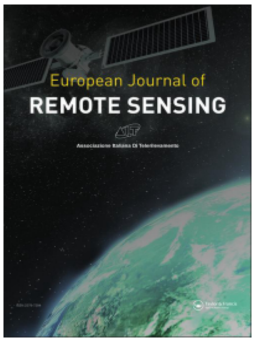

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Solar energy potential mapping in Ukraine through integration of GIS, remote sensing, and fuzzy logic

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ABSTRACT
The Green Deal strategic plan for the development of renewable energy until 2030 is of particular importance in the context of the restoration of Ukraine's post-war energy infrastructure. One of the key topics is the analysis of the possibilities of installing large solar power plants in Ukraine. In this article, a multi-criteria analysis of the suitability of the territory of Ukraine is carried out on the basis of climatic, topographic and land use criteria. To assess land suitability, criteria standardized using fuzzy logic with weights determined by experts through the method of pairwise comparisons were combined using a weighted sum model. Upon completing the study, a suitability map was generated, depicting zones with varying levels of suitability (ranging from 0 to 1) for solar power plant placement. It was found that more than 35.68% of the country has average values of the suitability index (0.65–0.7), and approximately 18.82% show high indicators (<0.7). Conditions are especially favorable in the south of Ukraine.

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Solar power; land suitability analysis; GIS; remote sensing; multi-criteria analysis; fuzzy logic

Introduction

The war in Ukraine has led to serious destructive consequences, particularly in the energy sector due to direct bombing and rocketing of infrastructural objects in different parts of the country. According to reports from the National Energy Company UkrEnergo, as of May 2023, Ukraine has lost about 27 GW of existing power generation facilities (Ukrinform, 2023). The energy facilities in the eastern and southern parts of Ukraine have suffered the most due to the conflict (Energy Charter Secretariat, 2023). For example, the Zaporizhzhya Nuclear Power Station has fallen under occupation, and the Kakhovka Hydroelectric Station has been destroyed. Alternative energy sources have also experienced significant negative impacts. According to the Minister of Energy of Ukraine Galushchenko, approximately half of the solar power plants have been taken out of operation (Ukrinform, 2022).

Recovery of the energy infrastructure is critically important for restoring prosperity and development to the country. Considering Ukraine's orientation towards integration with European Union, it is crucial not only to restore resources but also to develop within the context of the European Green Deal. This means shifting away from fossil fuels in favor of renewable energy sources. Moreover, the construction of traditional power sources such as hydroelectric, thermal or even nuclear power plants requires substantial material and financial investments, along with the involvement of a significant number of human resources. In contrast, the construction of solar power plants can be rapid and relatively accessible through the utilization of modern technologies and standardized components (Sharma et al., 2015).

However, successful utilization of solar energy requires the correct placement of solar station installations (Fouad et al., 2017). Optimal placement of solar panels allows for maximizing electricity production and ensuring optimal system efficiency. Incorrect location choices could lead to reduced productivity and underutilization of solar energy's full potential.

For identifying optimal territories for solar installations, remote sensing data is a valuable resource (Mahtta et al., 2014). The use of satellite data enables quick and efficient analysis of a large amount of information regarding potential solar installation sites.

Several studies have delved into the potential and challenges of installing large solar power plants across various countries. Besarati et al. (2013) assessed the potential of harnessing solar radiation in different regions of Iran, pinpointing significant potential in the central and southern parts of the country. Similarly, Ershad et al. (2016) showcased that solar PV and wind power plants in two provinces of Afghanistan could achieve penetration levels of 65%–70% without significant curtailment.

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Ruiz et al. (2020) provided a decision support system model for Indonesia for the development of large-scale solar power plants in tropical countries. Miguel and Corona (2018) discussed the economic viability of concentrated solar power for Spain, emphasizing its limitations due to high capital and operating costs. Mostafaeipour et al. (2020) evaluated 10 provinces in Canada for the construction of solar power plants. Wang et al. (2018) offered guidelines for solar power plant location selection in many countries, including Vietnam. Norwood et al. (2014) conducted a geospatial and temporal comparison of solar technologies across Europe and the US, highlighting significant regional differences in annual performance.

Saraçoğlu et al. (2018) identify criteria for selecting the optimal location for very large photovoltaic solar power plants on global and supergrid concepts. Rafique et al. (2020) emphasized the potential of solar power for cleaner production in Pakistan, while Ghasemi et al. (2019) demonstrate the technical potential of specific locations in southeast Iran to provide significant amounts of solar electricity. Kiefer and Del Río (2020) identify and rank the drivers and barriers to the deployment of concentrated solar power in the EU. Stević et al. (2019) discuss the possibilities for wider investment in solar energy implementation.

At the same time the potential for solar energy in Ukraine remains largely unexplored, with no notable publications addressing this topic specifically for the country.

Satellite data can provide information about climatic conditions (Mustafa et al., 2020; Shorabeh et al., 2019), terrain (Chitturi et al., 2018; Colak et al., 2020), land use, and other parameters that affect solar panel performance. To determine the most significant criteria for land suitability, a multi-criteria analysis method is commonly used. This method is often combined with the Analytic Hierarchy Process (AHP) to ascertain the importance of each criterion relative to others (Garni & Awasthi, 2017; Koç et al., 2019). However, Deveci et al. (2021) proposed evaluation of the most significant criteria a new approach based on the logarithmic additive estimation of weighting factors (LAAW) in a fuzzy environment. The research results confirmed that the proposed LAAW fuzzy model is a practical and reliable tool for determining the importance of criteria.

For direct land suitability calculation, Boolean Logic, Weighted Linear Combination (WLC), also called as Weighted Sum Model (WSM), or Fuzzy Overlay are employed.

WLC is a method to blend various factors by giving them different importance weights (Malczewski, 2011). It calculates a final score by multiplying each factor with its assigned weight and summing them up. Adjusting weights allows prioritizing certain factors, making it useful in data analysis and machine learning for creating composite scores or rankings.

Boolean Logic is used to combine different criteria or conditions using logical operators (AND, OR, NOT) (Cheng & Thompson, 2016). Boolean Logic helps define rules or conditions that determine whether a piece of land is suitable or not based on specific factors. For instance, using "AND" might mean that all criteria must be met for the land to be suitable, while "OR" could indicate that meeting any of the conditions is sufficient.

Both the Boolean and WLC methods employ discrete threshold values to determine suitability (Yousefi et al., 2018). The coefficients and weights in the models are typically defined by a group of experts. Both methods involve assumptions and a degree of uncertainty.

However, fuzzy logic offers a more adaptable approach that isn't confined by strict boundaries. Instead of straightforward categories with clear limits, it allows for multiple gradations to be employed. Take, for instance, the evaluation of the intensity of global horizontal solar irradiance. Within this context, fuzzy boundaries can be established to differentiate between categories like "highly intense", "moderately intense", and so forth, yielding results that more accurately reflect reality.

For example, Yousefi et al. (2018) succeed in performing the task of selecting sites for solar power plants by combining fuzzy and Boolean logic, taking into account economic, technical and environmental indicators. However, in this work, all criteria have the same weight, which can distort the results. Zoghi et al. (2017) showed that the combination of fuzzy logic, WLC and MCDM is characterized by high accuracy. Dhunny et al. (2019) demonstrated the successful application of fuzzy logic to estimate optimal locations not only for solar power plants, but also for wind and hybrid wind-solar power plants on the island of Mauritius, which has a very complex topography.

In this study, we analyze the suitability of Ukrainian territories for effective solar power station installation using an approach on the basis of multimodal geospatial data sources. By employing satellite observations on climate, terrain characteristics, and land usage, we merge multi-criteria analysis, pairwise comparison (derived from the Analytic Hierarchy Process), fuzzy logic, and WLC. Thus, our aim is to identify optimal zones for solar power plant construction that will ensure maximum energy production. Similar research has been conducted in Ukraine, according to Butenko et al. (2019), and Yelisieieva and Khazan (2016), but they do not account for all factors and lack a comprehensive method for determining suitability across the entire territory for solar farm placement.

The primary goal of our study is to locate territories where solar power stations will have the highest energy production potential. Additionally, we aim to analyze the appropriateness of the current locations and provide an assessment of the optimality of the placement of already built solar power stations in Ukraine to determine the overall effectiveness of solar energy in the country.

Data and materials

Study area

In our research, we aim to analyze the entire territory of Ukraine, not just specific regions as done by the authors of previous similar studies.

Ukraine is located in Eastern Europe and is the largest country on the continent, excluding Russia (Cooper & Gritzner, 2007). Covering an area of 603,700 km^2 or 5.7% of Europe, it is divided into 24 regions and the autonomous republic of Crimea (Figure 1). The latter has been under Russian occupation since 2014, a situation not recognized by the majority of the world's countries.

Ukraine has predominantly flat terrain (95% of the territory) with an average elevation of 175 meters. This includes lowlands, covering about 70% of the country's territory and located in the northern, eastern, and southern parts, as well as highlands, covering about 25% and situated in the western and central regions. Mountains make up about 5% of the country's territory and are located in the west (Carpathians) and south (Crimean Mountains).

To the south, Ukraine is bordered by the waters of the Black Sea, and to the southeast by the Sea of Azov – an arm of the Atlantic Ocean. The relative distance from the Atlantic Ocean influences the prevailing moderate continental climate over most of the country, varying from moderate continental in the majority of the territory to subtropical on the southern coast of Crimea.

In the following sections, we will provide a more detailed overview of the climatic and topographic features of Ukraine that may influence the potential for solar energy production.

Analysis of satellite data on the most significant criteria for selecting an optimal location for solar power plant installation

The efficiency of solar power plants depends on various criteria, including climatic, topographic, economic, and other parameters. Within the scope of this study, our focus is directed towards key criteria influencing the optimal selection of solar farm locations. Specifically, drawing from the experience of similar scientific research, we pay attention to the following primary aspects:

- Climatic conditions: global horizontal irradiance (GHI), temperature, precipitation, wind speed;

Figure 1. Study area - map of Ukraine.

- Topographic features: elevation and slope;
- Land cover and land use resources.

For the analysis of land cover and land use, we are utilizing a classification map for the year 2022 based on data from the Copernicus Sentinel-1 and Sentinel-2 missions (Ministry of Agrarian Policy and Food of Ukraine, 2023).

To analyze climatic and topographic parameters in the territory of Ukraine, we opted to independently develop climate and topographic maps using the Google Earth Engine platform, employing openly available satellite data (Shelestov et al., 2021).

Climatic conditions

For the climate analysis in the territory of Ukraine, we utilized hourly data from the ERA5-Land dataset with a spatial resolution of 9 km, provided by the Copernicus Climate Data Store. This dataset encompasses all the necessary parameters for our climate analysis, available since 1950:

- Global Horizontal Irradiance (GHI);
- Temperature at 2 meters above ground level;
- U and V wind components at 10 meters above ground level;
- Total precipitation including rain and snow.

To ensure accurate climate assessment and account for temporal changes, we refrained from using overly dated data. Instead, we limited our dataset to the years from 2015 to 2022. This approach allowed us to ensure the relevance of our research results.

Global Horizontal Irradiance (GHI). Solar activity, measured as Global Horizontal Irradiance (GHI), determines the amount of solar energy reaching the Earth's surface. It is the most critical factor for the effective operation of solar power plants. High solar activity ensures a greater amount of solar energy available for collection by solar panels, leading to higher power generation capacity of solar power plants. Therefore, locations with higher solar activity hold greater priority when selecting sites for establishing large solar farms.

To assess the distribution of direct solar irradiance across the territory of Ukraine, we conducted calculations for the total accumulated global horizontal irradiance (GHI) for each year from 2015 to 2022 separately (Figure 2).

Then we then averaged the obtained results to create the resulting map (Figure 3). This approach allows us to generate a more accurate map of solar energy distribution and identify areas with the greatest potential for solar power station utilization.

As evident from Figure 3, the accumulated solar irradiance consistently increases from north to south. The least direct solar light is localized in the north-western regions. Central Ukraine experiences a moderate influence of solar radiation (1200–1300 Wkh/m^2). The highest solar irradiance (above 1300 Wkh/m^2) is concentrated in the southern part of Ukraine, particularly reaching a peak on the Crimean Peninsula. High levels of GHI are observed in the Mykolaiv, Kherson, Odesa, Zaporizhia regions, as well as the Donetsk region. This indicates a significant amount of solar radiation reaching the Earth's surface and high potential suitability of these areas for the placement of solar power plants.

