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A Geographic Information System (GIS)–CRiteria Importance Through Intercriteria Correlation (CRITIC) Framework for Selecting Solar Photovoltaics Sites: A Case Study

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ABSTRACT

The energy transition in Lithuania requires a rapid increase in renewable electricity generation, but in a way that does not interfere with protected landscapes, agricultural use of the territory, settlements, and infrastructure planning. The current study proposes developing a GIS–CRITIC model to identify potential locations for large-scale photovoltaics in Lithuania. The proposed model combines environmental and land-use factors, topography, infrastructural accessibility, and solar radiation availability. The fuzzy membership function approach is used to standardize spatial layers, and the CRITIC approach is used to weight spatial criteria based on their spatial variability and correlation. A final suitability map for photovoltaic development is calculated using the weighted linear combination approach in spatial multicriteria decision analysis and tested with the equal-weighting sensitivity scenario. The analysis shows that the largest impact on site suitability comes from criteria related to infrastructural accessibility, including distance to settlements, road accessibility, and proximity to power lines. The high and very high suitability areas cover only 210.32 km², accounting for 0.33% of the classified area. Priority areas are located mainly in the western, south-western, and central parts of Lithuania, close to Klaipėda, Tauragė, and in parts of Kaunas county. Assuming utility-scale PV plants require 40 MW/km², these areas could hold 8.41 GW of capacity and generate around 8.11 TWh/year of electricity. The sensitivity analysis has confirmed that the main finding remains valid since even under the equal-weighting scenario, suitable areas remain scarce.

1 | Introduction

Due to technological advancements and increased energy demand, the world faces sustainability challenges [1, 2]. The decreasing supply of fossil fuels and their overconsumption are the primary drivers of rising atmospheric carbon dioxide (CO₂) concentrations, which result in the global climate crisis [3]. International frameworks such as the Paris Agreement (2015) and the European Green Deal have been implemented to create a clear path for transitioning from fossil fuels to clean,

renewable energy sources [4, 5]. Specifically, the European Green Deal aims to reduce emissions by 55% by 2030 and 90% by 2040 [6, 7].

Solar energy is widely considered one of the cleanest and most accessible sources of power currently available [8, 9]. The primary technology used to harvest solar energy, Solar Photovoltaics (PV), has been used significantly over the last decade [10, 11]. According to the International Energy Agency (IEA),

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solar PV has become the fastest-growing renewable energy technology, with a record 25% increase in electricity generation in 2023. Global installed capacity is expected to triple by 2030, meaning PV technology will surpass coal as the world's largest power source [12, 13]. The expansion of solar infrastructure is now undeniably linked to broader national energy security and societal progress [14, 15].

However, there are different limitations to solar farm construction worldwide. The performance and profitability of a solar project depend heavily on its geographical location [9]. Recent academic literature on solar site selection emphasizes that a poorly chosen site can lead to low energy production, high construction costs, and long-term land-use issues [16–19]. For instance, sites with high solar radiation might be considered unsuitable if they are too far from power lines, thereby increasing grid connection costs [20]. Moreover, sites that appear technically suitable might be located on high-value farmland or in protected forests, thereby creating environmental and social issues [21]. Therefore, site selection and the inclusion of multiple criteria in the evaluation are core components of solar PV project initiation. The locations need to offer the potential to maximize energy yield while minimizing costs and protecting the environment [17]. The objective is to balance selecting an area that maximizes energy output with minimizing capital expenditures and ecological impact [16, 17, 19]. This issue is particularly relevant for Lithuania, where renewable energy expansion is closely connected to national energy independence and energy security objectives. At the same time, the development of utility-scale solar PV is constrained by the country's land-use structure, including agricultural land, forests, wetlands, protected areas, settlement patterns, and the distribution of infrastructure. Therefore, a national-scale spatial assessment is needed to identify locations where solar PV expansion can be aligned with environmental protection, land-use regulation, and energy-system planning.

Taken together, there is a clear need for a decision-support framework that integrates high-resolution topographic, climatic, and infrastructural data with policy constraints and construction suitability tailored to Lithuania's regulatory environment. This study aims to address the aforementioned needs by developing a comprehensive, Geographic Information Systems (GIS)-based objective framework for identifying optimal utility-scale solar PV sites in Lithuania. To achieve the aim, the following objectives were set:

- Establishing a rigorous constraint model to filter out restricted areas in line with Lithuanian national policy and international environmental standards.
- Using the Criteria Importance Through InterCriteria Correlation (CRITIC) method to objectively weigh the included criteria and reduce dependence on subjective expert-based weighting.
- Integrating these weights with high-resolution spatial data, including Global Horizontal Irradiance (GHI), slope, surface roughness, and proximity to highways, railways, and power lines, to create a high-resolution national suitability map.
- Finally, analyzing the resulting suitability patterns in the context of Lithuania's energy goals provides a data-based

tool for policymakers and investors to optimize land use for PV farms.

The paper is structured as follows: Section 2 presents a literature review. Section 3 presents the methodology; Section 4 presents the results; Section 5 presents the sensitivity analysis; and Section 6 presents the discussion. Section 7 presents conclusions and policy implications.

2 | Literature Review

GIS, combined with Multi-Criteria Decision-Making (MCDM) methods, has been widely applied to solar PV site suitability studies. These methods allow simultaneous evaluation of qualitative and quantitative spatial criteria for selecting solar farm sites [22–24]. GIS serves as a tool for processing and analyzing multiple layers of information, such as GHI, land slope, and proximity to roads. It is commonly used to select solar farm sites at the local, national, and global levels [11, 25, 26]. Moreover, the MCDM method serves as a powerful analytical tool for combining qualitative and quantitative spatial criteria, ranking the most important indicators, and providing clear guidance for site selection [21, 27–30].

However, over the last few decades, decision-making has been dominated by the Analytic Hierarchy Process (AHP), which relies on expert opinion [25, 31–36]. While AHP provides a structured hierarchy, its primary weakness is its reliance on expert subjectivity. Human error and bias can lead to inconsistencies, especially when handling large volumes of data for national-scale assessments. Therefore, to address this gap, this paper uses the CRITIC method, which weights objective criteria based on data variability and intercriteria correlations, thereby eliminating the risk of human error and bias in the research. This makes the selection process more transparent and accurate. Table 1 summarizes selected GIS-MCDM studies on solar PV site suitability.

2.1 | Research Gap and Contribution

Lithuania has set a goal of achieving total energy independence [38, 39]. In 2025, the country achieved independence from importing gas, oil, and electricity from Russia. However, Lithuania's physical geography presents unique challenges for utility-scale solar development [40]. Strict environmental legislation, such as the 30% tree-canopy-cover threshold for forest protection, limits the available land for energy projects [41]. Despite numerous studies on solar farm site selection across regions, a significant research gap remains for the Baltic states, particularly Lithuania. Existing studies on solar energy development and the clean energy transition in the Baltic region remain limited in their integration of detailed spatial constraints for utility-scale solar PV site suitability assessment. Most existing models for the region lack the high-resolution data integration needed to account for specific local constraints, such as the detailed land-cover classifications required by Lithuanian law [42–44]. Moreover, the application of objective weighting methods, such as CRITIC, in the Lithuanian context has not been explored in prior literature. In addition, many GIS-based solar suitability studies present final suitability maps

TABLE 1 | Summary of selected GIS-MCDM studies on solar PV site suitability.

References	Country/region	Method	Main focus	Limitation relevant to this study
Colak et al. [20]	Türkiye	GIS-AHP	PV site selection using technical and infrastructure criteria	Expert-based weighting
Günen [35]	Türkiye	GIS-AHP	Solar PV farm suitability assessment	Limited objective weighting
Vagiona et al. [21]	Greece	GIS-MCDM	Offshore solar farm site selection	Different spatial and regulatory context
Demir et al. [25]	Türkiye	GIS-AHP	Large-scale PV farm site selection	Expert-driven weighting
Lindberg et al. [37]	Sweden	GIS and power-flow analysis	Utility-scale PV planning in a European context	Local/municipal scale
Rogna [19]	Italy	GIS screening	Large-scale solar plant screening	Limited MCDM weighting comparison
Present study	Lithuania	GIS-CRITIC-WLC	National-scale utility PV suitability with objective weighting and energy-potential estimation	—

without quantifying the area of each suitability class or translating spatial outputs into indicative installed capacity and electricity generation potential.

Therefore, the contribution of this study is threefold. First, it applies the CRITIC method to derive objective criterion weights based on spatial variability and intercriterion relationships. Second, it integrates Lithuanian environmental, agricultural, land-cover, topographic, solar-resource, and infrastructure constraints into a national-scale GIS suitability framework. Third, it quantifies the final suitability classes and estimates the indicative installed capacity and electricity-generation potential of the most suitable areas.

3 | Methodology

This research applies GIS-MCDM methodology to identify optimal site locations for PV farm project development in Lithuania. To ensure the technical and legal viability of the identified sites, the study follows the process of identifying suitability criteria based on the literature, establishing a policy-constraint exclusion model, and applying the CRITIC method. This approach moves beyond the subjectivity of expert-based models and keeps decision-making grounded in a nationally representative statistical data set.

3.1 | Spatial Criteria and Data Description

The criteria were selected after a rigorous review of recent utility-scale solar PV siting literature. The specific regulatory landscape of the Baltic region was also taken into account when selecting the criteria. The selected parameters are divided into four groups: environmental constraints, topographic factors, infrastructure proximities, and resource potential.

The thresholds for membership functions and buffer distances were established through a review of existing research on the

suitability of GIS for solar PV installation. Because previous literature reported a range of threshold values depending on geographical location, regulations, scale, and study type, a single set of values could not be applied uniformly in all cases. Therefore, the threshold values established by previous research were considered in light of Lithuania's geography, settlement patterns, infrastructure network, land-use system, environmental conditions, and other country-level conditions. From the range of values, only those that were technically feasible and relevant to Lithuania were selected.

3.1.1 | Land Cover and Environmental Constraints

Land cover is a crucial factor in solar PV site selection, ensuring that the expansion of solar farms does not harm the ecosystem or conflict with other essential land uses [45]. Ideal land covers are flat, with less shadow and greater sensitivity, to minimize environmental impact and avoid higher-grade agricultural lands [37]. Thus, the excluded land cover types in this research include built-up urban areas, rivers, wetlands, permanent water bodies, and other land surfaces unsuitable for solar PV farm development. Utility-scale PV is unsuitable for such surfaces due to environmental concerns, flood and erosion risks, and technical feasibility [46, 47].

