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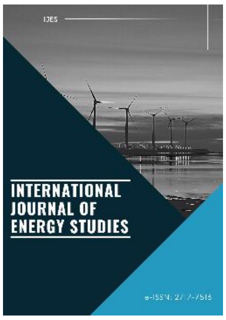

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A comparative approach for the identification and selection of sustainable energy alternatives based on green criteria: Classical and fuzzy WASPAS method

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Highlights

- Comparative analysis of classical and fuzzy WASPAS methods for sustainable energy selection under uncertainty.
- The enhanced sensitivity and reliability of fuzzy WASPAS in multi-criteria decision-making for regional energy planning are demonstrated.
- The most suitable renewable and sustainable energy alternative is selected by considering local geographical, environmental, and social factors.

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ABSTRACT

Increasing energy demand and environmental concerns are guiding decision-makers toward sustainable energy systems. In this study, classical and fuzzy WASPAS methods were jointly employed to evaluate sustainable energy sources and determine the most suitable alternative for Kilis, Turkey. The alternatives considered include solar energy (A1), wind energy (A2), biomass energy (A3), hydroelectric energy (A4), and geothermal energy (A5). The criteria selected are carbon emissions (C1), investment cost (C2), energy efficiency (C3), resource continuity (C4), environmental impact (C5), and local acceptance and social impact (C6). For the classical WASPAS method, criterion weights were assigned as C1=0.15, C2=0.15, C3=0.20, C4=0.20, C5=0.15, and C6=0.15, while for fuzzy WASPAS, the criterion weights were defined using triangular fuzzy numbers. According to the classical WASPAS results, the Q_i scores for the alternatives were A1=1.00000, A2=0.85859, A3=0.63089, A4=0.77590, and A5=0.68140, with solar energy ranking first. In the fuzzy WASPAS analysis, the E(Q) scores were A1=2.188, A2=1.542, A3=1.137, A4=1.278, and A5=1.188, confirming the superiority of solar energy when uncertainties are considered. The results obtained from both classical and fuzzy WASPAS methods were compared, and taking into account the geographical, economic, and social conditions of Kilis, solar energy emerged as the most advantageous alternative. The comparative performance analysis indicates that evaluations conducted in a fuzzy environment provide a more realistic and flexible assessment by incorporating uncertainties. This approach offers decision-makers strategic information based on robust foundations for sustainable energy planning. The study demonstrates the effectiveness of the fuzzy WASPAS method in multi-criteria decision-making and contributes to the development of sustainable energy policies at the local level. The results allow decision-makers to balance environmental, economic, and social factors while ensuring practical guidance for regional sustainable energy strategies. Furthermore, the flexibility provided by fuzzy WASPAS in handling uncertainties enables more reliable and robust evaluations in multi-criteria decision-making processes.

Keywords: Renewable energy systems, Energy management, Multi-criteria decision-making, Fuzzy logic, Classical and fuzzy WASPAS

1. INTRODUCTION

Rapidly growing energy demand, environmental concerns, and resource depletion risks necessitate sustainable energy solutions. Renewable sources such as solar, wind, biomass, hydro, and geothermal offer diverse technical, economic, environmental, and social trade-offs, performing differently across criteria including carbon emissions, investment costs, efficiency, resource continuity, environmental impact, and social acceptance. Selecting the optimal alternative requires multi-criteria decision-making (MCDM) capable of integrating both quantitative and qualitative data while accounting for uncertainties, as conventional methods are insufficient for this complex evaluation.

Many decision-making problems are too complex to be fully described using quantitative measures alone. In such cases, the values of qualitative criteria are often defined in an imprecise manner by decision-makers [1]. In traditional formulations of MCDM problems, human judgments are represented by exact numerical values [2]. Fuzzy set theory, however, enables the classification of data with boundaries that cannot be precisely defined, allowing for problem-solving approaches that align with human reasoning and real-world complexities [3]. Selecting among energy systems is a multi-criteria decision-making process characterized by uncertainty and subjectivity, requiring the integration of quantitative criteria, such as carbon emissions and investment costs, with qualitative factors including environmental impact and social acceptance. As qualitative assessments often rely on expert judgment rather than precise data, classical methods may be inadequate. Fuzzy logic effectively captures linguistic vagueness and uncertainty, converting terms like “high,” “low,” or “medium” into quantifiable fuzzy numbers, enabling systematic analysis of expert insights and reducing uncertainty in evaluating qualitative criteria while adding flexibility to the decision process.

In this context, the selection of sustainable energy alternatives constitutes a structurally multi-criteria and multi-dimensional decision problem. The problem requires the integration of criteria with diverse measurement units and evaluation structures into a unified decision-making function. In such decision problems, alternatives are not assessed directly; rather, their relative advantages are derived based on the criterion values. Consequently, the process encompasses a complex decision transformation mechanism through which ranking and preference structures are obtained from the available evaluation information. In particular, the determination of qualitative criteria based on expert judgments necessitates the design of a decision model capable of incorporating uncertainty and subjective assessments. Therefore, the fundamental concepts employed in this study, the mathematical structure of the decision mechanism, and the transformation logic of the evaluation process are presented in a clear and systematic manner.

The classical WASPAS (Weighted Aggregated Sum Product Assessment) method operates solely with precise numerical data. However, many decision-making problems—particularly those involving environmental, social, and sustainability-related criteria—employ linguistic expressions such as "high," "medium," or "low," where fuzzy logic becomes essential. Fuzzy WASPAS represents an extension of the classical WASPAS method, integrating fuzzy logic to handle uncertainty and linguistic terms. The fuzzy WASPAS approach is frequently applied in MCDM problems and allows for more realistic outcomes, particularly when qualitative, linguistic, or imprecise data are involved.

The main contribution of this study lies in not limiting the comparison of the classical and fuzzy WASPAS methods to outcome-based results alone; rather, it systematically evaluates these methods under the same decision problem in terms of their sensitivity to uncertainty, their ability to reflect expert judgments, and the stability of the resulting rankings. The study clearly demonstrates the added value of the fuzzy WASPAS approach in the decision support process, particularly in decision environments such as regional energy planning, where data uncertainty and qualitative assessments are predominant. In this respect, rather than claiming a methodological novelty, the study provides practice-oriented decision support insights for decision-makers regarding which WASPAS approach is more appropriate under specific conditions. In this context, the present study aims to determine the most suitable sustainable energy alternative using both classical and fuzzy WASPAS methods. The study provides a comparative analysis of the two approaches while contributing to sustainable energy planning from a decision-maker's perspective.

More specifically, the comparison conducted in this study allows for the explicit observation of:

- ✓ Whether ranking outcomes remain stable under weight perturbations – Analyses whether small changes in criterion weights affect the final alternative rankings.
- ✓ To what extent uncertainty modeling affects score dispersion among alternatives – Examines how modeling uncertainty influences the spread of scores and relative differences between alternatives.

- ✓ Whether fuzzy representation enhances the sensitivity of the model in distinguishing close-performing alternatives – Evaluates if using fuzzy logic improves the method's ability to differentiate alternatives with similar performance.

By empirically demonstrating these aspects through sensitivity and inter-method validation analyses, the study moves beyond a descriptive comparison and provides measurable evidence regarding the practical implications of selecting classical versus fuzzy WASPAS in energy planning problems.

The remainder of this paper is structured as follows: Section 2 presents the literature review. Section 3 highlights the significance of the study. Section 4 introduces the proposed approaches for selecting five alternative energy systems. In Section 5, the proposed methods are applied to evaluate and select the optimal sustainable energy system in Kilis Province, considering five alternative energy systems across six criteria, culminating in the ranking and selection of the alternatives. Section 6 provides an analysis of the application results, while Section 7 concludes with the study's findings and discussion.

