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Selection of Production Mix in the Agricultural Machinery Industry Considering Sustainability in Decision Making

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Abstract: Competition among companies is growing globally, with the need to increase productivity and efficiency in the product sector. However, there is also a growing concern about global warming and the depletion of natural resources, as well as their effects on human health. In this context, all human activities that involve intense usage of resources must take into account sustainability as one of the decision criteria. This work presents the application of decision-making methods to define the best product mix in the agricultural machinery industry. With this objective, the current schedule of the production line was identified, along with the production flow, by performing an inventory analysis and an environmental impact study (endpoint). A total of seven alternatives for the production mix of grain trailers were defined, considering different materials and production processes. The selection of the best schedule according to the different criteria was performed through the analytic hierarchy process (AHP) and data envelopment analysis (DEA) to evaluate the managerial implications for decision making. The results obtained through AHP identified a single alternative as being the best, which facilitates the decision making. The DEA method identified two alternatives as the most efficient, and in this case the manager can choose between a product mix that generates lesser environmental impact or greater profitability. Although applied to agricultural industry, the presented methodology can be easily adapted to other activities related to the built environment, such as construction industry.

Keywords: analytic hierarchy process (AHP); data envelopment analysis (DEA); sustainability; product mix; agricultural industry; decision making

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1. Introduction

The development of manufacturing technologies has led to a revolution in the most diverse areas of modern society and sustainable development, with advances in manufacturing, infrastructure, and technologies [1,2]. This has caused competition between companies to grow, with manufactures continually seeking higher productivities, product quality, and manufacturing efficiency [3]. For example, in Brazil, where agribusiness represents about 22.54% of GDP (and 36% of total exports), it is estimated that the agricultural machinery industry will grow by an average of 5.8% per year in the next years [4,5]. To avoid the impact of falling sales, the agricultural machinery industry has manufactured several product models (product mix) to make the production line more flexible. This has made it possible to maintain activity during seasonal periods, as 20.1% of the country's workforce is employed in various segments of agribusiness [6].

In addition to the need for the industry with a broad product mix, which makes production planning more complex, there are still problems facing the daily planning of orders for the shop floor [7]. The production planning and control (PPC) sector is generally concerned with two criteria: (1) sequencing of the production line, and (2) balancing the production line. These two criteria seek only to make better use of working time on the production lines and do not analyze the environmental impact of manufacturing technology. In this sense, important criteria in planning the production mix can be focused on, namely: working time, productivity, and profitability.

Several studies have been conducted on the importance of good planning for the production mix. For example, configuring the production line according to the products to obtain good synchronization, allocating the appropriate amount of human resources to the process to avoid delays [8]. In addition, the formulation of problems for the planning of aggregated production in the automotive industry makes the workforce more flexible, with changes in costs and the workload of operators [9]. Improving the allocation and distribution of labor in the industry, for the purpose of improving the productivity of operators and the hours worked, can be cited as the task carried out in the automotive, plastic, and service industries [9–12].

However, the industry seeks greater efficiency in production processes, where increased productivity and profitability are considered the primary criteria behind decision making. Improvements in the industry generally focus on reducing waste and process variability, while markets demand greater flexibility and lower product costs [13]. However, along with technological advances, increased productivity, and competitiveness, there are also environmental issues that need to be accounted for. In this sense, a strong relation can be observed between components of the built environment and climate change, with agriculture and industry being some of these components [14]. Unlike the natural environment, the built environment is comprised of manmade components. The built environment influences human choices, which in turn affect global climate and human health [15].

It has been noticed that the monitoring of sustainability becomes important for decision making and management of activities in organizations [16]. As for technological advances, in a study carried out in Ireland on the use of Smart Farming Technologies (SFT), it was observed that the cost and high initial investment are the factors that inhibit the adoption of new technologies by farmers. Another important aspect is the lack of infrastructure, such as the absence of the internet. However, the use of Cloud Computing technology among young farmers is higher compared to older farmers [17]. Another study in Australia's rice industry sought to understand the barriers to broader adoption of smart agriculture technologies. The study concluded that agricultural consultants and extension agents play an important role in assisting the farmer and encouraging smart agriculture [18].

