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Article

Is Labor a Suitable Input in LCA + DEA Studies? Insights on the Combined Use of Economic, Environmental and Social Parameters

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Abstract: Economic, social and environmental dimensions are usually accepted as the three pillars of sustainable development. However, current methodologies for the assessment of the sustainability of product systems fail to cover economic, environmental and social parameters in a single combined approach. Even though the perfect methodology is still far off, this article attempts to provide insights on the potentials of the five-step LCA + DEA method, based on both Life Cycle Assessment (LCA) and Data Envelopment Analysis (DEA) methodologies, to cope with operational (economic), environmental and social parameters when evaluating multiple similar entities. The LCA + DEA methodology has already been proven to be a suitable approach for the evaluation of a homogenous set of units from an operational and environmental perspective, while allowing the consideration of economic aspects. However, this is the first study focused on the implementation of social parameters in LCA + DEA studies. The suitability of labor as an additional DEA item is evaluated to validate this integrative LCA + DEA concept. Illustrative case studies are used to show the advantages and drawbacks associated with the use of labor in terms of number of workers and number of working hours. In light of the results, the integrative LCA + DEA concept is seen as an all-in-one methodology, which is easy to implement, even though relevant limitations should be discussed in order to guarantee an appropriate interpretation of the social results derived from the proposed method.

Keywords: Data Envelopment Analysis; eco-efficiency; Life Cycle Assessment; social indicator; sustainability

Abbreviations

BCC: Banker-Charnes-Cooper; CCR: Charnes-Cooper-Rhodes; CRS: constant returns to scale; DEA: Data Envelopment Analysis; DMU: decision making unit; LCA: Life Cycle Assessment; LCC: Life Cycle Costing; LCI: Life Cycle Inventory; LCIA: Life Cycle Impact Assessment; LCSA: Life Cycle Sustainability Assessment; PPS: production possibility set; SBM-I: input-oriented slacks-based measure of efficiency; SLCA: Social Life Cycle Assessment.

1. Introduction

Economic, social and environmental dimensions are considered the three pillars of sustainable development, which seeks continuous human development without threatening the ability of future generations to do so, as well [1]. Therefore, an important number of methodologies have arisen in the few past decades to assess these complementary areas of sustainable development. Some of these have developed based on the emergence of a life-cycle perspective, which acknowledges the existence of complex and varied elements in several stages of the life cycle of a product that can affect the outcome. For instance, Life Cycle Assessment (LCA) has arisen as the only internationally standardized environmental assessment tool [2,3]. Additionally, Life Cycle Costing (LCC) and Social Life Cycle Assessment (SLCA) have originated as methods for life-cycle evaluation in the economic and social dimensions, respectively [4].

However, current methodologies for the assessment of the sustainability of product systems fail to cover economic, environmental and social parameters in a single combined approach. Hence, further efforts are needed in order to set a solid and standardized basis for decision making from an integrated sustainability perspective [5,6]. Some of the most recent attempts have based their discussion frame on widening the concept of environmental LCA to the so-called Life Cycle Sustainability Assessment (LCSA) [7–9]. Introduction of LCSA in scientific discussion, as all neonate methodological concepts, has led up to a broad consideration on how the three dimensions of sustainable development should be integrated [5,7]. For instance, Kloepffer [8] suggested the application of LCSA through two possible routes. On the one hand, the assessment of the three different pillars of sustainability in parallel, under the same methodological assumptions (LCSA = LCA + LCC + SLCA). On the other hand, the enlargement of the scope of LCA to include economic and/or social impact categories (LCSA = LCA new). While it is essential to acknowledge and support the endeavor launched by the LCA community, risks may shape up if certain types of impacts are included in an LCA-based methodology [5]. From a current state-of-the-art perspective, the achievement of a perfect methodology, with or without adopting the preliminary considerations of the LCSA framework, is still far off.

An alternative option to broadening the scope of life-cycle studies to other dimensions of sustainability is the combination/integration of LCA with independent economic or social assessment tools [10]. In this respect, a joint technique based on LCA and Data Envelopment Analysis (DEA) implementation has been recently proposed and applied to the primary sector [11,12]. DEA constitutes a linear programming methodology to compute in empirical terms the relative operational efficiency of multiple similar entities, named decision making units (DMUs) [13]. DEA, due to its capability of handling multiple inputs and outputs, has proven to be appropriate to uncover certain relationships that remain unclear in other methodologies, while detecting and quantifying the sources of inefficiency for each individual DMU included in the production system [12,14]. Therefore, the birth of the LCA + DEA methodology responded to the necessity of fulfilling some of the limitations of LCA as a sole methodology. In the first place, handling multiple data in LCA has usually given rise to a broad range of concerns [15,16]. In this sense, the synergistic use of LCA and DEA avoids the use of average inventory data and manages to provide an individualized assessment of similar entities without hindering the clarity in terms of result interpretation at a global level [12,17]. Secondly, the inclusion of DEA in the assessment provides an economic dimension that enhances the decision-making capabilities of LCA [18], enabling an environmental and operational benchmarking of the assessed systems [19]. Finally, the operational and environmental benchmarks attained in the LCA + DEA methodology offer an eco-efficiency target point in order to reduce the environmental impacts via resource optimization [12,20].

