GIS-based multi-influencing factor (MIF) application for optimal site selection of solar photovoltaic power plant in Nashik, India

Nitin Liladhar Rane[1], Mehmet Akif Günen[2], Suraj Kumar Mallick[3], Jayesh Rane[4], Chaitanya B. Pande[5,6,7], Monica Giduturi[1], Javed Khan Bhutto[8], Krishna Kumar Yadav[9], Abebe Debele Tolche[10]* and Maha Awjan Alreshidi[11]

Abstract

The significant natural energy sources for reducing the global usage of fossil fuels are renewable energy (RE) sources. Solar energy is a crucial and reliable RE source. Site selection for solar photovoltaic (PV) farms is a crucial issue in terms of spatial planning and RE policies. This study adopts a Geographic Information System (GIS)-based Multi-Influencing Factor (MIF) technique to enhance the precision of identifying and delineating optimal locations for solar PV farms. The choice of GIS and MIF is motivated by their ability to integrate diverse influencing factors, facilitating a holistic analysis of spatial data. The selected influencing factors include solar radiation, wind speed, Land Surface Temperature (LST), relative humidity, vegetation, elevation, land use, Euclidean distance from roads, and aspect. The optimal sites of solar PV power plant delineated revealed that 'very low' suitability of site covering 4.866% of the study area, 'low' suitability of site 13.190%, 'moderate' suitability of site 31.640%, 'good' suitability of site 32.347%, and 'very good' suitability of site for solar PV power plant encompassing 17.957% of the study area. The sensitivity analysis results show that the solar radiation, relative humidity, and elevation are the most effective on the accuracy of the prediction. The validation of the results shows the accuracy of solar PV power plant prediction using MIF technique in the study area was 81.80%. The integration of GIS and MIF not only enhances the accuracy of site suitability assessment but also provides a practical implementation strategy. This research offers valuable insights for renewable energy policymakers, urban planners, and other stakeholders seeking to identify and develop optimal locations for solar energy power farms in their respective regions.

Keywords Multi-criteria decision-making (MCDM), Site selection, Multi-influence factor (MIF), Renewable energy, Solar power plant

*Correspondence:
Abebe Debele Tolche
abeberobe@gmail.com
Full list of author information is available at the end of the article

Introduction

Solar's availability across the globe is leading to increased demand in solar energy systems worldwide [1, 27, 91]. The need for solar power plants is global, and many regions of the world are now developing this new renewable technology [5, 95]. Every renewable energy technology is at a distinct stage of development, research, and commercialization [87, 93]. They differ as well in terms of expected costs both now and in the future, resource availability, the existing industrial base, and any potential impact on greenhouse gas emissions [7]. Solar Energy is identified as one of the most environmentally friendly energy sources that does not contribute to or threaten global warming is solar energy [10, 62, 84]. It is unique in nature due to its free, clean, and profuse source with the ability to meet the rising energy demands of earth [14, 68, 92]. Also assures that social and economic success will occur without environmental degradation or climate change effects, which will result in growth and sustainable development [14].

India is a tropical nation, and because of its location, it is well suited to harnessing solar energy through the use of solar PV systems and large-scale solar plants Mishra et al. [53]; [27, 70]. The daily needs of mankind can be fulfilled if the energy from the sun could be stored, eliminating the need for dependence on fossil fuels [11, 32]. India is undergoing extensive urbanization, and an uninterrupted energy supply is the essential factor driving such demographic expansion and rising GDP in these metropolitan areas [70]. By 2030, there will be a predicted increase in primary energy demand of more than 60, or 1.7% annually [84]. Therefore, the energy produced by non-conventional energy sources causes resource depletion and environmental damage [70]. Fossil fuels, which are currently the widely used sources of energy, have led to health concerns leading to respiratory diseases, asthma, lung infection, and cancer [36]. In nature, fossil fuels are limited and can get exhausted in the future at the current rate of consumption. The idea of carbon-negative or low-carbon sustainable energy systems has been a rising issue in society due to the impending concerns of unchecked climate change [57]. Hence it is all the more important to look for alternate and cleaner sources of energy for sustainable development.

India has committed significant resources to boost solar energy production to fulfill the country's rising energy needs and lessen its reliance on coal-based energy generation [38]. One such effort by the Ministry of New and Renewable Energy (MNRE) to fulfil the need for energy holistically through the Solar City Mission (SCM) programme. The SCM initiative targeted to reduce about 10% of the demand for conventional energy in urban areas by the use of RE sources, therefore encouraging to use solar energy technology. Approximately 5000 trillion kWh of solar energy are incident across India each year. Over 5 kWh/m^2 of global radiation is received annually over more than 56% of India's entire geographical area [52]. The Indian government's supportive policies give economic incentives, enticing tariff plans, and tax exemptions, all of which aid in the nation's sustainable development [38].

Solar energy is relatively affordable, clean, and has low operating expenses, which makes it more accessible due to its cheap contraction costs and high rate of power line distribution [51]. Optimal selection of location for solar photovoltaic panel installation is crucial and there have been several studies in the past, trying to address the problem. Mapping technique is one of the most widely used methods. These techniques, along with developing technology have been combined as a single system as GIS. One of the most beneficial GIS applications is the tool that is GIS based [65, 89]. Such techniques use an understanding of the geographical distribution of metropolitan areas, along with historical data and field surveys, and they are very time and money efficient [81]. The literature has included efforts to incorporate renewable energy sources across the globe into GIS bases [8, 94]. Remote sensing (RS) and GIS have been employed in other investigations of RE sources, such as wind, solar, and hybrid power plants, to identify places that meet ecological requirements [44]. The impact of land topography, slope, and surface characteristics on the dispersion of solar radiation on the earth's crust [27]. The factors that need to be considered includes distance to road, the availability of arid land, the distance from water bodies, the slope, the direction of the sun's radiation, the latitudes and longitudes, the neighbourhoods and the existing built-up area, etc. [68]. The overview of GIS and machine learning-based suitability assessment of global solar energy has been outlined in a tabular form (Table 1).

To maximize the resources of solar energy, a variety of strategies have been employed in research to determine the optimal site placement for the installation of solar PV panels. It is believed that the map-based overlay analysis technique is awkward. Both the technique and the evaluation parameters lack independent validation [81]. Additionally, the parameters used for evaluation lack suitable standardisations. MIF is a more straightforward, dependable, and adaptable overlay analysis technique for assessing the expansion of urban infrastructure than the more complex Analytic Hierarchy Process (AHP) [54]. To characterize intricate methods for estimating and decision-making, the AHP technique, which is a pair-wise comparison method of factors used in multi-criteria selection and is principally based on a matrix eigenvalue, has been utilized [72]. Artificial neural

Table 1 The overview of GIS-based suitability assessment of solar energy in national and global scale

Study area	Data and models used	Methodology	Key findings	Reference
Lisbon, Portugal	A digital surface model (DSM) built from Light Detection and Ranging (LiDAR) data and a solar	Direct and diffuse solar radiation was obtained from the ground, roof, and facades to calculate urban solar potential	Facades increase the solar potential by 10 to 15% although the average annual irradiance on a facade is one-third of the rooftops	[6]
European Union	Multivariate sampling, correlates the roof area and statistical data(e.g., population density, number of floors) European Settlement Map	CORINE Land Cover and the European Urban Atlas data sets were processed to adjust information on EU built-up areas later Photovoltaic GIS was used for the PV energy yield calculation	EU rooftops could potentially fulfil 24.4% (680TWh) of electricity needs annually by solar PV energy	[2]
Slovenia	LiDAR data and mathematical equations	Estimating the rooftop PV potential in terms of its physical, geographic, technical, and economic potential	The annual physical, geographic, technical and economic potentials were 1273.7 MWh, 1253.8 MWh, 14.2 MWh, and 279.1 Wh, respectively	[50]
Germany	Open Geospatial Consortium(OGC) Standard CityGML, LiDAR	Technical and economic potential (considering roof area and insolation thresholds) are investigated to determine the fraction of the electricity demand of the municipalities and the region	The available roof space (technical The available roof space (technical potential) can cover 77% of the region's electricity consumption and considering economic potential high irradiance roofs can cover 56% of it	[69]
United States	LiDAR data and statistical models	Combines lidar data, GIS tools with a validated analytical method for rooftop PV suitability employing	The roof area of 81.3 km² could host 1118 GW PV capacity, generating 1432 TWh of electricity per year	[16]
Victoria, Australia	LiDAR Data processed in MATLAB	Pixel-based approach to the estimation of solar energy potentials over pitched roofs in using a specific time interval by image visualization and processing in MATLAB	Coloured 3D map, reveal the roof's radiation distribution, due to objects the roofs and identifying roof areas with high solar potential for installing solar collectors	[41]
Philadelphia in PA, U.S. A	LiDAR data, building footprints and ArcGIS	Rooftop area analysis was based on slope and aspect, using LiDAR data, ArcGIS tools, and building footprint data	33.7% of building footprint data and 48.6% rooftop areas are suitable for PV systems	[4]
Switzerland	Combination of support vector machines (SVMs) and geographic information systems (GIS)	A combination of machine learning and GIS was used to calculate physical geographic and technical rooftop solar potential	The annual PV potential of Switzerland is 17.86 TWh which corresponds to 28% of its electricity consumption in 2015	[31, 32]
Mumbai, India	The satellite image from Google Earth with a spatial resolution of 0.5 m	Land use data and GIS-based analysis of satellite images to estimate Building Footprint Area (BFA) Ratio	With median efficiency panels, Mumbai city has a potential of 2190 MW which can fulfill 12.8–20% of average daily and 31–60% of peak morning demand	[80]
Odisha, India	Artificial neural network (ANN) and Generic algorithm (GA)	Off-grid systems such as photovoltaic lighting systems and water pumps have been designed and implemented	Mini solar street light, a 20 Wp polycrystalline solar panel has been used to charge a 12 V 10 Ah Li-ion battery in 6–7 sunny hours and can run a 12 V 9 W LED light up to 10 h per a day	[19, 20]

networks and cellular automata-based techniques have been used in this process [47]. MIF, on the other hand, is a non-sensitive technique that relies on a precise set of assumptions rather than input data. AHP also employs pair-wise comparison, which was based on consistency ratios. A comparison matrix's consistency should be less than 0.1 [79]. If there are any variations, the comparison questionnaire should be filled out more accurately to get near to the necessary consistency.

Modelling the geographical viability of solar energy resources employing GIS-based multicriteria decision analysis (MCDA) is one such approach [22]. The AHP is one among the MCDM methods which is been widely used in several research for installation of solar photovoltaic in suitable site [79]. The literature survey shows the lack of applications of MIF-based techniques that identify suitable site locations for the installation of solar PV, despite the fact that there have been numerous MIF-based studies conducted in the world in the areas of groundwater potential mapping [66], food evaluation [59], appropriateness of the site suitability for urban development [48], dam site suitability [63], ideal location for electric vehicle charging station [64], evaluation of the alluvial aquifer [86], estimating the possibility of land deterioration [48] and appropriate locations for water-saving technology [78]. The literature shows, there are limited studies with GIS-MIF integration in determining suitable site locations for PV solar plant installation [63]. It creates a nuanced layer to the decision-making process, ensuring a more precise and context-specific evaluation [47].

The major contribution of the proposed method lies in its innovative integration of GIS and the MIF technique for site selection of solar PV farms. The study addresses a critical aspect of renewable energy generation by systematically evaluating and delineating optimal locations for solar PV farms in Nashik, India. By considering a comprehensive set of influencing factors such as solar radiation, land surface temperature, relative humidity, wind speed, aspect, land use, distance from roads, elevation, and vegetation density, the proposed methodology goes beyond conventional approaches. The use of MIF for weight assignment adds a nuanced layer to the decision-making process, ensuring a more precise and context-specific evaluation. Furthermore, the study validates its findings with actual energy data generated from solar panels, demonstrating the practical utility and accuracy of the proposed approach. This comprehensive and validated methodology contributes significantly to the field of solar energy planning, offering a dynamic tool for decision-makers in both public and commercial sectors for identifying and delineating optimal sites for solar PV farms in diverse geographic areas.

Methodology

Study area

The study area is situated between latitudes 20°8′18.69″N to 19°48′50.72″N and longitude 73°36′17.10″E to 73°49′3.69″E. This study area (Fig. 1) has a total area of 890.35 km^2. The elevation of study area varies from 530 to 1068 m above mean sea level and situated in Maharashtra's North-West. The research area experiences substantial variability in its yearly rainfall, which is roughly 713.50 mm on average [3]. In the study area, spatiotemporal average temperatures ranges from 20.02 to 36.92 degrees Celsius and yearly rainfall ranges from 500 to 3400 mm. The temperature gets quite chilly throughout the winter, with low as 2 degrees Celsius [37]. The majority of Nashik's urban population lives close to the Ghats [40]. Spatio-temporal mean wind speeds in study area were 2.40–2.61 m/s and mean relative humidity was 59.86–62.77%, with minimum values occurring in the warmer months. Based on aridity indices, the region's climatic characteristics are described as semiarid [31].

