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ARTICLES

# IMPLEMENTATION OF THE BALANCED DECISION-MAKING METHOD FOR PRIORITIZING CROP PLANTING IN SMALL-SCALE RURAL PROPERTIES

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**ABSTRACT.** In response to the increasing uncertainties in agricultural decision-making, driven by market fluctuations and changes in environmental conditions, this research implemented the Balanced Decision-Making Method (BDMM) to improve crop selection on a farm in western Bahia. The BDMM integrates multiple decision-making methods—TOPSIS, PROMETHEE II, and the Borda method—to provide a comprehensive and balanced evaluation. Both qualitative and quantitative data were gathered from literature, insights from two decision-makers, and the authors of the article. Qualitative factors, such as cost estimates, market prices, and labor requirements, were sourced from various references, while quantitative data focused on customer demand and expert consensus regarding pest risk. The combination of these data sources and the application of the proposed method enabled a detailed analysis that reflected the combined preferences and needs of each producer. The BDMM facilitated consensus among the producers, supporting decisions that optimize both economic performance and environmental sustainability.

**Keywords**: TOPSIS, PROMETHEE II, borda method, agriculture, multicriteria decision aid method.

## 1 INTRODUCTION

Agriculture is fundamental for the sustenance of the global population, providing food, raw materials, and jobs for billions of people worldwide. According to the Food and Agriculture Organization of the United Nations (FAO), agriculture is the primary source of livelihood for about 40% of the world's population. Moreover, agricultural production is essential for food and nutritional

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security, especially in developing countries where agriculture represents a significant portion of the economy and employment (Fao et al., 2018). The World Bank highlights that growth in the agricultural sector is two to four times more effective at raising the incomes of the poorest people than growth in other sectors. Thus, investments in agriculture not only improve productivity and production but also promote environmental sustainability and climate resilience, critical factors in a world where climate change poses an increasing threat (The World Bank, 2021).

Decision problems in organizations inherently involve multiple and conflicting objectives, as highlighted by (Almeida et al., 2023a, b). Indeed, technically oriented decision-making is a constant demand in utilizing the soil resources of a region, and it is crucial for the success of associated economic activities. In this context, the initial stage of such utilization (agricultural planning for irrigation projects) is classified as an optimization problem that, at its most basic level, can be solved using classical Linear Programming (LP) methods.

An example of this is the decision regarding the internal subdivision of plots into parcels cultivated with crops compatible with the region's soil and climate resources. In simple problems of this nature, with only two types of crops suitable for planting on a known area of arable land (C1 and C2), the LP model can be solved even by graphical methods. In this case, an objective function representing the profit to be obtained, for which the maximum point is desired, can be easily constructed from data on productivity, labor costs, commercial demand, and market value of each crop. With the objective function in hand, the remainder of the modeling consists of determining the problem's constraints. The first constraint is the total area to be occupied by the considered crops, which can not exceed the total arable land area. The second constraint pertains to the availability of labor, where the total use of available labor in the cultivations cannot exceed the number of man-hours offered by the labor market. Finally, the third constraint concerns the consumer market's capacity to absorb the production. Thus, if crop C1 has a productivity of X units per hectare and the market can acquire up to Y units of it, then the productivity multiplied by the area planted with crop C1 cannot be greater than Y (Sarmento, 2020).

Not always does decision-making in irrigated agriculture involve solely objective and precise information, as mentioned in the simplified problem of agricultural planning for irrigated plots. In many situations, when decision-making includes subjective elements such as ease of cultivation, market perception, and cultural aspects, it becomes necessary to employ more sophisticated modeling approaches, such as intelligent systems, to optimize crop selection and plot division. Various approaches, such as expert systems, fuzzy control, neural networks, and multi-objective decision-making techniques, are used to enhance irrigation decision control (Chen et al., 2021; Kamyshova et al., 2021; Ardakani et al., 2024). These methods also work with objective parameters and consider factors such as soil moisture, water salinity, and crop characteristics to enhance agricultural practices in water-scarce regions (Ardakani et al., 2024).

Multi-criteria optimization techniques help determine the optimal parameters of the irrigation system for different crops, leading to higher yields and reduced costs (Kabildjanov et al., 2023). Furthermore, knowledge-based engineering and intelligent algorithms support decision-making in irrigation systems, resulting in higher decision accuracy and better crop growth compared to traditional methods (Zhai et al., 2021). By integrating modern technologies such as artificial intelligence and data science, intelligent irrigation systems can effectively guide farmers on what to plant and how to optimize plot division for sustainable agricultural development. Different decision-making methods significantly impact crop selection in agriculture. Machine learning algorithms such as decision trees, Naïve Bayes, and Random Forests play a crucial role in predicting crop selection based on soil characteristics with high accuracy (Singh et al., 2022).

The present article aims to implement a new integrated decision-making method, termed the Balanced Decision-Making Method (BDMM), which combines TOPSIS, PROMETHEE II, and the Borda method for a more comprehensive and balanced evaluation. This approach leverages the strengths of each method, where TOPSIS provides a straightforward mathematical ranking based on proximity to an ideal solution, while PROMETHEE II offers a more detailed preference modeling that considers the interactions between criteria. By integrating these methods alongside the Borda method for consensus building, BDMM ensures a holistic framework that minimizes biases and aligns decision outcomes with practical agricultural priorities in crop selection.

