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Research Paper

Application of Z-number based fuzzy MCDM in solar power plant location selection problem in Spatial planning

Ömer Ünsal [a], Gülay Demir [b], Can Bülent Karakuş [c], Dragan Pamučar [d,e,f,*]

[a] Institute of Social Sciences, Istanbul University, Istanbul 34116, Türkiye
[b] High School of Health Vocational Services, Sivas Cumhuriyet University, Sivas 58140, Türkiye
[c] Faculty of Fine Arts, Design and Architecture, Sivas Cumhuriyet University, Sivas 58140, Türkiye
[d] Széchenyi István University, Győr, Hungary
[e] Department of Industrial Engineering & Management, Yuan Ze University, Taoyuan City, Taiwan
[f] Department of Mechanics and Mathematics, Western Caspian University, Baku, Azerbaijan

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ABSTRACT

In order to achieve sustainable energy consumption and development goals, it is of great importance to find suitable locations for the construction of solar power plants. In this study, Geographic Information System (GIS) and Z-Number iteration of Fuzzy Logarithm Additive Weights Methodology (F-LMAW), a recently adopted Multi-Criteria Decision Making Analysis (MCDA) technique, are used to identify the best locations for solar power plant construction in Mersin province. Nineteen criteria were selected for the study and their relative weights and usefulness in ranking the solar power plant locations were estimated. The Weighted Linear Combination (WLC) technique was used to determine the suitability index for solar power plant siting in the study area. According to the analysis made by taking into account the expert opinions for the site selection of solar power plants, the solar radiation criterion was the most important criterion with a weight value of 0,0664, while the distance from the river criterion was the least important criterion with a weight value of 0,0265. A potential suitability map for the solar power plant was produced with the suitability index values. According to the suitability index values, the study area exhibited suitability degrees for solar power plant siting ranging from "suitable (0,0038 %)" to "moderately suitable (0,0034 %)" and "very slightly suitable (0,0033 %)". Silifke and Mut regions are considered as good locations for solar power plants in Mersin province. The robustness of the proposed technique was determined by sensitivity analysis.

1. Introduction

The energy sector, which is the backbone of developing countries, both meets the current needs of countries and paves the way for their progress. With population growth and urbanisation, the pressure on domestic resources has increased and accordingly, energy demand has also increased. The rise in energy consumption has led to a significant degree of reliance on pricey resources such imported power and fossil fuels (Raza et al., 2023). Fossil fuels, which have numerous drawbacks, currently account for 80 % of the world's energy supply. Consequently, societies around the globe have shifted from preference for renewable energy sources over fossil fuels (Hooshangi et al., 2023). Because fossil fuels are widely used, they have contributed significantly to the rise in health issues such as respiratory disorders, asthma, lung infections, and cancer (Griffin et al., 2019; Mathieu, 2002). Furthermore, the scarcity of fossil fuels has made the necessity for alternative energy for long-term growth inescapable (Halder et al., 2022). The most widely used renewable energy sources in underdeveloped nations are solar, geothermal, biomass, and wind energy because of their affordability, accessibility, and eco-friendliness (Raza et al., 2023).

Between 2010 and 2040, an increase of up to 56 per cent in energy consumption is estimated (U.S. Energy Information Administration, 2013). The use of renewable energy sources, particularly solar energy, has significantly increased as a result of the growing need for energy (Al Garni and Awasthi, 2020). In 2018, solar photovoltage energy accounted for about 40 percent of total installed renewable energy power globally (BP Energy Outlook, 2019). Among the various energy sources that supply electricity to many regions of the world, solar energy stands

* Corresponding author at: Széchenyi István University, Győr, Hungary.
E-mail addresses: gulaydemir@cumhuriyet.edu.tr (G. Demir), dragan.pamucar@fon.bg.ac.rs (D. Pamučar).

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out as being abundant, free, and püre (Doljak and Stanojevı́, 2017; Reshma et al., 2018; Kocabaldır and Yücel, 2023). Unlike fossil fuels, this energy source has little concerns to human health, ecosystems, energy security, and the environment (Ciriminna et al., 2016). Solar energy stands as the swiftest expanding renewable energy source globally, witnessing an 80 % reduction in costs, with projections indicating further declines in the upcoming years (Ferroukhi et al., 2014; Candelise et al., 2013). Turkey, with its abundant resources, has a considerable potential for renewable energy. Turkey's installed capacity is projected to be between 110,000 and 130,000 MW, and its 2023 power consumption is expected to be 500 billion kWh. By 2023, the goal is to boost energy efficiency and increase the percentage of renewable energy generation to 30 %, as stated in the National Renewable Energy Action Plan. At 5063 MW of installed capacity, or 2.6 % of total power output, in Turkey, solar energy is widely accepted as a renewable energy source. But wind energy continues to be the nation's most popular renewable energy source (Güner et al., 2021). The Ministry of Energy and Natural Resources was in charge of 679 registered solar power facilities in the Republic of Turkey as of 2023. The province of Mersin is home to twenty-five solar power facilities connected to the relevant ministry, totaling around 220 MW of installed capacity (URL1, 2023).

Solar power plants are vital for meeting future energy demands (Hassaan et al., 2021; Colak et al., 2020; Alami Merrouni et al., 2018). The most efficient operation of solar power plants is dependent on carefully selecting the optimal site. The initial use of operations research and decision theory is to find the optimal locations for solar power facilities (Nowzari et al., 2020). A variety of resource planning factors influence the ideal location for a solar power project. When deciding where to locate a solar power plant, a number of considerations must be made, such as the facility's geographic location, performance potential, and connectivity to the existing infrastructure (Al Garni and Awasthi, 2017). The location of solar power plants is of great importance in terms of identifying resources, making site suitability assessments, evaluating project feasibility and ensuring uninterrupted energy supply (Al Garni and Awasthi, 2018). Some of the studies in the literature where only MCDA methods are used to determine suitable locations for renewable energy facilities such as solar energy are shown in Table 1.

Table 1 shows that the AHP method is generally preferred in the methods used in the site selection of solar power plants in different regions. Some of the studies in which only GIS was used for mapping these suitable locations are given in Table 2.

Each study in Table 2 provides customised site selections for various uses of solar energy. In the literature, there are studies in which GIS-based MCDA methods are used both in the identification of suitable locations and in the mapping of these locations. These methods play an important role in including locations in the planning process, conducting feasibility studies and prioritising projects correctly (Shafiullah et al., 2016; Quiros-Tortos et al., 2017; Mardani et al., 2016). The most important benefit of GIS and MCDA integration is that it helps decision makers to select the most appropriate alternative(s) among the available options based on various criteria. GIS is a very effective tool in the context of quantifying, analysing and evaluating the factors used in site selection for solar power plants. GIS helps to evaluate potential locations for solar power plants and, when used in conjunction with MCDA, contributes to the identification and selection of the most suitable sites (Di Grazia and Tina, 2023). The main advantage of MCDA models is their capacity to provide appropriate weight values for criteria (Kannan et al., 2024; Kousar et al., 2024). Criteria weights are an important component of decision-making processes and the need for objectivity in the calculation of these weights is at the forefront (Kizielewicz and Sałabun, 2024). GIS-based MCDA can provide a unified site selection suitability map using all available geographic data (Anteneh et al., 2022). Following the literature review, some of the studies utilising GIS-based MCDA techniques in site selection for solar power plants are given in Table 3.

Table 1
Some studies using MCDM for site selection for solar power plants.

Ref.	Method	Area	Solved problem
Ara et al. (2024)	AHP	Bangladesh	Choosing the most suitable location for a solar power plant
Zhang et al. (2024)	SECA	China	Positioning of the solar hydrogen plant
Majumder et al. (2023)	Intuitionistic Fuzzy FUCOM-AHP		Feasibility of a solar power plant
Kuru, (2023)	AHP	Turkey	Site selection for solar power plants
Ahadi et al. (2023)	AHP	Iran	Site selection for solar power plant

AHP: Analytic Hierarchy Process, SECA: Simultaneous Evaluation of Criteria and Alternatives, FUCOM: Full Consistency Method

Table 2
Some studies using GIS for site selection for solar power plants.

Ref.	Method	Area	Solved problem
Dawoud et al. (2024)	GIS	Egypt	Optimal site selection for brackish groundwater solar desalination plant
Jiang et al. (2023)	GIS	China	Co-location of offshore wind and solar energy
Nguyen et al. (2022)	GIS	Vietnam	Solar farm site selection
Chen et al. (2022)	GIS	China	Evaluation of concentrated solar energy production potential
Karipoğlu et al. (2022)	GIS	Turkey	Selection of the optimum location for solar-powered hydrogen fuelling stations

ANP: Analytic Network Process, TOPSIS: Technique for Order Preference by Similarity to Ideal Solution, SWARA: Step Wise Weight Assessment Ratio Analysis, DEMATEL: Decision-Making Trial and Evaluation Laboratory, ELECTRE: Elimination and Choice Expressing Reality

As shown in Table 3, several similar criteria were employed in studies done in different locations and using different techniques, with the use of additional criteria varying based on the available data. In their study, Güner et al. (2021) employed the GIS-based AHP method to ascertain the ideal sites for solar power facilities within Mersin province. The researchers considered nine criteria, which included distance to residential and industrial zones, proximity to power transmission lines, accessibility to transportation networks, global radiation value, intensity of solar radiation, duration of sunlight, slope of terrain, aspect, and elevation. The following is a list of characteristics provided by the researcher that demonstrate the importance of the study's focus, the province of Mersin: The province of Mersin has several benefits over other areas, one of which is that it has a lot of sunlight hours all year round, which is good for renewable energy plants like solar power and wind plants. Additionally, its favorable topographical and climatic conditions further enhance its suitability for renewable energy projects. Situated in the Çukurova region, Mersin benefits from its designation as an energy corridor in Turkey's 11th Development Plan, further emphasizing its strategic importance in the country's energy landscape.

1.1. Contributions and novelty

The contributions of the research to scientific knowledge can be summarised as follows:

1.1.1. Use of innovative methods

The integration of fuzzy Z-number based MCDA and GIS brings a new perspective to scientific research by providing an innovative methodology for identifying suitable areas for solar power plants. This methodology can be applied for different energy sources and geographical regions in future studies, which shows that the methodology has a wide range of applications.

Table 3
Some studies using GIS-based MCDA for site selection for solar power plants.

Ref.	Method	Criterion	Area
Shorabeh et al. (2019)	GIS with AHP	Solar radiation, lst, sunshine, dust, rainfall, slope, distance from city, distance from road, NDVI, distance from fault	Mazandaran, Kermanshah, Razavi Khorasan, and Yazd (Iran)
Zambrano-Asanza et al. (2021)	GIS with AHP	Slope, land use and cover, average temperature, distance to power lines, distance to main roads, solar irradiation, distance to urban areas	Cuenca (Ecuador)
Razeghi et al. (2023)	GIS with AHP	Weather type, slope, GHI, distance from ground water aquifers, soil type, distance from the sea shoreline, distance from lakes and islands, distance from rivers, distance from power stations, distance from power lines, distance from the railway line, distance from roads, distance from the fault, distance from the airport, distance from protected areas, distance from cities	Iran
Raza et al. (2023)	GIS with AHP	Average temperature, solar irradiation, proximity to cities, slope, land aspects, proximity to power lines, land cover, proximity to roads,	Punjab, Sindh, Baluchistan and KhyberPakhtunkhwa (Pakistan)
Kocabaldır and Yücel, (2023)	GIS with AHP	Solar irradiation, duration of sunshine, distance to transmission lines, distance to substations, slope, average annual temperature, relative humidity, aspect, distance to highways, distance to residential areas, distance to water resources, distance to fault lines, distance to pit and quarry sites	Çanakkale (Turkey)
Hooshangi et al. (2023)	GIS with Fermatean Fuzzy (FF) TOPSIS	Solar irradiance, temperature, distance from transmission lines, distance from the main road, slope, sunshine hours, NDVI, distance from population centers, aspect, land cost energy consumption, land use, distance from rivers, distance from meteorological stations, distance from active faults, distance from dusty areas, population, rainfall	Iran
Hasti et al. (2023)	GIS with AHP, ANP and TOPSIS	Photovoltaic power generation potential, GHI, sunny hours, relative humidity, temperature, aspect, land use, slope, elevation, distance from power transmission lines, distance from urban roads, distance from cities, distance from rural roads, distance from protected areas, distance from active faults, distance from natural and artificial lakes, distance from rivers	Kurdistan (Iran)
Islam et al. (2024)	GIS with AHP	Distance from power line, solar irradiation, air temperature, slope, aspect, distance from urban, distance from road,	Bangladesh
Şahin et al. (2024)	GIS with intuitionistic fuzzy set	Slope, aspect, solar irradiation, land use, air temperature, land surface temperature, transportation network, elevation, transmission line	Netherlands
Rane et al. (2024)	GIS with multi-infuencing factor (MIF)	Wind speed, solar radiation, land surface temperature, vegetation, relative humidity, elevation, land use, aspect, distance from roads	Maharashtra (India)
Heidary Dahooie et al. (2022)	GIS with SWARA	Temperature, elevation, distance from the power line, distance from nearest fault, distance from the center of the province, distance from the nearest city distance from a water resource, distance from a road slope, distance from the railway network	The eastern regions of the Islamic Republic (Iran)
Badi et al. (2021)	GIS with SWARA-DEMATEL	Distance from residential areas, land use, slope, solar radiation, aspect, distance from transport links, distance from electricity-transmission network links, elevation	Misrata District (Libya)
Kuru, (2023)	GIS with AHP-WLC	Global horizontal irradiation, solar radiation, sunshine duration, aspect, average land cost, topographic shadow, distance to power lines, land cover, average precipitation, average temperature distance to settlements, distance to water resources distance to mineral extraction, TRI, distance to transportation, slope, distance to stream lines, distance to conservation areas, ecosystem services, NDVI, natural integration potential, land use capability, distance to stream lines, visibility, erosion	Kırklareli (Turkey)
Mirzaei, (2022)	SWARA and TOPSIS	Solar radiation, average sunshine, average temperature, distance from power transmission lines, distance from the main road, distance from population centers, land cost, earthquake risk, erosion risk, number of snowy days, number of rainy days, wind speed	Cities in southern Turkey
Rediske et al. (2020)	GIS with AHP and TOPSIS	Agrological capacity, land use, substation distance, distance from main roads, distance from urban areas, solar ırradiation, slope	Rio Grande do Sule (Brazil)
Sánchez-Lozano et al. (2014)	GIS with ELECTRE	Agrological capacity, slope, orientation, plot area, distance to main roads, distance to power lines, distance to town or village, distance to electricity transformers substations, solar radiation, average temperature	Murcia (Spain)
Yousefi et al. (2018)	GIS with Boolean-Fuzzy Logic Model	Distance to faults, distance to roads, distance to urban and rural area, slope, elevation, land use, distance to protected area, distance to rives	Markazi (Iran)
Dehshiri and Firoozabadi, (2023)	GIS with SWARA	Proximity to the settlements, roads and transmission lines, slope and aspect, global horizontal irradiance, temperature, dust optical thickness, dust deposition rate	Yazd (Iran)
Jong and Ahmed, (2024)	GIS with fuzzy TOPSIS	Solar radiation, temperature, slope, elevation, proximity to power transmission lines, proximity to roads, proximity to residental areas, proximity to urban facilities, distance from water, distance from protected areas, distance from settlement, population density	Malaysia
Almasad et al. (2023)	GIS with fuzzy AHP and PROMETHEE	Global horizontal irradiance, average temperature, precipitation, air pressure, surface albedo, relative humidity, slope, aspect, distance from transmission grids, distance from power lines, distance from highways, distance from major cities	Saudi Arabia
Aghaloo et al. (2023)	GIS wşth BWM-Fuzzy Logic	Wind speed, solar irradiation, elevation, aspect, slope, landcover, hazard rank, distance to rivers, distance to water bodies, population, infrastructure electricity, distance to roads, distance to railway, distance to cities	Bangladesh
Saraswat et al. (2024)	GIS with fuzzy AHP, TOPSIS, WASPAS, MAUT	Solar irradiation, wind velocity, slope, aspect, elevation, distance from coastlines, distance from waterbodies, distance from airports, distance to wildlife designations, land use, distance to urban areas, distance to urban areas, distance to road network, distance to transmission lines, distance from power plants	India