To assess the best production mix considering the production planning alternatives for various criteria, multi-criteria decision-making methods (MCDM) can be used. For example, the application of the analytical network process (ANP) for product mix selection by a semiconductor manufacturer [19], the development of a model to optimize the selection of suppliers for the apparel industry, using sustainability criteria [20], and the selection of suppliers using economic and environmental criteria in a technology company [21]. Decision making is also an important component for smart agriculture in the use and encouragement of new technologies [17,18].

A growing number of publications can be observed focusing on sustainability in the agricultural machinery industry, such as: the tractor engine load mode to determine fuel consumption and exhaust emissions [19]; in agriculture, the work in the rotary harrowing operation and comparative evaluation of the life cycle [20]; the tractor productivity evaluation that evaluated the efficiency in energy use, fuel consumption, and gas emissions for plowing work in fields with different lengths [21]; the evaluation of sustainability indicators focused on productivity and operational performance [22,23]. Nevertheless, there are still limitations in the analysis of the production mix, especially in the agricultural machinery industry, including the aspect of environmental impact. Several studies have been conducted on the environmental impact of various industries, such as choosing outsourced logistics providers [24], vehicle engine technologies [25], and strengths and weaknesses in the photovoltaic industry [26]. However, there is a lack of studies to identify the best product mix in the agricultural industry that considers the environmental impact as one of its criteria.

Based on this, this study aims to apply two multi-criteria methods for decision making, the analytic hierarchy process (AHP) and data envelopment analysis (DEA), for the definition of planning regarding the best production mix, with the environmental impact being one of the criteria. To achieve this goal, seven production mix configurations were evaluated. The products that make up the mix are grain trailers and machines used for transporting and storing fertilizers and fertilizers. Products were evaluated considering the following quantitative criteria: working time on the production line, productivity, profitability, and environmental impact which was measured with SimaPro software. After the results were obtained in each of the methods, AHP and DEA, a comparison was performed to assess the relationships and implications in the use of the methods, from the point of view of managerial implications, of the agricultural machinery industry for decision making.

The remainder of this article is structured as follows: The second section briefly describes the multi-criteria decision-making methods that are the focus of this study: AHP and DEA. The third section presents the methodology used. The results and discussion are presented in the fourth section. Finally, the conclusions and final considerations are presented.

2. Multi-Criteria Decision-Making

There is an increase in the amount of available information, which contributes to the complexity of decision-making. Generally, decisions are made based on the experience of the decision-maker, and the divergences between the analysis of decision-makers can be observed; there may be biased opinions that negatively influence the result [27]. In this context, the MCDM aims to support decision-makers in making the best choice, enabling the evaluation of various criteria [28].

Two decision-making methods were used for this study: the analytic hierarchy process (AHP) and data envelopment analysis (DEA). AHP is a multi-objective decision-making method that enables the analysis of qualitative and quantitative data [29,30] whilst DEA categorizes the criteria used as inputs and outputs, where the factors that need to be minimized are placed as inputs and the factors to be maximized are placed as outputs [31,32].

A literature review covering the years 1999 to 2017, in the area of mining engineering and mining processes, identified that the AHP method is the most used, both individually and in a hybrid manner [33]. More studies can be cited with the use of AHP in the automobile industry for manufacturing performance and production flow [15]. In the best use of equipment, eliminate bottlenecks, and enable training of operators [34].

AHP is one of the most powerful multi-criteria techniques, which was originally proposed by Saaty in 1980 and applied to a variety of uses, measures intangibles with the assistance of expert judgments through peer comparisons [35]. Once the criteria are selected, a paired comparison is performed, with the criteria weights calculated within the established hierarchy. First, a qualitative value is assigned to the criterion, and then a numerical value is assigned. Thus, the score is assigned in a way that looks reasonable, and the reciprocal pair comparisons performed in a carefully designed manner [36].

DEA aims to benchmark the performance of decision-making units (DMUs). Units that use the same inputs and outputs are evaluated and compared, where the calculated efficiency is the maximum value, making this simplification effective in avoiding subjective assumptions. Judgment takes place objectively, and DMUs that fall outside the efficient boundary can be considered underperforming and further analyzed to determine what can be done to improve their efficiency [37].

