IDENTIFYING EFFICIENT AGRICULTURAL PRACTICES IN CHILEAN VINEYARDS THROUGH ECO-EFFICIENCY WITH A CF+DEA METHOD

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RESUMO

A atividade agrícola tem impacto na sustentabilidade ambiental, em que a medição a eficiência dessa atividade e a identificação das melhores práticas é de suma importância. Assim, a definição eco-eficiência (produzir mais com menos recursos e diminuindo os impactos ambientais) desempenha um papel fundamental. Nesta pesquisa, a eco-eficiência das práticas de um grupo de vinhedos na região central do Chile é avaliada utilizando o método Carbon Footprint (FC) e a Análise Envoltória de Dados (DEA), CF + DEA. Depois de realizar da avaliação do ciclo de vida dos vinhedos, o CF é determinado. Os dados obtidos são utilizados nos modelos CCR e BCC para avaliar sua eco-eficiência e identificar melhores práticas, para os vinhedos ineficientes são determinadas metas a serem atingidas, a fim de implementar planos de melhoria em sua busca por práticas agrícolas mais sustentáveis. O CF alvo é usado posteriormente para determinar mudanças no uso dos recursos que contribuem para a CF.

PALAVRAS CHAVE. Eco-eficiência, LCA+DEA, práticas em agricultura.
Tópicos DEA, AG&MA – PO

ABSTRACT

The agricultural activity has impact on environmental sustainability, thus measuring the efficiency of this activity and identifying the best practices is of paramount importance. In this sense, the definition eco-efficiency (producing more with fewer resources and decreasing environmental impacts) plays a fundamental role. In this research, we assess the eco-efficiency of the practices of a group of vineyards in the central region of Chile using the Carbon Footprint (CF) and Data Envelopment Analysis (DEA) method, CF+DEA. After a Life Cycle Assessment (LCA) of the vineyards is performed, the CF is determined. We use both the CCR and BCC models to assess their eco-efficiency, to identify best practices, for those inefficient, targets to be reached are set, to implement improvement plans in their search for more sustainable agricultural practice. The target CF is used later to determine changes in the use of resources that contribute to the CF.

KEYWORDS. Eco-efficiency. LCA+DEA. Agricultural practices.
Paper topics DEA, AG&MA – PO

1. Introduction

In the last decades, the agriculture has taken an important place in the economic development of Chile (ODEPA, 2014). 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).

Conversely, the agricultural activity leads to implications and impacts on environmental sustainability. As (Rebolledo-Leiva *et al.*, 2017) stated, these impacts include contribution to emissions of greenhouse gases (Page, 2011), use of pesticides, herbicides and fungicides (Cross and Edwards-Jones, 2006; Mamy *et al.*, 2010), among others. Furthermore, there is a request for a rational use of resources in agriculture, with a sustainable management, due to a low resilience of ecosystems (Strano *et al.*, 2013). Additionally, global markets are favouring products from sustainable production or processes, with respect for environmental and social standards, especially for export products. In this way, assessing the eco-efficiency in the production activity has been of increasing concern, following the Business Council for Sustainable Development (WBCSD) for eco-efficiency, that means creating more goods and services with ever less use of resources, waste and pollution; that is, creating more value with less impact (Schmidheiny and Stigson, 2000).

In recent years, a tool to quantify and assess the environmental impacts throughout the life cycle of a product is Life Cycle Assessment (LCA). This tool assesses the impacts of a product through all the supply chain until its use/disposal, for this, multiple practices/processes concerned with said product are analysed. In the presence of multiple data sets, an average inventory is calculated. This may be a problem in the presence of high degree of variability (Vázquez-Rowe et al. 2010) because erroneous conclusions could be derived.

On the other hand, Data Envelopment Analysis (DEA) is a non-parametric method that measures the efficiency of units, called decision-making units (DMUs), which perform similar activities (Charnes *et al.*, 1978). DEA provides an efficiency index, identifies best practices (benchmarks) and for those inefficient DMUs, targets to become efficient are set along with their benchmarks, providing both operational and managerial efficient practices to follow.

