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A Methodology for the Feasibility Assessment of Using Crop Residues for Electricity Production Through GIS-MCD and Its Application in a Case Study

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Abstract: Over recent decades, human activities have essentially depended on fossil fuels. The last Intergovernmental Panel on Climate Change reports recommend a shift to renewables and a more energy-efficient economy. To fulfill the potential of bioenergy, tools are required to overcome the complexities of the decision-making processes for viable projects. This work presents a decision-making tool to select the most feasible biomass residues and a case study of the state of Minas Gerais, in Brazil. Among the 13 evaluated criteria, eucalyptus residues demonstrated the highest potential for electricity production, followed by sugarcane bagasse and coffee husks. The choice of Minas Gerais as a case study is important due to its diverse agricultural landscape and the potential for biomass residue generation. The presented methodology uses the Analytical Hierarchy Process (AHP), a multi-criteria decision-making method (MCDM). Thirteen criteria were required to enable the best choice of biomass residue alternatives for electricity generation, which experts in the bioenergy field evaluated. The technical criterion was shown to be the one with the highest degree of importance. The results of the study identified that CO_{2eq} emissions (11.46%) and electricity demand (ED) were the most relevant sub-criteria for prioritizing the viability of agricultural waste. Eucalyptus was ranked as the most promising biomass, followed by sugarcane bagasse and coffee husks. In addition, the use of GIS tools made it possible to map the regions with the greatest potential in Minas Gerais, providing a robust approach to identifying strategic sites for bioenergy.

Keywords: biomass energy; potential; Analytical Hierarchy Process; bioenergy; energy transition

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Academic Editors: Renjie Dong and Walter Stinner

Received: 24 December 2024
Revised: 20 January 2025
Accepted: 21 January 2025
Published: 3 February 2025

Citation: Dovichi Filho, F.B.; de Sousa, L.V.M.; Lora, E.E.S.; Palacio, J.C.E.; Borges, P.T.; Barros, R.M.; Jaen, R.L.; Errera, M.R.; Quintero, Q.R. A Methodology for the Feasibility Assessment of Using Crop Residues for Electricity Production Through GIS-MCD and Its Application in a Case Study. *Agriculture* **2025**, *15*, 334. https://doi.org/10.3390/agriculture15030334

1. Introduction

The significant variation in climate, exacerbated by greenhouse gas emissions, has necessitated a swift change in our energy consumption patterns. Reports from the United Nations have underscored the urgency of policies based on renewables and energy efficiency, which have come to be known as the energy transition [1].

Biomass has emerged as a critical component of the global renewable energy matrix due to its ability to provide a sustainable alternative to fossil fuels. The primary advantage of biomass lies in its renewable nature. Unlike fossil fuels, the carbon dioxide (CO_2) released during the combustion of biomass is offset by the CO_2 absorbed during the growth of the plants, making its contribution to atmospheric CO_2 minimal [2]. This balance underscores the role of biomass in reducing greenhouse gas (GHG) emissions while leveraging agricultural and forestry residues as valuable resources.

From all types of bioenergy, residual biomass would be a source readily available with no further strain on the environment or society [1]. According to Paul and Dutta, around 181.5 billion tons of residual biomass are generated annually globally [3]. Estimates show that a reduction of about 35% of global GHG could be attained when using fuels from biomass [4]. In addition, other economic and social factors may also be advantageous in the use of bioenergy [5,6].

According to Errera, the contribution of agroforestry residues and energy crops in the global bioenergy supply may increase by 250% by 2050 with the implementation of gasification and combustion technologies [1].

MCDM (AHP) has been mainly applied to the selection of biomass-based electricity generation technologies, described in some examples below, and was a viable methodological approach. Nkuna investigated the selection of feasible thermochemical conversion technology between combustion/incineration, plasma, gasification, and pyrolysis to valorize wastewater sludge (WWS) and plant allocation. Combustion (incineration) was pointed out as the most viable technology [7].

Costa et al. (2020) developed a model for optimal placement of bioenergy facilities using the GIS tool in sugarcane growing areas in Brazil [8]. The study detected 1737 potential sites for bioelectricity plant installation based on the application of the WLC methodology and attribution of weights from the AHP.

In Colombia, Rodriguez et al. (2017) identified twelve ideal sites for power or biofuel plants using cocoa crop residues [9]. They used the GIS tool integrated with the Fuzzy AHP method and logistical and economic criteria to identify physical and geographical constraints.

Delivand et al. (2015) applied an integrated approach, using a combination of GIS-MCA (multi-criteria analysis) methodologies to allocate enterprises from durum wheat straw waste, olive, and vineyard pruning [10].

Otherwise, MCDM method applications for selecting the most viable biomass residues and describing the specificity of this issue are rare [11–13].

Madhu et al. (2020) applied AHP in multi-criteria decision-making to select the most suitable biomass feedstock and obtain the maximum bio-oil yield during pyrolysis [14].

Singh and Srivastava used AHP to select potential biomass sources in the Indian context [12].

Howari et al. (2023) applied the TOPSIS MCDM technique based on AHP by calculating weights to rank different biomasses derived from agricultural and industrial residues. The proposed eight evaluation criteria considered the main elements of biomass chemical composition [15].

When numerous options are available for evaluating a product or process, selecting the optimal alternative becomes essential. This task, however, is often challenging due to the involvement of multiple, sometimes conflicting criteria. In response to these complexities, a wide array of multi-criteria decision-making (MCDM) methods has been developed to address decision-making challenges across various fields. The Analytical Hierarchy Process (AHP), a prominent MCDM method, has proven effective for prioritizing alternatives by structuring decisions hierarchically and incorporating expert evaluations [16].

This paper introduces an assessment methodology based on the (AHP) MSDM method and geographic data framework (GIS). It was applied to a case study of viability assessment for biomass residue power projects in the state of Minas Gerais (MG), Brazil. Overall, the novel assessment method considers the diversity, spatial distribution, and generation of biomass residues, logistics, technical feasibility, energy conversion route, ecological sustainability, social issues, and financial performance.

The main novelty of the paper is that MCDMs are more frequently used to select the most feasible among different conversion technologies rather than to rank the feasibility of different biomass residues for electricity or biofuel production and a GIS-based definition of plant locations.

2. Materials and Methods

Data were collected in 2021. This research methodology comprises four stages, as shown in Figure 1: (i) gathering problem information, (ii) model conception, (iii) the decision-making methodology definition per se, and (iv) application of the MCDM methodology with GIS tool to a case study.

In the first stage, the focus is on identifying the most significant crops in the region under analysis based on production volume and availability. This step ensures that the selection of crops reflects the region's actual agricultural profile, setting a foundation for subsequent analyses. For the case study centered on the state of Minas Gerais (MG), Brazil, data were sourced from the SIDRA database maintained by the Brazilian Institute of Geography and Statistics (IBGE) [17].

The SIDRA database is recognized as one of the most reliable sources of agricultural statistics in Brazil. It is built upon systematic and rigorous data collection processes, including the Levantamento Sistemático da Produção Agrícola (LSPA), which involves in loco verification of agricultural production data (IBGE, 2024). The LSPA methodology includes monthly field surveys and direct engagement with agricultural producers to obtain precise and detailed information on crop production, harvest areas, and yields. These practices minimize potential biases or inaccuracies in the data, enhancing its suitability for analytical purposes and ensuring a robust foundation for studies like this one [18].

While the SIDRA database is highly reliable, we acknowledge that any dataset may have inherent limitations, such as delays in updates or minor regional discrepancies. To address this, the study cross-referenced SIDRA data with expert evaluations and additional literature to ensure alignment with the agricultural reality of Minas Gerais. This complementary validation process strengthened the reliability of the input data used in the GIS-based analysis and AHP methodology, mitigating the potential impact of any minor discrepancies in the dataset.

Given the robustness of the SIDRA dataset and its systematic approach, we are confident that the data accurately represent the agricultural profile of Minas Gerais. This reliability supports the validity of the study's findings and reinforces the robustness of the methodology applied in this case study.

The second stage involves an in-depth review and selection of suitable MCDM methods used in energy-related applications. These include AHP, ELECTRE, TOPSIS, VIKOR, MAUT, PROMETHEE, and MACBETH. For this study, AHP was chosen due to its effectiveness in structuring complex decision-making scenarios and its proven application in similar contexts. Once the method was selected, theoretical and technical potentials were calculated, and the criteria and sub-criteria for the analysis were defined, following the guidelines proposed by [19–23].

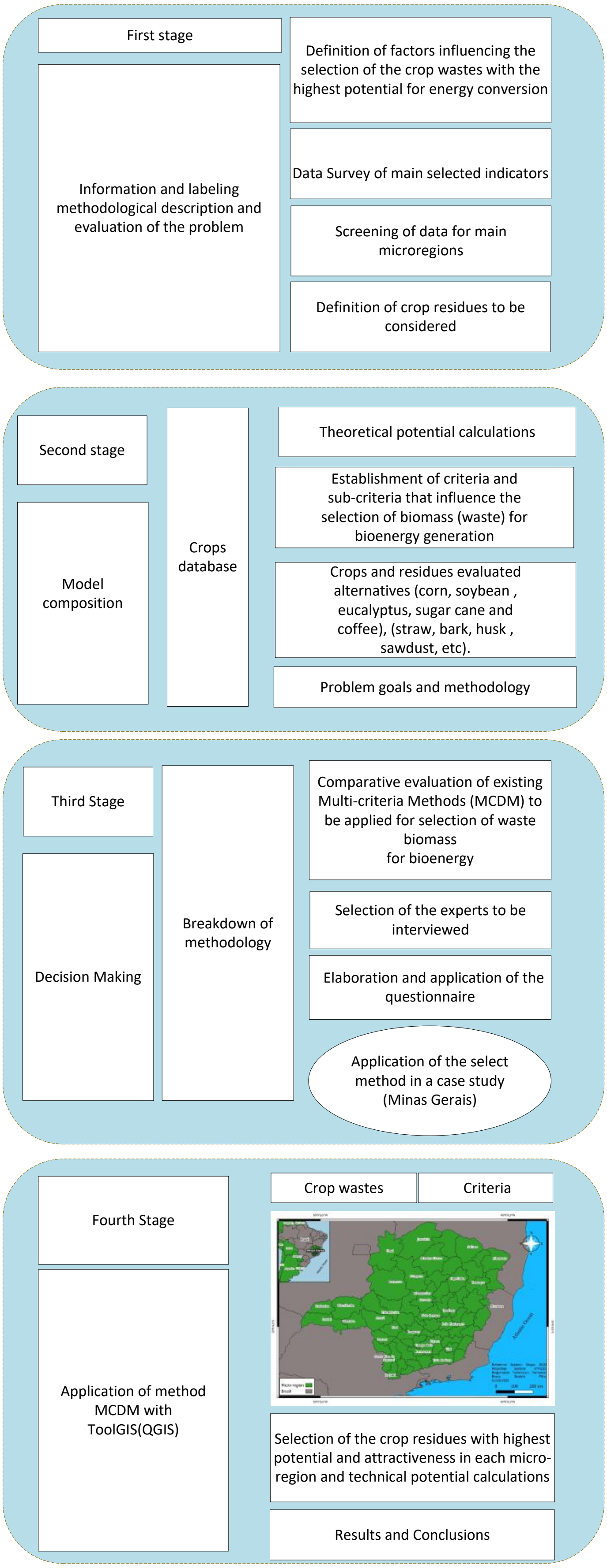

Figure 1. General description of the methodology.

