ECO-EFFICIENCY ASSESSMENT WITH THE JOINT USE OF CARBON FOOTPRINT (CF) AND DATA ENVELOPMENT ANALYSIS (DEA): THE CASE OF CHILEAN ORGANIC BLUEBERRIES ORCHARDS

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ABSTRACT

The evaluation of environmental impacts and the efficiency of farming are key factors in the export of products to the world. Chile is the main blueberries producer in the southern hemisphere. Therefore, this paper aims at assessing the eco-efficiency of five organic blueberry farms throughout three growing seasons with the joint use of Carbon Footprint (CF) and Data Envelopment Analysis (DEA). The Carbon Footprint is obtained through the Life Cycle Assessment (LCA) approach. Once the CF is determined for the blueberries orchards, we use DEA to assess the eco-efficiency of the orchards-season. Due to the reduced number of DMUs, different variables were taken into account, with two different returns to scale models, CCR and BCC. The results indicate that there is only one efficient orchard, and four deemed inefficient in all scenarios. For inefficient orchards, benchmarks and targets are obtained that indicate dramatic reductions of the CF.

KEYWORDS. Carbon Footprint (CF). Data Envelopment Analysis (DEA). Blueberries Orchards.

Paper topics: AG&MA, DEA

1. Introduction

The growing economic activity in Chile has led to improvements in the country's development rates. However, this growing could lead to problems from an environmental point of view because of the energy consumption in Chile, which is still dominated by non-renewable energy sources such as oil, natural gas and coal [MMA 2013]. By 2007, the worldwide contribution of Chile on gases that will impact on the global warming (greenhouse gas emissions - GHG) was equivalent to only 0.26%. Taking into account only CO2 emissions from combustion of hydrocarbons, Chile ranks position 44, from highest to lowest, among 186 countries [MMA 2011]. However, during the period 1984 - 2006, net emissions of GHG significantly increased from nearly 7 to 60 million tonnes of CO2 equivalent, being carbon dioxide (CO2) with the highest share (65%), followed by methane (CH4) (21%) and nitrous oxide (N2O) with 14% [MMA 2013]. Furthermore, the International Energy Agency (IEA) states that GHG emissions have increased by 152.4% for the period 1990 to 2012 [IEA 2014].

Within the economic development of Chile, agriculture has played an important role in recent decades owing to the internationalization of its products [ODEPA 2014]. In this context, according to the Foreign Trade Indicators of the Central Bank of Chile, the agricultural and livestock sector exports accounted for 15.2% of total exports in 2014, where agricultural products accounted for 88.7% of the sector. Highlighting the fruit category (US $ 6,348.5 million), followed by wine (US $ 1.856 million), seeds (US $ 430.8 million) and vegetables (US $ 297.3 million) [Banco Central 2014]. Specifically, blueberries are the fruit with the most productive area of the country, extending from the Atacama region to Los Lagos [ODEPA 2013a]. Concerning the blueberries production in the world, the largest area dedicated to this product is in North America (US and Canada) with 57% of the total, followed by South America (23%), Europe (11%), Asia Pacific (8%) and Africa 1%. In South America, Chile has the most productive area with 73%, far from Argentina and Uruguay have only 22% and 4.3% respectively [ODEPA 2013a]. In Chile, this relevance lies in the variety on the market: fresh, frozen, dried, canned and juice. Concerning the fresh blueberries type, Chile is the world's leading exporter with a share of 30.9% of the market [ODEPA 2013b]. The Chilean regions with greater participation in blueberries production are: Bío-Bío (33%), Maule (20%), Araucanía (12%), Los Lagos (12%), O'Higgins (7%) [ODEPA 2013b].