The link between LCA and DEA was initially proposed by (Lozano *et al.*, 2009) to compare the operational and environmental performance of entities operating in mussel cultivation. With the DEA models to analyse and assess efficiency using the LCA data from different practices, average inventory is avoided and the eco-efficiency indexes of said practices are known along with additional information on improving the inefficient ones. Since the initial joint use of LCA and DEA, called LCA + DEA, many researchers have used this approach to assess the eco-efficiency of different practices, mainly agricultural. This was done because it allows identifying sources of operational inefficiency and of unnecessary environmental impact. A review of applications can be found in (Vázquez-Rowe and Iribarren, 2015) and also a review focused in energy systems in (Martín-Gamboa *et al.*, 2017) which includes a review of LCA with multicriteria methods.

Among the many indicators determined by LCA to evaluate different impacts to environment, the CF seeks to assess the GHG emissions that contribute to Climate Change. In this paper, we use a CF + DEA approach proposed by (Rebolledo-Leiva *et al.*, 2017), the so-called Four-Step method, for using the LCA+DEA approach focusing on the CF. This method is applied for evaluating the eco-efficiency of nine Chilean vineyards for identifying the best vineyard practices. We also identify sources of inefficiency both operational and environmental; determine targets for production and CF and new levels for contributing factors to CF.

2. Materials and Methods

Life Cycle Assessment (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. In this way, it has emerged as a tool for estimating the environmental impacts of a product or process (Lozano *et al.*, 2009). Figure 1 shows the simplified life cycle (Klöpffer and Grahl, 2014), in which we can observe the extent of LCA.

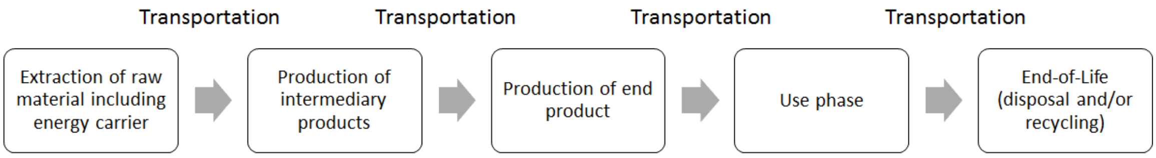

Figure 1. Simplified life cycle of a tangible product

This tool has been implemented in a wide range of agricultural activities as can be seen in (Blengini and Busto, 2009), (Iriarte *et al.*, 2011), (Yang *et al.*, 2013) and (Keyes *et al.*, 2015), among others. However, LCA inventories, called Life Cycle Inventory (LCI), often present high variability, a fact that would result in important differences. In this case, two choices are common solution. The first is to use average inventory and in this case, it is important to quantify this variability. The second is to carry individualized inventory. In this case, a second tool would be useful to carry a data analysis to interpret the results. Thus, (Lozano *et al*., 2009) proposed the use of Data Envelopment Analysis for analysing the data obtained from the inventory phase of the LCA.

Data Envelopment Analysis (DEA) (Charnes *et al.*, 1978) uses linear programming to evaluate the efficiency of DMUs that use multiples resources, called inputs, to produce the same multiple products, called outputs. They work under similar conditions and are homogeneous in the sense that use the same variables with differences in performance, in the way units are managed (Golany and Roll, 1989). A DMU is efficient if its score is 1 and inefficient otherwise. Besides the efficiency scores, targets and benchmarks (best practices) for inefficient units are set for an inefficient DMU to become efficient. This is done by defining a best-practice frontier, based on observed DMUs (Cook *et al.*, 2014). This way, it provides a tool for planning and management for improving efficiency. In the literature, many DEA models have been proposed. To choose among them, one should first 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, accounting for size and scale. In addition, an orientation has to be defined. The usual orientations are input or output oriented models. In the input oriented models, the objective is to minimize the inputs (resources) while maintaining outputs (products), whereas in the output oriented models the objective is to maximize the outputs (products) while maintaining the consumption of inputs (resources). Other assumptions concerning returns to scale or orientation can be made. For more models and details about their characteristics see (Cooper *et al.*, 2007). Moreover, DEA has been applied to a variety of fields. For a survey on the DEA literature see (Emrouznejad and Yang, 2017), on DEA applications see (Liu *et al.*, 2013) and on DEA on sustainability see (Zhou *et al.*, 2018).