A layout study for a precision part machining industry can be cited as an example of a combination of the AHP and DEA methods. Qualitative performance data were obtained by applying AHP, and DEA was applied to identify the efficiency scores considering the quantitative and qualitative performance data. This enabled determining the best global alternative [38]. The combination of methods was also used to assess the facility layout design, where AHP was applied to assess qualitative data for quality and flexibility [32]. Another study combined AHP and DEA methods to evaluate the performance of companies in the PV energy sector. The AHP was applied to collect expert opinions and the DEA to measure which companies are the most efficient [26], to evaluate the road safety performance of a set of European countries (or DMUs), combining the AHP and DEA method [39], and to classify organizational units, where each unit has multiple inputs and outputs [40].

3. Materials and Methods

3.1. Data Collection

The methodology proposed in this study was applied to a manufacturer located in southern Brazil, one of the largest agricultural machinery manufacturers in the country. It produces tools and machines for grain supply and transport, planting and harvesting, soil preparation and cleaning, fertilizer distribution, and spraying. The industry studied is unaware of the multi-criteria methods for decision-making and does not make use of environmental impact assessment in the manufacture of products.

Altogether, the industry produces five models of grain trailers with capacities of 10,500, 12,000, and 15,000 L, used to transport grains and/or granulated fertilizers. The product codes and configurations used by PPC for production planning are described below and are the same as those used in a previous study developed by the authors [41]:

- 10.5DcTmul represents an agricultural machine with 10,500 L of grain and fertilizer transport capacity. It has carbon steel storage and a multipurpose discharge pipe.
- 10.5DiTmul represents an agricultural machine with 10,500 L of grain and fertilizer transport capacity. It has stainless steel storage and a multipurpose discharge pipe.
- 12.0DiTmeci represents an agricultural machine with 12,000 L of grain and fertilizer transport capacity. It has stainless steel storage and a multipurpose discharge pipe.
- 15.0DcTmec represents an agricultural machine with 15,000 L of grain and fertilizer transport capacity. It has carbon steel storage and a multipurpose discharge pipe.
- 15.0DiTmul represents an agricultural machine with 15,000 L of grain and fertilizer capacity. It has stainless steel storage and multipurpose discharge pipes.

3.2. Criteria Evaluated

The next subsection details the four quantitative criteria evaluated: productivity, working time, profitability, and environmental impact. To perform comparisons, a functional unit of one square meter per product was considered. Energy consumption related to each product separately was not considered, once the industry does not have this information.

3.2.1. Productivity

The PPC prepares the production plan, where the product mix involves three machines a day, with the seven alternatives used by PPC for daily planning presented in Table 1. For example, Alternative 1 considers two 10.5DcTmul products and one 15.0DcTmec product and Alternative 2 considers two 10.5DcTmul products and one 12.0DiTmeci product.

Table 1. Product mix.

Products	Alternatives						
	1	2	3	4	5	6	7
10.5DcTmul	2	2	1				
10.5DiTmul				2	2		
12.0DiTmeci		1	1	1		1	
15.0DcTmec	1				1		1
15.0DiTmul			1			2	2
Total product/day	3	3	3	3	3	3	3

3.2.2. Working Time and Profitability

During the preparation of the master production plan, the PPC also obtains information regarding the working time of the production stations and the profitability. The industry considers this data important for workload planning and product profitability. Table 2 presents the working time (in hours) and profitability by the production mix (in US$).

Table 2. Working time and profitability referring to 1 m^2 of the production mix.

Production Mix Alternatives	Working Time (h)	Profitability ($)
Alternative 1	0.7211	$151.64
Alternative 2	0.8587	$173.76
Alternative 3	0.9390	$200.70
Alternative 4	1.0476	$202.69
Alternative 5	0.9100	$180.57
Alternative 6	1.0193	$227.65
Alternative 7	0.8817	$205.53

3.2.3. Environmental Impact Inventory Analysis

This step represents the collection of primary data along with the manufacturing process of the grain trailer. The life cycle inventory aims to identify and quantify the environmental interventions related to the systems, placing the results in a list of environmental inputs and outputs [42]. The environmental impact study was carried out utilizing the raw materials used to manufacture the parts for their completion on the assembly line and analysis from the cradle to the gate. The data was entered into the SimaPro software version 9.0.0.49, using the libraries (database): Ecoinvent 3 compiled November 2018, USLCI (the United States Life Cycle Inventory) library updated in September 2015, and Industry data 2.0 (several datasets were updated and added in April 2015, September 2015, March 2016, December 2017, and April 2018). The list of materials and processes used and the corresponding database are presented in Table 3.

Table 3. Origin of materials and manufacturing processes.