(*continued on next page*)

Table 3 (*continued*)

Ref.	Method	Criterion	Area
Karipoğlu et al. (2024)	GIS with fuzzy AHP	Global horizontal irradiance, elevation, surface area, human activities, distance to protected areas, distance to forest area, water pollution/marine effect, distance to eletrical grid, distance to main road, distance from land	Türkiye
Authors, 2024	GIS with Z-Numbers-F-LMAW (This study)	Distance from road, slope, elevation, aspect, solar radiation, temperature, average annual cloudy days number of snowy days, land use, distance from the settlement, distance from the river/surface water, distance from the disaster center, distance from the power lines, distance from the transformer center, land use capability classes, soil depth, problematic agricultural areas detection and remediation project (statip), land use planning	Mersin (Türkiye)

1.1.2. *Comprehensive criteria evaluation*

The inclusion of nineteen different decision criteria allows for a detailed assessment of all geographical and environmental factors that need to be considered in solar power plant siting. This allows for more comprehensive and reliable results.

This study presents several innovative directions by using a GIS-based Z-numbers F-LMAW approach to identify the most suitable locations for solar power plants in Mersin Province:

1.1.2.1. Z-numbers usage. Uncertainty Management: Z-numbers are a new mathematical approach to manage uncertainty and fuzziness more effectively. This study uses Z-numbers for criteria weighting and obtains more precise and reliable results than traditional methods.

1.1.2.2. GIS and F-LMAW integration. Comprehensive Geographical Evaluation: The F-LMAW method integrated with GIS provides an innovative solution for determining the most suitable locations by evaluating a large number of criteria together with geographical data.

1.1.2.3. Augmented criteria set. Detailed Analysis: The number of criteria used in this study has been increased. This expanded set of criteria enables a more comprehensive and detailed evaluation of site selection.

1.1.2.4. Sensitivity analysis. Map Validation: The study performs a comprehensive sensitivity analysis to ensure the accuracy and reliability of the identified suitability maps. This innovative approach increases the robustness and reliability of the results.

1.1.2.5. Multi-criteria decision making. Optimal Solutions: It aims to produce the most optimal solutions by comparing the results of analyses with different criteria sets and weights. This provides flexibility and better strategic options for decision makers.

1.1.2.6. Decision support system. For Local Governments and Energy Planners: The study provides an effective decision support system for local governments and energy planners, enabling them to make more strategic and sustainable decisions.

1.1.2.7. Policy recommendations. Renewable Energy Policies: The findings of the study contribute to the development of renewable energy policies, aiming to expand the use of solar energy.

1.1.2.8. Applicability to other regions. Generalisable Methodology: The methodology of the study offers an innovative approach that can serve as an example not only for Mersin Province but also for other regions with similar geographical and climatic characteristics.

In our study, the F-LMAW method was used to analyse the criteria. The advantages of the F-LMAW method are summarised (Pamučar et al., 2021a):

1.1.2.9. Stability and reliability. The LMAW method produces more stable results than methods based on principles such as defining the distances of alternatives with respect to reference points (e.g. TOPSIS). In particular, the robustness of the results is maintained even if the number of alternatives in the initial decision matrix changes. This increases the reliability of the method in a dynamic environment and guarantees consistency in the decision process in case the alternatives change.

1.1.2.10. Prevention of rank reversal problem. The F-LMAW method avoids the 'rank reversal' problem, which is frequently encountered in decision processes. This problem is the reversal of the ranking of alternatives as a result of adding or removing alternatives. The LMAW method is stable against this problem and prevents the ranking from being distorted even if the number of alternatives changes. Thus, the results obtained maintain their consistency and reliability.

1.1.2.11. Invariance of the mathematical framework. The mathematical structure of the method remains the same regardless of the number of alternatives and criteria. This increases the breadth of application of the method and makes it consistently applicable in different problem scenarios. The method can be used effectively even in complex cases with many alternatives and criteria.

1.1.2.12. Compatibility with qualitative and quantitative criteria. The F-LMAW method allows the evaluation of alternatives expressed by qualitative or quantitative criteria. This feature increases the flexibility of the method in cases where both numerical and verbal criteria are used together. The combination of different types of criteria allows decision makers to analyse multidimensional problems in a more comprehensive way.

1.1.2.13. Efficiency in group decision making situations. In group decision-making processes, the F-LMAW method uses the Bonferroni aggregation operator to combine the data. This operator allows for the effective combination of different opinions among decision makers and thus helps to achieve more robust and balanced results in group decision-making processes. Effective combining of group decisions supports the generation of collaborative solutions in multi-criteria decision-making problems.

These advantages of the F-LMAW method enable reliable and stable results to be obtained in decision processes dominated by uncertainty and complexity. This method has a wide application potential especially in multi-criteria decision-making problems where alternatives and criteria are diverse.

This study presents an innovative and effective application of the GIS-based Z-numbers F-LMAW method, which is considered as an important step to increase the success of solar energy projects and to popularise the use of sustainable energy sources. This method will contribute to the development and implementation of energy policies by providing a powerful decision support system for local governments and energy planners.

2. Material and method

2.1. Workspace

The workplace is the administrative border of Mersin province and is situated between 36°01′–37°25′ north latitude and 32°47′–35°23′ east longitude in a northwest–southeast direction. Located within Turkey's "energy corridor", Mersin Province is well known for having a nuclear power facility called Akkuyu as well strong wind and solar energy potential. The sunshine duration of the province is 4.64 hours in December and reaches 11.45 hours in July (URL1, 2023). These durations are at least 30 % higher than those of European countries such as Germany, which have serious solar power plant investments (URL4, 2023). In addition, more than 50 % of the province is flat and facing south (URL3, 2023). There are fertile plains in the coastal part of Mersin, neighbouring the Mediterranean Sea. Due to the presence of large rivers, the plains extend like a groove into the inland areas. Due to the large rivers, deltas are formed in the coastal area. In the coastal plains where intensive agriculture is carried out, the average annual temperature is 20 degrees. There are more plateaus at 1000–2000 m in the central parts. The lowest average temperature is 7.9 degrees Celsius on the Uzunkuyu Plateau at an altitude of 1962 m (URL3, 2023). These plateaus are generally fragmented by rivers flowing in the NW-SE direction (Sunkar and Uysal, 2014). Apart from the alluvium in the plains, most of the province consists of limestones. Soil thickness is less than 20 cm, especially at high elevations. In parallel with this, 84.7 % of the province has sixth, seventh, and eighth-class land use capability, which is least suitable for agriculture. The average altitude of the province is 1022 m, and the highest point is around 3500 m. The province's northeast has the highest regions (Fig. 1). The highest slope is 82°, although the average slope is 11°. Outside of the river basins, in the northeast and southwest of the province, are the most sloping regions (URL3, 2023).

2.2. Data supply and software

The criteria needed to develop solar power plants in Mersin province were established using the GIS-MCDA technique and prior research on the topic. The study's basic data were formed by 19 criteria based on information from the literature (Sánchez-Lozano et al. 2014; Noorollahi et al. 2016; Mokarram et al. 2020; Ruiz et al. 2020; Tercan et al. 2021; Giamalaki and Tsoutsos, 2019; Kırcalı and Selim, 2021; Settou et al. 2021; Macedo et al. 2021; Barzehkar et al. 2021; Zambrano-Asanza et al. 2021; Imamverdiev 2022; Rekik and El Alimi, 2023; Raza et al. 2023; Hasti et al. 2023; Gacu, et al. 2023).The study's basic data were formed by 19 criteria based on information from the literature, as shown in Table 5. The Open Street Map project (URL2, 2023) provides information on roads, settlements, rivers, and surface water sources. The Copernicus EUDEM v1.1 project (URL3, 2023) furnishes slope, elevation, and aspect data, while the Solar GIS project (URL4, 2023) Global Horizontal Irradiation (GHI) offers solar radiation data. Furthermore, the General Directorate of Meteorology in Ankara, Turkey, which is part of the Ministry of Environment, Energy and Climate Change (2008), provides climatic data, such as temperature, the number of overcast days, and the number of snowy days. CORINE (Copernicus Land Monitoring Service) Land Cover Programme for 2018 (URL5, 2023) was the source of the land use data, while the Ministry of Interior Disaster and Emergency Management Presidency (Ankara, Turkey) supplied the disaster center data. The General Directorate of Turkish Electricity Distribution (Ankara, Turkey) contributed data regarding power lines and substations. In the meanwhile, data on soil depth, STATIP (Problematic Agricultural Areas Detection and Remediation Project land use planning, and land use capacity classes were supplied by the Ministry of Agriculture and Forestry in Ankara, Turkey.

Raw data of road, settlement, river, surface water source and power line provided in vector data format showing line feature and raw data of disaster centers and transformer centers provided in vector data format showing point feature were analyzed according to Euclidean Distance method in Spatial Analysis tool of ArcGIS 10.8 software and criterion maps of relevant data were presented. Elevation criterion was obtained directly by using DEM data provided as raster data and mapping of slope and aspect criterion was performed by performing slope and aspect analysis in Spatial Analysis tool of ArcGIS 10.8 software depending on DEM data. GHI criterion was obtained directly as raster data from Solar GIS project. Temperature, cloudiness and number of snowy days data provided in Excell data format were analyzed by Inverse Weighted Distance (IDW) method in Spatial Analysis tool of ArcGIS 10.8 software and criterion maps of these data were presented. By converting vector data with polygon features such as land use, land use capability classes, soil depth, STATIP and land use planning into raster data format, criteria maps showing raster features of the relevant data were obtained (Table 4). The study employed ArcGIS Pro 3.2 software for all mapping and geographical studies, while Excel 2019 software was utilized for determining criterion weights, conducting sensitivity analysis, and identifying and prioritizing alternative regions. The general features of the criteria used in the study are presented in Table 4.

2.3. Method

The strategy used in this study for the province of Mersin is a combination of model construction for related studies, such as choosing where to build solar power, and the GIS-based Z numbers F-LMAW method. The following lists the steps of the study's methodology.

- ✓ A thorough examination of existing literature was conducted in order to determine the best standards for the selection of a site for a solar power plant. Table 4 displays the criteria that have been identified.
- ✓ Providing the data that is the primary source of these criteria and enabling their integration into the GIS environment.
- ✓ Creation of criteria maps in raster format, standardisation of criteria and reclassification of criteria
- ✓ Application of Z numbers F-LMAW method for determination of criteria weights and ranking of criteria according to weight values
- ✓ Using the classification criteria and criteria weights, site suitability maps for solar power plants can be produced using the WLC approach.
- ✓ To assess the validity and robustness of the study's procedures, a sensitivity analysis was carried out.

The flow diagram of the study's methodology, which includes thorough descriptions of each step, is shown in Fig. 2.

