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Multicriteria Decision-Making Approach for Optimum Site Selection for Off-Grid Solar Photovoltaic Microgrids in Mozambique

José Eduardo Tafula [1,2,3], Constantino Dário Justo [1,2], Pedro Moura [1,2,*], Jérôme Mendes [2] and Ana Soares [4]

[1] Energy for Sustainability Initiative, University of Coimbra, 3030-788 Coimbra, Portugal
[2] Institute of Systems and Robotics, Department of Electrical and Computers Engineering, University of Coimbra, 3030-290 Coimbra, Portugal
[3] Faculty of Engineering, Lúrio University, Pemba 958, Mozambique
[4] Institute for Systems Engineering and Computers at Coimbra, Department of Electrical and Computers Engineering, University of Coimbra, 3030-290 Coimbra, Portugal
* Correspondence: pmoura@isr.uc.pt

Abstract: Given the constraints associated with grid expansion costs, limited access to reliable electricity, and priorities in addressing the climate agenda and Sustainable Development Goals in low-income countries, microgrids and off-grid solar projects represent a viable solution for rural electrification. This type of solution has the advantage of being less expensive than conventional technologies, is rapidly scalable, affordable, environmentally sustainable, and can play a critical role in empowering rural communities. In this context, this study proposed a spatial framework for off-grid solar energy planning based on a Geographical Information System and Boolean logic, Fuzzy logic, and Analytic Hierarchy Process Multicriteria Decision-Making methods. The results of the applied methodology show that the selection of optimal locations for off-grid solar photovoltaic microgrid projects in Mozambique is significantly influenced by the following order of criteria: climatology, orography, technical and location, social, and institutional criteria. Geographically, about 49% or 344,664.36 km^2 of the total study area is initially suitable for an off-grid solar photovoltaic microgrid project; 4% is low suitable, 14% is moderately suitable, 18% is suitable, and 13% is highly suitable. However, 51% of the ranked areas fall into the not feasible and restricted areas, mainly in conservation areas, protected areas, and areas at high risk of flooding and cyclones, covering a total of 387,005.5 km^2 within the study area. In general, the approach helps to reduce uncertainty and increase flexibility to identify appropriate sites and strengthen indicators of sustainable development impacts of decentralized rural electrification.

Keywords: multicriteria decision-making; off-grid microgrid; solar photovoltaics; rural electrification; Mozambique

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1. Introduction

1.1. Motivation

The Sustainable Development Goals (SDGs) highlight the risks posed by the impacts of climate change, undermining and reversing decades of progress on equality, food and energy security, and other SDGs. Energy poverty remains widespread, with approximately 800 million people lacking access to electricity. Most of this population is in sub-Saharan Africa in sparse rural areas far from urban centers, where the cost of electrification is usually unaffordable. Mozambique is a country facing the same reality, with a very low electrification rate, with overall access to electricity estimated to be below 31% in 2020 and only around 8% in rural areas [1,2]. Despite this fact, the government of Mozambique has adopted the 2030 Agenda United Nations and is committed to achieving the SDGs [3]. One of the goals—SDG#7—establishes universal access to electricity by 2030. To achieve this goal, Mozambique has launched the Energy for All Programme, with the aim of reaching 100% electricity access via increasing the electrification rate, especially in rural areas, through the expansion of on-grid and off-grid solutions based on renewable and non-renewable energy [4].

Despite a tripling of the electrification rate between 2006 and 2018, most rural areas will not be electrified in the foreseeable future due to slow electrification, lack of basic infrastructure, institutional barriers, and low ability and willingness to pay for energy services [5,6]. Recognizing the limitations and costs of grid expansion, as well as the priorities in addressing the climate agenda and SDG#7, decentralization of energy generation to rural communities in Mozambique has recently become an opportunity and represents an important means of gaining prominence and making connections in the lives of rural residents [7]. Figure 1 shows a map with data on the electricity access rate in each province of Mozambique. It shows that electrification is mainly concentrated in urban and peri-urban areas.

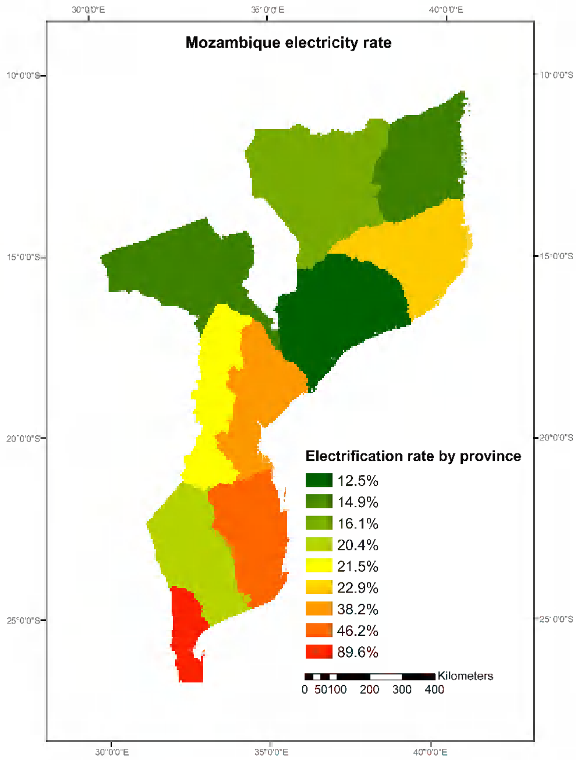


Figure 1. Mozambique electricity rate in 2020. Data from [8].

Moreover, more than 3 billion people worldwide rely on polluting solid fuels for cooking, causing an estimated 3.8 million premature deaths per year [9]. In this context, a transition of the global energy system is of utmost relevance, as energy use is responsible for the majority of global greenhouse gas (GHG) emissions. The accelerated expansion of power generation from renewable sources has contributed most to the reduction of emissions in the power sector since the share of renewable energy in global electricity generation increased from 19% in 2010 to 29% in 2020 [10]. However, the share of renewable energy in Mozambique, except for traditional hydropower, is still incipient. Despite the global irradiation varying between 1785 and 2206 kWh·m^{-2}·year^{-1} implying a significant potential for solar photovoltaic (PV) generation estimated at 23 TW$_P$ [11], the realistic potential capacity of solar energy in the country is estimated to be 2.5 GW [11,12]. Despite the shock from the pandemic (2019–2021), the expansion of renewables accelerated in 2020 with an approximately 40% increase in their contribution to emissions reduction in the power sector [13].

Decarbonization has become a major issue alongside climate change and resource depletion. To meet the increasing demand for energy sustainability, there is a fundamental need for greener and cheaper energy. Thanks mainly to renewable energy sources (RES), electricity has the potential to become an important green, relatively cheap, and powerful resource for future global development. However, providing electricity to rural communities that currently lack access to it usually requires systematic planning to find the cost-effective option between an extension of the existing grid and off-grid electrification to serve every non-electrified community with the most economical solution [14]. Such planning considers the availability of energy resources in each non-electrified rural area, as well as a reasonable timeframe and cost for grid expansion. In this context, identifying the most suitable locations is a crucial step in evaluating the feasibility and sustainability of developing a solar PV microgrid solution for rural area electrification.

An accurate, systematic, and effective decision-making framework is an essential tool to help policy and decision makers effectively plan strategies for solar PV microgrid siting, taking into account not only technical and economic competitiveness but also socio-cultural dynamics and environmental issues. It is well known that unsuitable locations can lead to a waste of energy and resources and affect the community and the environment in a harmful manner.

The scope of the present work is Mozambique. For energy planning problems, locating suitable sites for solar energy generation is a complex process that confuses decision makers [15]. In the case of a solar PV microgrid system, it is not only based on the availability of solar resources, but a variety of factors that depend on the site selection. However, selecting a site based on limited criteria can lead to the loss of opportunities for sustainable solar energy generation and failure to meet the climate agenda and SDG#7 [16]. A good selection process requires a comprehensive analysis to evaluate various aspects such as geographic, economic, social, technical, political, and environmental factors [17,18]. In fact, after reviewing the literature, many interesting studies have been found concerning the identification of the most suitable location for the installation of a solar PV power plant. Due to the complexity and several factors influencing the site selection, most studies have referred to the multicriteria decision-making (MCDM) method as a modern approach that is frequently employed in RES planning and policy and has higher accuracy compared to other methods [16,19,20].

Due to the multidimensional nature of sustainability goals and the complexity of environmental, technical, socio-economic systems, and institutional barriers involved in the energy sector, MCDM methods have been increasingly applied to different types of energy problems over the past four decades [21,22]. Moreover, choosing among available solutions that are unidimensional (cost-benefit) is not always correct. Generally, the MCDM problem for solar PV site selection implicates multiple alternatives that are evaluated based on multiple criteria. Moreover, due to the lack of literature in the field of off-grid solar PV microgrid system installation, the main motivation of this study is to determine the importance of criteria that influence the siting of off-grid solar PV microgrid projects for rural electrification in Mozambique through the application of MCDM methods. The MCDM process generally involves six main phases [15,23]: the formulation of the alternatives (definition of the problem and the study area), the selection of the criteria, the normalization of the data, the weighting of the criteria, the evaluation of the alternatives, and the validation of the results. In fact, many studies have been published in the literature concerning the application of multicriteria methods to support the decision-making process and the identification of unsuitable and suitable sites for solar PV power plant deployment and some are presented in the forthcoming subsection.

1.2. Related Work

Several works have proposed different solar PV site selection methods over the past decade, including mathematical programming, feasibility studies, and MCDM techniques to solve site selection problems [24,25]. On the other hand, given the fact that several criteria can influence site selection, geographic information systems (GIS) associated with MCDM techniques have proven to be a useful tool, combining spatial information, criteria weighting, and ranking to select a suitable location for solar energy plants [26]. In addition, many other MCDM methods are processed using GIS, including the Analytic Hierarchy Process (AHP) method based on the pairwise comparison, the Weighted Linear Combination (WLC), the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), the VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method based on scoring; the Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE), the Elimination and Choice Expressing Reality (ELECTRE) outranking based methods, and the fuzzy-based methods. In [27], it was shown that the use of several MCDM methods in energy facility siting problems is beneficial because it can help decision makers select the most sustainable sites while avoiding the drawbacks and taking advantage of the benefits of each method. Table A1 in Appendix A summarizes the recently reviewed works divided into single and hybrid MCDM approaches applied to solar PV site selection.

Saaty and Vargas's AHP is one of the most widely used MCDM methods among experts for renewable and conventional energy planning, energy resource allocation, building energy management, and electric utility planning [28,29]. In [30], AHP was used in the ArcGIS environment to compute the geographical, techno-economic potentials, and site evaluation for solar PV and CSP systems in Ghana and assessed suitability for 85% of the land. In Egypt, Elboshy [31] used the AHP approach to enable and determine the weights of the criteria and then aggregate them into GIS to produce the solar PV suitability map. Similarly, Günen [32] combined AHP with GIS for solar farm site selection in Kahramanmaras, Turkey. The main validation results show that the removed unsuitable areas are close to and overlapped by the most very low suitable areas so that the suitable areas fall, proving the consistency of the proposed framework (GIS-AHP-WLC). Ruiz [33], using the same approach in Indonesia, found that only 34% of the area was available for solar power plant construction when protected areas are considered. Using the same method, Rios [34] found that Peru is unsuitable for large-scale PV projects (about 69.52%) due to its location and ecosystem protection. Fang [35] used TOPSIS analysis to conduct solar site selection in China. It was shown that the approach does not require much prior information, which improves the efficiency and effectiveness of decision making. The proposed method incorporates social criteria, which are usually ignored in many solar site selection rankings.

Several hybrid methods based on fuzzy logic, ranking, and outranking have been proposed for integration into the MCDM framework to achieve optimal siting of photovoltaic systems. Recently, Villacreses [36] applied seven MCDM methods such as ARAS, OCRA, PSI, SMART, WLC weighted superposition, TOPSIS, and VIKOR for the geolocation of solar PV farms for a case study in Ecuador and found that the methods are highly correlated. Heidary Dahooie [24] proposed an integrated MCDM framework of TOPSIS, TODIM, WASPAS, COPRAS, ARAS, and MULTIMOORA ranking methods for solar site selection in Iran. The results show a great improvement in removing the limitations of non-combined methods. The authors in [20] proposed the MCDM model for the assessment of large PV farms in Brazil, using gvSIG software, AHP, and TOPSIS for weighting and ranking the alternatives. Kannan [25] developed a new hybrid approach based on BWM, GRA, and VIKOR to select the best site for the construction of solar plants for sustainable energy management in South Khorasan Province, Iran. With this approach, it was possible to obtain a global optimal weight of the final criteria using a linear mathematical model without the personal preferences of the experts having any influence on the results. Furthermore, in [37], the GIS-BWM-WLC approach was used not only for site selection for solar PV power plant projects but also to determine the significance of each decision criterion in site evaluation, with the best and worst criteria playing an important role in the decision-making process.

The outranking methods are also used combined with GIS and AHP as a hybrid approach, usually to compare the alternatives. In [38,39], the ELECTRE TRI method combined with AHP and GIS was demonstrated to be a helpful method for multicriteria decisions, and it was designed specially to address classification or segmentation problems. In [40], PROMETHEE and AHP methods were integrated with GIS to rank suitable areas for solar farm development. The combination of AHP, ANP, and PROMETHEE methods in [41] was useful to ensure the relationships among the several criteria.

The application of fuzzy logic in the MCDM framework for solar PV site selection has led to higher accuracy and reliability of results. Noorollahi [29] used AHP, fuzzy Boolean logic, WLC, and GIS to find suitable sites and estimate the PV power potential with high accuracy. Similarly, Saraswat [42] used the fuzzy AHP and GIS combined with the WLC approach to weight and rank the energy alternatives. AHP and fuzzy VIKOR were combined to determine the optimal site selection for solar plants in Pakistan [43]. In this study, a systematic research framework for comparative evaluation of potential PV cities has been presented, which is able to deal adequately with shortcomings, uncertainties, and inaccurate and vague data.

As previously mentioned, this study employs a method that combines AHP MCDM, fuzzy logic, Boolean logic, and the WLC approach along with spatial analysis using GIS. The reason for choosing this method is its ability to manage multiple conflicting decision criteria and consider the preferences of multiple decision makers [29,30]. Additionally, this method is also capable of decomposing a decision problem into a hierarchy of criteria and sub-criteria with relative importance assessments, and the aggregation of subjective judgments and preferences through a pairwise comparison matrix [31,36]. Furthermore, the AHP method allows for sensitivity analysis, which allows decision makers to evaluate the robustness of their decisions under different scenarios and criteria weighting schemes [32–34].

1.3. Contribution

In light of the above discussion, through a comprehensive and systematic review of the literature in the research areas and MCDM approaches for solar PV power plant site selection, it can be concluded that there is a lack of studies on the selection of suitable sites for the installation of solar technology based on off-grid mini-grids and/or microgrids, especially in countries with habitable rural areas scattered from each other, low population density, and predominantly low-income, which is the case of rural areas of Mozambique. In addition, only a few studies in the literature have begun to address social and institutional considerations in real-site selection processes using MCDM [44–46]. These social and institutional gaps are based on the flawed assumption that abstract support for the general idea of renewable energy should be positively associated with support for local renewable energy projects, regardless of other contextual factors [47]. Thus, the main contributions of this work are the following:

- This study provides a systematic and effective framework for prioritizing the factors influencing site selection for off-grid solar PV microgrid projects.
- This study presents the integration of social and institutional criteria in a GIS-MCDM-based framework for site selection for off-grid solar PV microgrid projects. This research is the first contribution in this direction.
- This study is unique in terms of suitable site selection for the installation of off-grid solar PV microgrid projects in Mozambique.
- This study presents a useful decision support tool to help decision makers prioritize suitable sites for off-grid solar PV system deployment in Mozambique, which satisfies environmental, climatic, orography, social, institutional, location, and technical criteria.

1.4. Paper Organization

The remainder of this paper is structured as follows. Section 2 presents the proposed overall methodological framework for sustainable site selection for rural electrification and energy access, namely presenting the GIS integration strategy with AHP, Fuzzy logic, and Boolean logic methods for selecting suitable sites. Section 3 describes the results achieved with the implementation of the proposed framework methodology, where Mozambique was selected as the study area to validate the new framework. Section 4 presents a discussion of the results. Finally, Section 5 presents the conclusion of the current research, the limitations of the applied framework, and provides suggestions for future studies.

2. Materials and Methods

After the literature review, this section presents the stages of the research methodology and explains in detail the methods, materials, and instruments used, as well as their applicability. To identify the suitable locations for off-grid solar energy installation in Mozambique, GIS is used with the MCDM approach, which is described in detail in the following section.

2.1. Proposed Methodology

2.1.1. Development of Criteria Maps and Restriction Factors

The Geographic Information System (GIS) running on ArcGIS 10.8 from the Environmental System Research Institute (ESRI), which is one of the remote infrastructure platforms that combines software, hardware, geo-referenced data, storage, management, calculation tools, and maps, has advanced and unique capabilities and flexible technologies for location-based analysis and visualization and processing of real geographic data to assist planning and decision making. The GIS-MCDM methodology includes geographic extent definition and information collection, factor standardization, scale and resolution definition, information rasterization, scale standardization and homogenization, and overlaying of maps leading to the selection of areas with high potential and exclusion of areas without the potential for solar PV microgrid development [40]. Moreover, the power of overlay analysis is combined with the MCDM approach to achieve faster and more reliable results in spatial analysis, using multiple map layers to integrate and evaluate seemingly conflicting criteria and produce map-based results as well as a decision support tool to resolve MCDM problems such as site selection and suitability modeling combining overlay analysis with the WLC method.

