii)} \\
&\qquad z^k \ge 0 && k = 1,\ldots,K && \text{(iii)}
\end{aligned}
\tag{17}
$$

Finally, the indicator of eco-efficiency in which value added is increased while environmental pressures are simultaneously decreased by the same proportion, namely eco-efficiency$_C$, is computed for decision-making unit k' from the program:

$$
\begin{aligned}
&\text{Maximize}_{\beta_C^{k'},z^k}\ \text{Eco-efficiency}_C^{k'} = \beta_C^{k'} \\
&\text{subject to:} \\
&\quad \left(1+\beta_C^{k'}\right)v^{k'} \leq \textstyle\sum_{k=1}^{K} z^k v^k && && \text{(i)} \\
&\quad \left(1-\beta_C^{k'}\right)p_n^{k'} \geq \textstyle\sum_{k=1}^{K} z^k p_n^k && n=1,\ldots,N && \text{(ii)} \\
&\quad z^k \geq 0 && k=1,\ldots,K && \text{(iii)}
\end{aligned}
\qquad (18)
$$

In this latter case, a score of, for example, 0.25 for the directional distance function would mean that decision-making unit k' could increase its value added by 25 per cent, while also reducing all environmental pressures by the same proportion.

It is worth noting that in programs (15) to (18) we have assumed that the technology exhibits constant returns to scale by allowing the sum of the elements of intensities vector to be free (see Banker et al., 1984). The choice of the properties of returns to scale in measuring eco-efficiency is not clear-cut. On the one hand, from an economic perspective, economies of scale are relevant in determining economic performance in most economic activities. On the other hand, from an ecological perspective, economic activity is commonly characterised by constant returns to scale, as what really matters from this perspective are the total pressures exerted on the environment and not their distribution among different firms (Picazo-Tadeo et al., 2011).

As eco-efficiency involves analysing economic and ecological performance jointly, both of the abovementioned considerations should be taken into account. Thus, the relevant question to be discussed is whether our pressure generating technology should be characterised as either variable or constant returns to scale. Considering the state-of-the-art in this field of research, we have opted for assuming constant returns to scale as this is the assumption most widely used. Actually, our formalisation of the concept of eco-efficiency is based on the proposal by Kuosmanen and Kortelainen (2005; 14), which points out that '*…the size of the firm or production activity… does not matter in this problem* (the assessment of eco-efficiency)*; we are only interested about the ratio of the value added to the environmental pressure. In DEA literature* (this) *is interpreted as a constant returns to scale model*'. Furthermore, while accounting for variable returns to scale in the computation of radial scores of eco-efficiency is really straightforward, the non radial nature of some of our measures of eco-efficiency based on directional distance functions makes this assumption difficult to consider. As pointed out by Torgersen et al. (1996; 396), '*we therefore prefer to leave the scale measures as radial concepts*'.

3. Empirical illustration

3.1. Dataset and variables

In this Section we carry out an empirical application of our indicators of eco-efficiency on a representative sample of olive-growing farmers located in the Southern Spanish region of Andalusia, which is by far the largest olive growing region in the world. Olive production in Andalusia has currently reached record levels by taking advantage of the favourable policy context provided by European Common Agricultural Policy.[9] Nonetheless, this rapid growth has also noticeably increased the pressures that olive farming exerts on the environment (see European Commission, 2010 for a brief summary of these pressures).

Our data come from a survey specifically designed in the context of a wider research project aimed at analysing the economic and environmental performance of olive growing in Spain (see Gómez-Limón et al., 2011 for further details). The survey was carried out on an extensive sample of olive farmers chosen randomly, and was completed by personal interviews between May and September 2010. The data used in this paper correspond to 45 farmers belonging to the traditional plain groves farming system; all farmers share the same technology of production.

Concerning the definition of the variables of interest for the analysis of eco-efficiency, on the one hand, our indicator of economic performance is the net income per hectare, as a proxy for value added[10], calculated for farm k as:

[9] In a recent paper, Amores and Contreras (2009) study the economic efficiency of olive farmers in Andalusia using DEA techniques, as a basis to provide information for a better assignment of European agricultural subsidies.