2.3.1. GIS processing

After establishing the criteria essential for solar plant site selection, the critical next step involves inputting the data associated with these criteria into the GIS program (such as ArcGIS 10.8), allowing for the evaluation and analysis of these datasets. In order to make the analyses, the data belonging to all criteria are converted into raster format. Raster criteria maps were produced as a consequence of using the procedures described in Table 4's last column to evaluate the data that were obtained in different forms. Subsequently, adjustments were made to the projection and cell size (25 m × 25 m) for each criterion converted to raster data format (ITRF TM33 (EPSG:5255).

2.3.2. Criteria standardization

To streamline the representation of each sub-criterion, various types of maps such as value maps (e.g., slope) or categorized maps (e.g., land use) can be utilized. In order to streamline the analysis and minimize dimensionality, these maps' values and classes are standardized or reduced to a single scale. Criteria standardization is the term used to describe this kind of transition. It is assured that one criteria scale is similar to the other with the aid of this method, which transforms the original values into common conformance values. Typically, 0–1, 0–10,

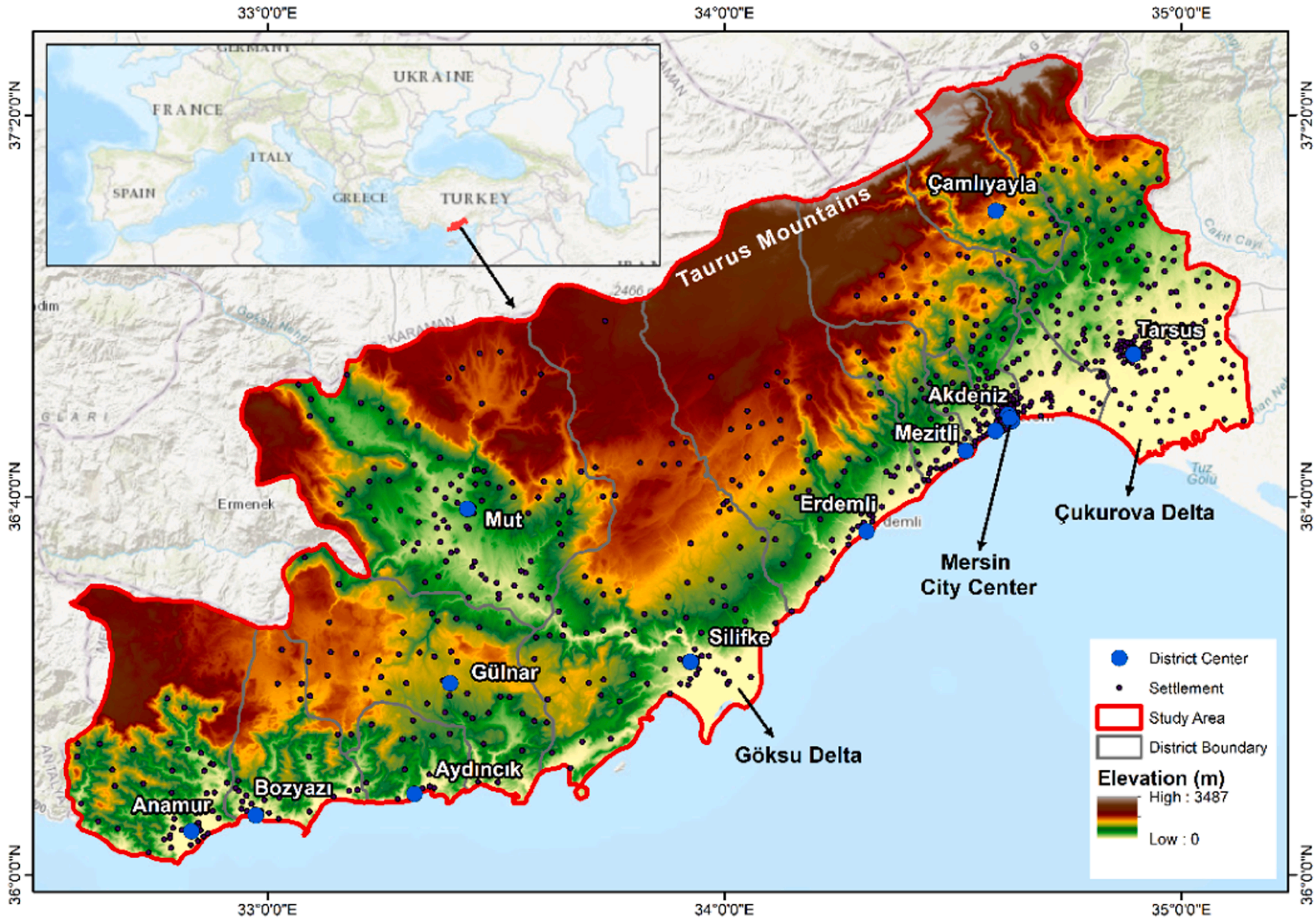

Fig. 1. Workspace location. It shows the map of Mersin province.

or 0–100 values are employed for standardizing criteria. This procedure involves breaking down all input datasets (criteria) into sub-criteria, assigning a score between 1 and 5 to each sub-criteria, reclassifying the criteria, and performing standardization in this manner (Makonyo and Msabi, 2022). Standardization and value assignment for each criterion may be accomplished with the reclassification tool found in ArcGIS 10.8 program (Quinta-Nova and Ferreira, 2022).

Based on how well they aligned with the overall criteria for choosing appropriate locations for solar power plants, the nineteen criteria in this study were further separated into sub-criteria. Each sub-criteria was given a score between 1 and 5, which allowed the criterion maps to be reclassified (Georgiou and Skarlatos, 2016; Habib et al., 2020; Raza et al., 2023). Each sub-criteria was scored in accordance with the information from the literature provided in Table 5.

2.3.3. *Z numbers F-LMAW method*

Z-number consists of two fuzzy components to indicate the reliability of information expressed in natural language: $Z = \left(\widetilde{A}, \widetilde{B}\right)$. The first element, $\widetilde{A}$ acts as a constraint or constraint on the values that a real-valued, uncertain variable X can take. It essentially captures the uncertainty or uncertainties associated with the variable. The second element, $\widetilde{B}$, measures the reliability or certainty of the constraints associated with the first component, $\widetilde{A}$. It provides information about the reliability or certainty of the constraints defined by $\widetilde{A}$ (Zadeh, 2011). Indeed, a Z-number offers a more flexible representation of uncertain information compared to traditional exact values. This flexibility enables the incorporation of uncertainty into decision-making processes, allowing for more robust and informed conclusions. It enables uncertainty and reliability modeling, especially in various real-world applications involving uncertain or incomplete information. Fuzzy Z-numbers provide a powerful tool for representing and processing uncertain information. The flexibility and versatility of fuzzy Z-numbers make them valuable in dealing with real-world problems where uncertainty and ambiguity are present (Ecer et al. 2024).

In general, Z numbers can be represented in the following format: $\widetilde{Z} = \{(a_1, a_2, a_3; w_A), (b_1, b_2, b_3; w_B)\}$. Z number may be converted into a classical fuzzy number by implementing the subsequent procedures (Aboutorab et al. 2018; Bobar et al. 2020; Puška et al. 2022).

Step 1. Conversion of the fuzzy number B into a crisp number by applying a regularization

$$\alpha = \frac{a_1 + a_2 + a_3}{3} \tag{1}$$

The difficulty with using this method for refinement is that if the fuzzy numbers are proportionately separated, the refinement result will always be a_2. As a result, it is critical to guarantee that the values of the fuzzy numbers are not proportional, as in the case of fuzzy numbers B, when this formula is used.

Step 2. Fuzzy number B's weight is added to fuzzy number A

$$\widetilde{Z}^{\alpha} = \{\langle x, \mu_{A^{\alpha}}(x)\rangle | \mu_{A^{\alpha}}(x) = \alpha\mu_A(x)\} \tag{2}$$

Step 3. Converting a weighted Z number to a typical fuzzy number

$$\widetilde{Z}' = \left\{\langle x, \mu_{Z'}(x)\rangle | \mu_{Z'}(x) = \mu_A\left(\frac{x}{\sqrt{\alpha}}\right)\right\} \tag{3}$$

Table 4
The criterion's properties and its application in determining the placement of solar power plants.

Criterion	Data	Source	Data Format	Analysis
Distance from road (C1)	Road	OSM	Vector-polyline layer	Euclidean distance
Slope (C2)	DEM	Copernicus EUDEM v1.1	Raster layer	Slope
Elevation (C3)	DEM	Copernicus EUDEM v1.1	Raster layer	
Aspect (C4)	DEM	Copernicus EUDEM v1.1	Raster layer	Aspect
GHI (C5)	DEM	Solar GIS	Raster Layer	-
Temperature (C6)	Temperature	TSMS	Excel (xlsx)	IDW
Cloudiness (C7)	Cloudiness	TSMS	Excel (xlsx)	IDW
Number of snowy days (C8)	Number of snowy days	TSMS	Excel (xlsx)	IDW
Land use (C9)	CORINE	Copernicus CORINE	Vector-polygon layer	Feature to Raster
Distance from the settlement (C10)	Settlement	OSM	Vector-point layer	Euclidean distance
Distance from river (C11)	River	OSM	Vector-polyline layer	Euclidean distance
Distance from surface water sources (C12)	Surface Water	OSM	Vector-point layer	Euclidean distance
Distance from disaster center (C13)	Disaster Center	DEMA	Vector-point layer	Euclidean distance
Distance from power lines (C14)	Power Lines	GDoTEDC	Vector-polyline layer	Euclidean distance
Distance from transformer center (C15)	Transformer Center	GDoTEDC	Vector-point layer	Euclidean distance
Land use capability classes (C16)	Land Use Capability Class	MoAF	Vector-polygon layer	Feature to Raster
Soil depth (C17)	Soil Depth	MoAF	Vector-polygon layer	Feature to Raster
STATIP Map	Problematic agricultural areas detection and remediation project map	MoAF	Vector-polygon layer	Feature to Raster
Land use planning (C19)	Land use planning	MoAF	Vector-polygon layer	Feature to Raster

DEM: Digital Elevation Model, OSM: Open Street Map, TSMS: Turkish State Meteorological Service, DEMA: Disaster and Emergency Management Authority, GDoTEDC: General Directorate of Turkish Electric Distribution Corporation, MoAF: Ministry of Agriculture and Forestry

$$\widetilde{Z} = \sqrt{a}.\widetilde{A} = \left(\sqrt{a}.a_1, \sqrt{a}.a_2, \sqrt{a}.a_3\right) \tag{4}$$

Kang et al. (2012) used $\sqrt{a}$ values in their investigation. Z-number is turned into an ordinary fuzzy number using these phases, and the techniques are the same as for ordinary fuzzy numbers.

Zadeh (1965) proposed the fuzzy idea to address uncertainty in variables and parameters. Numerous studies have used triangular fuzzy figures to translate qualitative remarks into quantitative assertions. A triangular fuzzy figure is made up of three integers (Gazi et al., 2024; Biswas et al., 2024). The lowest, most, and highest possible values are reflected by the first, second, and third numbers that constitute a fuzzy figure, in that order.

Eqs. (5)-(8) specify the mathematical calculations for two triangular fuzzy numbers, $\widetilde{A} = (a_l, a_m, a_u)$ and $\widetilde{B} = (b_l, b_m, b_u)$.

$$\widetilde{A} + \widetilde{B} = (a_l + b_l, a_m + b_m, a_u + b_u) \tag{5}$$

$$\widetilde{A} - \widetilde{B} = (a_l - b_u, a_m - b_m, a_u - b_l) \tag{6}$$

$$\widetilde{A}x\widetilde{B} = (\min(a_lb_l, a_lb_u, a_ub_l, a_ub_u), a_mb_m, \max(a_lb_l, a_lb_u, a_ub_l, a_ub_u)) \tag{7}$$

$$\frac{\widetilde{A}}{\widetilde{B}} = \left(\min\left(\frac{a_l}{b_l}, \frac{a_l}{b_u}, \frac{a_u}{b_l}, \frac{a_u}{b_u}\right), \frac{a_m}{b_m}, \max\left(\frac{a_l}{b_l}, \frac{a_l}{b_u}, \frac{a_u}{b_l}, \frac{a_u}{b_u}\right)\right) \tag{8}$$

Triangular fuzzy numbers might be turned into crisp numbers using various formulae. Eq. (9) is used in this study to defuzzify a fuzzy number, such as $\widetilde{A} = (a_l, a_m, a_u)$:

$$A = \frac{a_l + 4a_m + a_u}{6} \tag{9}$$

In the process of criteria weighting, there are various methods available in the literature (Sahoo et al., 2024). Among these methods, Linguistic Multi-Criteria Analysis Weighting (LMAW) (Radovanovic et al., 2024), Best Worst Method (BWM) (Phulara et al., 2024), Defining Interrelationships Between Ranking Criteria (DIBR) (Bozanic et al., 2023; Tesic and Marinkovic, 2023), Full Consistency Method (FUCOM) (Özkir and Değirmenci, 2023) and Ordinal Priority Approach (OPA) (Ataei et al., 2020a and 2020b) stand out as notable techniques. Each method offers different advantages in MCDM processes, and there are several reasons why the LMAW method is preferred in this study.

2.3.3.1. Handling uncertainty. The OPA technique reduces processing costs by avoiding the use of pairwise comparison matrices and normalization procedures common in traditional MCDM systems. However, OPA may neglect uncertainties, which are critical for making optimal decisions. LMAW offers a more effective approach to managing uncertainties. By integrating both qualitative and quantitative data, LMAW produces more robust and reliable results, particularly in uncertain and dynamic environments (Wang et al., 2022; Mahmoudi et al., 2021; Ataei et al., 2020a and 2020b).