2.1.2. Restrictions Factors and Areas

There are some constraints that represent the technical and environmental restrictions of the studied area, which were established according to the literature, study objectives, and current legislation (urban areas, agricultural areas, flood and cyclone areas, airports, special protection areas, etc.) in order to identify not suitable and very less suitable locations for the installation of off-grid solar PV microgrids and consequently to reduce the study area by eliminating these areas where solar projects are given less priority. After identifying these restriction factors and layers, a suitable buffer zone corresponds to the study areas that should not be considered. The restriction factors and areas for this study were identified based on the study objectives, literature review [48,49], and applicable national regulations [50,51].

To increase the reliability of the suitability map, the restriction layers included additional buffer zones immediately adjacent to their boundaries. The extent of these zones was selected based on a conservative analysis, information availability, and the available geo-referenced databases. Map normalization was performed through the reclassification process and the determination of the lowest suitable and constrained areas was performed using Boolean logic. Finally, a calculation and weighted overlay mapping of the lowest suitable and constrained areas were generated by applying the WLC approach, where the value of each pixel is one for permitted areas or zero for non-feasible areas.

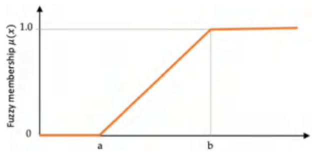
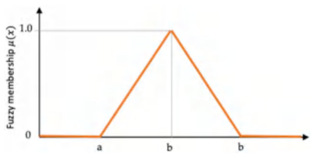
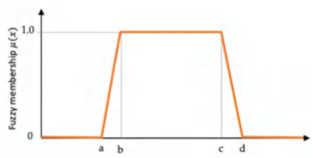
2.1.3. Criteria and Sub-Criteria Selection

Once the incompatible areas are identified, the compatible areas must be ranked according to their suitability for solar PV microgrid installation. This stage is one of the most important issues in the MCDM, namely the selection, weighting, and ranking of appropriate criteria to determine suitable locations for solar PV power plants. This depends on a complete and accurate understanding of the criteria and how they are selected considering the defined objective, study area, accessibility of datasets, and spatial scale. The criteria and sub-criteria selected in this study are based on a thorough and comprehensive literature review, surveys, and expert opinions. For rural electrification of developing countries through off-grid solar PV microgrid projects, the current study selected criteria that are relevant and can be processed, evaluated, and modeled according to six main categories: technical, climatological, orographic, social, institutional, and environmental criteria.

2.1.4. Criteria Layers Normalization and Standardization

Normalization and standardization of layers are the most important steps in the process of site selection. A fuzzy logic standardization approach will allow a more flexible analysis for decision-making, where there are no certain boundaries between suitable and unsuitable. Linear (ascending and descending), triangular, and trapezoidal functions were used for the fuzzification of the criteria layers, as shown by the equations presented in Table 1 [29,52]. For this study, for each map, the fuzzy value corresponding to each pixel was computed using the corresponding fuzzy membership function. For each criterion considered, the values of a cell in the fuzzy map indicate the degree of suitability of the cell concerning that criterion. The selection criteria were standardized by the respective fuzzy membership functions and thresholds considering the objective and field of study.

Table 1. Fuzzy membership functions [29,52].

Function	Mathematical Equation	Fuzzy Function
Linear ascending (LA)	$\mu(x) = \left\{ \begin{matrix} 0 & x \leq a \\ \frac{x-a}{b-a} & a < x < b \\ 1 & x \geq b \end{matrix} \right\}$	
Linear descending (LD)	$\mu(x) = \left\{ \begin{matrix} 1 & x \leq a \\ \frac{x-b}{a-b} & a < x < b \\ 0 & x \geq b \end{matrix} \right\}$	
Triangular (TR)	$\mu(x) = \left\{ \begin{matrix} 0 & x \leq a \\ \frac{x-a}{b-a} & a < x < b \\ \frac{c-x}{c-d} & b \leq x \leq c \\ 0 & x \geq c \end{matrix} \right\}$	
Trapezoidal (TZ)	$\mu(x) = \left\{ \begin{matrix} 0 & x \leq a \\ \frac{x-a}{b-a} & a < x < b \\ 1 & b \leq x \leq c \\ \frac{d-x}{d-c} & c < x < d \\ 0 & x \geq d \end{matrix} \right\}$	

To achieve the goal of spatial planning for solar PV microgrids in rural areas, it is necessary to evaluate the areas using a mathematical model. Because the different layers have different ranges, units, and information, the mapping layers of each criterion and the values of the sub-criteria must be converted into a common scale and unit so that they can be entered into the GIS database. In this way, a reclassification process that allows assigning criteria values to a raster map to create a common scale of values must be used.

2.1.5. Evaluation of the Weights of the Criteria

The Analytic Hierarchy Process (AHP) is a well-known form of the MCDM method that provides objective mathematics and logic for processing the inescapably subjective and personal preferences of an individual or group and can serve as a tool for solving decision problems in energy planning and location of RES, using a multi-level hierarchical structure for process evaluation in conjunction with GIS analysis. It was originally developed by Prof. Thomas L. Saaty in 1977 [53,54] and has the ability to include both qualitative and quantitative factors, and it gives simplicity for implementing the decision factors in the pairwise comparison matrix. The implementation of the AHP is based on three basic principles: (i) determining the problem structure as a hierarchy of goals, criteria, and alternatives; (ii) conducting a comparative decision-making preference matrix of criteria and alternatives at each level of the hierarchy (aggregation of expert judgments in a pairwise comparison matrix and inconsistency check); and (iii) determining the factor weights and analyzing the results. The extracted weights for the same hierarchy should sum to 1 (100%) [53,54]. These principles can be further elaborated by structuring them into a more comprehensive step process, as shown in Figure 2.

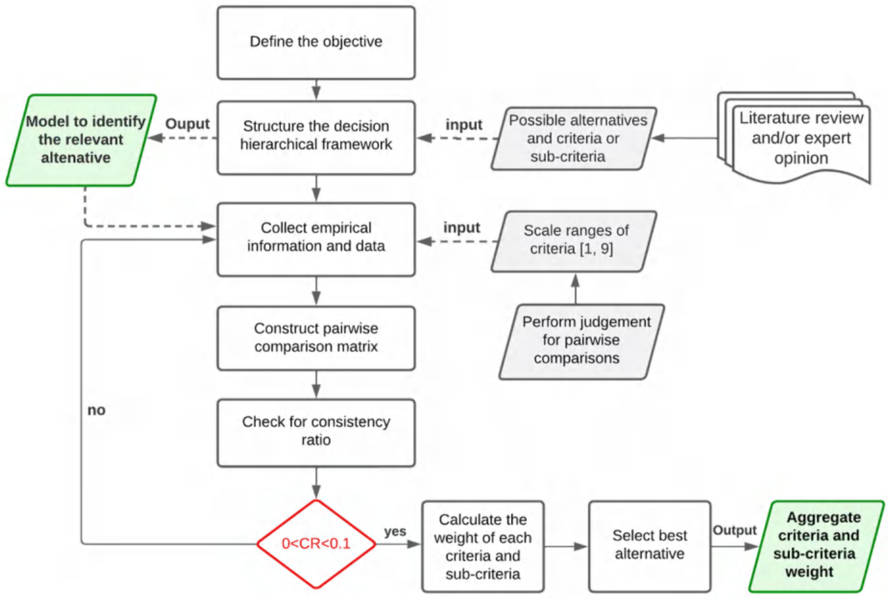


Figure 2. Flowchart of the Analytic Hierarchy Process (AHP) method.

According to the flowchart of the AHP (Figure 2), the formulation of the decision problem in the form of a hierarchy framework is the first step of the decision-making method, with the top level representing the goal or objective. At the middle levels, there are the identification and selection of criteria and sub-criteria, and the decomposition of the problem into a systematic hierarchical structure, with the model of decision alternatives as a result. Once a hierarchy framework is established, the pairwise comparison matrix is created using empirical information and data that represent the judgments of decision makers and experts when comparing the importance of each indicator relative to all other indicators. A scale of 1 to 9 was used to describe the intensity or degree of importance of the compared criteria. Here, the value of 1 for "equal importance" and 9 for criteria with "extreme importance" relative to the other criteria was used to form the pairwise comparison matrix, as shown in Table 2 [53,54]. The consistency check was performed to ensure that conclusions were consistent. If the accuracy ratio is found to exceed the threshold (10%), the pairwise comparisons should be reviewed and updated by the decision makers. Finally, in the prioritization phase of synthesis, each comparison matrix was solved by computing an eigenvector value to prioritize the rating of each parameter (criteria and sub-criteria) and the performance of the alternative. The procedure can be summarized as follows:

Table 2. Saaty's scale for pairwise comparison [53,54].

Score of Criteria i to Criteria $j(c_{ij})$	Definition
1	Equal importance (factors i and j are of equal importance); two requirements contribute equally to the objective
3	Moderate importance of one over another (factor i is slightly more important than j); experience slightly favors one requirement over another
5	Essential or strong importance (factor i is moderately more important than j); experience strongly favors one requirement or activity over another
7	Very strong importance (factor i is strongly more important than j); a requirement is strongly favored and its dominance is demonstrated in practice
9	Extreme importance (factor i is extremely more important than j); the evidence favoring one activity or requirement over another is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate values between the two adjacent judgments; this is when compromises are needed
Reciprocals	If activity i has one of the above numbers assigned to it when compared with activity j, then j has the reciprocal value when compared with i
Rationals	Ratios arising from the scale-if consistency were to be forced by obtaining n numerical values to span the matrix

An online questionnaire was created to evaluate and determine the importance of the criteria for the site selection of off-grid PV microgrid projects. The survey was submitted to 16 experts who have knowledge, skills, and expertise in the field of solar energy in Mozambique (academia, regulators, and the public and private sectors). The experts were asked to indicate the importance of all factors in the indicated range for each factor according to Saaty's scale (Table 2) and collected in terms of pairwise judgments [53,54]. Email invitations were sent for the online questionnaire, which was completed via Google Forms.

The geometric mean method (GMM) was used to consolidate or aggregate the 16-expert judgments. It was performed using the SpiceLogic AHP Software [55]. Moreover, the GMM was chosen because it preserves the reciprocal property of combining judgments [56]. For n number of members, aggregation of individual decisions using GMM is given by Equation (1) [57,58].

$$c_{ij}^{G} = \sqrt[n]{\prod_{k=1}^{n} c_{ij}^{k}}, k = 1, \ldots, n \tag{1}$$

where c_{ij}^{G} is the group decision for criterion i with criterion j; c_{ij}^{k} is the decision of individual k for criterion i with criterion j.

Given a finite set $\boldsymbol{M} = \{c_1, \ldots, c_n\}$ of alternatives, the pairwise comparisons of the alternatives are collected into a judgment matrix $\boldsymbol{M}$ (size $n \times n$), where n is the number of elements to be evaluated. The pairwise comparison matrix $\boldsymbol{M} = [c_{ij}]$ is constructed for the lower levels with a matrix in the level immediately above, as shown in Equation (2), where each element $(i, j = 1, \ldots, n)$ represents the measure of the criteria weights. In other words, the AHP method uses a pairwise comparison between multiple criteria to construct the matrix $\boldsymbol{M}$. Each entry scale (c_{ij}) in the comparison matrix represents the decision maker's rating of the relative importance or degree of preference of criterion i over j among two criteria based on the Saaty's scale mentioned in Table 2. The structure of a pairwise comparison matrix of order n is as follows in Equation (2):

$$\boldsymbol{M} = (c_{ij})_{n\times n} = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1n} \\ c_{21} & c_{22} & \cdots & c_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ c_{n1} & c_{n2} & \cdots & c_{nn} \end{bmatrix}, c_{ii} = 1, c_{ij} = {c_{ij}}^{-1}, c_{ij} \in \mathbb{R}^{+}, \forall_{i,j} = 1, \ldots, n \tag{2}$$

The value of $c_{ij} > 1$ represents higher importance for i criterion over the j criterion, whereas $c_{ij} < 1$ specifies the lower importance of i criterion over the j criterion. In other words, transposed elements are positive reciprocals $c_{ij} < 1 \Leftrightarrow \left({c_{ij}}^{-1}\right)$. The value $c_{ii} = 1 \Leftrightarrow c_{ij} = c_{ji} = 1$ when both i and j criteria have the same relative importance. However, each entry c_{ij} in the matrix $\boldsymbol{M}$ must comply with the reciprocal condition mentioned in Equation (3) [59].

If Equation (2) is satisfied, then $\boldsymbol{M}$ is called a consistent multiplicative reciprocal preference relation.

$$c_{ij=}c_{ik} \times c_{kj}, \forall_{i,j,k} = 1, \ldots, n \tag{3}$$

To establish a normalized pairwise comparison matrix ($\bar{\boldsymbol{M}}$) from $\boldsymbol{M}$:

i. Divide each entry (c_{ij}) in each column of matrix $\boldsymbol{M}$ by its column sum to create normalized pairwise comparison entries ($\bar{c_{ij}}$) as defined in Equation (4). The matrix becomes a normalized comparison matrix ($\bar{\boldsymbol{M}} = [\bar{c_{ij}}]$).

$$\bar{c_{ij}} = \frac{c_{ij}}{\sum_{l=1}^{n} c_{ij}} \tag{4}$$

ii. Each ($\bar{c_{ij}}$) should be in a way that the sum of each column in $\bar{\boldsymbol{M}}$ must be equal to 1.
iii. Calculate the vector for the evaluation-criteria weight ($\boldsymbol{W}$) or eigenvector using Equation (5). The normalized principal eigenvector (priority vector) is obtained by the average of each row of the last normalized matrix ($\bar{\boldsymbol{M}}$).

$$\boldsymbol{W} = \frac{\sum_{l=1}^{n} \bar{c_{ij}}}{n} \tag{5}$$

Because comparisons are made through the inescapably subjective and personal preferences of an individual or group, a reasonable degree of inconsistency is expected and therefore tolerated in all comparisons. Moreover, people's decisions and preferences are sometimes intransitive and inconsistent, which can cause interference in the calculation of the criteria eigenvector. A consistency check should be performed to hedge judgments and verify the consistency of the calculated weighted values.

The consistency-ratio (CR) is regarded as one of the most advantageous features of the AHP method [60] and is incorporated to measure the degree of consistency among the pairwise comparisons by computing the CR. The weights are consistent when the resultant of CR is less than 10% [54]. The CR is estimated as follows:

i. Firstly, the maximum or largest eigenvalue λ_{max} for each c_{ij} matrix is obtained following Equation (6).

$$\lambda_{max} = \frac{MW}{W_i}, \forall_i = 1, \ldots, n \tag{6}$$

ii. Equation (6) is used to calculate the consistency index CI.

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{7}$$

iii. Finally, the CR is calculated using Equation (7).

$$CR = \frac{CI}{RI}, 0 \leq CR \leq 0.10 \tag{8}$$

RI is the random consistency index of the matrix $\boldsymbol{M}$ and can be estimated from the literature [53,54] as a function of the value n given in Table 3. The result of the pairwise comparison is sufficient if the CR value is equal to or less than 0.10 ($\leq$10%). Otherwise, the steps need to be repeated according to the AHP flowchart in Figure 2.

Table 3. Saaty's random index for different values of the number of criteria [53,54].

n	1	2	3	4	5	6	7	8	9
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45

2.1.6. Determination of the Suitability Map Ranking

The weighted linear combination (WLC) approach is the widely used method in GIS-MCDM problems for renewable energy site selection [23,29]. To obtain the final suitability maps index of rural areas, a WLC approach uses the overlay analysis function of the ArcGIS environment, which combines the algebra toolset, the previous fuzzy standardized raster layer, the weighted AHP criteria, and the sub-criteria as a simple and accurate statistical method to produce the suitability index maps, where each grid cell in the fuzzy standardized score layer ($\boldsymbol{X}$) of a grid cell j under criterion i is multiplied by a relative weight (w) assigned to that layer or criteria and sub-criteria i, and n is the total number of weighted evaluation criteria. Finally, the results are summed to produce the initial suitability index grid cell (SI) weighted sum model (*WSM*) (Equation (9)) [49].

$$SI(WSM) = \sum_{i=1}^{n} w_i X_{ij} \tag{9}$$

To exclude unsuitable sites, a Boolean constraint is applied to each grid cell by multiplying the initial suitability maps by the product of the binary constraint maps, SI weighted product model (WPM) (Equation (10)) [49]. As a result, the locations corresponding to each pixel $\boldsymbol{B} = 1$ derived from Boolean logic approach in the final restriction map corresponding to permitted areas, and $\boldsymbol{B} = 0$ for non-potential areas.

$$SI(WPM) = \prod_{i=1}^{n} B_{ij} \sum_{i=1}^{n} w_i X_{ij} \tag{10}$$

2.2. Study Area

Rural areas in Mozambique were selected as the study area because 63% of the total population lives in this region and the electrification rate remains very low. This is mainly due to the lack of basic infrastructure as well as the high cost of expanding the electricity grid and the low ability and willingness to pay for energy services [61]. As previously mentioned, due to constraints and the need to democratize, digitalize, and decarbonize the energy sector, cost-effective, socio-economic, and socio-environmental solutions are needed to achieve SDG#7 and meet the climate agenda in sub-Saharan Africa.