The third stage encompasses applying the chosen MCDM method to identify the most promising crop residues for bioenergy production. A structured survey was distributed to a panel of experts in bioenergy, who were asked to evaluate the criteria using Saaty's pairwise comparison scale [24,25]. The survey results were compiled into a comparative matrix (matrix S), and the weights for each criterion were derived through the geometric mean. To ensure the reliability of the responses, the consistency index (CI) was calculated and analyzed to verify that the judgments met acceptable consistency thresholds.

The fourth and final stage uses a GIS tool (QGIS 3.34) to generate theoretical potential maps for the selected region. These maps visually represent the distribution of crops and highlight the micro-regions where the residues meet the established criteria for energy conversion. This step facilitates a spatial understanding of biomass availability and supports decision-makers in prioritizing locations for bioenergy projects. The comprehensive approach allows for the identification of biomass residues that align best with the technical, economic, and logistical criteria essential for energy generation.

2.1. Saaty's Methodology

Saaty proposed a multi-criteria analysis (MCA) methodology designed to establish a ranking among evaluated alternatives through a structured process of pairwise comparisons and criteria weighting [25]. This approach involves creating a comparison matrix where each element indicates the relative importance of one criterion over another [13]. The relative importance is determined using a fundamental scale, as outlined in Table 1, which provides a standardized framework for assigning weights based on expert judgments.

Table 1. Fundamental scale proposed by Saaty.

Intensity of Importance on an Absolute Scale, S_{ij}	Description	Explanation
1	The equal importance of both	Both criteria contribute equally to the goal
3	Moderate importance of one over the other	Experience and judgment strongly favor one activity over the other
5	One with clearly greater importance than the other	Experience and judgment strongly favor one activity over the other
7	Proven greater importance of one than the other	One activity is strongly favored, and its dominance is demonstrated in practice
9	The extreme importance of one over the other	The evidence favoring one activity over another is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate values between two adjacent judgments	When it is necessary to establish an agreement

The comparison matrix, denoted as matrix S, is constructed using Equations (1) and (2):

$$S_{ii} = 1 \tag{1}$$

$$S_{ij} = 1/S_{ji} \tag{2}$$

S_{ii}: Represents the self-comparison value of a criterion, which is always 1 in the Analytical Hierarchy Process (AHP), as a criterion is equally important when compared to itself.

S_{ij}: Represents the relative importance of criterion iii compared to criterion jjj.

S_{ji}: Represents the reciprocal of S_{ij}, as the importance of j relative to iii is the inverse of the importance of iii relative to j.

Therefore, the weights of these criteria will be established by the geometric mean of the S matrix as shown in Equation (3) and then translated into attribute weights using the normalized row geometric mean method, or the eigenvector method, to estimate the priority vector.

2.2. Analytical Hierarchy Process (AHP)

The AHP method was selected as the decision-making tool for analyzing the alternatives considered in this study [26]. The process involves three main steps: (i) structuring the hierarchy of criteria and alternatives, (ii) generating a pairwise comparison matrix, and (iii) calculating the weight values of the criteria and the performance scores for each alternative.

The AHP provides a systematic framework that enables decision-making by assigning numerical values to both criteria and alternative options and linking these values to an overarching objective. The implementation process is depicted in Figure 2, which outlines the primary stages: (i) conducting a literature review to identify and select criteria that influence the utilization of agricultural and industrial waste for electricity generation, (ii) evaluating the criteria weights and determining the score values for each type of crop residue, and (iii) employing an additive value function to rank the crop residues.

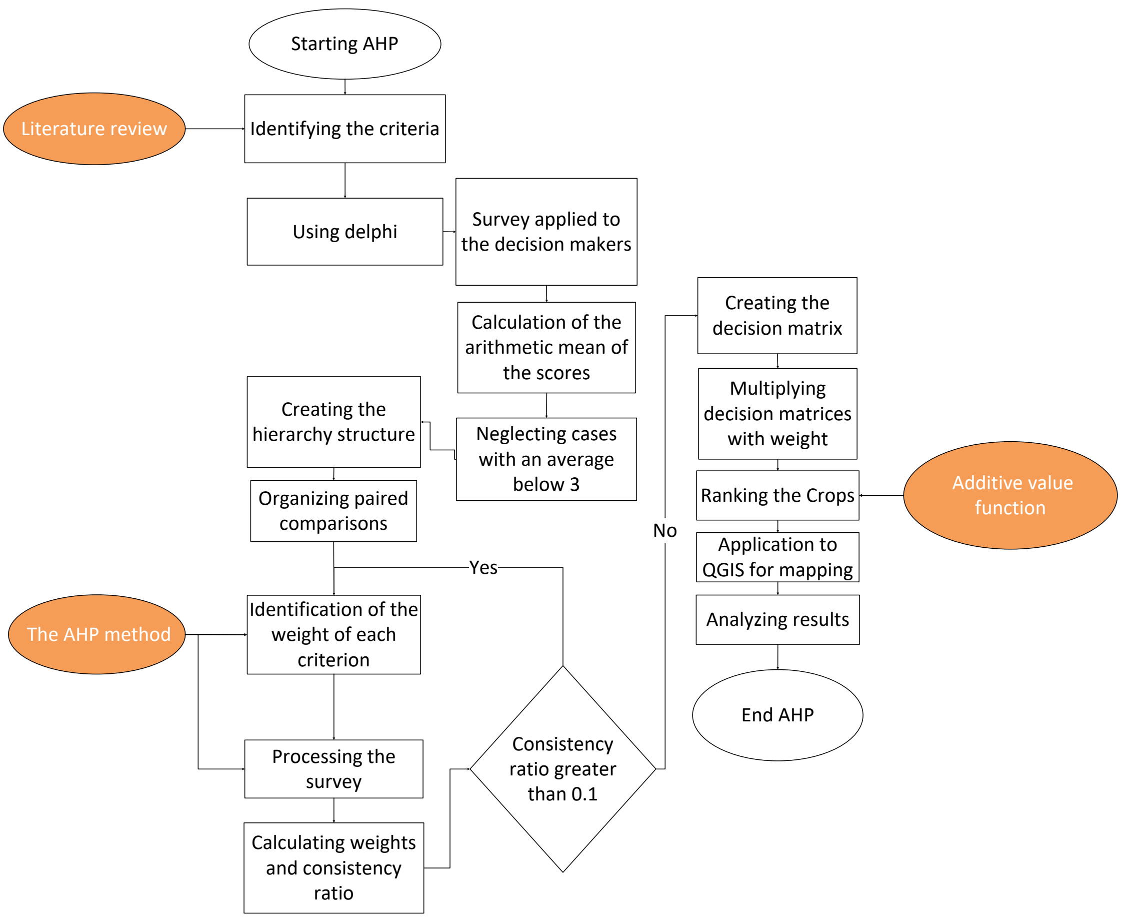

Figure 2. MCDM/AHP three-stage flowchart.

To evaluate the alternatives using the pairwise comparison matrix, this study followed the formulation proposed by Kheybari [24]. The matrix is represented as shown in Equation (3), where each row corresponds to a criterion, and the columns indicate the relative importance of that criterion compared to others:

$$A = \left(p_{ij}\right)_{n\times n} = \begin{pmatrix} p_{11} & p_{12} & \dots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \dots & p_{nn} \end{pmatrix} \quad (3)$$

A: The pairwise comparison matrix of dimension $n \times n$, where each element p_{ij} represents the relative importance of criterion iii compared to criterion j.

p_{ij}: The value indicating the importance of criterion i relative to j.

n: The total number of criteria being evaluated in the decision-making process.

The pairwise comparison matrix represents the relative importance value of a criterion (or alternative) compared to a criterion (or alternative), calculated through pairwise comparisons across all criteria. This comparison employs Saaty's nine-level fundamental scale. Each matrix row is then normalized as shown in Equation (4):

$$p^*_{ij} = \frac{p_{ij}}{\sum_{j=1}^{n} p_{ij}} \forall\, i, j = 1, 2, \dots, n \quad (4)$$

p^*_{ij}: The normalized value of p_{ij}, representing the relative weight or priority of element iii with respect to element j after normalization.

p_{ij}: The original pairwise comparison value indicating the relative importance of criterion iii compared to criterion j.

$\sum_{j=1}^{n} p_{ij}$: The sum of all pairwise comparison values for criterion iii across all n criteria. This sum is used to normalize the values for consistency.

n: The total number of criteria being compared in the decision-making matrix.

Equation (5) represents the degree of relative importance for each criterion, obtained by summing the normalized values:

$$w^*_i = \sum_{j=1}^{n} p^*_{ij} \,\forall\, i = 1, 2, \dots, n \quad (5)$$

w^*_i: The normalized weight or priority of criterion i. This represents the aggregated importance of i based on the normalized pairwise comparisons.

p^*_{ij}: The normalized pairwise comparison value of criterion i relative to criterion j, calculated as $p^*_{ij} = \frac{p_{ij}}{\sum_{j=1}^{n} p_{ij}}$.

$\sum_{j=1}^{n} p^*_{ij}$: The sum of normalized values for criterion iii over all n criteria. This aggregation provides the total normalized weight for i.

Finally, the weight vector of criteria $\vec{W} = (w_1, w_2, \dots, w_n)^{\mathrm{T}}$ is calculated according to Equation (6).

$$w_i = \frac{w^*_i}{\sum_{k=1}^{n} w^*_k} \forall\, i = 1, 2, \dots, n \quad (6)$$

w_i: The final normalized weight or priority of criterion i. This value represents the relative importance of i compared to all other criteria after full normalization.

w_i^*∗: The aggregated, unnormalized weight of criterion i, calculated as the sum of normalized pairwise comparison values (p_{ij}^*) for criterion i.

$\sum_{k=1}^{n} w_k^*$: The total sum of all unnormalized weights w_k^* across all n criteria. This step ensures that the weights are normalized to a scale of 0 to 1, maintaining consistency and comparability.

n: The total number of criteria being evaluated in the decision-making process.

In the MCDM process, the weights from Equation (6) are known as local weights. The local weights of all criteria and sub-criteria within a branch are multiplied to calculate the overall weight of the higher-level sub-criteria in each branch of the hierarchical structure. A consistency analysis is essential to ensure the reliability of the evaluations [27].

2.3. Consistency Index (CI) and Consistent Ratio of the Replies

The consistency index (*CI*) is a key measure in evaluating the linear independence between pairs of criteria within the comparison matrix. A *CI* value close to zero indicates better consistency of the matrix. The *CI* is defined by Saaty and is presented by Kheybari [16] as shown in Equation (7):

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{7}$$

λ_{max}: The largest eigenvalue of the pairwise comparison matrix.

n: The number of criteria in the matrix.

The maximal eigenvalue can be determined using Equation (8):

$$\lambda_{max} = \frac{1}{n}\sum_{i=1}^{n} \frac{(Aw)_i}{w_i} \tag{8}$$

λ_{max}: The largest eigenvalue of the pairwise comparison matrix. This value is used in calculating the consistency index (*CI*) in the AHP method.

n: The total number of criteria in the pairwise comparison matrix.