Temperature. High temperatures can have a negative impact on the ability of solar panels to convert solar radiation into electrical energy. This phenomenon is explained by the fact that increased temperature leads to enhanced conductivity of the semiconductor materials used in photovoltaic

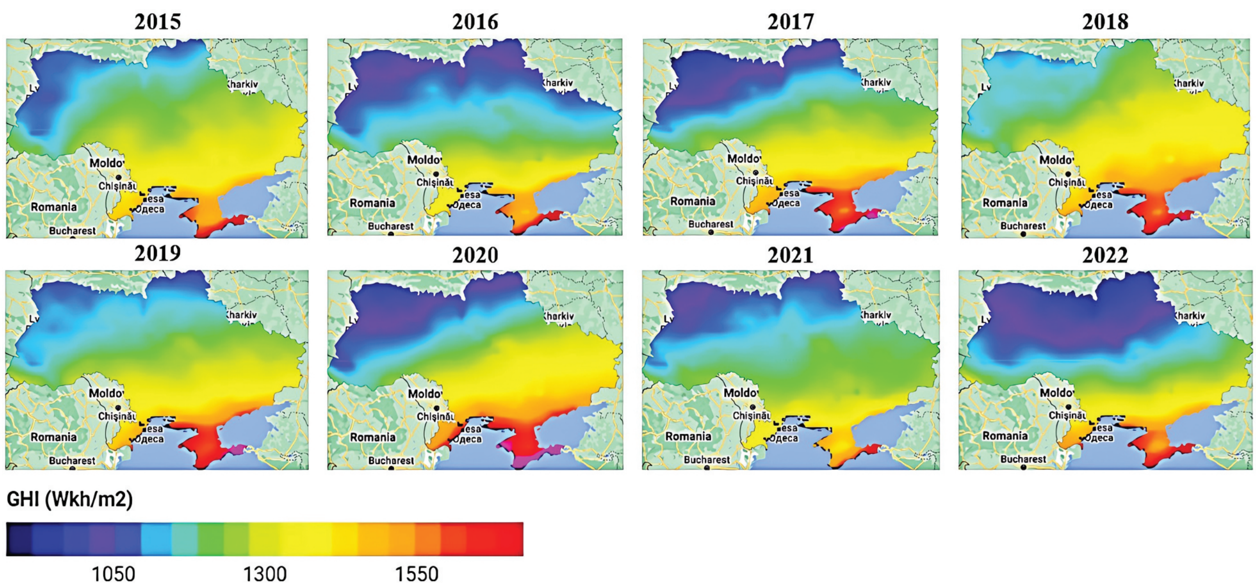


Figure 2. Accumulated annual GHI 2015–2022.

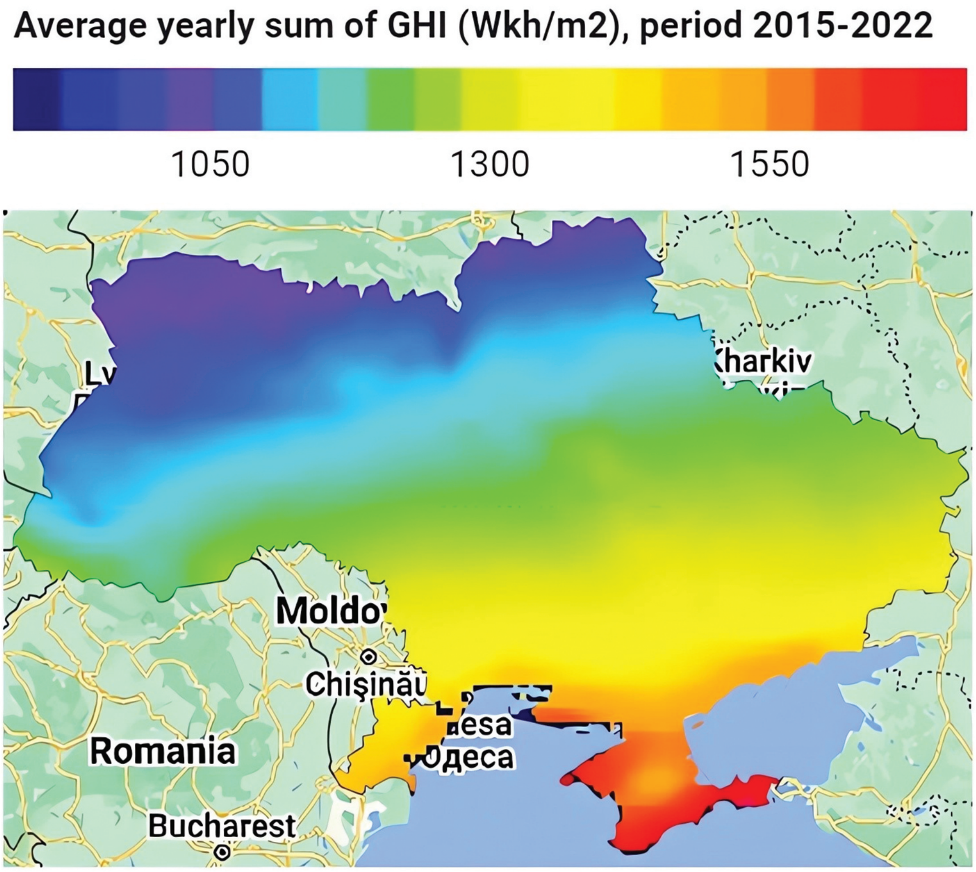


Figure 3. Accumulated annual GHI (Long term average, period 2015–2022).

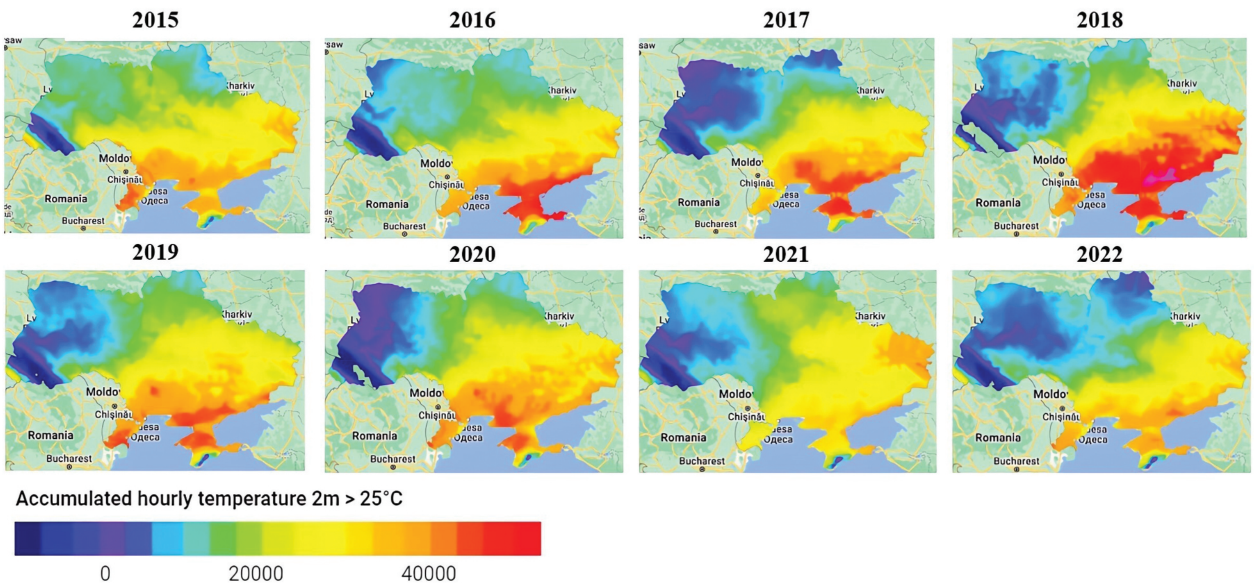


Figure 4. Accumulated annual hourly temperature at 2m > 25°C, 2015–2022.

elements (Fazelpour et al., 2013). The heightened conductivity of these semiconductor materials, in turn, results in an increased flow of charge carriers within the elements but also reduces the generated voltage. As a result, the efficiency of electricity production decreases.

The reduction in the efficiency of solar panels is observed when the temperature of the photovoltaic panel rises above 25°C (77°F) and is described by the temperature coefficient (Ibrahim et al., 2014; Idoko et al., 2018). This coefficient indicates how much the output power decreases for each degree Celsius above the reference temperature, typically set at 25°C. Therefore, optimal regions for solar farms are those where the temperature is maintained below 25°C degrees, as this mitigates the adverse effects of temperature on solar panel performance Figure 4.

To assess the distribution of temperatures that could negatively affect the productivity of solar farms, we selected temperature values from the available hourly data at 2 meters above ground level that exceeded 25°C (accounting for the temperature coefficient). Then, for each individual year, we calculated the sum of these hourly temperatures. In other words, we added up the temperatures recorded every hour throughout the year when they exceeded 25°C to determine how long the temperature is above this acceptable threshold. After that, we average the 2015–2022 data to create the resulting map (Figure 5). Through this process, we identify territories where the temperature effect could have the most significant negative impact on solar panels.

As evident from the map in Figure 5, the hottest zone is the steppe region of Ukraine, particularly the southern and eastern regions, including Crimea, Kherson, and Zaporizhia. Central Ukraine experiences relatively moderate temperatures. Lower temperatures are observed in western Ukraine and the Crimean Mountains area, while the coldest zone is the Carpathian Mountains (Zakarpattia region).

Precipitation. Another factor influencing the productivity of solar power plants is precipitation and air humidity (Kazem & Chaichan, 2015). Rain and snow can obstruct direct solar irradiation that reaches the solar panels, thus reducing the efficiency of electricity generation. Additionally, humid air scatters solar light and diminishes its penetration through the atmosphere, which also leads to decreased solar panel productivity. (Mekhilef et al., 2012)

When constructing precipitation maps, we calculate the accumulated rainfall and snowfall throughout the year. The maps of accumulated precipitation for the years 2015–2022 are presented in Figure 6, and the averaged results are shown in Figure 7.

From the map in Figure 7, it is evident that the highest annual precipitation amounts are found in the Carpathian Mountains region. Other areas with significant precipitation include the northwestern regions of Ukraine and the zone of the Crimean Mountains. The southern and eastern regions are the driest parts of the country with lower annual precipitation levels.

Wind Speed. Wind can have both positive and negative effects on a solar power station. On one hand, strong winds create mechanical loads on solar panels, causing vibrations and stresses that could potentially damage the structure of the power station (Laha et al., 2021). On the other hand, wind contributes to the cooling of solar power stations, helping to

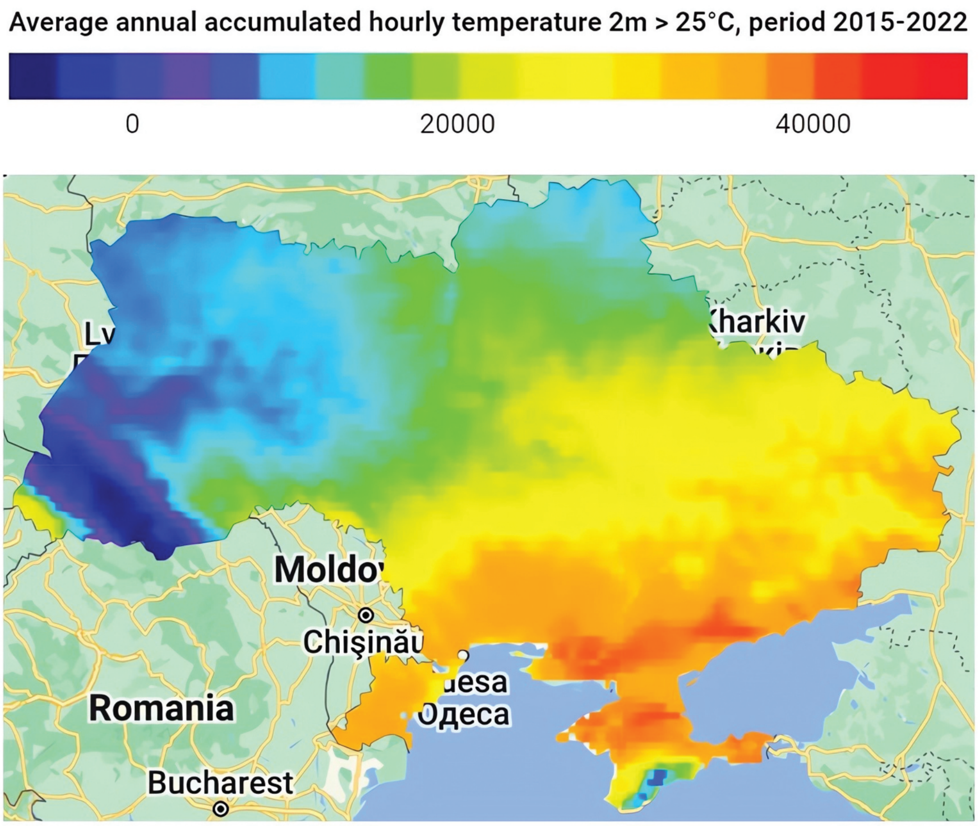


Figure 5. Accumulated annual temperature 2m > 25°C (Long term average, period 2015–2022).