## 2 LITERATURE REVIEW

### 2.1 The decision-making process in agriculture

Several Multicriteria Decision Analysis methods, such as Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE), have been extensively studied in recent research (Nedashkovskaya, 2022; Yudhana et al., 2022; Sikalo et al., 2023). These methods provide valuable tools for complex decision making processes, allowing problem decomposition, weight determination, and robust analysis of results. They are complemented by models such as ELECTRE and social methods such as Borda count and alternative negotiation, which influence crop selection based on the criteria of regional stakeholders, enhancing the acceptability and implementation of results (Honar et al., 2021).

Furthermore, using a decision-making model with a weighted aggregation analysis algorithm helps farmers achieve consistent and optimal crop selection decisions, surpassing conventional methods and improving agricultural development strategies (Mohanambal and Pethalakshmi, 2023). Factors such as product quality, price, flexibility, promotional support, and brand indirectly influence crop selection, affecting the availability and quality of agricultural inputs in the market (Ahn and Kim, 2023). In general, these diverse decision-making methods provide farmers and stakeholders with valuable tools to optimize crop selection processes and enhance agricultural productivity.

Market trends play a crucial role in guiding crop choices, providing valuable information for farmers to make informed decisions. The globalization of agricultural markets has led to profit pressures, influencing farmers to shift cultivated areas towards crops with higher revenue generation, thereby making crop portfolios more risky over time (Blank, 2001). The use of data science tools such as linear regression, density plots, and pie chart analysis can help analyze agricultural market data to optimize production based on Market trends, ensuring flexibility according to demand (Singh and Borate, 2022). Furthermore, implementing machine learning algorithms such as K-Means, K-Nearest Neighbor (KNN), Artificial Neural Networks (ANN) and Support Vector Machines (SVM) can help predict crop prices and market trends, allowing farmers to make data-driven decisions for optimal crop selection (Gaddam et al., 2022; Sajithabanu et al., 2022). By leveraging market trends and data-driven approaches, farmers can enhance their crop choices and maximize profitability in the ever-evolving agricultural sector.

In summary, when selecting crops, decision-making should prioritize economic factors to optimize choices effectively. Considerations such as expected profitability, input costs, and maximizing commercial profit play crucial roles in decision-making (Jung et al., 2018; Gall and Laff, 2022). Additionally, socio-economic factors such as arable land size, capital sources, and education level influence the choice of cultivation system, with larger land areas favoring the adoption of certain crops over others. Historical agricultural practices also guide crop selection, with farmers relying on traditional knowledge and past experiences to enhance productivity and economic growth (Sheetal Jagtap et al., 2018). Socio-economic factors such as net crop income, agricultural subsidies, and political orientation significantly impact crop choices, underscoring the importance of income generation and supportive policies in optimizing cropping structures and increasing farmers' income levels (Shu-qin et al., 2012).

The TOPSIS method was developed by Hwang et al. (1981) with the objective of arriving at the best decision based on Multicriteria. The aim is to find an alternative that has the shortest distance from the ideal positive solution and the farthest distance from the ideal negative solution (dos Santos and Schmidt, 2020). It calculates the similarity of each alternative to the ideal solution and the worst solution, ranking them based on their proximity to the ideal (Motia and Reddy, 2020). The positive ideal solution maximizes criterion benefits and minimizes costs, while the negative ideal solution maximizes criterion costs and minimizes benefits (Behzadian et al., 2012). The application of the TOPSIS method for weighting indicators involves the opinion and weight assignment by experts (dos Santos and Schmidt, 2020).

According to Duarte (2024), the TOPSIS method has numerous applications in agriculture, which the author thoroughly explored in his extensive literature review conducted over the last five years. Using the PRISMA methodology, the author mapped the relationship between TOPSIS and agriculture, providing insights into keywords, the most cited articles, and other key elements of the field. Furthermore, the review identified and incorporated the articles with the highest citation counts, which were included in the revised manuscript to strengthen the study's literature base (Li et al., 2019; Firouzi et al., 2021; Wang et al., 2022; Kurdyś-Kujawska et al., 2021; Wang et al., 2023). It plays a crucial role in various agricultural domains, such as crop system management and yield estimation (Lan et al., 2022). Furthermore, the TOPSIS method can be applied to optimize water use efficiency in agriculture, providing a systematic approach for selecting variables and building predictive models (Xie and Zhang, 2023).

Li et al. (2019) explored the role of sustainability in agriculture, particularly in the context of challenges like climate change, resource depletion, and shifting social demands. To evaluate the potential for sustainable agricultural development along the Silk Road, 25 indicators across five subsystems were chosen, and various techniques (including the entropy weight method, TOPSIS, and the coordination degree method) were employed. The study's findings revealed a fluctuating trend in the sustainable development scores, with a clear evolution of patterns from the west to the east along the route. The analysis of the factors influencing sustainable development emphasized key variables, including the level of economic development, agricultural investment, the agricultural workforce, and the degree of agricultural informatization.

A research study conducted by Firouzi et al. (2021) was carried out to identify and prioritize biomass resources for biofuel production using a hybrid Multicriteria Decision Making (MCDM) approach. The study utilized MCDM techniques, including TOPSIS, ARAS, and WASPAS. Following this, ranking aggregation methods, such as Borda, Copeland, and Rank Mean, were applied to combine the rankings derived from the MCDM methods. The case study was conducted in Guilan province, Iran, which was chosen due to its significant potential for producing first, second, and third-generation biofuels. The findings revealed that municipal solid waste, sewage, forest and agroforestry residues, and livestock and poultry waste were the most critical biomass resources for second-generation biofuel production in the region.

