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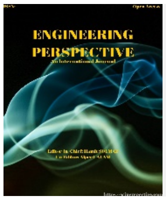

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Research Paper

Evaluating Biomass Energy Potential with Multi-Criteria Decision Methods: Insights for Policy Makers

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ABSTRACT

The global shift towards renewable and sustainable energy has accelerated in recent years due to the depletion of fossil fuels and their detrimental effects on the environment. Despite their environmental advantages, renewable energy technologies often require substantial investment, and the optimal siting of energy conversion facilities remains a critical challenge, particularly in ensuring cost-efficiency and environmental compatibility. Biomass based electricity production is a key contributor to sustainable energy transitions. This study develops a reliable decision-support framework for determining suitable locations for biomass power plants. Initially, an extensive literature review was conducted to identify and classify the evaluation criteria. Expert opinions from 21 professionals were then collected, and their judgments were tested for reliability using Kendall’s coefficient of concordance and statistical significance levels. The results confirmed a high degree of agreement among experts, providing robust weights for the criteria. These weights were subsequently applied in the TOPSIS and VIKOR methods to evaluate location alternatives. A comparison of the two approaches revealed strong consistency and methodological reliability. The findings demonstrate that integrating expert judgment validation with multi-criteria decision-making techniques provides a transparent and evidence-based tool for policy-makers in planning sustainable biomass energy investments.

Keywords: Biomass energy policy; Decision support for policymakers; Renewable energy investment; Site selection

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1. Introduction

1.1. Background on renewable and biomass energy

The global transition towards renewable and sustainable energy sources has intensified in recent decades, largely driven by the depletion of fossil fuel reserves and the severe environmental impacts of their combustion. According to the International Energy Agency renewable energy accounted for nearly 30% of global electricity generation in 2022, with biomass contributing approximately 6% of total renewable output. Biomass is considered a carbon-neutral energy source, as the CO_2 released during combustion is offset by the CO_2 absorbed during the feedstock’s growth cycle, thereby reducing net greenhouse gas emissions.

In addition to mitigating climate change, biomass energy plays a critical role in diversifying the energy portfolio, enhancing national energy security, and supporting circular economy principles by converting waste and residues into valuable energy. In the European Union, for instance, bioenergy (including solid biomass, biogas, and biofuels) represented over 55% of total renewable energy consumption in 2022 Turkey, with its abundant agricultural residues and forestry by-products, has significant potential for biomass-based electricity generation, aligning with its National Energy Plan and commitments under the Paris Agreement.

International frameworks such as the United Nations Sustainable Development Goal 7 (Affordable and Clean Energy) and the Paris Climate Agreement emphasize the urgency of deploying low-carbon energy systems, including biomass-based technologies. However, the optimal siting of biomass conversion facilities remains a crucial challenge, as it requires balancing cost-efficiency, environmental impact, and socio-economic benefits.

1.2. Background on renewable and biomass energy

Turkey possesses substantial biomass energy potential owing to its diverse agricultural production, rich forestry resources, and significant generation of municipal solid waste (MSW). Agricultural residues such as wheat straw, corn stalks, and pruning wastes, alongside livestock manure and the organic fraction of MSW, constitute a robust feedstock base for bioenergy generation. According to recent national assessments, the country's annual technical biomass potential is estimated at approximately 8-10 Mtoe, with considerable spatial variation across provinces. The western and central Anatolian regions, in particular, demonstrate favorable biomass availability, supported by both high resource density and logistical accessibility.

Governmental incentives, including the Renewable Energy Resources Support Scheme (YEKDEM), have fostered private sector investments in biomass-based power generation. Furthermore, Turkey's commitment to the Paris Agreement and its 2053 Net Zero Emissions target underscore the strategic importance of biomass in achieving low-carbon energy transition goals. Compared with other nations with similar agricultural and forestry profiles, such as Spain and Poland, Turkey's biomass potential remains underexploited, highlighting a significant opportunity for capacity expansion. This study aims to bridge the gap in spatially explicit decision-making tools for optimal biomass plant siting, integrating multi-criteria evaluation with regional resource assessments to inform both investors and policymakers.

1.3. Literature review on MCDM applications in biomass facility siting

The depletion of fossil fuels and the increasing environmental impacts of these fuels have led to a significant rise in the global demand for renewable and sustainable energy sources. In this context, biomass energy has attracted attention due to its potential to reduce carbon emissions, enhance energy independence, and support economic development, particularly in rural areas. Biomass power plants, which convert organic waste into energy, provide an environmentally friendly energy production model and are considered a critical component of sustainable energy production. However, in order for biomass energy to be utilized efficiently and effectively, these facilities must be located in suitable areas. Site selection is not only limited to economic factors but also holds critical importance in terms of environmental and social impacts, which directly affect the operability of the facilities. Therefore, this study comprehensively discusses the criteria that should be considered in the site selection process for biomass energy plants, along with a review of the existing literature and the methods employed.

Many studies have focused on the appropriate site selection for biofuel production from different biomass sources. [1] developed a model to assess the potential biofuel supply based on various biomass sources in the western United States and optimize the location of biorefineries. [2] presented a phased methodology combining GIS and transportation cost models to determine the optimal site for biofuel production in Michigan's Upper Peninsula. [3] focused on identifying suitable areas for the recovery of urban brownfields and sunflower-based biodiesel production in Pittsburgh. [4] investigated the optimal geographical locations for large-scale microalgae cultivation facilities in Western Australia. [5] analyzed the site selection process for large-scale microalgae cultivation in Chile. [6] used GIS to evaluate the potential of banana waste biomass for biofuel production in Ecuador and identified potential plant locations. [7] developed a biorefinery location model to identify suitable sites for bioethanol production in the United States. [8] assessed biorefinery site selection and biomass distribution in Texas and the United States, considering the impact of transportation infrastructure. [9] identified the optimal planting areas for biofuel production using Jatropha in Fars Province, Iran. [10] optimized the locations of biofuel conversion plants and assessed the feasibility of establishing new plants by analyzing the forest biomass supply chain in Queensland, Australia. [11] proposed the design of a microalgae-based biofuel supply chain with the goal of economic commercialization. [12] investigated the availability of forest product residues for biofuel production facilities in the Basilicata region and evaluated the environmental impact of biomass transportation.

Some studies have focused on the site selection of biogas plants. [13] designed an optimization model for biogas production using biomass waste from the palm oil industry in Malaysia. [14] developed a multi-criteria spatial decision support system to determine the most suitable locations for biogas plants producing biogas from dairy farm manure in Portugal. [15] focused on determining the spatial distribution of resources and potential biogas plant locations. [16] aimed to optimize the most profitable co-digestion mixtures for biogas production in Spain, considering geographical distribution and technical-economic parameters. [17] targeted the accurate planning of biogas plants in Spain's agro-silvo-pastoral systems under the effects of climate change. [18] developed a model to evaluate the potential for biogas production from livestock manure and rural household waste in Iran and identify suitable locations. [19] developed a model to minimize transportation distances and identify optimal locations for farm and centralized biogas plants. [20] proposed a design for biogas production plants in Sicily by evaluating the methanogenic potential of prickly pear biomass. [21] developed a GIS-based integrated model to assess the spatial and temporal availability of sustainable agricultural waste and determine optimal site selections for biogas plants. [22] included the identification of suitable locations for biogas plants by establishing strategic partnerships with raw material suppliers. [23] focused on identifying the most suitable site for a biogas plant in the Konya Closed Basin using GIS and MCDM.