On the other hand, farming leads to implications and impacts on environmental sustainability, including contribution to GHG emissions [Page et al. 2011], energy use [Girgenti et al. 2013], water consumption [Nuñez et al. 2013], land conversion and consequent loss of biodiversity [Vitousek et al. 1997], the use of pesticides, herbicides and fungicides [Cross and Edwards-Jones, 2006; Mamy et al 2010]. In addition, there is a low resilience of ecosystems, which enforces sustainable management of natural resources through rational use of resources in agriculture [Strano et al. 2013]. Therefore, there is a need to assess environmental impacts and the use of resources in this activity, as global markets show interest in negotiating with companies whose concerns lies not only in the quality of products, but in the manufacturing processes and respect for environmental and social standards. Following this, several developed countries impose regulations that opt for sustainable production, in which has become a key factor for exporters in emerging economies such as Chile [ProChile 2015]. In light of this, the concept of eco-efficiency plays a key role in the production activity. For the World Business Council for Sustainable Development (WBCSD) in [Schmidheiny 2000], this concept is defined as the delivery of goods and services, with a gradual reduction of environmental impacts, that is, deliver greater value but with less impact, thus it is simultaneously an efficiency from both an economic and ecological perspective.

A tool to quantify and assess the environmental impacts throughout the life cycle of a product is the Life-Cycle Assessment (LCA) [Vázquez-Rowe et al. 2010]. The Carbon Footprint is considered a part of the LCA. The Carbon Footprint (CF) measures the GHG emissions over the whole life of a product (goods or services).

On the other hand, Data Envelopment Analysis (DEA) is a non-parametric method that measures the relative efficiency of a number of units considered homogeneous, called decision-taking units (DMU), which perform similar productive activities [Banaeian et al. 2012]. The link between LCA and DEA is proposed by [Lozano et al. 2009] to compare the operational and environmental performance of entities operating in the aquaculture area, indicating that the data obtained through the Life Cycle Inventory (LCI), including CF, may be considered for additional efficiency assessment through DEA. This approach has been used primarily to assess agricultural systems [Vázquez-Rowe and Iribarren 2015].

In Chile, there is little research regarding the measurement of productive performance of agricultural activity, specifically any for growing blueberries from the operational and environmental terms. In particular, there is no research that integrates LCA and DEA techniques to assess the eco-efficiency. LCA and DEA will be used successively, the first one to determine the life-cycle inventory (specifically CF) and, once the data is obtained, DEA models will be used to assess the eco-efficiency of Chilean blueberry orchards. This is the aim of this study, which also presents a new application for the joint use of these tools to identify best practices in sustainable production from an operational and environmental point of view, and also their efficiency scores. In this way, it is possible to set targets for the reduction of emissions and, consequently, the environmental impact of agricultural production. The article is divided as follows: Section 2 presents the literature review; Section 3 shows the methodology used; Section 4 shows the results, while Section 5 presents a discussion and final comments regarding this paper.

2. Life Cycle Assessment (LCA) and Data Envelopment Analysis (DEA)

LCA is a methodology for assessing the environmental impacts of products and services throughout the supply chain, from the extraction of raw materials to its use or disposal. So, it has emerged as a tool for estimating the environmental impacts of a product or process [Lozano et al. 2009], where one of the impacts calculated is the Carbon Footprint (CF). This tool has been implemented in a wide range of agricultural activities [Blengini and Bust 2008; Cappelletti et al. 2010; Strano et al. 2013; Lo Giudice et al. 2013; Yan et al. 2013; Keyes et al. 2015]. While the LCA importance in estimating potential environmental impacts is unquestionable, it relies entirely in the quality of data, so in the presence of a high number of units that are needed for the inventory, it would present important differences. In this case, one alternative is to present the outcomes as average values that may carry high variability, that is, significant standard deviations. The other alternative is to develop LCA for each individual, which the joint use of other tools for data analysis that would help interpret results [Lozano et al. 2009].