## 3 METHODOLOGY

### 3.1 TOPSIS method

According to Hwang et al. (1981), the TOPSIS method is applied following a step-by-step process developed to find the best alternative based on established criteria. The matrix $X$ is referred to as the evaluation matrix: $X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}$

The decision matrix values are normalized using Equation 1:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{1}$$

- $r_{ij}$ : Are the normalized values.
- $x_{ij}$ : This denotes the element in the $i$-th row and $j$-th column of the decision matrix X, which contains the performance values of each alternative $i$ for each criterion $j$.
- $\sqrt{\sum_{i=1}^{m} x_{ij}^2}$ : This part calculates the sum of squares of the values in the $j$-th column of matrix $X$, where $m$ is the number of alternatives. It represents the normalization factor, ensuring that $r_{ij}$ is scaled appropriately relative to the magnitude of values in column $j$.

Next, the decision matrix is weighted according to Equation 2:

$$p_{ij} = w_j \times r_{ij} \tag{2}$$

- $p_{ij}$ : This represents the weighted performance score of alternative $i$ on criterion $j$.
- $w_j$ : This denotes the weight assigned to criterion $j$, influencing its contribution to the overall decision.

To determine the positive ideal solution (Equation 3)

$$A^+ = (p_1^+,\ p_2^+, \cdots,\ p_n^+) \tag{3}$$

$$p_j^+ = \begin{cases} \max_i (p_{ij}),\ \text{if the criterion is for benefit} \\ \min_i (p_{ij}),\ \text{if the criterion is for cost} \end{cases}$$

For the criterion negative ideal solution (Equation 4):

$$A^- = (p_1^-,\ p_2^-, \cdots,\ p_n^-) \tag{4}$$

$$p_j^- = \begin{cases} \min_i (p_{ij}),\ \text{if the criterion is for benefit} \\ \max_i (p_{ij}),\ \text{if the criterion is for cost} \end{cases}$$

As next steps, the normalized weight vectors are calculated, as shown in Equation 5 and Equation 6:

$$d_i^+ = \sqrt{\sum_{j=1}^{m} (p_{ij} - p_j^+)^2} \tag{5}$$

$$d_i^- = \sqrt{\sum_{j=1}^{m} (p_{ij} - p_j^-)^2} \tag{6}$$

The fifth step is to calculate the proximity coefficient of each alternative according to Equation 7:

$$C_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{7}$$

It is noteworthy that the closer the proximity coefficient (result from Equation 7) is to1, the closer the crop cultivation is to the ideal solution. Conversely, the closer it is to 0, the further the crop cultivation is from the ideal solution. Finally, compare the values of $C_i$ and perform the ranking of alternatives.

### 3.2 PROMETHEE II method

PROMETHEE II (Preference Ranking Organization Method for Enrichment Evaluations) is a multi-criteria decision-making method that ranks alternatives based on multiple criteria. The process begins with defining the criteria and assigning weights based on their importance. Preference functions are then chosen for each criterion to quantify the preference of one alternative over another. Positive and negative outranking flows are calculated for each alternative, where the positive flow represents how much an alternative outranks others, and the negative flow represents how much it is outranked by others. The net flow score is computed by subtracting the negative flow from the positive flow, and alternatives are ranked based on these scores, with higher scores indicating better alternatives (Brans and Vincke, 1985).

According to Taherdoost and Madanchian (2023) the PROMETHEE II method offers several key features that make it a robust tool for multi-criteria decision-making. These criteria can be either positive, indicating benefits, or negative, representing drawbacks (Harjanti et al., 2023). PROMETHEE II calculates an overall net flow for each alternative, derived from a weighted comparison of criteria values, ensuring a transparent ranking process (Harjanti et al., 2023), as demonstrated by Equation 8.

$$Phi(a) = Phi^{+}(a) - Phi^{-}(a) \tag{8}$$

The positive flow (Phi*) (Equation 9) represents the sum of the forces with which an alternative surpasses all others, measuring the degree to which an alternative is preferred compared to the others (Brans and Mareschal, 2005):

$$Phi^{+}(a) = \frac{1}{n-1} \sum_{b\ \varepsilon\ A} \pi(a,\ b) \tag{9}$$

Where $\pi(a,\ b)$ is the preference index of alternative $\alpha$ over b, and $n$ is the total number of alternatives.

The negative flow (Phi$^{-}$) represents the sum of the forces with which all other alternatives surpass the evaluated alternative, measuring the degree to which an alternative is disadvantaged compared to the others (Equation 10).

$$Phi^{-}(a) = \frac{1}{n-1} \sum_{b\ \varepsilon\ A} \pi(b,a) \tag{10}$$

### 3.3 Borda method

The Borda method, or Borda count, is a voting system that aggregates individual preferences by assigning points based on rankings. This approach is particularly effective in decision-making scenarios, as it balances the influence of extreme rankings, promoting a compromise solution that reflects collective preferences. Its adaptability and theoretical consistency make it a valuable tool across various fields, often integrated with other methodologies to enhance decision-making processes. In the Borda method, when there are $n$ alternatives and a decision-maker is asked to rank them, they assign points based on the position of each alternative in their ranking. The most preferred alternative receives $n - 1$ points, the second most preferred receives $n - 2$ points and so on, until the least preferred alternative receives 0 points (Borda, 1781). This process is repeated for each decision-maker. After all decision-makers have ranked the alternatives, the points assigned to each alternative are summed. The total points accumulated by each alternative reflect its overall popularity, with the alternative that has the highest total points being considered the best, or the most preferred, among the decisions.

