SOLAR POWER PLANT SITE SUITABILITY ANALYSIS IN CHATTOGRAM DISTRICT, BANGLADESH: A MULTI-CRITERIA GIS-FUZZY AHP APPROACH

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ABSTRACT

Rising demand for energy and climate change in Bangladesh have created an urgency to shift toward renewable energy sources such as solar power. But solar power plant placement requires suitable sites to achieve maximum results. Chattogram is one of the largest districts in Bangladesh, and being so, it has a significant energy demand. This study aims to identify the best locations for establishing solar power plants in the Chattogram district, incorporating Geographic Information System (GIS) and Fuzzy Analytic Hierarchy Process (F-AHP) to address this energy issue. Solar resource parameters, terrain factors, weather conditions, and infrastructural constraints were the four main categories of factors that should be taken into account for conducting the study. The analysis considered 12 criteria, including Global Horizontal Irradiance (GHI), Direct Normal Irradiance (DNI), slope, aspect, elevation, distance from roads, distance from power stations, distance from waterbodies, distance from settlements, distance from fault lines, average temperature, and wind speed, all of which fall under the four main categories. The fuzzy AHP method is employed as a weighting technique, where pairwise comparisons are synthesized using the geometric mean method. According to the normalized weights derived from our methodology, Global Horizontal Irradiance (GHI) is the most important factor, followed by Direct Normal Irradiance (DNI), which indicates the strong influence of solar parameters on site selection. On the other hand, distance from the fault lines has the least impact on the site potential. The normalized weights are then applied in the GIS environment to prepare a suitability map using the fuzzy overlay tool. Further, the resulting suitability map is classified into five classes: not suitable, less suitable, moderately suitable, suitable, and highly suitable. Finally, our study discovered that Banshkhali holds the highest potential as a solar power plant site, as 22.28% (in percentage) of the area of it is “Highly suitable” for the purpose. Moreover, Lohagara (88.99%), Patenga (83.36%), and Chittagong Port (82.97%) are among the areas that fall into the “Suitable” class with the highest proportion. Among all locations, Fatikchhari comprises the largest proportion of its area in the “not suitable” class, which reflects its lower opportunity as a suitable location for a solar power plant. Therefore, the results reflect valuable insights into the variation in the distribution of solar energy potential across the Chattogram district. It provided a strong framework for solar power plant site suitability assessment that can be adapted to other regions facing similar energy transition issues. In the end, this study paved the way for sustainable development in the energy sector.

Keywords: *Renewable energy, Solar power plant, GIS, Fuzzy Analytic Hierarchy Process*

1. INTRODUCTION

In recent decades, energy demand has risen rapidly as it acts as a prime pillar of economic development and growth (Rekik & El Alimi, 2024). Valuable resources such as fossil fuels and imported energy dependence have increased with the rise in energy consumption (Ünsal et al., 2024). Oil, coal, and natural gas are the major sources of energy production, accounting for more than 80% of the world's energy demand (Rodríguez et al., 2017). The reliance on non-renewable energy sources has intensified global warming by surging greenhouse gas emissions (Koc et al., 2019). Many countries are trying to adapt renewable energy sources with a view to achieving a sustainable, secure, and zero-carbon-emission future (Güney, 2021). Solar, geothermal, biomass, and wind energy are mostly used renewable energy sources in underdeveloped countries as they are cost-effective, accessible, and environmentally friendly (Raza et al., 2023). Solar energy is one of the most promising of these due to its economic feasibility and environmental advantages (Ipcc, 2022). Power derived from sunlight can be converted to electricity using photovoltaics or by concentrating solar power, or both. Several countries around the world possess strong potential for establishing solar power plants. Suitable site selection influences the efficiency and effectiveness of solar power plants to make proper use of solar energy (Luthra et al., 2015).

Bangladesh is moving towards increasing power generation from renewable sources, and solar energy holds one of the most potential among all due to its geographic location. Bangladesh has small-scale solar power plants as of now (Abrar & Hasan, 2019). Chattogram is the second-largest city of Bangladesh, and it is the busiest port city (Mia et al., 2015). According to the Bangladesh Power Development Board, Chattogram requires 1050 MW of electricity to fulfill its demand. Chittagong has a considerable number of sunshine hours annually (Alam et al., 2023) and its annual Global Horizontal Irradiance is approximately 1777.8 kWh/m^2. This reflects immense scope for solar power generation in the Chattogram district. Establishing solar power plants without considering physical, infrastructure, and environmental factors can be risky and inefficient, as Chattogram is exposed to coastal hazards. Therefore, selecting a potential site very much depends on its topographical and geographical features (Al-Shammari et al., 2021).

GIS offers spatial data integration and analysis capabilities to combine land-use, solar information, topography, infrastructure proximity, and environmental constraints. On the other hand, MCDM techniques offer the formal means to weight and aggregate these varied criteria into reproducible suitability maps (Di Grazia & Tina, 2024). Before using decision-making models like AHP or Fuzzy AHP, the spatial filtering capability of GIS enables the exclusion of unsuitable lands such as forest reserves, wetlands, and steep slopes, thereby reducing the number of feasible zones (Noorollahi et al., 2022). Technically, GIS ensures data interoperability and scalability, i.e., various data sources (satellite imagery, meteorological data, digital elevation models) can be incorporated and updated easily as new datasets become available. GIS not only chooses suitable areas but also creates visual maps that can easily communicate between planners, policymakers, and stakeholders (Asakereh et al., 2017).