The area considered in this study (Figure 3) is located on the east coast of southern Africa, between the parallels 10°27′ north and 26°52′ south and between meridians 30°12′ east and 40°51′ west, with a coastline of about 2700 km and a total area of 801,509 km^2. Topographically, Mozambique is divided mainly into mountainous and hilly regions (in the north and west of the country) with high altitudes, plateaus in the center, and parts of the south characterized by vast coastal alluvial plains. The state borders Malawi, South Africa, Swaziland, Zambia, and Zimbabwe. A long stretch of the Rovuma River forms the border with Tanzania to the north. Part of the northwestern border runs through Lake Nyasa. Mozambique also shares maritime borders with Comoros, Madagascar, and the island of Mayotte. Administratively, Mozambique is divided into 11 provinces, which in turn are subdivided into 161 districts, 408 administrative divisions, 1132 localities, and 53 municipalities [62].

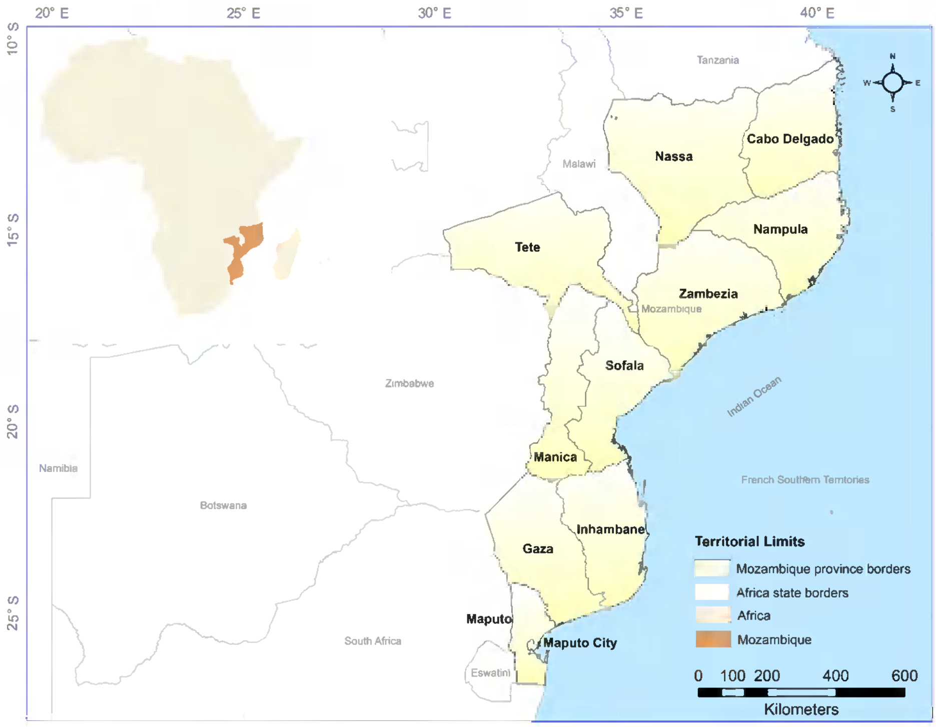


Figure 3. The geographical and spatial position of the study area.

Mozambique has a variety of warm subtropical and tropical climates with two seasons, a wet or summer season and a dry or winter season. The average annual temperature ranges from 20 to 22 °C in the winter months (May to September) to 24 to 26 °C in the summer months (October to April). Precipitation is more abundant in the central and northern regions of the country, with values ranging from 800 and 1200 mm per year. The average annual sunshine duration is up to 2760 h with global irradiation between 1785 and 2206 kWh·m^{-2}·year^{-1}, which corresponds to an estimated potential of 23 TW. Such high sunshine duration and solar irradiation imply that Mozambique has extensive potential to develop solar energy. However, Mozambique's geographical location poses enormous challenges for establishing energy investment projects due to its particular characteristics and vulnerability to flooding and tropical cyclones [63]. Therefore, it is necessary to provide specific and systematic information for the selection of sites for solar technologies according to the location, and climatic, economic, social, political, orographic, and environmental conditions of the country.

2.3. Framework Overview for Site Selection of Solar PV Microgrid Deployment

Figure 4 presents the proposed framework methodology with an overview of the implementation and integration of GIS and MCDM methods. The framework includes the following steps: (1) The first step is to determine the constrained and lowest suitable areas where the restriction factors are defined using the georeferenced database and maps. Twelve data layers were identified and used to analyze the unfavorable areas. (2) Nineteen sub-criteria layers were selected based on the study objective, resulting in five main criteria layers. (3) The commercial computer software ArcGIS 10.8 from the Environmental System Research Institute (ESRI) was used to calculate and map the regulated buffer zones for unfavorable and favorable areas by performing buffer analysis. (4) The Boolean logic perspective was used to identify and map the constrained zones. (5) The reclassification process was used to normalize and reassign new output values to the data layers of the constrained and sub-criteria maps. (6) The WLC approach was used to create the final restriction map of the study area by calculating and overlaying the raster layers. (7) The fuzzy logic approach is used to standardize the different sub-criteria maps and layers. The

AHP approach was used to assign weights to each suitability criterion and rank them based on the literature review and expert judgment. (8) The ArcGIS tools were then used to generate suitability maps by applying the weighted sum-overlay approach of the WLC. After applying the proposed approach to generate the suitable and not suitable maps according to the different criteria and constraintsthe WLC approach was used to create and rank the final suitability map. (9) A theoretical potential assessment was conducted, first considering five suitability scales (high suitable, suitable, moderately suitable, low suitable, and constrained and lowest suitable areas), using the established suitability framework [49,64]. Finally, the potential areas in different rural areas were explored in terms of universal access to modern energy in Mozambique.

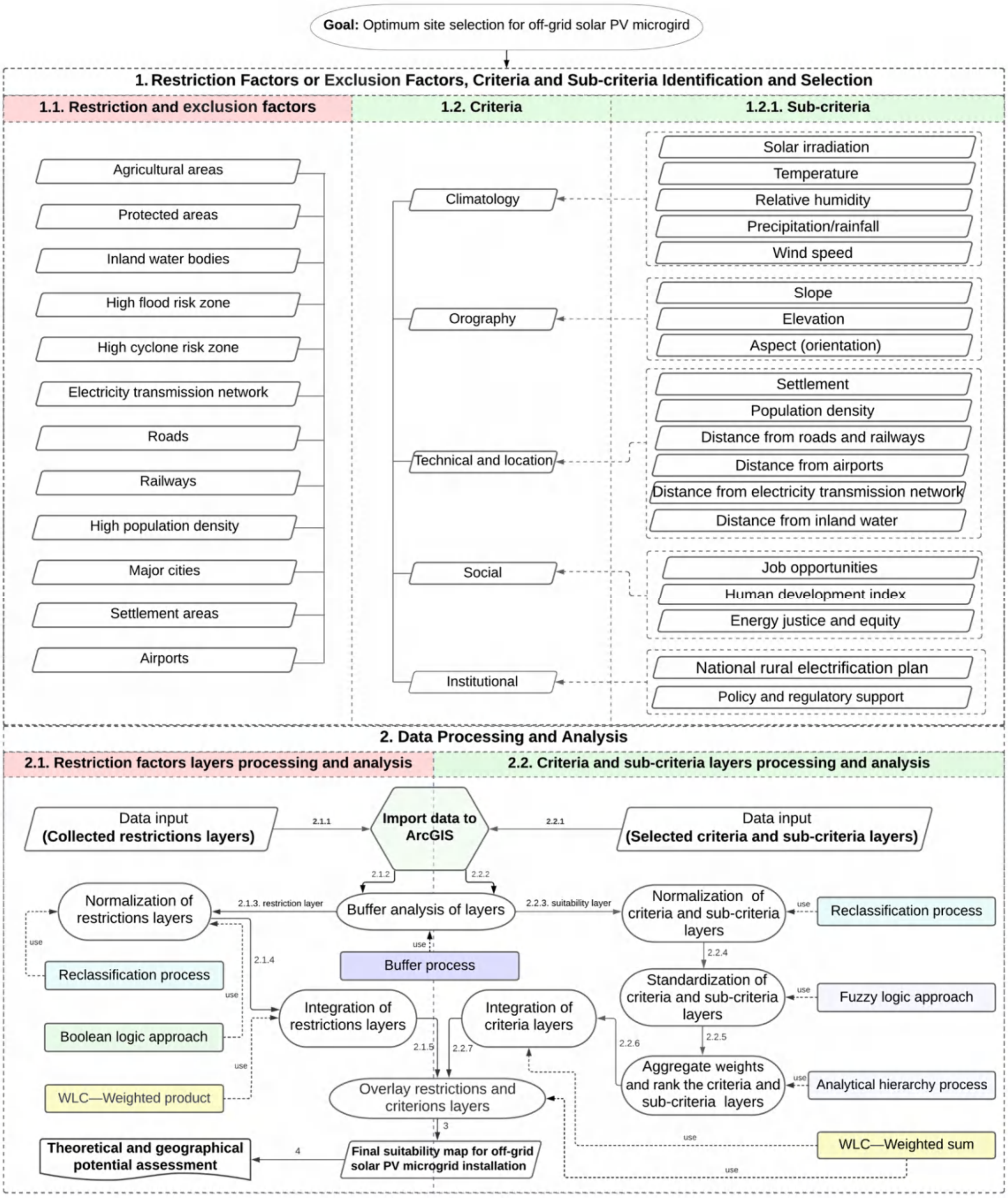


Figure 4. A framework for the proposed methodology.

3. Results

3.1. Existing PV Solar Power Plants in Mozambique

As in many developing countries, rural electrification in Mozambique began with the extensive use of diesel generators to provide electricity to remote communities [65]. Later, in 1997, the government established the FUNAE to provide off-grid solutions, including micro- and mini-hydropower plants, and solar PV micro and mini-grids for the electrification of rural areas [66]. This fund is in line with the national electrification strategy, which aims to expand access to electricity for all by 2030. On the other hand, grid-connected projects are entrusted to the state-owned electricity company EDM, which also has exclusive rights to operate and expand the existing electrical infrastructure for generation, transmission, and distribution, as well as to supply electricity to consumers at the national level.

Figure 5 shows the existing energy infrastructure in Mozambique. Based on the available data sources from the first half of 2022 (FUNAE online map of implemented mini-grid projects, EDM reports, and statistics), PV mini-grids (with capacity from 4 kW to 550 kW) and 3 large PV power plants (with capacity from 30 MW to 41 MW) were identified and harmonized in a new and single geodata layer. The existing solar power infrastructure was combined with additional spatial information on the existing power grid and the extent of human settlements to illustrate the current status of rural electrification of each settlement by solar power sources. However, the methods for prioritizing and validating off-grid solar projects still lack a multicriteria analysis to make them sustainable in the short, medium, and long term.

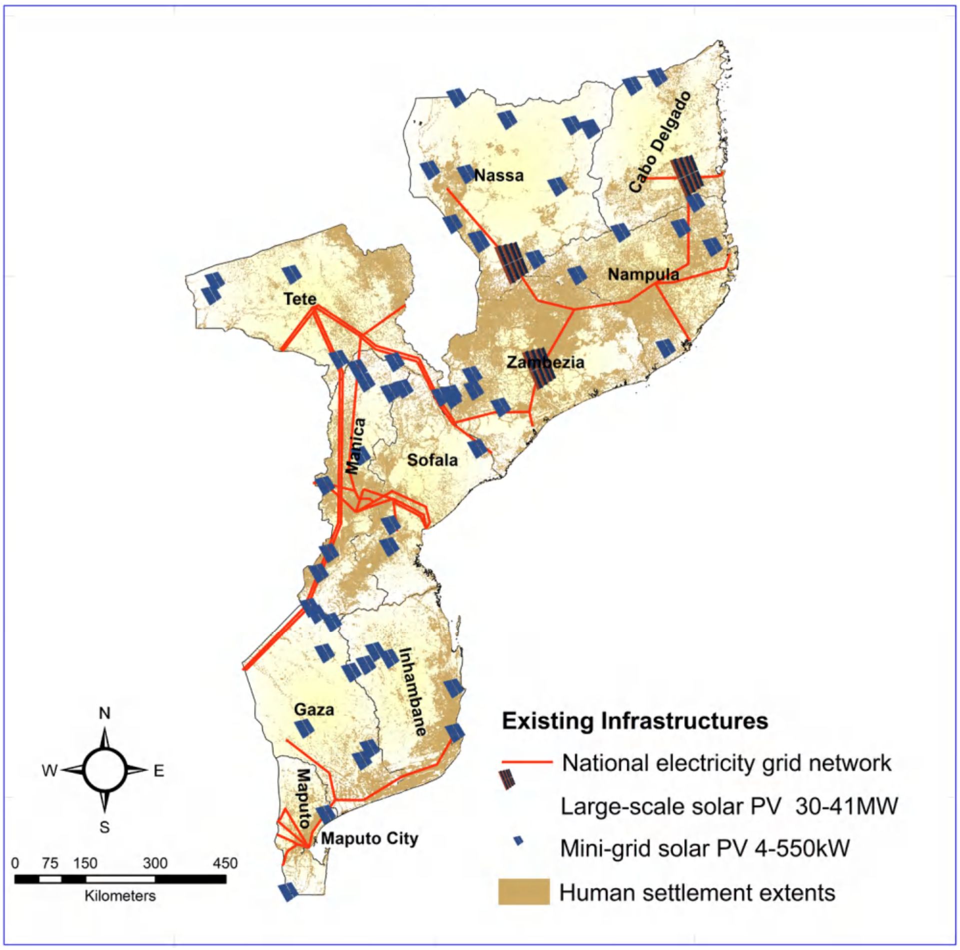


Figure 5. Existing energy infrastructure in Mozambique (solar power stations and existing network) and human settlement extents.

3.2. Data Collection and Map Layers Development

To create the required map of sites suitable for PV microgrid projects in Mozambique, geospatial information and attribute data were collected from secondary sources to cover the various criteria and constraints selected for this case study. Each of the raw spatial data of thematic layers listed in Table 4 represents specific georeferenced cartographic information of the studied areas of the Mozambican territory (see Figure 4). Then, the original layers were processed with the ArcGIS tools in suitable formats that can be immediately integrated into the Boolean logic, fuzzy logic, and the AHP model to perform the spatial analysis.

Table 4. Collected data sets to identify suitable sites for the installation of solar PV microgrids.

Source	Subject	Description	Format	Resolution
[67]	Solar irradiation	Long-term yearly GHI (kWh·m^{-2}·year^{-1})	Raster	25 m × 25 m
[67]	Temperature	Yearly temperature at 2 m above ground (°C)	Raster	25 m × 25 m
[68]	Relative humidity	The average relative humidity over one year.	Raster	83 m × 83 m
[69]	Precipitation	Data set from classification System (PERSIANN-CCS) satellite precipitation (mm.year^{-1})	Raster	4 km × 4 km
[70]	Wind speed	The mean wind speed in m·s^{-1} measured at 10 m high above the ground level	Raster	13 m × 13 m
[71]	Slope	Reclassified Shuttle Radar Topography Mission (SRTM) 30 m	Raster	30 m × 30 m
[71]	Elevation	Digital Elevation Model (DEM) from SRTM; 30 m image elevation above sea level	Raster	30 m × 30 m
[71]	Aspect	Reclassified SRTM 30 m images	Raster	30 m × 30 m
	Agriculture areas	Land use for farmland, farmyards and orchards	Vector	-
[51,72]	Protected areas	Protected Areas and other effective area-based conservation measures	Vector	-
[73]	Inland water	Groundwater and surface water in a given land area (including lakes, rivers, and canals)	Vector	-
[74]	Flood areas	Qualitative classification of flood	Vector	-
[75–77]	Cyclone zones	Cyclone hazard (idai, kenneth, gombe, eloise, and dineo)	Vector	-
[78]	Electricity Transmission Network	Existing transmission and distribution infrastructure	Vector	-
[79]	Roads	Road attributes: highway, primary, secondary, and tertiary roads, arterial and residential streets	Vector	-
[80]	Railways	Existing railways	Vector	-
[81]	Airports	Existing airports	Vector	-
[82]	Major cities	Mozambique administrative areas	Vector	-
[83]	Population density	The dataset of spatial distribution of population density at a resolution of 30 arc	Raster	100 m × 100 m
[84]	Settlements and built-up areas	Human settlement based on the presence of buildings detected in satellite imagery	Vector	-

3.3. Restrictions Factors

Restriction maps and factors related to the study areas help to map and identify areas that are not suitable and prohibited for the installation of solar PV microgrids projects to ensure that the project does not negatively impact the environment, agriculture, or local communities while meeting the study's objectives for selecting optimal sites in remote rural off-grid areas. To obtain these maps, appropriate geographic input layers and buffer zones for each restriction and exclusion zone were constructed as indicated in Table 5, considering the current literature, the nature of the study area, the objective, and expert opinions in the field of energy planning, and the experience of the authors. Furthermore, no policy and legal restrictions on the construction of solar power plants in Mozambique have been identified. The following sections explain the adopted buffer zones and threshold values, restriction factors, and exclusion zones. Table 5 presents the threshold values used for excluded and selective factors in the study case.

Table 5. Buffer zones and threshold values used in the spatial analysis for off-grid solar PV micro-grid siting.

