Optimizing Utility-Scale Solar PV Site Selection Using GIS and MCDM Approaches: A Case Study in Bhutan

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Abstract

Solar energy is widely regarded as the cleanest renewable energy source, with an increasing global adoption in the environment and the depletion of fossil fuels. Bhutan, despite its dependence on hydropower, has set ambitious targets in its 2013 alternative renewable energy policy and the 13th Five-Year Plan to expand solar energy capacity to 500 MW by 2025 and 1000 MW by 2030 through utility-scale solar projects. However, identifying optimal locations for solar photovoltaic (PV) farms requires a systematic approach that considers climatological, environmental, and economic factors. Therefore, this study employs Geographic Information Systems (GIS) and Multi-Criteria Decision-Making (MCDM) techniques, including Fuzzy Analytic Hierarchy Process (FAHP), Multi-Objective Optimization by Ratio Analysis (MOORA), and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), to evaluate and rank potential solar PV sites across Bhutan. Key factors such as solar radiation, temperature, rainfall, slope, aspect, elevation, land use/land cover (LULC), and proximity to roads and settlements were used during the analysis. The data presents the distribution of solar PV suitability with 1304.33 km2 (3.39%) as highly suitable and 22463.95 km2 (38.01%) as suitable for solar PV in Bhutan. Furthermore, the result highlights that Haa, Samtse, Bumthang, Paro, Chhukha, Thimphu, Trashigang, and Dagana as the most suitable districts for solar PV deployment in the country. The result shows a strong alignment with existing solar plants deployed, such as Shangsa, Dechencholing, Sephu, and Rubesa, validated through sensitivity analysis. The study demonstrates the effectiveness of hybrid GIS-MCDM models in optimizing renewable energy planning and provides actionable insights for policymakers to achieve Bhutans solar energy goals.

Keywords— Solar PV, GIS, MCDM, FAHP, MOORA, TOPSIS, Site suitability, Bhutan

1 Introduction

There is an increasing demand for energy and associated services to satisfy social and economic development goals and enhance human welfare and health. Energy and services are needed to support productive activities and basic human requirements such as lighting, cooking, space comfort, mobility, communication, etc. Globally, fossil fuels (coal, oil, and gas) dominate the supply of energy with a rapid increase in carbon dioxide (CO2) emissions.

The special report of the Intergovernmental Panel on Climate Change (IPCC) confirms that approximately 87% of the global energy sources use fossil fuels and only 13% use non-combustible renewable energy (solar energy 0.1%, ocean energy 0.002%, wind energy 0.2%, hydropower 2.3%, geothermal 0.1% and bioenergy 10.2%). The use of fossil fuels accounts for the majority of global greenhouse gas [1]. There are several ways to reduce the energy system's GHG emissions while still meeting the demand for energy services worldwide. Some of these possible options include solar power, wind power, hydropower, geothermal energy, and biomass [2][4]. Solar energy is the cleanest among renewable energy sources due to its silent operation and lack of carbon dioxide (CO2) or other emissions [5]. Solar photovoltaic (PV) technology is rapidly expanding worldwide [6].

In Bhutan, with the launch of the National Energy Policy 2025, Bhutan aims to strengthen hydropower and accelerate solar renewable sources. The policy targets 25,000MW of installed capacity by 2040, 20,000 MW of hydropower and 5000 MW of solar, becoming a high-income Gross National Happiness (GNH) economy by 2034 [7]. With Bhutan's geographical area of 38,394 km2, about 72% of the Kingdom is covered by forest, 7% with year-round snow and glaciers, nearly 3% is cultivated or agricultural areas, and 4% is meadows and pastures [8]. Identifying optimal locations with the best solar potential is crucial to meet the growing electricity demand [9], [10].

The choice of sites for solar power plants is closely linked to factors such as meteorological conditions, economic considerations and environmental [11], [12]. For example, solar radiation (solar irradiance) at the Earth's surface shows considerable spatial and temporal variation as the most crucial factor. In light of these considerations, this study uses several important factors such as environmental (slope, elevation, aspect and land use/land cover), economic (proximity to road and settlements), and climatic (solar radiation, temperature and rainfall). In the past, several studies have been conducted worldwide for site suitability analysis for solar PV site selection via satellite remote sensing techniques [13][17]. The combination of GIS tools and MCDM techniques has shown to be effective in solving the complex challenge of selecting sites for solar installations [9], [10], [13][16], [18]. A hybrid model comprising Fuzzy-based MCDM, MOORA and TOPSIS methods has been applied for selecting the optimal location for solar PV site selection. [19][21]. In FAHP, comparisons of criteria are expressed using fuzzy numbers to handle uncertainty and imprecision in human judgment [22], [23].

MOORA is an MCDM method developed to solve complex decision problems involving multiple conflicting criteria, which was first introduced by Brauers and Zavadskas in 2006 [24]. MOORA is known for its simplicity, effectiveness, and ability to handle both quantitative and qualitative criteria [25], [26]. TOPSIS Analysis allows for the consideration of both positive and negative aspects of criteria, accommodating trade-offs and conflicting objectives. TOPSIS provides a clear and easily interpretable ranking of alternatives, facilitating decision-making and communication [27][29].

Therefore, in this study, the site suitability analysis was performed for optimal solar energy for utility-scale with different approaches and validated by performing sensitivity analysis. The successful implementation of this project will contribute to identifying the optimal location with the best solar energy generation in the country. Additionally, the study also aligns with the broader global goal of increasing the adoption of renewable energy sources and reducing reliance on fossil fuels, thereby contributing to a more sustainable and environmentally friendly energy future. Thus, selecting the right sites for solar energy plant installation is increasingly significant for investments and positively impacts both the environment and society.