The Analytic Hierarchy Process (AHP) is one of the most popular MCDM techniques because of its transparency in combining both qualitative and quantitative opinions. Studies for Saudi Arabia (Al Garni & Awasthi, 2017), Morocco (Alami Merrouni et al., 2018; Jbaihi et al., 2022), and other countries demonstrated the applicability of the technique to planners. These GIS-MCDM studies are typically supplemented with other and integrated methods (TOPSIS, VIKOR, ANP, SWARA, DEMATEL, etc.) to address particular decision situations or for cross-validation purposes (Asadi & PourHossein, 2019; Badi et al., 2021; Kengpol et al., 2013). As the conventional AHP can be prone to vagueness and contradictory expert judgments, researchers have increasingly favored Fuzzy AHP (FAHP), which was first formulated by Chang in 1996. It employs fuzzy set theory for the translation of linguistic ratings to fuzzy numbers and thus better captures uncertainty in weight elicitation. Using FAHP with GIS has been proven to be stronger in ranking possible locations and addressing vagueness than crisp AHP in a study of Iran (Asakereh et al., 2017). Thus, it's making FAHP an ideal choice for solar site suitability where stakeholder opinions and fuzzy data dominate. This study aims to identify the most suitable locations for establishing solar power plants using a GIS-based Fuzzy AHP approach to overcome the lack of spatially detailed renewable energy planning in the

Chattogram district. By integrating fuzzy logic with multi-criteria decision analysis, this research improves the reliability of site suitability assessments.

2. METHODOLOGY

2.1 Study Area

Chattogram district, the principal seaport and commercial capital of Bangladesh, has been selected for conducting the study because of its geographic location, rising energy demand, and notable industrial growth. It covers an area of approximately 5282 km², and is located between 20°35′ and 22°59′ N latitude and 91°27′ and 92°22′ E longitude (*Chattogram District*, n.d.). Chattogram is home to a population of 7,913,365 (*Chattogram District*, n.d.). It accommodates around 623 heavy industries and 4,323 small industries, all of which contribute to high energy consumption. The combination of rising energy demand, industrial growth, and the scarcity of conventional energy sources emphasizes the need to shift towards renewable energy options, particularly solar energy. Furthermore, Chattogram exhibits significant potential for the development of large-scale photovoltaic energy, with an average annual Global Horizontal Irradiance (GHI) of 1,777.8 kWh/m² (*Global Solar Atlas*, n.d.). The best locations for solar power plants to meet current and future electricity demands, can be identified through this study.

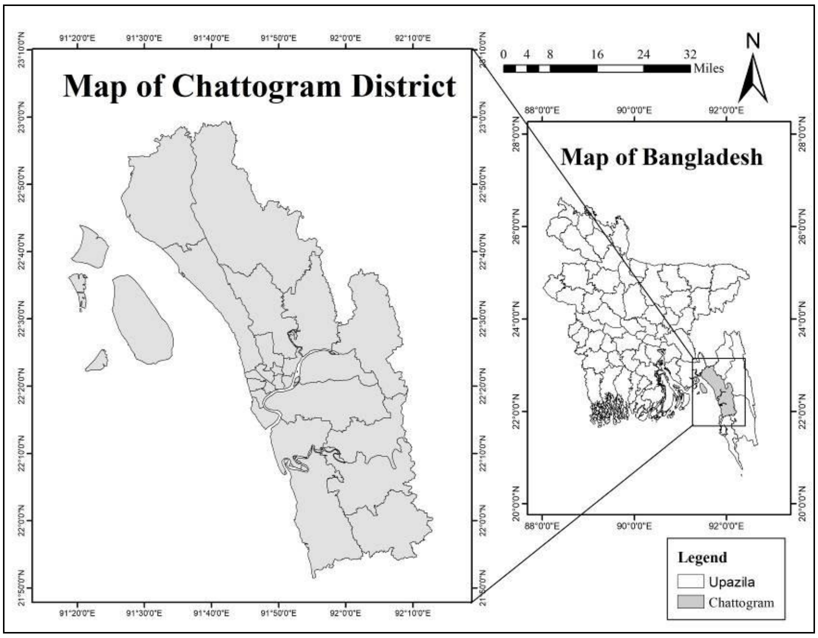

Figure 1 Study Area Map

2.2 Criteria Selection & Data Collection

The criteria for selecting a solar power plant site in the Chattogram district were based on their relevance to the physical, environmental, and infrastructural factors influencing solar power generation. A total of 12 criteria were selected for the study. Distance from roads, settlements, and waterbodies was considered since proximity to roads increases accessibility for building and maintenance, while keeping a safe distance from settlements and waterbodies helps to avoid land conflict and reduce the risk of flooding and ecological disruption, respectively. Elevation, slope, and aspect data were used to assess terrain features that influence the potential for solar installation, as flat, south-facing terrain is more likely to receive sunlight and is easier to build on. To assess solar energy potential, which is crucial for this study, solar parameters, including Global Horizontal Irradiance (GHI) and Direct Normal Irradiance (DNI), were taken into account. The location of power stations was obtained to identify the areas with better grid connectivity and lower transmission losses.