Ref.	Factor	Restriction Factors	Units	Threshold
[49]	Climatology	Solar irradiation	kWh·m^{-2}·year^{-1}	<1461
[48]		Temperature	°C	<3 and >27
[32,85]		Relative humidity	%	>65
[86]		Precipitation	mm	<20
[42,87]		Wind speed	m·s^{-1}	<1.5
[18,48]	Orographic	Slope	%	>10
[88]		Aspect (orientation of PV panels)	-	=True north
[43,48]		Elevation	m	>1500
[48,49]	Environmental	Agriculture areas	m	<500
[48,49]		Protected areas	m	<500
[49,89]	Locational	Inland water bodies	m	<500
[48]		High flood risk zone	m	<1000
[75,77]		High cyclone risk zone	m	<1000
		Electricity transmission network	m	<3000
[90]		Roads and railways	m	<500
		Major cities	m	<40,000
[90]		Airports	m	<3000
[91]		High population density	people·km^{-2}	>350
[48]		Settlement areas	m	<2000

Climatology factors: These play an important role in determining the technical and economic viability of a solar PV microgrid. In order to ensure the best possible performance, factors such as solar irradiation, temperature, humidity, precipitation, and wind speed must be considered. Therefore, off-grid sites with an average annual solar irradiance of less than 1461 kWh·m^{-2}·year^{-1} (4 kWh·m^{-2}·day^{-1}) are not considered suitable for the installation of a solar PV microgrid [49]. Areas with values greater than 27 °C [48], 60% [32,85], and 20 mm [86] for annual average temperature, relative humidity, and precipitation, respectively, were also considered very less suitable, and values of less than 1.5 m·s^{-1} [42,87] for wind speed at 10 m height above the ground level were considered very less suitable. All these factors affect the PV system's solar energy conversion and electricity output.

Orographic factors: The elevation, slope, and aspect increase land use capacity and ensure economic viability for off-grid solar energy projects. In this study, sites with slopes greater than 10% [18,48] are classified as very less suitable areas for solar PV microgrid installation. Similarly, the elevation in the spatial model is of technical and economic importance and values above 1500 m [43,48] are classified as extremely high altitudes and very less suitable areas due to the high cost of construction and operation of the system in these areas, despite low temperatures, high irradiation, and humidity that positively affect the PV efficiency. Moreover, the recommended orientation (aspect) for the installation of solar PV panels in Mozambique is towards the north, as this orientation is considered the most favorable for maximizing solar energy conversion and electricity output [88].

Environmental factors: Solar PV projects should use low-value land. Agriculture and protected areas are considered exclusion areas to preserve agricultural production and avoid interference with the natural environment, national parks, and ecological reserves. After reviewing the regulations and previous studies conducted in Mozambique, this study assumes a buffer of 500 m for the development of solar PV microgrids [48,49,51].

Locational factors: These have economic and risk implications for solar PV microgrid projects and help identify a potential rural area for system development. To identify an off-grid and rural area, regions that are far from the electricity transmission network, areas with low population density, near roads and railways, far from airports, inland waters, and flood and cyclone areas are considered. Based on the data from various literary works, a significant buffer zone with a 3 km radius around all electricity transmission networks and airports should be considered for off-grid solar PV systems [48,49,89]. In addition, areas with a population density of more than 350 people·km^{-2} (major cities, suburban, and urban areas) are considered very less suitable areas [91], and a 2 km radius buffer zone around settlements is adopted in view of negative social–environmental hazards such as ecosystem impacts and visual pollution, as well as a favorable buffer distance to ensure safety conditions [48]. In addition, good and easy accessibility to main roads and railways has an impact on the economic viability of solar PV projects. Therefore, a buffer zone of 500 m around the main roads and railways was considered [90]. Mozambique has a large number of inland water bodies (rivers, lakes, and water bodies). To protect water resources from pollution and avoid adverse impacts such as flooding, a buffer radius of 1 km around high-risk floodplains was considered. In addition, to prevent adverse effects and any destruction of solar PV power plants, a buffer zone of more than 1 km to the high-risk areas for cyclone zones is defined [75,77].

3.3.1. Constraint and Not Suitable Area Maps

The Spatial Analyst Toolbox of ArcGIS 10.8 software was used to systematically filter out areas where energy resources are technically unsuitable. For each reference layer, the buffer zone distance (see Table 5) was applied using ArcGIS's buffer tool. Values of 0 are assigned for unsuitable sites (forbidden zones) and 1 for feasible sites (permitted zones) for solar PV projects in Mozambique and then converted to a raster format. The restriction layers are presented in Figures A1 and A2 in Appendix B.

3.3.2. Final Restriction Areas

All restriction layers were normalized using the reclassification process and Boolean logic and overlaid using the WLC approach. All restriction layers were considered with the same percentage influence in the weighted overlay to create the overall binary restriction map (exclusion and lowest suitable areas), which was classified as the lowest suitable and removed from the final suitability map to increase and ensure the accuracy of the site selection for off-grid solar PV microgrid projects. Figure 6 shows the final map of unsuitable and lowest suitable areas. The constrained areas with the restriction masks for off-grid solar PV microgrids constitute roughly 51% (387,005.24 km^2) of the total land area of the study area. Most of the restricted sites for off-grid PV microgrid projects belonged to nature reserves and protected areas (prohibited areas), which were responsible for 34% (131,581 km^2), followed by the high flood risk areas in the southern and central regions and the cyclone areas in the central and northern regions, which were responsible for 16% and 7%, respectively. Additionally, a large part of inland waterways was classified as restricted, which accounted for 3%, as well as the total area of power transmission networks, which accounted for 5% of the country's total area, which are constrained and lowest suitable areas for the installation off-grid solar PV microgrid.

3.4. Standardization and Evaluation of Criteria Using Fuzzy Functions

After reclassifying the raster map based on the boundary parameters, threshold value, and buffer zones, a fuzzy logic approach was used in each map to standardize the scale and fuzzify each pixel using the fuzzy membership function (see Tables 1 and 6). The raster maps were evaluated from zero (not membership) to one (full membership degree) to indicate the degree of suitability of the cell. Therefore, linear ascending or increasing fuzzy membership functions (MFs) were used in this study for the sub-criteria of solar irradiation, major cities, and electricity transmission network.

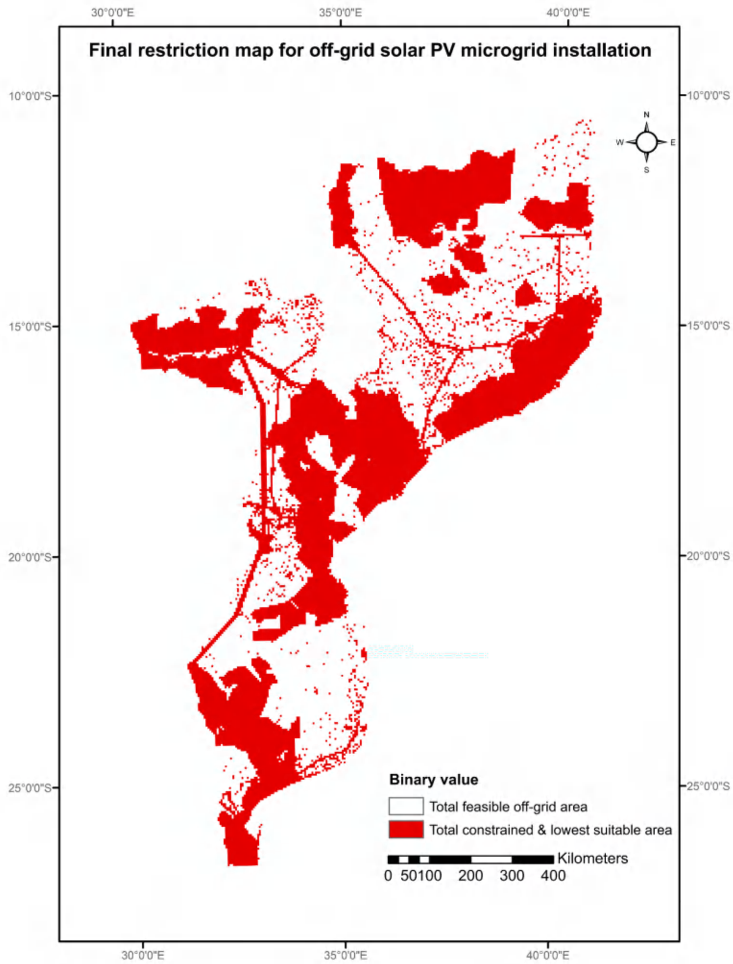


Figure 6. The final map of constrained and lowest suitability areas for off-grid solar PV microgrid sites in Mozambique.

The sub-criteria slope, elevation, precipitation, and population density are characterized by linear descending MFs. Temperature and distance from roads, railways, and airports, which are criteria characterized by triangular MFs, were established as their lower and the upper boundary were assigned a value of 0, and the middle or highest region was assigned a value of 1. In addition, triangular membership functions (MFs) were established for this sub-criteria. This sub-criteria affects the efficiency and economic viability of PV projects in certain distance and temperature ranges. The ranges include: first extreme base points to buffer distance, abscissa value to optimal distance, and second extreme base points to non-optimal distance. The temperature ranges include: first extreme base point of −3 °C, abscissa value of 25 °C, and second extreme base point of 27 °C. These ranges and MFs are shown in Table 6. Finally, trapezoidal MFs were defined for relative humidity, wind speed, distance from inland waters, and settlements. In addition, the trapezoidal function for the sub-criteria was determined based on the efficiency and techno-economic viability of PV projects in specific distance ranges, weather conditions, and locations.

The results of the fuzzification process for each climate criterion as a raster layer are shown in Figure A3 in Appendix B. The pixel suitability of the study area was ranked in the maps from low-scoring areas (zero) to high-scoring areas (one). It is important to note that the raster map of solar irradiation, shown in Figure A3a, has values higher than the minimum solar irradiation recommended for the technical–economic feasibility of solar projects across the country (<4 kWh·m^{-2}·day^{-1}). The average temperatures in the center and northwest are more appropriate than the average temperatures in the rest of the country

(Figure A3b). Nevertheless, the country has minimum and maximum average temperatures that can be considered reasonable for the efficient operation of solar PV systems.

Table 6. Membership functions for each criterion standardization for Mozambique's off-grid solar PV microgrid site selection.

Criteria	Sub-Criteria	Units	[1] MF	Boundary			
				a	b	c	d
Climatology	Solar Irradiation	$kWh \cdot m^{-2} \cdot year^{-1}$	LA	1460	[2] Max.	-	-
	Temperature	°C	TR	3	25	27	-
	Relative humidity	%	TZ	61	63	65	80
	Precipitation	mm	LD	20	2000	-	-
	Wind speed	$m.s^{-1}$	TR	1.5	4	6	15
Orography	Slope	%	LD	[3] Min.	10	-	-
	Aspect	-	LA	Flat	North	-	-
	Elevation	m	LD	[3] Min.	1500	-	-
Technical and Location	Distance from inland water	m	TZ	500	12,000	65,000	85,000
	Distance from the electricity transmission grid	m	LA	20,000	[2] Max.	-	-
	Distance from railways	m	TR	500	100,000	225,000	-
	Distance from roads	m	TR	500	15,000	100,000	-
	Distance from airports	m	TR	3000	115,000	205,000	-
	Distance from major cities	m	LA	40,000	[2] Max.	-	-
	Population density	$people \cdot km^{-2}$	LD	[3] Min.	350	-	-
	Distance from settlements	m	TZ	2000	4000	8000	100,000
Social	Job opportunities	index	LD	Low	High	-	-
	Energy justice and equity	index	LD	Low	High	-	-
	Human Development Index	index	LD	Low	High	-	-
Institutional	National rural electrification plan	existence	LD	[3] Min.	[2] Max.	-	-

[1] Membership function (MF): Linear ascending (LA), Linear descending (LD), Triangular (TR), and Trapezoidal (TZ). [2] Max. (Maximum value in the map). [3] Min. (Minimum value in the map).

The wind speed required to avoid dust and cool the solar PV panels, thereby increasing the performance of PV systems, is more prevalent in the southern region, Tete province in the center, and provinces in the coastal regions (Figure A3c) In general, the percentage of relative humidity is higher in the eastern region than in the rest of the country, indicating that these regions are less suitable for the implementation of PV microgrid projects because a lot of moisture can penetrate into the PV cells through the cracks, resulting in a loss of solar radiation energy and reduced solar cell productivity due to absorption or reflection by the water layer (Figure A3d). The minimum annual precipitation required for regular cleaning of PV modules has been verified in all regions and is considered more favorable in the southern region and less favorable in some specific regions in the central and northern parts of the country (Figure A3e).

The fuzzy raster map of orography criteria in Figure A4 in Appendix B indicates that Mozambique has good topographical conditions (Figure A4a). Significant areas of the provinces have moderate to high potential for the construction, operation, and maintenance of off-grid PV microgrids, of which the southeast to southwest and the middle east to northeast regions are the most suitable elevations. The conditions for the slope criteria are similar to those for the elevation criteria (Figure A4b). North and northeast to northwest oriented regions have a higher potential to receive solar radiation and are therefore more suitable. These regions are more likely to be found in the country's north and center, as seen in the aspect raster map in Figure A4c.

The proximity to roads, railways, and airports, taking into account the given buffer zone, is presented in Figure A5 in Appendix B. This result can help reduce the final installation cost and environmental degradation that the construction of solar PV microgrids would cause. However, most of the roads shown in Figure A5a near the off-grid and rural areas are not paved, and this criterion should be reconsidered and carefully analyzed in terms of economic impact. The existing railway network in Mozambique dates from the colonial era and was geared toward a service economy that connected the hinterland to the outside world through Mozambique's ports and coal exports, rather than the socio-economic development of rural or off-grid areas. Nevertheless, after reclassifying and fuzzifying the distance, Figure A5b shows that the country has an acceptable railway infrastructure that allows the feed-in of off-grid solar PV microgrid projects, thus increasing the economic viability of these projects in rural and off-grid areas of the country. In terms of distance from airports to rural and off-grid areas, the northern and central regions have less distance than the southwest region of the country, as shown in Figure A5c. In this study, off-grid areas are considered as areas 20 km away from the national electricity transmission and distribution network. Therefore, the highest priority regions for these criteria are in the north, followed by the extreme center in the west and a large part in the southeast, as shown in Figure A5d.

Inland waters are classified as a technical criterion in this study because they have a significant impact on the efficiency of the solar systems, since a relevant quantity of water is needed for the regular cleaning of the PV modules and Mozambique is crossed by several waterways, rivers, and banks, as shown in Figure A5e.

Population density is considered in this particular study as a social and techno-economic criterion that helps identify where the demand is to provide the most cost-effective solutions. Regions with low population density are considered more suitable for electrification based on off-grid solar PV microgrid projects since people cannot afford electricity from the main grid due to their remote location, high cost of grid expansion, and socio-economic conditions. As can be seen in Figure A5f, after the reclassification and fuzzification of the population density map, the country has large areas for the installation of off-grid solar PV projects.

Beyond the commonly used criteria (climatological, orographic, technical, and location), there is a need for holistic research that leaves no society behind and works toward a just transition and a decarbonized, digitized, and democratized energy economy. Therefore, this study applied social and institutional criteria to the GIS, Boolean logic, fuzzy logic, and AHP MCDM framework based on regulations, the national rural electrification plan, socio-economic factors and indicators of the country, and the job opportunities and formation factor, which constitutes an innovative and novel approach. The national off-grid rural electrification plan map was developed and illustrated based on the FUNAE dataset [66], especially data from the portfolio of solar energy projects, and the regulation of energy access in off-grid areas [50] published in 2019 and 2021, respectively.

The method adopted by FUNAE for the selection of the solar PV micro- and mini-grid project sites followed a set of variables such as population density and its dispersion; availability of energy resources; economic and social activities that are developed locally; existing infrastructure; and priorities set under existing programs. However, the portfolio as well as some variables can vary greatly depending on the ongoing feasibility studies. Figure 7a presents the reclassification and fuzzification of the national rural electrification plan map, in which a value of 1 represents a completed membership degree or an existing rural electrification plan in the region.

The Human Development Index (HDI) sub-criteria were created according to the socio-economic profile and performance of a population based on a dataset from [92] and [93] by performing a principal component analysis to combine the national index such as socio-economic vulnerability and the percentage of people living in a household whose head does not have access to education and health facilities. The integration of social and institutional factors into the framework can play an important role in improving the HDI of rural populations. The HDI map highlights the most vulnerable populations with limited options in the center and north of the country and in Gaza province in the south of the country. Most of the central and northern regions were reclassified and fuzzified as priority regions for renewable energy projects based on the dataset results from the raster map, the knowledge of the authors, and the objectives of the study, as shown in Figure 7b.