[10] Empirical analyses carried out for olive farming systems consider that net income is a better indicator of economic performance than conventional value added. The reason is that labour is

$$v^k = \text{Net income}^k = \frac{\text{Sales}^k - \text{Direct costs}^k}{\text{Land}^k} \tag{19}$$

The numerator has been obtained by subtracting direct costs[11] from the income obtained from the sale of olives (both measured in constant euros at 2010 prices), while the denominator is the surface devoted to olive groves (hectares). Thus, this indicator measures economic performance per hectare: the higher its value the better the economic performance.

On the other hand, three of the most representative environmental pressures generated by olive grove production have been chosen for illustrative purposes; they are represented by the variables pesticide risk, nitrogen ratio and energy ratio. *Pesticide risk* provides information about the overall toxicity released into the environment through the pesticides used for olive production. This toxicity has been estimated by the potential lethality of live organisms by the active matters included in these agrochemicals, measured in kilograms of rat per hectare. Formally, this pressure is computed for farm k as:

$$p_1^k = \text{Pesticide risk}^k = \sum_{m=1}^{M} 1{,}000 \frac{\text{Quantity in commercial product}_m^k}{\text{Lethal dose } 50_m}, \tag{20}$$

where the numerator is the quantity of the product m used in farm k (in kilograms per hectare) and the denominator is the lethal dose 50 per cent of the commercial product m (in grams of m per kilogram of rat). The higher the pesticide risk, the greater the pressure on the environment.

The *energy ratio* is used here as a proxy of greenhouse gas (GHG) emissions and has been calculated for farm k as:

$$p_2^k = \text{Energy ratio}^k = \frac{\sum_{t=1}^{T} \text{Energy in inputs}_t^k}{\text{Energy in output}^k}, \tag{21}$$

the most important input in olive growing, accounting for an average of 60 per cent of total costs (Pérez-Hernández, 2008).

[11] Direct costs include costs due to the use of labour (own and hired), fertilisers, pesticides, energy, contracted services and fixed costs directly related to olive production (machinery depreciation and maintenance). Own labour has been priced according to the price of hired labour, as an opportunity cost.

where the numerator measures the energy virtually included in the inputs used in every farming task t implemented in farm k, and the denominator is the energy fixed by olive groves and exported by the output harvested (olives). Both are calculated in kcal per hectare. Thus, the higher the value of this indicator, the worse the ecological performance of farm k is from an energy perspective.

Finally, the *nitrogen ratio* is quantified for farm k using the following formula:

$$p_3^k = \text{Nitrogen ratio}^k = \frac{\text{Nitrogen in input}^k}{\text{Nitrogen in output}^k}, \qquad (22)$$

where the numerator represents the quantity of nitrogen used to fertilise the olive groves and the denominator the quantity of nitrogen extracted by the olives harvested by farm k, both measured in kg per hectare. This ratio provides information about ecological performance in the use of input nitrogen; the higher its value, the lower performance.

Table 1 displays some descriptive statistics for the data.

Please, insert table 1 around here

3.2. Results and discussion

Using the dataset and the variables described above, we have computed the indicators of eco-efficiency proposed in Section 2.2 by solving separately for each one of the 45 farms in our sample programs (15) to (18). The main descriptive statistics for these results are in table 2.

Please, insert table 2 around here

At first glance, our results point to the existence of a high level of eco-inefficiency. For instance, the potential to proportionally reduce all environmental pressures while maintaining economic performance (eco-efficiency$_A$) reaches an average of 0.491; this means that by managing their business eco-efficiently, olive-growing farmers in the sample could reduce the pressures exerted on the environment by almost 50 per cent without decreasing value added per hectare. Similarly, eco-efficiency scores assessing farms' potential increases in economic performance while maintaining ecological performance (eco-efficiency$_B$) indicate that value added could be increased on average by 170 per cent without increasing the pressures exerted on the environment.

Scores of eco-efficiency computed in the scenario where the purpose is to assess potential reductions in particular environmental pressures without increasing the remaining pressures and also maintaining value added at observed levels, show that the greatest potential for reduction corresponds to the nitrogen ratio, with an average eco-efficiency score of 0.670, followed by pesticide risk (score of 0.645) and the energy ratio (score of 0.548). As these results assess the capacity of farms to decrease particular environmental pressures, they might provide environmental policymakers in the area with sound information to make strategic choices, e.g., to legislate environmental regulations aimed at reducing particular environmental pressures. Finally, scores for the indicator eco-efficiency$_c$ indicate that value added could be increased by 36.8 per cent while at the same time reducing environmental pressures by the same proportion.