To date, the LCA + DEA methodology has been successfully applied to mussel rafts [11,17], fishing fleets [21], dairy farms [22], vine-growing exploitations [23] and soybean farms [24]. However, the aim of these case studies focused mainly on the integration of the environmental and economic dimensions of sustainability, while neglecting social aspects [25]. Even though Mohammadi *et al.* [24] incorporate labor as a DEA element in the analysis, an interpretation of the social results deriving from the LCA + DEA methodology is still missing. The present article attempts to provide insights on the potentials of the LCA + DEA methodology to cope with operational (economic), environmental and social parameters when evaluating multiple similar entities. In particular, this study was conducted to (i) explore the validity of the LCA + DEA methodology for the inclusion of social parameters, (ii) assess the methodological assumptions that must be made when including this social pillar and (iii) perform result interpretation for social LCA + DEA.

2. Material and Methods

2.1. The Five-Step LCA + DEA Method

Although different approaches to the joint implementation of LCA and DEA are possible [17,26], the five-step LCA + DEA method has been recently proposed as the preferred approach given its methodological consistency [19]. The five-step LCA + DEA method constitutes a regular protocol for the combined operational and environmental assessment of multiple DMUs [12].

In the first place, inventory data are collected as in regular LCAs in order to develop an individual Life Cycle Inventory (LCI) of each of the considered DMUs (step 1). Thereafter, the Life Cycle Impact Assessment (LCIA) is performed for each DMU, which enables us to obtain the specific environmental profile of the existing DMUs (step 2). DEA is applied by establishing a matrix with the most relevant inputs and outputs extracted from the LCIs, with the aim of calculating the operational efficiency of the different units (step 3). In addition to efficiency scores, target DMU values are determined, that is, virtual DMUs that consume a lower amount of inputs relative to the generated outputs. Once the target values for inefficient DMUs are known, these entities undergo a second LCIA with modified LCI data, leading to the computation of the potential environmental impacts linked to target DMUs (step 4). Finally, a comparison is established between current and target DMUs, which allows us to quantify the environmental and economic consequences regarding inefficient operational activities (step 5).

It is important to note that when DEA is computed, the selected input minimization or output maximization perspective will determine the orientation of the selected DEA model (input-oriented, output-oriented or mixed orientation). Most of the LCA + DEA studies available in the scientific literature have used an input-oriented approach, based on the fact that it guarantees focusing on the reduction of input consumption and, therefore, of the input-related environmental burdens [12,21–23], while maintaining unvaried the output production. This perspective contrasts with the output-oriented model, which aims at maximizing outputs, while using the same amount of inputs [27].