Similarly, in a textile company, a hybrid model combining Borda and PROMETHEE was applied to select maintenance strategies, highlighting its versatility across industries (Oufella, 2024).

However, it is important to note that the Borda method does not always align with majority rule outcomes, which can present challenges in scenarios requiring unanimous consensus (Moreno and Salmaso, 2024).

### 3.4 The Balanced Decision-Making Method (BDMM)

The proposed methodology combines weights based on the distance of individual decision makers weight vectors from the equal weights vector. First, the Euclidean distance is calculated for each weight vector $W_k$ from the equal weights vector $W_{eq}$, which ensures no criterion is prioritized by assigning each an equal value of $\frac{1}{m}$ , where $m$ is the total number of criteria. The Euclidean distance $d_k$ for each weight vector is showed by Equation 11:

$$d_k = \sqrt{\sum_{l=1}^{m} (w_{kl} - w_{eql})^2} \tag{11}$$

Once distances $d_k$ or all weight vectors are computed, they are normalized to ensure comparability. The normalized distance for each vector is calculated by dividing its distance $d_k$ by the total sum of distances across all vectors:

$$\text{Normalized Distance for } W_k = \frac{d_k}{\sum_{k=1}^{m} d_k} \tag{12}$$

This normalization produces a relative measure of each vector's distance compared to the others. To prioritize vectors closer to the equal weights vector, an adjusted weight is computed as:

$$\text{Adjused Weight for } W_k = 1 - \text{Normalized Distance for } W_k \tag{13}$$

Vectors with smaller distances (closer to equal weights) receive higher adjusted weights, reflecting their greater importance in the final aggregation. Finally, the combined weight vector $W_{comb}$ is calculated as a weighted average of all individual weight vectors, where the adjusted weights serve as the weighting factors (Equation 14):

$$w_{comb} = \sum_{l=1}^{m} (\left(1 - \frac{d_k}{\sum_{l=1}^{m} d_k}\right) \times w_{kl}) \tag{14}$$

Subsequently, the TOPSIS and PROMETHEE II methods are applied. In the next step, a new analysis is performed by employing a weighted approach based on the distances of the individual weight vectors from the equal weight vector. This strategy ensures a more refined evaluation, where the weights are adjusted proportionally according to their deviation from the equal weight distribution, providing a sensitivity analysis of the criteria's influence. By combining the results obtained with the weighted approach and those derived from an equal weights strategy, a robust comparison may be achieved. In the PROMETHEE II method, employed in the BDMM, the same preference functions are applied to all criteria, ensuring consistency in evaluating each alternative's performance. The positive and negative net flows reflect how each alternative ranks across all criteria under the weighted adjustments. Finally, the Borda method is used to consolidate the results, integrating both the equal weight and adjusted weight strategies, thereby generating a final ranking that reflects a balanced yet sensitive evaluation of the alternatives.

### 3.5 Case Study

The study was conducted in the city of Luís Eduardo Magalhães, located in the mesoregion of Western Bahia. According to Instituto Brasileiro de Geografia e Estatística (2024), Luís Eduardo Magalhães has a territorial area of 4,036,094 km$^2$, a population of 107,909 inhabitants. The Western region is characterized by abundant water resources, strong solar radiation, a dry season from May to September, and a rainy season from October to April (Jesus Santos and Gonçalves dos Santo, 2023). The main economic activity in the city is agribusiness.

The partnership between the producers, referred to as Decision Maker 1 (producer 1) and Decision Maker 2 (producer 2), began four years ago when they decided to transition from working for others to starting their own agricultural venture. They share responsibilities and profits from activities conducted on a 5 hectare plot of land located 14 kilometers from the city of Luís Eduardo Magalhães, Bahia, Brazil. This study selected their enterprise due to reports of business management challenges, particularly difficulties in selecting crops for each planting cycle, influenced by factors such as resource availability and land constraints. For the application of the TOPSIS method, producers were asked about the criteria they consider when deciding on which crop to plant. The crops currently under consideration as planting alternatives are listed in Table 1.

**Table 1 –** Planting alternatives.

| Alternatives | Options for Culture |
|---|---|
| A1 | Sweet Potato |
| A2 | Green Corn |
| A3 | Bell Pepper |
| A4 | Tomato |
| A5 | Watermelon |

The criteria matrix was constructed with contributions from both producers and the researchers of the study, considering the time required for planting and other relevant factors. The producers have over 10 years of experience in their profession, bringing practical and field-based insights. Additionally, the researchers possess expertise in the area of mathematical modeling, ensuring a robust and scientifically grounded approach to the construction of the matrix. The criteria used were based on the local reality, with small-scale producers being consulted to identify the factors they typically consider when selecting crops to cultivate. Additionally, the researchers provided their specialized knowledge. The definition of the criteria, which are detailed in Table 2, was essential for the development of the analysis.

