Renewable Energy Communities in Rural Areas: A Hybrid GIS-MCDM Approach for Agrivoltaic Systems Site Selection

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Abstract: Given the environmental challenges, developing efficient methodologies for renewable energy systems is essential. Renewable Energy Communities (RECs) promote collective participation in photovoltaic systems, optimising self-consumption and reducing grid dependence. Agrivoltaics combine solar energy production with agricultural activity on the same land, improving land use efficiency and supporting energy and food production. This study uses Geographic Information Systems (GIS) and Multi-Criteria Decision Making (MCDM) techniques to create a strategic framework for selecting agrivoltaics sites. The methodology integrates data layers, including topography, infrastructure, and environmental factors. Criteria are weighted using subjective (Best-Worst Method) and objective (Entropy Method) approaches, and the TOPSIS method ranks sites by suitability. An ABC analysis categorises these sites into high, moderate, and low suitability based on TOPSIS scores. The case study demonstrates the approach's effectiveness, with significant land areas identified as highly suitable for agrivoltaic development due to factors like flat terrain, proximity to infrastructure, and regulatory compliance. This work contributes to the strategic sizing of agrivoltaics, facilitating novel REC initiatives that connect rural and urban areas.

Keywords: Energy Communities; GIS; MCDM; Renewable Energy Sources; Site Selection

1. Introduction

Renewable Energy Communities (RECs) can contribute to the transition from a centralised to a decentralised energy management approach, allowing the optimisation of the flows of self-produced and self-consumed energy. A key benefit of RECs is their focus on energy consumers, both individuals and non-energy small and medium-sized enterprises, thus enhancing their significance within the energy sector. Prosumers actively participate in the energy system by consuming and producing electricity or heat from renewable sources, or by providing auxiliary services such as storage. The EU RED-II and the transposed Italian law (D.M. CACER n. 414, 7/12/2023) provide a proper regulation framework to support collective energy projects where prosumers have the right to consume, store, or sell the energy produced by their own plants.

The Italian REC framework broadens the concept of geographical proximity, traditionally limited to users within the same building, to support energy projects that connect urban and peri-urban areas, engaging a diverse user base. Agricultural operators can now join RECs and become prosumers, benefiting from new public funding that promotes agrivoltaic installations in Italy (European Commission 2023). Agrivoltaics integrates agricultural activity and energy production on the same land, maintaining its agricultural use (Walston et al. 2022). Suitable areas for agrivoltaics may include both unused agricultural lands and those already in use. To maximise the combined benefits of crop and power production, careful planning of PV system design and installation is essential, coordinated with planting cycles (Kumpanalaisatit et al. 2022). Agricultural activities within these systems may extend beyond crop cultivation to include animal rearing, grazing, and beekeeping in existing or unused areas, ensuring compatibility with local soil and environmental conditions (Sirnik et al. 2023).

So, the site selection for agrivoltaic installations must prioritise locations with optimal solar exposure, minimal shading, and fertile soil for agriculture. The terrain should be flat to facilitate photovoltaic panel installation and farming operations. Proximity to infrastructure like water sources and roads, as well as compliance with local land use and environmental regulations, is crucial. Integrating these factors into a geospatial-based analysis ensures informed and sustainable site selection.

Geographic information system (GIS) is part of geospatial technologies, encapsulating modern tools for acquiring, storing, and analysing geo-specific data. GIS combines spatial and attribute data via software applications. Data structures typical of GIS, known as geodatabases, are categorised into two types. The first, vector data, entangles points, lines, and polygons (e.g., perimeters of factories, residential, reserve areas, buffers, lakes, and forests). The latter, raster data, is a cell-based data type useful for thematic, spectral, and imagery analysis. GIS has several advantages when compared to other analysis tools. It enables the visualisation and processing of spatial and environmental data, providing geo-referenced results. Moreover, GIS facilitates the identification of potential restricted areas and assists in selecting strategic market locations, considering the proximity to essential infrastructure (Nuhu et al. 2021).

