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Abstract

Joint cost-environmental efficiency analysis based on the material balance principle (MBP) has an important short-coming, in that the measures of allocative efficiency it produces do not fully integrate environmental and economic outcomes. Their limitation lies in their failure to take into account some decision-making units (DMU) use a combination of inputs that is more environmentally-harmful than that of the least-cost unit, or, more rarely, more costly than that of the least-polluting unit. Input substitution can therefore bring both environmental and economic benefits. This paper develops a method for differentiating between environmental allocative efficiency gains that involve an economic trade-off and those that do not. Drawing insight from the literature on multi-criteria analysis, we extend the MBP approach to new measures of cost-constrained environmental efficiency using data envelopment analysis (DEA). The proposed approach is illustrated by an application geared to assessing the efficiency of a sample of greenhouse horticultural production units in Almeria, Spain. The results for this case show that it is possible to increase environmental allocative efficiency by up to 34 % on average without incurring additional costs.

Keywords

Cross constrained cost-environmental efficiency, material balance condition, nitrogen pollution, green house horticulture

JEL-Codes

C61, D24, Q12, Q50

1 Introduction

During last decade efficiency frontier models based on the material[1] balance principle (MBP) have been increasingly applied in the measurement of firm and regional level environmental performance costs (Coelli et al., 2007; Hoang and Coelli, 2011; Lauwers et al., 1999, Lauwers et al. 2003; Reinhard et al., 2000). The main acknowledged advantage of the MBP approach over other methods is that it is founded upon on the Law of the Conservation of Matter (Lauwers, 2009). According to this law, pollutant emissions from production activities are considered waste residuals (Ayres, 1995; Ayres and Kneese, 1969; Pethig, 2006) and are measured as the balance between the potentially pollutant materials that enter the production system (nutrients from agricultural fertilizers, for example) and the materials that are transformed into final goods (the nutrients that plants draw from the soil, for example). From this perspective, it is of significant importance to control the quantity and composition of inputs in the production process when dealing with the problem of environmental degradation, [2] because the pollution generated by producing a given level of output will vary according to the quality and quantity of the inputs.

Following this logic, several authors (Lawers, 2009; Van Meensel et al., 2010a) have shown that the integration of the MPB in efficiency models also has major implications for environmental planners. They show that a strategy for a more efficient management of inputs to reduce pollution generation may provide "win- win" outcomes that conciliate the economic interest of firms with the environmental concern of society. For instance, reducing the overuse of inputs by improving technical efficiency has a twofold benefit, since it reduces both production costs and environmental burden. Likewise, it is implicit in the MBP approach that part of the improvement in environmental allocative efficiency can be achieved while decreasing costs. For example, Lauwers (2009) and Van Meensel et al. (2010a; 2010b) find that half the farms in a sample are able to achieve simultaneous improvements in cost allocation efficiency and environmental efficiency by changing the proportions of their input factors to combinations more environmental friendly and less costly. Evidence obtained by Nguyen et al. (2012) also suggests that there exists a positive economic–environmental trade-off path for allocative efficiency.

Despite this evidence, typical MBP measures of environmental allocative efficiency (Coelli et al., 2007; Nguyen et al., 2012; Welch and Barnum, 2009) do not integrate production costs; just as cost-efficiency measures do not consider environmental impacts. Thus, in our view, allocative

[1] Some energy-efficiency studies (Hoang, 2014; Hoang and Rao, 2010) are also based on Energy Balances.

[2] Although, MBP models have recently been extended to include abatement activities (Färe et al., 2013; Hampf, 2014; Lozano, 2015; Murty et al. 2012), most studies focus on pollutant generation processes in production activities. This paper does not consider abatement activities.

efficiency measures have at least two shortcomings. First, they only allow comparison of the firm's current performance with that of the least cost unit or the least polluting unit. Therefore they mask intermediate efficient input substitution options that could potentially lead to environmental gains (economic gains) with no detriment to the economic (environmental) outcome. Secondly, a basic function of environmental efficiency measures is to provide information for decision-making. A key issue when designing environmental planning strategies is to make a distinction between environmental objectives that could be achieved while still safeguarding or promoting economic competitiveness and policies that would restrict economic activity. This distinction is difficult when using measures of environmental allocative efficiency that are not based on an integrated pollution and cost indicator.

In this paper, we propose to integrate cost and environmental pollution in two alternative measures of constrained allocative efficiency. These measures enable us to distinguish improvements in allocative efficiency that involve no detriment either to the firm's cost performance or its environmental performance (constrained measures) from those that involve a positive or negative trade-off. For this purpose, we apply the constrained multi-objective optimization method, which is extensively used to map efficient solutions in multi-criteria analysis (Chankong and Haimes, 1983; Haimes et al., 1971; Marler and Arora, 2004). The advantage of this method is that it identifies efficient solutions without requiring ex ante specification of a utility function. Our work adapts the variation proposed by Mavrotas (2009) to find the optimal emissions-to-cost ratio. The efficiency indices are computed from these optimal values.

To illustrate the usefulness of this method, we apply the efficiency measures to a sample of greenhouse horticultural farms in Spain. In doing so, we focus on the environmental impact of nitrogen fertilizers. Our approach enables quantification of the potential reduction in environmental pressure that can be achieved with no increase (and even a potential reduction) in costs, by improving both technical and allocative efficiency.

The paper is organized as follows. In the next section, we describe the methodology. Section 3 presents sample description and empirical results, and the subsequent sections contain a discussion of the results and the conclusions to be drawn from them.

2 Methodology

In this section we reproduce the standard MBP joint cost and environmental efficiency model (Coelli et al., 2007) and extend it to include some new cost-constrained environmental allocative efficiency indicators. Our cost-constrained environmental allocative efficiency indexes are computed with fixed outputs and fixed costs. The environment-constrained cost allocative efficiency indicator is determined reciprocally. Finally, the proposed method enables a distinction between environmental (cost) allocative efficiency gains involving no economic (environmental) trade-off and those requiring a cost increase (environmental degradation).

