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Wind farm site selection using geographic information system and fuzzy decision making model

Gülay Demir [a,*,1], Muhammad Riaz [b,2], Muhammet Deveci [c,d,e,3,*]

[a] Vocational School of Health Services, Sivas Cumhuriyet University, Sivas 58140, Turkey
[b] Department of Mathematics, University of the Punjab, Lahore, Pakistan
[c] Department of Industrial Engineering, Turkish Naval Academy, National Defence University, 34942 Tuzla, Istanbul, Turkey
[d] The Bartlett School of Sustainable Construction, University College London, London WC1E 6BT, United Kingdom
[e] Department of Electrical and Computer Engineering, Lebanese American University, Byblos, Lebanon

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ABSTRACT

As the demand for renewable energy sources increases, finding the right places to install wind turbines becomes more and more important. The goal of this research is to create and implement a technique that uses geographic information system (GIS) technology to discover appropriate wind farm locations utilizing multi-criteria decision-making (MCDM) approaches. The complexity of this decision-making process, which includes multiple criteria and uncertainty, requires the use of advanced techniques. Fuzzy MCDM methods provide a framework for evaluating and prioritizing potential wind farm sites, taking into account subjective judgments and linguistic terms. In this article, Fuzzy Stepwise Weight Evaluation Ratio Analysis (F-SWARA) is preferred for prioritizing and ranking the criteria in the wind farm installation, while Fuzzy Measurement Alternatives and Ranking by Compromise Solution (F-MARCOS) are used to determine the most suitable location for the wind farm. A database of alternatives and criteria was created using GIS, which was converted into a fuzzy decision matrix via triangular fuzzy numbers. In order to make this evaluation, Sivas province, located in the middle of Turkey, was chosen as the study area. Results obtained show that 36,5% of the whole study area is very suitable for wind farm, and Gürün and Kangal districts are suitable for wind farm. According to the result of F-SWARA method used to evaluate the criteria, wind speed is the most important criteria with a weight of 0,45039. According to the F-MARCOS method used for wind farm site selection, Ulaş district was determined the most suitable location. Furthermore, a sensitivity analysis was performed to test the robustness of the proposed methodology and the results revealed that the proposed integrated MCDM framework is feasible.

1. Introduction

Wind power, which is eco-friendly, is a sustainable and limitless source of renewable energy. Wind energy's contribution to electricity generation has steadily increased in many countries. Governments and organizations worldwide are investing in wind energy projects and providing incentives to promote their adoption (Gigovic et al., 2017; Rezaian & Jozi, 2016).

The reality that wind vitality is free and ceaseless has driven the foundation of numerous wind ranches in nearly every nation. The choice of a suitable site for a wind farm plays a crucial role in maximizing its efficiency and profitability while minimizing potential environmental impacts (Wu et al., 2017). To address this complex decision-making process, fuzzy Multi-Criteria Decision Making (MCDM) methods have emerged as valuable tools for evaluating and prioritizing potential wind farm sites (Petrović et al., 2019). In this piece, we investigate the use of fuzzy MCDM techniques in the choice of wind farm sites and talk about their advantages in promoting well-informed decision-making.

Wind farm location selection involves considering various factors and their associated uncertainties. Key factors include wind speed, wind direction, terrain conditions, environmental impacts, proximity to transmission lines, and community acceptance. These criteria often

* Corresponding authors at: Department of Industrial Engineering, Turkish Naval Academy, National Defence University, 34942 Tuzla, Istanbul, Turkey.
E-mail addresses: gulaydemir@cumhuriyet.edu.tr (G. Demir), muhammetdeveci@gmail.com (M. Deveci).
[1] ORCID: 0000-0002-3916-7639.
[2] ORCID: 0000-0001-8115-9168.
[3] ORCID: 0000-0002-3712-976X.

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possess inherent ambiguity and vagueness, making traditional decision-making techniques less effective. Fuzzy MCDM methods provide a framework to handle such uncertainty and make informed decisions based on expert judgments and linguistic terms. Fuzzy MCDM methods are often used to address real-world complexity (Abbas & Zhang, 2021; Demir et al. 2022; Moslem, 2023; Abbas & Zhang, 2023; Moslem et al. 2023; Vahidinia & Hasani, 2023; Baker et al. 2023; Rezazadeh et al. 2023; Demir, 2023). These methods are known for their ability to deal with situations such as uncertainty, imprecise information and complex relationships. However, these methods themselves can sometimes be complex and difficult for practitioners to understand. Fuzzy MCDM methods often involve mathematical models and complex calculations. The use of fuzzy logic and fuzzy sets may require conceptual understanding for decision makers. Decision makers may have difficulty interpreting and correctly structuring the complexity between fuzzy concepts and relationships. The interpretation and explanation of the results obtained by fuzzy MCDM methods can be difficult for decision makers. Despite these difficulties, fuzzy MCDM methods can be useful in complex decision-making situations involving uncertainty. However, it is important to provide training, practical experience and appropriate tools for practitioners and decision makers to understand and effectively use these methods. The utilization of Fuzzy MCDM methods offers several advantages in wind farm location selection:

- Inclusion of linguistic variables: Fuzzy MCDM techniques enable experts to articulate their preferences using linguistic terms, which more accurately capture subjective assessments and uncertainties.
- Flexibility in handling imprecise data: Wind farm location selection involves dealing with incomplete or uncertain information. Fuzzy MCDM methods can handle imprecise data and provide decision support despite limited data quality.
- Comprehensive evaluation: Fuzzy MCDM methods enable the consideration of multiple criteria simultaneously, providing a holistic assessment of potential wind farm locations. This approach helps avoid overlooking important factors and enhances the overall decision-making process.

However, it is essential to acknowledge the challenges associated with fuzzy MCDM methods, such as the subjectivity of expert judgments, the selection of appropriate linguistic variables, and the complexity of the decision models. Cautious thought and approval of these strategies are fundamental to guarantee the unwavering quality and precision of the comes about. Geographic Information Systems (GIS) play a significant role in identifying optimal site selection alternatives for particular objectives. Simply relying on GIS-based multidimensional analysis is not enough for choosing the appropriate site. From the choices available in the GIS setting, it is necessary to opt for the option regarded as the most fitting. To ensure a sound decision-making process, utilizing MCDM, weighting techniques, and alternate location recommendations can facilitate a ranking system based on decision criteria and guide the selection of the most fitting choice. Most of the problems faced in selecting a suitable location are geographical and therefore combining GIS with MCDM method has the potential to solve such complex decision-making problems (Saraswat et al., 2021). Integrating the analytical power of GIS and fuzzy MCDM methods into the decision-making process enables comprehensive and objective decisions that take into account geographical data and spatial relationships. The basic components of this combined process are shown in Fig. 1.

Geographic data may inherently contain factors such as uncertainties and measurement errors. Fuzzy systems offer an ideal framework for dealing with these uncertainties. Fuzzy logic processes geographic data through fuzzy sets or rules, and this provides a convenient way to handle uncertainty. The capabilities of GIS to collect, store, analyse and present geographic data, combined with the use of fuzzy systems, provide a comprehensive solution for managing uncertainty. This integration allows to reduce uncertainties in decision-making processes and to make more precise, reliable decisions. The geographical data provided by GIS are processed through fuzzy systems, helping to reduce uncertainties and make decisions based on more accurate information in the decision-making process. This enables more effective use of geographical data and management of uncertainty in decision-making processes. This integration increases the ability of geographic data management to cope with uncertainties, enabling more reliable and knowledge-based decisions to be made. Table 1 presents a selection of the research articles that demonstrate the GIS-reliant MCDM approach in determining appropriate locations for wind farms. These articles also highlight the criteria utilized to establish these suitable sites.

According to Table 1, the present study uses unique GIS-based methods such as F-SWARA and F-MARCOS to identify suitable locations for wind energy in Turkey. It includes most of the criteria mentioned in other studies, but the prominent differences are;

- Comprehensive Criteria: The present study utilised a wide range of criteria to determine the appropriate site selection for wind energy. These criteria include factors ranging from rainfall to population density, settlements and surface water. This can provide a broader assessment.
- Different Evaluation Methods: While other studies generally focused on specific analysis and decision-making methods such as AHP, TOPSIS, PROMETHEE, etc., the present study used a different approach such as F-SWARA and F-MARCOS, which are fuzzy methods. These methods can offer a unique perspective in determining the weight of the criteria and determining the appropriate location.

When each study is evaluated in terms of its methods and the criteria

Fig. 1. Geographic Data Processing Process with GIS and Fuzzy System.

Table 1
Studies for mapping the wind farm location.

Authors	Methods	Area	Criteria
Qutaina et al., 2023	GIS with AHP	Palestinian	proximity to gridlines, wind speed, slope, distance from residential areas, distance to roads, land use and land cover.
Asadi et al., 2023	GIS with AHP	Iran	wind power density, distance from power lines, terrain slope, distance from road networks, distance from urban areas, and distance from protected areas.
Karamountzou and Vagiona, 2023	GIS with AHP and TOPSIS	Greece	the number of wind turbines, wind velocity, distance from settlements, distance from high electricity grid, year of operation, slope, distance from protected areas, distance from the road network, distance from protected areas, and installed capacity.
Badi et al., 2023	BWM-AHP-MARCOS	Libya	economy and benefit, policy, safety and quality, environment and ecology, policy, regulation, and social impression.
Wang et al., 2022	Spherical fuzzy AHP, WASPAS	Vietnam	economic impact, construction and maintenance conditions, environmental impact, wind resources, societal impact, conditions onshore,
Albaheem and Evlaki, 2023	GIS with AHP	Saudi Arabia	slope, distance to roads, wind speed, distance to settlement areas, and distance to power lines.
Yegizaw and Mengistu, 2023	GIS with AHP	Ethiopia	geology, distance from the grid, slope, wind speed, distance from towns, distance from the road.
Josimović et al., 2023	GIS with PROMETHEE	Serbia	distance from environmentally protected areas, proximity to nearest populated areas and residential structures for noise, proximity to energy infrastructure for wind farm connection, frequency of freezing days per year, geological and engineering characteristics of the soil, topographical features such as slopes, local community's approval of the site, distance from bodies of water, distance from culturally significant landmarks, proximity to nearest populated areas and residential structures for shadow flicker impact, proximity to nearest populated areas and residential structures for visual impact, land zoning, accessibility for transportation, distance from transportation infrastructure, arrangement of the land, land ownership, seismic activity, exposure of the landscape at the site.
Rekik and Alimi, 2023	GIS with AHP	Tunisia	power lines, slope, wind speed, urban areas, proximity to road networks, and land use.
Ecer, 2021	FUCOM	Turkey	land cover, distance to power transmission lines, distance to fault lines, proximity to transportation networks, installation and maintenance cost, slope, elevation, distance to protected areas,, wind potential, distance to settlements, proximity to the labor force, and contribution to employment.
Present Study	GIS with F-SWARA and F-MARCOS	Turkey	rainfall, wind speed, elevation, wind power density, slope, aspect, land use, distance to road, distance to population density, distance to settlement, distance to the railway, distance to surface water, distance to the airport, distance to disaster center, distance to the tourism center, distance to a protected area, distance to birds habitat area

it focuses on, it is hoped that the present study will contribute to the literature for the solution of site selection problems with its wide scope and unique methods.