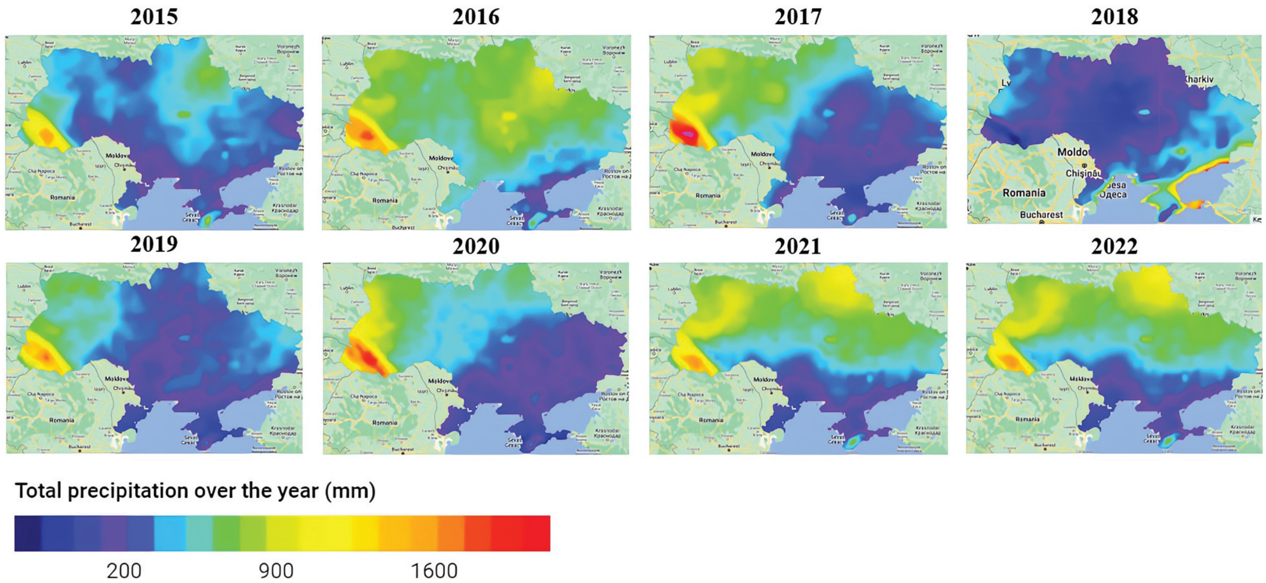


Figure 6. Accumulated annual precipitation, 2015–2022.

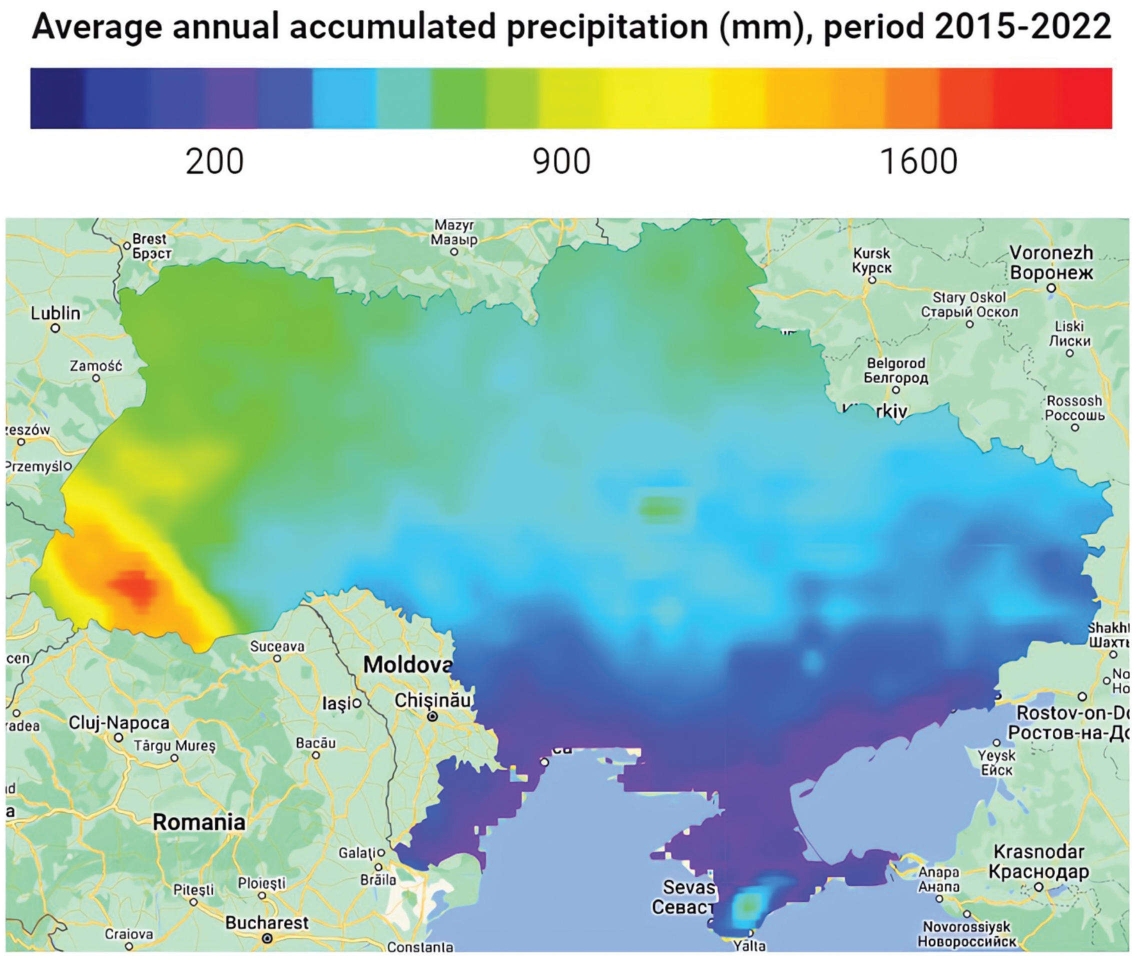


Figure 7. Accumulated annual precipitation (Long term average, period 2015–2022).

mitigate the adverse impact of high ambient temperatures and ensuring an optimal operating temperature for the solar panels (Gökmen et al., 2016). Given the use of reliable panel mounting systems, the detrimental effects of winds can be minimized. In this study, we primarily consider wind as a positive factor influencing the productivity of solar power plants.

Since ERA5-Land does not provide direct information on wind speed, we calculate it independently for the wind speed map by taking the square root of the

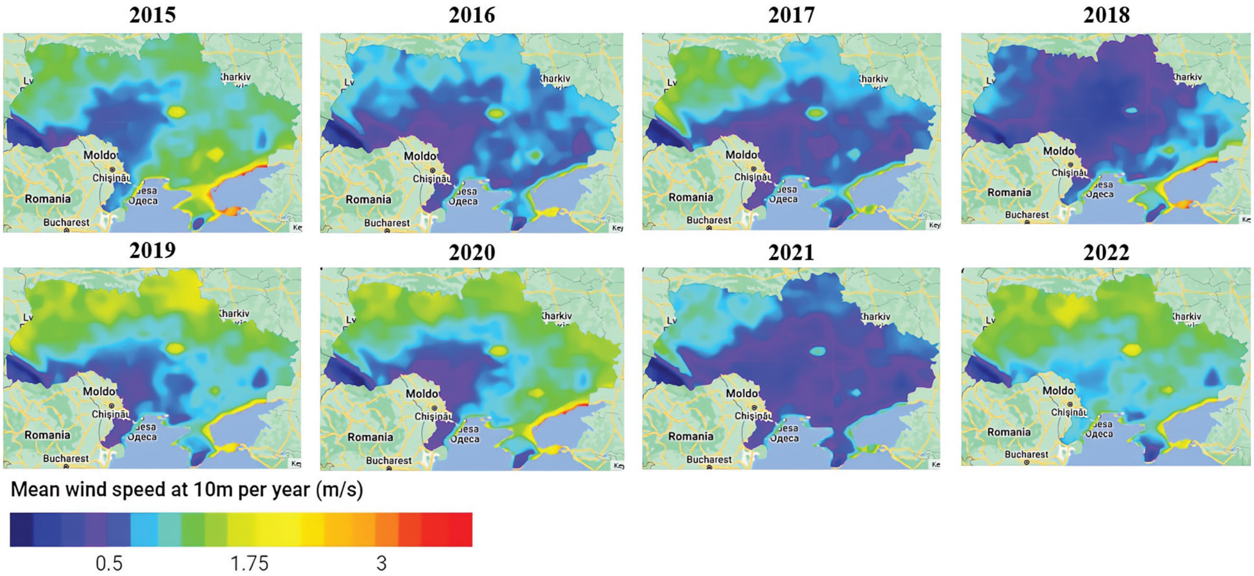


Figure 8. Mean yearly wind speed, 2015–2022.

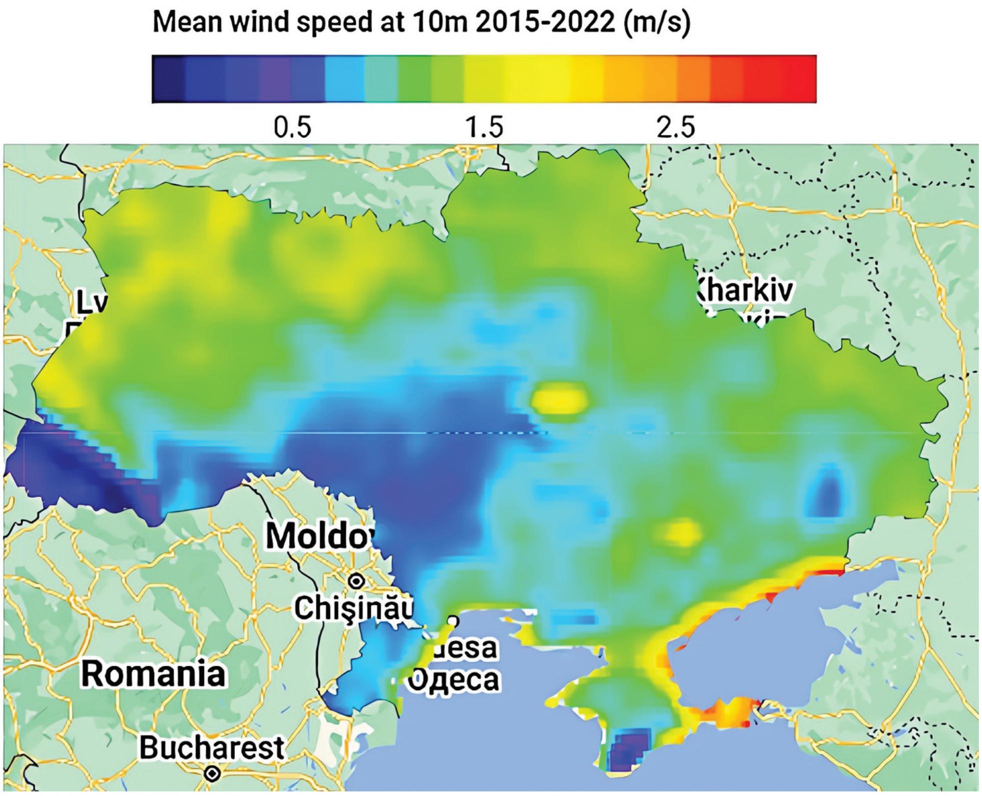


Figure 9. Mean yearly wind speed (Long term average, period 2015–2022).

sum of squares of the eastward (u) and northward (v) wind components available in the ERA5-Land dataset, using the formula:

$$wind_{speed} = \sqrt[2]{u\_wind^2 + v\_wind^2}, \tag{1}$$

For each year (2015–2022), we compute the average annual wind speed (Figure 8) and generate an averaged map based on the results (Figure 9).

From Figure 9, it can be observed that the strongest winds are concentrated near the coast of the Azov Sea, in the Crimean Peninsula, and in the Donetsk and Zaporizhia regions. Across the main territory of Ukraine, moderate wind speeds (1–2 km/h) are typical, while the weakest winds are observed in the Zakarpattia, Vinnytsia, Odesa regions, and near the Crimean Mountains.

Topographic features

For creating maps that depict the terrain features of Ukrainian territories, we utilized the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) dataset. These data provide a global representation of the Earth's surface with a spatial resolution of 90 meters, covering even inaccessible land areas.

Elevation. The elevation of the terrain impacts the productivity of solar panels for several reasons. Firstly, at higher elevations, the air temperature is lower and wind speeds are higher, reducing the likelihood of solar power station overheating and promoting cooling. Secondly, solar panels are more efficient at greater altitudes (Chitturi et al., 2018), where they experience a stronger influence of direct solar radiation due to a thinner atmospheric barrier compared to sea level.

