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Site Selection of Solar Power Plants Using Hybrid MCDM Models: A Case Study in Indonesia

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Abstract: Among developing countries in Asia, Indonesia has realized the importance of transitioning from fossil fuels to renewable energy sources such as solar power. Careful consideration must be given to the strategic placement of solar power installations to fully leverage the benefits of solar energy. This study proposes a methodology to optimize the site selection of solar power plants in Indonesia by integrating Data Envelopment Analysis (DEA), Fuzzy Analytic Hierarchy Process (F-AHP), and Fuzzy Measurement of Alternatives and Ranking according to Compromise Solution (F-MARCOS) models. The proposed methodology considers quantitative and qualitative criteria to evaluate potential locations for solar power plants. In the first stage, DEA is used to identify the most efficient locations based on quantitative measures such as solar radiation, land availability, and grid connectivity. In the second stage, qualitative factors such as technological, economic, environmental, and socio-political aspects are evaluated using F-AHP to prioritize the most important criteria for site selection. Finally, F-MARCOS ranks potential locations based on the selected criteria. The methodology was tested using data from Indonesia as a case study. The results show that the proposed hybrid model optimizes Indonesia's solar power plant site selection. The optimal locations can contribute to a cost-effective long-term renewable energy supply nationwide. The findings from this study are relevant to policymakers, industry stakeholders, and researchers interested in renewable energy development and site selection. However, to promote sustainable solar energy development, governments and local authorities must also enact supportive policies and mechanisms that encourage the adoption and growth of renewable energy technologies in Indonesia.

Keywords: Indonesia; renewable energy; solar power; site selection; data envelopment analysis; multi-criteria decision making

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1. Introduction

The availability of energy significantly impacts global economic and industrial progress. More than 80% of the world's energy is produced through coal, oil, and natural gas [1]. With 270 million people, Indonesia has the fastest-growing power demand in Asia-Pacific, highlighting the urgent need for a secure, affordable, and long-term energy transition in Southeast Asia [2]. Power demand has been growing at a rate of 6.1% per year, and infrastructure is under pressure to capitalize on the growth potential of the growing economy [3]. Solar photovoltaic projects of utility, commercial, and industrial scale have a tremendous chance to rapidly establish economies of scale to meet the 23% renewable energy goal by 2025 [4]. By 2030, projections anticipate a potential installed capacity of 47 GW, a significant increase compared to just over 9 GW estimated in the Reference Case. In light of this, plans are underway to utilize solar photovoltaic (PV) technology to power approximately 1.1 million off-grid households. Rooftop and utility-scale solar PV systems can be expanded significantly in Indonesia, particularly in Java-Bali (which accounts for 70% of power demand in Indonesia) due to the ample area, robust infrastructure, and growing need for electricity in the region [5]. In addition, these types of resources are numerous and excellent for local development and utilization. Unlike the possible depletion of fossil fuels, renewable energy can be naturally replenished. Multiple countries have enacted legislation for renewable energy development, and various applications for renewable energy have evolved. It is projected that renewable energy sources will play a significant part in the global energy supply in the future [6,7]. Solar energy development in Indonesia is promising, but progress is slow despite the country's significant potential. Various factors contribute to this slow growth, such as limited financial and human resources, institutional challenges, market-controlled processes, unclear policies, and inconsistent norms, despite the availability of modern technology. The public and government agencies know the country's situation and resources. The three primary challenges for utility-scale solar PV are inadequate transmission grid capacity, complex administrative procedures, and insufficient engagement with local communities. According to the available research, solar site selection in Indonesia has yet to be thoroughly investigated regarding sustainable development [8,9].

A reliable, systematic, and effective decision-making framework is required to aid policymakers in selecting optimal locations for solar power facilities [10]. Sites that could be better can save time and money, cause trouble for local citizens and harm the environment. This study was undertaken to determine the best places in Indonesia to build solar PV systems for long-term sustainability. In-depth literature reviews and interviews with industry professionals help identify potential sites for solar installations and other parameters that will affect the deployment of these systems [11,12]. Due to the numerous factors that must be considered, experts have turned to multi-criteria decision-making (MCDM) approaches [13]. These methods use the strengths of techniques such as the Data Envelopment Analysis (DEA), Fuzzy Analytic Hierarchy Process (F-AHP), and Fuzzy Measurement Alternatives and Ranking according to the Compromise Solution (F-MARCOS) to determine the most suitable locations for solar energy generation prioritization. Among the many firsts of this study is its in-depth examination of a topic that has yet to be previously discussed in the literature: solar site selection in Indonesia. The evaluation criteria are broad and thorough, covering quantifiable and qualitative aspects of identifying priority areas for sustainable development. In addition, this is the first time that DEA, F-AHP, and F-MARCOS have been combined to form a single appropriate and successful methodology for site selection. The developed model aims to provide decision-makers with a comprehensive aid tool for selecting the best site for solar power plants.

The structure of this paper is organized as follows: Section 2 presents a review of relevant research on solar power plant site selection techniques. Section 3 discusses the Data Envelopment Analysis (DEA), Fuzzy Analytic Hierarchy Process (F-AHP), and Fuzzy Multi-Attribute Rating Comparison System (F-MARCOS) methodologies. Section 4 discusses the Indonesian case study, which demonstrates the practical application of the proposed hybrid approach. Finally, Section 5 provides conclusions and highlights potential directions for future research in this area.

2. Literature Review

The growth of solar energy production in many countries has drawn the attention of universities, governments, and organizations worldwide [14]. However, one of the significant challenges in deploying large-scale solar systems is determining the priorities of different regions on a national level. Establishing new solar farms requires substantial real estate, capital, and labor. Thus, identifying technological, technical, economic, environmental, societal, risk-aspect, and political factors is crucial to avoid delays in central and government approval procedures and establishing new solar farms [15]. Prioritizing appropriate areas before investing in costly solar farms can result in optimal production, lower socioeconomic costs, reduced negative environmental impacts, and progress in concerned regions. In order to make informed decisions, criteria are derived from a review of relevant literature and consensus among experts on environmental, technological, financial, and societal factors, as outlined in Table 1.

Table 1. Considered primary criteria and parameters that determine the suitability for solar PV implementation.

Main Criteria	Criteria	References
Climatic	Air temperature	[16–21]
	Wind speed	[17,22,23]
	Relative humidity	[17,18,21,22,24]
	Precipitation	[17,24]
	Air Pressure	
	Sunshine hour	[16–18,24,25]
	Irradiation	[16–21,24,26–28]
	Elevation	[18,20,24]
Technical	Assistance and guidance with technical matters	[16]
	Geology	[17,22,27]
	Availability of skilled workers	[16]
Economic	Consumption of electricity	[17,26,28]
	Costs	[16,17,20,25,28,29]
	Terms of network accessibility	[16,17,27]
	Proximity to public transportation	[16–19,21,22,24]
	Proximity to residential areas	[16,17,19,22,24]
Social	Residents attitude	[16,29]
	Rules and regulations of the government	[16,17,28,29]
	Land acquisition	[16,21,28,29]
	Facilitating factors	[16,17,25,28,29]
Environmental	Impact of Wildlife and endangered species	[16,17,27]
	Noxious pollutant emission	[16,20]
	Benefits of conserving energy	[25,26]

The planning of renewable energy sources (RES) often involves the use of multi-criteria decision-making (MCDM) techniques, which assist decision-makers in selecting the best option from competing alternatives in site selection challenges [30]. Although numerous MCDM techniques are available, few have been applied when combining DEA with MCDM [9]. The fuzzy set theory incorporates uncertainty and ambiguity into the evaluation process. Uyan [31] used GIS and the AHP technique to identify promising areas for solar farms in the Karapinar region of Konya, Turkey. Sindhu et al. [16] investigated solar site selection in India using a combination of AHP and fuzzy TOPSIS analysis. Lee et al. [32] also used AHP and fuzzy TOPSIS analysis for solar site selection in India. Al Garni & Awasthi [33] used a GIS-AHP-based approach to select solar PV power plant sites in Saudi Arabia; their study contributes to SDG 7 (Affordable and Clean Energy) and SDG 13 (Climate Action). Seyed Alavi et al. [34] employed multi-criteria decision-making methods to identify optimal locations for wind power plants in eastern Iran. Wu et al. [35] also improved site selection for solar power installations in China by employing an MCDM framework based on fuzzy Preference Ranking Organization Methods for Enrichment Evaluations (PROMETHEE) II. Table 2 summarizes how MCDM methods have been applied to solar site selection research. These studies demonstrate the importance of integrating MCDM techniques with DEA for RES planning and provide valuable insights into selecting optimal solar sites.

Table 2. The literature review on MCDM techniques.

Reference	Location	Res	MCDM Technique
[35]	US	Wind-Solar PV	ANP
[25]	China	Solar thermal power plant	Linguistic Choquet operator/fuzzy measure
[36]	Southeast Spain	Solar PV	AHP and TOPSIS
[37]	Spain	Solar Thermal powerplant	AHP/ANP
[26]	China	Wind-Solar PV	ELECTRE
[28]	Iran	Solar PV	ELECTRE-II
[22]	UK	Wind-Solar PV	AHP
[38]	Murcia, Spain	CSP	SWARA and WASPAS
[24]	Iran	Solar Power Plant	AHP/fuzzy logic/WLC
[32]	Taiwan	Solar PV	AHP, Fuzzy TOPSIS, and ELECTRE
[39]	Iran	Solar PV	Fuzzy ANP and VIKOR
[40]	Afghanistan	Wind-Solar PV/CSP	MCDA
[16]	Haryana, India	Solar PV	Fuzzy AHP
[41]	Turkey	SPP	AHP/ELECTRE/TOPSIS/VIKOR
[20]	Northwest China	Solar PV	AHP and Fuzzy TOPSIS
[42]	Fars, Iran	Wind-Solar PV	Grey Cumulative Prospect Theory
[33]	Saudi Arabia	Solar PV	GIS-AHP
[27]	Turkey	Solar PV	Fuzzy TOPSIS
[43]	China	Solar PV	AHP and Fuzzy VIKOR
[8]	Indonesia	Solar PV	AHP-GIS
[17]	Taiwan	Solar PV	PROMETHEE
[44]	Western Libya	Solar PV	SWARA and DEMATEL
[45]	Iran	Solar PV	SWARA
[46]	Morocco	Solar PV	AHP-GIS
[9]	Vietnam	Solar PV	DEA/AHP/TOPSIS

After conducting a comprehensive review of the literature across multiple fields and methodologies, it has become clear that there is a lack of studies focused on selecting optimal solar locations in Indonesia. This research fills this gap by combining DEA, F-AHP, and F-MARCOS methodologies to identify the most suitable locations for solar PV installations. DEA is a powerful tool for comparing energy industry options based on measurable criteria, as it enables comparisons of locations in terms of their efficiency in converting inputs to outputs. F-AHP and F-MARCOS are flexible techniques incorporating human evaluations of immeasurable variables. Stankovi'c et al. [47] created the fuzzy MARCOS in 2019 to provide a strong sorting of alternatives in the fuzzy environment irrespective of the scale, which generates a basic, comprehensive decision-making information scheme using the ratio method and the reference point method. The fuzzy MARCOS approach is an effective tool for maximizing a number of objectives. By proposing an algorithm for examining the link between alternatives and reference points, fuzzy MARCOS revitalizes the MCDM domain. In order to make a strong decision, the fuzzy MARCOS method integrates the following elements: defining reference points (fuzzy ideal and fuzzy anti-ideal values), figuring out how alternatives relate to these values, and defining the utility level of alternatives concerning fuzzy ideal and fuzzy anti-ideal solutions. Because the results of the ratio approach and reference point sorting approach were combined, the results obtained by the fuzzy MARCOS method are more logical. In the research of Stević et al. [48] on sustainable supplier selection, it was proven that the robustness and stability of MARCOS outperformed TOPSIS in assessing the decision-making units. By combining DEA, F-AHP, and F-MARCOS, this study aims to provide a comprehensive approach to identifying optimal solar locations in Indonesia.