1.1. Aims of the study

This article, it is aimed to determine the location of the most suitable wind farm for Sivas province. To this end, this study provides a practical evaluation framework based on fuzzy theory for those who want to set up a wind farm. The introduced evaluation framework is based on the integration of F-SWARA, F-MARCOS approaches. Within the framework of the evaluation, the F-SWARA and GIS approach is recommended to find the optimum weights of importance of the critical factors affecting the correct positioning of wind farms. In addition, suitable locations for the wind farm are prioritized and evaluated with the help of the F-MARCOS approach.

Prioritizing the idea of harnessing wind energy poses a significant decision-making challenge for investors. For the stated purpose, this article presents a case study based on appropriate criteria in the province of Sivas. It also provides managerial and practical information for decision-makers related to the sector in order to develop the renewable energy sector and create a sustainable wind energy system. In conclusion, this article aims to fill the research gaps identified in the previous literature with a robust integrated methodology.

1.2. Research questions

Based on the current literature gap, this article attempts to address the following research questions:

Q1. Are there any mathematical methods or decision support models applied in the wind energy sector to determine the appropriate wind farm location?
Q2. What are the main factors influencing the decision-making process in wind farm installation?
Q3. Does the use of fuzzy multi-criteria decision-making methods in GIS-based studies facilitate decision-making?
Q4. Which location is more convenient than the others?

Through these research questions that highlight gaps that exist in the literature, researchers can identify a realistic, reliable, and applicable methodological framework for determining the appropriate location for the wind farm.

1.3. Contributions and novelty

Taking advantage of renewable energy sources and evaluating them appropriately is a very important issue. This study proposes a hybrid MCDM framework based on fuzzy theory to determine the optimal location for the wind farm. The main contributions of the proposed decision-making model can be summarized as follows:

- This study provides a methodological framework for the solution process of determining the appropriate position for decision-makers in the field of wind energy.
- The F-SWARA method is proposed as a subjective weighting. Thus, the most important performance indicators are determined in order to determine the optimal position.
- With the help of GIS, the most appropriate weight is determined by running the weights obtained with F-SWARA.
- The F-MARCOS approach, based on combining GIS and F-SWARA method weights, was used for the first time in the MCDM literature for positioning. The proposed approach provides a workable methodology for determining wind farm locations.
- The proposed evaluation framework could be useful in determining the location of the wind farm and for resolving other multi-criteria decision-making issues, as well as applicable to other areas of installation of renewable energy sources.

2. Material and methods

2.1. Study area

The province of Sivas is situated in the upper Kızılırmak Area of Central Anatolia. With a land area of 27,386 km^2, it is the second-biggest province in Turkey. The province of Sivas, positioned between 36° and 39° east longitudes and 38° and 41° north latitudes, is shown in Fig. 2.

Sivas province generally forms a plateau with valleys between individual mountainous or mountainous groups, flat plains and hills. Sivas is the coldest province in central Anatolia. Summers are scorching and arid, while winters are bitterly freezing. Summer is a brief duration. There are notable temperature fluctuations between the summer and winter periods and between daytime and nighttime. During the summer, the mercury can climb up to 40 °C, whereas, in the winter, it can plummet to –33 °C. The research region typically exhibits an elevation ascending towards the north-northeast and south-southeast of the downtown area. The altitude of the research region above sea level usually ranges between 581–3012 m.

The mean yearly wind velocity of the province ranges from 1,25 m/s to 3,48 m/s. The areas with the minimum mean wind velocity (1,25–1,87 m/s) are located in and near the downtown area of Sivas, the maximum areas (2,95–3,48 m/s) are clustered in and near the regions of Gürün and Suşehri. The minimum average wind velocity values (0,76–1,27 m/s) are observed during the fall season; the maximum values (3,76–4,63 m/s) are witnessed during the summer period. In the last thirty years, the velocity of wind has shown a decline, with values ranging from 0,97 m/s to 3,19 m/s. The areas with the greatest wind velocity (2,48–3,19 m/s) are near Ulaş and Gürün. The minimum mean wind velocity (0,76–1,27 m/s) was recorded during fall, while the greatest figures (2,98–3,75 m/s) can be observed in the summer season (Karakuş & Demiroğlu, 2022).

2.2. Information supply and utilized software

Previous studies on wind farm location selection (Atici et al., 2015; Latinopoulos & Kechagia, 2015; Gigovic et al., 2017; Pamučar et al., 2017; Arca & Keskin Citiroglu, 2020; Kizielewicz et al., 2020; Zalhaf et al., 2021; Doljak et al., 2021; Barzehkar et al., 2021; Gkeka-Serpetsidaki & Tsoutsos, 2021; Ajanaku et al., 2022; Jani et al., 2022) and expert viewpoints have been considered and the criteria for this study have been established.

In this direction; rainfall, wind speed, elevation, wind power density, slope, aspect, land use, distance to road, distance to population density, distance to settlement, distance to the railway, distance to surface water, distance to the airport, distance to disaster center, distance to the tourism center, distance to a protected area, distance to birds habitat area constituted basic criteria of the study. Elevation, aspect and slope criteria were obtained from DEM) with 30 m spatial resolution (ESRI, 2017). The data of road, settlement, railway, surface water, airport and protected areas taken from the 1/100.000 scale environmental plan were analyzed with the help of the Euclidean Distance tool of ArcGIS 10.8 software, and the distance criteria of these data were obtained. The annual average precipitation data obtained from the Meteorology Directorate (Sivas/Turkey) covering the 30-year (1990–2020) time period was mapped with the help of the IDW (Inverse Distance Weighted) tool of the ArcGIS 10.8 software, and the precipitation criterion of the study area was obtained. The wind speed and wind power density criteria with an altitude of 100 m were obtained as raster data (. TIFF) from the Global Wind Atlas. The 2018 CORINE Land Cover program (Copernicus Land Monitoring Service) obtained the land use criterion. Population density data of all districts were calculated with Excel 2017 software using the population data of all districts obtained from the relevant institution and the real values of the district borders. This calculated population density data was mapped with the IDW method and the population density criterion of the study area was determined. Detailed information is given in Table 2.

As seen in Table 2, the data of disaster centers, tourism centers, and bird habitat areas obtained from the relevant sources were mapped with the Euclidean Distance and the distance criteria of these data were obtained. Projection (UTM 37N, ED50) and cell size (10 m × 10 m) adjustments of all criteria stored in raster data format were performed. ArcGIS 10.8 software was used for criteria and classified criteria mapping and final suitability location mapping of wind power plants.

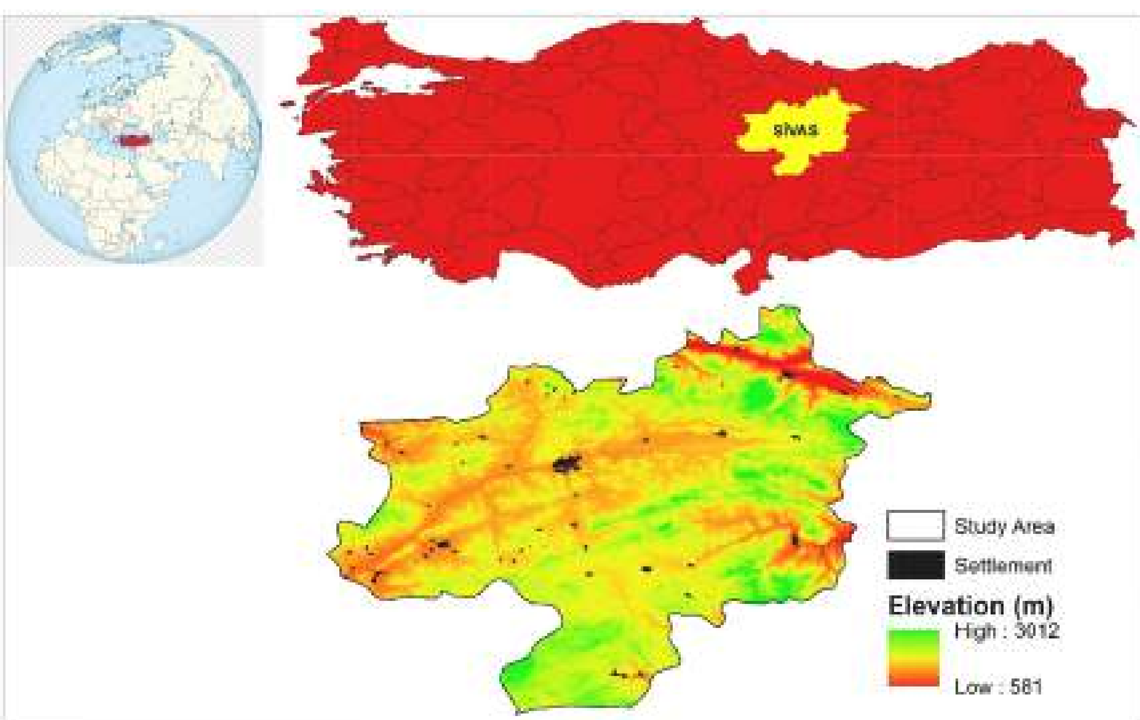

Fig. 2. Work area location.

2.3. Method

In this research, the integration of GIS and MCDM methods was employed to identify the optimal sites for wind farm installations within the confines of Sivas province. The flow diagram of the work structured in 6 steps is shown in Fig. 3.

According to Fig. 3, which consists of 6 different process steps;

Step 1. The aim of the study is defined.
Step 2. After an extensive review of the literature, the criteria utilized in identifying suitable locations for wind farms were established, with the primary source of these criteria being obtained. Subsequently, the criteria were derived from the information gathered during this stage and subsequently transformed into a raster data format within a GIS setting.
Step 3. The criteria were standardized and reclassified.
Step 4. The importance of the criteria was established using the MCDM (F-SWARA) method.
Step 5. The categorization standards and weightings predominantly coincided with using the Raster Calculator in the GIS system, and the mapping of suitable locations for wind power plants was carried out. During this stage, the research area was divided into 5 classifications "very high", "high", "medium", "low" and "very low" based on the appropriateness of wind power plants, and the most appropriate regions for wind power plants were identified.
Step 6. The Fuzzy MARCOS method was used to assess the most appropriate locations for the wind power plant identified in the 5th stage, and the procedure of prioritizing the different areas was conducted.

