Optimal design of sustainably efficient biorefineries supply chains

Lucas M. Machin Ferrero[1,2], Richard Cabrera Jiménez[3], Jonathan Wheeler[1,2], Carlos Pozo[4] and Fernando D. Mele[1,2][0000-0003-4401-7878]

[1] Univ. Nac. de Tucumán, Av. Independencia 1800, T4002BLR S. M. de Tucumán, Argentina
[2] Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET)
[3] Univ. Rovira i Virgili, Av. Països Catalans 26, 43007 Tarragona, Spain
[4] Univ. Politècnica de Catalunya, Av. Eduard Maristany 16, 08019 Barcelona, Spain
lmachinferrero@herrera.unt.edu.ar
fmele@herrera.unt.edu.ar

Abstract. A more comprehensive use of biomass as raw material to produce food, energy and products would result in an important contribution towards the Sustainable Development Goals. The concept of biorefinery allows regions with abundant natural resources to make the most of available biomass for these purposes, achieving progressive independence from fossil resources. This study presents a framework for the multi-criteria design of biorefinery supply chains (SC) under sustainability considerations. Therefore, an optimization approach of different scenarios is performed followed by a ranking based on the Data Envelopment Analysis (DEA) model to assess the efficiency according to different economic, environmental and social indicators. The capabilities of this approach are demonstrated through a case study of the biomass SC centered in the Northwest of Argentina.

Keywords: Biomass, Multi-criteria decision-making, Data Envelopment Analysis

1 Introduction

Given the various risks at the global level such as climate change, world population increase and non-renewable resources depletion, there is a latent need and urgency to implement policies ensuring the sustainability of conventional production systems [1]. Consequently, actions are being conducted and planned in the countries' agro-industrial sectors to achieve the Sustainable Development Goals (SDGs), such as those related to responsible consumption and production (SDG 12) and climate action (SDG 13) [2].

More comprehensive use of biomass as raw material to produce food, energy and products would result in an important contribution towards the goals pursued. The concept of biorefinery allows regions with abundant natural resources to make the most of available biomass for these purposes, achieving progressive independence from fossil resources [3].

Decisions regarding the raw materials used, the design of bioproducts, production planning and distribution tasks must be addressed and evaluated together to ensure a sustainable management of the biorefinery supply chains (SC) [4][5]. Thus, the focus must be placed on the different SC echelons, during the design and planning stages, with well-defined sustainability criteria, involving economic, environmental and social indicators.

The use of mathematical programming is well established as a tool for Supply Chain Management (SCM). However, the problem becomes more complex when incorporating multiple sustainability criteria, multiple raw materials (biomass) to be processed and an extensive portfolio of bioproducts [6]. The main goal of this work is to develop a decision support tool for the design of sustainable biorefinery SC (production-storage-market) including the three sustainability dimensions: economic, environmental and social. This multi-criteria approach combines optimization, through mixed-integer linear programming (MILP), to find the most economical SC configurations; and Data Envelopment Analysis (DEA), to classify and find those that are more sustainable, incorporating their environmental and social performance. The capabilities of the approach are demonstrated through a case study addressing the SC of biorefineries in the northwest of Argentina.

2 Proposed approach

A three-stage strategy is proposed to select the bioproducts to produce and the most convenient SC topology based on sustainability aspects: (S1) MILP that minimize the total SC costs to satisfy certain products demand patterns, (S2) SC environmental and social indicators assessment, (S3) DEA to evaluate the SC networks obtained in S1 considering the economic, environmental and social indicators from S2 (Fig. 1).