2. LITERATURE REVIEW

In this section, studies on the application of classical and fuzzy WASPAS methods for the selection and ranking of sustainable energy systems are briefly reviewed. A study by [4] proposed an MCDM model for ranking renewable energy sources in Vietnam. In this study, criterion weights were determined using Grey AHP (G-AHP), and alternatives were evaluated with the classical WASPAS method. Solar energy emerged as the most suitable source with a score of 0.8822, followed by wind, biomass, and solid waste energy. The model provided a framework that can serve as a decision support tool for renewable energy investments. In another study [5], the proposed hybrid method was applied for optimal site selection for green energy projects in India. The Delphi method was used to identify green energy location criteria, the MEREC method prioritized the factors, and the Fermatean fuzzy WASPAS technique evaluated the alternative sites. Among 11 candidate regions, Kunta city in Andhra Pradesh was identified as the most suitable site, with "policy strategies and objectives" ranked as the highest-priority factor. This approach demonstrated the effectiveness of hybrid methods in multi-criteria decision-making under uncertainty. [6] applied the interval-valued Pythagorean fuzzy WASPAS method to evaluate renewable energy alternatives in Turkey. The study compared the Pythagorean fuzzy WASPAS results with those of interval intuitionistic fuzzy WASPAS and classical WASPAS, identifying biomass as the highest-scoring alternative. This highlighted the flexibility provided by fuzzy set models in decision-making under uncertainty. In [7], a hybrid SWOC-FAHP-WASPAS method was used for solar power plant site selection in the Mekong Delta, Vietnam. The SWOC method identified the criteria, fuzzy AHP calculated the weights, and classical WASPAS scored potential sites. Long Xuyen (in An Giang Province) was selected as the optimal site with a score of 0.8937. This framework represented the first SWOC-FAHP-WASPAS application in Vietnam, serving as a reference for similar renewable energy projects. Additionally, [8] developed a decision support model integrating Spherical Fuzzy AHP and WASPAS for the location selection of energy-from-waste plants considering economic, environmental, and social criteria. In [9], a hybrid fuzzy BWM–COPRAS–WASPAS model was applied for strategic green supplier selection in Iran's renewable energy supply chain. Nine strategic supplier criteria were identified via literature review, weights were calculated using fuzzy BWM, and suppliers were ranked with both fuzzy COPRAS and fuzzy WASPAS methods. The study conducted a comparative analysis of different hybrid methods to highlight the advantages and limitations of the proposed model. Finally, [10] applied spherical fuzzy AHP (SF-AHP) integrated with classical WASPAS for wind turbine supplier selection. Criterion weights were determined via SF-AHP, and supplier alternatives were evaluated using WASPAS. The resulting ranking reflected the preference priorities among candidate suppliers, demonstrating the applicability of fuzzy multi-criteria approaches in renewable energy supplier selection. The literature review (refer to Table 1) shows that many prior studies have utilized diverse methods and combined approaches to assess and choose appropriate sustainable energy systems.

Table 1. A summary of previous research on sustainable energy system selection methods

Author(s)	Method Used	Application Area
[11]	Extended WASPAS (CASPAS) and Dempster Intuitionistic Fuzzy Set (D-IFS)	Solar panel selection
[12]	Entropy and Classical WASPAS	Performance analysis of electric buses
[13]	SWARA and Classical WASPAS	Financial performance analysis of renewable energy companies
[14]	Entropy and WASPAS	Renewable energy source selection
[15]	Interval-Valued Pythagorean Fuzzy Sets (IVPFS) and WASPAS	Evaluation of renewable energy sources
[16]	Fuzzy AHP-WASPAS	Green supplier selection in the energy sector
[17]	MACBETH-WASPAS	Selection of suitable centers for waste battery recycling

In recent years, beyond fuzzy multi-criteria decision-making approaches, data-driven learning models have also gained increasing attention in sustainable energy planning and evaluation problems. In particular, Artificial Neural Networks (ANN) have demonstrated strong performance in modeling complex and nonlinear relationships in areas such as energy demand forecasting, renewable energy generation prediction, and system optimization [18, 19]. However, ANN-based models typically require large-scale historical datasets and primarily focus on prediction-oriented problems rather than structured alternative ranking processes.

To overcome these limitations, hybrid approaches integrating fuzzy logic and neural networks—such as Adaptive Neuro-Fuzzy Inference Systems (ANFIS)—have been developed in the literature. These neuro-fuzzy models combine the uncertainty modeling capability of fuzzy logic with the adaptive learning ability of neural networks, providing flexible solutions for complex and uncertain environments [20, 21]. Although such models have proven effective in energy performance estimation and operational optimization, they are generally designed for data-driven forecasting and simulation purposes. Their applicability to transparent, expert-based multi-criteria alternative evaluation and ranking problems remains relatively limited.

In contrast, multi-criteria decision-making methods such as WASPAS provide a structured, transparent, and interpretable mathematical framework for ranking alternatives based on predefined criteria and expert evaluations [22, 23]. Especially under conditions where qualitative assessments and linguistic judgments are dominant and large datasets are unavailable, fuzzy MCDM approaches offer a practical and systematic decision-support mechanism. This study delineates the methodological distinctions between neural network-based learning models and fuzzy MCDM approaches in the literature, highlighting the role of expert-based MCDM frameworks in selecting sustainable energy alternatives.

Although classical and fuzzy WASPAS methods have been successfully applied in the evaluation of sustainable energy alternatives across different geographical contexts, the existing literature largely focuses either on a single method or presents only limited and superficial methodological comparisons. In particular, systematic comparisons of classical and fuzzy WASPAS approaches under the same decision problem, identical criteria set, and the same expert knowledge base remain very scarce. Moreover, although the superior capability of fuzzy approaches in modeling uncertainty is frequently emphasized in the literature, their practical impact on decision support processes in local and regional energy planning has not been sufficiently demonstrated. In the context of Turkey, comparative WASPAS applications at the regional level within multi-criteria decision-making frameworks are especially limited. This gap is even more pronounced in regions such as border provinces, where investment-related uncertainties are relatively high and decision-makers require comprehensive analytical guidance. In this regard, Kilis Province offers a distinctive decision environment due to its high solar energy potential, limited industrial infrastructure, and local acceptance dynamics. Accordingly, this study conducts a comparative analysis of classical and fuzzy WASPAS methods using the same criteria set and expert committee within the specific context of Kilis, and evaluates their decision support performance from an application-oriented perspective in local energy planning problems characterized by high uncertainty.

3. RESEARCH SIGNIFICANCE

For countries and institutions aiming to achieve sustainable development goals, it has become essential to prioritize energy systems that are environmentally responsible, economically viable, and socially acceptable. Renewable sources such as solar, wind, biomass, hydro, and geothermal aim to reduce environmental impacts, but selecting the optimal alternative involves evaluating multiple, often conflicting criteria, including carbon emissions, investment costs, energy efficiency, resource continuity, environmental impact, and social acceptance. While some criteria are quantitative, others rely on expert judgment, making classical MCDM methods less effective. Fuzzy logic addresses this complexity by converting uncertain or linguistic information into mathematical models. The fuzzy WASPAS method, combining the Weighted Sum and Weighted Product models, enables comprehensive evaluation and more reliable selection, particularly for qualitative criteria such as social acceptance and environmental impact. Consequently, the application of the fuzzy WASPAS method in the selection of sustainable energy systems enables the minimization of uncertainty, the effective integration of expert judgments, and the simultaneous analysis of multidimensional criteria. This approach allows decision-makers to identify the most suitable energy system in a more reliable and flexible manner, considering environmental, economic, and social dimensions concurrently.

4. PRELIMINARIES

In this section, the procedural steps of the classical and fuzzy WASPAS methods are presented sequentially. The decision problem addressed in this study is structured as a multi-criteria evaluation comprising five alternatives and six criteria. Each alternative is assessed under criteria that differ in measurement units and impact directions. Consequently, the decision-making process relies on a mathematical integration mechanism that transforms heterogeneous data structures into a unified performance metric.

The WASPAS method first normalizes the criterion values in the decision matrix to make them comparable and then aggregates them using the respective criterion weights to produce a single composite performance score for each alternative. This framework represents a decision transformation process in which the relative ranking of alternatives is derived from multi-dimensional evaluation data. Therefore, the model functions not as a direct optimization problem but as a systematic aggregation mechanism that translates criterion-based assessment data into a final preference ranking.

While the classical WASPAS approach executes this process using precise numerical values, the fuzzy WASPAS approach represents both the decision matrix and criterion weights as fuzzy numbers, performing aggregation operations according to fuzzy arithmetic rules. In this way, the model integrates the uncertainty and linguistic expressions inherent in expert judgments into a mathematical framework, providing a more flexible and realistic evaluation environment.

4.1. Classical WASPAS Method

The WASPAS method, one of the MCDM approaches, integrates both additive and multiplicative evaluation approaches to enable decision-makers to select the most suitable alternative among multiple options [24]. The procedural steps of the classical WASPAS method are listed below:

Step 1: The criteria and alternatives to be evaluated in the selection problem are identified.

Step 2: Construction of the decision matrix. In this step, a decision matrix containing the performance of alternatives with respect to the criteria is constructed. The Alternatives (A_1, A_2 ,..., A_n) and criteria (C_1, C_2, ..., C_m) are defined. The decision matrix is formulated as follows:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{1}$$

Here, m denotes the number of criteria, n denotes the number of alternatives, and x_{ij} represents the value of the i-th alternative with respect to the j-th criterion.

Step 3: Normalization of the decision matrix. The decision matrix is normalized in two ways: as benefit criteria and as cost criteria.

a) For benefit criteria:

$$(r_{ij}) = x_{ij}/max(x_j) \tag{2}$$

b) For cost criteria:

$$(r_{ij}) = Min(x_j)/x_{ij} \tag{3}$$

Consequently, the normalized decision matrix can be expressed as follows [25]:

$$R = [r_{ij}] \tag{4}$$

Step 4: Calculation of the weighted normalized matrix. In this step, the normalized values are multiplied by the weight w_j of each criterion. Here:

a) For the Weighted Sum Method (WSM):

$$Q_1(i) = \sum_{j=1}^{n} w_j * r_{ij} \tag{5}$$

b) For the Weighted Product Method (WPM):

$$Q_2(i) = \prod_{j=1}^{n} (r_{ij})^{w_j} \tag{6}$$

Here, both $Q_1(i)$ and $Q_2(i)$ scores are calculated for each alternative [26].