2 Materials and Methods

2.1 Study Area

In this study, a holistic framework adopting a nationwide (Bhutan) scope is considered. The study includes all 20 Dzongkhags of Bhutan, spanning a wide range of topographical and climatic conditions. In Bhutan, elevation varies dramatically from 100 m in the southern foothills to 7,500 m in the northern Himalayan peaks, creating distinct microclimates and solar energy potential across regions. Annual solar radiation level ranges from 500 to 1,800 kWh/mš/year, with higher elevations generally receiving stronger irradiance due to a thinner atmosphere. The study area ensures the inclusion of diverse geographic, climatic, environmental, and socio-economic factors, enabling a thorough and inclusive site suitability analysis. Further, the approach supports national energy objectives by identifying regions with the highest solar potential while minimizing environmental and social impacts

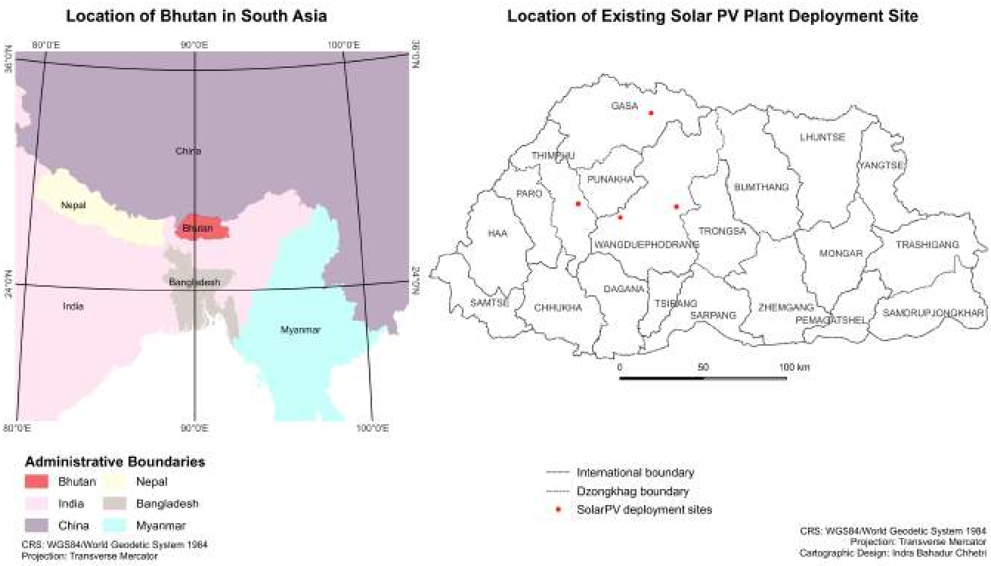

Figure 1: Study area showing the location of existing Solar PV sites in Bhutan

2.2 Data Collection

The study utilizes a combination of environmental, economic, and climatological datasets to assess Bhutan's solar energy potential. Environmental data, including slope, aspect, and elevation, were derived from the 30m resolution Shuttle Radar Topography Mission (SRTM), digital elevation model (DEM) sourced from USGS Earth Explorer (https://www.usgs.gov/). Economic factors such as roads and settlement locations were sourced as vector layers from the National Land Commission Secretariat (NLCS) of Bhutan. For climatological variables, solar radiation estimates (P50, typical year) were acquired from the National Solar Radiation Database sourced at (https://nsrdb.nrel.gov/) at 2km resolution, while historical temperature and rainfall records, 30 m resolution from ground station data provided by the National Center for Hydrology Meteorology (NCHM), Bhutan. These multi-source datasets ensure a comprehensive evaluation of solar energy feasibility across Bhutans diverse geographic and climatic conditions. The land use/land cover (LULC) map is sourced from the National Spatial Data Infrastructure (NSDI) portal (https://nsdi.systems.gov.bt/map), Bhutan.

2.3 Methods

Due to its simplicity in the evaluation process and wide development of MCDM technique, this study is explicitly based on weighted averages, priority setting and outranking using a hybrid approach such as the FAHP, MOORA and TOPSIS. Figure 2 shows the overall methodological flow of our study. An MCDM approach based on questionnaires from experts is sought to assess various criteria that impact the sites suitability. The questionary survey consists of two major groups consisting of quantitative and qualitative, based on three criteria, including climatic, environmental, and economic. The questionnaire included the categories of questions for evaluation, such as (1) criteria importance evaluation, (2) factor criteria weight assessment used in suitability, and (3) pairwise comparison with other factors. Table 1 shows the profile of the agency/institution contacted during the questionnaire survey. To evaluate solarPV site suitability mapping, the nine most influential criteria or factors or elements were considered, including elevation, slope, aspect, LULC, proximity to road and settlements, solar radiation, temperature, and rainfall. These elements were specifically selected based on a survey questionnaire and relevant literature reviews.