However, noncultivated cropland, grassland, shrubland, and bare/sparsely vegetated land were retained as potentially suitable land-use layers, as these land-cover types remain feasible for solar PV development and impose fewer physical constraints. Additionally, selecting agricultural land for solar PV can be connected to further issues with land competition and social constraints [48, 49], which are addressed through additional proximity/constraint layers in the suitability model.

Moreover, the methodological strength of this study lies in the use of a 30% tree canopy cover threshold. Aligning with internationally accepted definitions from the FAO (Food and Agriculture Organization of the United Nations), UNFCCC, and

Copernicus, this rule ensures that only sparsely vegetated or degraded lands are considered for solar PV development [41, 50, 51]. This rule allows forests to be preserved while accurately identifying legally and environmentally available open land for PV infrastructure.

Additionally, farmland is usually considered one of the most suitable land cover types due to its flatness and exposure to the sun [52]; however, in this model, its use is restricted to protect national food security. By excluding active agricultural zones, specifically farmland, meadows, orchards, vineyards, and plant nurseries, this study ensures that solar PV system development occurs only on noncompeting land types, such as shrublands or bare soil.

Finally, protected areas and nature reserves are strict exclusion zones due to their ecological sensitivity and legal protection concerns [26, 53, 54]. Considering these constraints as binary constraints prevents selecting a site that would cause environmental harm and ensures compliance with national and EU conservation policies.

Although active agricultural lands have not been considered potential sites for utility-scale solar PV to eliminate direct conflict between agriculture and utility-scale PV deployment in this research, this approach is consistent with using only ground-mounted PV installations. With the use of novel technologies like agrivoltaics, solar electricity and agriculture can be combined on the same plot of land. Thus, this assumption of excluding agricultural lands should be considered conservative.

3.1.2 | Topographic Layers: Slope and Roughness

Terrain geometry is a critical factor in determining both the total capital expenditure and the engineering feasibility of the solar PV farm [22]. Land terrain includes the complexity of land structures and the extensive work required for solar PV development. Steeper slopes tend to increase construction costs and increase the risk of self-shading, where rows of PV panels shadow one another and lose efficiency [55, 56]. This study applies a descending fuzzy logic to slope, prioritizing flat or gently inclined surfaces (0%–3%) as fully suitable. Between 3% and 10%, suitability decreases linearly; terrain exceeding 10% is considered unsuitable to ensure maximum operational efficiency.

Slope represents the overall tilt, and terrain roughness indicates micro-topographic irregularities and surface obstacles. High roughness is characterized by uneven terrain, which complicates PV system installation [20, 47]. Smooth terrain is technically preferable to minimize land preparation efforts [57]. Accordingly, a descending linear fuzzy membership function was applied to the roughness layer using Lithuania-specific thresholds. Surfaces with a roughness index ≤ 5 are considered fully suitable (membership = 1), while suitability decreases linearly for values between 5 and 15. Any terrain with a roughness index ≥ 15 is classified as unsuitable (membership = 0).

While flat and moderately sloping terrains are indeed desirable for developing solar PV installations, they might also serve as suitable sites for farming, urban expansion, and other purposes. Therefore, the assessment of the slope criterion is by no means sufficient to reveal the actual availability of land. The present

research only partially resolves this problem by excluding lands already used for agriculture or other purposes.

3.1.3 | Infrastructure and Safety Proximity Layers

Proximity to existing networks is an economic necessity for the development of utility-scale solar PV projects [58–60]. In this study, infrastructure factors are assessed using fuzzy logic to account for safety, legal requirements, and economic needs. A linear scale is used for these distances to allow a gradual transition from unsuitable to highly suitable.

Power line proximity: while proximity to the grid reduces connection costs, safety regulations limit direct connection to transmission corridors [61]. In accordance with European transmission safety guidelines, a 100 m exclusion buffer was applied. Suitability increases linearly between 100 and 1000 m, considered highly suitable due to reduced safety restrictions and land-use conflicts ($\mu = 1$)

$d \leq 100$ m: unsuitable ($\mu = 0$)

$100 < d \leq 1000$ m: suitability increases linearly

$d \geq 1000$ m: highly suitable ($\mu = 1$)

Road proximity: roads are essential for logistics and site accessibility [32]. However, a minimum exclusion buffer of 100 m was applied to account for safety and legal constraints. Beyond this, suitability increases linearly up to 400 m, at which point it reaches high suitability. For a distance d :

$d \leq 100$ m $\rightarrow$ unsuitable (membership = 0)

$100 \text{ m} < d \leq 400 \text{ m} \rightarrow$ suitability increases linearly

$d > 400$ m $\rightarrow$ highly suitable (membership = 1)

Railway proximity: railway corridors are connected to specific safety, vibration, and access-control constraints [62]. Similar to roads, areas within 100 m are considered unsuitable, with suitability increasing linearly up to a 400 m threshold. For a distance d :

0–100 m: unsuitable ($\mu = 0$)

100–400 m: suitability increases linearly

≥ 400 m: highly suitable ($\mu = 1$)

Building proximity: this layer addresses land-use conflicts and social acceptance [63]. Sites within 300 m of a building are considered unsuitable, with suitability increasing gradually up to 700 m. Where x is the distance in meters from the nearest building, the fuzzy membership function $\mu_U(x)$ is defined as:

$$\mu_U(x) = 0, x \leq 300$$

$$\mu_U(x) = (x - 300)/400, 300 < x \leq 700$$

$$\mu_U(x) = 1, x > 700$$

3.1.4 | Resource Potential

GHI is one of the most fundamental parameters in solar energy planning [64]. GHI represents the total radiation incident on a surface horizontal to the ground and is the primary determinant of the site's energy generation potential. In utility-scale projects, GHI directly influences annual energy yield and, therefore, the financial return on investment (ROI) and cost of energy [10, 65, 66]. Moreover, minor variations of GHI can significantly impact the long-term economic viability of a PV farm [67]. In this study, GHI data were treated as a continuous suitability factor, using a linearly increasing membership function to prioritize locations with the highest energy-generation potential. Areas with a $GHI \leq 2.74$ are considered unsuitable (membership = 0). Suitability increases linearly from 2.74 to 2.98, while values ≥ 2.98 are classified as fully suitable (membership = 1), ensuring the model identifies the most efficient solar-harvesting sites. Table 2 summarizes MCDM layers, constraints, and criteria for solar PV site selection.

The proximity criteria used in the present study aim to represent the bare minimum distance required to ensure safety and planning buffers from infrastructure. Therefore, the fuzzy criteria used in this study become more suitable when the minimum exclusion distance is exceeded. However, for certain types of infrastructure, such as power lines and roads, excessive distance can render economic conditions infeasible due to high connection and access costs. The present study does not include an absolute maximum distance exclusion criterion but only partially incorporates distance-based economic feasibility through continuous proximity suitability criteria.

3.2 | Spatial Sampling and CRITIC Implementation

Before starting spatial sampling and weighted-overlay analysis, all data sets were preprocessed using QGIS software. Vector

TABLE 2 | Summary of MCDM layers, constraints, and criteria for solar PV site selection.

Category	Layer/criterion	References
Constraint layers	Natural reserves (Raster)	[45, 56, 61, 68–72]
	Wetlands	
	Agricultural lands	
	Forest	
	Land cover	
	River	
Topographic layers	Slope	[45, 56, 68–74]
	Roughness	
Infrastructure layers	Highways proximity	[61, 63, 68–71, 74, 75]
	Railway proximity	
	Power line proximity	
	Building proximity	
Resource potential	GHI	[10, 56, 65, 67, 71–73]

layers were converted into raster format where necessary, while all spatial layers were projected to the LKS92/Lithuania TM projection system. Data sets were clipped to the Lithuanian national border and standardized to a uniform spatial resolution of about 30.24×30.24 m, the same extent, and a matching grid. Continuous layers, such as GHI, topographic, and proximity rasters, were interpolated bilinearly, while categorical and binary constraint layers were resampled using the nearest-neighbor method to maintain their class values. The slope raster created using the DEM was used as the reference grid for cell size, extent, origin, and alignment. NoData was used for cells beyond the Lithuanian border, while 0 was used for excluded cells inside the country. After standardizing, continuous criteria were converted to fuzzy values between 0 and 1, while binary constraints were set to 0 and 1.

To use the CRITIC method for weight calculation, a representative dataset was created from the continuous suitability layers. Because the CRITIC method uses a numerical decision matrix that contains observations and criteria, the spatial sampling procedure was conducted across the entire study area of Lithuania. Ten thousand random points were generated uniformly within the national boundary using a GIS-based random spatial sampling approach. Random points were chosen because a uniform sampling distribution ensures equal probability of selection at all locations within the study area, minimizing spatial bias and increasing the representativeness of the statistical analysis. The chosen number of 10,000 points was considered sufficient to estimate variability and inter-criteria correlations while maintaining the computational simplicity of the matrix-based approach.

After generating random points, the suitability values for each criterion layer were extracted at each point. Only continuous suitability criteria were used for CRITIC analysis; binary exclusion layers, forests, wetlands, agriculture, rivers, protected areas, and land cover types were used independently as spatial constraints. The six criteria used for CRITIC analysis were:

- slope suitability,
- terrain roughness suitability,
- road proximity suitability,
- railway proximity suitability,
- power line proximity suitability,
- building proximity suitability.

Before extracting values, all raster layers were harmonized with respect to CRS (LKS94/Lithuania TM), resolution, and extent. All criteria were also transformed into fuzzy suitability rasters with values ranging from 0 to 1.

Using GIS raster sampling tools, the suitability value for each criterion was extracted at each point. The result was a spatial decision matrix containing 10,000 observations (rows) and 6 criteria (columns). Each row corresponded to a sampled location, while each column represented a suitability criterion. The constructed matrix was exported as a CSV dataset for further CRITIC analysis. Next, the CRITIC method was used to objectively estimate the relative importance of the selected criteria

purely based on their statistical properties. In contrast to expert-based methods like AHP, CRITIC uses a data-driven approach to assign criterion weights based on their variability and mutual conflict.

At first, all criteria were normalized using min-max normalization. Next, the standard deviation of every criterion was calculated to estimate criterion contrast and spatial discrimination capacity. A criterion with high variability contains more information, since it better discriminates between suitable and unsuitable locations. The standard deviation of each criterion was calculated as follows (Equation 1):

$$\sigma_j = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_{ij} - \bar{x}_j)^2}, \quad (1)$$

where:

- σ_j is the standard deviation of criterion j ,
- x_{ij} is the normalized value of criterion j for observation i ,
- $\bar{x}_j$ is the mean value of criterion j ,
- n is the number of observations.

