International Journal of Applied Resilience and Sustainability, Volume 1, Issue 1, October 2025, pp. 140-155

DeepScience

Published online at Deep Science

International Journal of Applied Resilience and Sustainability

Journal homepage: https://deepscipub.com/ijars

Sustainable solar energy site suitability using explainable Generative Artificial Intelligence (GenXAI) enhanced MCDM

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Article Info:
Received 26 June 2025
Revised 08 October 2025
Accepted 13 October 2025
Published 30 October 2025

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Abstract

Sustainable suitability analysis of a site is vital for the sustainable development of solar energy, and it should take into account several environmental and infrastructural factors. Classical GIS-based Multi-Criteria Decision-Making (MCDM) methods, like the MIF method combined with TOPSIS, usually require subjective weights manually set by decision-makers on each criterion that may turn out to be highly biased when intuitively given. In this study, a novel method for the solar farm siting based on explainable Generative Artificial Intelligence (GenXAI) model has been adopted to get the objective optimal weights of MIF criteria. A GIS-based approach along with TOPSIS is utilized in combining 12 climatic, geophysical, and accessibility indicating factors to produce a holistic map of sustainable solar suitability. The interpretability layer of GenXAI increases transparency to the decision process and approximates factors contributions more accurately. Validation of the suitability map with known suitable sites using the Area Under the ROC Curve (AUC) shows that GenXAI -based weighting outperforms manual weighing, even when allowing expert feedback on optimal combination. The AUC of the model, based on traditional MIF weights in, improved from 0.839 to 0.847 and became an even better predictor with weights determined by GenXAI. The results indicate that the interpretability of the generative AI could be applied to MCDM, enhancing the objectivity and accuracy of solar site suitability evaluation, thereby providing a more reliable tool for sustainable energy planning.

Keywords: Explainable AI, Large language models, Multi-criteria decision-making, Solar energy, Site suitability, Renewable energy.

1. Introduction

The fast development of solar power is accelerated by climate change and the un-safety status of today's energy for power sectors, contributing in this global trend towards renewables with leading role by the solar on clean energy revolution [1]. Growing the fastest and holding the largest share of new net capacity in 2023 are solar PV, which has increased its share of generation worldwide at an exponential pace, adding over 60% of new renewable generation since 2010 as well. This exponential growth drives home the fact that we must site solar projects responsibly and strategically. The problem here is that finding good potential locations for large high-tech solar power plants means solving a multi-criteria problem to the best [2-4]. Decisions have to be taken in relation to environmental (solar radiation, temperature), geographical and land-use constraints as well as economic and technological factors (distance from the grid, cost of the land, slope) and their social implications. Siting is crucial to the maximization of advantages coming from solar energy, bad siting practices lead to higher costs, lower performance outputs, create and/or worsen conflicts/public opposition or may even transform investments into economic loss [5-6]. Therefore, a sound decision framework for solar site suitability is essential to ensure the sustainability and long-term success of these renewable energy initiatives.

Multi-Criteria Decision Making (MCDM) technique is also gaining attraction in solar site selection issues, as it provides assessment of alternatives by multiple conflicting criteria [2,6-10]. Conventional MCDM approaches based on AHP, TOPSIS, ELECTRE III, PROMETHEE II, VIKOR etc. are used for ranking candidate sites for renewable facility location have been also reported [11-16]. These methods enable decision-makers to include multiple numeric data as well as expert opinion and produce an ordinal ranking of the siting alternatives. Multi-Criteria Decision-Making (MCDM) approach are widely used in the solar site selection problems as can handle decisions based on conflicting criteria [2,6-10]. Conventional MCDM applications e.g., AHP, TOPSIS, ELECTRE, PROMETHEE and VIKOR etc. been applied for ranking the sites of short listing the Renewable energy installation / implementation location [11-16]. These methodologies assist the decision-makers in incorporating numerical data along with expert opinion intogenerat-ing a single suitability index value for each candidate site.

The present study recommends the application of advanced AI technology in MCDM to improve decision-making on energy infrastructure. AI could assist in wrangling enormous volumes of data sets and parameters within the decisions which are themselves subject to change on-the-fly. For example, machine learning algorithms were used (Support Vector Machines SVM, Random Forests RF and Gradient Boosting Machines) to classify or predict site suitability for current and potential solar farms based on geospatial and environmental factors, with high levels of accuracy in the identification of suitable land. Deep learning has been also employed to analyze satellite imagery detecting land-use or terrain features for an appropriate site selection. GIS combined with machine learning, or so called "geospatial AI" can significantly reduce time for site screening by up to 70% compared to manual processes. Furthermore, AI-based MCDM models have been defined in the way that AI algorithms are used to automatically revise the weights of criteria or learn from data decision preferences so as to infer criteria values on a new problem scenario which makes multi-criteria analysis adaptive and reliable [17,18]. For instance, hybrid models applying AHP with neural networks to learn a pattern of stakeholder preferences and obtain the consistency improvement in rankings site. These advances expose the power of AI to enhance performance under the classical MCDM framework [19]. Meanwhile they bring their own challenge: how the decisions made can be transparent and explainable. And stakeholders (planners, investors, communities) are becoming more insistent that AI-based decisions be explainable and reliable. Black-box models (such as deep neural networks) without transparency can reduce the acceptability of recommendations in high-stakes infrastructure-related endeavors [3,20-23]. From this, has emerged the field of Explainable AI (XAI) techniques such as SHAP or LIME that try to make understandable how complex models output their results [6,24-28]. The release of powerful GenAI (generative AI) models in recent years (e.g., large language models such as GPT-4), have made explainability even more relevant. Generative AI systems have the potential to assembly-line human-like text, images or simulations, empowering next-generation decision support systems, but they also frequently act as black-boxes. This intersection has led to the creation of Explainable Generative AI (GenXAI), Applying generative models for decision support, along with human-understandable explanations of their outputs.