Database	Materials and Manufacturing Processes	un.
Industry data 2.0	Steel, engineering steel	kg
USLCI	Steel, stainless	kg
Industry data 2.0	PVC pipe	kg
Ecoinvent 3	Epoxy resin, liquid	kg
USLCI	Automotive painting, electrocoating	m^2
Ecoinvent 3	Laser machining, metal, with CO_2	h
Ecoinvent 3	Welding, gas, steel	m
Ecoinvent 3	Welding, gas, stainless	m
Ecoinvent 3	Zinc coat, pieces	m^2

The materials and processes contained in the database were allocated to the products under study. The amount of raw materials used to manufacture 1 m^2 of the product (grain trailer) is listed in Table 4, and the processes are presented in Table 5 [43].

Table 4. Materials used per m^2 of product [44].

Materials	un.	10.5DcTmul	10.5DiTmul	12.0DiTmeci	15.0DcTmec	15.0DiTmul
Steel, engineering steel	kg	103.2165	69.7484	55.8541	106.2000	72.9938
Steel, stainless	kg	0.0586	25.1762	37.8624	0.0508	34.2421
PVC pipe	kg	2.7527	2.7527	0.0000	0.0000	2.7527
Epoxy resin, liquid	kg	0.0089	0.1503	0.1503	0.0089	0.1527

Table 5. Manufacturing processes used per m^2 of product [44].

Manufacturing Processes	un.	10.5DcTmul	10.5DiTmul	12.0DiTmeci	15.0DcTmec	15.0DiTmul
Automotive painting, electrocoating	m^2	0.7064	0.3102	0.1880	0.7539	0.3212
Laser machining, metal, with CO_2	h	0.0905	0.1100	0.1106	0.1073	0.1175
Welding, gas, steel	m	8.2091	7.6495	5.2768	8.6174	7.5135
Welding, gas, stainless	m	0.0000	1.0963	1.4728	0.0000	1.1454
Zinc coat, pieces	m^2	0.1821	0.1821	0.0281	0.1342	0.1821

The ReCiPe 2016 Endpoint (H) V1.03/World (2010) H/H methodology was used to measure the environmental impact. For this study, only the environmental impact information of a single endpoint score was used, covering the sum of aspects of human health, ecosystem quality, and scarcity of resources. The data are listed in Table 6.

Table 6. Single endpoint score environmental impact values.

Production Mix Alternatives	Environmental Impact (Pt)			
	Human Health	Ecosystems	Resources	Total
Alternative 1	14.50	2.21	0.342	17.052
Alternative 2	19.80	3.87	0.431	24.101
Alternative 3	25.40	5.48	0.528	31.408
Alternative 4	27.10	6.08	0.553	33.733
Alternative 5	21.80	4.42	0.463	26.683
Alternative 6	31.00	7.09	0.626	38.716
Alternative 7	25.60	5.43	0.536	31.566

The three categories (human health, ecosystems, and resources) can be divided into 22 midpoint impact categories. At the midpoint, it can be seen that the categories with the greatest impact are: global warming, fine particulate matter formation, water consumption, and scarcity of fossil resources. The use of steel and cutting with a laser machine generates greater global warming, with the emission of greenhouse gases and particulate matter. Stainless steel and laser cutting also generate the greatest impacts on water consumption, as it is used to generate energy in the turbines. Energy consumption also generates a scarcity of fossil resources, which are obtained from oil, natural gas, and coal. It is observed that the product mix that most uses stainless steel and laser cutting is the one that generates the greatest environmental impact [45].

3.2.4. Data Normalization

Table 7 presents the seven alternatives and the four quantitative criteria, namely: the criteria of working time, productivity, and profitability must be maximized, and the environmental impact criterion must be minimized (values in bold indicate the best value).

Table 7. Measured criteria values for alternatives.

Product Mix Alternatives	Working Time (h)	Productivity	Profitability ($)	Environmental Impact (Pt)
Alternative 1	0.7211	3	$151.64	**17.052**
Alternative 2	0.8587	3	$173.76	24.101
Alternative 3	0.9390	3	$200.70	31.408
Alternative 4	**1.0476**	3	$202.69	33.733
Alternative 5	0.9100	3	$180.57	26.683
Alternative 6	1.0193	3	**$227.65**	38.716
Alternative 7	0.8817	3	$205.53	31.566

Bold is to stress the best result.