DEA [Charnes et al. 1978] is a non-parametric tool that uses linear programming to evaluate the efficiency of organizational units, called DMUs (Decision Making Units) that use multiple resources, called inputs, which produce multiple products, called outputs. A DMU is efficient if its score is 1 and inefficient otherwise. Besides the efficiency scores, targets and benchmarks for inefficient DMUs are set in order to become efficient. This is done by defining a best-practice frontier through linear programming. This way it provides a tool for planning and management in order to improve efficiency. Many models have been proposed to assess the efficiency of DMUs, to choose among them it should determine in which scale the DMUs operate, constant or variable are the most frequent. Simply put, in the first case, DMUs are said to be working at the optimum scale, without taking into account size or scale, or in competitive market, also because the increase in inputs produces a proportional increase in outputs and this proportion is constant. If these conditions are not present, DMUs operate at variable returns to scale. Also, an orientation has to be defined. In input oriented models the objective is to minimize the use of inputs (resources), while maintaining outputs (production). Whereas in the output oriented models the objective is to maximize the outputs (products), while maintaining the consumption of inputs (resources). Some models aim to minimize inputs and maximize outputs simultaneously (see [Lozano et al. 2009]). Other models take into account different settings or circumstances, see for example [Cooper et al. 2007]. DEA has been applied to a variety of fields including agricultural production, using variables such as energy, labour, machinery, fuel, chemicals, fertilizers, irrigation water, electricity, among others [Khoshnevisan et al. 2013; Mohammadi et al. 2011]. Applications can be found in [Khoshnevisan et al. 2013], [Khoshnevisan et al. 2014], [Nabavi-Pelesaraei et al. 2014], [Mobtaker et al. 2012], [Banaeian et al. 2011, 2012], among others.

The first publication integrating LCA and DEA methodologies was conducted by [Lozano et al. 2009] to compare the operational and environmental performance of similar operating companies in the aquaculture sector. They highlighted that introducing LCI data in the DEA modelling has the advantage of detecting and removing technical inefficiencies that are the source of unnecessary environmental impacts. They proposed a three step approach to implement the joint use of LCA and DEA. [Vázquez-Rowe et al. 2010] proposed a five step approach for the joint use of the approaches. These approaches have been developed primarily to assess agricultural systems [Vázquez-Rowe and Iribarren 2015]. However, recently it has been used as a tool for the analysis of other activities such as assessment of wind farms and the "emerging" useful energy systems [Iribarren et al. 2014]. Subsequent research has classified the use of LCA and DEA in different approaches [Vázquez-Rowe and Iribarren 2015] and also been used in a variety of areas by many researchers [Lozano et al. 2010; Iribarren and Vázquez-Rowe 2013; Iribarren et al. 2014; Mohammadi et al. 2014; Vázquez-Rowe et al. 2010; Avadi et al. 2014; Barba-Gutierrez et al. 2009; Lozano et al. 2011; Sanjuan et al. 2011; Jan et al. 2012; Ramos et al. 2014] among others). Concerning only CF, [Vázquez-Rowe and Iribarren 2015] presented a variation of the five step approach for CF and DEA for energy policy making.

In this paper, LCA, specifically CF, and DEA are used in an approach similar to the proposed by [Lozano et al. 2009] which is depicted in Figure 1 [Irribarren et al. 2010].

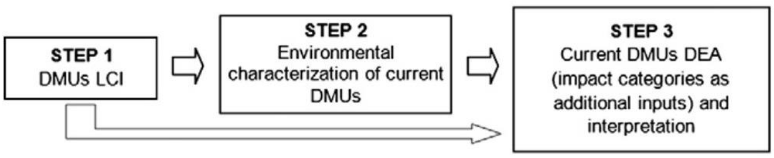

Figure 1. Three step approach for LCA + DEA

3. Methodology

Following the application procedure for DEA proposed by [Golany and Roll 1989], we will first define and select the DMUs for the analysis, then select variables for the analysis and, finally, we apply the DEA models and analyse the outcomes. Both DMUs' definition and variables selection may be performed after analysing the available data.