This study presents a comprehensive methodology for the site selection of agrivoltaic installations compatible with the establishment of RECs, developed using open source data and the software QGIS. In Section 2, a literature review is provided to offer an overview of recent developments. Section 3 describes the method and criteria in detail. Section 4 presents a case study, and Section 5 outlines the results. Section 6 provides the conclusion of the paper.

2. Literature Review

GIS and MCDM integration offer valuable features for decision-makers. GIS provides analysis, management, and storage capabilities for handling geospatial information, while MCDM states various techniques for rationalising decision problems (Bohra & Anvari-Moghaddam 2022).

Sánchez-Lozano et al. (2013) carried out a pivotal study on integrating GIS and MCDM to determine the best locations for solar power plants in Cartagena, Spain. Their approach involved using a comprehensive cartographic and alphanumeric database, enhanced by the Analytic Hierarchy Process (AHP), to assess factors like location, geomorphology, and climate. The selection of alternatives was performed with the TOPSIS method. Tahri, Hakdaoui & Maanan (2015) investigated comparable GIS-MCDM frameworks in Morocco, focusing on the Ouarzazate solar energy project. Their research underscored climate as a crucial determinant of potential electricity output, incorporating further analyses of orography and land orientation.

Al Garni & Awasthi (2017) built upon previous research by applying the AHP approach to site selection for utility-scale solar PV projects in Saudi Arabia. The study introduced a land suitability index model to classify potential sites according to economic, technical, and environmental criteria, utilising actual climatological and legislative data. Doorga, Rughooputh & Boojhawon (2019) conducted an in-depth analysis of the use of AHP for selecting suitable sites for solar farms in Mauritius. The study incorporated a wide range of criteria, such as legal and cultural factors, and used the Weighted Linear Combination (WLC) technique to create a detailed solar resource potential atlas. Hassan, Alhamrouni & Azhan (2023) introduced a new hybrid framework that combines two MCDM techniques to evaluate suitable sites for large-scale solar PV systems in Saudi Arabia. The study utilised the CRITIC technique for determining the weights of factors and implemented TOPSIS for ranking alternatives, offering a significant methodological enhancement in the field. Elkadeem et al. (2024) developed a five-step GIS-MCDM approach that integrates relevant spatially explicit information, considering twelve technical and socio-economic parameters, to assess the agrivoltaic systems potential in Sweden.

3. Methodology

The methodology implemented is illustrated in Figure 1 and detailed comprehensively in the subsequent sections.

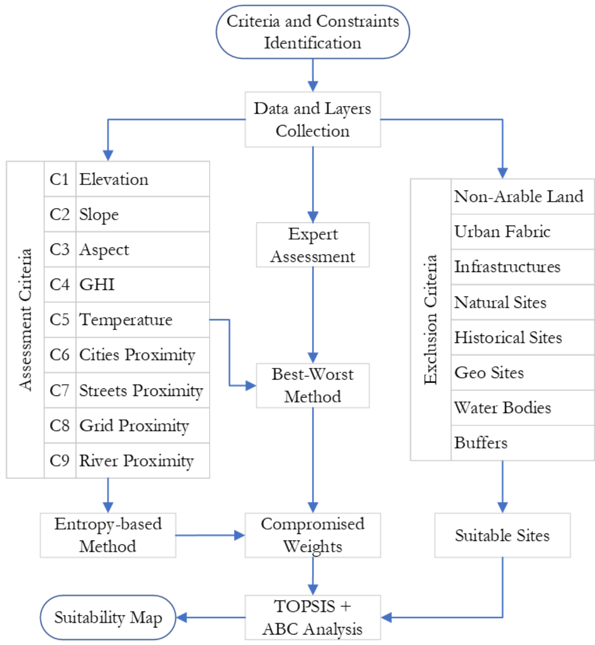

Figure 1 Methodology Diagram

3.1 Unsuitable Areas Cleaning

The initial step is to eliminate areas considered unsuitable for construction. The unacceptable areas are the ones that do not allow for agrivoltaic placement. Environmental constraints include protected areas, such as sites of community importance, important bird areas, and other protected natural areas that restrict developments to preserve biodiversity. Technical constraints often involve safety distances from energy infrastructure. Regulatory constraints are dictated by land use plans and specific buffer zones around infrastructure like roads and railways, urban or territorial plans, and areas designated for public green, agricultural, or industrial use that cannot be easily changed. Socio-cultural constraints protect historical and cultural sites and maintain the scenic value of landscapes.

