

Article

Photovoltaic Panel Identification and Potential Assessment Based on Remote Sensing and Deep Learning: A Case Study of Yancheng City

Jiayi Wu ¹, Lu Shi ², Kun Wu ^{1,3}, Xiaochen Zhu ^{1,*}  and Rangjian Qiu ⁴

¹ Jiangsu Provincial University Key Laboratory of Agricultural and Ecological Meteorology, Nanjing University of Information Science and Technology, Nanjing 210044, China; jiayi_wu@nuist.edu.cn (J.W.); kun_wu@nuist.edu.cn (K.W.)

² Xiangshui Meteorological Bureau, Yancheng Meteorological Bureau, Yancheng 224600, China; ceeyes_sl0509@163.com

³ School of Ecology and Applied Meteorology, Nanjing University of Information Science and Technology, Nanjing 210044, China

⁴ State Key Laboratory of Water Resources Engineering and Management, Wuhan 430072, China; qiurangjian@whu.edu.cn

* Correspondence: xiaochen.zhu@nuist.edu.cn

Highlights

What are the main findings?

- UNet outperforms PSPNet and DeepLabV3+ across rooftop, water, and bare land, achieving IoU > 94% for all surface types.
- A total of 26.56% of Yancheng's PV area (18.89 km²) lies within ecological protection zones, revealing a major spatial conflict.

What are the implications of the main findings?

- The model comparison offers practical guidance for selecting deep learning architectures tailored to different surface types in PV mapping.
- The quantified ecological conflict underscores the necessity of integrating conservation constraints into PV potential assessments for sustainable planning.

Abstract

The rapid expansion of PV power stations necessitates precise spatial mapping and balanced development planning, yet trade-offs between PV deployment and ecological conservation remain underexplored. This study evaluates the spatial distribution and development potential of PV installations in Yancheng City, China, by integrating deep learning, multi-source data, and ecological constraints. Three deep learning models (UNet, PSPNet, and DeepLabV3+) were applied to identify PV panels on rooftops, water bodies, and bare land. PV maps were overlaid with ecological protection zones to quantify spatial conflicts, and the Analytic Hierarchy Process combined with Entropy-Weighted TOPSIS was employed to assess district-level development potential. UNet achieved the highest Intersection over Union (IoU) for rooftops (97.09%), water bodies (95.78%), and bare land (94.79%). The total PV area reached 71.11 km², with rooftops accounting for 60.35%, of which 26.56% overlapped ecological protection zones. Areas suitable for future PV development constituted 8.44% of the city, with Dafeng District, Dongtai City, and Tinghu District exhibiting the highest potential. Resource endowment, particularly building coverage (weight = 0.5410), emerged as the dominant factor. This framework provides a replicable approach for integrating ecological constraints into PV potential assessments and supports region-specific planning in urban and peri-urban contexts.



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Keywords: deep learning; PV; suitability; AHP; TOPSIS

1. Introduction

Solar energy, as one of the most promising renewable energy sources, plays a pivotal role in new energy development [1]. Currently, photovoltaic (PV) power generation dominates solar energy utilization [2–4]. By the end of 2024, China—the world’s largest carbon emitter—had a cumulative installed PV capacity of approximately 887 million kilowatts, with over 200 million kilowatts added that year, generating 838.3 billion kilowatt-hours of electricity [5,6].

The development and utilization of PV power plants encompass aspects such as site identification and extraction [7], suitability analysis [8–10], site selection [11,12], and power generation potential assessment [13,14]. Traditional PV monitoring methods rely heavily on manual sampling and statistical analysis, which are often inefficient, data-intensive, and inaccurate, limiting their ability to meet the rapid development of the PV industry [15,16]. In contrast, remote sensing enables near-real-time detection of land-use changes, and advances in computational algorithms have enhanced the capacity of machine learning to address complex, real-world problems [17]. Consequently, Random Forest (RF), Support Vector Machine (SVM), and their variants have been widely applied for PV extraction from remote sensing imagery [18–21]. While traditional machine learning methods offer computational efficiency, their high false-positive rates in complex environments constrain their generalizability. Recently, deep learning-based semantic segmentation models, particularly UNet, PSPNet, and DeepLabV3+, combined with backbones such as ResNet and EfficientNet, have substantially improved PV recognition accuracy in complex scenarios [22–26]. However, model performance varies across topographies and surface conditions, highlighting the need for systematic evaluation to select optimal single or combined network solutions.