The data used for this study belong to the central regions of Chile, concentrating main organic producers of blueberries, such as the Bío-Bío and Maule regions. Data from five blueberry producers (identified by A, B, C, D, E) are obtained from three harvest seasons, 2011/2012, 2012/2013 and 2013/2014. As it was not possible to obtain all data for the 2011/2012 season for producer A, that season for this producer is not considered [Cordes 2014]. Therefore, in order to assess the eco-efficiency of the five orchards and verify their evolution through the different seasons, this study will assess the efficiency of 14 DMUs: A-12/13, A-13/14, B-11/12, B-12/13, B-13/14, C-11/12, C-12/13, C-13/14, D-11/12, D-12/13, D-13/14, E-11/12, E-12/13 and E-13/14.

Concerning the variables, the first step is the application of Life-Cycle Assessment (LCA) to each season of the five producers to determine the CF of the production of blueberries. Using Life Cycle Inventory (LCI) performed by [Cordes 2014], in which the required data is collected to analyse the agriculture system, inputs and outputs need to be identified and selected for DEA. After analysing the data, resources such as organic fertilizers, organic pesticides, use of energy (diesel, electricity, gasoline, etc.) and size of the orchard are identified as inputs. As outputs, total production and waste. Using LCA, the CF achieved by each orchard is estimated each season. The functional unit (FU) used was 1 kg of harvested blueberries, and the software GaBi 4 is used for modelling the agricultural system. Table 1 contains the description of each variable in the LCI.

Table 1. Variables considered in the study

Variable	Description
Orchard Size	Number of hectares used for growing blueberries
Organic fertilizers	Total amount and type of organic fertilizers used in cultivation, in kilograms
Organic Pesticides	Total amount and type of organic pesticides used in cultivation, in kilograms
Energy	Total amount of fossil fuel (diesel, gasoline, Two-stroke) and electrical energy used for production, in MJ
Production	Total amount of blueberries produced, in kilograms
Waste	Total amount of plastics (polypropylene and polyethylene) waste derived from blueberry production, in kilograms
Blueberry Carbon footprint	Total amount of direct and indirect greenhouse gases emitted into the atmosphere from activities of blueberries production (in kilograms of CO_2-e)

Once performed the LCA, the set of variables and their values are obtained to carry out the implementation of data envelopment analysis (DEA) (Table 2).

Table 2. Data Set for DEA

Orchard-Season	DMU	Orchard Size (Ha)	Fertilizers (Kg/season)	Pesticides (Kg/ season)	Energy (MJ/ season)	Production (Kg/ season)	Waste (Kg/ season)	Carbon footprint (Kg CO_2-e/season)
A-12/13	1	10.8	9,248	217	78,832	104,000	136,344	32,240
A-13/14	2	10.8	7,094	784	87,809	106,000	111,936	25,440
B-11/12	3	13.8	29,857	2128	163,162	123,800	196,842	55,710
B-12/13	4	13.8	17,886	88	150,497	162,200	136,735	47,038
B-13/14	5	10.6	7,611	140	121,043	125,100	96,327	36,279
C-11/12	6	10.7	9,408	16	17,661	58,580	7,844	16,402
C-12/13	7	10.7	9,280	14	17,734	51,763	4,296	17,599
C-13/14	8	10.7	11,567	16	17,793	35,408	23,405	43,198
D-11/12	9	7.5	850	158	131,343	62,000	19,437	18,600
D-12/13	10	7.5	1,176	209	131,580	85,000	23,384	19,550
D-13/14	11	7.5	2,069	218	129,126	52,000	54,688	19,240
E-11/12	12	8.5	46,303	624	170,200	85,000	89,165	91,800
E-12/13	13	8.5	47,172	47	171,367	102,300	120,203	50,127
E-13/14	14	8.5	39,119	790	135,972	82,300	129,869	40,327

Before the use of any DEA model, and in order to obtain a good discrimination (distinguishing the efficient from the inefficient orchards and differences among inefficient ones), it is necessary to determine the total amount of variables (inputs and outputs) to choose for the efficiency assessment. At this moment, there are 14 DMUs and also 7 variables from the LCI. This is not recommended, since most authors agreed that the number of DMU should be three times the number of variables, the rule of thumb [Cooper et al. 2007]. In order to determine if there is a high degree of dependence of variables and to select the most representative variables, a correlation analysis among variables is performed. Table 3 shows the correlation coefficients indexes among variables obtained.

