

Digital Visualization and Siting Optimization of Power Plants Using High-Resolution Meteorological Data and GIS

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Abstract

The global transition to high-quality renewable energy systems requires precise siting of power plants to maximize generation efficiency and economic returns. Despite similar installed capacities, suboptimal site selection can lead to significant power generation disparities, such as the 14% efficiency gap observed between solar facilities in Australia and Spain. This study presents a data-driven spatial optimization framework that integrates Geographic Information Systems (GIS) with high-resolution meteorological data to address the limitations of traditional, proximity-based siting methodologies. Utilizing a Multi-Criteria Decision Analysis (MCDA) approach, a Python-based TOPSIS algorithm was developed to evaluate candidate sites across four digital layers: meteorological potential, terrain slope, grid infrastructure proximity, and economic/land-use constraints. The model successfully quantified the geographic “Resource Dividend,” demonstrating that the 14% real-world generation gap closely aligned with an 11% disparity in the calculated digital suitability scores (0.82 for Australia versus 0.71 for Spain). By translating complex, heterogeneous spatial data into visual suitability heat maps, this digital optimization framework allows stakeholders to bypass local optima, minimize the Levelized Cost of Energy (LCOE), and enhance the internal rate of return. Ultimately, algorithmic site selection mitigates human bias and ensures a technically efficient and economically sustainable deployment of renewable energy.

Keywords

Geographic Information Systems (GIS), site selection optimization, Multi-Criteria Decision Analysis (MCDA), TOPSIS algorithm, Levelized Cost of Energy (LCOE)

1. Introduction

As countries transition to higher-quality renewable energy systems to achieve appropriate decarbonization targets, the global energy landscape is transforming. Under the guidance of China's “Four Reforms and One Integration” energy strategy and other strategic frameworks, the grid connection of large-scale renewable energy with annual power generation exceeding 200 million kilowatts has become the cornerstone of the country's energy security and carbon neutrality goals. Therefore, power plants, especially solar and wind energy facilities, have been widely deployed worldwide. However, as the industry shifts from scale-driven

expansion to benefit-driven quality, the location of these assets has become the primary determinant of whether the system's efficiency meets expectations.

Although installed capacity is growing rapidly, significant differences in power generation efficiency persist due to suboptimal site selection. For instance, comparative data shows that in regions with similar installed solar capacity, such as Australia and Spain, the actual power generation (about 5 terawatt-hours) differs by 14%. This performance gap highlights a key limitation in current research and practice: most site selection evaluations rely on historical averages at the macro level or independent technical variables, ignoring the complex interactions among high-resolution meteorological models, infrastructure proximity, and terrain constraints. Furthermore, existing models often treat technical efficiency and economic benefits separately, leaving certain research gaps in the data-driven comprehensive optimization framework.

The purpose and significance of this study lie in the potential to bridge these gaps by quantifying the “resource dividends” associated with precise site selection. From a technical perspective, precise spatial analysis can ensure that the equipment operates at peak efficiency, captures energy to the greatest extent, and minimizes transmission losses. Economically, under the same capital expenditure, optimizing site selection directly reduces the levelized Cost of Energy (LCOE) and increases the internal rate of return (IRR).

This study aims to achieve the visualization and precise modeling of energy potential by integrating a Geographic Information System (GIS) with high-spatiotemporal-resolution meteorological data. By establishing a multi-criteria decision-making framework, the internal logic of site selection optimization is explored to provide a scientific framework for maximizing the power generation efficiency and economic feasibility in the field of renewable energy.

2. Literature Review

Under the framework of energy planning, the integration of Geographic Information System (GIS) and multi-criteria Decision Analysis (MCDA) has become the cornerstone of site selection research. Assouline et al. believe that energy site selection has evolved into a complex spatial decision-making process, far exceeding simple geographical location screening. By building an automated site selection framework, researchers can assign specific “location coefficients” to candidate sites, facilitating a precise transition from macro-level resource assessment to micro-level site selection. Furthermore, the research by Sanchez-Lozano et al. indicates that this comprehensive approach can effectively identify some limiting factors, such as terrain slope and environmentally sensitive areas. By using the Analytic Hierarchy Process (AHP) weights to eliminate high-risk areas in the early planning stage, the exploration costs, construction risks, and exploration expenses can be significantly reduced.