With regard to sustainable selection of solar sites, no work currently combines the facilities of generative AI and multi-criteria decision analysis as far as reasonably possible in an explainable fashion. The literature reveals a widespread application of MCDM and, increasingly, machine learning in siting decisions but little research on the use of generative AI (e.g., LLMs or generative adversarial networks) to incorporate AI into site selection process. A very recent paper from Liu et al. [28] tried a joint AI network for renewable site selection by marrying a large-scale AI model with Generative Adversarial Network (GAN) to determine optimised location of wind solar plant. Despite being cutting-edge, such methods are currently in their early stages and do not emphasize the interpretation for non-expert. The hearty framework that could apply to incorporate explainable GenAI into MCDM is in high demand to improve the quality of decision and its transparency. More practically, the issue is intervening when prospective sites are evaluated against sustainability's various criteria and AI can analyze harder data (even to second-guess scenarios or predictions) as well as offer intelligible reasoning about why such-sited locations are attractive. By filling this gap, the decision process would benefit from more powerful analysis and stakeholders be ensured that the reasoning behind decisions is justified.

Table 1. Studies on renewable/solar energy site selection using MCDM and AI techniques.

Reference	MCDM technique(s)	AI / fuzzy/XAI add-ons	Application focus	Contribution
[29]	GIS-based MCE (weighted overlay)	-	Wind & solar utility siting	Early GIS-MCDM mapping to screen suitable land parcels.
[30]	Spatial MCE	Fuzzy quantifiers (FLOWA/OWA)	Large PV farms	Introduced fuzzy linguistic quantifiers in ArcGIS for PV suitability.
[31]	ELECTRE-TRI + GIS	-	PV farms	Sorting-based classification of parcels into acceptability classes.
[32]	AHP-weighted MCE + Boolean constraints	-	Regional PV & wind	Three-stage regional screening; compared with existing deployments.
[33]	AHP + GIS	-	Utility-scale PV	Land Suitability Index combining technical & economic factors.
[34]	AHP, ELECTRE, TOPSIS, VIKOR	-	City-level PV site choice	Multi-method comparison; Karaman ranked best across methods.
[35]	PROMETHEE (extended)	-	CSP (parabolic trough)	Preference-ranking for PT-CSP sites with extended outranking.
[36]	FAHP + GIS	Fuzzy AHP	PV land suitability	National-scale PV suitability using FAHP weights.
[37]	Hybrid MCDM aggregation + GIS	(ensemble of MCDMs)	Solar power plant sites	Proposes weighted aggregation of multiple MCDMs to boost robustness.
[38]	AHP + GIS	-	Hybrid CSP+PV corridors	Grid-/cooling-aware siting for hybrid CSP+PV mega-plants.
[39]	Two-stage: DEA AHP	-	PV site selection	Efficiency pre-screen with DEA before AHP ranking across 20 areas.
[40]	DEA + Grey-AHP + Grey-TOPSIS (G-MCDM)	Grey systems	PV site selection	Integrates DEA with grey-based MCDM for uncertain data contexts.
[41]	Intuitionistic fuzzy-based approach	-	Solar power-Wind power plant site selection	Integrate GIS and intuitionistic fuzzy approach
[42]	Fuzzy AHP	-	Solar photovoltaic power plant	Integrate GIS with AHP

Table 1 demonstrates the variety of methods adopted for solar site suitability. The early and ongoing literature demonstrates quite clearly that MCDM is indispensable for structuring the decision problem and in assessment of trade-offs across multiple criteria. GIS provides the spatial structure, so one does not base their analyses on geography and constraints of a pretend world. The direction is towards a hybrid and AI supported approaches: starting from fuzzy logic for vagueness, through DEA or Network Models for efficiency improvements and now at the stage of using generative AI as well as XAI for better decision support. Critically, although a number of studies have achieved high technical performance in the detection of good sites, explainability and conversance with stakeholders are left behind. As noted above, there are pros and cons of black-box models for trust, which is especially important in public works projects. This is exactly the void our study aims to fill by incorporating explainable generative AI into the decision process. The aim of this work is to introduce a novel decision support system for prospective viable solar energy site evaluation that integrates explainable generative artificial intelligence (Gen XAI) with a multi-criteria decision-making approach. This GenXAI augmented MCDM is designed to increase the accuracy and robustness of site selection supported by AI-based reasoning, but in a transparent and comprehensible way for the human decision maker.