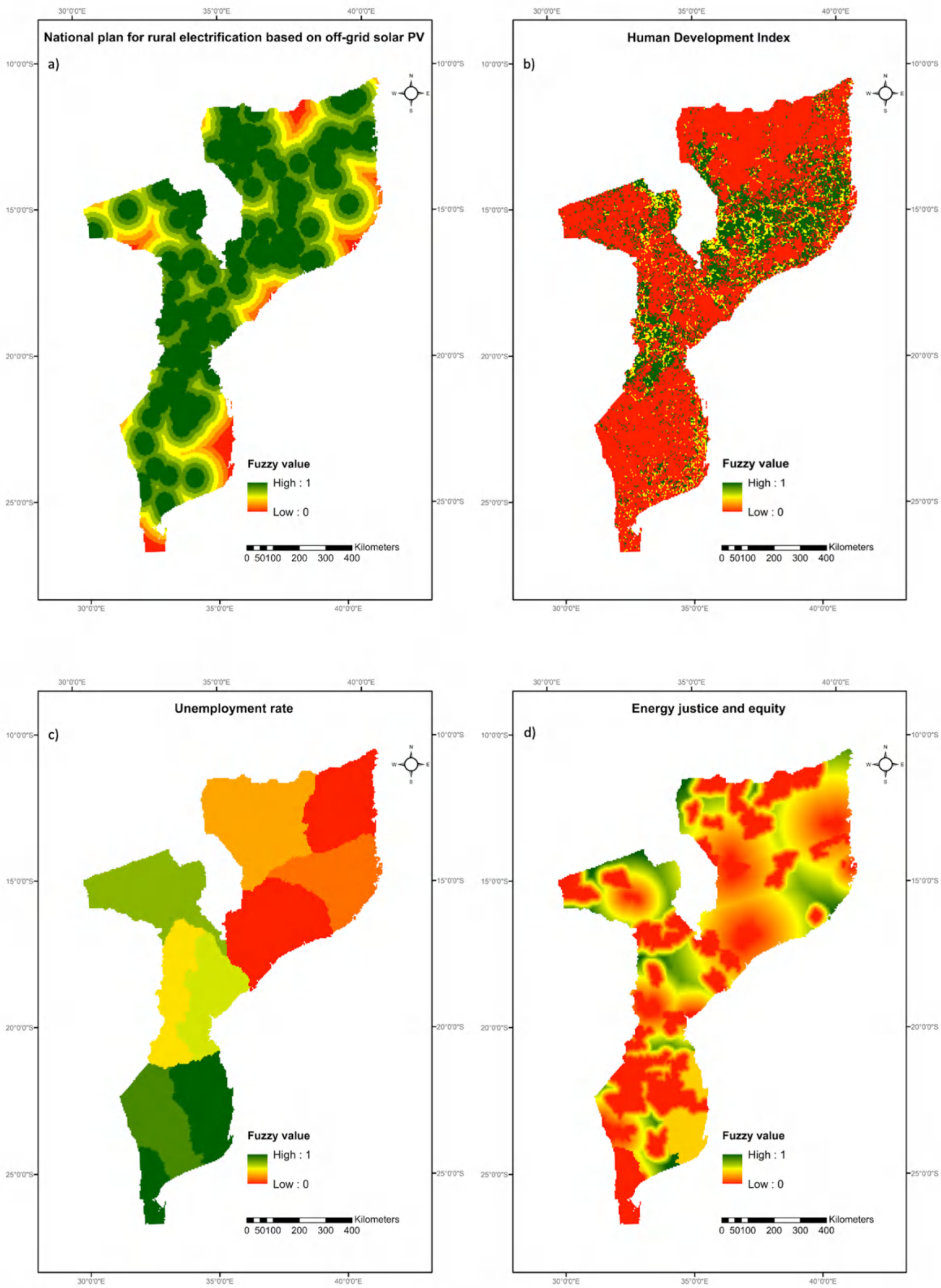


Figure 7. Standardized (reclassified and fuzzified) raster maps of institutional criteria and social criteria to the spatial suitability of off-grid solar PV microgrid projects in Mozambique. (**a**) National plan for rural electrification, (**b**) Human Development Index, (**c**) unemployment rate, and (**d**) energy justice and equity.

Unemployment rates are also determined by the HDI, resulting in fewer opportunities for young men and women. Nevertheless, Mozambique shows a decrease in the unemployment rate from 20.7% in 2014–2015 to 17.5% ± 3.2% in 2019–2020. In urban areas, the unemployment rate is extremely high compared to that in rural areas, at 28.9% compared to 11.4% [94]. The province of Zambezia and the northern region of the country have the lowest unemployment rate. Based on the unemployment rate map and the goals of this study, the regions with the highest unemployment rates in the country were reclassified and fuzzified as priority areas for solar energy projects, as shown in Figure 7c. Associating the unemployment rate and the job opportunities that renewable energy has been generating in the last decade, the deployment of off-grid solar PV projects can provide a great opportunity for job creation and alternatives to support the household, commercial, and agricultural sectors' needs and contribute to rural development.

According to data from IRENA 2022, solar PV employment retains the top spot in the world, with 4.3 million in 2021, up from about 4 million in 2020, and 56% of these jobs are located in rural areas, with parts of sub-Saharan Africa and South Asia at 372,000 full-time equivalent jobs [95]. Mozambique has already begun to harness its solar potential and promote job creation in the renewable energy sector. One example is the creation of approximately 1209 direct and 410 indirect jobs in the grid-connected Mocuba and Metoro projects, respectively. The uptake of off-grid solar energy for productive use also promotes direct job creation throughout the energy value chain in Mozambique, with approximately 380 jobs.

To make universal access to electricity and the transition to a more sustainable energy system equitable, several dimensions of social justice must be considered. The energy justice network used in this study aims to reduce the current vulnerability of communities by analyzing the various existing power plants (solar PV mini-grids, large PV power plants, thermal, and hydropower plants) as well as the electrification rates. Using the Euclidean distance and the fuzzy logic approach to classify areas that are harmed or not equitable in terms of access to electricity and existing power plants in the country, it was found in Figure 7d that the central and northern areas are slightly behind the southern regions of the country. It can be assumed that this result is related to the electrification rate in the southern region, which is over 52%. Therefore, in order to reduce energy inequality, the central and northern regions of the country should be considered as a priority for solar PV microgrid projects.

Figure A6 in Appendix B shows the reclassified and fuzzified raster maps for lower priority and restricted areas and their respective buffer zones as well as the fuzzy ranking considering the objectives of the study area. To ensure that solar PV microgrid projects in rural areas are given priority, all major cities were excluded, and a buffer zone of 40 km was established. The regions are prioritized in ascending order, as shown in Figure A6a (major cities), and the prioritization order for the criteria of settlement, agriculture, tropical cyclones, protected areas, and floodplains is also ascending.

3.5. Implementation of the AHP for the Weighting Criteria Process

In this study, a questionnaire method was used to collect the evaluations and ratings of 16 experts regarding their gender, entity, country, and self-assessment and evaluation of the criteria. While 25% of the experts were female, 75% were male (Figure 8a). Figure 8b shows the three expert groups, namely private sector/company, public sector/government institutions, and academia/researchers, with a contribution of 6%, 13%, and 81%, respectively. The experts were from the fields of environmental engineering, renewable energy, energy planning, renewable energy integration planning, sustainable energy systems, electrical engineering, on-grid and off-grid renewable energy systems, energy efficiency, and management specialties based in Mozambique (81%), Angola (13%) and Portugal (6%) and were asked to evaluate, score, and weight the criteria for each category. As shown in Figure 8d, the experts rated the criteria for installing off-grid solar PV microgrid projects in Mozambique from high to very low priority criteria.

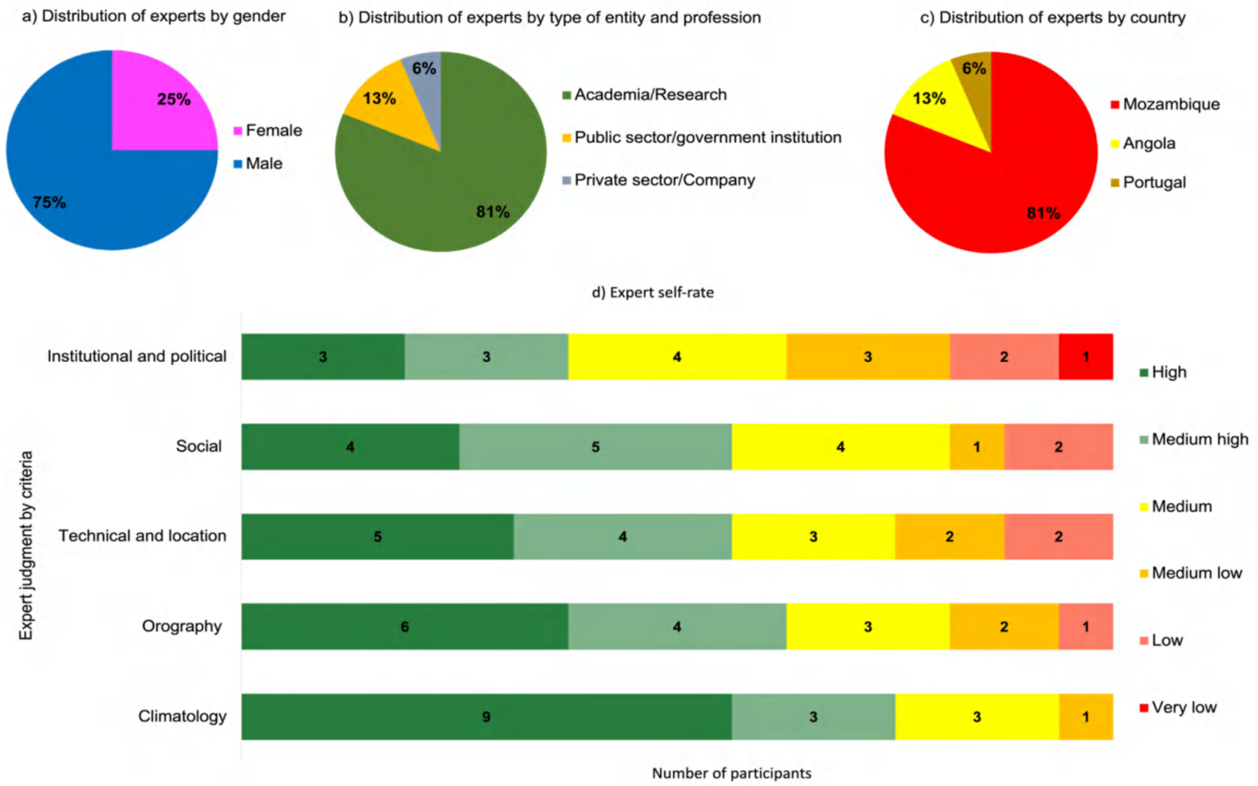


Figure 8. The main characteristics of experts and criteria judgment.

As mentioned in the methodology, the second step was to define the hierarchical decision framework, which had to be aligned with the strategic objectives of the study. For the current study area, the AHP was created by considering climatological, orographic, technical and location, social, and institutional criteria. The following set of nineteen sub-criteria (level three) and five alternatives (level four) were accepted and grouped into five categories (level two), as shown in the hierarchy in Figure 9.

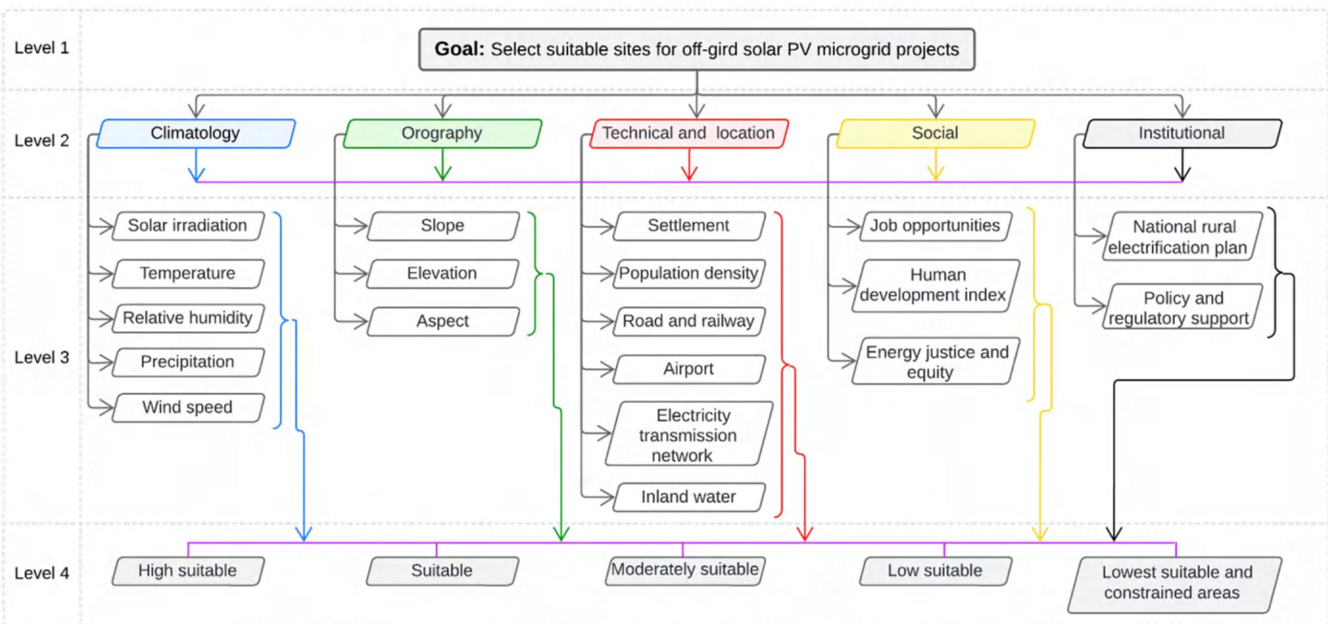


Figure 9. Hierarchy of criteria applied to the AHP for siting off-grid solar PV microgrid projects.

3.5.1. Pairwise Comparison Matrix for the Solar PV Microgrid Projects

Once the hierarchy was established, the second important step was to create the comparison matrix using SpiceLogic AHP Software [55] to check the consistency of the aggregated multiple judgment of the criteria and sub-criteria (Equation (2)). The evaluation began by determining the relative weight of the initial five groups of criteria (Figure 9). First, the climatological criteria were considered by the experts as the most important criteria because they define the output power of the solar PV microgrid (see Figure 8). Next were the orographic criteria, as they determine the amount of irradiation on the solar modules (slope and orientation) and the economic viability (elevation). These criteria were reevaluated and pondered by the authors based on expert opinion, in which the expert evaluated technical and location criteria as the second most important. From a techno-economic perspective, the experts and the authors rated technical and location criteria and, in the following order, social and institutional criteria as the least important factors to consider in the decision analysis for the siting of off-grid solar PV microgrid projects. Based on the reasoning mentioned above and the expert evaluation, the pairwise comparison matrix of size 5 × 5 elements of main criteria $C_i|C_j$ was constructed, as shown in Table 7. The $C_i|C_j$ (climatology, orography, technical and location, social, and institutional) are the set of criteria evaluated and C_{ij} are values from the nine-level (one to nine) comparison scale (see Table 2) conferred by the expert's judgment (see Figure 8).

Table 7. Comparison matrix of the adopted decision criteria obtained from experts' judgments.

[1] **Criteria**	**CL**	**OR**	**TEL**	**SO**	**IN**
CL	1	2	5	7	9
OR	1/2	1	3	5	7
TEL	1/5	1/3	1	3	5
SO	1/7	1/5	1/3	1	3
IN	1/9	1/7	1/5	1/3	1

[1] Criteria: climatic (CL), orographic (OR), technical and location (TEL), social (SO), and Institutional (IN).

After the pairwise comparison matrix had been created, to interpret and give relative weight to each criterion, the normalization of the comparison matrix was calculated by dividing each value by the total value of the column.

The third important step was to compute the priority weights, checking for consistency and assessing the robustness of decisions across various scenarios and criteria. The AHP was used to calculate and extract the eigenvector, which denotes the priority weight of each criterion. The sum of all extracted weights should equal one or 100%, as shown in the summary of AHP results (Table 8). The weighted values of each main criterion and consistency ratio (CR) were calculated based on Equation (6) ($\lambda_{max} = 5.28$), Equation (7) ($CI = 0.046$), Table 3 ($RI = 1.12$), and Equation (8) ($CR = 0.041$); because CR (Equation (7)) is less than 0.10, the AHP results are considered acceptable and the CR shows that the compatibility among the experts' judgments or the evaluation criteria was appropriate. Table 8 shows the relative priority weights for the sub-criteria. The CR index for sub-criteria was computed in the range of [0, 0.078] (<0.1), indicating that the judgments made for the sub-criteria are reliable, consistent, and can serve as a basis for informed decision making. As previously mentioned, the climatological group with a weight of 0.479 was selected as the most important group by expert evaluation due to its significant effect on energy generation.

3.5.2. Initial Site Suitability Maps

Figure 10 shows the initial preparation of the solar PV microgrid suitability map for each climatological, orographic, technical, locational, social, and institutional sub-criterion. The weighted linear sum method from WLC was applied after the AHP process and the aggregation of weights in each sub-criterion in the ArcGIS environment.

Table 8. Criteria and sub-criteria priority weights obtained from authors' and experts' judgments.