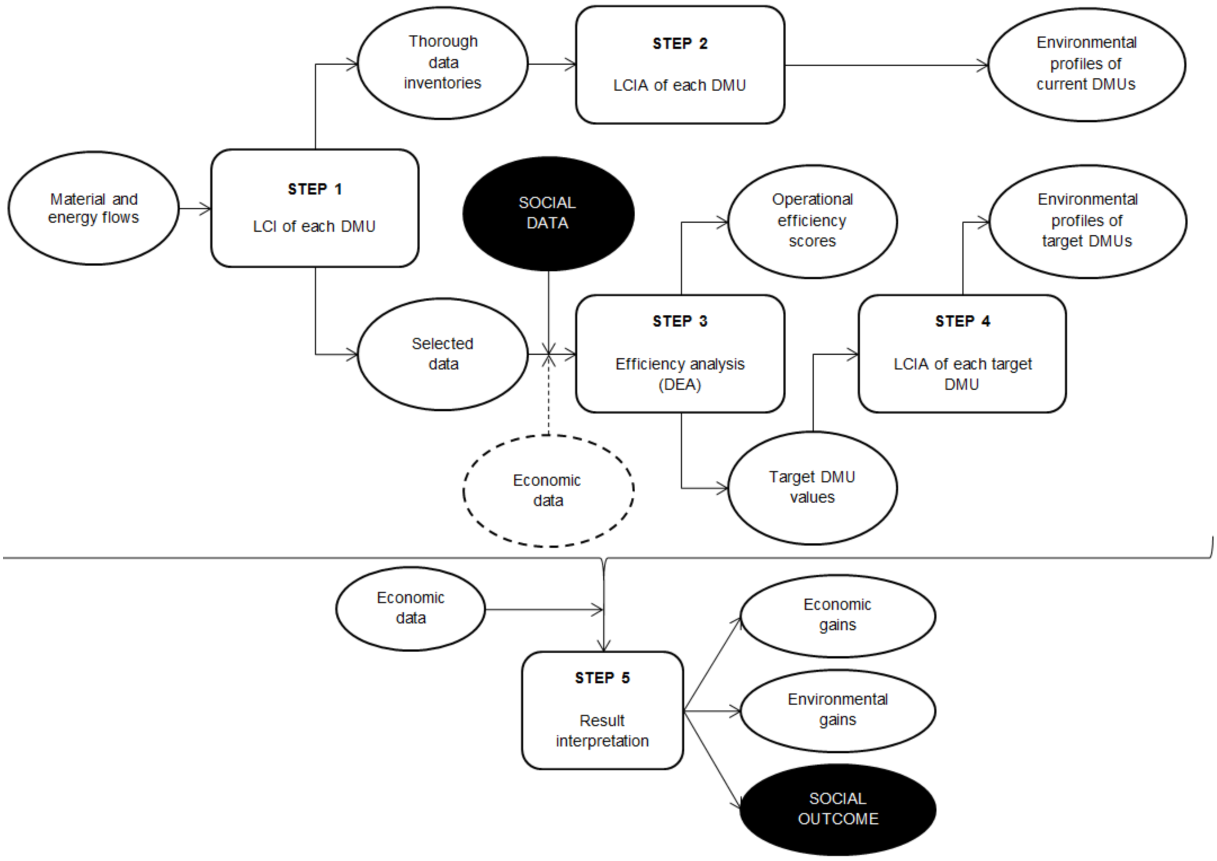
2.2. Selection of Inputs and Outputs

To date, LCA + DEA studies have had a two-headed policy regarding the selection of inputs and outputs. On the one hand, LCA includes a thorough inventory of material and energy flows, in order to cover with accuracy the entire production system under study. On the other hand, input and output selection for DEA is limited to those items that (i) entail a strong environmental effect (based on existing LCA studies in comparable production systems) and/or (ii) entail important cost reductions if minimized. Furthermore, it is important to take into account that the number of inputs/outputs in the DEA matrix is constrained by the number of DMUs included in the system [13] and, generally, by the assumption of independent items (e.g., if diesel is included as an input for minimization, its direct emissions are not included in the matrix to avoid duplication, since they are also being minimized indirectly).

For instance, Iribarren *et al.* [22] identified a set of fodder products and energy inputs as the main DEA inputs in dairy milk farms, while the output was the production of milk along with a series of "bad outputs" (emissions linked to the animals and wastewater), which were modeled as inputs. Vázquez-Rowe *et al.* [23], when studying vine-growing plots, identified fertilizers, pesticides and diesel as the main DEA inputs, although water from nature and concrete for infrastructure were also included. In this particular case, the chosen DEA output was grape production for vinification. Finally, Vázquez-Rowe *et al.* [21], when identifying different operational patterns between fishing fleets, used diesel, hull material, nets and anti-fouling as DEA inputs, whereas the output in this case was purely economic: the catch value of each vessel under evaluation. Therefore, in general terms, previous LCA + DEA studies have explored operational traits of the evaluated systems and combined them with a final commercial product or its economic value.

However, given the flexible characteristics of the DEA methodology regarding the nature of the selected inputs and outputs, the inclusion of social parameters seems a feasible upgrade when implementing the five-step LCA + DEA method. Figure 1 outlines this integrative LCA + DEA concept. As observed, the main innovation is the addition of social data to the DEA matrix, so that the efficiency analysis performed in step 3 includes the benchmarking of the considered social aspects, allowing these to be taken into consideration when it comes to interpreting the results (step 5). Section 3 examines the feasibility of this integrative LCA + DEA concept through the inclusion of potential social parameters in illustrative case studies.

Figure 1. The integrative Life Cycle Assessment (LCA) + Data Envelopment Analysis (DEA) concept. Implementation of social elements into the traditional five-step LCA + DEA method.



3. Implementation of Labor into LCA + DEA Studies

The inclusion of labor as an additional DEA item has been suggested as a potential measure to boost the socioeconomic dimension of LCA + DEA studies [23]. In this section, two approaches for the implementation of labor according to the integrative LCA + DEA concept are developed. In the first place, the number of workers is considered as a DEA item. Secondly, the number of working hours is evaluated as an alternative social parameter. Both approaches are herein tested using illustrative case studies. These case studies refer to two different fishing fleets: a trawling fleet and a long-lining fleet, which were selected based on data availability. In fact, it should be stressed that the core requirement for the application of the LCA + DEA methodology to any sector is the availability of multiple input/output data for multiple similar entities [12].

Table 1 presents the DEA matrix for each illustrative fleet when using the crew size or, alternatively, the number of working hours as social DEA elements. As observed, labor was modeled as an input in all cases. The implications of this important choice are discussed later in Section 4.1.

Table 1. DEA matrices for the illustrative case studies using the number of workers or working hours as an input.