The final values, referring to the normalization of the criteria, are shown in Table 7, and were used to determine the best alternative using the AHP methods. To calculate the

DEA, the values in Table 6 for working time, productivity, and profitability were adopted, with the environmental impact value taken from Table 8.

Table 8. Normalized criteria values.

Product Mix Alternatives	Working Time	Productivity	Profitability	Environmental Impact
Alternative 1	0.113	0.143	0.113	**0.229**
Alternative 2	0.135	0.143	0.129	0.162
Alternative 3	0.147	0.143	0.149	0.124
Alternative 4	**0.164**	0.143	0.151	0.116
Alternative 5	0.143	0.143	0.134	0.146
Alternative 6	0.160	0.143	**0.170**	0.101
Alternative 7	0.138	0.143	0.153	0.123

Bold is to stress the best result.

It is important to note that in DEA, the environmental impact value was considered an output criterion. In the AHP, the harmonization and normalization of this value were carried out, considering that the lower the value, the better. Therefore, the lowest environmental impact value was assigned the highest weight. In this sense, the final result in the DEA indicates that the value is maximized, but as the value has been harmonized and normalized, it is possible to interpret how to minimize the environmental impact.

In AHP it is possible to include the subjective evaluation of experts. Reliability is verified through the Consistency Index (CI) and the Coherence Ratio (CR). The consistency ratio is calculated by the CI/RI ratio, where CI is the consistency index and RI is the random index, whose value depends on the number of criteria being compared. The comparison between pairs is considered consistent if CR is less than 0.1 [46]. If CR values exceed the 0.1 thresholds, it indicates that the judgment is inconsistent. In such cases, experts need to review the values in the pairwise comparison matrix [47].

4. Results and Discussion

4.1. Assessment with the AHP Method

The evaluation of the AHP method was performed considering two situations: (1) all criteria with the same weights and (2) evaluation of the criteria weights by experts. Table 9 shows the comparison matrix obtained when the same importance was attributed to the four criteria (0.250).

Table 9. Comparison matrix with equal weights between criteria.

Indicator	Working Time	Productivity	Profitability	Environmental Impact	Weight
Working time	1	1	1	1	0.250
Productivity	1	1	1	1	0.250
Profitability	1	1	1	1	0.250
Environmental impact	1	1	1	1	0.250

With equal weights in all criteria, a CI = 0 was obtained, indicating coherence between the weights of the criteria [37]. Table 10 shows the weight of each criterion and presents the final results for each alternative in the last column.

With a sensitivity analysis, there was a change in the preference of alternatives in working time (alternative 1 to 4 in 0.34) and profitability (alternative 1 to 6 in 0.33), but productivity showed no change in preference for alternatives. A comparison between pairs regarding the criteria was performed, considering the opinions of three experts: a maintenance coordinator, an industrial manager, and a PPC coordinator. Considering the evaluation of these specialists a CI = 0.153 was obtained, which divided by the RI led to a CR value of 0.17, being necessary to conduct a new round of evaluations due to its inconsistency. The weights of the criteria obtained from the second round of evaluations are shown in Table 11.

Table 10. Criteria weights and final result.

Product Mix Alternatives	Working Time	Productivity	Profitability	Environmental Impact	Final
	0.250	**0.250**	**0.250**	**0.250**	
Alternative 1	0.113	0.143	0.113	**0.229**	**0.149**
Alternative 2	0.135	0.143	0.129	0.162	0.142
Alternative 3	0.147	0.143	0.149	0.124	0.141
Alternative 4	**0.164**	0.143	0.151	0.116	0.143
Alternative 5	0.143	0.143	0.134	0.146	0.142
Alternative 6	0.160	0.143	**0.170**	0.101	0.143
Alternative 7	0.138	0.143	0.153	0.123	0.139

Bold is to stress the best result.

Table 11. Comparison matrix with expert weights.

Indicator	Working Time	Productivity	Profitability	Environmental Impact	Weight
Working time	1	3	1/3	1/3	0.161
Productivity	1/3	1	1/3	1/3	0.093
Profitability	3	3	1	1/2	0.309
Environmental impact	3	3	2	1	0.437

In the second evaluation of these three specialists a CI = 0.162 was obtained, leading to an acceptable CR = 0.071. The final result is shown in Table 12, with a preference for Alternative 1 indicated.