A: The pairwise comparison matrix (nxn).

w: The normalized weight vector, where each element w_i represents the relative weight of criterion i.

$(Aw)_i$: The i-th element of the vector resulting from multiplying the matrix A by the weight vector w.

In this equation, Aw_i represents the product of the original comparison matrix A by the vector of weights w, and n is the number of criteria being evaluated within the comparison matrix. Essentially, n corresponds to the number of criteria listed for the specific decision-making problem analyzed using the AHP method [15,28].

For a perfectly consistent comparison matrix, *CI* = 0 e λ_max = n. However, achieving (*CI* = 0) is generally not realistic in practice. Thus, to better assess the consistency of the judgments, the consistency ratio (*CR*) is calculated according to Equation (9):

$$CR = \frac{CI}{RI} \tag{9}$$

CR (Consistency Ratio): A measure used to evaluate the consistency of judgments in the pairwise comparison matrix within the Analytical Hierarchy Process (AHP). A *CR* value below 0.1 is generally considered acceptable for reliable results.

CI (Consistency Index): A value that quantifies the degree of inconsistency in the pairwise comparison matrix.

The random index (RI), which varies according to the number of criteria, is shown in Table 2. When n < 3, the comparison matrix is inherently consistent, and the RI value is considered random. Consistency and reliability in the matrix are indicated when *CR* < 0.1.

When $CR \geq 0.1$, adjustments to the judgment matrix are necessary to achieve acceptable consistency levels [25,29].

Table 2. RI values are based on selected criteria. Source: [25,26].

Matrix Size	1	2	3	4	5	6	7	8	9
Random Index	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45

2.4. Data Analysis

The data analysis was conducted using the R 0.4.1 computational package, which processes and refines the aggregated data to achieve the consistency value of the questionnaire responses, as outlined by Cho [30]. This ensures the reliability of the AHP results and helps validate the matrix consistency.

The "ahpsurvey" tool from the R package was employed to quantify the inconsistency in the responses and make automatic adjustments to align them with Saaty's consistency condition. This tool streamlines the process by recalibrating the data, ensuring that the consistency index (CI) and consistency ratio (CR) meet acceptable thresholds. The final values for each alternative were calculated using Equation (10):

$$V_i = \sum_{j=1}^{n} W_j \cdot U_{ij} \tag{10}$$

V_i: The overall score or value for alternative i. This represents the weighted sum of the utility values across all criteria for the alternative.

W_j: The normalized weight of criterion j, indicating its relative importance in the decision-making process.

U_{ij}: The utility value of alternative i with respect to criterion j. This reflects the performance of alternative iii under criterion j.

n: The total number of criteria considered in the analysis.

In this equation, Wj represents the weight of each criterion, as determined in the earlier step, and Uij denotes the performance score of each alternative for each criterion.

2.5. Case Study

The case study was conducted in the state of Minas Gerais (MG), Brazil (Figure 3), which is notable for its significant agricultural production, including crops such as sugarcane, hardwood, corn, beans, and coffee [30]. The aim was to apply the AHP methodology to identify the most suitable crop residues for bioenergy production and assess their potential for electricity generation.

This analysis considered five biomass types: sugarcane bagasse, corn stover, coffee husk, hardwood residues, and bean straw. These were selected based on their high availability and relevance to the region's agricultural landscape. Data obtained from the SIDRA database and regional production statistics informed the selection of these specific biomasses.

The decision-making process involved a panel of 32 experts in bioenergy, including researchers, engineers, and industry professionals. This diverse representation ensured a comprehensive range of perspectives, encompassing both theoretical knowledge and practical experience in bioenergy projects. According to recommendations outlined in the literature [31,32], the ideal number of participants for AHP studies typically ranges between 2 and 100 experts. This range ensures a balance between the diversity of opinions and the feasibility of organizing and analyzing the data collected.

The experts were consulted through structured surveys, including pairwise criteria comparisons using Saaty's nine-level fundamental scale. The survey responses were collected via online submissions, ensuring comprehensive and representative data collection.

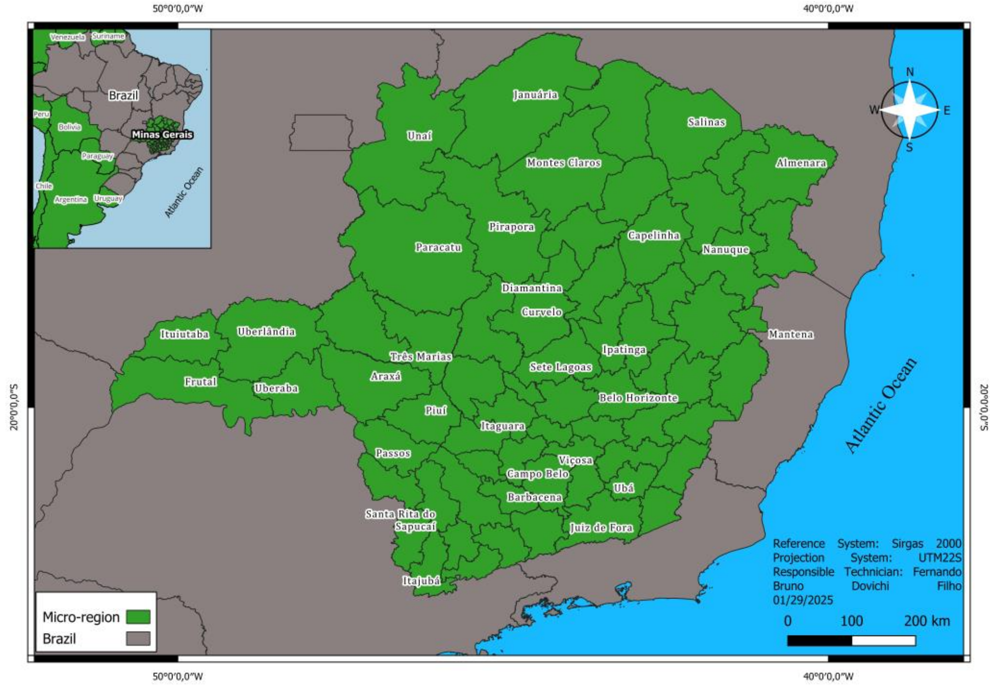

Figure 3. Micro-regions in the State of Minas Gerais.

The selection of criteria for this study was based on an analysis of diverse bibliographic references and aligned with the availability of reliable datasets. This approach ensures that the chosen criteria comprehensively represent the factors influencing biomass feasibility while minimizing the influence of subjective judgments. By grounding the selection process in established literature and verified data sources, such as the IBGE's SIDRA database, the study reduces the potential for biases inherent in expert-based methodologies.

The criteria for evaluating the potential of each biomass included technical feasibility, economic viability, environmental impact, and logistical considerations. These criteria were chosen based on a thorough literature review and consultations with the expert panel to align with the region's key factors influencing bioenergy projects. Each criterion was weighted and evaluated using the AHP process, incorporating the methodologies and equations outlined in Sections 2.1–2.4.

Additionally, the use of expert input was complemented by consistency checks, as described in Section 2.3, to validate the coherence and reliability of the pairwise comparisons. This combination of data-driven criteria selection and expert validation reinforces the robustness of the Analytical Hierarchy Process (AHP) framework applied in this research.

The technologies considered for converting biomass to electricity included conventional Rankine cycle systems, organic Rankine cycle (ORC) systems, and internal combustion engines with gasifiers. These technologies were selected due to their varying efficiencies and applicability to different types of biomass. The assessment aimed to identify which crop residues would perform best under these technological conditions, providing a clear framework for future bioenergy initiatives in Minas Gerais.

The analysis outcomes included the ranking of the biomass alternatives and insights into how the selected criteria influenced the decision-making process. The structured approach ensured that the study's results were also practical, offering valuable guidance for stakeholders involved in bioenergy development within the state.

3. Results and Discussion

3.1. Definition of Criteria and Sub-Criteria and Hierarchical Structuring

The criteria used in this study were categorized into four main groups: economic, technical, environmental, and social, with 13 sub-criteria distributed among these groups. These criteria and sub-criteria were selected based on a combination of quantitative and qualitative data, which provided a comprehensive foundation for evaluating the potential of different biomass residues. Figure 4 illustrates the hierarchical structure applied in this decision-making analysis for biomass resource planning.

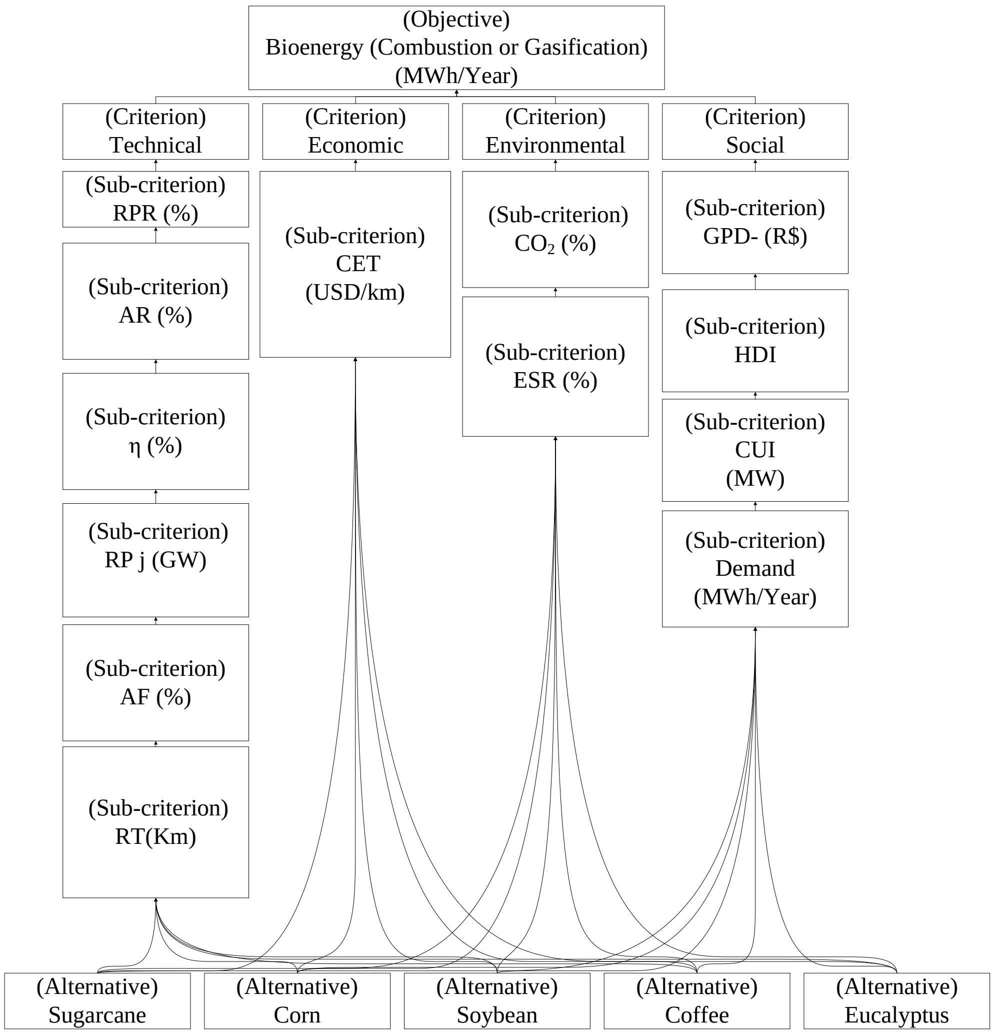

Figure 4. Hierarchical structure of the decision-making investigation for biomass resource planning.

