



Article

Solar PV Power Plant Site Selection and Energy Production Potential in Southeastern Europe Using GIS, Remote Sensing, and Fuzzy AHP

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Abstract

Due to increasing demand and consumption of electricity, as well as the need to decarbonize and mitigate climate change, solar energy is an important factor in the transition to emission-free energy sources. This study focuses on identifying the most suitable locations for the construction of large solar photovoltaic (PV) power plants while respecting environmental, economic, and technical standards. The study area covers the mainland part of Southeastern Europe (796,039 km²), including the following countries: Slovenia, Croatia, Bosnia and Herzegovina, Serbia, Montenegro, North Macedonia, Albania, Greece, Bulgaria, Romania, Moldova, and Türkiye. Using geographic information systems (GIS) and remote sensing methods, nine factors (topographic, climatic, hydrological, ecological, vegetation, and anthropogenic) were analyzed with a spatial resolution of 100 m. A fuzzy analytic hierarchy process (F-AHP) pairwise comparison matrix was constructed to quantify the relative importance of the selected criteria. The F-AHP weighting results indicate that photovoltaic output (17.9%) and land use (15.7%) are the most important among the evaluated criteria. The results show that 6.7% of Southeastern Europe is very highly suitable for installing solar PV plants, with the most suitable areas located in Moldova (14.5%) and Greece (10.5%). Through spatial analysis of the final results, 24 of the most suitable locations for large-scale solar PV power plant development were identified, with a potential to generate approximately 30.2 TWh of electricity annually. In such a scenario, the forecast indicates that 24 large-scale solar power plants would supply electricity to more than 6.7 million households, corresponding to over 17 million inhabitants. The final spatial patterns provide decision-makers at the international level with a significantly more effective basis for planning solar energy development in order to increase the share of green energy and clean technologies in this part of Europe.

Keywords: clean energy technologies; energy optimization; decarbonization; renewable energy; solar energy; photovoltaic (PV) systems; fuzzy logic; multi-criteria decision-making (MCDM); Analytic Hierarchy Process (AHP); geographic information systems (GIS)

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1. Introduction

The energy sector represents one of the key pillars of economic and social development, providing the foundation for the functioning of all other sectors of the economy [1]. A stable and secure supply of energy and energy products, both in sufficient quantities and of adequate quality, constitutes the cornerstone of energy policy and a prerequisite for the sustainable development of every country [2]. At the same time, the continuous growth of global energy demand remains one of the greatest challenges of the modern era [3,4]. Energy systems across Europe are currently undergoing profound structural transformations driven by a combination of economic, technological, and environmental factors, as well as commitments undertaken within national and international development frameworks [5]. This process reflects a comprehensive transformation of economies and societies aimed at reducing the negative environmental impacts of the energy sector, particularly by lowering greenhouse gas emissions and enhancing energy efficiency [6].

Energy transition is thus a central component of the broader sustainability paradigm, which seeks to balance socio-economic development with the planet's limited ecological capacity [7]. In this context, the 2030 Agenda for Sustainable Development identifies “affordable and clean energy” (SDG 7) as a crucial objective for achieving global sustainability [8]. The adoption of renewable energy sources represents an effective pathway to reducing greenhouse gas emissions and mitigating climate change [9]. Among these sources, solar energy stands out as one of the most promising options due to its virtually inexhaustible nature, wide spatial availability, and flexibility of integration—from urban settings to rural and depopulated areas. However, one of the key limiting factors for photovoltaic (PV) development lies in the relatively low specific power per unit of area, which necessitates the occupation of large land surfaces [10].

Although solar energy has experienced rapid global expansion in the past decade, Southeastern Europe continues to lag behind in its full implementation. This delay cannot be justified by natural conditions, as, for example, in Serbia, the average solar radiation is approximately 40% higher than the European average [11]. Nevertheless, many countries in this region face considerable energy challenges, primarily reflected in outdated infrastructure and limited renewable energy capacity within their national energy mixes [12]. The overall energy import dependence in this part of Europe remains below the European average, largely due to the intensive use of domestic coal (e.g., lignite in Bulgaria, Romania, or Greece), and brown coal in Bosnia and Herzegovina and hydropower for electricity generation, as well as a substantial share of biomass in final energy consumption [13]. However, import dependence is particularly pronounced in the oil and natural gas sectors.

According to analyses by the European Environment Agency, Southeastern Europe is among the regions most vulnerable to climate change in Europe [14]. Climate model projections indicate increases in average temperatures exceeding the European mean, accompanied by more frequent heatwaves, droughts, and instability in hydrological regimes [15]. These changes have a direct impact on energy security, as well as on other sectors such as agriculture, tourism, and urban planning [16]. Consequently, the identification of potential sites for solar power plant development in this region carries not only energy-related but also broader developmental importance, especially in light of the 2020 Sofia Declaration on the Green Agenda for the Western Balkans, through which Southeastern European countries committed to contributing to Europe's goal of becoming a carbon-neutral continent by 2050 [17].

This study pursues several objectives:

- A large-scale spatial analysis of natural and anthropogenic conditions across South-eastern Europe for the application of solar energy;
- Determination of weighting coefficients for all criteria with globally available data using the Fuzzy AHP method;
- Identification of suitable locations for solar PV power plant development across the territory of 12 countries for the purposes of environmental sustainability;
- Spatial–energy analysis of the largest suitable areas identified for solar PV power plant installation, along with an assessment of energy production potential.

This method provides an appropriate framework for addressing multi-criteria decision-making problems under uncertainty, allowing for more reliable assessments and stable ranking of potential alternatives. The proposed approach enables an integrated evaluation of technical, economic, environmental, and social criteria, while adequately modeling uncertainty and subjectivity in the decision-making process. In this way, the research contributes to strengthening the scientific and practical foundations for sustainable energy planning in the region, in line with the goals of energy transition and climate neutrality. The energy transition itself entails the adoption of modern technologies, innovation, digitalization, and intelligent management of energy systems, which further underscores the relevance and timeliness of this study.

Based on the conducted literature review, this is one of the few regional-scale studies that estimate spatial suitability for siting a solar PV power plant using GIS and MCDA procedures, particularly Fuzzy AHP. A high-resolution (100 m) spatially explicit suitability map was created by applying commonly cited constraints and criteria that can be mapped, using publicly available open-access datasets. This research, for the first time, addresses some areas within Southeastern Europe with low solar PV capacity penetration that have not previously undergone this type of assessment.

2. Literature Review

The strategic siting of solar photovoltaic (PV) installations has become a central concern in renewable energy planning, particularly as nations seek to balance energy expansion with environmental sustainability [18]. Researchers can now consider a variety of criteria such as solar irradiance, slope, land use, proximity to infrastructure and many more, by combining Geographic Information Systems (GIS) with Multi-Criteria Decision-Making (MCDM) techniques [19–54]. Rekik and El Alimi (2023) exemplify this approach by applying GIS-AHP to identify optimal solar and wind sites in Tunisia, integrating climatological, topographical, and accessibility factors [55]. Their study shows the potential of hybrid energy zones, a concept that is becoming more and more relevant in areas with limited land or that are ecologically sensitive, and emphasizes the significance of constraint filtering using Boolean logic.

The evolution of MCDM techniques has led to the incorporation of fuzzy logic to address uncertainty in expert judgments. Since crisp exclusion models are unable to capture the gradational nature of land suitability, Noorollahi et al. (2022) suggest a hybrid framework that combines Fuzzy-Boolean logic and AHP [56]. A systematic basis for repeatable modeling is provided by their division of criteria into climatic, economic, orographic, and environmental categories. Similar to this, Türk et al. (2021) apply Intuitionistic Fuzzy Sets (IFS) to determine solar siting in Türkiye, highlighting the significance of ecological risk and land surface features in determining PV efficiency [57]. Expert hesitancy and confidence can be nuancedly represented by these fuzzy extensions, which is especially useful in areas with complicated topography or sparse data.

Hybrid energy modeling is another emerging topic in the literature. Effat and El-Zeiny (2022) integrate solar and wind resource layers using AHP and Weighted Linear Combination (WLC) in Egypt's Assiut Governorate [58]. Their review underscores the scarcity

of hybrid-focused studies and the need for multi-layered modeling frameworks that can accommodate both resource potential and environmental constraints. This dual-resource approach promotes decentralized energy planning in developing areas and is consistent with more general energy transition objectives.

Regional studies also reveal methodological gaps. Doljak and Stanojević (2017) assess PV siting in Serbia using GIS-based natural condition analysis, but they do not integrate MCDM, which limits the model's applicability to complex decision environments [59]. By using structured decision-making tools that take ecological vulnerability and land-use conflict into account—areas where hazard simulation and wildfire modeling can provide insightful information—this gap offers a chance to close the gap between local and international standards.

Wang et al. (2022) contribute a novel hybrid framework that combines Data Envelopment Analysis (DEA) with Gray-AHP and Gray-TOPSIS to evaluate solar PV sites in Vietnam [60]. Their two-phase model first chooses locations based on technical efficiency and then ranks them using expert-driven gray linguistic assessments. This strategy offers a flexible and scalable methodology for solar siting under uncertainty by striking a balance between subjective stakeholder priorities and objective performance metrics. Gray theory integration is especially pertinent for regions with imprecise or incomplete data because it also addresses the shortcomings of crisp scoring systems.

The thematic scope is further broadened by open-access reviews. In their research of rooftop solar potential in Indonesian cities, Ummah et al. (2021) emphasize the importance of building geometry and energy audits in maximizing solar deployment [61]. In their discussion of smart energy management and Solar Energy System Integration (SESI), Hajialigol et al. (2024) suggest future paths for demand-side optimization, storage, and distributed generation [62]. The significance of combining solar planning with more comprehensive energy system design, such as electrification and resilience tactics, is emphasized by these studies.

In conclusion, the literature reveals a clear progression from exclusion-based models toward fuzzy, hybrid, and scenario-driven frameworks, while also highlighting the dominance of technical and financial criteria and the underrepresentation of ecological sensitivity and hazard integration. Bridging this gap through the application of repeatable, GIS-based MCDM models that explicitly incorporate environmental risks, can significantly improve the strategic planning of solar energy systems. Such an approach not only promotes more sustainable land use but also supports regional development priorities and aligns with the broader objectives of the global energy transition.

3. Materials and Methods

3.1. Study Area

The study area covers the continental part of Southeastern Europe, including fully or partially 12 countries: Slovenia, Croatia, Bosnia and Herzegovina, Serbia, Montenegro, North Macedonia, Albania, Greece, Bulgaria, Türkiye (European part), Romania, and Moldova (Figure 1). Island territories were not considered due to their high ecological importance (isolated island ecosystems). The total area of the studied area is 796,039 km².

The continental part of Southeastern Europe is bounded by the Adriatic Sea to the west, the Ionian, Mediterranean, and Aegean seas to the south, and the Black Sea to the east [63]. The land borders are with Italy, Austria, Hungary, and Ukraine. Different natural conditions affect the possibility of building solar PV power plants. In this territory, there are mountain ranges of folded mountains in the west (the Dinarides and a small part of the Alps) and the east (the Carpathian-Balkan Mountains), which are separated by a belt of fault mountains in the central part of the Balkan Peninsula [64]. The most extensive plains are the Pannonian Plain (in the northern part of this territory), the Wallachian-

Pontian Plain in Romania and Bulgaria, and the Thracian Plain [65]. In contrast, smaller plains are represented on the coasts and in the hinterland of the sea surrounding this territory.