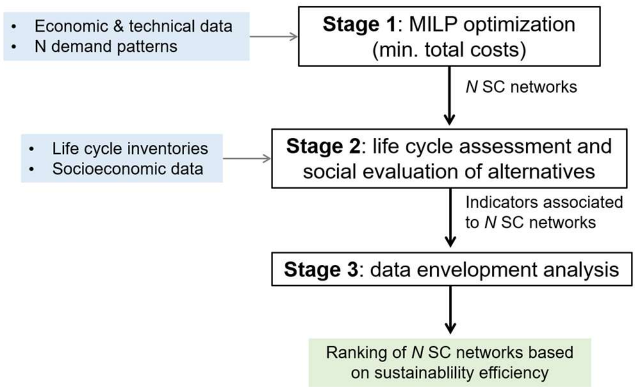

Fig. 1. The three-stage approach for assessing the efficiency of a set of biorefinery SC networks.

The SC structure includes biomass feedstocks, production and storage facilities, and demand locations. Different types of biomass could be selected and, in production steps, different technologies could be selected for producing food, biofuels and bioenergy. Various means of transportation between nodes are considered (for transporting biomass, solid products and liquid products).

Decisions to be made in S1 include the type (technologies), number, location, capacity and production level of the biorefinery plants, warehouses to be set up in different regions, transportation links and transportation modes that need to be established in the network, and product rates delivered to the markets. These decisions are those that ensure that the total costs are minimum for a given product portfolio.

In S2, given life cycle inventories of the SC nodes and socioeconomic data of regions, environmental and social indicators are calculated for each optimized SC result. Finally, in S3, DEA ranks the obtained SC configurations based on the indicators selected to represent the SC sustainability.

3 Methods

In this section, the mathematical formulation for each stage is presented, describing the most relevant equations.

3.1 Stage 1: Optimization model

A MILP model previously presented [7] is used as a basis. It is a multi-period, multi-raw material and multi-product formulation. Present total costs (SC_{costs}) associated to the SC act as the objective function. They include costs related to biomass production (TMC_t), installation of biorefineries and their production levels (TBC_t), energy consumption of biorefineries related to natural gas (TGC_t) and electricity (TEC_t), installation of warehouses and their average inventory levels (TSC_t), and transportation links setting for raw materials and products (TTC_t) along the SC (Eqs. 1 and 2). Indices and sets are shown in section Nomenclature.

$$SC_{COSTS} = TC_{t=1} + \sum_{t\geq 1} \frac{TC_t}{(1+\alpha)^{t-1}} \tag{1}$$

$$TC_t = TMC_t + TBC_t + TEC_t + TGC_t + TSC_t + TTC_t \quad \forall t \tag{2}$$

3.2 Stage 2: Environmental and social evaluation

Environmental impact assessment. The environmental performance of the SC network is quantified following the first three phases of Life Cycle Assessment (LCA) [8]: goal and scope definition, inventory analysis, and impact assessment. In this stage, the calculation of environmental indicators uses the results obtained in the previous stage (i.e., the optimization problem). To do this, the following calculation scheme is proposed.

The total impact of the SC referred to the impact category e (SC_e) over the time horizon is calculated using Eq. 3. This value accumulates the impacts associated with each SC activity: $I_{M_{e,t}}$ is the impact associated with the production and collection of raw materials, $I_{B_{e,t}}$ is that associated with the installation and operation of biorefineries, $I_{T_{e,t}}$ is that generated by the different transportation instances along the SC, $I_{S_{e,t}}$ is the one related to storage tasks, $I_{E_{e,t}}$and $I_{G_{e,t}}$ are the impacts associated with the production and use of external energy, electricity and natural gas, respectively.

$$SC_e = \sum_t \left[I_{M_{e,t}} + I_{B_{e,t}} + I_{T_{e,t}} + I_{S_{e,t}} + I_{E_{e,t}} + I_{G_{e,t}} \right] \forall e \quad (3)$$

$I_{M_{e,t}}$ is calculated as the impact of raw materials $i \in IR(i)$ produced and used both in the same regions $g \in GB(g) \cap GH(g)$ (represented by variable $H_{i,g,t}$) and produced in region $g \in GH(g)$ but transported and used in other regions $g' \in GB(g)$ (represented by variable $Q_{i,l,g,g',t}$). In Eq. 4, $ImpCat_{M\,i,e}$ is the impact per tonne of raw material $i \in IR(i)$ referred to impact category *e*.