3.2 Weights of the selection criteria

The weights of positioning criteria are calculated via compromised weighting method, combining weights from Best-Worst Method (BWM), the subjective method, and Entropy method. The purpose behind this methodology is to obtain a more cautious and reasonable array of coefficients, that joint the advantages of subjective and objective methods while smoothing the inefficiencies. From one side, BWM offers a straightforward and effortless framework to pinpoint decision-maker's priorities, avoiding biases and time waste through the use of low-effort comparison vectors (Rezaei 2015). Nevertheless, as many subjective MCDM methods do, BWM is prone to incomplete information effects as it is completely based on the expert's opinions as to the subjective judgments (Singh & Pant 2021). Objective methods, such as Entropy method, objectively calculates weights avoiding human intervention relying on intrinsic information contained in the criteria (Kasim & Jemain 2020).

In the first step, the decision-maker selects the relative importance of each criterion using BWM. BWM fundamentally relies on comparing most and least favourable criteria against all other relevant criteria. This is done through Best-to-Others (BtO) and Others-to-Worst (OtW) vectors. The BtO vector is denoted as $BtO = (a_{B1}, \dots, a_{Bn})$, and the OtW vector is denoted as $OtW = (a_{1W}, \dots, a_{nW})^T$. Here, a_{Bj} represents the preference of the most favourable criterion over criterion j, and a_{jW} represents the preference of criterion j over the least favourable criterion. The variables w_B and w_j represent the weights of the most favourable criterion and criterion j, while j ranges from 1 to n, where n is the total number of criteria. The optimal weights vector $(w_1^B, \dots, w_n^B)$ is determined by solving a linear programming problem, as presented in Eq. 1-3.

$$\min \max_j \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \left| \frac{w_j}{w_W} - a_{jW} \right| \right\} \qquad 1$$

$$s.t. \sum_j w_j = 1 \qquad 2$$

$$w_j \geq 1 \; \forall j \qquad 3$$

The Entropy-based method starts by normalising the decision matrix, through the calculation method in Eq. 4. The variable x_{ij} represents the value of the j-th criterion for the i-th alternative, where i ranges from 1 to m (alternatives) and j ranges from 1 to n (criteria).

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}} \qquad 4$$

Entropy which characterizes uncertainty is traditionally used as the average measure of information contained in a message. Eq. 5 extends the use of entropy as an estimate of the degree of uncertainty among alternatives j within each criterion (Zeleny 2012).

$$E_j = \frac{\sum_{i=1}^{n} p_{ij} \cdot \ln(p_{ij})}{\ln(n)} \qquad 5$$

Furthermore, the complement of uncertainty, that is, certainty is taken as the proxy measures of criteria weights, as in Eq. 6.

$$w_j^E = \frac{1 - E_j}{\sum_{j=1}^{m} (1 - E_j)} \qquad 6$$

Finally, the combined weights of each criterion w_j^* are calculated as follows in Eq. 7.

$$w_j^* = \frac{w_j^B \cdot w_j^E}{\sum_{j=1}^{m} w_j^B \cdot w_j^E} \qquad 7$$

3.3 Suitable Sites Ranking

There are a variety of techniques within the MCDM to select alternatives. Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a distance-method, which calculates the distance of each alternative from both the positive-ideal and negative-ideal solutions.