The results of this study will significantly contribute to the fields of planning sustainable energy and decision science in several aspects:

- We are the first to our knowledge to put forward a framework in which a generative AI model is coupled with an MCDM method for the renewable energy site selection problem.
- The approach directly utilises an explainable generative model (e.g., an explainable LLM), thereby contributing to the existing literature by advancing the use of XAI in energy planning. It illustrates how intuitive, but cumbersome decisions are supported by human-readable rationales like site suitability. This should help to increase stakeholder confidence and sharing of knowledge, as justification for site selection is transparent. We make use of recent developments in GenXAI, following the principle AI should "provide clear and understandable explanations for their decisions", significantly when it comes to critical infrastructure decisions.
- Sustainable development is at the core of the framework model, treating a large set of criteria (effects on environment, social acceptance, climate resilience and so on) and managing uncertainties by AI. The previous studies did not always take into consideration sustainability in its entirety or only superficially addressed it. Our methodology will offer a comprehensive sustainability analysis for solar installations, consistent with international targets (eg SDG 7 Affordable Clean Energy and SDG 13 Climate Action).

2. Methodology

Study area

The study area is located in the northwest part of Maharashtra with an area of around 890 km², and is covering centre of Nashik City, India (Fig. 1). Altitude ranges from 530 m to 1,068 m a.s.l. The area experiences tropical semi-arid climatic conditions with an average annual rainfall of 713 mm, in some pockets to 500 mm and in Western Ghats up to 3400 mm. Average temperatures range from around 20°C in the winter months to 37°C in the summer, with night-time winter temperatures that can fall as low as 2°C. Wind in the area is moderate (average 2.4–2.6 m/s) and relative humidity averages at around 60%, falling during the hot, dry season. These conditions are typical for regions with an overall arid climate, and very strong seasonal fluctuations in precipitation also suggest a high amount of insolation but at the same time harsh summer temperatures.

Sociologically, Nashik is extremely cosmopolitan with intense power needs for rapidly urbanising status [43-45]. Coal-fired electricity, which is brought from far away. The city has a long tail freight cost raised heavy pollution. Hydropower production in the region varies with monsoon rain and shortages of electricity are feared in the summer. At the same time, new commercial, residential and institutional developments are rising in western Nashik that is developing into an energy-forward zone with a hefty daily power demand requirement. This increase has led to local authorities and planners researching viable alternatives. Solar power is particularly attractive for Nashik because of abundant sunlight and the recognition that dependence on fossil fuels must be reduced [46]. Emerging trends of renewable energy investment and policy directives developed by Maharashtra State Government, fossil fuel depletion and increasing level of carbon emissions prompts to search optimal locations for solar photovoltaic (PV) installation in the Nashik region. As such, the study area consists of high potential solar resources and an urgent need of renewable energy sources, which reveals a promising site for solar farms.