As seen from Figure 10, most of Ukraine is characterized by plains. Lowlands are observed along the Black Sea coastline (Odesa, Mykolaiv, Kherson regions) and along the Dnipro River. Highlands dominate in western Ukraine (Lviv, Ternopil, Ivano-Frankivsk regions) and are partially present in the east (Donetsk region). The Carpathian Mountains are situated in the Zakarpattia region, while the Crimean Mountains are located in the southeastern part of the Crimean Peninsula.

Slope. The optimal tilt of solar panels allows for the maximum utilization of potential solar energy. However, placing panels at the correct angle on steep slopes can be quite challenging. Incorrect or insufficiently correct panel orientation leads to a reduction in the amount of solar radiation reaching the photovoltaic elements, consequently decreasing the electricity generation efficiency. Additionally, the need to level the ground increases the installation cost of solar power stations.

The SRTM DEM dataset contains elevation information, but by using built-in functions in the Google Earth Engine (GEE) cloud environment, we were able to compute slope, providing additional valuable information for our study.

When calculating the slope of the terrain (Slope), the GEE algorithm determines the angle of the surface inclination at each point of the digital elevation model, indicating how steep or gentle a specific area of the Earth's surface is. The slope value is measured in degrees and represents the angle of the surface inclination. For instance, a value of 0 corresponds to a flat surface, while higher values indicate significant incline (ranging from 0 to 90 degrees).

From Figure 11, it can be observed that the majority of Ukraine has a relatively flat terrain without steep slopes.

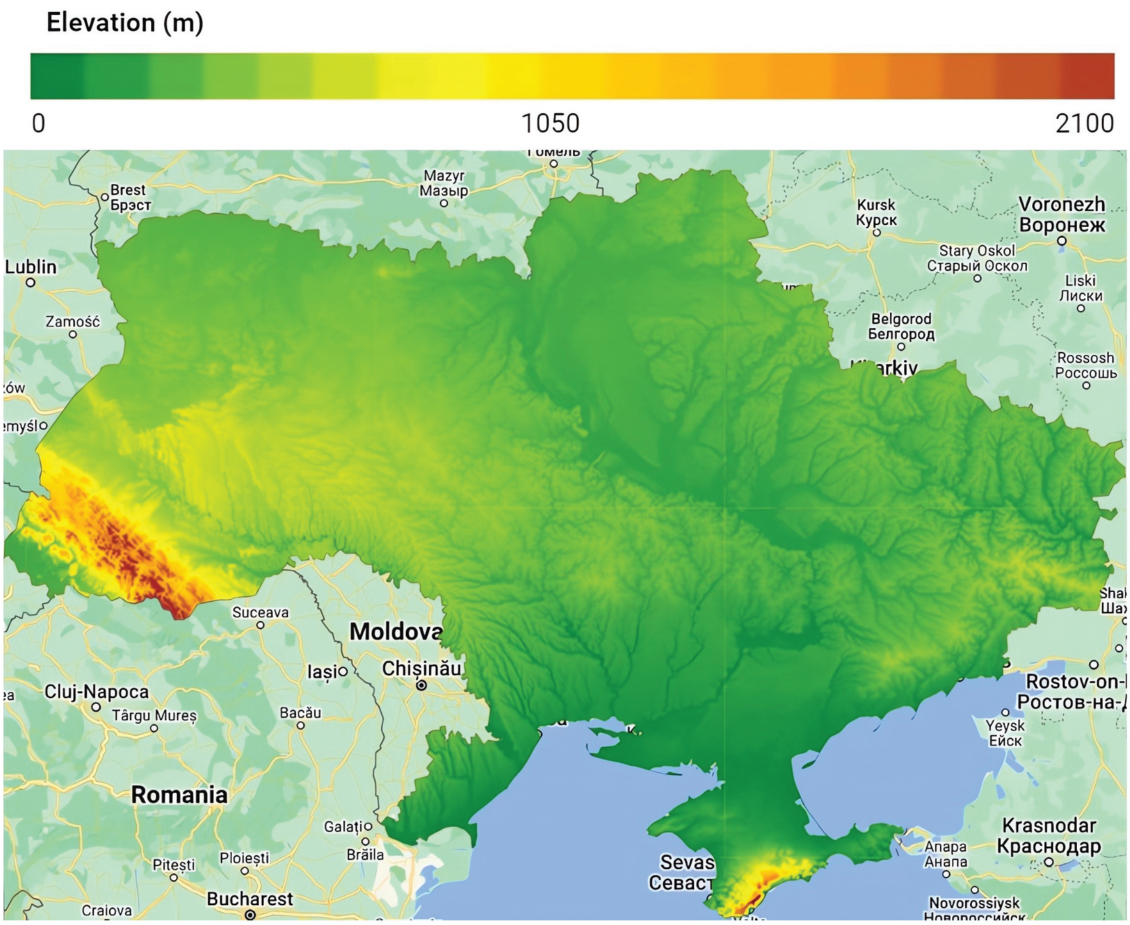


Figure 10. Elevation map.

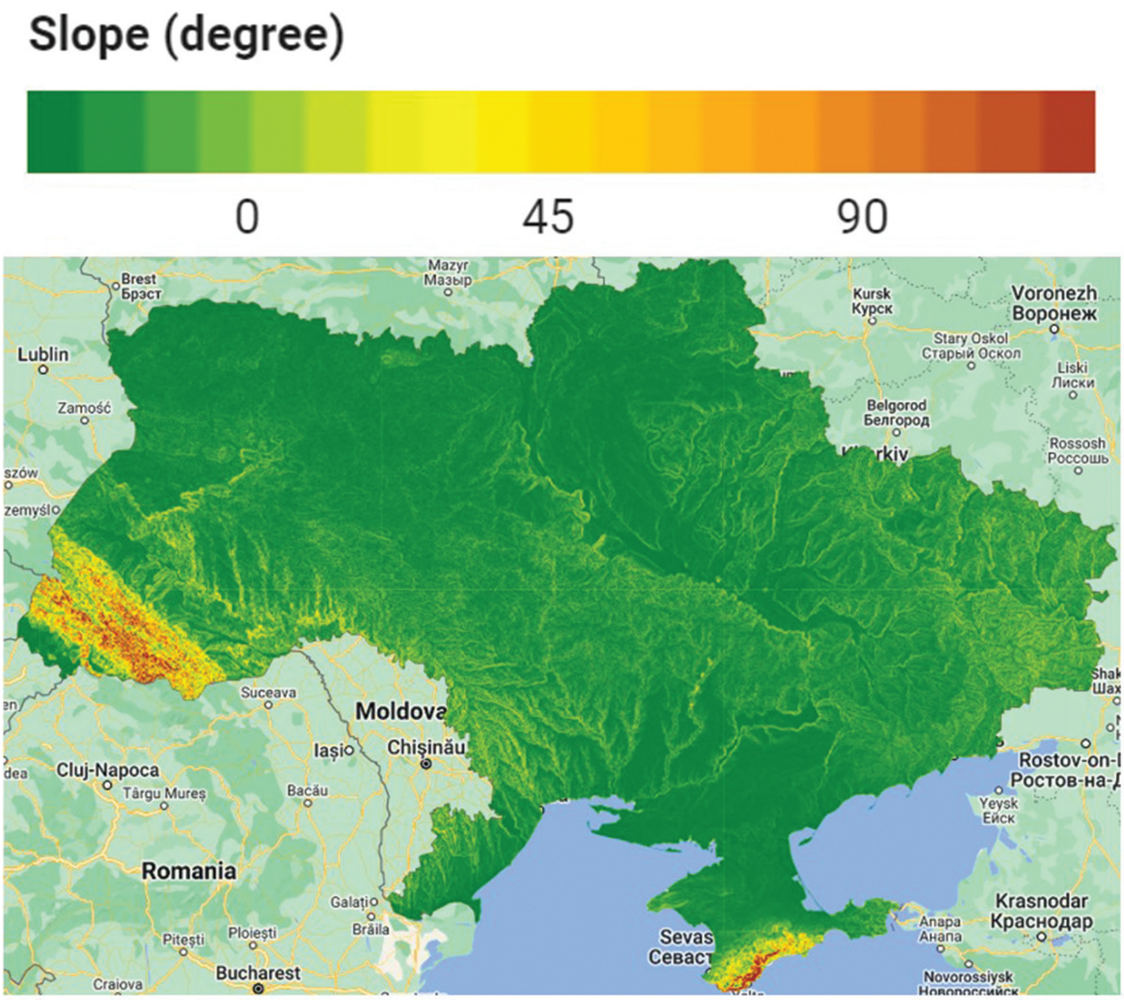


Figure 11. Slope map.

Figure 12. Land classification map of Ukraine for 2022.

Uneven terrain is prevalent mainly in the Carpathian and Crimean Mountain regions. Gentle slopes are evenly distributed across the entire country, except for the northern part (Polissia zone), parts of the Kherson region, and the Crimean Peninsula.

Land cover and land use

Solar power stations cannot be installed in areas with unsuitable land cover, such as swamps, rivers, or dense forests.

Additionally, the selection of solar power station locations must be harmonized with other land use needs to ensure the most efficient use of the territory. Therefore, solar farms are prohibited from being established in reserves, national parks, and similar areas.

The most suitable zones for solar power station placement are vacant and uncultivated plots of land. To a lesser extent, agricultural fields and sparse woodlands are also suitable (Adeh et al., 2019). Agrovoltaics, which involves integrating solar panels with agricultural activities, is gaining attention as a sustainable approach, allowing for dual land use and potential benefits for both energy production and agriculture (Dupraz et al., 2011; Miskin et al., 2019; Weselek et al., 2019).

The land cover classification map for 2022 is depicted in Figure 12 and includes 16 classes. Among them, 8 classes correspond to agricultural crops. The map provides information about non-cultivated fields, forests, parks, and other land types that impact the selection of locations for solar panels (Kussul et al., 2015).

As can be observed, the largest areas of non-cultivated land are predominant in the southern part of Ukraine. The northern and western regions of the country are rich in forests. Agricultural fields are evenly distributed across the rest of the Ukrainian territory.

Collecting the data on the largest solar power facilities in Ukraine

Based on climatic, topographic, and land classification maps, we aim not only to assess the potential of Ukrainian territories for the construction of efficient solar power plants but also to analyze and evaluate the suitability of the existing largest solar energy facilities in Ukraine.

To obtain data on the locations of the largest solar power plants in Ukraine, we utilized open maps provided by the Wikimapia platform.

Wikimapia is an online cartographic platform that allows users to create, edit, and view geographic information about various objects on the map. By using Wikimapia, we gained access to up-to-date information about the most powerful solar energy facilities in Ukraine and their locations.

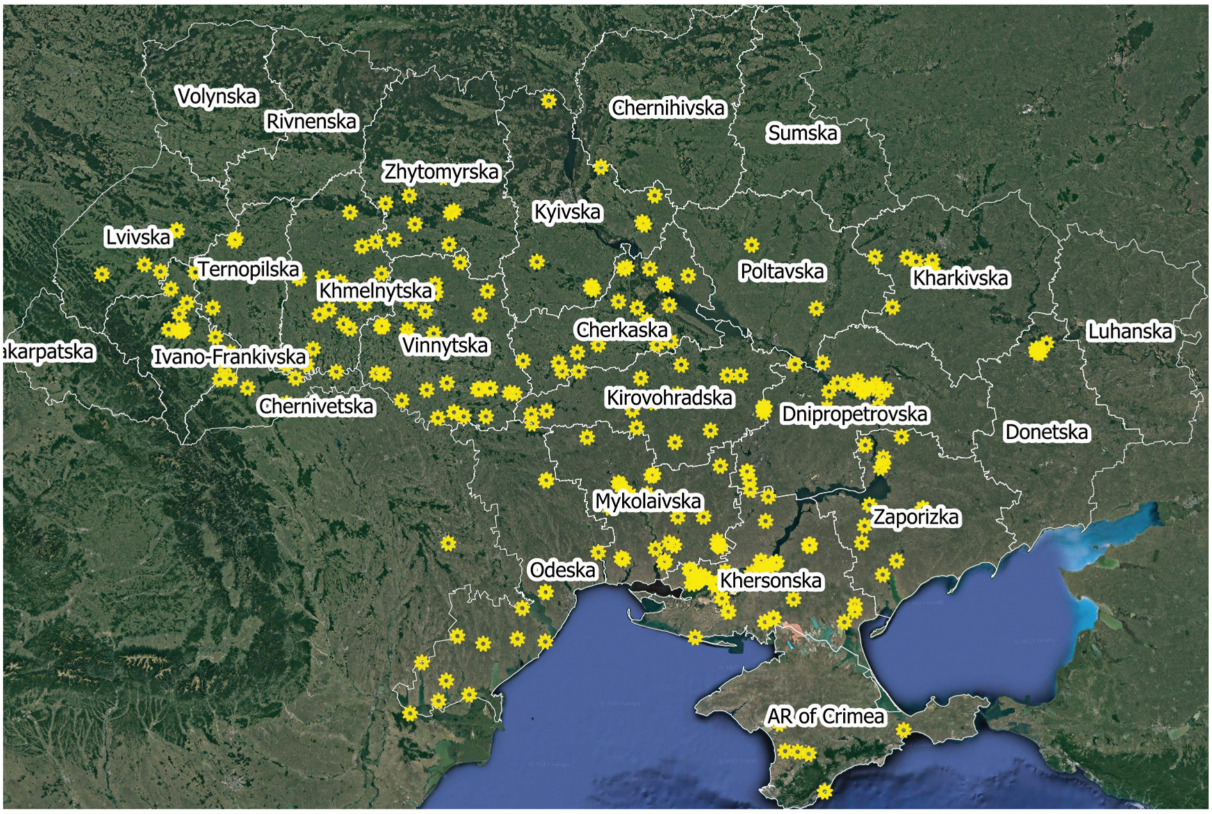


Figure 13. Major solar power plants in Ukraine.