Studies focusing on Biomass Power Plant and Supply Chain Optimization: A group of studies has addressed the topics of biomass power plant site selection and biomass supply chain optimization. [24] developed a methodology to determine the suitable locations, optimal sizes, and numbers of pellet plants through transportation cost optimization for a region. [25] and [26] developed new methods to find the optimal geographical distribution of power plants and satellite depots in China. [27] addressed the scope of biomass growth, optimal bioenergy plant locations, and related supply areas in Pakistan. [28] focused on identifying the optimal locations for biomass-to-electricity conversion plants in Southern Italy. [29] presented an integrated approach to identify suitable locations for biomass power plants by considering economic criteria. [30] focused on determining suitable areas for biomass-to-electricity production plants in Madrid. [31] analyzed the supply and demand of wood fuel and aimed to contribute to new energy strategies. [32] focused on evaluating the sustainable availability of agricultural waste and identifying suitable locations for biorefinery plants. [33] evaluated different alternative locations for biomass power plants by considering environmental, economic, and social criteria. [34] focused on identifying suitable sites for waste biomass-based supply chains. [35] developed a simulation-based framework to determine the optimal locations of storage facilities in biomass supply chains. [36] focused on identifying suitable locations for biomass energy plants in Tasmania using forest harvesting residues. [37] developed a GIS method based on transportation optimization to compare centralized and decentralized biomass supply systems. [38] addressed the transportation of biomass raw materials to biomass-based energy conversion plants and their placement in suitable locations. [39] aimed to determine the most suitable locations for biomass power plants in Vietnam. [40] introduced a prototype of a web-based tool developed for biomass plant site selection. [41] aimed to maximize supply chain profits and carbon credits by evaluating the optimal locations, sizes, and numbers of biopower production plants in Wisconsin. [42] aimed to identify the most suitable areas for establishing biorefineries from olive waste in Spain’s Andalusia region. [43] developed a multi-criteria approach based on various criteria to determine biomass power plant sites using provinces in Turkey. [44] presented a framework to assess the suitability of small biomass power plants for reactive power markets. [45] aimed to determine optimal plant locations for converting different biomass sources into value-added products in Alberta, Canada. [46] examined the environmental and economic benefits of hybrid power plant site selection and logistics analysis for biomass energy production from urban waste. [47] evaluated the identification of suitable locations for biomass power plants in provinces in eastern and northeastern Iran. [48] aimed to enhance the efficiency of biomass raw material supply chains by incorporating cost and carbon emission metrics in the selection of straw collection and storage facilities. [49] focused on determining the optimal number of biomass power plants and making decisions about their locations. [50] identified the most suitable areas for biomass power plants in Balikesir Province using GIS. [51] focused on identifying suitable locations for the installation of Hybrid Concentrated Solar-Biomass power plants. [52] highlighted the necessity of customizing regional strategies by evaluating the integration of solar, wind, and biomass energy systems in Iraq. [53] identified suitable locations for biomass power plants by evaluating biomass energy potential in Nigeria.

Other biomass evaluation and site selection studies are as follows: [54] focused on developing a supply chain for a collection system consisting of road/rail infrastructure and storage areas that would contribute to European energy strategies. [55] examined the impact of road infrastructure's curvature factor on biofuel plant evaluation. [56] aimed to analyze geographical, technical, economic, and environmental criteria to assess the feasibility of food waste valorization strategies. [57] focused on determining suitable sites for biomass facilities in Spain's Extremadura region in terms of long-term sustainability. [58] provided quantitative analysis and mapping of biomass sources from forests, considering environmental and economic factors. [59] aimed to identify areas with high microalgal production potential in Mexico. [60] aimed to develop a multi-criteria decision support tool that simultaneously considers economic, environmental, and social criteria to determine the site of biorefinery facilities. [61] focused on determining suitable locations for biomass supply chains. [62] analyze the design and siting processes of bioeconomic industrial clusters. [63] focus on identifying renewable energy development areas in South-Central Chile and evaluating potential tradeoffs between energy supply and priority ecosystem services. [64] comparatively examine the regional siting potential of various low-carbon energy plants in the Yangtze River Delta.

A synthesis of reviewed studies reveals that the criteria used can be grouped into seven main categories: (1) Economic, (2) Environmental, (3) Geographical, (4) Accessibility-related, (5) Technical, (6) Social, and (7) Strategic factors. Among these, accessibility, environmental, and geographical factors appear most frequently, while strategic and technical factors are less common. This classification provides a structured foundation for subsequent comparative analysis. In Table 1 below, the studies are presented from this perspective. The details of the factors used in the studies presented above are provided in Table 1. The abbreviations for the factors shown in Table 2.

The general conclusions from the literature review are as follows:

Identified trends and limitations:

- Scale: Approximately 80% of studies are regional/local, with only ~20% adopting a national-scale approach.
- Methodology: Comparative analyses across different MCDM techniques are relatively rare; most studies adopt a single method without exploring methodological robustness.
- Criteria weighting: Many works rely on expert judgement but lack transparent, replicable frameworks for determining and weighting criteria.
- Sensitivity analysis: Few studies test the stability of their results against parameter variations.
- Integration of hybrid systems: Although increasing, studies on hybrid renewable siting remain limited.
- Visualization: GIS-based mapping is common regionally but scarce for national-scale biomass suitability assessments.

The distribution of studies by country is presented in Table 3.

Table 1. Selection Criteria Related to Studies in the Literature

Author(s)	Year	Selection area	Factors						
			Economic Factors	Environmental Factors	Geographical Factors	Accessibility Related Factors	Technical Factors	Social Factors	Strategic Factors
[1]	2010	Western States, USA	TC	BP	X	DTR, DTRW, DTS	X	X	X
[13]	2011	Selangor, Malaysia	TC	BP	A	X	X	X	X
[2]	2011	USA	TC	X	X	DTR, DTRW, DTS	X	X	X
[24]	2012	Alberta, Canada	TC	X	S	DTR, DTPL, DTS DTIA, DTWS	X	X	DTCP
[25]	2012	Zhanjiang, China	TC	BP	X	DTR	X	X	X
[26]	2012	Zhanjiang, Çin	TC	BP	X	DTR	X	X	X
[3]	2013	Pittsburgh, USA	X	X	S	DTWS, DTAgrA DTS	X	X	X
[54]	2014	Styria, Austria	X	C	S	DTR, DTAgrA, DTWS, DTIA DTS	X	DTPA	X
[14]	2014	EntreDouro e Minho, Portugal	X	X	S	DTWS, DTR, DTRW, DTIA DTS, DTEG, DTAgrA	X	DTPA	X
[55]	2014	Alberta, Canada	TC	X	S	DTR, DTEG, DTWS, DTA DTS	X	DTP, DTPA	DTCP
[27]	2015	Pakistan	TC	BP	X	X	X	X	X
[4]	2015	Western Australia	X	SR	S, LS	DTWS, DTS, DTR	X	DTPA, DTC	DTW
[5]	2015	Chile	X	SR	S	DTAgrA, DTR, DTRW, DTEG	X	DTPA, DTC	
[15]	2015	East Midlands, United Kingdom	TC	X	X	X	X	X	X
[28]	2015	Apulia, Basilicata, Campania, Italy	X	BP	S	DTIA, DTR, DTWS, DTS DTAgrA	X	DTPA, DTC, DTAS	X
[29]	2015	Lubelskie, Poland	TC	BP	S	DTAgrA, DTRW, DTR, DTEG	X	DTPA	X
[30]	2015	Madrid, Spain	X	BP	S	DTEG, DTR, DTWS, DTS	X	DTPA	DTCP
[31]	2015	Asturias, Spain	X	BP	S	DTR, DTWS DTS	X	DTPA	X
[6]	2016	El Oro, Ecuador	TC	BP	X	X	X	X	X
[32]	2016	Georgia, USA	TC	X	S	DTAgrA, DTWS, DTS, DTR, DTRW	X	DTPA	X