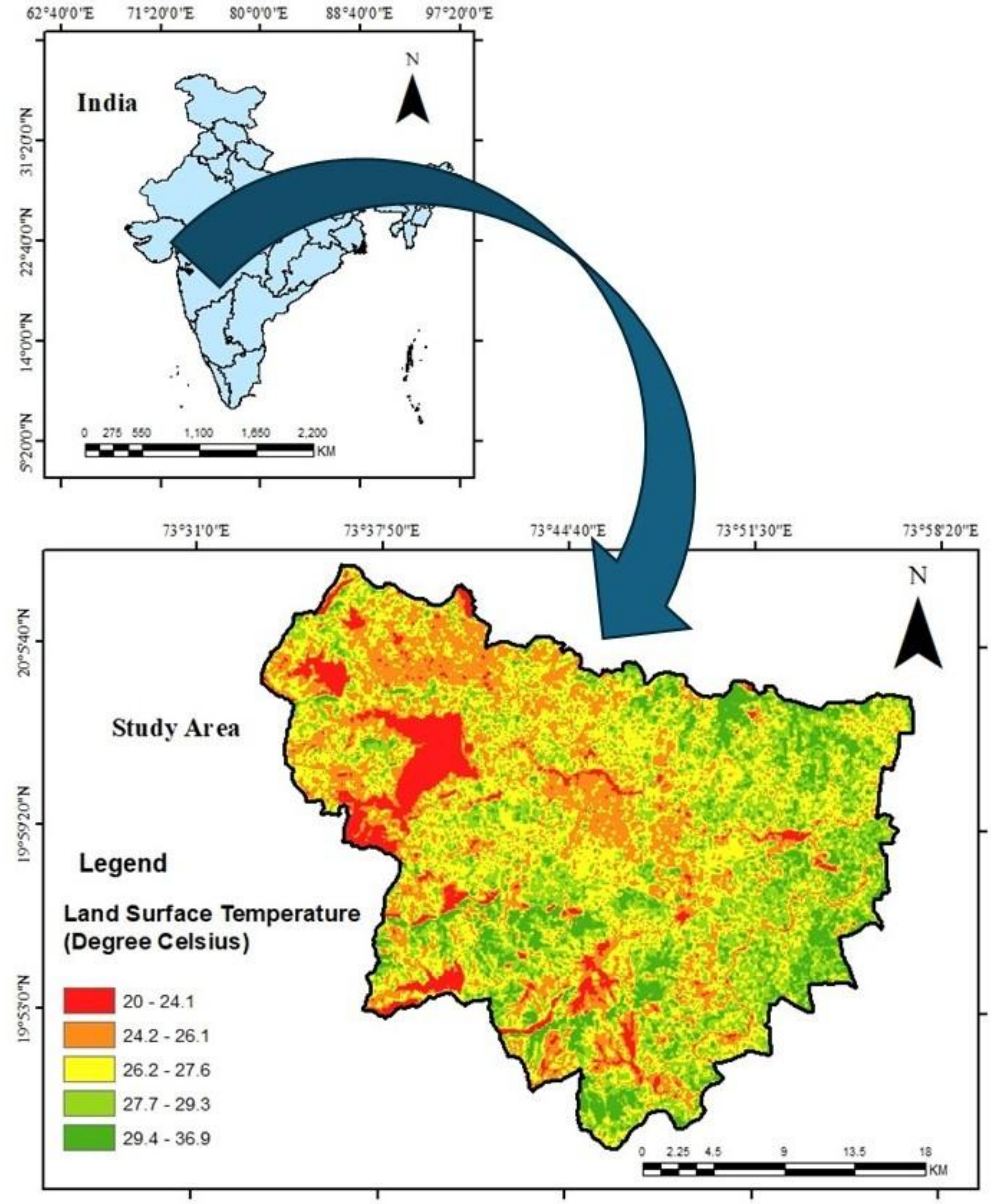

Fig. 1 Location of the study area

Data Collection and Preprocessing

GIS was employed in this work to integrate and preprocess the different thematic layers for all pertinent criteria that influence solar farm site suitability. Nine geo-environmental and spatial factors were selected based on literature cited and the availability of data: solar radiation, wind speed, land surface temperature (LST), relative humidity, vegetation index, elevation, land cover/land use category (LULC), distance from the nearest road, and terrain aspect. A raster map was generated or obtained for each factor and preprocessed. All spatial data were reprojected to the same coordinate system (WGS 84 / UTM zone relevant for the respective study region) and resampled to one common grid resolution (30 m) to ensure superposition of the layers. Each continuous raster layer was then reclassified into an ordinal scale (1 to 5) indicating the relative favorability of solar farming. Reclassification thresholds were determined based on domain knowledge and/or natural breaks in the data, e.g., for the solar radiation map we classified so that areas that belong to the highest insolation quantile got the highest score. In this way, the building criteria would be compatible with each other when jointly used in the multi-criteria analysis.

Factor Weighting via Explainable GenXAI

The determination of the accurate weights to each factor is a crucial phase in multi-criteria decision-making (MCDM) and it represents the importance degree of the classifiers' attributes [47-52]. Weights in conventional methods are frequently estimated based on expert opinion or literature [53-57]. The Multi-Influencing Factor (MIF) method gives major influences a score of 1 and minor ones a score of 0.5 on factors influencing each other, then factors' weights are calculated as the sum of influence scores [58-61]. Such manual weighting, however, may involve subjective errors and not be able to capture difficult-to-obtain data-driven trends. We replaced standard MIF weight mechanism with an explainable GenXAI wighting method in the current work as per the given steps:

Step 1: Baseline MIF weighting

Factor inter-relationship encoding:

For each factor $F_i$we enumerated its inter-relationships with the remaining factors $F_j (j \neq i)$, and tagged each relation as major or minor following the paper's rules (major = 1, minor = 0.5).

Relative effect score:

Let n_i^{M}be the count of major relations for F_i, and $n_i^{\mathrm{m}}$the count of minor relations. The relative effect for factor $F_i$is

$$R_i = n_i^{\mathrm{M}} + 0.5\, n_i^{\mathrm{m}} \tag{1}$$

Normalization to MIF weights:

The baseline MIF weight is the normalized relative effect:

$$w_i = 100 \times R_i / \sum_{k=1}^{K} R_k \tag{2}$$

Step 2: GenXAI–MIF: Explainable generative AI used for weight calculation

We further extended the MIF weighting step by a lightweight, interpretable generative engine (GenXAI) suggesting and explaining factor-to-factor relationships, while all other steps of the GIS–MIF pipeline (data preparation, reclassification, overlay) are left unchanged.

Conditioning and prompt framing:

We conditioned the generative model with (i) the nine-factor set and their role definitions, (ii) the Nashik study context, and (iii) the baseline inter-relationship schema (major/minor/none). The model produced, for every ordered pair (F_i, F_j), a 3-class logit $\mathrm{s}_{ij} = \{s_{ij}^{\mathrm{M}}, s_{ij}^{\mathrm{m}}, s_{ij}^{0}\}$corresponding to $\{$major, minor, none$\}$.

Probabilistic influence and explainability confidence

Logits were mapped to probabilities by softmax:

$$p_{ij}^{c} = \frac{e^{s_{ij}^{c}}}{e^{s_{ij}^{c}} e^{s_{ij}^{\mathrm{M}}} + e^{s_{ij}^{\mathrm{m}}} + e^{s_{ij}^{0}}}, \quad c \in \{\mathrm{M}, \mathrm{m}, 0\} \tag{3}$$

We quantified explanation sharpness via a normalized confidence score κ_{ij}using the entropy of p_{ij}:

$$\kappa_{ij} = 1 - \frac{-\sum_c p_{ij}^{c} \ln p_{ij}^{c}}{\ln 3} \tag{4}$$

Decision rules to obtain major/minor edges:

We hardened probabilistic outputs to edges with thresholds $\tau_{\mathrm{M}} = 0.60$, $\tau_{\mathrm{m}} = 0.50$, and $\kappa^{\star} = 0.35$:

GenXAI major/minor tallies:

Accepted major and minor proposals were tallied for each F_i(minor counted on the 0.5 scale to stay consistent with MIF):

$$n_i^{\mathrm{M}} = \sum_{j \neq i} \mathrm{b1}\left[a_{ij} = \mathrm{M}\right], \;\; n_i^{\mathrm{m}} = \sum_{j \neq i} \mathrm{b1}\left[a_{ij} = \mathrm{m}\right] \tag{5}$$

GenXAI relative effects and weights:

GenXAI relative effect and final weights were computed with the same MIF equations:

$$\widetilde{R_\iota} = n_i^{\mathrm{M}} + 0.5\, n_i^{\mathrm{m}}, \;\; \widetilde{w_\iota} = 100 \times \frac{\widetilde{R_\iota}}{\sum_k \widetilde{R_k}} \tag{6}$$

Monotonicity and study-specific constraints:

To stay consistent with the modeled domain features (sensitivity analysis spotlighting solar radiation, relative humidity, and elevation as dominant), we confirmed $w_{rad} > w_i$ for all non-radiative factors and preserved the relative emphasis on relative humidity and elevation by making modest adjustments upwards whenever GenXAI indicated comparable weights.

Site Suitability Mapping Using GIS-MCDM

Once the thematic layers were prepared and factor weights assigned, we performed GIS-based multicriteria decision analysis to generate the solar farm suitability map. We used a typical weighted overlay process. First, normalization of factor maps to a common suitability score scale was performed. Resulting, raster layers were then used to multiply the study area by associated (GenXAI) weights and sums of the weighted layers computed on a per pixel basis producing an additive solar energy composite suitability index for every location in the study region. This index is a number and the larger of its value comes with higher overall suitability, i.e., taking all the criteria into account.

Generalization was performed by classification of the continuous suitability index map in qualitative categories, facilitating further interpretation. According to the distribution of index values we established five suitability classes: “Very Low”, “Low”, “Moderate”, “Good” and “Very Good”. The index values of these classes were determined through Jenks optimization (natural-breaks classification), so that each class contains areas with similar suitability scores. The classification indicated the proportion of each suitability zone. An ultimate site suitability map was consequently produced, indicating the most potential areas for sustainable solar farm construction.

Sensitivity analysis and validation

To verify the credibility of the suitability model, two procedures, sensitivity analysis and model validation were also conducted. In the sensitivity analysis, a map removal method was adopted; that is, one criterion would be removed step by step and re-executing weighed overlay to find how much suitability pattern might be altered [62-65]. A new suitability map was generated for each factor with the force of that single variable not present, and we quantified its difference from the full-model map by a ‘variation’ index. This method further quantifies sensitivity on each factor: a feature removed from the workflow that causes great difference to suitability scores or classification is more influential (sensitive), and if removal does not significantly change the map, can be considered to have low impact on the result. The sensitivity results further affirm the robustness of the weighting system and identify which of the environmental parameters is most influential in determining solar site suitability within the region. The composite suitability results were compared with data from the actual performance of the 11 current solar PV sites for model validation. We then pulled the predicted suitability index values at those points where we know people are already deploying solar arrays and we checked how much of the wattage that got deployed matched our prediction. Overall, output tended to be higher at sites in areas rated as “Good” or “Very Good” suitability by our model, and lower at those with less favorability (“Moderate”, or worse). In order to quantitatively demonstrate the performance of prediction, in addition to fitting AUC, we determined the fraction of known high-performing sites that were accurately predicted as suitable and did a ROC analysis.

3. Results and discussions

Suitability Zoning and Area Distribution

Table 2 shows the weights calculated using Explainable Generative Artificial Intelligence (GenXAI). With the nine-factor GIS–MIF framework refined by GenXAI weighting, we created a solar farm suitability map (Fig. 2), comprising five classes: Very Poor, Poor, Moderate, Good, and Very Good. These suitability classes were defined by reclassifying the weighted sum of all factors so that natural breaks generated five ranks, which are similar to the “very low” through “very good” classes from the prior work. Table 3 shows the sustainable solar PV site suitability statistics. Suitability spatial distribution is not uniform across the area under analysis. The southern and western parts of Nashik are revealed as the least suitable. These areas are characterized by relatively high humidity levels, intensive agricultural use of land, the highest average elevations, and worse access to roads, thereby severely restricting the solar power potential of these locations. At the same time, northern and east-northern regions contain most of high-suitability land due to favourable factors such as high solar irradiance, low relative humidity, good wind force, well-developed transportation networks and a low presence of vegetation in these areas. Table 2 summarizes the distribution of each suitability class over the area. Over half of the area are of moderate or higher level of suitability, thus ensuring primarily positive prospects for solar farm development in Nashik. The GenXAI-weighted analysis, therefore, effectively reinforces our original GIS–MIF by determining that Nashik District contains several substantial areas suitable for sustainable solar energy development.