For our research, vector polygons of 298 major solar power plants in Ukraine were downloaded (Figure 13).

These polygons represent the shapes of the facilities and contain information about their geographical coordinates, names, and types (solar farm, solar array, etc.). With this dataset, we can perform geospatial analysis to assess the adequacy of the placement of the largest solar power plants in Ukraine and identify areas whose potential is not yet fully utilized.

Methodology

In order to identify the most optimal sites for the placement of solar power stations across Ukraine's territory, we utilize a comprehensive methodology. This approach combines the weighted linear combination method, the pairwise comparison method (derived from the Analytic Hierarchy Process or AHP), which aids in determining weight coefficients, and the application of fuzzy logic to standardize criteria.

Figure 14 schematically illustrates the process of creating a suitability map for the installation of solar power stations. At the first step, we identify criteria, including climatic, topographic parameters influencing solar power station efficiency, and land usage. We obtain raster data for these criteria, as described in the previous section.

In the subsequent stage, we standardize the data using fuzzy logic, transforming it into a range of 0 to 1. Here, 0 signifies absolute unsuitability of a criterion for solar power station installation, while 1 represents the ideal value of the criterion. This procedure yields fuzzy suitability maps for each criterion.

Simultaneously, to accurately account for the impact of each criterion on land suitability for solar power station installation, we determine weight coefficients based on expert recommendations.

After obtaining the suitability maps and corresponding weight coefficients for each criterion, we employ weighted linear combination. As a result, we generate a land suitability map for solar power station installation.

A more detailed description of each step of the algorithm is provided below.

Fuzzy logic standardization of input geospatial data

While the weighted overlay method is typically used for suitability analysis without employing fuzzy logic, in our study, dividing climate and topographic parameters into crisp suitability classes for solar panel installation is not feasible. This is due to the difficulty in definitively assigning specific numerical ranges to highly suitable, moderately suitable, or unsuitable classes.

Incorporating fuzzy logic allows for a more flexible consideration of ambiguities and uncertainties in data that can arise during territorial analysis. This helps render decisions more realistic and adaptable to diverse conditions. Therefore, to delineate Ukraine's territory into suitable or unsuitable zones for each of the input climate and topographic parameters, we employ fuzzy logic, specifically a method called Fuzzy Logic Standardization. Fuzzy logic standardization is the process of transforming a crisp set of input data into a fuzzy set, assigning degrees of membership within the range of 0 to 1. This transformation is achieved through the application of a carefully selected membership function, which defines the level of membership that each data point possesses within the fuzzy set.

To create a fuzzy set for each input criterion considered in the analysis of the territory's suitability for solar panel installation in this study, several steps need to be taken:

1. Choosing Fuzzy Membership Functions:

In this step, we define a mathematical function that determines the degree of an element's membership to a certain set or category. This membership function can take various forms, such as triangles, trapezoids, Gaussians (normal distributions), and others. In our study, for each criterion, we select a membership function for the "suitable" fuzzy set and utilize triangular or trapezoidal functions that best represent the nature of the input data.

2. Defining Boundary Points:

To specify the membership function within a particular numerical range, we establish extreme boundary values for each criterion. These values signify complete membership in the "suitable" set (probability 1) or complete non-membership (probability 0). The value after which the probability becomes 0 is referred to as the "suitability threshold".

3. Calculating Membership Probability:

After determining the membership function, domain, and boundary points for each input parameter, we construct corresponding term sets and calculate the probability of membership in the "suitable" fuzzy set. This probability ranges from 0 to 1 for intermediate values between the extreme points of "completely suitable" and "completely unsuitable".

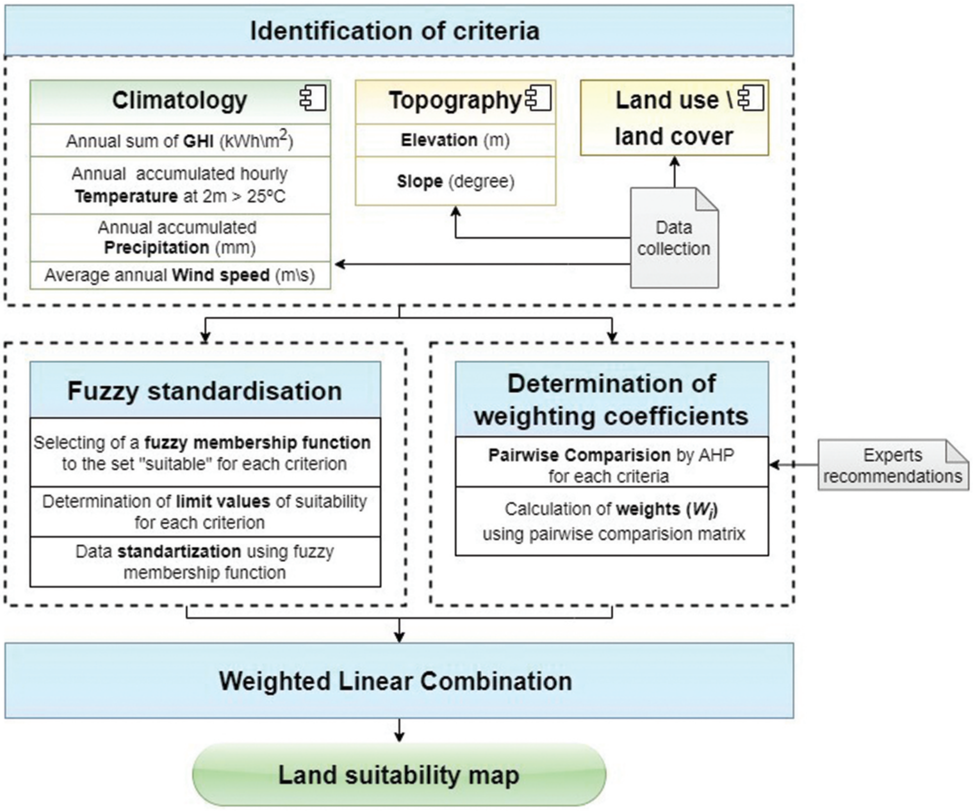


Figure 14. Creating a land suitability map for solar power station installation.

To achieve this, we employ the Fuzzify tool from the Saga module in the QGIS software. The boundary points defined in the previous step serve as input parameters for running the Fuzzify algorithm, which directly builds the membership function and assigns fuzzy values to each criterion.

The fuzzification process for climate and topographic criteria is described in Table 1.

The land use map provided is presented in the form of discrete, crisp values corresponding to each class. To describe the suitability of the territory for solar panel installation in relation to land use, we initially conducted a reclassification of this land use map. To achieve this, we evaluated each class on a scale of 1 to 5, where 1 represents absolute unsuitability of the territory and 5 signifies complete suitability (Table 2).

Territories unsuitable for solar panel installation due to specific land cover characteristics, such as rivers, swamps, and dense forests, were categorized as class 1. Orchards, parks, and sparse forests have fewer constraints but are still moderately unsuitable due to legal restrictions (prohibition of solar panel installation in reserves or national parks) or usage considerations; hence, they were classified as class 2.

Small solar stations for domestic use or industrial needs can be installed on building rooftops. Agricultural fields, particularly with the efficiency of modern agrophotovoltaic systems that combine agriculture and solar energy production, are well-suited for solar farm installations. However, the most suitable areas for solar power plants, especially large solar farms, are uncultivated fields, bare lands, and meadows.

After the reclassification, the land use map was subjected to fuzzification, similar to the approach taken with the maps of climatic and topographic components. Fuzzification was carried out using the extreme points of 1 (absolutely unsuitable land) and 5 (completely suitable land) to define the degree of suitability.

We divided the fuzzy set of "suitability", obtained as a result of fuzzification, into 5 equal ranges, each of which is described by a corresponding linguistic variable (Table 3).

Thus, for each climatic and topographic parameter, as well as the land-use map, we constructed new maps conditionally divided into 5 fuzzy ranges (Figure 15). In these maps, each pixel describes the probability of the corresponding parameter's membership in the "Suitability" fuzzy set for solar panel installation.

Because the initial climate, topography, and land use data came from different sources, the maps had different spatial resolutions, which could lead to inaccurate survey results. To solve this problem and ensure proper use of data, we reprojected all maps to a common spatial resolution of 100 meters.

Table 1. Fuzzification of climate and topographic parameters.

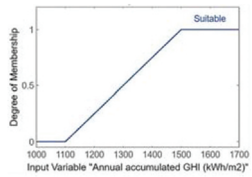
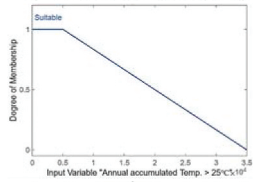
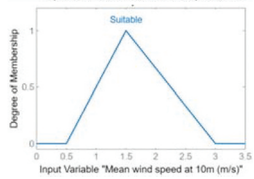
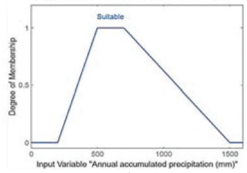
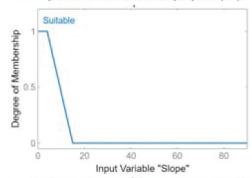
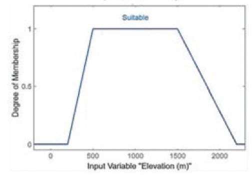
Variable	Suitability threshold	Membership function	Membership function plot
GHI	<1100 kWh/m^2	$\mu(x) = \begin{cases} 0, x < 1100 \\ 1 - \frac{1500-x}{400}, 1100 \leq x < 1500 \\ 1, x \geq 1500 \end{cases}$	
Temperature	$\geq$ 35000 ℃	$\mu(x) = \begin{cases} 1, x < 5000 \\ \frac{35000-x}{30000}, 5000 \leq x < 35000 \\ 0, x \geq 35000 \end{cases}$	
Wind speed	<0.5 m/s and $\geq$ 3 m/s	$\mu(x) = \begin{cases} 0, x < 0,5 \\ \frac{1,5-x}{1}, 0.5 \leq x < 1,5 \\ 1, x = 1,5 \\ \frac{3-x}{1,5}, 1,5 < x < 3 \\ 0, x \geq 3 \end{cases}$	
Precipitation	<200 mm and ≥ 1500 mm	$\mu(x) = \begin{cases} 0, x < 200 \\ 1 - \frac{500-x}{300}, 200 \leq x < 500 \\ 1, 500 \leq x < 700 \\ \frac{1500-x}{800}, 700 \leq x < 1500 \\ 0, x \geq 1500 \end{cases}$	
Slope	≥15°	$\mu(x) = \begin{cases} 1, x < 1 \\ \frac{15-x}{11}, 1 \leq x < 15 \\ 0, x \geq 15 \end{cases}$	
Elevation	<0 m and ≥ 2200 m	$\mu(x) = \begin{cases} 0, x < 0 \\ 1 - \frac{500-x}{500}, 0 \leq x < 500 \\ 1, 500 \leq x < 1500 \\ \frac{2200-x}{700}, 1500 \leq x < 2200 \\ 0, x \geq 2200 \end{cases}$	

Table 2. Reclassification of land use map.

Class Id	Class name	Score
1	Artificial	3
2	Wheat	4
3	Rapeseed	4
5	Maize	4
7	Sunflower	4
8	Soybeans	4
9	Other crops	4
10	Forest	1
11	Grassland	5
12	Bare land	5
13	Water	1
14	Wetland	1
15	Barley	4
18	Gardens, parks, low trees	2
19	Grape	4
22	Non Cultivated	5

Table 3. Fuzzy linguistic variable for the "Suitability" fuzzy set.

Range	Linguistic variable
<0.2	Very low suitable
0.2–0.4	Low suitable
0.4–0.6	Moderate suitable
0.6–0.8	High suitable
>0.8	Very high suitable

Weighting coefficient determination using pairwise comparison method

Description of the method

Since climate, topographic factors, and land-use have varying degrees of importance in determining the suitability of areas for solar power installations, it's necessary to establish weighting coefficients for each of these parameters. To determine these weighting coefficients, we employ a pairwise comparison method derived from the Analytical Hierarchy Process (AHP).