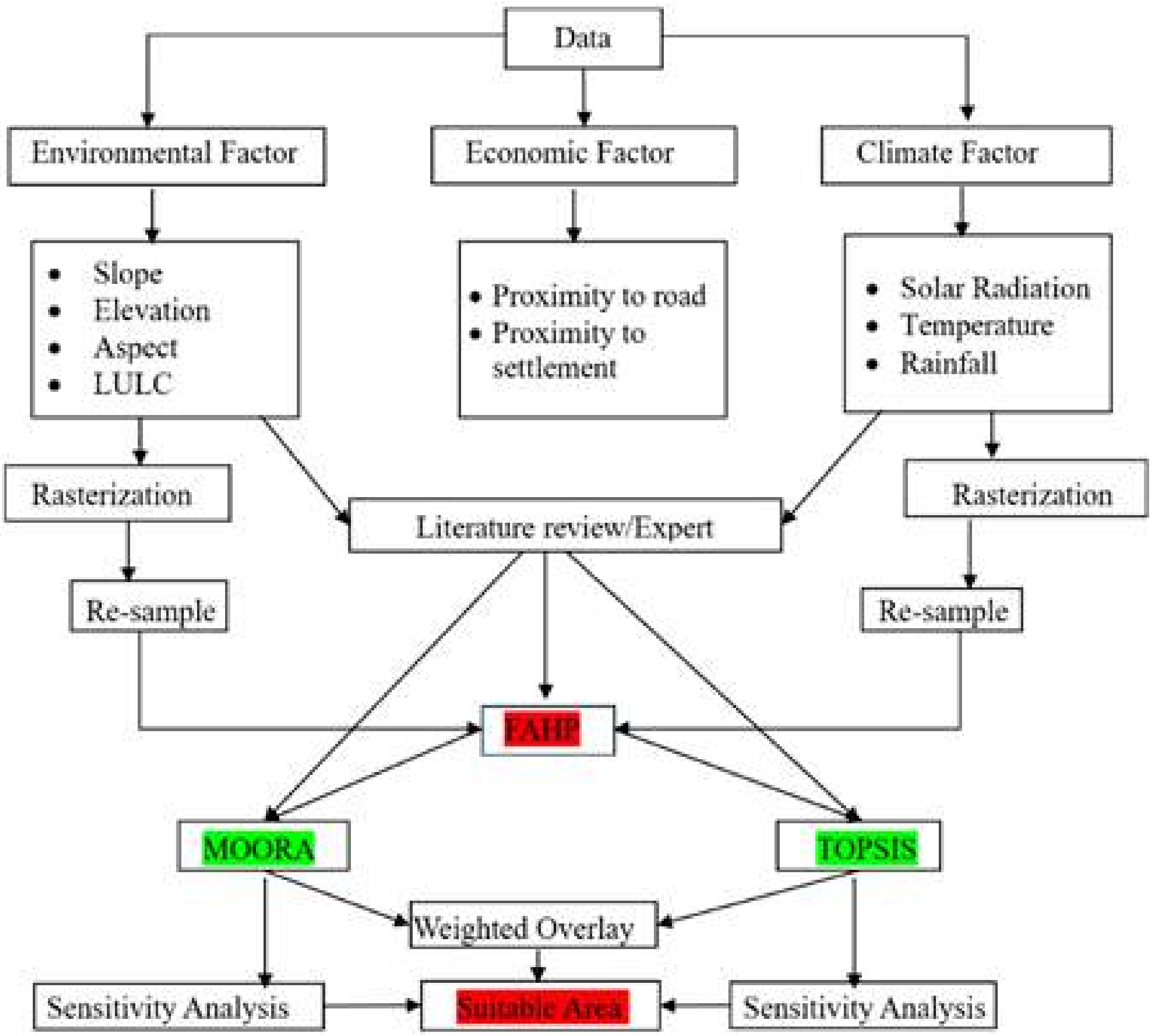

Figure 2: A schematic diagram showing land suitability mapping via a GIS approach

Table 1: List of Institutions/Agencies for sample collection

Sl. No.	Name of agency/institution	Sample	Remarks
1	Electrical and Electronics Engineering Department (JNEC)	5	Electrical engineering faculty
2	Thimphu Thromde	2	GIS officer
3	Department of Energy (MoENR)	6	Engineers
4	Druk Green Power Corporation Limited (DGPC)	6	Engineers

The FAHP is based on the traditional analytic hierarchy process (AHP), utilizing expert evaluations as input. In the first stage, criteria and alternatives are compared two at a time via Saatys 19 scale measurements [30] to express relative importance or preference, creating a pairwise comparison matrix. Next, the result of the AHP is validated via the CR, which is calculated via Equation (2), using the consistency index (CI) computed via Equation (1).

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

where CI is the consistency index, n is the number of elements being compared, and $\lambda_{\max}$ is the largest (principal) eigenvalue of the eigenvalue matrix.

$$CR = \frac{CI}{RI} \tag{2}$$

where the RI (random index) is the average of the resulting consistency index depending on the eigenvalue matrix. To ensure the reliability of the pairwise comparisons between criteria, a decision matrix was developed to assess consistency, resulting in a consistency ratio of 8.8%, which is within the acceptable threshold. Next, a pairwise comparison matrix is formulated to evaluate the relative weights for all the criteria with comparison scores expressed as fuzzy numbers. Finally, the normalized weight is determined using the four key approaches: computation of geometric mean, derivation of fuzzy weight, calculation of defuzzied weight, and determination of normalized weight proposed by James H. Buckley in 1985 [31]. MOORA then evaluates alternatives by normalizing data, applying the FAHP-derived weights, and distinguishing between benefit and cost criteria, while TOPSIS evaluates and ranks alternatives by measuring their relative closeness to the ideal site (best criteria value) and the non-ideal site (worst criteria value). In the MOORA method, estimation of assessment values involves subtracting the sum of the criteria value with the cost value from the sum of the criteria value with the benefit value using Equation (3).

$$y_i = \sum_{j=1}^{g} Z_{ij} \quad \sum_{j=g+1}^{n} Z_{ij} \tag{3}$$

where $j = 1, 2, \ldots, g$ is the number of benefit criteria, $i = g + 1, g + 2, \ldots, n$ is the number of cost criteria, y_i is the normalized assessment value from alternative i to all criteria, and z_{ij} is the value of alternative i on criterion j:

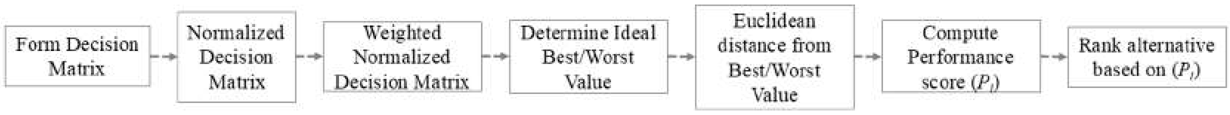

Figure 3: FAHP-TOPSIS methodology flowchart

Finally, sensitivity analysis is used to assess the stability and the dependency of the outcomes; it entails methodically modifying key inputs, weights of criteria or the performance values to examine how much variations influence the overall performance. It is used during the decision-making approach across a range of weight variation scenarios of the FAHP-MOORA and FAHP-TOPSIS. The step-by-step methods are explained in detail below:

1. *Forming a decision matrix*

   The FAHP-TOPSIS method begins with determining the decision matrix, which consists of different alternatives to various criteria. The decision matrix is obtained using Equation (4).

$$x_{i_j} = \begin{bmatrix} x_{11} & x_{12} & x_{1n} \\ x_{21} & x_{22} & x_{2n} \\ x_{m1} & x_{m2} & x_{mn} \end{bmatrix} \tag{4}$$

   Where x_{ij} is the comparison matrix response of alternative i to criterion j, n is the number of criteria, and m is the number of alternatives.