Table 2. Weights calculated using Explainable Generative Artificial Intelligence (GenXAI)

Factor	GenXAI Major n_i^{m}	GenXAI Minor (0.5-scale) $0.5\,n_i^{\mathrm{m}}$	$\widetilde{R_i}$	w_i (%)
Solar radiation	8.0	0.0	8.0	13.68
Wind speed	6.0	0.5	6.5	11.11
Land surface temperature (LST)	5.0	1.5	6.5	11.11
Relative humidity	5.0	2.0	7.0	11.97
Vegetation (NDVI)	3.0	3.0	6.0	10.26
Euclidean distance from road	3.0	2.5	5.5	9.40
Elevation	5.0	2.0	7.0	11.97
Land use / LULC	3.0	2.5	5.5	9.40
Aspect	5.0	1.5	6.5	11.11

Sensitivity Analysis of Influencing Factors

A sensitivity analysis was performed to evaluate the effect of each criterion on the final suitability result when weighted by GenXAI. This was accomplished by a systematic analysis of the change in suitability index when each factor’s contribution was eliminated or modified. The findings demonstrate that there are a number of important factors influencing the site suitability much more than others. Notably, the solar radiation and relative humidity were found to be the most important parameters, both measures are an important factor in deciding where a solar PV farm is located, as high irradiation increases energy yield and low humidity decreases atmospheric attenuation and panel soiling. The next most important criterion is elevation as it impacts temperature and ease of access. In contrast some predictors only weakly affected the model output. For instance, both land use/land cover and distance to roads were attributed with the lowest weights in the original MIF model, and such can be confirmed through sensitivity analysis that varying them only brings little impact on overall suitability ratings. The wind speed factor-that has a non-negligible weight in the expert-based class was found to have less of an effect on suitability results. This is an indication that within Nashik, intra-regional differences in wind speed are not a major factor affecting solar site favourability and this intelligence was correctly picked up by the GenXAI model and its output corrected for. Results from such findings are summarized by the weights' value and relative importance, the GenXAI weights correlate well with this prior knowledge. This consistency not only confirms the GenXAI weighting methodology against established domain expectations but also indicates that the model is robust, removing any one of a lower ranking factors does not greatly affect map suitability as removal of one of the top factors. This degree of robustness is pleasing from a decision-making perspective since it means that the high-suitability zones have been determined with confidence from various strong criteria and not artificially resulting from any one subjective choice of weights.