Energy issues and rationale of the study area

The daily coal need for Nashik is between 12 and 13 thousand million tonnes. Western Coalfields and Southeastern Coalfields are connected to Nashik for the supply of coal. Due to Nashik's remote location from the collieries, the freight component is significant and typically accounts for 80–100% of the cost of coal [77]. Since the hydro power plants are dependent on rain, the electricity situation in the summertime gets affected [9, 90]. In Western Nashik part, new construction is taking place in the commercial, residential, and institutional sectors. As a result, the western area can be seen as an energy-forward metropolis where solar energy resources have the potential to be used to lower energy consumption. By utilizing green building methods, new structures can lower their energy requirements [12, 43, 76]. By installing solar water heating systems and switching to energy-saving appliances, individuals can actively participate in city energy management. Building Integrated Photovoltaics (BIPV) systems enable commercial and institutional buildings to produce their own electricity. The commercial sector in western Nashik has the greatest daily energy needs, followed by institutional, at 4569879.6 and 1065240 kW, respectively. The average daily demand for the residential sector is 443139.84 kW. Street lighting requires 14919 kW, while other types of lighting, such as signal lighting, hoarding lighting, and park lighting, need 7959.5 kW [77]. The industrial Estates of the Maharashtra Industrial Development are where most of the industrial activity
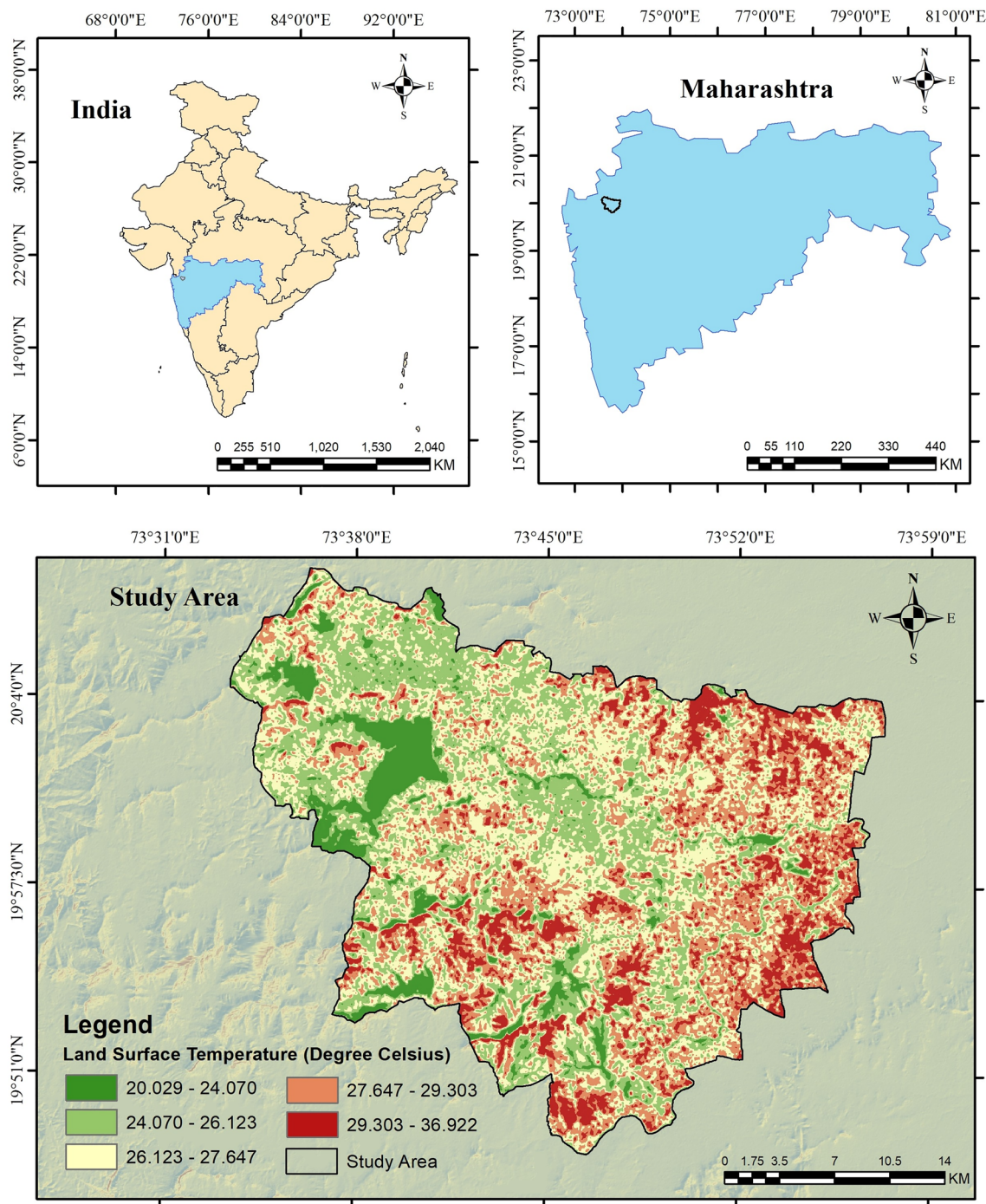
Fig. 1 Location of study area with Land Surface Temperature (LST)

in the Nashik Municipal Corporation area is primarily concentrated namely, the Ambad Industrial Estate and the Satpur Industrial Estate. There is a chance that businesses producing solar technology will be included in this well-planned and established industrial area [34, 76]. Moreover, the importance of switching to alternative

energy sources has increased due to the increasing depletion of fossil fuels in Maharashtra State [56, 79]. The demand for energy across the Maharashtra state has been increasing in recent years due to the rapid growth of the population [35, 43, 67]. PV is foremost effective method of producing electricity [15, 74]. In addition to preventing
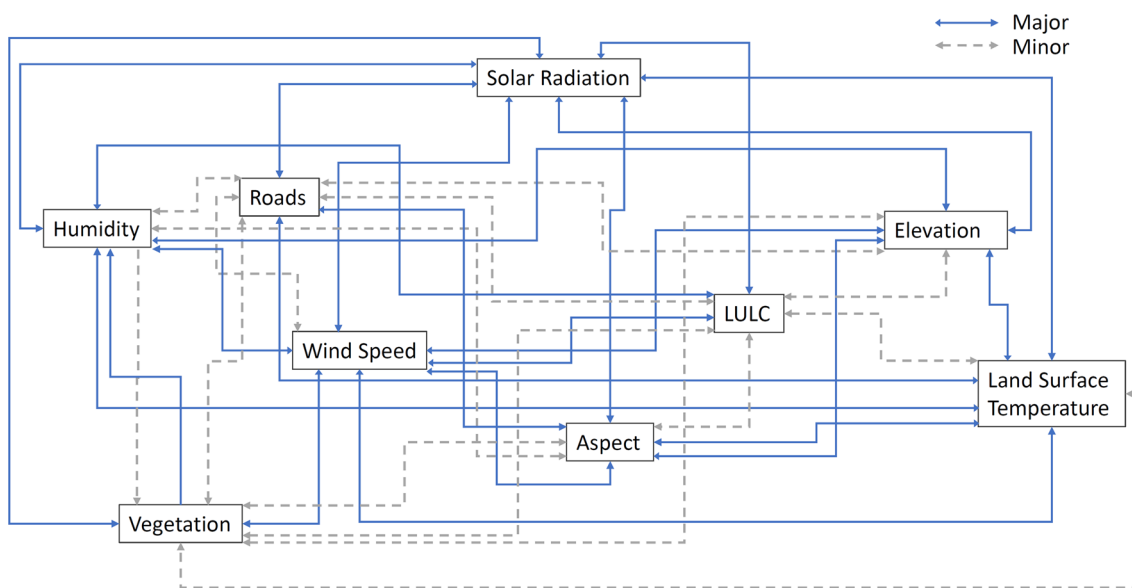
Fig. 2 Relation between the MIF of optimal solar PV farms

an energy catastrophe, this also assists to lessen carbon footprint and protect the environment [33].

Data acquisition and preparation

Several influencing factors, such as solar radiation, wind speed, land surface temperature, relative humidity, vegetation, elevation, land use, aspect, etc., control the ideal site location for solar PV power plants. The elements that affect the selection of the best location for solar photovoltaic farms were taken into account by taking into account the effects of the parameters as well as the field observed and geospatial datasets availability. In the present study, nine geo-environmental, and geo-physical factors were selected to evaluate the optimal site for solar PV farms, and for each influencing factor, the thematic layers were prepared. The land use layer was prepared using support vector machine supervised

classification approach. The primary reason for using supervised classification rather than the CORINE dataset was to use up-to-date datasets [73]. The vegetation density was prepared using Normalized Difference Vegetation Index (NDVI) from the Landsat-8/OLI sensor datasets and sum to prepare the vegetation thematic layer. The ArcGIS spatial analyst tool was used to develop aspect and elevation layers using the 30 m Shuttle Radar Topography Mission (SRTM) DEM data. The gathered toposheets from Survey of India (SOI) were employed to digitize the distance from the road network in the study area and checked utilizing Landsat-8/OLI imagery. The LST was prepared using the thermal datasets (band-10) of Landsat-8/OLI acquired from the U.S. Geological Survey. The energy data of eleven solar PV power plant sites were collected from the solar energy facility owner and supplier. In addition to above geospatial data, solar

Table 2 influence factors with interrelated effects and weights

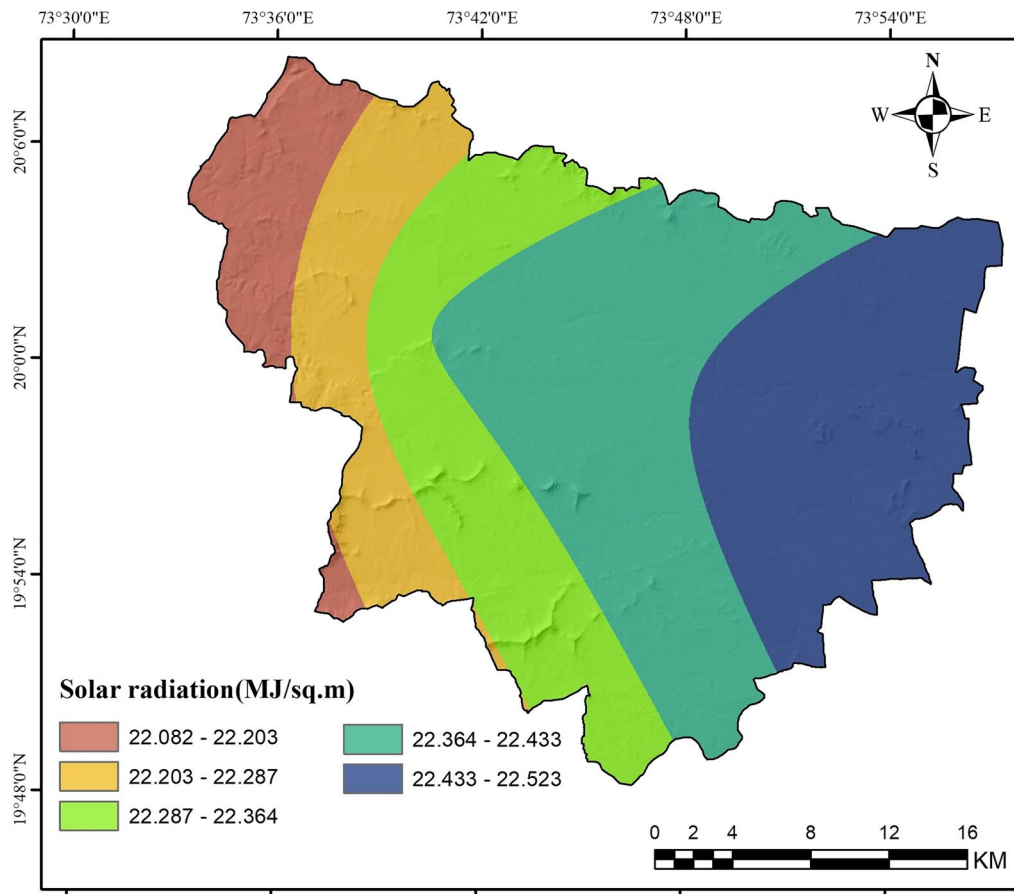| Factors	Major effect (E_a)	Minor effect (E_b)	Relative effect (E_a) + (E_b)	Relative weights
Solar radiation	8	0	8	13.56
Wind speed	7	0.5	7.5	12.71
LST	6	1	7	11.86
Relative humidity	5	1.5	6.5	11.02
Vegetation	3	3	6	10.17
Euclidean distance from road	3	2.5	5.5	9.32
Elevation	5	1.5	6.5	11.02
LULC	3	2.5	5.5	9.32
Aspect	5	1.5	6.5	11.02

Fig. 3 Distribution of solar radiation in study area

radiation, wind speed, and relative humidity data were extracted from the China meteorological assimilation driving datasets and merged to prepare the thematic layers.

Demarcation of optimal sites for solar PV farms

The integration of GIS-MCDM in site selection studies for solar PV farms has been accomplished in a number of research in the literature. The weight or importance of the factor/criteria is typically determined from the literature in MCDM methods. The MCDM methods that are often utilized in the literature are the analytical hierarchy process (AHP), fuzzy logic index models, ranking based, frequency ratio, best–worst, certainty factor, weights-of-evidence, and multi-influencing factors. The AHP introduced by Saaty [72] is a superb and well-known technique that is frequently employed to produce an adequacy map. The AHP already has been regarded as among the most significant methods for determining weights. The AHP involves the computation of the eigenvectors and eigenvalues of a square

preference matrix of order "K" that includes the complete preference information of all potential constellations of pairings of the k criteria. For members of interest groups and decision-makers, it could be challenging to explain how the principal eigenvector is used to derive criteria weights [55]. The MIF technique is particularly useful for estimating the site of solar PV power plants since it considers the interrelationship among the influencing factors and offers an economical, quick, and accurate evaluation. The MIF technique is well-fitted for incorporating multiple factors that influence solar energy potential, such as land availability, slope, distance to infrastructure, and environmental constraints. It allows for a comprehensive assessment of site suitability [48]. The MIF technique is flexible in its application, and can be adapted to different geographical contexts and data availability. It can also be easily updated as new data becomes available. The MIF technique is a transparent and reproducible method that means the decision-making process is clearly documented and can be replicated by others. Nevertheless, its application in GIS-based integrated site selection applications for polar

PV power plants is quite restricted. However, a decision-making process based on an interrelationship between influencing factors can be made mathematically more simpler using the MIF technique. The spatial correlations between both the independent and dependent variables are determined by the MIF techniques. It is developed based on the score assigned for the important and minor relevant factors that influencing the suitable solar PV power plant sites. The MIF approach basically follows the procedures which is illustrated in Fig. 2. First, each factor is allocated a rank based on its relative importance to a suitable sites for solar PV farm location. In present study, the major and minor interrelationship between the influencing factors found out using extensive literature survey [11, 17, 23, 24, 29, 58, 71, 75, 85, 91]. The more significant the factor, the higher its weight. The major factors were given a weight of 1, while the minor factors were given a weight of 0.5. The sum of all weights from each element determines the relative score (W_{M_i}) of a factor impacting solar PV power plant potential [64].