Step 5: Calculation of the WASPAS score. In this step, the final score is obtained by combining the two methods described above:

$$Q_i = \lambda * Q_1(i) + (1 - \lambda) * Q_2(i) \tag{7}$$

Here, λ is usually taken as 0.5 (equal-weighted combination), and Q_i represents the final WASPAS score of each alternative.

Step 6: Ranking of alternatives and selection of the best option. In this step, the obtained Q_i scores are ranked, and the alternative with the highest score is determined as the best choice.

4.2. Fuzzy WASPAS Method

The fuzzy WASPAS method, one of the MCDM approaches, is used to address uncertainty and the imprecision of expert judgments in selection problems. The procedural steps of the fuzzy WASPAS method are listed below:

Step 1: The criteria and alternatives to be evaluated in the selection problem are identified.

Step 2: Determination of the fuzzy decision matrix and weights. In this step, once the Alternatives (A_1, A_2 ,..., A_n) and criteria (C_1, C_2, ..., C_m) are defined, the fuzzy decision matrix is formulated as follows:

$$\tilde{X} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1m} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{n1} & \tilde{x}_{n2} & \cdots & \tilde{x}_{nm} \end{bmatrix} \tag{8}$$

Here, $\tilde{x}_{ij} = (l_{ij},\ m_{ij}, u_{ij})$ represents the fuzzy performance values of the alternatives, and the criterion weights are also expressed as fuzzy numbers $\widetilde{w}_{ij} = (l_{ij},\ m_{ij}, u_{ij})$. In this context, l denotes the lower bound, m the middle value, and u the upper bound.

Step 3: Normalization of the fuzzy decision matrix. In this step, the normalization process is performed in two ways depending on the type of criterion.

a) For benefit criteria:

$$\tilde{r}_{ij} = \left(\frac{l_{ij}}{u_j^{max}}, \frac{m_{ij}}{m_j^{max}}, \frac{u_{ij}}{l_j^{max}}\right) \tag{9}$$

b) For cost criteria:

$$\tilde{r}_{ij} = \left(\frac{l_j^{min}}{u_{ij}}, \frac{m_j^{min}}{m_{ij}}, \frac{u_j^{min}}{l_{ij}}\right) \tag{10}$$

In this step, $\tilde{r}_{ij}$ represents the normalized fuzzy values obtained [25].

Step 4: Calculation of the weighted normalized values. In this step, each normalized value is multiplied by the weight of the corresponding criterion. Here:

$$\tilde{v}_{ij} = \tilde{r}_{ij} * \widetilde{w}_{ij} \tag{11}$$

Step 5: Calculation of the fuzzy Weighted Sum Method (WSM) and fuzzy Weighted Product Method (WPM) scores.

a) Fuzzy Weighted Sum (B-WSM) score [27]:

$$\tilde{Q}_1(i) = \sum_{j=1}^{n} \tilde{v}_{ij} \tag{12}$$

b) Fuzzy Weighted Product (B-WPM) score [27]:

$$\tilde{Q}_2(i) = \prod_{j=1}^{n} (\tilde{r}_{ij})^{\widetilde{w}_j} \tag{13}$$

Step 6: Calculation of the fuzzy WASPAS score. In this step, the final score is obtained by combining the two methods described above:

$$\tilde{Q}_i = \lambda * \tilde{Q}_1(i) + (1 - \lambda) * \tilde{Q}_2(i) \tag{14}$$

Here, λ is usually taken as 0.5 (equal-weighted combination), and since the sum and product scores are fuzzy numbers, this operation is also performed using fuzzy addition [25].

Step 7: Ranking of alternatives and selection of the best option. In this step, the fuzzy WASPAS scores $\tilde{Q}_i$ are defuzzified to rank the alternatives. The centroid (average) method is used for this purpose:

$$E(\tilde{Q}) = \frac{l + m + u}{3} \tag{15}$$

Here, the alternative with the highest E score is determined as the best choice [28].

5. APPLICATION OF THE PROPOSED METHOD(S)

In this section, the classical WASPAS and fuzzy WASPAS methods, whose steps were described above, have been applied to the selection problem of renewable and sustainable alternative energy systems.

5.1. Decision Model

In this study, an analysis was conducted to identify the most suitable renewable and sustainable energy systems for Kilis province, taking into account its geographical, environmental, and socio-economic characteristics. For this purpose, a four-member expert committee comprising field specialists was established. Six evaluation criteria, determined through a literature review and expert committee opinions, were used to assess five candidate eco-friendly energy system alternatives. In determining the criteria set, the regional characteristics of Kilis Province, data availability, and the common consensus of expert opinions were taken into consideration. Criteria frequently addressed in the energy planning literature—such as land use, grid compatibility, and intermittency risk—were initially examined by the expert committee during the preliminary assessment phase. However, due to the limited scale of the existing energy infrastructure in Kilis, the similarity of grid connection conditions across all alternatives, and the study's focus on strategic sustainability evaluation rather than detailed technical design, these criteria were considered to have limited discriminatory power.

Furthermore, the experts explicitly concluded that these excluded criteria were non-discriminatory based on consensus judgment and negligible variance observed across all candidate alternatives during preliminary scoring. This approach ensured transparency and strengthened the justification for focusing on the six core criteria that directly represent environmental, economic, technical, and social dimensions, adequately capturing the decision problem without introducing redundant or non-influential factors.

Therefore, the study employs six core criteria that directly represent environmental, economic, technical, and social dimensions and explain the decision problem in a concise yet comprehensive manner. Table 2 presents the six criteria and the five alternatives along with their descriptions. Figure 1 illustrates a three-level hierarchical decision problem representing the structure of the evaluation.

Table 2. Criteria used for the selection of alternatives and descriptions of the alternatives

Criteria	Description
C1: Carbon Emissions	Refers to the amount of carbon released into the atmosphere during the energy production process. Low carbon emissions are preferred for environmentally friendly systems.
C2: Investment Cost	Encompasses the installation and initial investment costs of the energy system. Cost-effective systems are more sustainable from an economic perspective.
C3: Energy Efficiency	Indicates how efficiently the system produces energy in terms of input-output ratio. High efficiency provides an advantage.
C4: Resource Continuity (Sustainability)	Represents the long-term availability and continuous usability of the energy source. Renewable sources are advantageous in this regard.
C5: Environmental Impact (Eco-Friendliness)	Refers to the overall effect of energy production on the environment. Impacts on flora, fauna, water resources, and air quality are evaluated.
C6: Local Impact and Social Acceptance	Encompasses the community's overall acceptance, public perception, regional infrastructure impact, employment potential, and social effects. High social and local acceptance is critical for project sustainability.
Alternatives	**Description**
A1: Solar Energy	Renewable energy obtained from sunlight using photovoltaic panels or thermal systems to generate electricity or heat.
A2: Wind Energy	A clean and sustainable energy source in which kinetic energy is converted into electricity via wind turbines.
A3: Biomass Energy	A renewable energy option produced by burning plant waste, animal waste, or organic matter.
A4: Hydroelectric Energy	Energy generated using the power of water through turbines, typically via rivers or dams.
A5: Geothermal Energy	Sustainable energy derived from the heat of the Earth's crust, used for electricity generation or direct heating.

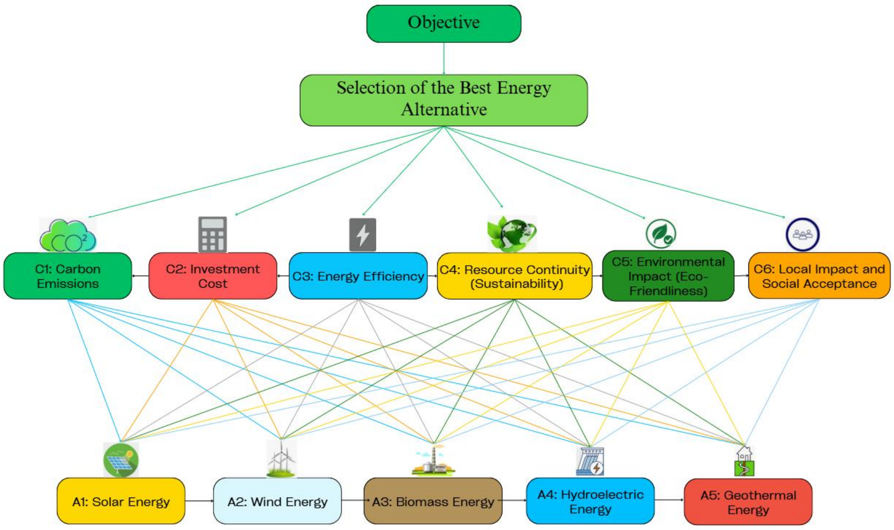

Figure 1. Hierarchical structure of the decision problem

5.2. Information on the Expert Committee Formed for the Study

In this study, a four-member expert committee was established to ensure the systematic and transparent incorporation of expert judgments into the evaluation process of sustainable energy alternatives. The experts specialize in energy technologies, environmental engineering, economic evaluation, and social impact analysis, and each possesses at least five years of professional experience in their respective fields. The interdisciplinary structure of the expert committee enabled the decision-making process to comprehensively address technical, environmental, economic, and social dimensions. Expert evaluations were conducted independently. Each expert assessed the relative importance of the criteria and the performance of the alternatives without being influenced by the others. This approach was adopted to reduce individual biases and to enhance the objectivity of the evaluation process. Prior to being incorporated into the decision model, individual expert judgments were transformed into numerical form using triangular fuzzy numbers. Subsequently, criterion weights and alternative performance values were aggregated by taking the arithmetic fuzzy mean of the individual expert evaluations. This aggregation approach is widely used in the MCDM literature and assigns equal importance to each expert's opinion. Potential disagreements or uncertainties among experts were handled within the model through the inherent flexibility of fuzzy logic. In this way, a realistic and adaptable evaluation environment was established that does not require strict consensus but instead incorporates all expert judgments. Moreover, no dominance rules or forced consensus mechanisms were imposed to eliminate differences among experts; rather, the uncertainty modeling capability of the fuzzy WASPAS method was utilized to reflect expert diversity in a balanced manner.