DMU	Input 1	Input 2	Input 3	Alternative Input 3	Output
	Diesel (kg/year)	**Hull material** (kg/year)	**Crew size** (units)	**Working hours** (h/year)	**Catch value** (€/year)
Trawling fishing fleet					
Vessel T-1	404,000	3,933	8	21,120	443,996
Vessel T-2	404,000	3,074	9	25,920	718,655
Vessel T-3	404,000	2,416	9	25,920	718,655
Vessel T-4	440,000	4,333	10	26,400	917,952
Vessel T-5	480,000	4,333	10	26,400	917,952
Vessel T-6	404,000	4,840	10	24,240	796,224
Vessel T-7	350,000	4,707	10	28,800	1,214,898
Vessel T-8	347,000	3,330	10	28,800	1,214,898
Vessel T-9	404,000	3,032	10	26,400	521,226
Vessel T-10	404,000	3,712	10	26,400	521,226
Vessel T-11	330,000	2,781	8	21,120	1,005,718
Vessel T-12	355,000	2,390	8	21,120	1,005,718
Vessel T-13	292,900	3,257	7	18,480	1,326,989
Vessel T-14	305,000	1,827	7	18,480	1,326,989
Vessel T-15	383,800	2,222	12	31,680	1,353,235
Vessel T-16	242,400	3,234	7	16,968	575,377
Vessel T-17	250,400	3,773	7	16,968	575,377
Vessel T-18	303,000	3,029	8	19,392	660,298
Vessel T-19	378,375	2,809	10	24,240	928,290
Vessel T-20	242,400	3,029	9	21,816	565,931
Long-lining fishing fleet					
Vessel L-1	680,000	3,138	16	36,000	1,633,578
Vessel L-2	654,000	3,450	16	36,000	1,583,310
Vessel L-3	952,000	6,320	16	48,000	945,792
Vessel L-4	349,550	4,067	15	42,000	472,936
Vessel L-5	315,000	3,983	14	40,600	726,600
Vessel L-6	300,000	4,240	15	33,750	691,900
Vessel L-7	340,000	4,182	16	36,800	690,700
Vessel L-8	325,000	2,829	15	36,750	792,410
Vessel L-9	320,000	2,954	14	35,700	643,910
Vessel L-10	258,400	5,000	16	43,200	771,328
Vessel L-11	163,200	2,819	16	43,200	732,448
Vessel L-12	353,600	5,067	15	40,500	849,152

After the establishment of the DEA matrices, they were analyzed using an input-oriented slacks-based measure of efficiency (SBM-I) model with constant returns to scale (CRS) [14], in accordance with the recommendations in Vázquez-Rowe *et al.* [21] for LCA + DEA implementation in these types of fleets. The DEA model was formulated as follows [21,22]:

$$\Phi_0 = \mathrm{Min}\left(1 - \frac{1}{M}\sum_{k=1}^{M}\frac{\sigma_{k0}}{x_{k0}}\right) \tag{1}$$

subject to:

$$\sum_{j=1}^{N}\lambda_{j0}x_{kj} = x_{k0} - \sigma_{k0}\ \forall\ k \tag{2}$$

$$\sum_{j=1}^{N}\lambda_{j0}y_j = y_0 \tag{3}$$

$$\lambda_{j0} \geq 0\ \forall\ j, \sigma_{k0} \geq 0\ \forall\ k \tag{4}$$

With N: number of vessels; j = 1, 2,..., N: index on the vessel; M: number of inputs; k = 1, 2,…, M: index on inputs; x_{kj}: amount of input k demanded by vessel j; y_j: amount of output generated by vessel j; 0: index of the vessel under assessment; $(\lambda_{10}, \lambda_{20}, \ldots, \lambda_{N0})$: vector of coefficients of linear combination for assessing vessel 0; σ_{k0}: slack (*i.e.*, potential reduction) in the demand of input k by vessel 0; and Φ_0: efficiency score for vessel 0.

The target input values for each vessel ($\hat{x}_{k0}$) were computed according to the following equation:

$$\hat{x}_{k0} = \sum_{j=1}^{N}\lambda_{j0}x_{kj} = x_{k0} - \sigma_{k0}\ \forall\ k \tag{5}$$

The selection of the model was based on its best fit to the objectives of the study as compared to other commonly used models in DEA computation (*e.g.*, Charnes-Cooper-Rhodes (CCR) or Banker-Charnes-Cooper (BCC) models). The main reason for this was the fact that an SBM model allows efficiency calculation of the entities regardless of the units of measure that are foreseen for the different items. Moreover, the SBM model shows non-radial metrics in order to compute the reduction potentials (*i.e.*, benchmarks) of each input independently from one another [13].

The input-oriented perspective was chosen based on the rationale developed in other DEA studies for fisheries [28], since the limiting factor in fisheries is the abundance of the natural resource. Hence, it seems unfeasible to maximize the output rather than propose minimized inputs to arrive to equal yield values. Regarding the display of the production possibility set (PPS), the CRS approach was considered based on the assumption that all vessels operate in a competitive market [17,29].