2. *Normalization of the decision matrix*

   Determine the normalized decision matrix using Equation (5),

$$x^*_{i_j} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{m} x_{ij}^2}} \tag{5}$$

   Where x_{ij} is the response of the i-th alternative to the j-th criterion, $i = 1, 2, 3, \ldots, m$ is the alternative sequence number, $j = 1, 2, 3, \ldots, n$ is the criterion sequence number, and x^*_{ij} represents the normalized value of the i-th alternative with respect to the j-th criterion.

3. *Weighted normalized decision matrix*

   The Weighted normalized decision matrix is determined by multiplying each element of the normalized decision matrix by the FAHP weights using Equation (6),

$$Z_{ij} = x^*_{ij} \cdot w_j \tag{6}$$

   Where z_{ij} is the weighted normalized value of the i-th alternative with respect to the j-th criterion, and x^*_{ij} represents the normalized value of the i-th alternative with respect to the j-th criterion.

4. *Determination of ideal best/worst value* To determine ideal best and ideal worst value, for non-beneficial criteria (Cost), lower value is desired thus minimum value from j criterion is taken as ideal best and maximum value from j criterion is taken as ideal worst but for beneficial criteria higher value is desired thus maximum value from j criterion is taken as ideal best and minimum value from j criterion is taken as ideal worst.

   Were,

   x_j^+ = indicates the ideal best value for the j-th criterion

   x_j^- = indicates the ideal worst value for the j-th criterion

5. *Euclidean distance calculation from ideal best/worst value* Euclidean distance from the ideal best is calculated using Equation (7)

$$D_i^+ = \sqrt{\sum_{j=1}^{m} \left(z_{ij} - x_j^+ \right)^2} \tag{7}$$

   Where z_{ij} is the weighted normalized value of the i^{th} alternative for the j^{th} criterion, x^+ is the ideal best value for the j^{th} criterion, and D^+ represents the Euclidean distance of the i^{th} alternative from the ideal best value of the j^{th} criterion.

The Euclidean distance from the ideal worst is calculated using Equation (8).

$$D_i^- = \sqrt{\sum_{j=1}^{m} \left(z_{ij} - x_j^-\right)^2} \tag{8}$$

Where z_{ij} is the weighted normalized value of the i^{th} alternative for the j^{th} criterion, x^- is the ideal worst value for the j^{th} criterion, and D^- represents the Euclidean distance of the i^{th} alternative from the ideal worst value of the j^{th} criterion.

6. *Comparison of performance score* (P_i) *for each alternative* Finally, the sorting of criteria based on the performance score (P_i) is calculated using Equation (9),

$$P_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{9}$$

Where D_i^- is the Euclidean distance of the i^{th} alternative from the ideal worst value of the j^{th} criterion, D_i^+ is the Euclidean distance of the i^{th} alternative from the ideal best value of the j^{th} criterion, and P_i represents the performance score of the i^{th} alternative.

3 Results and Discussion

Firstly, the criteria for each factor were set based on the context of Bhutan using the experts opinion or the judgment collected by circulating the survey questionnaire. The spatial layers were classified into four suitability classes: highly suitable, suitable, moderately suitable, and less suitable suitability levels (see Table 2).

Table 2: Factor criteria weight assessment used in the suitability analysis

	Criteria			
Factor	**Highly suitable**	**Suitable**	**Moderately suitable**	**Less suitable**
Slope (degree)	0–5	5–10	10–21	>21
Aspect (Direction)	S, SE, SW	E and W	NE and NW	Flat and North
Proximity from Road (Km)	<3	3–7	7–12	>12
Proximity to Settlements (Km)	<3	3–7	7–12	>12
Solar radiation (kWh/m^2/year)	>1500	1000–1500	500–1000	<500
Elevation (m)	<500	500–1000	1000–1500	>2000
Temperature (řC)	<15	20	30	40
Rainfall (mm)	<200	200–400	400–600	>600
LULC	Non-built-up and meadows	Alpine shrubs	Vegetation and rocky outcrops	Built-up and agriculture

The pairwise comparison matrix is formulated to evaluate the relative weights for all the criteria with comparison scores expressed as fuzzy numbers (see Table 4). The normalized weight matrix of all the criteria using FAHP is shown in Table 3. The nine most influential criteria used are: slope, aspect, elevation, proximity to road, proximity to settlements, temperature, rainfall, and LULC. Topography plays an important role in the selection of suitable sites for solar PV and is highly affected by the land slope. Installation of solar PV is affected by the gradient of the site; however, there is no definite acceptable slope percentage.

The different threshold values are adopted according to the site. The efficiency of the slope reduces as the slope increases by over 4% due to shadowing of the panels. The expert evaluation results were utilized to develop the slope factor. This factor is classified into four criteria for assessment: 05, 510, 1021, and greater than 21 (see Table 2). The efficiency of the solar PV depends on the orientation, i.e. its exposure to solar radiation. The south-facing slopes ensure panels are exposed to consistent maximum insolation, which directly correlates to energy production [32]. Accordingly, expert evaluations of aspect are: (1) South (S), Southeast (SE) and Southwest (SW), (2) East (E) and West (W), (3) Northeast (NE) and Northwest (NW) and (4) Flat and North arranged in decreasing order of their influence (also see Table 2).

Elevation is inversely proportional to atmospheric thickness and has a regression correlation of 95% with temperature and precipitation. The solar energy in higher areas is maximum compared to lowland areas. Elevation can be a reliable predictor of climate variables in the solar PV suitability analysis [33]. The elevation factor is classified into four criteria: <500 m, 500-1000 m, 1000-1500 m and >2000 m (see Table 2). Regarding LULC, some of the land classes may be utilized as suitable for the installation of the solar PV farm, whereas other classes may be constraints for the installation [34].