3. Methods

This section outlines the photovoltaic (PV) power plant site selection methodology, as illustrated in Figure 1. The proposed approach combines Data Envelopment Analysis (DEA), Analytic Hierarchy Process (AHP), and Fuzzy Measurement Alternatives and

Ranking according to the Compromise Solution (MARCOS) to develop a comprehensive decision-making framework for selecting optimal sites for PV power plants in Indonesia.

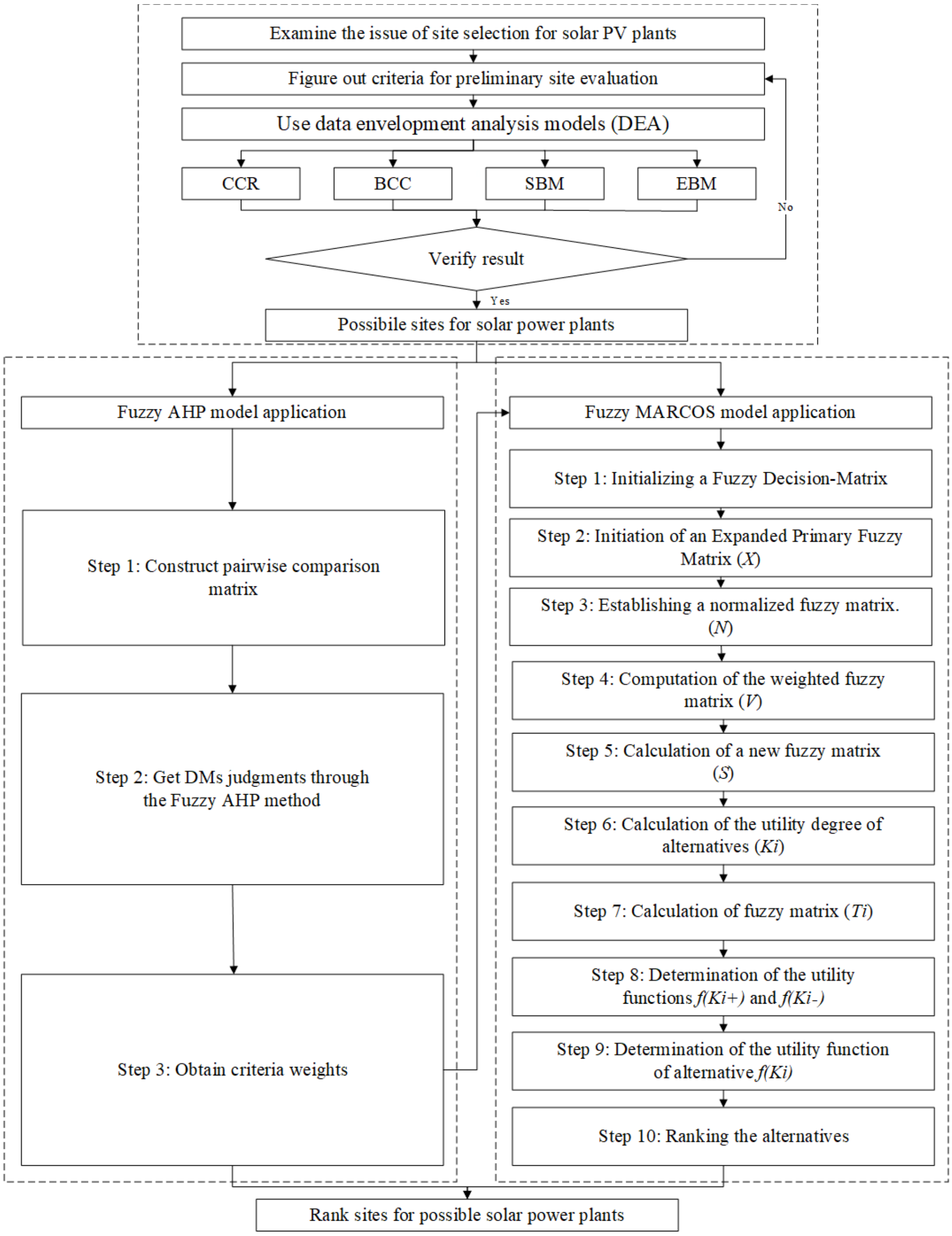

Figure 1. The process of the research.

3.1. Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) is a commonly used mathematical approach to measure the efficiency of Decision Making Units (DMUs) based on multiple inputs and outputs. This study uses DEA to screen and select the most efficient locations to host solar installations. The CCR, BCC, SBM, and EBM models are examples of DEA models that can assess DMU efficiency. These models differ in terms of the assumptions they make about inputs and outputs, as well as the type of efficiency measured [49].

3.1.1. Charnes, Cooper, Rhodes Model (CCR)

The CCR model is a DEA model commonly used to evaluate the efficiency of Decision-Making Units (DMUs) based on multiple inputs and outputs. This model measures the technical effectiveness of a DMU, assuming that each DMU can be represented by a set of inputs and outputs specified in the model (1).

$$
\begin{gathered}
\theta^* = \min_{\theta,\lambda,s^-} \theta \\
\text{subject to} \\
\theta x_0 = X\lambda - s^- \\
y_0 \leq Y\lambda, \\
\lambda \geq 0, s^- \geq 0
\end{gathered} \tag{1}
$$

The CCR model measures the technical efficiency of a DMU by comparing its input-output ratio with those of other DMUs in the dataset. A DMU is considered efficient if its efficiency score θ^* equals 1, indicating that the DMU is operating on the efficient frontier. Conversely, a DMU is considered inefficient if its efficiency score is less than 1, implying that the DMU is operating below the efficient frontier and could potentially improve its efficiency by adjusting its input-output ratio.

3.1.2. Banker, Charnes, and Cooper Model (BCC)

The Banker, Charnes, and Cooper (BCC) model, developed by Banker et al. [50], extends the DEA model to account for variable returns to scale (VRS). This model introduces a non-Archimedean element (ε), and s_i^- and s_r^+ represent the input and output slack variables, respectively.

$$
\begin{gathered}
min\varnothing - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \\
\text{subject to} \\
\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \varnothing x_{i0} (i = 1, .., p) \\
\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro} (r = 1, .., q) \\
\sum_{k=1}^{n} \lambda_k = 1 \\
\lambda_k \geq 0, k = 1, 2, \ldots, n \\
s_i^- \geq 0, i = 1, 2, \ldots, p \\
s_j^+ \geq 0, j = 1, 2, \ldots, q
\end{gathered} \tag{2}
$$

The BCC model evaluates DMUs based on their technical efficiency at various operational scales. This allows for the differentiation between technical inefficiency and scale inefficiency. The model recognizes growth, decline, constant return scales, and other scale types. The BCC model's efficiency metric is sometimes called "pure technical efficiency" to highlight its focus on technical performance independent of scale effects.

3.1.3. Slacks-Based Measure Model (SBM)

The effectiveness of a DMU is determined by a ratio known as the "slacks-based measure" (SBM) score. This value is determined by dividing the DMU's actual output by the minimal number of inputs required to achieve that output, depending on the inputs and outputs of the other DMUs included in the analysis. A DMU with an SBM score of 1 is technically efficient, while a DMU with an SBM score of less than 1 is inefficient.

$$
\begin{gathered}
\tau^* = \min 1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}} \\
\text{subject to} \\
x_{i0} = \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- (i = 1, \ldots, m) \\
y_{i0} \leq \sum_{j=1}^{n} y_{ij}\lambda_j (i = 1, \ldots, s) \\
\lambda_j \geq 0(\forall j), s_i^- \geq 0(\forall i)
\end{gathered} \tag{3}
$$

In this model, τ^* represents the SBM score, and λ_j is the weight assigned to each DMU. The input and output variables are represented by x_{i0} and y_{i0}, respectively. The input slack variables, s_i^-, represent the excess inputs that can be reduced without affecting the output. The objective of the SBM model is to minimize the sum of the input slacks relative to the input levels, thus maximizing the efficiency of the DMU. This model provides a more accurate efficiency measure, directly incorporating input and output slack variables into the efficiency evaluation.

3.1.4. Epsilon-Based Measure Model (EBM)

The Epsilon-Based Measure (EBM) [51] model is a variant of Data Envelopment Analysis (DEA) that accounts for the diversity or dispersion of the observed data set by calculating a scalar epsilon. This model aims to address the limitations of the CCR and SBM models by combining the radial and non-radial approaches, which emphasize proportional changes in inputs and outputs and incorporate slack, respectively. The input-oriented EBM model with a constant return to scale is formulated as follows:

$$
\begin{gathered}
\delta^* = \underset{\theta,\lambda,s^-}{Min}\, \theta - \varepsilon_x \textstyle\sum_{i=1}^{m} \frac{w_i^- s_i^-}{x_{io}} \\
\text{subject to} \\
\sum_{j=1}^{n} x_{ij}\lambda_j = \theta x_{io} - s_i^- (i = 1, \ldots, m) \\
\sum_{j=1}^{n} y_{rj}\lambda_j \geq y_{ro} (r = 1, \ldots, s) \\
\lambda_j \geq 0, j = 1, 2, \ldots, n \\
s_i^- \geq 0, i = 1, 2, \ldots, m
\end{gathered} \tag{4}
$$

In this model, δ^* represents the EBM score, λ_j is the weight assigned to each DMU, and the subscript "o" represents the DMU under evaluation. The input slack variables, s_i^-, indicate the excess inputs that can be reduced without affecting the output, and w_i^- denotes the weight assigned to the i-th input. The parameter ε_x specifies the radial qualities and is determined by the degree of input dispersion.

3.2. F-AHP

Table 3 shows that the fuzzy triangular numbers are the linguistic terms for the pairwise comparison scale and the fuzzy scale assigned. The relative importance of the two criteria is ranked on a scale from 1 to 9 based on the linguistic variables provided. A tilde sign () is placed above the parameter symbol to indicate uncertainty. Thus, the following are the details of the F-AHP process [16].

Table 3. Explanation of the F-AHP scale.

Fuzzy Set	Definition	Fuzzy Scale
$\tilde{1}$	Equal importance	(1, 1, 1)
$\tilde{2}$	Weak importance	(1, 2, 3)
$\tilde{3}$	Not bad	(2, 3, 4)
$\tilde{4}$	Preferable	(3, 4, 5)
$\tilde{5}$	Importance	(4, 5, 6)
$\tilde{6}$	Fairly importance	(5, 6, 7)
$\tilde{7}$	Very important	(6, 7, 8)
$\tilde{8}$	Absolute	(7, 8, 9)
$\tilde{9}$	Perfect	(8, 9, 10)

Step 1: To produce the integrated fuzzy pairwise comparison matrix used in the FAHP calculation, we apply the geometrical integration seen in Equation (5). $\tilde{l}_{ij}$ denotes the importance of the i^{th} criterion over the j^{th} criterion.

$$\tilde{M} = \begin{pmatrix} 1 & \tilde{l}_{12} & \cdots & \tilde{l}_{1n} \\ \tilde{l}_{21} & 1 & \cdots & \tilde{l}_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \tilde{l}_{n1} & \tilde{l}_{n2} & \cdots & 1 \end{pmatrix} = \begin{pmatrix} 1 & \tilde{l}_{12} & \cdots & \tilde{l}_{1n} \\ 1/\tilde{l}_{12} & 1 & \cdots & \tilde{l}_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ 1/\tilde{l}_{1n} & 1/\tilde{l}_{2n} & \cdots & 1 \end{pmatrix} \tag{5}$$

$$\tilde{l}_{ij} = \begin{cases} \tilde{9}^{-1}, \tilde{8}^{-1}, \tilde{7}^{-1}, \tilde{6}^{-1}, \tilde{5}^{-1}, \tilde{4}^{-1}, \tilde{3}^{-1}, \tilde{2}^{-1}, \tilde{1}^{-1}, \tilde{1}, \tilde{2}, \tilde{3}, \tilde{4}, \tilde{5}, \tilde{6}, \tilde{7}, \tilde{8}, \tilde{9} & \textit{such that } i \neq j \\ 1 & \textit{such that } i = j \end{cases}$$

Step 2: Equation to determine the fuzzy geometric mean of each criterion (6).

$$\tilde{r}_i = \left(\prod_{j=1}^{n} \tilde{l}_{ij}\right)^{1/n} \textit{such that } i = 1, 2, \ldots, n \tag{6}$$

where $\tilde{r}_i$ approximated by the fuzzy geometric mean, and $\tilde{l}_{ij}$ is a fuzzy comparison value generated by a panel of decision–makers based on the i^{th} criterion over the j^{th} criterion.