The first publication integrating the LCA and DEA methodologies was by (Lozano *et al.*, 2009). In this paper, the authors compared the operational and environmental performance of rafts in mussel cultivation. This method was later called by (Iribarren *et al.*, 2010) the Five-Step approach, which was later formally formulated by (Vázquez-Rowe *et al.*, 2010). The Three-Step approach was presented by (Lozano *et al.*, 2010). All these methods try to reflect the definition of eco-efficiency by the Business Council for Sustainable Development (WBCSD), which means creating more goods and services with ever less use of resources, waste and pollution (Schmidheiny and Stigson, 2000). Later, for a better interpretation of the eco-efficiency definition, (Rebolledo-Leiva *et al.*, 2017) proposed the Four-Step method. This method includes an output oriented DEA model in Step 3 as we explain later. Figure 2 shows the step-by-step of this method.

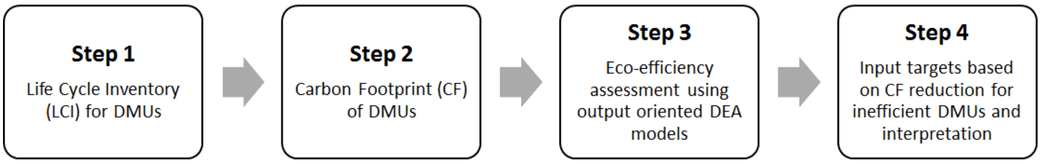

Figure 2. Four-Step method

As can be seen in Figure 2, Step 1 is the complete inventory performed by LCA. This step accounts for all inputs and outputs of the system under study, including raw resources or materials, energy by type and emissions to air, water and land by specific substances. For this case study, data of the season 2015/2016 from nine vineyards located in the Chilean Central Valley were collected.

The environmental characterization, specifically the Carbon Footprint (CF), is determined for each vineyard in Step 2. In this step, we consider as functional unit, 1 kg of harvested grape. The system boundary is set from cradle-to-farm gate. The method used to evaluate the CF for each vineyard follows the ISO 14040 general framework (ISO, 2006) and the CF is calculated according to PAS 2050 standard (BSI, 2011) with its specification for horticulture PAS 2050-1 (BSI, 2012). Thus, to estimate the CF of each agricultural factor that contributes do CF (e.g., pesticides, diesel use, fertilizers), the following steps are necessary (Rebolledo-Leiva *et al.*, 2017). First, equation (1) indicates that the mass of GHG *e* (eg, CO_2, CH_4) emitted during activity *ac* (e.g., fertilizer transport, fertilizer production, fertilizer application) is obtained by multiplying the mass of resource used during activity *ac* times the emission factor *e* (the ratio between the amount of a given GHG and the amount of a given resource or raw material) for the agricultural factor *k*.

$$GHG_{e,ac,k} = activity_{ac,k} \times EF_{e,ac,k} \quad (1)$$

Where, for using an agricultural factor k, $GHG_{e,ac,k}$ is the mass of GHG *e*, $activity_{ac,k}$ is the mass of resource used in activity *ac* and $EF_{e,ac,k}$ is the emission factor *e*.

Second, in equation (2), the GHG emissions *e* from all activities carried out for using agricultural factor k $\left(GHG\ agrifactor_{k,e}\right)$ are added up to estimate the total mass of GHG emitted.

$$GHG\ agrifactor_{k,e} = \sum_{ac \in A_k} GHG_{e,ac,k} \quad (2)$$

Finally, in equation (3), the CF of each agricultural factor *k* is obtained by multiplying the mass of GHG in each activity times their respective global warming potential (the total contribution to global warming resulting from the emission of one unit of a gas relative to one unit of the reference gas, carbon dioxide, which is assigned a value of 1).

$$CF\ agrifactor_k = \sum_{e \in E} GHG\ agrifactor_{k,e} \times GWP_e \quad (3)$$

Where, $CF\ agrifactor_k$ is the CF of the agricultural factor k (kg CO_2-eq), $GHG\ agrifactor_{k,e}$ is the total amount of GHG *e* emitted from agricultural factor *k* and GWP_e is the global warming potential of greenhouse gas *e*, over a timeframe of 100 years.

The assessment of CF was modelled in Ccalc2 v1.43.