Table 12. Weights of the experts' criteria and final result.

Product Mix Alternatives	Working Time	Productivity	Profitability	Environmental Impact	Final
	0.161	**0.093**	**0.309**	**0.437**	
Alternative 1	0.113	0.143	0.113	**0.229**	**0.1662**
Alternative 2	0.135	0.143	0.129	0.162	0.1456
Alternative 3	0.147	0.143	0.149	0.124	0.1374
Alternative 4	**0.164**	0.143	0.151	0.116	0.1369
Alternative 5	0.143	0.143	0.134	0.146	0.1416
Alternative 6	0.160	0.143	**0.170**	0.101	0.1354
Alternative 7	0.138	0.143	0.153	0.123	0.1368

Bold is to stress the best result.

In the opinion of experts, environmental impact received the greatest weight. This was related to the greater dissemination of sustainable development goals (SDGs) in the media. The SDGs currently represent the most important policy decision-making process on a global scale defined by the UN [48] and can be used to assist in the implementation of strategies for sustainable development, both in the public and private sectors [2]. It was therefore assumed that the weights attributed by experts must be influenced by the current situation owing to the coronavirus disease pandemic. Several epidemiological predictions indicate that human lives will continue to suffer from physical distance and social isolation [49].

With the sensitivity analysis, a change in the preference of alternatives was observed in working time (Alternative 1 to 4 in 0.53), profitability (Alternative 1 to 6 in 0.52), with no change observed in productivity amongst the alternatives. To the sensitivity analysis in the AHP, in both cases (equal weights and expert weights), there is a change in preferences in alternative 1, being replaced by alternative 4 or 6. The reason for this behavior is a greater working time in alternative 4, while alternative 6 is more profitable. In the productivity criterion an inversion of preference for alternatives can be observed, as shown in Figure 1 to normalized values of the criteria.

It is observed that the criteria are conflicting, once less working time leads to lower profitability and lower environmental impact (alternative 1). The greater the profitability, the greater the environmental impact (alternative 6). A longer working time also results in high values of environmental impact (alternative 4).

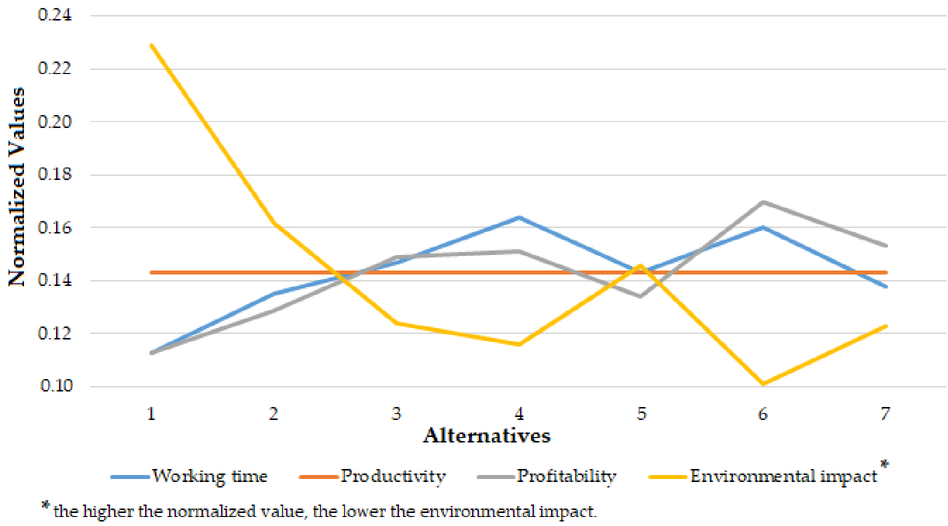

Figure 1. Behavior of alternatives in relation to normalized values.

4.2. Evaluation with the DEA Method

Two multi-criteria analyses were performed using the DEA: input orientation-type (CRS) and output orientation-type (CRS). In both analyses, it was possible to observe the efficiency pattern and backlash. Working time was considered as input data, and productivity, profitability, and environmental impact as output data, as shown in Table 13.

Table 13. Input and output data.