Criteria	Weights × 100%	Sub-Criteria	Weights × 100%	*CR*
Climatology	0.479	Solar irradiation	0.55136	0.014
		Temperature	0.21213	
		Relative humidity	0.13107	
		Precipitation	0.05551	
		Wind speed	0.04993	
Orography	0.288	Slope	0.17818	0.028
		Elevation	0.07042	
		Aspect (Orientation)	0.75140	
Technical and Location	0.133	Settlement	0.28422	0.078
		Population density	0.34411	
		Roads	0.13863	
		Railways	0.09012	
		Airports	0.06183	
		Electricity transmission network	0.01651	
		Inland water	0.06458	
Social	0.065	Job opportunities	0.17818	0.028
		Human Development Index	0.75140	
		Energy justice and equity	0.07042	
Institutional	0.034	National rural electrification plan	0.6667	0
		Policy and regulatory support	0.3333	

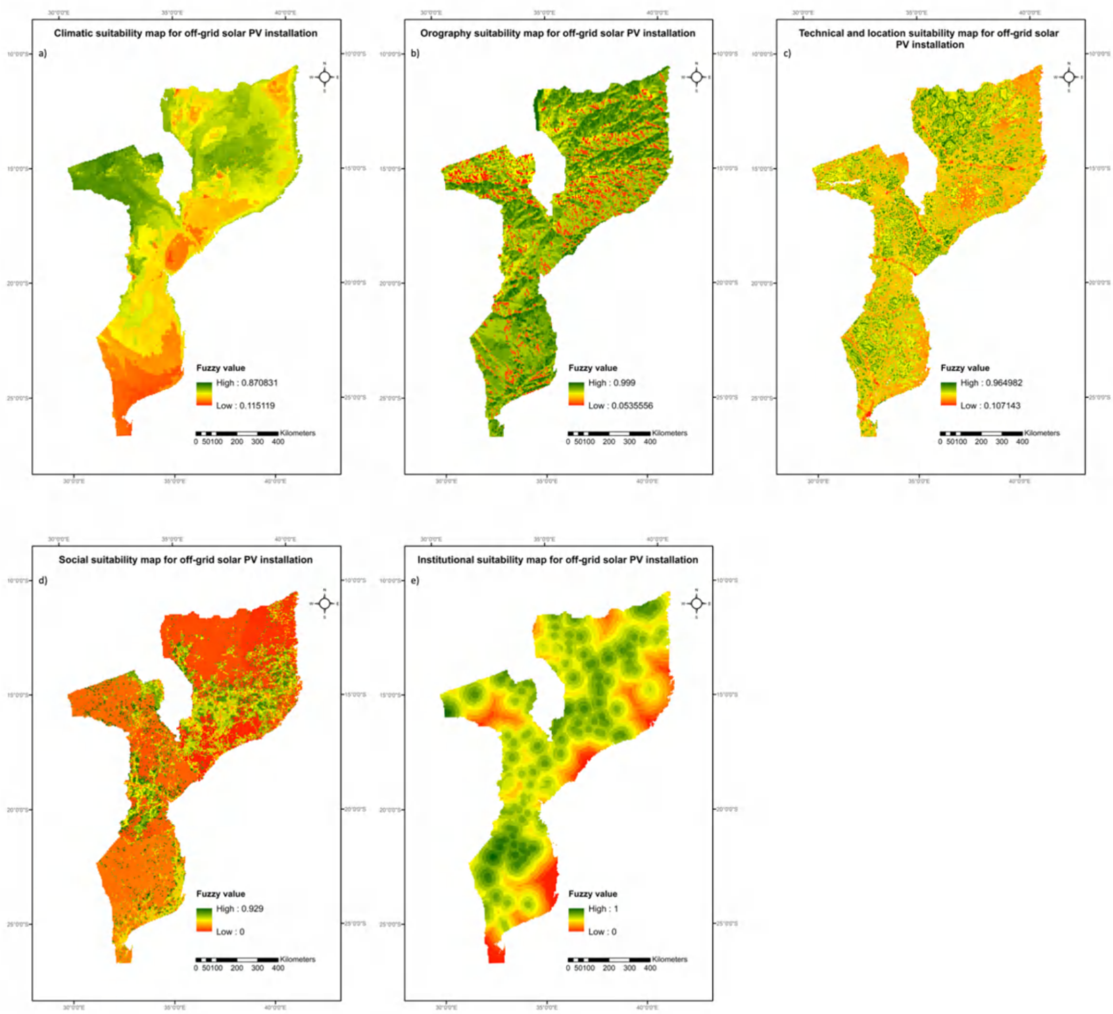


Figure 10. Initial suitability areas applied in the AHP. (**a**) Climatic, (**b**) orography, (**c**) technical and location, (**d**) social, and (**e**) institutional suitability map for off-grid solar PV microgrid deployment.

The initial site suitability map for off-grid solar PV microgrid installation in Mozambique was obtained by fuzzy overlaying the climatic, orographic, technical and location, social, and institutional criteria layers with corresponding weights calculated by a combination of AHP and expert judgment with values of 0.479, 0.288, 0.133, 0.065, and 0.034, respectively (see Tables 7 and 8). The resulting weighted maps are then overlaid to generate raster maps of suitable sites (see Figure 11).

3.5.3. Final Site Suitability Maps

To obtain the final suitability models, unfavorable areas were identified and eliminated according to the objective of the study and the socio-economic and socio-environmental conditions of the country. Thus, all the constraint layers were reclassified and, using Boolean logic and the WLC approach, the final thematic constraint layers were obtained, as shown in Figure 6. These were then used to mask the lowest suitable and constrained areas to increase the accuracy of the resulting site suitability map for off-grid solar PV microgrid projects. Therefore, the elimination of constraints is performed by combining the standardized final restriction map and the initial site suitability map through the fuzzy overlay of the WLC. Figure 12 shows the thematic maps of the lowest suitable and constrained areas and suitable sites for the installation of off-grid solar PV microgrid projects in Mozambique. The indicated classification—lowest suitable and constrained areas, low suitable, moderately suitable, suitable, and high suitable—represent the different priorities and ranking to allocate off-grid solar PV microgrid projects.

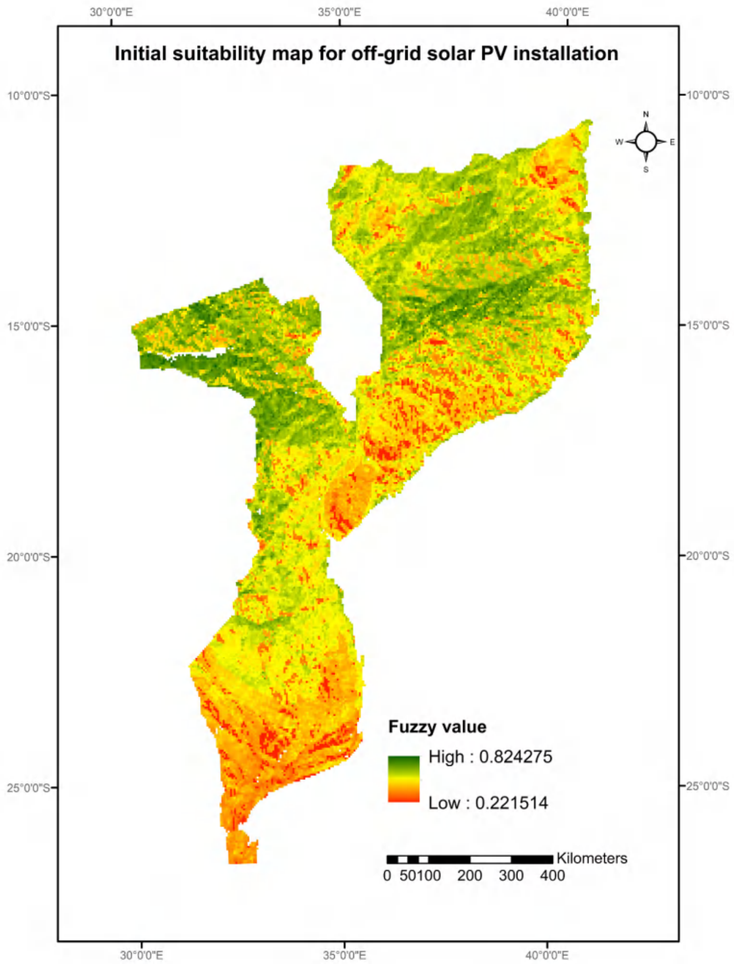


Figure 11. Initial site suitability map for off-grid solar PV microgrid deployment.

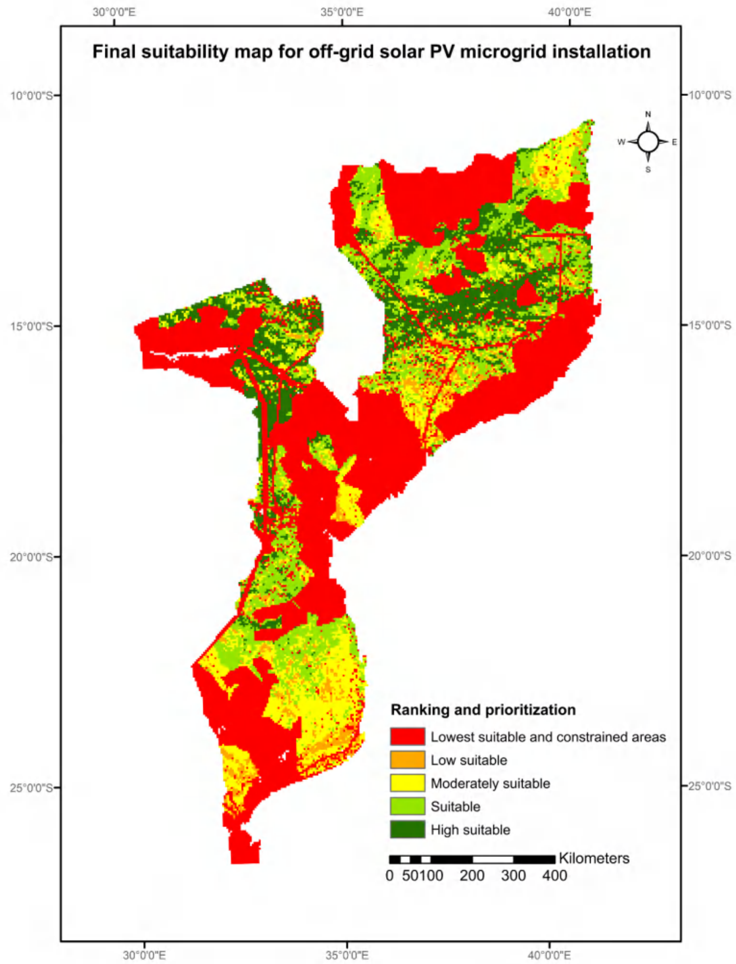


Figure 12. Final site suitability map for off-grid solar PV microgrid deployment.

4. Discussion

The world is making progress toward achieving Goal 7 (SDG#7) and there are encouraging signs that energy is becoming more sustainable and available. Access to electricity in low-income countries has begun to accelerate, energy efficiency continues to improve, and renewable energy is making impressive progress in the electricity sector [96]. Mozambique is also taking important steps in this direction, and one of the fastest-growing resources is solar power. However, decision-making processes for the development of off-grid solar PV microgrid projects are in some cases proposed without a real assessment or in-depth consideration of the social, institutional, technical, economic, and environmental aspects; spatial planning of areas that could be identified as suitable areas; or of areas where the construction of such projects is impractical or highly inadvisable [97].

Moreover, most of the literature lacks quantifiable models that consider social, institutional, and environmental aspects. This analysis involved diverse experts who evaluated different criteria and factors for modeling site suitability for off-grid solar PV microgrid installation in Mozambique. The identification and mapping of these areas is an essential element for sustainable rural electrification planning in Mozambique.

This study has highlighted an important framework for determining the most suitable locations for off-grid solar PV microgrid projects. The use of the proposed mathematical approaches, such as Boolean logic, fuzzy set theory, and AHP, in a GIS-MCDM analysis has proven to be an efficient method for decision support in the selection of suitable areas for off-grid solar PV projects. The employed hybrid model offers better results and makes a solar project more economically, technically, and socially feasible.

To select the optimum sites for an off-grid solar PV microgrid in the study area, 12 restriction factors and 19 criteria were used to perform the GIS-MCDM analysis. The use of the Boolean logic strategy and fuzzy logic approach to standardize the criteria had a direct impact on the accuracy of the potential map results. The decision-making plan was based on the construction of a hierarchical spatial model using a multiple comparison pairwise matrix of the AHP, which allowed a judgment or decision to be made based on the weights for the criteria and sub-criteria, whereas the WLC technique was used to sum the weights and identify and rank the optimal areas. A similar methodology was used in the studies [29,52,98–101].

According to the initial site suitability map in Figure 11, the degree of site suitability ranges from 0.22 to 0.83, with 0.22 indicating the lowest suitability and 0.83 indicating the best suitability of the site for installing an off-grid solar PV microgrid. The final values of the ranking and prioritization map are divided into 5 suitability intervals for the different regions of the study area, with values of [0, 0.09] (constrained location), [0.09, 0.22] (lowest suitability), [0.22, 0.45] (low suitability), [0.45, 0.56] (moderate suitability), [0.56, 0.65] (good suitability), and values above 0.65 (excellent suitability) indicating the theoretical potential for installing an off-grid solar PV microgrid in Mozambique.

According to the resulting map in Figure 12, the excellent or highly suitable rural locations for off-grid solar PV microgrids solution in Mozambique are concentrated in the central west of Manica and Tete provinces, the northwest of Zambézia and Nampula provinces, and the southwest of Niassa and Cabo Delgado. This is followed by the northern provinces of Inhambane with good suitability. Likewise, good suitability was found in wide areas almost throughout the country, except for a few separate areas, including in Maputo province, in the northwest and southwest of Sofala provinces, and in the north of Gaza province. Moderate suitability was found in the north of Maputo province and almost in the whole country. Additionally, the low suitability locations areas were found in the extreme north of Maputo province. Table 9 shows and summarizes the different percentages of actual land area suitability at both regional and national levels.

Table 9. Share of solar PV microgrid potential per suitability class.

Rural Areas by Province	Suitability Area Classification									
	High		Good		Moderate		Low		Lowest	
	%	km^2	%	km^2	%	km^2	%	km^2	%	km^2
Cabo Delgado	24.63	19,237	26.85	20,971	17.08	13,340	3.73	2913	27.70	21,635
Niassa	13.59	17,578	17.91	23,166	11.93	15,431	3.69	4773	52.88	68,399
Nampula	15.10	11,833	17.06	13,369	13.19	10,336	4.71	3691	49.94	39,135
Zambézia	11.00	11,334	15.00	15,456	12.00	12,365	7.00	7213	55.00	56,672
Tete	12.70	12,822	17.78	17,950	8.25	8329	6.33	6391	54.93	55,456
Manica	12.82	7997	16.37	10,211	14.76	9207	2.75	1715	53.31	33,254
Sofala	5.91	4003	8.13	5507	7.92	5364	2.11	1429	75.93	51,428
Inhambane	18.73	12,881	31.53	21,684	28.94	19,903	3.19	2194	17.61	12,111
Gaza	5.74	4335	16.28	12,296	10.09	7621	3.39	2560	64.50	48,717
Maputo	6.94	24.13	16.39	56.99	16.27	56.57	3.30	11.47	57.10	198.55
Total	12.7	102,044.5	18.3	140,667.1	14.0	101,952.8	4.0	32,890.8	50.9	387,005.2

The final site suitability map for off-grid PV microgrid installations (Figure 12) provides a good understanding and high-level overview of the potential site suitability of PV technology in the study area based on GIS and MCDM. In the AHP, it is found that the climatic hierarchy group has a weight of 47.9%, compared to the orographic group with 28.8%, the technical and location group with 13.3%, the social group with 6.5%, and the institutional group with 3.4%. Thus, the climatic criteria are the most important group in this study, as they determine the potential electricity generation of PV technology, as shown in works such as [29,31,32,34,35].

The available area was classified into five degrees of suitability: lowest suitability and constrained areas, low suitability, moderately suitable, suitable, and highly suitable. It was found that 49% of the study area is suitable for the development of off-grid solar PV microgrids. The result of the study shows that the central western and northern regions of the country have the highest priority and cover 13% of the total area, followed by good suitability and moderate suitability with 18% and 14%, respectively (Figure 13). The locations suitable for off-grid solar PV microgrid projects have several significant characteristics, including high solar irradiation, low temperature, low relative humidity, low slope, and a north orientation, as well as low population density and low Human Development Index.

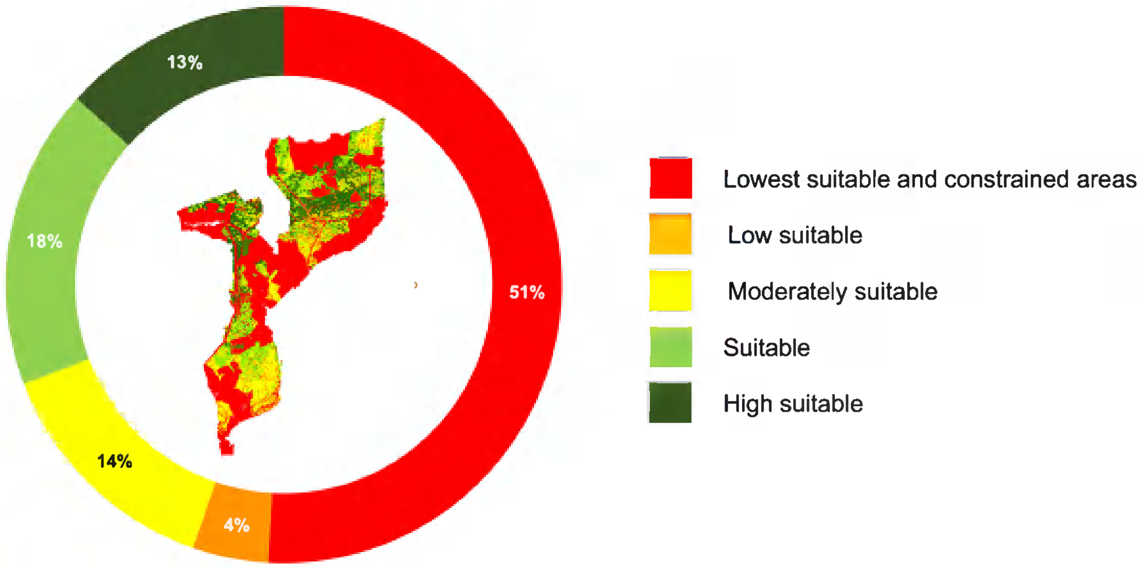


Figure 13. Boolean logic, Fuzzy logic, and AHP GIS-MCDM spatial analysis results per suitability for off-grid solar PV microgrid installation.