DEA-Solver Pro 9 was the software used for DEA computation [30]. At this stage, efficiency scores and target values constitute the main outcome. Efficiency scores lead to discrimination between efficient and inefficient DMUs. For those entities identified as inefficient, target values define a virtual DMU with efficient input consumption levels, which are considered to be feasible according to the PPS established through DEA computation. Table 2 presents the efficiency scores and the target values for the considered case studies when using crew size as a DEA input. Note that, for those DMUs found to be efficient (*i.e.*, 100% efficiency score), current and target values are identical.

Table 2. Efficiency scores and target values for the illustrative case studies using the number of workers as an input.

DMU	Efficiency score (%)	Target 1	Target 2	Target 3
		Diesel (kg/year)	**Hull material** (kg/year)	**Crew size** (units)
Trawling fishing fleet				
Vessel T-1	23.36	102,050	611	2
Vessel T-2	38.40	165,178	989	4
Vessel T-3	41.32	165,178	989	4
Vessel T-4	41.84	210,985	1,264	5
Vessel T-5	40.51	210,985	1,264	5
Vessel T-6	36.65	183,007	1,096	4
Vessel T-7	59.80	279,237	1,672	6
Vessel T-8	64.93	279,237	1,672	6
Vessel T-9	26.94	119,800	717	3
Vessel T-10	25.49	119,800	717	3
Vessel T-11	62.05	231,158	1,384	5
Vessel T-12	63.12	231,158	1,384	5
Vessel T-13	100.00	292,900	3,257	7
Vessel T-14	100.00	305,000	1,827	7
Vessel T-15	74.79	311,032	1,863	7
Vessel T-16	40.80	132,247	792	3
Vessel T-17	39.05	132,247	792	3
Vessel T-18	41.21	151,765	909	3
Vessel T-19	50.26	213,362	1,278	5
Vessel T-20	37.52	130,076	779	3
Long-lining fishing fleet				
Vessel L-1	100.00	680,000	3,138	16
Vessel L-2	96.17	654,000	3,092	16
Vessel L-3	42.67	393,699	1,817	9
Vessel L-4	36.51	196,866	908	5
Vessel L-5	60.63	302,458	1,396	7
Vessel L-6	57.51	288,013	1,329	7
Vessel L-7	52.86	287,514	1,327	7
Vessel L-8	69.76	325,000	1,571	8
Vessel L-9	56.89	268,037	1,237	6
Vessel L-10	71.25	258,400	2,106	11
Vessel L-11	100.00	163,200	2,819	16
Vessel L-12	62.53	353,472	1,631	8

The second approach to integrate labor in the five-step LCA + DEA method raises the use of the number of working hours as an appropriate DEA element. Following the same procedure as in the first approach (number of workers), Table 3 presents the main results from DEA computation.

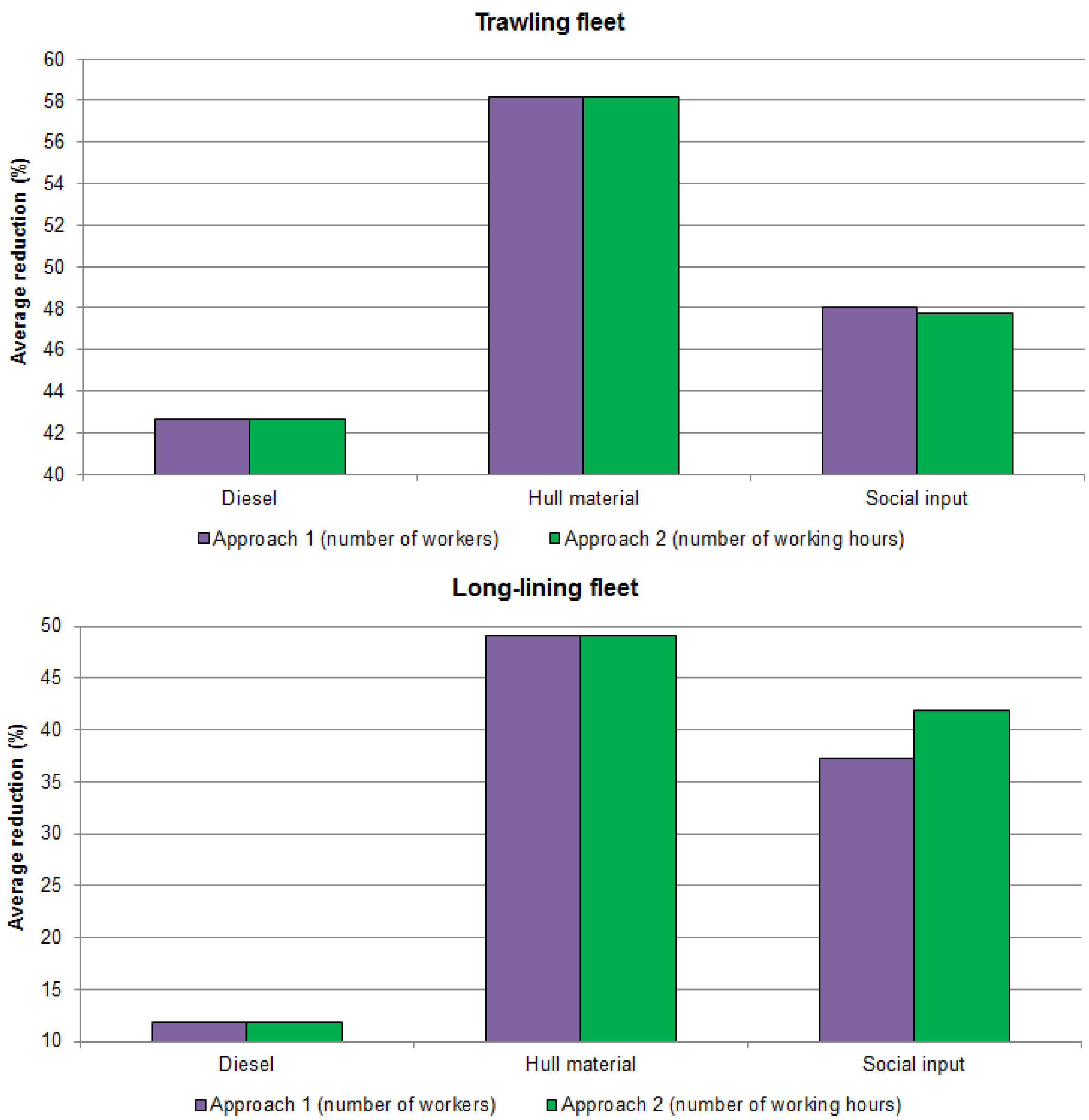
Table 3. Efficiency scores and target values for the illustrative case studies using the number of hours as an input.