These experts provided input based on their extensive knowledge and practical experience, ensuring that the criteria comprehensively represent the technical, economic, environmental, and social dimensions critical to biomass feasibility.

To minimize subjective bias, the criteria were structured hierarchically and cross-verified against established frameworks in bioenergy research. Furthermore, the pairwise comparison matrices were subjected to consistency ratio (CR) checks, with adjustments made as needed to ensure that the CR values fell below the acceptable threshold of 0.1, as recommended by Saaty (1980) [25].

This methodological rigor provides confidence that the selected criteria sufficiently encompass the relevant factors impacting biomass feasibility. While subjective judgments are inherent to AHP, the consistency checks and diverse expert panel mitigate potential biases. Additionally, the methodology can be adapted and expanded to include new criteria as regional or technological priorities evolve, enhancing its robustness and applicability.

While 32 panel members represent a robust sample size within the context of multi-criteria decision-making studies, care was taken to balance the panel composition to avoid potential biases associated with overrepresentation from any single sector or region. Moreover, the structured survey methodology, combined with pairwise comparisons, allowed individual judgments to be aggregated into a consistent and representative framework.

Expert input was integral to this process. A structured survey was distributed to 32 bioenergy professionals, who provided pairwise comparisons for the criteria and sub-criteria based on Saaty's fundamental scale. The consistency of their responses was evaluated using the consistency ratio (CR), ensuring reliable and coherent judgments. The resulting weights reflect the aggregated expert assessments, providing a robust basis for the analysis.

To further mitigate potential limitations, the consistency ratio (CR) of the pairwise comparisons was rigorously evaluated, and any inconsistencies were addressed by recalibrating the matrices using the R computational package. This step ensured that the expert evaluations met the reliability threshold recommended by Saaty ($CR < 0.1$).

The weighting system emphasized criteria reflecting regional and technological priorities. Future studies could further expand the panel's size and diversity to increase representativeness, especially in broader assessments. This adaptability ensures the methodology remains robust and responsive to evolving bioenergy challenges.

The inclusion of diverse perspectives and the application of robust consistency checks enhance the validity of the results, reducing the likelihood of skewed outcomes due to panel composition. Nevertheless, as with any AHP application, future studies could expand the panel size and diversity to further enhance representativeness, especially in broader regional or global assessments.

The consistency of these evaluations was verified to ensure reliability, as detailed in Section 2.3. The expert assessments were used to calculate the local weights of each criterion and sub-criterion, which were subsequently aggregated to derive the global weights. This weighting system highlighted the relative importance of each criterion in the decision-making process, reflecting real-world priorities and challenges associated with biomass utilization for energy production.

3.2. Generalizability of the Methodology

While the case study focuses on the state of Minas Gerais, Brazil, the methodology developed in this research is designed to be broadly applicable. The approach combines the Analytical Hierarchy Process (AHP) with Geographic Information System (GIS) tools, utilizing publicly available and standardized data sources. This ensures that the framework is adaptable to different regions, provided that equivalent datasets and geospatial information are accessible.

The strength of the methodology lies in its flexibility. The AHP process allows for the customization of criteria and sub-criteria to reflect regional or local conditions, such as variations in agricultural practices, types of biomass, or socio-economic factors. Similarly, GIS tools can incorporate region-specific geospatial data to ensure accurate spatial analyses. The framework is not inherently tied to Minas Gerais but was demonstrated in this context as a practical application of its capabilities.

Furthermore, the datasets used in this study, such as those from the IBGE, are analogous to data available from statistical agencies in many other countries. This makes the methodology particularly suitable for broader applications, enabling decision-makers in various regions to assess the feasibility of biomass residues for energy production under their unique conditions.

Future research could expand the application of this methodology to other regions, incorporating diverse datasets and criteria to validate its generalizability. This adaptability underscores the methodology's potential as a valuable tool for biomass feasibility assessments worldwide, supporting the development of tailored energy solutions that address local needs while contributing to global renewable energy goals.

3.3. Technical Criteria

The technical criteria encompass the theoretical and technical energy potentials of the biomass residues considered in this study.

3.3.1. Theoretical Potential

Quantifies the maximum amount of energy that can be extracted from a given biomass source, based on its production volume, lower heating value (*LHV*), and residue-to-product ratio [33]. This potential is quantified using Equation (11):

$$E_{theoretical}=\sum_{1}^{n} P \cdot A_f \cdot LHV \cdot RPR[GW] \tag{11}$$

$E_{theoretical}$: Theoretical energy potential, expressed in gigawatts (GW). This represents the total potential energy that can be produced from the biomass residues.

P: Biomass productivity or the total annual production of the biomass residue in question (e.g., tons per year).

A_f: Availability factor, representing the fraction of biomass that is practically available for energy production after accounting for non-energy uses and losses.

LHV: Lower Heating Value, which is the amount of energy released during the combustion of a unit mass of biomass (e.g., MJ/kg or MJ/ton).

RPR: Residue-to-Product Ratio, indicating the amount of residue generated per unit of primary agricultural product (e.g., kg of residue per kg of product).

n: The total number of biomass types or crops considered in the analysis.

In this equation, p refers to the production volume, A_f is the annual waste availability factor, *LHV* represents the lower heating value, and RPR is the residue-to-product ratio. The data for the *LHV* of the residues analyzed in this study are detailed in Table 3.

Table 3. HV residues on a dry basis. Source: [34–37].

Crop	Residue	LHV (MJ/kg)
Sugarcane	Straw	16.585
Coffee	Husk	17.036
Corn	Stover	16.236
Soybean	Straw	15.895
Eucalyptus	Sawdust	16.372

3.3.2. Technical Potential

The technical potential is calculated after selecting a suitable biomass conversion technology. For this study, the conventional Rankine cycle was chosen due to its widespread commercial use and high technological maturity [38]. The technical potential is estimated by applying Equation (12) with an efficiency factor:

$$E_{technical} = E_{theoretical} \cdot \eta \tag{12}$$

$E_{technical}$: Technical energy potential, expressed in gigawatts (GW). This represents the portion of the theoretical energy potential that can be realistically converted into usable energy, considering system efficiencies.

$E_{theoretical}$: Theoretical energy potential, expressed in gigawatts (GW). This is the maximum potential energy calculated without accounting for efficiency losses.

η: Conversion efficiency factor, which accounts for the technical efficiency of the energy conversion process (e.g., from biomass to electricity). It is a dimensionless value typically ranging between 0 and 1.

3.3.3. Technical Sub-Criteria

Several sub-criteria were evaluated under the technical criteria, as outlined below.

(a) RPj (Residue-to-Product Ratio): Represents the ratio of biomass residue generated relative to the main agricultural product, indicating resource availability (as shown in Table 4).

Table 4. Residue-to-product ratio for considered crops. Source: [34,36,39].

Crop	Residue	(RPj) (%)
Corn	Stover	1.68
Eucalyptus	Sawdust	0.45
Soybean	Straw	2.30
Sugarcane	Straw	0.22
Coffee	Husk	0.59

(b) AF (Annual Waste Availability Factor): The percentage of time during the year that the waste is available for collection and use (as shown in Table 5).

Table 5. Waste availability factor (AF). Source: [36,39–41].

Crop	Residue	AF (%)
Corn	Stover	40
Eucalyptus	Sawdust	80
Soybean	Straw	40
Sugarcane	Straw	50
Coffee	Husk	58

(c) AR (Residue Recovery Rate): The percentage of biomass residues that can be feasibly collected and recovered for energy generation, considering limitations in extraction and transport (Table 6).

Table 6. The recovery rate for crop wastes. Source: [36,37].

Crop	Residue	AR (*w*/*w* db %)
Corn	Stover	100
Eucalyptus	Sawdust	50
Soybean	Straw	100
Sugarcane	Straw	65
Coffee	Husk	50

(d) RT (Average Transport Distance): The average distance between the crop plantations and the proposed biomass power plant, as shown in Figure 5. This factor impacts logistical feasibility and overall project costs.

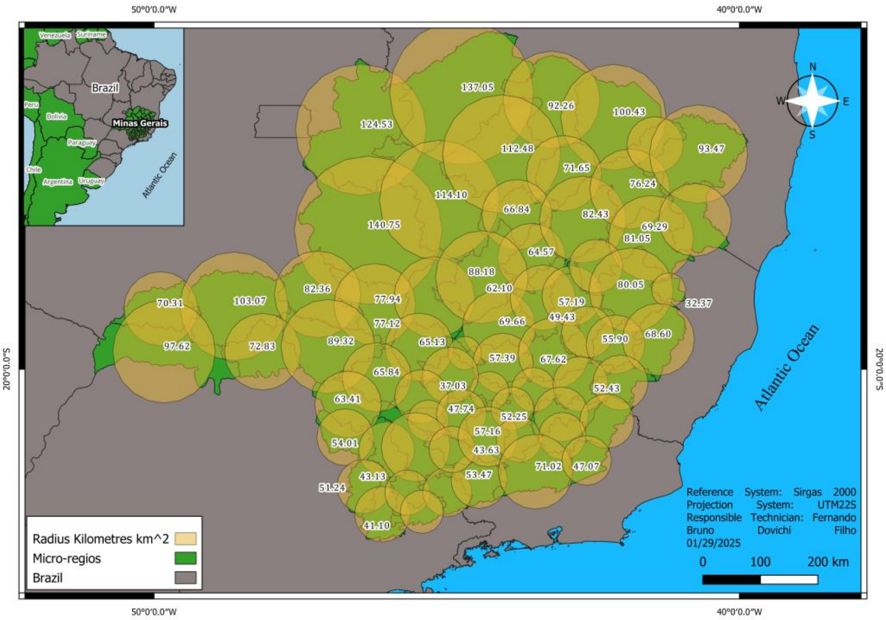

Figure 5. RT (km) Average distance from crop plantations to proposed thermal power plant locations in Minas Gerais.

3.4. Environmental Criteria

Two sub-criteria were defined to evaluate the environmental aspects associated with the use of biomass residues: net emissions of greenhouse gases (CO_{2eq}) and the environmentally sustainable removal rate (ESR) [36]. The CO_{2eq} sub-criterion quantifies the greenhouse gas emissions during the combustion of different biomass residues, as shown in Table 7. This table highlights the variation in CO_2 emissions for each type of residue, reflecting their environmental impact when used for energy generation.

Table 7. Total CO_2 emissions during biomass combustion by crop type. Source: [42–45].

Crop	Residue	CO_2 (%)
Sugarcane	Straw	11.95%
Corn	Stover	12.17%
Soybean	Straw	11.58%
Coffee	Husks	11.46%
Eucalyptus	Sawdust	11.84%

(a) CO_2 [%]: This represents the percentage of carbon dioxide in exhaust gases released by biomass burning under stoichiometric conditions. It is a relative measurement of net CO_2 emissions per type of biomass crop (Table 7).