The significance of each factor (W_i) was then determined using Eq. 1 based on the relative of the scores.

$$W_i = \frac{W_{M_i}}{\sum_{i=1}^{9} W_{M_i}} \times 100, \, W_{M_i} \\ = minor \, effect + major \, effect$$

(1)

Figure 2 shows the relation among the multi-influence factors of suitable solar PV farms site. The results obtained with MIF are presented in Table 1.

Development of thematic factor layers

It is essential to make thematic numerical maps of the factors before performing PV farm site selection with GIS-MCDM. Nine thematic layers that considers the relative effects of the influencing factors were constructed to assess the best locations for solar PV farm in the study area. Solar radiation, wind speed, land surface temperature, relative humidity, vegetation, elevation, aspect, and land use were chosen as affecting factors by considering
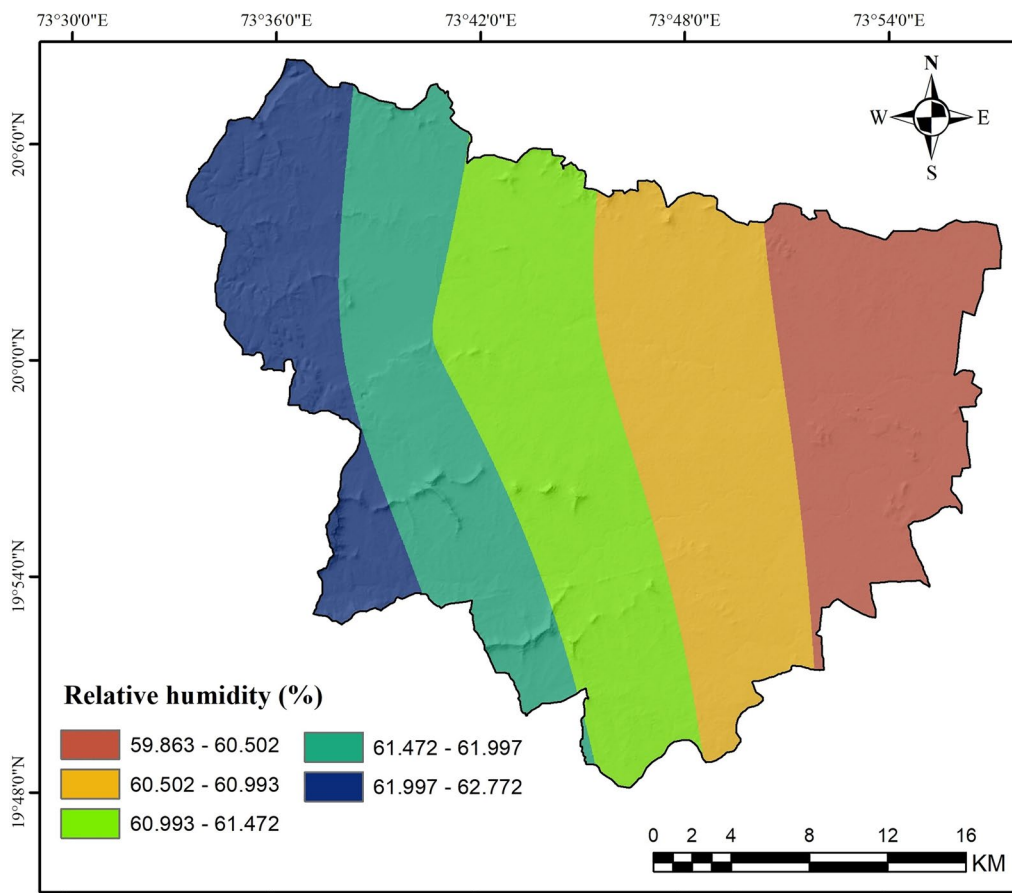

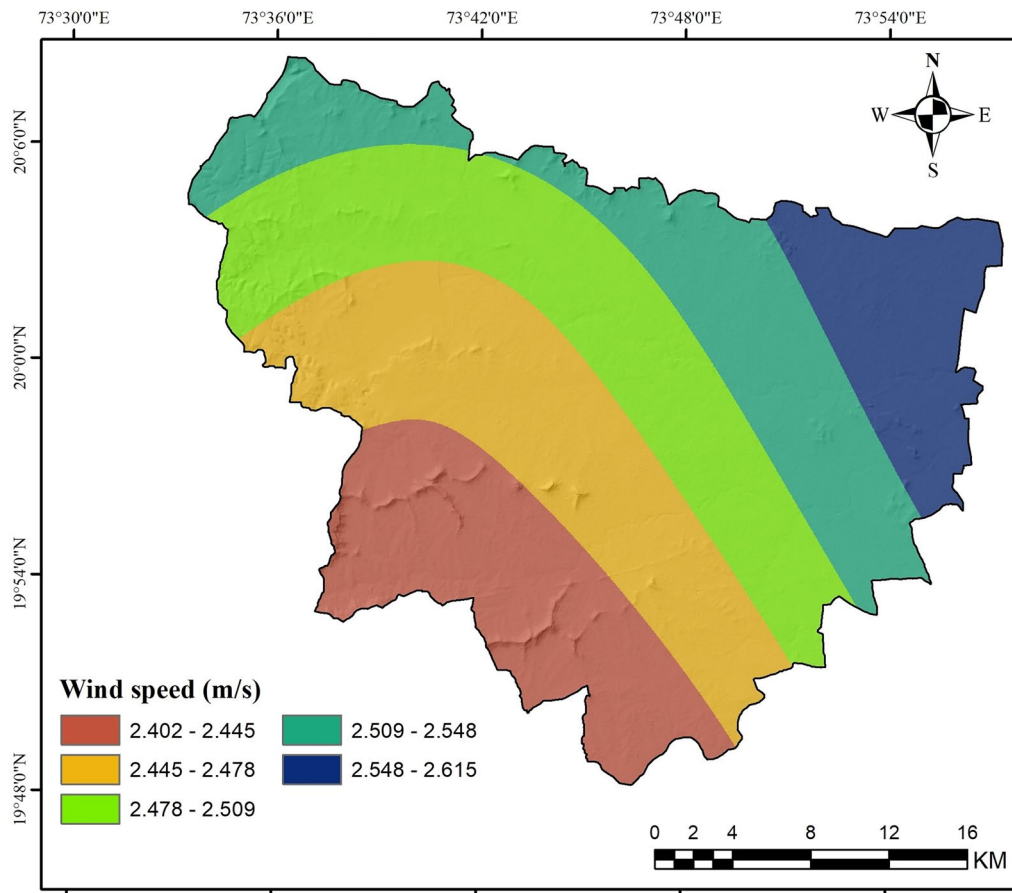**Fig. 4** Distribution of relative humidity (RH) in percentage

Fig. 5 Wind speed variation in study area

the effects of the components and the availability of field observation with spatial variations. The most prevalent in the literature and freely available for the study area were selected while choosing the relevant factors (Table 2).

Solar radiation: The efficiency of higher solar radiation regions is better suited for solar PV power plants. The efficiency is impacted by high solar radiation, and it is crucial to use the data provided for the area because solar radiation, such as the duration of sunshine, differs by state. The amount of solar radiation that is absorbed by the environment is called solar irradiance, and it is measured in units of area by a particular surface (MJ/m^2) [24, 30]. The reclassified Solar radiation map is presented in Fig. 3.

Land surface temperature (LST): An important indicator that reflects the impact of solar PV farm on the local environment and the impact of temperature on the farm is land surface temperature. During the day, each solar panel in the power plants converts energy into electricity, however, the electrical converter and convection equipment operate as heaters for the panels. A rise in land temperature from the outside will raise the optimum

working temperature of the panels, resulting in a loss of performance. Also, the solar panels can warm up from behind thanks to the surface's quick heat radiation [28, 88]. Figure 1 shows the LST map that has been reclassified. The steps listed below are mainly used to prepare the LST map.

1) B_{10} from Landsat-8 OLI was used to calculate top of atmospheric spectral radiance.

$$L\lambda = M_L \times Q_{CAL} + A_L \qquad (2)$$

where, $L\lambda$ is top of atmospheric spectral radiance, M_L multiband radiance, Q_{CAL} is the band 10 image, and A_L is the band-specific additive rescaling factor.

2) To estimate the brightness temperature, radiance is transformed to at-sensor temperature through the thermal constants given in Landsat-8 metadata. where, BT refers to brightness temperature, the band-specific thermal conversion constants from metadata are denoted by the K_1 and K_2. To obtain
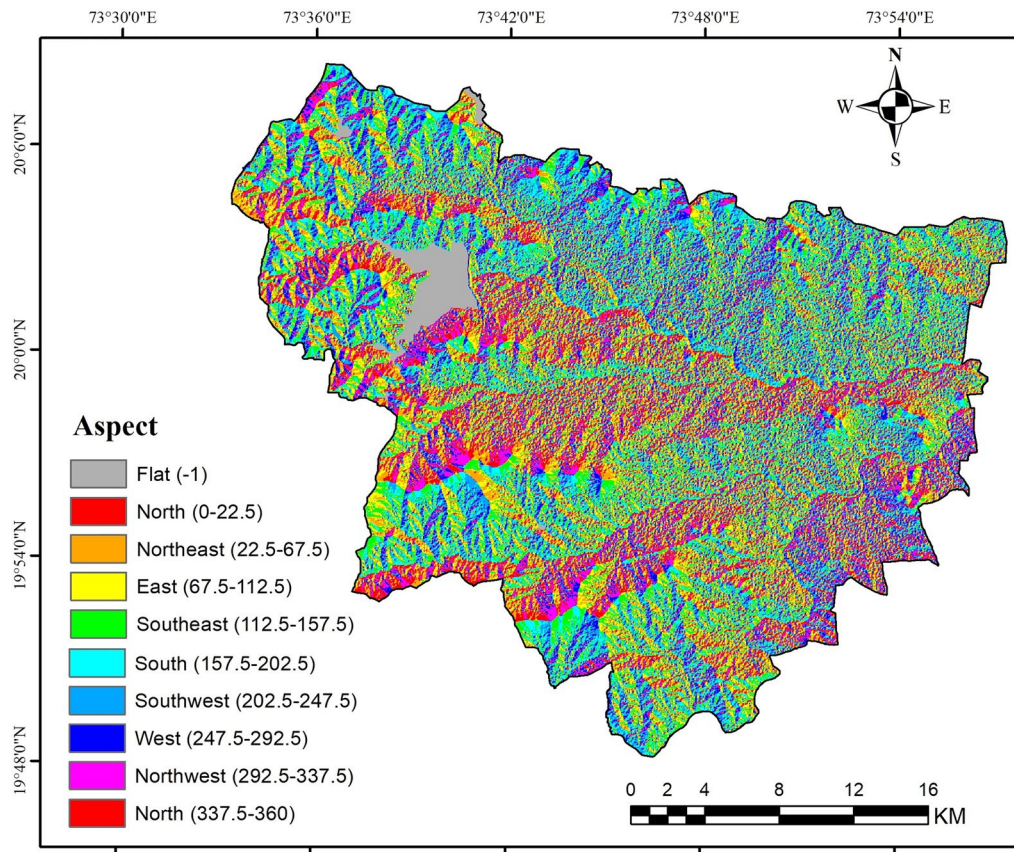
Fig. 6 Aspect shows the slope direction in study area

the data in °C, the radiant temperature is adjusted by adding absolute zero.

$$BT = \frac{K_2}{ln\left(\frac{K_1}{L\lambda} + 1\right)} - 273.15 \qquad (3)$$

3) Vegetation Proportion Calculation.where, where the $NDVI_s$ and $NDVI_\upsilon$ values are the soil and vegetation pixel thresholds.

$$p\upsilon = \left(\frac{NDVI - NDVI_s}{NDVI_\upsilon - NDVI_s}\right)^2 \qquad (4)$$

4) Using an NDVI-based relationship to predict surface emissivity.where, ε is land surface emissivity based on NDVI.

$$\varepsilon = 0.004 \times p\upsilon + 0.986 \qquad (5)$$

5) Computation of land surface temperature.where LST is the land surface temperature in °C, λ is the

wavelength of radiance emitted, is the computed emissivity based on the proportion of vegetation ($p\upsilon$) [48].

$$LST = \frac{BT}{\left(1 + \frac{\lambda \times BT}{14380}\right)ln\varepsilon} \qquad (6)$$