2.3.3.2. Prevention of rank reversal problem. The rank reversal problem is an issue where the ranking of alternatives can change when alternatives are added or removed, which is frequently observed in methods such as BWM and FUCOM. The LMAW method, with its flexible mathematical structure, prevents this issue. The rankings remain consistent even if the number of alternatives changes, ensuring that the results are reliable and stable (Cheng and Chen, (2024);

2.3.3.3. Applicability to complex and multi-criteria problems. FUCOM, BWM, and DIBR methods rely on pairwise comparisons, which can become increasingly complex as the number of criteria grows. LMAW, on the other hand, is better suited for complex and multi-criteria problems. Its mathematical structure remains resilient to changes in the number of alternatives, maintaining its performance even in large-scale problems (Chakraborty and Saha, 2024; Ghanbari Ghoushchi et al., 2023).

2.3.3.4. Suitability for group decision-making processes. The LMAW method can be effectively used in group decision-making processes. Unlike other methods, LMAW employs the Bonferroni aggregation operator to combine the opinions of various experts, providing a powerful tool for synthesizing diverse viewpoints.

2.3.3.5. Flexibility and reliability of mathematical structure. The mathematical structure of LMAW is unaffected by changes in the number of

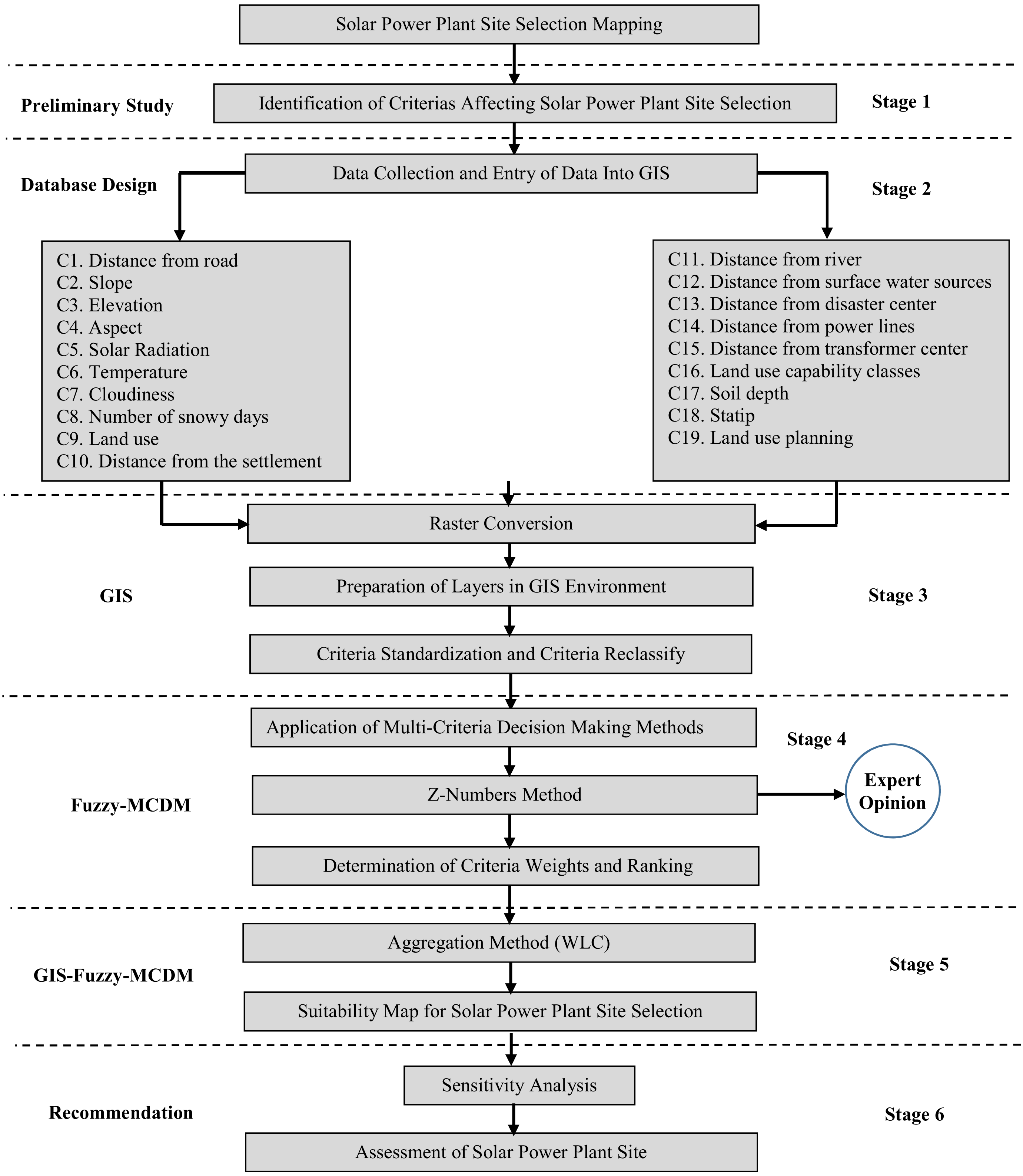

Fig. 2. Flow chart for choosing the site of solar power plants.

Table 5
Appropriate solar power plant siting levels and scores.

Criteria		Suitability Levels and Scores					
		Highly Suitable	Suitable	Moderately Suitable	Less Suitable	Not Suitable	Reference
	Unit	5	4	3	2	1	
Distance from road (C1)	km	0–2	2–4	4–6	6–8	>8	Georgiou and Skarlatos, (2016); Habib et al., (2020)
Slope (C2)	Degree (°)	0–2.5	2.5–3.5	3.5–5	5–8	> 8	Al Garni and Awasthi, (2017); Raza et al. (2023); Jong and Ahmed, (2024)
Elevation (C3)	m	3000–3500	2000–3000	1000–2000	500–1000	0–500	Noorollahi et al., (2016); Elboshy et al., (2022)
Aspect (C4)		S, Flat	SE, SW	E, W	N, NE	NW	Rekik and El Alimi, (2023); Raza et al. (2023)
GHI (C5)	(kWh/ m^2)	5–6.59	4–5	3–4	2–3	0.64–2	Tercan et al., (2021); Raza et al. (2023); Almasad, 2023
Temperature (C6)	°C	8–11	11–14	14–17	17–20	> 20	Koç et al., 2019; Raza et al. (2023); Sun et al., (2023)
Average annual cloudy days (C7)		10.44–12	12–14	14–15	15–16.5	>16.5	Noorollahi et al., (2016); Imamverdiev, (2022)
Number of snowy days (C8)		1–1.75	1.75–2.45	2.45–3.2	3.2–4.5	> 4.5	Tercan et al., (2021)
Land use (C9)		Bare / Sparse vegetation	Grassland	Shrubland	Cropland	Permanent water bodies / Herbaceous wetland / Tree cover / Built-up	Halder et al. (2022); Giamalaki and Tsoutsos, (2019); Karipoğlu et al., (2024)
Distance from the settlement (C10)	km	0–1	1–5	5–10	10–20	> 20	Aly et al., (2017); Yushchenko et al., (2018)
Distance from river (C11)	km	1–3	3–5	5–10	> 10	0.1–1	Tercan et al., (2021); Aghaloo et al., (2023)
Distance from surface water sources (C12)	km	1–3	3–5	5–10	> 10	0.1–1	Tercan et al., (2021); Bostancı et al., (2024)
Distance from disaster center (C13)	km	> 5	3–5	2–3	1–2	0–1	Akinci and Özalp, (2022); Aghaloo et al., (2023)
Distance from power lines (C14)	km	0–1	1–4	4–7	7–10	> 10	Giamalaki and Tsoutsos, (2019); Saraswat et al., (2024)
Distance from transformer center (C15)	km	0–3	3–6	6–9	9–12	> 12	Günen, 2021; Bostancı et al., (2024)
Land use capability classes (C16)		VI/VII/ VIII	V	IV	III	I/II/Other	Al Garni and Awasthi, (2017); Raza et al. (2023); Jong and Ahmed, (2024)
Soil depth (C17)		0–20 cm/Lithosolic					
STATIP (C18)		Dry marginal lands, wet marginal lands					
Land use planning (C19)		Dry marginal lands, wet marginal lands					

alternatives. In contrast, methods like BWM and FUCOM, which are based on pairwise comparisons, can become more complex as the number of alternatives increases. LMAW remains stable and consistent regardless of the number of alternatives, ensuring reliability across different scenarios (Moslem et al., 2020; Gholamizadeh et al., 2024).

Pamučar et al. (2021b) created the LMAW technique. Božanić et al. (2022) describe an implementation of the complete F-LMAW algorithm. Only the procedures for calculating the criterion weight coefficients of the LMAW approach are presented (Božanić et al. 2022).

Step 1. Prioritising the criterion

The fuzzy linguistic scale assigns substantial values to the most important criteria, and vice versa. The priority vectors for each specialist are acquired separately $\widetilde{P}^e = \left(\widetilde{\gamma}^e_{C_1}, \widetilde{\gamma}^e_{C_2}, \ldots, \widetilde{\gamma}^e_{C_n}\right)$.

Step 2. Determine the fuzzy absolute anti-ideal point $(\widetilde{\gamma}_{AIP})$

Experts establish this fuzzy number, which is less than the least value for all priority vectors combined. Those who introduced the approach into literature utilized it as $\widetilde{\gamma}_{AIP} = (0.5, 0.5, 0.5)$.

Step 3. Determining the fuzzy relationship vector $(\widetilde{R}^e)$

Eq. (10) establishes the relationship between the priority vector's items and the exact opposite ideal point.

$$\widetilde{\eta}^e_{C_n} = \left(\frac{\widetilde{\gamma}^e_{C_n}}{\widetilde{\gamma}_{AIP}}\right) = \left(\frac{\gamma^{(l)e}_{C_n}}{\gamma^{(r)}_{AIP}}, \frac{\gamma^{(m)e}_{C_n}}{\gamma^{(m)}_{AIP}}, \frac{\gamma^{(r)e}_{C_n}}{\gamma^{(l)}_{AIP}}\right) \tag{10}$$

Step 4. Calculating the weight coefficient vectors (w^e_j)

Eq. (11) produces the fuzzy score of the weight coefficients of each expert's criterion.

$$\widetilde{w}^e_j = \left(\frac{\ln\left(\widetilde{\eta}^e_{C_n}\right)}{\ln\left(\prod_{j=1}^{n}\widetilde{\eta}^e_{C_n}\right)}\right) = \left(\frac{\ln\left(\eta^{(l)e}_{C_n}\right)}{\ln\left(\prod_{j=1}^{n}\eta^{(r)e}_{C_n}\right)}, \frac{\ln\left(\eta^{(m)e}_{C_n}\right)}{\ln\left(\prod_{j=1}^{n}\eta^{(m)e}_{C_n}\right)}, \frac{\ln\left(\eta^{(r)e}_{C_n}\right)}{\ln\left(\prod_{j=1}^{n}\eta^{(l)e}_{C_n}\right)}\right) \tag{11}$$

All experts' weight considerations have been obtained in the shape $w^e_j = \left(\widetilde{w}^e_1, \widetilde{w}^e_2, \ldots, \widetilde{w}^e_n\right)^T$.

Step 5. Calculating the weight coefficients' combined fuzzy vectors

The weight coefficients' combined fuzzy vectors are computed using the Bonferroni aggregator and Eq. (12). $w_j = \left(\widetilde{w}_1, \widetilde{w}_2, \ldots, \widetilde{w}_n\right)^T$.

$$\tilde{w}_j = \left(\frac{1}{k(k-1)} \sum_{\substack{i,j=1 \\ i \neq j}}^{k} \tilde{w}_i^{e(p)} \tilde{w}_j^{e(q)} \right)^{\frac{1}{p+q}} = \left\{ \left(\frac{1}{k(k-1)} \sum_{\substack{i,j=1 \\ i \neq j}}^{k} w_i^{(l_e)p} w_j^{(l_e)q} \right)^{\frac{1}{p+q}}, \left(\frac{1}{k(k-1)} \sum_{\substack{i,j=1 \\ i \neq j}}^{k} w_i^{(m_e)p} w_j^{(m_e)q} \right)^{\frac{1}{p+q}}, \left(\frac{1}{k(k-1)} \sum_{\substack{i,j=1 \\ i \neq j}}^{k} w_i^{(r_e)p} w_j^{(r_e)q} \right)^{\frac{1}{p+q}} \right\} \quad (12)$$

Step 6. Calculating the weighted criteria's final value.

As shown in Eq. (9), the final weight coefficient values of the criteria are produced by clarification based on $w_j = (w_1, w_2, \ldots, w_n)^T$.

The experts determined the degree of importance of each criterion, while at the same time defining the degree of certainty of this rating. This process allows for more reliable and detailed analyses (Puška et al., 2022).