5.3. Flowchart of the Methods Used in This Study

The flowchart of the classical and fuzzy WASPAS methods used in this study is presented in Figure 2.

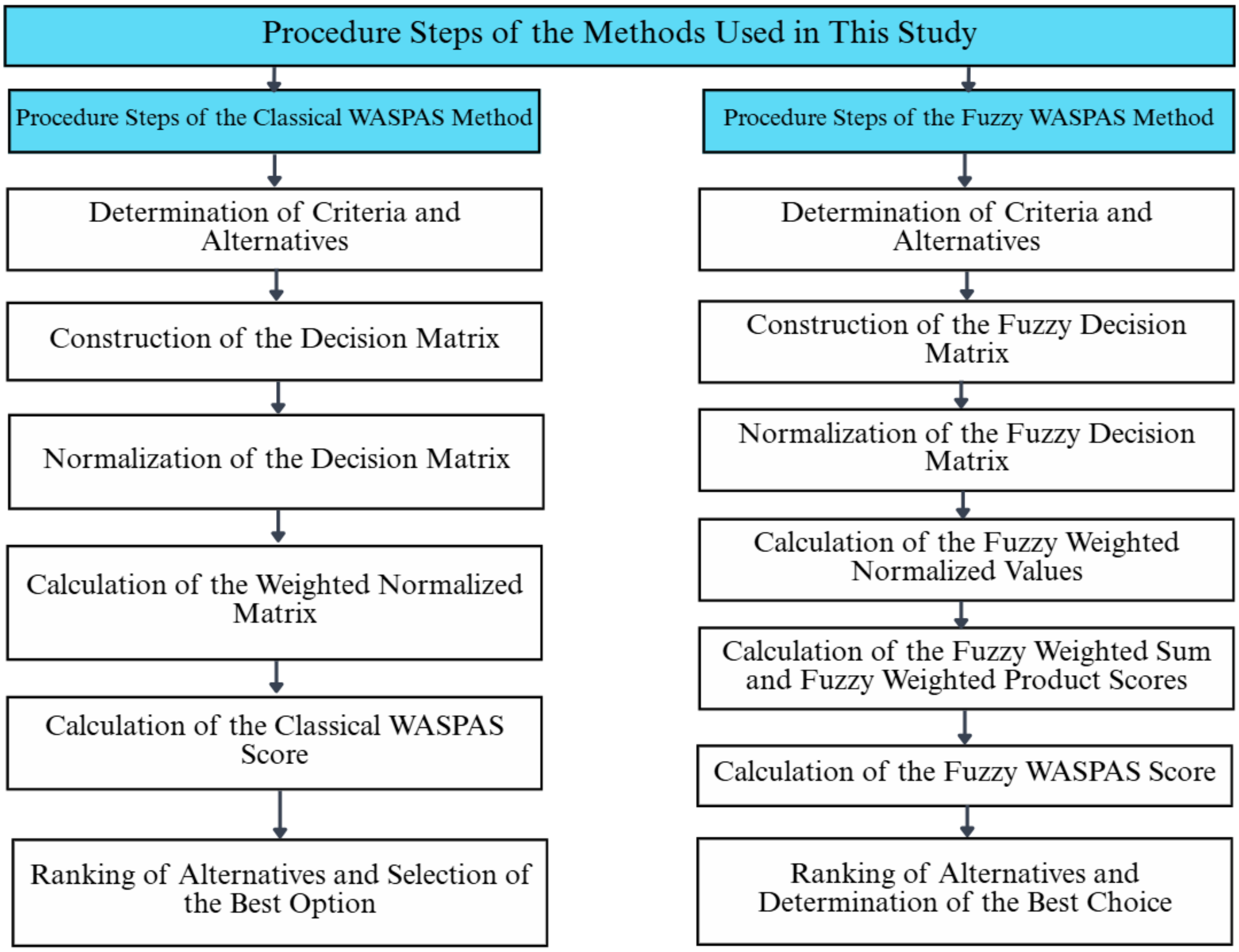

Figure 2. Flowchart of the methods used in this study

5.4. Application of the Classic WASPAS Method

In this section, the step-by-step applicability of the classical WASPAS method to the selection problem of alternative energy systems is demonstrated.

Step 1: In this step, five alternatives and six criteria were identified for use in evaluating the problem, based on a literature review and the assessments of the established expert committee (see Table 2).

Step 2: Construction of the Decision Matrix. In this step, the decision matrix representing the evaluation of the five alternatives against the six identified criteria, as assessed by the expert committee, is presented in Table 3.

Table 3: Decision matrix for evaluating alternatives according to criteria

Alternatives	**Criteria**					
	C1 (gCO_2/kWh) (Minimize)	**C2 (Milyon TL/MegaWatt (MW)) (Minimize)**	**C3 (%) (Maximize)**	**C4 (%) (Maximize)**	**C5 (%) (Maximize)**	**C6 (%) (Maximize)**
A1	5	95	82	90	88	85
A2	10	115	75	80	80	70
A3	30	130	65	60	70	60
A4	8	110	78	75	75	65
A5	6	100	80	85	82	75

(Note: This table was developed by the expert committee taking into account the geographical, environmental, and socio-economic characteristics of Kilis province.)

Step 3: Normalization of the Decision Matrix. In this step, the normalized values for each alternative were calculated using Equation 2 for criteria to be maximized (benefit) and Equation 3 for criteria to be minimized (cost), as presented in Table 4.

Table 4. Normalized decision matrix

Alternatives	**Criteria**					
	C1 (Minimize)	**C2 (Minimize)**	**C3 (Maximize)**	**C4 (Maximize)**	**C5 (Maximize)**	**C6 (Maximize)**
A1	1.000	1.000	1.000	1.000	1.000	1.000
A2	0.500	0.864	0.951	0.944	0.955	0.941
A3	0.167	0.731	0.854	0.667	0.795	0.706
A4	0.333	0.792	0.915	0.889	0.886	0.882
A5	0.250	0.760	0.793	0.778	0.818	0.765

Step 4: Calculation of the Weighted Normalized Matrix. In this step, to balance the technical, environmental, and social significance, the criterion weights were determined based on the expert committee evaluations and a literature review as follows: Carbon Emissions (C1): 0.15; Investment Cost (C2): 0.15; Energy Efficiency (C3): 0.20; Resource Continuity (C4): 0.20; Environmental Impact (C5): 0.15; Local Impact and Social Acceptance (C6): 0.15. The WSM and WPM values calculated using Equations 4 and 5 based on the data in Table 4 are presented in Table 5.

Table 5. Calculated WSM and WPM values

Alternatives	**WSM Score**	**WPM Score**
A1	1.000	1.000
A2	0.868	0.849
A3	0.664	0.598
A4	0.795	0.757
A5	0.703	0.660

Step 5: Calculation of classical WASPAS scores. In this step, the WASPAS scores (Q_i) calculated for each alternative using Equation 7 are presented in Table 6.

Table 6. Q_iValues Calculated for each alternative according to the classical WASPAS method

Alternatives	WSM Score	WPM Score	Q_i Score (WASPAS)
A1	1.000	1.000	1.000
A2	0.868	0.849	0.859
A3	0.664	0.598	0.631
A4	0.795	0.757	0.776
A5	0.703	0.660	0.681

Step 6: Ranking of alternatives and selection of the best option. In this step, the obtained Q_i scores are ranked. The alternative with the highest score is identified as the best choice. Accordingly, Accordingly, the ranking performance of the alternatives based on the Q_i values in Table 6 is as follows: A1 > A2 > A4 > A5 > A3.

5.5. Application of the Fuzzy WASPAS Method

In this section, the applicability of the fuzzy WASPAS method to the alternative energy systems selection problem will be demonstrated step by step. Triangular fuzzy sets will be employed in the application, and the triangular fuzzy linguistic terms determining the importance levels of the criteria are presented in Table 7. In this study, triangular fuzzy numbers were preferred. The rationale for this choice lies in their computational simplicity, widespread use in the literature, and their ability to appropriately model the uncertainty inherent in expert evaluations. Moreover, the weights and scores obtained using triangular fuzzy numbers can reflect decision-makers' assessments in a clear, simple, and effective manner.