Distance from fault lines was also considered to minimize geohazard threats and ensure the structure's long-term stability. Average temperature and wind speed appeared to be important criteria that need to be examined, as moderate temperature and stable wind speed are necessary for ensuring efficiency.

2.3 Criteria Analysis in GIS

After selecting 12 criteria for solar power plant site selection in Chattogram district, the corresponding datasets were input into ArcMap 10.7 for spatial processing and analysis. Regardless of whether they were vector or raster, all datasets were converted into raster format to ensure analytical consistency. All raster layers were projected into a common coordinate system and standardized to a consistent 30×30 m cell size, to ensure spatial alignment after conversion. Table 1 contains the information about how the raster criteria maps were prepared.

Table 1 Criteria for solar power plant site suitability analysis, and their data format, source, and GIS analysis methods

Criteria	Data	Data Format	Source	Analysis
GHI	DEM	Raster layer	Global Solar Atlas	-
DNI	DEM	Raster layer	Global Solar Atlas	-
Distance from Roads	Road	Vector- polyline layer	OpenStreetMap	Euclidean Distance
Elevation	DEM	Raster layer	OpenTopography	-
Slope	DEM	Raster layer	OpenTopography	Slope
Aspect	DEM	Raster layer	OpenTopography	Aspect
Distance from Fault Lines	Fault lines	Vector- polyline layer	USGS	Euclidean Distance
Distance from Power Stations	Power stations	Vector- point layer	World Resources Institute	Euclidean Distance
Distance from Settlements	Settlements	Vector- polygon layer	OpenStreetMap	Euclidean Distance
Distance from Waterbodies	Waterbodies	Vector- polygon layer	OpenStreetMap	Euclidean Distance
Average Temperature	Temperature	Excel (xlsx)	WorldClim	IDW
Wind Speed	Wind speed	Raster layer	Global Wind Atlas	-

2.4 F-AHP

F-AHP was employed to determine the relative importance of location selection criteria to generate a reliable suitability map for solar power plant development.

Table 2 F-AHP Scale Interpretation

Fuzzy Set	Definition	Fuzzy Scale
1	Equal importance	(1, 1, 1)
2	Weak importance	(1, 2, 3)
3	Not bad	(2, 3, 4)
4	Preferable	(3, 4, 5)
5	Importance	(4, 5, 6)
6	Fairly importance	(5, 6, 7)
7	Very important	(6, 7, 8)
8	Absolute	(7, 8, 9)
9	Perfect	(8, 9, 10)

Step 01: Pairwise Comparison Matrix
We used geometric integrations shown in equation (1) to generate the integrated fuzzy pairwise comparison matrix used in the F-AHP computation.

A is a Decision matrix of n×n dimensions.

$$\begin{bmatrix} a11 & \dots & a1n \\ a21 & \dots & a2n \\ an1 & \dots & ann \end{bmatrix} \tag{1}$$

$[A_{ij}]$, where i,j= 1, 2, …., n

A_{ij} is a fuzzy number (l, m, u) and for reciprocal

$$A^{-1} = (l, m, u)^{-1} = (\frac{1}{u}, \frac{1}{m}, \frac{1}{l}) \tag{2}$$

$A_{ij} = 1$ for i=j

Step 02: Geometric Mean

To calculate the Fuzzy geometric mean of each criterion, equation (3) was employed.

$$r_i = A_1 \otimes A_2 \otimes \dots \otimes A_n = (l_1 \times l_2 \times \dots \times l_n, m_1 \times m_2 \times \dots \times m_n, u_1 \times u_2 \times \dots \times u_n)^{\frac{1}{n}} \tag{3}$$

Where n is the number of criteria, r_i is the fuzzy geometric mean.

Step 03: Relative Fuzzy Weight

The fuzzy preference weight for each criterion was calculated using equation (4).

$$w_i = r_i \times (\sum_{k=1}^{n} r_k)^{-1} \tag{4}$$

Where w_i is the fuzzy weights.