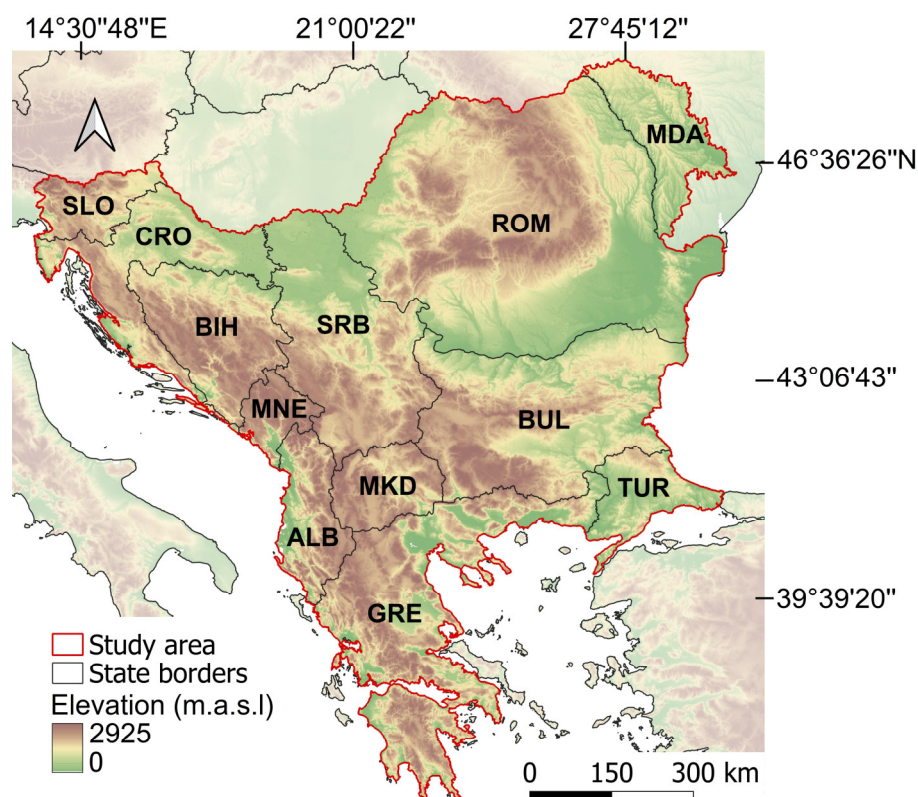


Figure 1. Geographical position of Southeastern Europe.

Various climatic factors (latitude, altitude, influence of the surrounding seas, changes in the vegetation cover) caused the presence of numerous types of climate in this territory [66]. Continental and moderately continental climates are represented in the largest part of the territory [64]. The Mediterranean climate is present on the coast. In the hinterland of the sea (the territories of Greece, Albania, and the coast of Croatia), which surround this territory, and due to the greatest number of sunny hours, the most favorable conditions for the formation of solar fields are there. Areas with altitudes higher than 2000 m are characterized by a mountain climate, primarily found in the Carpathian-Balkan mountains and the mountainous regions of Slovenia. The valleys of larger rivers, mainly in lowland areas, such as the Danube, Sava, Velika Morava, Vardar, and Marica, are the zones of concentration of the largest number of inhabitants [67].

According to data from 2025, approximately 72.3 million people lived in this territory [68,69]. The largest country in terms of population is Romania (18.4 million inhabitants), and the smallest is Montenegro (632,436 inhabitants). The largest population concentration is in the agglomerations of Istanbul, Athens, Bucharest, Belgrade, Sofia, and Thessaloniki [70]. The most economically developed areas are in the lowland and coastal regions. Although Southeastern Europe is an economically less developed region compared to most regions in Europe, it has great potential for the use of renewable energy sources, with solar energy being a notable standout [71]. Furthermore, there is a particular need to investigate solar energy potential in this region, as many Southeastern European countries still rely heavily on electricity generation from fossil fuels, highlighting the importance of accelerating the transition toward sustainable and low-carbon energy systems.

3.2. Dataset Construction

For geospatial analysis of natural and anthropogenic conditions, a large number of different sources were utilized, thereby creating a comprehensive database for the territory of Southeastern Europe. For the map of the study area, a digital elevation model (DEM) with a spatial resolution of 1×1 km was used, downloaded from the European Environment Agency platform [72]. The borders of the countries were obtained in vector format by downloading content from the Eurostat geoportal [73].

From an energy perspective, photovoltaic (PVout) output was used as the key indicator. The thematic map was generated using data from the Global Solar Atlas [74]. PVout values were derived using Solargis algorithms, considering global irradiation at the optimal tilt and air temperature as input parameters. The original spatial resolution of these data is 800 m, but to ensure consistency with the other input layers, the raster was resampled to 100 m. The map shows spatial variations in solar energy potential across the region, with photovoltaic output ranging from 633 to 1664 kWh/kWp per year. Higher values represent areas with greater potential for solar energy production.

Topographic features are shown by terrain slope and aspect (Figure 2). Both geomorphological conditions were obtained using a digital elevation model (EU-DEM) with a spatial resolution of 100 m [75].

The terrain slope in Southeastern Europe ranges from 0° (flat surfaces) to 61° (very steep slopes), illustrating the diversity of the relief morphology. In addition, the exposure (aspect) map classifies slopes according to their orientation direction into nine classes, which is important for analyzing insolation and spatial planning. Spatial data on land use were obtained from Sentinel-2 satellite images, which have a spatial resolution of 10 m [76,77]. Due to the need to unify the values of the criteria, pixels were resampled to 100 m. Land use was divided into eight classes: water surfaces, forests, flooded areas, agricultural land, settlements, bare surfaces, snow/ice, and grasslands/meadows.

The socio-economic aspect plays an important role in identifying suitable locations for solar energy development. In this study, three main criteria of this type were identified: distance from power lines, distance from roads, and distance from settlements (Figure 3). Vector data (lines) depicting power lines were obtained by downloading content from the Geofabrik geoportal [78]. Distance from power lines varies from 0 to 59.2 km, indicating significant differences in accessibility to electricity infrastructure. Roads were processed from the Open Street Map platform, and for this purpose, all types of roads (highways, motor roads, and local roads) were included [79]. Within the study area, the distance from roads ranges from 0 to 37.7 km, indicating that some parts have direct access to transport infrastructure, while others are significantly isolated. This spatial variability affects the potential availability of resources, connectivity for development, and planning opportunities for future solar PV power plants. Data on water surfaces were obtained from Sentinel-2 satellite images, which have a spatial resolution of 10 m [77]. A large number of lakes and watercourses were identified for the purposes of this analysis. Pixels of all anthropogenic conditions were resampled to a resolution of 100 m. As a hydrological factor, distance from water surfaces (0–26.1 km) is a significant factor because proximity to water bodies can carry ecological constraints and flood risks.

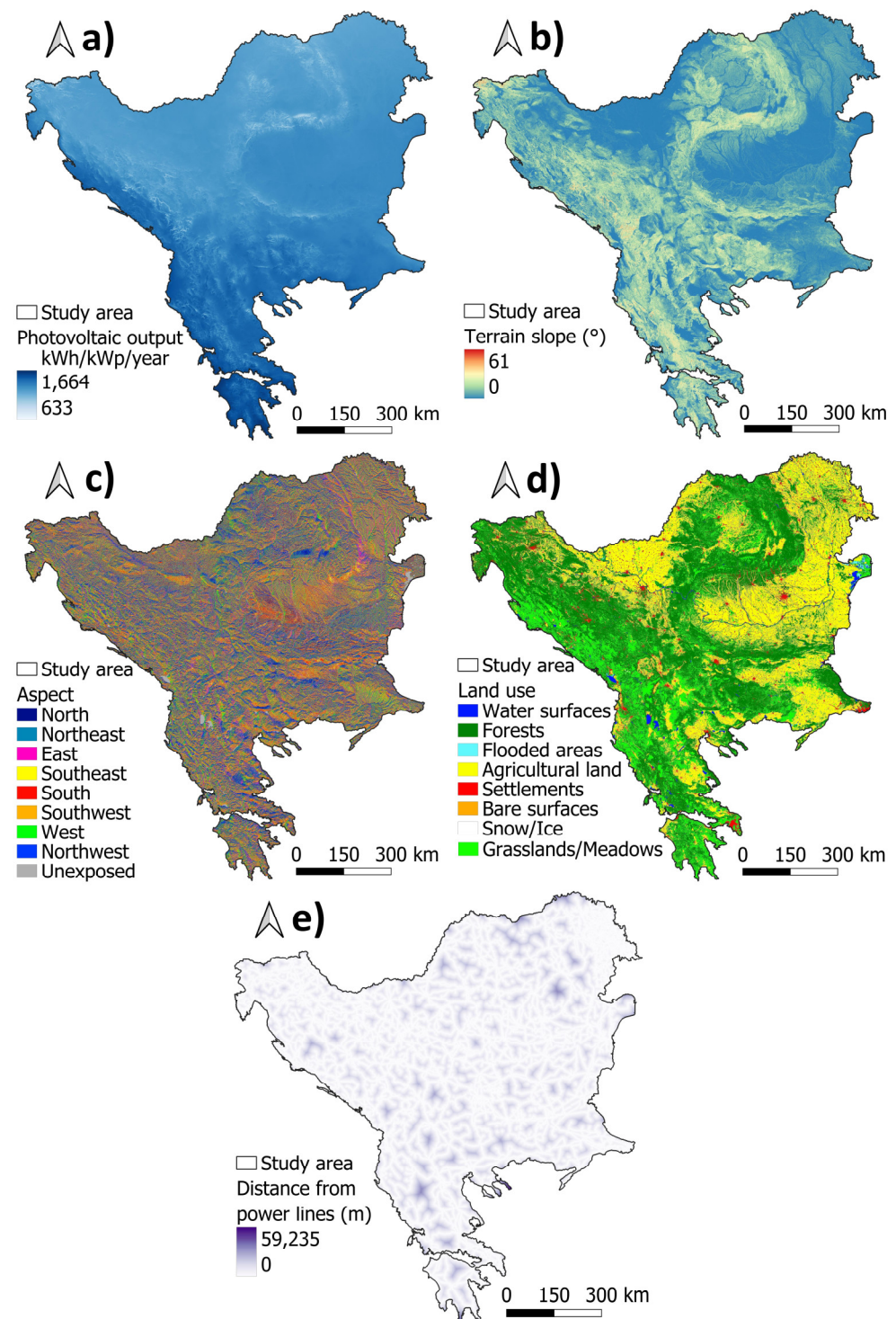


Figure 2. Thematic maps: (a) Photovoltaic output; (b) Terrain slope; (c) Aspect; (d) Land use; (e) Distance from power lines.