$$I_{M_{e,t}} = \sum_{g \in GH} \sum_{i \in IR} ImpCat_{M\,i,e} \, (H_{i,g,t} + \sum_{g,g' \in GB, g' \neq g} \sum_{i,l \in IL} Q_{i,l,g,g',t}) \;\; \forall \mathrm{e}, t \quad (4)$$

Regarding biorefineries' environmental impact (Eq. 5), it depends on the technologies selected and their production levels $X_{k,b,g,t}$. $ImpCat_{B\,k,e}$ is the impact per quantity of reference flow of technology k, referred to impact category *e*.

$$I_{B_{e,t}} = \sum_{g \in GB} \sum_b \sum_k ImpCat_{B\,k,e} \, X_{k,b,g,t} \, \forall e, t \quad (5)$$

For transportation impacts, $I_{T_{e,t}}$, the impacts generated by the transportation of raw materials $i \in IR(i)$ from biomass producing regions $g \in GH(g)$ to biomass processing regions $g \in GB(g)$, those corresponding to the transportation of products $i \in IM(i)$ from the biorefineries to regions with warehouses $g \in GS(g)$, and the transportation of products $i \in IM(i)$ from the warehouses to the points of demand $g \in GD(g)$ are considered. Eq. 6 shows the calculation for the first transportation step mentioned above; here $NL_{i,l,g,g',t}$ is the number of required trips for transportation of material i by means of transportation mode l from region g to region g' in time period t, $d_{g,g'}$ is the distance between regions g and g', $ImpCat_{TF_{l,e}}$ and $ImpCat_{TE_{l,e}}$ are the impacts generated per kilometer traveled by the transportation mode *l* fully or empty, respectively.

$$I_{T_{e,t}} = \sum_l \sum_{g \in GH} \sum_{g' \in GB, g' \neq g,} \sum_{i \in IR} NL_{i,l,g,g',t} (ImpCat_{TF_{l,e}} d_{g,g'} + ImpCat_{TE_{l,e}} \, d_{g',g}) \, \forall e, t \quad (6)$$

Considering the possibility of circular economy implementations, the model in S1 can decide to install technologies to produce energy streams, such as biogas from liquid wastes or electricity from lignocellulosic materials to reduce the external energy consumption. This decision is reflected in the calculation of the environmental impact of the SC through Eqs. 7-9. In Eq. 7, the impact related to external electricity ($I_{EP\,e,t}$) is calculated considering the balance of electricity purchased from the grid ($EP_{g,t}$) and the electricity exported to the grid ($EX_{g,t}$). In this case, $ImpCat_{E_e}$ is the impact e of consuming electricity from the external grid, per kWh. The impact related to electricity produced *in situ* by the biorefinery ($I_{EC_{e,t}}$) is calculated from the quantity of electricity generated by technology k in biorefinery b, region g and time period t ($X_{k,b,g,t}$) and its specific environmental impact ($ImpCat_{B_{k,e}}$) per kWh produced (Eq. 8).

$$I_{EP_{e,t}} = \sum_{g \in GB} ImpCat_{E_e}(EP_{g,t} - EX_{g,t})\ \forall e,t \quad (7)$$

$$I_{EC_{e,t}} = \sum_{g \in GB} \sum_b \sum_{k=Cogeneration} ImpCat_{B_{k,e}} X_{k,b,g,t}\ \forall e,t \quad (8)$$

$$I_{E_{e,t}} = I_{EP_{e,t}} + I_{EC_{e,t}} \forall e,t \quad (9)$$

Finally, the impacts of consuming electricity from the network and those of producing it internally are added (Eq. 9). The biogas or natural gas impact calculation is similar to these for electricity. The impacts associated with storage are neglected with respect to the other SC impacts.