In Step 3, the data obtained in the inventory and the CF are used within an output oriented model, namely production and CF, for the eco-efficiency assessment. We can notice that the CF is an undesirable output, then we propose to deal with undesirable outputs using the multiplicative inverse transformation proposed by (Golany and Roll, 1989). In using an output oriented model, we are able to identify efficient vineyards that maximize production with low CF emissions. Moreover, we use both the CCR model (Charnes *et al.*, 1978), that assumes constant returns to scale (CRS), and the BCC model (Banker *et al.*, 1984), that assumes variable returns to scale (VRS). In (4), the output oriented version of the BCC model (Banker et al., 1984) is presented.

$$
\begin{aligned}
&\text{Max } \phi_o \\
&\text{subject to} \\
&\sum_j x_{ij}\lambda_j \le x_{io}, \forall i \\
&\sum_j y_{rj}\lambda_j \ge \phi_o y_{ro}, \forall r \\
&\sum_j \lambda_j = 1 \\
&\lambda_j \ge 0, \forall j \\
&\phi_o \in \Re
\end{aligned} \tag{4}
$$

Where ϕ_o is the proportional increase of the outputs, so the efficiency of DMU_o is $1/\phi_o$, λ_j is the contribution intensity of benchmark j to the target of DMU_o, x_{ij} is the input i of DMU j, and y_{rj} is the output r of DMU j. If the CCR model is chosen for a DEA output oriented assessment, the constraint $\sum_j \lambda_j = 1$ must not be included. This version of the model is called the envelopment model. The dual of this model is called the multipliers model.

The complete system boundary, the variables of LCI and for the DEA assessment can be seen in Figure 3.

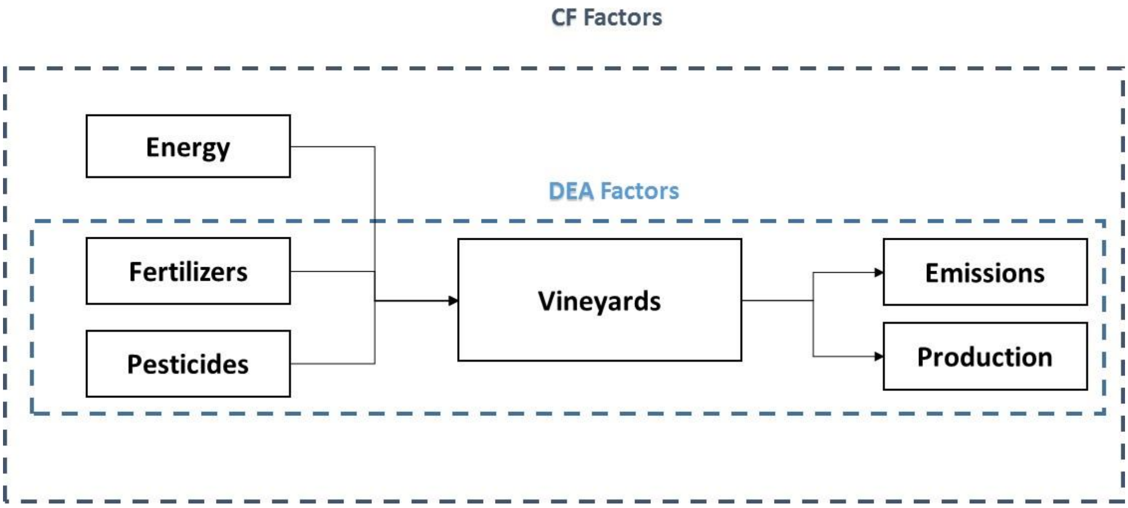

Figure 3. System boundary.

Finally, in Step 4, the new levels for factors (resources) that contribute to the CF are determined for the inefficient producers based on the information of benchmarks determined in the previous step. These are the "input targets" to be reached in order to achieve the target CF determined in the previous Step. The use of benchmarks on this step aims to replicate benchmark practices (the best practices of real vineyards). The sub-steps of Step 4 are shown in Figure 4 (Rebolledo-Leiva *et al*., 2017).