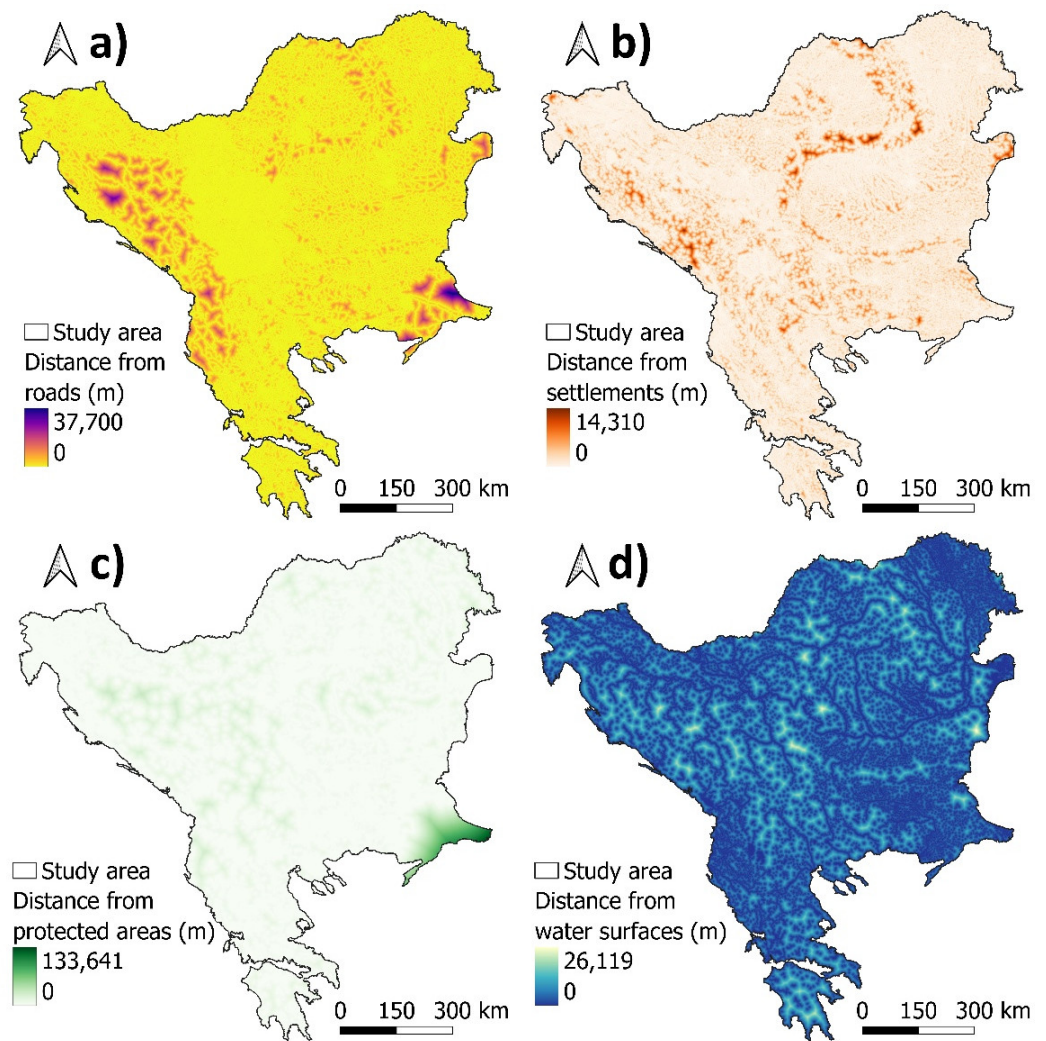


Figure 3. Thematic maps: (a) Distance from roads; (b) Distance from settlements; (c) Distance from protected areas; (d) Distance from water surfaces.

Regarding the ecological aspect, all protected natural areas (at the national or international level) were eliminated from the evaluation for solar PV power plants due to their rich biodiversity. In addition, the spatial distance from protected areas was calculated. Data were downloaded from the World Database on Protected Areas platform, which contains updated protected areas as of 2024 [80] (Table 1). Spatial data were open for download within all countries except Türkiye, for which there are no open data on protected natural areas. The distance from protected areas ranges from 0 to 133.6 km, and this is a critical environmental criterion because construction in their immediate vicinity can threaten biodiversity and disrupt natural ecosystems. Therefore, it is desirable to position solar PV power plants at greater distances from protected areas to minimize negative environmental impacts and ensure compliance with nature protection regulations. All nine thematic maps were generated using geographic information systems, specifically QGIS v3.28.10 [81]. Geographic Information Systems (GIS) play a crucial role in solar site selection studies by enabling the analysis, integration, management, and visualization of multiple spatial criteria within a unified framework. GIS facilitates the spatial representation and overlay of environmental, technical, economic, and infrastructural factors, allowing the identification of optimal locations for photovoltaic development. Through spatial analysis and suitability mapping, GIS presents an effective decision-support tool for renewable energy planning at local, regional, and national scales [6,11]. Although GIS provides a powerful framework for integrating and analyzing spatial datasets, the reliability

of suitability maps depends heavily on the quality, resolution, and temporal consistency of the input data. Consequently, the generated suitability maps should be interpreted as decision-support tools rather than definitive indicators of site feasibility. For the purposes of scaling and consistency of spatial variables, a spatial resolution of 100 m has been standardized on all maps.

Table 1. Data sources and characteristics used in the analysis.

Criteria	Year	Spatial Resolution	Source
Photovoltaic output	2025	100 m (resampled from 800 m)	Global Solar Atlas
Terrain slope	2016	100 m	European Environment Agency
Aspect	2016	100 m	European Environment Agency
Land use	2024	100 m (resampled from 10 m)	Environmental Systems Research Institute
Distance from power lines	2025	100 m	Geofabrik
Distance from roads	2025	100 m	Open Street Map
Distance from settlements	2024	100 m (resampled from 10 m)	Environmental Systems Research Institute
Distance from protected areas	2024	100 m	World Database on Protected Areas
Distance from water surfaces	2024	100 m (resampled from 10 m)	Environmental Systems Research Institute

3.3. Methodology

3.3.1. Fuzzy Analytic Hierarchy Process

Fuzzy Analytic Hierarchy Process (F-AHP) is a multi-criteria decision-making technique that extends the traditional AHP method by incorporating fuzzy logic and fuzzy sets in order to handle uncertainty and subjectivity in expert judgment [82,83]. The traditional AHP uses precise numerical values for pairwise comparisons, whereas the Fuzzy AHP method employs triangular fuzzy numbers (TFNs).

A fuzzy number A is represented by a TFN. The membership function $f_A: R \rightarrow [0, 1]$ can be expressed as follows [84]:

$$f_A = \begin{cases} (x-l)/(a-l), & l \leq x \leq a \\ (x-u)/(a-u), & a \leq x \leq u. \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

Linguistic values are usually provided by experts; however, it is often difficult to work with such descriptions. Therefore, these descriptions are represented by TFNs defined on the interval $[0, 1]$.

Fuzzy AHP method involves several steps. The first step is to define the problem (goal) and structure the hierarchy. At the second level, the fuzzy comparison matrix is calculated [85]:

$$A = (a_{ij})_{n \times n} = \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \dots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{pmatrix}, \quad (2)$$

where a_{ij} define the relative importance of criteria i over criteria j . This matrix defines the relative importance of criteria (C) and alternatives (A) according to the goal (G). The most commonly used TFN is [86]:

$$a_{ij} = (l_{ij}, m_{ij}, u_{ij}), \quad (3)$$

where l_{ij} represents lower bound of fuzzy degree of judgment, u_{ij} is upper bound and m_{ij} is the most likely (modal) value ($l < m < u$). For each TFN, the inverse form is defined as [87]:

$$\hat{a}_{ij} = 1/a_{ij}, \quad (4)$$

or

$$\hat{a}_{ij} = \left(\frac{1}{u_{ij}}, \frac{1}{m_{ij}}, \frac{1}{l_{ij}} \right). \quad (5)$$

The format of the fuzzy AHP comparison matrix is then:

$$\begin{pmatrix} 1 & \hat{a}_{12} & \dots & \hat{a}_{1n} \\ 1/\hat{a}_{12} & 1 & \dots & \hat{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/\hat{a}_{1n} & 1/\hat{a}_{2n} & \dots & 1 \end{pmatrix}. \quad (6)$$

Besides the introduction of the fuzzy triangular elements, another difference compared to the classical AHP is that the preference intensities provided by the expert are not limited to the interval $[1/9, 9]$, but can be taken more generally form $[1/s, s]$ for a chosen value $s > 1$ [88]. The mathematical theory is described in [87,88] (where procedures and examples are given) and has been implemented in a free software tool that implements the fuzzy AHP method. In our case, the results are transformed online using the Fuzzy AHP solver and reported as an interval $[1/4, 4]$ (Table 2).

Table 2. Modified fuzzy AHP scale of relative importance on interval $[1/4, 4]$.

Judgment Term	Saaty's Value (Classic)	Fuzzy Value F-AHP on $[1, 9]$	Inverse Fuzzy Value on $[1/9, 1]$
Equally important	1	1, 1, 1	1, 1, 1
Weakly important	3	2, 3, 4	0.25, 0.33, 0.5
Strongly important	5	4, 5, 6	0.17, 0.20, 0.25
Very strongly im- portant	7	6, 7, 8	0.125, 0.14, 0.17
Absolute important	9	9, 9, 9	0.11, 0.11, 0.11
Intermediate values	2, 4, 6, 8	$x - 1, x, x + 1$	$1/x + 1, 1/x, 1/x - 1$
Judgment term		Fuzzy value F-AHP on $[1, 4]$	Inverse fuzzy value on $[1/4, 1]$
Equally important		1, 1, 1	1, 1, 1
Weakly important		1.375, 1.750, 2.125	0.471, 0.571, 0.727
Strongly important		2.125, 2.500, 2.875	0.348, 0.400, 0.471
Very strongly im- portant		2.875, 3.250, 3.625	0.276, 0.308, 0.348
Absolute important		4, 4, 4	0.250, 0.250, 0.250
Intermediate values		$x - 1, x, x + 1$	$1/x + 1, 1/x, 1/x - 1$

Figure 4 illustrates the membership function of a triangular fuzzy number (TFN), defined by the lower (l), modal (m), and upper (u) values.

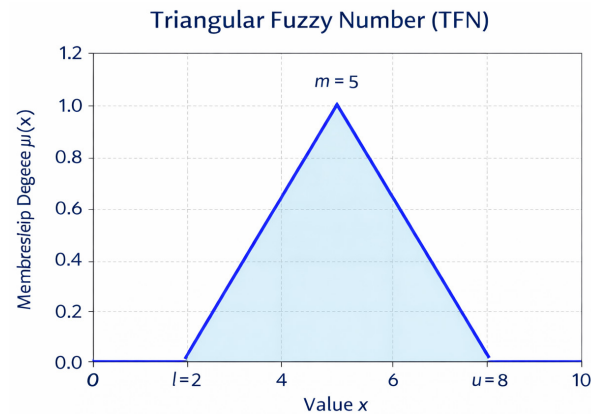


Figure 4. Membership Function of a Triangular Fuzzy Number (TFN).

The next step involves calculating the fuzzy geometric mean for each criterion, which is performed as follows [89]:

$$\hat{r}_i = (l_1, m_1, u_1) \otimes (l_2, m_2, u_2) \otimes (l_3, m_3, u_3), \quad (7)$$

Or more precisely

$$\hat{r}_i = (l_1 \cdot l_2 \cdot l_3, m_1 \cdot m_2 \cdot m_3, u_1 \cdot u_2 \cdot u_3). \quad (8)$$

In general, the fuzzy geometric mean and fuzzy weights in a pairwise comparison matrix of alternatives A, are calculated by the following formula:

$$\hat{r}_i = \prod_{j=1}^n (a_{ij})^{\frac{1}{n}}, \quad (9)$$

where $\hat{r}_i$ is the fuzzy geometric mean value of alternative $i = 1, 2, \dots, n$; n is the number of alternatives. Then the fuzzy weight $\hat{\omega}_i$ is calculated as follows:

$$\hat{\omega}_i = \hat{r}_i \otimes [\sum_{i=1}^n \hat{r}_i]^{-1}. \quad (10)$$

The next step in the F-AHP is defuzzification. To transform the fuzzy weight coefficients into scalar values we apply the center of area method (COA) known also, as centroid method [90]:

$$\omega_i = \frac{\hat{\omega}_l + \hat{\omega}_m + \hat{\omega}_u}{3}. \quad (11)$$

The final step in the fuzzy AHP method is the normalization of the values obtained by COA method:

$$\bar{\omega}_i = \frac{\omega_i}{\sum_{i=1}^n \omega_i}. \quad (12)$$

The obtained crisp values represent the final priority weights. These weights can then be used to rank the alternatives or criteria in order of importance, leading to a decision based on the opinions and preferences of the decision-makers.

The parameter λ_{max} denotes the maximum eigenvalue of the comparison matrix:

$$\lambda_{max} = \frac{1}{n} \sum_{i=1}^n (\bar{\omega}_i \cdot \sum_{j=1}^n a_{ij}). \quad (13)$$

The consistency index (CI) is calculated using the following formula:

$$CI = \frac{\lambda_{max} - n}{n - 1}, \quad (14)$$

where λ_{max} —maximum eigenvalue of the matrix; n —number of criteria.