For example, land classes such as moraines, landslides, agricultural lands, water bodies, settlements, and glaciers are considered less suitable for solar PV site selection. The expert rating of the LULC classification is presented in Table 2. One of the other important factors is solar radiation. The solar radiation serves as a decisive indicator for assessing the energy generation potential and its ability to meet energy demands [35]. The solar radiation factor is classified into four criteria: <500, 500-100, 1000-1500 and >1500 (kWh/m2/year) (see Table 2).

Similarly, temperature and rainfall classification are based on expert opinion, and the literature is shown in Table 2. Economic factors such as proximity to roads and proximity to settlements are also considered during the analysis [36]. For example, roads can reduce construction infrastructure costs and lower maintenance expenses, whereas closer proximity to settlements ensures that the generated power reaches the consumer more quickly. The spatial distribution maps of the environmental, economic and climatic factors used in this study are shown in Figures 4, and 5.

Table 3: Weighted normalized matrix of FAHP

Factor	Fuzzy weight	Weight	Normalized weight	Normalized weight	Normalized weight (%)
Slope (degree)	0.168	0.234	0.336	0.246	23.64
Aspect (Direction)	0.152	0.215	0.296	0.221	21.00
Proximity from Road (Km)	0.016	0.021	0.031	0.023	2.00
Proximity to Settlements (Km)	0.019	0.028	0.046	0.031	3.00
Solar radiation (kWh/m^2/year)	0.185	0.267	0.374	0.275	26.36
Elevation (m)	0.061	0.081	0.111	0.085	8.00
Temperature (řC)	0.036	0.049	0.068	0.051	5.00
Rainfall (mm)	0.043	0.065	0.097	0.068	7.00
LULC	0.026	0.039	0.059	0.041	4.00

Finally, using the benefit attributes and cost attributes in the weighted normalized decision matrix in FAHP-MOORA and the ideal best and ideal worst value, for non-beneficial criteria (cost) analysis in FAHP-TOPSIS, the alternative ranking of the suitability index of each Dzongkhag is shown in Table 5. Figure 6 presents the optimal areas for solar PV site selection in Bhutan, analyzed using the FAHP method. The suitability mapping is categorized into four classes: highly suitable, suitable, moderately suitable, and less suitable. Most of the area is classified as suitable (58.41%) and moderately suitable (38.01%), indicating strong potential for solar energy deployment.

However, the result shows a smaller portion as highly Suitable (3.39%) of the total area of Bhutan, while less suitable areas are minimal (0.19%).

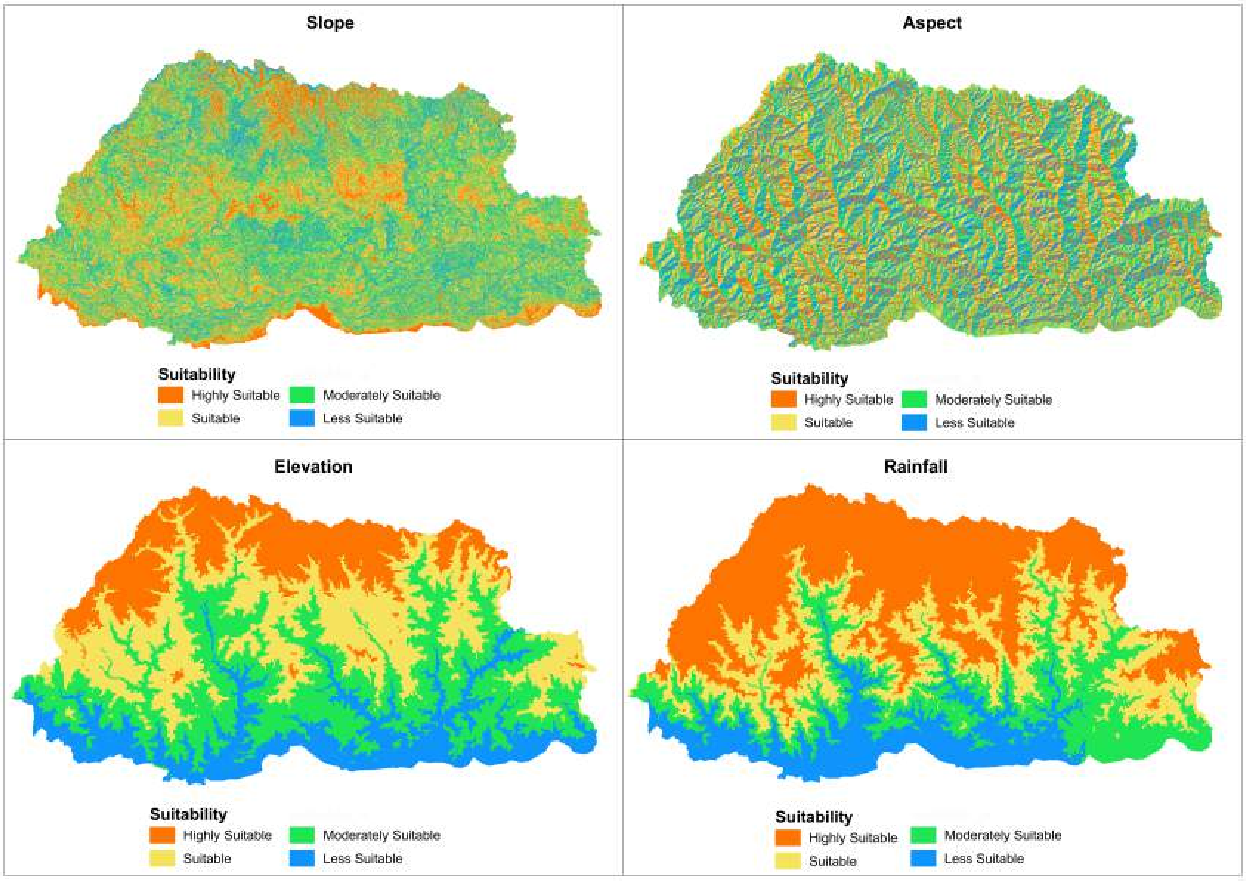

Figure 4: Figure showing the criteria distribution maps of slope, aspect, elevation, and rainfall

Overall, the region shows favorable conditions for solar PV development, with most areas falling into mid–high suitability categories (see Figure 5). According to the findings from FAHP–MOORA, Haa has the highest assessment value ($y_i = 0.025$), making it the most suitable area for solar PV deployment. It is followed by Samtse ($y_i = 0.020$), Bumthang ($y_i = 0.025$), Paro ($y_i = 0.018$), and Thimphu ($y_i = 0.017$). On the other hand, Pemagatshel has the lowest value ($y_i = -0.010$), indicating that it is the least suitable Dzongkhag for solar PV deployment (see Table 5).