Step 04: Average Weight

Equation (5) illustrates how the average weight method was employed for defuzzification to derive a crisp value from the fuzzy weights.

$$w_i = \frac{(l_i + m_i + u_i)}{3} \tag{5}$$

Step 05: Normalized Weight

The normalized preference weight determined the relative importance of each criterion by using equation (6).

$$Normalized\ weights = \frac{w_i}{\sum_{i=1}^{n} w_i} \tag{6}$$

2.5 Fuzzy in GIS

Once the normalized preference weights were calculated, the next step was to apply the fuzzy logic approach in ArcMap 10.7 to generate the final suitability map. At the first step, all raster criteria were converted to fuzzy membership maps representing the degree of suitability on a scale from 0 (not suitable) to 1 (highly suitable), with appropriate fuzzy membership functions selected for each criterion. Next, each fuzzy membership maps were multiplied by its respective normalized preference weights using the raster calculator tool, applying the following formula,

$$\textit{Raster Calculator} = \textit{Fuzzy Membership layer} \times \textit{normalized weight} \tag{7}$$

The weighted raster layers were then summed by applying the Fuzzy Overlay (SUM) tool to prepare the final suitability map, where all the criteria are considered together. Finally, the final suitability map is then classified into 5 classes: not suitable, less suitable, moderately suitable, suitable, and highly suitable.

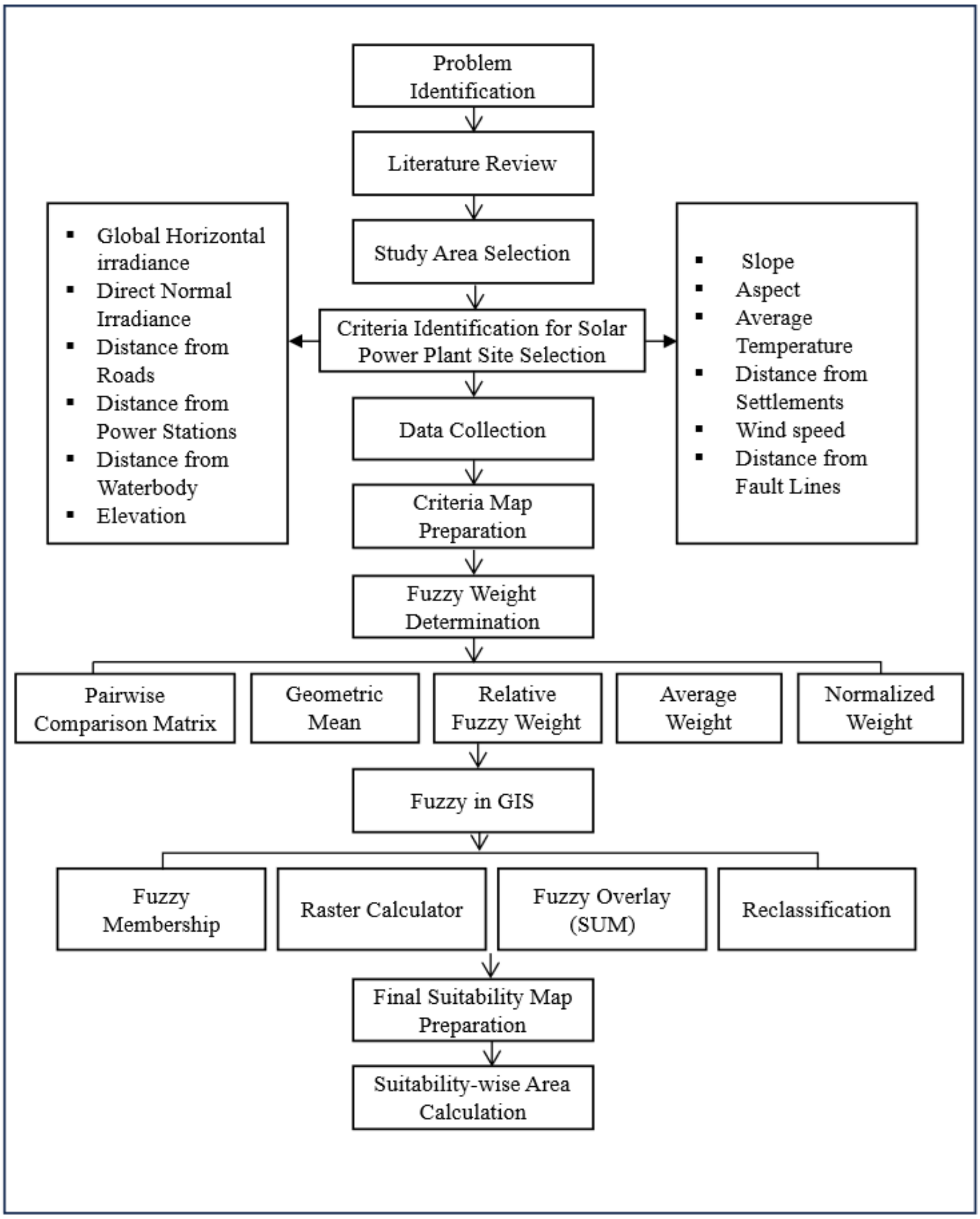

Figure 2 Methodology Flowchart

3. DATA ANALYSIS AND FINDINGS

GHI and DNI maps depict that the high solar intensity makes the Southern and Southwestern coastal areas favourable for solar power plant establishment. Slope and Aspect also strengthen this result as they also showed hilly northern and northeastern areas as less suitable for the purpose. Lower distance from infrastructure factors like roads and power stations is considered more suitable, so urban and semi-urban areas like Chittagong Port, Patenga, and Bakalia are preferable according to these criteria. On the other hand, areas near waterbodies and settlements showed less suitability due to land use restrictions.