Relative humidity: The performance of the project's yearly energy yield and the solar PV power plants' long-term deterioration rate are both somewhat impacted by the ambient air humidity. The term "air humidity" refers to the water vapor conveyed by the air. Relative humidity is a measurement of humidity factor, including the quantity of water vapor in the atmosphere. The amount of moisture that can be carried increases as temperature rises. High relative humidity areas are not suitable for solar energy generation. It increases the likelihood of rain because the water's attempt to mix with the surrounding air will lead the vapor to condense and turn into liquid [26, 88]. The reclassified relative humidity map is presented in Fig. 4.
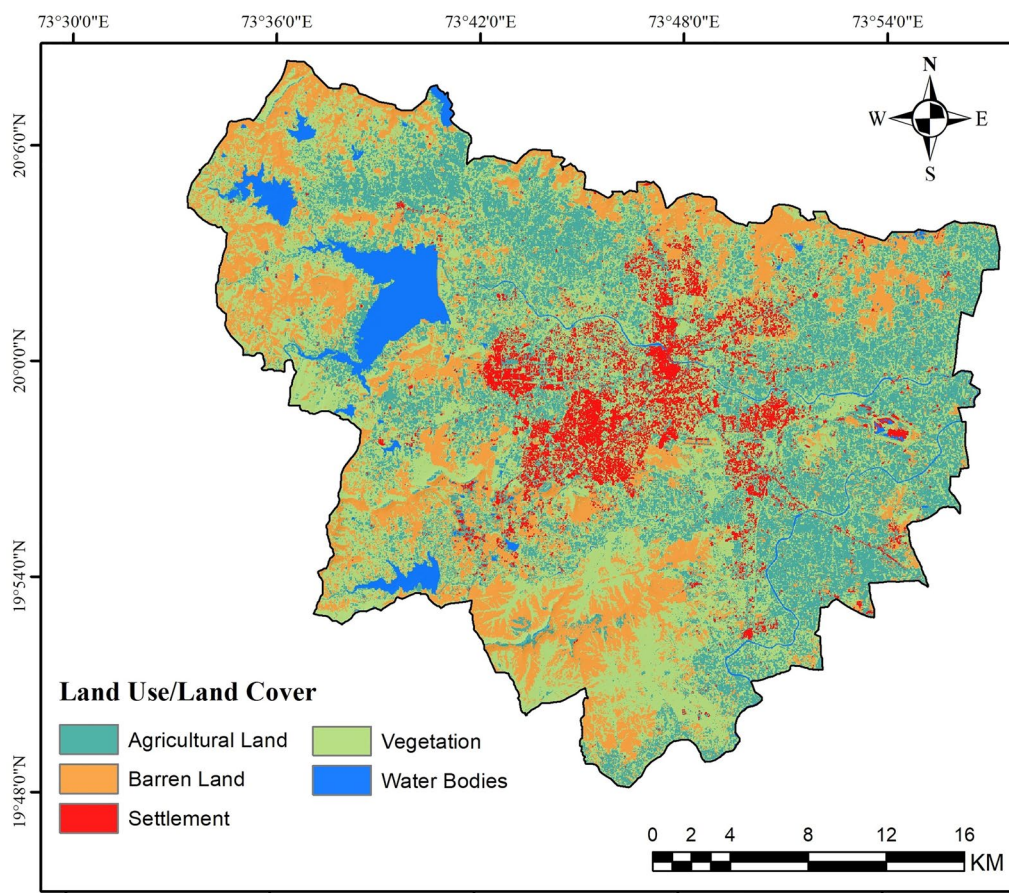
Fig. 7 Land use/land cover scenario in the study area

Wind speed: Wind direction and speed are two of the most important factors for reducing solar PV farms' temperatures. To provide safer solar PV farms designing and operating conditions, wind speed is a significant factor. It does not have a strong wind cooling function since the wind direction in the study area is generally the wind that conveys hot air [21, 88]. The reclassified wind speed map is presented in Fig. 5.

Aspect: Land aspect indicates the slope direction. In other words, it impacts a location's angle with respect to the sun, which in turn impacts how long it is sunny. The best solar PV power plants are chosen to have the south direction in the aspect maps made using DEM because, depending on the season, the south-facing sites in northern hemisphere countries receive lots of sunlight. The aspect map generated from the DEM depicts aspects in 10 distinct directions [18, 25]. The reclassified aspect mapping is presented in Fig. 6.

Land use: The solar PV farms construction requires the determination of suitable and unsuitable land use. Solar PV farms are not appropriate for all types of land. In some countries, for example, it is forbidden to cut

down trees such as olives, tea, and hazelnuts, and any construction in these regions is prohibited. Furthermore, soil types are a consideration that has a direct impact on the cost. While hard floors raise the cost of power plants, slippery floors inflict more damage to power facilities during natural catastrophes such as earthquakes and landslides. Land use maps were classified into five different land-use classes in the study using the support vector machine classification approach. The main reason for using supervised classification because of its worldwide acceptability. The reclassified land use land cover map is presented in Fig. 7.

Euclidean distance from road: Roads and railroads, as well as other forms of transportation, are vital factors for the development of every region. It is expected that the road network should be established to lower costs since the installation of solar PV power plants requires a significant quantity of building, supplies, and operation to the region [23, 88]. The reclassified road network map is presented in Fig. 8.

Elevation: Precipitation and temperature have a relationship with elevation. Solar radiation increases as
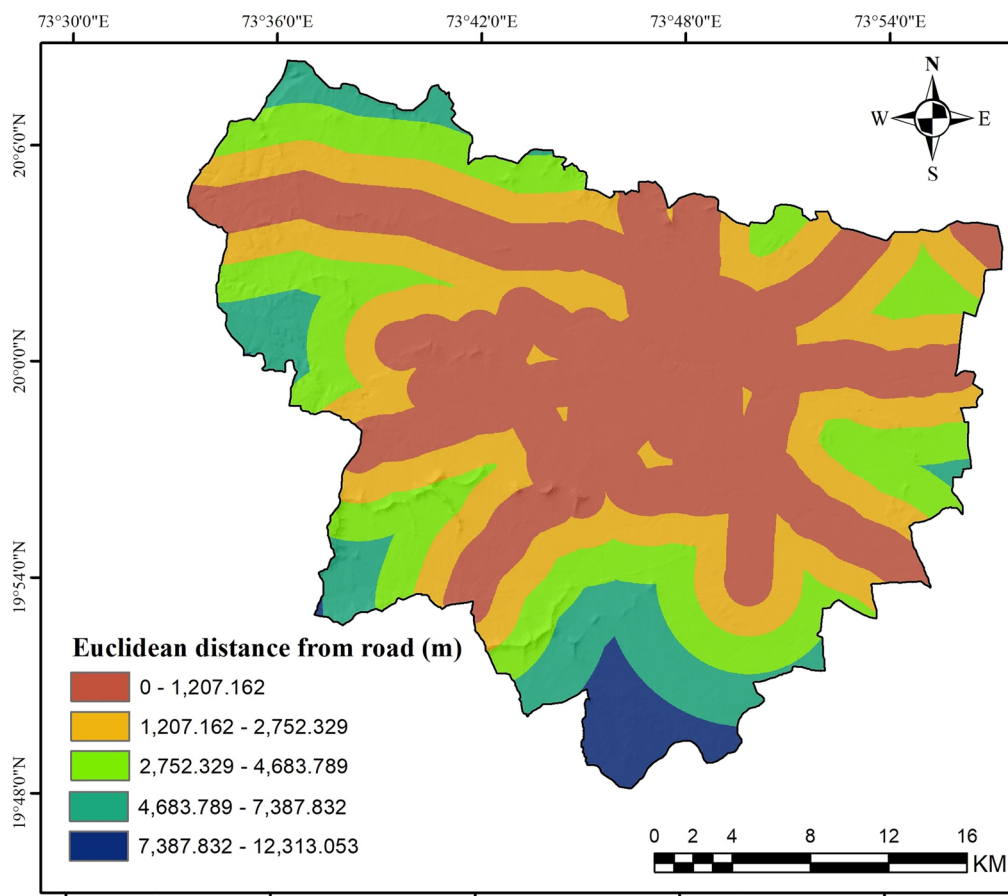
Fig. 8 Euclidean distance from the major roads

altitude increases due to a decrease in the thickness of the atmospheric layer, and the efficiency performance of solar panels increases due to a decrease in temperature at high altitudes. However, installing photovoltaic farms at high elevation is not suggested because the rise in altitude impedes transportation and raises project costs [26, 83]. The reclassified elevation map is presented in Fig. 9.

Vegetation health: The significance of land use has already been stated. Building a solar PV farm in areas with poor vegetation health, on the other hand, is a poor decision. As a result, detecting and investing in areas with low plant health is critical for sustainable agriculture and the protection of natural life. As a result, it was calculated using Eq. 7 and classified into five classes based on NDVI Landsat 8 OLI data describing vegetation health [18, 38]. The reclassified vegetation map is presented in Fig. 10.

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)} \tag{7}$$

Sensitivity analysis

Sensitivity analysis is a valuable tool in identifying the significance of important factors. Sensitivity analysis is the process of examining how changes in the input variables affect the analysis's results. Sensitivity analysis can help increase the model's accuracy in situations where the ambiguity of the inputs prevents accurate decision-making. In this research, the sensitivity analysis method was utilized to verify and assess the effectiveness of the MIF results and rank the dominancy of the factor. Map removal sensitivity is a measure of the sensitivity of eliminating one or many variables from the suitability analysis in the resulting suitability mapping. By eliminating any factors and generating a new suitability map each time, map removal is a crucial sensitivity analysis for assessing the possible suitability of a solar PV power plant site. Thus, the relative importance of the factors is determined [42]. The mathematical notation of map removal is given in Eq. 8.
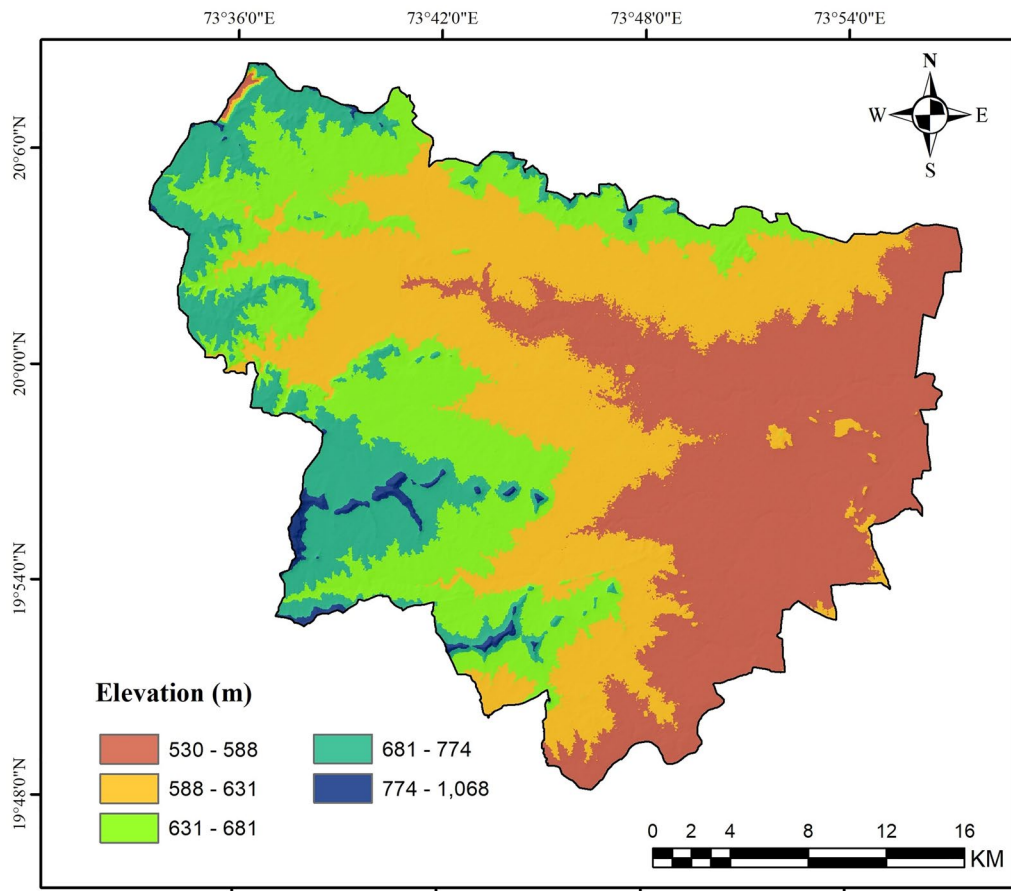
Fig. 9 Elevation map of the study area

$$SM = \frac{\left|\left(\frac{PSA}{N}\right) - \left(\frac{PSA\prime}{N\prime}\right)\right|}{PSA} \times 100 \qquad (8)$$

where the total number of factor layers utilized to create Photovoltaic Sensitivity Analysis (PSA) is N, while the number of factor layers considered to create PSA is N′, SM refers factor related sensitivity index, the analysis for suitability of the solar PV farms by all factor layers is represented by PSA. Finally, Solar PV power plant site selection through MIF technique has been shown in a flowchart (Fig. 11).

Results

Characteristics of spatial variations of the influence factor

The evaluation of a suitable site for optimal site for solar PV farms is a critical component of renewable energy generation. Following is the geo-environmental, and geo-physical factors that influence optimal site for solar photovoltaic power plant. The integration of these influencing factors determines the degree of suitability and useful for identifying and delineating the unsuitable zone.