Although there is a risk of illogical judgments, it is still advisable to assess the consistency of the system, especially during the initial stage of forming the pairwise comparison matrix. If the Consistency Ratio (CR) is less than 0.1, the pairwise comparisons are

considered consistent; otherwise, the evaluations should be revised. The Consistency Ratio (CR) is calculated as the ratio of the Consistency Index (CI) to the Random Index (RI):

$$CR = \frac{CI}{RI}. \quad (15)$$

Random index depends on the number of criteria n , and is given in the next Table 3.

Table 3. Values of random index (RI).

n	1	2	3	4	5	6	7	8	9
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45

Before the evaluation, all experts received detailed instructions outlining the study's objective, the definition of each criterion, and the application of the modified Fuzzy AHP linguistic scale presented in Table 2. Each of the 11 experts independently compared all criteria in pairs. After collecting the individual pairwise comparison matrices, the consistency of each matrix was evaluated, and all matrices satisfied the acceptable consistency threshold. The final fuzzy pairwise comparison matrix presented in Table 4 was obtained by directly aggregating the individual expert judgments using the fuzzy geometric mean method, without any subsequent modification.

Table 4 presents the fuzzy pairwise comparison matrix for the selected criteria, where each element is expressed as a triangular fuzzy number to capture uncertainty in the relative importance of the criteria.

Table 4. Fuzzy pairwise comparison matrix of the criteria.

Criteria	PVO	LU	DPL	TS	DPA	DFS	DFR	ASP	DFW
PVO	1,	1.1,	1.2,	1.3,	1.4,	1.5,	1.6,	1.7,	1.8,
	1,	1.2,	1.4,	1.6,	1.8,	2,	2.2,	2.4,	2.6,
	1	1.3	1.6	1.9	2.2	2.5	2.8	3.1	3.4
LU	0.77,	1,	1.1,	1.2,	1.3,	1.4,	1.5,	1.6,	1.7,
	0.83,	1,	1.2,	1.4,	1.6,	1.8,	2,	2.2,	2.4,
	0.91	1	1.3	1.6	1.9	2.2	2.5	2.8	3.1
DPL	0.63,	0.77,	1,	1.1,	1.2,	1.3,	1.4,	1.5,	1.6,
	0.71,	0.83,	1,	1.2,	1.4,	1.6,	1.8,	2,	2.2,
	0.83	0.91	1	1.3	1.6	1.9	2.2	2.5	2.8
TS	0.53,	0.63,	0.77,	1,	1.1,	1.2,	1.3,	1.4,	1.5,
	0.63,	0.71,	0.83,	1,	1.2,	1.4,	1.6,	1.8,	2,
	0.77	0.83	0.91	1	1.3	1.6	1.9	2.2	2.5
DPA	0.45,	0.53,	0.63,	0.77,	1,	1.1,	1.2,	1.3,	1.4,
	0.56,	0.63,	0.71,	0.83,	1,	1.2,	1.4,	1.6,	1.8,
	0.71	0.77	0.83	0.91	1	1.3	1.6	1.9	2.2
DFS	0.40,	0.45,	0.53,	0.63,	0.77,	1,	1.1,	1.2,	1.3,
	0.50,	0.56,	0.63,	0.71,	0.83,	1,	1.2,	1.4,	1.6,
	0.67	0.71	0.77	0.83	0.91	1	1.3	1.6	1.9
DFR	0.36,	0.40,	0.45,	0.53,	0.63,	0.77,	1,	1.1,	1.2,
	0.45,	0.50,	0.56,	0.63,	0.71,	0.83,	1,	1.2,	1.4,
	0.63	0.67	0.71	0.77	0.83	0.91	1	1.3	1.6
ASP	0.32,	0.36,	0.40,	0.45,	0.53,	0.63,	0.77,	1,	1.1,
	0.42,	0.45,	0.50,	0.56,	0.63,	0.71,	0.83,	1,	1.2,
	0.59	0.63	0.67	0.71	0.77	0.83	0.91	1	1.3
DFW	0.29,	0.32,	0.36,	0.40,	0.45,	0.53,	0.63,	0.77,	1,
	0.38,	0.42,	0.45,	0.50,	0.56,	0.63,	0.71,	0.83,	1,
	0.56	0.59	0.63	0.67	0.71	0.77	0.83	0.91	1

Note: PVO—Photovoltaic output; LU—Land use; DPL—Distance from power lines; TS—Terrain slope; DPA—Distance from protected areas; DFS—Distance from settlements; DFR—Distance from roads; ASP—Aspect; DFW—Distance from Water surfaces.

The consistency test confirmed that the pairwise comparison matrix was highly consistent, with $\lambda_{max} = 9.18$; $CI = 0.022$, and $CR = 0.015$, indicating an acceptable level of consistency.

The experts were selected based on their scientific expertise and professional experience in fields directly related to solar PV site selection, including GIS, remote sensing, solar energy, electrical power engineering, geoinformatics, climatology, environmental protection, sustainable development, energy economics, and multi-criteria decision-making (Table 5). All experts possessed substantial research and/or practical experience, ranging from 10 to 40 years, ensuring a comprehensive evaluation of the criteria used in the Fuzzy AHP framework.

Table 5. Expert experience and scientific field.

Decision Makers	Experience	Scientific Fields
Expert 1	11 years	GIS, remote sensing; solar energy, energetics, ecology
Expert 2	16 years	Electrical power engineering, fuzzy logic, solar energy
Expert 3	19 years	Fuzzy logic, geoinformatics, climate change, remote sensing
Expert 4	28 years	Mathematical statistics, stochastic analysis, fuzzy set theory
Expert 5	12 years	Sustainable development, energy economics, geostatistics
Expert 6	10 years	GIS, solar energy, remote sensing
Expert 7	40 years	Ecology, land use planning, environmental protection
Expert 8	17 years	GIS, sustainable development, remote sensing
Expert 9	25 years	Geoinformatics, energetics, multi-criteria analysis
Expert 10	36 years	Climatology, big data, GIS, sustainable development
Expert 11	40 years	Solar energy, electrical power engineering, GIS

3.3.2. Spatial Assessment and Energy Production Potential

To calculate the potential annual electricity production (AEP) in MWh, it is necessary to collect detailed, accurate spatial data on the following parameters: the surface area of the potential solar PV power plant (SA), installed capacity (IC), and photovoltaic energy output (PVout).

The surface area of the potential solar PV power plant (SA) is obtained by digitizing the most suitable parcels for solar energy development based on the final results derived from Geographic Information Systems (GIS) and appropriate basemaps (e.g., Google Satellite imagery). SA is typically expressed in hectares (ha). Installed capacity (IC) represents the photovoltaic power density, defined as the maximum installed power (MW) under standard test conditions. According to the guidelines of the International Renewable Energy Agency (IRENA), utility-scale ground-mounted solar PV power plants typically require approximately 1–2 ha of land per MW of installed capacity. In the present study, a conservative land-use efficiency of 0.5 MW per hectare (equivalent to 2 ha/MW) was adopted for estimating the installed capacity of the selected sites [91]:

$$IC = SA \cdot 0.5, \quad (16)$$

where IC —Installed capacity expressed in MW; SA —Surface area expressed in hectares (ha).

Photovoltaic energy production (PV_{out}) denotes the long-term energy yield generated per unit of installed photovoltaic capacity and is expressed in kilowatt-hours per kilowatt-peak of the system (kWh/kWp). Data on PV_{out} are available from the Global Solar Atlas platform [74].

The annual electricity production (AEP) is calculated based on the following formulation:

$$AEP = IC \cdot PV_{out}, \quad (17)$$

where AEP —annual electricity production expressed in MWh; IC —installed capacity expressed in MW; PV_{out} —Photovoltaic energy production expressed in kWh/kWp .

The number of households supplied was estimated based on contemporary studies and reports on average annual household electricity consumption. For illustrative purposes, an average annual household electricity consumption of 4.5 MWh was adopted for Southeastern Europe, providing an indicative estimate of the potential number of households that could be supplied with electricity [92]. Accordingly, the number of households supplied is calculated using the following formula:

$$NHS = \frac{AEP}{4.5}, \quad (18)$$

where NHS —Number of households supplied; AEP —annual electricity production expressed in MWh.

4. Results and Discussion

4.1. Fuzzy Weights and Spatial Distribution of Criteria

The application of the fuzzy AHP method involved the selection of criteria that capture both spatial and socio-economic conditions relevant to the assessment of terrain suitability for solar PV power plant development [93–96]. These criteria were defined through a comprehensive review of the literature, consideration of the specific characteristics of the study area, and the technical requirements of photovoltaic systems [97–100]. Each selected criterion represents a distinct component of the evaluation framework and is assigned a corresponding weight, reflecting its relative importance in determining overall suitability.

Photovoltaic output represents the most important criterion in the suitability assessment, as it directly reflects the solar energy potential of a given location. Areas with higher annual values of solar irradiation enable greater electricity production and improved economic feasibility of photovoltaic systems. Consequently, locations with the highest energy yield were assigned the highest suitability scores (Table 6) [6].

Land use is a critical constraint in spatial planning, as it determines whether a location is physically and legally available for solar PV power plant development. Water bodies and flooded areas are considered unsuitable due to technical limitations, while forests and urban areas are less favorable because of environmental protection and land-use conflicts. In contrast, agricultural land, grasslands, and bare surfaces are generally more suitable, as they allow easier installation and lower environmental impact [10].

Distance from power lines is a key infrastructural factor, since proximity to the electrical grid significantly reduces connection costs and energy losses. Locations closer to existing power lines are therefore more attractive for development and were assigned higher suitability scores, while distant areas require additional investments in grid expansion [11].

Terrain slope is an essential topographic parameter influencing both construction feasibility and system performance. Gently sloping terrains (0 – 5°) are the most suitable, as they provide stability, reduce construction costs, and allow optimal panel placement.

As slope increases, technical constraints become more pronounced, leading to higher installation costs and reduced efficiency [13].

Distance from protected areas reflects environmental and legal restrictions. Areas located within or near protected zones are generally excluded or assigned low suitability due to conservation priorities and regulatory limitations. Conversely, locations at greater distances from protected areas are more appropriate for development, as they minimize ecological impact and potential legal conflicts [12].

Distance from settlements has a complex role in the evaluation process. While proximity to settlements can facilitate access to infrastructure and workforce, it may also lead to visual impact, land-use conflicts, and public opposition. Therefore, locations situated at moderate to greater distances from settlements are considered more suitable [6].

Table 6. Reclassification categories, scores, areas, and percentage distribution of solar PV site selection criteria.