Next, Pearson's correlation coefficient was determined for all pairs of criteria in order to measure their redundancy and interdependence. High correlation indicates redundancy of information, while low correlation indicates greater independence of information for assessing suitability.

The information content of each criterion was calculated using Equation 2:

$$C_j = \sigma_j \sum_{k=1}^m (1 - r_{jk}), \quad (2)$$

where:

- C_j represents the information content of criterion j ,
- r_{jk} is the Pearson correlation coefficient between criteria j and k ,
- m is the total number of criteria.

Finally, the objective criterion weights were obtained by normalizing the information content values using Equation (3):

$$w_j = \frac{C_j}{\sum_{k=1}^m C_j}, \quad (3)$$

where:

- w_j represents the final normalized weight of criterion j ,
- C_j is the information content value of criterion j .

According to CRITIC, criteria that contain more spatial information are assigned a higher weight. This means that greater variation of a criterion across space and lower correlation with other criteria imply a higher weight for that criterion. High variation implies better discrimination power of the criterion,

whereas low correlation signifies that the criterion provides unique information. Hence, the weight of the CRITIC cannot be treated as an assessment of the expert importance of the criterion in policy making.

3.3 | Weighted Overlay and Final Suitability Map Generation

After calculating objective weights using the CRITIC technique, the suitability map for installing a PV energy system was generated using the Weighted Linear Combination (WLC) model, applied within a spatial MCDM framework in the QGIS platform. The weighted overlay was calculated using the Raster Calculator, in which the suitability rasters, after fuzzification, were multiplied by their respective objective weights obtained from the CRITIC algorithm and then aggregated. Binary exclusion layers, including forests, wetlands, rivers, agriculture, protected areas, and urban areas, were employed as the constraints in the weighted overlay process. As such, the areas containing the above-mentioned constraints were excluded from the suitability index analysis and assigned no data values. The weighted overlay model was constructed using Equation (4):

$$SI = w_1R + w_1B + w_1P + w_1Ra + w_1Ro + w_1S, \quad (4)$$

where:

- SI represents the final solar PV suitability index,
- R represents terrain roughness suitability,
- B represents building proximity suitability,
- P represents power line proximity suitability,
- Ra represents railway proximity suitability,
- Ro represents road proximity suitability,
- S represents slope suitability,
- and $w_1 - w_6$ represent the CRITIC-derived objective weights assigned to each criterion.

All raster layers were reprojected to a common coordinate system, resolution, and extent before performing the overlay operation to ensure that all data used is spatially consistent. The final raster represents a suitability map, where higher values indicate greater suitability for constructing large solar power plants. To simplify interpretation and enable spatial comparison of suitability within Lithuania, the obtained suitability raster layer was classified in QGIS using the equal-interval method into five suitability classes.

3.4 | Sensitivity Analysis

To assess the stability of the suitability results from the final analysis, a sensitivity analysis was conducted by comparing the original CRITIC-based weight allocation with an equal-weight scenario. The idea behind the sensitivity analysis is to check whether the primary spatial patterns generated by the CRITIC-based model remain the same when the objective weights are set to equal weights.

4 | Results

4.1 | CRITIC Weighting Results

The CRITIC approach was used to estimate the objective weights of the six selected suitability criteria based on their variability and correlations with other criteria. According to these weights, the infrastructure-related criteria provide the strongest statistical contribution to spatial differentiation in the suitability model. Among all considered criteria, the highest weight (0.245163) was assigned to the settlement proximity criterion, followed by the road proximity (0.227127) and power line proximity (0.184955). The high weight of settlement proximity indicates that this layer has strong spatial variability and provides relatively nonredundant information compared with the other criteria. These results highlight the important role of preventing land-use conflicts in large-scale solar projects, along with the difficulty of gaining public support. At the same time, the second criterion underscores the relevance of transport accessibility issues for installing such power plants. Finally, the relatively high significance of the third criterion indicates the need to pay attention to power line proximity, given the potential to save on grid connection costs.

Topographic criteria, such as slope (0.132829) and terrain roughness (0.124962), were estimated with moderately high weights. This result can be explained by the relatively weak variability of topography in Lithuania. In other words, although considering such features is necessary for technical reasons, it cannot serve as the key discriminant factor in utility-scale projects. Finally, railway proximity received the lowest weight (0.084965). This suggests that the railway layer contributes less additional spatial information to the model, either because its spatial variability is lower or because part of its information overlaps with other infrastructure-related criteria. This result does not mean that railway proximity is irrelevant in practice, but rather that it has a lower statistical contribution within the CRITIC weighting structure. In general,

the CRITIC results indicate that infrastructure-related criteria have stronger discriminatory power than topographic criteria within the Lithuanian suitability data set.

4.2 | Constraint Layers

Constraint analysis involves identifying regions where utility-scale solar PV development could be environmentally inappropriate due to the current land-use regime. The following constraint layers were incorporated to avoid spatial conflicts and to increase the accuracy of the final suitability assessment. Based on the results, several areas of constraint in Lithuania can be identified. The overall spatial extent of the excluded areas appears significant. Agricultural and forested landscapes, wetlands, protected nature, and river constraints are observed throughout the study area. However, each of the abovementioned constraints exhibits its particular geographic pattern and spatial extent. The constraints' composite constraints are shown in Figure 1. In the constraint-layer maps, values of 0 indicate areas excluded from further suitability assessment, while values of 1 indicate areas retained for subsequent analysis.

Among all environmental and land-use constraints, agricultural regions appear to be among the most extensive exclusion zones in Lithuania. There are large agricultural zones in central Lithuania where land use is quite intensive, and there is a lack of suitable land available for the development of utility-scale solar power plants. Agricultural regions experience intense competition for land use, especially in productive agricultural areas. Figure 2 shows agricultural regions in Lithuania.

Constraints concerning forest cover cover an equally significant proportion of Lithuania. Forests are widespread in eastern and southeastern Lithuania. These regions include fragmented patches of land unsuitable for development. It is crucial to

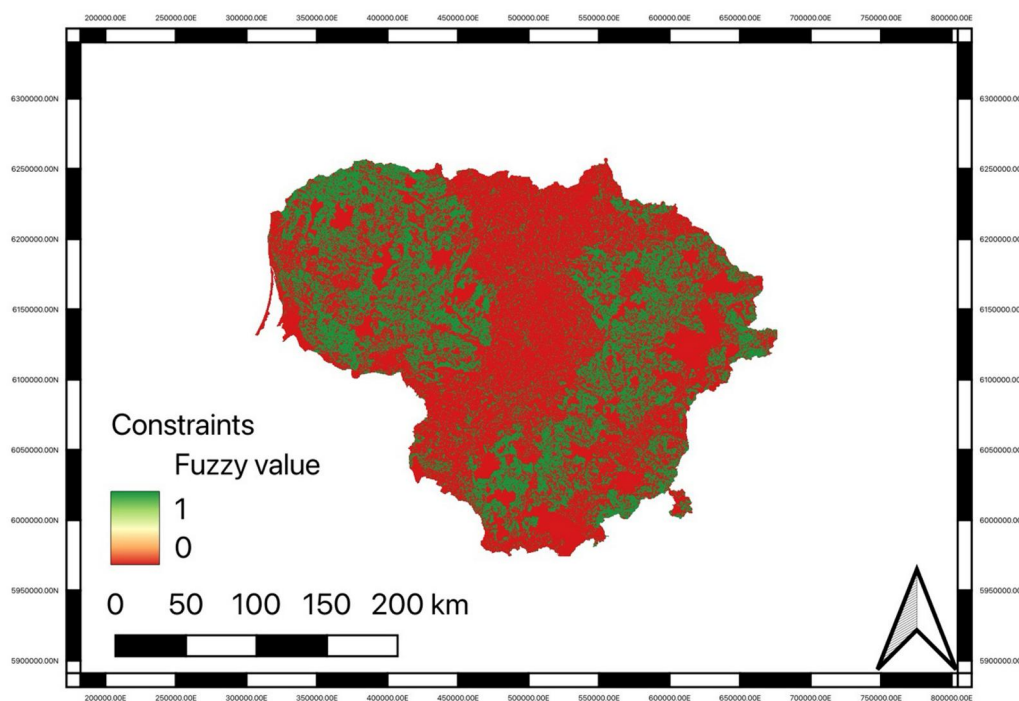


FIGURE 1 | Constraints composite.

exclude forested land from the analysis, given the contribution utility-scale solar power plants make to vegetation removal and habitat fragmentation. Figure 3 shows forests in Lithuania.

Environmental constraints, such as protected and natural reserves, tend to be localized and have a very restrictive spatial distribution. Although their overall spatial extent is lower when compared to agricultural and forest constraints, they remain important environmentally sensitive areas that require protection, thus making it impossible to develop

utility-scale solar PV in those areas. Some clustered protected areas are present in the southern and northeastern regions of Lithuania. Figure 4 shows the natural reserves in Lithuania.

The spatial distribution of wetlands is fragmented but spans numerous regions throughout the area. Even though wetlands occupy relatively small areas individually, their ecological value warrants their exclusion from the analysis. Figure 5 shows wetlands in Lithuania.

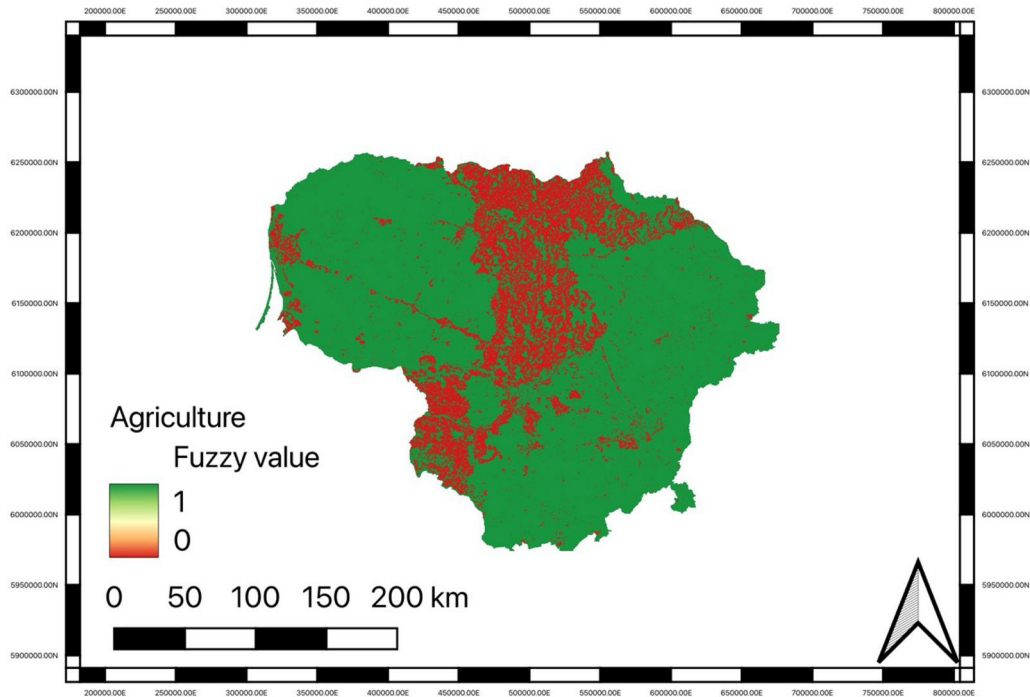


FIGURE 2 | Agricultural regions.