Social impact assessment. In pursuit of a social indicator that represents the performance of the installation and operation of biorefineries, while keeping the importance of regional features, the indicator developed by [9] is selected. This indicator considers socioeconomic data from the regions where biorefineries are installed, and the number of direct job generated by technologies at each biorefinery.

The socioeconomic parameters necessary to calculate this social indicator are: economically active population at each region g (EAP_g, as % of people with a job or looking for one), the open unemployment rate at each region g (OUR_g, as % of the unemployed population in relation to EAP_g) and the number of inhabitants in each region g (Hab_g). These parameters will be different for each region that is analyzed and easily accessible through national census reports.

From the number of technologies and biorefineries that are decided to be installed in S1 for different product portfolios, the number of jobs generated could be calculated (Eq. 10). $LE_{g,t}$ is the number of local jobs generated in each region $g \in GB(g)$ when a plant is installed (i.e., when binary variable $z_{k,b,c,g,t}$, from S1, takes value of 1). N_{OL_k} is the operating labor requirement (number of jobs generated) for technology k operation (Eq. 10).

$$LE_{g,t} = \sum_b \sum_k \sum_c z_{k,b,c,g,t}\, N_{OL_k}\ \forall g \in GB(g), t \quad (10)$$

$$SI_{g,t} = \frac{\gamma_g\, LE_{g,t}}{Hab_g EAP_g - \lambda_g Hab_g EAP_g OUR_g} \forall g \in GB(g), t \quad (11)$$

$$SC_S = \sum_{g \in GB} \sum_t SI_{g,t} \quad (12)$$

Eq. 11 is the expression used to calculate the social index for the region g and time period t, where $\gamma_g$and $\lambda_g$are factors that allow weighting local employees and unemployed, respectively. Finally, in Eq. 12, the social index of the SC (SC_S) over the time horizon is calculated. Remarkably the indicator is always positive. The higher the indicator, the greater the number of jobs generated in regions with higher unemployment rate. For each region g, it is assumed that the number of jobs generated can be absorbed by the inhabitants.

3.3 Stage 3: DEA model

After obtaining SC configurations for different product portfolios (in S1) and characterizing each of them in social and environmental terms (in S2), in this stage, a ranking of the SCs is generated based on certain sustainability performance indicators. Multi-criteria decision-making tools has resulted effective to deal with this purpose (e.g., analytical hierarchy process, multi-attribute value theory and DEA). DEA, one of the most used tools, has the advantage of combining multiple indicators into a single score, with no need to define weights between the indicators avoiding subjectivity. DEA evaluates the relative efficiency of a set of N similar entities called decision-making units (DMU), which convert multiple inputs into multiple outputs. Inputs and outputs can be any performance indicator. According to the methodology, inputs and outputs are quantities to minimize and maximize, respectively [10]. Depends on the formulation, there are undesirable outputs, which are outputs to the production process one might want to reduce (Fig. 2). A performance or efficiency score is calculated for each DMU, taking values between 0 and 1. DMUs with score equal to 1, are efficient becomes part of an efficient frontier. On the other hand, DMUs with scores lower than 1 are considered inefficient. DEA allows the identification of the improvements that the inefficient DMUs should target to become efficient.

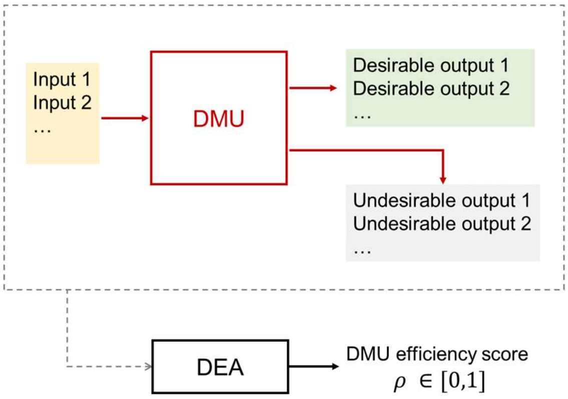

Fig. 2. Schematic of DEA operation.