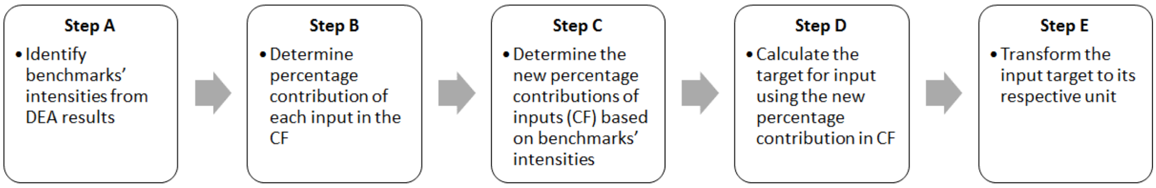

Figure 4. Sub-steps to determine factor targets, Step 4.

Thus, the sub-steps to determine the new levels for the factors that contribute to CF, that is, the factor targets procedure is as follows:

a) Identify, for each inefficient DMU_o, the set of benchmarks, B_o, and the benchmark intensities, $\lambda_j, j \in B_o$, from DEA results.
b) Identify the percentage contribution of factor k, of benchmark j, f_{kj}, to the CF, k∈K, j∈Bo.
c) Determine the new percentage contribution of factor k to the CF of DMUo, h_{ko}, as in equation (5):

$$h_{ko} = \sum_{j \epsilon B_o} f_{kj} * \lambda_j, k \in K \quad (5)$$

d) Calculate the target for factor k (in kg CO2-eq), z_{ko}^*, using the new percentage contribution according to equation (6):

$$z_{ko}^* = h_{ko} . g_{CF_o}^* \quad (6)$$

e) Transform the target for factor k, previously calculated (z_{ko}^*), into its respective unit (a_{ko}^*), using equation (7). For calculating a_{ko}^*, it is assumed that each factor is directly proportional to the CF.

$$a_{ko}^* = a_{ko} \times z_{k_o}^* / g_{CF_{ko}} \quad (7)$$

where a_{ko} is the current amount of factor k, in its respective unit, and $g_{CF_{ko}}$ is the current kg CO_2-eq of factor k as calculated by equation (3) ($CF\ agrifactor_k$).

This can be seen as an inverse procedure of the Step 2, with an initial CF for determining the mix of factors to reach the target CF in Step 3.

3. Results

In Step 1, for each vineyard, the data were obtained in several face-to-face interviews. The non-productive stages of the crop (e.g., planting and growing) and pruning residue treatments (burning, mulching, etc.) are excluded from this evaluation.

Next, in Step 2, we determine the CF of the vineyards considering operational variables as presented in Figure 3. In Figure 5, it is possible to note that, in average, 50% of CF comes from fertilizers, while 46% corresponds to pesticides. On the other hand, energy contributes only 4% in average.

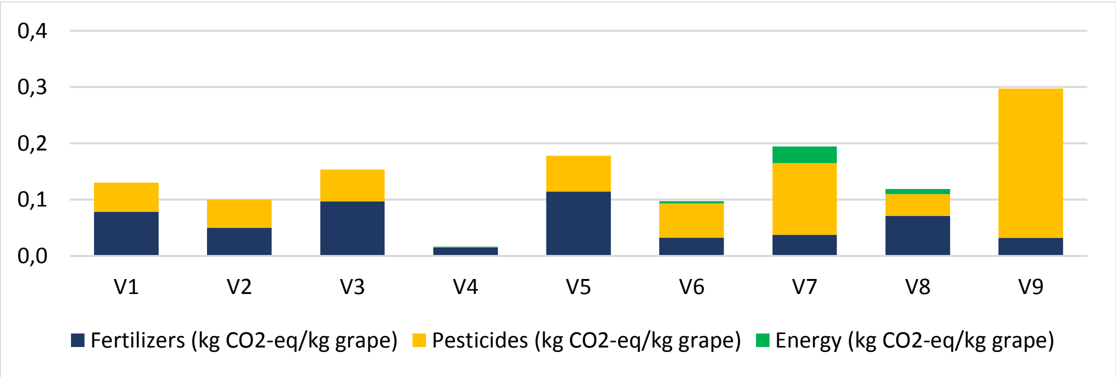

Figure 5. Contribution of the vineyards' resources to the CF

The next step is the eco-efficiency assessment. As mentioned before, the CCR and BCC models are used. The inputs and outputs for this assessment are presented in Table 1, as well as, the efficiency indexes. It is important to notice that Energy is not included in this assessment; this is done because of the number of DMUs (nine) and the number of variables (five), when the recommended relation is 3 to 1 (Cooper *et al.*, 2007). We decided to maintain the largest contributors to CF, fertilizers and pesticides, and exclude Energy. These two inputs with the two outputs exceed this relation, but represented well the production process.