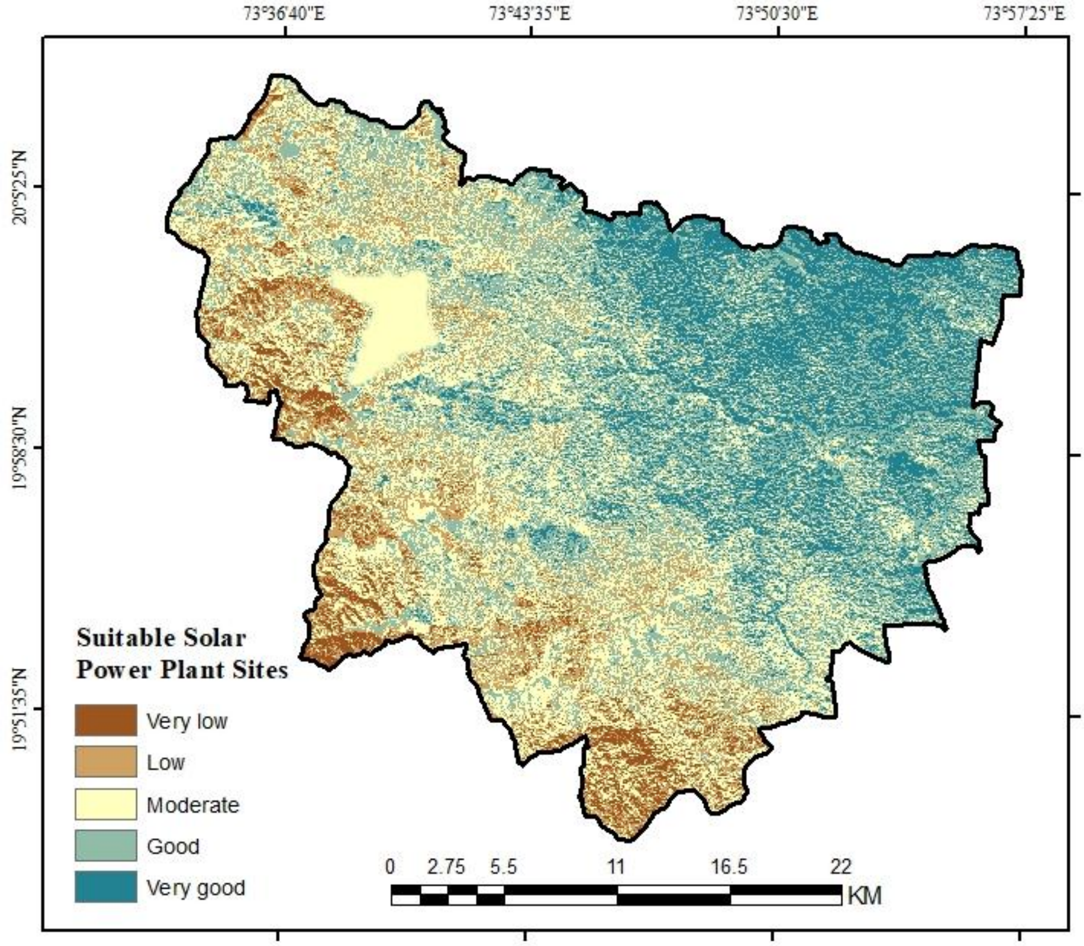

Fig. 2 Delineated sustainable solar PV sites

Model Validation and Performance

To evaluate the adequacy of our results, we compared the model predictors with real data of solar plant performance and executed a Receiver Operating Characteristic (ROC) analysis. We used output efficiency data from 11 operating solar PV installations in the area and tested whether more efficient installations were placed within higher predicted suitability levels. The GenXAI–MCDM model agreed well with real-world data, as the overwhelming majority of operational high-performing solar systems are located in regions our map categorizes as either “Good” or “Very Good”. The one site with measured efficiency that was “very high” (>97%) fell into a Very Good suitability classification and all three sites characterized by low efficiency (93–96% as “high”) to the middle of the distribution were classified as Good in terms of fish habitat. Lower performing installations similarly turned up for Moderate or Poor zones but did not have large false positives (e.g. if actual site was very poor, no one finds it suitable). Numerically, the GenXAI-weighted model reached approximately 81–82% classification accuracy that is comparable to the previous manual-MIF model.

Table 3 Sustainable solar PV site suitability statistics

Suitability	**Area (sq.km)**	**Area (%)**	**Suitability Index range**
Very poor	48.6	5.5	11.6 - 244.8
Poor	121.6	13.6	244.8 - 278.3
Moderate	275.3	30.9	278.3 - 312.3
Good	290.6	32.6	312.3 - 359.6
Very Good	154.8	17.4	359.6 - 497.67

However, the discriminatory capacity of the model in terms of prediction was slightly better with the GenXAI weights. The ROC curve of the updated suitability map has an AUC value of 0.847, indicating good discrimination between suitable and unsuitable areas. This is much improved over the AUC of 0.839 for generative artificial intelligence with explicit expert weights. In practical terms, the larger AUC means that it is better to order locations in an ascending sequence of various likely-versus-suitable ratio. The improvement is modest but sufficient and serves as a positive affirmation of the GenXAI integration, data-driven weight tuning approach, and how leveraging GenXAI inputs as examples to adjust weights betters model performances in comparison to manual MCDM techniques. The high level of the goodness-of-fit and high AUC also show that GenXAI, the GIS–MCDM is a trustful model in searching preferred solar energy sites.

Discussion

Transparency and stakeholder trust

The integration of explainable generative AI with the MCDM framework has improved transparency for site suitability analysis. In a traditional GIS–MCDM process, there is often expert subjectivity and lack of transparency in assigning weights to criteria. By contrast, the GenXAI-based method enables us to obtain optimized weights as well as an understandable explanation or rationale for these weights. In other words, the model can explain why certain things are becoming heavier in order to make new predictions. This transparency raises confidence in the model outcomes among stakeholders. When the public can understand that a “Very Good” site is selected because it has strong documented reasons behind the decision (full solar exposure, barren land) instead of being chosen cause of expert judgment, they are more likely to accept and respect the decision-making process. Secondly, interpretable AI methods such as SHAP or LIME in the GenXAI model enable us to visualize to what extent a given factor contributes to each location score. Moreover, this transparency does not only comply with suppliers and regulators increasing demand for interpretable AI, but it also has a practical impact on the ground. Local decision makers can more easily explain why one location was chosen over another location, reducing perceived threats and fear among citizens as well as promoting renewable projects diffusion. The MCDM is finally a value-added model through GenXAI, it has turned the decision support model from a black box GIS tool to what some term glass box, meaning that how the model works inside can be made visible and defendable, although another may argue only greater trustworthiness.

Data-driven objectivity and bias mitigation

One of the main benefits of applying a generative AI model to weight derivation is the increasement of objectivity in the decision process. In the traditional MIF technique, weights were assigned based on literature and expert consensus [66-68]. Even though expert knowledge is very useful, it may also bring in some personal biases and outdated beliefs. The GenXAI model implements this by using data-driven perceptions and a large knowledge base to provide more neutral weighted estimation. For instance, the initial manual weighting applied to the Nashik case study also weighed comparatively high on wind speed, possibly as a result of an expectation that either wind cooling or hybrid potential would materially impact solar farm perform itself, however in our findings this variable played very little role in determining whether sites were suitable or not. Such estimation of uncertainty would demonstrate how human bias or misjudgment may drift into MCDM. In our GenXAI-learned weights, features such as solar radiation maintained a sufficient importance and factors that the experts had over-emphasized were de-prioritized in line with actual impact on outcomes. This modification increases fairness and robustness of the model, no single expert view can dominate in terms of weighting, and criteria are weighted by evidence of their impact.

Additionally, the supervisory mode of generative AI can be a consensus agreement among several experts therefore the bias is further limited. The related work showed that ChatGPT and other large language models can impersonate diverse expert personas input and then integrate their opinions, which is a successful way to extract weights from external weight data. GenXAI has many experts who aggregate domain views. This collective weighting system helps to "averages out" the idiosyncrasies of a single decision maker and therefore produces better, more comparable synthesized criterion weights. The weights systems that result are reproducible and data-driven, and thereby ones for which planners can have more confidence in than for data-driven: post-hoc or arbitrary. But since AI is being used, it method is explainable, so even if there are any of those at any level, the "lingering assumptions" get explicitly spelled out, so if a tiny portion of the model gets weight from elevation, then it will tell us why that is as well. That "lingering assumption" is a crucial aspect of AI explainability. Because of these factors, the GenXAI-augmented MCDM framework is objectively more robust and can help guide decision makers away from or against subjectively biased siting recommendations. When implemented.