In this work, we use a non-radial slack-based measure (SBM) proposed by Tone [11] where undesirable outputs are considered inputs for evaluating DMUs efficiency scores. This nonlinear formulation is transformed into a linear one using the Charnes–Cooper transformation [12] (see model M).

$$\rho^* = \min t - \frac{1}{m}\sum_{i=1}^{m} \frac{S_i^-}{x_{i0}} \tag{M}$$

s.t.

$$1 = t + \frac{1}{k}\sum_{r=1}^{k}\frac{S_r^+}{y_{r0}}$$
$$\sum_{j=1}^{n}\Lambda_j X_{ij} + S_i^- = x_{i0}\ t\ \forall i$$
$$\sum_{j=1}^{n}\Lambda_j Y_{rj} - S_r^+ = y_{r0}\ t\ \forall r$$
$$S_i^- > 0\ \forall i, S_r^+ > 0\ \forall r, \Lambda_j > 0\ \forall j$$
$$t > 0$$

In this model, ρ^* is the SBM-efficiency score, X_{ij} is the value of input i of DMU j, Y_{rj} is the value of output r of DMU j, x_{i0} and y_{r0} are the values of input i and output r, respectively, of the DMU o (under evaluation), S_i^- and S_r^+ are the input and output slacks (i.e., the distance from the DMU assessed to the efficient frontier).

4 Case study

The aforementioned methodology is applied for the design of the SC of the Argentine Northwest agroindustry, considering the possibility of establishing biorefineries in the province of Tucumán, which is the largest producer of sugar, bioethanol (from sugar-cane), and lemons in the country [13] [14].

Table 1. Available biomass distribution, in tonnes per year. SHR: sugarcane harvest residues, LHR: lemon harvest residues, LP: lemon peel.

Region	SHR	Cane	LHR	LP
G01	1.59E+05	4.51E+05	7.35E+04	4.36E+05
G02	8.55E+04	2.11E+06	1.84E+04	1.09E+05
G03	2.40E+05	1.13E+06	9.64E+03	5.72E+04
G04	5.09E+04	3.18E+06	2.24E+04	1.33E+05
G05	3.28E+04	6.74E+05	0.00E+00	0.00E+00
G06	3.41E+04	4.35E+05	9.40E+03	5.58E+04
G07	5.40E+04	7.15E+05	1.52E+04	9.04E+04
G08	2.73E+05	3.62E+06	0.00E+00	0.00E+00
G09	4.58E+04	6.06E+05	1.21E+04	7.19E+04
G10	1.20E+05	1.58E+06	1.96E+04	1.16E+05
G11	7.72E+04	1.02E+06	7.16E+03	4.25E+04
G12	2.75E+02	3.64E+03	0.00E+00	0.00E+00
G13	2.00E+05	2.64E+06	0.00E+00	0.00E+00
G14	0.00E+00	0.00E+00	0.00E+00	0.00E+00
G15	1.79E+03	2.37E+04	2.27E+04	1.35E+05
G16	0.00E+00	0.00E+00	0.00E+00	0.00E+00
G17	5.50E+02	7.28E+03	6.86E+03	4.07E+04

Geographic scope. This case study considers 23 provinces of Argentina and 17 departments of Tucumán (i.e., 40 geographic regions). Biomass producing regions, $GH(g)$, and regions of potential location of biorefineries, $GB(g)$, are G01 to G17 (within Tucumán). Also, potential location of warehouses, $GS(g)$, are G18 to G40 (out of Tucumán province) while regions with product demands, $GD(g)$, depends on the final product considered.

Biomass availability. Table 1 shows the biomass considered and the amount available in each region $g \in GH(g)$: sugarcane, sugarcane harvest residues (SHR), lemon peel (LP) and lemon harvest residues (LHR). Technical and economic data for sugarcane and biomass residues are taken from literature [7], while for lemon biomass are estimated from regional studies and reports [15] [16].