2.3.1. Fuzzy set theory

The fuzzy set theory was initially suggested by Zadeh (1965). Fuzzy versions of MCDM methods were then created. Fuzzy methods make it possible to include qualitative values for alternative analysis that are closer to human thinking (Ayub et al., 2022). This represents an advantage of fuzzy methods over simple MCDM methods. To work with qualitative values in the form of linguistic values, fuzzy methods use membership functions to convert qualitative values into the fuzzy numbers used in fuzzy methods. Fuzzy sets are sets whose membership degrees are determined as real numbers in the scope of [0,1]. Fuzzy numbers constitute distinct subsets of fuzzy sets. Fuzzy numbers can occur in theory and practicality in various manners. These are modes of representation developed to convey uncertain quantities. In this research, it was chosen to utilize triangular fuzzy numbers. In a fuzzy set ($\widetilde{N}$), triangular fuzzy numbers are represented as (l, m, u). Taking into account the values represented; l is the minimum conceivable value, m is the most anticipated value, and u is the maximum conceivable value. Let x be a random variable with a triangular probability distribution defined on the closed interval [l, u]. Because each element $x \in$ [l, u] has a triangle possibility for the interval [l, u], the arbitrary basic random event has a triangular occurrence probability for the random variable x. The $\widetilde{N} = (l, m, u)$ is a random variable having a triangular distribution over the interval [l, u]. The related triangular possibility density function $\widetilde{f}(x)$ is as follows (Wang, 2021):

$$\widetilde{f}(x) = \begin{cases} \dfrac{2(x-l)}{(m-l)(u-l)}, l \le x \le m \\ \dfrac{2(u-x)}{(u-m)(u-l)}, m \le x \le u \\ 0, otherwise \end{cases}$$

It is clear that $0 \le \widetilde{f}(x) \le \frac{2}{(u-l)}$ and $\int_{-\infty}^{\infty} \widetilde{f}(x) = 1$.

If $\widetilde{A} = (a_l, a_m, a_u)$ and $\widetilde{B} = (b_l, b_m, b_u)$ are two triangular fuzzy numbers, the mathematical calculations for them are defined by Eqs. (1)–(4).

$$\widetilde{A} + \widetilde{B} = (a_l + b_l, a_m + b_m, a_u + b_u) \tag{1}$$

$$\widetilde{A} - \widetilde{B} = (a_l - b_u, a_m - b_m, a_u - b_l) \tag{2}$$

$$\widetilde{A} x \widetilde{B} = (min(a_l b_l, a_l b_u, a_u b_l, a_u b_u), a_m b_m, max(a_l b_l, a_l b_u, a_u b_l, a_u b_u)) \tag{3}$$

Table 2
Information on the criteria used in the installation of a wind farm.

Criteria	Data	Data Source	Data Format	Analysis
Wind speed	Wind speed	https://globalwindatlas.info/ (accessed on 14 October 2022)	Raster layer (TIFF)	–
Wind power density	Wind power density	https://globalwindatlas.info/ (accessed on 14 October 2022)	Raster layer (TIFF)	–
Rainfall	Rainfall	Meteorology Department (Sivas/Turkey)	Excel (xlsx)	Inverse Distance Weighting (IDW)
Elevation	DEM	USGS	Raster layer	–
Slope	DEM	USGS	Raster layer	Slope
Aspect	DEM	USGS	Raster layer	Aspect
Land use	Land use	CORINE (European Union)	Vector-polygon layer	Feature to raster
Distance to road	Road	MEUCC/Landscaping Plan (Ankara/Turkey)	Vector-line layer	Euclidean distance
Distance to population density	Districts	TSI (Ankara/Turkey)	Vector-point layer	Point density
Distance to settlement	Settlement area	MEUCC/Landscaping Plan (Ankara/Turkey)	Vector-polygon layer	Euclidean distance
Distance to railway	Railway	MEUCC/Landscaping Plan (Ankara/Turkey)	Vector-line layer	Euclidean distance
Distance to surface water	Surface water	MEUCC/Landscaping Plan	Vector-line layer	Euclidean distance
Distance to airport	Airport	MEUCC/Landscaping Plan	Vector-polygon layer	Euclidean distance
Distance to disaster center	Disaster center	GDME	Vector-point layer	Euclidean distance
Distance to tourism center	Tourism center	Google Earth Maps/Sivas Atlas	Vector-point layer	Euclidean distance
Distance to protected area	Protected area (Historical, archaeological and landscape sites)	MEUCC/Landscaping Plan	Vector-point and polygon layer	Euclidean distance
Distance to birds habitat	Birds habitat	GPS Point	Vector-point layer	Euclidean distance

Note: DEM: Digital Elevation Model, USGS: United States Geological Survey, Digital Elevation Model, MEUCC: Ministry of Environment, Urbanization and Climate Change, CORINE: Coordination of Information on the Environment Program, MFAL: Ministry of Food, Agriculture and Livestock, TSI: Turkish Statistical Institution, GDME: General Directorate of Mineral Exploration/Earth Sciences Mapping.

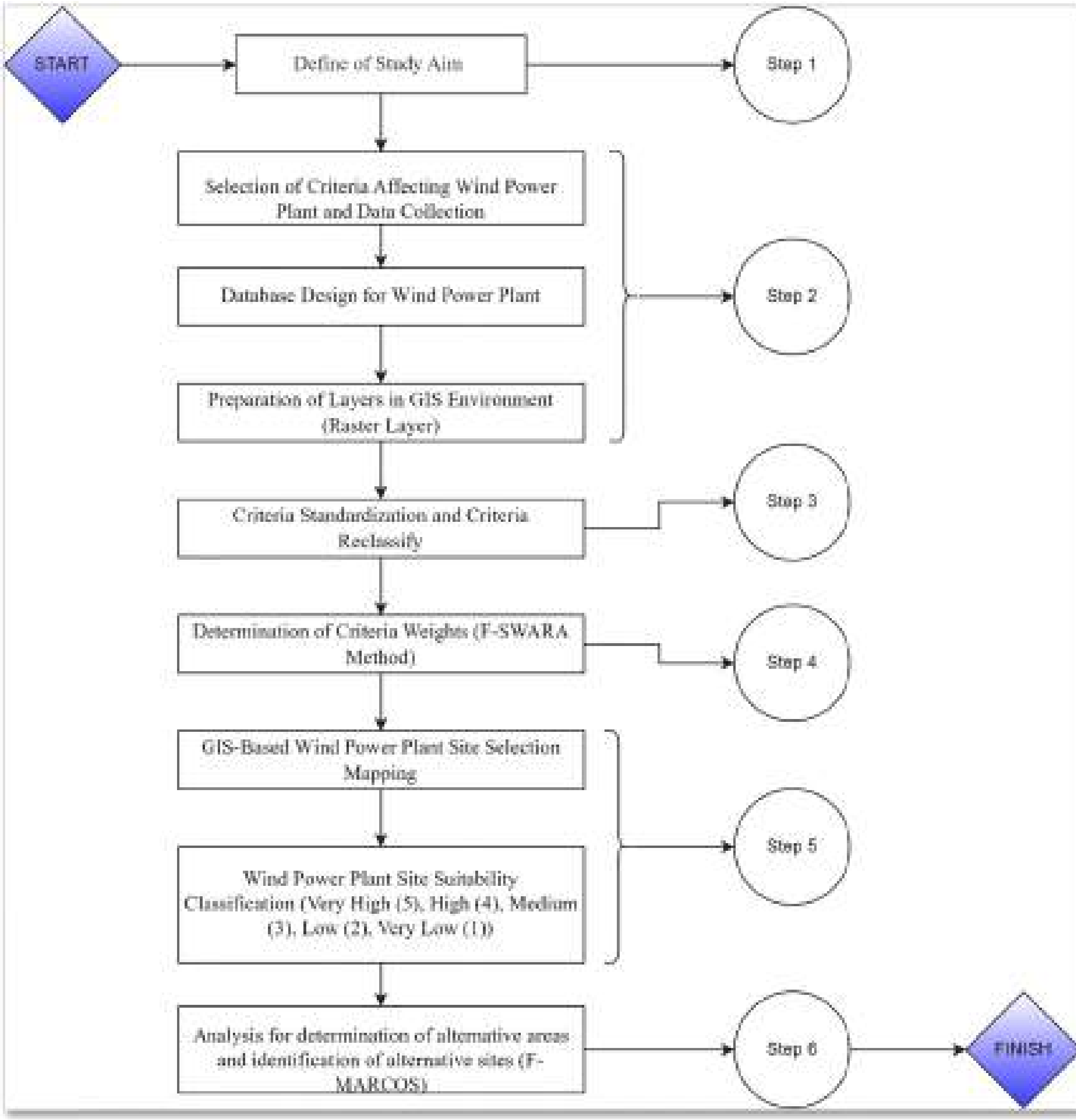

Fig. 3. Flowchart of the study.

$$\frac{\widetilde{A}}{\widetilde{B}} = \left(min\left(\frac{a_l}{b_l}, \frac{a_l}{b_u}, \frac{a_u}{b_l}, \frac{a_u}{b_u}\right), \frac{a_m}{b_m}, max\left(\frac{a_l}{b_l}, \frac{a_l}{b_u}, \frac{a_u}{b_l}, \frac{a_u}{b_u}\right) \right) \tag{4}$$

Triangular fuzzy numbers could be transformed into crisp numbers with the help of different equations. For this study, Eq. (5) is employed to defuzzify a fuzzy number like $\widetilde{A} = (a_l, a_m, a_u)$:

$$A = \frac{a_l + 4a_m + a_u}{6} \tag{5}$$

2.3.2. Calculating procedure of F-SWARA method

The fuzzy extension F-SWARA was developed by Mavi, Goh and Zarbakhshnia in 2017 (Keršuliene et al., 2010; Mavi et al., 2017). Table 3 provides an overview of current studies.

This method is applied with the following steps (Mavi et al., 2017; Madenoğlu, 2020; Ulutaş et al., 2020):

Step 1. The criteria are ranked by experts according to their significance.

The criteria "j" are evaluated by the decision makers based on their importance (from the highest importance level to the lowest importance level).

Step 2. Comparison of criteria using linguistic values.

Beginning with the second criteria $(j-1)$. criteria j. compared to the criteria. In this comparison, experts use linguistic values that express $\widetilde{b}_j$ "comparative significance of mean value" (Chang, 1996). Table 4 presents these linguistic values and their fuzzy values $(\widetilde{b}_j)$.

Step 3. Fuzzy coefficients calculation $\left(\widetilde{e}_j\right)$.

Fuzzy coefficients are obtained using Eq. (6).

$$\widetilde{e}_j = \begin{cases} \widetilde{1}j = 1 \\ \widetilde{b}_j + 1j > 1 \end{cases} \tag{6}$$

Step 4. Calculation of the importance vector $(\widetilde{f}_j)$

The importance vector $(\widetilde{f}_j)$ is obtained using Eq. (7).

$$\widetilde{f}_j = \begin{cases} \widetilde{1}j = 1 \\ \dfrac{\widetilde{f}_{j-1}}{\widetilde{e}_j} j > 1 \end{cases} \tag{7}$$

Step 5. Calculation of fuzzy weights ($\widetilde{w}_j = \left(w_j^l, w_j^m, w_j^u\right)$) *of the criteria*

Fuzzy weights are obtained using Eq. (8).

$$\widetilde{w}_j = \frac{\widetilde{f}_j}{\sum_{j=1}^{n} \widetilde{f}_j} \tag{8}$$

These fuzzy weights $\left(\widetilde{w}_j = \left(w_j^l, w_j^m, w_j^u\right)\right)$ are converted to crips weights (w_j) using Eq. (9).

$$w_j = \frac{w_j^l + w_j^m + w_j^u}{3} \tag{9}$$

The pseudocode written to express the steps of the F-SWARA method in a simple and understandable way is given below.