DMU	**Efficiency score** (%)	**Target 1**	**Target 2**	**Target 3**
		Diesel (kg/year)	**Hull material** (kg/year)	**Working hours** (h/year)
		Trawling fishing fleet		
Vessel T-1	23.36	102,050	611	6,183
Vessel T-2	37.23	165,178	989	10,008
Vessel T-3	40.15	165,178	989	10,008
Vessel T-4	41.84	210,985	1,264	12,784
Vessel T-5	40.51	210,985	1,264	12,784
Vessel T-6	37.90	183,007	1,096	11,088
Vessel T-7	58.02	279,237	1,672	16,919
Vessel T-8	63.15	279,237	1,672	16,919
Vessel T-9	26.94	119,800	717	7,259
Vessel T-10	25.49	119,800	717	7,259
Vessel T-11	62.05	231,158	1,384	14,006
Vessel T-12	63.12	231,158	1,384	14,006
Vessel T-13	100.00	292,900	3,257	18,480
Vessel T-14	100.00	305,000	1,827	18,480
Vessel T-15	74.79	311,032	1,863	18,846
Vessel T-16	42.09	132,247	792	8,013
Vessel T-17	40.34	132,247	792	8,013
Vessel T-18	42.51	151,765	909	9,195
Vessel T-19	51.72	213,362	1,278	12,928
Vessel T-20	38.50	130,076	779	7,881
		Long-lining fishing fleet		
Vessel L-1	100.00	680,000	3,138	36,000
Vessel L-2	96.41	654,000	3,092	35,861
Vessel L-3	37.84	393,699	1,817	20,843
Vessel L-4	34.49	196,866	908	10,422
Vessel L-5	56.83	302,458	1,396	16,012
Vessel L-6	57.51	288,013	1,329	15,248
Vessel L-7	52.55	287,514	1,327	15,221
Vessel L-8	68.52	325,000	1,571	18,389
Vessel L-9	55.13	268,037	1,237	14,190
Vessel L-10	69.73	258,400	2,106	28,967
Vessel L-11	100.00	163,200	2,819	43,200
Vessel L-12	59.45	353,472	1,631	18,713

When the results in Tables 2 and 3 for the two approaches are compared, similar results are obtained for the efficiency scores, while identical target values are calculated for the operational inputs. In particular, the same efficient DMUs were identified through both approaches.

Figure 2 shows a graphical representation of the average reduction in the input levels benchmarked for each illustrative case study according to the two proposed approaches. Within each case study, the same reduction in input consumption was achieved for the operational items regardless of the selected approach. However, different reductions in the social input were observed. Regarding the sensitivity of the selected inputs on the efficiency [31], diesel and hull material were found to have significantly higher sensitivity than the social inputs in all cases.

Figure 2. Average reduction in the selected inputs for the illustrative case studies using the number of workers or working hours as social inputs.



The final step of the method deals with the interpretation of the results from a combined operational, economic, environmental and social perspective. As observed in Figure 2, relevant average reductions were found to be feasible for the selected inputs, which would translate into significant environmental gains. Since only operational inputs constitute an actual reduction in environmental impacts, and given that identical reductions in the operational inputs were benchmarked for both approaches, the same environmental gains would be estimated regardless of the selected approach for the implementation of labor. The calculation of these reductions in the environmental impacts is out of the scope of the present paper, as it has already been addressed in previous studies [21]. Similarly, the economic savings linked to lower input levels could be easily estimated [19]. It should be noted that the environmental impacts linked to human labor were excluded from the environmental assessment in steps 2 and 4, following common practice in life-cycle studies.