Table 2. Inputs and outputs for each technology k. SHR: sugarcane harvest residues, LHR: lemon harvest residues, LP: lemon peel, DLP: dehydrated lemon peel.

Technology	Inputs	Outputs	Technology	Inputs	Outputs
K00	- Cane	- Cane juice - Bagasse	K10	- Cane juice	- Ethanol - Vinasses
K01- K02	- SHR - Bagasse - LHR	- Hexoses - Xiloses	K11	- Hexoses	- Ethanol
K03	- Hexoses - Cane juice - Honey - Molasses	- Citric acid	K12	- Hexoses - Xiloses	- Ethanol
K05	- SHR - Bagasse - LHR - LP	- Methanol	K13	- Hexoses - Cane juice - Honey - Molasses	- Lactic acid
K06	- Cane juice	- White sugar - Raw sugar - Molasses	K14	- SHR - Bagasse - LHR - LDP	- Electricity
K07	- Cane juice	- White sugar - Raw sugar - Honey	K15	- Vinasses	- Biogas
K08	- Molasses	- Ethanol - Vinasses	K16	- LP	- Hexoses - Xiloses - Limonene
K09	- Honey	- Ethanol - Vinasses	K17	- LP	- DLP

Biomass processing. The final products considered are: white and raw sugar, first- and second-generation ethanol, citric acid, lactic acid, methanol, biogas and electricity. Technologies can process 17 raw material and intermediate flows. Technical and economic parameters came from literature for sugarcane and from [16] [17] for lemon processing. Table 2 sums up possible inputs and outputs for each technology k. Technologies could be installed with two different capacities (small or large). Transportation and storage parameters are taken from previous works [7] [18].

Scenarios. Eight scenarios (E1-E6) are proposed with different possibilities of products to offer and with different progressions over the time horizon. Table 3 shows regions $g \in GD(g)$ and its demands of bioproducts. The annual demand of conventional products (sugar and ethanol) is taken from national reports [13]. Demands for new bioproducts to be produced (citric acid, lactic acid and methanol), are estimated with the aim of replacing country imports of these products [19] and covering these requirements with national products produced from regional biomass. Each scenario is described in Table 4; increasing, decreasing and constant demands for bioproducts are proposed according to the scenario analyzed. The time horizon is 5 year long.

Table 3. Product demand (tonne/year).

Province		White sugar	Ethanol	Citric acid	Lactic Acid	Methanol
Buenos Aires	G18	96281	34718	12745	894	826
Córdoba	G19	105721	38122	12745	671	-
Corrientes	G20	31968	11527	-	-	-
La Plata	G21	476625	171867	-	671	-
La Rioja	G22	12208	4402	-	-	-
Mendoza	G23	54748	19742	-	-	-
Neuquén	G24	17243	6218	-	-	-
Entre Ríos	G25	39645	14296	-	-	112
Misiones	G26	34108	12299	-	-	-
Chubut	G27	14474	5219	-	-	-
Chaco	G28	33227	11981	-	-	-
Santa Cruz	G29	7173	2587	-	-	-
Salta	G30	38639	13933	-	-	-
San Juan	G31	22025	7942	-	-	-
San Luis	G32	13844	4992	6372	-	86
Jujuy	G33	21521	7760	-	-	-
Santa Fe	G34	101945	36761	-	-	3792
La Pampa (General Pico)	G35	10572	3812	-	-	204
Santiago	G36	27311	9848	-	-	76
Catamarca	G37	10824	3903	-	-	-
Río Negro (General Roca)	G38	18879	6808	-	-	-
Formosa	G39	16990	6127	-	-	-

Tierra del Fuego	G40	4027	1452	-	-	-

Table 4. Scenarios. C: constant demand over time horizon, V: variable demand over time horizon with % of increment or decrement annual in brackets, X: no demand over time horizon.