2.3.4. *Solar power plant site selection mapping using the WLC method*

The WLC methodology (Barzehkar et al., 2016) is one of the most often used ways for combining various raster layers in ArcGIS GIS software. With the use of many criteria, WLC assesses a site's suitability for a given location by weighing each criterion's relative importance (Jamshidi-Zanjani and Rezaei, 2017). This method involves multiplying criteria weight values produced by a specific way by standardized criterion maps to get conformance mapping. The WLC approach is commonly used to aggregate all weighted spatial layers and generate site selection, suitability maps (Giamalaki and Tsoutsos, 2019). Within the GIS literature, the WLC is the most widely used methods for decision-making due to their simplicity (Charabi and Gastli, 2011; Drobne and Lisec, 2009). The WLC approach is commonly used to aggregate all weighted spatial layers and generate site selection, suitability maps (Giamalaki and Tsoutsos, 2019). The WLC method is expressed by Eq. (13) below (Sahani, 2019; Ali et al., 2019):

$$SI = \sum_{i=1}^{n} W_i . S_i \quad (13)$$

where, SI: Suitability index of the area, n: Number of criteria, W_i: weight value of criterion i, S_i: standardised suitability score of criteria i.

The Raster Calculator in the Spatial Analysis plug-in of ArcGIS Pro program was utilized to evaluate the weight values of the criteria acquired by the F-LMAWtechnique within the context of the WLC method. Using the formula given in Eq. (13), this method made it possible to create a suitability map (Fig. 5) for solar power plants in the research region. High Suitability Index (SI) locations are seen to be the best options when choosing a location for solar power facilities (Chaudhary et al., 2022; Âmin et al., 2022).

2.3.5. *Sensitivity analysis*

Once the "most important criteria (Cn)" have been established based on the weight values determined in accordance with the criterion weighting method, sensitivity analysis can be performed by varying the weight of the "most important criteria (Cn)" to observe how the suggested model affects ranking performance.

To start, a new vector for the weight factors is generated using the technique. Every iteration entails a 20 % reduction in the weight value of the most important criterion in order to create a new weight factor vector. Vrtagić et al. (2021) demonstrate how to use Eq. (14) to determine the updated weight value of the criteria. Through this iterative approach, the sensitivity of the decision-making model to shifts in the relative weight of the criteria may be evaluated, offering insights into how reliable the choice results are.

$$w_{n\beta} = (1 - w_{n\alpha}) \left(\frac{w_\beta}{1 - w_n} \right) \quad (14)$$

where the new weight values determined for the criterion are shown by $w_{n\beta}$. $w_{n\alpha}$ indicates the criteria's decreased value. The initial value of the lowered criteria is represented by w_n whereas the original value of the criteria is shown by w_β.

3. Result and discussion

3.1. *Reclassification of suitability criteria*

All of the criteria's sub-criteria were given numerical values between 1 and 5 (Table 5), and raster maps (Fig. 3) were made in accordance with the value ranges. Fig. 3 illustrates how all criteria, with regard to the suitability of solar power plants, can be categorized into one of five groups: extremely appropriate (5), suitable (4), moderately suitable (3), less suitable (2), and not suitable at all (1). The spatial distribution values of the criteria used in the study are presented in Table 6.

3.1.1. *Distance from road (C1)*

It is quite suitable to construct solar energy projects in locations where the distance to the motorways is lower (Solangi et al., 2019). Proximity to existing highways is an important criterion to minimise investment costs. The areas between 0 and 2 km (81.81 %) are categorised as "highly suitable" and the areas more than 8 km (0.11 %) are categorised as "not suitable" in the criterion of proximity to the highway in the construction and operation activities of these investments requiring large area usage. For the most part of the research region, the distribution is homogeneous based on the criterion of distance from roadways. The roads utilized in modest amounts and at certain times of the year to offer access to settlements and plateaus provide attraction and readiness for such investments because of the availability of valleys from the coastal area to the upper sections and occasionally unexpectedly developed mountainous areas. Compared to mostly flat provinces, it can be expected that the amount of area close to highways will be higher in provinces with mountainous and plateau units. Therefore, the areas between 0 and 2 km of motorways can reach 81.81 % in provinces such as Mersin (Table 6, Fig. 3a).

3.1.2. *Slope (C2)*

The greatest locations for solar power plants are those with low slope or level ground since these features facilitate the installation and upkeep of solar energy panels (Aly et al., 2017). The slope criterion comes to the forefront in solar energy investments, like many other investments. For investors, the high daily prices of the work equipment that will be utilized in the solar power plant development are crucial. Therefore, areas with a slope between 0 and 2.5 degrees reach an area of 16.75 % in Mersin province. The majority of these locations are found in the Çukurova and Göksü deltas, along with the coastal regions. Due to the presence of high biodiversity in these areas as well as the presence of agricultural and urban areas, especially flat areas on plateaus, they become more suitable for such investments. In addition, although it increases the costs for investors, areas with a slope between 2.5 % and

3.5 % can also be preferred. Therefore, these areas are categorised as "suitable" (6.50 %). On the other hand, "not suitable" areas reach 52.08 % due to the presence of mountainous areas and valleys (Table 6, Fig. 3b).

3.1.3. Elevation (C3)

The air layer gets thinner from ground level and receives more solar radiation due to the reduction in temperature at high elevations, which enhances the effectiveness and performance of solar panels (Solangi et al., 2019). 0.21 % of the study area is classified as "highly suitable". Especially the areas between 1000 and 2000 m correspond to an area of 41.21 %. It can be said that these areas have more of a plateau appearance. The areas classified as "less suitable" and "not suitable" correspond to almost half of the study area. The majority of these places are found in lowlands and along the shore (Table 6, Fig. 3c).

3.1.4. Aspect (C4)

Flat and south-facing slopes should be considered for solar power plant locations since they give strong sunshine depending on the season (Miller and Lumby, 2012). 58 % of the study area is classified as "highly suitable" or "suitable". This is due to geological and geomorphological reasons and the fact that it extends in the SW-NE direction and faces south. In addition, as can be seen in the slope map, flat areas in the coastal and delta plains were also effective. The reason why the areas facing the northern directions (N, NE, and NW) are less than the other directions (around 17 %) is that the north of the water division line, especially in mountainous areas, is located in provinces such as Karaman, Konya, and Nide. In this respect, Mersin province is advantageous (Table 6, Fig. 3d).

3.1.5. GHI (C5)

High sun radiation levels greatly enhance electricity production and encourage economic expansion (Sun et al., 2021). In Mersin, one of the southernmost provinces of Turkey, the increased amount of radiation, especially after 1500 m, is an advantage. 55 % of the study area is classified as "highly suitable" or "suitable". Approximately 10 % of this region, which rises as a result of geological and geomorphological processes, is classified as "less suitable" and "not suitable". These regions mostly correspond to the valley interiors (Table 6, Fig. 3e).

3.1.6. Temperature (C6)

Installing solar power plants in regions with lower average temperatures is desirable in order to maximize their efficiency (Günen, 2021a). Lapse rate, which decreases with altitude, also showed its effect in Mersin. Especially the decrease after 1500 m is reflected in the average air temperature map. Conversely, though approximately 46 % of the study area, which is elevated by geological and geomorphological processes, is classified as "highly suitable" and "suitable". The suitability level decreases with the warm air penetrated by the coastal area, delta plains, and the valley formed by the Göksu River (Table 6, Fig. 3f).

3.1.7. Average annual cloudy days (C7)

Solar power plants generate less electricity due to poor solar radiation on overcast days (Elboshy et al., 2022). The research region, particularly the southwest portion, is assessed as "suitable". Cloudiness is very low in the Göksu Valley and nearby regions. Approximately 74 % of the research area is characterized as "highly suitable", "suitable", or "moderately suitable". These districts are most concentrated in the southwest side of the city center. There are a few "highly suitable" and "suitable" locations in the NE section of the city center. The "less suitable" and "not suitable" lands are concentrated in the NE section of the province, namely in the Çukurova delta. These locations account for roughly 26 % of the study area (Table 6, Fig. 3g).

3.1.8. Number of snowy days (C8)

The high frequency of snowy days has a detrimental effect on how well solar power plants function in terms of energy production (Deline, 2009; Tercan et al., 2021). The influence of maritimeness results in a

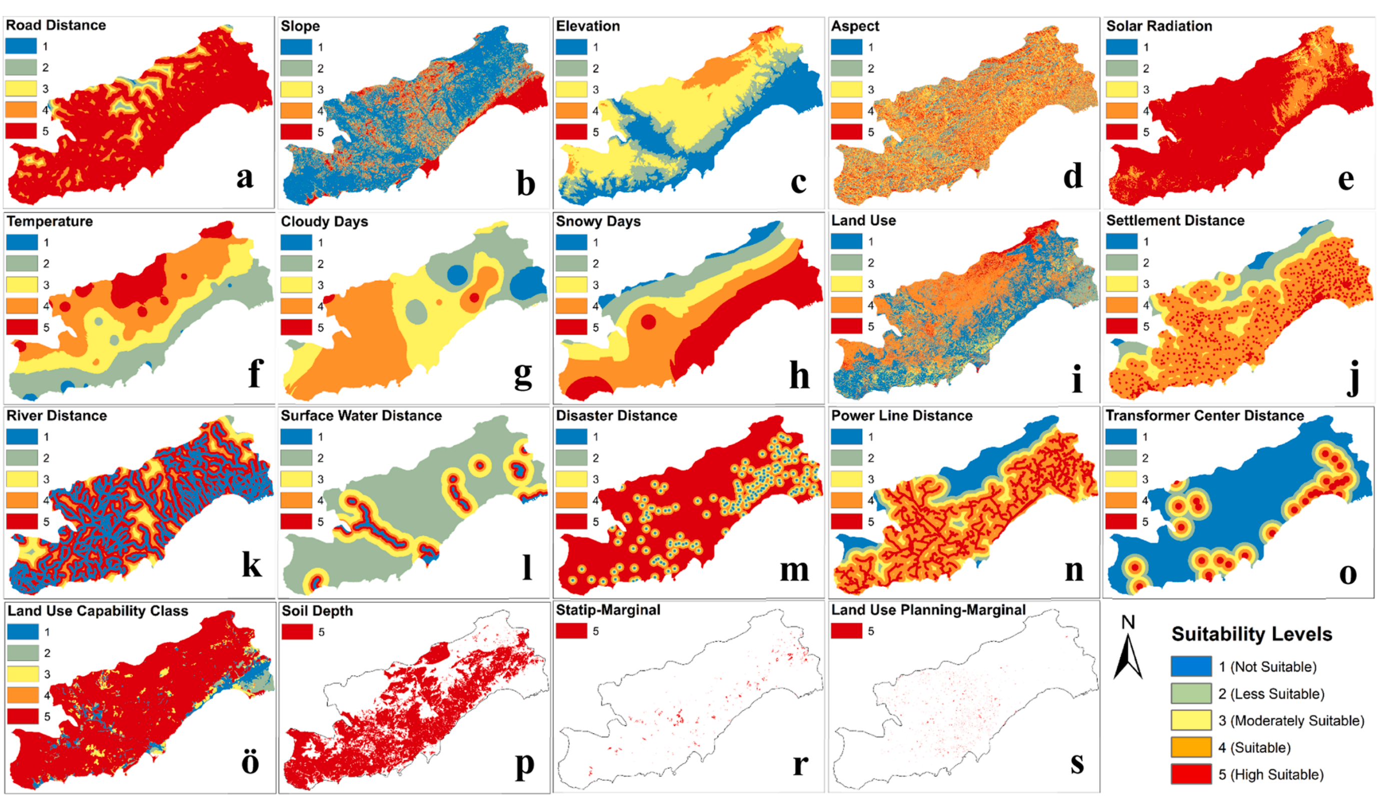

Fig. 3. Classified maps with defined criteria for solar power plant site selection.

Table 6
Areal distribution values of the criteria used in the evaluation of solar power plant site selection.