The different thematic layers are designed to achieve the objective. GIS was used in this study to create nine different factor maps, the weights of which were calculated by MIF, to aid select highest and lowest suitable site. Five classes—all but aspect—have been used to classify the created maps. The class dynamic ranges, geographic areas they cover, and the percentage distributions of the factors are shown in Table 3. Since Nashik, India, is primarily flat, there aren't many areas with significant elevation. There are few places where transportation is poor because the road network exists, even if it is only one lane. Between 59 and 63% is the range for relative humidity, which is still a high level. In contrast, wind speed is not a significant impact in urban areas. Looking at the city as a whole, many regions are covered with vegetation, and many of these areas have high NDVI values, indicating that they are in generally good health. The Kriging method, which is deterministic spatial interpolation, was used to create maps of solar radiation, relative humidity, and wind speed. Multiple buffer analysis was performed while preparing the road network map.
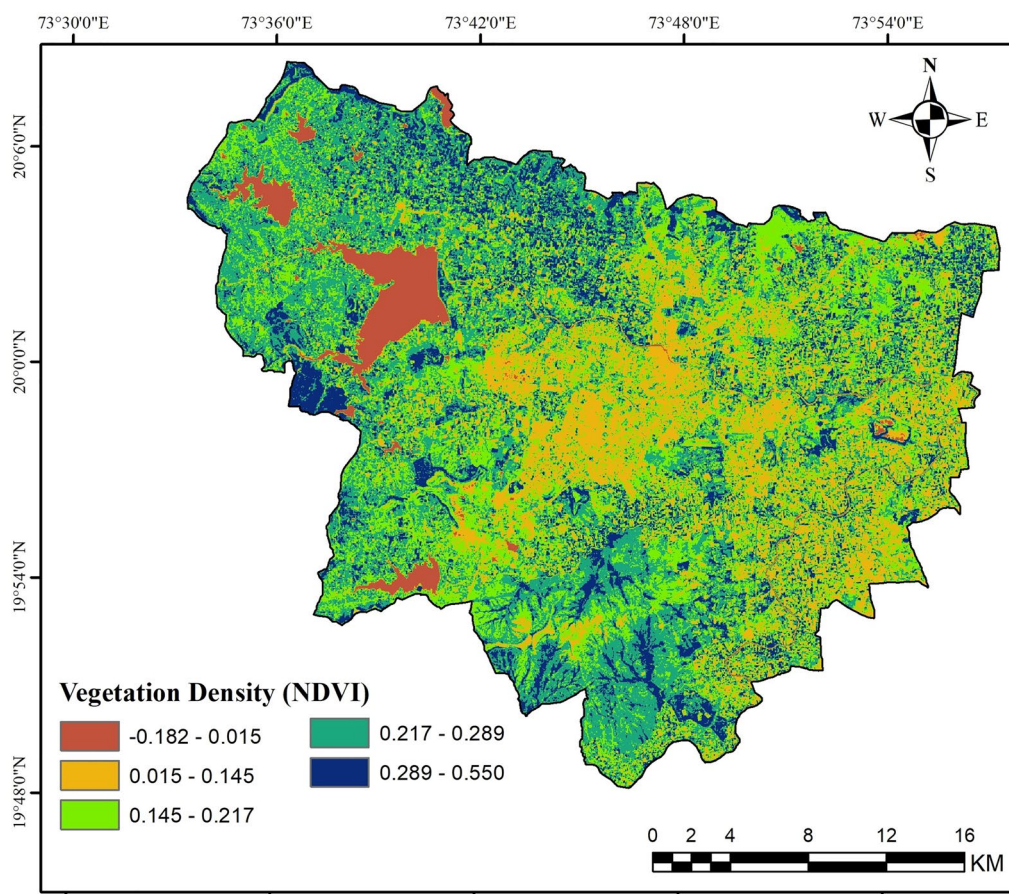
Fig. 10 Vegetation density map showing the vegetation cover in the study area

Delineation of optimal site for solar PV farms in study area

The most crucial factor that directly influences the outcomes of site selection procedures using GIS-MCDM investigations is weight assignment. The primary argument for MIF's use in this study is the lack of widespread MIF utilization in site selection studies for solar PV farms. The literature and the expertise of the paper's authors were utilized to determine the degree of importance of the factors. Weight assignment results performed with MIF are presented in Table 4. The weight of solar radiation is largest, whereas the weight of land usage and land cover is lowest. There is equal weighting given to relative humidity, aspect, and elevation. The suitability map, whose weighted sum is the final outcome, is affected differently by them because of the differences in their total weights.

The weights of the factors determined by the MIF approach were used to construct a weighted layer map as part of the process of creating the reclassification suitability map (Fig. 12). For the relative humidity map, for instance, the features of the thematic layer range shown in Tables 3 and 4 were reclassified after digital

maps using the Kriging method based on measurement points were constructed. The method of reclassification differs depending on the kind of data type that was utilized to create each factor map. In other words, making an elevation map does not require interpolation. The weighted sum of the factors using the weights generated with MIF was then used to create suitability maps shown in Fig. 11. The suitability maps in this study were quartile-divided into five grades. Final suitability maps were reclassified as very good, good, moderate, low, and very low. Spatial distributions of these areas are presented in Table 5. The study region is appropriate for the solar PV farms installation, according to the general abundance of good and very good areas. In comparison to other suitability fields, there are comparatively few very low fields. This is another indication of the Nashik's suitability. The unsuitable regions of Nashik are in the south and west. Despite having high elevations, these areas are humid, have transportation issues, and have agricultural areas. The northeast, in general, is the strategic site due to the region's high levels of solar radiation, strong wind speeds, low levels of humidity,
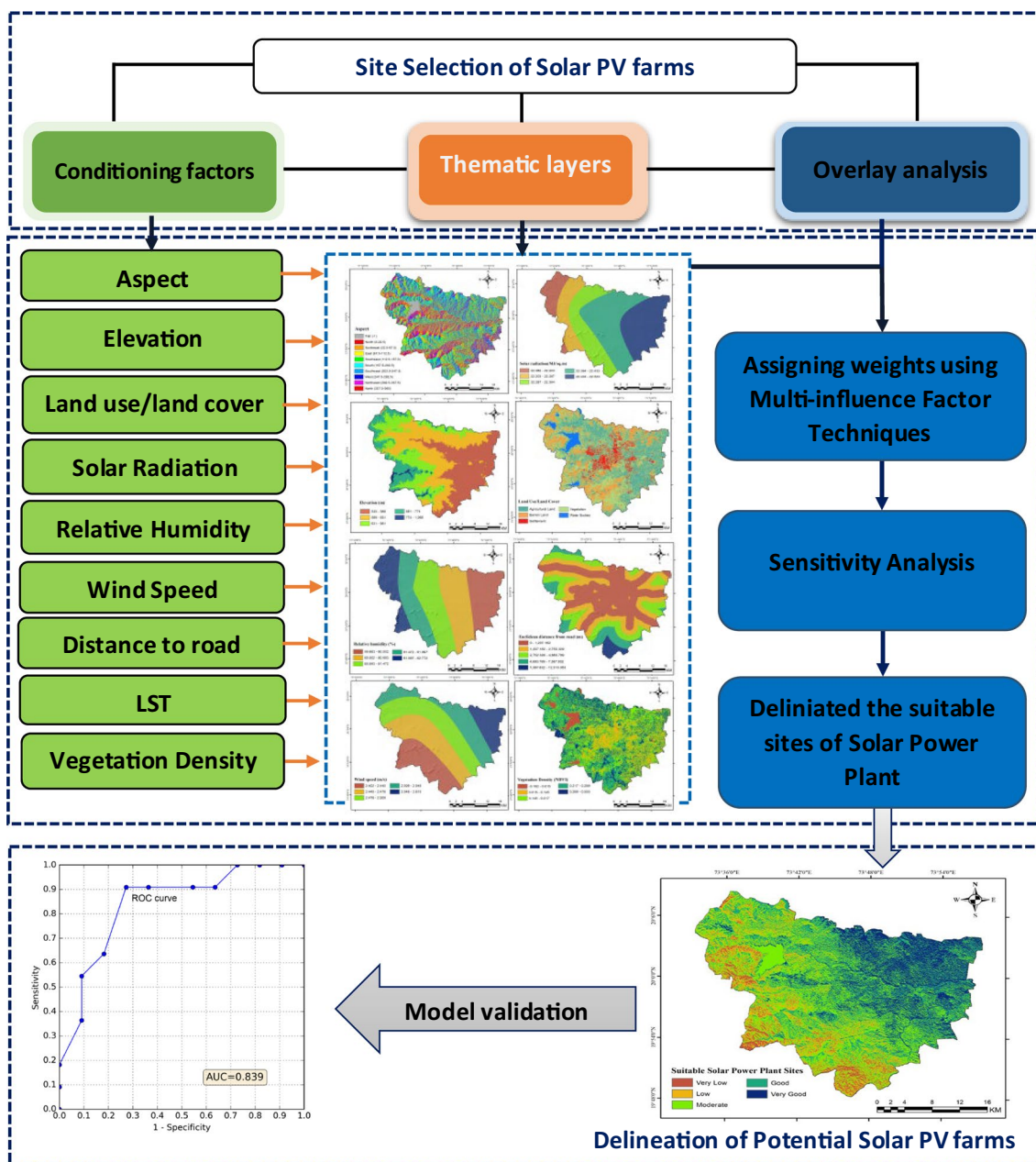
Fig. 11 Flowchart of solar PV farms site selection using the MIF

efficient transportation, and abundance of low-plant unhealthy areas.

The optimal sites of solar PV power plant delineated using MIF technique revealed that 'very low' suitability of site for solar PV power plant covering 4.866% (43.370 sq.km.) of the study area, 'low' suitability of site for solar PV power plant 13.190% (117.553 sq. km.), 'moderate' suitability of site for solar PV farm 31.640% (281.988 sq.km.), 'good' suitability of site for solar PV farm 32.347% (288.292 sq.km.), and 'very

good' suitability of site for solar PV farm encompassing 17.957% (160.036 sq.km.) of the study area.

Sensitivity analysis

Because the thematic layer removal evaluates the sensitivity of processes between factor layers and demonstrates the value of each layer for delineating the potential site for solar PV farms in Nashik, map removal technique is chosen and used in this study.

Table 3 Thematic layers with their classes and areas occupied

Sr. No	Thematic layers	Features	Area (sq.km)	Area (%)
1	Solar radiation (MJ/m^2)	22.08–22.20	76.96	8.64
		22.20–22.28	113.91	12.79
		22.28–22.36	181.91	20.43
		22.36–22.43	286.33	32.16
		22.43–22.52	231.20	25.96
2	Land Surface Temperature (LST) ^{o}C	20.02–24.07	62.956	7.071
		24.07–26.12	215.220	24.173
		26.12–27.64	299.291	33.616
		27.64–29.30	219.502	24.654
		29.30–36.92	93.361	10.486
3	Relative humidity (%)	59.86–60.50	170.568	19.158
		60.50–60.99	207.742	23.333
		60.99–61.47	216.33	24.29
		61.47–61.99	169.19	19.00
		61.99–62.77	126.49	14.20
4	Wind speed (m/s)	2.40–2.44	165.95	18.63
		2.44–2.47	210.16	23.60
		2.47–2.50	228.54	25.67
		2.50–2.54	185.48	20.83
		2.54–2.61	100.18	11.25
5	Aspect	Flat (− 1–0)	21.69	0.024
		North (0–22.5)	58.85	0.066
		Northeast (22.5–67.5)	108.32	0.122
		East (67.5–112.5)	122.06	0.137
		Southeast (112.5–157.5)	129.47	0.145
		South (157.5–202.5)	121.55	0.137
		Southwest (202.5–247.5)	106.93	0.120
		West (247.5–292.5)	92.08	0.103
		Northwest (292.5–337.5)	90.87	0.102
		North (337.5–360)	38.46	0.043
6	Land use	Built-up	58.91	6.61
		Water Body	35.52	3.99
		Bare Land	189.27	21.25
		Agriculture	254.36	28.56
		Vegetation	352.27	39.56
7	Distance from road (m)	0–1207	367.22	41.24
		1207–2752	234.41	26.32
		2752–4683	174.60	19.61
		4683–7387	85.15	9.56
		7387–12,313	28.92	3.24
8	Elevation (m)	530–588	276.06	31.00
		588–631	294.41	33.06
		631–681	201.82	22.66
		681–774	108.02	12.13
		774–1068	9.99	1.12

Table 3 (continued)

Sr. No	Thematic layers	Features	Area (sq.km)	Area (%)
9	Vegetation Density (NDVI)	− 0.182–0.015	33.01	3.70
		0.015–0.145	164.08	18.43
		0.145–0.217	264.57	29.71
		0.217–0.289	306.89	34.47
		0.289–0.550	121.75	13.67

Sensitivity test results are presented in Table 6. According to the results of the sensitivity analysis, the most precise estimate is obtained when all nine factors are considered. It is true that solar radiation and relative humidity have a significant role in the decision to construct a solar PV farm. MIF gave the least weight to factors including land use, and distance to road, and sensitivity analysis confirmed that this was the case. Additionally, it has been found that choosing the best solar PV power plant site is not greatly influenced by wind speed, although having a relatively large weight compared to other criteria.

Validation of the predicted solar PV farms sites

The validation of the delineated solar energy potential zones is conducted using the actual energy data generated through the solar panels system. The efficiency of the solar farms is compared with the delineated potential zones of solar PV farms. The solar energy capacity of the plant in the considered sites ranged from 3 to 15 KW. The components of the solar plant in the study area encompass solar PV panels, an inverter, Alternating Current Distribution Box (ACDB) and Direct Current Distribution Box (DCDB), earthing electrode, structure, and a solar PV power meter. The solar PV panels consist of polycrystalline modules. Each solar PV module, with a power range of 270 to 310 Watts, is comprised of 72 cells in series, featuring an X-Pitch of 938 mm and a Y-Pitch of 1155 mm. The dimensions of the solar PV module measure $1955 \times 989 \times 40$ mm, with a weight of 28 kgs. The module's efficiency varies from 14.0 to 16.0. The maximum output power (PMP) spans from 270 to 310 Watt, open-circuit voltage (Voc) ranges from 43.2 to 44.0 Volts, short-circuit current (ISC) ranges from 8.21 to 9.11 Amperes, maximum power voltage (VMP) spans from 36.0 to 36.5 Volts, and maximum power current (IMP) varies from 7.52 to 8.50 Amperes. The solar cells within the module consist of 156×156 mm high-efficiency polycrystalline 3 bus bar cells. The junction box is equipped with 3 bypass diodes.