Similarly, findings from FAHP–TOPSIS show that Haa has the highest performance score ($P_i = 0.654$), making it the most suitable area for solar PV deployment. It is followed by Samtse ($P_i = 0.580$), Chhukha ($P_i = 0.575$), Trashiyangtse ($P_i = 0.563$), and Dagana ($P_i = 0.552$). On the other hand, Pemagatshel has the lowest value ($P_i = 0.289$), indicating that it is the least suitable Dzongkhag for solar PV deployment (see Table 5).

Furthermore, spatial alignment was observed between the FAHP model's suitability classifications and the actual deployed solar PV projects, such as the 33 kWp solar mini-grid at Shangsa in Gasa, the 500 kWp solar installation at Dechencholing in Thimphu, the 22.38 MW Sephu project, and the 180 kWp grid-tied solar PV plant at Rubesa in Wangdue Phodrang. These findings strongly validate the model's accuracy in identifying optimal locations for solar PV farm development, with most deployed projects predominantly falling within zones categorized as highly suitable or suitable (see Figure 7).

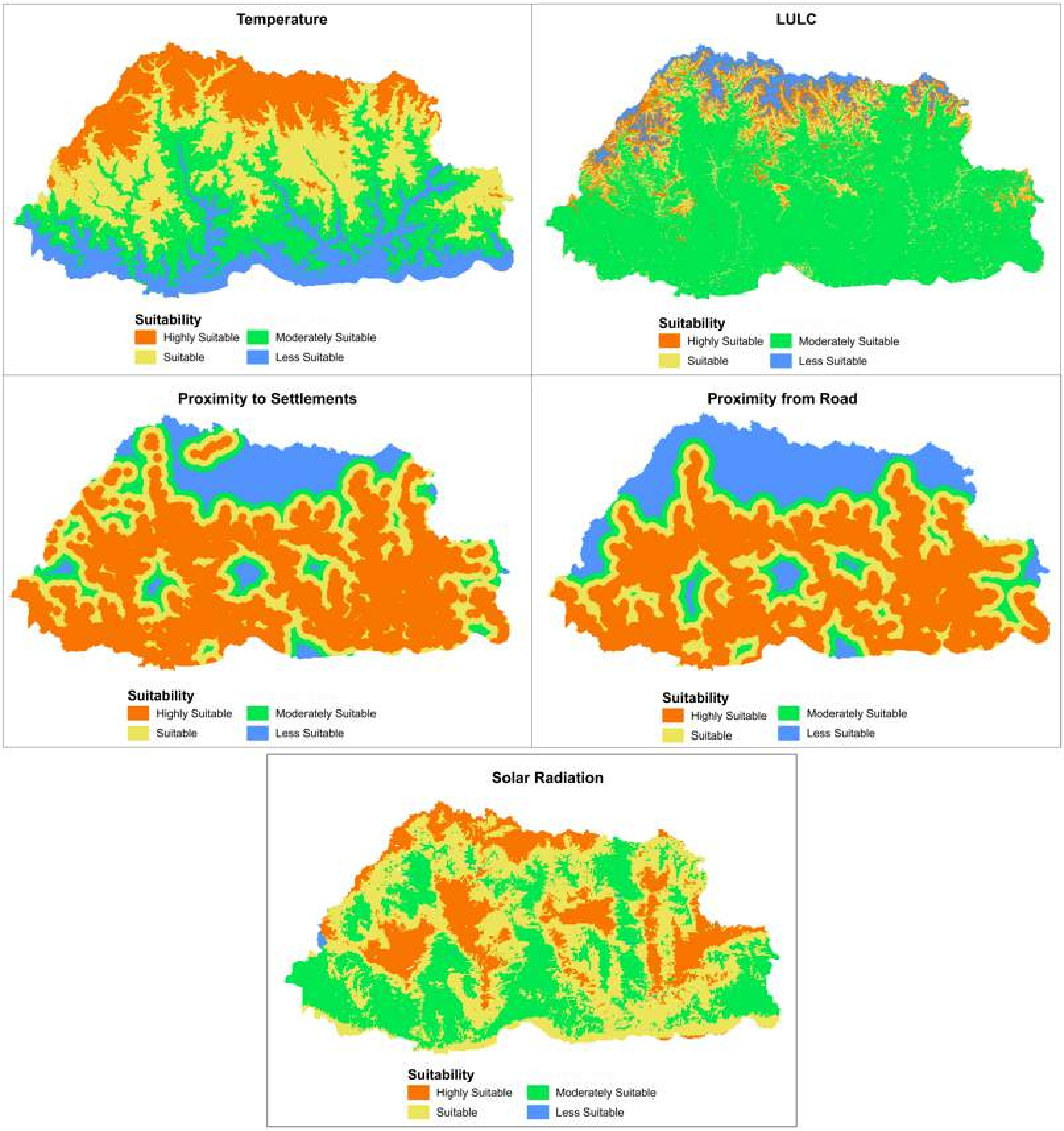

Figure 5: Figure showing the criteria distribution maps of slope, aspect, elevation, and rainfall