Scenario	White sugar	Ethanol	Other bioproducts
E1	C	C	X
E2	V (-5%)	V (+5%)	X
E3	V (-10%)	V (+10%)	X
E4	C	C	C
E5	C	C	V*
E6	X	V (+10%)	C
E7	X	X	C
E8	X	C	V*

* It is planned to cover the demand in 5 years with an increase in production of 20% per year.

Environmental aspects. For the quantification of the environmental parameters described in Section 3.2, the inventories of each SC stage are built with a gate-to-gate approach following the LCA guidelines. In this case study, only one category impact referring to climate change is quantified: the Global Warming Potential (GWP) indicator of the ReCiPe 2016 methodology. Inventories for biomass and conventional technologies are taken or adapted from literature and previous works [7] [18] [20] [21] [22]; for new technologies are built based on literature previously cited in [7] [16]; for transportation and for production and use of external natural gas and electricity are taken from Ecoinvent 3.8 [23].

Social aspects. For the calculation of the social index (Section 3.2), direct jobs generated by technologies, N_{OL_k}, are estimated using the method proposed by [24] based on a correlation that depends on the number of steps (reactors, towers, heaters, exchangers, etc.) involved in each technology. For the calculation are considered three shifts per day as is common in industrial activities in these industrial activities. Socioeconomic parameters (i.e., Hab_g, EAP_g and OUR_g) for each region where biorefineries could be installed, $GB(g)$, are taken from INDEC [25].

DEA. The eight optimal SC networks resulting from S1 (one for each scenario) are. considered as DMUs of the DEA model. For this case study, the following indicators are selected as DEA parameters, previously calculated in S1 and S2 from the optimization results:

*Percentage of utilization of raw material (*η*).* The purpose of a biorefinery is to obtain the largest amount of bioproducts from a given amount of biomass to promote its maximum use. This indicator is calculated by dividing the total amount of final products produced in the biorefineries by the amount of raw material required. This is a desired output in the model.

Indicator of related to the benefits, f(c). All production activities seeks to maximize its benefits by minimizing costs for a given business objective, biorefineries would not be an exception. Given the great uncertainty presented by the estimation of prices of bioproducts in the market, it is decided to incorporate as an economic indicator a cost function represented by a large enough number from which the total costs associated with SC is subtracted. This is a desired output in the model.

Global warming potential, GWP. This environmental indicator calculated for the entire SC under study (Eq. 3, $SC_{e=GWP}$) is an undesired output of the model.

Social index, SC_S. The social index presented in section Methodology and evaluated for the entire SC under study (Eq. 12) is a desired output of the model.

Stages S1 and S2 are solved together, implemented in GAMS®, by using the MILP solver CPLEX 11.0 on a DELL DESKTOP-OMKAB82 PC with an Intel(R) Core (TM) i5-9500, 3.00 GHz and 8 Gb of RAM. The resulting model contains 129,699 equations, 181,313 continuous variables, and 5760 discrete variables. The CPU time spent to find the optimal solutions is in the order of 10^3 seconds to a less than 5% optimality gap (averages of all scenarios). The DEA model (S3) is also implemented in GAMS® and solved as a linear problem with negligible statistics with respect to the aforementioned one (less than one second per DMU analyzed).

5 Results

Table 5. S2 results in terms of indicators considered as parameters in DEA model.

Scenario	η	$f(SC_{COSTS})$	SC_{GWP}	SC_S
E1	0.46	0.15	0.95	0.75
E2	0.46	0.15	0.88	0.90
E3	0.42	0.16	0.88	1.00
E4	0.47	0.18	0.88	0.60
E5	0.46	0.15	1.00	1.00
E6	0.27	0.61	0.28	0.25
E7	0.24	0.55	0.36	0.35
E8	0.25	0.61	0.28	0.30

The capabilities and results of the optimization model in S1 and their analysis were presented in previous works [7]; hence, in this work, the emphasis is placed on the results provided by S2 and S3. Table 5 and Fig. 3 summarize the main results obtained. Table 5 presents the normalized indicators calculated for each scenario in S2. Fig. 3 shows the efficiency frontier representing the normalized social and environmental indicators of each scenario as ordered pairs.