Table 3. Coefficient Correlation Indexes

	Orchard Size	Fertilizers	Pesticides	Energy	Production	Waste	Carbon footprint
Orchard Size	1,000	-	-	-	-	-	-
Fertilizers	0,030	1,000	-	-	-	-	-
Pesticides	0,365	0,361	1,000	-	-	-	-
Energy	-0,170	0,515	0,406	1,000	-	-	-
Production	0,558	0,251	0,324	0,571	1,000	-	-
Waste	0,486	0,535	0,668	0,602	0,775	1,000	-
Carbon Footprint	0,175	0,807	0,382	0,529	0,346	0,522	1,000

The correlation suggests that the variables with greater dependence correspond (as expected) to Pesticides, CF, Production and Waste and Energy, which would be five variables for the 14 DMUs, this is within the recommended number of variables. However, aware of the importance of each variable in the assessment of the orchards eco-efficiency, not only these five variables will be considered. Therefore, various scenarios will be evaluated, varying the variables in each scenario. We will also consider four variables scenarios following the rule of thumb mentioned previously.

Next, a DEA model must be chosen for this analysis. In this study, both CCR [Charnes et al. 1978] and BCC [Banker et al. 1984] models will be used with the different scenarios. This will help in defining efficient DMUs taking into account constant and variable returns to scale with the different scenarios, and also to analyse if it is possible to remove some of the variable if it does not contribute to the assessment of eco-efficiency. Moreover, the selected orientation for models will be to outputs. This will maximize production, which follows in part the definition of eco-efficiency (WBCSD in [Schmidheiny 2000]). Moreover, Waste and CF are undesirable results of the agricultural activity (production of blueberries), therefore they will be treated as undesirable outputs, as called in DEA, which are outputs or results of the process whose reduction is required. In order to efficiently work with these variables, they will be treated with an indirect approach [Scheel 2001], where the inverse of the variable is used as output. In this model, orienting to outputs will maximize production and minimize waste and carbon footprint simultaneously.

Hence, the envelopment formulation for the output oriented CCR model is presented in (1). In this model, ϕ_o is the increasing factor of the outputs j which this model maximizes. If the observed DMU is efficient, ϕ_o will be equal to 1. If the observed DMU is inefficient, ϕ_o will be greater than 1. λ_k is the intensity or the contribution of a DMU k to the efficient projection of the observed DMU for each of the inputs i (in the first set of restriction) and each of the outputs j (in the second set of restrictions).

$$
\begin{aligned}
& Max\ \phi_o \\
& subject\ to \\
& \sum_{k=1}^{n} x_{ik}\lambda_k \leq x_{io}, \quad \forall i \qquad\qquad (1) \\
& \sum_{k=1}^{n} y_{jk}\lambda_k \geq \phi_o y_{jo}, \ \forall j \\
& \lambda_k \geq 0,\ \forall k;\ \ \phi_o \in \Re
\end{aligned}
$$

The BCC model is obtained by adding restriction (2) to the model (1), which guarantees the convexity and taking into account variable returns to scale. For more details see [Cooper et al 2007]. The software IBM ILOG CPLEX v12.6 is used to implement the DEA models.

$$\sum_{k=1}^{n} \lambda_k = 1 \qquad (2)$$

4. Results

The CCR and the BCC models were applied to all scenarios. A summary of results for the different scenarios are depicted in Table 4.