2.1 Standard MBP cost and environmental efficiency model

Consider a set of firms that use N inputs, $x \in R_+^N$ to produce M outputs $y \in R_+^M$ using a technology that may be represented by the feasible production set [3] as:

$$T = \{(x, y) \in R_+^{N+M} : x \text{ can produce } y\} \tag{1}$$

Assume that production technology satisfies the standard axioms (Shephard, 1970) including convexity and free disposability of inputs and outputs.

The production activity also generates $z \in R_+^S$ pollutant emissions as by-products, and by the material balance equation:

$$z = a'x - b'y \tag{2}$$

where a and b are (N×S, M×S) vectors of constant coefficients which represent the units of substance z_s contained in the input and in the output. There exists the possibility that some inputs and outputs may contain a zero amount of substance z_s. For the rest of the exposition we will consider that there is only one pollutant emission, $s=1$, and are thus able to remove the subindex s. [4]

The standard MBP cost and environmental efficiency model presents two separate cost and environmental overall efficiency measures. These measures are decomposed into a common measure of technical efficiency and two independent measures of allocative efficiency. In this section, we adhere very closely to the format used in Coelli et al. (2007), where the output y is fixed, and overall efficiency in costs and environment is defined by first calculating the minimum feasible cost and minimum feasible input environmental burden for each level of output.

The minimum cost for each level of output is written as:

$$C(y, w) = \underset{x}{Min}\{w'x \mid (x, y) \in T\} \tag{3}$$

[3] This representation does not include pollution as by product because we do not consider abatement activities.

[4] Coelli et al. (2007) generalizes the model to various types of pollutants using pre-established environmental damage coefficients. This generalization is not included here.

If x_c is the vector of inputs that solves (3), the cost efficiency of a firm can be defined by the following ratio of the actual cost for the firm and the minimum cost to produce the output y:

$$CE = \frac{w'x_c}{w'x} \tag{4}$$

Likewise, the minimum of the potentially pollutant material contained in the inputs $a'x$ used to produce output y is estimated by means of the following optimization procedure:

$$E(y,a) = \underset{x}{Min}\{a'x | (x,y) \in T\} \tag{5}$$

Taking x_e to be the vector of inputs that solves (5), the environmental efficiency of a firm can be written as:

$$EE = \frac{a'x_e}{a'x} \tag{6}$$

where $a'x$ is the actual pollutant content of inputs and $a'x_e$ is the minimal content for the same level of output y.

Both cost efficiency and environmental efficiency are decomposed into a common technical efficiency indicator and two specific allocative efficiency indicators. A firm's radial technical efficiency (TE) in inputs (Farrell, 1957) indicates the greatest possible reduction in inputs the firm is able to make in order to reach the technology efficient frontier. Radial technical efficiency is estimated by means of the following optimization procedure:

$$TE(x,y) = \underset{\theta}{Min}\{\theta | (\theta x, y) \in T\} \tag{7}$$

Let us suppose that $x_t = \theta x$ is the technically efficient input vector. Then, technical efficiency can be expressed as the costs (environmental load) of x_t relative to the current costs (environmental load):

$$TE = \theta = \frac{w'x_t}{w'x} = \frac{a'x_t}{a'x} \tag{8}$$

Cost efficiency can therefore be decomposed by following the standard procedure:

$$CE = TE \times CAE \tag{9}$$

where CAE is cost allocative efficiency, which determines whether the combination of inputs is optimal at current market prices with the available technology. Allocative efficiency is usually computed as a residual of the decomposition of overall efficiency. CAE is therefore determined by the following ratio:

$$CAE = CE / TE = {w'x_c}\Big/{w'x_t} = {C(y,w)}\Big/{w'x_t} \tag{10}$$

Environmental efficiency, meanwhile, is decomposed as follows:

$$EE = TE \times EAE \tag{11}$$

where *EAE* is environmental allocative efficiency, which, analogously with the case for *CAE*, is determined by the ratio between the lowest level of pollution and the technically-efficient level of pollution.

Therefore, the MBP approach shows that improvements in technical efficiency generate both economic and environmental benefits (Lauwers, 2009). The efficiency benchmark used in allocative efficiency measures, however, is either the minimum cost or the minimum amount of pollution. Thus these measures do not relate costs and pollutant emissions. In the next sub-section, this standard model is extended to define a set of allocative efficiency measures that integrate both criteria. First, let us present a simple diagram to illustrate the efficiency measures mentioned so far.

Figure 1 depicts the very simple case of a technology involving two inputs, x_1 and x_2, the isoquant or frontier of technical efficiency, the isocost line, which shows all combinations of inputs that cost the same total amount, $w'x$, and the isomaterial line which shows all combinations of inputs that contain the same quantity of pollutants, $a'x$. [5]

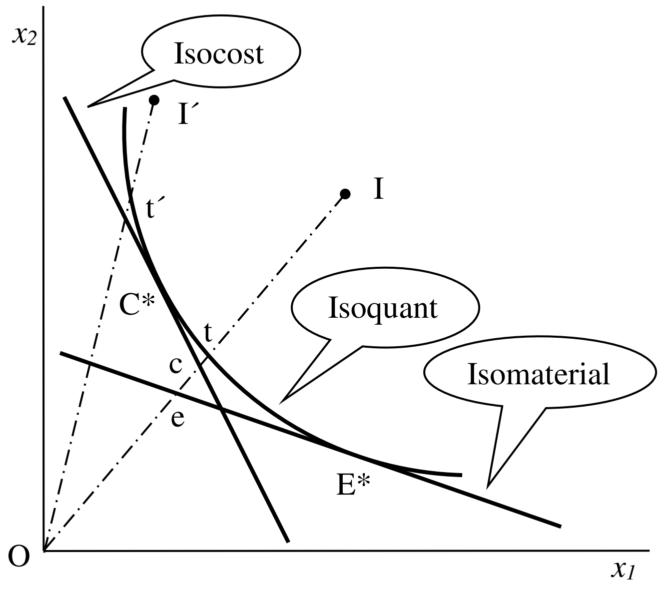

Figure 1. Cost and pollution input content frontiers

[5] It is assumed that both inputs contain pollutant material. See Nguyen et al. (2012) for a depiction of the case in which only one of the inputs is potentially pollutant.