The frames feature 15 microns silver-anodized aluminum frames, while the front glass is constructed from 3.2 mm low-iron tempered glass. The energy data of 11 solar PV power plant show that 1 'Very high' (97–100% efficiency) solar PV power plant out of 1 energy site falls under 'very good' potential zone for solar PV farms and 3 'high' (93–96% efficiency) solar PV power plant out of 3 energy site falling under 'good' suitable site for solar farms. Moreover, 2 out of 2 'medium' (89–92% efficiency) solar PV power plant falling in 'moderate' suitable site for solar power plant, 3 out of 4 'poor' (85–88% efficiency) solar PV power plant falling under 'low' suitable site for solar power plant and 0 out of 1 'very poor' (80–84% efficiency) solar PV power plant falling under 'very low' suitable site for solar power plant. The number of solar PV power plant that agreed with actual energy data are 9, and the number of solar PV power plant that disagree with the actual energy data are 2. As a result, the MIF technique's accuracy for solar PV power plant delineation in the research area is 81.80%. To validate the delineated solar PV farms more comprehensively, the Receiver Operating Characteristic (ROC) analysis has been conducted [48, 49]. The Area Under Curve (AUC) of ROC for the predicted site mapping is shown in Fig. 12. The value of the AUC for the delineated site was 0.839 shows the acceptable performance of the MIF technique applied in study area (Fig. 13).

Discussions

The significance of this study can be described that the interrelationship among the multi-influence factors by integrating GIS and MIF as well as validation using actual solar energy data with ROC analysis. This comprehensive study is utilized to present alternative locations for solar PV farms in Nashik using the most updated geographic information for the design and development of solar PV power plants in India. The planning and design method used in this research study could be used to install solar PV power plants in a number of study regions. Recently, some of the studies related to solar

Table 4 Factors relative weights with normalized and total weights for each features

Sr. No	Thematic layers	Weight	Features	Number of pixels in domain	Ranks	Normalized weights	Total weights
1	Solar radiation (MJ/m^2)	13.56	22.08–22.20	85,512	1	13.560	0.741
			22.20–22.28	1,26,573	2	27.120	1.481
			22.28–22.36	2,02,123	3	40.680	2.222
			22.36–22.43	3,18,149	4	54.240	2.963
			22.43–22.52	2,56,897	5	67.800	3.704
2	Land surface temperature (LST) in °C	11.86	20.02–24.07	69,951	5	59.300	3.239
			24.07–26.12	2,39,133	4	47.440	2.592
			26.12–27.64	3,32,545	3	35.580	1.944
			27.64–29.30	2,43,891	2	23.720	1.296
			29.30–36.92	1,03,734	1	11.860	0.648
3	Relative humidity (%)	11.02	59.86–60.50	1,89,520	5	55.100	3.010
			60.50–60.99	2,30,824	4	44.080	2.408
			60.99–61.47	2,40,368	3	33.060	1.806
			61.47–61.99	1,87,998	2	22.040	1.204
			61.99–62.77	1,40,545	1	11.020	0.602
4	Wind speed(m/s)	12.71	2.40–2.44	1,84,391	1	12.710	0.694
			2.44–2.47	2,33,517	2	25.420	1.389
			2.47–2.50	2,53,939	3	38.130	2.083
			2.50–2.54	2,06,092	4	50.840	2.777
			2.54–2.61	1,11,316	5	63.550	3.472
5	Aspect	11.02	Flat (0)	24,107	6	66.120	3.612
			North (0–22.5)	1,08,128	1	11.020	0.602
			Northeast (22.5–67.5)	1,20,357	2	22.040	1.204
			East (67.5–112.5)	1,35,630	4	44.080	2.408
			Southeast (112.5–157.5)	1,43,863	7	77.140	4.214
			South (157.5–202.5)	1,35,062	9	99.180	5.418
			Southwest (202.5–247.5)	1,18,821	8	88.160	4.816
			West (247.5–292.5)	1,02,313	5	55.100	3.010
			Northwest (292.5–337.5)	1,00,974	3	33.060	1.806
6	Land use	9.32	Built-up	65,465	4	37.280	2.036
			Water body	39,470	3	27.960	1.527
			Bare land	2,10,308	5	46.600	2.546
			Agriculture	2,82,630	1	9.320	0.509
			Vegetation	3,91,421	2	18.640	1.018
7	Distance from road (m)	9.32	0–1207	4,08,029	5	46.600	2.546
			1207–2752	2,60,462	4	37.280	2.036
			2752–4683	1,94,007	3	27.960	1.527
			4,683–7387	94,618	2	18.640	1.018
			7387–12,313	32,139	1	9.320	0.509
8	Elevation (m)	11.02	530–588	3,06,740	1	11.020	0.602
			588–631	3,27,130	2	22.040	1.204
			631–681	2,24,254	3	33.060	1.806
			681–774	1,20,027	4	44.080	2.408
			774–1068	11,104	5	55.100	3.010

Rane *et al. Environmental Sciences Europe*   (2024) 36:5

Page 19 of 25

Table 4 (continued)

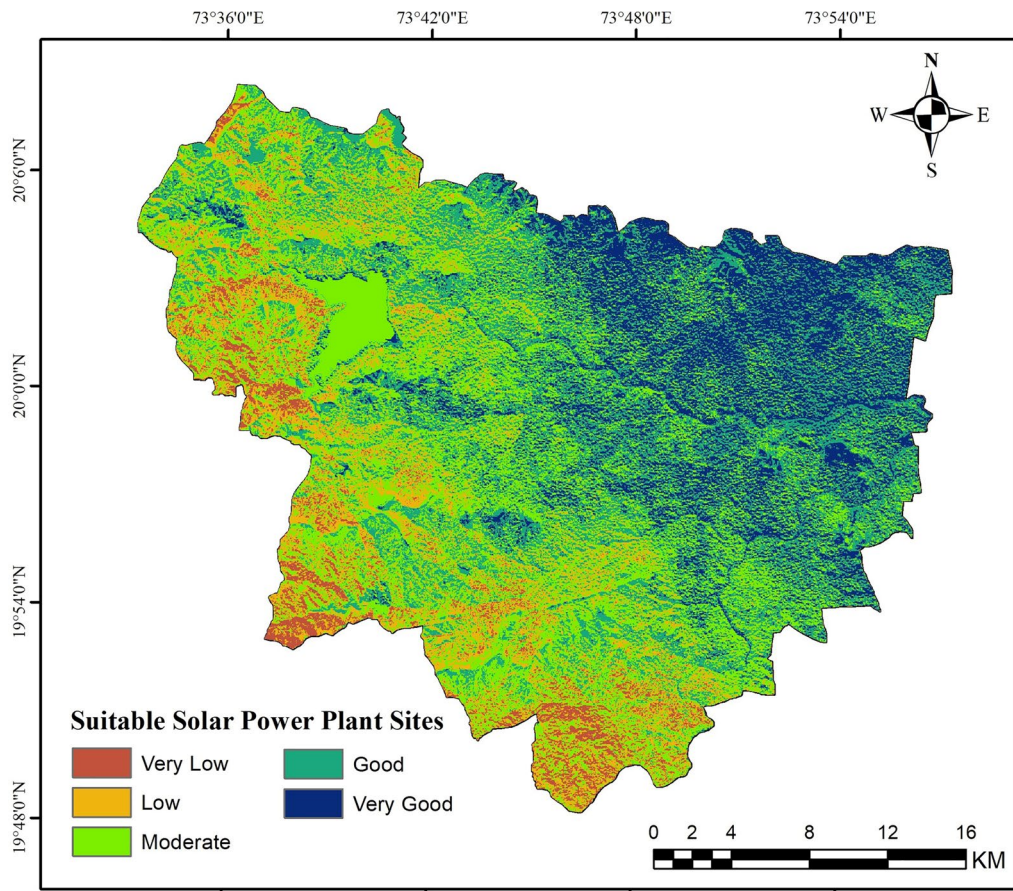| Sr. No	Thematic layers	Weight	Features	Number of pixels in domain	Ranks	Normalized weights	Total weights
9	Vegetation density (NDVI)	10.17	− 0.182–0.015	36,686	5	50.850	2.778
			0.015–0.145	1,82,316	4	40.680	2.222
			0.145–0.217	2,93,971	3	30.510	1.667
			0.217–0.289	3,40,993	2	20.340	1.111
			0.289–0.550	1,35,288	1	10.170	0.556

Fig. 12 Delineated optimal sites for in solar PV farms in study area

Table 5 Optimum site selection statistics through MIF model

Suitability of site	Area in km²	Area in %	Selection index
Very low	43.370	4.866	9.320–240.055
Low	117.553	13.190	240.055–272.635
Moderate	281.988	31.640	272.635–319.993
Good	288.292	32.347	319.993–367.352
Very good	160.036	17.957	367.352–492.380

energy farm development across the Globe [2, 16] as well in India [80, 82] have executed for renewable energy mission. Nowadays, solar energy development and suitable site assessment is very much required to enhance the capacity of the renewable resources especially for the highly population-based countries like India, Bangladesh, and so others. Doljak, & Stanojevi´c [14]

Table 6 Sensitivity analysis statistics with variation index

Thematic layers	Variation index				Rank
	Standard deviation	Mean	Max	Min	
Solar radiation	72.488	264.014	470.340	0.000	1
Land Surface Temperature	63.137	259.832	437.280	0.000	7
Relative humidity	69.780	256.010	442.400	0.000	2
Wind speed	62.539	240.031	393.200	0.000	8
Aspect	68.443	266.036	455.100	0.000	4
Land use	65.752	257.896	455.100	0.000	5
Euclidean distance from road	61.613	248.854	433.900	0.000	9
Elevation	68.741	263.934	448.310	0.000	3
Vegetation Density	63.964	257.981	428.830	0.000	6

implied a GIS-based natural process for the selection of solar PV power plant. Similarly, this study also tried to delineate the solar PV farms in Nashik using different geo-physical and environmental parameters. In western part of Nashik, different commercial, residential, and institutional activities impacted on the high solar energy resources consumption that needs to be reduced into lower energy consumption. Otherwise, this problem can be shorted out by utilising green building methods, new structures can lower their energy requirements [12, 43, 76]. Even, by installing solar water heating systems and switching to energy-saving appliances, individuals can actively participate in city energy management [76]. Building Integrated Photovoltaics (BIPV) systems enable commercial and institutional buildings to produce
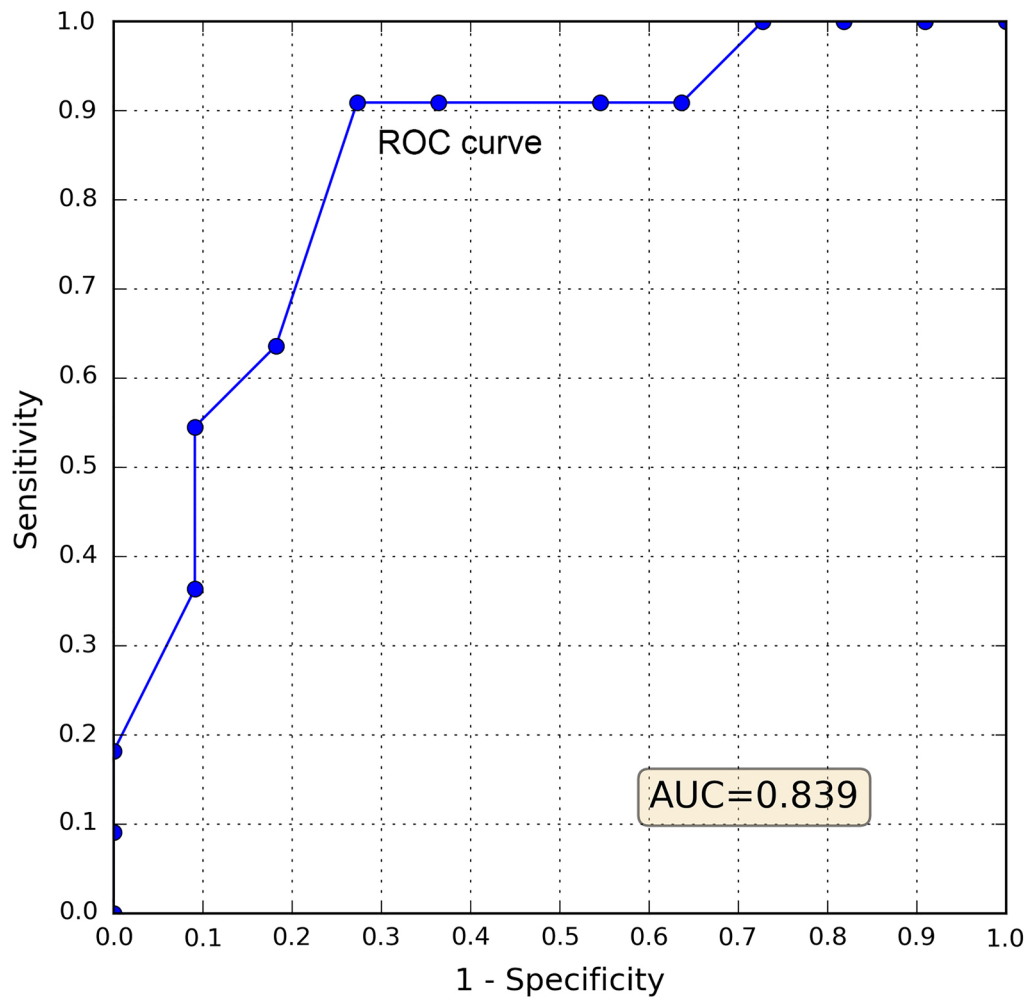

Fig. 13 ROC curve shows that the AUC value has successfully checked the error, and validated the MIF model

Table 7 Details study of sensitivity analysis statistics with variation index

Author(s) and published year	Study area	Methodology	Major findings
Rane et al. (Current study)	Nashik, India	GIS-based integrated method namely MIF technique is used	According to the result, solar radiation, relative humidity, and elevation are more sensitive as well as the dominant factors for optimal site selection of Solar PV power plants in the study area
[25]	Kahramanmaraş, Turkey	Multi-criteria decision making (MCDM) technique namely AHP method	Four MCDM methods yielded effective results according to the proposed criteria, and most of the existing solar PV power plants match the convenient regions on the suitability map provided by AHP method
[75]	India	GIS and MCDM techniques	Rajasthan state in India has the highest suitable land for the installation of solar plants (20,881 km^2) as well as wind farms (6323 km^2). The proposed model can be used for the development of policies related to renewable energy resources and the assessment of suitability
[83]	Pakistan	AHP-fuzzy VIKOR method	The outcome of the sensitivity analysis revealed that obtained results are reliable and robust for the installation of solar PV power projects in Pakistan
[29]	China	GIS-based analysis	The results show that there is a large area suitable for solar power stations in the northwestern regions with sufficient radiation, sparse surface vegetation and gentle surface gradient
[80]	Mumbai, India	GIS-based image analysis of sample satellite images	Large scale deployment of Rooftop Solar PV Systems can provide 12.8–20% of the average daily demand and 31–60% of the morning peak demand for different months, even with median conversion efficiency panels. This method can be used to obtain the PV potential for any region
[91]	Southern England	MCDM framework including AHP approach	This method can be used to assist appropriate site selection for onshore renewable energy projects across large geographical areas, helping to minimise their environmental impacts

their own electricity [77, 80]. Table 7 is used for better understanding of the GIS-based integrated results of MIF techniques.