After gathering the required data for each option and setting up the decision matrix $(x_{ij})_{m \times n}$, which includes m alternatives and n criteria, the TOPSIS method first vector-normalizes the decision matrix (Eq. 8). Subsequently, it multiplies each element of the newly formed $(f_{ij})_{m \times n}$ matrix by its respective weight, derived from the previous step, to produce the matrix $(t_{ij})_{m \times n}$.

$$f_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}}} \qquad 8$$

For each criterion, the best possible outcomes are represented by Z^+ for the positive-ideal solutions and Z^- for the negative-ideal solutions. In the case of benefit criteria J^+, Z^+ is assigned to the maximum value and Z^- to the minimum. Conversely, for cost criteria J^-, the maximum value is assigned to Z^- and the minimum to Z^+.

Next, TOPSIS determines the extent to which each alternative deviates from both the positive-ideal t_j^+ and negative-ideal t_j^- solutions, as described in Eq. 9-10.

$$d_i^+ = \sqrt{\sum_{j=1}^{n} \left(t_{ij} - t_j^+\right)^2} \quad \forall i = 1, \dots, m \qquad 9$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} \left(t_{ij} - t_j^-\right)^2} \quad \forall i = 1, \dots, m \qquad 10$$

The final step in the decision-making process involves calculating the relative closeness rc_i to the positive ideal solution (Eq. 11). The alternative with the highest relative closeness value is deemed the best.

$$rc_i = \frac{d_i^-}{d_i^+ + d_i^-} \quad \forall i = 1, \dots, m \qquad 11$$

Finally, an ABC analysis was performed to reclassify terrains based on the TOPSIS relative closeness value per pixel, segmenting the data into distinct categories reflecting varying levels of suitability.

4. Case Study

To illustrate the process practically, we consider a detailed case study situated in Puglia, specifically on the Gargano peninsula in the province of Foggia, encompassing the municipalities of Chieuti, Lesina, and Serracapriola (Figure

2). The proximity to the Tavoliere delle Puglie, one of Italy's most expansive plains and a leading national area for the production of durum wheat and buckwheat, offers additional synergies for agrivoltaics and local communities.

Now, we present the various constraints associated with the site. Initially, the land does not feature scenic roads but rather a road of value for the landscape. To establish and evaluate any necessary buffer zones, guidance is provided by local authorities through documents and reports included in the Piano Urbano Generale (PUG) under Regional Law 20/2001. The site does not contain Special Protection Areas (SPAs), Ramsar sites, Important Bird and Biodiversity Areas (IBA), or isolated natural cores. However, there is a Site of Community Importance (SCI), likely designated as a regional natural reserve.

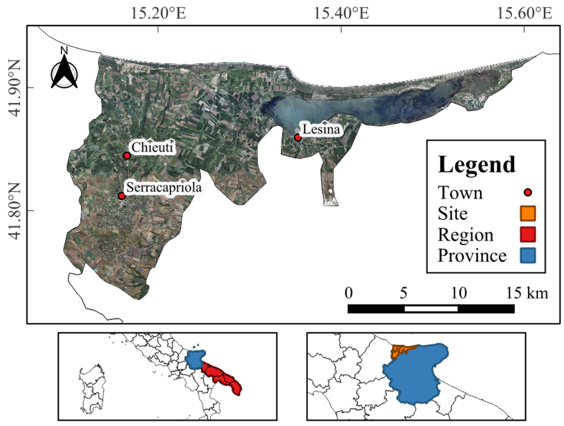

Figure 2 Study area map

Additionally, the land is flanked by two significant watercourses, one to the east and one to the west. It is also noted that there are three densely populated centres, corresponding to the three municipalities (Figure 3). Moreover, lands classified as non-arable were excluded from consideration, focusing solely on arable land, specifically non-irrigated types, derived from the European inventory CORINE Land Cover (CLC) (Cover 2000).