[33]	2016	Aegean Region, Turkey	IC, TC	BP	X	X	X	X	ABS
[8]	2017	Texas, USA	TC	X	X	DTAgrA	X	X	X
[56]	2017	Basque Country, Spain	TC	X	X	DTR	X	X	X
[7]	2017	USA	X	X	S	DTR, DTRW, DTEG, DTWS, DTA	X	DTPA	X
[16]	2018	Spain	TC	BP	X	DTEG, DTR, DTS	X	UR	X
[17]	2018	Extremadura, Spain	TC	BP, BD, RA, T	S, LS	DTR, DTAgrA, DTWS	X	X	X
[57]	2018	Hervas, Spain	TC	BP, RA	S, LS	DTR, DTAgrA, DTWS	X	X	X
[35]	2018	Great South Plains, USA	TC	X	X	X	X	X	X
[21]	2018	Ohio, USA	X	X	S, DTFZ	DTAgrA, DTWS, DTS, DTR, DTRW	X	DTPA	X
[34]	2018	Mexico	X	BP	NDR, S	DTR, DTA, DTRW, DTEG, DTWS, DTS	X	DTPA	X
[18]	2018	Iran	X	BP	DTFZ	DTAgrA, DTR DTRW, DTA DTWS, DTS	X	DTPA	X
[19]	2019	Finland	TC	X	X	X	X	X	X
[36]	2019	Tasmania, Australia	X	BP	A, S	DTIA, DTR, DTWS	X	LER, P	X
[37]	2019	Quebec, Canada	X	BP	S	DTR, DTS, DTA, DTWS, DTEG	X	X	X
[58]	2019	Badajoz, Spain	X	BP	S	DTR, DTWS	X	DTPA	X
[59]	2019	Mexico	X	T, E, SR, RA	S, LS	DTWS, DTR, DTA, DTS	X	DTPA	X
[60]	2019	Cascades-to Pacific, USA	VC	GWP	X	X	X	JC, SA	X
[38]	2019	Santa Cruz, Bolivia	X	BP	S	DTR, DTEG, DTWS, DTA, DTS	X	DTPA	DTCP
[61]	2019	Mexico	X	BP	S, NDR	DTR, DTA, DTRW, DTEG, DTWS, DTS	X	DTPA	X
[39]	2019	Mekong Delta, Vietnam	IC, PC	BP	LS	X	TM, R, C	LER	DTW, TEI
[20]	2020	Sicily, Italy	X	BP	X	DTIA, DTR	X	X	X
[40]	2020	Hervas, Spain.	TC	BP	S, LS	DTR, DTAgrA, DTWS	X	X	X
[11]	2020	Texas, United States of America	X	T	A	DTR, DTA, DTRW, DTWS	X	DTPA, DTC	X
[62]	2020	Ostfold, Norway	X	BP	X	DTR, DTRW, DTS	X	DTEI	X

[12]	2020	Basilicata, Italy	X	EIT	X	DTR, DTEG, DTS	X	DTPA	X
[10]	2020	Queensland, Australia	X	BP	X	DTR	X	X	X
[41]	2021	Wisconsin, USA	X	X	LS	DTEG, DTS, DTWS, DTR	X	X	DTPL
[42]	2021	Andalusia, Spain	X	X	S	DTF, DTIA	X	DTPA	X
[22]	2021	Parana, Brazil.	X	BP	X	DTR, DTEG	X	X	X
[43]	2021	Turkey	X	BP	S	DTWS, DTR, DTRW, DTS	X	PD	X
[44]	2021	Sao Paulo, Brazil	X	X	X	DTEG	X	X	X
[45]	2021	Alberta, Canada	X	BP	X	DTR	X	X	X
[46]	2021	Iran	TC, LC	BP, AWS	NDR	DTEG	X	QL, UR	SP, GSL, TEI
[47]	2021	Iran	X	CDD, T, RA	A,S, NDR	DTCC, DTR, DTEG	X	P, PD	X
[9]	2022	Fars, Iran	X	C	A,S	DTAgrA, DTR, DTS, DTWS	X	X	X
[48]	2022	Jilin, China	TC	X	X	X	X	X	X
[63]	2022	Biobio and Nuble, Chile	X	X	S	DTAgrA, DTS	X	DTPA	X
[64]	2022	Yangtze River Delta, China	X	BP	A,S	DTWS, DTS, DTR DTRW, DTEG	X	P, DTPA	X
[50]	2023	Balikesir, Turkey	X	BP	S, LS, NDR	DTR, DTS, DTWS	X	X	X
[49]	2023	Fuxin, China	TC	X	A, S, LS	DTR, DTVT	X	PD, CA	X
[23]	2023	Konya Basin, Turkey	X	X	S, LS	DTR, DTS, DTWS, DTEG, DTIA	X	DTPA	X
[51]	2023	Pakistan	X	DNI, BP	A, LS	DTR, DTWS	X	X	X
[52]	2024	Iraq	X	WD, AWS, SR	A,S, NDR	DTR, DTRW, DTWS, DTCC	PI	P	X
[53]	2024	Nigeria	X	LC, OSW	S, LS	DTAgrA, DTWS, DTR	X	X	X

Table 2. Abbreviations for the factors

Economic Factors	Technical Factors
Transportation Cost (TC)	Technology Maturity (TM)
Investment Cost (IC)	Reliability (R)
Land Cost (LC)	Capacity (C)
Variable Costs (VC)	Power Infrastructure (PI)
Production Cost (PC)	
Accessibility Related Factors	
Distance to City Center (DTCC)	
Distance to Roads (DTR)	
Distance to Railways (DTRW)	
Distance to Settlements (DTS)	
Distance to Airports (DTA)	
Distance to Industrial Areas (DTIA)	
Distance to Water Sources (DTWS)	
Distance to Agricultural Areas (DTAgrA)	
Distance to Electrical Grids (DTEG)	
Distance to Industrial Zones (DTIZ)	
Distance to Forests (DTF)	
Distance to Villages and Towns (DTVT)	
Social Factors	
Unemployment Rate (UR)	
Local Employment Rate (LER)	
Population (P)	
Population Density (PD)	
Quality of Life (QL)	
Distance to Archaeological Sites (DTAS)	
Job Creation (JC)	
Social Assets (SA)	
Cultural Assets (CA)	
Distance to Educational Institutions (DTEI)	
Distance to Protected Areas (DTPA)	
Distance to Coasts (DTC)	
Distance to Parks (DTP)	
Strategic Factors	
Tax Exemptions and Incentives (TEI)	
Government Subsidies and Low-interest Loans (GSL)	
Alternative Biomass Sources (ABS)	
Distance to Conversion Plants (DTCP)	
Distance to Workforce (DTW)	
Security and Peace (SP)	
Distance to Public Lands (DTPL)	
Environmental Factors	
Biomass Potential (BP)	
Biodiversity (BD)	
Rainfall Amount (RA)	
Temperature (T)	
Orientation (Sun and Wind) (OSW)	
Direct Normal Irradiance (DNI)	
Wind Direction (WD)	
Average Wind Speed (AWS)	
Solar Radiation (SR)	
Evaporation (E)	
Global Warming Potential (GWP)	
Environmental Impact of Transport (EIT)	
Land Cover (LC)	
Cold Degree Days (CDD)	
Climate (C)	

These observations underscore the need for comprehensive, data-driven, and methodologically robust nationwide assessments (addressing multiple MCDM methods, transparent criteria determination, and sensitivity analysis) particularly in the context of Turkey, where biomass energy potential is significant but underexplored at the national level.

Table 1. The distribution of studies by country

The distribution of studies by country					
USA	11	Brazil	2	Iraq	1
Spain	9	Pakistan	2	Malaysia	1
China	6	Chile	2	Nigeria	1
Iran	4	Austria	1	Norway	1
Canada	4	UK	1	Poland	1
Turkey	4	Bolivia	1	Portugal	1
Australia	3	Ecuador	1	Thailand	1
Italy	3	Finland	1	Vietnam	1
Mexico	3				

1.4. Research gap and aim of the study

Despite significant progress in the literature on biomass facility siting, several gaps remain. Most studies are constrained to regional or local scales, with limited efforts to conduct systematic, nationwide assessments. The determination and weighting of site selection criteria often lack standardized, replicable procedures, and few works employ comparative MCDM analyses that could strengthen methodological reliability.

In the context of Turkey, there is a scarcity of studies that evaluate the suitability of provinces for biomass-based electricity generation through a transparent, data-driven, and multi-criteria framework.

This study addresses these gaps by applying a comparative MCDM-based methodology to assess the suitability of candidate cities across Turkey using a set of clearly defined criteria. The approach ensures replicability, integrates structured weighting procedures, and produces outputs that can guide policymakers, investors, and researchers in making informed decisions on the sustainable deployment of biomass energy at the national scale.