Results regarding a widespread eco-inefficient management in Spanish olive farming should not come as a surprise, as similar results have been obtained recently in other Spanish agricultural systems. Picazo-Tadeo et al. (2011) assesses pressure-specific eco-efficiency for a sample of farmers operating in the rain-fed agricultural system of Campos County (Spain), finding that they are highly eco-inefficient, with few differences emerging among specific environmental pressures. Moreover, Gómez-Limón et al. (2011) uses DEA techniques and conventional distance functions to assess the eco-efficiency of olive-growing farmers at farm level in Andalusia (Spain), also reaching the conclusion that eco-inefficient management is a widespread practice among farmers.

At least three main reasons could explain such as high eco-inefficient management of olive farms. First, a generalised technical inefficiency; second, the consideration of environmental pressures as externalities that do not influence farmers' personal utility function; and third, farmers' decision-making based on a multi-criteria framework rather than just on economic criteria. However, further analysing the sources of eco-inefficient olive farmers' behaviour goes far beyond the aim of this paper, which is primarily methodological.

In our view, the scores of eco-efficiency we have computed in our empirical application might be interesting on their own for both policymakers and farm managers, as they assess eco-efficiency in different scenarios representing different objectives regarding both economic and ecological performance. In addition, this paper poses a final question concerning whether or not our indicators of eco-efficiency order olive-growing farms in the sample in a similar way. For this purpose, we have performed a Spearman's rank correlation test. Computed scores of eco-efficiency involve a certain number of zeros, i.e., scores for eco-efficient farms[12], creating ties in the calculation of ranks. In order to account for this circumstance, we have ranked the efficient farms according to their importance as benchmarks, measured by the number of times they appear as a peer for other eco-inefficient farms (Charnes et al., 1985; see also Adler et al., 2002 for a review of ranking methods of efficient units in a DEA context).

The coefficients of correlation computed indicate that the rankings of farms derived from the different indicators of eco-efficiency are not statistically different at the standard confidence levels.[13] However, changes in the position of certain farms are important. For instance, farm number three in our sample is ranked 8th according to its capacity to proportionally decrease all environmental pressures while maintaining value added (eco-efficiency$_{A}$). However, it drops to 30th when the potential to reduce the risk of pesticides without increasing the remaining pressures and also maintaining value added is assessed (eco-efficiency$_{A1}$). This farm once again rises to 8th position when ranked according to its ability to reduce the energy ratio (eco-efficiency$_{A2}$) and falls to 18th position when assessing its potential to reduce the nitrogen ratio (eco-efficiency$_{A3}$). These rankings show that, when compared to other farms in the sample, farm number three has particularly high potential to reduce the pesticide it releases into the environment.

[12] Three farms are found to be fully eco-efficient in all scenarios.

[13] In fact, as our indicators of eco-efficiency are computed under the assumption of constant returns to scale, scores from programs (15), (17) and (18) lead exactly to the same rankings.

4. Concluding remarks and suggestions for further research

The simplicity of the notion of eco-efficiency and its built-in advantage of considering economics and ecology simultaneously have made of this concept a matter of practical interest for researchers, politicians and firm managers. Furthermore, assessing eco-efficiency is being increasingly used as an instrument to support decisions that contribute to sustainable development. Accordingly, from the end of the 1990s onwards, a growing literature has emerged aimed at assessing eco-efficiency at firm, industry or economy level.

Our paper contributes to this emerging literature by showing how directional distance functions can be used in a Data-Envelopment-Analysis-based framework to assess different facets of eco-efficiency. Assuming different scenarios for the direction vector allows us to formulate a range of indicators of eco-efficiency which might represent different objectives of policymakers and/or firm managers regarding economic and ecological performance. For illustrative purposes, we apply our indicators of eco-efficiency to a sample of olive-growing farmers in Spain. Our findings reveal that eco-inefficient management is a widespread practice among olive farmers.