This diagram shows four decision making units: the least-cost unit, C*, the least-emissions unit, E*, and two inefficient units, I and I´. The *TE* of I is given by the quotient of Ot/OI; its *CE* is given by the Oc/OI; and its environmental efficiency, EE, is given by Oe/OI. Its cost allocative efficiency (*CAE*) is given by Oc/Ot; and its environmental allocative efficiency (*EAE*) is given by Oe/Ot.

The efficiency measures for unit I´ could be shown analogously. However, there is an important difference between I and I´. The I technically efficient reference unit, t, lies on the portion of the isoquant between C* and E* that is Pareto efficient. In other words, unit I can not achieve allocative environmental (cost) gains without negative economic (environmental) trade-offs. Conversely, unit I´ is projected by technical efficiency to t´, which is not Pareto efficient. There are several movements from t´ that would improve its efficiency. For example, t´ can move to C*, thus simultaneously reducing its costs and its emissions. Also, t´ can move to t thereby reducing its emissions without increasing its costs (we assume that t and t´ have the same cost) and move from t to E* facing an environmental-economic trade-off.

Standard MBP joint cost and environmental efficiency models do not define measures of environmental allocative efficiency that represent the movement from t´ to t, that is, the type of measures that lead to gains in one objective with no detriment to the other, or to joint environmental and cost allocative efficiency gains. In the next subsection, the standard model is extended to include all these measures.

2.2 Cross-constrained allocative efficiency

In order to include in the analysis both the environmental and the economic components of allocative efficiency, we propose to use a two-stage procedure. In the first stage, the DMU's technical efficiency is measured. Let us denote the technically efficient pollutant content in the inputs by $a'x_t$ and technically efficient costs by $w'x_t$. In the second stage, two alternatives will be considered: a move towards higher environmental allocative efficiency with no cost increase, and a move towards higher cost-allocative efficiency with no increase in environmental pressure.

If the environment-oriented option is taken, constrained environmental allocative efficiency tells us how much the environmental burden can be reduced without pushing costs above the technically efficient level, $w'x_t$. The aim is to find the point on the technically-efficient frontier that marks the lowest environmental load that is possible without costs exceeding $w'x_t$. This is done by adapting the constrained method to obtain a procedure for finding local optima. The constrained method is used in multi-objective optimization to map efficient solutions (Marler and Arora; 2004; Messac et al., 2003). The method looks for Pareto efficient solutions by optimizing a target function and using the other objective functions as constraints. The values of these constraints should vary along the range of objective functions over the efficient set (Messac et al., 2003). For the case in hand, we drop the condition that the constrained objective values must be from the efficient set, and thus adapt the method to find an efficient local solution (Mavrotas, 2009). The procedure goes as follows.

First, find the minimum level of emissions for output level y and technically-efficient costs $w'x_t$, which takes the following functional form

$$E(y,a,w'x_t) = \underset{x}{Min}\{a'x|(x,y)\in T \text{ and } w'x \leq w'x_t\} \tag{12}$$

Now, denote by x_{ce} the combination of inputs that solves the constrained minimization of pollutant emissions (12). It is now possible to define a cost-constrained environmental allocative efficiency measure (*CCEAE*).

$$CCEAE = \frac{E(y,a,w'x_t)}{a'x_t} = \frac{a'x_{ce}}{a'x_t} \tag{13}$$

This measure should indicate how much a DMU is able to reduce emissions by means of input reallocation without pushing costs above the technically-efficient level.

It is a proven fact that a constrained minimum, such as $a'x_{ce}$, is always greater than or equal to a non-constrained minimum, such as $a'x_e$ (Primont, 1993). Therefore, the *CCEAE* will always be greater than or equal to the *EAE*. Taking into consideration that the *EAE* is the ratio between the minimum level of emissions and the technically-efficient level of emissions for a given level of output, we can decompose as follows:

$$EAE = \frac{a'x_e}{a'x_t} = \frac{a'x_e}{a'x_{ce}} \times \frac{a'x_{ce}}{a'x_t} = \frac{a'x_e}{a'x_{ce}} \times CCEAE \tag{14}$$

We will call this relationship $a'x_e/a'x_{ce}$ in (14) costly environmental allocative efficiency (*CEAE*). It is interpreted as the additional improvement in environmental efficiency that is required to achieve the minimal level of emissions per unit of output, after the unit has exhausted all its possibilities to improve environmental performance without increasing costs. Thus, environmental allocative efficiency in the standard MBP model can be decomposed into two parts: the *CCEAE*, which represents environmental performance gains that can be achieved by reallocating inputs without increasing costs and the *CEAE*, which represents the additional improvement in environmental performance to reach the most environmental friendly position. Usually it is considered that improving the *CEAE* imply an economic trade-off because represents a movement towards more restrictive environmental conditions.

However, in the case of firms where the input mix is more costly than that of the most environment-friendly unit, these restrictions do not hold. Then any improvement in environmental allocative efficiency can go hand in hand with a reduction in costs. In this case, we define joint cost allocative efficiency (*JCAE*) by the ratio $w'x_{ce}/w'x_t$, [6] where $w'x_{ce}$ is the production costs of the most environmental-friendly unit. This indicates the proportional joint cost reduction that would result from increasing environmental allocative efficiency.

The decomposition of cost allocative efficiency is symmetrical to that of environmental allocative efficiency. Where cost allocative efficiency is decomposed into environment-constrained cost allocative efficiency (*ECCAE*) and polluting cost allocative efficiency (*PCAE*):

$$CAE = ECCAE \times PCAE \tag{15}$$

The *PCAE* could be seen as the potential cost decrease due to an elimination of restrictions in pollution emissions in its technical efficient level. If the unit freely increase the pollution content of inputs they would be able to move to the minimum cost position. This movement could imply an increase of pollution emissions, but not always.