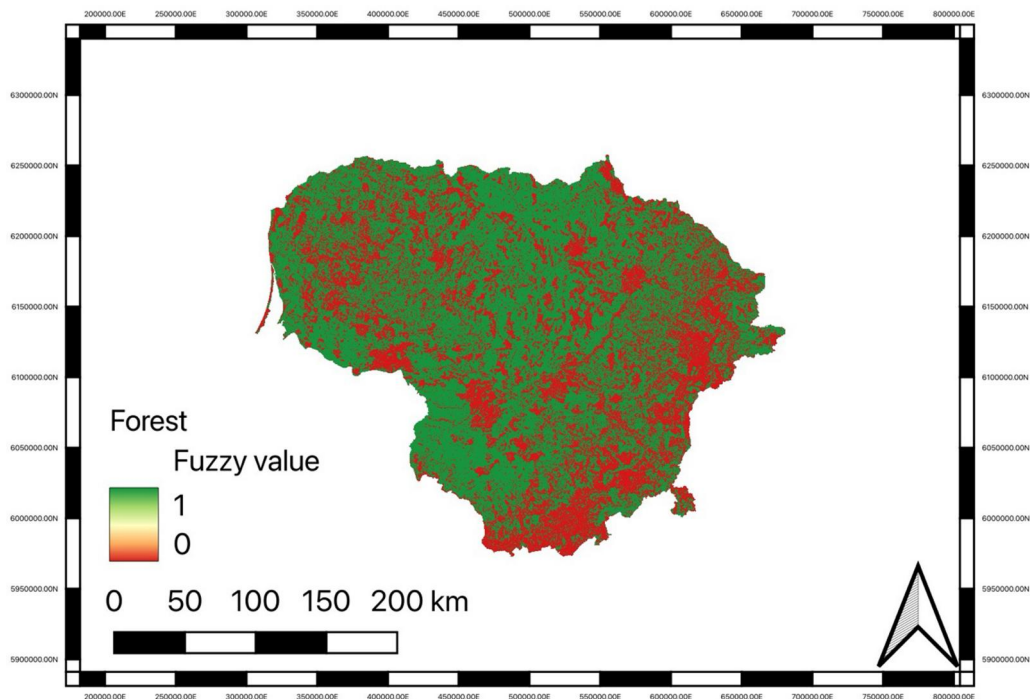


FIGURE 3 | Forests.

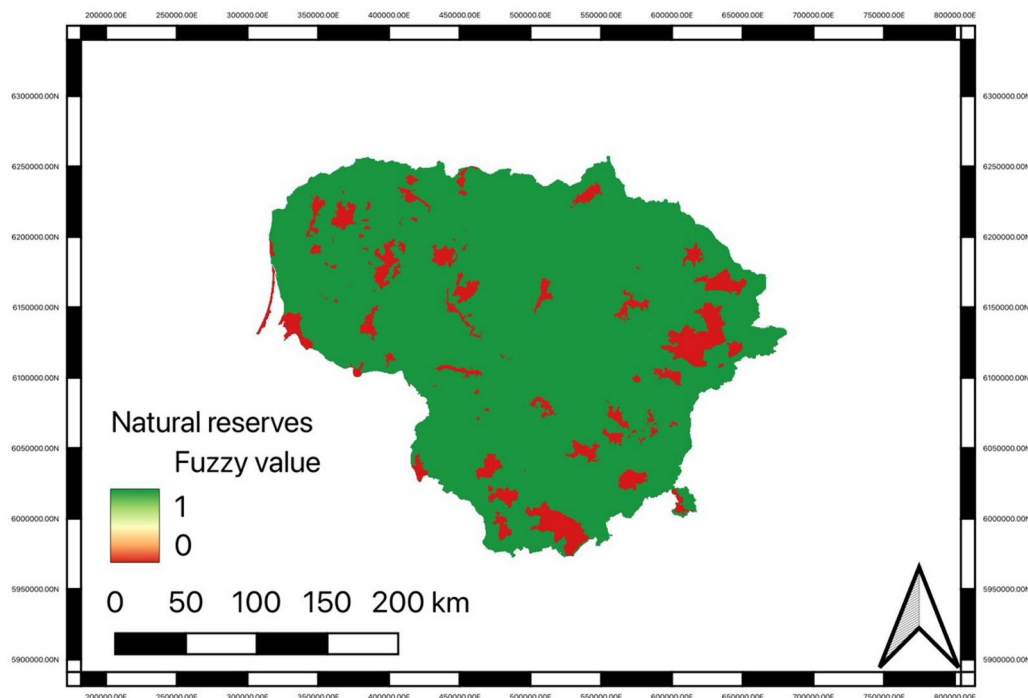


FIGURE 4 | Natural reserves.

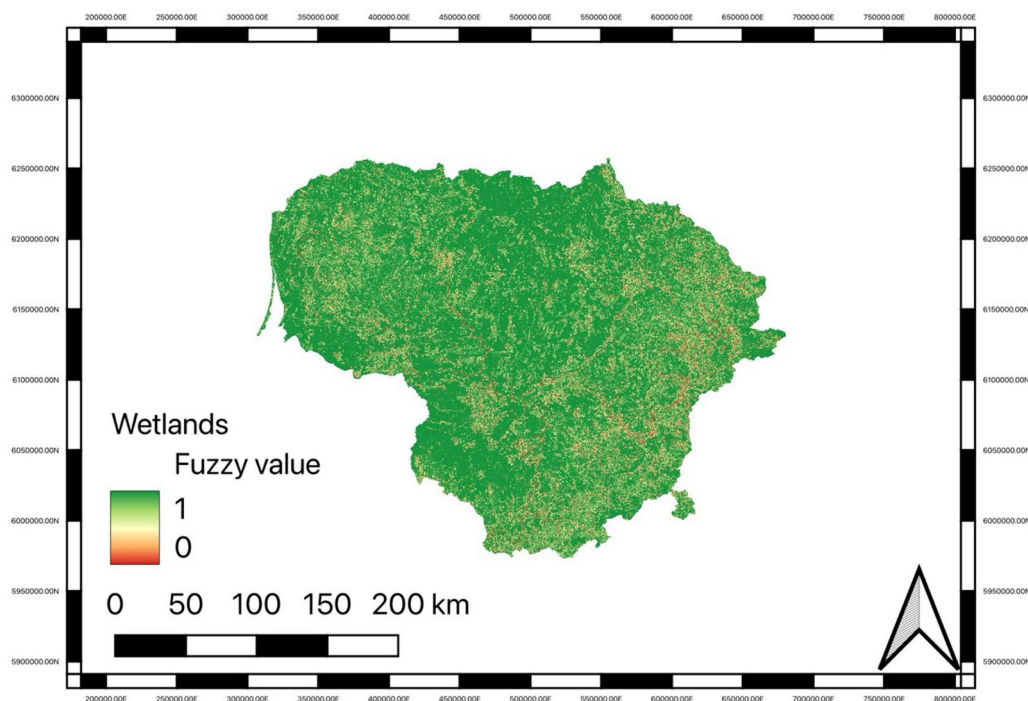


FIGURE 5 | Wetlands.

River constraints exhibit a relatively lower level of exclusivity compared to others; however, they correspond to important river and hydrographic systems in Lithuania. As shown in Figure 6, river-based exclusions mainly consist of narrow linear features, with relatively lower extents than forest- and agriculture-based exclusions. Nevertheless, their application is necessary to protect aquatic life and avoid disturbance to the environment around water bodies.

The land cover restriction layer was used to filter out land cover types that could not be considered for solar energy generation,

such as artificial land and environmentally protected lands. According to Figure 7, the filtered land cover areas include urbanized zones, lakes, swamps, coastal zones, and other non-buildable areas in Lithuania. Such land uses were discarded due to environmental concerns, flood and erosion risks, land-use conflicts, and difficulties implementing utility-scale photovoltaics in those areas. In turn, agricultural lands, grasslands, scrublands, and barren lands were identified as potentially suitable land cover classes for utility-scale photovoltaics due to their high availability.

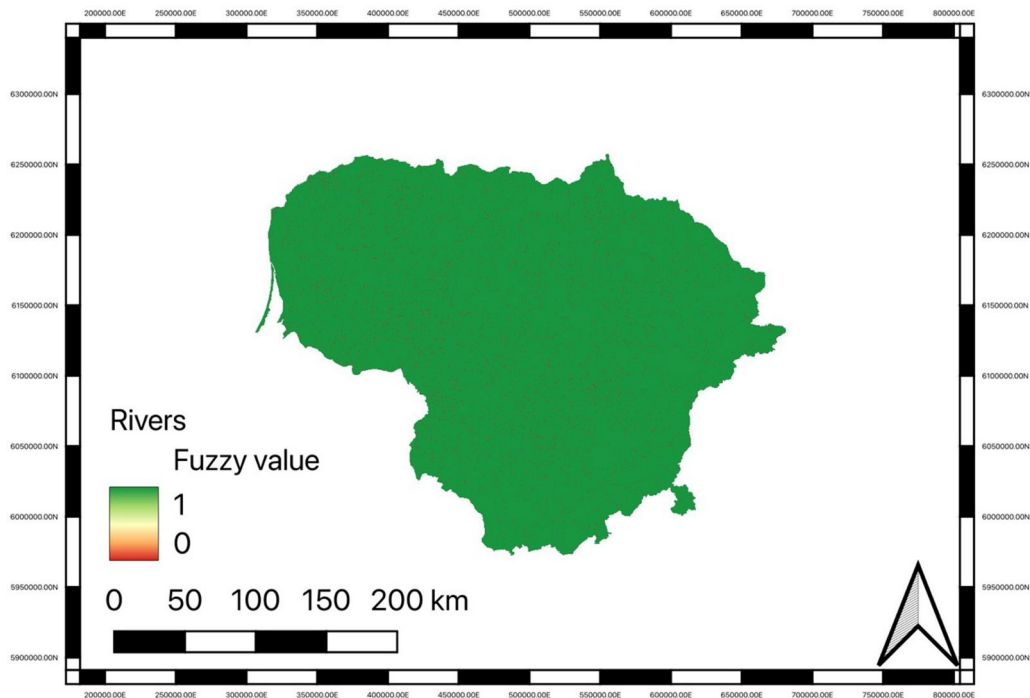


FIGURE 6 | Rivers.