Production Mix Alternatives	Inputs	Outputs		
	Working Time (h)	Productivity	Profitability ($)	Environmental Impact
Alternative 1	0.7211	3.00	$151.64	**0.229**
Alternative 2	0.8587	3.00	$173.76	0.162
Alternative 3	0.9390	3.00	$200.70	0.124
Alternative 4	**1.0476**	3.00	$202.69	0.116
Alternative 5	0.9100	3.00	$180.57	0.146
Alternative 6	1.0193	3.00	**$227.65**	0.101
Alternative 7	0.8817	3.00	$205.53	0.123

Bold is to stress the best result.

The DEA model with the orientation of input-type (CRS) was when the input of resources was changed to maintain the same results (outputs). Table 14 shows the results of comparing the production mix alternatives.

Table 14. DEA Input orientation-type: CRS.

DMU (Mix Alternatives)	Final	Backlash			
	Standard Efficiency	Working Time	Quantity of Products	Profitability	Environmental Impact
Alternative 1	**1**	0	0	0	0
Alternative 2	0.92	0.0717	0	0	0.023
Alternative 3	0.92	0.0717	0	0	0.008
Alternative 4	0.83	0.1744	0	0	0.013
Alternative 5	0.89	0.1027	0	0	0.026
Alternative 6	0.96	0.0427	0	0.32	0.035
Alternative 7	**1**	0	0	0	0

Bold is to stress the best result.

Alternatives 1 and 7 (bolded in Table 14) are the most efficient, with a default efficiency of 1. Alternative 4 is the least efficient, with a default efficiency of 0.83. Regarding the analysis of backlash, it was observed that it was not necessary to change profitability to obtain maximum standard efficiency but working times must be reduced (alternatives 2 to 6), the number of products must be increased (alternative 6), and the environmental impact must be reduced (alternatives 2 to 6). For the most efficient alternatives, it was assumed that there was a good relationship between working time on the production line, with an adequate output of products, profitability, and environmental impact. Alternative 1 had shorter working hours, resulting in lower profitability and environmental impact. Alternative 7 was the fifth alternative with increased hours of work, and the second alternative that generated the greatest environmental impact. However, this factor was offset by profitability, which makes this an efficient alternative.

In the DEA model with output orientation-type: CRS, the results (output) were changed while maintaining the same resource input. Table 15 shows the results of comparing the seven production mix alternatives.

Table 15. DEA output orientation-type: CRS.

DMU (Mix Alternatives)	Final	Backlash			
	Standard Efficiency	Working Time	Quantity of Products	Profitability	Standardized Environmental Impact
Alternative 1	**1**	0	0	0	0
Alternative 2	0.92	0	15.83	0.27	0.040
Alternative 3	0.92	0	16.59	0.25	0.019
Alternative 4	0.83	0	40.47	0.60	0.038
Alternative 5	0.89	0	22.97	0.38	0.048
Alternative 6	0.96	0	9.96	0.47	0.041
Alternative 7	**1**	0	0	0	0

Bold is to stress the best result.

With the output orientation, it can be seen that for alternatives 2 to 6 to obtain maximum efficiency, it was necessary to increase profitability and the quantities of products and reduce the environmental impact. Alternatives 1 and 7 were the most efficient.

4.3. Comparison of AHP and DEA Results

Table 16 shows the comparison of the results with the AHP and DEA in the evaluation of the four models.

Table 16. Ranking of alternatives.

Product Mix Alternatives	AHP (Equal Weights)	AHP (Weights of Experts)	DEA Input–Type: CRS	DEA Output–Type: CRS
Alternative 1	**1°**	**1°**	**1°**	**1°**
Alternative 2	4°	2°	4°	4°
Alternative 3	6°	4°	3°	3°
Alternative 4	2°	5°	6°	6°
Alternative 5	5°	3°	5°	5°
Alternative 6	3°	7°	2°	2°
Alternative 7	7°	6°	**1°**	**1°**

Bold is to stress the best result.

In the four evaluations, Alternative 1 (two 10.5 DcTmul products and one 15.0 DcTmec product) was the best for planning the production mix, considering the criteria of working time, productivity, profitability, and environmental impact. Alternatives 2 and 5 showed the same behavior, considering the AHP with equal weights and DEA. The alternatives of specialists in the AHP method (2 to 7) presented a divergence in the ranking compared to the DEA method. Furthermore, it was difficult to obtain as the best solution a single model that combines a maximum economic result with a low environmental impact. The alternatives presented criteria that were in conflict. It is generally perceived that in the industry, a greater profitability will inevitably result in a higher environmental impact. Therefore, to generate a lower environmental impact, it is necessary to have a lower production rate and profitability. Such results were also observed in other studies, where the three pillars of sustainability conflict with one another. The concern was to obtain a model that can improve processes and satisfactorily address environmental, economic, and social aspects [50]. Achieving greater profitability can have negative social and environmental consequences [51]. Economic growth stimulates demand and favors the growth of human, material, and financial resources; however, such growth conflicts with the environment [52].