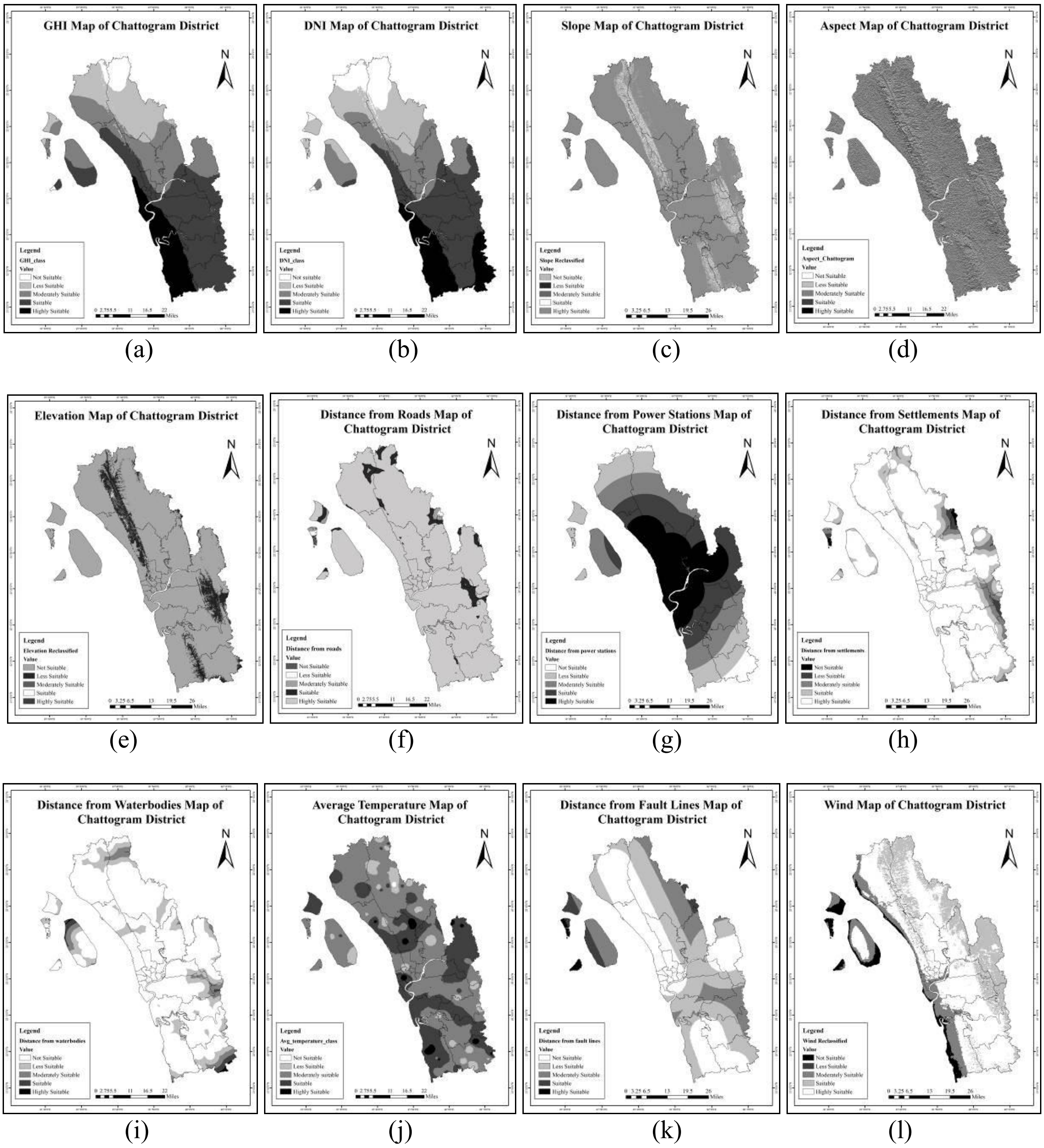

Figure 3 (a) Classified suitability map of GHI, (b) Classified suitability map of DNI, (c)Classified suitability map of slope, (d) Classified suitability map of aspect, (e) Classified suitability map of elevation, (f) Classified suitability map of distance from roads, (g) Classified suitability map of distance from power stations, (h) Classified suitability map of distance from settlements, (i) Classified suitability map of distance from waterbodies, (j) Classified suitability map of average temperature, (k) Classified suitability map of distance from fault lines, and (l) Classified suitability map of wind speed