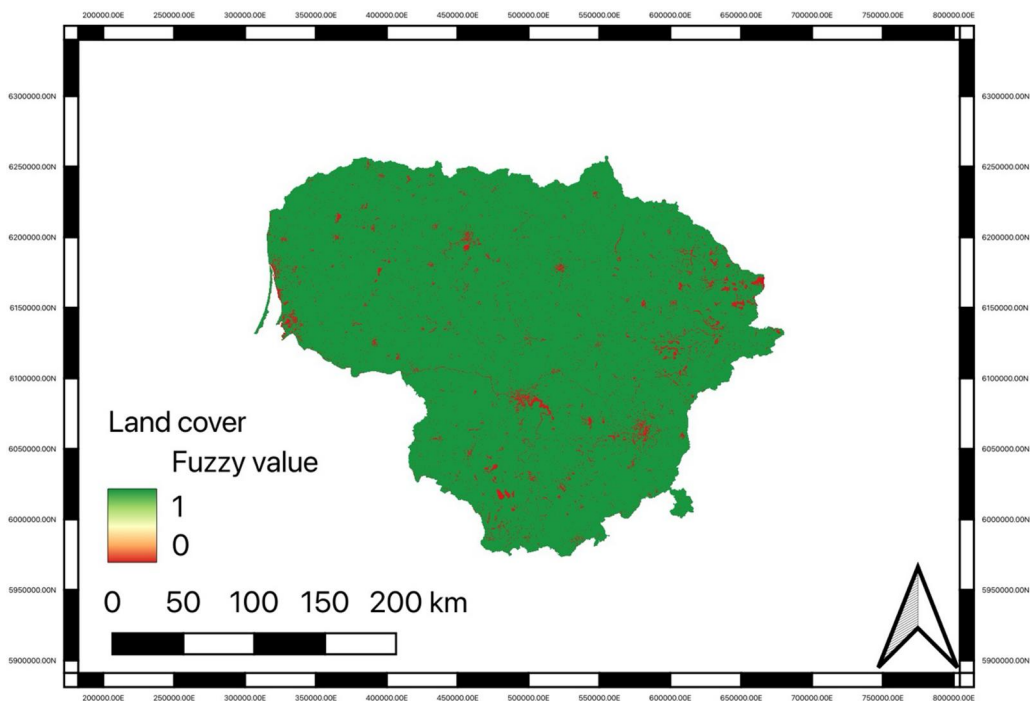


FIGURE 7 | Land cover.

The combination of constraints makes it possible to eliminate numerous lands that cannot be developed for renewable energy production.

4.3 | Topographic Layers

Figure 8 presents the spatial distribution of the criterion “slope suitability” in Lithuania. Generally speaking, Lithuania appears to be quite suitable in terms of topography, as it is mostly

characterized by a plain, relatively flat terrain. Therefore, a large share of the territory in Lithuania exhibits low gradients, which are suitable for constructing utility-scale solar panels. The comparatively small number of territories with low suitability can be considered highly scattered and is associated with higher topographic gradients. In general, these findings imply that there are no significant restrictions concerning the topographic suitability of the examined territory for installing PV farms. In the suitability-layer maps, values closer to 0 indicate lower suitability, while values closer to 1 indicate higher suitability.

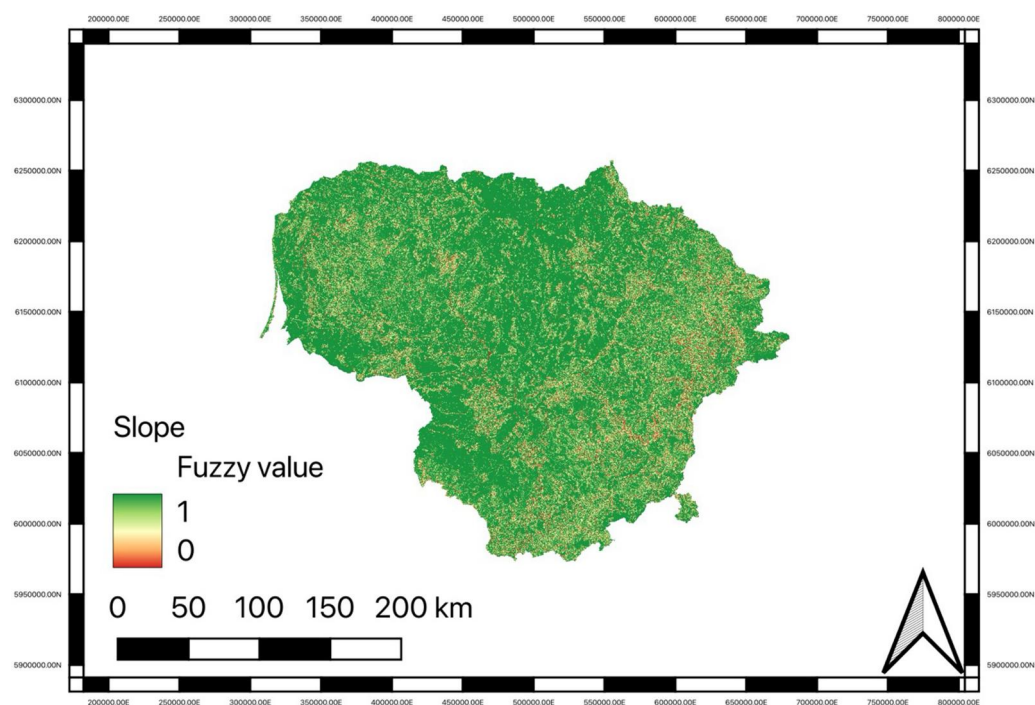


FIGURE 8 | Slope.

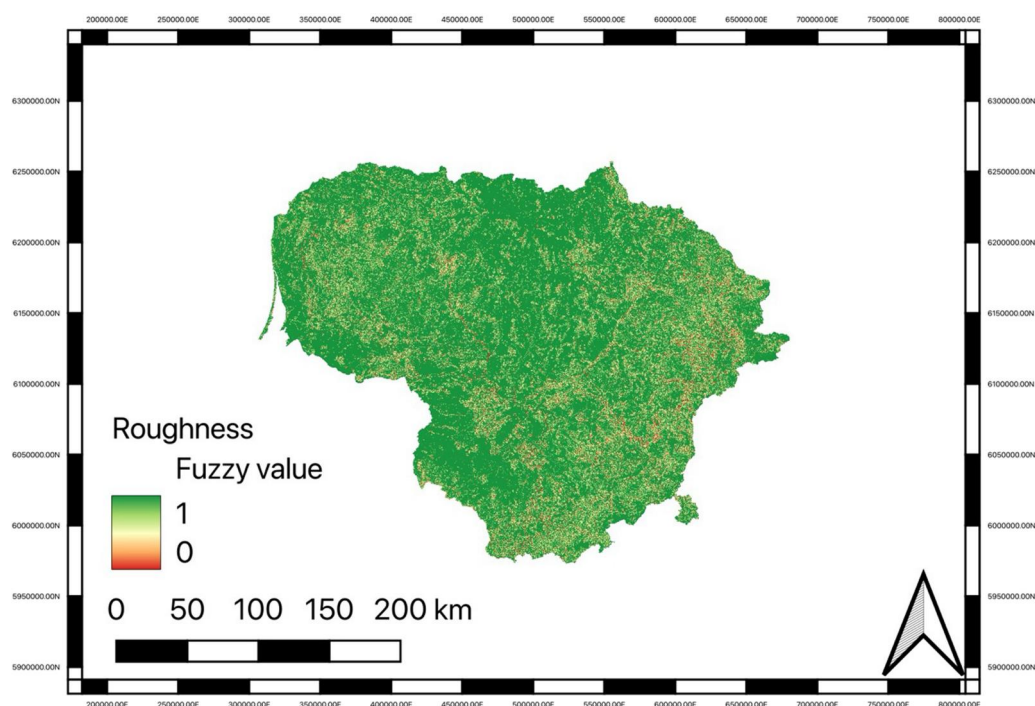


FIGURE 9 | Roughness.

Figure 9 presents suitability regarding “terrain roughness.” The distribution map of this parameter shows a spatial pattern similar to that of the slope suitability criterion above. As shown in Figure 9, most areas in Lithuania have relatively rough terrain, making them highly suitable for installing solar panels. At the same time, low suitability values are observed in scattered areas characterized by greater terrain roughness and topographic heterogeneity. Overall, these findings indicate that, as a restriction factor, terrain roughness plays a rather insignificant role in PV installation suitability.

4.4 | Infrastructure Layers

Figure 10 presents suitability based on proximity to the power transmission network. As shown in Figure 11, highly suitable regions are primarily located adjacent to major transmission lines and at connected nodes within the electric network distributed across the country. The presence of numerous power transmission lines greatly enhances opportunities for PV farm development. The low suitability of remote regions can be explained by the higher costs of connecting to power infrastructure. Overall,

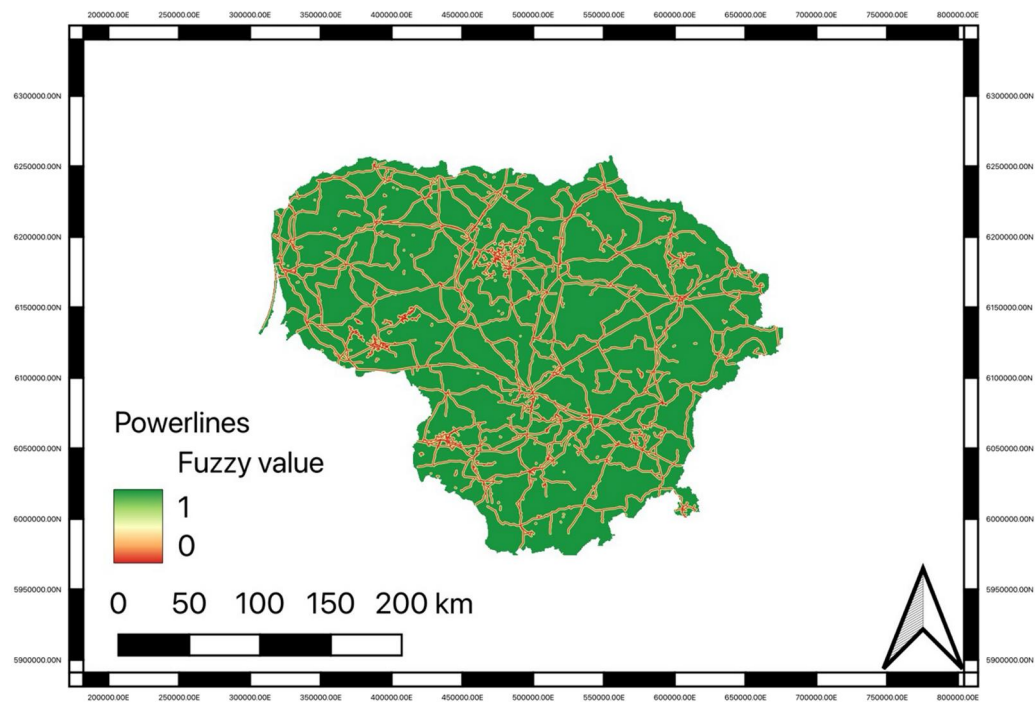


FIGURE 10 | Powerlines.