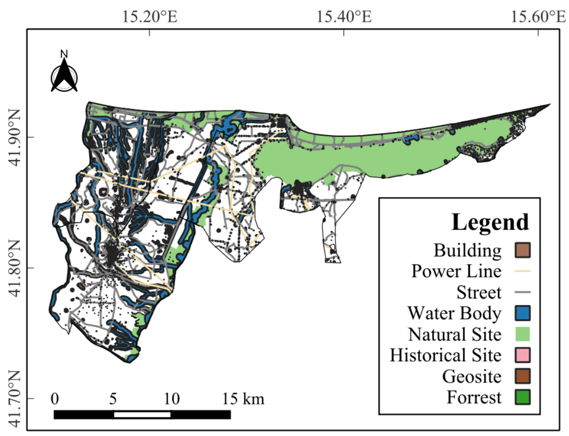

Figure 3 Identified exclusion zones

The considered buffer zones are listed in Table 1. The Digital Elevation Model (DEM) file in Figure 4 allows for the analysis of terrain elevation variability. This process utilises the DEM file, which can be accessed from the TINITALY portal (TIN of ITALY), a digital terrain model (DTM) of Italy that was created using a Triangulated Irregular Network (TIN)-based approach (Tarquini et al. 2023).

Table 1 Buffer areas considered

Restriction	Buffer	Unit
Natural Sites	>100	m
Water Bodies	>100	m
Lakes	>300	m
Historical Sites	>100	m
Slope	<5	°

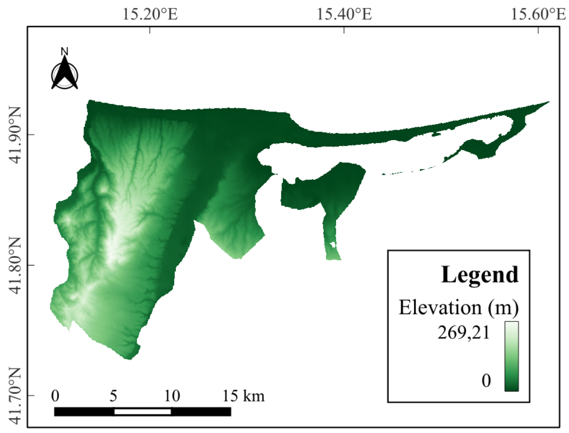

Figure 4 Digital Elevation Map (C1 – Elevation)

The slope of the land is crucial in the placement of photovoltaic installations as it directly affects the angle of the solar panels relative to the sun. This optimises the absorption of sunlight and maximises energy efficiency. Despite the land not being burdened by significant slopes, we represent this through a raster analysis conducted in. We performed an analysis to exclude slopes steeper than 5° in Figure 5.

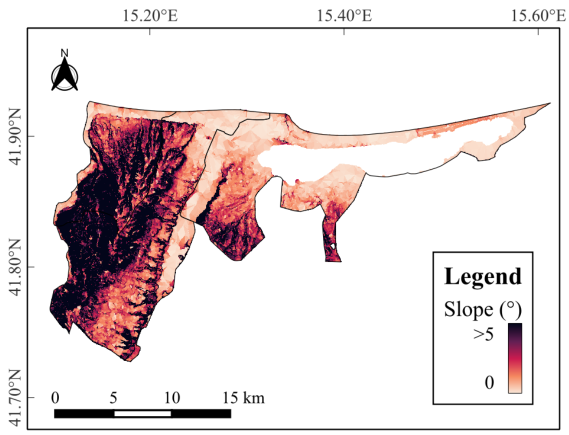

Figure 5 Slope map (C2 – Slope)

In Figure 6, it is possible to view the various slopes and their exposures. A south-facing slope is considered an ideal orientation for solar sites, as it maximises the amount of sunlight exposure throughout the day, enhancing the efficiency of the solar panels. Solar radiation, defined as the amount of solar energy received at a specific point on the

Earth's surface, is crucial for determining the electricity generation capacity of a PV system. Near coastal areas, the Global Horizontal Irradiance (GHI) tends to decrease due to factors such as humidity, temperature, and evaporation, which all impact solar radiation levels. GHI (kWh/m^2) per year represents incident radiation, such as in Figure 7.