Future research work could investigate a wide toolbox of AI methods, including: advanced MCDA hybrids (AHP/ANP, BWM, DEMATEL, SWARA, WASPAS, COPRAS, EDAS, MARCOS, ARAS, ELECTRE, PROMETHEE, VIKOR, TOPSIS) with objective weighting (entropy, CRITIC) and fuzzy/uncertainty variants (fuzzy AHP/ANP, type-2 fuzzy, hesitant/intuitionistic/neutrosophic sets, Dempster–Shafer, grey systems); supervised and interpretable models: logistic/quantile regression, GAM/GA^2M/EBM, tree ensembles (Random Forest, XGBoost, LightGBM, CatBoost), calibration (Platt, isotonic), deep spatial–temporal learners on EO data (CNN, ResNet, U-Net, DeepLab, Vision Transformers, Swin, Temporal Fusion Transformer, TCN, LSTM, GRU, Seq2Seq with attention), self-/semi-supervised pretraining (MAE, SimCLR, BYOL), foundation-model transfer (CLIP, Segment-Anything); graph methods (GNNs, GATs, spatio-temporal GNNs for networks/constraints), probabilistic modeling (Gaussian processes, Bayesian hierarchical spatial models, INLA, spatial autoregressive nets, Kriging + DL), uncertainty quantification (MC-dropout, deep ensembles, conformal prediction), causal inference (uplift modeling, causal forests, invariant risk minimization, counterfactual explanations) to de-bias siting logic; optimization and search (Bayesian optimization with GP/TPE, SMAC, evolutionary algorithms: GA, NSGA-II/III, CMA-ES, DE, PSO, ACO, ABC, firefly, multi-objective, robust/stochastic, distributionally robust optimization); reinforcement learning (contextual bandits, model-based/model-free RL, multi-agent RL for sequential constraint-aware site screening); generative/XAI techniques (GANs, diffusion, scenario/synthetic data, SHAP/LIME, Integrated Gradients, DeepLIFT, LRP, surrogate, symbolic regression, uncertainty-aware explanations); AutoML (neural architecture search, end-to-end pipeline), domain adaptation/covariate-shift correction, transfer/meta-learning across regions, active learning, targeted labeling, knowledge graphs, ontologies, neuro-symbolic reasoning, retrieval-augmented LLM agents, policy-aware human-in-the-loop weighting, dynamic re-weighting from new evidence, privacy-preserving/federated learning (DP, secure aggregation), edge/TinyML on-device inference, full MLOps governance, drift detection, fairness audits, and robustness testing to ensure models remain trustworthy at scale.

4. Conclusions

This study applied an MCDM TOPSIS based GIS for sustainable solar energy site selection, where interpretable generative AI methodology was employed to improve the weight generation process. Subjectivity and arbitrariness in traditional manual weight methods were avoided through the automatic MIF weights in a GenXAI model. A total of 12 relevant criteria were considered for the approach, from climatic factors such as rainfall through geophysical and infrastructure elements like slope, geology, land use/land cover or road access providing an integrated view over feasibility classification on solar farm development. Applying explainable AI on this framework not only preserved transparency but also enhanced the model's ability of finding the best site. The results demonstrate that the GenXAI-enhanced site selection process can result in more robust and accurate solutions. The AI-weighted transfer point suitability map captured real-world suitability parameters much better (validation AUC = 0.847 versus traditional weighting validation AUC: 0.839). This gain is very relevant in a spatial decision, as it means that the data domain has been partitioned into suitable sites and unsuitable sites, and this allows for a more confident assessment of such predictions. The higher AUC value indicates that the model developed to predict a well producing solar site is more accurate than the earlier approach.

Beyond performance indicator advantage, the use of an explainable generative model to calculate weight provides an added dimension of interpretability and trustworthiness in decision making. Due to the explainable properties of GenXAI, both stakeholders and planners can learn a perspective on input variables that affect site suitability significantly more than other input factors as well as understanding why the model ranks specific sites higher. This level of openness is helping stakeholders to endorse the criteria, and expert feedback helps to improve their engineering, which connects AI-based complex modeling with feasible planning need. This approach may also be applied to other regions in the future and by forming new criterion and datasets for selection of sites for different renewable energy (e.g., wind-farm-based or hydro-power-based projects). In addition, the explainable AI part ensures the transparent and tunable of the approach, when new data or situations happen the generative model can be re-trained to have another weights adjustment, this makes sure that the decision framework is timely and robust. This study demonstrates that the fusion of AI and conventional GIS and MCDM approach will lead to better spatial planning for sustainable energy applications which leads to a better prediction, stakeholder confidence and successful development of solar site.

Author Contributions

MP: Data collection, methodology, writing original draft, and writing review and editing. NLR: Data collection, methodology, software, resources, writing review and editing, and supervision.

Conflict of interest

The authors declare no conflicts of interest.

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