(b) ESR (Environmentally Sustainable Removal Rate, %): The ESR represents the percentage of biomass residues that should remain in the field to maintain soil health and sustainability and not compromise the land's long-term productivity. Only 30% of the available residues are typically collected to align with sustainable practices [36].

3.5. Economic Criteria

The economic criterion selected for this analysis focuses on the comprehensive costs associated with the biomass supply chain, including collection, storage, loading, and transportation to the power generation plant. This criterion, represented as CET [$/km], reflects the financial viability and logistical expenses necessary to ensure a cost-effective biomass supply for electricity generation.

3.6. Social Criteria

The social criteria were chosen to capture the broader socio-economic impacts of biomass utilization. The sub-criteria are detailed below:

(a) GDP: The GDP reflects the economic output of the regions involved, visualized in Figure 6.

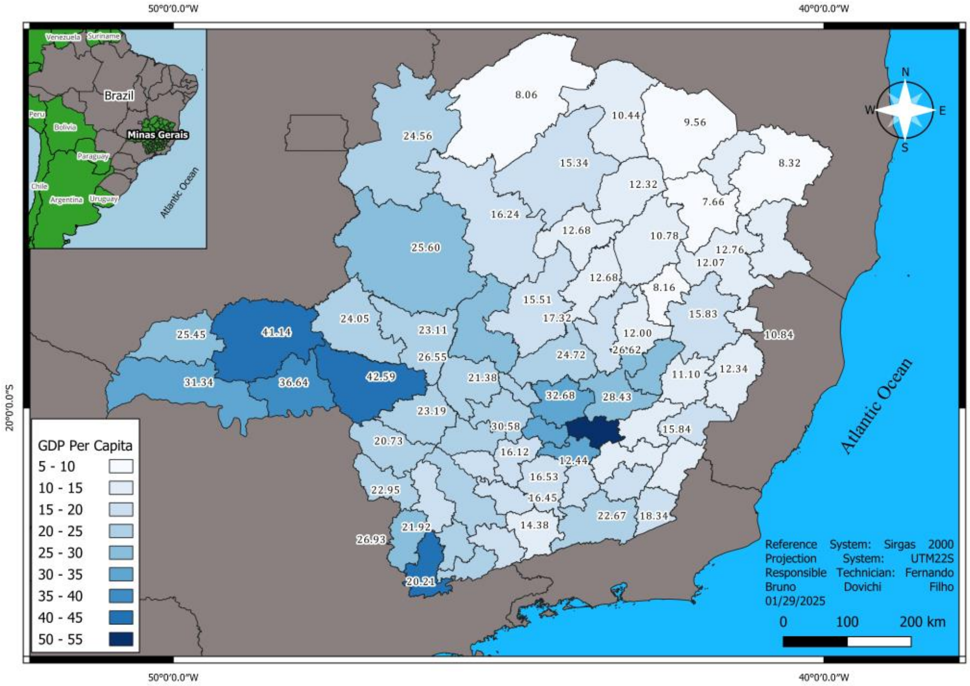

Figure 6. GDP (R$ × 1000) per capita in the different micro-regions of Minas Gerais.

(b) GDP: The GDP reflects the economic output of the regions involved, visualized in Figure 6. HDI: The human development index (Figure 7) [46].

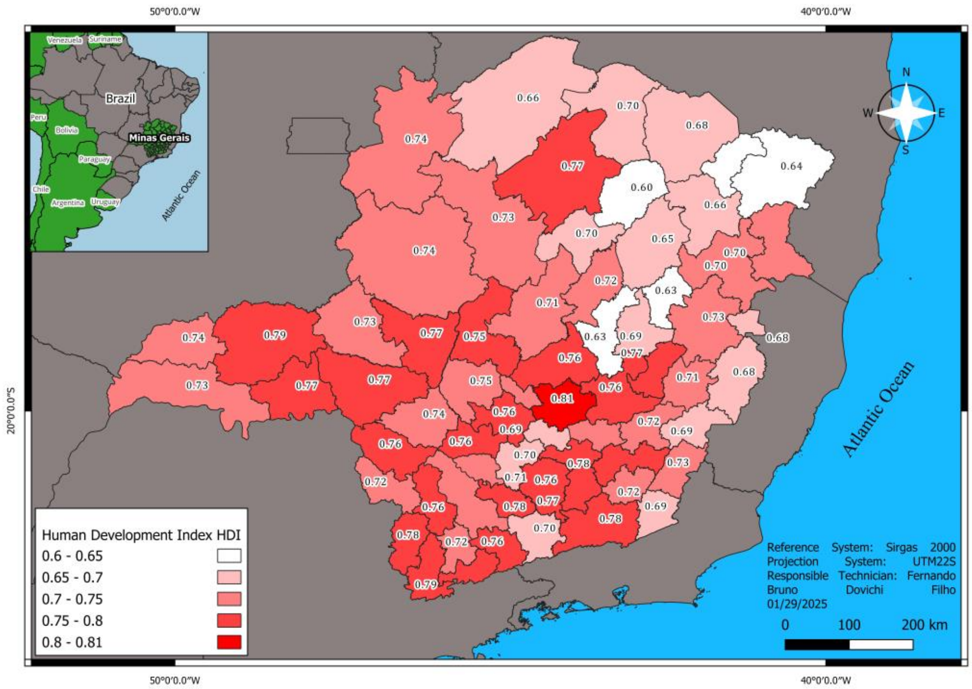

Figure 7. HDI in the different micro-regions of Minas Gerais.

(c) Electricity demand (ED): Average amount of electricity needed to supply all the loads the consumer unit will use to carry out its operations during a given period (Figure 8) [47].

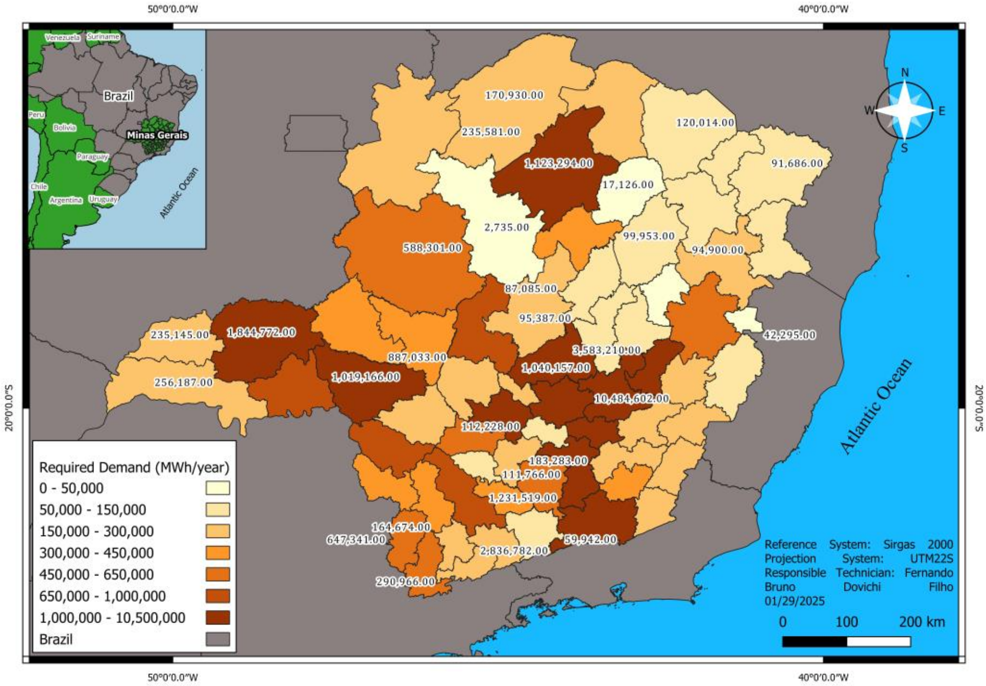

Figure 8. ED [MWh/year] by micro-region of Minas Gerais.

(d) CUI (Capacity Utilization Index): The Capacity Utilization Index (CUI) measures the electric power generated by existing biomass power plants in each micro-region (Figure 9).

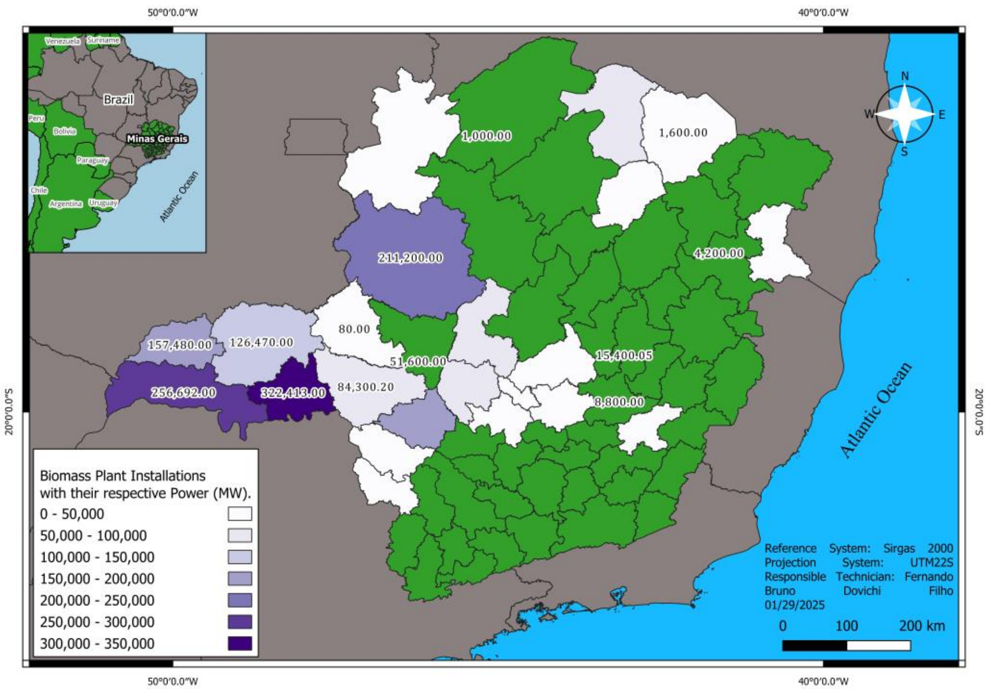

Figure 9. CUI: Biomass plants operating in each micro-region of Minas Gerais (MW).

3.7. AHP Implementation Process

The problem statement aimed to determine, using AHP, which biomass residue would be the most promising for power generation projects in each micro-region.

3.7.1. The Pairwise Matrix

Survey data were used to construct matrices reflecting pairwise comparisons among the 13 sub-criteria, as outlined by Equation (1). The data were then processed using Equations (2)–(6), and their consistency was assessed according to Equations (7)–(9).

Table 8 displays the resulting pairwise comparison matrix, with a color-coded design to enhance interpretability. The green-shaded cells highlight the sub-criteria with higher relative importance, reflecting greater weights or influence within the hierarchy. Meanwhile, the gray-shaded cells correspond to values with lower relative importance or closer to a neutral influence in the comparison process.