Although, GIS-MCDM methods offer convenience and flexibility, it should not be ignored that there are some limitations that must be taken into consideration when carrying out the process [13, 19, 20]. The primary drawback of GIS-based site selection is the cost involved when high spatial and temporal resolution data are required [46]. GIS data collection and analysis may call for specialized tools and software. For this reason, when collecting data, only reliable data suppliers should be used. GIS data often tends to become outdated (i.e., land use data, LST, and vegetation density, etc.). This means that the data used for site selection become obsolete and need to be updated over time.

Conclusions and policy making approach

This research attempted to provide a practical methodology for identifying the solar PV farms' suitability index by integrating the interrelationship-based MIF technique with RS and GIS. Applying the MIF technique with nine influencing factors; solar radiation, wind speed, LST, relative humidity, vegetation, elevation, land use, Euclidean distance from road, and aspect, were assigned to identify optimal locations of solar power farms. Using the MIF process, weights were allocated to the thematic layers, and rankings were given to the criteria of each layer. Based on the site suitability index, the optimal location of the site where solar PV farms could be installed was delineated. The major findings of this study are given below:

- The optimal sites of solar PV power plant delineated using MIF technique revealed that 'Very low' suitable site for solar PV farms covering 4.86% and 'low' suitable site 13.19% in the southern section of the study area. Followed by 'moderate' suitable site 31.64%, 'good' suitable site 32.34%, and 'very good' suitability of site for solar PV farms encompassing

17.95% in the north and north-east section of the study area.

- Sensitivity analysis was employed in this study to assess how the dominant factor influence the solar PV farms site selection, according to this study, solar radiation, relative humidity, and elevation are more sensitive as well as the dominant factors for optimal site selection in the study area.
- The validation of the delineated solar energy potential zones is conducted using the actual energy data generated through the solar panels system. The prediction accuracy of solar PV power plant prediction using MIF technique in the study area found to be 81.80%. Moreover, the ROC analysis results showed that the MIF approach achieved AUC of 0.839 was acceptable in delineating an accurate mapping of Solar PV farms for the Nashik City.

However, the integrated GIS-based planning method adopted for the study area has the potential to offer inclusive and practical advances for different geographic areas. The proposed methodology presents several notable advantages. Firstly, the integration of GIS and the MIF technique provides a systematic and comprehensive approach to site selection for solar PV farms. The consideration of multiple influencing factors ensures a nuanced evaluation, capturing the complexity of the environmental and geographical context. Additionally, the validation of the delineated solar energy potential zones with actual energy data underscores the practical utility and effectiveness of the proposed approach.

In the policy perspectives, the major contribution of the proposed method lies in its innovative integration of GIS and the MIF technique for site selection of solar PV farms in Maharashtra, India. The study addresses a critical aspect of renewable energy generation by systematically evaluating and delineating optimal locations for solar PV farms in Nashik, Maharashtra, India. By considering a comprehensive set of influencing factors such as solar radiation, land surface temperature, relative humidity, wind speed, aspect, land use, distance from roads, elevation, and vegetation density, the proposed methodology goes beyond conventional approaches. The use of MIF for weight assignment adds a nuanced layer to the decision-making process, ensuring a more precise and context-specific evaluation. Furthermore, the study validates its findings with actual energy data generated from solar panels, demonstrating the practical utility and accuracy of the proposed approach. This comprehensive and validated methodology contributes significantly to the field of solar energy planning, offering a dynamic tool for decision-makers in both public and commercial sectors

for identifying and delineating optimal sites for solar PV farms in diverse geographic areas in Maharashtra. Additionally, the use of MIF for weight assignment enhances the accuracy and relevance of the decision-making process, contributing to a more reliable identification of optimal sites in a large-scale. Finally, it can be explicated that in the renewable energy contexts, promoting a broader application of the GIS-MIF integration for sustainable energy planning in the field of solar PV farms energy-based research to achieve the UN's SDG-7 about clean and affordable energy.

Abbreviations

GIS	Geographic information system
kWh	Kilowatt-hour
LiDAR	Light detection and ranging
LST	Land surface temperature
MCDM	Multi-criteria decision-making
MIF	Multi-influence factor
MNRE	Ministry of new and renewable energy
NDVI	Normalized difference vegetation index
PSA	Photovoltaic sensitivity analysis
PV	Photovoltaic
RE	Renewable energy
RH	Relative humidity
ROC	Receiver operating characteristic
RS	Remote sensing
SCM	Solar city mission
SDG	Sustainable development goal
SRTM	Shuttle radar topography mission
SOI	Survey of India
SR	Solar radiation
TWh	Terawatt-hour

Author contributions
NLR: Conceptualization, methodology, formal analysis, writing original draft. MAG: Formal analysis and data curation. SKM: Validation, writing, review & editing. JR: Formal analysis, writing, review & editing, data analysis. CBP: Formal analysis, writing original draft, Validation, writing, review & editing, data curation, Supervision. MG: Background study, writing, review & editing. JKB: writing, review & editing, KKY: Writing, review & editing. ADT: writing, review & editing, and Supervision. MAA: Writing, review & editing.

Availability of data and materials
Data will be made available on reasonable request.

Declarations

Declarations
The authors declare that the work described has not been published previously and not under consideration for publication elsewhere. The publication is approved by all authors and tacitly or explicitly by the responsible authorities where the work was carried out.

Rane *et al. Environmental Sciences Europe*   (2024) 36:5

Page 23 of 25

Author details
[1]Architecture, Vivekanand Education Society's College of Architecture (VESCOA), Mumbai 400074, India. [2]Department of Geomatics, Gümüşhane University, Gümüşhane, Turkey. [3]Department of Geography, Shaheed Bhagat Singh College, University of Delhi, New Delhi 110017, India. [4]Electronics and Telecommunication Engineering Department, Pillai HOC College of Engineering & Technology, Rasayani, India. [5]Indian Institute of Tropical Meteorology, Pune 411008, India. [6]Institute of Energy Infrastructure, Universiti Tenaga Nasional, 43000, Kajang, Malaysia. [7]New Era and Development in Civil Engineering Research Group, Scientific Research Center, Al-Ayen University, Thi-Qar, Nasiriyah 64001, Iraq. [8]Department of Electrical Engineering, College of Engineering, King Khalid University, Abha, Saudi Arabia. [9]Faculty of Science and Technology, Madhyanchal Professional University, Ratibad, Bhopal 462044, India. [10]School of Water Resources and Environmental Engineering, Haramaya Institute of Technology, Haramaya University, P.O. Box 138, Dire Dawa, Ethiopia. [11]Department of Chemistry, University of Ha'il, 81441 Ha'il, Saudi Arabia.

References

1. Al-Garni HZ, Awasthi A (2017). A Fuzzy AHP and GIS-Based Approach to Prioritize Utility-Scale Solar PV Sites in Saudi Arabia. In Proceedings of the IEEE International Conference on Systems, Man and Cybernetics (SMC), Banff, AB, Canada, 5–8.
2. Bódis K, Kougias I, Jäger-Waldau A, Taylor N, Szabó S (2019) A high-resolution geospatial assessment of the rooftop solar photovoltaic potential in the European Union. Renew Sustain Energy Rev 114:109309
3. Borse K, Agnihotri PG (2020) Trends of rainfall, temperature and rice yield of Nashik Region of Maharashtra. Int J Innov Technol Explor Eng 9(5):395–398
4. Boz MB, Kirby C, Brownson J (2015) An automated model for rooftop PV systems assessment in ArcGIS using LIDAR. AIMS Energy 3(3):401–420
5. Breyer C, Khalili S, Bogdanov D, Ram M, Oyewo AS, Aghahosseini A, Sovacool BK (2022) On the history and future of 100% renewable energy systems research. IEEE Access 10:78176–78218
6. Brito MC, Redweik P, Catita C, Freitas S, Santos M (2019) 3D solar potential in the urban environment: a case study in Lisbon. Energies 12(18):3457
7. Bull SR (2001) Renewable energy today and tomorrow. Proc IEEE 89(8):1216–1226
8. Castro-Santos L, Garcia GP, Simões T, Estanqueiro A (2019) Planning of the installation of offshore renewable energies: a GIS approach of the portuguese roadmap. Renew Energy 132:1251–1262
9. Chen L, Ding Y, Li H, Jin G (2017) Long-term reliability evaluation for small hydro-power generations based on flow runoff theory. J Eng 2017(13):1708–1712
10. Chen H, Wu H, Kan T, Zhang J, Li H (2023) Low-carbon economic dispatch of integrated energy system containing electric hydrogen production based on VMD-GRU short-term wind power prediction. Int J Electr Power Energy Syst 154:109420. https://doi.org/10.1016/j.ijepes.2023.109420
11. Colak HE, Memisoglu T, Gercek Y (2020) Optimal site selection for solar photovoltaic (PV) power plants using GIS and AHP: a case study of Malatya Province, Turkey. Renew Energy 149:565–576
12. Dawn S, Tiwari PK, Goswami AK, Mishra MK (2016) Recent developments of solar energy in India: perspectives, strategies and future goals. Renew Sustain Energy Rev 62:215–235
13. Deb S, Li D, Sinha S, Malik P, Raina G, Wang J. (2023). Local Energy System: A Comprehensive Review of Modelling, Tools and Pilot Projects. In 2023 International Conference on Power Electronics and Energy (ICPEE) (pp. 1–6). IEEE.
14. Doljak D, Stanojevi´c G (2017) Evaluation of natural conditions for site selection of ground-mounted photovoltaic power plants in Serbia. Energy 127:291–300
15. Ferreira A, Kunh SS, Fagnani KC, De Souza TA, Tonezer C, Dos Santos GR, Coimbra-Araújo CH (2018) Economic overview of the use and production of photovoltaic solar energy in Brazil. Renew Sustain Energy Rev 81:181–191
16. Gagnon P, Margolis R, Melius J, Phillips C, Elmore R (2018) Estimating rooftop solar technical potential across the US using a combination of GIS-based methods, lidar data, and statistical modeling. Environ Res Lett 13(2):024027
17. Gastli A, Charabi Y (2010) Solar electricity prospects in Oman using GIS-based solar radiation maps. Renew Sustain Energy Rev 14(2):790–797
18. Georgiou A, Skarlatos D (2016) Optimal site selection for sitting a solar park using multi-criteria decision analysis and geographical information systems. Geosci Instrum Methods Data Syst 5(2):321–332
19. Giri NC et al (2023) Access to solar energy for livelihood security in Odisha, India. In: Rani A, Kumar B, Shrivastava V, Bansal RC (eds) Signals, machines and automation. SIGMA 2022 lecture notes in electrical engineering. Springer, Singapore
20. Giri NC, Mohanty RC, Pradhan RC, Abdullah S, Ghosh U, Mukherjee A (2023) Agrivoltaic system for energy-food production: a symbiotic approach on strategy, modelling, and optimization. Sustain Comput Inform Syst 40:100915
21. Gökmen N, Hu W, Hou P, Chen Z, Sera D, Spataru S (2016) Investigation of wind speed cooling effect on PV panels in windy locations. Renew Energy 90:283–290
22. Greene R, Devillers R, Luther JE, Eddy BG (2011) GIS-based multiple-criteria decision analysis. Geogr Compass 5(6):412–432
23. Guaita-Pradas I, Marques-Perez I, Gallego A, Segura B (2019) Analyzing territory for the sustainable development of solar photovoltaic power using GIS databases. Environ Monit Assess 191(12):1–17
24. Günen MA (2021) Determination of the suitable sites for constructing solar photovoltaic (PV) power plants in Kayseri, Turkey using GIS-based ranking and AHP methods. Environ Sci Pollut Res 28(40):57232–57247
25. Günen MA (2021) A comprehensive framework based on GIS-AHP for the installation of solar PV farms in Kahramanmaraş, Turkey. Renew Energy 178:212–225
26. Hafeznia H, Yousefi H, Astaraei FR (2017) A novel framework for the potential assessment of utility-scale photovoltaic solar energy, application to eastern Iran. Energy Convers Manage 151:240–258
27. Halder B, Banik P, Almohamad H, Al Dughairi AA, Al-Mutiry M, Al Shahrani HF, Abdo HG (2022) Land suitability investigation for solar power plant using GIS, AHP and multi-criteria decision approach: a case of megacity Kolkata, West Bengal, India. Sustainability 14:11276
28. Hua Y, Chai J, Chen L, Liu P (2022) The influences of the desert photovoltaic power station on local climate and environment: a case study in Dunhuang photovoltaic industrial park, Dunhuang City, China in 2019. Atmosphere 13(8):1235
29. Huang T, Wang S, Yang Q, Li J (2018) A GIS-based assessment of large-scale PV potential in China. Energy Procedia 152:1079–1084
30. Jain A, Mehta R, Mittal SK (2011) Modeling impact of solar radiation on site selection for solar PV power plants in India. Int J Green Energy 8(4):486–498
31. Kadbhane SJ, Manekar VL (2015) Evaluation of water requirement of grape crop using CROPWAT model in Nashik district, India, HYDRO 2015 INTERNATIONAL IIT Roorkee, India, 17-19 December, 2015 20th International Conference on Hydraulics, Water Resources and River Engineering
32. Kalaiselvan M, Purushothaman BM, Kalaiselvan M, Purushothaman BM (2016) GIS based site suitability analysis for establishing a solar power park in Namakkal District, Tamil Nadu. Int J Innov Res Sci Technol 2:204–209
33. Kannan N, Vakeesan D (2016) Solar energy for future world:-a review. Renew Sustain Energy Rev 62:1092–1105
34. Kar SK, Sharma A, Roy B (2016) Solar energy market developments in India. Renew Sustain Energy Rev 62:121–133
35. Kataria A, Khan TI (2021) Necessity of paradigm shift from non-renewable sources to renewable sources for energy demand. In: Kateja Alpana, Jain Rashmi (eds) Urban growth and environmental issues in India. Springer, Singapore