Main Criteria	Sub-Criteria	Suitability Level	Area (km^2)	Area (%)
Distance from road (km) (C1)	0–2	Highly Suitable	18.92	81.81
	2–4	Suitable	207.67	12.69
	4–6	Moderately Suitable	651.49	4.06
	6–8	Less Suitable	2032.60	1.29
	> 8	Not Suitable	13,099.19	0.11
Slope (°) (C2)	0–2.5	Highly Suitable	2674.41	16.75
	2.5–3.5	Suitable	1038.08	6.50
	3.5–5	Moderately Suitable	1455.84	9.11
	5–8	Less Suitable	2480.60	15.53
	> 8	Not Suitable	8314.32	52.08
Elevation (m) (C3)	3000–3500	Highly Suitable	33.8	0.21
	2000–3000	Suitable	1356.21	8.48
	1000–2000	Moderately Suitable	6587.97	41.21
	500–1000	Less Suitable	3309.56	20.7
	0–500	Not Suitable	4696.46	29.38
Aspect (C4)	S, Flat	Highly Suitable	2521.39	15.79
	SE, SW	Suitable	6737.52	42.2
	E, W	Moderately Suitable	3855.01	24.14
	N, NE	Less Suitable	1405.29	8.8
	NW	Not Suitable	1444.03	9.04
GHI (kWh/m^2) (C5)	5–6.59	Highly Suitable	3590.99	22.48
	4–5	Suitable	5319.58	33.31
	3–4	Moderately Suitable	5370.25	33.63
	2–3	Less Suitable	1266.41	7.93
	0.64–2	Not Suitable	421.3	2.63
Temperature (°C) (C6)	8–11	Highly Suitable	2114.21	13.2
	11–14	Suitable	5337.22	33.33
	14–17	Moderately Suitable	3841.39	23.99
	17–20	Less Suitable	4539.78	28.35
	> 20	Not Suitable	117.25	1.1
Average annual cloudy days (C7)	10.44–12	Highly Suitable	114.38	0.71
	12–14	Suitable	6928.95	43.27
	14–15	Moderately Suitable	4810.5	30.04
	15–16.5	Less Suitable	3196.56	19.96
	> 16.5	Not Suitable	959.47	5.99
Number of snowy days (C8)	1–1.75	Highly Suitable	4925.53	30.76
	1.75–2.45	Suitable	54.85.46	34.26
	2.45–3.2	Moderately Suitable	2629.97	16.42
	3.2–4.5	Less Suitable	2359.76	14.73
	> 4.5	Not Suitable	609.14	3.8
Land use (C9)	Bare/Sparse vegetation	Highly Suitable	957.27	5.94
	Grassland	Suitable	6864.85	42.63
	Shrubland	Moderately Suitable	1249.28	7.75
	Cropland	Less Suitable	1040.13	6.46
	Permanent water bodies/Herbaceous wetland/Tree cover/Built-up	Not Suitable	5989.34	37.2
Distance from the settlement (km) (C10)	0–1	Highly Suitable	2008.90	12.54
	1–5	Suitable	9921.54	61.97
	5–10	Moderately Suitable	2314.4	14.45
	10–20	Less Suitable	1486.71	9.28
	> 20	Not Suitable	278.32	1.73
Distance from river (km) (C11)	1–3	Highly Suitable	6499.49	40.59
	3–5	Suitable	1986.07	12.4
	5–10	Moderately Suitable	1010.42	6.31
	> 10	Less Suitable	67.47	0.42
	0.1–1	Not Suitable	6446.42	40.26
Distance from surface water sources (km) (C12)	1–3	Highly Suitable	877.27	5.47
	3–5	Suitable	1008.09	6.29
	5–10	Moderately Suitable	2901.18	18.12
	> 10	Less Suitable	10,718.88	66.95
	0.1–1	Not Suitable	504.45	3.15
Distance from disaster center (km) (C13)	> 5	Highly Suitable	10,927.63	67.9
	3–5	Suitable	2669.74	16.59
	2–3	Moderately Suitable	1238.12	7.69
	1–2	Less Suitable	920.65	5.72
	0–1	Not Suitable	335.73	2.08
Distance from power lines (km) (C14)	0–1	Highly Suitable	4112.66	25.68
	1–4	Suitable	7138.375	44.58
	4–7	Moderately Suitable	1788.37	11.17
	7–10	Less Suitable	856.74	5.35
	> 10	Not Suitable	2113.72	13.2
Distance from transformer center (km) (C15)	0–3	Highly Suitable	746.3	4.66
	3–6	Suitable	1551.66	9.69
	6–9	Moderately Suitable	1796.97	11.22
	9–12	Less Suitable	1759.36	10.99
	> 12	Not Suitable	10,149.91	63.42
Land use capability classes (C16)	VI/VII/VIII	Highly Suitable	13,509.91	84.7
	V	Suitable	4.03	0.02
	IV	Moderately Suitable	767.3	4.81
	III	Less Suitable	654.72	4.1
	I/II/Other	Not Suitable	1013.85	6.35
Soil depth (cm) (C17)	0–20/Lithosolic	Highly Suitable	8232.93	51.42
STATIP (C18)	Dry marginal lands, wet marginal lands	Highly Suitable	122.9	0.76
Land use planning (C19)	Dry marginal lands, wet marginal lands	Highly Suitable	55.43	0.34

large drop in the frequency of snowy days, particularly in the research area’s coastline portion. However, it was shown that the influence of elevation increased the number of snowy days in mountainous places. The frequency of snowy days decreases in the Göksu valley and its environs in tandem with the temperature. In this instance, there are almost 65 % more locations categorized as “suitable” than as “highly suitable”. The hilly regions of Mersin contain the majority of the places categorized as “less suitable” and “not suitable”, with a ratio of almost 18 % (Table 6, Fig. 3h).

3.1.9. Land use (C9)

Among the top sites for solar power plant building are arid and underproductive regions. (MEECC, 2008). The research region is mostly barren or grassland with minimal vegetation, particularly in the higher elevations. These areas classified as "highly suitable" and "suitable" cover approximately 49 % of the study area. The areas classified as "less suitable" and "not suitable" correspond to approximately 44 % of the study area in parallel with the agriculture in the coastal plains and valley interiors and the absence of forested areas after a certain height (Table 6, Fig. 3i).

3.1.10. Distance from the settlement (C10)

Reducing transmission power losses and costs can be achieved in part by placing solar power facilities close to residential areas (Turney and Fthenakis, 2011). Due to geographical factors, rural settlements in the study area are more dispersed than in flat provinces. In addition to this, it can be said that most of the settlements in Mersin are located up to 1500 m in order to avoid difficult living conditions. In parallel with the dispersed settlements, approximately 74 % of the study area is in areas classified as "highly suitable" and "suitable". This situation in Mersin Province brings many advantages for many investments, such as energy investments and agricultural activities. In addition, there are not many settlements, especially after 1500–2000 m of altitudeSimultaneously, around 11 % of the research area is categorized as "less suitable" or "not suitable". (Table 6, Fig. 3j).

3.1.11. Distance from the river/surface water (C11-C12)

In order to preserve the natural world and the ecological balance, solar power facilities shouldn't be situated close to bodies of water. But occasionally, solar panels that have been polluted by dirt, excrement, or dust may need to be cleaned (Günen, 2021b). Solar power plants can help provide some of the energy needed for agricultural irrigation (Colak et al., 2020). There are rivers flowing directly to the sea, especially in the NE half, due to the effect of the mountains that run parallel to the coast and rise suddenly. In addition to this, there are different drainage patterns in the SW half with the effect of the rivers connected to the Göksu River. Due to the widespread river network, 40.26 % of the study area is classified as "not suitable". Approximately 12 % of the study area is classified as "highly suitable" and "suitable" due to the water surfaces collected mostly in Göksu valley, with the effect of mountainous areas in the study area (Table 6, Figs. 3k, 3l).

3.1.12. Distance from the disaster center (C13)

The best places for solar power plants are those that are farthest from areas where geological risks (disaster centers) are most likely to occur (Li et al., 2023). The research area's geological and geomorphological features cause disasters like landslides and earthquakes to be unevenly dispersed throughout it. This has the benefit that 84 % of the research region is categorized as "suitable" and "highly suitable" (Table 6, Fig. 3m).

The values in Table 6 show the areal distribution of the criteria used in the evaluation of solar power plant site selection.

3.1.13. Distance from the power lines (C14)

It is less expensive to build a network connecting solar power plants to electricity transmission lines and simpler to connect them to the grid when they are close to these transmission lines (Saraswat et al., 2021). Energy transmission lines are found throughout a significant portion of the research region, depending on the distribution features of the settlements. This means that 71 % of the research region is categorized as "suitable" or "highly suitable." There are no electricity transmission lines running parallel to the road network or settlement, particularly above 2000 m (Table 6, Fig. 3n).

3.1.14. Distance from the transformer center (C15)

The cost of solar power plants can be reduced by their closeness to a substation, depending on the amount of energy they generate, as this avoids the need to build additional substations (Koc et al., 2019). Consequently, according to (Table 6, Fig. 3o), only 14.35 % of the research area is categorized as "suitable" and "highly suitable".

3.1.15. Land use capability classes (C16)

According to land use capability classifications; agriculture is generally not suitable in the sixth, seventh, and eighth classes (URL6, 2024). In this sense, it is best to construct solar power plants in areas that are not suitable for farming. Owing to the impact of many geographical elements, 84.7 % of the research region is categorized as "highly suitable". Especially the delta plains and valley bottoms, where there are areas suitable for agriculture, cover approximately 10 % of the study area (Table 6, Fig. 3ö).

3.1.16. Soil depth (C17)

The ideal sites for solar power plants should be those with lithosolic soils or those with soil depths ranging from 0 to 20 cm. The majority of the research area's hilly sections are those that haven't gotten deep enough yet. In 51 percent of the research region, the soil is less than 20 cm deep. These regions are often found outside of valley bottoms and delta plains (Table 6, Fig. 3p).

3.1.17. STATIP (C18)

A project called STATIP has been implemented in order to identify problematic agricultural areas in Turkey and implement improvement strategies accordingly. In this project, an assessment of the current situation was made. One of the types of areas produced within this scope is dry and irrigated marginal agricultural areas. Some criteria were determined for the marginal agricultural areas class. These are areas with high soil and topographical limitations, low agricultural potential, slope of at least 12 %, lower yields in crops grown compared to the immediate environment and soil depth less than 50 cm. The selection of marginal agricultural lands for the development of solar power plants is crucial in this context. 0.76 % of the study area is of dry or wet marginal area type. These areas are classified as "highly suitable". It can be said that they do not have any clustering and are mostly distributed between 500 and 2000 m (Table 6, Fig. 3r).

3.1.18. Land use planning (C19)

Future-focused classification was applied to land use planning data from the Ministry of Agriculture and Forestry. Within the scope of this planning, dry and irrigated marginal agricultural areas were determined with a more detailed and accurate classification than the STATIP project. Similarly, it is recommended to prefer the regions planned as marginal areas for physical investments. 0,34 % of the study area is a dry or irrigated marginal agricultural area in land use planning. These places are designated as "highly suitable". They are often seen in the regions north of Silifke. There is no homogenous distribution (Table 6, Fig. 3s).

3.2. Criteria weights and ranking

Experts were asked to score the criteria using a nine-level value scale (Table 7). When translated to Z numbers, this scale reflects the A fuzzy number. A five-point rating system is used by decision makers to gauge their level of confidence in their choices. When translated to Z numbers, this value scale reflects a fuzzy B number.

To establish the weight values, a panel of three solar panel installation specialists assessed the criteria in accordance with Table 7. Table 8 presents the opinions that were gathered.

Z-numbers were created once the language values were translated into matching fuzzy numbers (Table 8) based on the experts' evaluations of the significance of each criterion. Converting the Z-numbers into traditional fuzzy numbers was the next stage. Eqs. (1)-(4) were used to carry out the transformation (Table 9).

A classical fuzzy number is converted from the Z-number to provide an initial (expert) judgment matrix. Initially, the F-LMAW approach is being applied. Step 3, which determines the absolute fuzzy anti-ideal point, comes next. Next, fuzzy relationship vectors were developed. Next, the vector of weight coefficients for each expert had to be determined individually. Using Bonferroni aggregators, the whole vector of fuzzy weight coefficients was then computed. Table 10 displays the final criteria values for each step that was completed using the stabilization that was provided in the stage prior.

The C5 (solar radiation) criterion ranked top with a weight value of 0.0664, while the C11 (distance from the river) criterion ranked last with a weight value of 0.0265, according to the analysis done by taking into consideration the expert opinions for site selection of solar power plants. The criteria with the highest weight values are C7 (cloudiness) and C14 (distance from power lines); the criteria with the lowest weight values are C12 (distance from surface water sources) and C17 (soil depth) (Table 10).

Table 7
Linguistic values to assess the relative relevance of criteria and alternatives.

Linguistic Value	Fuzzy Number A	Linguistic Value	Fuzzy Number B
Absolutely low (AL)	(1, 1, 1)	Very small (VS)	(0, 0, 0.2)
Very low (VL)	(1, 1.5, 2)	Small (S)	(0.1, 0.25, 0.4)
Low (L)	(1.5, 2, 2.5)	Medium (M)	(0.3, 0.5, 0.7)
Medium low (ML)	(2, 2.5, 3)	High (H)	(0.55, 0.75, 0.95)
Equal (E)	(2.5, 3, 3.5)	Very high (VH)	(0.8, 1, 1)
Medium high (MH)	(3, 3.5, 4)		
High (H)	(3.5, 4, 4.5)		
Very high (VH)	(4, 4.5, 5)		
Absolutely high (AH)	(4.5, 5, 5)		

3.3. Map of site selection for solar power plants

SI mapping technique has been used for the identification of the best sites for solar power plants. The weight values of each criterion (Table 10) and the categorized raster maps (Fig. 3) made in accordance with the criteria's effect levels on the selection of the location for solar power plants (Table 5) were assessed using the WLC technique for this mapping procedure. This is how the *SI* was determined:

$$SI = [(0.0601 \ x \ (C1)) + (0.0654 \ x \ (C2)) + (0.0482 \ x \ (C3)) + (0.0627 \ x \ (C4)) + (0.0664 \ x \ (C5)) + (0.0484 \ x \ (C6)) + (0.0660 \ x \ (C7)) + (0.0591 \ x \ (C8)) + (0.0600 \ x \ (C9)) + (0.0454 \ x \ (C10)) + (0.0265 \ x \ (C11)) + (0.0342 \ x \ (C12)) + (0.0541 \ x \ (C13)) + (0.0661 \ x \ (C14)) + (0.0655 \ x \ (C15)) + (0.0546 \ x \ (C16)) + (0.0394 \ x \ (C17)) + (0.0368 \ x \ (C18)) + (0.0411 \ x \ (C19)]$$

The calculated *SI* values varied between 3.06 and 4.23. When these *SI* values were classified into 5 classes, the values in the range of 3.97–4.23, 3.81–3.97, 3.66–3.81, 3.49–3.66, and 3.06–3.49 were represented by the classes of "highly suitable", "suitable", "moderately suitable", "less suitable" and "not suitable", respectively (Table 11). The three classifications of this classification (appropriate, somewhat suitable, and less suitable) found in Table 9 were used to guide the mapping of potential solar power plant sites (Fig. 4).

Concerning the potential of solar plants, the most widespread classes in the study area are "moderately suitable (0.0034 %)" and "less suitable (0.0033 %)". A general analysis of the study area reveals that approximately 0.0038 % of the area constitutes suitable locations for solar power suitability (Tablo 11). Due to the amount of marginal areas used in STATIP and land use planning data, very few areas are reflected in the suitability classes in the site selection map.