Table 3 Fuzzified Pair-wise Comparison Matrix

Criteria	GHI	DNI	Slope	Aspect	Elevation	Distance from road	Distance from power station	Distance from settlement	Distance from waterbody	Average Temperature	Distance from fault line	Wind speed
C1	(1,1,1)	(4, 5, 6)	(4, 5, 6)	(6, 7, 8)	(9, 9, 9)	(4, 5, 6)	(4, 5, 6)	(9, 9, 9)	(6, 7, 8)	(6, 7, 8)	(9, 9, 9)	(6, 7, 8)
C2	(1/6, 1/5, 1/4)	(1, 1, 1)	(4, 5, 6)	(4, 5, 6)	(6, 7, 8)	(4, 5, 6)	(4, 5, 6)	(9, 9, 9)	(6, 7, 8)	(6, 7, 8)	(6, 7, 8)	(4, 5, 6)
C3	(1/6, 1/5, 1/4)	(1/6, 1/5, 1/4)	(1,1,1)	(2, 3, 4)	(4, 5, 6)	(1/6, 1/5, 1/4)	(1/6, 1/5, 1/4)	(1/8, 1/7, 1/6)	(6, 7, 8)	(6, 7, 8)	(4, 5, 6)	(4, 5, 6)
C4	(1/8, 1/7, 1/6)	(1/6, 1/5, 1/4)	(1/4, 1/3, 1/2)	(1,1,1)	(2, 3, 4)	(1/6, 1/5, 1/4)	(1/6, 1/5, 1/4)	(4, 5, 6)	(2, 3, 4)	(3, 4, 5)	(2, 3, 4)	(1/4, 1/3, 1/2)
C5	(1/9, 1/9, 1/9)	(1/8, 1/7, 1/6)	(1/6, 1/5, 1/4)	(1/4, 1/3, 1/2)	(1,1,1)	(1/8, 1/7, 1/6)	(1/8, 1/7, 1/6)	(2, 3, 4)	(4, 5, 6)	(2, 3, 4)	(1,1,1)	(1/6, 1/5, 1/4)
C6	(1/6, 1/5, 1/4)	(1/6, 1/5, 1/4)	(4, 5, 6)	(4, 5, 6)	(6, 7, 8)	(1,1,1)	(1,1,1)	(6, 7, 8)	(6, 7, 8)	(6, 7, 8)	(6, 7, 8)	(2, 3, 4)
C7	(1/6, 1/5, 1/4)	(1/6, 1/5, 1/4)	(4, 5, 6)	(4, 5, 6)	(6, 7, 8)	(1,1,1)	(1,1,1)	(6, 7, 8)	(6, 7, 8)	(6, 7, 8)	(6, 7, 8)	(2, 3, 4)
C8	(1/9, 1/9, 1/9	(1/9, 1/9, 1/9)	(6, 7, 8)	(1/6, 1/5, 1/4)	(1/4, 1/3, 1/2)	(1/8, 1/7, 1/6)	(1/8, 1/7, 1/6)	(1,1,1)	(1/4, 1/3, 1/2)	(1/4, 1/3, 1/2)	(2, 3, 4)	(1/4, 1/3, 1/2)
C9	(1/8, 1/7, 1/6)	(1/8, 1/7, 1/6)	(1/8, 1/7, 1/6)	(1/4, 1/3, 1/2)	(1/6, 1/5, 1/4)	(1/8, 1/7, 1/6)	(1/8, 1/7, 1/6)	(2, 3, 4)	(1,1,1)	(1/4, 1/3, 1/2)	(4, 5, 6)	(1/6, 1/5, 1/4)
C10	(1/8, 1/7, 1/6)	(1/8, 1/7, 1/6)	(1/8, 1/7, 1/6)	(1/5, 1/4, 1/3)	(1/4, 1/3, 1/2)	(1/8, 1/7, 1/6)	(1/8, 1/7, 1/6)	(2, 3, 4)	(2, 3, 4)	(1,1,1)	(2, 3, 4)	(1/6, 1/5, 1/4)
C11	(1/9, 1/9, 1/9)	(1/8, 1/7, 1/6)	(1/6, 1/5, 1/4)	(1/4, 1/3, 1/2)	(1, 1, 1)	(1/8, 1/7, 1/6)	(1/8, 1/7, 1/6)	(1/4, 1/3, 1/2)	(1/6, 1/5, 1/4)	(1/4, 1/3, 1/2)	(1,1,1)	(1/8, 1/7, 1/6)
C12	(1/8, 1/7, 1/6)	(1/6, 1/5, 1/4)	(1/6, 1/5, 1/4)	(2, 3, 4)	(4,5,6)	(1/4, 1/3, 1/2)	(1/4, 1/3, 1/2)	(2, 3, 4)	(4, 5, 6)	(4, 5, 6)	(6, 7, 8)	(1,1,1)

Table 4 Normalized Criteria Weights and Ranking Using Fuzzy Geometric Mean Method