Step 3: The fuzzy preference weight for each criterion is determined using the following Equation (7).

$$\tilde{w}_i = \tilde{r}_i \otimes \left(\tilde{r}_1 \oplus \tilde{r}_2 \oplus \ldots \oplus \tilde{r}_n\right)^{-1} \tag{7}$$

where $\tilde{w}_i$ is the fuzzy weight of the i^{th} criterion.

Step 4: To obtain a clear result, we need to defuzzify the preference weights using the average weight criterion G_i, as shown in Equation (8).

$$G_i = \frac{lw_i + mw_i + uw_i}{3} \tag{8}$$

where $\tilde{w}_i$ is the fuzzy weight of the i^{th} criterion, which can be presented as $\tilde{w}_i = (lw_i, mw_i, uw_i)$, such that lw_i, mw_i, uw_i are the lower-bound, middle-bound, and upper-bound of $\tilde{w}_i$, respectively.

Step 5: The relative importance of each criterion, as determined by the normalized preference weight H_i, as seen by Equation (9).

$$H_i = \frac{G_i}{\sum_{i=1}^{n} G_i} \tag{9}$$

3.3. F-MARCOS

For multi-criteria decision-making (MCDM) situations with a set of criteria and potential solutions, fuzzy measurement of alternatives and ranking based on compromise solutions (F-MARCOS) can help reduce the uncertainty. Decision-makers can improve the stability of MCDM in fuzzy situations by using this strategy, which has three pillars: reference points, relationships between choices, and alternative utility levels [47]. The process of F-MARCOS is as below.

Step 1: Defining an initial fuzzy decision-making matrix including n criteria (i.e., criteria) and m alternatives.

Step 2: Defining an extended initial fuzzy decision-making matrix by introducing the fuzzy ideal $\widetilde{A}(ID)$ and anti-ideal $\widetilde{A}(AI)$ solutions

$$\widetilde{X} = \begin{array}{c} \\ \widetilde{A}(AI) \\ \widetilde{A}_1 \\ \widetilde{A}_2 \\ \cdots \\ \widetilde{A}_m \\ \widetilde{A}(ID) \end{array} \begin{array}{c} \overbrace{\begin{array}{cccc} \widetilde{C}_1 & \widetilde{C}_2 & \cdots & \widetilde{C}_n \end{array}} \\ \begin{bmatrix} \widetilde{x}_{ai1} & \widetilde{x}_{ai2} & \cdots & \widetilde{x}_{ain} \\ \widetilde{x}_{11} & \widetilde{x}_{12} & \cdots & \widetilde{x}_{1n} \\ \widetilde{x}_{21} & \widetilde{x}_{22} & \cdots & \widetilde{x}_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \widetilde{x}_{m1} & \widetilde{x}_{m2} & \cdots & \widetilde{x}_{mn} \\ \widetilde{x}_{id1} & \widetilde{x}_{id2} & \cdots & \widetilde{x}_{idn} \end{bmatrix} \end{array} \tag{10}$$

The fuzzy $\widetilde{A}(ID)$ is an alternative with the best performance, while the fuzzy $\widetilde{A}(AI)$ is the worst alternative. Depending on the type of the criteria, $\widetilde{A}(ID)$ and $\widetilde{A}(AI)$ are defined by applying Equations (11) and (12):

$$\widetilde{A}(ID) = \underset{i}{max} \widetilde{x}_{ij} if j \in B \; and \; \min_i \widetilde{x}_{ij} if j \in C \tag{11}$$

$$\widetilde{A}(AI) = \min_i \widetilde{x}_{ij} if j \in B \; and \; \underset{i}{max} \widetilde{x}_{ij} if j \in C \tag{12}$$

where B and C are a set of benefit and cost criteria, respectively.

Step 3: Determining the normalization of the extended initial fuzzy decision-making matrix, which is $\widetilde{N} = \left[\widetilde{n}_{ij}\right]_{m \times n}$ using Equations (13) and (14):

$$\widetilde{n}_{ij} = \left(n_{ij}^l, n_{ij}^m, n_{ij}^u\right) = \left(\frac{x_{ij}^l}{x_{id}^u}, \frac{x_{ij}^m}{x_{id}^u}, \frac{x_{ij}^u}{x_{id}^u}\right), j \in B \tag{13}$$

$$\widetilde{n}_{ij} = \left(n_{ij}^l, n_{ij}^m, n_{ij}^u\right) = \left(\frac{x_{id}^l}{x_{ij}^u}, \frac{x_{id}^l}{x_{ij}^m}, \frac{x_{id}^l}{x_{ij}^l}\right), j \in C \tag{14}$$

where elements x_{ij}^l, x_{ij}^m, x_{ij}^u, and x_{id}^l, x_{id}^m, x_{id}^u represent the elements of the matrix $\widetilde{X}$.

Step 4: Determining the weighted fuzzy matrix $\widetilde{V} = \left[\widetilde{v}_{ij}\right]_{m \times n}$, calculated by multiplying matrix $\widetilde{N}$ with the fuzzy weight coefficients of the criteria $\widetilde{w}_j$ as follows.

$$\widetilde{v}_{ij} = \left(v_{ij}^l, v_{ij}^m, v_{ij}^u\right) = \widetilde{n}_{ij} \otimes \widetilde{w}_j = \left(n_{ij}^l \times w_j^l, n_{ij}^m \times w_j^m, n_{ij}^u \times w_j^u\right) \tag{15}$$

where $\widetilde{w}_j = \left(w_j^l, w_j^m, w_j^u\right)$ represents the elements of the fuzzy weight of the criteria.

Step 5: Calculating the fuzzy matrix $\widetilde{S}_i$ using Equation (16) below.

$$\widetilde{S}_i = \sum_{i=1}^{n} \widetilde{v}_{ij} \tag{16}$$

where $\widetilde{S}_i = \left(s_i^l, s_i^m, s_i^u\right)$ is the sum of the elements of the weighted fuzzy matrix $\widetilde{V}$.

Step 6: Calculating the utility degree of alternative $\widetilde{K}_i$ using Equations (17) and (18):

$$\widetilde{K}_i^- = \frac{\widetilde{S}_i}{\widetilde{S}_{ai}} = \left(\frac{s_i^l}{s_{ai}^u}, \frac{s_i^m}{s_{ai}^m}, \frac{s_i^u}{s_{ai}^l}\right) \tag{17}$$

$$\widetilde{K}_i^+ = \frac{\widetilde{S}_i}{\widetilde{S}_{id}} = \left(\frac{s_i^l}{s_{id}^u}, \frac{s_i^m}{s_{id}^m}, \frac{s_i^u}{s_{id}^l}\right) \tag{18}$$

Step 7: To determine the fuzzy matrix $\widetilde{T}_i$, we use Equation (19):

$$\widetilde{T}_i = \widetilde{t}_i = \left(t_i^l, t_i^m, t_i^u\right) = \widetilde{K}_i^- \oplus \widetilde{K}_i^+ = \left(k_i^{-l} + k_i^{+l}, k_i^{-m} + k_i^{+m}, k_i^{-u} + k_i^{+u}\right) \tag{19}$$

Then, a new fuzzy number $\widetilde{D}$ is determined by Equation (20):

$$\widetilde{D} = \left(d^l, d^m, d^u\right) = \max_i \widetilde{t}_{ij} \tag{20}$$

Following that, it is necessary to defuzzify the number $\widetilde{D}$ using the expression $df_{crisp} = \frac{l+4m+u}{6}$ obtaining the number df_{crisp}.

Step 8: Determining the utility function to the ideal $f\left(\widetilde{K}_i^+\right)$ and anti-ideal $f\left(\widetilde{K}_i^-\right)$ solutions using Equations (21) and (22):

$$f\left(\widetilde{K}_i^+\right) = \frac{\widetilde{K}_i^-}{df_{crisp}} = \left(\frac{k_i^{-l}}{df_{crisp}}, \frac{k_i^{-m}}{df_{crisp}}, \frac{k_i^{-u}}{df_{crisp}}\right) \tag{21}$$

$$f\left(\widetilde{K}_i^-\right) = \frac{\widetilde{K}_i^+}{df_{crisp}} = \left(\frac{k_i^{+l}}{df_{crisp}}, \frac{k_i^{+m}}{df_{crisp}}, \frac{k_i^{+u}}{df_{crisp}}\right) \tag{22}$$

Finally, calculating the defuzzification of $\widetilde{K}_i^-$, $\widetilde{K}_i^+$, $f\left(\widetilde{K}_i^-\right)$, and $f\left(\widetilde{K}_i^+\right)$ values using the same defuzzification formula.

Step 9: Alternative utility functions $f(K_i)$ can be calculated with Equation (23):

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1-f\left(K_i^+\right)}{f\left(K_i^+\right)} + \frac{1-f\left(K_i^-\right)}{f\left(K_i^-\right)}} \tag{23}$$

Step 10: The order of the alternatives is determined by the final values of the utility degree function. Favored is the alternative with the superior utility function value.

As shown in Table 4, a new linguistic scale has been established for assessing alternatives in addition to the F-MARCOS method. There are nine words in total, and each assigned its fuzzy triangular number.

Table 4. The linguistic equivalent of a rating system for alternatives.

Symbol	Definition	Scale of Triangular Fuzzy Number
EP	Extremely poor	(1, 1, 1)
VP	Very poor	(1, 1, 3)
P	Poor	(1, 3, 3)
MP	Medium poor	(3, 3, 5)
M	Medium	(3, 5, 5)
MG	Medium good	(5, 5, 7)
G	Good	(5, 7, 7)
VG	Very good	(7, 7, 9)
EG	Extremely good	(7, 9, 9)

4. A Case Study in Indonesia

In this subsection, we put into action the aggregated technique proposed for determining which of Indonesia's 32 provinces would best host solar power installations (Figure 2). The evaluation's criterion system and examined alternatives were created by consultation with experts and subsequent interactive conversations, in addition to reviewing the relevant literature.