Criteria	Categories	Mark	Area (km ²)	Percentage (%)
Photovoltaic output (kWh/kWp/year)	633–839	1	91.8	0.01
	839–1045	2	2437.9	0.3
	1045–1251	3	154,745.2	19.4
	1251–1457	4	537,831.6	67.5
	1457–1664	5	101,800.2	12.8
Land use	Water surfaces	0	9699.1	1.2
	Flooded areas, snow	1	1441.5	0.2
	Forests	2	325,894.1	40.9
	Settlements	3	46,522.4	5.8
	Agricultural land	4	263,501.5	33.1
	Bare surfaces, grasslands/meadows	5	149,414.9	18.8
Distance from power lines (m)	0–2000	5	253,820.5	31.9
	2000–4000	4	160,067.2	20.1
	4000–6000	3	114,738.4	14.4
	4000–8000	2	83,996.5	10.5
	>8000	1	184,288.3	23.1
Terrain slope (°)	0–5	5	390,253.7	48.9
	5–10	4	164,181.2	20.6
	10–15	3	102,125.3	12.8
	15–20	2	66,588.5	8.4
	>20	1	74,201.0	9.3
Distance from protected areas (m)	0–100	0	216,927.0	27.2
	100–400	1	29,941.5	3.8
	400–800	2	37,221.7	4.7
	800–1200	3	33,250.7	4.2
	1200–1600	4	32,152.4	4.0
	>1600	5	447,417.6	56.1
Distance from settlements (m)	0–300	1	143,556.9	18.0
	300–600	2	102,516.8	12.9
	600–900	3	94,089.3	11.8
	900–1200	4	79,387.9	10.0
	>1200	5	377,359.9	47.3
Distance from roads (m)	0–2500	5	623,604.2	78.3
	2500–5000	4	105,947.4	13.3

	5000–7500	3	31,709.1	3.9
	7500–10,000	2	15,054.7	1.9
	>10,000	1	20,595.5	2.6
Aspect	North	1	88,998.5	11.2
	Northeast, Northwest	2	191,609.7	24.0
	West, East	3	199,339.7	25.0
	Southeast, Southwest	4	211,650.6	26.6
	South, Flat areas	5	105,312.4	13.2
Distance from water surfaces (m)	0–300	1	31,194.1	3.9
	300–600	2	27,571.3	3.5
	600–900	3	30,610.8	3.8
	900–1200	4	31,343.0	3.9
	>1200	5	676,191.6	84.9

Distance from roads is important for ensuring accessibility during both construction and operational phases. Sites located closer to road infrastructure allow easier transportation of equipment and materials, reducing overall project costs. As distance from roads increases, logistical complexity and associated expenses also rise [16].

Aspect influences the amount of solar radiation received at a micro-location level. South-facing slopes and flat terrains are the most favorable in the Northern Hemisphere, as they receive the highest solar exposure. In contrast, north-facing slopes are less suitable due to reduced sunlight availability [11].

Distance from water surfaces is considered primarily from an environmental and safety perspective. Locations in close proximity to water bodies may be exposed to flooding risks, soil instability, or regulatory constraints. Therefore, areas farther from water surfaces are generally more suitable for solar PV power plant development [4]. Protected areas and water bodies were treated as hard exclusion criteria. They were removed from further analysis, whereas settlements and specific land-use classes, including flooded areas and permanent snow cover, were retained in the evaluation process but assigned very low suitability scores due to their unfavorable conditions for large-scale solar PV development.

The results of the fuzzy AHP weighting procedure reveal a clear prioritization of criteria influencing the suitability assessment for solar PV power plant development. Among all evaluated factors, photovoltaic output has the highest weight (0.179), confirming that solar energy potential is the dominant determinant in the decision-making process (Table 7). This is followed by land use (0.157), which reflects the importance of spatial constraints and land availability, and distance from power lines (0.137), emphasizing the role of grid accessibility in reducing infrastructure costs. Terrain slope (0.120) also shows a significant contribution, indicating the relevance of topographic conditions for construction feasibility and system performance.

Table 7. Fuzzy weight coefficients of the selected criteria.

Criteria	Fuzzy Weight Coefficients
Photovoltaic output	0.179
Land use	0.157
Distance from power lines	0.137
Terrain slope	0.120
Distance from protected areas	0.104
Distance from settlements	0.091
Distance from roads	0.080
Aspect	0.070

Distance from water surfaces

0.062

The remaining criteria exhibit gradually lower weights, but still play an important role in refining the spatial suitability model. Distance from protected areas (0.104) highlights the need to incorporate environmental restrictions, while distance from settlements (0.091) and distance from roads (0.080) reflect socio-economic and accessibility considerations. The lowest weights are assigned to aspect (0.070) and distance from water surfaces (0.062), suggesting that these factors act primarily as supplementary criteria in the overall evaluation. Overall, the distribution of weights indicates that the model is primarily driven by energy potential and land-related constraints, followed by infrastructural and environmental factors, while secondary physical characteristics have a comparatively smaller influence on the final suitability assessment.

4.2. Solar Power Plant Suitability Mapping

The spatial distribution of solar PV power plant suitability classes at the level of Southeastern Europe reveals a heterogeneous but clearly structured pattern. Excluded areas account for the largest share of the total territory (27.6%), indicating that more than one quarter of the region is unsuitable for solar power development due to environmental constraints, land use limitations, or regulatory restrictions (Figure 5). A similarly high proportion is observed for areas classified as having medium suitability (26.8%), suggesting that a substantial part of the study area possesses moderate potential, which could be utilized with additional planning, technological adaptation, or investment.

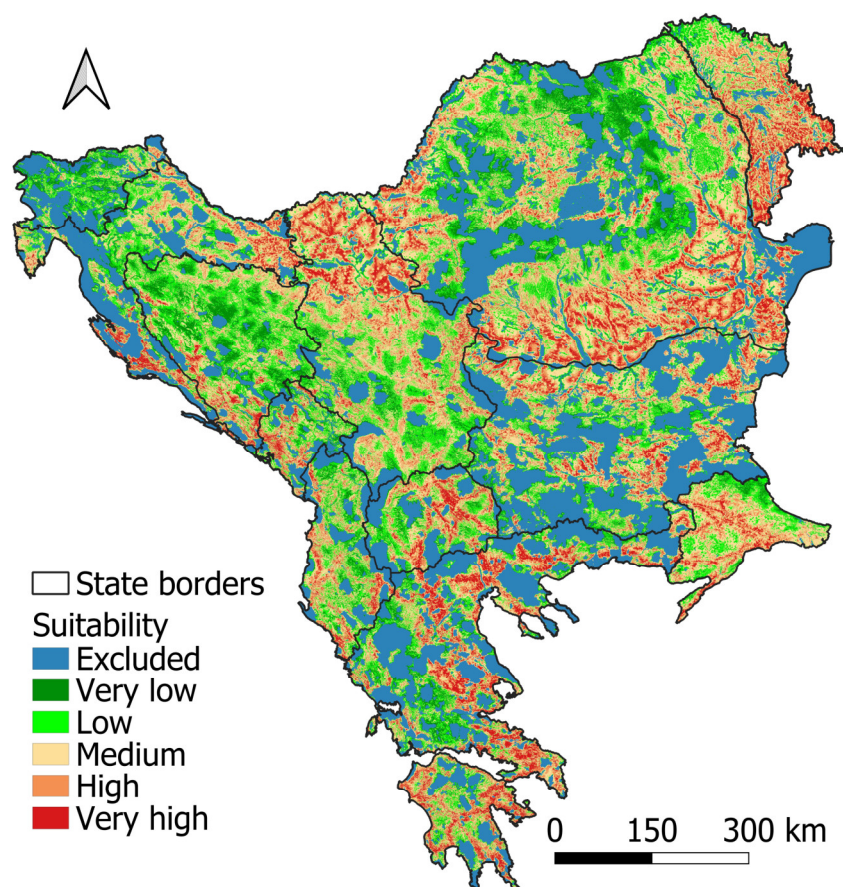


Figure 5. Solar PV power plant suitability map.

Lower suitability classes are also significantly represented. Low suitability areas cover 17.8% of the territory, while very low suitability accounts for 7.2%, together com-

prising one quarter of the region (Table 8). These areas are generally characterized by less favorable combinations of criteria, such as lower solar potential, greater distance from infrastructure, or more restrictive land use conditions.

Table 8. Spatial distribution of solar PV power plant suitability classes.

Suitability	Area (km ²)	Percentage in Total Area (%)
Excluded	219,603	27.6
Very low	57,567	7.2
Low	141,545	17.8
Medium	213,581	26.8
High	110,296	13.9
Very high	53,447	6.7
Total	796,039	100.0

On the other hand, areas with the highest development potential—classified as high (13.9%) and very high suitability (6.7%)—together make up 20.6% of the total area. Although these areas represent a smaller share compared to excluded or medium categories, they are of primary importance for strategic planning, as they offer the most favorable combination of natural, infrastructural, and environmental conditions (Figure 6).

Overall, the results indicate that while a considerable portion of Southeastern Europe is constrained for solar PV power plant development, there remains a substantial and spatially significant potential concentrated in medium to highly suitable areas. This distribution highlights the importance of targeted spatial planning and prioritization of optimal zones for future solar energy investments.

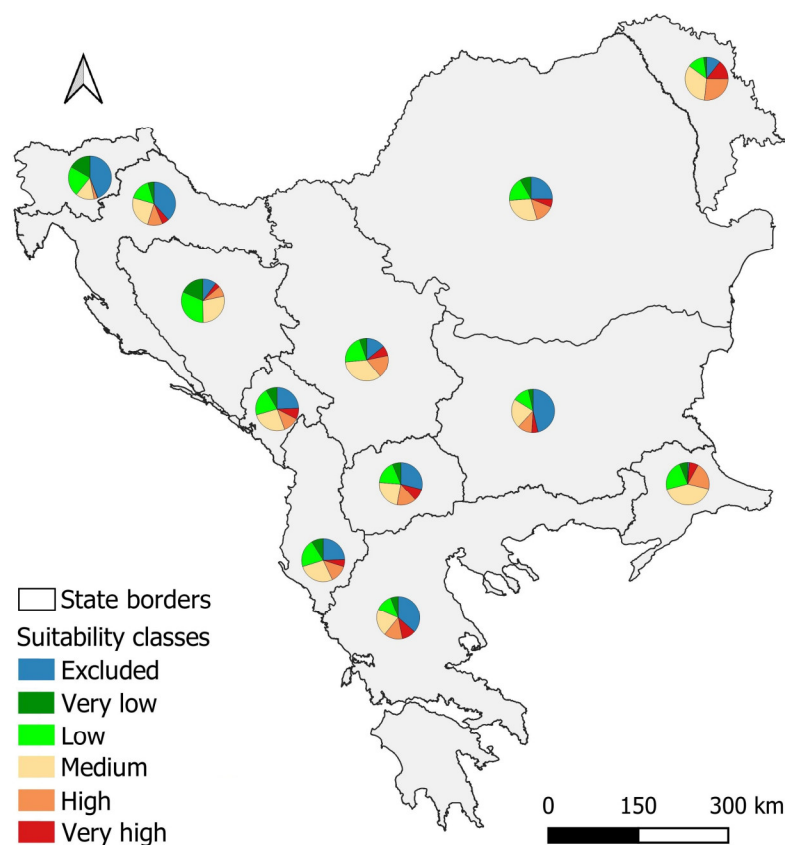


Figure 6. Spatial distribution (%) of solar PV power plant suitability classes by countries.

The comparative analysis of solar PV power plant suitability across Southeastern European countries reveals pronounced regional disparities, reflecting differences in natural conditions, land use patterns, and infrastructural development (Table 9).

Table 9. Spatial distribution (%) of solar PV power plant suitability classes by countries (EXC—Excluded; VL—Very low; L—Low; M—Medium; H—High; VH—Very high).

Country	EXC	VL	L	M	H	VH
Slovenia	44	16.7	22.4	14	2.6	0.3
Croatia	38.3	4.6	16	24.5	11.3	5.3
Bosnia and Herzegovina	10.3	18.4	31.7	28.3	7.7	3.6
Serbia	14.2	5.6	20.9	34.3	17.4	7.6
Montenegro	24.5	8.5	20.8	26.3	11.8	8.1
Albania	24.5	8.9	20.9	27.3	13.1	5.3
North Macedonia	29	6.3	17.4	23.5	14.5	9.3
Greece	36.4	5.7	12.8	20.6	14	10.5
Bulgaria	46.3	3.6	12.6	21.9	11	4.7
Romania	25.2	8.2	18.0	28.3	14.3	5.9
Moldova	10.6	2.2	12.7	33.4	26.6	14.5
Türkiye (European part)	1.2	6.2	22.8	42.2	20.7	6.8

At one end of the spectrum, Bulgaria and Slovenia stand out with the highest shares of excluded areas (44.0% and 46.3%, respectively), indicating strong environmental constraints and limited availability of suitable land. In Slovenia, this is further reflected in the very low proportion of highly suitable areas (only 2.6% high and 0.3% very high), suggesting minimal potential for large-scale solar power expansion. A similar pattern is observed in Bulgaria, where, despite relatively lower shares of low suitability classes, the dominance of excluded areas significantly limits development opportunities.