The AHP method, developed by Thomas Saaty, is based on using pairwise comparison matrices to determine the relative importance of different variables. The nine-point scale described in Table 4 is utilized to facilitate comparisons between these variables, following Triantaphyllou et al. (1994). The values on this scale range from 1 to 9, where 1 signifies equal importance of the variables and 9 indicates an extremely strong preference for one variable over another.

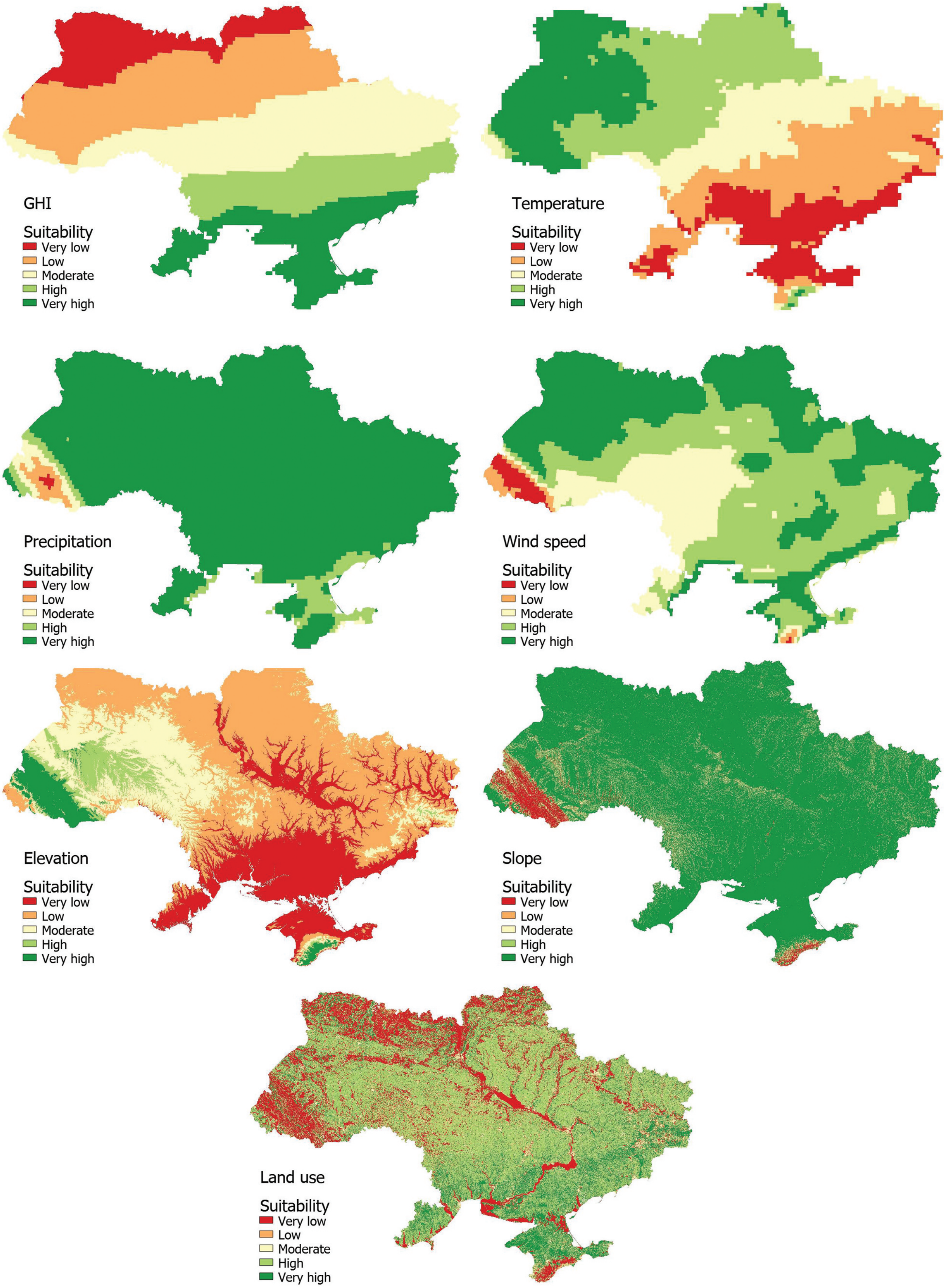


Figure 15. Fuzzy maps.

Table 4. The Fundamental Scale for Pairwise Comparisons.

Importance Level	Definition	Explanation
1	Equal Importance	Two actions contribute equally to achieving the goal
3	Weak importance of one over the other	Experience and judgment slightly favor one action over another
5	Essential or strong importance	Experience and judgment strongly favor one action over another
7	Demonstrated importance	Preference for one action over another is very strong. Its superiority is nearly evident
9	Absolute Importance	Evidence in favor of preferring one action over another is overwhelmingly preferred
2, 4, 6, 8	Intermediate values between the two adjacent judgements	Situation where a compromise decision is needed, determined between neighboring values

As a result of comparing each of the criteria with each other, we get a matrix of pairwise comparisons, which is described by the following formula:

$$A = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & \cdots & a_{2n} \\ \cdots & \cdots & \ddots & \cdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{bmatrix} \quad (2)$$

where:

- A – is the pairwise comparison matrix,
- a_i - is the importance level,
- n – is the number of criteria

To determine the weighting coefficient for each criterion using the matrix of pairwise comparisons, it is first necessary to calculate the geometric mean for each variable (geometric mean in rows) according to formula 3:

$$GM_i = \sqrt[n]{\prod_{j=1}^{n} a_{ij}} \quad (3)$$

where:

- GM_i - is the geometric mean for the i-th variable (criterion).
- a_{ij} - is the elements of the pairwise comparison matrix.
- n - is the number of criterion.

Then, the resulting values are normalized using formula:

$$W_i = GM_i / \sum_{1}^{n} GM_i \quad (4)$$

The normalized values of the geometric means is the weight coefficients for each criterion.

To complete the matrix of pairwise comparisons, experts with extensive knowledge and experience in the relevant field are engaged. In the context of this study, the experts were professionals who specialize in the installation of solar power plants.

Even with highly qualified experts, incorporating their assessments can lead to incorrect results due to human errors. To identify potential inaccuracies and ensure objectivity in expert comparisons, there is a method for checking the level of inconsistency widely known as the consistency ratio (CR). The CR serves as a tool for quality control of expert evaluations and can uncover cases where experts provide contradictory or incorrect responses.).

CR is calculated using the following formula:

$$CI = (\lambda max - n)/(n - 1) \quad (5)$$

$$CR = CI/RI \quad (6)$$

where:

- CI - consistency index;
- n - is the number of criteria.
- λmax- specifies the largest correct number of the matrix.
- RI - table value based on the number of criteria, so-called random index.
- CR - consistency ratio value.

The CR value is compared to a certain consistency threshold. Saaty (1990) suggests that the CR value

Table 6. CR of the obtained pairwise comparisons matrix.

λmax	CI	RI	CR
7,2657	0,0443	1,3200	**0,0335**

Table 5. The pairwise comparisons matrix obtained from authors' and experts' judgments.

	GHI	Temperature	Precipitation	Wind Speed	Elevation	Slope	Land use	GM_i	W_i
GHI	1,00	2,00	5,00	6,00	5,00	2,00	4,00	3,04	0,33
Temperature	0,50	1,00	4,00	4,00	3,00	2,00	2,00	1,92	0,21
Precipitation	0,20	0,25	1,00	2,00	2,00	0,33	0,50	0,62	0,07
Wind	0,17	0,25	0,50	1,00	0,33	0,20	0,33	0,33	0,04
Elevation	0,20	0,33	0,50	3,00	1,00	0,25	0,25	0,48	0,05
Slope	0,50	0,50	3,00	5,00	4,00	1,00	2,00	1,63	0,18
Land Use	0,25	0,50	2,00	3,00	4,00	0,50	1,00	1,06	0,12
Sum	2,82	4,83	16,00	24,00	19,33	6,28	10,1	9,08	1,00

should be less or equal to 0.1. If CR exceeds this threshold, the matrix is considered inconsistent, and it's necessary to review or adjust the values in the pairwise comparison matrix.

Calculating weighting coefficients

1. To fill out the matrix of pairwise comparisons, we used the results of a survey of experts in the field of solar energy (Prieto-Amparán et al., 2021; Tafula et al., 2023; Taoufik et al., 2021). Table 5 taken into account in this study to determine the suitability of land for the installation of solar power plants.

Analyzing the pairwise comparison matrix, GHI, Temperature, and Slope emerge as the most influential criteria for selecting solar power plant locations, as they possess relatively higher values compared to others. Precipitation, Wind Speed, and Elevation hold less significance in this context, while Land Use demonstrates moderate importance in the site selection for solar power plants.

To verify the consistency of the obtained matrix, we calculate the CR using exceptions 4–5. As indicated in Table 6, the CR is determined to be 0.0335.

This value signifies the consistency of the obtained matrix, thus enabling the utilization of the resulting weight coefficients for conducting accurate subsequent calculations.

Weighted sum model

After standardizing the criteria values using fuzzy logic and determining the weight coefficients for each criterion through pairwise comparisons, the subsequent and final step of the process of selecting the optimal location for solar power stations is the application of the weighted sum model (WSM).

WSM is the sum of the weighted standardized criteria in the suitability analysis, which is described by formula 7:

$$S_i = \sum_{i=1}^{n} Criteria_i * W_i \tag{7}$$

where:

- *Criteria* - is a parameter standardized with the help of fuzzification used to select the location of solar power plants in the given investigat
- W_i - is the weight coefficient assigned to criterion through pairwise comparisons (Table 5)
- n - is the number of criteria
- S_i – is the suitability index

Thus, we get a map of the suitability of territories for the installation of solar power plants, the values of pixels on which will vary in the range 0–1, where 1

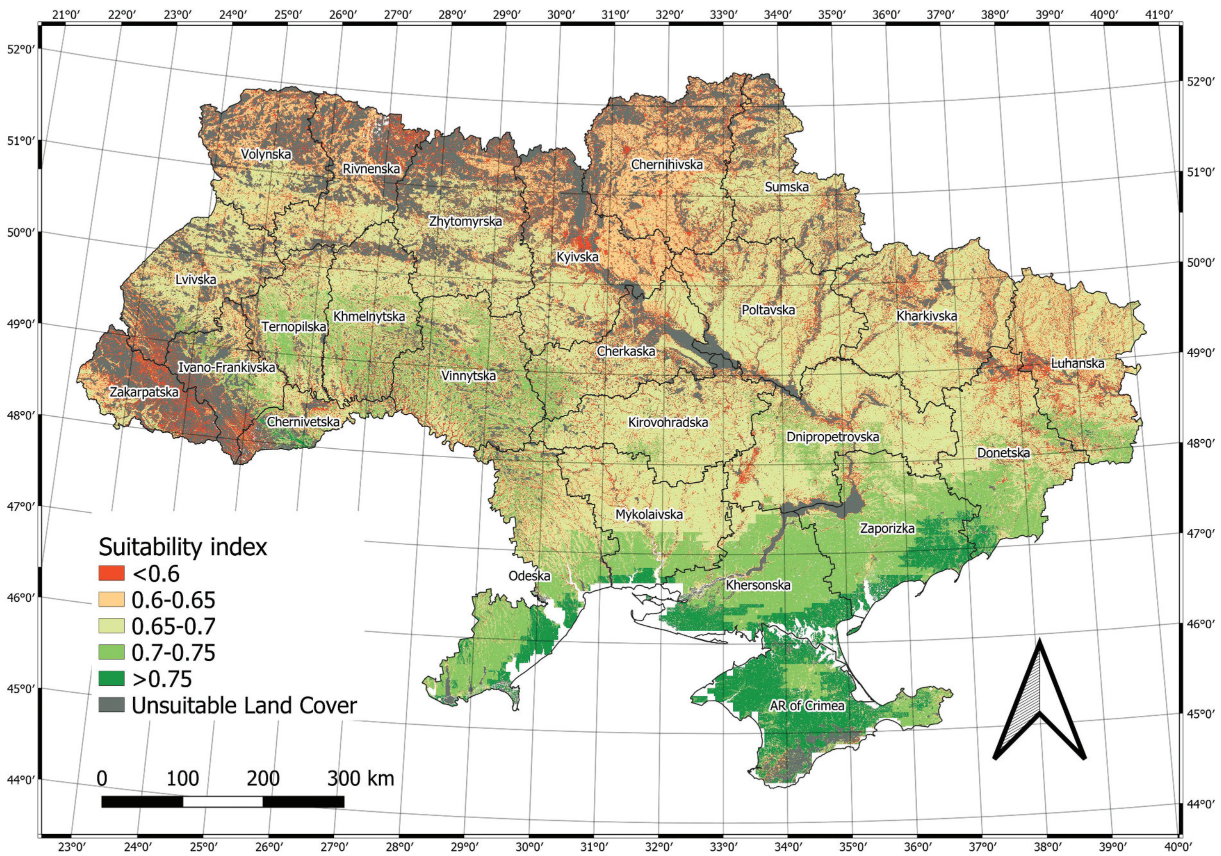


Figure 16. Land suitability map for placement of solar power plants.

means ideal suitability, and 0 - an absolutely unsuitable territory.