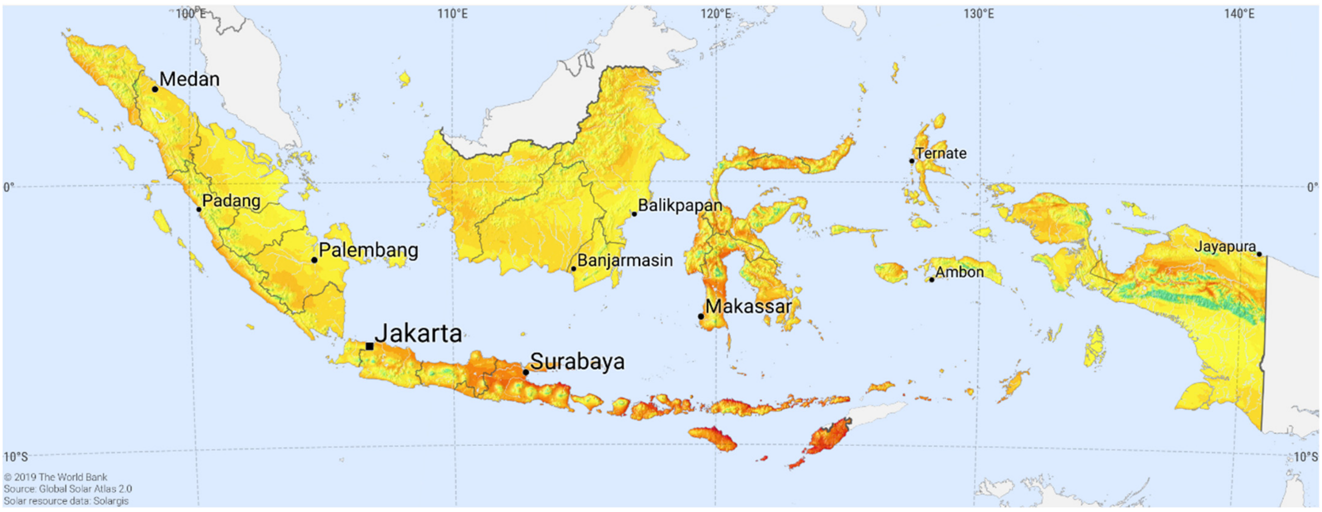

Figure 2. The map of solar radiation in Indonesia.

4.1. Using DEA Models to Screen Prospective Locations

As seen in Table 5, the initial stage of the DEA model-based research considered 32 provincial locations as decision-making units (DMUs). As illustrated in Figure 3, five inputs (air temperature, wind speed, relative humidity, rainfall, and air pressure) and three outputs (hours of sunshine, solar irradiance, and altitude) were analyzed to identify DMUs with ideal efficiency ratings (equal to 1).

Table 5. List of Indonesian locations (DMUs).

No.	Location	DMU	Irradiation (kWh/m^2/Year)
1	Aceh	DMU-01	1686.30
2	Bali	DMU-02	1799.45
3	Bangka Belitung	DMU-03	1653.45
4	Banten	DMU-04	1679.00
5	Bengkulu	DMU-05	1708.20
6	Gorontalo	DMU-06	1803.10
7	Jakarta	DMU-07	1726.45
8	Jambi	DMU-08	1627.90
9	Jawa Barat	DMU-09	1737.40

Table 5. *Cont.*

No.	Location	DMU	Irradiation (kWh/m^2/Year)
10	Jawa Tengah	DMU-10	1806.75
11	Jawa Timur	DMU-11	1879.75
12	Kalimantan Barat	DMU-12	1682.65
13	Kalimantan Selatan	DMU-13	1657.10
14	Kalimantan Tengah	DMU-14	1679.00
15	Kalimantan Timur	DMU-15	1668.05
16	Lampung	DMU-16	1708.20
17	Maluku	DMU-17	1679.00
18	Maluku Utara	DMU-18	1737.40
19	Nusa Tenggara Barat	DMU-19	1941.80
20	Nusa Tenggara Timur	DMU-20	2014.80
21	Papua	DMU-21	1631.55
22	Papua Barat	DMU-22	1679.00
23	Riau	DMU-23	1649.80
24	Sulawesi Barat	DMU-24	1708.20
25	Sulawesi Selatan	DMU-25	1777.55
26	Sulawesi Tengah	DMU-26	1700.90
27	Sulawesi Tenggara	DMU-27	1755.65
28	Sulawesi Utara	DMU-28	1755.65
29	Sumatera Barat	DMU-29	1646.15
30	Sumatera Selatan	DMU-30	1689.95
31	Sumatera Utara	DMU-31	1671.70
32	Yogyakarta	DMU-32	1861.50

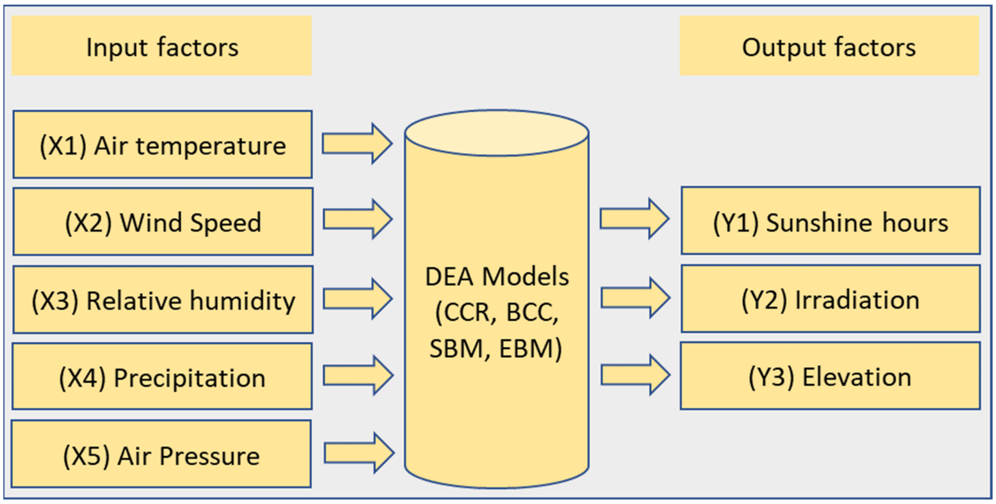

Figure 3. The input and output factors used in DEA models.

Input factors:

(X1) Air temperature (°C): Solar panel performance is affected by the panels' temperatures, which are affected by the surrounding temperature and the amount of sunlight they are exposed to. Simply put, solar panels produce more electricity when the temperature is lower. When the panel's operating temperature rises, the voltage it produces drops, and its efficiency drops.

(X2) Wind speed (m/s): The ability to withstand wind uplift and loads is essential for solar installations. Damage to machinery and increased wear and tear on operating components have been linked to the wind. Having more dust settles on the solar modules' surfaces due to increased wind speeds is another factor that can reduce production.

(X3) Relative humidity (%): Due to the absorption of short-wave solar radiation by atmospheric water vapor, locations with high humidity have limited potential for solar energy harvesting. In addition to diminishing power production, excessive humidity can cause dew to collect on the surfaces of solar panels, making it easier for airborne dust to settle on the modules.

(X4) Precipitation (mm/year): Precipitation, whether rain, snow, sleet, or hail. When clouds block out the sun, solar power plants are less efficient in producing electricity.

(X5) Air Pressure (Hpa): Air pressure is the force that air's weight exerts on the earth's surface. Air pressure decreases with increasing height. The ambient temperature decreases as altitude increases, allowing the solar system to function more efficiently. Due to fewer air layers that scatter, absorb, and reflect sunlight, there is more direct sunlight.

Output factors:

(Y1) Sunshine hour (hour/year): The sunshine hour of irradiation describes the duration of sunlight in a given area over a given period (year). Solar radiation of at least 120 W/m^2 is considered sunlight.

(Y2) Irradiation (kWh//m^2/year): The quantity of energy produced by the sun during a given period (in kWh) and surface area (in m^2) (year).

(Y3) Elevation (m): Solar potential characteristics are modified by a region's elevation above sea level. Specifically, solar panels can capture more energy from the sun at higher altitudes due to the thinner atmosphere's reduced absorption of solar radiation.

Statistical analysis of input and output factors is presented in Table 6.

Table 6. Factor statistical analysis.

Factors	Maximum	Minimum	Average	Standard Deviation
Air temperature	28.40	19.72	26.44	1.98
Wind speed	3.10	0.35	1.61	0.58
Relative humidity	90.59	77.18	84.36	3.14
Precipitation	4878.50	1770.40	2947.29	791.14
Air Pressure	1014.90	924.10	1009.18	15.32
Sunshine hours	2687.60	1203.80	1841.80	330.61
Irradiation	2014.80	1627.90	1731.35	89.41
Elevation	1653.00	2.00	137.16	343.14

The data collection on input and output factors of 32 locations are collected, as can be seen in Table A1 (Appendix A). According to the results presented in Table 7 of the journal, the DEA analysis shows that a total of 11 DMUs have attained perfect efficiency scores of 1. This suggests that these DMUs are operating at the highest level of efficiency possible given the inputs and outputs used in the analysis, which are Jawa Barat (DMU-09), Jawa Timur (DMU-11), Lampung (DMU-16), Maluku (DMU-17), Maluku Utara (DMU-18), Nusa Tenggara Barat (DMU-19), Nusa Tenggara Timur (DMU-20), Papua (DMU-21), Riau (DMU-23), Sulawesi Selatan (DMU-25), and Sulawesi Utara (DMU-28). In the second step, 11 DMUs are chosen for analysis because they are deemed the most promising locations for solar projects.

Table 7. The DEA score for efficiency.

No.	Location	DMU	CCR-I	BCC-I	SBM-I-C	EBM-I-C
1	Aceh	DMU-01	0.8847	0.9352	0.8303	0.8831
2	Bali	DMU-02	0.9918	0.9997	0.8715	0.9476
3	Bangka Belitung	DMU-03	0.8708	0.9552	0.8210	0.8648
4	Banten	DMU-04	0.9120	0.9908	0.8828	0.9042
5	Bengkulu	DMU-05	0.8812	0.9746	0.7863	0.8480
6	Gorontalo	DMU-06	1.0000	1.0000	1.0000	0.9948
7	Jakarta	DMU-07	0.9946	1.0000	0.9512	0.9798
8	Jambi	DMU-08	0.9394	0.9742	0.9011	0.9387
9	Jawa Barat	DMU-09	1.0000	1.0000	1.0000	1.0000
10	Jawa Tengah	DMU-10	0.9648	0.9932	0.9250	0.9554

Table 7. *Cont.*

No.	Location	DMU	CCR-I	BCC-I	SBM-I-C	EBM-I-C
11	Jawa Timur	DMU-11	1.0000	1.0000	1.0000	1.0000
12	Kalimantan Barat	DMU-12	0.9167	0.9527	0.8824	0.9153
13	Kalimantan Selatan	DMU-13	0.8973	0.9576	0.8452	0.8934
14	Kalimantan Tengah	DMU-14	0.9024	0.9499	0.8466	0.8941
15	Kalimantan Timur	DMU-15	0.8731	0.9662	0.8194	0.8656
16	Lampung	DMU-16	1.0000	1.0000	1.0000	1.0000
17	Maluku	DMU-17	1.0000	1.0000	1.0000	1.0000
18	Maluku Utara	DMU-18	1.0000	1.0000	1.0000	1.0000
19	Nusa Tenggara Barat	DMU-19	1.0000	1.0000	1.0000	1.0000
20	Nusa Tenggara Timur	DMU-20	1.0000	1.0000	1.0000	1.0000
21	Papua	DMU-21	1.0000	1.0000	1.0000	1.0000
22	Papua Barat	DMU-22	0.8862	0.9705	0.8350	0.8795
23	Riau	DMU-23	1.0000	1.0000	1.0000	1.0000
24	Sulawesi Barat	DMU-24	0.9482	0.9938	0.9237	0.9450
25	Sulawesi Selatan	DMU-25	1.0000	1.0000	1.0000	1.0000
26	Sulawesi Tengah	DMU-26	0.9952	0.9963	0.9815	0.9910
27	Sulawesi Tenggara	DMU-27	0.9778	0.9924	0.9487	0.9694
28	Sulawesi Utara	DMU-28	1.0000	1.0000	1.0000	1.0000
29	Sumatera Barat	DMU-29	0.8653	0.9603	0.7847	0.8447
30	Sumatera Selatan	DMU-30	0.8871	0.9835	0.8602	0.8816
31	Sumatera Utara	DMU-31	0.9004	0.9768	0.8610	0.8928
32	Yogyakarta	DMU-32	0.9762	0.9811	0.9520	0.9718

4.2. Rank the Remaining Locations Using F-AHP and F-MARCOS Values

In the second part of the study, F-AHP and F-MARCOS models are used to conduct additional analysis and rank the locations that were given efficiency scores of 1. F-AHP is utilized to assign relative importance to criteria, and F-MARCOS is then used to order the rank of potential sites. The criteria and their performance grade are assessed based on expert judgment.