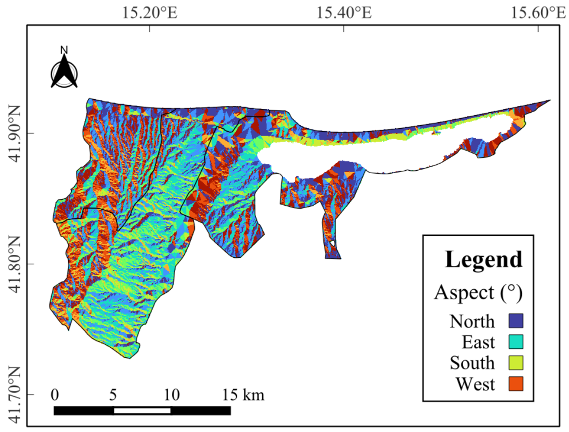

Figure 6 Land aspect (C3 – Aspect)

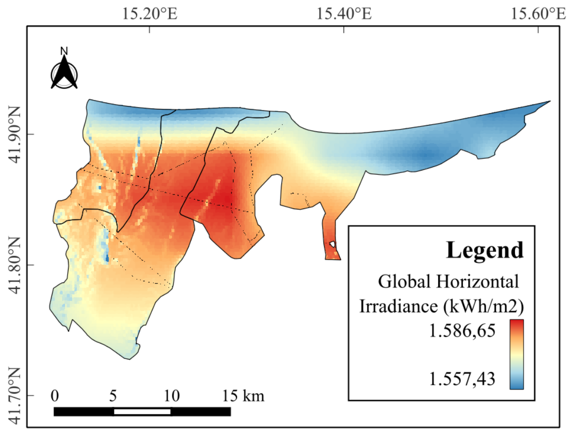

Figure 7 Global Horizontal Irradiance (C4 – GHI)

High temperatures decrease the efficiency of PV systems; each 1°C rise above 25 °C reduces energy output by about 0.4% to 0.5%. Below 25 °C, efficiency increases (Doorga et al. 2019). Additionally, PV panels can benefit from increased reflectance from vegetation, boosting energy production (Fattoruso et al. 2024) (Figure 8).

Access to well-maintained roads is crucial for the construction and maintenance of PV systems, as it facilitates the transport of heavy equipment and materials, reducing costs and logistical challenges (Figure 10).

Sites near the grid can significantly lower the expenses and complexities involved in extending transmission lines and constructing new infrastructure while also improving efficiency (Figure 11).

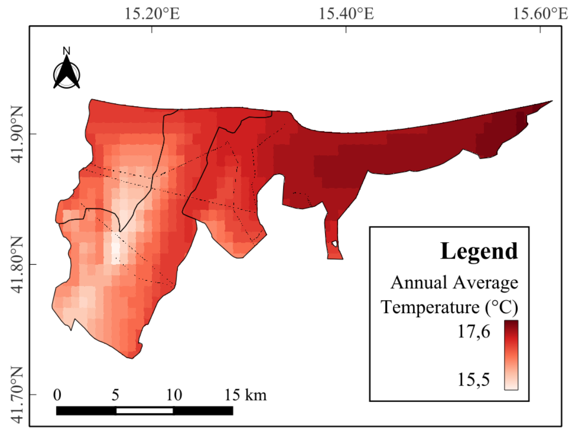

Figure 8 Average temperature (C5 – Temperature)

Figure 9 shows a rasterization of distances from major urban settlements, noting that proximity to cities reduces power losses, enhancing efficiency.

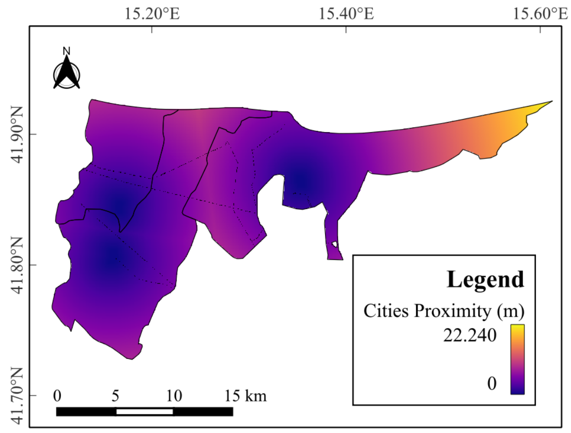

Figure 9 Cities proximity (C6 – Cities Proximity)