As seen in the suitability map (Fig. 4), the majority of the potential areas are concentrated in Silifke and Mut districts. Although the altitude values are not high in these districts, the suitability of meteorological criteria, high solar radiation values, and proximity of these districts to energy transmission lines and highways have been effective in this situation. In addition, contrary to the disaster intensity in the northeast of the study area, this region is quite far from the disaster points. Land prices, which were not used in the study but are known by the authors, are lower in this region compared to the coastal area.

Fig. 4 shows the potential solar power plant site suitability categories. More realistic maps can be produced by using digital elevation models in the production of temperature, precipitation, and cloudiness maps. In this way, more accurate analyses can be made. Since tornado events in Turkey are not recorded by official institutions, they could not be used as a disaster in the study. The level of trust in the tornado data collected from open sources and its collection according to social notifications were effective in not being used during the study. In countries where tornado data are collected by official institutions, it would be useful to use them in planning various investments, such as solar energy. The study area's marginal land use planning regions are primarily found north of Silifke. This data acquired from the Ministry of Agriculture and Forestry may not yet be available across the province. Therefore, it can be said that it is clustered in a certain area.

One of the important criteria in investment planning is restricted and protected areas. Following the study, various data from the Ministry of Agriculture and Forestry were utilized to personally check the appropriate locations. These are water surfaces, landslide risk areas, protected forests, mining areas licensed under the mining law, geothermal resource areas, afforestation areas, special environmental protection zones, national parks, nature parks, wetlands, registered forests, gene protection areas, wildlife development areas, and large plains protected by law. In solar power plants that contribute to environmental sustainability, it is very important to plan investments in accordance with such protection areas.

3.4. Application of sensitivity analysis

According to Table 8, the criteria with the highest weight value (0.0664) is solar radiation. A total of 24 scenarios were obtained using Eq. (14). Unlike these 24 scenarios, the scenario corresponding to the original weight value of the wind speed criterion was accepted as Scenario0 (S0). According to these scenarios; solar radiation =0.0531 represented the weight value in Scenario1 (S1), while solar radiation =0.0003 represented the weight value in Scenario24 (S24). Eq. (14) was used to derive the weights of the other criteria after each adjustment of solar radiation. For example, the calculation for the first scenario (S1) was made as follows: The actual weight value of the wind speed criterion (0.0664) was reduced by 20 % and the weight value for scenario S1 was found as 0.0531 [0,0664- (0,0664*0.20) = 0,0531]. The weight values of all criteria except wind speed were then calculated according to the 24 scenarios using Eq. (14) as follows:

$$\text{Distance to motorways} = \frac{(1-0{,}0531)*0{,}0654}{(1-0{,}0664)} = 0{,}0610\ldots\ldots\ldots$$

$$\text{Land use planning} = \frac{(1-0{,}0531)*0{,}0411}{(1-0{,}0664)} = 0{,}0416$$

Fig. 5 depicts the adjusted criterion weight values based on 24 situations.

After acquiring the revised criterion weights, as shown in Fig. 5, the suitability maps for solar power plants based on 24 scenarios are generated and presented in Fig. 6.

Table 8
Evaluations by experts.

—	C1		C2		C3		C4		C5		C6		—	—
	A	B	A	B	A	B	A	B	A	B	A	B		
E1	AH	M	AH	H	H	S	AH	H	AH	H	E	M		
E2	AH	M	AH	H	H	S	AH	H	AH	H	E	M		
E3	H	H	H	VH	MH	VH	MH	H	AH	H	MH	H		
	C7		**C8**		**C9**		**C10**		**C11**		**C12**			
	A	B	A	B	A	B	A	B	A	B	A	B		
E1	VH	VH	H	M	AH	VH	ML	H	L	S	L	M		
E2	VH	H	H	H	AH	M	ML	H	L	S	L	M		
E3	VH	VH	H	VH	E	H	ML	H	L	H	L	H		
	C13		**C14**		**C15**		**C16**		**C17**		**C18**		**C19**	
	A	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**
E1	AH	S	AH	M	AH	H	H	H	MH	M	E	M	H	M
E2	AH	S	AH	H	AH	H	H	H	MH	M	E	VH	H	H
E3	VH	H	AH	H	VH	H	E	M	VL	M	AL	H	AL	H

C: Criteria, E: Expert

Table 9
Conversion of Z-numbers into classical fuzzy numbers.

	C1			**C2**			**C3**			**C4**		
E1	3,1820	3,5355	3,5355	3,8971	4,3301	4,3301	1,7500	2,0000	2,2500	3,8971	4,3301	4,3301
E2	3,1820	3,5355	3,5355	3,8971	4,3301	4,3301	1,7500	2,0000	2,2500	3,8971	4,3301	4,3301
E3	3,0311	3,4641	3,8971	3,3813	3,8644	4,3474	2,8983	3,3813	3,8644	2,5981	3,0311	3,4641
	C5			**C6**			**C7**			**C8**		
E1	3,8971	4,3301	4,3301	1,7678	2,1213	2,4749	3,8644	4,3474	4,8305	2,4749	2,8284	3,1820
E2	3,8971	4,3301	4,3301	1,7678	2,1213	2,4749	3,4641	3,8971	4,3301	3,0311	3,4641	3,8971
E3	3,8971	4,3301	4,3301	2,5981	3,0311	3,4641	3,8644	4,3474	4,8305	3,3813	3,8644	4,3474
	C9			**C10**			**C11**			**C12**		
E1	4,3474	4,8305	4,8305	1,7321	2,1651	2,5981	0,75	1	1,25	1,0607	1,4142	1,7678
E2	3,1820	3,5355	3,5355	1,7321	2,1651	2,5981	0,75	1	1,25	1,0607	1,4142	1,7678
E3	2,1651	2,5981	3,0311	1,7321	2,1651	2,5981	1,2990	1,7321	2,1651	1,2990	1,7321	2,1651
	C13			**C14**			**C15**			**C16**		
E1	2,25	2,5	2,5	3,1820	4,3301	4,3301	3,8971	4,3301	4,3301	3,0311	3,4641	3,8971
E2	2,25	2,5	2,5	3,8971	4,3301	4,3301	3,8971	4,3301	4,3301	3,0311	3,4641	3,8971
E3	3,4641	3,8971	4,3301	3,8971	4,3301	4,3301	3,4641	3,8971	4,3301	1,7678	2,1213	2,4749
	C17			**C18**			**C19**					
E1	2,1213	2,4749	2,8284	1,7678	2,1213	2,4749	2,4749	2,8284	3,1820			
E2	2,1213	2,4749	2,8284	2,4152	2,8983	3,3813	3,0311	3,4641	3,8971			
E3	0,7071	1,0607	1,4142	0,8660	0,8660	0,8660	0,8660	0,8660	0,8660			

Table 10
Final criteria weights.

Criteria	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**
w_i	0.0601	0.0654	0.0482	0.0627	0.0664	0.0484	0.0660	0.0591	0.0600	0.0454
Criteria	**C11**	**C12**	**C13**	**C14**	**C15**	**C16**	**C17**	**C18**	**C19**	
w_i	0.0265	0.0342	0.0541	0.0661	0.0655	0.0546	0.0394	0.0368	0.0411	

As can be seen in Fig. 4, the districts of Silifke and Mut are the best locations for solar power plants in all 24 scenarios. The site selection map for the solar power plant (Fig. 4) has been drawn up according to the weighting values calculated on the basis of Scenario 0 (S0), and the suitability mapping obtained according to the other 24 scenarios (Fig. 6) supported the accuracy of the suitability mapping obtained according to Scenario 0 (S0) (Fig. 4).

Table 11
Choosing a location for solar power plants: Suitability level and covered areas.

Appropriate location selection for solar power plants	**Index Value**	**Area (ha)**	**Area (%)**
Highly Suitable	3.97–4.23	26.25	0.0016
Suitable	3.81–3.97	36.75	0.0022
Moderate Suitable	3.66–3.81	55.25	0.0034
Less Suitable	3.49–3.66	53.06	0.0033
Not Suitable	3.06–3.49	11.87	0.0007

4. Discussion, future directions, practical implications and limitations

This research presents an innovative approach to determining ideal locations for solar power plants, yielding significant findings. The integration of fuzzy Z-number based MCDA and GIS provides a comprehensive and detailed analysis for solar energy investments. By evaluating the suitability levels for the Mersin region of Turkey using nineteen criteria, the study achieves reliable results by considering both technical and environmental factors.

The findings of the research indicate that the Mersin region has a high technical potential for solar power plants across a wide geographical area. Specifically, regions such as Silifke and Mut stand out as "optimal" areas due to their favorable climate and topographical features. This study identifies GHI (C5), cloudiness (C7), and distance from power lines (C14) as the most important factors for site selection of solar power plants in the Mersin province. These criteria are supported by various MCDA techniques (AHP, ANP, Fuzzy OWA, Fuzzy-AHP, Gray Cumulative Prospect Theory, VIKOR, ELECTRE-TRI, SWARA, DEMATEL) in the literature (Rekik and El Alimi, 2023; Islam et al., 2024;

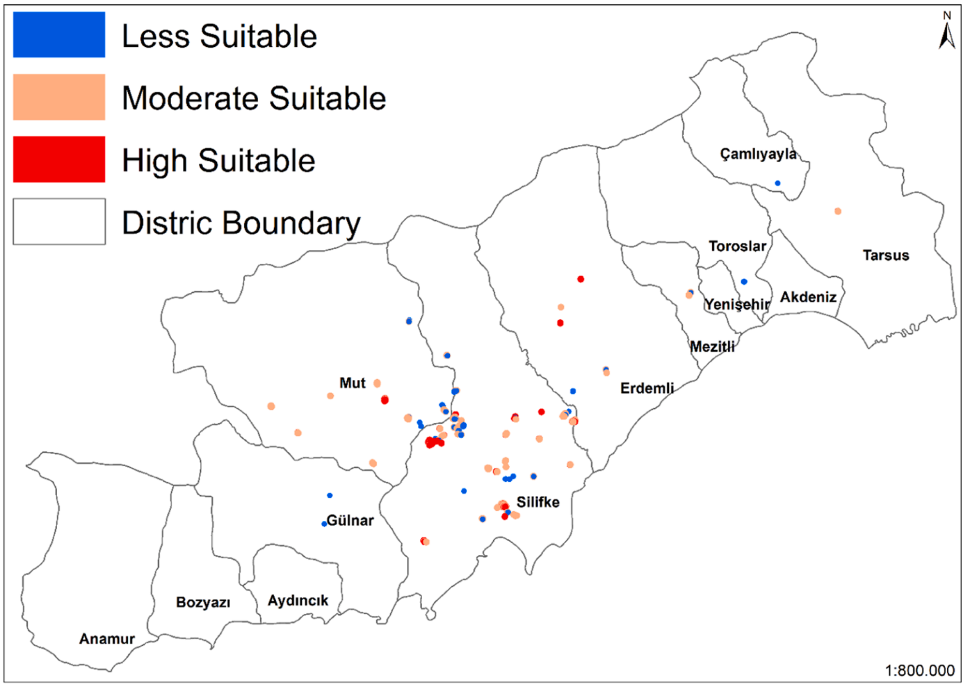

Fig. 4. Potential solar power plant site suitability categories for the study area.

Zambrano-Asanza et al., 2021; Bandira et al., 2022; Mokarram et al., 2020; Zoghi et al., 2017; Doorga et al., 2019; Noorollahi et al., 2016). This alignment with the literature confirms the validity of the weightings of these criteria.

On the other hand, criteria with the lowest weight in this analysis include soil depth (C17), distance from surface water sources (C12), and distance from rivers (C11). This finding has also been similarly noted and validated in other studies in the literature (Tercan et al., 2021; Kocabaldır and Yücel, 2023; Hasti et al., 2023; Saraswat et al., 2021; Halder et al., 2022; Rekik and El Alimi, 2024). These results confirm that the key factors for the establishment of solar power plants have been correctly and reliably weighted. This proves that the proposed model is not only theoretical but also practical. According to the expert evaluations in this study for solar power plant site selection; C5 criterion (GHI) ranked first with a weight value of 0.0664, while C11 criterion (distance from river) ranked last with a weight value of 0.0265. C7 (Cloudiness) and C14 (distance from power lines) criteria are the other criteria with the highest weight values, while C12 (distance from surface water sources) and C18 (STATIP) criteria are the other criteria with the lowest weight values. In this study; For solar power plant location selection, GHI (C5), cloudiness (C17) and distance to power lines (C14) criteria have the highest weight values, and these criteria have been found to be the criteria with the highest weight in many studies (Kocabaldır and Yücel, 2023; Rane et al., 2024; Zambrano-Asanza et al., 2021; Xuan et al., 2022; Mokarram et al., 2020; Marques-Perez et al., 2020; De Luis-Ruiz et al., 2024; Saraswat et al., 2021; Minaei et al., 2021) with different MCDA methods (AHP, ANP, Multi-Influencing Factor (MIF), SWARA,). In addition; distance from river (C11), distance from surface water sources (C12) and STATIP (C18) criteria were found to be the criteria with the lowest weight in this study. This situation also supported the literature information (Kocabaldır and Yücel, 2023; Tercan et al., 2021; Saraswat et al., 2021; Halder et al., 2022; Hasti et al., 2023; Minaei et al., 2021). No information was found in the literature regarding the STATIP (C18) criterion used in the study. The WLC method is a widely used method in the literature (Faqe Ibrahim et al., 2024; Tafula et al., 2023; Qasimi et al., 2023; Zambrano-Asanza et al., 2021; Firozjaei et al., 2019; Hasti et al., 2023; Suuronen et al., 2017) with multi-criteria decision-making methods (such as AHP, SWARA, BEST&WORST) on solar power plant location selection, and in this study, the WLC method was preferred in determining the final solar power plant location by evaluating the criterion weights and classified criterion maps together.