Table 7. Triangular fuzzy linguistic labels determining the importance levels of the criteria

Linguistic Terms	Triangular Fuzzy Values
Low	(0.010, 0.100, 0.300)
Medium Low	(0.200, 0.400, 0.600)
Medium	(0.400, 0.500, 0.600)
Medium High	(0.600, 0.700, 0.800)
High	(0.700, 0.900, 1.000)

Considering the conditions related to sustainable energy systems specific to Kilis Province (e.g., climate, geography, economy, social structure, environmental sensitivities, etc.), the weight values of the criteria (as triangular fuzzy numbers) are presented in Table 8.

Table 8. Criteria weights determined by the expert committee

Criteria	Triangular Fuzzy Values	Justification/Explanation
C1	(0.600, 0.800, 1.000)	Carbon emissions are significant due to the agricultural structure and the need for clean air.
C2	(0.700, 0.900, 1.000)	Cost emerges as a determining factor due to the limited economic resources.
C3	(0.500, 0.700, 0.900)	Importance arises from the limited energy infrastructure and demand.
C4	(0,400, 0.600, 0.800)	While long-term energy supply is important, short-term needs are prioritized.
C5	(0.600, 0.800, 1.000)	Environmentally friendly solutions are preferred due to agriculture and the natural environment.
C6	(0.300, 0.400, 0600)	The public's familiarity with new technologies is moderate, which may affect approval processes. Additionally, the impact on local infrastructure and land use is considered moderate.

Now, let us explain the step-by-step application of the fuzzy WASPAS method to the selection problem of the considered alternatives:

Step 1: Based on a literature review and the recommendations of the expert committee, six criteria and five alternatives have been identified for evaluation in the selection problem (see Table 2).

Step 2: Determination of the fuzzy decision matrix and weights. In this step, the performance of each alternative with respect to each criterion was obtained by integrating the independent evaluations of all experts in the expert committee. The experts assessed the alternatives using the linguistic terms presented in Table 7. These individual evaluations were aggregated based on majority opinion and common tendency, resulting in an aggregated linguistic decision matrix that represents the combined judgments of all experts, as presented in Table 9. Subsequently, the linguistic terms in Table 9 were converted into their corresponding triangular fuzzy numbers to construct the fuzzy decision matrix, which is provided in Table 10.

Table 9. Aggregated fuzzy decision matrix based on expert evaluations

Alternatives / Criteria	C1 (Low Preferred)	C2 (Low Preferred)	C3 (High Preferred)	C4 (High Preferred)	C5 (High Preferred)	C6 (High Preferred)
A1	Low	Medium	High	Medium High	High	High
A2	Low	Medium High	Medium High	Medium	Medium High	Medium

A3	Medium High	Medium	Medium	Medium	Medium Low	Medium
A4	Medium	High	Medium High	Medium High	Medium High	Medium
A5	Medium	Medium	Medium	Medium	Medium	Medium Low

Based on the decision matrix constructed from the evaluations of the expert committee (Table 9), the fuzzy decision matrix corresponding to the linguistic labels is presented in Table 10.

Table 10. Fuzzy decision matrix for the evaluation of alternatives according to the criteria

Alternatives / Criteria	**C1**	**C2**	**C3**
A1	(0.010, 0.100, 0.300)	(0.400, 0.500, 0,600)	(0.700, 0.900, 1.000)
A2	(0.010, 0.100, 0.300)	(0.600, 0.700, 0,800)	(0.600, 0.700, 0,800)
A3	(0.600, 0.700, 0.800)	(0.400, 0.500, 0,600)	(0.400, 0.500, 0,600)
A4	(0.400, 0.500, 0.600)	(0.700, 0.900, 1.000)	(0.600, 0.700, 0,800)
A5	(0.400, 0.500, 0.600)	(0.400, 0.500, 0,600)	(0.400, 0.500, 0,600)
Alternatives / Criteria	**C4**	**C5**	**C6**
A1	(0.600, 0.700, 0.800)	(0.700, 0.900, 1.000)	(0.700, 0.900, 1.000)
A2	(0.400, 0.500, 0.600)	(0.600, 0.700, 0.800)	(0.400, 0.500, 0.600)
A3	(0.400, 0.500, 0.600)	(0.200, 0.400, 0.600)	(0.400, 0.500, 0.600)
A4	(0.600, 0.700, 0.800)	(0.600, 0.700, 0.800)	(0.400, 0.500, 0.600)
A5	(0.400, 0.500, 0.600)	(0.400, 0.500, 0.600)	(0.200, 0.400, 0.600)

Step 3: Normalization of the decision matrix. In this step, the normalized values for each alternative were calculated using Equation 9 for criteria to be maximized (benefit criteria) and Equation 10 for criteria to be minimized (cost criteria). The calculated normalized values are presented in Table 11.

Table 11. Normalized fuzzy decision matrix for the evaluation of alternatives according to the criteria

Alternatives / Criteria	**C1**	**C2**	**C3**
A1	(1.000, 1.000, 1,000)	(1.500, 1.290, 1.000)	(0.700, 1.000, 1.430)
A2	(1.000, 1.000, 1,000)	(1.000, 0.930, 0.750)	(0.600, 0.780, 1.140)
A3	(0.050, 0.140, 0,170)	(1.500, 1.290, 1.000)	(0.400, 0.560, 0.860)
A4	(0.080, 0.200, 0,250)	(0.860, 0.710, 0.600)	(0.600, 0.780, 1.140)
A5	(0.080, 0.200, 0,250)	(1.500, 1.290, 1.000)	(0.400, 0.560, 0.860)
Alternatives / Criteria	**C4**	**C5**	**C6**
A1	(0.750, 1.000, 1.330)	(0.700, 1.000, 1.430)	(0.700, 1.000, 1.430)
A2	(0.500, 0.710, 1.000)	(0.600, 0.780, 1.140)	(0.400, 0.560, 0.860)
A3	(0.500, 0.710, 1.000)	(0.200, 0.440, 0.860)	(0.400, 0.560, 0.860)

A4	(0.750, 1.000, 1.330)	(0.600, 0.780, 1.140)	(0.400, 0.560, 0.860)
A5	(0.500, 0.710, 1.000)	(0.400, 0.560, 0.860)	(0.200, 0.440, 0.860)

Step 4: Calculation of weighted normalized values**.** In this step, using Table 11, each normalized value is multiplied by the weight of the corresponding criterion according to Equation 11 (see Table 8). The resulting weighted normalized values are presented in Table 12.

Table 12. Weighted normalized fuzzy decision matrix for the evaluation of alternatives according to the criteria

Alternatives / Criteria	**C1**	**C2**	**C3**
A1	(0.600, 0.800, 1.000)	(1.050, 1.160, 1.000)	(0.350, 0.700, 1.290)
A2	(0.600, 0.800, 1.000)	(0.700, 0.840, 0.750)	(0.300, 0.490, 1.030)
A3	(0.030, 0.110, 0.170)	(1.050, 1.160, 1.000)	(0.200, 0.390, 0.770)
A4	(0.050, 0.160, 0.250)	(0.600, 0.640, 1.000)	(0.300, 0.550, 1.030)
A5	(0.050, 0.160, 0.250)	(1.050, 1.160, 1.000)	(0.200, 0.390, 0.770)
Alternatives / Criteria	**C4**	**C5**	**C6**
A1	(0.300, 0.600, 1.060)	(0.420, 0.800, 1.430)	(0.210, 0.400, 0.860)
A2	(0.200, 0.430, 0.800)	(0.360, 0.640, 1.140)	(0.120, 0.220, 0.520)
A3	(0.200, 0.430, 0.800)	(0.120, 0.350, 0.860)	(0.120, 0.220, 0.520)
A4	(0.300, 0.600, 1.060)	(0.360, 0.620, 1.140)	(0.120, 0.220, 0.520)
A5	(0.200, 0.430, 0.800)	(0.240, 0.450, 0.860)	(0.060, 0.180, 0.520)

Step 5: Calculation of fuzzy weighted sum method (B-WSM) and fuzzy weighted product method (B-WPM) scores. In this step, the weighted normalized fuzzy values calculated in Table 12 are used to compute the B-WSM and B-WPM scores using Equations 12 and 13. The B-WSM and B-WPM scores calculated with Equations 12 and 13 are presented in Table 13.

Table 13. Calculated B-WSM and fuzzy B-WPM values

Alternatives	**B-WSM Score ($\widetilde{Q}_1(i)$)**	**B-WPM Score ($\widetilde{Q}_2(i)$)**
A1	(1.705, 3.334, 5.955)	(0.104, 0.318, 1.710)

A2	(1.332, 2.597, 4.769)	(0.047, 0.100, 0.406)
A3	(1.041, 2.031, 3.675)	(0.004, 0.014, 0.058)
A4	(0.972, 2.033, 4.477)	(0.011, 0.028, 0.146)
A5	(1.107, 2.135, 3.755)	(0.007, 0.022, 0.101)

Step 6: Calculation of the fuzzy WASPAS scores. In this step, the fuzzy WASPAS scores ($\tilde{Q}_i$) calculated for each alternative using Equation 14 based on the data in Table 13 are presented in Table 14 (with the λ value set to 0.5 for an equally weighted combination).