Table 4. Variable used in each scenario and results

Inputs	Outputs	DEA model	N° efficient DMUs	N° inefficient DMUs	Efficient DMUs	Inefficient DMUs
- Size - Fertilizers - Pesticides - Energy	- Production - Carbon footprint - Waste	CCR	9	5	1-2-4-5-6-7-9-10-13	3-8-11-12-14
		BCC	10	4	1-2-4-5-6-7-9-10-11-13	3-8-12-14
- Fertilizers - Pesticides - Energy	- Production - Carbon footprint - Waste	CCR	8	6	1-2-4-5-6-7-9-10	3-8-11-12-13-14
		BCC	8	6	1-2-4-5-6-7-9-10	3-8-11-12-13-14
- Fertilizers - Pesticides - Energy	- Production - Carbon footprint	CCR	8	6	1-2-4-5-6-7-9-10	3-8-11-12-13-14
		BCC	8	6	1-2-4-5-6-7-9-10	3-8-11-12-13-14
- Size - Fertilizers - Energy	- Production - Carbon footprint	CCR	8	6	1-2-4-5-6-9-10-13	3-7-8-11-12-14
		BCC	10	4	1-2-4-5-6-7-9-10-11-13	3-8-12-14
- Size - Pesticides - Energy	- Production - Carbon Footprint	CCR	9	5	1-2-4-5-6-7-9-10-13	3-8-11-12-14
		BCC	10	4	1-2-4-5-6-7-9-10-11-13	3-8-12-14
- Fertilizers - Energy	- Production - Carbon Footprint - Waste	CCR	5	9	2-6-7-9-10	1-3-4-5-8-11-12-13-14
		BCC	8	6	1-2-4-5-6-7-9-10	3-8-11-12-13-14
- Pesticides - Energy	- Production - Carbon footprint - Waste	CCR	2	12	6-7	1-2-3-4-5-8-9-10-11-12-13-14
		BCC	4	10	4-6-7-10	1-2-3-5-8-9-11-12-13-14
- Size - Energy	- Production - Carbon footprint	CCR	8	6	1-2-4-5-6-9-10-13	3-7-8-11-12-14
		BCC	9	5	1-2-4-5-6-9-10-11-13	3-7-8-12-14
- Fertilizers - Energy	- Production - Carbon footprint	CCR	4	10	2-6-9-10	1-3-4-5-7-8-11-12-13-14
		BCC	8	6	1-2-4-5-6-7-9-10	3-8-11-12-13-14
- Pesticides - Energy	- Production - Carbon footprint	CCR	2	12	6-7	1-2-3-4-5-8-9-10-11-12-13-14
		BCC	4	10	4-6-7-10	1-2-3-5-8-9-11-12-13-14

In this Table, only when considering all the variables five Orchards-Season with the CCR model and four with the BCC model were inefficient. This scenario does not provide enough discrimination when considering making a ranking from best to worst. Additionally, the high efficiency scores allow reduced improvements in Production, Waste and CF.

On the other hand, the most discriminating scenarios are two, which are highlighted in Table 4. The first one is the five variable case mentioned previously, Pesticides and Energy as inputs and Production, CF and Waste as outputs. The second case is a four variable scenario case, which does not only include Waste. Both scenarios provide the same efficient and inefficient Orchard-Seasons. For this reason, we have chosen the four case scenario, a "lean" model, and its results for both the CCR and BCC models are depicted in Table 5.

Table 5. Efficiency indexes for four variables scenario

Orchard - Season	DMU	Efficiency index CCR Model	Efficiency Index BCC Model
A-12/13	1	39,77%	97,83%
A-13/14	2	36,39%	95,80%
B-11/12	3	22,88%	78,37%
B-12/13	4	51,55%	100%
B-13/14	5	31,15%	90,50%
C-11/12	6	100%	100%
C-12/13	7	100%	100%
C-13/14	8	61,01%	61,05%
D-11/12	9	14,23%	92,82%
D-12/13	10	19,47%	100%
D-13/14	11	12,14%	86,17%
E-11/12	12	15,06%	52,40%
E-12/13	13	60,64%	99,37%
E-13/14	14	18,25%	67,42%

For this scenario, targets for the BCC model, levels to be achieved by an inefficient DMU (orchard-season) to be efficient, for the undesirable output, CF are shown in Figure 2. Furthermore, Figure 3 shows targets for blueberries Production for each orchard-season.