	Inputs		Outputs		Efficiency Index (%)	
DMU	Fertilizers (kg)	Pesticides (kg)	Production (kg)	CF (kg CO2-eq)	CCR	BCC
V1	6000	797	147049	19195	20	80
V2	610	111	23436	2348	30	50
V3	3644	415	72650	11143	20	60
V4	325	3	41243	689	100	100
V5	7832	821	131847	23504	10	60
V6	1068	393	63063	6124	50	90
V7	7000	5039	362143	70343	40	100
V8	8090	775	220387	26182	20	100
V9	731	890	44547	13240	50	70

Table 1. Data and efficiency indexes of the vineyards using the CCR and BCC models

In this table, we can see that there are three efficient vineyards (V4, V7, V8), three best practices, while CCR model identifies only one efficient vineyard (V4). Even though vineyards are homogenous, they have differences in size and scale; therefore, we will focus on the results of the BCC model to go on Step 4. Thus, the targets for Production and CF for the six inefficient vineyards, their actual levels and their benchmark intensities are shown in Table 2.

Inefficient Vineyards	Production (kg)	Production Target (kg)	CF (kg $CO_{2\text{-eq}}$)	CF Target (kg $CO_{2\text{-eq}}$)	Benchmarks
V1	147049	180968	19195	15597	λ_{V4} = 0,262; λ_{V7} = 0,053; λ_{V8} = 0,686
V2	23436	50820	2348	716	λ_{V4} = 0,961; λ_{V7} = 0,018; λ_{V8} = 0,021
V3	72650	120954	11143	1186	λ_{V4} = 0,570; λ_{V7} = 0,019; λ_{V8} = 0,411
V5	131847	217207	23504	12290	λ_{V4} = 0,031; λ_{V7} = 0,017; λ_{V8} = 0,953
V6	63063	70422	6124	769	λ_{V4} = 0,894; λ_{V7} = 0,072; λ_{V8} = 0,034
V9	44547	60762	13240	733	λ_{V4} = 0,939; λ_{V7} = 0,061

Table 2. Target for Production and CF and benchmarks intensities

In this Table, we notice that the vineyards V1 and V5 have best practice vineyard V8 as their main benchmark; vineyards V2, V6 and V9 have best practice V4 as their main benchmark; whereas, vineyard V3 has both, V4 and V8. Best practice vineyard V7 is the benchmark with the lowest intensity for every inefficient vineyard, which may indicate that is using the resources in a way somewhat different to be efficient.

Next, following Step 4, the information in Table 2 is used to determine the new levels of the factors in order to reach the target CF for each inefficient vineyard. The new levels for fertilizers and pesticides are shown in Table 3.

Inefficient Vineyards	Fertilizers (kg)	Target of Fertilizers (kg)	Pesticides (kg)	Target of Pesticides (kg)
V1	6000	5312	797	441
V2	610	331	111	4
V3	3644	472	415	20
V5	7832	3769	821	403
V6	1068	338	393	7

V9	731	59	890	9

Table 3. Input targets for CF reduction

The changes in production and CF and the impacts of the reductions in fertilizers and pesticides are better observed by comparing actual levels with their targets graphically. Therefore, in Figure 6, this comparison for the outputs, production and CF for each inefficient vineyard is depicted. As expected because of its efficiency index (50%), V2 has the largest changes in production and CF.

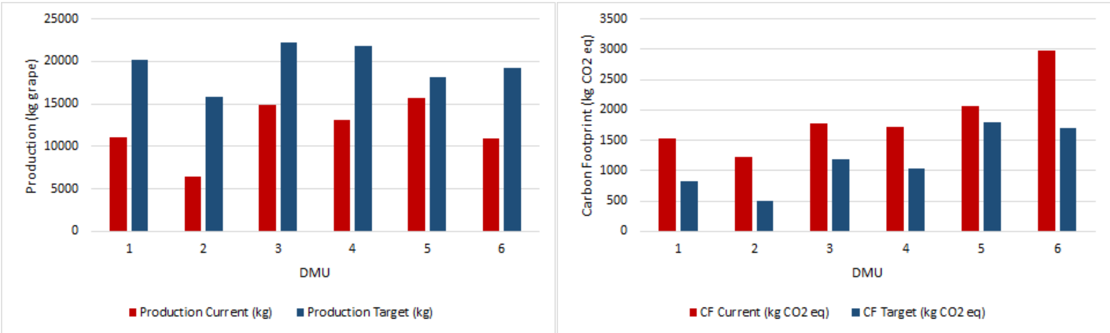

Figure 6. Comparison of actual and target levels for production and CF.