To assist in the development of the criteria, several references were used. Agricultural cost studies (C1) are crucial for understanding the economic viability of farming operations, considering

**Table 2 –** Criteria matrix considered in prioritizing planting crops.

| Criterion | Legend | Description | Unit of Measurement | Consulted Source |
|---|---|---|---|---|
| C1 | Cost per planting unit | Includes all estimated expenses until delivery to the final customer (labor, fertilizer, electricity and logistics) | R$/hectare | Hazell (2013) and Timothy et al. (2021) |
| C2 | Profit | Profit per planted hectare | R$/hectare | Ricker-Gilbert et al. (2019) |
| C3 | Market demand | Amount required weekly | Kg/week | Current market conditions |
| C4 | Planting time | Time form planting to crop harvest | Days | Bach et al. (2021), EOS Data Analytics (2024) |
| C5 | Pesticide Cost | Cost associated per hectare of pesticide | R$/hectare | Köhler and Triebskorn (2013) |
| C6 | Probability of pest infestation | Risk associated with acquiring pests based on producers' experience | % / hectare | Oliveira et al. (2004) |

all production factors such as labor, fertilizers, and logistics. These studies help identify key cost drivers and assess profitability, providing valuable insights that guide decisions on resource allocation and operational efficiency (Hazell, 2013; Timothy et al., 2021). Profit (C2) was based both on the practical experience of farmers and the findings of Ricker-Gilbert et al. (2019), who analyze participation in the rural land rental market and its impact on smallholder farms in Malawi. The market demand conditions (C3) considered in the study reflect the current realities faced by agricultural producers, offering a view of the economic context in which they operate. For C4, information from Bach et al. (2021) on potato production, EOS Data Analytics (2024) on green corn, and FAO (2024) for other crops were utilized. C5, regarding agricultural input expenditures, was based on global research, with Köhler and Triebskorn (2013) detailing the different pesticide classes used across various countries. Additionally, for the likelihood of pest infections, pest monitoring guidelines from Oliveira et al. (2004) were used, along with the extensive experience of the involved farmers.

### 3.6 Evaluation matrix and criteria weight assignment

Based on the previously described Tables, it was possible to construct the evaluation matrix in Table 3.

**Table 3 –** Evaluation Matrix for Planting Alternatives.

| Alternative | C1 | C2 | C3 | C4 | C5 | C6 |
|---|---|---|---|---|---|---|
| A1 | 16,000 | 14,000 | 6,160 | 120 | 700 | 20 |
| A2 | 11,300 | 21,000 | 1,000 | 90 | 1,000 | 50 |
| A3 | 30,000 | 26,000 | 3,000 | 80 | 1,000 | 50 |
| A4 | 24,000 | 73,000 | 12,000 | 90 | 8,000 | 70 |
| A5 | 8,000 | 2,000 | 10,000 | 90 | 1,000 | 50 |

To define the weights, the Swing Weighting Technique (SWING), developed by Von Winterfeldt and Edwards (1993), was used. This approach determines weighting factors indirectly through the systematic comparison of attributes relative to the most important one. The method involves two main activities: first, ordering the attributes according to the relative importance of incremental changes in their values, considering the full range of possibilities; second, selecting the most important attribute as a reference point and evaluating the relative importance of the other attributes in comparison to this point. The calculation of attribute weights is done by the ratio of the points assigned to each attribute to the total points assigned to all attributes. The SWING technique follows four steps: ordering the attributes, establishing the reference attribute, estimating the importance of the other attributes relative to the reference., The weights obtained are demonstrated by Table 4:

**Table 4 –** Weight preferences by the SWING method.

| Productor | C1 | C2 | C3 | C4 | C5 | C6 |
|---|---|---|---|---|---|---|
| P1 | 0.18 | 0.15 | 0.3 | 0.05 | 0.12 | 0.2 |
| P2 | 0.2 | 0.3 | 0.2 | 0.05 | 0.125 | 0.125 |

The differences in weights assigned by Decision Maker 1 and Decision Maker 2 reflect their distinct priorities and operational contexts. Decision Maker 1 places more value on market demand and pest risk mitigation, while Decision Maker 2 is more focused on profit and minimizing planting costs. These variations indicate that cultivation strategies and operational decisions should be adapted to meet the specific needs of each producer, providing a more personalized and effective approach to agricultural management.

# 4 RESULTS

## 4.1 TOPSIS Method Results

In this section, the results obtained from the use and application of the TOPSIS method for selecting the best crop. For first analysis, the application of the TOPSIS method resulted in different crop rankings for Decision Makers 1 and 2, as presented in Tables 5 and 6.

**Table 5 –** Ranking of alternatives for Decision Maker 1.

| Alternatives | Normalized Ęi | Selected Culture |
|---|---|---|
| A4 | 0.243 | Tomato |
| A5 | 0.239 | Watermelon |
| A1 | 0.215 | Sweet Potato |
| A2 | 0.154 | Green Corn |
| A3 | 0.149 | Bell Pepper |

**Table 6 –** Ranking of alternatives for Decision Maker 2.

| Alternatives | Normalized Ęi | Selected Culture |
|---|---|---|
| A4 | 0.296 | Tomato |
| A5 | 0.180 | Watermelon |
| A1 | 0.179 | Sweet Potato |
| A2 | 0.176 | Green Corn |
| A3 | 0.169 | Bell Pepper |

Decision-makers rank alternative A4 (Tomato) as the preferred choice. This suggests a significant consensus regarding the high importance or preference for tomato cultivation. In both tables, A3 (Bell Pepper) occupies the last position, indicating a relatively low preference for this crop. While Producer 1 sees a clear hierarchy with small diferences in values, Producer 2 presents a more uniform distribution among alternatives A5, A1, and A2, which may indicate greater flexibility or less certainty in their preferences. To determine the order of crop selection, the ranking of proximity to the ideal solution obtained through TOPSIS (Tables 5 and 6) was used. Since A4 (Tomato) was ranked as the best alternative for both decision-makers (P1 and P2), priority was given to the producer with the largest difference between their top two alternatives. P2 shows a greater difference between A4 (0.296) and A5 (0.180), whereas P1 has a smaller distinction between A4 (0.243) and A5 (0.239). Thus, P2 initiates the selection, and P1 makes the next choice. This approach minimizes competition and promotes dynamic balance in the process.