Considering that wetlands, rivers, and dense forests are inherently unsuitable for the installation of solar power stations due to their specific characteristics and ecological importance, we completely exclude these areas from the resulting map using formula 8:

$$Si = Land_{restriction} * \sum_{i=1}^{n} Criteria_i * W_i, \qquad (8)$$

where $Land_{restriction}$ is a binary land cover classification map in which wetlands, rivers, and forests are 0 and all other classes are 1.

Therefore, the final suitability map displays only the locations that are truly suitable for the installation of a solar power station.

Results

Evaluation of the land suitability of Ukraine for the installation of solar power plants

As a result of our research, Figure 16 illustrates the land suitability map for the installation of solar power plants. To provide a more detailed representation of land suitability for solar power stations, we have divided this map into uneven intervals, allowing us to clearly delineate different suitability zones.

As evident from this map, almost the entire territory of Ukraine has a land suitability index for the installation of solar power plants above 0.55, indicating the high energy production potential of country. The exception is the area with the Carpathian Mountains, which limit the impact of sunlight for efficient solar panel operation due to complex steep terrain and significant precipitation. Additionally, it can be observed that in the Carpathian region and in the Polissia area, there are many territories that are completely unsuitable for setting up solar power stations due to the characteristics of the soil cover – dense forests prevail here.

The land suitability index for establishing solar power stations increases from north to south and reaches the highest values (above 0.75) on the Crimean Peninsula, partly in the Odessa, Mykolaiv, Kherson, and Zaporizhia regions.

In the central part of Ukraine, the suitability of territories for solar power station placement is predominantly within the range of 0.65–0.7. Interestingly, in the central-western regions, the suitability index is higher. Specifically, in the Chernivtsi, Vinnytsia, Khmelnytskyi, and Ternopil regions, it rises to 0.7–0.75. On the other hand, in the eastern regions, there

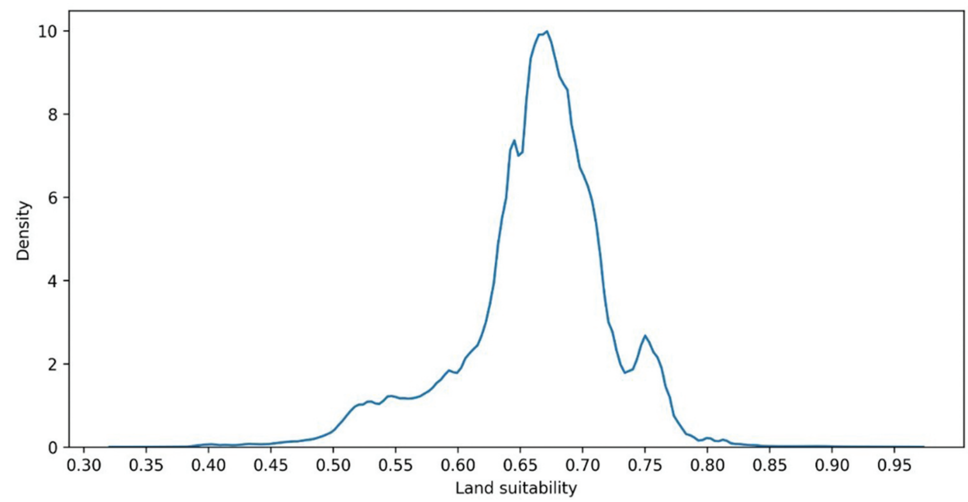
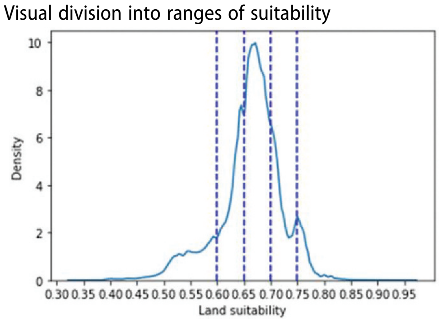


Figure 17. Distribution of the suitability index.

Table 7. Division of zones in the appropriate interval of the suitability index into fuzzy linguistic variables.

Suitability Index	Linguistic variable	Visual division into ranges of suitability
<0.6	Very low suitable	
0.6–0.65	Low suitable	
0.65–0.7	Moderate suitable	
0.7–0.75	High suitable	
>0.75	Very High Suitable	

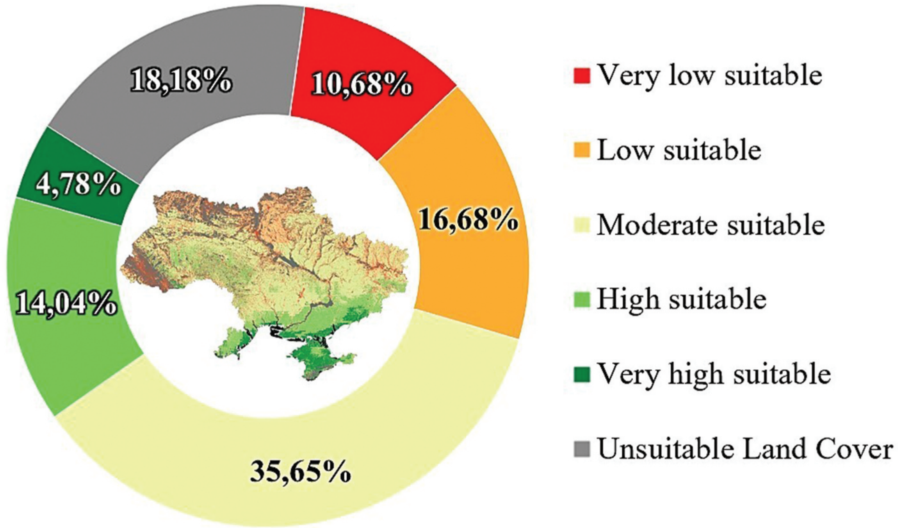


Figure 18. Distribution of areas of Ukraine according to the land suitability index for the installation of solar power plants.

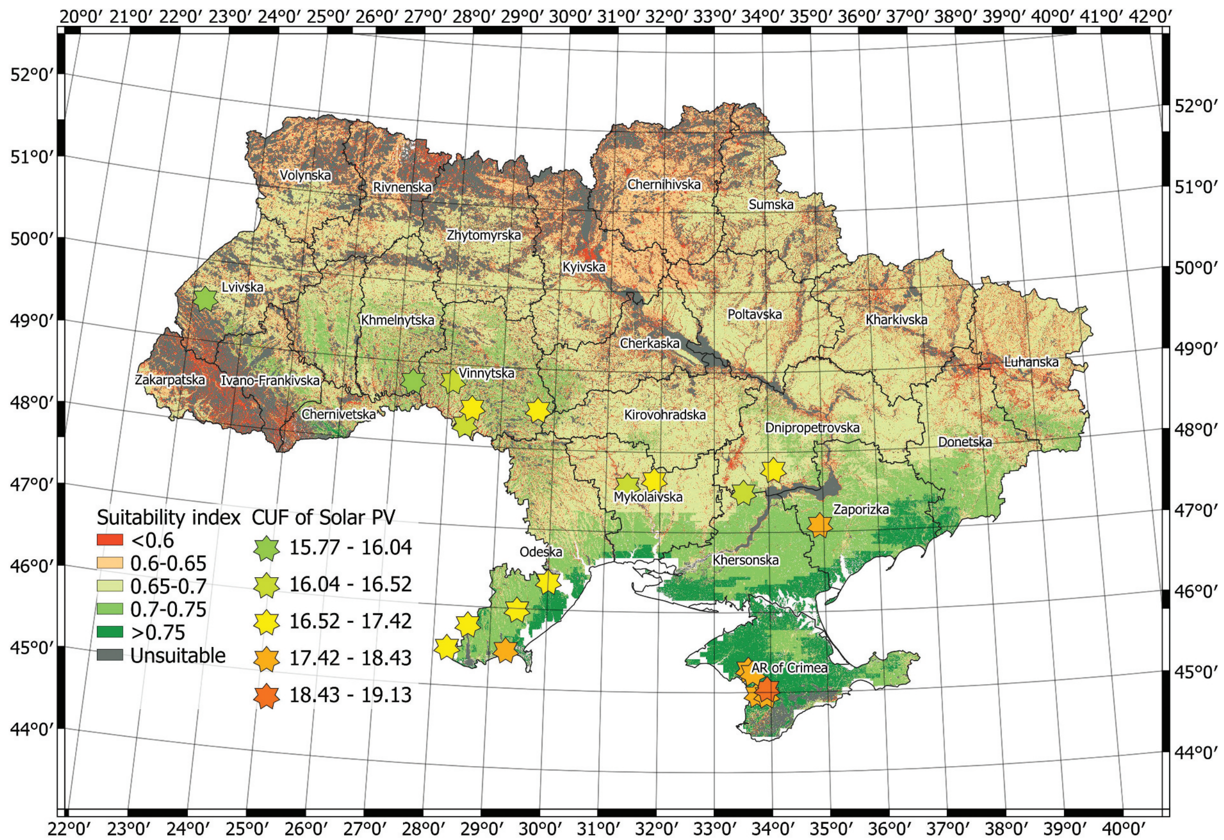


Figure 19. Geographical distribution of the Capacity Utilization Factor of solar power plants in Ukraine.

are areas with suitability ranging from 0.55–0.65. This can be explained by the fact that in the west of Ukraine, temperatures are lower than in the east, with almost the same intensity of GHI.

In the northern territories of Ukraine, the suitability indicator is even lower but does not fall below 0.55, indicating a moderate level of suitability for effective solar power station operation.

To understand the distribution of the suitability index across the country in a numerical range, we have constructed a density plot as shown in Figure 17.

From this graph, it is evident that the land suitability for solar panel installation spans approximately from 0.45 to 0.85, with a peak around 0.65.

Based on the distribution, we have identified 5 main intervals within which the suitability index lies.

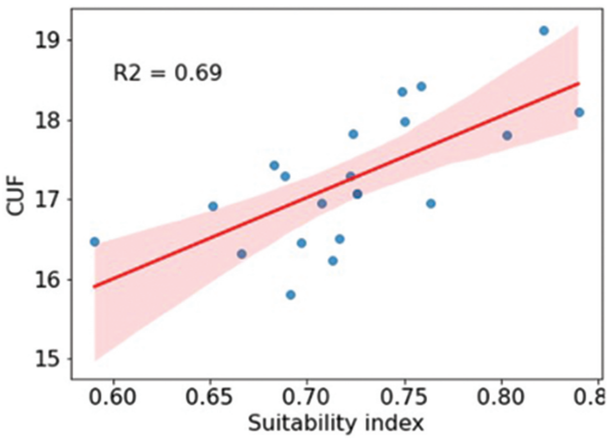


Figure 20. Plot of the relationship between Capacity Utilization Factor and land suitability index for placement of solar power plants.

Using these values, we have created corresponding linguistic variables for the fuzzy land suitability set, with parameters as shown in the Table 7 below:

As can be seen from the results shown in Figure 18, there is a certain percentage of land with a very low (10.68%) and low (16.68%) suitability index, as well as completely unsuitable plots (18.18%) due to the presence of water bodies and forests.

At the same time, more than a third (35.65%) of the land area of Ukraine has a promising average suitability index. Zones with high and very high suitability account for 14.4% and 4.78% of the territory, respectively, which provides an opportunity for the development and effective use of solar energy on the territory of Ukraine.

To validate the developed land suitability map, we utilized data from 21 solar power stations in Ukraine from the Global Power Plant Database provided by the World Resources Institute. These stations have varying nominal capacities and are located in different regions of Ukraine. For each of them, we calculated the Capacity Utilization Factor (CUF) to assess productivity, using available data in the database on their annual generation and nominal capacity (Mhundwa et al., 2020). The results showed that CUF ranges from 15.74 to 19.12 for the Sambir II station in the Lviv region and the Rodnikova Solar Power Station in Crimea, respectively. As shown in Figure 19, the highest CUF is recorded in southern Ukraine, decreasing from south to north and from west to east. These observations are in good agreement with the suitability map constructed in this study.

Furthermore, we determined the Pearson correlation coefficient between the CUF of solar power stations in Ukraine and the land suitability index obtained in this research (Figure 20). A high level of correlation between these variables was found, equal to 0.66, confirming the significance of the land suitability map we developed for the placement of solar power plants in Ukraine.