In fact, very often production units are so inefficient that show an input mix that is more contaminant than that of the minimum cost unit. Of course, in this situation environmental restrictions are not binding in cost minimization. And, it is possible achieve costs and contamination reductions in parallel. Then, we define joint environmental allocative efficiency *(JEAE)* to represent these contingencies. This measure varies between cero and one to indicate the proportional reduction in emissions that would result from increasing cost allocative efficiency. When *JEAE* is lower than one a more restrictive environmental regulation could push the firms to improve at the same time environmental and economic performance.

Then, we have extended the MBP efficiency model to include cross-constrained allocative efficiency measures, which draw a distinction between allocative efficiency gains that involve a negative environmental-economic trade-off, those that involve no such trade-off, and those that generate a joint cost and environmental benefit. All this indicators are illustrated graphically in

[6] In multicriteria optimization, such firms would be units with costs beyond the range of efficient values (Messac et al., 2003) where the constrained optimization of program (12) would yield a weakly efficient solution. Furthermore, the solution of program (12) does not allow direct identification of x_{ce}. To find a joint cost-and-environment efficient solution, it is necessary to specify another interaction (Mavrotas, 2009) to obtain the efficient cost level. In this iteration costs are minimized by constraining emissions to the level $a'x_{ce}$ using the following program: $C(y, w, a'x_{ce}) = \underset{x}{Min}\{w'x | (x, y) \in T \text{ and } a'x \le a'x_{ce}\}$

Appendix A. Here we only want to note that the information provided by these measures may be of relevance for environmental policy because it enables the identification of three distinct pollution-control approaches: one that is in line with the firm's cost-reducing interests, one that that would not harm its economic performance and one that would simply increase costs.

2.3 An application of data Envelopment Analysis (DEA) to compute efficiency measures

To compute the efficiency measures defined above, we use Data Envelopment Analysis. DEA is a non-parametric method of measuring the efficiency of a DMU, [7] originally developed by Charnes et al. (1978) for the estimation of technical efficiency, and frequently used in studies involving MBP-based efficiency measures.

The programs used to compute the efficiency measures in section 2.1 are the standard DEA programs reported in the literature (Coelli et al., 2007; Färe et al., 1994) and are therefore not specified here.

The measures presented in section 2.2 are estimated using a two-stage procedure. For purposes of example, we show the procedure and program for the estimation of cost-constrained environmental allocative efficiency. [8] First, radial technical efficiency is measured by linear programming as follows:

$$\begin{aligned} & EFT(y_o, x_o) = \underset{\theta,\lambda}{Min}\, \theta \\ & \text{subject to} \\ & Y\lambda \geq y_o \\ & X\lambda \leq \theta x_o \\ & \lambda \geq 0 \end{aligned} \tag{16}$$

where x_o and y_o are, respectively, the N inputs and M outputs of the DMU_o. X and Y the input and output matrixes, N×K and M×K, of the K DMUs in the sample and λ is a vector K×1 for the impact of each sample unit on the shape of the efficient frontier.

After computing its technical efficiency score, we specify a technically-efficient input vector for the unit by scaling the original inputs:

$$x_{to} = \theta x_o \tag{17}$$

[7] For a comparison of the advantages and disadvantages of DEA with respect to stochastic models, see Simar and Wilson (2015, 2008).

[8] The remaining programs for the estimation of constrained efficiency measures in section 2.2 are run analogously. They are omitted to save space, but are available from the author upon request.

Starting from this technically-efficient input vector, we estimate the cost-constrained minimum emission level $E(y_o,a,w'x_{to})$ by means of the following program:

$$\begin{aligned}
&E(y_o, a, w'x_{to}) = \underset{x_{ce},\lambda}{Min}(a'x_{ce}) \\
&\text{subject to} \\
&x_{ce} \geq X\lambda \\
&y_o \leq Y\lambda \\
&w'x_{ce} \leq w'x_{to} \\
&\lambda \geq 0
\end{aligned} \tag{18}$$

where the solution, x_{ce}, is conditional to costs not exceeding the technically efficient cost $w'x_{to}$, for output level y_o.. Having determined the cost-constrained minimum emission, cost-constrained environmental allocative efficiency can be computed as specified in (18).

Note that in programs (16) and (18) the technology is assumed to yield constant economies of scale by leaving free positive weight λ of each sample DMU. This specification was selected because the production technology in the empirical case to be analyzed below exhibits constant economies of scale as implied by a Cobb–Douglas production function. [9] For the specification of technologies with other types of returns to scale, it is sufficient to introduce additional constraints on λ in the DEA model (Banker et al., 1984).

3 Empirical application

The proposed method was applied to a sample of greenhouse tomato farms in Almeria, Spain. The necessary data were collected in a survey conducted in 2010. Greenhouse horticulture creates a significant amount of pollutant emissions due to the use of nitrogen-enriched fertilizers (Torrellas et al., 2012). The following application of the efficiency model considers a single pollutant, nitrogen. [10]

The sample comprises of 105 conventional horticultural farms randomly selected from the total population of such farms in the Nijar area of Almería. Seven farms were dropped from the original sample due to incomplete responses and the remainder was reduced to 88 after filtering the data

[9] Note, also, that by specifying constant economies of scale, we are measuring the environmental efficiency of firms' production activities as a ratio between output or economic outcome and environmental damage, regardless of firm size. This way of addressing the problem appears coherent both with the social approach and the ecological efficiency approach (Kuosmanen and Kortelainen, 2005).

[10] Other MBP-based studies consider several different pollutants aggregated into a single environmental pressure index according to criteria fixed *a priori*.

and removing outliers (Chen and Johnson, 2010; Jahanshahloo et al., 2004; Pastor et al., 1999; Simar, 2003).