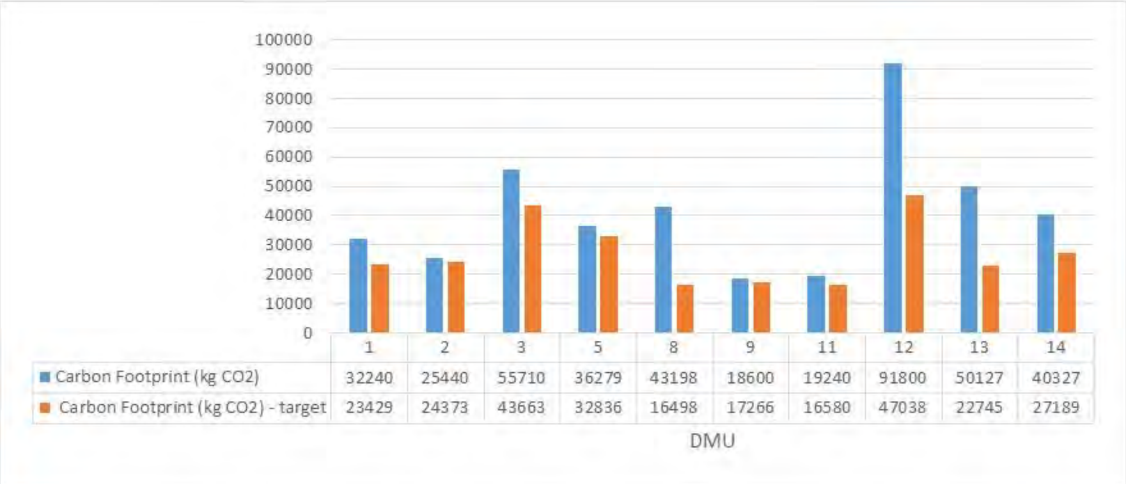

Figure 2. Targets for the variable CF

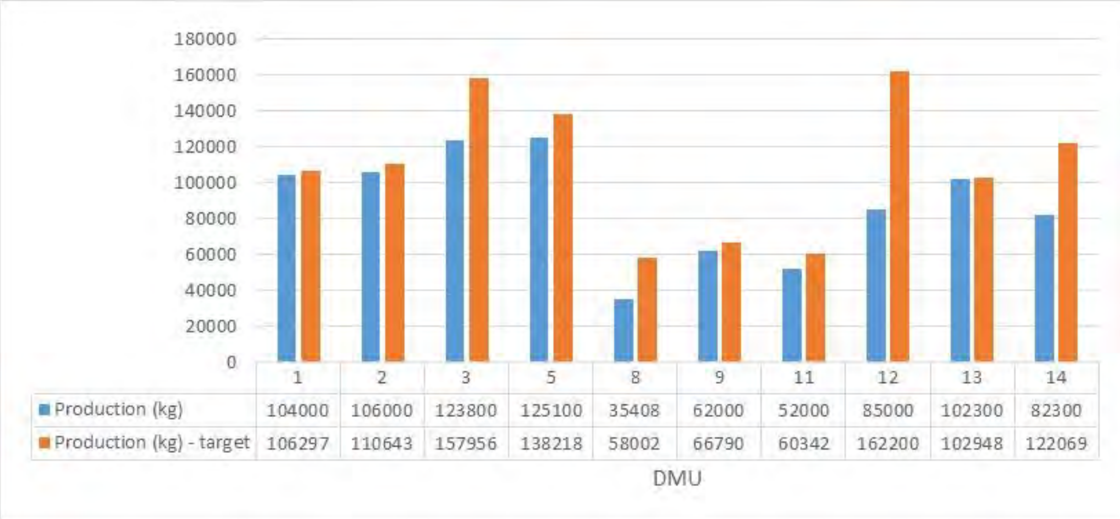

Figure 3. Targets for variable Production

5. Discussion and Final Comments

The CCR and the BCC model were both applied to the 14 DMUs (orchards-season) with different combinations of inputs and outputs. As expected the CCR efficiency indexes were lower than the BCC's, allowing to stablish a ranking of orchards-season due to the increased discrimination. However, this study does not suggest that the CCR model is the appropriate model to be used when assessing the eco-efficiency of blueberries orchards. First, the CCR model requires constant returns to scale, which means that an increase in inputs will produce a proportional increase in outputs and this proportion is constant independent of the size or scale in which the DMU operates. In this case, BCC model seems adequate as there is no guarantee that such constant proportion exist. Second, differences in size and scale of orchards, the BCC model takes into account these differences in size, scale and operation. Nevertheless, the use of the CCR model was interesting because it allows to verify the efficiency scores when considering that all orchards are operating at the optimum scale. Moreover, if all DMUs were working in a competitive market, then it could be assumed that they work at their optimal scale and the CCR model would have to be used [Banker et al. 1984]. Thus, CCR was also used to identify orchards-season operating under the assumption of perfect market competition.

Different scenarios were tested due to the reduced number of DMUs, instead of just choosing the most correlated variables. The different scenarios approach gave us additional advantages. First, it gave us the opportunity to verify what happens all variables are taken into account (five or four at a time) and what are the outcomes in the efficiency scores and therefore the targets. Second, it allowed us to verify which DMUs are always efficient and the one that are always inefficient. And lastly, it allowed us to verify two scenarios with nearly identical results. Specifically, the results indicate that DMU 6 (Orchard C-season 11/12) is the only one that appears efficient in all scenarios (with different variables), followed by DMU 10 (Orchard D-season 12/13) which is considered efficient by 90%. On the other hand, DMUs 3 (Orchard B-season 11/12), 8 (Orchard C-season 13/14), 12 (Orchard E-season 11/12) and 14 (Orchard E-season 13/14) are considered inefficient in all scenarios, so they can be considered fully and truly inefficient.