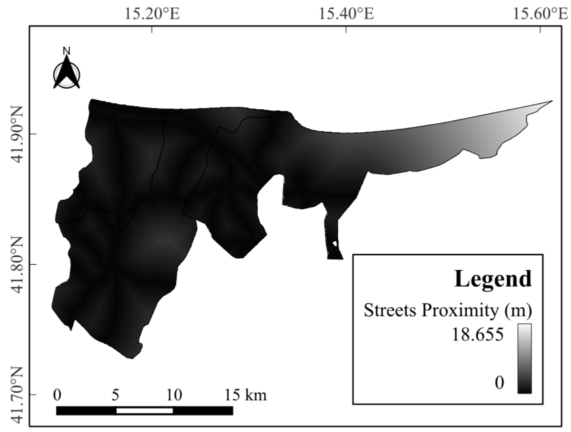

Figure 10 Streets proximity (C7 – Streets Proximity)

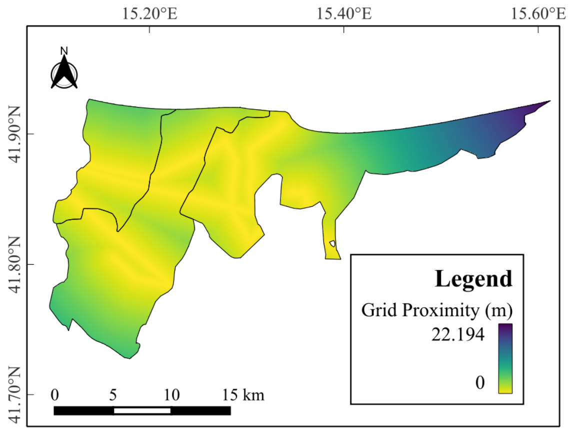

Figure 11 Grid proximity (C8 – Grid Proximity)

One of the most significant threats from climate change is the increased frequency and intensity of flooding. Rivers that experience sudden and severe flood events can pose substantial risks to nearby PV installations (Figure 12).

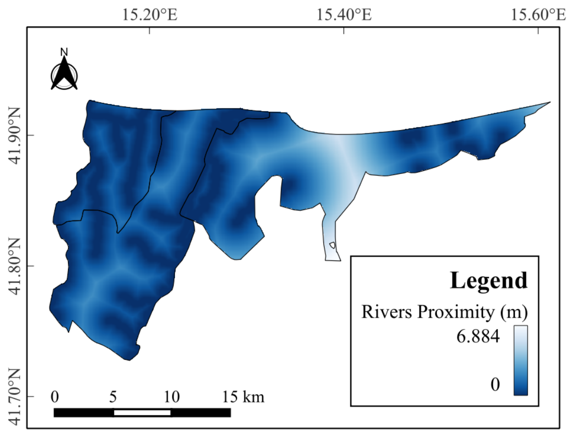

Figure 12 River proximity (C9 – River Proximity)

5. Results and discussion

Following BWM, the decision-maker, an energy expert with a master's degree and two years of experience, identified C4 as the most favourable criterion due to its critical importance in energy generation, thus assigning it the highest priority. C7 was rated as the least favourable due to its perceived lower impact and potential risks associated with climate change-related events. Using the Entropy method, C1, C3, and C2 emerged as the criteria with the highest weights, indicating that these factors exhibit the lowest degree of uncertainty. Their consistent data across potential sites makes them reliable indicators for influencing the decision on site selection for photovoltaic systems. The method provides a balanced view of the criteria, revealing which factors are more consistent across potential sites and which exhibit more variability. The integration of results from both the BWM and the Entropy method using the compromised weighting method provides a balanced set of weights for the site selection criteria (Figure 13). This approach effectively bridges the gap between expert opinion, which leverages experiential knowledge and subjective assessments, and data-driven insights that reflect objective measures of variability and certainty within the criteria.