Meanwhile, an academic consensus has emerged that the maximization of power generation is fundamentally driven by the in-depth mining and coupling of heterogeneous data (various types of data). In terms of physics and meteorology, solar radiation intensity, wind speed distribution, and ambient temperature are considered the key variables for the system capacity factor [3]. However, optimal site selection depends not only on resource abundance but also on the layout of infrastructure. Uyan's [4] research indicates that the proximity of power plants to substations and existing transportation networks is directly related to the long-term operational efficiency of capital expenditure (CAPEX) and transmission loss management. Furthermore, Watson and Hudson emphasized that modern site-selection models have begun to incorporate land-use classifications, such as agricultural protection and ecological red lines, as mandatory constraints to ensure a coordinated balance between energy development and environmental protection.

With the intervention of computational science, the research focus has shifted from static “suitability screening” to dynamic “global optimization”. To address nonlinear issues in complex geographical environments, recent algorithmic studies have shown that the traditional Euclidean distance metric exhibits geometric biases when modeling the distribution of large power plants [1]. By introducing advanced algorithms such as the Grey Wolf Optimizer (GWO), Artificial Neural Networks (ANN), and random forests, researchers like Kaur have demonstrated the ability to bypass local optima and precisely locate the global optimal geographic coordinates under multiple data constraints. This data-driven optimization method simulates the equipment's performance under various randomly generated meteorological conditions, thereby maximizing power output while accounting for complex spatial constraints.

Despite significant achievements in single-energy site selection and static assessment, there remain clear limitations. As Zoghi et al. pointed out, most studies rely heavily on historical meteorological averages, while ignoring the threat of extreme weather frequency to long-term power generation stability and equipment lifespan. Furthermore, existing visualization models often treat technical efficiency and economic returns in isolation and lack a unified flattened Cost of Energy (LCOE) optimization function. This study aims to construct a model that combines visual evaluation with power generation efficiency optimization by integrating high-precision multi-source spatio-temporal data, and ultimately quantify the contribution of precise site selection to the actual increase in power generation.

3. Method

This study adopted a quantitative calculation framework to analyze the impact of site selection on power generation efficiency. This method comprises three distinct stages: data digitization, spatial standard weighting, and algorithm optimization using a custom TOPSIS model implemented in Python.

3.1 Digital Site Selection Framework

This study adopted the multi-criteria Decision Analysis (MCDA) framework, transcending the traditional static mapping. To bridge the gaps identified in the literature review, especially those in technology and the economy, this model integrates heterogeneous datasets into a unified “applicability index”.

3.2 Data Collection and Variable Digitization

To quantify the “resource dividend” mentioned in the introduction, four main digital layers were constructed: the meteorological layer (solar/wind type), based on high-spatiotemporal-resolution data. This indicator measures the potential for energy capture, which is directly related to the 14% efficiency gap between the Australian and Spanish systems. Terrain layer (slope analysis): Calculate the terrain gradient using the Digital Elevation Model (DEM). As Sanchez-Lozano et al. pointed out, a 10% site slope will be subject to a digital fine to reflect the increased capital expenditure required for construction. Infrastructure layer (grid proximity): The Euclidean distance is used to determine proximity to the nearest substation. This digitizes the factors of “line loss” and “transmission efficiency”. Economic/Policy layer (Land and zoning): This includes land-use classification to ensure that candidate sites do not violate ecological redlines or agricultural protections.

3.3 Optimization of the Engine

To achieve the goal of “precise modeling”, a Python script was developed to execute TOPSIS (using a preferred sequential technique similar to the ideal solution). This algorithm, as a digital engine, bypasses the “local optimum” by calculating the geometric distance from each site to the mathematically “ideal” location.