Additionally, Figure 7 shows a comparison actual and target levels for fertilizers and pesticides obtained by copying their benchmarks practices. The most dramatic change in the use of fertilizers corresponds to V5, which has to increase their use more than 3 times and reduce its use in pesticides in approximately 70%. This may seem to make no sense, to increase the consumption of a resource to reduce CF; however, this increase with the reduction in pesticides, together with changes in the operational process that copy their benchmarks (V4, V7 and mainly V8) makes the target CF possible. In general, the average reduction of fertilizers is approximately 59%, while an average decrease of approximately 81% of pesticides is estimated.

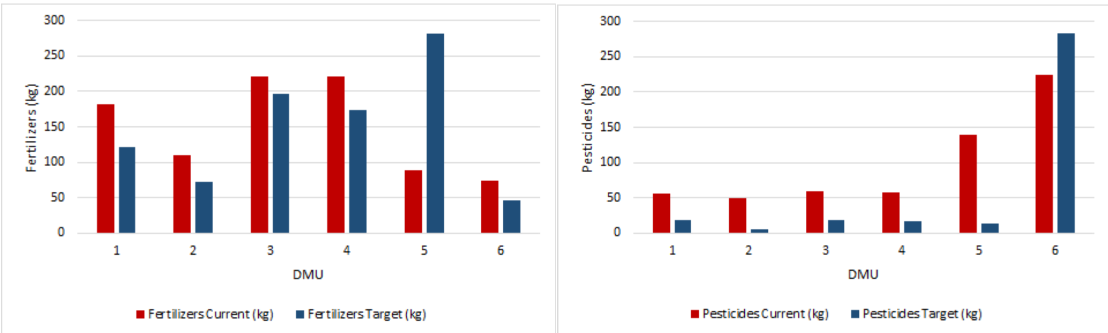

Figure 7. Comparison of actual and target levels for fertilizers and pesticides.

4. Conclusions and Final Comments

In this paper, we use the Four-step method that implements the LCA+DEA approach to determine the eco-efficiency and to identify best practices in a group of vineyards in the central zone of Chile. In total, 9 vineyards were analyzed. In the DEA eco-efficiency assessment not all variables from the LCI were used. This was done because of the relation between the number of DMUs and the number of variables. The variables selected for the eco-efficiency assessment were those that contributed more to the CF.

On the other hand, the CCR and the BCC model were applied. As expected, the CCR efficiency indexes were lower than the BCC and the CCR model identify one vineyard as efficient, whereas the BCC model identify three vineyards as efficient. Moreover, we focus on the BCC results because of the differences in size and scale of the vineyards. However, the use of the CCR model was interesting because it allows verifying the efficiency scores when considering that all vineyards are operating at optimum scale. In a case, where all vineyards work in a competitive market then it can be assumed that they work at their optimal scale and the CCR model has to be used.

Finally, we expect that inefficient vineyards follow the operational and managerial guidelines of their related benchmarks. When an inefficient vineyard has more than one benchmark, it is necessary to identify which ones have greater intensities, because that means these benchmarks have similar characteristics than the inefficient vineyard.

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 to achieve efficiency in two stages, taking into account size or scale and then market conditions.

It is important to point that the use of the Four-Step method with an output oriented DEA model allows us to identify the eco-efficient vineyards, those who produce more with less CF, and the necessary changes in the use of resources for an inefficient vineyard to become efficient. This in a way more aligned to the eco-efficiency definition: to produce more with fewer resources and with decreasing environmental emissions.

For future works, other variables that affect eco-efficiency will be considered and using other DEA models to consider simultaneously the reduction of inputs and increase of outputs.

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