Table 4: Decision matrix of FAHP

Criteria	**Slope**	**Aspect**	**Elevation**	**LULC**	**Prox. Road**	**Prox. Settl.**	**Solar Rad.**	**Temp.**	**Rainfall**
Slope	[1, 1, 1]	[1, 1, 1]	[4, 5, 6]	[4, 5, 6]	[6, 7, 8]	[5, 6, 7]	[0.3, 0.5, 1]	[6, 7, 8]	[6, 7, 8]
Aspect	[1, 1, 1]	[1, 1, 1]	[4, 5, 6]	[4, 5, 6]	[4, 5, 6]	[6, 7, 8]	[1, 1, 1]	[6, 7, 8]	[1, 2, 3]
Elevation	[0.2, 0.2, 0.3]	[0.2, 0.2, 0.3]	[1, 1, 1]	[6, 7, 8]	[6, 7, 8]	[4, 5, 6]	[0.2, 0.2, 0.3]	[1, 1, 1]	[1, 1, 1]
LULC	[0.2, 0.2, 0.3]	[0.2, 0.2, 0.3]	[0.1, 0.1, 0.2]	[1, 1, 1]	[2, 3, 4]	[1, 2, 3]	[0.1, 0.1, 0.2]	[1, 1, 1]	[0.3, 0.5, 1]
Proximity to Road	[0.1, 0.1, 0.2]	[0.2, 0.2, 0.3]	[0.1, 0.1, 0.2]	[0.3, 0.3, 0.5]	[1, 1, 1]	[1, 1, 1]	[0.2, 0.2, 0.3]	[0.2, 0.3, 0.3]	[0.1, 0.2, 0.2]
Proximity to Settlements	[0.1, 0.2, 0.2]	[0.1, 0.1, 0.2]	[0.2, 0.2, 0.3]	[0.3, 0.5, 1]	[1, 1, 1]	[1, 1, 1]	[0.2, 0.2, 0.3]	[0.3, 0.5, 1]	[0.3, 0.5, 1]
Solar Radiation	[1, 2, 3]	[1, 1, 1]	[4, 5, 6]	[6, 7, 8]	[4, 5, 6]	[4, 5, 6]	[1, 1, 1]	[6, 7, 8]	[6, 7, 8]
Temperature	[0.1, 0.1, 0.2]	[0.1, 0.1, 0.2]	[1, 1, 1]	[1, 1, 1]	[4, 5, 6]	[1, 2, 3]	[0.1, 0.1, 0.2]	[1, 1, 1]	[1, 1, 1]
Rainfall	[0.1, 0.1, 0.2]	[0.3, 0.5, 1]	[1, 1, 1]	[1, 2, 3]	[5, 6, 7]	[1, 2, 3]	[0.1, 0.1, 0.2]	[1, 1, 1]	[1, 1, 1]