In contrast, Moldova and the European part of Türkiye exhibit the most favorable suitability structures. Moldova shows exceptionally high shares of high (26.6%) and very high suitability (14.5%), meaning that more than 40% of its territory is highly suitable for solar energy development. Likewise, Türkiye (European part) is characterized by a very low proportion of excluded areas (1.2%) and a dominant medium suitability class (42.2%), complemented by substantial shares of high (20.7%) and very high suitability (6.8%) areas, indicating strong overall potential.

Serbia demonstrates a balanced and favorable distribution, with medium suitability dominating (34.3%), followed by significant shares of high (17.4%) and very high suitability (7.6%) classes. This points to considerable development potential, particularly in areas where optimal combinations of solar radiation, land use, and infrastructure are present. Similar patterns, though slightly less pronounced, are observed in Romania and Albania, where medium suitability prevails, accompanied by moderate shares of highly suitable areas.

Other countries, such as Croatia, Montenegro, North Macedonia, and Greece, show mixed suitability structures. Croatia is characterized by a relatively high share of excluded areas (38.3%) but also a notable proportion of high and very high suitability zones (16.6% combined). North Macedonia and Greece stand out for their relatively high shares of very high suitability (9.3% and 10.5%, respectively), reflecting favorable solar conditions, particularly in southern regions. Montenegro and Albania display moderate distributions across all classes, indicating diversified but somewhat constrained potential.

Bosnia and Herzegovina presents a distinct profile, with a relatively low share of excluded areas (10.3%) but a dominance of low and medium suitability classes (31.7% and

28.3%), suggesting that while large portions of the territory are available, their overall suitability is limited by less favorable combinations of criteria.

The results highlight a clear spatial differentiation within Southeastern Europe, where countries with fewer environmental constraints and higher solar potential demonstrate significantly greater opportunities for solar energy development. These differences underline the need for country-specific approaches in spatial planning and renewable energy policy.

The identified spatial patterns not only reveal the most promising areas for development but also emphasize the importance of balancing energy potential with environmental and socio-economic constraints. Such an approach enables more informed decision-making and supports the strategic allocation of investments in the renewable energy sector.

4.3. Solar Energy Transition and Deployment in Southeastern Europe

The redirection of gas export from Russia through the Nord Stream 1 and 2 pipelines towards China, coupled with the Middle East conflict that has disrupted the flow of oil and natural gas via the Strait of Hormuz, poses a long-term threat in Europe to secured energy supply [101]. When considering these energy issues alongside the climate crisis, it becomes clear that accelerating the clean energy transition is Europe's most viable solution.

Recently, the European Commission adopted the REPowerEU Plan to reduce Europe's dependence on fossil fuels and fast-track the green energy transition [102]. This led to the revision of the Renewable Energy Directive, which increased the binding target for 2030 to 42.5%, with the ambition to reach a 45% share of renewables in the EU's overall energy consumption [103]. Solar energy is seen as a key driver of this increase, with overall installed capacity reaching 600 GW by 2030. Currently, rooftop PV systems represent the most prevalent form of solar energy deployment, and their potential is projected to remain substantial in the future. However, the development of utility-scale PV systems will significantly accelerate the shift to clean energy production. The main obstacles for developing ground-mounted utility-scale PV projects are related to land-use competitiveness (settlement, food and forest production systems, infrastructure, nature conservancy, etc.), public acceptance, and impact on biodiversity, which result in long and complex permit-granting procedures. To overcome these issues, the EU Solar Energy Strategy proposes mapping spatial suitability for developing utility-scale PV systems through geospatial assessment and designating "go-to areas," where permitting will be simpler and faster than usual and compatible with ecosystem restoration, agriculture, and conservation of natural and cultural heritage [104].

The aforementioned objectives pertain to both member states (Greece, Slovenia, Bulgaria, Romania, and Croatia) and those that are Contracting Parties to the Energy Community (Bosnia and Herzegovina, Serbia, Montenegro, North Macedonia, Albania, and Moldova) in Southeastern Europe. The International Renewable Energy Agency (IRENA, 2025) reports that the installed capacity of solar PV in Southeastern Europe (excluding the European part of Türkiye) is approx. 22 GW in 2024. Greece, Romania, and Bulgaria account 80% of regional capacity, while share of Serbia, Bosnia and Herzegovina, and Montenegro are the lowest. In 2023, the proportion of domestic electricity generated by photovoltaics in Greece (17.9%) surpasses the European average (8.6%) and the global average (5.4%) [105]. Because of the high level of investment interest, the Greek PV market continues to grow more than any other technology and raised cumulative capacity to 9.7 GW in 2024 [106]. Bulgaria is another country in the region that has made a big step forward. In 2014, it produced more electricity from solar PV power plants than the European average. Its total capacity is now 3.9 GW. In 2024, Romania installed 1.7 GW, officially exceeding 5

GW of installed solar PV capacity, with a target of achieving 10 GW by the end of the decade [107].

4.4. Most Suitable Locations and Energy Production Potential

Following GIS-based spatial analysis of the most suitable locations, a total of 24 sites were identified where adequate conditions exist for the construction of large-scale solar PV power plants. Two suitable areas were selected for each country. Candidate sites were selected within areas classified as high and very high suitability, with surface area serving as the primary factor in identifying the most suitable locations for large-scale solar PV development.

In Slovenia, the first location (site 1) is situated 11 km east of Slovenska Bistrica, between the settlements of Podova and Starošince. The site covers 445 ha and enables the installation of solar panels with a total capacity of 222.5 MW. The estimated annual electricity production is approximately 283,688 MWh, which corresponds to the energy demand of around 63,042 households. The second location (site 2), located 8 km southeast of Murška Sobota, between the settlements of Lipa and Gančani, covers 419 ha and has a capacity of 209.5 MW, supplying energy to approximately 58,660 households.

In Croatia, two significant locations were identified. Site 3 is located 7 km west of Varaždin, between the settlements of Kapelec and Nova Ves Petrijanečka, covering an area of 938 ha with a potential installed capacity of 469 MW, sufficient to meet the needs of approximately 132,050 households. Site 4 is located 14 km west of Trilj, between the settlements of Kamensko and Ljut, spans 700 ha, and has a capacity of 350 MW, providing electricity to around 113,089 households (Figure 7).

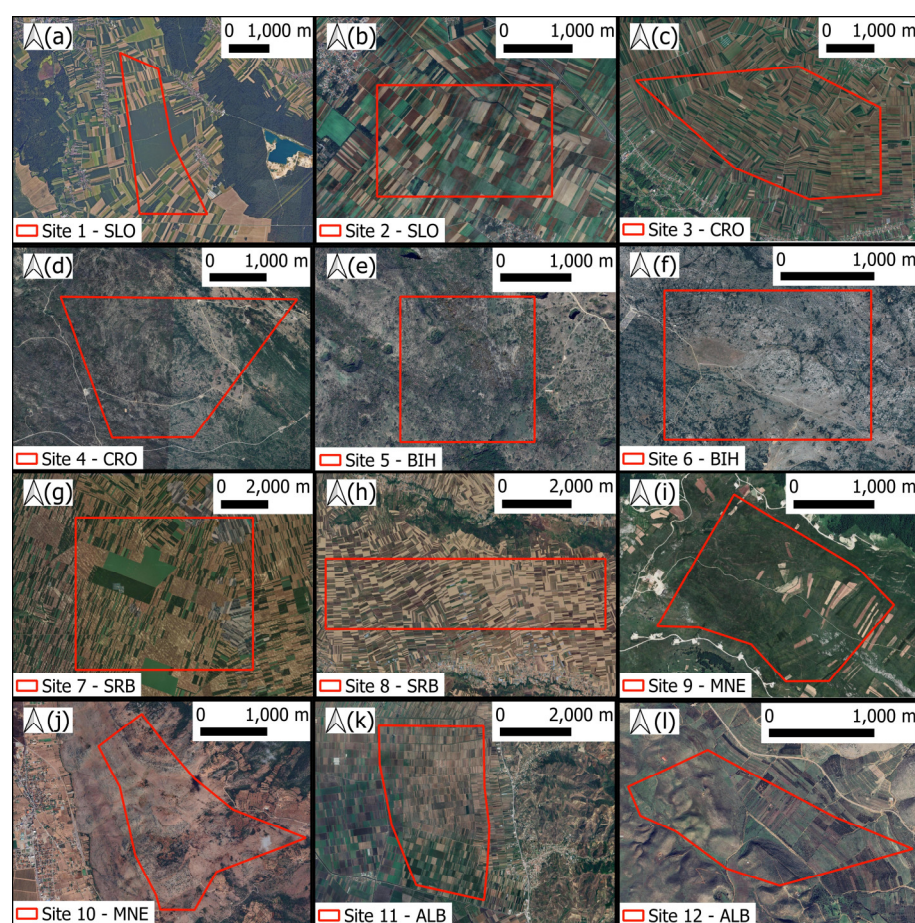


Figure 7. The most suitable locations in Slovenia (a,b), Croatia (c,d), Bosnia and Herzegovina (e,f), Serbia (g,h), Montenegro (i,j), and Albania (k,l).

In Bosnia and Herzegovina, site 5 is located 8 km southwest of Tomislavgrad, between the settlements of Tubolja and Dobrići. With an area of 394 ha, it allows for an installed capacity of 197 MW, supplying electricity to approximately 64,091 households. Site 6, situated 17 km southeast of Mostar, between the settlements of Žulja and Kružanj, covers 356 ha and has a capacity of 178 MW, sufficient for about 58,780 households.

Within Serbia, locations with exceptionally high potential were identified. Site 7, located 32 km west of Vršac, between the settlements of Padina and Seleuš, extends over 5000 ha and has a potential installed capacity of 2500 MW, enabling the supply of electricity to approximately 718,333 households. Site 8 is situated 11 km southwest of Niš, between the settlements of Samarinovac and Gradište, covering 1668 ha, with a capacity of 834 MW and the potential to supply around 243,157 households.

In Montenegro, site 9 is located 17 km northeast of Nikšić, between the settlements of Gvozd and Donja Bijela, covering 367 ha and with a capacity of 183.5 MW, providing electricity to approximately 58,190 households. Site 10 is situated 10 km southeast of Podgorica, between the settlements of Tuzi and Skorać, and extends over 378 ha (Table 10), with a capacity of 189 MW, sufficient to supply around 62,664 households.

Table 10. Geographical location and area of suitable sites.