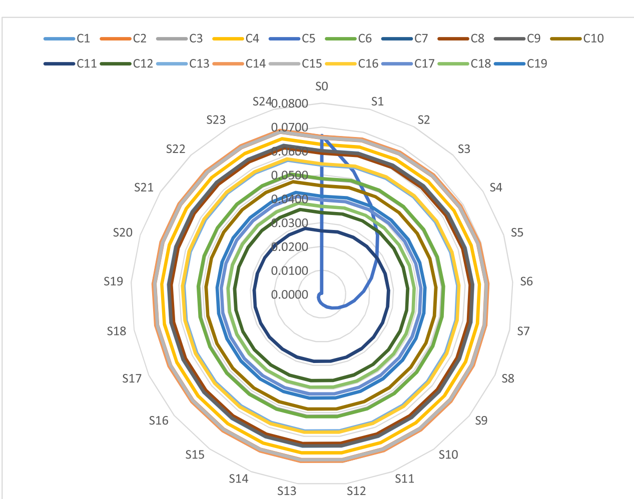

Fig. 5. Modifications in weights based on different scenarios.

4.1. Future research directions

- Integration of Additional Factors: Future studies should extend beyond the technical and environmental criteria used in this research to include additional factors such as land ownership and regulatory constraints. These factors play a critical role in the feasibility and implementation of solar energy projects. Understanding land ownership and regulatory requirements can help address legal and logistical challenges that may hinder the establishment of solar power plants.

- Social and Community Factors: Evaluating social factors, such as community acceptance and local participation, should be a key focus for future research. Social acceptance can greatly influence the success of

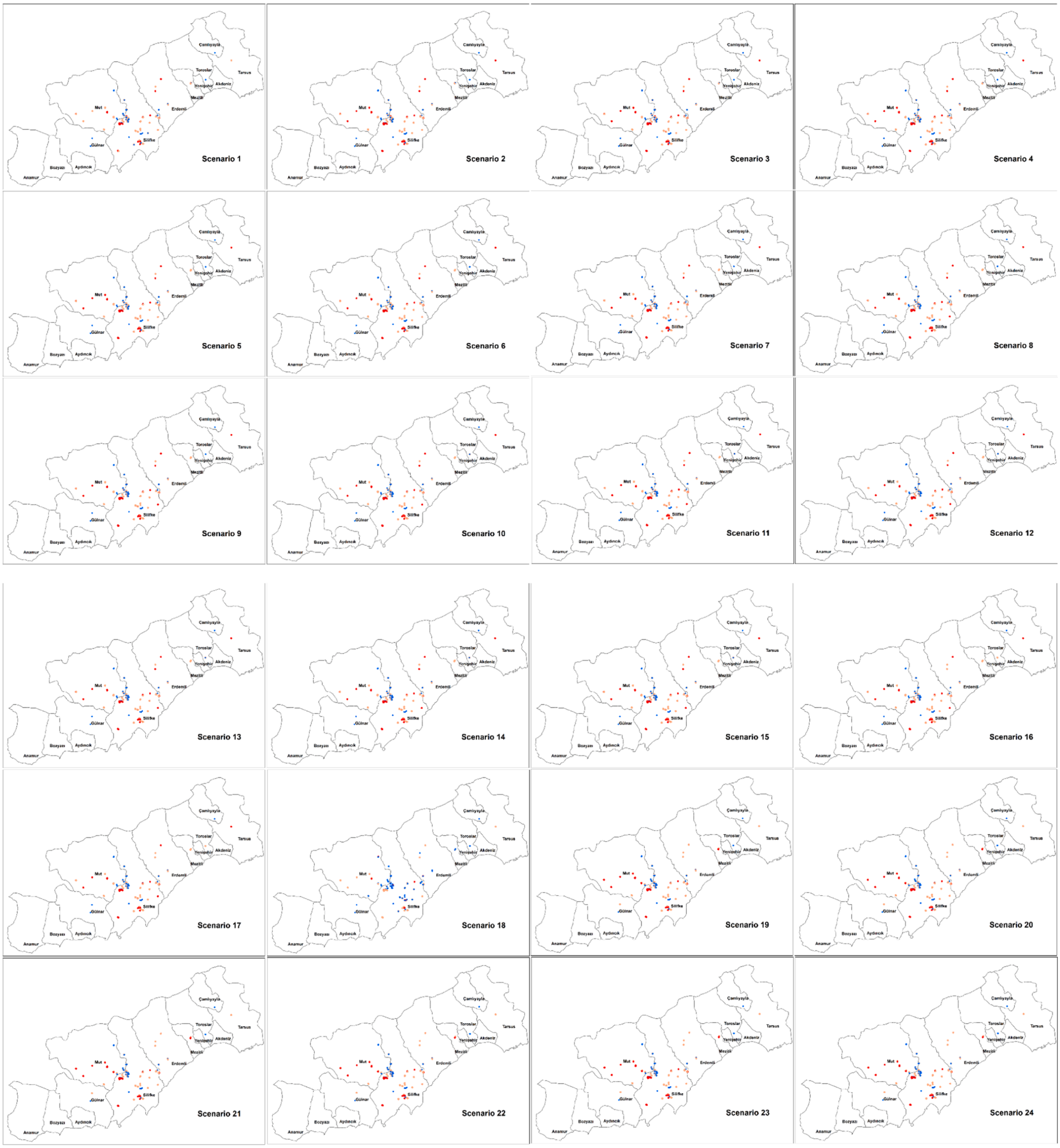

Fig. 6. Solar power plant site potential suitability categories obtained according to new criterion weights.,.

solar projects. Assessing community feedback and social dynamics can enhance the sustainability and acceptability of solar power plants. This can be achieved through surveys, community engagement initiatives, and stakeholder consultations.

- Integration of New Technologies: As technology advances, incorporating new technologies into site selection methodologies can provide more accurate and dynamic evaluations. For example, advancements in remote sensing, satellite imagery, and machine learning can improve the accuracy of environmental and technical assessments. Integrating these technologies can enhance the analysis of factors such as solar radiation patterns, land use changes, and climate variability.

- Regional and Global Comparisons: Comparative studies between different regions and countries can offer valuable insights into how various factors influence solar power plant site selection. Such studies can help identify best practices and strategies, contributing to a global knowledge base that can be adapted for different regions.

4.2. Practical applications

- Policy and Regulatory Framework: The findings underscore the importance of integrating technical criteria into the policy development process for energy investments. Policymakers should consider key factors such as solar radiation and proximity to power lines when developing guidelines and regulations for solar power plant installations. This can facilitate the approval process and encourage investments in solar energy.

- Investment Decisions: Investors and developers can use the research findings as a guide in their decision-making processes. By considering regions with high technical potential (e.g., Silifke and Mut) and key site selection factors (e.g., solar radiation and cloudiness), investors can optimize site selection processes and enhance project success.

- Community Engagement and Education: Engaging with local communities and educating them about the benefits of solar energy can build positive relationships and support. Involving communities in planning and decision-making can address concerns and build trust, facilitating project implementation and long-term success.

- Sustainability and Environmental Impact: The research highlights the need for a holistic approach that considers both technical and environmental factors in site selection. Prioritizing areas with minimal environmental impact and suitable environmental conditions can contribute to the sustainable development of future solar energy projects and reduce adverse environmental effects.

4.3. Limitations

This study has some limitations. Notably, important factors such as land ownership and regulatory constraints have not been considered. These factors can present significant barriers to the establishment of solar power plants. Land ownership issues can complicate the acquisition of necessary land for investors, while regulatory constraints may pose legal and administrative challenges for project implementation. Therefore, future research should expand to include these additional factors. This would provide a more comprehensive and practical analysis, enhancing our understanding of the feasibility and execution of solar energy projects. Furthermore, evaluating social factors such as community acceptance and local participation is crucial. Social acceptance can significantly impact the success of solar projects. Considering community feedback and social dynamics can improve the sustainability and acceptability of projects. Thus, incorporating social factors and community engagement is essential for supporting the long-term success of these projects. The impact of these limitations and factors can be significant in determining the success and feasibility of solar energy projects. A comprehensive evaluation of land ownership, regulatory constraints, social acceptance, and local participation can help identify potential barriers early in the project planning and implementation phases. Therefore, future research and practices should adopt a more holistic approach that considers these elements to contribute to the development of more effective and sustainable energy projects. In conclusion, this study advances scientific knowledge by providing an innovative contribution to the methodologies used for identifying suitable areas for solar power plants. The integration of fuzzy Z-number based MCDA and GIS assists in making more accurate and reliable decisions for energy investments, while also serving as an important model that other countries can emulate. Such studies play a critical role in adopting more sustainable and environmentally friendly solutions in Turkey's energy policy, shaping future energy projects.

5. Conclusion and suggested areas for future research

This study employs a fuzzy Z-number based MCDA and GIS integration to perform a geographical analysis for identifying ideal locations for solar power plants in Turkey. The proposed framework serves as a dynamic tool offering innovative options for policymakers and investors across various potential sites. The analysis considers nineteen decision criteria, including distance from roads, slope, elevation, aspect, solar radiation, temperature, average annual cloudy days, number of snowy days, land use, distance from settlements, distance from rivers, distance from surface water sources, distance from disaster centers, distance from power lines, distance from transformer centers, land use capability classes, soil depth, and problematic agricultural areas. These criteria are based on land use planning, expert opinions, and similar works, tailored to the characteristics of the study region. According to the experts' report, according to the criteria weight values determined according to the F-LMAW method, the C5 (GHI) criterion ranked first with a weight value of 0,0664, while the C11 (distance from the river) criterion ranked last with a weight value of 0,0265. SI values, which are the most important indicator of solar power plant distribution, are classified as 3,97–4,23 (very suitable), 3,81–3,97 (suitable), 3,66–3,81 (moderately suitable), 3,49–3,66 (less suitable) and 3,06–3,49 (not suitable). The most common classes of solar power plant potential in the study area are "moderately suitable (%0,0034)" and "less suitable (%0,0033)" classes. Approximately 0,0038 % of the study area is suitable for solar power plants. The suitability maps obtained according to the 24 scenarios determined according to the sensitivity analysis supported the accuracy of the suitability map created according to the criteria weight values determined before the sensitivity analysis. The findings reveal that Turkey has numerous locations with excellent technical potential for solar power plants. Silifke and Mut, among other areas, are highlighted as "optimal" sites due to their favorable climate and topography. In contrast, the northern regions are considered less suitable primarily due to their land use types, such as mountains and agricultural crops. The model's consistency is validated by the alignment of identified projects with ongoing and planned initiatives in "most suitable" and "appropriate" regions. This indicates that Turkey has significant opportunities to reduce its carbon footprint and reliance on fossil fuels. However, the study has limitations. It does not account for factors such as land ownership and regulatory restrictions, which can significantly affect the installation and profitability of solar power plants. Incorporating these factors could lead to a more comprehensive evaluation of site suitability. Additionally, considering community involvement and social acceptability is crucial for the successful implementation of large-scale solar farms. Transparent and effective communication throughout the project can build trust and address potential conflicts or issues.

Further research should explore the integration of cost analysis and potential revenue generation to provide a clearer understanding of the financial viability of solar power projects. Investing in solar infrastructure could boost employment and the economy, contributing to a more sustainable future and serving as a model for other countries.

5.1. Suggested areas for future research

The research outlines several specific areas for future investigation, providing a roadmap for enhancing the identification of suitable locations for solar power plants. Key areas for further study include:

- Land Ownership Analysis: Future research should focus on a detailed examination of land ownership issues, including legal and logistical barriers associated with acquiring land for solar projects. Developing models that incorporate land ownership data can help address these challenges and facilitate smoother land acquisition processes for investors.

- Regulatory Constraints Assessment: Analyzing regulatory and administrative barriers is crucial for understanding how these constraints affect the feasibility of energy projects. Studies should explore the impact of existing legal and regulatory frameworks on project planning and propose strategies to overcome these obstacles.

- Social Acceptance and Community Participation: Investigating the impact of social factors, such as community acceptance and local involvement, is essential for the success of solar projects. Research should focus on methods for gathering community feedback and understanding social dynamics through surveys, focus groups, and public consultations.

- Integration of New Technologies: As technology evolves, integrating advancements such as remote sensing, satellite imagery, and machine learning into site selection methodologies can provide more accurate and dynamic assessments. Future studies should explore how these technologies can be applied to enhance the analysis of solar radiation patterns, land use changes, and climate variability.

-Regional and Global Comparisons: Comparative studies between different regions and countries can offer valuable insights into how various factors affect solar power plant site selection. Such research can help identify best practices and adaptable strategies, contributing to a global knowledge base.

By addressing these areas, future research can provide a more comprehensive understanding of the factors influencing solar power plant development, leading to more effective and sustainable energy projects.

CRediT authorship contribution statement

Gülay Demir: Writing – review & editing, Writing – original draft, Validation, Methodology. **Can Bülent Karakuş:** Writing – review & editing, Validation, Supervision. **Dragan S Pamucar:** Writing – review & editing. **Ömer Ünsal:** Writing – review & editing, Validation, Software, Resources, Methodology.

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

Data will be made available on request.

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