## 4.2 PROMETHEE Method Results

The results were obtained using the Visual PROMETHEE software under its academic license. The results from Table 7 show that A1 is the best alternative for producer P1, with the highest net flow of 0.195, reflecting a good balance between Phi+ (0.597) and Phi- (0.402) factors. A5 follows closely, with a net flow of 0.18, showing a positive flow of 0.497 and a negative flow of 0.317, indicating slightly lower performance than A1. A4 has a net flow of 0.04, with a Phi+ of 0.507 and a Phi- of 0.467, placing it in an intermediate position.

**Table 7 –** Net Flow for Decision Maker 1.

| Alternatives | Phi | Phi + | Phi - |
|---|---|---|---|
| A1 | 0.195 | 0.597 | 0.402 |
| A5 | 0.18 | 0.497 | 0.317 |
| A4 | 0.04 | 0.507 | 0.467 |
| A3 | -0.205 | 0.317 | 0.522 |
| A2 | -0.21 | 0.302 | 0.512 |

A3 and A2 have the worst performances, with net flows of -0.205 and -0.21, respectively, being strongly impacted by negative factors. In summary, A1 and A5 are the most favorable alternatives, while A3 and A2 are the least favorable.

A comprehensive result of the disaggregated perspective of PROMETHEE II on the impact of various criteria is shown through the PROMETHEE-rainbows (Figure 1). The analysis took into account the classification of factors, with weak points represented by the lower line and strong points by the upper line (Biswas et al., 2024). For alternative A1, the most prominent criteria were C5, C6, C1, and C3, reflecting a strong performance in these areas. However, criteria C2 and C4 demonstrated weak contributions, limiting the overall preference for this alternative. For alternative A5, the results indicate strength across most criteria, with C2 being the only one showing a weak influence. Alternative A2 is notably impacted by the weakness in criterion C3, which diminished its performance despite a relatively balanced contribution from the other criteria. On the other hand, alternative A4 exhibited the most balanced profile, with no single criterion showing extreme weakness or dominance. This balance across criteria positions A4 as a strong and consistent alternativein the decision-making process.

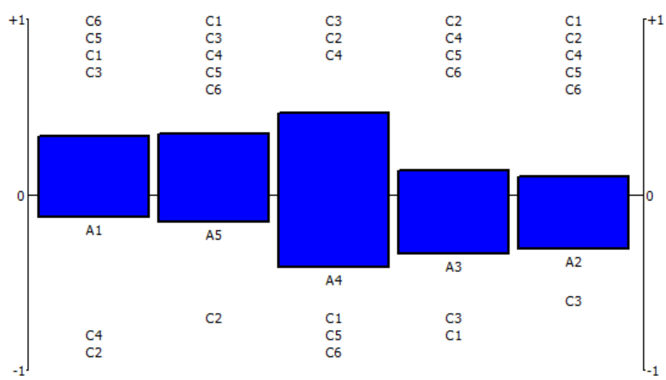


**Figure 1 –** PROMETHEE-rainbows for Decision Maker 1.

The analysis of Table 8 provides insights into the net flow for P2. Alternative A1 emerges as the most preferred alternative, with the highest net flow (0.15) indicating a strong overall performance. Its positive flow Phi+ (0.562) and Phi- (0.412), highlighting its strengths relative to the other alternatives. Alternative A4 presents a neutral option, with a net flow of 0, reflecting an equilibrium between its positive Phi+ (0.425) and negative Phi- (0.425). These results are visually supported by the PROMETHEE-rainbow diagram for P2, as shown in Figure 2. This diagram provides a comprehensive perspective on the strengths and weaknesses of the alternatives across the evaluated criteria, reinforcing the interpretation of Table 8.

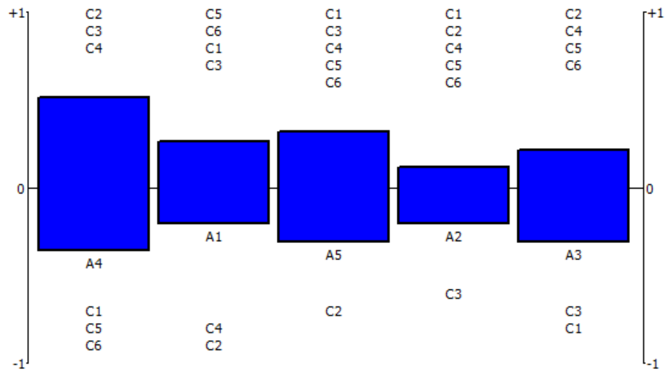


**Figure 2 –** PROMETHEE-rainbows for Decision Maker 2.

**Table 8 –** Net Flow for Decision Maker 2.

| Alternatives | Phi | Phi + | Phi - |
|---|---|---|---|
| A1 | 0.15 | 0.562 | 0.412 |
| A5 | 0.05 | 0.525 | 0.475 |
| A4 | 0 | 0.425 | 0.425 |
| A3 | -0.1 | 0.375 | 0.475 |
| A2 | -0.1 | 0.387 | 0.487 |