Table 14. $\tilde{Q}_i$Values calculated for each alternative according to the fuzzy WASPAS method

Alternatives	$\tilde{Q}_i$ Score (Fuzzy WASPAS)
A1	(0.905, 1.826, 3.833)
A2	(0.690, 1.349, 2.588)
A3	(0.523, 1.023, 1.867)
A4	(0.492, 1.031, 2.312)
A5	(0.557, 1.079, 1.928)

Step 7: Ranking of alternatives and selection of the best option. In this step, the fuzzy WASPAS scores $\tilde{Q}_i$ are defuzzified to rank the alternatives. The fuzzy $\tilde{Q}_i$ values calculated using Equation 15 (see Table 14) are converted into crisp values $E(\tilde{Q})$. The resulting $E(\tilde{Q})$ values are presented in Table 15. The alternative with the highest EEE score is identified as the best choice.

Table 15. $\tilde{Q}_i$ Values calculated for each alternative according to the fuzzy WASPAS method

Alternatives	$E(\tilde{Q})$ Score
A1	2.188
A2	1.542
A3	1.137
A4	1.278
A5	1.188

Accordingly, the ranking performance of the alternatives based on the E values in Table 15 is as follows: A1 > A2 > A4 > A5 > A3.

5.6. Sensitivity Analysis

In this study, a sensitivity analysis was conducted to examine the degree to which the alternative rankings obtained using the classical and fuzzy WASPAS methods remain stable under possible variations in criterion weights. In MCDM problems, criterion weights are generally based on expert judgments; therefore, analyzing how small changes in these weights influence the final rankings is of critical importance for assessing the reliability of the decision model. Within the scope of the sensitivity analysis, weight perturbations were applied by focusing on the criteria with the highest weights. Accordingly, for the classical WASPAS method, the weight of the selected criterion (C3) was varied by ±10%, while the weights of the remaining criteria were proportionally re-normalized so that the total weight equaled one. In addition, for the fuzzy WASPAS method, the weight of the selected main criterion (C2) was increased and decreased by ±10%, and the fuzzy weights of the other criteria were inversely re-scaled to preserve the overall criterion weight structure. In this way, methodological consistency was ensured, and it was guaranteed that any changes in the rankings were solely attributable to shifts in criterion priorities. For each scenario:

- The classical WASPAS method,
- The fuzzy WASPAS method

were re-applied independently, and the resulting alternative rankings were compared. The sensitivity scenarios developed within this framework are presented in Tables 16 and 17.

Table 16. Sensitivity scenarios constructed for criterion weights (classical WASPAS)

For the classical WASPAS method (Modified criterion: C3)						
Senaryolar	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**
S1(-10%)	0.154	0.154	0.180	0.205	0.154	0.154
S2 (-7%)	0.153	0.153	0.186	0.203	0.153	0.153
S3 (-4%)	0.152	0.152	0.192	0.202	0.152	0.152
S4 (+4%)	0.149	0.149	0.208	0.198	0.149	0.149
S5 (+7%)	0.147	0.147	0.214	0.197	0.147	0.147
S6 (+10%)	0.146	0.146	0.220	0.195	0.146	0.146

Table 17. Sensitivity scenarios constructed for criterion weights (Fuzzy WASPAS)

For the fuzzy WASPAS method (Modified criterion: C2)			
Scenarios	**C1**	**C2**	**C3**
S1(-10%)	(0.093, 0.150, 0.180)	(0.630, 0.810, 0.900)	(0.077, 0.090, 0.100)
S2 (-7%)	(0.087, 0.140, 0.170)	(0.651, 0.837, 0.930)	(0.068, 0.085, 0.090)
S3 (-4%)	(0.082, 0.130, 0.160)	(0.672, 0.864, 0.960)	(0.068, 0.080, 0.090)
S4 (+4%)	(0.068, 0.120, 0.150)	(0.728, 0.936, 1.000)	(0.068, 0.075, 0.090)
S5 (+7%)	(0.063, 0.115, 0.140)	(0.749, 0.963, 1.000)	(0.053, 0.070, 0.085)
S6 (+10%)	(0.058, 0.110, 0.130)	(0.770, 0.990, 1.000)	(0.048, 0.065, 0.080)
Scenarios	**C4**	**C5**	**C6**
S1(-10%)	(0.062, 0.090, 0.100)	(0.093, 0.150, 0.180)	(0.046, 0.050, 0.060)
S2 (-7%)	(0.056, 0.085, 0.095)	(0.088, 0.140, 0.170)	(0.044, 0.050, 0.060)
S3 (-4%)	(0.054, 0.080, 0.090)	(0.082, 0.130, 0.160)	(0.041, 0.050, 0.060)
S4 (+4%)	(0.045, 0.075, 0.085)	(0.068, 0.120, 0.150)	(0.050, 0.050, 0.060)
S5 (+7%)	(0.042, 0.070, 0.080)	(0.063, 0.115, 0.140)	(0.050, 0.050, 0.060)
S6 (+10%)	(0.039, 0.065, 0.075)	(0.058, 0.110, 0.130)	(0.050, 0.050, 0.060)

The alternative rankings obtained for each scenario of the classical and fuzzy WASPAS methods are presented in Table 18.

Table 18. Alternative scores according to sensitivity scenarios

Classical WASPAS					
Scenarios	**A1**	**A2**	**A3**	**A4**	**A5**
S1(-10%)	1.000	0.856	0.627	0.773	0.679
S2 (-7%)	1.000	0.858	0.629	0.776	0.681
S3 (-4%)	1.000	0.859	0.633	0.778	0.683
S4 (+4%)	1.000	0.861	0.636	0.778	0.673
S5 (+7%)	1.000	0.862	0.639	0.778	0.672
S6 (+10%)	1.000	0.864	0.640	0.779	0.670
Fuzzy WASPAS					
Senaryolar	**A1**	**A2**	**A3**	**A4**	**A5**
S1(-10%)	1.132	0.813	0.518	0.722	0.634
S2 (-7%)	1.125	0.810	0.512	0.715	0.625
S3 (-4%)	1.120	0.805	0.510	0.710	0.620
S4 (+4%)	1.118	0.802	0.508	0.708	0.618
S5 (+7%)	1.115	0.798	0.505	0.705	0.615
S6 (+10%)	1.112	0.795	0.503	0.703	0.613

The scenario-based final score variations of the alternatives are presented in Figure 3, based on the data in Table 18.

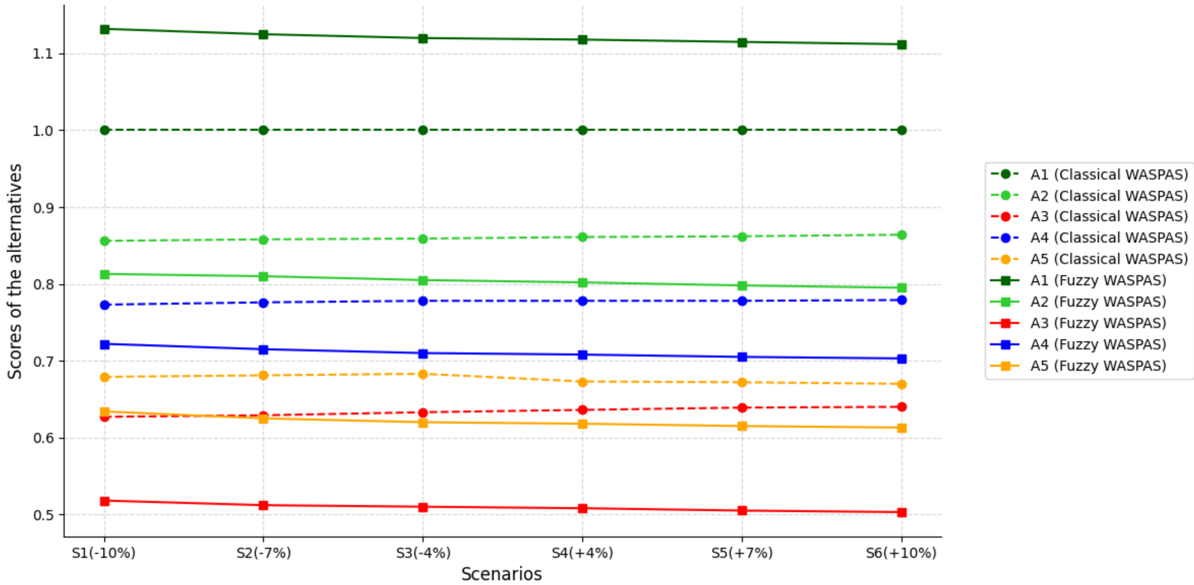

Figure 3. Scenario-based score variations of the alternatives in the classical and fuzzy WASPAS methods

According to the sensitivity analysis results presented in Table 18, the classical WASPAS method exhibits relatively low sensitivity in the ranking of alternatives; A1 consistently ranks first by a clear margin in all scenarios, while changes in the rankings among the remaining alternatives are quite limited. This indicates that the classical method provides stable rankings but has a limited capacity to capture small performance differences among alternatives. In contrast, the fuzzy WASPAS method demonstrates more pronounced score variations across scenarios and reveals more sensitive distinctions among alternatives. Although A1 maintains the first position in all scenarios, the rankings among A2–A5 show slight scenario-dependent changes, and the relative performance differences between alternatives are reflected more clearly. These observations suggest that the fuzzy approach is more effective in distinguishing subtle differences among alternatives. Overall, the sensitivity analysis results indicate that while the classical WASPAS method ensures ranking stability, the fuzzy WASPAS method offers a more detailed and sensitive representation of the relative performances of alternatives, enabling decision-makers to better observe ranking differences. Furthermore, the sensitivity analysis confirms the applicability and computational consistency of the employed methods, demonstrating that the ranking results obtained across all scenarios are generally stable. This finding supports the methodological robustness of both the classical and fuzzy WASPAS applications.