Procedure F-SWARA Method

// Step 1: Criteria are ranked by experts according to their significance
Input: Criteria list C, ranked by importance
// Step 2: Comparison of criteria using linguistic values
For each criterion j from 2 to length(C)
Compare criterion j with criterion j-1 using linguistic values
Assign fuzzy value bj based on Table 4
// Step 3: Fuzzy coefficients calculation ($\widetilde{e}_j$)
For each criterion j from 1 to length(C)
If j == 1 then
$\widetilde{e}_j = 1$
Else
$\widetilde{e}_j = \widetilde{b}_j$
// Step 4: Calculation of the importance vector ($\widetilde{f}_j$)
For each criterion j from 1 to length(C)
If j == 1 then
$\widetilde{f}_j = 1$
Else
$\widetilde{f}_j = \widetilde{f}_{(j-1)} / \widetilde{e}_j$
// Step 5: Calculation of fuzzy weights ($\widetilde{w}_j$)
Sum $\widetilde{f}_j$ *= Sum(*$\widetilde{f}_j$ *for all j from 1 to length(C))*
For each criterion j from 1 to length(C)
$\widetilde{w}_j = \widetilde{f}_j$ */ Sum* $\widetilde{f}_j$
// Convert fuzzy weights to crisp weights
For each criterion j from 1 to length(C)
w_j *crisp =* $(w_j^l + w_j^m + w_j^u) / 3$
Output: Crisp weights w_j *for each criterion*
End Procedure

These crips weights will be employed in both the GIS-based search for potential alternative regions and the F-MARCOS technique.

2.3.3. Calculating procedure of F-MARCOS method

Stanković, Stević, Das, Subotić and Pamučar fuzzed the MARCOS approach in 2020 (Stević et al., 2020; Stanković et al., 2020). Table 5 gives an overview of current research.

The significance of the criteria in the F-MARCOS technique is established by digitizing linguistic expressions. Table 6 contains linguistic expressions that can be employed, as well as the scale that corresponds to these expressions.

The algorithm of this method is given below (Stanković et al., 2020):

Step 1. Determine the initial fuzzy decision matrix.

The decision matrix obtained from the alternatives and criteria evaluated by "k" number of experts according to Table 6 is indicated by Eq. (10).

$$\widetilde{X} = \left[\widetilde{x}_{ij}\right]_{mxn} \tag{10}$$

where, $\widetilde{x}_{ij}$ is the value given to the comparison of the alternative i. with criteria j.

Using Eq. (11), the matrices created by the experts are combined, thus obtaining the initial fuzzy decision matrix.

Table 3
Studies with F-SWARA.

Authors	Methods	Application Area
Mishra et al., 2023	Intuitive fuzzy set based SWARA, MEREC, ARAS	Evaluation of industrial building options
Ai et al., 2023	M-SWARA, based on quantum spherical fuzzy sets ELECTRE	Researching the components of the fintech ecosystem
Seikh and Mandal, 2023	SWARA, PROMETHEE II	Evaluation of biomedical waste
Jafarzadeh et al., 2023	Spherical fuzzy set SWARA, CODAS	Evaluation of clean energy barriers
Bouraima et al., 2023	Fuzzy SWARA based on fuzzy Bonferroni aggregation	Ranking of regional transport infrastructure programs
Mikhaylov et al., 2023	q-ROF Multi-SWARA	Evaluation of Bitcoin mempool priorities
Ghiaci and Ghoushchi, 2023	Pythagorean fuzzy set based SWARA, MOORA	Evaluating the barriers to the circular economy with IoT
Akram et al., 2023	T-spherical Fuzzy SWARA, 2-Tuple Linguistic COPRAS	Evaluation of hydroelectric power plants
Puška et al., 2023	Fuzzy SWARA, Fuzzy CRADIS	Determining the locations of distribution centers
Martínez et al., 2023	M-SWARA, ELECTRE	Measuring the impact of renewable energy investments through a new service development process.

$$\widetilde{x}_{ij} = \prod_{k=1}^{K} \left(\widetilde{x}_{ij}\right)^{1/K} \tag{11}$$

Step 2. Construction of the extended fuzzy matrix

Based on the criteria, the best preference values ideal solution (AI) and the worst preference values anti-ideal solution (AAI) of the alternatives are obtained. These values are incorporated into the enlarged fuzzy decision matrix. The highest value regards the benefit criteria as the optimal option, while the lowest value regards the cost criteria as the least favorable option. Based on the cost criteria, the smallest value represents the ideal solution and the largest value represents the anti-ideal solution. The enlarged fuzzy decision matrix is formulated as shown in Eq. (12).

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

Step 3. Generating the normalized fuzzy matrix

By utilizing Eqs. (13) and (14), the normalized fuzzy matrix $\widetilde{N} = \left[\widetilde{n}_{ij}\right]_{mxn}$ is acquired.

Table 4
Linguistic and Fuzzy Values.

Linguistic Values	$\widetilde{b}_j$
Equally Important	(1, 1, 1)
Moderately Less Important	(2/3, 1, 3/2)
Less Important	(2/5, 1/2, 2/3)
Very Little Important	(2/7, 1/3, 2/5)
Much Less Important	(2/9, 1/4, 2/7)

Table 5
Studies with F-MARCOS.

Authors	Methods	Application Area
Majumder, 2023	SVNF-MARCOS, TrF-FUCOM	Efficiency analysis of water treatment plant
Bouraima et al., 2023	IMF SWARA, fuzzy MARCOS	Ranking of transport infrastructure programs
Görçün and Doğan, 2023	Fuzzy BWM, Fuzzy MARCOS	Mobile crane selection in project logistics operations
Tadić et al., 2023	Fuzzy AHP, Fuzzy MARCOS	Evaluation of sustainability categories of city logistics initiatives
Tešić et al., 2023	Fuzzy LMAW, Grey MARCOS	Choosing a dump truck
Kılıç and Erkayman, 2023	Fuzzy FUCOM, Fuzzy MARCOS	Determination of production technology according to the critical characteristics of intelligent production systems
Pamučar et al., 2023	Fuzzy rough Aczel–Alsina OPA-MARCOS	Choice of healthcare waste management process
Chaurasiya and Jain, 2023	Pythagoras fuzzy-based MEREC, SWARA, MARCOS	Determining the best hospital management software
Saha et al., 2023	Fermetean fuzzy Delphi, MARCOS	Choosing a bin location for the automotive industry
Wang et al., 2023	Fermatean fuzzy MARCOS	Assessment of occupational risk

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

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

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

Step 4. Creating of weighted fuzzy matrix.

With Eq. (15), the elements of the weighted fuzzy matrix are obtained by multiplying the elements of the $\widetilde{V} = \left[\widetilde{v}_{ij}\right]_{mxn}$ normalized fuzzy matrix ($\widetilde{N}$) by the fuzzy weight coefficients $\left(\widetilde{w}_j\right)$.

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

Step 5. Determining the total weight value for each alternative

Using Eq. (16), the sum of a weighted normalized matrix $\widetilde{S}_i$ is calculated concerning the i. alternative.

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

Similarly, the total weighted values are obtained for ideal ($\widetilde{S}_{ai}$) and anti-ideal ($\widetilde{S}_{aai}$) solutions respectively.

Step 6. Calculate the degree of utility of alternatives.

Eqs. (17) and (18) are applied to find the degree of utility of the alternatives ($\widetilde{K}_i$).

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

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

Step 7. Obtaining the total utility of each alternative.

Using Eq. (19), the fuzzy matrix ($\widetilde{T}_i$) expressing the total utility degrees is calculated.

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

A new fuzzy number ($\widetilde{D}$) is then obtained using Eq. (20).

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

and then Eq. (21) is used to obtain the number df_{crisp}.

$$df_{crisp} = \frac{d^{l} + 4d^{m} + d^{u}}{6} \tag{21}$$

Step 8. Utility function for ideal and anti-ideal solution

Eqs. (22) and (23) are applied to calculate the utility functions with respect to the ideal solution $f\left(\widetilde{K}_i^{+}\right)$ and the anti-ideal solution $f\left(\widetilde{K}_i^{-}\right)$.

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

$$f\left(\widetilde{K}_i^{-}\right) = \frac{\widetilde{K}_i^{+}}{df_{crisp}} = \left(\frac{k_i^{+l}}{df_{crisp}}, \frac{k_i^{+m}}{df_{crisp}}, \frac{k_i^{+u}}{df_{crisp}}\right) \tag{23}$$

Step 9. Determining the utility function for each alternative

Eq. (24) is used to calculate the utility function (fK_i) of the alternatives.

$$f(K_i) = \frac{K_i^{+} + K_i^{-}}{1 + \frac{1 - f\left(K_i^{+}\right)}{f\left(K_i^{+}\right)} + \frac{1 - f\left(K_i^{-}\right)}{f\left(K_i^{-}\right)}} \tag{24}$$

where K_i^{+}, K_i^{-}, $f\left(K_i^{+}\right)$, $f\left(K_i^{-}\right)$ are defuzzified values.

Step 10. Ranking of alternatives according to the final values of the utility functions.

The highest value of the utility function is identified as the best alternative.

The pseudocode written to express the steps of the F-MARCOS method in a simple and understandable way is given in Appendix A.

Table 6
Linguistic scale for evaluating alternatives.

Linguistic Terms	Triangle Fuzzy Numbers
Extremely poor	(1,1,1)
Very poor	(1,1,3)
Poor	(1,3,3)
Medium poor	(3,3,5)
Medium	(3,5,5)
Medium good	(5,5,7)
Good	(5,7,7)
Very good	(7,7,9)
Extremely good	(7,9,9)

2.3.4. Criteria standardization and reclassification

Each element in the list of criteria can be depicted by a distinct kind of map, like a categorized map (e.g. land utilization) or a numeric map (e.g. slope). To facilitate decision-making, the numerical values and categories of all maps should be standardized to a shared scale in order to decrease complexity. This transformation is called criteria standardization (Sharifi & Retsios, 2004; Rahman et al., 2012). In this process, all input datasets (criteria) are divided into sub-criteria for suitability siting

Table 7
Criteria for the selection of wind farm sites and their characteristics.