Location	Country	Longitude (E)	Latitude (N)	Surface Area (ha)
Site 1	SLO	15°42'53"	46°25'35"	445
Site 2	SLO	16°16'17"	46°37'7"	419
Site 3	CRO	16°12'53"	46°18'15"	938
Site 4	CRO	16°54'48"	43°37'27"	700
Site 5	BIH	17°10'2"	43°39'18"	394
Site 6	BIH	17°58'21"	43°13'59"	356
Site 7	SRB	20°49'31"	45°8'5"	5000
Site 8	SRB	21°45'3"	43°14'59"	1668
Site 9	MNE	19°6'56"	42°52'58"	367
Site 10	MNE	19°21'24"	42°21'49"	378
Site 11	ALB	19°38'17"	41°0'40"	1250
Site 12	ALB	20°8'27"	39°40'11"	168
Site 13	MKD	22°2'24"	41°53'10"	1873
Site 14	MKD	22°9'38"	41°30'29"	998
Site 15	GRC	21°53'52"	40°23'18"	1390
Site 16	GRC	22°9'56"	39°12'51"	3267
Site 17	BUL	23° 7'31"	43°45'38"	6260
Site 18	BUL	27°29'17"	43°20'55"	3707
Site 19	ROM	25°25'2"	44°15'10"	3016
Site 20	ROM	28°15'53"	44°23'8"	6182
Site 21	MDA	29°25'7"	47°10'41"	2204
Site 22	MDA	28°25'46"	45°45'0"	2405
Site 23	TUR	27°54'50"	41°1'25"	253
Site 24	TUR	26°43'13"	40°29'30"	1104

In Albania, site 11 is located 37 km west of Elbasan, between the settlements of Konjat and Bishtcukas. With an area of 1250 ha and a capacity of 625 MW, this site can supply approximately 214,167 households. Site 12, located 2 km west of Konispol, covers 168 ha and has an installed capacity of 84 MW, serving around 29,008 households. Regarding land use, the identified sites are primarily located on agricultural land, pastures, and grasslands, with the dominant land-cover type varying among individual locations.

In North Macedonia, site 13 is located 7 km east of the town of Sveti Nikola, between the settlements of Burilovci and Nemanjići. The 1873 ha area has a capacity of 936.5 MW,

serving approximately 304,258 households. Site 14 is located 5 km northeast of Negotino, between the settlements of Pepelište and Brusnik. It spans 998 ha, has a capacity of 499 MW, and can supply around 159,015 households (Table 11).

Table 11. Energy potential within the 14 suitable sites.

Location	IC (MW)	PVout (kWh/kWp/year)	AEP (MWh)	Number of Households Supplied
Site 1	222.5	1275	283,688	63,042
Site 2	209.5	1260	263,970	58,660
Site 3	469	1267	594,223	132,050
Site 4	350	1454	508,900	113,089
Site 5	197	1464	288,408	64,091
Site 6	178	1486	264,508	58,780
Site 7	2500	1293	3,232,500	718,333
Site 8	834	1312	1,094,208	243,157
Site 9	183.5	1427	261,855	58,190
Site 10	189	1492	281,988	62,664
Site 11	625	1542	963,750	214,167
Site 12	84	1554	130,536	29,008
Site 13	936.5	1462	1,369,163	304,258
Site 14	499	1434	715,566	159,015
Site 15	695	1475	1,025,125	227,806
Site 16	1633.5	1477	2,412,680	536,151
Site 17	3130	1318	4,125,340	916,742
Site 18	1853.5	1336	2,476,276	550,284
Site 19	1508	1236	1,863,888	414,197
Site 20	3091	1332	4,117,212	914,936
Site 21	1102	1268	1,397,336	310,519
Site 22	1202.5	1310	1,575,275	350,061
Site 23	126.5	1433	181,275	40,283
Site 24	552	1464	808,128	179,584

Note: IC—installed capacity; Pvout—photovoltaic energy production; AEP—annual electricity production.

In Greece, two highly suitable locations were identified. Site 15 is located 13 km northeast of Kozani, between the settlements of Ryaki and Galani, covering 1390 ha with a capacity of 695 MW, providing energy for approximately 227,806 households. Site 16, located 20 km southwest of Farsala, between the settlements of Leontari and Grammatiko, covers 3267 ha with a capacity of 1633.5 MW, sufficient to supply around 536,151 households (Figure 8).

In Bulgaria, site 17 is located 40 km north of Montana, between the settlements of Lom and Dinkovo, covering 6260 ha with a capacity of 3130 MW, enabling the supply of electricity to as many as 916,742 households. Site 18 is located 35 km southwest of Dobrich, between the settlements of Suvorovo and Momchilovo, and extends over 3707 ha, with a capacity of 1853.5 MW, sufficient to supply approximately 550,284 households.

In Romania, site 19 is located 55 km southwest of Bucharest, between the settlements of Galateni and Sericu, covering 3016 ha with a capacity of 1508 MW, providing electricity for approximately 414,197 households. Site 20 is located 35 km northwest of Constanța, between the settlements of Dorobantu and Tortoman. It covers 6182 ha with a capacity of 3091 MW, sufficient to supply around 914,936 households.

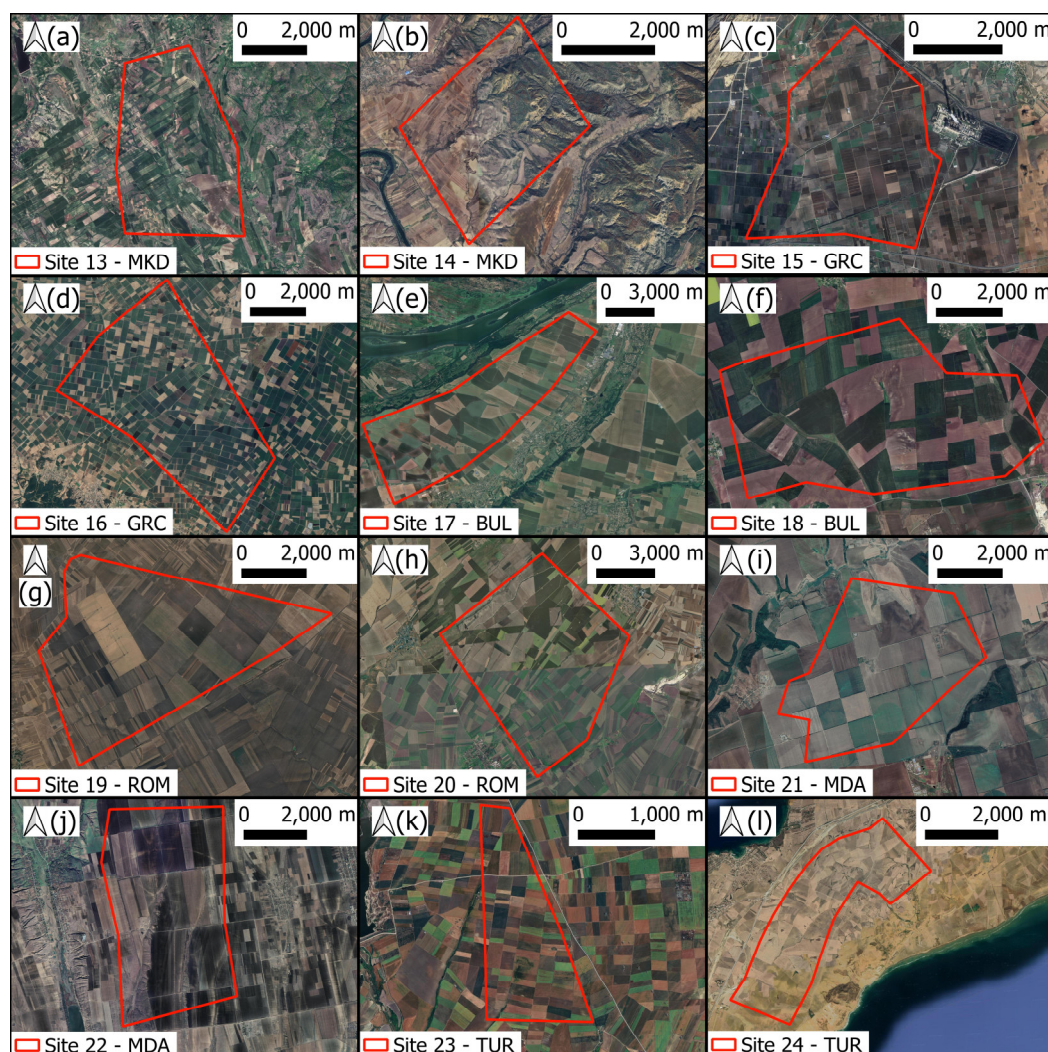


Figure 8. The most suitable locations in North Macedonia (a,b), Greece (c,d), Bulgaria (e,f), Romania (g,h), Moldova (i,j), and Türkiye (k,l).

In Moldova, site 21 is located 45 km northeast of Chişinău, between the settlements of Crasnoe and Shibka. The 2204 ha area enables the installation of 1102 MW, supplying approximately 310,519 households. Site 22 is situated 25 km southeast of Cahul, between the settlements of Iujnoe and Gavanoasa. It spans 2405 ha and has a capacity of 1202.5 MW, sufficient to supply around 350,061 households.

Finally, in the European part of Türkiye, two locations were identified. Site 23 is located 34 km east of Tekirdağ, between the settlements of Türkmenli and Sultanköy, covering 253 ha with a capacity of 126.5 MW, providing energy for approximately 40,283 households. Site 24 is located 83 km southwest of Tekirdağ, between the settlements of Güneyli and Bolayır. It covers 1104 ha with a capacity of 552 MW, enabling the supply of electricity to around 179,584 households.

As shown in Table 12, all 24 proposed sites were evaluated as highly or very highly suitable across all applied criteria for solar PV development, with criterion scores ranging from 4 to 5. This indicates that each candidate site satisfies the key technical, environmental, and spatial requirements for large-scale photovoltaic deployment. The average suitability score for each proposed site exceeded 4.5, indicating a high potential for the development of large-scale solar PV power plants. Furthermore, the selected sites were delineated as compact areas with a minimum surface area exceeding 1.5 km².

Table 12. Evaluation of the 24 proposed sites based on the applied criteria.

Site	PVO	LU	DPL	SLO	DPA	DFS	DFR	ASP	DFW	AVG
1	4	4	5	5	5	4	5	4	5	4.6
2	4	4	5	5	5	5	5	4	5	4.7
3	4	4	5	5	5	5	5	4	5	4.7
4	4	5	5	4	5	5	5	4	5	4.7
5	5	5	4	5	5	5	4	4	5	4.7
6	5	5	5	4	5	5	5	5	5	4.9
7	4	4	5	5	5	5	5	4	5	4.7
8	4	4	5	5	5	4	5	4	5	4.6
9	4	5	5	5	5	5	5	4	5	4.8
10	5	5	5	4	5	5	5	4	5	4.8
11	5	4	5	5	5	5	5	4	5	4.8
12	5	5	5	4	5	5	5	4	5	4.8
13	5	5	4	5	5	5	5	4	5	4.8
14	4	5	5	5	5	5	5	5	5	4.9
15	5	4	5	5	5	4	5	5	5	4.8
16	5	4	5	5	5	5	5	4	5	4.8
17	4	4	5	5	5	5	5	4	5	4.7
18	4	4	5	5	5	5	4	4	5	4.6
19	4	4	5	5	5	5	5	4	5	4.7
20	4	4	5	5	5	5	5	4	5	4.7
21	4	4	5	5	5	5	5	4	5	4.7
22	4	4	5	5	5	5	4	4	5	4.6
23	4	4	5	5	5	5	5	5	5	4.8
24	5	4	5	4	5	5	5	4	5	4.7

Note: PVO—Photovoltaic output; LU—Land use; DPL—Distance from power lines; SLO—Terrain slope; DPA—Distance from protected areas; DFS—Distance from settlements; DFR—Distance from roads; ASP—Aspect; DFW—Distance from water surfaces; AVG—Average suitability from FAHP raster layer.

These values represent estimates of the energy forecasting of large-scale solar PV power plants if constructed at the 24 identified locations. In total, if all proposed solar power plants were developed, the annual electricity generation would amount to approximately 30.2 TWh, which could meet the electricity demand of 6,719,066 households in Southeastern Europe, corresponding to approximately 17–20 million inhabitants. The estimated solar energy potential of 30.2 TWh corresponds to approximately 2.6 million tons of oil equivalent (Mtoe) of primary energy, indicating that its full utilization could effectively replace an equivalent amount of fossil fuel consumption. Before planning and constructing large solar parks, it is necessary to conduct field investigations and validate results from desk-based analysis.