From a comparative perspective, the sensitivity analysis provides an important methodological insight. While both classical and fuzzy WASPAS approaches preserved the top-ranked alternative (A1) across all scenarios, the classical method produced almost identical ranking structures with very limited score dispersion, indicating strong stability but lower discrimination power among mid-ranked alternatives. In contrast, the fuzzy WASPAS approach exhibited greater score differentiation and minor scenario-dependent shifts among A2–A5, suggesting a higher sensitivity to weight perturbations. This finding demonstrates that the added value of the fuzzy approach does not lie in altering the final decision outcome, but rather in enhancing the model's ability to reflect subtle performance differences and uncertainty-driven variations. Therefore, the comparative sensitivity results provide empirical evidence of how uncertainty modeling affects ranking behavior under controlled decision environments.

5.7. Evaluation of Method Validity Through Comparative Analysis

In this study, a comparative analysis was conducted to test the reliability and stability of the alternative rankings obtained using the classical and fuzzy WASPAS methods. Based on the same criterion weights and the normalized decision matrix, the rankings of the alternatives were recalculated using the fuzzy TOPSIS and VIKOR methods. These methods were selected to examine the degree of consistency between the classical and fuzzy WASPAS results and those obtained from other MCDM approaches. Table 19 presents the alternative ranking performances derived from the classical and fuzzy WASPAS methods, as well as from the fuzzy TOPSIS and VIKOR methods.

Table 19. Ranking performance of alternatives: comparison of WASPAS, TOPSIS, and VIKOR

Alternatives	Classical WASPAS		Fuzzy WASPAS		Fuzzy TOPSIS		Fuzzy VIKOR	
	Score Value	**Ranking Performance**	**Score Value**	**Ranking Performance**	**Score Value**	**Ranking Performance**	**Score Value**	**Ranking Performance**
A1	1.000	1.	2.188	1.	1.000	1.	0.000	1.
A2	0.859	2.	1.542	2.	0.597	3.	0.540	3.
A3	0.631	5.	1.137	5.	0.303	5.	1.000	5.
A4	0.776	3.	1.278	3.	0.601	2.	0.730	4.
A5	0.681	4.	1.188	4.	0.475	4.	0.530	2.

An examination of the comparative analysis results presented in Table 19 indicates that alternative A1 consistently ranked first across all methods, demonstrating the highest relative performance. This finding confirms that A1 represents a robust and reliable option under all applied multi-criteria decision-making approaches. Alternative A2 ranked second in both the classical WASPAS and fuzzy WASPAS methods, while it was positioned third in the fuzzy TOPSIS and fuzzy VIKOR methods, respectively. This indicates that the relative performance of this alternative may exhibit minor method-dependent variations. Alternative A4 ranked second and fourth in the fuzzy TOPSIS and fuzzy VIKOR methods, respectively, suggesting that rank shifts among the top-performing alternatives are limited and manageable across different methods. For the lower-ranked alternatives, A3 and A5, some rank changes were observed between methods; however, these variations were not substantial enough to alter the overall ranking trend. Overall, the comparative analysis results demonstrate a high level of consistency among the top-ranked alternatives, particularly due to A1 maintaining the first position across all methods. The limited ranking differences observed between the classical and fuzzy WASPAS methods and the fuzzy TOPSIS and fuzzy VIKOR methods stem from the structural differences in their evaluation approaches, such as additive/multiplicative scoring and compromise-based solutions. This finding indicates that the proposed methods reliably reflect the overall ranking performance and that the relative priorities among alternatives vary only slightly depending on the method employed. The results demonstrate that the proposed approach provides consistent and reliable rankings across different MCDM methods, thereby enabling decision-makers to more accurately assess the relative priorities of the alternatives. Furthermore, to quantitatively evaluate the relationship among the rankings obtained from different methods, Spearman's rank correlation analysis was applied, and the results are presented in Table 20.

Table 20. Inter-Method Spearman Rank Correlation Values

	Classical WASPAS	Fuzzy WASPAS	Fuzzy TOPSIS	Fuzzy VIKOR
Classical WASPAS	1.000			
Fuzzy WASPAS	1.000	1.000		
Fuzzy TOPSIS	0.900	0.900	1.000	
Fuzzy VIKOR	0.700	0.700	0.600	1.000

According to the Spearman rank correlation analysis presented in Table 20, the results indicate an overall high level of consistency among the four methods. Perfect agreement ($\rho = 1.000$) is observed between the classical WASPAS and fuzzy WASPAS methods, demonstrating that the rankings obtained by both approaches exhibit strong stability, particularly with respect to the top-ranked alternatives. The correlation between the classical and fuzzy WASPAS methods and fuzzy TOPSIS is also high ($\rho = 0.900$), indicating that the relative performance of the alternatives is largely preserved under different methodological frameworks. In contrast, the correlations between the fuzzy VIKOR method and the other methods are relatively lower ($\rho = 0.600 - 0.700$), with minor rank changes observed especially among the mid-ranked alternatives. This outcome can be attributed to the structural characteristics of the VIKOR method, which is based on the "compromise solution" approach and emphasizes relative balance among criteria, thereby generating certain differences in the ranking of alternatives.

Overall, the high correlation coefficients observed among the rankings produced by the four methods confirm that the proposed classical and fuzzy WASPAS approaches, together with the comparative methods, reliably reflect the relative performance of the alternatives and that the ranking results are robust and consistent. In particular, the strong agreement exhibited by fuzzy WASPAS and fuzzy TOPSIS for the top-ranked alternatives highlights the capability of these methods to accurately capture decision-makers' preferences and priorities. Consequently, the comparative analysis and correlation results support the validity of the methods applied in this study and indicate that the obtained rankings (results) can be considered reliable.

5.8. Literature-Based Experimental and Practical Support

The technical and economic feasibility of the renewable energy alternatives considered in this study is supported by measurement data, simulation results, and field applications reported in the literature. Therefore, the obtained rankings can be interpreted not only as theoretical evaluations but also as results that are consistent with practical implementations and experimental evidence. Turkey's renewable energy installed capacity structure is reflected in official statistics through the shares of hydroelectric, solar, wind, geothermal, and other resources within the total installed power capacity. Renewable energy sources account for approximately 57–60% of the total installed capacity, with hydropower representing the largest share at about 27%, followed by solar energy at approximately 16–19% and wind energy at around 10–11%. These figures indicate that renewable energy sources play a significant role in real-world field applications [29,30]. In terms of solar energy, Turkey's geographical location provides a high solar radiation potential, and simulation studies on the performance of photovoltaic (PV) systems demonstrate that this potential can be effectively converted into electricity generation. For instance, studies conducted using simulation software such as PVSyst have comprehensively modeled the performance of PV systems in different regions of Turkey and evaluated their efficiency based on annual global solar radiation data [31]. Moreover, technical studies such as meteorological measurements and statistical wind data analyses have employed scientific data and methods to determine the wind energy potential across various regions of Turkey. In these studies, parameters such as wind speed and wind power density have been analyzed using statistical and mathematical techniques, and potential assessments have been presented for different regions [32]. In addition, Turkey's installed wind power capacity reached 13,391 MW as of May 2025, indicating that wind energy holds a substantial share in practical field applications [33]. Geothermal energy is also strongly supported by field applications in Turkey. The country possesses significant geothermal heating and electricity generation capacity on a global scale, with all geothermal power plants located in the western Anatolia region and a reported total installed capacity of approximately 2 GW. These field applications demonstrate the continuity and practical feasibility of geothermal energy as a reliable renewable resource [34].

These literature-based studies, supported by large-scale field data and simulation results, demonstrate that the renewable energy alternatives considered in this study are not merely theoretical options but are associated with real-world applications that can be directly linked to empirical implementation data. This integrated perspective substantially enhances the reliability and practical applicability of the rankings obtained through the classical and fuzzy WASPAS methods, thereby strengthening their relevance and usefulness for decision-makers.

6. CONCLUSION, DISCUSSION AND RECOMMENDATIONS

This study was conducted using the case of Kilis Province to demonstrate the effectiveness of MCDM techniques in the evaluation of sustainable energy resources. Based on evaluations conducted using both the classical and fuzzy WASPAS methods, solar energy emerged as the most suitable alternative. This finding not only highlights the alignment of regional conditions with specific energy types but also underscores the importance of strategies that minimize the environmental impacts of investments [35].