This visual distinction aids in quickly identifying the dominant sub-criteria and their respective relationships, ensuring a comprehensive understanding of the matrix and the prioritization of sub-criteria as calculated through the AHP methodology.

3.7.2. Results of the AHP Method Application

Among the more than 70 types of crop cultivated in Minas Gerais, five were selected based on their geographic availability, the volume of residues produced, and the characteristics of these residues: corn, soybeans, sugarcane, coffee, and eucalyptus.

Applying the AHP method indicated that the most influential sub-criteria were CO_{2eq} and ED. Other sub-criteria, including $RPRj$, AR, η, RPj, AF, L, CET, VHS, GDP, HDI, and CUI, were also assigned weights according to their relative importance in the decision-making process.

3.8. Consistency and Reliability of Expert Judgments

The Analytical Hierarchy Process (AHP) relies on pairwise comparisons to determine the relative importance of criteria and sub-criteria. To ensure the reliability of these comparisons, this study rigorously evaluated the consistency of expert judgments using the consistency ratio (CR), as proposed by Saaty [25]. A CR value below 0.1 is considered the acceptable threshold, indicating reliable judgments.

A structured questionnaire was developed to evaluate the relative importance of criteria and sub-criteria. In this study, pairwise comparison matrices were constructed based on responses from 32 bioenergy experts. The initial CR values were calculated, and some matrices presented inconsistencies exceeding the threshold of 0.1. To address this, a systematic recalibration of inconsistent responses was performed using the "ahpsurvey" package in R, which is specifically designed to evaluate and adjust for inconsistencies in AHP applications (Cho [29]). The recalibration process reduced all CR values to below 0.1, with the highest adjusted CR value recorded at 0.04, well within the acceptable range.

The application of this rigorous consistency evaluation ensured the reliability of the expert judgments and the validity of the results. Furthermore, the use of a diverse panel of experts, encompassing academic, governmental, and industry professionals, contributed to minimizing potential biases and enhancing the robustness of the AHP analysis.

While achieving perfect consistency in pairwise comparisons is challenging, the methodological steps implemented in this study—such as recalibration and consistency verification—provide strong evidence for the reliability and robustness of the AHP results. These measures ensure that the final weights assigned to criteria and sub-criteria are both consistent and representative of expert consensus.

Table 8. The thirteen chosen sub-criteria used a pairwise comparison matrix with weight definitions.

	RPR_j	A_R	η	RP_j	A_F	RT(L)	CET	ESR	CO_2	GDP	HDI	Demand	CUI
RPR_j	1.00	2.018440	0.601389	0.998586	0.333304	0.494626	0.375355	0.580585	0.579845	1.087353	1.103181	0.893817	0.692287
A_R	0.50	1.00	0.9124702	0.7489284	0.8471975	1.0456068	0.5111821	0.8157115	0.6144169	1.0747574	1.036514	0.7182063	0.8236084
η	1.66	1.10	1.00	1.7124259	0.7363481	0.8591789	0.8660849	1.1964664	0.8841415	1.7766892	1.447095	1.2054319	1.4601446
RP_j	1.00	1.34	0.58	1.00	1.0784203	1.6433275	1.1231877	1.2792348	0.6864374	1.307754	1.357037	1.2279492	1.2305995
A_F	3.00	1.18	1.36	0.93	1.00	1.7294468	0.9037597	1.6703975	0.7183851	1.8038775	1.186646	1.2112527	1.3842952
RT(L)	2.02	0.96	1.16	0.61	0.58	1.00	0.5334702	0.620989	0.5459906	1.4964468	1.501402	0.5859778	0.6290464
CET	2.66	1.96	1.15	0.89	1.11	1.87	1.00	1.0902504	0.6914938	1.278933	1.452774	1.2097598	1.0802162
ESR	1.72	1.23	0.84	0.78	0.60	1.61	0.92	1.00	1.3660031	1.657561	1.550325	1.0566826	0.9547213
CO_2	1.72	1.63	1.13	1.46	1.39	1.83	1.45	0.73	1.00	2.9479092	1.738376	1.5973279	2.5162083
GDP	0.92	0.93	0.56	0.76	0.55	0.67	0.78	0.60	0.34	1.00	1.041512	0.4923066	0.8413104
HDI	0.91	0.96	0.69	0.74	0.84	0.67	0.69	0.65	0.58	0.96	1.00	0.9386112	0.884583
Demand	1.12	1.39	0.83	0.81	0.83	1.71	0.83	0.95	0.63	2.03	1.07	1.00	2.2320369
CUI	1.44	1.21	0.68	0.81	0.72	1.59	0.93	1.05	0.40	1.19	1.13	0.45	1.00

The findings of this research have indicated the necessity of employing a sufficient yet not excessive number of criteria and expert evaluators. The utilization of a substantial number of criteria in the context of a paired-answering approach can potentially amplify the likelihood of subjective errors, stemming from factors such as bias and the possibility of confusion among the experts. The implementation of preliminary training for each expert, utilizing a series of meticulously delineated examples, has been shown to contribute to the mitigation of uncertainties.

The Consistency Ratio

Figure 10 shows the initial consistency ratio (CR) values, which indicate that the expert judgments had uncertainties exceeding the acceptable threshold of 0.1. To address this, a refinement method was applied to adjust these responses. Figure 11 presents the refined values, where the highest adjusted CR was 0.04, well within acceptable limits. The final CR values for the main criteria, detailed in Table 9, confirm the consistency of the analysis, with all values below the threshold of 0.1.

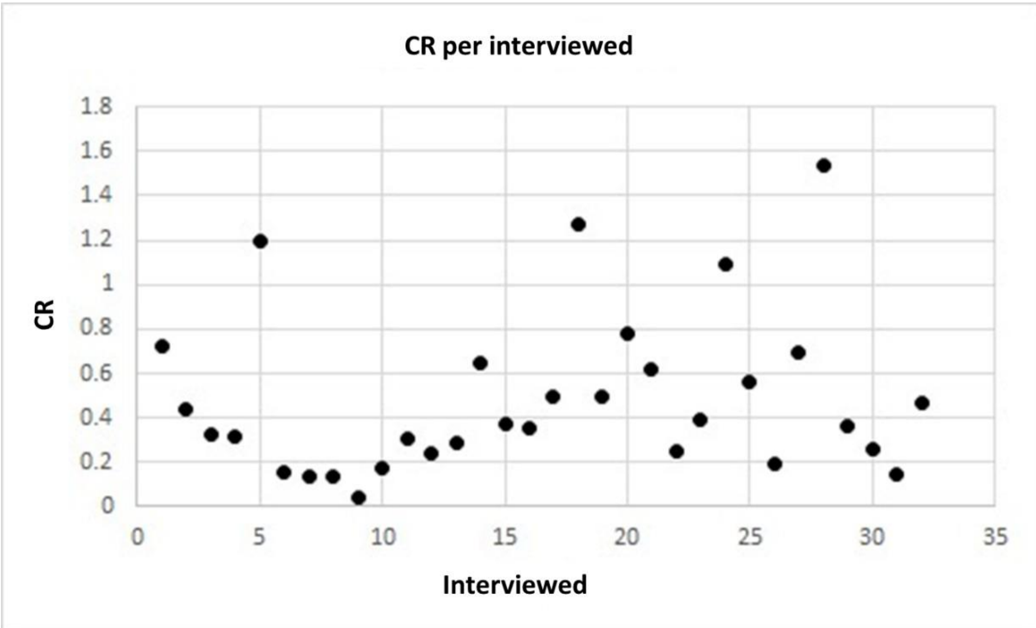

Figure 10. An expert interviewed the CR without the application of package R.

Table 9. Consistency ratio (*CR*) for the different criteria and sub-criteria.

Categories	CR
Primary goal criteria	0.0220
Economic	0.0000
Technical	0.0890
Social	0.0300
Environmental	0.0000

New refined values have the highest consistency value found, which is 0.04, as shown in (Figure 11).

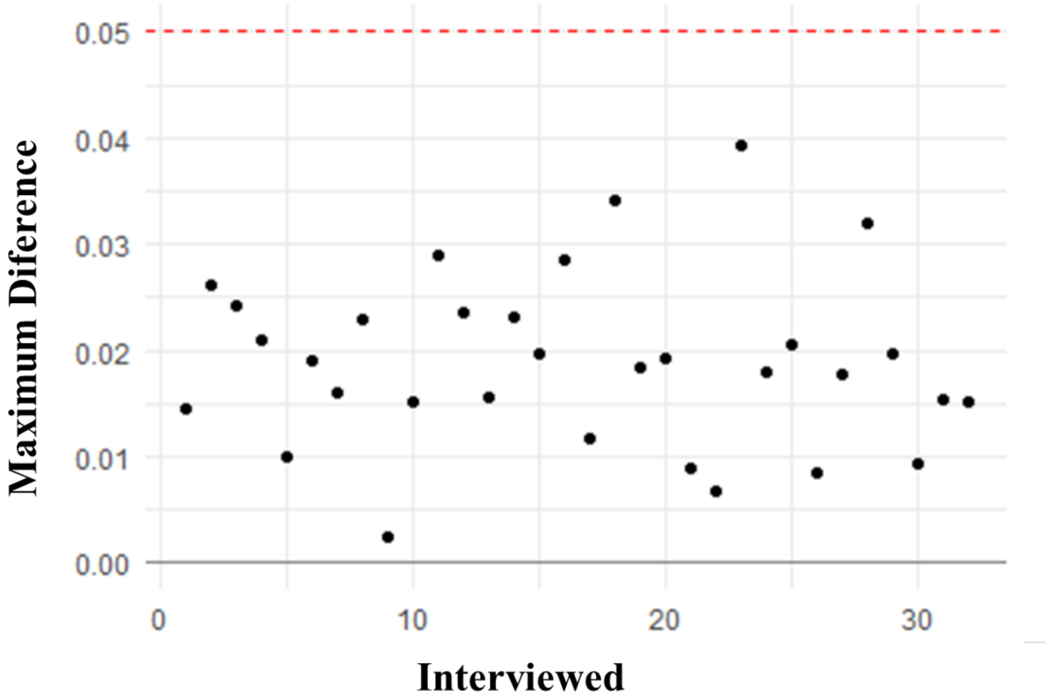

Figure 11. The CR of the expert's responsesadjusted using the package R tool.

3.9. Criteria and Sub-Criteria Weights

The technical criterion emerged as the most significant, followed by the social, environmental, and economic criteria (Figure 12). This reflects the critical importance of maximizing potential electricity generation.