However, 51% of the cataloged areas coincide with unfeasible and restricted areas. This is due to the aforementioned large number of unfeasibility and constraint criteria used for this study, such as protected and agricultural areas, inland waters, flood and storm cyclone hazards, roads, railways and airports, high population density and settlements, and areas with power transmission networks. Consequently, the model developed in this study for off-grid solar PV microgrid projects is more complete because it uses a larger number of criteria and different sources, most with finer spatial resolution. In addition, the developed model easily allows for re-evaluation if any of the criteria are updated, or the weighting of the criteria is changed.

The Government of Mozambique has planned the use of renewable energy, mainly solar energy, in the coming years as part of the national program for off-grid electrification of rural areas implemented by FUNAE. To this end, the government launched the solar energy project portfolio [66] and the regulation of energy access in off-grid areas [50] in 2021 and 2019, respectively. From the portfolio data, 70% of the planned solar PV mini-grids and microgrids are located in areas with significant potential for solar PV projects, as shown in the model results. However, the model also identified 30% of solar PV projects planned in impractical, lowest suitability, and constrained areas, as shown in Figure 14a. Additionally, the model performance was evaluated for large-scale solar PV power plants, minigrids, and microgrids (Figure 14b). The study shows that the three existing large-scale solar PV power plants in Cuamba, Metoro, and Mocuba districts are in excellent (highly suitable), good (suitable), and moderate (moderately suitable) suitable areas, respectively. A total of 50% of the implemented minigrids and microgrids match locations in the model which are classified as excellent, good, and moderately suitable. However, another 50% of implemented solar PV minigrid and microgrids are in areas considered lowest suitable and restricted, namely 25% in protected areas, 15% in flood risk areas, and 10% in cyclone-risk areas.

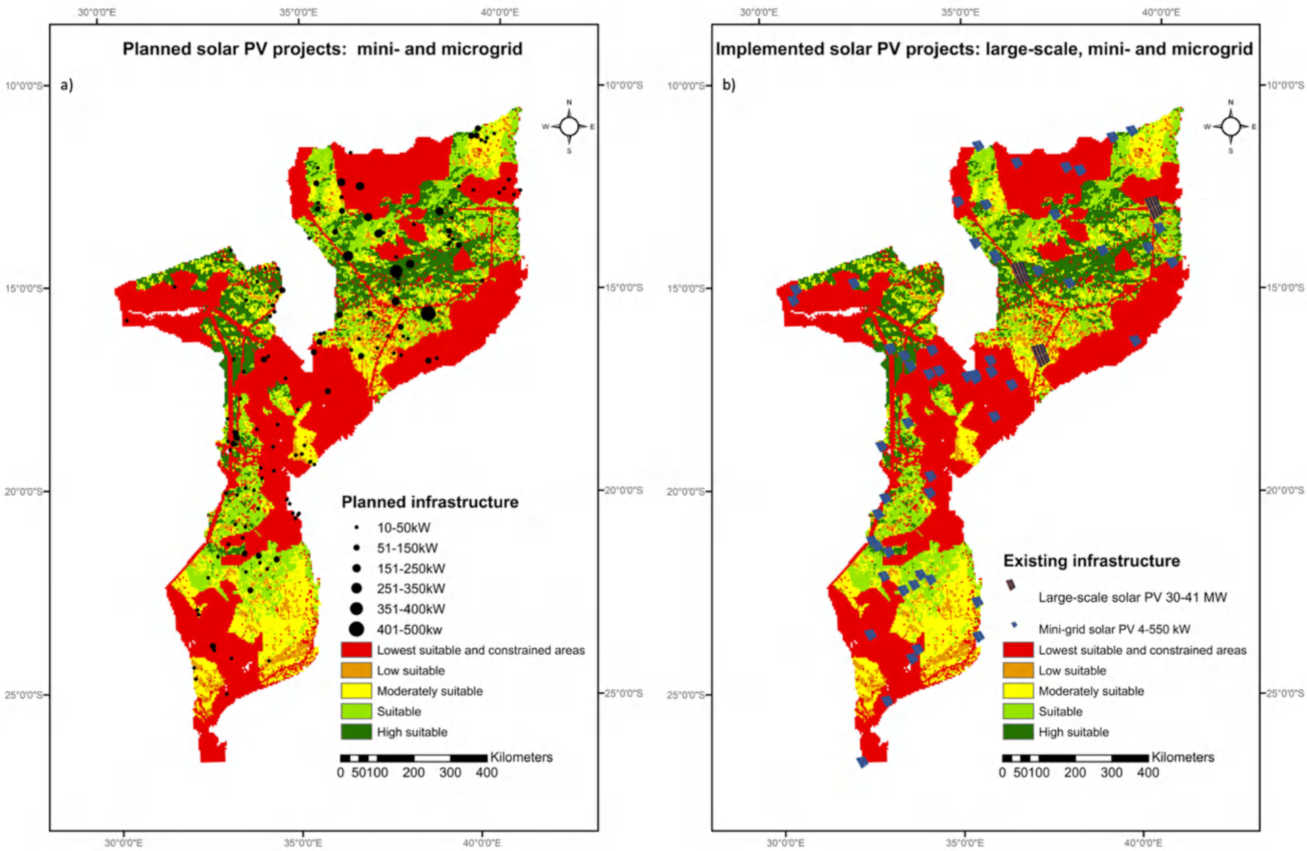


Figure 14. Model performance verification: (**a**) planned minigrid and microgrid solar PV projects and (**b**) implemented large-scale, minigrid and microgrid solar PV projects.

5. Conclusions

This study presents a hybrid methodology for solar PV system mapping with a particular focus on off-grid solar PV microgrids. The spatial planning strategy proposed for off-grid areas in Mozambique can provide comprehensive and applicable innovations for different geographic regions. This strategy demonstrates how the combined application of Boolean logic, fuzzy logic, AHP, and WLC approaches based on GIS-MCDM formulates a meaningful, clear, and reproducible research framework that incorporates climatological, orographic, technical, economic, environmental, social, and institutional data related to site selection for off-grid solar PV microgrid installations. It is noteworthy that the GIS-MCDM study conducted a comprehensive examination of social and institutional factors, including job opportunities and creation, Human Development Index, energy justice and equity, and national regulations and plans for off-grid rural electrification through solar energy systems in Mozambique. This examination is novel and relevant in the context of off-grid rural electrification in Mozambique.

The integration of GIS-MCDM methods has become a highly effective way to systematically deal with extensive geographic information data and manipulate important variables to identify the best locations for off-grid solar PV projects. Thus, the results of the research framework will support policy makers in spatial planning and investors in off-grid solar PV microgrids in both the public and private sectors in Mozambique. The main findings of this study are as follows:

- Spatial decision-making analysis shows that the potential areas for installing off-grid solar PV microgrid systems cover 344,664.36 km^2, which is approximately 49% of the

study area and is mainly concentrated in the central western and northern areas of the country. Conversely, the lowest suitability or not recommended for installation level accounts for 51% (387,005.24 km^2) of the total study area.
- The final suitability map analysis reveals that 13% of the study area exhibits high suitability, 18% shows good suitability, followed by moderate and low suitability in 14% and 4%, respectively.
- The research framework enabled the conclusion that climatic criteria, followed by orographic criteria, have the greatest influence on the selection of suitable sites for the integration of this technology, but also explicitly acknowledges and considers other criteria that may not only limit the potential of certain sites, but even exclude regions that are classified as lowest suitable and constrained areas. These strategies can help Mozambique and other sub-Saharan African countries achieve their solar power plant locations and SDG goals for a more sustainable energy future.

Despite the large amount of data sets, modeling, and analysis involved in this paper, some limitations remain. One is the strong dependence of the accuracy of the results on the opinion of experts. This limitation is addressed by a new method based on fuzzy-AHP, which eliminates the imprecise judgments of experts in the construction of the comparison pair matrix. Although the proposed method provides an accurate and efficient mechanism for selecting suitable sites for off-grid solar PV microgrid projects, the evaluation of the economic potential and the estimation of the PV power potential of an off-grid solar PV microgrid system in Mozambique is not investigated here. This requires a comprehensive and detailed study of the effective economic parameters and can be considered in future research. To further strengthen the proposed methodology, appropriate multiple criteria and constraints related to other RES-based site selection problems such as wind, biomass, geothermal, and other RES should be considered.

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Abbreviations

AHP	Analytic Hierarchy Process
ANP	Analytic Network Process
ARAS	Additive Ratio Assessment
BWM	Best Worst Method
CL	Climatology
COP-21	Paris Agreement
COPRAS	Complex Proportional Assessment of Alternatives
CSP	Concentrated solar power
DEM	Digital Elevation Model
EDM	*Electricidade de Moçambique*
ELECTRE	Elimination and Choice Expressing Reality
ESRI	Environmental System Research Institute
FUNAE	Energy Fund

GHG	Greenhouse Gases
GIS	Geographical Information System
GMM	Geometric Mean Method
GRA	Grey Relational Analysis
HDI	Human Development Index
IN	Institutional
LA	Linear ascending
LD	Linear descending
MCDM	Multi-criteria Decision-Making
MULTIMOORA	Multi-Objective Optimization On The Basis Of Ratio Analysis Plus Full Multiplicative Form
OCRA	Operational Competitive Rating Assessment
OR	Orographic
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluations
PSI	Preference Selection Index
PV	Photovoltaic
RES	Renewable Energy Sources
SO	Social
TEL	Technical and location
TODIM	Interactive Multicriteria Decision-Making
TR	Triangular
TZ	Trapezoidal

Appendix A

Table A1. Recent works conducted on applications of MCDM methods in PV power plant site selection.

Ref.	Year	Case Study	MCDM	* Evaluation Criteria							
				EN	CL	OR	TE	EC	LO	SO	PO
[30]	2022	Ghana	GIS-AHP	X	X		X	X	X		
[31]	2022	Egypt	GIS-AHP	X	X				X		
[36]	2022	Ecuador	GIS-AHP-ARAS-OCRA, PSI-SMART-TOPSIS-VIKOR-WLC	X	X			X			
[32]	2021	Turkey	GIS-AHP-WLC		X	X			X		
[34]	2021	Peru	GIS-AHP-WLC		X		X	X	X		
[33]	2020	Indonesia	GIS-AHP		X	X	X	X			
[35]	2018	China	TOPSIS	X				X		X	
[24]	2022	Iran	TOPSIS-TODIM-WASPAS-COPRAS-ARAS-MULTIMOORA		X	X	X	X	X		
[42]	2021	India	GIS-FAHP-WLC	X			X	X		X	
[29]	2022	Iran	GIS-FAHP-WLC	X	X	X		X			
[20]	2020	Brazil	AHP-TOPSIS	X	X	X			X		
[25]	2021	Iran	BWM-VIKOR-GRA	X	X		X			X	
[37]	2020	China	GIS-BWM-WLC		X	X		X	X		
[101]	2021	Iran	GIS-FBWM-WLC		X			X	X		
[43]	2019	Pakistan	AHP-FVIKOR	X	X	X		X	X	X	
[38]	2016	Spain	AHP-ELECTRE TRI	X	X	X			X		
[39]	2014	Spain	GIS-ELECTRE TRI	X	X	X			X		
[102]	2014	China	ELECTRE-II	X	X			X	X	X	
[41]	2022	Turkey	AHP-ANP-PROMETHEE		X			X	X		
[27]	2021	Greece	PROMETHEE II	X	X	X		X			
[40]	2020	Spain	AHP-PROMETHEE-WLC	X				X			X

* Evaluation criteria: environmental (EN), climatological (CL), orographic (OR), technical (TE), economic (EC), location (LO), social (SO), and political (PO).

Appendix B

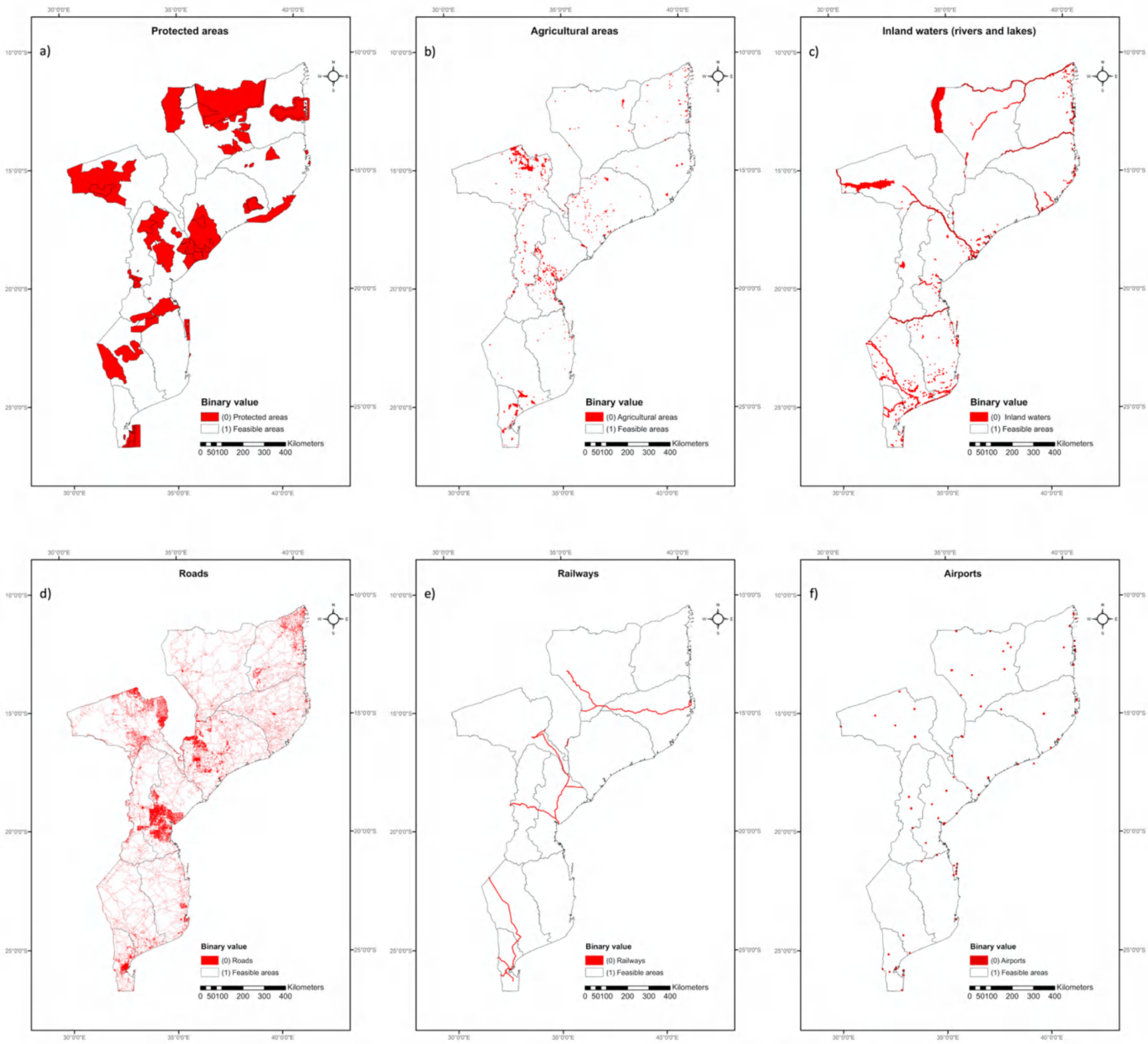

Figure A1. Maps with constraints considered for the analysis of the spatial suitability of off-grid solar PV microgrid projects in Mozambique. (**a**) Protected areas, (**b**) agricultural areas, (**c**) inland waters, (**d**) roads, (**e**) railways, and (**f**) airports.