4.2.1. Weighting the Criteria with F-AHP

In the process of using F-AHP, relative preference weights for each criterion are calculated. This involves dividing the criteria into categories, such as technical, economic, social, and environmental, and evaluating the relative importance of each criterion within each category. In order to calculate the consistency ratio and relative weights (eigenvectors) of the main factors, the assessment criteria are usually written down in depth in a table, such as Table 8. This table can help illustrate the steps involved in calculating the consistency ratio and relative weight of each factor. Overall, using F-AHP can help decision-makers consider various factors in the site selection process and make more informed decisions regarding the location of solar power plants or other developments. It makes evaluating the relative importance of different criteria and can help to ensure that decisions are made consistently and transparently.

The integrated fuzzy comparison matrix of F-AHP is shown in Table A3 (Appendix A). Table 9 and Figure 4 present the results of the F-AHP analysis. Based on the information provided, it can be seen that the top three impact criteria identified through the F-AHP analysis are “Facilitating factors,” “Benefits of conserving energy,” and “Terms of network accessibility.” These criteria are particularly important in certain decisions, such as site selection for solar power plants or the development of energy conservation programs. It is important to note that the specific criteria and their relative importance depend on the specific context of the decision or project and may vary depending on the decision maker’s goals and objectives. F-AHP helps decision-makers to consider multiple factors in the decision-making process and make more informed decisions based on a comprehensive evaluation of the relative importance of various criteria.

Table 8. The criteria and their respective definitions.

Main Criteria	Criteria	Definition
C1. Technical	C11. Assistance and guidance with technical matters	Assistance from local or worldwide experts to obtain reliable and available data if solar facilities are to be developed.
	C12. Geology	Processes that shape and alter the earth's surface, including its structure and composition
	C13. Availability of skilled workers	Installers, technicians, and other personnel with sufficient training and experience in the field of solar energy
C2. Economic	C21. Consumption of electricity	A regional breakdown of the amount of energy used in each area
	C22. Costs	Operating and maintenance expenses
	C23. Terms of network accessibility	Proximity to existing power transmission lines
	C24. Proximity to public transportation	Measuring the distance from a nearby road to various potential locations
	C25. Proximity to residential areas	Distance between the population centers (cities or towns) and the many potential sites
C3. Social	C31. Local residents attitude	The perceptions of local residents toward solar power projects
	C32. Rules and regulations of the government	Affectation of legislation and regulations on solar energy system development
	C33. Land acquisition	Maximum land available for solar installations is subject to government approval and discussion with property owners
	C34. Facilitating factors	Depending on local conventions, a political or local commitment to encouraging solar installations, such as feed-in tariffs, attractive financing, tax savings, or other subsidies
C4. Environmental	C41. Impact of wildlife and endangered species	The effects of solar power facilities on animal habitats and critical species
	C42. Noxious pollutant emission	During the production and collection of photovoltaic (PV) panels, there is a negative impact on metropolitan areas from the use of hazardous chemicals
	C43. Benefits of conserving energy	The indicator of energy-saving advantages refers to the beneficial environmental consequences that result from the operation of the project

Table 9. The relative significant fuzzy weights of F-AHP.

Criteria	Fuzzy Geometric Mean			Triangular Fuzzy Weights			Significant Level
C11. Assistance and guidance with technical matters	0.5597	0.6841	0.8652	0.0268	0.0445	0.0768	0.0436
C12. Geology	0.5907	0.7758	1.0326	0.0282	0.0505	0.0916	0.0502
C13. Availability of skilled workers	0.4982	0.6889	0.9640	0.0238	0.0448	0.0855	0.0454
C21. Consumption of electricity	0.5767	0.8094	1.1322	0.0276	0.0527	0.1005	0.0532
C22. Costs	0.7305	1.0048	1.3692	0.0349	0.0654	0.1215	0.0653
C23. Terms of network accessibility	0.9881	1.3157	1.7447	0.0472	0.0856	0.1548	0.0847
C24. Proximity to public transportation	0.7772	1.0612	1.4230	0.0372	0.0691	0.1263	0.0685
C25. Proximity to residential areas	0.7053	0.9772	1.2930	0.0337	0.0636	0.1147	0.0625
C31. Local residents attitude	0.7819	1.0884	1.4797	0.0374	0.0708	0.1313	0.0706
C32. Rules and regulations of the government	0.9143	1.2398	1.6709	0.0437	0.0807	0.1482	0.0803
C33. Land acquisition	0.6522	0.8775	1.2273	0.0312	0.0571	0.1089	0.0581
C34. Facilitating factors	0.9923	1.3911	1.8910	0.0474	0.0905	0.1678	0.0901
C41. Impact of wildlife and endangered species	0.7644	1.0565	1.4792	0.0365	0.0688	0.1312	0.0697
C42. Noxious pollutant emission	0.7754	1.0670	1.5009	0.0371	0.0694	0.1332	0.0706
C43. Benefits of conserving energy	0.9641	1.3276	1.8434	0.0461	0.0864	0.1635	0.0872

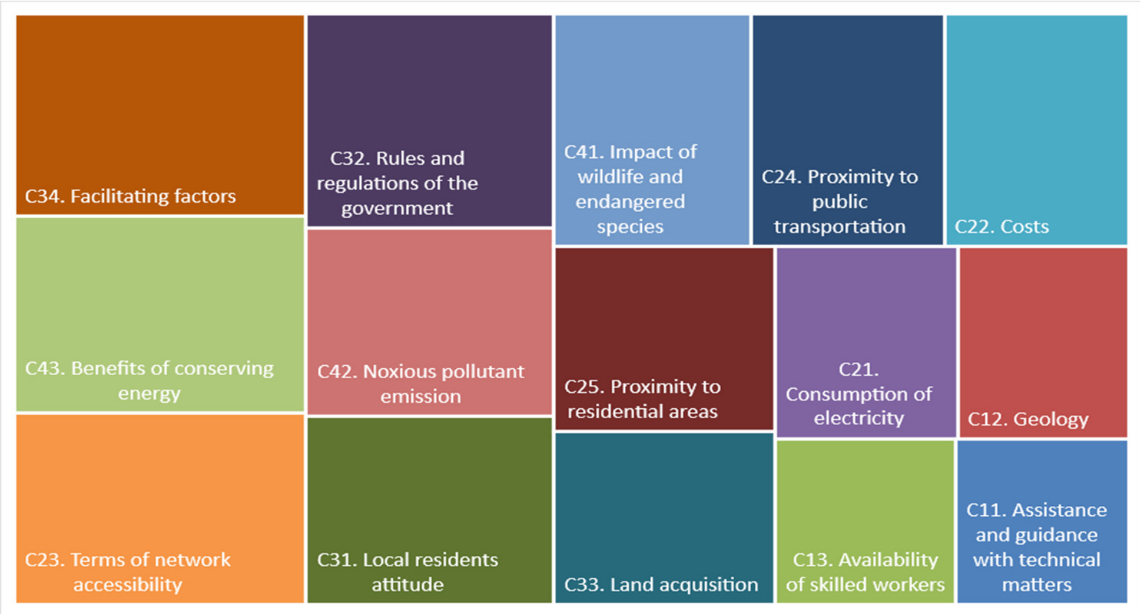

Figure 4. The significant level of criteria of F-AHP.

4.2.2. Ranking the Locations with F-MARCOS

The integrated normalized fuzzy decision matrix of F-MARCOS is shown in Table A3 (Appendix A). The F-MARCOS model has been used to evaluate the efficiency ranking of 11 different locations in Indonesia: Jawa Barat (DMU-09), Jawa Timur (DMU-11), Lampung (DMU-16), Maluku (DMU-17), Maluku Utara (DMU-18), Nusa Tenggara Barat (DMU-19), Nusa Tenggara Timur (DMU-20), Papua (DMU-21), Riau (DMU-23), Sulawesi Selatan (DMU-25), and Sulawesi Utara (DMU-28). The decision hierarchy tree for selecting solar power plant locations is depicted in Figure 5. The integrated matrix and linguistic matrix calculations of the experts' assessments can be seen in Table 10. The utility function and the final ranking of locations are shown in Table 11. Based on these results, the top three ranked locations are {DMU-09, DMU-20, DMU-23}, which occupy the first, second, and third positions with utility function values of 0.8272, 0.8211, and 0.8201, respectively. These locations are considered suitable for solar power generation based on the factors evaluated by the MARCOS fuzzy model. Figure 6 displays the final location ranking from the MARCOS fuzzy model. It is important to note that the ranking and utility function scores will depend on the attributes and criteria considered in the F-MARCOS analysis and the relative importance given to each attribute. F-MARCOS helps decision makers to consider various factors in the site selection process and make more informed decisions based on a comprehensive evaluation of the relative suitability of various sites.

In order to validate the location ranking, four different fuzzy MCDM models are considered, which are the fuzzy multi-attributive border approximation area comparison (fuzzy MABAC) [52], the fuzzy weighted aggregated sum product assessment (fuzzy WASPAS) [53], the fuzzy combined compromise solution (fuzzy CoCoSo) [54], and the fuzzy simple additive weighting (fuzzy SAW) [55]. During the comparative analysis, the same weight of criteria is used, and the results are provided in Table 12 and Figure 7. The findings show that there is no significant difference in the top three rankings of the solar location (Jawa Barat, Nusa Tenggara Timur, Riau). Hence, the proposed model is validated and applicable.