The survey data include individual quantities and values of a large number of inputs and outputs: land, equipment and machinery, expenditure on fertilizers and crop protection, variable expenditures (seed, energy, water, etc.) and quantities of 15 types of nitrogen-enriched fertilizers. To reduce the dimension of the DEA program, the data were aggregated into a single output and five inputs.

Tomatoes production was the main source of income of farmers (more than 80 % of farm revenue). Other vegetables crops (melon, water-melon and courgette) were of minus importance but not negligible. We have considered the possibility using the value of total farm production as an aggregate output. However, we found a very high volatility in vegetable prices which has an asymmetric effect across the sample farms. This makes inappropriate the use of values and the construction of output cross price index to deflate production values. Then we have decided to calculate an average price index of vegetables for each farm using the prices reported by each individual farmer. An implicit output quantity index is generated by the ratio of the value of production to the average price of vegetables. This procedure prevents the distortions of cost and environmental efficiency measures by random price variation or by the strictly commercial ability of farmers. However, inherent differences in the quality and composition of the output are not reflected in the quantity index and, thereafter, are no incorporated to the estimation of efficiency. We weighed this inconvenience and we considered that is lower in relation to the bias generated by the high volatility in prices.

Inputs were aggregated into 5 groups: hectares of land, annual work units (AWU) of labour, expenditure in pesticides, expenditure in fertilizers and “other inputs”. “Other inputs” is an aggregate of capital depreciation and other variable costs. Variable selection tests (Pastor et al., 2002) and input aggregation tests were run (Simar and Wilson, 2001) in order to determine input relevance and aggregation validity.

In the calculation of cost efficiency, land and family labour are treated as opportunity costs. This is done by multiplying the price per hectare of land in the area by the interbank interest rate and labour by the farm labour wage rate.

The nitrogen burden depends on the nitrogen content of soil and fertilizers. Flows of nitrogen from soil were calculated as the coefficients of atmospheric deposition and nitrate fixation by microorganisms taken from OECD (2001). The values for nitrogen content in each type of fertilizer were taken from the farm survey data. Given the large number of fertilizers employed by the sample farms we have aggregated the nitrogen content of fertilizers into a single input.

To reduce aggregation bias and ensure consistency between technical efficiency and the various overall (cost and environmental) efficiency measures [11], technical efficiency is estimated using two aggregators for fertilizer input: one is a costs aggregate and the other is a nitrogen content aggregate.

Table 1 displays some descriptive statistics for the data. The nitrogen per ha spread is wider than the cost spread and narrower than the output spread. Similarly, there is greater variability in nitrogen inputs than in farm land input.

Table 1. Descriptive statistics of the variables

	Average	**Variation coeff.**
Output quantity index	221.4	0.87
Inputs		
Land (ha)	1.9	0.67
Labour(AWU)	2.5	0.05
Fertilizer (€)	11077.8	0.97
Pesticides (€)	9461.3	0.94
Other (€)	28129.6	0.67
Cost (€)	78565.6	0.63
Nitrogen (kg)	1669.5	0.78

4 Results

The standard efficiency measures and the proposed decomposition of allocative efficiency are presented separately.

4.1 Standard cost and environmental efficiency measures

Using the dataset and the variables described above, we began by computing the standard efficiency scores proposed on section 2.1. These results are shown in Table 2. At first sight, the results reveal low levels of both economic and environmental efficiency in the sample farms. For example, the average score in cost efficiency (CE) is 55.89 %, which means that the average reduction in costs that is possible by improving management efficiency is 44.11%. This cost efficiency is attributable in similar measure to the technical efficiency (77.96 %) and to the cost allocative efficiency (71.01 %).

[11] Technical efficiency measures obtained using aggregated input costs are biased towards allocative efficiency (Färe et al., 2004). Aldanondo and Casasnovas (2015, 2014) show that aggregation bias is reduced by including several aggregates of different inputs, which not only ensures consistency between technical efficiency and different overall efficiency criteria (economic and environmental, for example) but also improves the accuracy of the estimator.

Table 2. Standard measures of cost and environmental efficiency

	Mean	S.D.	Min	Max
Technical efficiency (*TE*)	77.96	17.49	39.76	100.00
Cost allocative efficiency (*CAE*)	71.01	15.64	30.48	100.00
Cost efficiency (*CE*)	55.89	19.41	22.33	100.00
Environmental allocative efficiency (*EAE*)	55.01	14.78	24.55	100.00
Environmental efficiency (*EE*)	42.58	14.95	17.22	100.00

Analogously, the average environmental efficiency stands at 42.58 %, which shows that, if the sample farms were to use environmentally-safe fertilizers, they could reduce their nitrogen surplus by 67.42 % with no drop in production. The average environmental efficiency score can be decomposed into technical efficiency (77.96 %) and environmental allocative efficiency (55.01 %). These results show that one of the main causes of environmental inefficiency is the highly pollutant input mix used by farmers.

At this point, it is worth recalling that the technical efficiency score is an indicator of a farm's potential to achieve improvements in environmental and economic performance. Improving technical efficiency by proportionally reducing input quantities without reducing output would enable farms to reduce production costs and nitrogen emissions simultaneously by 22.04 %, whereas the allocative efficiency scores are independent. The cost allocative efficiency score indicates that costs could be reduced by a further a maximum of 28.99 % by changing the combination of inputs, disregarding the potential environmental impact of such a shift. Similarly, the environmental allocative efficiency score shows the maximum potential for farms to reduce nitrogen emissions (44.99 %) by adjusting the input mix, keeping constant output quantity and without considering the possible economic impact of that shift.

The results show that the farms perform better in cost efficiency than in environmental efficiency. These differences between environmental efficiency and farm costs can be explained in theoretical terms as the result of farmers' treating environmental impacts as externalities and failing to make them integral to their decision-making processes. The differences observed between the scores of the cost-allocative efficiency and the scores of the environmental allocative efficiency are consistent with this hypothesis, since we have found that the current combination of inputs in the sample farms is closer to the optimal cost mix than to the optimal environment mix.