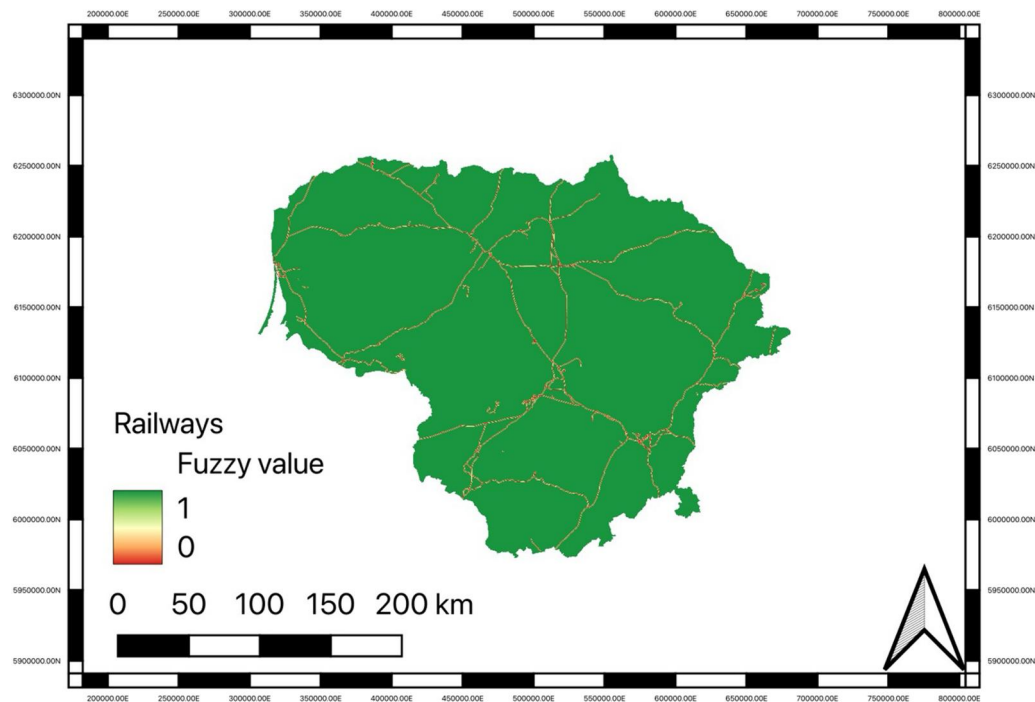


FIGURE 11 | Railways.

this parameter plays an essential role in restricting PV suitability. In the suitability-layer maps, values closer to 0 indicate lower suitability, while values closer to 1 indicate higher suitability.

Figure 11 demonstrates the spatial distribution of suitability based on proximity to railway transportation lines. Unlike roads and power lines, railway infrastructure constitutes a rather limited network with few major corridors. Hence, highly suitable regions are concentrated along the major transport corridors connecting large urban centers and other important places.

At the same time, it should be noted that a relatively large portion of Lithuania's territory remains distant from railway infrastructure. These findings are quite logical since the railway network constitutes an important limitation criterion of relatively low weight.

Figure 12 shows the suitability distribution map according to proximity to the road transport network. As mentioned previously, the road infrastructure covers almost the entire territory of Lithuania. Therefore, a relatively large portion of the territory

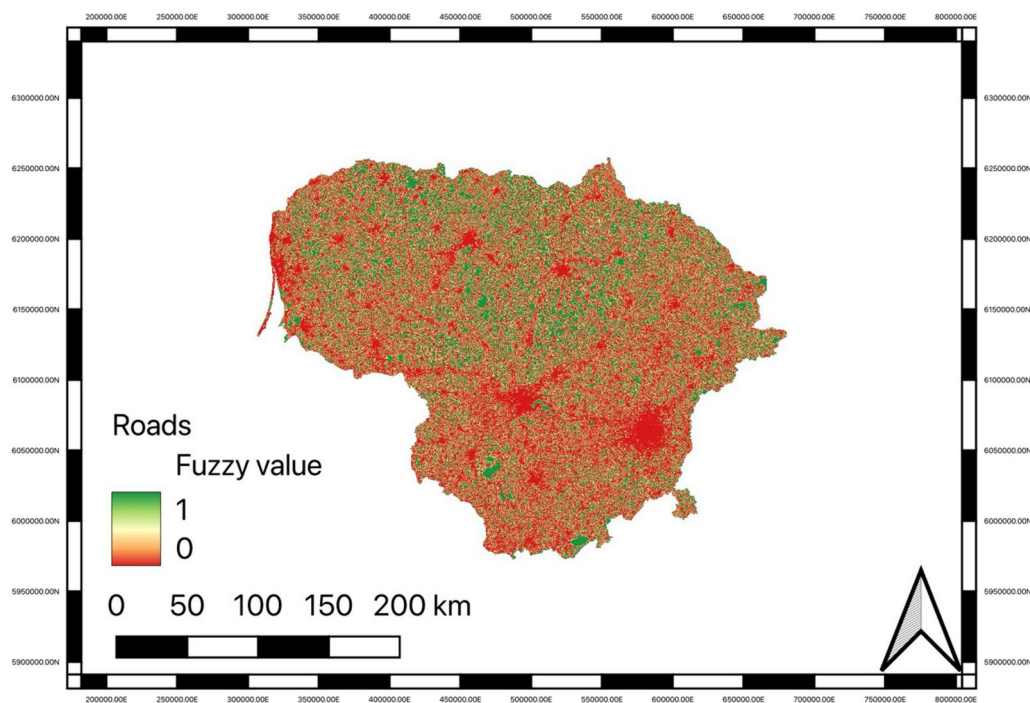


FIGURE 12 | Roads.

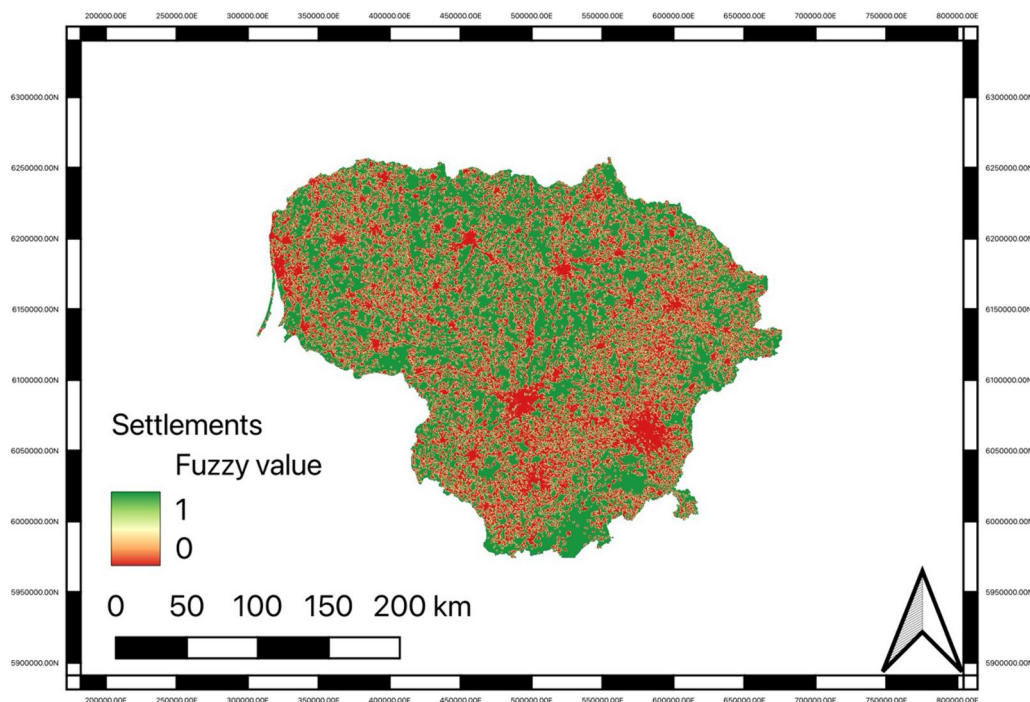


FIGURE 13 | Settlements.

exhibits high suitability values due to the presence of roads. As shown in Figure 13, these highly suitable regions are characterized by major transport corridors and zones of urbanization. The road transport network plays a particularly important role in enabling logistical opportunities for PV farm development.

Figure 13 demonstrates suitability distribution based on proximity to settlements. In turn, highly suitable regions are characterized by low population. As mentioned earlier, locations near settlements impose additional restrictions on PV suitability

due to land-use conflicts and other factors. Accordingly, such factors determine comparatively low suitability of these areas for PV farm development. Settlement proximity proved to be the most significant among all other restrictions.

4.5 | Resource Potential

Figure 14 shows suitability according to the GHI criterion. In contrast to the topography-related criteria, this parameter

demonstrates some spatial variability in Lithuania. According to Figure 10, highly suitable territories are located in the western and southwestern parts of the studied area, while the remaining part shows comparatively lower suitability values. This means that solar energy is not evenly distributed across the studied area. Nevertheless, the vast majority of territories exhibit moderate to high GHI suitability, making them suitable for installing large PV farms. In the suitability-layer maps, values closer to 0 indicate lower suitability, while values closer to 1 indicate higher suitability.