When the performance of the alternatives is further examined on a criterion-by-criterion basis, the underlying reasons for the obtained rankings become more transparent. Accordingly, alternative A1 ranks at the top by achieving high scores in terms of investment cost (C2), energy efficiency (C3), resource continuity (C4), and environmental impact (C5). Alternative A2 attains the second position by exhibiting moderate performance with respect to carbon emissions (C1), investment cost (C2), and resource continuity (C5). In contrast, alternatives A3 and A5 receive relatively low scores in the criteria of social acceptance (C6) and environmental impact (C5), which leads to their placement in lower ranking positions. Alternative A4, on the other hand, demonstrates a balanced performance across all criteria and therefore occupies a middle position in the overall ranking (see Table 12). This analysis not only presents the final ranking but also provides decision makers with a more detailed evaluation by identifying the criteria in which each alternative exhibits strengths or weaknesses. In addition, the sensitivity and comparative analyses enable a more thorough assessment of the reliability and methodological consistency of the obtained rankings. In the sensitivity analysis conducted using the classical and fuzzy WASPAS methods, ±10% variations in criterion weights resulted in only limited ranking changes among alternatives A2–A5, indicating that both methods yield stable and robust results. Furthermore, within the scope of the comparative analysis, the results obtained from the classical and fuzzy WASPAS methods were validated using the fuzzy TOPSIS and VIKOR approaches. The analyses reveal that alternative A1 consistently retains the first position across all methods, while the remaining alternatives exhibit only minor ranking shifts between methods. Moreover, the Spearman rank correlation coefficients show high values ($\rho = 1.000$ for classical WASPAS–fuzzy WASPAS and $\rho = 0.900$ for classical WASPAS–fuzzy TOPSIS). These findings clearly demonstrate that the proposed methods reliably and consistently reflect the relative priorities among alternatives, allow decision makers to confidently interpret ranking differences, and significantly enhance the methodological robustness of the evaluation framework.

The findings obtained from this study clearly demonstrate that, for the province of Kilis, solar energy emerges as the most suitable alternative for sustainable energy planning. However, it should be emphasized that this result depends not only on the final ranking itself but also on the ability of the fuzzy WASPAS method to represent uncertainties and to comprehensively incorporate expert judgments into the decision-making process. While the classical WASPAS approach performs evaluations based on precise numerical inputs, the fuzzy WASPAS method more realistically integrates criteria that are difficult to define strictly in quantitative terms—such as local climatic conditions, resource continuity, social acceptance, and environmental impacts—into the decision process. This characteristic enables policymakers to assess not only the "best" alternative, but also which alternative provides a more stable and reliable option under varying conditions. In this context, for the formulation of regional energy policies:

- Solar energy investments should be evaluated not only on the basis of technical efficiency, but also in conjunction with social acceptance and environmental sustainability criteria,
- Local authorities should utilize fuzzy MCDM outputs to determine incentives, subsidies, and investment priorities in a more flexible and context-sensitive manner,
- It is recommended that the public be actively involved in decision-making processes through energy cooperatives and similar participatory models, thereby enhancing the acceptability of policy implementation.

Moreover, this study demonstrates that fuzzy decision-making models, compared to classical methods, provide a broader perspective in policy design by moving beyond a focus on a single deterministic outcome and enabling a more comprehensive evaluation of the decision space. In this respect, the fuzzy WASPAS method can be regarded as a powerful decision-support tool for the development of evidence-based, flexible, and sustainable public policies, particularly in domains such as energy investments, where uncertainty is high and long-term impacts are significant.

A review of the literature indicates that studies conducted in the field of renewable energy support the findings of the present study. In the study conducted by [36], the fuzzy AHP (Analytic Hierarchy Process) method was employed to evaluate renewable energy resources in Turkey.

Thirty criteria were identified, and their respective weights were calculated. The results showed that economic, political, technical, environmental, and social criteria were the most significant main criteria in descending order of importance. Furthermore, alternatives such as solar, wind, hydroelectric, biomass, and wave energy were assessed based on these criteria, and the findings were found to support the results of the present study. In the *Solar Futures Study* conducted by the U.S. Department of Energy and the National Renewable Energy Laboratory (NREL), it is projected that solar energy could supply up to 40% of the U.S. electricity grid by 2035. This study emphasizes the significant role that solar energy is expected to play in future energy systems [37]. Similarly, the International Energy Agency (IEA) forecasts that solar photovoltaic (PV) energy will become the largest renewable energy source by 2029. This projection highlights the importance and growth potential of solar energy in global electricity generation [38]. Furthermore, a review of previous studies reveals that various MCDM methods have been employed in the evaluation of renewable energy alternatives. The majority of these studies emphasize the similarity of the resulting rankings; however, the capacity of the employed methods to model uncertainty, handle criterion interactions, and reflect decision-maker behaviors has been discussed only to a limited extent. In contrast to prior research, this study comparatively examines the classical WASPAS and fuzzy WASPAS methods under the same set of criteria, the same set of alternatives, and within the same regional context (Kilis province). Consequently, the differences between the methods are assessed not only in terms of ranking outcomes but also regarding uncertainty modeling, the integration of expert judgments into the system, and the interpretability of decision outputs. Moreover, focusing on a region such as Kilis province, which exhibits high solar irradiation potential but limited wind and hydropower resources, allows for a clearer observation of the influence of contextual factors (such as climatic conditions, local acceptance, and resource continuity) on the method outcomes. In this respect, the study not only confirms the similarity of results but also critically discusses the role of methodological choices and local conditions in shaping decision-making outputs. In conclusion, this study demonstrates the critical role of locally responsive decision support systems in energy planning. Analyses using both classical and fuzzy methods indicate that sustainable energy investments in Kilis should prioritize solar energy. In this context, decision support systems can guide policymakers, investors, and local authorities in developing more strategic and sustainable energy policies [1, 39, 40, 41].

Beyond confirming the most suitable alternative, the systematic comparison conducted under identical criteria sets, expert evaluations, and regional conditions provides a clear methodological insight. Although both classical and fuzzy WASPAS approaches yield consistent top-ranked results, the fuzzy extension enhances ranking sensitivity and score dispersion without compromising stability. This indicates that the principal advantage of fuzzy WASPAS is not necessarily the production of a different final ranking, but the provision of a more nuanced and uncertainty-aware evaluation structure. In practical decision environments involving qualitative judgments and imperfect information—as in regional energy planning—the fuzzy formulation offers improved interpretability of marginal differences among alternatives. Therefore, the study empirically demonstrates the conditions under which the fuzzy approach provides added value beyond the classical formulation.

Furthermore, the classical and fuzzy WASPAS methods employed in this study, as widely accepted in the literature, are based on the assumption of independence among criteria. However, in sustainability-oriented decision problems, indirect or direct interactions may exist between criteria such as carbon emissions, environmental impact, social acceptance, and energy efficiency, which should not be overlooked. In this study, these interactions were excluded from the analysis in order to preserve the simplicity and applicability of the model. Therefore, the omission of inter-criteria relationships is considered one of the methodological limitations of the study. Future research could benefit from employing methods capable of modeling interdependencies among criteria, such as ANP, DEMATEL, or integrated hybrid approaches, thereby yielding more comprehensive and realistic results. Additionally, the study has certain other limitations. Specifically, the limited number of experts involved in the evaluation process implies that the obtained criteria weights and alternative rankings may vary when assessed by different expert groups. Although it is well recognized in the literature that small yet domain-expert panels are commonly employed in MCDM studies, analyses conducted with larger and more interdisciplinary expert groups could enhance the generalizability of the results. Furthermore, while the set of criteria used in this study was specifically selected to capture the key economic, environmental, and social dimensions influencing renewable energy investments in Kilis province, the inclusion of additional criteria in the model may be warranted in response to policy priorities, technological advancements, or changes in regional dynamics. In this context, maintaining a fixed set of criteria may be regarded as another limitation of the study. On the other hand, the use of triangular fuzzy numbers for modeling fuzzy uncertainty offers advantages in terms of computational simplicity and interpretability for decision-makers; however, it possesses limited expressive power compared to q-rung, intuitionistic, or interval-valued fuzzy sets, which can capture more complex uncertainty structures. Future research could enhance methodological robustness by comparing results obtained using different fuzzy set frameworks. Future studies should consider comparative analyses using alternative sets of criteria and different uncertainty modeling methods to further support energy planning. In future research, increasing the number of criteria and alternatives can test the applicability and performance of these methods in more complex decision problems.

NOMENCLATURE

MCDM	Multi-Criteria Decision-Making
WASPAS	Weighted Aggregated Sum Product Assessment
C1	Carbon Emissions
C2	Investment Cost
C3	Energy Efficiency
C4	Resource Continuity (Sustainability)
C5	Environmental Impact (Eco-Friendliness)
C6	Local Impact and Social Acceptance
A1	Solar Energy
A2	Wind Energy
A3	Biomass Energy
A4	Hydroelectric Energy
A5	Geothermal Energy

DECLARATION OF ETHICAL STANDARDS

The author of the paper submitted declares that nothing which is necessary for achieving the paper requires ethical committee and/or legal-special permissions

CONTRIBUTION OF THE AUTHORS

Müslüm ÖZTÜRK: Analysed the case, wrote the manuscript.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

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