2. Methodology

2.1. Study area

Turkey was chosen as the study area due to its substantial and diversified biomass energy potential. According to [65] Turkey's total biomass energy potential is approximately 33 Mtoe, with some 17 Mtoe deemed technically recoverable. A more recent study [66] supports these figures and reports that annual energy potential obtained from agricultural and garden plant residues is around 908,119 TJ and 90,354 TJ, respectively.

Turkey's geographic diversity spans multiple climatic zones, causing considerable regional variation in the availability and composition of biomass. This variability plays a critical role in determining the logistical and economic feasibility of biomass power plants.

At the policy level, the 2022 Turkey National Energy Plan (NEP) underscores the importance of utilizing domestic renewable resources (including biomass) to meet national energy and climate goals in line with the Paris Agreement

In this context, this study considers all provinces in Turkey as candidate locations for biomass-based power generation. The nationwide scope allows for a comprehensive evaluation of site suitability that accounts for regional differences in resource availability, infrastructure access, environmental constraints, and socio-economic conditions. Such an approach aims to support policymakers, investors, and planners by offering a robust, data-driven, and spatially-aware decision-support framework for the strategic development of the country's biomass energy infrastructure.

2.2. Criteria selection and classification

These criteria, grounded in both technical feasibility and socio-economic sustainability, provide a robust framework for a nationwide MCDM assessment of biomass facility locations.

Following the literature review, criteria applicable at the national scale were identified through an iterative process combining academic evidence and expert judgment [39]. The selected criteria (electricity production/consumption ratio, biomass potential (plant-based waste, animal waste, municipal solid waste), slope, employment rate, and earthquake risk) were chosen to ensure a comprehensive evaluation of site suitability for biomass-based electricity generation facilities.

The electricity production to consumption ratio is a fundamental indicator of a province's balance between local electricity supply and demand over a given period. In this study, the ratio is adopted as a critical criterion for siting biomass based power plants because provinces where local generation falls short of consumption yield higher marginal benefits from new capacity in meeting regional demand. Prioritizing such locations reduces transmission losses and network congestion, strengthens energy security and system flexibility, lowers logistics costs, mitigates environmental impacts, and generates socio economic gains via local employment [67]. For these reasons, the production to consumption ratio is employed as a significant1 input within the nationwide multi criteria decision making framework.

Biomass potential is a primary determinant in site selection for such facilities. Provinces with higher availability of plant-based residues, animal manure, and municipal solid waste present greater opportunities for sustained feedstock supply, reducing transportation costs and improving operational efficiency [46,50].

Slope is a critical topographical parameter in facility siting. Slope refers to the steepness of the terrain, typically measured as a percentage, which is determined by the ratio of vertical rise to horizontal distance. Steep terrain (generally above 15%) poses engineering challenges and increases construction costs, whereas flatter land facilitates infrastructure development and reduces site preparation expenses [39]. Therefore, evaluating slope is vital as it directly impacts the feasibility, cost-effectiveness, and safety of the construction project.

The employment rate is included to capture the socio-economic dimension of biomass facility deployment. Biomass plants can stimulate local economies by creating jobs in feedstock collection, transportation, and plant operation, making employment a relevant criterion for regional development considerations [67].

Finally, earthquake risk addresses the vulnerability of high-investment energy infrastructure to natural hazards [68] Given Turkey's seismic profile, avoiding high-risk zones can mitigate potential damage and ensure operational resilience over the plant's lifespan.

These criteria, grounded in both technical feasibility and socio-economic sustainability, provide a robust framework for a nationwide MCDM assessment of biomass facility locations.

2.3. Criteria weighting process

Following the identification of the evaluation criteria, the relative importance of each factor was determined through expert elicitation. Instead of a formal panel meeting, the process relied on collecting individual expert opinions to ensure independent judgments without group influence. A total of 21 experts participated, representing diverse backgrounds from academia, government agencies, and the renewable energy industry.

Experts were selected based on three main criteria:

- Academic expertise in renewable energy systems, biomass supply chains, or multi-criteria decision-making methodologies.
- Professional experience in policy-making, regulation, or infrastructure planning for energy projects.
- Practical involvement in the design, operation, or management of renewable energy facilities, particularly biomass and bioenergy plants.

Each expert was asked to assign weights to the identified criteria according to their perceived significance for biomass-based electricity generation facility siting in Turkey. To ensure comparability, all weight sets were normalized to sum to unity.

The elicited weights were then aggregated using the arithmetic means, a standard approach in multi-criteria decision-making studies [69-71]. To evaluate the consistency of expert judgments, Kendall's coefficient of concordance (W) was calculated. The results revealed a high degree of consensus ($W = 0.880$, $X^2=70.43$, $p < 0.001$), confirming both the reliability of the expert elicitation process and the robustness of the final weights.

The normalized expert data and the final average weights are summarized in Table 4 and were used as inputs for the subsequent TOPSIS analysis.

Table 2. Weighting of the Criteria

#	Electricity production/ consumption ratio	Biomass Potential	Slope	Employment Rate	Earthquake Risk
1	0.073	0.541	0.161	0.112	0.114
2	0.066	0.558	0.162	0.092	0.122
3	0.068	0.574	0.168	0.084	0.106
4	0.066	0.564	0.167	0.093	0.109
5	0.084	0.556	0.160	0.085	0.114
6	0.072	0.552	0.165	0.095	0.118
7	0.063	0.567	0.157	0.088	0.126
8	0.060	0.580	0.145	0.089	0.126
9	0.077	0.562	0.159	0.097	0.105
10	0.063	0.558	0.172	0.104	0.103
11	0.072	0.546	0.150	0.104	0.128
12	0.078	0.540	0.154	0.101	0.127

13	0.066	0.565	0.151	0.089	0.130
14	0.081	0.543	0.165	0.101	0.110
15	0.072	0.565	0.157	0.114	0.092
16	0.078	0.562	0.157	0.101	0.100
17	0.067	0.556	0.173	0.094	0.110
18	0.064	0.559	0.161	0.093	0.123
19	0.071	0.566	0.152	0.096	0.115
20	0.055	0.564	0.163	0.100	0.118
21	0.057	0.568	0.160	0.094	0.121
Average	0.07	0.56	0.16	0.10	0.12

2.4. Data collection

After the criteria were established, province-level datasets were collected from publicly accessible repositories maintained by official Turkish governmental institutions. Specifically, socio-economic and demographic data, including employment rates, were obtained from the Turkish Statistical Institute (TurkStat.), while biomass potential and related energy resource information were retrieved from the Ministry of Energy and Natural Resources' Biomass Energy Potential Atlas (BEPA) database.

All datasets correspond to the most recent year available at the time of analysis and were compiled at the provincial scale to ensure consistency across criteria. The processed data, categorized by criterion, are presented in Table 5, serving as the quantitative basis for the subsequent TOPSIS evaluation.