To determine the order of crop selection, the net flows (Phi) calculated by PROMETHEE II (Tables 7 and 8) were used as the primary criterion. Alternative A1 (Sweet Potato) emerged as the most preferred by both decision-makers. However, Decision Maker 2 displays a larger difference between its top two alternatives, A1 (Phi = 0.15) and A5 (Phi = 0.05), indicating a stronger preference. In contrast, Decision Maker 1 has a smaller difference between A1 (Phi = 0.15) and A5 (Phi = 0.05), suggesting more flexibility in its initial choices. Based on this, it was decided that Decision Maker 2 would initiate the selection, prioritizing its more distinct preference, followed by Decision Maker 1 to ensure a fair and balanced alternation process.

### 4.3 Balanced Decision-Making Method (BDMM)

The combined weight vector method integrates the individual preferences of decision-makers to create a single set of weights that represents a balanced compromise. In this case, the method was applied to Table 9, where the combined weights $w_{combj}$ for each criterion (C1 to C6) are as follows:

**Table 9 –** Weight Preferences using the combined weight vector Method.

| | C1 | C2 | C3 | C4 | C5 | C6 |
|---|---|---|---|---|---|---|
| $w_{combj}$ | 0.190 | 0.226 | 0.249 | 0.050 | 0.123 | 0.162 |

After applying the combined weights using the TOPSIS and PROMETHEE II methods, the results show that the top-ranked crops, based on normalized scores, are Tomato, Watermelon, Sweet Potato, Green Corn, and Bell Pepper, respectively (Table 10). These crops were selected due to their ability to meet the established criteria in a balanced manner, reflecting both economic considerations and agricultural management practices.

**Table 10 –** Ranking of alternatives combined weight vector.

| Alternatives | Normalized Ęi | Selected Culture |
|---|---|---|
| A4 | 0.267 | Tomato |
| A5 | 0.206 | Watermelon |
| A1 | 0.198 | Sweet Potato |
| A2 | 0.168 | Green Corn |
| A3 | 0.161 | Bell Pepper |

**Table 11 –** Net Flow for combined weight vector.

| Alternatives | Phi | Phi + | Phi - |
|---|---|---|---|
| A4 | 0.150 | 0.562 | 0.412 |
| A1 | 0.050 | 0.525 | 0.475 |
| A5 | 0.000 | 0.425 | 0.425 |
| A2 | -0.100 | 0.375 | 0.475 |
| A3 | -0.100 | 0.387 | 0.487 |

In the PROMETHEE II method, the net flows presented in Table 11 provide a more detailed overview of the alternatives' performance. A4 (Tomato) has the highest positive net flow (0.1500), indicating a dominant position compared to the other alternatives. This result is reinforced by the high positive flow Phi+ (0.5625) and a moderate negative flow Phi- (0.4125). A1 (Sweet Potato), although with a lower positive net flow (0.0500), still shows competitive performance, with Phi+ of 0.5250 and Phi- of 0.4750, suggesting a balance between dominance and being dominated. On the other hand, A5 (Watermelon) has a neutral net flow (0.0000), with equal values for positive and negative flows (0.4250), indicating an intermediate position where it neither dominates nor is significantly dominated. Meanwhile, A2 (Green Corn) and A3 (Bell Pepper) have negative net flows (-0.1000), indicating they are less preferred compared to the other alternatives. A2 has a positive flow Phi+ of 0.3750 and a negative flow Phi- of 0.4750, while A3 has a Phi+ of 0.3875 and the highest negative flow Phi- (0.4875), making it the most dominated alternative among all.

When comparing the net flows and normalized scores, it is observed that A4 (Tomato) stands out as the most preferred alternative, showing the best performance under the combined weight context. A1 (Sweet Potato) also exhibits favorable performance, consolidating its position as one of the most balanced alternatives. A5 (Watermelon), while showing good relative performance, displays a tendency toward neutrality in the PROMETHEE II analysis. Alternatives such as A2 (Green Corn) and A3 (Bell Pepper) consistently remain in lower positions, reinforcing their weaker dominance across the evaluated criteria.

A comprehensive result of the disaggregated perspective of PROMETHEE-II on the impact of various criteria is shown through the PROMETHEE-rainbows. The analysis took into account the classification of factors, with weak points represented by the lower line and strong points by the upper line (Figure 3).