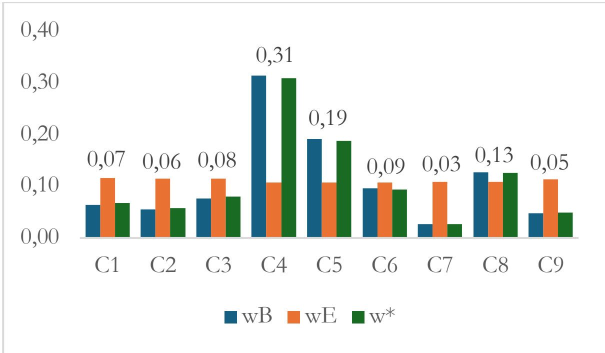

Figure 13 Selection criteria weights

The analysis conducted utilises the results from the TOPSIS method as input values for a raster. Subsequently, these values are reclassified through an ABC analysis, which divides the data into chunks of 70%, 15%, and 5% cumulative value. These divisions correspond to areas of high, moderate, and low suitability, respectively, as presented in Figure 14.

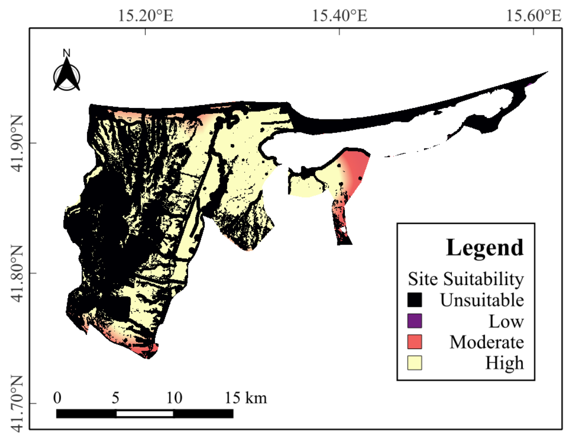

Figure 14 Suitability map

The analysis categorises land suitability into four classes to guide strategic land use planning. The largest category, highly suitable, spans 90.7 km² and aligns optimally with the evaluative criteria. Moderately suitable areas cover 15.8 km² and, despite not fully aligning with the criteria, hold potential with strategic adjustments. The smallest category of low suitability includes 5.3 km² , suitable only for specific uses due to limited criteria compatibility. The largest area, at 204.1 km², is unsuitable for intended uses and should be excluded. In conclusion, the assessment confirms the region's high suitability for agrivoltaic projects. Its large areas of flat, rainfed agricultural land, along with proximity to infrastructure and the national electricity grid, make it ideal for innovative agricultural-energy integration projects.

6. Conclusion

The integration of GIS and MCDM techniques offers a sophisticated framework for strategically selecting PV installation sites. This study applied these methodologies in Puglia, Italy, classifying land for agrivoltaic projects. A significant portion of the land was identified as highly suitable, aligning well with agricultural and renewable energy production objectives and leveraging regional advantages for agrivoltaic systems. The TOPSIS method, combined with a compromised weighting approach using BWM and Entropy methods, facilitated a detailed evaluation of potential sites.

The findings highlight the strategic value and feasibility of agrivoltaic systems in the region, showing how integrating agriculture with renewable energy on the same land not only optimises land use but also supports sustainability goals. This model can guide similar efforts to enhance energy security, lower carbon emissions, and help local communities transition to a sustainable, decentralised energy future.

Future developments could include a pre-assessment of urban solar community potential using data on solar capacity, building and household characteristics, and compatibility with agrivoltaic setups. Additionally, integrating agricultural building rooftops into agrivoltaic systems could increase the area available for solar panels and boost farm energy self-sufficiency. Developing optimised models for system sizing could maximise energy production while leveraging Italy's REC incentives, and using technological, regulatory, and planning tools to create sustainable, economically viable, community-focused renewable energy systems.

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