Among the different variables used, Orchard Size has a unique characteristic, which is to be constant for each orchard in the three seasons (except for the last season of the producer B). Therefore, the inclusion in the assessment of efficiency is debatable in this study because it does not add additional and important information that influences the efficiency of orchard throughout the different seasons. Also, its inclusion implies on more DMUs turning efficient (as another variable is included) which does not allow adequate discrimination. Consequently, the inclusion of this variable, though it is a very used variable in other DEA studies, is not recommended in this study. Besides this variable does not affect CF.

As mentioned, results when using the most correlated 5 variables (Pesticides, Energy, Production, Waste and CF) are the same (efficient and inefficient orchards) to those obtained when using 4 variables (Pesticides, Energy, Production and CF). Moreover, when using only four variables the discrimination among DMUs slightly increases. However, the efficiency scores are very similar for both scenarios, for the CCR and BCC model, the largest difference being lower than 1%.

Concerning targets for inefficient DMUs, as expected, those obtained by the CCR model are more demanding than those obtained by the BCC. Again, the targets chosen to be used depend on the market conditions and scale. However, it can be said that both targets may be used as a way to achieve efficiency in two stages, first BCC targets and then CCR targets, taking into account scale and then market conditions.

In this paper the use of a result form the LCA, CF, was used in DEA modelling, which ads and environmental component to the operational efficiency evaluation. As mentioned earlier in this paper, DEA solves problems that arise in LCA when dealing with different or a high number of units, allowing to score eco-efficiency and identify benchmarks. For future works, other variables that affect eco-efficiency will be considered and also using other DEA models to consider simultaneously the reduction of inputs and increase of outputs.

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