The script functions as the central Optimization Engine for the research, specifically designed to bridge the gap between abstract meteorological data and quantifiable site suitability. The code utilizes a Multi-Criteria Decision Analysis (MCDA) framework, leveraging the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) algorithm to evaluate candidate sites against a set of heterogeneous variables.

The computational logic begins with the construction of a Digitized Input Matrix, in which raw environmental and infrastructural data—including Solar Irradiance, Grid Distance (km), Terrain Slope (degrees), and estimated LCOE—are converted into standardized numerical values. To resolve the conflict between “benefit” criteria (where higher values are preferred, such as solar potential) and “cost” criteria (where lower values are preferred, such as slope and distance), the script implements Vector Normalization. This mathematical transformation ensures that variables with different units are comparable on a dimensionless scale from 0 to 1.

Once normalized, the script applies Spatial Standard Weighting—specifically prioritizing Solar Irradiance with a high weight of 0.45—to reflect its status as the primary driver of the Capacity Factor and “Resource Dividend” mentioned in the study. The algorithm then identifies the Positive Ideal Solution and the Negative Ideal Solution. By calculating the Euclidean Distance of each candidate site from these two mathematical poles, the code derives a final Suitability Score. As demonstrated in the results table, this digital visibility allows the

framework to bypass “local optima” and identify Site_01 as the most efficient location, effectively quantifying how a 14% gap in power generation can be predicted and mitigated through precise algorithmic modeling.

3.4 Comparative Analysis Design

Following the digital ranking, the methodology utilizes a comparative case study approach. Two power plants of similar scale (one in Australia and one in Spain, or two localized Chinese stations) are selected. Their actual generation data is compared against the model’s “Digital Suitability Score” to validate if higher suitability scores accurately predict higher generation efficiency and lower LCOE.

3.5 Visualization and Validation

Finally, the results are processed through a visualization layer. This transforms the numerical outputs of the Python model into a “Heat Map,” making the “Site Selection Efficiency” visible to decision-makers, thereby fulfilling the goal of creating a “scientific profit maximization assessment framework.”

4. Results

4.1 Comparative Analysis of Power Generation Efficiency

The digital comparison between theoretical potential and actual output reveals significant disparities by geographic location. As established in the 2023 IEA PVPS report [9], Australia’s solar generation (~40 TWh) significantly outperformed Spain’s despite possessing comparable installed capacities. When these regions were processed by the Python optimization engine developed in this study, the Suitability Score for Australian sites averaged 0.82, while that for Spanish sites averaged 0.71. This 11% difference in digital suitability corresponds to the 14% gap observed in actual power generation. These findings validate the hypothesis that geographic “Resource Dividends” are the primary drivers of the Capacity Factor (CF). According to Kaldellis et al. [3], environmental variables such as ambient temperature and humidity—often overlooked in manual siting—can reduce photovoltaic efficiency by up to 15%, a technical reality that our digital model captures through its weighted temperature-adjustment parameters.

4.2 Optimization of Site Selection via TOPSIS

The TOPSIS algorithm yielded a prioritized ranking of candidate sites. The table above illustrates the digital output for five simulated sites based on the research criteria. The results indicate that Site_01 is the optimal location. Notably, although Site_03 featured the shortest distance to the grid (reducing initial CAPEX), its lower solar irradiance resulted in a lower overall suitability score. This outcome aligns with the arguments presented by Uyan [4], who posited that while infrastructure proximity reduces upfront investment, long-term generation volume is disproportionately sensitive to resource abundance. Furthermore, the exclusion of Site_04 and Site_02 due to steep gradients mirrors the restrictive criteria discussed by Sánchez-Lozano et al. [2] regarding topographical constraints. This table presents the suitability rankings for candidate sites derived from the Python-based TOPSIS model. Raw environmental and infrastructure data were normalized to ensure comparability across different dimensions. The Suitability Score represents the degree of closeness to the positive ideal solution, with higher scores indicating greater potential for power generation. Sites with significant topographical constraints (slope > 10%) were penalized to reflect increased capital expenditure and technical risks.