Criteria	Suitability Levels and Scores					
	Highly Suitable 5	Suitable 4	Moderately Suitable 3	Less Suitable 2	Not Suitable 1	Reference
Wind speed (m/sn)	>6	5–6	4–5	3–4	<3	(Saraswat et al., 2021; Nagababu et al., 2022)
Wind power density (W/m^2)	>300	250–300	150–250	100–150	<100	(Ayodele et al., 2018)
Rainfall (mm)	<300	300–500	500–600	600–700	>700	(Al-Shabeeb et al. 2016)
Elevation (m)	<500	500–1000	1000–1500	1500–2000	>2000	(Saraswat et al., 2021; Nagababu et al., 2022)
Slope (degree)	0–6	6–9	9–12	12–15	>15	(Saraswat et al., 2021; Nagababu et al., 2022)
Aspect	E, SE, Flat	NE	N, S	NW, SW	W	(Gigovic et al., 2017)
Land use	Natural and semi-natural areas		Agriculture	Forest	Settlement, artificial zones, water bodies	(Al-Shabeeb et al., 2016; Ali et al., 2019)
Population density (p/km^2)	<10	10–50	50–90	90–110	>110	(Gigovic et al., 2017)
Distance to road (km)	<10	10–20	20–30	30–40	>40	(Gkeka-Serpetsidaki and Tsoutsos, 2022)
Distance to settlement (km)	>40	30–40	20–30	10–20	<10	(Tercan, 2021)
Distance to railway (km)	<5	5–10	10–20	20–50	>50	(Gkeka-Serpetsidaki and Tsoutsos, 2022)
Distance to surface water (km)	>6	4–6	2–4	0.5–2	<0.5	(Mokarram et al., 2022)
Distance to airport (km)	>28	21–28	14–21	7–14	<7	(Saraswat et al., 2021; Nagababu et al., 2022)
Distance to disaster center (km)	>6	4–6	2–4	0.5–2	<0.5	(Elkadeem et al., 2022)
Distance to tourism center (km)	>4	3–4	2–3	1.5–2	<1.5	(Gigovic et al., 2017)
Distance to protected area/Historical and archaeological sites (km)	>5	3.5–5	3.5–4	2.5–3	<2.5	(Elkadeem et al., 2022)
Distance to protected area/Environmental protected areas (km)	>5	3.5–5	3.5–4	2.5–3	<2.5	(Elkadeem et al., 2022)
Distance to birds habitat (km)	>5	4–5	3–4	2.5–3	<2.5	(Aydin et al., 2010)

analysis, each sub-criterion of the criteria is given score between 1–5, and the criteria are reclassified and standardized in this way. The scores of 5, 4, 3, 2 and 1 correspond to the categories of "highly suitable", "suitable", "medium", "less suitable" and "unsuitable" respectively (Radwan et al., 2019; Makonyo & Msabi, 2022).

In this study; rainfall, wind speed, slope, wind power density, elevation, aspect, land use, distance to roads, population density, distance to settlements, distance to railways, distance to surface water sources, distance to airports, distance to disaster centers, distance to tourism centers, distance to protected areas and distance to bird habitat areas were wind farm were grouped according to their suitability in the choice of location and each group was given a score between 1 and 5. (Ettazarini, 2021; Balkhair & Ur-Rahman, 2021; Karakuş & Yıldız, 2022). Considering the impact level scores of the criteria given in Table 7 in the wind farm location selection suitability mapping, thematic maps of criteria were reclassified with the Spatial Analyst module of ArcGIS 10.8 program and shown in Fig. 4.

2.3.5. *Suitability index and wind farm site selection mapping*

The Weighted Linear Combination (WLC) approach, one of the most commonly utilized techniques for merging various tiers, is a method that assesses appropriateness based on the relative significance of the factors and is employed in the calculations of the suitability index (Barzehkar et al., 2016; Jamshidi-Zanjani & Rezaei, 2017). The final site suitability map for a wind farm is created using this methodology by multiplying each fuzzy standardized criterion and its weight and aggregating all criteria based on the WLC method in ArcGIS software using the raster analysis tool (Tavana et al., 2017). Eq. (25) shows the mathematical formula for the appropriateness index (Barzehkar et al., 2021). High suitability index values suggest the best locations for ultimate site appropriateness selection.

$$SI = \sum_{i=1}^{n} w_i{}^{*}x_i \tag{25}$$

where; *SI*: Relevance index, w_i: criteria *i*'s relative importance weight, x_i: criteria *i*'s standardized relevance score and *n*: total number of criteria.

The criterion scoring and weighting processes with the F-SWARA approach were carried out in this study while taking prior studies (see Table 1) on wind farm location selection into account. The geometric mean values based on expert opinions were evaluated together with the GIS-based F-SWARA method, and the wind power plant site selection suitability map of the study area was obtained and shown in Fig. 5.

The pseudocode written to express the *SI* calculation in a simple and understandable way is given below.

```
Procedure Calculate Suitability Index
  // Step 1: Define the input parameters
  Input: List of criteria weights w, list of criteria scores x, total number of criteria n
  // Step 2: Initialize suitability index (SI) to 0
  SI = 0
  // Step 3: Calculate the suitability index using the WLC approach
  For i from 1 to n
  SI = SI +( wi*xi)
 // Step 4: Output the suitability index
  Output: SI
End Procedure
```

2.3.6. *Sensitivity analysis*

After determining the "most important criteria (Cn)" according to the weight values determined according to the criterion weighting method, sensitivity analysis can be performed by changing the weight of the "most important criteria (Cn)" to observe the effect of the proposed model on the ranking performance. In this method, a new weight factor vector is created first. In each case, the weight value of the most important criterion is reduced by 15 % and a new weight factor vector is created. Using Eq. (26), the new weight value of the criteria can be calculated as follows (Vrtagić et al., 2021).

$$w_{n\beta} = (1 - w_{n\alpha})\left(\frac{w_\beta}{1 - w_n}\right) \tag{26}$$

where $w_{n\beta}$ indicates the new weight values calculated for the criteria.

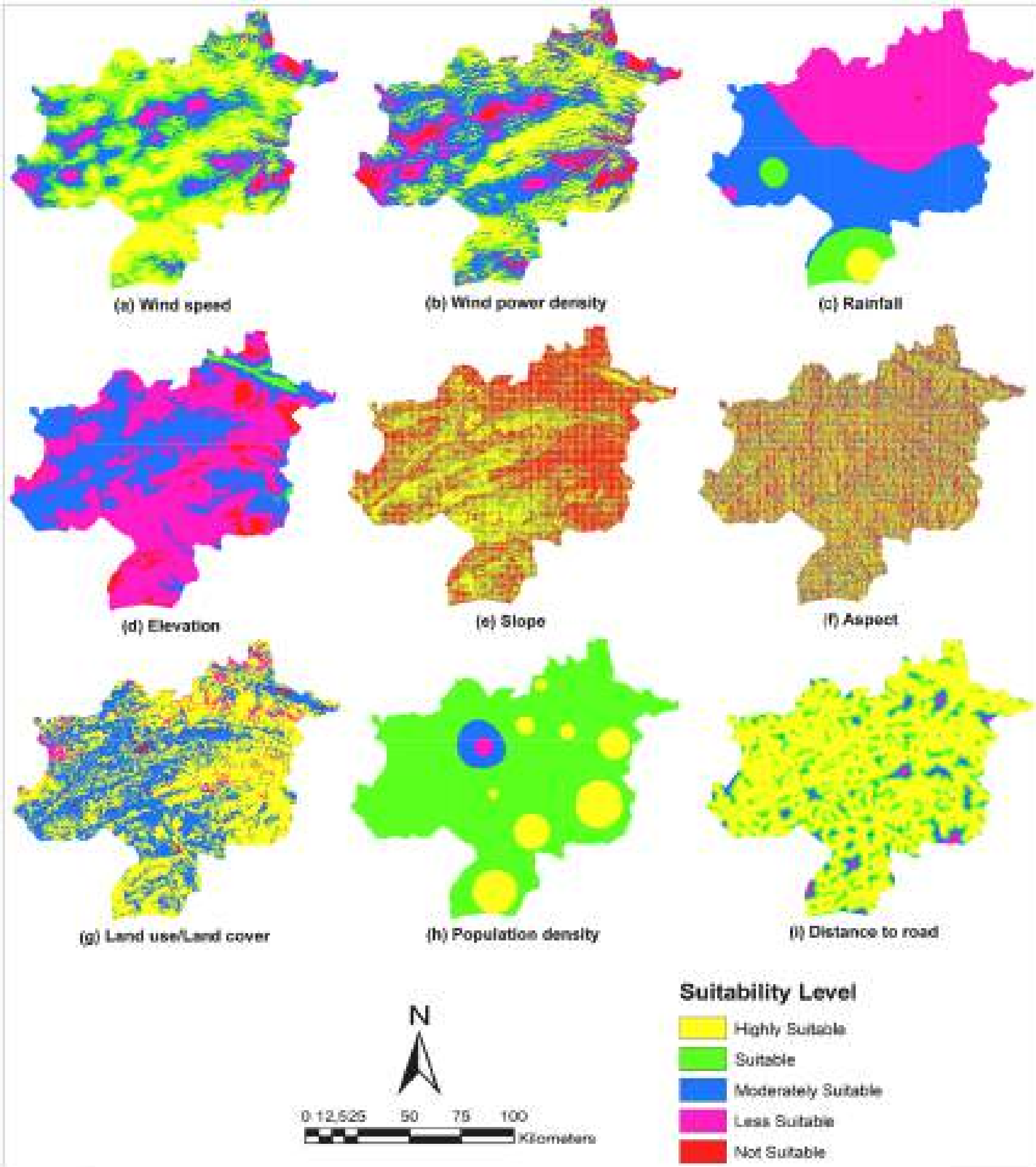

Fig. 4. Standardized and classified maps of the criteria.