Criteria	Fuzzy Geometric Mean	Fuzzy weight	Normalized weight	Rank
1	(4.9961, 5.6656, 6.2947)	(0.1572, 0.1960, 0.2448)	0.197	1
2	(3.8883, 4.4922, 5.0674)	(0.1223, 0.1554, 0.1971)	0.156	2
3	(2.0197, 2.2665, 2.4844)	(0.0636, 0.0784, 0.0966)	0.078	4
4	(1.4628, 1.6893, 1.8776)	(0.0460, 0.0584, 0.0730)	0.058	6
5	(1.2599, 1.3733, 1.4628)	(0.0396, 0.0475, 0.0569)	0.047	7
6	(2.8161, 3.2238, 3.5987)	(0.0886, 0.1115, 0.1399)	0.112	3
7	(2.8162, 3.2238, 3.5987)	(0.0886, 0.1115, 0.1399)	0.112	3
8	(1.2301, 1.2888, 1.3348)	(0.0387, 0.0446, 0.0519)	0.044	9
9	(1.1892, 1.2532, 1.3032)	(0.0374, 0.0434, 0.0506)	0.043	10
10	(1.1892, 1.3161, 1.4142)	(0.0374, 0.0455, 0.05501)	0.045	8
11	(1, 1, 1)	(0.0314, 0.0346, 0.0389)	0.034	11
12	(1.84303, 2.1119, 2.3449)	(0.0579, 0.0731, 0.0912)	0.073	5

Global Horizontal Irradiance (GHI) achieved the highest normalized weight, which is 0.197, making it the most influential criterion. The importance of DNI in determining the intensity of solar radiation was evident from its ranking as the second most significant factor, with a normalized weight of 0.156. Other factors like distance from settlements, distance from waterbodies, and average temperature were of less importance. But distance from fault line was given the lowest weight (0.034), suggesting its little influence on the suitability analysis.

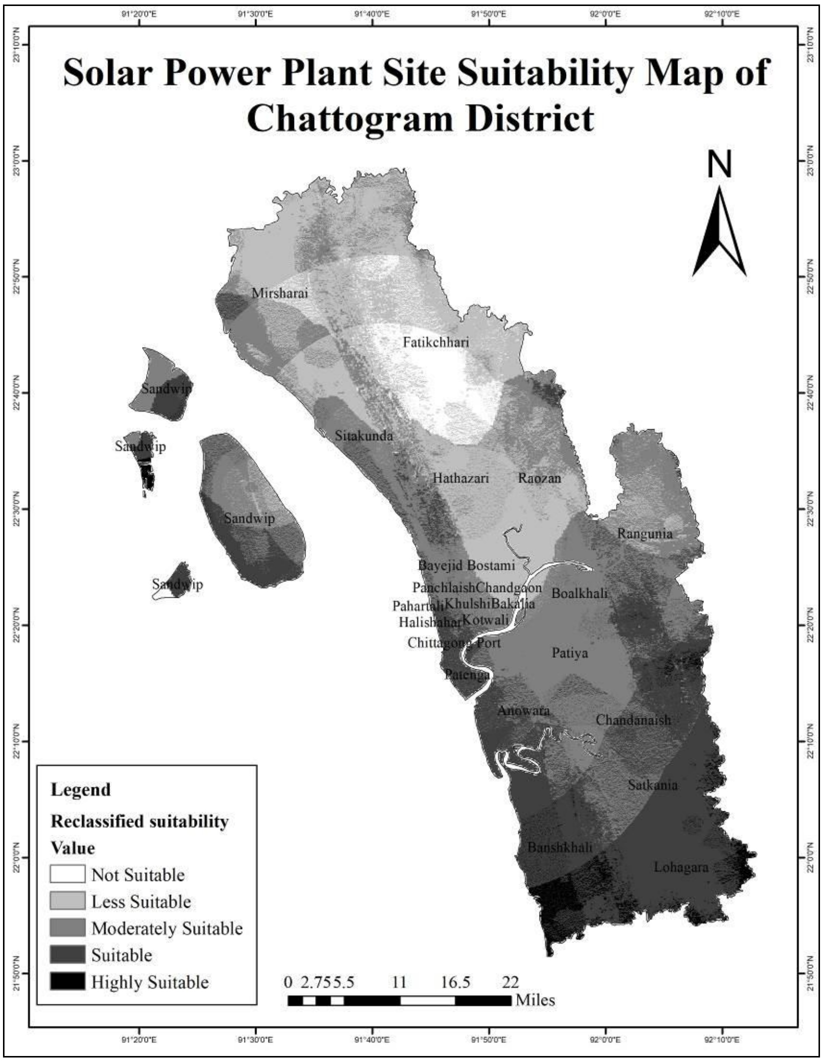

Figure 4 Suitability Map of Solar Power Plant Site Selection in Chattogram District