However, not all substitutions between factors involve a conflicting choice between reducing costs and reducing emissions. Many of the farmers in the sample could opt for factor combinations that would improve their environmental performance with no cost increase. For example, 44 % of the sample farms combine inputs in proportions that are more pollutant than that used by the minimum cost unit and 7.3 % of the farms report more costly input combinations than the most environment-friendly combination. These results suggest that, in their current situation, there is an opportunity for these farms to improve in cost (environmental) allocative efficiency with no detriment to their environmental (cost) allocative efficiency. The allocative efficiency scores reported so far do not show what degree of improvement in allocative efficiency would bring benefits in both environmental and cost-saving terms, how much could be achieved without the need to trade one benefit off against the other, and how much would involve a negative trade-off between the two. The results in the next section highlight this distinction.

4.2 Decomposition of allocative efficiency

In this section, we calculate the new allocative efficiency measures proposed in section 2.2, which enable us to quantify the amount of improvement in allocative efficiency that can be achieved without the need for environmental-economic tradeoffs, and isolate it from the rest. The estimated efficiency scores are presented in Table 3.

Table 3. Decomposition of cost- and environment-oriented allocative efficiencies

Cost-oriented allocative efficiency	**Mean**	**S.D.**	**Min**	**Max**
Cost Allocative Eff. (*CAE*)	71.01	15.64	30.48	100.00
Environmental-Constrained Cost All. Eff. (*ECCAE*)	81.33	10.45	55.43	100.00
Joint Environmental Allocative Eff. (JEAE)	*91.11*	*15.00*	*45.93*	*100.00*
Polluting Cost All. Eff. (*PCAE*)	87.20	14.76	49.34	100.00
Environment-oriented allocative efficiency	**Mean**	**S.D.**	**Min**	**Max**
Environmental All. Eff. (*EAE*)	55.01	14.78	24.55	100.00
Cost-Constrained Cost All. Eff. (*CCEAE*)	78.12	14.69	42.70	100.00
Joint Cost Allocative. Eff. (JCAE)	*99.03*	*4.74*	*61.78*	*100,00*
Costly Environmental All. Eff. (*CEAE*)	70.42	14.11	53.86	100.00

The average environment-constrained cost allocative efficiency is 81.33 % and average joint environmental allocative efficiency is 91.11 %. This shows that the sample farms can make cost-saving adjustments to the input mix without increasing their nitrogen emissions. This allocative improvement would enable them, on average, to reduce their costs by a further 18.67 % and their nitrogen load by 8.89 %, from the technical efficiency level. If the aim is to reduce costs to the minimum, the average polluting cost allocative efficiency score (87.20 %) tells us that they can reduce costs by a further 12.80 % by reallocating factors of production, albeit to the detriment of their environmental performance.

Likewise, the allocative efficiency scores estimated in a context in which the aim is to reduce environmental damage while keeping costs below the technical efficiency target reveal an average nitrogen emission reduction potential of 21.88%, which can be achieved in conjunction with an average cost saving of 0.97% on the technically efficient level. Thus, the potential for reducing emissions through factor substitution is greatly diminished when there is reluctance to compromise on economic performance. Indeed, in order to minimize emissions per unit output, farms would have to reduce their nitrogen burden by a further 29.58 %, although this would increase costs.

Like the average efficiency scores, the individual efficiency scores also provide interesting information on the position of each farm on the cost and environmental efficiency frontier. The results show, for example, that only 5 % percent of the sample farms are allocatively efficient in terms of both costs and emissions. For these farms, therefore, any movement towards cost (emissions) reduction will involve a trade-off in the form of increased emissions (costs).

Closer examination of the individual efficiency scores reveals further ways of achieving efficiency gains. It is very important to discern which farms use an inputs mix that is so contaminant and costly that they have the opportunity to minimize cost improving its environmental performance or, more rarely, to minimize pollution burden by improving its cost. We show how the efficiency scores shed light on this issue in Table 4, where we present the most dramatic results in this respect, that is, those derived from the breakdown of cost allocative efficiency. The farms are divided into two groups. Group A represents the 44% of the sample farms that use proportions of inputs that are more polluting than those used by the minimum cost unit. Thus, the nitrogen load restriction is not effective when a firm is pursuing cost minimization. Not only that, but there is room for these farms to achieve environmental improvements while still seeking to optimize their costs. Group B represents the rest of the sample farms, including the efficient ones. The characteristic feature of these farms is that their technically efficient nitrogen load is lower than that of the most cost-efficient unit, showing that the nitrogen load restriction is effective under a cost-minimizing approach. [12]

[12] We note in this respect that, although some of these farms are located on the isoquant between the lowest-cost unit and the lowest-emissions unit, they are not necessarily cost- and environmentally- efficient in the Pareto sense. The reason for this apparent paradox could be that only two of the five specified inputs contain nitrogen. The same pattern emerges from sub-vector estimates of efficiency (Färe et al., 1994) obtained using fixed values for all non-nitrogen containing input factors. Having clarified this point, we avoid any further discussion, since it has no bearing on the conclusions of this study.