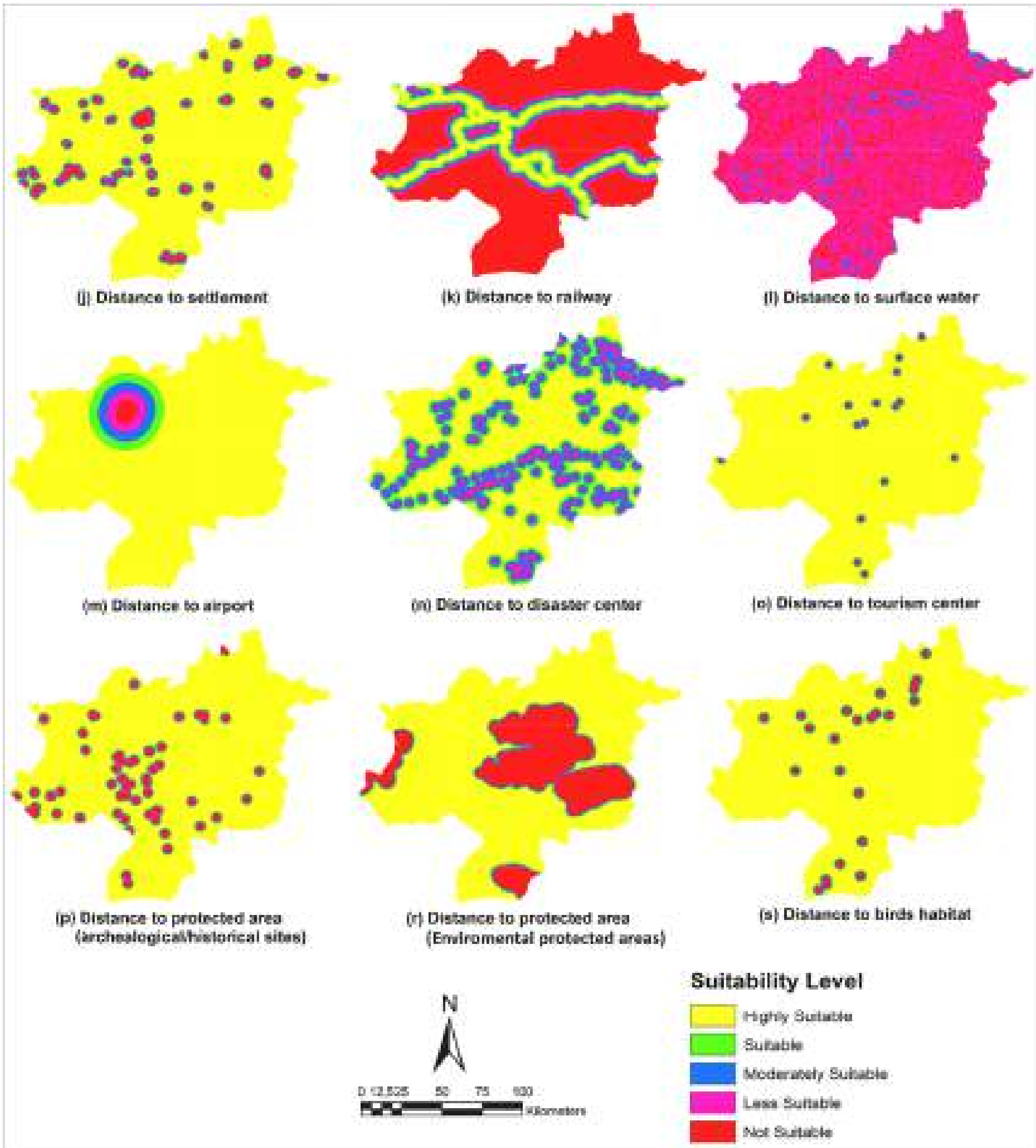

Fig. 4. (*continued*).

$w_{n\alpha}$ denotes the reduced value of the criteria. While the original value of the criteria is denoted by w_{β}, the original value of the reduced criteria is denoted by w_n.

3. Result and discussion

3.1. Wind farm site selection mapping

Six specialists working in the energy sector and with extensive expertise were consulted for the research. The experts were first asked to rate the criteria in order of priority (beginning with the most important 1), and then the subsequent criteria were compared with the linguistic variables in Table 4 using Eqs. (6) and (7). Appendix B contains the evaluation matrices that were generated. Table 8 presents the fuzzy weights and crips weights computed from Eqs. (8)-(9).

When an evaluation is made in terms of criterion weight values obtained with the help of F-SWARA method; wind speed, wind power density, and slope criteria are identified as the criterion with the greatest weight values in wind farm site selection.

To get the wind farm site selection mapping of the research region, the suitability index approach based on the weighted linear combination method was utilized. To map the appropriateness of wind farms, the site suitability index in the research region was derived using Eq. (20) by applying the criteria's scores (see Table 3) and the weight values obtained by the F-SWARA approach (see Table 4).

$$\begin{aligned} SuitabilityIndex(SI) = {} & (WindSpeed*0.45039) + (WindPowerDensity*0.20517) + (Rainfall*0.05483) + (Elevation*0.08133) + (Slope*0.10120) \\ & + (Aspect*0.00302) + (LandUse*0.00868) + (DistancetoRoads*0.00708) + (DistancetoPopulationDensity*0.00785) \\ & + (DistancetoSettlement*0.01920) + (DistancetoRailway*0.00659) + (DistancetoSurfaceWater*0.00885) \\ & + (DistancetoAirport*0.00402) + (DistanceToDisasterCenter*0.00392) + (DistanceToTourismCenter*0.00302) \\ & + (DistancetoProtectedArea*0,02015) + (DistancetoBirdsHabitat*0.01471) \end{aligned}$$

The classified raster maps (see Fig. 4) created according to the impact levels of the criteria on the wind power plant site selection mapping and the criteria weights obtained with the F-SWARA method (see Table 4) were used to create a wind farm suitability map (see Fig. 5). The computed suitability index values for the research region ranged from (1,44–4,73). The suitability categories revealed by the obtained wind power plant suitability maps were categorized as "highly suitable (3,98–4,73)", "suitable (3,47–3,98)", "moderately suitable (2,99–3,47)", "less suitable (2,46–2,99)", "not suitable (1,44–2,46)". The suitability categories of "highly suitable" and "suitable" showed a homogeneous distribution in the study area and the areas in this category constituted the majority of the study area. The areas in the "highly suitable" class constituted 36,50 % of the study area, while the areas in the "suitable" class constituted 25,17 % of the study area. The districts

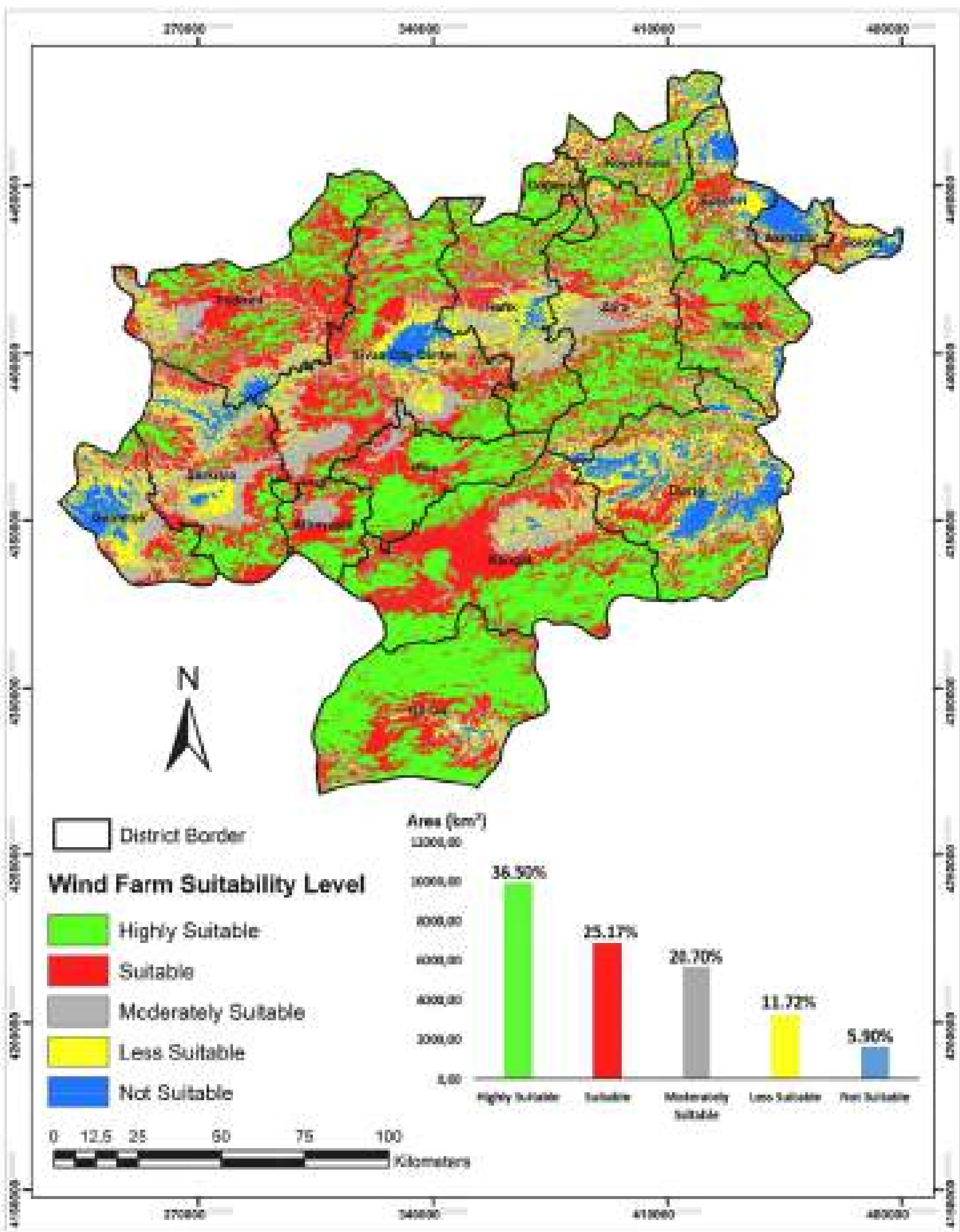

Fig. 5. Wind farm suitability categories for the study area.

Table 8
The benchmark weight values obtained by F-SWARA method.

Criteria	$\widetilde{w}_i$			w_i
	l	m	u	
Wind speed	0,37817	0,44993	0,47963	0.45039
Wind power density	0,16845	0,20042	0,22683	0.20517
Rainfall	0,03527	0,05022	0,07370	0.05483
Elevation	0,05750	0,07608	0,10257	0.08133
Slope	0,07568	0,09573	0,12242	0.10120
Aspect	0,00022	0,00129	0,00725	0.00302
Land use	0,00173	0,00548	0,01801	0.00868
Distance to roads	0,00169	0,00464	0,01422	0.00708
Distance to population density	0,00172	0,00510	0,01596	0.00785
Distance to settlement	0,00794	0,01551	0,03228	0.01920
Distance to railway	0,00129	0,00405	0,01378	0.00659
Distance to surface water	0,00230	0,00603	0,01737	0.00885
Distance to airport	0,00039	0,00188	0,00941	0.00402
Distance to disaster center	0,00042	0,00193	0,00903	0.00392
Distance to tourism center	0,00023	0,00129	0,00725	0.00302
Distance to protected area	0,00794	0,01622	0,03436	0.02015
Distance to birds habitat	0,00501	0,01123	0,02646	0.01471

with the highest concentration of areas classified as “highly suitable” were Ulaş, Gürün and Kangal districts. Although there are suitable areas in Gemerek, Şarkışla, Yıldızeli, Sivas center, Divriği, Akıncılar and Gölova districts, unsuitable areas in these districts are shown in Fig. 5.

3.2. Ranking/comparison of alternative sites

To select the most appropriate districts among Gürün, Kangal, Ulaş, Zara and Imranlı districts in the highly suitable class, the opinions of 3 different company representatives interested in the installation of wind energy turbines were taken. Using Table 6, the initial matrix evaluating the 5 districts classified as highly suitable is presented in Appendix C. The decision matrices were combined using Eqs. (10) and (11). Then, the utility function was obtained using Eqs. (12)–(24) and presented in Table 9.

Among the alternatives classified as highly suitable according to the F-MARCOS method, A3 (Ulaş) district was found to be the most suitable location compared to the others. These results show that Ulaş district stands out in terms of wind energy potential compared to other alternatives and is the most favourable location for a wind farm.