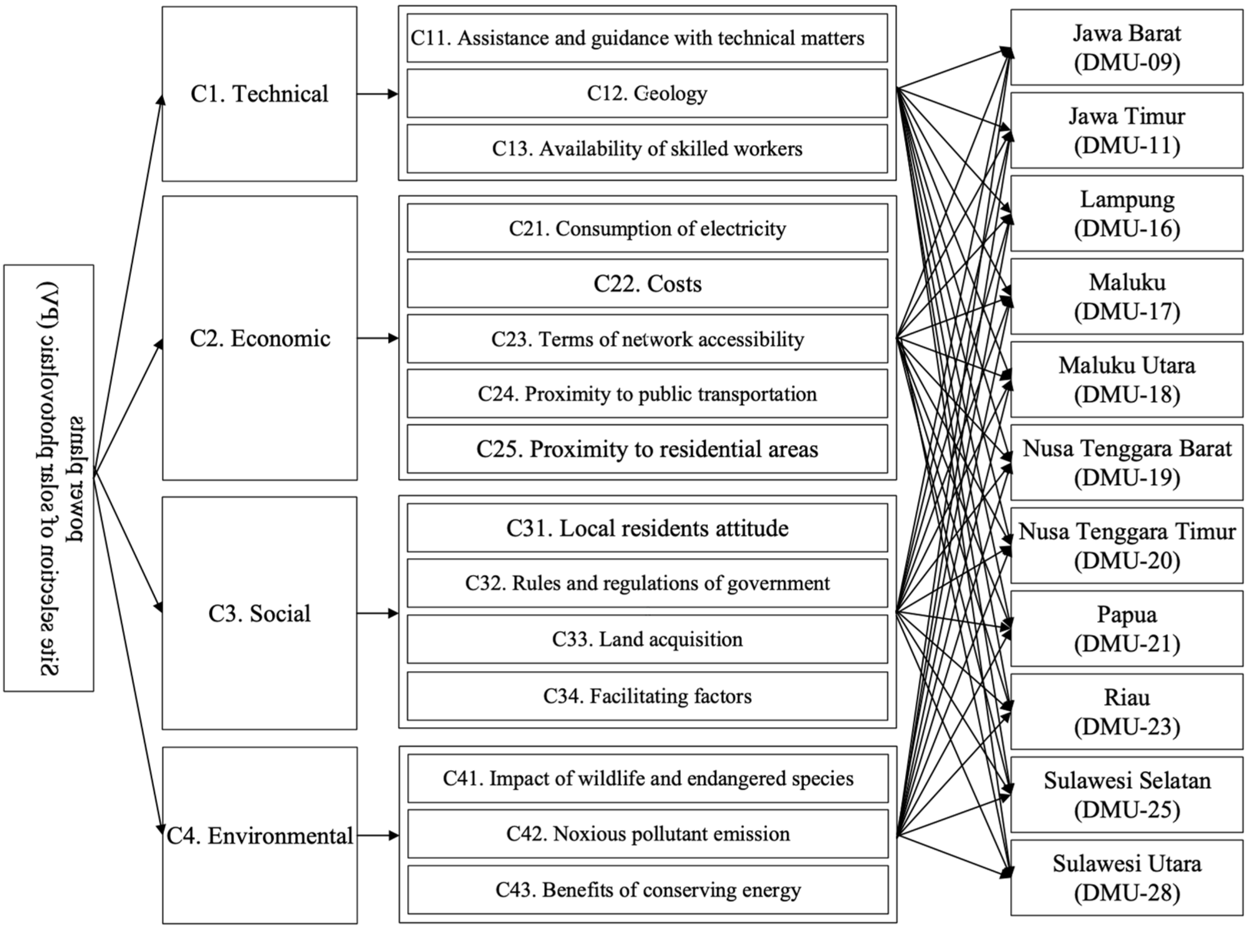

Figure 5. The hierarchy tree for selecting solar PV power plants.

Table 10. Utility degree and fuzzy matrix of $\tilde{\tilde{T}}_i$.

Location	Fuzzy $\tilde{S}_i$			Fuzzy $\tilde{\tilde{K}}_i^-$			Fuzzy $\tilde{\tilde{K}}_i^+$			Fuzzy $\tilde{T}_i$		
	l	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*
A (AI)	0.1355	0.2521	0.4699									
Jawa Barat	0.2750	0.6254	1.3822	0.5852	2.4804	10.2012	0.1482	0.6254	2.5650	0.7334	3.1058	12.7662
Jawa Timur	0.2046	0.5501	1.3959	0.4354	2.1816	10.3025	0.1103	0.5501	2.5904	0.5457	2.7317	12.8929
Lampung	0.2227	0.5099	1.3167	0.4739	2.0224	9.7180	0.1200	0.5099	2.4435	0.5939	2.5324	12.1615
Maluku	0.2138	0.5683	1.3116	0.4549	2.2538	9.6805	0.1152	0.5683	2.4341	0.5701	2.8220	12.1146
Maluku Utara	0.2510	0.5878	1.3421	0.5341	2.3313	9.9051	0.1353	0.5878	2.4905	0.6693	2.9191	12.3956
Nusa Tenggara Barat	0.2084	0.5742	1.4113	0.4435	2.2773	10.4162	0.1123	0.5742	2.6190	0.5558	2.8515	13.0352
Nusa Tenggara Timur	0.2591	0.6169	1.3956	0.5513	2.4466	10.2999	0.1396	0.6169	2.5898	0.6909	3.0634	12.8897
Papua	0.2194	0.5227	1.4009	0.4668	2.0731	10.3394	0.1182	0.5227	2.5997	0.5850	2.5958	12.9391
Riau	0.2584	0.6034	1.4232	0.5499	2.3931	10.5042	0.1393	0.6034	2.6412	0.6892	2.9965	13.1454
Sulawesi Selatan	0.2113	0.5828	1.3383	0.4496	2.3113	9.8774	0.1139	0.5828	2.4836	0.5635	2.8941	12.3609
Sulawesi Utara	0.2785	0.6266	1.3467	0.5925	2.4851	9.9393	0.1501	0.6266	2.4991	0.7426	3.1117	12.4384
A (ID)	0.5389	1.0000	1.8558							df_{crisp} = 4.3204		

Table 11. Utility functions and final ranking of locations.

Location	Fuzzy $f\left(\tilde{K}_i^-\right)$			Fuzzy $f\left(\tilde{K}_i^+\right)$			K_i^-	K_i^+	$f(K_i^-)$	$f(K_i^+)$	$f(K_i)$	Rank
	l	m	u	l	m	u						
Jawa Barat	0.0343	0.1448	0.5937	0.1354	0.5741	2.3612	3.4513	0.8691	0.2012	0.7988	0.8272	1
Jawa Timur	0.0255	0.1273	0.5996	0.1008	0.5050	2.3846	3.2441	0.8168	0.1891	0.7509	0.7225	8
Lampung	0.0278	0.1180	0.5656	0.1097	0.4681	2.2493	3.0469	0.7672	0.1776	0.7052	0.6305	11
Maluku	0.0267	0.1315	0.5634	0.1053	0.5216	2.2406	3.1917	0.8037	0.1860	0.7388	0.6974	9
Maluku Utara	0.0313	0.1361	0.5765	0.1236	0.5396	2.2926	3.2940	0.8295	0.1920	0.7624	0.7470	6
Nusa Tenggara Barat	0.0260	0.1329	0.6062	0.1027	0.5271	2.4109	3.3281	0.8380	0.1940	0.7703	0.7639	5
Nusa Tenggara Timur	0.0323	0.1428	0.5994	0.1276	0.5663	2.3840	3.4396	0.8662	0.2005	0.7961	0.8211	2
Papua	0.0274	0.1210	0.6017	0.1080	0.4798	2.3931	3.1831	0.8015	0.1855	0.7368	0.6932	10
Riau	0.0322	0.1397	0.6113	0.1273	0.5539	2.4313	3.4377	0.8657	0.2004	0.7957	0.8201	3
Sulawesi Selatan	0.0264	0.1349	0.5748	0.1041	0.5350	2.2862	3.2620	0.8214	0.1901	0.7550	0.7313	7
Sulawesi Utara	0.0347	0.1450	0.5784	0.1371	0.5752	2.3005	3.4120	0.8593	0.1989	0.7897	0.8068	4

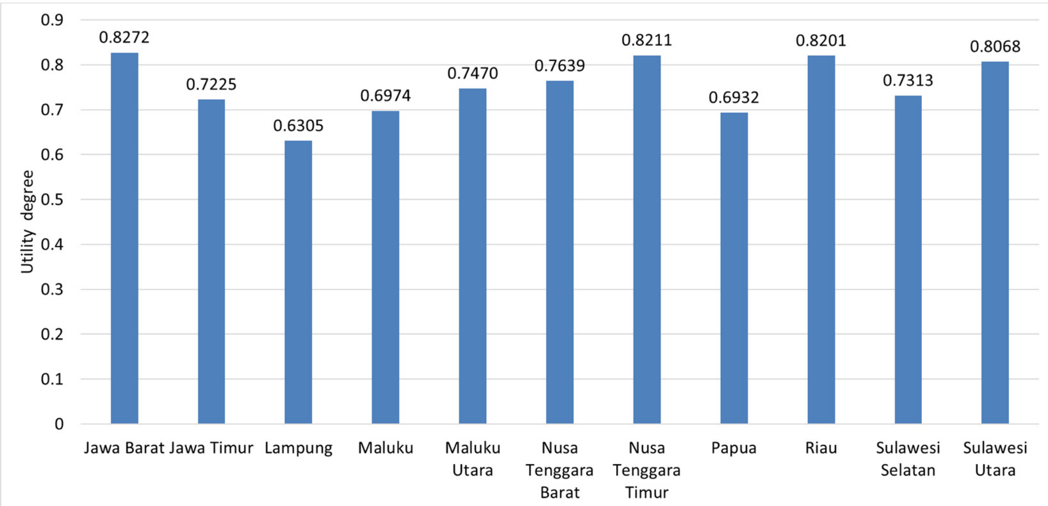

Figure 6. The final location ranking.

Table 12. Comparative analysis of MCDM methods.

Location	Fuzzy AHP and Fuzzy MARCOS		Fuzzy AHP and Fuzzy MABAC		Fuzzy AHP and Fuzzy WASPAS		Fuzzy AHP and Fuzzy CoCoSo		Fuzzy AHP and Fuzzy SAW	
	Value	Rank	Value	Rank	Value	Rank	Value	Rank	Value	Rank
Jawa Barat	0.8272	1	0.0848	2	0.5217	1	2.9004	3	0.6426	1
Jawa Timur	0.7225	8	−0.0279	8	0.4570	8	2.6586	8	0.5508	9
Lampung	0.6305	11	0.0401	6	0.4719	7	2.8513	4	0.5535	8
Maluku	0.6974	9	−0.0426	9	0.4491	10	2.6022	9	0.5355	11
Maluku Utara	0.7470	6	0.0631	4	0.5039	5	2.9111	2	0.6042	5
Nusa Tenggara Barat	0.7639	5	−0.0501	10	0.4550	9	2.5418	10	0.5570	7
Nusa Tenggara Timur	0.8211	2	0.1164	1	0.5199	2	3.0370	1	0.6239	4
Papua	0.6932	10	0.0230	7	0.4732	6	2.8024	6	0.5599	6
Riau	0.8201	3	0.0667	3	0.5069	4	2.8346	5	0.6256	3
Sulawesi Selatan	0.7313	7	−0.0584	11	0.4299	11	2.3403	11	0.5418	10
Sulawesi Utara	0.8068	4	0.0442	5	0.5071	3	2.7714	7	0.6390	2

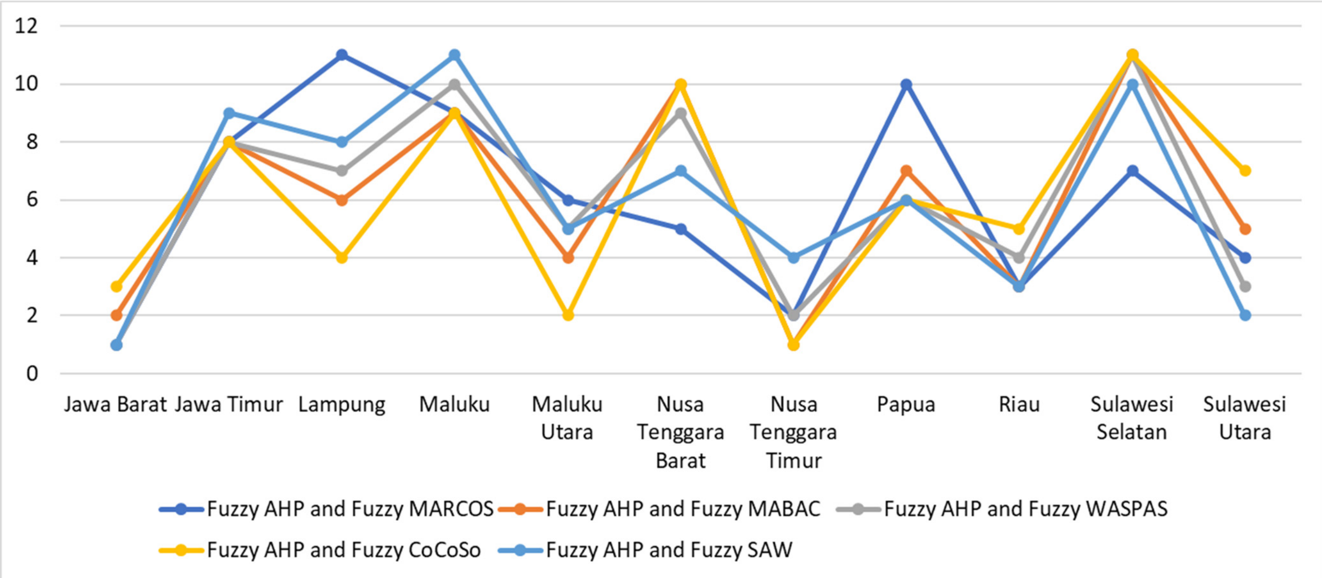

Figure 7. Comparison of proposed model with other MCDM methods.