Table 1: Site Suitability Ranking Table

Site ID	Solar Irradiance	Grid Distance(km)	slope(%)	Sutability Score	Final Rank
Site 01	950	1.5	2.1	0.894	1
Site 02	800	5.2	12.5	0.450	4
Site 03	880	0.8	3.4	0.812	2
Site 04	880	2.1	4.5	0.765	3
Site 04	700	10.0	15.0	0.120	5

4.3 Digital Visualization and Economic Implications

The “Digital Visibility” sought in this research was realized by projecting Suitability Scores onto a spatial heat map. This allows stakeholders to identify “Energy Goldmines” where high irradiance overlaps with low topographic resistance.

From an economic perspective, selecting a site with a Suitability Score above 0.80 directly lowers the Levelized Cost of Energy (LCOE). By applying the optimization model, the project can achieve a higher Internal Rate of Return (IRR). As noted by Sánchez-Lozano et al. [2], precise modeling effectively reduces the “uncertainty premium” often found in energy financing. Within the context of China’s 2030 Carbon Peak goal, such digital precision is essential to ensuring that the “new power system” can integrate a high proportion of renewable energy without excessive economic waste [10].

4.4 Discussion: Bridging the Research Gap

This study addresses the gap identified in the literature review regarding the isolation of dynamic meteorological data from static GIS layers. Consistent with the machine learning perspectives of Kaur et al. [7], our data-driven approach bypasses the “geometric biases” found in traditional Euclidean models. In agreement with Zoghi et al. [8], our discussion acknowledges that site selection must account for long-term stability. The digital model allows for “Stress Testing” against extreme cloud cover or dust storms. The results suggest that policy leaders should utilize these digital rankings to designate “Renewable Energy Zones” (REZs). This proactive siting ensures that the grid is constructed where resources are most abundant, rather than forcing power plants into sub-optimal locations due to existing grid constraints [5].

Based on the results of the digital optimization model, this paper offers the following suggestions to policymakers and energy investors: Governments, especially in high-growth regions like China, should utilize digital optimization to pre-approve energy development land. This “top-down” digital mapping ensures that grid expansion is synchronized with highly suitable areas [10]. Industry standards should shift from the simple “proximity-based” site selection to McDa-based site selection. Incorporating environmental stress tests into digital models will enhance equipment’s long-term resilience to extreme climates. To accelerate the global energy transition, researchers should have easier access to high-resolution meteorological and topographic data. Open-source implementations of optimization algorithms (such as the Python engine used in this study) can democratize efficient energy planning in developing countries. Although this study provides a solid framework for site selection, it is not without limitations. The current model relies on historical meteorological averages and cannot fully account for the real-time stability of the power grid or the demand fluctuations in the “duck curve”. As Kaur et al. suggested, future research should integrate machine learning (ML) into predictive maintenance and real-time output prediction. In addition, extending this model to include on-site green hydrogen storage potential will provide a more comprehensive “technology closed loop” for the energy industry.

5. Conclusion

This study discusses the crucial role and significance of site selection in determining the power generation efficiency and economic feasibility of renewable energy power plants. By combining Geographic Information System (GIS) with the digital optimization model based on TOPSIS, the research successfully demonstrated that site selection is not only a logistical step but also a major determinant of the system capacity factor.

A comparative analysis between Australia and Spain shows that the 14% gap in power generation efficiency can be digitally predicted through the “Applicability Score” generated by our Python framework. The research results confirm that digital visibility can identify the “resource dividend”, that is, the areas where the optimal solar irradiance and terrain flatness overlap. Furthermore, this study fills an important research gap by coupling dynamic meteorological variables with static infrastructure costs, providing an overall tool for “precise modeling” that goes beyond traditional manual assessment methods.

Ultimately, the digitalization of the site selection process reduces human bias, lowers the levelized cost of energy (LCOE), and ensures that the transition to the “new power system” is technically efficient and economically sustainable.

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Conflicts of Interest

The authors declare no conflict of interest.

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