Table 3. Collected Data

Province	Production/ consumtion	Plant-based waste	Animal waste	Municipal solid waste	Slope	Employment Rate	Earthquake Risk
Adana	2.78	3343131.1	3021663.6	761724.9	20.4	43.7	2
Adıyaman	0.47	599167.8	1332141.4	182357.8	7.1	39.4	2
Afyonkarahisar	0.58	1009098.9	5365747.2	307205.5	13.9	50.5	2
Agrı	0.16	228216.2	3913212.8	157579.8	14.4	41.5	2
Aksaray	0.19	861912	3059093.3	135398.5	10.4	46.6	5
Amasya	1.02	770722.5	1922033.3	110871.4	21	47.4	1
Ankara	0.53	2176313.5	6104697.2	2571461.8	9.6	48.5	4
Antalya	0.49	2647448.1	2609340.6	885620	21.4	55.1	2
Ardahan	3.14	39727.4	2149576.2	28880.9	15.6	58.2	2
Artvin	7.5	33911.5	580976.8	57162.3	34.8	51.4	3
Aydın	2.12	719799.9	4192258	464785.6	17.1	47.4	1
Balıkesir	2.2	1096114.3	6885871.2	519331.8	15.6	49.2	1
Bartın	0.1	60066.2	536012	65371.1	22.4	50.7	1
Batman	0.19	345408.6	1590406.2	174938	10.6	37.0	2
Bayburt	1.76	99056.3	725632.5	27027.1	34.8	49.4	3

Bilecik	0.2	205588.5	614734.6	94607.8	15.6	49.3	1
Bingol	6.36	44280.3	1481914.1	82111.8	22.9	44.3	1
Bitlis	0.31	176410	1300466	102023.6	22.9	42.2	1
Bolu	1.78	194707.7	2080589.1	102429.6	22.4	53.3	1
Burdur	0.32	367844	2370706.9	88670.7	21.4	52.2	1
Bursa	0.51	1512406.7	3004653.3	1355320.2	15.6	51.3	1
Canakkale	6.91	972829.7	2745719.3	228916.3	15.6	49.1	1
Cankiri	0.35	325345	1388480.8	71074.9	10.4	49.2	2
Corum	0.6	1158899.3	2387788.5	176234.7	21	44.3	2
Denizli	1.22	900172.2	3487428.2	435162.9	17.1	50.3	1
Diyarbakır	1.36	2139758.8	5987023.4	632324.5	10.6	35.9	2
Duzce	0.22	143879.4	665491.6	127406.7	22.4	53.5	1
Edirne	0.59	1755666.1	1714314	173207.8	5.4	54.8	4
Elazig	3.52	308232	2341642	173926.3	22.9	43.3	2
Erzincan	1.27	222529.3	1405249.6	68922	22.9	45.4	1
Erzurum	1.74	301617.1	6215934.3	280264.5	15.6	48.1	2
Eskisehir	0.29	1212082.2	2247288.3	298904.2	9.6	48.7	2
Gaziantep	0.13	679688.1	2959810.7	696000	7.1	44.4	3
Giresun	2.66	222052.9	909744.3	149110.1	34.8	53.4	3
Gumushane	3	77495.1	672812.9	53462.7	34.8	44.5	3
Hakkari	0.36	36605.1	979013.5	76946.9	35.5	38.2	1
Hatay	1.93	918766.2	1672426.2	528837.7	20.4	38.0	1
Igdir	0.15	124621.1	2256632.5	57657.1	15.6	48.0	2
Isparta	0.64	337229.8	1665402.2	145003.8	21.4	50.6	1

Istanbul	0.2	345642.9	1005106.6	7039640.7	11.6	51.9	1
Izmir	0.66	1403234.4	8342244.2	2018546.5	17.1	47.9	1
Kahramanmaras	1.13	1048482.5	2537994.9	376083.6	20.4	39.0	1
Karabuk	1.07	30755.6	396986.2	81472.6	22.4	43.7	1
Karaman	1.31	1167006.1	1301494.8	82753.4	6.4	50.8	5
Kars	1.32	112770.3	3776997.9	84352.4	15.6	52.5	2
Kastamonu	0.22	192102.2	2419379.7	125938	22.4	51.2	1
Kayseri	0.43	932054.5	3658242.6	476799.2	10.4	45.2	3
Kirikkale	9.82	496276.6	678981.4	94148.7	10.4	41.1	1
Kirklareli	2.22	1067270.9	1710214.1	152788.2	8.6	49.4	4
Kirşehir	1.38	654454.3	2123398.2	79453.6	10.4	39.5	1
Kilis	0.09	210797.9	307891.4	48905.8	20.4	44.6	3
Kocaeli	0.49	149095.4	1133270.7	862832.6	11.6	53.3	1
Konya	0.53	5764117.3	10866849.5	756744.4	6.4	48.9	4
Kutahya	2.56	486781.1	2168877.9	244700.2	13.9	48.5	2
Malatya	0.22	246476.1	1798371.9	232734.5	22.9	43.9	1
Manisa	2.06	1630121.6	4388271.1	605310.9	17.1	53.8	1
Mardin	0.86	1578937.3	1820103.1	272390.6	10.6	39.0	3
Mersin	0.48	1927221.8	2919327.6	662280.9	20.4	46.0	3
Mugla	2.12	657303.7	2586930.5	409634	17.1	52.0	1
Mus	1.38	454539.5	3221945.3	119133.6	14.4	43.8	1
Nevsehir	0.41	599519.3	953600.9	98004.4	10.4	50.1	3
Nigde	0.26	634810	2187491.8	119806.2	10.4	44.2	4

Ordu	0.79	368666	1270654.3	253579.6	21	50.8	3
Osmaniye	0.42	831667.2	927776.9	175555.3	20.4	39.4	1
Rize	1.02	5972.5	199296.1	114517.8	34.8	52.5	4
Sakarya	0.84	643709	2230372.9	457442.9	11.6	53.7	1
Samsun	2.01	1078247.7	3047984.3	458284.2	21	50.2	2
Siirt	2.24	163729.8	1445413.1	96847.6	10.6	35.5	1
Sinop	1.35	158603.2	843649.8	72182.3	22.4	51.0	5
Sivas	1.96	933353.1	3386345	212410.7	13.5	45.9	3
Sanliurfa	0.63	3014998.7	4680709.5	594456.2	7.1	41.0	3
Sirnak	1.99	314927	1548453.1	153063.5	35.5	36.9	2
Tekirdag	0.22	1706775.9	1688142.3	466144.9	5.4	56.2	2
Tokat	2.08	950551.2	2675578.4	201254.2	21	50.3	1
Trabzon	0.78	140759.8	1177593.5	265396.2	34.8	52.5	4
Tunceli	2.34	38524.6	621655.6	25753.8	22.9	45.4	2
Usak	0.24	433403.7	1790440	155605.4	13.9	48.5	2
Van	0.35	159747.9	4122998.9	328144.9	18.7	38.5	2
Yalova	1.51	28166.8	140575.7	111029.8	15.6	48.1	1
Yozgat	0.25	1004330.9	2395967.5	139606.2	10.4	49.2	3
Zonguldak	13.27	72072.1	836577.1	197000.8	22.4	46.9	2

2.5. TOPSIS application

The TOPSIS methodology was applied to evaluate the location alternatives. The procedure follows the classical steps of normalization, construction of the weighted decision matrix, determination of the positive ideal and negative ideal solutions, calculation of the Euclidean distances, and derivation of the relative closeness coefficient. The formulations are presented under the following sub-sections.

2.5.1. Data normalization

The collected data have been normalized using Equation (1). A detailed explanation of the parameters involved in the equation is presented below:

$r_{i,j}$: Normalized value (for alternative i, criterion j)

$x_{i,j}$: Original value (for alternative i, criterion j)

n: Number of alternatives

$$r_{i,j} = \frac{x_{i,j}}{\sqrt{\sum_{i=1}^{n} {x_{i,j}}^2}} \quad (1)$$

2.5.2. Weighted data

The normalized data were multiplied by the weights provided Section 2.3.

2.5.3. Calculation of distances and determining the closeness coefficient

The distance of each alternative to the ideal solution (positive solution) is calculated. The ideal solution is determined by taking the maximum value for each criterion. The distance to the ideal solution is calculated as follows:

$$D_i^+ = \sqrt{\sum_{j=1}^{n}(V_{i,j} - V_j^+)^2} \quad (2)$$

D_i^+: The distance of alternative i to the ideal solution

$V_{i,j}$: The normalized value of alternative i for criterion j

V_j^+: The ideal (maximum/minumum) value for criterion

n: Number of criteria

The distance of each alternative to the anti-ideal solution (negative solution) is calculated. The anti-ideal solution is determined by taking the minimum value for each criterion. The distance to the anti-ideal solution is calculated as follows:

$$D_i^- = \sqrt{\sum_{j=1}^{n}\left(V_{i,j} - V_j^-\right)^2} \quad (3)$$

D_i^-: The distance of alternative i to the anti ideal solution

$V_{i,j}$: The normalized value of alternative i for criterion j

V_j^-: The anti ideal (minumum/maximum) value for criterion

n: Number of criteria

The closeness coefficient Ci of each alternative is determined by calculating the ratio of the distance to the anti-ideal solution to the sum of the distance to the ideal solution and the distance to the anti-ideal solution. This ratio indicates how close each alternative is to the ideal solution. The formula for the closeness coefficient is as follows:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (4)$$

2.5.4. Determination of the most suitable location using the TOPSIS decision-making framework

Following the completion of all TOPSIS computations, the alternatives are ranked in descending order of their closeness coefficient (C_i) values. The alternative with the highest C_i value represents the most preferable option according to the TOPSIS methodology. Ranking of the provinces is given Table 6.