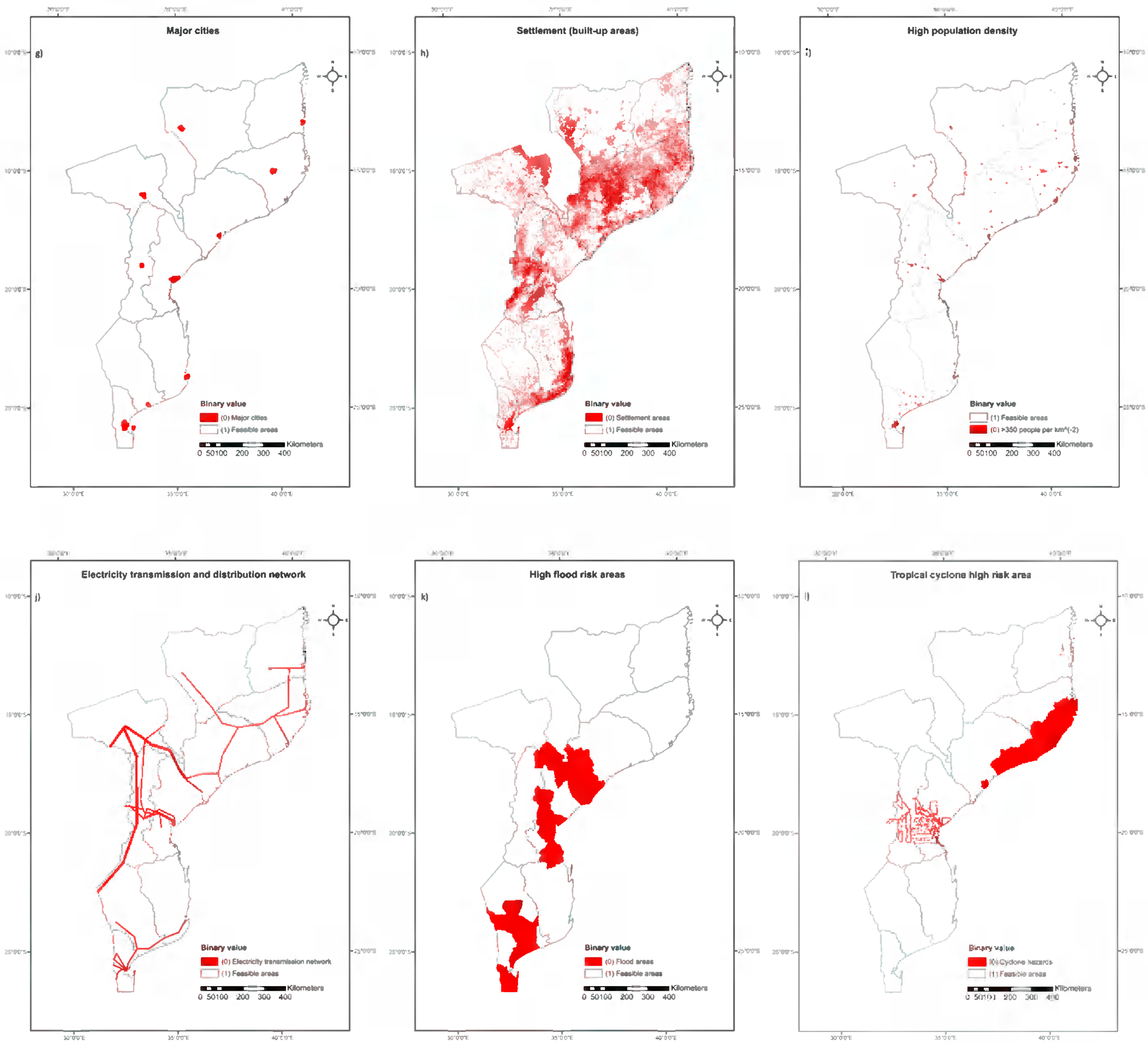

Figure A2. Maps with constraints considered for the analysis of the spatial suitability of off-grid solar PV microgrid projects in Mozambique. (**g**) Major cities, (**h**) settlement, (**i**) high population density areas, (**j**) electricity transmission and distribution network, (**k**) high flood risk areas, and (**l**) tropical cyclone high risk areas.

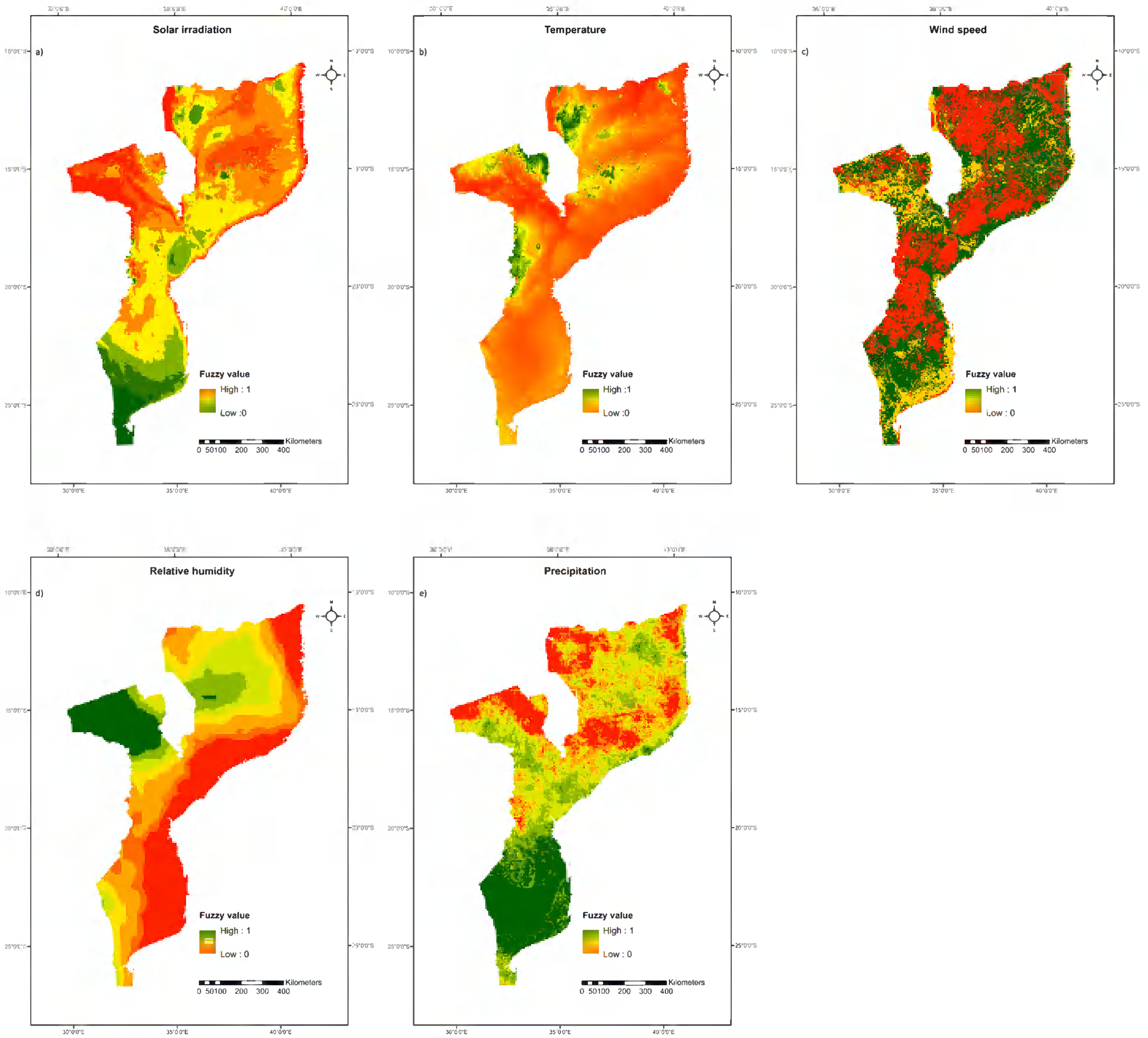

Figure A3. Standardized (reclassified and fuzzified) raster maps of climatology criteria applied to the spatial suitability of off-grid solar PV microgrid projects in Mozambique. (**a**) Solar irradiation, (**b**) temperature, (**c**) wind speed, (**d**) relative humidity, and (**e**) precipitation.

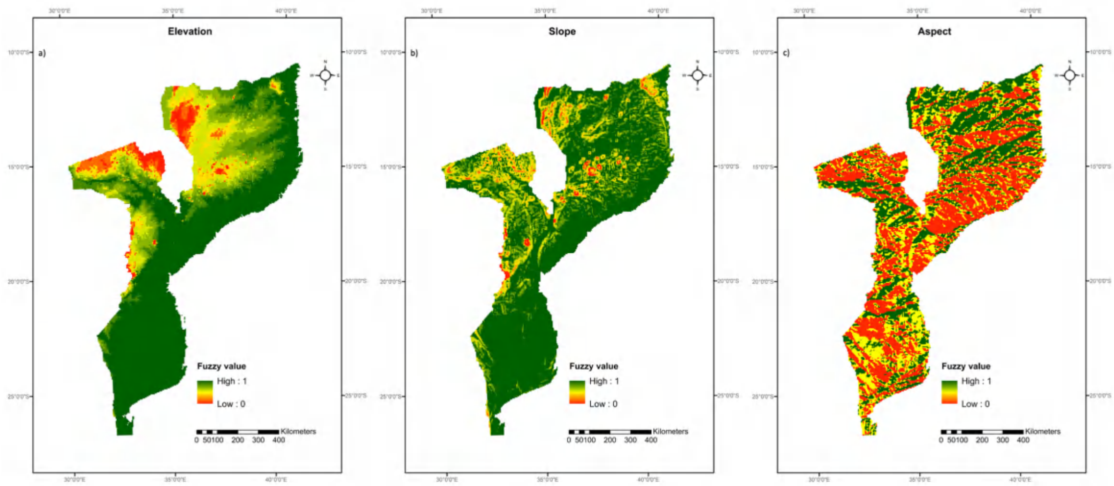

Figure A4. Standardized (reclassified and fuzzified) raster maps of orography criteria applied to the spatial suitability of off-grid solar PV microgrid projects in Mozambique. (**a**) Elevation, (**b**) slope, and (**c**) aspect.

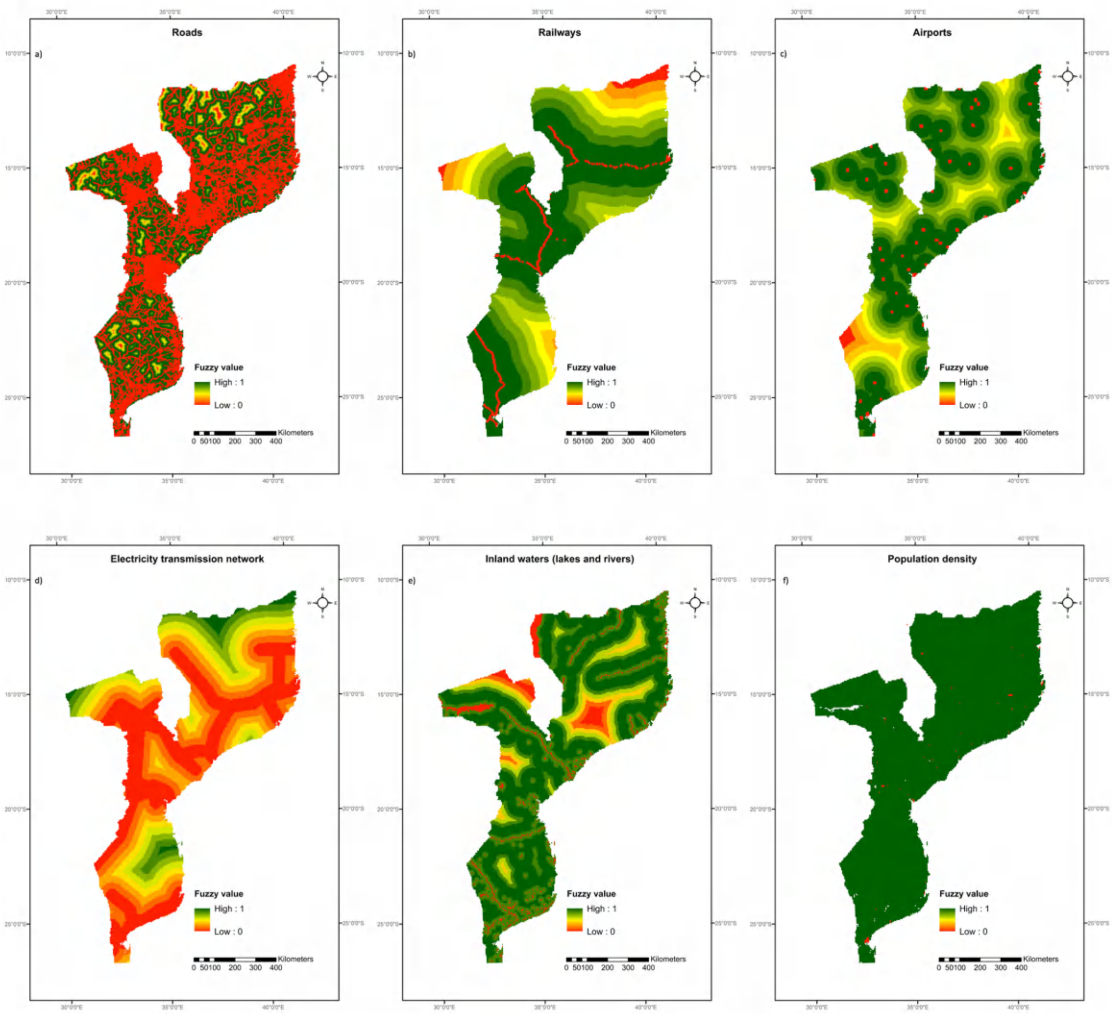

Figure A5. Standardized (reclassified and fuzzified) raster maps of technical-location criteria applied to the spatial suitability of off-grid solar PV microgrid projects in Mozambique. (**a**) Distance from roads, (**b**) distance from railways, (**c**) distance from airports, (**d**) distance from the electricity transmission network, (**e**) distance from inland waters, and (**f**) areas of low population density.

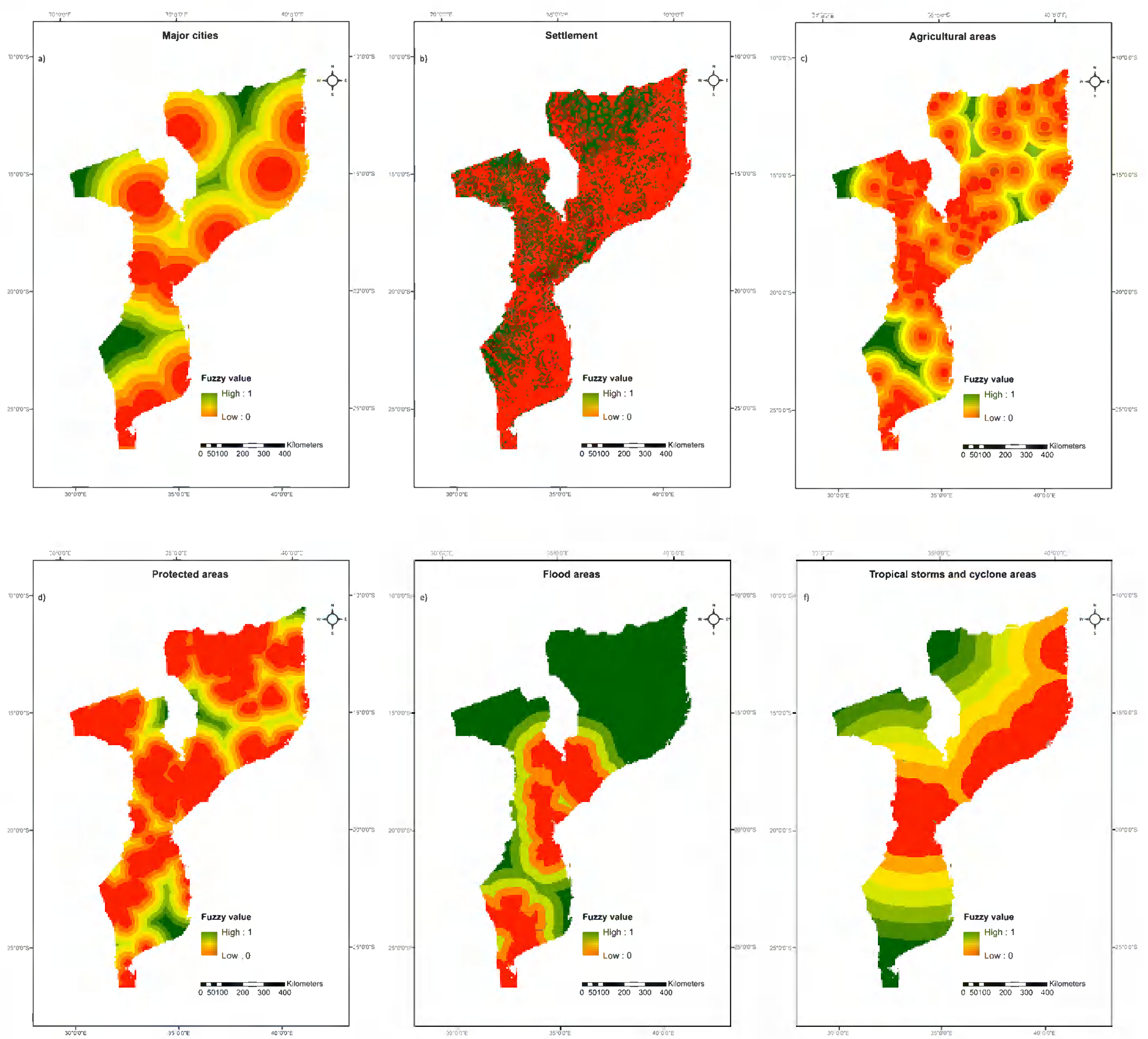

Figure A6. Standardized (reclassified and fuzzified) raster maps of location restriction applied to the spatial suitability of off-grid solar PV microgrid projects in Mozambique. (**a**) Major cities, (**b**) settlements, (**c**) agricultural areas, (**d**) protected areas, (**e**) flood areas, and (**f**) tropical storms and cyclone areas.

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