4.6 | Final Solar Suitability Map

Figure 15 shows the final suitability map for utility-scale solar photovoltaics, developed by integrating environmental constraints, topography, solar potential, and infrastructure accessibility in a GIS-CRITIC model. Spatial patterns shown in Figure 15 indicate notable regional diversity in the suitability of solar PV development and reveal several areas that are relatively favorable for solar energy development.

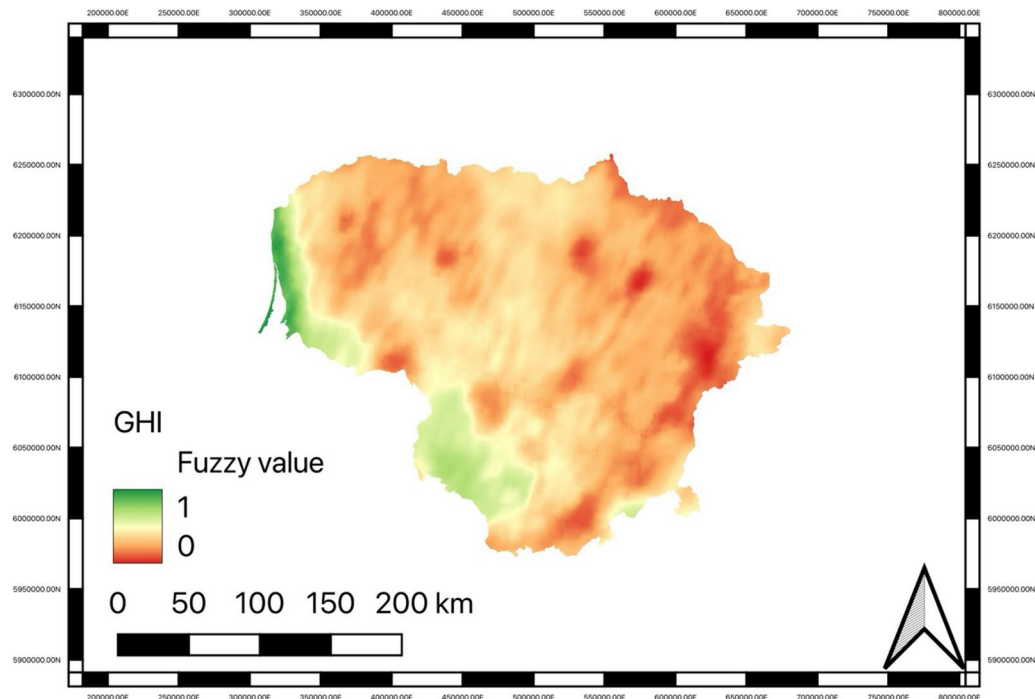


FIGURE 14 | GHI.

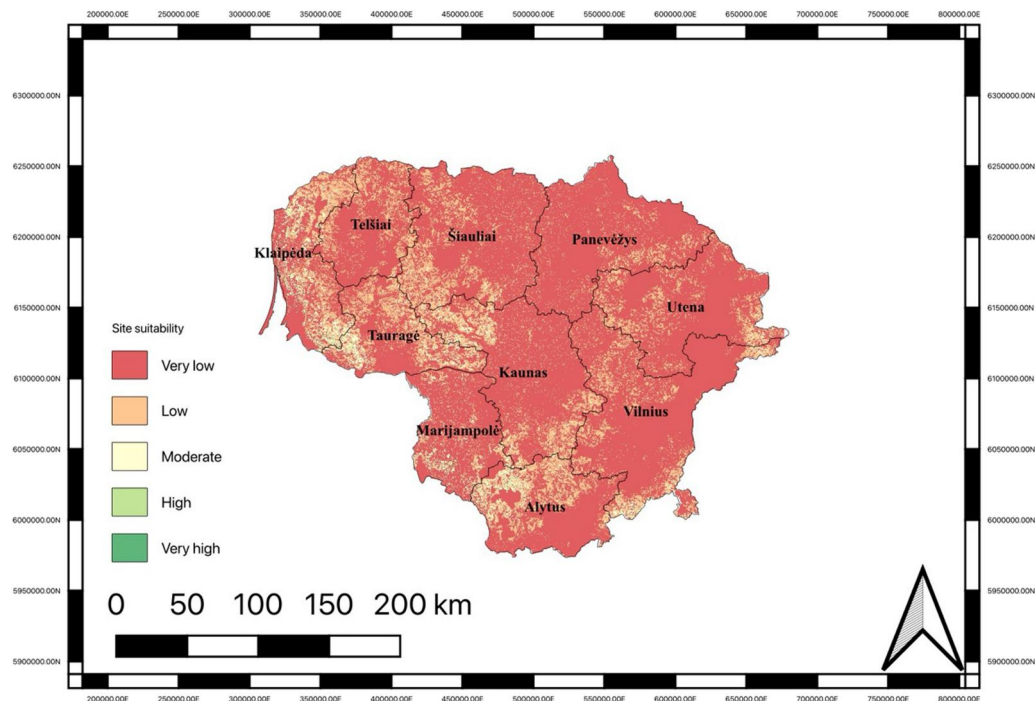


FIGURE 15 | Solar suitability map.

TABLE 3 | GIS-verified area distribution of solar PV suitability classes in Lithuania.

Class	Area km ²	Share %
1 Very low	50,500.70	78.15
2 Low	11,847.02	18.33
3 Moderate	2060.95	3.19
4 High	202.58	0.31
5 Very high	7.74	0.01
Total classified area	64,618.98	100

Note: Class areas were verified directly from the classified suitability raster using the QGIS Raster Layer Unique Values Report in the LKS94/Lithuania TM projected coordinate system. Values may not sum exactly because of rounding.

According to Figure 15 and Table 3, many regions in Lithuania are characterized by low suitability, mainly due to environmental constraints, restrictions on placement near settlements and in forested areas, and land-use prohibitions. The largest proportion of very low to low suitability occurs in the eastern and northeastern parts of Lithuania, where the following factors limit PV suitability: fragmented landscape and forest cover, environmental restrictions, limited solar irradiation, and poor access to infrastructure. Notable zones of relatively low suitability are also located near Utena, Panevėžys, and some parts of eastern Vilnius county. The area calculation shows that only 210.32 km², representing 0.33% of the classified area, falls within the high and very high suitability classes. This confirms that highly suitable land for conventional utility-scale solar PV development is spatially limited under the applied environmental, land-use, and infrastructure constraints.

The suitability class areas for the five suitability classes have been validated using the “QGIS Raster Layer Unique Values Report” tool applied to the suitability classification of the raster. This tool worked in the LKS94/Lithuania TM projected coordinate system, using a spatial resolution of 30.244 m. It calculated the area covered by each class of the raster layer, expressed in square meters, which was further converted into square kilometers and presented in Table 3.

To provide a policy-oriented interpretation of the suitability map, the area of each suitability class was calculated from the classification output. The raster layer has a spatial resolution of 30.24 × 30.24 m, which amounts to 914.47 m². The number of pixels in each suitability class was then converted to square kilometers. In the classified area, the most abundant classes are very low and low suitability. The very low suitability class covers 50,500.70 km², or 78.15% of the classified area, and the low suitability class covers 11,847.02 km², or 18.33% of the classified area. The moderate suitability class area totals 2,060.95 km², or 3.19% of the classified area. In comparison, the high suitability areas cover 202.58 km², and the very high suitability areas cover 7.74 km². Overall, the area of the high and very high suitability classes totals 210.32 km², or 0.33% of the classified area.

Thus, the results confirm the fact that the availability of land suitable for utility-scale solar PV deployment under the strict conditions used in this research in Lithuania is rather scarce. Based on calculations of the high-suitability zone area, a simple

estimate of technical potential was made. These estimates cannot replace project-specific feasibility studies, since the exact figures depend on land ownership, availability of a grid connection, module placement options, permitting, and investment conditions. However, it provides some insight into the possible contribution of these zones to national RE planning. Based on the conservative assumption that utility-scale PV land-use density is 40 MW/km², 210.32 km² of high- and very-high-suitability zone area would be able to host about 8.41 GW of solar PV capacity. At a capacity factor of 11%, this would result in annual electricity generation of about 8.11 TWh.

According to statistics for the year 2025, domestic electricity generation in the state was approximately 9.72 TWh, meeting around 77% of the country's total electricity consumption. Thus, it implies that the annual demand for electricity in the country is around 12.62 TWh. For the same year, the installed solar PV capacity amounted to about 3.2 GW, while solar power plants produced about 1.78 TWh of electricity. The estimated annual generation of 8.11 TWh from the analysis will account for 64.3% of Lithuania's electricity consumption in 2025 and 83.4% of its domestic generation. Furthermore, the capacity of 8.41 GW is nearly 2.6 times Lithuania's installed solar PV capacity at the end of 2025 [76–78]. This shows that although areas with high and very high suitability are small relative to the country's size, they have significant energy potential at the national level. However, the presented numbers only indicate the technical potential in space, not immediate capacity.

Regions characterized by high suitability are more abundant in the western, southwestern, and central parts of the country. The most suitable clusters are found near Klaipėda and Tauragė, as well as in parts of Kaunas county. Flatter relief, good access to roads and the electric grid, and a relative absence of environmental constraints are among the factors contributing to greater suitability in these regions. In addition, western regions receive comparatively greater solar irradiation than eastern territories. In central Lithuania, several notable suitability corridors along roads and electricity networks are clearly visible. In particular, moderately to highly suitable areas extend through the territories surrounding Kaunas City and toward Šiauliai and Panevėžys Counties. This result is explained mainly by improved accessibility from existing roads and power grid connections, as well as the absence of significant terrain constraints.

Certain suitability clusters occur in southern Lithuania, specifically around Alytus and Marijampolė. However, fragmented forests and restricted areas limit the suitability of these regions for further development. Finally, the southeastern part of Lithuania is characterized by low suitability due to dense forest cover, a fragmented landscape, environmental restrictions, and the presence of settlements. In general, the spatial concentration of highly suitable areas indicates the significant impact of the infrastructural variables identified in the CRITIC weight analysis. Regions with high transportation and transmission density generally correlate with higher suitability for solar PV installation. To conclude, it can be argued that several geographically confined zones with relatively high suitability for further solar PV development exist in Lithuania. At the same time, there are substantial regions with low suitability due to environmental constraints and land-use conflicts.

5 | Sensitivity Analysis

To test the robustness of the GIS-CRITIC suitability assessment, a sensitivity analysis was conducted by comparing the original CRITIC-weighted model with an equal-weight scenario. The purpose of this analysis was to assess whether the final suitability pattern produced by the model is highly sensitive to the weights of objective criteria derived from the CRITIC approach, or whether the key spatial results would be resilient to an alternative weighting strategy.