Those SCs resulting from scenarios E3, E6 and E8 turn out to be the efficient ones in terms of the evaluated indicators. The other scenarios present some distance from the frontier whose distance depends on the indicators analyzed.

Among the efficient scenarios, E6 and E8 show certain similarity, with identical economic and environmental indicators (low environmental impact and good economic performance), showing a compromise relationship between the efficient use of resources and social impact. Instead, the E3 solution represents a very different situation with a high environmental impact and low performance from the economic point of view, being a desired solution from the social point of view. This clearly demonstrates the existing trade-off between the selected indicators. E3 is characterized by the decrease in sugar consumption and the increasing production of ethanol, that is, a trend towards autonomous distilling. The installation of biorefineries with sugar and ethanol production technologies and treatment of vinasses takes place in regions that have a positive influence on the social indicator. In addition, the use of raw material (sugarcane) is one of the highest compared to other scenarios. Technologies installed in the first period in this scenario are K00, K06, K07, K08, K09, K10 and K15, while in the second and third period K10 technologies are installed to obtain ethanol directly from sugarcane juice. In total, seven biorefineries are installed in the first period in regions G02, G04, G06, and G13-G16.

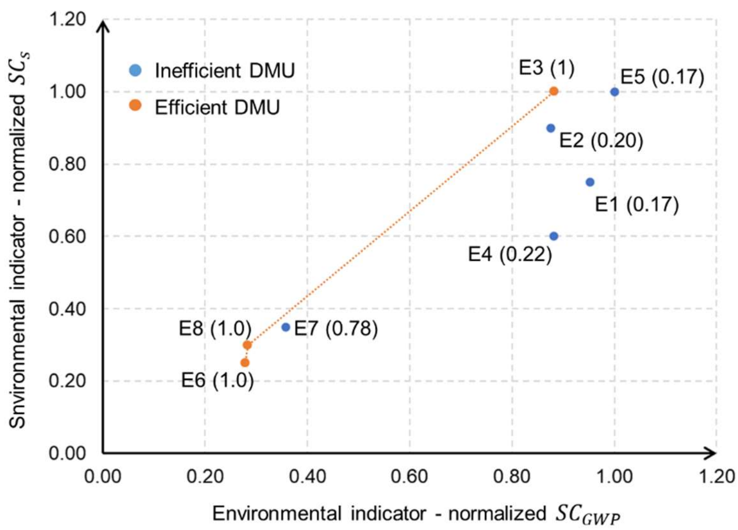

Fig. 3. Efficiency frontier. Values in brackets are the efficiency score for each scenario E.

It should be noted that the E7 solution is close to the efficiency frontier and through some modifications an efficient scenario could be obtained.

6 Conclusions

This paper presents a framework for the multi-criteria design of biorefinery SCs under sustainability considerations. Therefore, an optimization approach of different scenarios is performed followed by a ranking based on the DEA model to assess the efficiency according to different economic, environmental and social indicators. Future work projections include adding new indicators, performing super-efficiency analysis onto the efficient points, and proposing improvements on the SCs to make them more efficient.

Nomenclature

Indices
c = capacity
e = impact category
g = regions
i = materials
k = technologies
l = transportation modes
t = time periods

Sets
$GH(g)$ = subset of regions that can produce raw materials
$GB(g)$ = subset of regions that can install biorefineries
$GS(g)$ = subset of regions that can install storage facilities
$GD(g)$ = subset of regions that have products demand requirements
$IL(i, l)$ = set of set of ordered pairs that link materials i to transport modes l
$IR(i)$ = subset of materials that are raw materials
$II(i)$ = subset of materials that are intermediate materials (produced and consumed in the biorefinery)
$IM(i)$ = subset of materials that are final products
$K^{-}(k, i)$ = set of ordered pairs that link technologies k that consume materials i
$K^{+}(k, i)$ = set of ordered pairs that link technologies k that produce materials i

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