The present study focuses on the social dimension of the integrative LCA + DEA concept. In this sense, further interpretation of the results for the third input (number of workers/working hours) is needed. As seen in Figure 2, notable reductions are feasible in terms of both crew size and working hours. However, caution is needed when interpreting the social input minimization, as discussed later in Section 4.1.

When comparing the suitability of the two approaches for the implementation of labor, it should be noted that the second approach, which is based on the number of working hours, includes implicitly the employees, as it is calculated taking into account the number of (i) working days, (ii) working hours per day and (iii) workers. This fact suggests that an hour-based approach is more suitable and realistic than a worker-based one, when integrating labor as a socioeconomic parameter in the five-step LCA + DEA method. It is also important to note that the inclusion of both social inputs in the same DEA matrix could lead to inconsistent results, given the relationship between both inputs.

4. Discussion

4.1. Limitations of Labor as a Social Item in LCA + DEA Studies

The main strength observed for the inclusion of labor is that it succeeds in providing the five-step LCA + DEA method with a social dimension, thus offering an all-in-one methodology that is easy to implement, provided that multiple inventory data are available for multiple DMUs (*i.e.*, for multiple similar entities under evaluation). Another notable advantage of the inclusion of social indicators in LCA + DEA studies is the quantitative nature of them. Whereas SLCA is constituted by a joint use of qualitative and quantitative impact categories (which makes their assessment, weighting and normalization complex), the use of the LCA + DEA methodology allows a greater adaptation to the characteristics of the analyzed systems, permitting direct and quantitative assessments of the social dimension between multiple comparable production systems. In fact, the perspective recently suggested for SLCA studies, in which social databases at the sector or national level would be used [32], while allowing a higher malleability of the already hard to retrieve social data, would hinder its usability to detect differences between similar production systems or units. Moreover, the quantitative inclusion of the three pillars of sustainability in LCA + DEA allows more sensible decision making by stakeholders or other actors interested in a particular production system [18,33].

However, some limitations of the proposed methodology must be discussed. In the first place, the integrative LCA + DEA concept developed in this study focuses on the environmental and operational performance of the entities subject to assessment. The economic and social components of the sustainability assessment fail to reach the level of detail observed for the environmental component. The methodological structure of the proposed LCA + DEA approach can make the use of social parameters (other than labor) difficult to implement. This observation is in line with the concern stated by Udo de Haes [5] on potential risks when certain types of impacts are included in an LCA-based methodology. Additionally, the inclusion of working hours or number of workers in the DEA matrix does not take into consideration the whole set of background processes that widen human labor activities to the economic and environmental dimensions, such as activities in non-working hours that are seen as essential for sustaining human labor [34].

Secondly, it is necessary to be cautious when interpreting the results obtained from the integrative LCA + DEA concept. The suitability of choosing labor as a DEA input is highly conditioned by the perspective taken by the social actors involved in the analysis (workers, managers, policy makers, *etc.*). This is associated with the resource optimization performed through DEA, especially when choosing an input-oriented model. In this respect, when using labor as a DEA input, all actors should understand labor minimization as a virtual means toward the redefinition of tasks with socioeconomic growing purposes, but not as a tool for the identification of useless job positions. The latter would be socially unacceptable and a wrong economic decision. For instance, the identification of fruitless hours should lead to the redefinition of tasks by reallocating these hours to activities, such as training or research, which would result in future benefits for both the employee and the company. Hence, from a societal perspective, labor minimization does not mean a rise in unemployment, but a track toward socioeconomic growth. In fact, the main aim of integrating social parameters in LCA + DEA analysis, in the same way as in SLCA studies, is linked to the improvement of social conditions [35,36].

This concern on the interpretation of the social results is closely linked to the use of input-oriented DEA models. While potential reasons for using this orientation in LCA + DEA studies have been stated in Section 2.1, the integration of social inputs within this perspective can offer perilous outcomes. For instance, for the illustrative case studies used in Section 3, it may be argued that a minimization of the social input in the terms presented in this study may imply a reduction in crew sizes, with a subsequent decrease in jobs in the fishing sector, which constitutes a wrong interpretation of the social results of the method as previously discussed [36].

Regarding result interpretation, the use of LCA + DEA presents similar flaws to those observed for SLCA, since the identification of the social input benchmarks disregards the social impacts linked to the new scenario [32]. This unequivocally leads to the need of applying consequential thinking in SLCA, since result transfer for decision support can only be raised when the full scope of the risks and consequences of the benchmarks are fully understood. Nevertheless, the current implementation of such a scheme rebounds back to the other main limitation of computing social impacts: data availability.