Finally, we would like to point out some lines for further research in the field of assessing eco-efficiency. In the first place, we believe that practitioners might be interested in extending the use of directional distance functions to the analysis of wider notions of eco-efficiency, including not only the economic and ecological performance of firms, industries or regions, but also other dimensions of performance such as social performance. Moreover, from a methodological viewpoint, a possible extension of our directional-distance-functions-based analysis would be to account for slacks, mainly pressure excesses, and compute other non-radial slack-based measures of eco-efficiency. In doing so, recent papers by Färe and Grosskopf (2010a) and (2010b), which introduce slack-based measures of efficiency based on directional distance functions, would be really helpful. Exploring further assumptions as regard the scale properties of technology in assessing eco-efficiency, perhaps benefiting from recent work by Sueyoshi and Goto (2011), could also be an interesting line of future research. Furthermore, recent research on the construction of composite indicators with non-linear structures (see, for example, Zhou et al., 2010) might also be of some help for integrating a schedule of non-linear preferences in the construction of the composite indicator of environmental pressures involved in DEA-based models of eco-efficiency.

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Table 1

Sample description

Variable	Mean	Standard deviation	Maximum	Minimum
Economic performance				
Net income *(euro/ha)*	735	313	1,525	377
Environmental performance				
Pesticide risk *(kg of rat/ha)*	4,965	2,237	10,199	1,558
Energy ratio *(adimensional)*	0.275	0.096	0.482	0.133
Nitrogen ratio *(adimensional)*	1.214	0.464	2.091	0.280

Table 2

Indicators of eco-efficiency

Indicator	Mean	Standard deviation	Maximum	Minimum
Eco-efficiency$_{A}$	0.491	0.278	0.841	0
Eco-efficiency$_{A1}$ (pesticide risk)	0.645	0.253	0.923	0
Eco-efficiency$_{A2}$ (energy ratio)	0.548	0.296	0.874	0
Eco-efficiency$_{A3}$ (nitrogen ratio)	0.670	0.274	0.935	0
Eco-efficiency$_{B}$	1.706	1.571	5.295	0
Eco-efficiency$_{C}$	0.368	0.238	0.726	0

Figure 1

The pressure generating technology and eco-efficiency indicators (i)

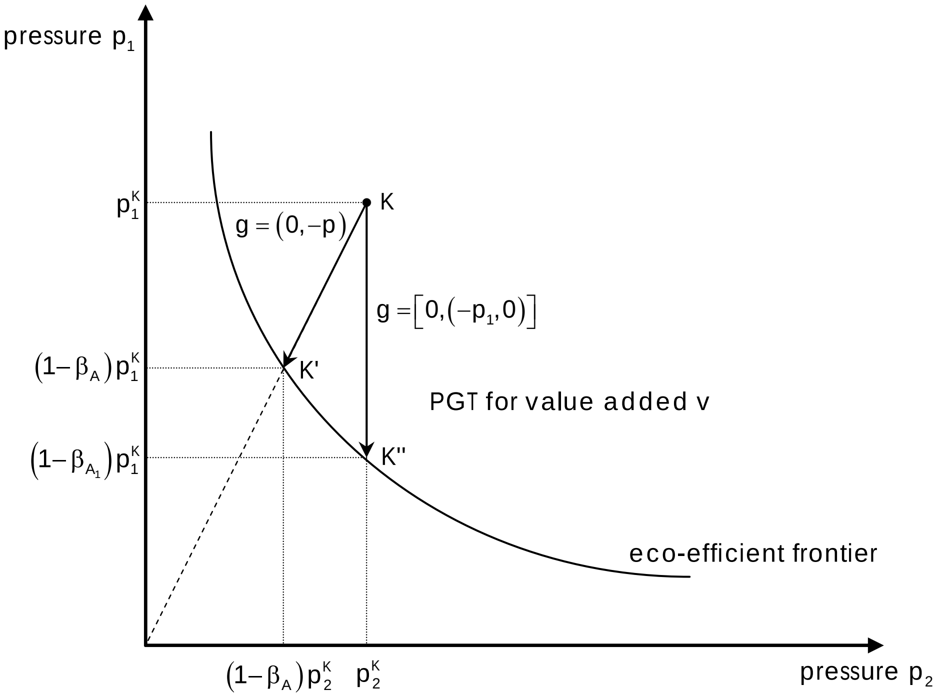

Figure 2

The pressure generating technology and eco-efficiency indicators (ii)