For the original model, the weights of the criteria were determined using the CRITIC method, which accounts for the spatial variability and redundancy of each criterion when assessing their importance. For the sensitivity scenario, the weights of the six suitability criteria used in the model were set equal. As six criteria were used for weighted overlay (i.e., slope, terrain roughness, proximity to roads, proximity to railways, proximity to power lines, and proximity to settlements), each criterion was assigned a weight of 0.1667. The same GHI layer and exclusion mask were used in order to isolate the effect of changing the weighting strategy.

The equal-weight suitability map was classified using the same five suitability classes as the CRITIC model: very low, low, moderate, high, and very high. The area of each class was computed from the classified raster map. A comparison of the class areas in the CRITIC and equal-weight scenarios is presented in Table 4.

Thus, the suitability model ultimately demonstrates rather moderate sensitivity to the weight-assignment method used. When all criteria have equal weight, the total area considered to have high and very high suitability expands from 210.32 km² under the CRITIC weighting approach to 359.98 km². It shows that using the CRITIC weighting process leads to greater spatial discrimination. This is explained by the fact that infrastructure-related criteria are weighted quite high in the original model. At the same time, equal weighting does not distinguish between criteria and leads to the expansion of the area with moderate and high suitability.

However, a common tendency is observed in both approaches. The vast majority of Lithuanian territory falls into either the very low or low suitability classes. In the case of the CRITIC-based model, the area with high and very high suitability accounts for just 0.33% of the entire classified territory, whereas

under the equal weighting condition, it is 0.56%. In general, the sensitivity analysis demonstrates the stability of the GIS-CRITIC model with respect to the weight assignment technique used. While the exact area of high suitability may vary, the overall conclusion remains: it is rather small and located in certain parts of Lithuania.

6 | Discussion

The results of this research demonstrate that the development of utility-scale solar PV plants in Lithuania is significantly influenced by the interplay of several key factors, including land-use restrictions, environmental constraints, infrastructure access, and solar resource availability. While there is great interest in increasing renewable energy capacity, suitable areas for constructing conventional ground-mounted solar PV are limited. Based on the results obtained, it can be concluded that the area of high and very high suitability is limited to 210.32 km², or 0.33% of the classified area. Such areas are mostly located in western, southwestern, and central regions of Lithuania, including locations near Klaipėda, Tauragė, Kaunas, and Alytus counties.

The CRITIC weight analysis shows that infrastructure criteria have the most significant impact on the spatial differences in the suitability model. High weights for settlement proximity, road accessibility, and proximity to power lines suggest that solar PV planning in Lithuania is defined not only by the amount of solar irradiation or topographic conditions but also by the spatial relationships among potential locations, the infrastructure network, and land-use restrictions. For international researchers, this result is important for the GIS-CRITIC model's usefulness, as it demonstrates that infrastructure and socio-spatial factors should be included in national-scale suitability modeling of renewable energy sources, particularly in countries characterized by land-use fragmentation or strict environmental restrictions.

The quantitative analysis of the suitability map strengthens the practical relevance of the results. Based on the conservative assumption about infrastructure density, high and very high suitability areas might potentially accommodate up to 8.41 GW of solar PV capacity and generate up to 8.11 TWh of energy per year. This value is indicative and does not imply any project feasibility analysis because it requires additional data on land ownership, grid capacity, permitting, investment costs, and local acceptance. However, this estimation might be used as an example of the potential contribution of the most suitable areas to national renewable energy planning.

The lack of agricultural land is a major component of the land limitations identified in this study. This is because this study focuses on conventional utility-scale ground-mounted photovoltaic (PV) plants and aims to avoid competition with agricultural production in terms of land use. As a result, the calculated land area of 210.32 km² of high and very high suitability with the technical potential of 8.41 GW may be regarded as conservative estimations for conventional ground-mounted PV power plants, but not as the solar potential of Lithuania as a whole. Another technology which might provide a possibility for combining agricultural production and electricity generation in the same land area includes agrivoltaic solutions. The

TABLE 4 | Sensitivity analysis comparing CRITIC-based and equal-weight suitability results.

Suitability class	CRITIC-based area km ²	Equal-weight area km ²
Very low	50,500.70	47,381.56
Low	11,847.02	13,897.84
Moderate	2,060.95	2972.95
High	202.58	347.47
Very high	7.74	12.51
High + very high	210.32	359.98

interest in agrivoltaics increased in Germany and other countries in Europe thanks to successful demonstrations of the technology, emerging policies, and increasing willingness to engage in this solution from the agricultural sector of the economy. For example, in one survey in Germany, 72.4% of participating farmers believed that agrivoltaics might be applied on their farmland. In another study, conducted in Europe, it was noted that a small share of agricultural land allocated for agrivoltaics might help generate considerable additional PV capacity [79, 80]. It may be concluded that allowing technically and environmentally feasible agricultural lands to participate in an agrivoltaic solution would considerably increase Lithuania's estimated solar PV capacity. However, it is impossible to calculate this potential in the framework of the present model, since agrivoltaic potential depends on many factors such as crop type, productivity, soil conditions, access to machinery, system design, access to grid, and national policy.

The sensitivity analysis additionally confirms the reliability of the main conclusion. In the equal-weight scenario, the area of high and very high suitability increases to 359.98 km². However, the area of highly suitable land remains quite limited and geographically concentrated. Thus, the main conclusion does not depend on the weight scheme derived using CRITIC. For international application, this comparison proves that the GIS-CRITIC model should be additionally tested through sensitivity analysis if its results might influence the decision-making process and spatial planning.

The GIS-CRITIC framework is applicable not only to Lithuania. Many countries face similar problems balancing the expansion of renewable energy with agricultural land protection, biodiversity conservation, infrastructure issues, and public acceptance. Therefore, it is possible to apply the framework in order to integrate exclusion criteria, fuzzy suitability layers, objective weighing of criteria, spatial MCDA, and estimation of energy potentials. International researchers might adapt the framework to different situations using different constraint layers, threshold values, infrastructure criteria, and policy assumptions.

Compared with conventional expert-based methodologies such as the AHP, the CRITIC approach has both benefits and drawbacks. On the one hand, it makes it possible to incorporate the knowledge of experts and stakeholders, as well as regulatory priorities and regional experience, into the weighting process. On the other hand, the results can be affected by expert selection, bias, and inconsistency in pairwise comparisons, which is not the case with the CRITIC methodology. However, in the CRITIC methodology, the weights are determined based on the discriminatory power of the criteria from a statistical point of view; therefore, criteria without high spatial variability will be weighted less, regardless of the significance of the criterion itself. Thus, there is no better approach in terms of absolute value.

7 | Conclusions

This paper develops a national-scale GIS-CRITIC-based model to pinpoint sites of potential utility-scale solar PV development in Lithuania. This model integrates environmental constraints, land-use constraints, topography, access to infrastructure, and solar energy potential within the MCDA framework.

The findings suggest that land with high suitability for utility-scale solar PV deployment is relatively scarce. High and very high suitability areas take up 210.32 km², which corresponds to 0.33% of the study area. Based on conservative calculations, these areas could support about 8.41 GW of solar capacity and produce 8.11 TWh of electricity annually.

The sensitivity analysis demonstrates that these conclusions are valid under the equal-weight scenario. Despite an increase in the total size of high and very high suitability areas, the available land resources are still spatially limited and geographically concentrated.

Thus, in general terms, this paper contributes to a decision-making model for solar PV site identification. Such an approach can help stakeholders define renewable energy zones, taking into account energy security, infrastructure accessibility, land-use regulations, and environmental constraints.

7.1 | Policy Implications

These findings provide several key policy implications for the Lithuanian energy transition and renewable energy planning. First, the identified high-suitability areas can serve as priority development corridors for future utility-scale solar PV investments. National policymakers could use the developed GIS solar PV suitability maps as an evidence-based decision-support tool when creating plans for energy expansion and spatial energy strategies.

Second, since the most influential criteria concerned infrastructure accessibility and availability, improving the electric grid and road network in moderately suited regions would enhance the feasibility of solar PV. Consequently, grid modernization programs in future years could target areas where moderate suitability could become high with certain investments.

Third, these findings highlight the importance of balancing the interests of renewable energy and environmental protection during solar PV deployment. Given that forests, wetlands, nature conservation territories, and agricultural lands are important factors that preclude the development of solar areas, future national energy policies should promote the use of degraded, low-productivity, brownfield, and other less valuable lands to increase the feasibility of solar PV.

Fourth, Lithuania's energy independence policy can benefit from regionally differentiated planning for renewable energy. Therefore, regional renewable energy planning should prioritize western, southwestern, and central Lithuania while also considering complementary strategies in less suitable regions.

7.2 | Research Limitations and Future Research Directions

The current study has several limitations. First, the focus of this analysis was on suitability and did not consider economic factors (land and electricity connection costs, levelized cost of electricity, and investment feasibility). Incorporating these parameters into the model would add practical value to the results obtained during the analyses.

Second, although the CRITIC weighting methodology reduced dependence on expert-driven weighting, incorporating expert opinions and subjective weighting would provide additional benefits for decision-makers.

Third, climate change and future dynamics of environmental factors, which may affect both solar resource potential and environmental restrictions on solar PV implementation, were not considered during the analyses. Further research could use scenario analysis or climate change predictions to assess the sustainability of the selected locations.

Fourth, the analysis focused only on utility-scale ground-mounted solar photovoltaics. Future research could consider hybrid renewable systems (agrivoltaics, floating solar systems, rooftop solar potential, etc.) alongside standard utility-scale systems. Future studies could develop an alternative agrivoltaic suitability scenario that conditionally preserves selected agricultural lands instead of completely disregarding them. In addition, such an alternative scenario should classify agricultural lands according to the criteria related to crop suitability, land productivity, machinery needs, environmental sensitivity, and applicable planning rules. Comparative assessment of standard ground-mounted PVs and agrivoltaics would reveal how much dual-use land could increase the potential of suitable land, installed capacity, and power generation in Lithuania.

Fifth, further research could apply advanced machine learning models, explainable AI methods, and optimization algorithms to refine the results and create automated solar PV siting systems. Comparative research for the Baltic States can also prove informative.

Author Contributions

Mahyar Kamali Saraji: conceptualization, methodology, software, data curation, investigation, validation, formal analysis, supervision, visualization, writing – original draft, writing – review and editing. **Mariam Kasradze:** writing – original draft, writing – review and editing, conceptualization, resources. **Dalia Streimikiene:** supervision, funding acquisition, project administration, validation. **Vishnu Suresh:** supervision, validation.

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Data Availability Statement

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

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