Where there is special interest in the social dimension of the LCA + DEA study, and provided that the conditions of the system under assessment are not violated, output-oriented models could be used, as they maximize production levels, while maintaining the same labor levels. However, in many cases (*e.g.*, the illustrative case studies used through this article), system conditions are violated, and input-oriented models are, therefore, more appropriate. For instance, when assessing quota systems, such as dairy farms [22], fisheries [21] and vineyards [23], input-oriented models are usually preferred due to strict production limits [28].

Finally, the lack of standardized inventory data for social indicators is recognized as a general hurdle in sustainability assessments [32,37], the integrative LCA + DEA concept not being an exception in this matter. In this context, there is little space for objectively choosing appropriate data for implementation in sustainability evaluations, especially taking into consideration that social indicators may be influenced by cultural perceptions [37]. Nevertheless, whereas the inclusion of operational inputs in the DEA matrix is subject to relevant environmental effects or economic gains, the choice of social parameters is most likely to be determined by data availability.

Regarding data availability, the application of LCA + DEA methodology usually implies the use of a set of multiple entities that are located in a specific site. This fact could limit the number of parameters suitable for social LCA + DEA. It should be noted that the geographical specificity of LCA + DEA studies is not a requirement itself, but a common result of the homogeneity requirement included in the DMU concept. While geographical specificity (regionalization) can be considered as a constraint due to the limited scope of the analysis, it can also provide highly specific results for a localized activity or geographical area, since many social parameters, such as employment or housing, may be highly site-specific in many cases [38]. Hence, the LCA + DEA approach could be attractive at a local or regional level concerning decision making.

4.2. Perspectives

Despite the limitations discussed, the integrative LCA + DEA concept is expected to be useful as a simple procedure to encompass operational, economic, environmental and social aspects when multiple inventory data are available for multiple similar entities. A sensible interpretation of the results from this type of integrative LCA + DEA study is of paramount importance. Further examination on the potentials of LCA and DEA could result in novel uses of the integrative concept. For instance, in combination with the use of super-efficiency models [39], it could be used for policy-making purposes [19].

The focus of the integrative LCA + DEA concept is on the environmental dimension of the sustainability assessment, even though both social and economic parameters can be successfully implemented. Regarding social elements, labor (preferably in terms of working hours) is regarded as an easy-to-implement item. The use of other employment parameters, as well as of other dimensions of social sustainability, is conditioned by their capability to strengthen the social dimension of the five-step LCA + DEA method. For instance, in fishing fleets, the inclusion of accidents and injuries may be an interesting additional input to be included in future studies, due to the high resilience of labor work-related accidents in this sector [40,41]. Income (*i.e.*, the general compensation of employees) could also be considered as an additional parameter in future studies [41,42]. However, the inclusion of certain social issues, mainly related to macro-scale indicators (*e.g.*, regional GDP, net migration rate, *etc.*) does not appear as a further potential in LCA + DEA, since it would not be feasible from a methodological perspective to optimize them in sector-specific multiple entity systems.

The number of workers and the number of working hours are expected to be the most common socioeconomic elements implemented in LCA + DEA studies. More specifically, the use of working hours seems to be a more scientifically sound selection rather than number of workers. The preference for the use of working load links to its more comprehensive nature, with underlying assumptions regarding work quality or stability, rather than a mere quantification of jobs.

Since the integrative LCA + DEA concept is not a substitute for SLCA, a future improvement of the former could be the inclusion of SLCA impact categories within the LCA + DEA framework once these social categories are well established. In this way, the five-step LCA + DEA method would include a double-headed LCI and LCIA, by converging social and environmental analysis, mainly affecting steps 1 and 2 of the methodology (Figure 1). As long as widely-accepted social categories are not available and a consensus regarding the weighting of the midpoint categories is not attained [38], the LCA + DEA methodology offers a straightforward approach for the integration of social parameters, such as labor, into the operational and environmental assessment of multiple similar entities.

5. Conclusions

The use of the five-step LCA + DEA method enables the integration of environmental, economic and social parameters in a single methodological approach, rather than the parallel assessment of these three pillars of sustainability. Labor as a social element in LCA + DEA studies proved to enrich the results of the sustainability assessment. In particular, working load could be easily incorporated as a suitable item. Thus, the integrative LCA + DEA concept was found to be a valid framework to broaden the scope of current LCA + DEA studies. Nevertheless, some limitations exist concerning the scope and level of detail of the social dimension, the interpretation of the social results, the orientation of the DEA model and data availability.

In the context of the integrative LCA + DEA concept, resource optimization should be understood and interpreted as a means to economic enhancement, ideally leading to the generation of job positions. More efforts are needed to develop further uses of the LCA + DEA methodology, as well as for defining a wider range of social items suitable for their integration into the novel LCA + DEA integrative framework.

To sum up, and coming back to the title of this work: is labor a suitable input in LCA + DEA studies? Yes, it is, but cautious result interpretation is required.

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Conflict of Interest

The authors declare no conflict of interest.

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