4.5. Sensitivity Analysis of the Model and Results

To evaluate the stability of the spatial distribution of suitable locations, a sensitivity analysis was conducted based on variations in criterion weights and suitability classes. The analysis comprised four scenarios: (i) the original model with the initial criterion weights, (ii) an equal-weight scenario in which all criteria were assigned identical weights, (iii) a scenario with a 10% increase in the weights of the three most influential criteria, and (iv) a scenario with a 10% decrease in the weights of the same three criteria relative to their original values (Table 13).

Table 13. Criterion weights used in the sensitivity analysis scenarios.

Criteria	Original	Equal	+10% (PVO, LU, DPL)	−10% (PVO, LU, DPL)
Photovoltaic output	0.179	0.111	0.197	0.161
Land use	0.157	0.111	0.173	0.141
Distance from power lines	0.137	0.111	0.151	0.123
Terrain slope	0.120	0.111	0.109	0.122
Distance from protected areas	0.104	0.111	0.095	0.116
Distance from settlements	0.091	0.111	0.083	0.102
Distance from roads	0.080	0.111	0.073	0.090
Aspect	0.070	0.111	0.064	0.079
Distance from water surfaces	0.062	0.111	0.055	0.066

The three alternative scenarios were subsequently implemented in the raster analysis to classify areas with high and very high suitability across Southeastern Europe. The sensitivity analysis demonstrated that the spatial distribution of the most suitable areas remained highly stable under all analyzed scenarios. In the original model, the high and very high suitability classes covered 13.9% and 6.7% of the study area, respectively. Under the equal-weight scenario, the proportion of high suitability areas decreased to 11.4%. In comparison, the proportion of very high suitability areas increased to 8.1%, indicating a redistribution between the two highest suitability classes rather than a substantial change in the overall extent of suitable land. Scenarios with $\pm 10\%$ changes in the weights of the three most influential criteria showed only minor deviations from the original model. The proportion of areas classified as highly suitable ranged from 13.6% to 14.3%, whereas the proportion of very highly suitable areas varied between 6.8% and 7.0% (Table 14). These results confirm the model's robustness and indicate that moderate variations in criterion weights do not significantly affect the identification of the most suitable areas.

Table 14. Spatial distribution of high and very high suitability classes across sensitivity analysis scenarios.

Scenario	High Suitability (%)	Very High Suitability (%)
Original	13.9	6.7
Equal	11.4	8.1
+10% (PVO, LU, DPL)	13.6	6.8
−10% (PVO, LU, DPL)	14.3	7.0

For the 24 selected candidate sites, a comparative analysis of the average suitability scores was performed across all four scenarios, and the results are presented in Table 15.

Table 15. Suitability scores of the 24 selected sites across different sensitivity analysis scenarios.

Site	Original	Equal	+10% (PVO, LU, DPL)	−10% (PVO, LU, DPL)
1	4.7	4.5	4.7	4.7
2	4.7	4.5	4.7	4.7
3	4.7	4.5	4.7	4.7
4	5.0	4.7	5.0	5.0
5	5.0	4.6	5.0	5.0
6	5.0	4.7	5.0	5.0
7	4.8	4.5	4.8	4.8
8	4.9	4.6	4.9	4.9
9	4.9	4.5	4.9	4.9
10	4.8	4.5	4.9	4.8

11	4.9	4.6	4.9	4.9
12	5.0	4.7	5.0	5.0
13	5.0	4.6	5.0	5.0
14	4.9	4.6	4.9	4.9
15	5.0	4.5	5.0	4.9
16	5.0	4.6	5.0	5.0
17	4.8	4.6	4.8	4.9
18	4.8	4.5	4.8	4.9
19	4.8	4.6	4.8	4.9
20	4.8	4.5	4.8	4.8
21	4.9	4.6	4.9	4.9
22	4.8	4.5	4.8	4.9
23	5.0	4.6	5.0	5.0
24	4.8	4.5	4.9	4.7

Across all analyzed scenarios, the suitability scores remained consistently high, ranging from 4.5 to 5.0. The largest deviations were observed under the equal-weight scenario, in which several sites showed a slight decrease in suitability scores. In contrast, scenarios with a $\pm 10\%$ adjustment to the weights of the three most influential criteria resulted in negligible changes, generally not exceeding 0.1. Despite these minor variations, all 24 proposed candidate sites retained their corresponding suitability classification across all analyzed scenarios. These findings confirm that moderate changes in criterion weights do not significantly influence site selection, demonstrating the high robustness and reliability of the developed model.

4.6. Comparison with Previous Studies

In scientific literature, two methods are used to evaluate spatial suitability for developing PV power plants. The first method involves applying spatial multi-criteria decision analysis (GIS-MCDA), while the second method focuses on existing locations of PV power plants (PVPP) to create predictive models [108]. The assessment of regional suitability for development utility-scale, land-based, PV solar power plant in present study relay on GIS-MCDA method. In contrast to the previous regional assessment conducted by Falcan et al. (2022), which fully covered the study area (except the European part of Türkiye), this analysis incorporates additional criteria—distance from power lines, roads, settlements, water surfaces, slope and aspect of terrain [109]. Additionally, photovoltaic output, which already includes irradiation at the ideal tilt, air temperature, and certain technical features (free-standing fixed-mounted c-Si modules) of the PV power plant were used as resource yield criteria.

The earliest estimation that used similar methodology and criteria by Castillo et al. (2016) did not include Western Balkan countries (Albania, Bosnia and Herzegovina, North Macedonia, Serbia, and Montenegro) or the Republic of Moldova [110]. Present studies fill this gap and enable estimation of the technical potential for the whole region.

Kiesecker et al. (2024) identify suitable land and power potential for PV power plant by combining two map: (1) development potential map (which merges constraint and estimated solar yield maps) and (2) conflict index map (incorporating Landcover and Protected areas conflict) [111]. The pixel values (potential locations) on maps are then ranked according to two scenarios: (1) Business-as-Usual and (2) Low-Conflict, to achieve country-level targets for 2030, 2035, 2040, and 2050 set by three development pathways. Genuine contradictions with the present study relate to the optimal siting strategy. One of the two strategy scenarios presented by Kiesecker et al. (2024) is conservation primacy, where optimal sites are defined by their “low-conflict” status [111]. This approach intentionally

avoids high-potential areas that overlap with high-risk regions, as near-future expansion in these areas may conflict with biodiversity, climate, or environmental assets. The present study has a growth-oriented optimization strategy (giving primacy to technical/economic criteria); there is no binary grading system for land use criteria (1 = high conflict, 0 = low conflict) like in the Kiesecker et al. (2024) study [111]. Instead, a spectrum of grades, ranging from 0 (unsuitable) to 5 (very suitable), are used for various land use practices. Additionally, potential development areas are categorized into six suitability classes: 0 (Excluded), 1 (Very low), 2 (Low), 3 (Medium), 4 (High), and 5 (Very high). These areas are not prioritized based on specific targets or development scenarios. The primary objective of this study is to assess the spatial suitability for the development of PV power plants, identify areas with very high suitability, and provide a rough estimate of their technical potential. This analysis also includes 24 selected potential locations across the Southeastern Europe region.

The higher values of estimated technical potential for PVPP development stem from the specific model configuration used in this study. The estimated electricity generation potential for areas with very high suitability is more than tenfold higher than the figures reported by Falcan et al. (2022) [109]. This discrepancy is even more pronounced when paired with the low-conflict land potential findings in Kiesecker et al. (2024) [111].

4.7. Advantages, Limitations and Future Research Directions

The application of GIS in conjunction with MCDM methods provides policymakers with an enhanced understanding for selecting optimal locations for renewable energy system development, balancing the trade-off between the intricate interplay of private interests (e.g., maximizing energy yield) and public interests (e.g., food security, biodiversity). Uncertainty in MCDM methods related to criteria weights (through the expert pairwise comparison matrix) and criteria values is addressed using the Fuzzy AHP method, which captures the vagueness, ambiguity, and subjectivity that are inherent in human judgment. Performing Weighted Overlay Analysis in GIS facilitated automated, spatially extended, and detailed assessment, replicable across different areas [21]. Nonetheless, all MCDM approaches face limitations, such as data staticity, limited dynamic optimization, and insufficient studies on social acceptance. This indicates a need for hybrid spatial modeling that utilizes predictive models (such as Random Forest) to pinpoint broad areas of interest. Subsequently, MCDM models can be applied to refine the selection based on specific socio-economic constraints or local planning policies.

Additionally, one limitation of this study concerns the social acceptability of the identified suitable locations from a land-use perspective. Since the most suitable areas are predominantly located on grassland and agricultural land, it is necessary to consult decision-makers and local communities, particularly from an agronomic perspective, and assess whether potential conflicts may arise with food production needs. However, this issue may be less pronounced in the study region, which is characterized by ongoing depopulation and deagrarianization processes. Furthermore, it is necessary to investigate the ownership structure of the most suitable locations, as areas owned by private individuals rather than the state may require additional administrative procedures, land acquisition processes, and associated costs, which could affect the feasibility and implementation of future solar energy projects. The suitability assessment for Türkiye should be interpreted with caution, as the lack of comparable protected-area data limits the consistency of cross-country comparisons.

To address potential social pressures in the region, it is essential to incorporate broad cultural, socio-economic, and ecological values into the assessment [112–129]. The cultural values, including cultural sites, visually appealing landscapes, recreational areas, and tourist zones, can significantly influence individual identities and perceptions. They may

also enhance people's quality of life, such as by improving mental health and overall well-being. Socio-economic values, as highlighted in Gašparović & Gašparović (2019), along with factors such as population, number of tourist nights, electricity consumption, and unemployment, offer insights into regions with vulnerable populations and the potential risks associated with land and resource rights [130]. To minimize the negative impact of photovoltaic (PV) development on environmental features, assessments must consider data on forest cover, the distribution of freshwater systems, agricultural land, critical habitats, and species migration corridors [130].

5. Conclusions

The study examines the territory of continental Southeastern Europe to identify suitable locations for the construction of large-scale solar PV power plants and the development of solar energy. A methodology based on fuzzy logic and the Analytic Hierarchy Process (AHP), supported by GIS and remote sensing, proved effective for assessing land suitability. For 12 countries (Slovenia, Croatia, Bosnia and Herzegovina, Serbia, Montenegro, North Macedonia, Albania, Greece, Bulgaria, Romania, Moldova, and Türkiye), a database was created comprising nine natural and anthropogenic criteria: photovoltaic output, terrain slope, aspect, land use, distance from power lines, distance from roads, distance from settlements, distance from protected areas, and distance from water surfaces. Using the fuzzy AHP method, decision-makers identified the most influential criteria (PVout and land use) and the least influential (aspect and distance from water surfaces).

In accordance with environmental standards and by excluding protected areas from the spatial analysis, the results indicate that 6.7% of the territory of Southeastern Europe is highly suitable for photovoltaic installations. Among the analyzed countries, Moldova has the highest share of suitable areas (14.5%), while Slovenia has the lowest (0.3%). Following the identification of suitable areas, a spatial-energy assessment was conducted, resulting in the selection and digitization of 24 of the most suitable locations for construction, two within each analyzed country. If large-scale solar parks were to be developed across all identified sites, the estimated total annual electricity production would be approximately 30.2 TWh, which would significantly enhance national and regional energy policies and substantially reduce greenhouse gas emissions. However, before any decisions are made or plans are implemented, it is essential to conduct field investigations of the suitable locations and perform a technical feasibility assessment in order to obtain a comprehensive understanding of their characteristics and development potential.

Given the final maps with 100 m spatial resolution, the results enable decision-makers at both local and national levels to precisely determine the most suitable locations and identify additional potential areas beyond the 24 selected sites. The study has international significance, as it encompasses 12 countries actively striving toward sustainable development through increased adoption of renewable energy sources, aiming to mitigate climate change and reduce negative environmental impacts.

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