Table 4. Ranking of the provinces with TOPSIS

#	Province	D_i^+	D_i^-	C_i	#	Province	D_i^+	D_i^-	C_i
1	Konya	0.098904	0.158288	0.615447	42	Amasya	0.160785	0.074618	0.316981
2	Izmir	0.107695	0.116015	0.518594	43	Batman	0.165326	0.0765	0.316343
3	Ankara	0.103067	0.106571	0.508357	44	Osmaniye	0.165255	0.076137	0.315409
4	Istanbul	0.130639	0.133216	0.504884	45	Mugla	0.155289	0.071437	0.315082
5	Sanliurfa	0.125763	0.097856	0.437601	46	Kirşehir	0.160891	0.073784	0.31441
6	Diyarbakir	0.125175	0.096629	0.435651	47	Adiyaman	0.164589	0.075363	0.314076
7	Balikesir	0.132306	0.095678	0.419671	48	Isparta	0.165333	0.075172	0.312559
8	Adana	0.131604	0.086412	0.396357	49	Cankiri	0.167589	0.075355	0.310174
9	Antalya	0.135543	0.08858	0.39523	50	Bitlis	0.169173	0.07593	0.309788
10	Afyonkarahisar	0.140354	0.090739	0.392652	51	Hatay	0.157039	0.070432	0.309631

11	Bursa	0.135949	0.085761	0.386817	52	Bilecik	0.172709	0.076264	0.306315
12	Erzurum	0.144487	0.089827	0.383362	53	Nevsehir	0.167861	0.073798	0.30538
13	Manisa	0.136324	0.083317	0.379331	54	Duzce	0.172746	0.075817	0.305022
14	Mersin	0.141176	0.083192	0.370785	55	Bartin	0.174794	0.076288	0.303836
15	Kayseri	0.146844	0.082157	0.358761	56	Karaman	0.163015	0.070882	0.303047
16	Van	0.153029	0.083537	0.353124	57	Hakkari	0.172894	0.074903	0.302276
17	Tekirdag	0.15127	0.081917	0.351294	58	Ordu	0.16659	0.071128	0.299212
18	Agri	0.155006	0.083679	0.350582	59	Bolu	0.165013	0.070292	0.298727
19	Gaziantep	0.150173	0.080949	0.350245	60	Erzincan	0.168638	0.071244	0.296996
20	Denizli	0.148144	0.079632	0.349607	61	Kilis	0.175391	0.073746	0.296005
21	Aydin	0.146381	0.078434	0.348881	62	Kirklareli	0.160293	0.066688	0.293804
22	Eskisehir	0.153433	0.079885	0.342386	63	Trabzon	0.169891	0.069765	0.291103
23	Aksaray	0.155282	0.079695	0.33916	64	Kutahya	0.160852	0.066003	0.290948
24	Edirne	0.154756	0.078539	0.33665	65	Karabuk	0.175801	0.071142	0.288091
25	Kahramanmaras	0.152539	0.076769	0.334785	66	Siirt	0.16876	0.067291	0.285069
26	Yozgat	0.156233	0.078551	0.334566	67	Sirnak	0.167071	0.065931	0.282964
27	Corum	0.154611	0.07764	0.334292	68	Yalova	0.176985	0.069312	0.281416
28	Mardin	0.153883	0.076541	0.332176	69	Sinop	0.173791	0.066259	0.276021
29	Kars	0.157565	0.077562	0.329874	70	Rize	0.178092	0.067577	0.275075
30	Sakarya	0.156382	0.076967	0.329837	71	Ardahan	0.167274	0.062566	0.272216
31	Samsun	0.149087	0.073126	0.329081	72	Elazig	0.162927	0.060876	0.272008
32	Mus	0.156617	0.076732	0.32883	73	Bayburt	0.174812	0.064532	0.26962

33	Burdur	0.161879	0.078503	0.326577	74	Tunceli	0.175419	0.06294	0.264055
34	Kastamonu	0.162794	0.078931	0.326534	75	Giresun	0.171895	0.060084	0.259005
35	Sivas	0.151371	0.073341	0.326377	76	Canakkale	0.157835	0.052669	0.250203
36	Nigde	0.161031	0.076256	0.321365	77	Gumushane	0.175543	0.057784	0.247654
37	Igdir	0.164866	0.077677	0.320261	78	Bingol	0.172944	0.046759	0.212829
38	Kocaeli	0.162904	0.076692	0.320088	79	Kirikkale	0.178142	0.033854	0.159692
39	Malatya	0.164546	0.077402	0.319911	80	Artvin	0.18029	0.034155	0.15927
40	Usak	0.163669	0.076534	0.318623	81	Zonguldak	0.186401	0.02011	0.097379
41	Tokat	0.154679	0.072303	0.318541					

2.6. Comparative analysis with VIKOR

The VIKOR methodology was employed to rank the location alternatives. The procedure involves constructing the normalized decision matrix, identifying the best and worst values for each criterion, calculating the utility and regret measures, deriving the VIKOR index (Q), and finally obtaining the ranking of alternatives. This approach enables a compromise solution that balances between group utility maximization and individual regret minimization. The formulations are presented under the following sub-sections [72,73].

2.6.1. Notation and inputs

Let the decision matrix be

$X = X_{i,j}$ where i=1,2,.. m (provinces) j=1, 2,…,n (criteria) (5)

Let wj be the weight of criterion j with

$$\sum_{j=1}^{n} w_j = 1 \quad (6)$$

Define the set of benefit criteria B and cost criteria C.

- Benefit criteria: Production/consumption, Plant based waste, Animal waste, Municipal solid waste, Employment Rate.
- Cost criteria: Slope, Earthquake Risk.

In this study, the same decision matrix and same weights used in TOPSIS are used for VIKOR.

2.6.2. Determine best and worst values per criterion

For each criterion j,

- If $j \in B$: $f_j^* = max_i X_{i,j}$, $f_j^- = min_i \; X_{i,j}$ (7)
- If $j \in C$: $f_j^* = min_i X_{i,j}$, $f_j^- = max_i \; X_{i,j}$ (8)

2.6.3. Compute normalized regret terms

For each alternative i and criterion j,

- If $j \in B$: $R_{i,j} = \frac{f_j^* - X_{i,j}}{f_j^* - f_j^-}$ (9)
- If $j \in C$: $R_{i,j} = \frac{X_{i,j} - f_j^*}{f_j^* - f_j^-}$ (10)

2.6.4. Aggregate group utility (S) and individual regret (R)

$$S_i = \sum_{j=1}^{n} w_j R_{i,j}, \; R_i = max_j \; (w_j R_{i,j}) \quad (11)$$

- S_i : overall (group) utility shortfall of alternative i.
- R_i : the worst weighted shortfall among all criteria for alternative i.

2.6.5. Compute the VIKOR index (Q)

Let $S^* = \; min_i S_{i,}$ (12)

$S^- = max_i S_i \quad R^* = \; min_i R_{i,} \quad R^- = max_i R_i$ (13)

For a compromise parameter v∈ [0,1]. (here we use v= 0.5 to balance group utility and individual regret):

$$Q_i = v.\frac{S_i - S^*}{S^- - S^*} + (1-v).\frac{R_i - R^*}{R^- - R^*} \quad (14)$$

2.6.6. Ranking and compromise solution

Rank alternatives by ascending Q_i(best = smallest Q). Let $A^{(1)}$ be the best by Q, $A^{(2)}$the second.