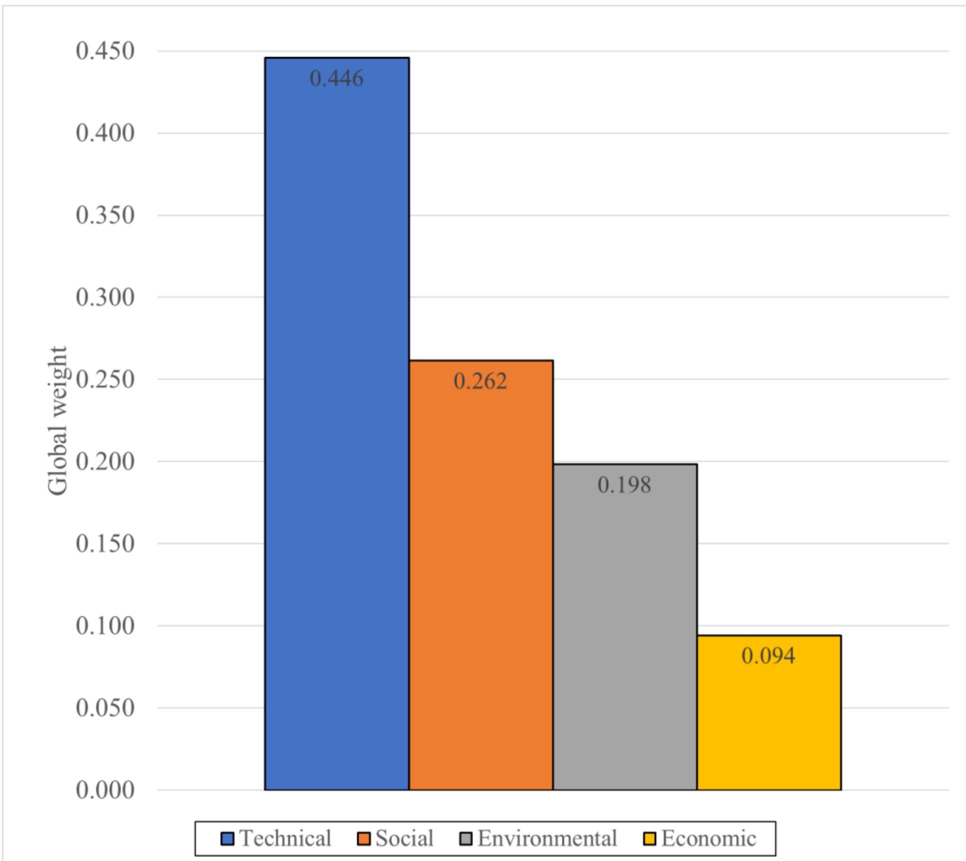

Figure 12. The weighting of the four main evaluated criteria.

Figure 13 displays the weights of the technical sub-criteria, where AF was identified as the most crucial. AF represents the annual availability and supply of crop residues, which directly influences the power capacity of thermoelectric plants.

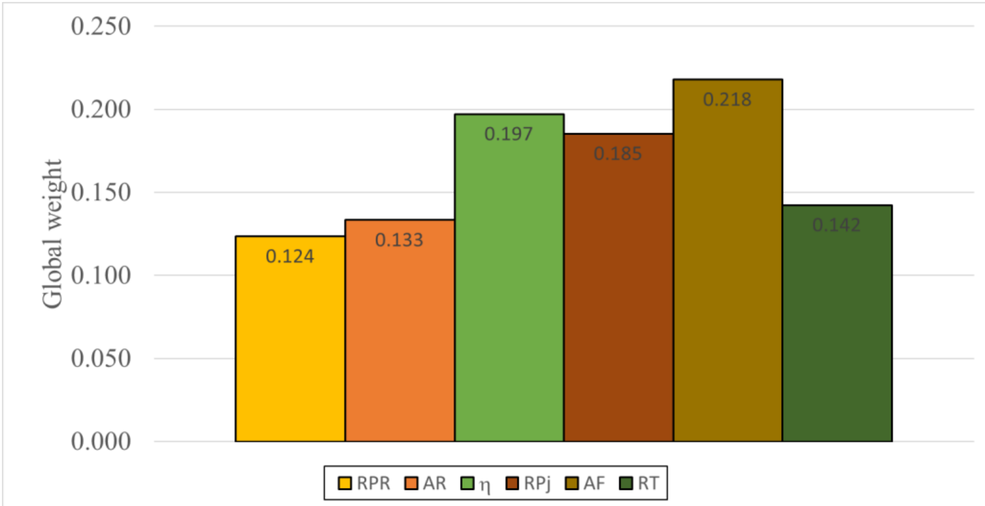

Figure 13. Weighting of technical sub-criteria.

Figure 14 shows the classification of social sub-criteria, with PD (electricity demand) being the most influential factor.

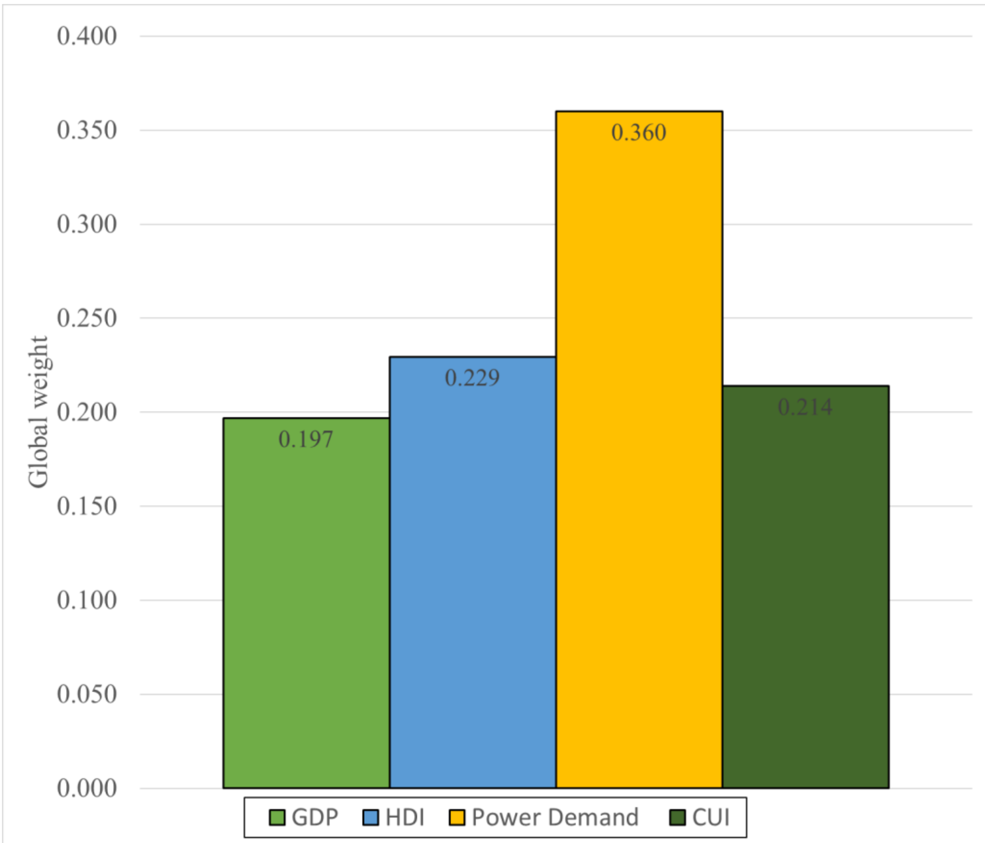

Figure 14. Weighting of social sub-criteria.

Table 10 outlines the global priority levels of the 13 sub-criteria, as calculated using Equations (5)–(11), illustrated in Figure 15. The CO_{2eq} sub-criterion received the highest weight, while *GDP* had the lowest priority.

Table 10. Sub-criteria global weights percentage after the AHP.

Sub-criteria	Global Weight	Classification
CO_2	11.46%	1
A_F	9.72%	2
CET	9.43%	3
η	8.79%	4
ESR	8.37%	5
RP_j	8.27%	6
Power demand	8.24%	7
CUI	6.74%	8
RT	6.35%	9
HDI	5.95%	10
A_R	5.95%	11
RPR	5.51%	12
GDP	5.22%	13

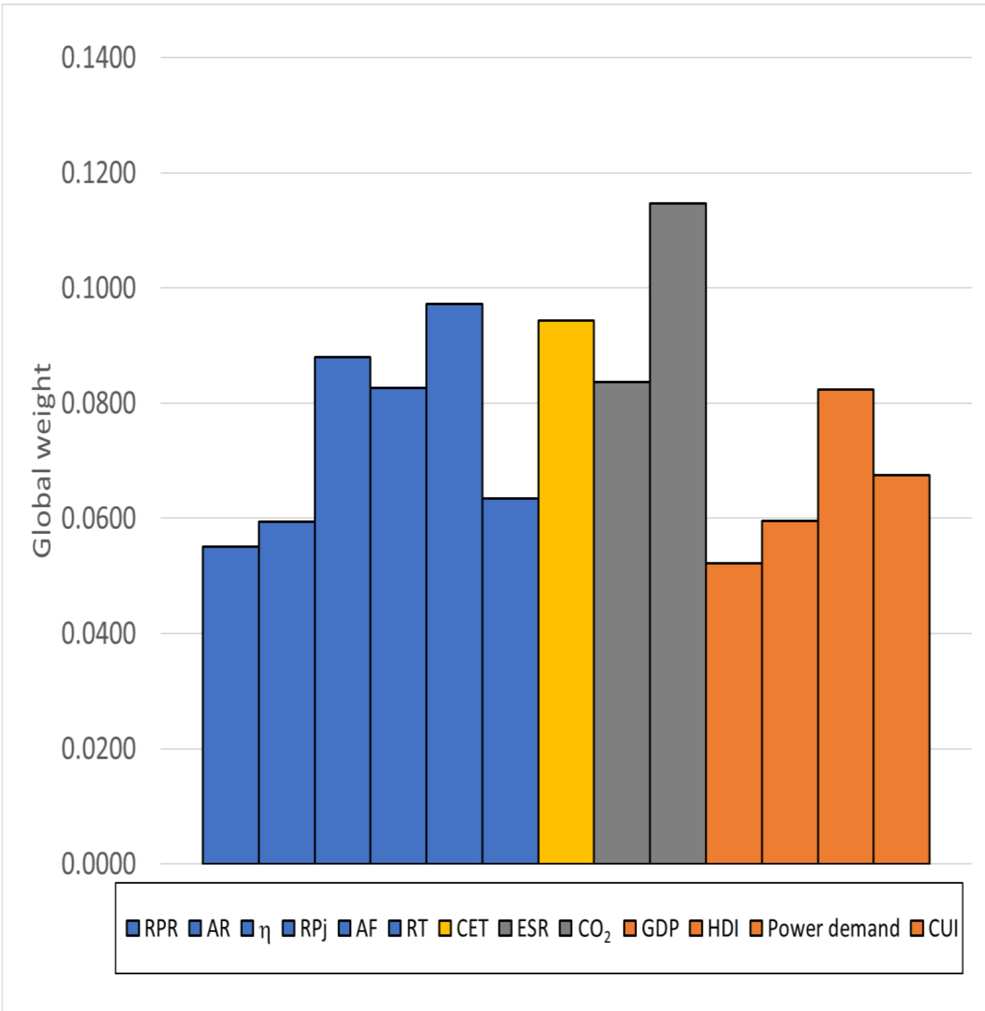

Figure 15. Sub-criteria weights obtained through AHP.

AHP-GIS-Based Biomass Viability Assessment

The results facilitated the creation of a biomass feasibility map for Minas Gerais using QGIS 3.34 software (Figures 16 and 17). Additionally, the AHP-GIS method ranked the most feasible residues for bioenergy projects, as depicted in Figure 17.