36. Keswani A, Akselrod H, Anenberg SC (2022) Health and clinical impacts of air pollution and linkages with climate change. NEJM Evid 1(7):2200068

37. Kharake AC, Raut VS (2021) An assessment of water quality index of Godavari river water in Nashik city, Maharashtra. Appl Water Sci 11(6):1–11

38. KhareSaxena A, Saxena S, Sudhakar K (2020) Solar energy policy of India: an overview. CSEE J Power Energy Syst 4(4):319. https://doi.org/10.1777/CSEEJPES.2020.03080

39. Kocabaldir C, Yücel MA (2020) GIS-based multi-criteria decision analysis of site selection for photovoltaic power plants in Çanakkale Province. Int J Environ Geoinform 7(3):347–355

40. Kumari P, Patra A, Ramesh C, Singh A (2018) Real time flood forecasting in the Godavari basin at Nashik, Maharsatra. India Ann Arbor 1001:48106

41. Li Y, Liu C (2017) Estimating solar energy potentials on pitched roofs. Energy Build 139:101–107

42. Lodwick WA, Monson W, Svoboda L (1990) Attribute error and sensitivity analysis of map operations in geographical informations systems: suitability analysis. Int J Geogr Inform Syst 4(4):413–428

43. Madurai Elavarasan R, Selvamanohar L, Raju K, Rajan Vijayaraghavan R, Subburaj R, Nurunnabi M, Das N (2020) A holistic review of the present and future drivers of the renewable energy mix in Maharashtra, state of India. Sustainability 12(16):6596

44. Mahtta R, Joshi PK, Jindal AK (2014) Solar power potential mapping in India using remote sensing inputs and environmental parameters. Renew Energy 71:255–262

45. Maity B, Mallick SK, Rudra S (2020) Spatiotemporal dynamics of urban landscape in Asansol municipal corporation, West Bengal, India: a geospatial analysis. GeoJ. https://doi.org/10.1007/s10708-020-10315-z

46. Malik P, Awasthi M, Sinha, S. (2019). Analysis of sensitive parameters influencing a SPV/WT/Biomass/Battery based hybrid system. In 2019 8th International Conference on Power Systems (ICPS) (pp. 1–6). IEEE.

47. Mallick SK (2021) Prediction-adaptation-resilience (PAR) approach- a new pathway towards future resilience and sustainable development of urban landscape. Geogr Sustain 2(2):127–133

48. Mallick SK, Rudra S, Maity B (2022) Land suitability assessment for urban built-up development of a city in the Eastern Himalayan foothills: a study towards urban sustainability. Environ Dev Sustain. https://doi.org/10.1007/s10668-022-02857-8

49. Marzban C (2004) The ROC curve and the area under it as performance measures. Weather Forecast 19(6):1106–1114

50. Mavsar P, Sredenšek K, Štumberger B, Hadžiselimović M, Seme S (2019) Simplified method for analyzing the availability of rooftop photovoltaic potential. Energies 12(22):4233

51. Mierzwiak M, Calka B (2017) Multi-criteria analysis for solar farm location suitability. Rep Geod Geoinform 104:20–32

52. Ministry of New and Renewable Energy (MNRE) (2019). Physical Progress (Achievements), Ministry of New and Renewable Energy, Government of India. 2022 https://pib.gov.in/newsite/PrintRelease.aspx?relid=186228

53. Mishra T, Rabha A, Kumar U, Arunachalam K, Sridhar V (2020) Assessment of solar power potential in a hill state of India using remote sensing and geographic information system. Remote Sens Appl Soc Environ 19:100370

54. Misra SK, Sharma S (2015) Site suitability analysis for urban development: a review. Int J Recent Innov Trends Comput Commun 3(6):3647–3651

55. Munier N, Hontoria E (2021) Uses and limitations of the AHP method. Springer International Publishing, Cham

56. Naresh M, Ray S, Guha A, Nigam MK (2022) Mitigating environmental impact by optimizing base load generation in energy mix. J Instit Eng 103(1):143–151

57. Pandey A, Pandey P, Tumuluru JS (2022) Solar energy production in India and commonly used technologies—an overview. Energies 15(2):500

58. Pillot B, Al-Kurdi N, Gervet C, Linguet L (2020) An integrated GIS and robust optimization framework for solar PV plant planning scenarios at utility scale. Appl Energy 260:114257

59. Prakash S, Mahapatra S (2018) Flood susceptibility pattern mapping along Visakhapatnam coastal zone of India, using multi-infuencing-factor (MIF) technique in conjunction with remote sensing data. Int J Adv Innov Res 5(4):21–33

60. Li R, Xu D, Tian H, Zhu Y (2023) Multi-objective study and optimization of a solar-boosted geothermal flash cycle integrated into an innovative combined power and desalinated water production process: application of a case study. Energy 282:128706. https://doi.org/10.1016/j.energy.2023.128706

61. Li X, Aftab S, Abbas A, Hussain S, Aslam M, Kabir F, Ansari MZ (2023) Advances in mixed 2D and 3D perovskite heterostructure solar cells: a comprehensive review. Nano Energy 118:108979. https://doi.org/10.1016/j.nanoen.2023.108979

62. Lin L, Zhang J, Gao X, Shi J, Chen C, Huang N (2023) Power fingerprint identification based on the improved V-I trajectory with color encoding and transferred CBAM-ResNet. PLoS ONE 18(2):e0281482. https://doi.org/10.1371/journal.pone.0281482

63. Rane NL, Achari A, Choudhary SP, Mallick SK, Pande CB, Srivastava A, Moharir KN (2023) A decision framework for potential dam site selection using GIS, MIF and TOPSIS in Ulhas river basin, India. J Clean Prod 423:138890

64. Rane NL, Achari A, Saha A, Poddar I, Rane J, Pande CB, Roy R (2023) An integrated GIS, MIF, and TOPSIS approach for appraising electric vehicle charging station suitability zones in Mumbai India. Sustain Cities Soc. https://doi.org/10.1016/j.scs.2023.104717

65. Rane N, Jayaraj GK (2021) Stratigraphic modeling and hydraulic characterization of a typical basaltic aquifer system in the Kadva river basin, Nashik, India. Model Earth Syst Environ 7(1):293–306

66. Rane NL, Jayaraj GK (2022) Comparison of multi-influence factor, weight of evidence and frequency ratio techniques to evaluate groundwater potential zones of basaltic aquifer systems. Environ Dev Sustain 24(2):2315–2344

67. Rane NL, Jayaraj GK (2022) Enhancing SWAT model predictivity using multi-objective calibration: effects of integrating remotely sensed evapotranspiration and leaf area index. Int J Environ Sci Technol. https://doi.org/10.1007/s13762-022-04293-7

68. Reshma R, Ramesh M, Stephen J, Jaganathan R (2018) GIS based site suitability modelling for locating solar power park in thiruvannamalai district, Tamil Nadu i-Manag. J Electr Eng 11:43

69. Romero Rodríguez L, Duminil E, Sánchez Ramos J, Eicker U (2017) Assessment of the photovoltaic potential at urban level based on 3D city models: a case study and new methodological approach. Sol Energy 146:264–275

70. Roychowdhury K, Bhanja R (2021) A spatial investigation of the feasibility of solar resource energy potential in planning the solar cities of India. In: Kumar Pavan, Sajjad Haroon, Chaudhary Bhagwan Singh, Rawat JS, Rani Meenu (eds) Remote sensing and GIScience. Springer, Cham

71. Ruiz HS, Sunarso A, Ibrahim-Bathis K, Murti SA, Budiarto I (2020) GIS-AHP multi criteria decision analysis for the optimal location of solar energy plants at Indonesia. Energy Rep 6:3249–3263

72. Saaty TL (1980) The analytic hierarchy process (AHP). J Oper Res Soc 41(11):1073–1076

73. Salata S (2021) The utilization of supervised classification sampling for environmental monitoring in Turin (Italy). Sustainability 13(5):2494

74. Sampaio PGV, González MOA (2017) Photovoltaic solar energy: conceptual framework. Renew Sustain Energy Rev 74:590–601

75. Saraswat SK, Digalwar AK, Yadav SS, Kumar G (2021) MCDM and GIS based modelling technique for assessment of solar and wind farm locations in India. Renew Energy 169:865–884

76. Sharma NK, Tiwari PK, Sood YR (2012) Solar energy in India: strategies, policies, perspectives and future potential. Renew Sustain Energy Rev 16(1):933–941

77. Sharma AS, Kumar EA (2022) Mainstreaming solar energy into residential sectors of Nashik City. Global J Res Eng 22(J2):1–6

78. Shinde SP, Barai VN, Gavit BK, Kadam SA, Atre AA, Bansod RD. (2022). Assessment of Groundwater Potential Zone mapping approach for semi-arid environments using GIS-based Analytical Hierarchy Process (AHP) and Multiple Influence Factors (MIF) and multi-criteria decision analysis (MCDA) techniques in Buchakewadi Watershed, Maharashtra, India

79. Singh R (2021) Solar-city plans with large-scale energy storage: metrics to assess the ability to replace fossil-fuel based power. Sustain Energy Technol Assess 44:101065

Rane *et al. Environmental Sciences Europe*   (2024) 36:5

Page 25 of 25

80. Singh R, Banerjee R (2015) Estimation of rooftop solar photovoltaic potential of a city. Sol Energy 115:589–602
81. Singh L, Saravanan S, Jennifer JJ, Abijith D (2021) Application of multi-influence factor (MIF) technique for the identification of suitable sites for urban settlement in Tiruchirappalli City, Tamil Nadu, India. Asia-Pac J Region Sci 5(3):797–823
82. Singla MK, Gupta J, Nijhawan P, Singh P, Giri NC, Hendawi E, Abu El-Sebah MI (2023) Parameter estimation techniques for photovoltaic system modeling. Energies 16(17):6280
83. Solangi YA, Shah SAA, Zameer H, Ikram M, Saracoglu BO (2019) Assessing the solar PV power project site selection in Pakistan: based on AHP-fuzzy VIKOR approach. Environ Sci Pollut Res 26(29):30286–30302
84. Solangi KH, Islam MR, Saidur R, Rahim NA, Fayaz H (2011) A review on global solar energy policy. Renew Sustain Energy Rev 15:2136–2149
85. Sunarso A, Ibrahim-Bathis K, Murti SA, Budiarto I, Ruiz HS (2020) GIS-based assessment of the technical and economic feasibility of utility-scale solar PV plants: case study in West Kalimantan province. Sustainability 12(15):6283
86. Taheri K, Missimer TM, Taheri M, Moayedi H, Pour FM (2019) Critical zone assessments of an alluvial aquifer system using the multi-infuencing factor (MIF) and analytical hierarchy process (AHP) models in Western Iran. Nat Resour Res. https://doi.org/10.1007/s11053-019-09516-2
87. Tian H, Li R, Salah B, Thinh P (2023) Bi-objective optimization and environmental assessment of SOFC-based cogeneration system: performance evaluation with various organic fluids. Process Saf Environ Prot 178:311–330. https://doi.org/10.1016/j.psep.2023.07.040
88. Türk S, Koç A, Şahin G (2021) Multi-criteria of PV solar site selection problem using GIS-intuitionistic fuzzy based approach in Erzurum province/Turkey. Sci Rep 11(1):1–23
89. United Nations (2004) Integration of GPS, digital imagery and GIS with census mapping. United Nations Statistics Division, New York
90. Wagner T, Theme M, Schüppel A, Gobiet A, Stigler H, Birk S (2017) Impacts of climate change on stream flow and hydro power generation in the Alpine region. Environ Earth Sci 76(1):1–22
91. Watson JJ, Hudson MD (2015) Regional Scale wind farm and solar farm suitability assessment using GIS-assisted multi-criteria evaluation. Landsc Urban Plan 138:20–31
92. Wang L, Jiang Y, Li S, Chen X, Xi F, Wan X, Deng R (2023) Scalable synthesis of N-doped Si/G@voids@C with porous structures for high-performance anode of lithium-ion batteries. Rare Metals. https://doi.org/10.1007/s12598-023-02472-0
93. Yang X, Liu K, Han X, Xu J, Bian M, Zheng D, Yang X (2023) Transformation of waste battery cathode material LiMn2O4 into efficient ultra-low temperature NH3-SCR catalyst: proton exchange synergistic vanadium modification. J Hazard Mater 459:132209. https://doi.org/10.1016/j.jhazmat.2023.132209
94. Yue CD, Wang SS (2006) GIS-based evaluation of multifarious local renewable energy sources: a case study of the Chigu area of southwestern Taiwan. Energy Policy 34(6):730–742
95. Zhao M, Zhou Y, Li X, Cheng W, Zhou C, Ma T, Huang K (2020) Mapping urban dynamics (1992–2018) in Southeast Asia using consistent nighttime light data from DMSP and VIIRS. Remote Sens Environ 248:111980. https://doi.org/10.1016/j.rse.2020.111980

Publisher's Note