Acceptable advantage (C1):

$$Q\;(A^{(2)}) - Q\;(A^{(1)}) \geq DQ, \; DQ = \frac{1}{1-m} \quad (15)$$

Acceptable stability (C2):

$A^{(1)}$should also be best by at least one of S or R rankings.

- If both C1 and C2 hold → $A^{(1)}$ is the compromise solution.
- If C1 fails but C2 holds → propose a set of top alternatives up to the first where $Q\;(A^{(2)}) - Q\;(A^{(2)}) - Q\;(A^{(1)}) \leq DQ$
- If C1 holds but C2 fails → propose two compromise solutions: the best by Q and the best by (S or R)

2.6.7. Determination of the most suitable location using the VIKOR multi-criteria decision-making framework

Following the completion of all VIKOR computations, the alternatives are ranked in ascending order of their Q values. The alternative with the smallest Q value represents the most preferable option according to the VIKOR methodology. Ranking of the provinces ise given Table 7.

Table 7. Ranking of the provinces with TOPSIS

Q Rank	Province	S	R	Q	Q Rank	Province	S	R	Q
1	Konya	0.369937	0.125359	0.012880	42	Amasya	0.707188	0.222907	0.677305
2	Izmir	0.484544	0.129083	0.137687	43	Igdir	0.738801	0.214568	0.679591
3	Ankara	0.574025	0.125359	0.212374	44	Edirne	0.697633	0.228083	0.685730
4	Balikesir	0.531111	0.138174	0.214403	45	Isparta	0.716758	0.229302	0.708607
5	Diyarbakir	0.602138	0.121606	0.226974	46	Usak	0.731423	0.226186	0.712249
6	Afyonkarahisar	0.610524	0.140750	0.300868	47	Bingol	0.706817	0.233875	0.714582
7	Manisa	0.561764	0.161448	0.324238	48	Kocaeli	0.683450	0.242563	0.721558
8	Sanliurfa	0.613949	0.154160	0.350238	49	Hatay	0.731979	0.229127	0.722885
9	Erzurum	0.614881	0.161691	0.376995	50	Kirklareli	0.735543	0.228185	0.723137
10	Aydin	0.623455	0.166332	0.401299	51	Mardin	0.750314	0.225447	0.728178
11	Denizli	0.632384	0.183897	0.470309	52	Nigde	0.784392	0.216291	0.730069
12	Kars	0.669617	0.176681	0.481940	53	Malatya	0.752450	0.225988	0.732124
13	Bursa	0.608199	0.195928	0.487957	54	Zonguldak	0.669210	0.249957	0.733013
14	Adana	0.619216	0.195504	0.497271	55	Kirikkale	0.656003	0.253884	0.733581
15	Canakkale	0.597153	0.202380	0.499304	56	Cankiri	0.731584	0.236203	0.746782
16	Van	0.735233	0.168058	0.516488	57	Siirt	0.746349	0.234784	0.756346
17	Agri	0.717422	0.173286	0.517019	58	Erzincan	0.748962	0.235785	0.762335
18	Kayseri	0.696592	0.179640	0.518463	59	Adiyaman	0.754745	0.237607	0.774240
19	Mus	0.676570	0.190513	0.536205	60	Batman	0.779600	0.231171	0.776448

20	Antalya	0.623590	0.205779	0.536809	61	Karaman	0.770313	0.238371	0.792078
21	Sivas	0.699102	0.186416	0.544170	62	Bitlis	0.775782	0.238396	0.797513
22	Samsun	0.671919	0.194848	0.546536	63	Ordu	0.780216	0.239139	0.804396
23	Mugla	0.646180	0.206337	0.560807	64	Nevsehir	0.759311	0.247040	0.811077
24	Tokat	0.658389	0.204128	0.565160	65	Duzce	0.742145	0.254220	0.818937
25	Sakarya	0.643437	0.215223	0.588619	66	Bilecik	0.740492	0.255485	0.821662
26	Mersin	0.708019	0.198054	0.592827	67	Osmaniye	0.768094	0.247684	0.821871
27	Gaziantep	0.714231	0.197045	0.595437	68	Sirnak	0.838697	0.232216	0.837803
28	Ardahan	0.670500	0.217236	0.621983	69	Bartin	0.762363	0.257447	0.849774
29	Eskisehir	0.680307	0.214801	0.623213	70	Giresun	0.806667	0.248133	0.861117
30	Tekirdag	0.632074	0.228735	0.623885	71	Artvin	0.783167	0.256326	0.866263
31	Burdur	0.695428	0.211726	0.627439	72	Yalova	0.749623	0.267301	0.871138
32	Kahramanmaras	0.712770	0.207557	0.630083	73	Tunceli	0.794174	0.255312	0.873544
33	Istanbul	0.580714	0.245757	0.632096	74	Trabzon	0.852780	0.241458	0.883286
34	Kastamonu	0.707086	0.210513	0.634671	75	Karabuk	0.787453	0.260911	0.886188
35	Kutahya	0.696011	0.216755	0.645269	76	Hakkari	0.842825	0.246407	0.890538
36	Yozgat	0.716157	0.211096	0.645540	77	Bayburt	0.843385	0.252721	0.912755
37	Aksaray	0.775880	0.194571	0.647207	78	Sinop	0.858065	0.249780	0.917011
38	Bolu	0.691341	0.218955	0.648255	79	Gumushane	0.854082	0.254038	0.927728
39	Kırsehir	0.705624	0.217889	0.658556	80	Kilis	0.844690	0.263131	0.949757
40	Corum	0.730619	0.211300	0.660376	81	Rize	0.881452	0.265838	0.994978
41	Elazig	0.738276	0.212450	0.671808					

3. Results and Discussion

3.1 Results

The comparative analysis of the TOPSIS and VIKOR rankings revealed a high degree of consistency between the two multi-criteria decision-making (MCDM) methods, particularly in the top-ranked provinces. Table 8 presents the TOPSIS and VIKOR ranking results for the provinces. This table enables a side-by-side comparison of the rankings obtained by the two methods, facilitating the examination of similarities and differences in the relative positions of the provinces.

Table 8. Ranking of the provinces with TOPSIS

Province	TOPSIS_Rank	VIKOR_Rank
Konya	1	1
Izmir	2	2
Ankara	3	3
Istanbul	4	33
Sanliurfa	5	8
Diyarbakir	6	5
Balikesir	7	4
Adana	8	14
Antalya	9	20
Afyonkarahisar	10	6
Bursa	11	13
Erzurum	12	9
Manisa	13	7
Mersin	14	26
Kayseri	15	18
Van	16	16
Tekirdag	17	30
Agri	18	17
Gaziantep	19	27
Denizli	20	11
Aydin	21	10
Eskisehir	22	29
Aksaray	23	37
Edirne	24	44
Kahramanmaras	25	32
Yozgat	26	36
Corum	27	40
Mardin	28	51
Kars	29	12
Sakarya	30	25
Samsun	31	22
Mus	32	19
Burdur	33	31
Kastamonu	34	34
Sivas	35	21
Nigde	36	52
Igdır	37	43
Kocaeli	38	48
Malatya	39	53
Usak	40	46
Tokat	41	24
Amasya	42	42
Batman	43	60
Osmaniye	44	67
Mugla	45	23
Kirsehir	46	39
Adiyaman	47	59
Isparta	48	45
Cankiri	49	56
Bitlis	50	62
Hatay	51	49
Bilecik	52	66
Nevsehir	53	64
Duzce	54	65
Bartin	55	69
Karaman	56	61
Hakkari	57	76
Ordu	58	63
Bolu	59	38
Erzincan	60	58
Kilis	61	80
Kirklareli	62	50
Trabzon	63	74
Kutahya	64	35
Karabuk	65	75
Siirt	66	57
Sirnak	67	68
Yalova	68	72
Sinop	69	78
Rize	70	81
Ardahan	71	28
Elazig	72	41
Bayburt	73	77
Tunceli	74	73
Giresun	75	70
Canakkale	76	15
Gumushane	77	79
Bingol	78	47
Kirikkale	79	55
Artvin	80	71
Zonguldak	81	54

Spearman's rank correlation coefficient between the two rankings was calculated as p = 0.79, indicating a strong positive correlation.