5. Conclusions

This study identifies the most suitable locations for solar power plants in Indonesia. This study uses data envelopment analysis (DEA) to identify areas of high efficiency based on measured inputs and outputs. These areas were further evaluated using F-AHP to weigh the evaluation criteria and F-MARCOS to rank the provinces. Based on the analysis, this study identified 32 provinces in Indonesia that are excellent for solar power generation. These provinces have favorable conditions for solar power generation, such as high levels of solar radiation, availability of suitable land, and adequate infrastructure. DEA, F-AHP, and F-MARCOS allow for a comprehensive evaluation of the relative suitability of various locations for solar power generation based on several criteria. The most significant findings and achievements of this research are as follows:

- The potential for solar deployment in Indonesia was evaluated based on 23 criteria, and suitable locations were identified using a novel combination of DEA, F-AHP, and F-MARCOS techniques.
- According to F-AHP, the three most important elements were "Facilitating factors," "Benefits of conserving energy," and "Terms of network accessibility." Figure 4 displays the results of applying this technique to calculate the weights.
- Based on the final F-MARCOS ranking, the three best provinces in Indonesia to install solar power plants are Jawa Barat, Nusa Tenggara Timur, and Riau.

Future researchers are recommended to continue exploring the potential of renewable energy sources in Indonesia and other countries. Renewable energy sources such as solar, wind, and hydropower have the potential to play an important role in meeting the growing demand for energy while reducing the environmental impact of energy production. In addition to these established renewable energy sources, researchers are encouraged to explore the potential of newer technologies such as wave, geothermal, tidal, and hybrid systems (e.g., solar-wind and solar-biomass PV) in Indonesia and other countries. These technologies have the potential to provide additional sources of clean, renewable energy and can help diversify the energy mix. Assessing the ability to generate diverse renewable energy sources is also an important issue in the energy market, as decision-makers need to weigh the relative costs and benefits of different technologies to determine the best energy source. By continuing to research and develop new renewable energy technologies, researchers are improving the sustainability of energy systems and supporting the transition to a more renewable energy future.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Data of input and output of the DEA model.

No.	Location	DMU	X1	X2	X3	X4	X5	Y1	Y2	Y3
1	Aceh	DMU-01	26.81	1.50	89.28	3648.40	1010.70	1670.70	1686.30	3
2	Bali	DMU-02	27.31	3.10	81.68	2992.80	1011.30	2658.00	1799.45	4
3	Bangka Belitung	DMU-03	26.45	1.75	89.32	3012.90	1011.40	1646.50	1653.45	6
4	Banten	DMU-04	27.80	1.77	81.49	2290.50	1010.60	1710.50	1679.00	14
5	Bengkulu	DMU-05	27.01	2.52	83.59	3691.80	1011.00	2327.40	1708.20	12
6	Gorontalo	DMU-06	27.24	1.53	85.50	2285.50	1011.00	1931.40	1803.10	33
7	Jakarta	DMU-07	28.40	1.48	77.18	2394.60	1011.00	1532.00	1726.45	4
8	Jambi	DMU-08	27.01	0.72	86.23	3218.40	1011.40	1574.20	1627.90	24
9	Jawa Barat	DMU-09	26.06	1.09	84.16	3786.60	924.10	1862.40	1737.40	207
10	Jawa Tengah	DMU-10	28.12	1.99	81.06	2476.80	1011.90	2274.90	1806.75	6
11	Jawa Timur	DMU-11	24.10	1.93	79.53	2447.80	1011.80	2060.70	1879.75	590
12	Kalimantan Barat	DMU-12	26.80	1.26	87.70	3281.20	1011.80	1788.30	1682.65	15
13	Kalimantan Selatan	DMU-13	27.07	1.42	87.08	2996.20	1013.10	1418.70	1657.10	2
14	Kalimantan Tengah	DMU-14	26.96	1.29	87.02	4132.20	1013.90	1799.40	1679.00	10
15	Kalimantan Timur	DMU-15	27.60	1.89	83.52	2902.00	1012.90	1203.80	1668.05	3
16	Lampung	DMU-16	26.84	1.12	84.18	2063.50	1012.10	1810.60	1708.20	71
17	Maluku	DMU-17	26.58	0.97	89.08	2695.90	1012.40	1960.20	1679.00	10
18	Maluku Utara	DMU-18	26.35	0.67	90.59	3928.20	1013.00	1724.20	1737.40	130
19	Nusa Tenggara Barat	DMU-19	27.26	2.58	80.25	1770.40	1014.20	2687.60	1941.80	10
20	Nusa Tenggara Timur	DMU-20	19.92	2.02	87.55	4493.40	1011.00	2062.10	2014.80	1070
21	Papua	DMU-21	19.72	2.38	83.30	1933.50	1011.10	1751.60	1631.55	1653
22	Papua Barat	DMU-22	27.52	1.81	82.66	2891.60	1011.50	1433.00	1679.00	3
23	Riau	DMU-23	26.75	0.35	83.44	3072.20	1010.50	1502.90	1649.80	15
24	Sulawesi Barat	DMU-24	27.59	1.72	81.79	2268.10	1012.50	2122.00	1708.20	29
25	Sulawesi Selatan	DMU-25	26.98	1.16	84.00	4448.20	1013.10	2178.60	1777.55	14
26	Sulawesi Tengah	DMU-26	27.25	0.97	85.56	2372.80	1011.90	1653.00	1700.90	10
27	Sulawesi Tenggara	DMU-27	28.04	1.51	80.61	2420.80	1012.80	1831.30	1755.65	14
28	Sulawesi Utara	DMU-28	23.15	1.24	87.69	2220.40	1012.30	1518.50	1755.65	204
29	Sumatera Barat	DMU-29	26.70	1.83	85.02	4878.50	1010.90	2007.20	1646.15	6
30	Sumatera Selatan	DMU-30	27.21	2.13	82.76	2297.90	1011.00	1716.60	1689.95	10
31	Sumatera Utara	DMU-31	27.25	1.72	84.22	2543.40	1010.60	1623.20	1671.70	25
32	Yogyakarta	DMU-32	26.37	2.04	82.40	2456.70	1014.90	1896.20	1861.50	182

Table A2. The integrated fuzzy comparison matrix of F-AHP.