From the perspective of managerial implications in the industry for decision-making, it is possible that:

- The best result was focused on a lower environmental impact with the use of AHP. While using DEA, two efficient alternatives could be obtained: one with less environmental impact and the other with better economic aspects. In this sense, the industry may prefer a production mix that focuses more on the best economic criteria.
- The AHP method allowed for the assessment of both qualitative and quantitative criteria [34,35,41]. This aspect is important in the agricultural industry, as some additional qualitative criteria considered relevant by management could be included in the analysis.
- Using the AHP method, it was possible to obtain a single alternative as the better one in the two situations evaluated. This facilitates decision-making from a managerial perspective.
- A disadvantage of the AHP method is that many comparisons must be made by experts, based on their subjective and possibly conflicting opinions [43]. In the case study, two rounds of evaluations were needed to achieve acceptable values [39].
- The DEA method allowed each alternative to list its weights [35]. In this sense, quantitative values were used, implying that it was only necessary to harmonize and normalize the value of the environmental impact so that it could be coherently assessed using the DEA method.
- The DEA method performs a global assessment of alternatives; DMUs that fall outside the efficient boundary were considered underperforming, and they needed to be further analyzed to determine the measures to improve their efficiency [40]. In this study, the results obtained in the backlash were an indication of what can be improved in each of the alternatives. In the AHP method, the sensitivity analysis to determine the inversion of preference in the alternatives was considered more laborious.
- One of the disadvantages of DEA is that two or more alternatives can be considered efficient [35]. In the case studied, two alternatives were considered more efficient: one with less environmental impact and the other with better economic criteria. Depending on the situation, such a result can cause difficulties for the decision-maker.
- The AHP method is the most commonly used, both in single and hybrid modes [36]. In this study, the weights of the environmental impact criterion calculated using the harmonization and normalization of the AHP were also applied to the DEA.

In this study, the application of the AHP and DEA methods sought to evaluate the best alternative for planning the production mix in the agricultural machinery industry. However, it was important to consider that the economic criteria of the study are real aspects used by management in decision-making. The environmental impact criterion was also added, which is considered relevant given the global context around sustainability. Although the AHP was also subjectively assessed, the weights attributed may vary depending on the specialist's area of expertise. With the application of MCDM, it was possible to obtain an alternative that was common to both the AHP and DEA methods. The AHP was considered to enable an improved decision from the managerial aspect, as it indicated only a single result, and was possible to work in a hybrid way and with qualitative criteria. The study had limitations in the number of criteria that were evaluated; however, the four study criteria were considered the most important for the industry under study. Although MCDM has been applied in the agricultural industry, it presented satisfactory results that can be replicated in other areas, despite the lack of application of these models in this area.

5. Conclusions

This article proposes the application of multicriteria methods to define the best product mix in the production planning of the Brazilian agricultural machinery industry. Seven alternatives and four criteria were evaluated based on the environmental impact of the decision criteria. In this practical case, the AHP and DEA methods identified the best production mix, and a second production mix was also identified by the DEA as being equally efficient. In this sense, it is possible to assess that the criteria are conflicting, because selecting a lower environmental impact leads to lower profitability.

From a managerial point of view, the AHP method identified a best alternative, which facilitates decision-making. However, for the elaboration of the matrix, paired evaluations are necessary, and this study required two rounds of evaluations with experts. Furthermore, the AHP method allows the use of qualitative criteria for a future evaluation, in the interest of the management. The DEA method identified two alternatives as being the most efficient, wherein the manager needs to choose a mix that generates less environmental impact or greater profitability. Because of the conflicting criteria, decision making requires further analysis of the final result. However, the positive aspect of applying the DEA is a global view, with benchmarking of the performance of the DMUs, making it possible to obtain improvement with less efficient alternatives.

Although applied to agricultural industry, the presented methodology can be easily adapted to other products and activities related to the built environment, such as the construction industry.

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