Although the corresponding p-value ($p \approx 2.81 \times 10^{-18}$) is extremely small, denoting statistical significance at the 5% level, the interpretation of this result is especially meaningful in the context of investment decision-making, where ranking stability provides decision-makers with greater confidence.

A closer inspection shows that the top three provinces (Konya, Izmir, and Ankara) are identical in both methods, underscoring the robustness of the prioritization outcome for the highest-potential investment regions. This alignment suggests that for strategic investment planning, the choice of MCDM method is unlikely to affect the selection of the very top candidates, which is an important insight for policymakers and practitioners aiming to minimize decision uncertainty.

Beyond the top three, a proportional match analysis was conducted to further assess ranking consistency. Within the top 10, the two methods agreed on 70% of the provinces, while the top 20 showed an even higher agreement of 80%. This finding demonstrates that while some positional differences occur in mid-ranking provinces, the broader investment priority set identified by both methods remains largely consistent.

However, certain provinces exhibited notable differences in rank position between the two methods. For example, Istanbul ranked 4th in TOPSIS but 33rd in VIKOR, and Antalya shifted from 9th (TOPSIS) to 20th (VIKOR). Such discrepancies may stem from the inherent methodological differences between TOPSIS which emphasizes the shortest distance to the ideal solution and VIKOR which incorporates a compromise solution concept balancing group utility and individual regret. These shifts highlight that while both methods align strongly at the upper end, their sensitivity to tradeoffs in mid-tier alternatives can lead to divergent outcomes.

From an applied perspective, the strong correlation combined with the high agreement rates in the upper ranks provides assurance for investors and policymakers that either method can be reliably employed to identify the most attractive investment locations for biomass facility development. The differences observed in the mid- and lower-ranked provinces, however, suggest that sensitivity analyses or the use of hybrid approaches could be beneficial when investment resources allow for broader expansion beyond the top priorities.

This general pattern is consistent with prior reports in the MCDM literature [74-76] (e.g., Opricovic & Tzeng, 2004, 2007; Mardani et al., 2015), where strong overlap at the upper end and method-sensitive divergence across the middle tier are commonly observed. In addition, a Turkish comparative application involving six AHP-weighted composting alternatives found that TOPSIS and VIKOR produced identical positions for 3 of the 6 options (1st, 2nd, and 5th), with differences concentrated mainly in mid ranks [77]. This finding indicates that the "strong upper tier, agreement mid-tier sensitivity" profile emerges not only in this province-based analysis but also across different problem contexts, supporting the view that reporting both methods together provides a more robust assessment framework.

3.2 Discussion

This study aims to evaluate siting priorities for biomass-based electricity generation facilities across Turkey in a comprehensive manner. The design covers all provinces at the national level using a multi criteria decision making approach; economic, environmental, geographic, accessibility, and related criteria are considered together to reveal relative priorities among provinces. The methodological choices are intended to provide an assessment framework that is practical for investment planning, scalable, and updatable.

The literature shows that site selection studies for biomass and related technologies are largely concentrated at regional or local scales, often rely on a single method, and include limited robustness checks. National scale assessments that combine holistic visualization with comparative methods are relatively rare. Many studies focus on a particular biomass resource, basin, or technology, while cross method comparison and method sensitivity to weighting, normalization, and parameter choices receive limited attention. This makes it harder for decision makers to see, at a national scale, the method dependent uncertainties and tradeoffs in a systematic way.

The present study addresses this gap in three ways. First, it provides national coverage by assessing all provinces under a single framework, thus offering macro scale visibility beyond regional analyses. Second, it adopts a comparative methods perspective, showing how different multi criteria decision making approaches position themselves on the same data and criteria set, which enables a high level discussion of how method choice affects outcomes in upper and middle priority tiers. Third, it applies robustness oriented design principles so that decision support rests not on a single computational pipeline but on an interpretation informed by cross method consistency and sensitivity differences. Together, these elements enable the rare combination of national scale, method comparison, and a robustness mindset.

Within this framework, the overall picture suggests two types of use for decision makers. For defining the top priority set, there is a relatively resilient basis against method differences, providing a reference list for near term investment focus. For expansion toward the middle priority set, systematic scenario work is recommended among alternatives that are sensitive to preferences and policy priorities. This approach helps portfolio selection rest not only on techno economic scores but also on policy dimensions such as accessibility, infrastructure readiness, and sustainability goals.

The assessment has limitations. The scope is bounded by the recency and spatial granularity of available data. The choice of criteria and the weighting approach could be compared with alternative designs. Future work could incorporate additional environmental and social indicators, systematize uncertainty and scenario analyses, broaden comparisons with other multi criteria decision making families, and, where appropriate, use rank aggregation techniques. These steps would further strengthen methodological robustness for national scale decision support.

4. Policy Implications

The comparative analysis between TOPSIS and VIKOR demonstrates that MCDM approaches can offer robust and consistent insights for prioritizing provinces in biomass energy investment planning. The alignment in the top-ranked provinces particularly the identical top three provides a strong foundation for strategic decision-making, suggesting that such rankings are resilient across different evaluation methods. This consistency strengthens the reliability of policy decisions related to regional energy planning and resource allocation.

From a policy perspective, the results provide a practical tool for national and local governments to identify priority regions for biomass and bioenergy investments. By integrating such MCDM frameworks into national energy strategies, policymakers can ensure that investment decisions are based on a combination of economic, environmental, and technical criteria, thereby improving the efficiency and sustainability of the biomass energy sector. Furthermore, the high agreement within the top 10 and top 20 rankings reinforces the credibility of the identified priority provinces, enabling targeted incentives, infrastructure development, and capacity-building programs.

In the context of sustainable energy transitions, this study offers a replicable decision-support framework that can be adapted to different countries and contexts. By incorporating these methods into policy design, decision-makers can balance short-term implementation feasibility with long-term sustainability goals, fostering resilient, low-carbon energy systems that align with both national commitments and global climate targets.

5. Conclusion

This study contributes both theoretically and practically to the field of renewable energy planning by establishing a structured methodology that combines validated expert opinions with multi-criteria decision-making approaches. The integration of expert-derived criteria weights into TOPSIS and VIKOR ensures that decision-making is grounded in both academic rigor and practical insights. The reliability of expert judgments, confirmed by Kendall's coefficient and significance testing, enhances the credibility of the weighting process and reduces subjectivity in the evaluation of biomass power plant locations.

The comparative application of TOPSIS and VIKOR revealed high levels of consistency, which strengthens confidence in the robustness of the results. While both methods rely on different mathematical formulations, their converging outcomes underline the reliability of the decision-support framework developed in this study. Such methodological triangulation provides an added layer of assurance to policy-makers, enabling them to base investment and planning decisions on sound and validated evidence.

From a policy perspective, the study demonstrates the critical importance of combining expert input with systematic decision-making tools when addressing complex energy planning problems. This approach ensures that diverse sustainability, environmental, technical, and socio-economic factors are accounted for in an integrated manner. By providing transparent and evidence-based outcomes, the framework not only supports investment decisions but also enhances stakeholder trust and alignment with long-term sustainability targets.

In addition, this research highlights the potential of multi-criteria decision-making techniques as reliable instruments for guiding renewable energy strategies. Future studies may extend this work by incorporating additional decision-making methods, conducting sensitivity analyses under varying parameter assumptions, or applying the framework to other renewable energy sources and geographical contexts. Such extensions would further validate the generalizability and robustness of the approach.

Overall, this study offers a comprehensive and reliable methodological framework that can serve as a reference point for policy-makers, researchers, and practitioners engaged in the sustainable expansion of biomass-based electricity production.

Conflict of Interest Statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this study

CRediT Author Statement

Betül Mutlu: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization. **Bahar Özyörük:** Conceptualization, Resources, Writing - Review & Editing, Supervision.

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