Table 4. Cost-oriented allocative efficiencies by farm position*

Group A, pollution outside the range of the efficient set values	**Mean**	**S.D.**	**Min**	**Max**
Cost Allocative Efficiency (*CAE*)	81.33	10.67	55.43	98.80
Environmental-Constrained Cost All. Eff. (*ECCAE*)	81.33	10.67	55.43	98.80
Joint Environmental All. Eff. (JEAE)	*78.17*	*16.63*	*45.58*	*98.74*
Polluting Cost Allocative Eff. (*PCAE*)	100.00	0.00	100.00	100.00
Group B, pollution between the range of efficient values	**Mean**	**S.D.**	**Min**	**Max**
Cost Allocative Efficiency (*CAE*)	63.53	14.41	30.48	100.00
Environmental-Constrained Cost All. Eff. (*ECCAE*)	81.45	10.28	61.59	100.00
Joint Environmental All. Eff. (JEAE)	*100.00*	*0.00*	*100.00*	*100.00*
Polluting Cost Allocative Eff. (*PCAE*)	77.92	13.05	49.34	100.00

* Group A represents the 44% of sample and Group B the 56% of the sample

The results reveal two clearly distinct groups and quantify their potential efficiency gains. By looking at the efficiency scores of group A, for example, we can see that the *ECAE* and *CAE* coincide and that all the farms qualify as efficient in terms of *PCAE* and inefficient in terms of *JEAE*. This corroborates the finding that it is in the interests of any farm in the group to could achieve joint economic and environmental benefits by using a cost-optimization approach. These joint efficiency improvements would consist of a potential average cost-reduction of 18.67 % and a potential average nitrogen load reduction of 21.83 %. The cost allocative efficiency scores of the farms in Group B, on the other hand, show that if they were to try to improve their cost allocative efficiency without compromising their environmental performance, they could reduce their costs by 18.55 %, which would place them at a point on the cost and environmental efficiency frontier between the least cost vertex and the least emissions vertex. To move from this point to the minimum cost point, they would need to reduce their costs by a further 22.08 %, but this shift would jeopardize their environmental performance. Thus, our proposed method further enables us to locate farms on the cost and environmental efficiency frontier, as well as to obtain direct measures of the joint cost and environmental allocative efficiency gains.

Thus, in synthesis, the results indicate that an important part of cost allocative efficiency and of nitrogen allocative efficiency could be attained by means of changes in the combination of inputs that would require no trade-off in either direction, and could lead to performance gains in both objectives. Cross-constrained indicators of allocative efficiency integrating both cost and environmental objectives have enabled us to bring to light this key aspect of the issue.

Overall, the above results show that improvements in technical efficiency and input allocative efficiency in the Almeria intensive greenhouse horticulture sector could lead simultaneously to substantial cost and environmental benefits. These findings illustrate the explanatory power of our methodological proposal and its capacity to measure the potential that exists for greenhouse vegetable producers to attain higher levels of economic and environmental sustainability by simultaneously addressing technical and allocative efficiency.

5 Discussion

One important feature of efficiency analysis based on the MBP is the focus on input allocation adjustments as a means to reduce both the costs and the pollution associated with production activities. The standard technical efficiency measures used in the MBP approach are consistent with this logic, since they indicate simultaneous economic and environmental benefits. The mutually-independent cost and environmental allocative efficiency indicators reported in the literature, by contrast, capture potential gains in only one of the two objectives. This paper contributes to the MBP approach by using a multi-objective constrained optimization method to define allocative efficiency measures that integrate both cost and environmental criteria. Since no previous measures of this type exist, we are unable to find any MBP-based efficiency frontier model with which to compare our work. However, papers by Lauwers (2009) and Van Meensel et al. (2010a, 2010b) compare allocative MBP efficiency scores, finding that approximately one half of the units in a Dutch pig-farm sample are more allocatively inefficient in terms of environmental objectives than the least-cost unit and that the other half use combinations of inputs that are intermediate between the least-cost unit and the least-emissions unit. In our sample, 44 % of the farms combine inputs in proportions that generate more emissions than the least-cost unit and are therefore more allocatively inefficient in environment terms. Van Meensel et al. (2010a, 2010b) identify the inefficient units and compute the positive economic and environmental trade-offs that could be gained by moving from the technical efficiency point towards the minimum cost point or the minimum emissions point. Our contribution is precisely to extend the Van Meensel et al. (2010a, 2010b) framework providing indicators of allocative efficiency that measure all the potential benefits.

In terms of empirical findings, the discovery of a low level of management efficiency in the Almería greenhouse sector is not strange in the context of agriculture, given that similar results have emerged from other analyses of the environmental efficiency of agricultural production systems in Spain and other countries. In a study using environmentally-adjusted production efficiency models, Aldanondo and Casasnovas (2014) find similar levels of environmental efficiency in the dryland viticulture sector in Navarra, Spain. MBP-based studies of nutrient use efficiency on Korean rice farms (Nguyen et al., 2012) and agricultural sectors in OECD countries (Hoang and Coelli, 2011) also report low efficiency levels.

As far as relative farm performance is concerned, an usual conclusion of MBP agricultural efficiency studies is that farms are more efficient in cost allocation than in the allocation of resources for environmental challenges. The ratio of the cost efficiency scores to the nitrogen efficiency scores in the present study is in line with that found in other studies (Hoang and Coelli, 2011; Hoang and Nguyen, 2013; Nguyen et al., 2012). One possible theoretical explanation for this is that farmers consider environmental impact of agricultural production as an externality that is not included in its utility function.

However, although our results confirm that farmers run their businesses with a cost-minimization approach, they also reveal that this is not the only reason for their low environmental efficiency levels. In this study, we have found that a large proportion of environmental allocative inefficiency is simply inefficiency in the Pareto sense, because it could be redressed without any detriment to farm economic performance. Nearly all (95 %) of the sample units have room to move further towards combinations of inputs that are both cheaper and less harmful for the environment. Our methodological proposal also enables us to bring to the fore the important fact that a significant portion of the environmental gains that the sample farms could achieve through improvements in allocative efficiency require no economic trade-off. We consider this another way in which analysis by the MBP approach is able to provide key decision-making information.

Finally, note that DEA is highly sensitive to data errors and dimensionality problems. This study includes various tests for outliers in order to remove data errors. With respect to the potential curse of dimensionality, a sample comprising of 88 observations could be too small to estimate technical efficiency with five inputs and one output using DEA. We could expand the sample by including farms of other produced areas, but for the sake of comparability we opted to compare farms from one homogenous agro climatic area rather than enlarge the sample by including farms from several different areas. Dimensionality problems can lead to an overestimation of technical efficiency and an underestimation of allocative efficiency. Thus, the use of aggregated inputs or outputs to reduce the number of variables might bias the technical efficiency index in the opposite direction by capturing some of the allocative inefficiency. As already noted, this study uses aggregated inputs to reduce the dimension of the problem of estimating technical efficiency. To check the sensitivity of the analysis to the aggregation of inputs we have run various statistical tests on the relevance of the variables and on the aggregation of inputs in DEA models.