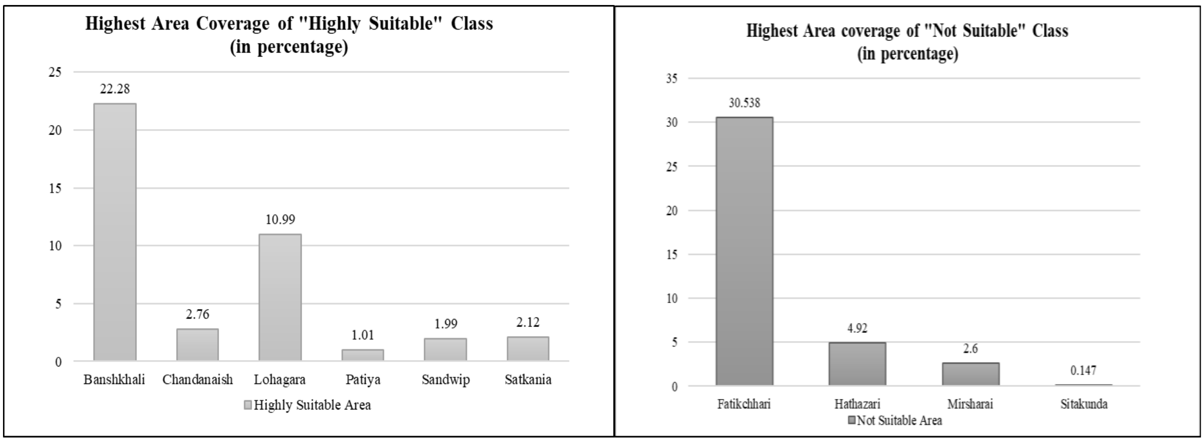

Figure 5 Area Coverage of Different Classes (in percentage)

All the layers of the 12 criteria were combined to acquire the final suitability map, and as a result, we found five classes of suitability around the Chattogram district (Figure 4) . A specific portion of land of each district falls into one of the five suitability classes.

Table 5 Area Coverage by Each Suitability Class (in percentage)

Location	**Not Suitable Area**	**Less Suitable Area**	**Moderately Suitable Area**	**Suitable Area**	**Highly Suitable Area**
Anowara	0	0	40.58	59.42	0
Bakalia	0	8.98	91.018	0	0
Banshkhali	0	0	7.672	70.04	22.28
Bayejid Bostami	0	45.29	52.384	2.33	0
Boalkhali	0	8.08	72.21	19.46	0.26
Chandanaish	0	0.0018	34.81	62.426	2.76
Chandgaon	0	94.104	5.895	0	0
Chittagong Port	0	0	17.03	82.97	0
Double Mooring	0	0	55.789	44.21	0
Fatikchhari	30.538	54.603	13.915	0.912	0.023
Halishahar	0	0	24.05	75.95	0
Hathazari	4.92	74.67	18.094	2.31	0
Khulshi	0	0	97.34	2.66	0
Kotwali	0	2.62	93.38	3.99	0
Lohagara	0	0	0.008	88.99	10.99
Mirsharai	2.6	61.17	33.998	2.23	0
Pahartali	0	0	62.9	37.099	0
Panchlaish	0	17.96	81.972	0.071	0
Patenga	0	0	16.64	83.36	0
Patiya	0	0.03	72.76	26.195	1.01
Rangunia	0	14.13	70.96	14.906	0.0062
Raozan	0	59.711	38.45	1.83	0.00076
Sandwip	0	5.8	48.68	43.532	1.99
Satkania	0	0	29.45	68.427	2.12
Sitakunda	0.147	17.108	69.34	13.408	0

Banshkhali holds the highest area coverage (22.28%) under the highly suitable class. Khulshi, Kotowali, and Bakalia are identified as moderately suitable locations showing 97.34%, 93.38%, and 91.018% area of the location boundary under the moderately suitable class, respectively (Table 5). Among the 25 locations mentioned in the study, the majority of them showed no portion of their areas classified as not suitable. This indicates that each location of the Chattogram district has at least some potential for solar power plant establishment (Table 5).

The suitability results have been verified for qualitative analysis by comparing them with the existing, proposed, and planned solar station locations in Chattogram District. Operational solar station locations, such as the "Kaptai 7.4 MW solar power station" and the "Anwara 16 MW solar power station," along with major proposals like the "Banshkhali 200 MW (Eleris)" and "Chattogram 600 MW (APSCL-Eleris)" solar stations (*RE Generation Mix | National Database of Renewable Energy*, n.d.), support the identification of Banshkhali, Anwara, Rangunia, and Patenga as suitable areas for solar power plant establishment. In addition, the already permitted solar projects like the Baraiyarhat 50 MW (SOSPL) solar station and the Rangunia 55 MW (Metito) solar station (*Energy Transition Bangladesh (ETB)*, n.d.), located in Moderately Suitable locations, further validate the results obtained from this analysis.

Due to the limited availability of publicly available plant-level performance data, the validation is qualitative in this study. Future research may use sensitivity analysis and quantitative performance measures for increasing reliability of the results.

4. CONCLUSIONS

This study presents a systematic suitability assessment for solar power plant development using a multi-criteria decision-making framework integrated with geospatial analysis in the Chattogram district. Banshkhali, Lohagara, Patenga, and Chittagong port cover a more suitable area than other areas of the Chattogram district, primarily due to high solar irradiance and availability of open, low-lying land. Northern and hilly places like Fatikchari and Mirsharai are mostly less suitable or not suitable because of rugged terrain and limited accessibility. The spatial similarity between the suitability results and the existing as well as planned solar power plants increased the relevance of the study. This assessment will serve as a decision support tool for policymakers and investors to explore the renewable energy sector. However, due to limited data, quantitative analysis, such as sensitivity analysis, was not conducted in this assessment. Future work may incorporate quantitative analysis to enhance the accuracy of the study.

DECLARATION OF USE OF AI

AI tools were used for conceptualizing the methodology section, while the manuscript was written by the author.

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