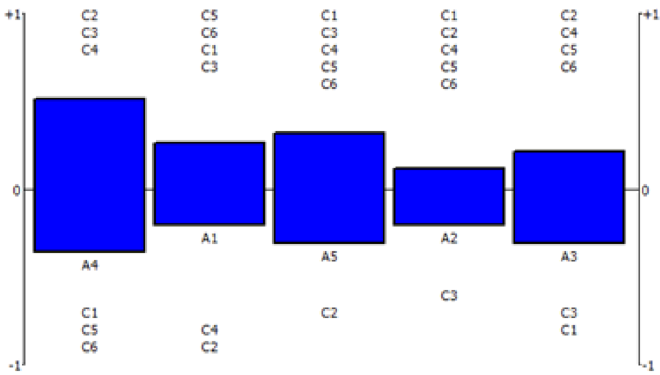


**Figure 3 –** PROMETHEE-rainbows for combined weight vector.

Alternative A1 emerges as the most dominant alternative, with significant positive contributions from C2, C3, and C4.. Alternative A1 shows prominent strengths in C1, C3, C5, and C6, with relatively minor weaknesses in C2 and C4. This indicates a solid but slightly uneven performance across the criteria. Alternative A5 demonstrates strengths in C2 and other criteria, its only notable weakness is in C3, suggesting a nearly balanced performance with minor shortcomings. Alternative A2 reveals a strong contribution from C3, but it also shows noticeable weakness in C1, which impacts its overall ranking negatively. Alternative A3 performs well in C1 and C3 but struggles with C5 and C6, indicating room for improvement in these specific criteria.

### 4.4 Borda Method for the Combined Weight Vector

The Borda method was applied to combine the rankings obtained from the TOPSIS and PROMETHEE II decision-making models, as shown in the Table 12.

**Table 12 –** The Borda method for each ranking

| Alternatives | TOPSIS Value | Promethee II Value |
|---|---|---|
| A4 | 5 | 5 |
| A1 | 3 | 4 |
| A5 | 4 | 3 |
| A2 | 2 | 2 |
| A3 | 1 | 1 |

Alternative A4 ranks 1st in both TOPSIS and PROMETHEE II, achieving the maximum score of 5 points from each method. This strong and consistent performance across both approaches highlights A4 as the most dominant alternative. Alternative A1 ranks 3rd in TOPSIS with 3 points but improves to 2nd in PROMETHEE II, earning 4 points. This indicates a favorable evaluation with slight variation across the methods. Alternative A5 secures 2nd place in TOPSIS with 4 points but drops to 3rd in PROMETHEE II with 3 points, showing a consistent yet slightly weaker performance in PROMETHEE II. Alternative A2 consistently ranks 4th in both methods, receiving 2 points, which reflects moderate performance without significant variation. Alternative A3 remains in 5th place across both methods, scoring only 1 point, indicating its consistently lower performance.

Table 13 presents the Borda method scores for the five alternatives (A1 to A5), combining points derived from the TOPSIS and PROMETHEE II decision-making methods. The total score represents the aggregate performance of each alternative across the two approaches.

**Table 13 –** Borda method score of the alternatives.

| Alternatives | Score |
|---|---|
| A4 | 10 |
| A1 | 7 |
| A5 | 7 |
| A2 | 4 |
| A3 | 2 |

Alternative A4 achieves the highest total score (10 points), demonstrating strong consensus and superior performance across both methods. Alternatives A1 and A5 follow closely, with a total score of 7 points each, indicating comparable performance but slightly lower than A4. Alternative A2 ranks fourth with 4 points, showing moderate performance relative to the top alternatives. Finally, alternative A3 obtains the lowest total score (2 points), reflecting consistently weaker performance across both methods. This ranking highlights A4 as the most favorable option, with alternatives A1 and A5 also performing strongly. Comparing these results with the net flow values for the two decision-makers (Tables 7 and 8), we observe a consistent alignment of preferences. Despite the slight differences in individual rankings, there is a clear consensus between the decision-makers in the final outcomes, especially when looking at the overall results from the Borda method. Both Decision Maker 1 and Decision Maker 2 favor A1 and A5 over A4, but A4 still maintains a strong position in the final score, suggesting that it is a broadly acceptable choice from a broader perspective. The similarity in rankings, particularly for the top three alternatives, demonstrates that the Borda method successfully synthesizes the individual preferences of both decision-makers into a consensus outcome.

## 5 CONCLUSIONS

The application of the new multicriteria decision-making method, integrating TOPSIS, PROMETHEE II, and the Borda method, proved effective in evaluating and comparing the alternatives, providing a balanced and objective analysis. The new method stands out for its integrated and equitable approach, assigning equal weights to the criteria, avoiding biases, and ensuring an impartial analysis. The use of TOPSIS to assess proximity to the ideal solution, combined with the flexibility of PROMETHEE II for pairwise comparisons and the Borda method for final consolidation, ensures well-founded and comprehensive evaluations. The versatility of the method makes it applicable to a wide range of decision-making problems, from agricultural practices to investment choices, enabling more informed and consensus-driven decisions. For future work, the approach can be expanded by exploring larger farm sizes, incorporating additional criteria to capture more diverse factors influencing agricultural decision-making, and including more planting alternatives. Additionally, integrating dynamic elements, such as climate change projections or market trend forecasting, could enhance the robustness and adaptability of the decision-making model. Given that two decision-makers were involved in this study, it would also be valuable to include more decision-makers. This would further refine the collective decision-making process and improve strategies for building consensus among stakeholders.

### Conflicts of Interest

The autors declare no conflicts of interest

### Data Availability Statement

The data available from the research are provided in the following repository: https://osf.io/y9evh.

### Author Contributions

Natasha Nazaré Cruz: Investigation, Conceptualization, and Writing – original draft. Francisco Jácome Sarmento: Data curation, Formal analysis, Visualization, Validation and Writing – review & editing. Abdeladhim Tahimi: Data curation, Formal analysis, Validation, Resources, Writing – review & editing. Armando Dias Duarte: Conceptualization, Investigation, Methodology, Writing – review & editing and Supervision.

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