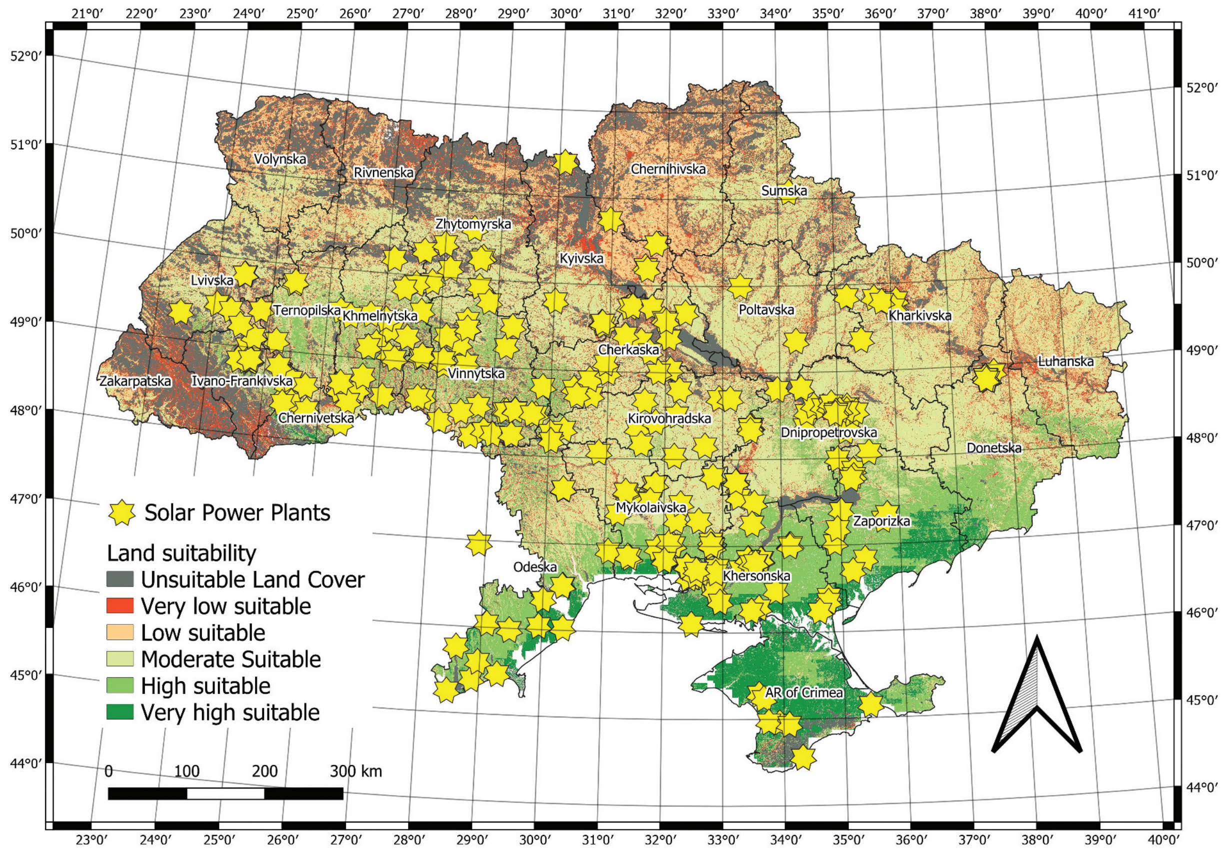


Figure 21. Location of the most powerful solar power plants in Ukraine.

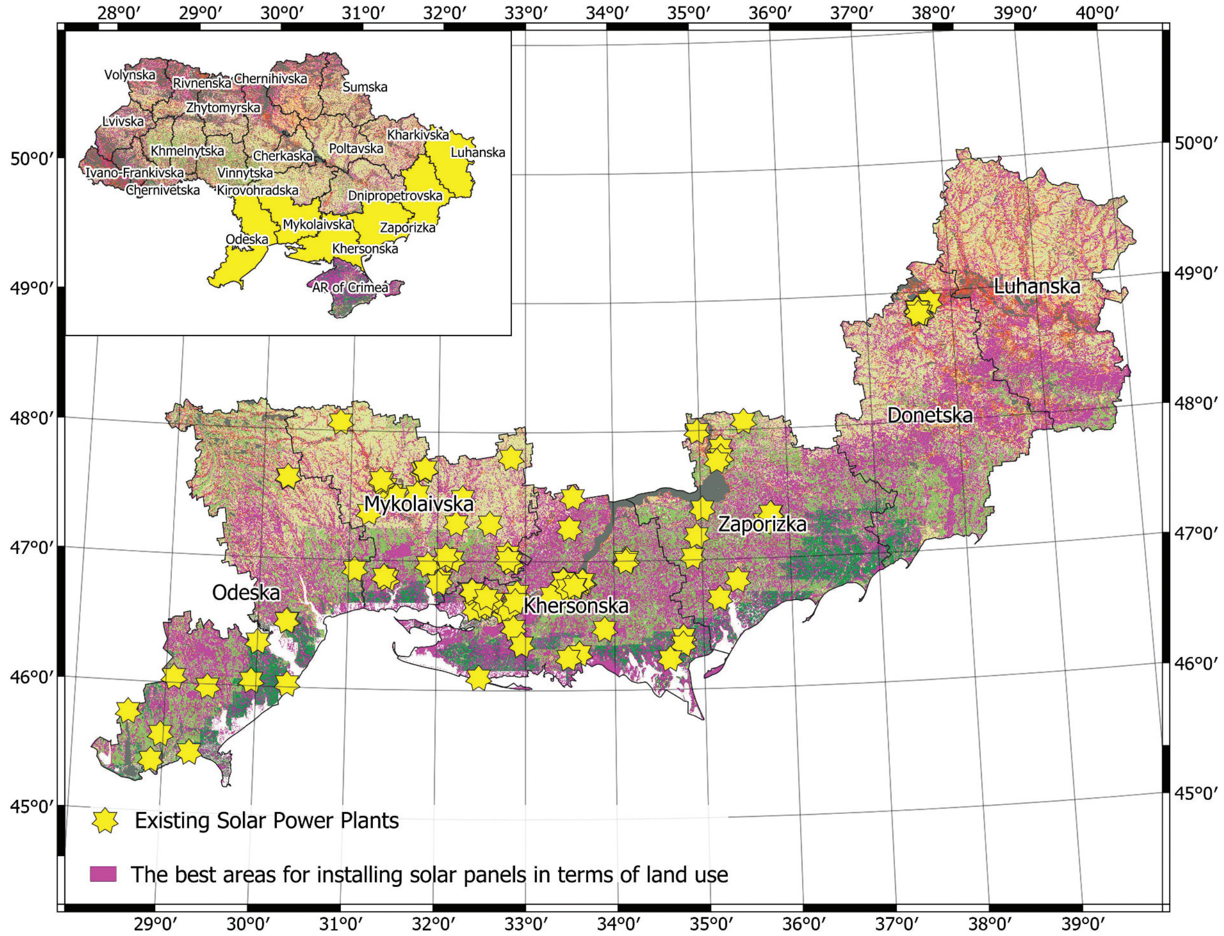


Figure 22. Identifying the best areas for installing solar panels in terms of land suitability and land use.

Assessment of the optimal location of already installed solar power plants on the territory of Ukraine and the search for potential places for the installation of new solar farms

Using the obtained suitability map, we decided to evaluate the optimality of the location of the most powerful power plants already installed on the territory of Ukraine and to find areas where efficient solar farms can potentially be installed.

To assess the optimal placement of the largest solar power plants already installed (298 objects) on the territory of Ukraine, we used information on the location of solar farms from Wikimapia.

Figure 21 shows that the largest solar power plants are located mainly in the south, in central and western Ukraine, which corresponds to areas with very high, high or moderate suitability.

In the north of Ukraine, in turn, there are almost no large solar power plants, which is most likely caused by taking into account unfavorable climatic features. However, the potential of some areas remains unrealized. For example, in the Poltava region, where the suitability of the territories is moderate, there are practically no solar power plants. A similar situation is observed in Dnipropetrovsk, Kharkiv, Donetsk and Luhansk regions. Underutilized territories with a high and very high suitability index are Zaporizhzhia and the north of Odesa Oblasts. Therefore, in the future, it is worth paying attention to these areas and considering the possibility of installing solar power plants there in order to use the potential of these areas for the efficient production of solar energy.

To determine the suitability of these areas not only according to our suitability map but also directly in terms of land use, we have identified territories within the Odessa, Mykolaiv, Kherson, Zaporizhia, Donetsk, and Luhansk regions that correspond to the most appropriate land cover classes for the installation of solar power stations – classes of uncultivated fields, bare land, or grassland.

As evident from Figure 22, these regions are not only well-suited for solar panel installation considering the climate and topography but also possess a significant number of available plots, ideally suited for the construction of solar power plants in terms of land use.

These regions hold great promise for the development of a sustainable and environmentally clean energy system in Ukraine, leading towards achieving energy independence and opening up new prospects for the country's enduring growth and advancement.

Discussion

Our research uses multi-criteria analysis and fuzzy logic to assess the suitability of the territory of Ukraine for the placement of solar power plants. The use of fuzzy logic provides us with a number of numerous advantages, including increasing the flexibility and accuracy of the model. In particular, our approach has certain parallels with the methodology used by Seyedmohammadi and Navidi (2022), who determined the suitability of land for growing wheat using the ANP-fuzzy method and traditional parametric methods. They found that the ANP-fuzzy method provides a more accurate assessment of land suitability, as confirmed by the coefficient of determination (R2) between wheat yield and land suitability index.

In addition, Seyedmohammadi et al. (2018) integrated ANP and fuzzy set techniques to assess land suitability for irrigated maize crops and showed that the fuzzy logic-based method proved to be a better method than the square root method.

In our study, we similarly found a strong positive correlation between the CUF of solar power plants and the calculated land suitability index, which highlights the benefits of applying fuzzy logic and multi-criteria analysis.

Although our methodological approach to assessing the suitability of the territory of Ukraine for the placement of solar power plants proved to be effective, it has certain limitations that should be taken into account for further improvement. In particular, our work focuses on climatic, topographic and land-use criteria, but ignoring economic and social factors can limit understanding of the financial and social viability of solar energy projects.

It is important to include analysis of economic factors, distance to roads and power lines, as was done in the study by Colak et al. (2020) and Zambrano-Asanza et al. (2021) as location near existing grids is critical for optimal energy distribution.

In addition, public perception and environmental impact are important to ensure the acceptability and sustainability of solar projects. A study by López-Bravo et al. (2024) emphasizes the importance of social support in renewable energy projects.

It's worth noting that the study mentions but does not account for the potential influence of political factors, especially considering the ongoing conflict in Ukraine. The construction and operation of solar power plants can become the object of military operations, which threatens the quality of performance and the safety of workers.

Thus, in further research, we should focus on improving the methodology, including economic, social and political aspects. This will contribute to the creation of a more comprehensive and adaptive framework for the sustainable introduction of solar energy in Ukraine.

Conclusion

The analysis conducted in this study demonstrates the significant potential for solar power utilization across the territory of Ukraine. The comprehensive methodology employing satellite observations, multi-criteria analysis, fuzzy logic, and weighted linear combination allowed for an effective delineation of optimal zones for constructing solar farms.

The resulting suitability map indicates that the southern regions, particularly the Crimean Peninsula, possess the greatest promise for solar power station placement, with a suitability index exceeding 0.75. However, even in the northern territories, the index remains moderately high, not falling below 0.55. Overall, more than 50% of Ukraine's land area shows moderate to very high suitability.

Through evaluating the locations of existing major solar power plants, it was determined that many are situated in appropriate regions. However, certain areas, like the Poltava and Donetsk Oblasts, are currently underutilized despite suitable conditions for solar farm construction. Our identification of territories possessing high suitability and ideal land cover indicates specific zones in the Odessa, Mykolaiv, and Zaporizhia regions that could be leveraged for effectively harnessing solar energy.

The methodology and findings presented facilitate the selection of optimal sites across Ukraine for installing solar power stations that will ensure maximum productivity. The approach developed can serve as a valuable tool for supporting the expansion of solar energy and strengthening Ukraine's power system. Utilizing the country's extensive solar potential will be critical for achieving energy independence, aligning with European Green Deal objectives, and enabling sustainable national growth.

In the future, there are plans to expand the research taking into account also economic, social and political criteria and, based on the obtained suitability map, utilize regression analysis to determine the potential amount of electricity that future solar power stations could generate. This approach will enable us to conduct a more detailed assessment of the territories and identify the optimal locations for establishing robust and productive solar power stations. 1

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Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

The data that support the findings of this study are available from the corresponding author, Sofiia Drozd, upon reasonable request.

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