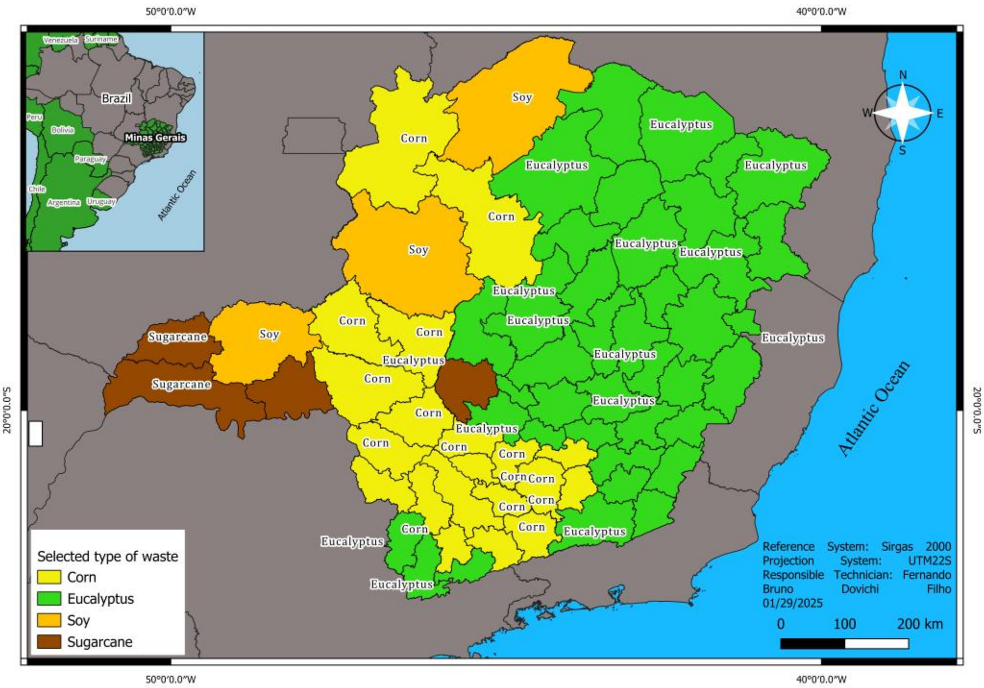

Figure 16. Higher feasibility crop residue selected in each micro-region after the AHP-GIS implementation.

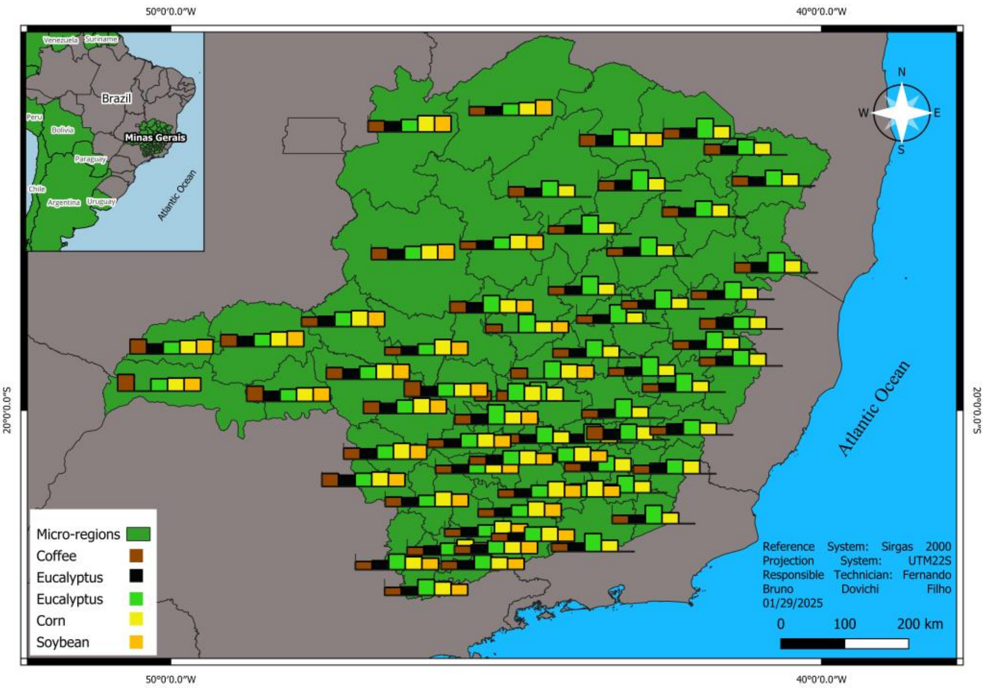

Figure 17. Ranking of the selected crop residues for each micro-region.

3.10. Comparison with Related Studies

This study combines the Analytical Hierarchy Process (AHP) with Geographic Information System (GIS) tools to provide a comprehensive evaluation of biomass feasibility. This integrated approach contrasts with traditional methodologies, which often focus on specific aspects of biomass feasibility without considering the interplay of multiple criteria.

For instance, Miziara (2013) developed a logical algorithm for selecting biomass energy production alternatives, emphasizing technical viability and factors such as biomass availability and characteristics. However, the study did not employ a multi-criteria framework like AHP, which allows for the structured prioritization of diverse and conflicting factors [48].

Similarly, Teixeira (2023) introduced a GIS-based methodology for prospecting forest biomass energy units in Minas Gerais. While effective for geographic planning, the study did not incorporate hierarchical prioritization of criteria through AHP, limiting its ability to address trade-offs among technical, economic, and environmental factors [49].

Machado (2021) conducted an economic feasibility analysis for reusing sludge as biomass in boilers, focusing on specific economic parameters. However, the study lacked a broader multi-criteria approach that could integrate social and environmental considerations alongside economic factors [50].

Traditional methods often adopt unidimensional analyses or statistical models that fail to capture the complexity and interdependence of factors influencing biomass feasibility. For example, studies focusing solely on carbon storage quantification in forests use direct or indirect methods without integrating economic or social aspects. Similarly, approaches for identifying potential areas for biomass cultivation often emphasize agronomic and land-use factors without involving expert opinions or multi-criteria analyses.

In contrast, the AHP-GIS methodology presented in this study addresses these limitations by integrating multiple criteria—technical, economic, environmental, and social—into a structured decision-making framework. This approach leverages expert input and spatial data to identify high-priority areas with greater precision and balance among competing objectives. By combining these elements, the methodology provides a robust tool for decision-makers, offering actionable insights tailored to the specific context of Minas Gerais while remaining adaptable to other regions and datasets.

4. Conclusions

This study introduced a comprehensive methodology combining the Analytical Hierarchy Process (AHP) and Geographic Information System (GIS) tools to assess the potential of bioenergy generation from agricultural residues in Minas Gerais, Brazil. The approach, which integrated expert evaluations and spatial analysis, facilitated a detailed examination of the technical, economic, environmental, and social aspects influencing bioenergy viability.

This research provides a scientifically robust methodology that integrates the Analytical Hierarchy Process (AHP) with Geographic Information Systems (GIS) to evaluate and prioritize biomass residues for electricity production. The scientific justification of this study lies in addressing the complexity of multi-criteria decision-making (MCDM) in bioenergy feasibility assessments. By incorporating economic, technical, environmental, and social criteria, this methodology ensures a comprehensive evaluation that aligns with the principles of sustainability and regional applicability. The findings demonstrate the utility of this integrated approach in identifying the most viable biomass residues while maintaining agricultural and environmental sustainability. Furthermore, the methodology is adaptable to other regions and scenarios, offering a replicable framework for advancing renewable energy planning globally

The application of the AHP method, supported by expert input from 32 bioenergy professionals, allowed for the prioritization of key criteria and sub-criteria. The analysis identified CO_{2eq} emissions and electricity demand (ED) as the most significant sub-criteria, emphasizing the dual importance of environmental sustainability and meeting energy needs. Eucalyptus emerged as the most promising biomass source among the evaluated crops due to its favorable technical properties and broad availability.

In addition to providing a robust methodology for biomass feasibility assessments, this study opens several avenues for future research. One potential continuation could involve expanding the scope of the methodology to include additional biomass types and regions, enabling a broader analysis of bioenergy potential. Furthermore, integrating dynamic modeling tools to account for temporal variations in biomass availability and energy demand could enhance the adaptability of the approach. Another area for exploration is the development of hybrid MCDM techniques that combine AHP with other decision-making frameworks, such as TOPSIS or PROMETHEE, to further refine the prioritization process. Lastly, incorporating life-cycle assessments (LCA) into the analysis could provide deeper insights into the environmental and economic trade-offs associated with different biomass utilization strategies.

The results provide actionable insights for policymakers and stakeholders involved in energy planning. The findings highlight that strategically selecting biomass residues based on a multi-criteria approach can optimize the bioenergy supply chain by balancing technical efficiency, cost-effectiveness, and environmental impact. The GIS-based mapping further enriched the analysis by visualizing the distribution of biomass potential across different micro-regions, offering a practical tool for regional energy infrastructure planning.

This methodology proves robust and adaptable, capable of supporting decision-making in bioenergy projects beyond the context of Minas Gerais. It can be tailored to include additional criteria or adapted for different types of agricultural residues and regions. Incorporating stakeholder input ensures that the decision-making process aligns with real-world constraints and priorities, enhancing the relevance and applicability of the study. The proposed AHP-GIS framework is an effective tool for guiding bioenergy development by systematically evaluating multiple criteria. Future research could extend this approach to include emerging technologies and a broader array of biomass sources, supporting the diversification and resilience of the bioenergy sector. The methodology's adaptability makes it valuable for expanding the renewable energy matrix and fostering sustainable energy solutions.

Author Contributions: Conceptualization, E.E.S.L., F.B.D.F. and J.C.E.P.; Methodology, E.E.S.L., F.B.D.F. and J.C.E.P.; Software, F.B.D.F., L.V.M.d.S., P.T.B. and R.L.J.; Validation, F.B.D.F., L.V.M.d.S., P.T.B., R.L.J. and Q.R.Q.; Formal analysis, F.B.D.F., E.E.S.L., P.T.B. and M.R.E.; Investigation, F.B.D.F., L.V.M.d.S., J.C.E.P., P.T.B. and R.L.J.; Resources, E.E.S.L.; Data curation, E.E.S.L.; Writing—original draft, F.B.D.F.; Writing—review and editing, R.M.B., M.R.E. and Q.R.Q.; Visualization, R.M.B., M.R.E. and Q.R.Q.; Supervision, E.E.S.L. and J.C.E.P.; Project administration, E.E.S.L.; Funding acquisition, E.E.S.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Coordination for the Improvement of Higher Education Personnel (CAPES), the Minas Gerais State Agency for Research and Development (FAPEMIG), and the National Council for Scientific and Technological Development (CNPq), which provided scholarships for researchers and graduate students. Our acknowledgements to these funding agencies.

Institutional Review Board Statement: Ethical review and approval were waived for this study, as it involved the analysis of publicly available data and did not include human participants or animals. This type of study is exempt from ethical approval according to the national regulations and institutional guidelines.

Data Availability Statement: Data supporting this study are public and referenced within the article.

Conflicts of Interest: All authors declare no conflicts of interest.

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