3.3. Application of sensitivity analysis

According to Table 8, the criterion with the highest weight value (0.45039) is wind speed. A total of 15 scenarios were obtained using Eq. (26). Unlike these 15 scenarios, the scenario corresponding to the original weight value of the wind speed criterion was accepted as Scenario 0 (S0). According to these scenarios; wind speed = 0.45039 represented the weight value in Scenario 1 (S1), while wind speed = 0.03344 represented the weight value in Scenario 15 (S15). Eq. (21) was used to derive the weights of the other criteria after each adjustment of wind speed. For example, the calculation for the first scenario (S1) was made as follows: The actual weight value of the wind speed criterion (0.45039) was reduced by 15 % and the weight value for scenario S1 was found as 0.38283 [0,45039 − (0,45039 * 0.15) = 0,38283]. Then, the weight values of all criteria except wind speed were calculated according to the 15 scenarios using Eq. (26) as follows:

$$\text{Wind power density} = \frac{(1-0,38283)^*0,20517}{(1-0,45039)} = 0,23038\cdots\cdots$$

$$\text{Distance to birds habitat} = \frac{(1-0,38283)^*0,01471}{(1-0,45039)} = 0,01652$$

Based on 15 scenarios, the updated weight values of the criteria are shown in Fig. 6.

After obtaining the new criteria weights as shown in Fig. 6, the suitability maps in terms of wind farms according to 15 scenarios are obtained again and given in Fig. 7.

According to Fig. 7, Ulaş district is considered as the most suitable area in terms of wind farm location in all 15 scenarios as in Fig. 4. The wind farm location potential map (Fig. 5) was created according to the weight values calculated based on S0, and the suitability mapping obtained according to the other 15 scenarios (see Fig. 7) supported the accuracy of the suitability mapping obtained according to S0 (see Fig. 4).

4. Conclusion

Wind farm location selection requires a comprehensive evaluation of multiple criteria while considering uncertainties and subjective judgments. Fuzzy MCDM methods offer a valuable approach to addressing these challenges and facilitate informed decision-making. By incorporating linguistic terms, fuzzy numbers, and mathematical techniques, these methods allow decision-makers to handle imprecise and ambiguous information effectively.

This study describes a multi-criteria index strategy that uses GIS-based F-SWARA and F-MARCOS methodologies to find a suitable location for a wind farm in Sivas province. In line with the reason and strategy of the consideration, 17 criteria (wind speed, wind power density, rainfall, elevation, slope, aspect, land use, distance to roads, distance to population density, distance to settlement, distance to railway, distance to surface water, distance to airport, distance to disaster center, distance to tourism center, distance to protected area, distance to birds habitat) were utilized. According to the F-SWARA method, while the wind speed criterion has the highest importance, the distance to tourism center and aspect criteria have the lowest weight values The regions with the finest location are often clustered in the study area’s center and south. According to the F-SWARA approach, about 36,50 % of the research area is deemed “highly suitable”, while approximately 25,17 % of the study area is deemed “suitable”. The districts with the highest concentration of areas in the “highly suitable” class were Ulaş, Gürün and Kangal districts. In terms of making a recommendation to government authorities and investors for wind farm siting, it can be argued that district A3 (Ulaş) is the appropriate location.

This study not only exhibits the use of GIS tools but also indicates how a combination of fuzzy techniques from distinct multi-criteria methodologies (in this example, F-SWARA and F-MARCOS) may be used to address a trending choice issue like wind farm siting. Furthermore, the current study supplements past work in which the decision-making criteria are determined by actual values rather than linguistic labels or triangular fuzzy numbers.

Table 9
Ranking out the best wind farm locations.

Alternatives	$f\left(\widetilde{K}_i^+\right)$	$f\left(\widetilde{K}_i^-\right)$	K_i^+	K_i^-	$f(K_i^+)$	$f(K_i^-)$	K_i
Gürün (A1)	(0,2720;0,4858;0,9019)	(0,2228;0,3842;0,6867)	0,0069	0,0088	0,5195	0,4077	0,0044
Kangal (A2)	(0,2772;0,5258;0,8883)	(0,2270;0,4158;0,6764)	0,0072	0,0092	0,5448	0,4278	0,0051
Ulaş (A3)	(0,2988;0,5249;0,9595)	(0,2447;0,4151;0,7306)	0,0074	0,0094	0,5596	0,4393	0,0053
Zara (A4)	(0,2814;0,4804;0,9017)	(0,2304;0,3799;0,6866)	0,0068	0,0087	0,5174	0,4061	0,0044
Imranlı (A5)	(0,2806;0,4739;0,9364)	(0,2298;0,3747;0,7130)	0,0069	0,0087	0,5187	0,4069	0,0043

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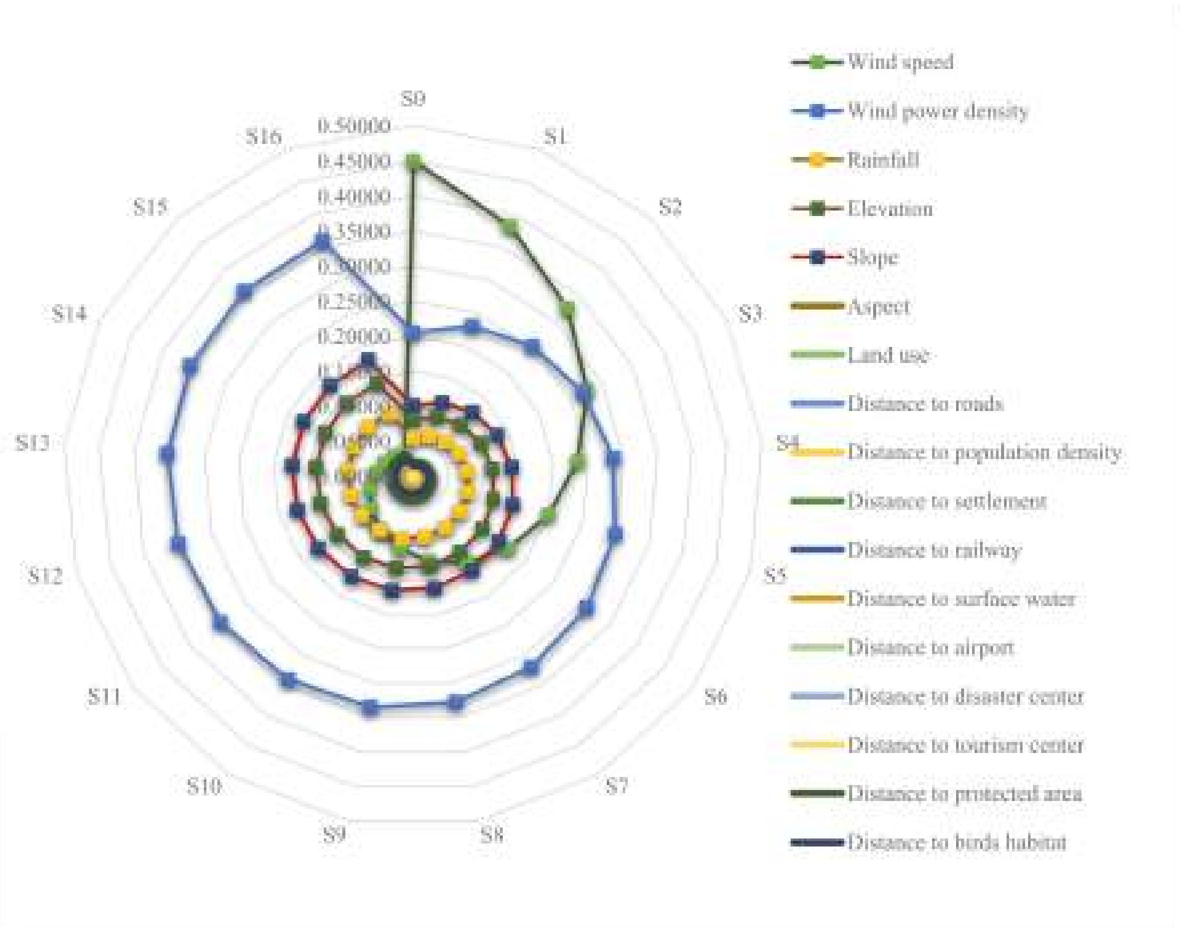

Fig. 6. Modifications in weights based on different scenarios.

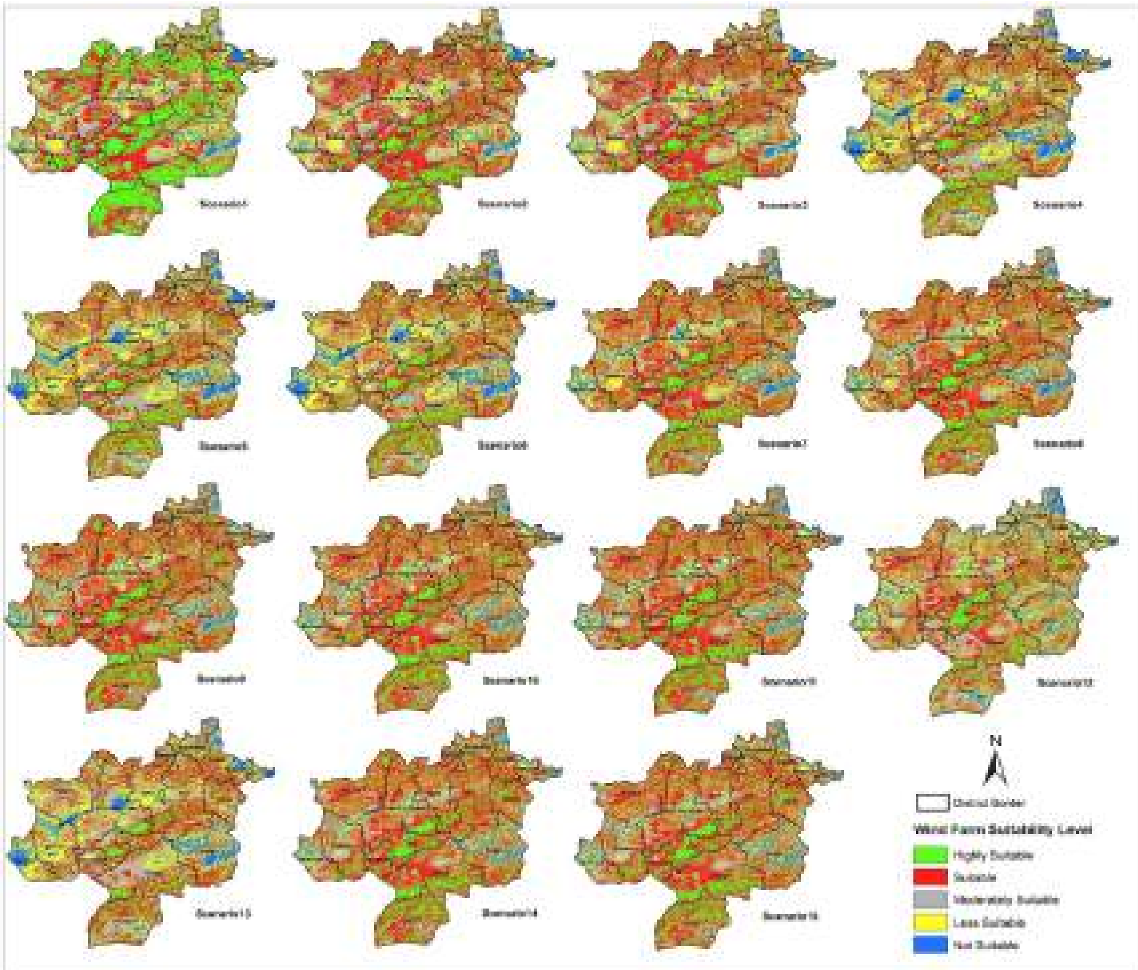

Fig. 7. Wind farm suitability categories obtained according to the new criteria weights.