6 Conclusion

Much of the environmental pressure generated by production activities originates from the flow of residuals of material inputs from the production process to the environment. One important finding of the MBP approach to environmental efficiency analysis is to show that addressing the overuse of inputs to increase technical efficiency is a sensitive strategy for environmental improvement and also brings firms economic benefits.

This paper underlines the important potential of management efficiency gains as a means to increase cost efficiency while also reducing environmental pressure, and makes a further step towards incorporating the MBP into environmental efficiency frontier models. Our contribution fits into the research area of joint costs and environmental efficiency analysis and defines new measures of input allocation efficiency, which has the potential to reduce both costs and environmental impacts. The constrained multi-criteria optimization method is chosen in order to accommodate costs, output, and environment in two allocative efficiency indexes which measure the simultaneous reductions that can be achieved in costs and environmental load, respectively, by altering the input mix in one direction or another. These measures enable us to determine a dual-criterion efficiency frontier, taking into account both economic costs and environmental impact, against which to plot the farm sample data. The resulting technical efficiency and allocative efficiency indexes, jointly incorporating cost and environmental criteria, are estimated by means of DEA techniques.

The measures presented in this paper enable the break-down of environmental allocative efficiency into two components: one representing environmental performance gains without increased costs, the other, representing those that involve an economic trade-off. We also provide estimates of the joint benefit of reduced costs and less environmental impact obtained by increasing environmental allocative efficiency. Cost allocative efficiency is broken down analogously. Although the interest of this paper is to make a distinction between technical efficiency and allocative efficiency, the proposed method could be applied directly to determine overall ecological efficiency. We leave this exercise for future research.

The efficiency measures described above are estimated for a sample of tomato production units in Almeria, Spain. In terms of standard efficiency measures, 77.97 % are technically efficient; 44 % are allocatively efficient with respect to the environment; and 55 % are cost efficient.

In terms of allocative efficiency, our measures show that changes to the input mix can simultaneously address cost reduction and care for the environment. Not all allocation efficiency improvements involve an economic-environmental trade-off. On average, farmers can improve their allocative efficiency by opting for combinations of inputs that simultaneously reduce their costs by 18.67 % and their nitrogen load by 8.89% or, alternatively, by selecting combinations of inputs that enable them to reduce their nitrogen load by 21.88 % while still reducing their costs by 0.97 %. In order to reach the point of least environmental impact, however, they would need to reduce their nitrogen load by a further 29.58 % and face the associated costs. Our proposed efficiency measures have thus enabled us to reflect upon the ample room that exists for improving environmental efficiency with no increase (and even a potential reduction) in production costs. This information therefore has implications for policy makers seeking to improve the environment without compromising industrial competitiveness.

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Appendix A. Graphical illustration of cross constrained allocative efficiency

The Figure 2 describes the same DMUs as Figure 1 and will be useful to illustrate the efficiency measures.

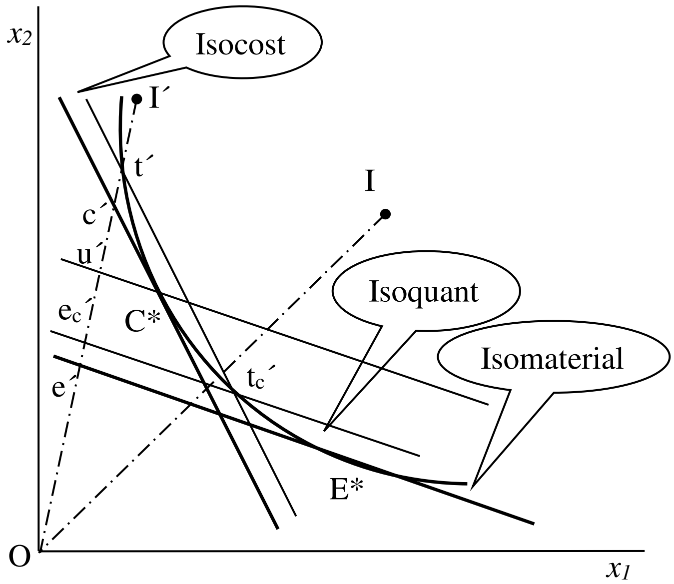

Figure 2. Integrated measures of allocative efficiency

Unit I in the diagram represents a Pareto allocative efficient DMU. Once it achieves technical efficiency it cannot improve its allocative efficiency without an economic-environmental trade-off. So this unit is ranked as efficient by the above-defined cross- constrained allocative efficiencies.

Unit I´, on the other hand, is Pareto allocative inefficient. Its projection on the isoquant, t´, produces more emissions than the minimum cost unit, C*. In this case, the environment-constrained and cost allocative efficiency measures coincide and are plotted as the ratio Oc´/Ot´. Furthermore, a shift from t´ to C* to improve cost allocative efficiency implies a joint environmental allocative efficiency gain (Ou´/Ot´).

For the environment-oriented allocation efficiency, we can note in the diagram that t´ could not reach the minimum emission point E* on the isoquant without increasing costs. Starting from t´, the best environmental performance that can be achieved without increasing costs is given by point t_c´ on the isoquant. In this case, non-constrained environmental allocative efficiency (Oe´/Ot´) is split into two components: cost-constrained environmental allocative efficiency (Oe_c´/Ot´) and costly environmental allocative efficiency (Oe´/Oe_c´). Meanwhile, joint cost allocative efficiency (Oe´/Oe´) is unitary, and the unit cannot reach the vertex of least emissions by reducing costs.