Criteria		**C11**			**C12**			**C13**			**C21**	
C11	1.0000	1.0000	1.0000	0.8920	1.1107	1.4241	0.4663	0.5776	0.7496	0.2245	0.2716	0.3425
C12	0.7022	0.9003	1.1211	1.0000	1.0000	1.0000	0.6507	0.8116	1.0532	0.6507	0.8116	1.0532
C13	1.3341	1.7313	2.1446	0.9494	1.2321	1.5368	1.0000	1.0000	1.0000	0.6711	1.0371	1.4902
C21	2.9196	3.6814	4.4541	0.9494	1.2321	1.5368	0.6711	0.9642	1.4902	1.0000	1.0000	1.0000
C22	0.9349	1.2099	1.5029	0.9494	1.2321	1.5368	0.9883	1.4788	2.2442	0.7017	1.0000	1.5368
C23	0.7242	0.9338	1.1722	0.6654	0.8610	1.0770	0.7708	1.1534	1.7826	0.8060	1.1962	1.8384
C24	0.7242	0.9338	1.1722	0.6654	0.8610	1.0770	0.7708	1.1534	1.7826	0.8060	1.1962	1.8384
C25	0.9494	1.2321	1.5368	0.9349	1.2099	1.5029	1.8206	2.7629	3.8043	2.9612	4.0774	5.1412
C31	2.8552	3.6149	4.3860	1.4963	2.0180	2.6586	1.0481	1.4368	1.9871	1.0334	1.5337	2.3144
C32	0.9521	1.2372	1.5468	2.3868	3.1469	4.2117	1.2671	1.8421	2.6531	1.0334	1.5337	2.3144
C33	2.0009	2.5262	3.0737	0.5296	0.6935	1.0118	1.0184	1.3797	1.8541	1.0334	1.5337	2.3144
C34	0.9669	1.2599	1.5817	1.3580	2.1161	3.0837	1.8206	2.7629	3.8043	1.8206	2.7629	3.8043
C41	0.9669	1.2599	1.5817	1.3580	2.1161	3.0837	1.8206	2.7629	3.8043	0.9330	1.3636	1.9537
C42	0.9669	1.2599	1.5817	0.7490	1.1076	1.6632	1.8206	2.7629	3.8043	0.9330	1.3636	1.9537
C43	1.4022	1.7654	2.1540	0.7490	1.1076	1.6632	0.9756	1.4142	2.0148	0.6711	0.9642	1.4902
Criteria		C22			C23			C24			C25	
C11	0.6654	0.8265	1.0696	0.8531	1.0709	1.3808	0.8531	1.0709	1.3808	0.6507	0.8116	1.0532
C12	0.6507	0.8116	1.0532	0.9285	1.1614	1.5029	0.9285	1.1614	1.5029	0.6654	0.8265	1.0696
C13	0.4456	0.6762	1.0118	0.5610	0.8670	1.2973	0.5610	0.8670	1.2973	0.2629	0.3619	0.5493
C21	0.6507	1.0000	1.4251	0.5439	0.8360	1.2407	0.5439	0.8360	1.2407	0.1945	0.2453	0.3377
C22	1.0000	1.0000	1.0000	0.5330	0.7548	1.0960	0.5551	0.7768	1.1207	1.4200	1.8684	2.3144
C23	0.9124	1.3249	1.8760	1.0000	1.0000	1.0000	1.0718	1.5436	1.9977	0.7222	1.0371	1.4933
C24	0.8923	1.2873	1.8015	0.5006	0.6478	0.9330	1.0000	1.0000	1.0000	1.1161	1.4902	2.0123
C25	0.4321	0.5352	0.7042	0.6697	0.9642	1.3847	0.4969	0.6711	0.8960	1.0000	1.0000	1.0000
C31	0.4321	0.5352	0.7042	0.6697	0.9642	1.3847	0.9479	1.3259	1.6843	0.7832	1.0718	1.6174
C32	0.7995	1.1207	1.6141	0.4693	0.6084	0.7687	0.7017	1.0098	1.4758	1.4614	2.0939	3.0539
C33	0.8414	1.2011	1.8015	0.4693	0.6084	0.7687	0.5318	0.6881	1.0021	0.7832	1.0718	1.6174
C34	1.3195	2.0320	2.8772	0.4621	0.5974	0.7517	0.5318	0.6881	1.0021	1.4614	2.0939	3.0539
C41	0.6418	0.9103	1.3741	0.5345	0.7146	0.9502	0.5318	0.6881	1.0021	0.5574	0.7277	1.0740
C42	0.6418	0.9103	1.3741	0.3335	0.4234	0.5676	0.8394	1.1390	1.6174	0.7832	1.0718	1.6174
C43	1.2873	1.8541	2.5832	0.4512	0.5949	0.7628	0.8394	1.1390	1.6174	1.4614	2.0939	3.0539
Criteria		C31			C32			C33			C34	
C11	0.2280	0.2766	0.3502	0.6465	0.8083	1.0503	0.3253	0.3959	0.4998	0.6322	0.7937	1.0342
C12	0.3761	0.4955	0.6683	0.2374	0.3178	0.4190	0.9883	1.4420	1.8882	0.3243	0.4726	0.7364
C13	0.5032	0.6960	0.9541	0.3769	0.5428	0.7892	0.5394	0.7248	0.9819	0.2629	0.3619	0.5493
C21	0.4321	0.6520	0.9677	0.4321	0.6520	0.9677	0.4321	0.6520	0.9677	0.2629	0.3619	0.5493
C22	1.4200	1.8684	2.3144	0.6196	0.8923	1.2508	0.5551	0.8326	1.1885	0.3476	0.4921	0.7579
C23	0.7222	1.0371	1.4933	1.3010	1.6438	2.1308	1.3010	1.6438	2.1308	1.3303	1.6740	2.1639
C24	0.5937	0.7542	1.0549	0.6776	0.9903	1.4251	0.9979	1.4532	1.8805	0.9979	1.4532	1.8805
C25	0.6183	0.9330	1.2769	0.3274	0.4776	0.6843	0.6183	0.9330	1.2769	0.3274	0.4776	0.6843
C31	1.0000	1.0000	1.0000	0.6183	0.9330	1.2769	0.3274	0.4776	0.6843	0.6183	0.9330	1.2769
C32	0.7832	1.0718	1.6174	1.0000	1.0000	1.0000	1.0000	1.3830	1.8303	0.6084	0.8569	1.1548
C33	1.4614	2.0939	3.0539	0.5464	0.7231	1.0000	1.0000	1.0000	1.0000	0.2288	0.3026	0.4592
C34	0.7832	1.0718	1.6174	0.8659	1.1671	1.6438	2.1778	3.3051	4.3700	1.0000	1.0000	1.0000
C41	0.6711	0.9642	1.4902	0.5464	0.7231	1.0000	1.8206	2.7629	3.8043	1.0334	1.5337	2.3144
C42	0.6711	0.9642	1.4902	0.5464	0.7231	1.0000	1.0334	1.5337	2.3144	0.7017	1.0000	1.5368
C43	0.9883	1.4788	2.2442	1.1598	1.5332	2.0927	1.0334	1.5337	2.3144	0.5296	0.6790	0.9622
Criteria		C41			C42			C43				
C11	0.6322	0.7937	1.0342	0.6322	0.7937	1.0342	0.4642	0.5665	0.7132			
C12	0.3243	0.4726	0.7364	0.6012	0.9029	1.3351	0.6012	0.9029	1.3351			
C13	0.2629	0.3619	0.5493	0.2629	0.3619	0.5493	0.4963	0.7071	1.0250			
C21	0.5119	0.7334	1.0718	0.5119	0.7334	1.0718	0.6711	1.0371	1.4902			
C22	0.7277	1.0986	1.5582	0.7277	1.0986	1.5582	0.3871	0.5394	0.7768			
C23	1.0524	1.3994	1.8708	1.7617	2.3618	2.9987	1.3110	1.6808	2.2162			
C24	0.9979	1.4532	1.8805	0.6183	0.8780	1.1914	0.6183	0.8780	1.1914			
C25	0.9311	1.3741	1.7941	0.6183	0.9330	1.2769	0.3274	0.4776	0.6843			
C31	0.6711	1.0371	1.4902	0.6711	1.0371	1.4902	0.4456	0.6762	1.0118			
C32	1.0000	1.3830	1.8303	1.0000	1.3830	1.8303	0.4778	0.6522	0.8622			
C33	0.2629	0.3619	0.5493	0.4321	0.6520	0.9677	0.4321	0.6520	0.9677			
C34	0.4321	0.6520	0.9677	0.6507	1.0000	1.4251	1.0392	1.4727	1.8882			
C41	1.0000	1.0000	1.0000	0.2629	0.3619	0.5493	0.4321	0.6520	0.9677			
C42	1.8206	2.7629	3.8043	1.0000	1.0000	1.0000	0.2629	0.3619	0.5493			
C43	1.0334	1.5337	2.3144	1.8206	2.7629	3.8043	1.0000	1.0000	1.0000			

Table A3. The integrated normalized fuzzy decision matrix of F-MARCOS.

Location	**C11**			**C12**			**C13**			**C21**		
	l	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*
DMU-09	0.5603	0.7284	0.8401	0.1901	0.2050	0.2486	0.8521	1.0335	1.1144	0.8064	0.9780	1.0546
DMU-11	0.2922	0.4690	0.5746	0.5508	0.9963	1.0485	0.2126	0.3300	0.4956	0.2012	0.2012	0.3765
DMU-16	0.4618	0.6154	0.7466	0.3485	0.5796	0.6420	0.3655	0.4709	0.6502	0.3287	0.3459	0.5950
DMU-17	0.2777	0.5194	0.5556	0.7221	0.7997	1.1702	0.2649	0.2934	0.5489	0.1713	0.2507	0.2777
DMU-18	0.7290	0.8340	0.9780	0.2750	0.3425	0.4201	0.6186	0.7703	0.8813	0.4772	0.5854	0.7290
DMU-19	0.2945	0.4094	0.5654	0.6809	1.3061	1.3061	0.1622	0.3112	0.4326	0.1535	0.1535	0.2945
DMU-20	0.6262	0.7928	0.8770	0.3202	0.3732	0.5465	0.5677	0.6617	0.8377	0.3668	0.5372	0.6262
DMU-21	0.4736	0.5654	0.7409	0.4234	0.6809	0.7541	0.3112	0.5004	0.5974	0.2659	0.2945	0.4736
DMU-23	0.8340	0.9222	1.0815	0.1854	0.2174	0.2404	0.6186	0.7703	0.8813	0.1232	0.2134	0.3312
DMU-25	0.1447	0.1447	0.2593	0.6809	1.3061	1.3061	0.1622	0.3112	0.4326	0.1535	0.1535	0.2945
DMU-28	0.8626	1.0285	1.1090	0.2140	0.2366	0.3073	0.6893	0.8953	0.9900	0.8626	1.0285	1.1090
Location	C22			C23			C24			C25		
DMU-09	0.2896	0.3960	0.5277	0.4226	0.5824	0.7700	0.2511	0.2925	0.4000	0.2892	0.3955	0.5269
DMU-11	0.4976	0.9000	0.9472	0.2354	0.2478	0.4482	0.3900	0.5025	0.9089	0.4969	0.8987	0.9458
DMU-16	0.3148	0.5237	0.5800	0.3845	0.4405	0.7084	0.2973	0.3179	0.5288	0.3144	0.5229	0.5791
DMU-17	0.6523	0.7225	1.0572	0.2109	0.3087	0.3419	0.3521	0.6588	0.7296	0.6514	0.7215	1.0557
DMU-18	0.2485	0.3094	0.3795	0.5876	0.7208	0.8976	0.2193	0.2509	0.3125	0.2611	0.3089	0.4230
DMU-19	0.7662	1.1800	1.1800	0.1890	0.1890	0.3626	0.4468	0.7738	1.1916	0.6803	1.1783	1.4678
DMU-20	0.2893	0.3372	0.4938	0.4517	0.6614	0.7710	0.2307	0.2921	0.3405	0.3199	0.3367	0.6142
DMU-21	0.4269	0.6151	0.6813	0.3274	0.3626	0.5831	0.3235	0.4311	0.6212	0.4930	0.6142	1.1783
DMU-23	0.5469	0.8487	1.4699	0.1517	0.2628	0.4078	0.2193	0.2509	0.3125	0.2481	0.3255	0.3790
DMU-25	0.6151	1.1800	1.1800	0.1890	0.1890	0.2910	0.7055	1.2638	1.2638	0.6142	1.0638	1.1783
DMU-28	0.1933	0.2138	0.2777	0.8032	1.0432	1.1536	0.1649	0.1779	0.2121	0.1930	0.2135	0.2773
Location	C31			C32			C33			C34		
DMU-09	0.6609	0.7697	0.9342	0.3432	0.4573	0.6254	0.8521	1.0335	1.1144	0.8521	1.0335	1.1144
DMU-11	0.3846	0.4956	0.6725	0.1912	0.2012	0.3640	0.2021	0.2126	0.3846	0.2021	0.2126	0.3846
DMU-16	0.6079	0.6502	0.8738	0.3123	0.3459	0.5753	0.3300	0.3655	0.6079	0.3300	0.3655	0.6079
DMU-17	0.2934	0.5677	0.5871	0.1713	0.2507	0.2777	0.2498	0.3250	0.3476	0.1453	0.2373	0.2957
DMU-18	0.7703	0.7967	1.0335	0.4772	0.6927	0.7290	0.2649	0.4111	0.5489	0.4518	0.5542	0.7319
DMU-19	0.3112	0.4627	0.5974	0.1535	0.1535	0.2945	0.1796	0.1796	0.3328	0.2255	0.3136	0.5043
DMU-20	0.8521	1.0335	1.1144	0.8064	0.9780	1.0546	0.3250	0.5677	0.6279	0.2788	0.3658	0.5086
DMU-21	0.5004	0.6609	0.7829	0.2659	0.2945	0.4736	0.2911	0.3627	0.5346	0.2021	0.2498	0.4792
DMU-23	0.4792	0.5769	0.7448	0.4772	0.6927	0.7290	0.8813	0.9745	1.1428	0.8813	0.9745	1.1428
DMU-25	0.1529	0.1529	0.2740	0.1447	0.1447	0.2593	0.1302	0.1302	0.2255	0.2255	0.3136	0.5043
DMU-28	0.6893	0.8953	0.9900	0.8626	1.0285	1.1090	0.6893	0.8953	0.9900	0.2788	0.3658	0.5086
Location	C41			C42			C43					
DMU-09	0.3197	0.3447	0.4181	0.2211	0.2385	0.2892	0.7887	0.9185	1.1149			
DMU-11	0.7189	0.9263	1.6755	0.6407	1.1589	1.2197	0.4825	0.6326	0.8368			
DMU-16	0.5479	0.5861	0.9748	0.4054	0.6743	0.7468	0.7494	0.8300	1.0780			
DMU-17	0.6491	1.2143	1.3450	0.8400	0.9303	1.3613	0.4148	0.7494	0.7880			
DMU-18	0.4043	0.4625	0.5759	0.4887	0.8908	1.0928	0.6550	0.8035	0.9749			
DMU-19	0.7065	0.9823	1.5798	0.5185	0.6795	0.6795	0.3972	0.5522	0.7497			
DMU-20	0.5484	0.7316	1.0172	0.3725	0.4341	0.6358	0.7494	0.9997	1.0780			
DMU-21	0.7435	0.9192	1.7633	0.4157	0.5740	0.6358	0.6380	0.7887	0.9905			
DMU-23	0.4043	0.4625	0.5759	0.4490	0.5995	0.9303	0.6614	0.8735	0.9993			
DMU-25	0.7065	0.9823	1.5798	0.3203	0.3790	0.5223	0.8300	1.0169	1.1531			
DMU-28	0.3599	0.3979	0.5169	0.2489	0.2753	0.3575	0.6774	0.7896	0.9997			

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