After the sensitivity analysis scenarios, Ulaş was determined as the most suitable location. The consistency in obtaining the same server as a result of both Fuzzy MCDM and spatial analysis supports the validity of the criteria weights and ranking of alternatives obtained in this study. The results of this study have the potential to evaluate the energy from wind energy in the context of Turkey's national energy strategy and planning. In particular, the identification of Sivas-Ulaş region as the most productive wind farm location emphasises the strategic importance of investments in wind power generation in this region. These findings suggest that when integrated into national energy policies, investments in wind energy infrastructure can contribute to meeting Turkey's energy needs and utilisation of sustainable energy resources. At the international level, the results of the study provide a valuable reference point for other countries in terms of identifying key factors in wind farm location selection. These results suggest that criteria such as wind speed can contribute to international efforts to meet energy demands through renewable sources. Integrated into international discourse and co-operation efforts, these criteria can accelerate the global adoption of sustainable energy systems. The study was constrained by the establishment of the identified criteria and the research framework, including feasible alternatives, based on geographic information system data and expert inputs.

Finally, it should be noted that this study includes a location study as well as essential technical criteria and the expertise of an experienced advisory panel. This study might be expanded by including parameters such as land pricing and even institutional considerations.

CRediT authorship contribution statement

Gülay Demir: Conceptualization, Data curation, Formal analysis, Methodology, Validation, Investigation, Writing – original draft. **Muhammad Riaz:** Conceptualization, Data curation, Formal analysis, Methodology, Investigation, Supervision, Validation, Writing – original draft, Writing – review & editing. **Muhammet Deveci:** Investigation, Validation, Writing – original draft, Writing – review & editing.

Declaration of competing interest

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 paper.

Data availability

The data that has been used is confidential.

Appendix

Appendix A Pseudo code of the F-MARCOS method

```
Procedure F-MARCOS_Method
  // Step 1: Determine the initial fuzzy decision matrix
  Input: linguistic decision matrices from K experts
  Output: initial fuzzy decision matrix (X̃)
  Initialize matrix X̃ with size (m x n)
  For each expert k from 1 to K
    For each alternative i from 1 to m
      For each criterion j from 1 to n
        Convert linguistic term to triangular fuzzy number using Table 6
        Update x̃_ij using the geometric mean of fuzzy numbers given by experts
  End For
  End For
  End For
  // Step 2: Construction of the extended fuzzy matrix
  Calculate ideal (AI) and anti-ideal (AAI) solutions for benefit and cost criteria
  Extend matrix X̃ to include AI and AAI
  // Step 3: Generate the normalized fuzzy matrix
  Initialize normalized matrix Ñ with size (m + 2 x n)
  For each criterion j from 1 to n
    For each alternative i from 1 to m
      If j is a cost criterion
        Normalize using Eq. (13)
      Else
        Normalize using Eq. (14)
  End For
  End For
  // Step 4: Creating the weighted fuzzy matrix
  Initialize weighted matrix Ṽ with size (m x n)
  For each alternative i from 1 to m
    For each criterion j from 1 to n
      Calculate weighted fuzzy values using Eq. (15)
  End For
  End For
  // Step 5: Determining the total weight value for each alternative
  Initialize total weighted values S̃, S̃_ai, and S̃_aai
  For each alternative i from 1 to m
    Sum the weighted values for alternative i using Eq. (16)
  Calculate S̃_ai for ideal solution
  Calculate S̃_aai for anti-ideal solution
  // Step 6: Calculate the degree of utility of alternatives
  Initialize utility degrees K̃_i^+ and K̃_i^-
  For each alternative i from 1 to m
    Calculate K̃_i^- using Eq. (17)
    Calculate K̃_i^+ using Eq. (18)
  // Step 7: Obtaining the total utility of each alternative
  Initialize total utility matrix T̃ with size (m x 3)
  For each alternative i from 1 to m
    Calculate T̃_i using Eq. (19)
  Calculate fuzzy number D̃ using Eq. (20)
  Calculate df_crisp using Eq. (21)
  // Step 8: Utility function for ideal and anti-ideal solution
  Initialize utility functions f(K_i^+) and f(K_i^-)
  For each alternative i from 1 to m
    Calculate f(K_i^+) using Eq. (22)
    Calculate f(K_i^-) using Eq. (23)
  // Step 9: Determining the utility function for each alternative
  Initialize final utility function f(K_i) for each alternative
  For each alternative i from 1 to m
    Calculate f(K_i) using Eq. (24)
  // Step 10: Ranking of alternatives according to the final values of the utility functions
  Sort alternatives based on final utility values
  Output: Ranked list of alternatives based on utility functions
End Procedure
```

Appendix B. Criteria importance rankings and linguistic importance for F-SWARA

	DM1				DM2				DM3			
Order of importance	**Criteria**	*l*	*m*	*u*	**Criteria**	*l*	*m*	*u*	**Criteria**	*l*	*m*	*u*
1	C1				C1				C1			
2	C2	0,9	1	1	C2	0,9	1	1	C2	0,9	1	1
3	C4	0,7	0,9	1	C5	0,9	1	1	C4	0,7	0,9	1
4	C5	0,7	0,9	1	C4	0,7	0,9	1	C3	0,9	1	1
5	C3	0,5	0,7	0,9	C3	0	0,1	0,3	C5	0,5	0,7	0,9
6	C7	0,3	0,5	0,7	C10	0	0,1	0,3	C10	0,3	0,5	0,7
7	C16	0,1	0,3	0,5	C16	0,7	0,9	1	C16	0	0,1	0,3
8	C17	0,9	1	1	C7	0,3	0,5	0,7	C12	0,7	0,9	1
9	C12	0,7	0,9	1	C12	0,3	0,5	0,7	C11	0,3	0,5	0,7
10	C8	0,7	0,9	1	C17	0,5	0,7	0,9	C17	0,3	0,5	0,7
11	C11	0	0,1	0,3	C8	0	0,1	0,3	C8	0,1	0,3	0,5
12	C9	0,3	0,5	0,7	C14	0	0,1	0,3	C9	0,1	0,3	0,5
13	C10	0,3	0,5	0,7	C9	0	0,1	0,3	C7	0,1	0,3	0,5
14	C13	0	0,1	0,3	C13	0,1	0,3	0,5	C13	0,3	0,5	0,7
15	C14	0	0	0,1	C11	0,1	0,3	0,5	C15	0,7	0,9	1
16	C15	0	0	0,1	C15	0	0,1	0,3	C6	0	0,1	0,3
17	C6	0	0	0,1	C6	0	0	0,1	C14	0	0	0,1

DM4				DM6				DM6			
Criteria	l	m	u	**Criteria**	l	m	u	**Criteria**	l	m	u
C1				C1				C1			
C2	0,9	1	1	C2	0,9	1	1	C5	0,9	1	1
C5	0,7	0,9	1	C5	0,7	0,9	1	C2	0,9	1	1
C3	0	0,1	0,3	C4	0,7	0,9	1	C4	0,7	0,9	1
C4	0,5	0,7	0,9	C3	0,5	0,7	0,9	C3	0,5	0,7	0,9
C17	0,5	0,7	0,9	C10	0,7	0,9	1	C9	0	0,1	0,3
C10	0,1	0,3	0,5	C9	0	0,1	0,3	C10	0,3	0,5	0,7
C16	0,7	0,9	1	C16	0,3	0,5	0,7	C17	0	0,1	0,3
C12	0,7	0,9	1	C17	0,1	0,3	0,5	C16	0,7	0,9	1
C11	0,3	0,5	0,7	C8	0,3	0,5	0,7	C8	0,3	0,5	0,7
C8	0,1	0,3	0,5	C7	0,1	0,3	0,5	C11	0,3	0,5	0,7
C7	0	0,1	0,3	C11	0,1	0,3	0,5	C12	0	0,1	0,3
C14	0	0,1	0,3	C12	0,3	0,5	0,7	C13	0,1	0,3	0,5
C13	0,1	0,3	0,5	C14	0,5	0,7	0,9	C14	0	0,1	0,3
C9	0,7	0,9	1	C6	0,1	0,3	0,5	C15	0,5	0,7	0,9
C15	0	0	0,1	C15	0	0,1	0,3	C6	0	0	0,1
C6	0	0	0,1	C13	0	0	0,1	C7	0	0	0,1

Appendix C. Evaluation of alternatives for F-MARCOS

Criteria	A1 (Gürün)	A2 (Kangal)	A3 (Ulaş)	A4 (Zara)	(A5) İmranlı
C1	EG, VG, EG	EG, EG, EG	EG, VG, VG	VG, VG, EG	VG, VG, EG
C2	G, VG, MG	G, VG, MG	EG, EG, VG	VG, VG, G	G, VG, MG
C3	EG, EG, EG	VG, VG, EG	VG, VG, EG	VG, G, VG	VG, G, VG
C4	MP, M, P	M, MP, MP	M, M, M	MP, M, MP	MP, MP, M
C5	P, MP, VP	MP, P, P	MP, MP, P	P, P, VP	P, MP, VP
C6	MG, G, MG	MG, G, G	M G, G, G	MG, G, G	MG, G, MG
C7	VG, VG, G	G, VG, VG	G, VG, VG	G, G, G	VG, G, G
C8	VG, VG, MG	EG, VG, VG	EG, VG, VG	VG, VG, MG	EG, EG, VG
C9	EG, VG, EG	VG, EG, EG	G, VG, G	G, G, G	EG, VG, VG
C10	M, MP, M	P, P, VP	MP, MP, M	M, M, MP	MP, M, MP
C11	P, MP, P	VG, G, G	VG, G, G	G, G, VG	VG, VG, VG
C12	P, MP, MP	VP, P, P	P, P, P	P, VP, MP	VP, P, P
C13	EG, VG, EG	EG, VG, VG	EG, VG, EG	EG, VG, VG	EG, VG, VG
C14	G, MG, G	G, MG, G	M, MP, MP	G, MG, M	MG, M, G
C15	EG, EG, VG	VG, VG, VG	VG, EG, G	VG, EG, G	EG, VG, VG
C16	MG, M, G	VG, VG, G	M, MG, MG	M, MG, MG	EG, VG, VG
C17	G, MG, G	VG, G, G	VG, G, VG	G, MG, VG	EG, VG, EG

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