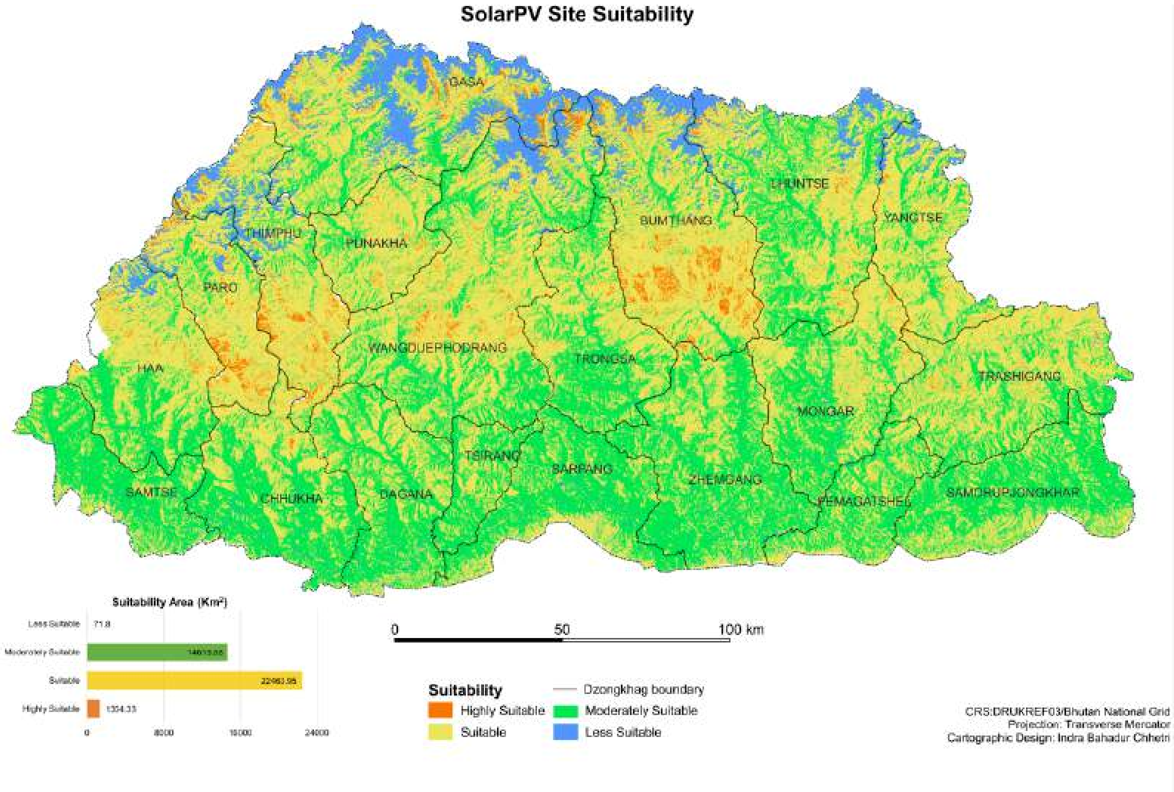

Figure 6: Optimal suitability areas for solar PV development in Bhutan

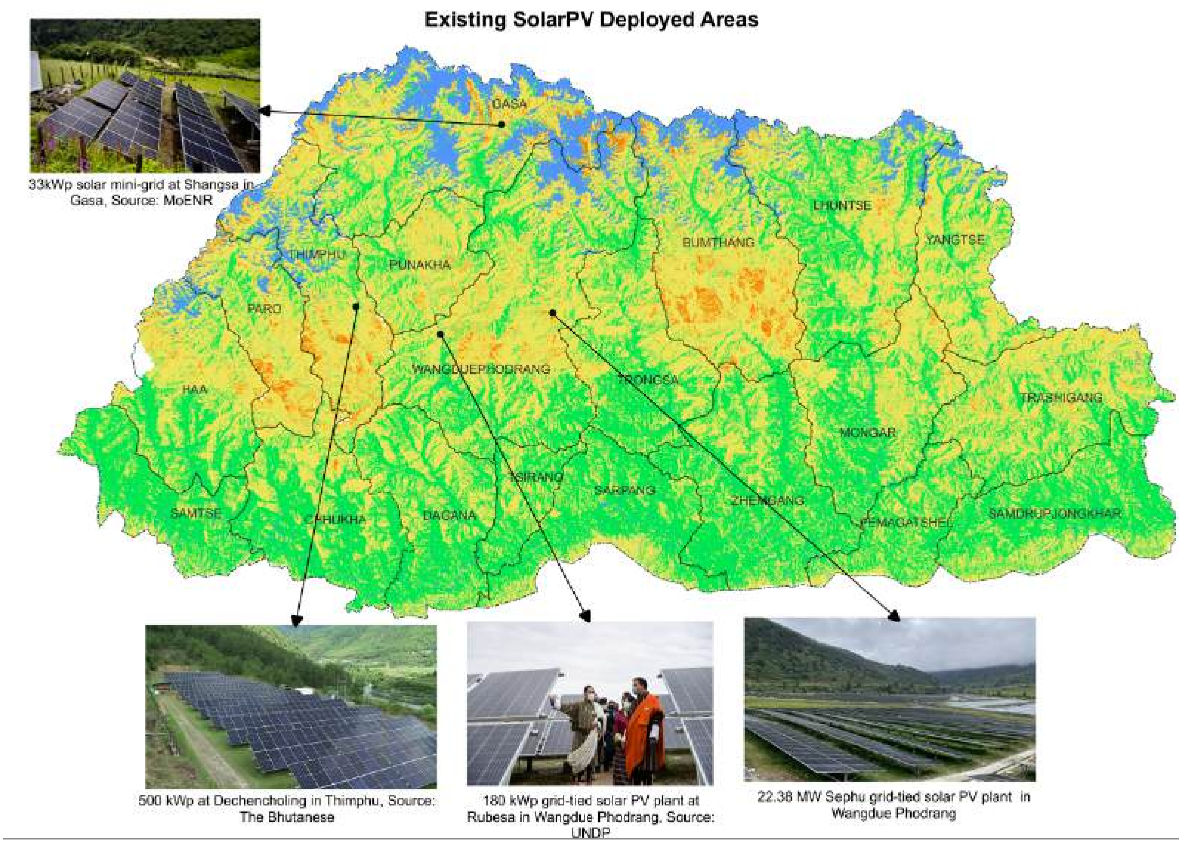

Figure 7: Figure showing existing solar PV deployed sites used for validation

Table 5: Alternative ranking of Dzongkhags based on FAHP-MOORA and FAHP-TOPSIS

Dzongkhag	FAHP-MOORA		FAHP-TOPSIS				
	yi (Benefit-Cost)	Rank	Di+	Di-	S = Di+ + Di-	Pi = Di-/S	Rank
Bumthang	0.018	3	0.028	0.026	0.055	0.483	9
Chhukha	0.016	7	0.022	0.029	0.051	0.575	3
Dagana	0.011	11	0.023	0.028	0.051	0.552	5
Gasa	0.011	12	0.031	0.026	0.057	0.463	12
Haa	0.025	1	0.015	0.028	0.043	0.654	1
Lhuntse	0.013	8	0.022	0.024	0.046	0.524	8
Mongar	-0.001	16	0.029	0.016	0.045	0.365	17
Paro	0.017	4	0.027	0.024	0.051	0.466	11
Pemagatshel	-0.010	20	0.034	0.014	0.048	0.289	20
Punakha	-0.003	18	0.034	0.016	0.050	0.321	19
Samdrup Jongkhar	0.012	9	0.023	0.027	0.050	0.540	7
Samtse	0.020	2	0.024	0.033	0.057	0.580	2
Sarpang	0.011	10	0.025	0.030	0.056	0.544	6
Thimphu	0.017	5	0.028	0.025	0.052	0.475	10
Trashigang	0.007	15	0.027	0.018	0.046	0.404	16
Trashiyangtse	0.016	6	0.020	0.025	0.045	0.563	4
Trongsa	-0.004	19	0.032	0.016	0.048	0.329	18
Tsirang	0.009	14	0.025	0.020	0.046	0.444	14
Wangdue Phodrang	0.010	13	0.025	0.021	0.046	0.449	13
Zhemgang	-0.002	17	0.028	0.020	0.048	0.412	15

4 Conclusion

The study on optimizing utility-scale solar PV site selection in Bhutan uses GIS and MCDM approaches. The technique utilizes four environmental factors, two economic factors, and three climatic factors. Further, the methodology employed advanced techniques such as FAHP, FAHP-MOORA, and FAHP-TOPSIS to evaluate and rank the Dzongkhags according to their potential. During the process, expert opinions and literature reviews were used as essential information for computing the criteria weightage using the selected methodological approaches.

The findings revealed that most of the area is classified as suitable (22,463.95 km^2) and moderately suitable (14,619.88 km^2), indicating strong potential for solar energy deployment. However, the result shows a smaller portion as highly suitable (1,304.33 km^2) of the total area of Bhutan, while less suitable areas are minimal (71.80 km^2).

The FAHP-MOORA highlighted Haa, Samtse, and Bumthang as the top-ranking Dzongkhags for solar PV farms, emphasizing their suitability based on benefit-cost ratio analysis. Additionally, the FAHP-TOPSIS further validated the results, with Haa and Samtse as the most favorable locations due to their proximity to ideal conditions for solar PV deployment in Bhutan.

The findings from this research not only support Bhutans transition to clean energy but also serve as a model for similar regions seeking to harness solar power through systematic, data-driven site selection. The research entails providing energy planners with a robust, data-driven approach for selecting the optimal sites promoting efficient, cost-effective, and sustainable energy development.

5 Recommendation

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