PV suitability assessment has a long research history [12,27–31]. Weighting methods critically affect evaluation reliability. The Analytic Hierarchy Process (AHP) leverages expert knowledge but may introduce subjective bias, whereas the entropy weighting method is objective and reproducible but can overemphasize indicators with low variability [32]. The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) ranks alternatives based on their proximity to ideal solutions and is widely used in multi-criteria decision-making [33]. Hybrid approaches such as AHP-TOPSIS and Entropy-Weighted TOPSIS have become standard. Evaluation indicators typically cover meteorological, topographical, vegetation, and cultural factors but often neglect current development status, ecological protection areas, and land-use policies [34–36]. Integrating current status identification and ecological constraints into potential assessments remains underdeveloped.

The rapid expansion of PV installations poses environmental and ecological risks [37,38]. As a national carbon peaking pilot city, Yancheng, Jiangsu Province, has emerged as a leader in China’s new energy sector. By September 2025, its grid-connected new energy capacity reached 20.34 GW, making it the first city in the Yangtze River Delta region to surpass the 20 GW milestone, with PV accounting for approximately 51% of the total installed capacity [39,40]. At the provincial level, Jiangsu has issued the Implementation Plan for Offshore PV Development and Construction (2025–2030), targeting 10 GW of cumulative grid-connected offshore PV by 2027 and 15 GW by 2030, with 14 projects totaling 10.46 GW planned for Yancheng. At the municipal level, Yancheng has issued the Guiding Opinions on Promoting High-Quality Development of Distributed Photovoltaics, covering the full project lifecycle from planning and grid integration to operation and safety management. However, rapid expansion has created spatial conflicts, particularly between tidal flat PV

development and ecological conservation areas. Initiatives like “fishery–solar synergy” aim to mitigate these conflicts, but coordinating intensive land use with conservation remains challenging. Regional disparities in PV development further complicate planning. Supported by local policies, Yancheng aims to optimize PV spatial layout, enhance solar resource efficiency, and promote high-quality, sustainable PV deployment through diversified models, such as agrivoltaics and fishery–solar integration, tailored to local resource endowments.

Despite advances, systematic comparisons of deep learning models across diverse land-cover types are lacking, hindering model selection. PV potential assessments often focus on resource endowment while overlooking spatial constraints from ecological conservation. Evaluation frameworks frequently separate “suitability” from “current development status,” leaving a gap in comprehensive assessment from potential identification to spatial implementation. To address these limitations, this study introduces the following innovations:

- (1) Systematic comparison of UNet, PSPNet, and DeepLabV3+ for three land-cover types—rooftops, water bodies, and bare land—revealing model-specific applicability and providing a benchmark that is lacking in studies applying a single architecture or surface type.
- (2) Quantification of spatial conflicts between PV development and ecological conservation by overlaying PV distribution data with the Global Protected Areas Database. This conflict layer is not merely mapped but treated as a binding constraint in subsequent evaluations—a step typically absent from conventional suitability assessments that focus on physical potential alone.
- (3) An integrated AHP-entropy-weighted TOPSIS framework that incorporates current development status, ecological protection, and socioeconomic factors. Unlike resource-oriented assessments that evaluate “where is suitable,” this framework introduces a Development Ratio indicator to distinguish untapped potential from already-used land, shifting the evaluation toward an ecologically coordinated, status-aware approach.
- (4) Comprehensive district- and county-level evaluations and rankings of PV development potential to support differentiated, region-specific planning decisions. Study Area and Data.

1.1. Study Area

Yancheng City, located in the central coastal region of Jiangsu Province (Figure 1), spans from 32°34′ to 34°28′N and from 119°27′ to 121°16′E and covers a total area of approximately 16,900 km². The city administers three districts, five counties, and one county-level city. The terrain is predominantly flat, with an average elevation of approximately 5 m above sea level. Yancheng possesses abundant solar energy resources and hosts well-developed PV applications. Land use is mainly characterized by cropland, water bodies, and built-up areas; consequently, PV installations are distributed across open fields, water surfaces, and building rooftops, offering representative conditions for identifying PV facilities on diverse land-cover types. The region has a subtropical monsoon climate with distinct seasons, abundant sunshine, and precipitation concentrated during the warm season. In addition, Yancheng contains several ecologically sensitive areas, including the Dafeng Milu National Nature Reserve and the Yancheng Wetland Rare Birds National Nature Reserve, making the coordination between ecological conservation and renewable energy development increasingly important. In recent years, Yancheng has actively promoted the photovoltaic industry, leading to the formation of concentrated PV power station

clusters in Dongtai City, Dafeng District, and Tinghu District. These clusters provide a representative basis for assessing county-level PV development potential in this study.

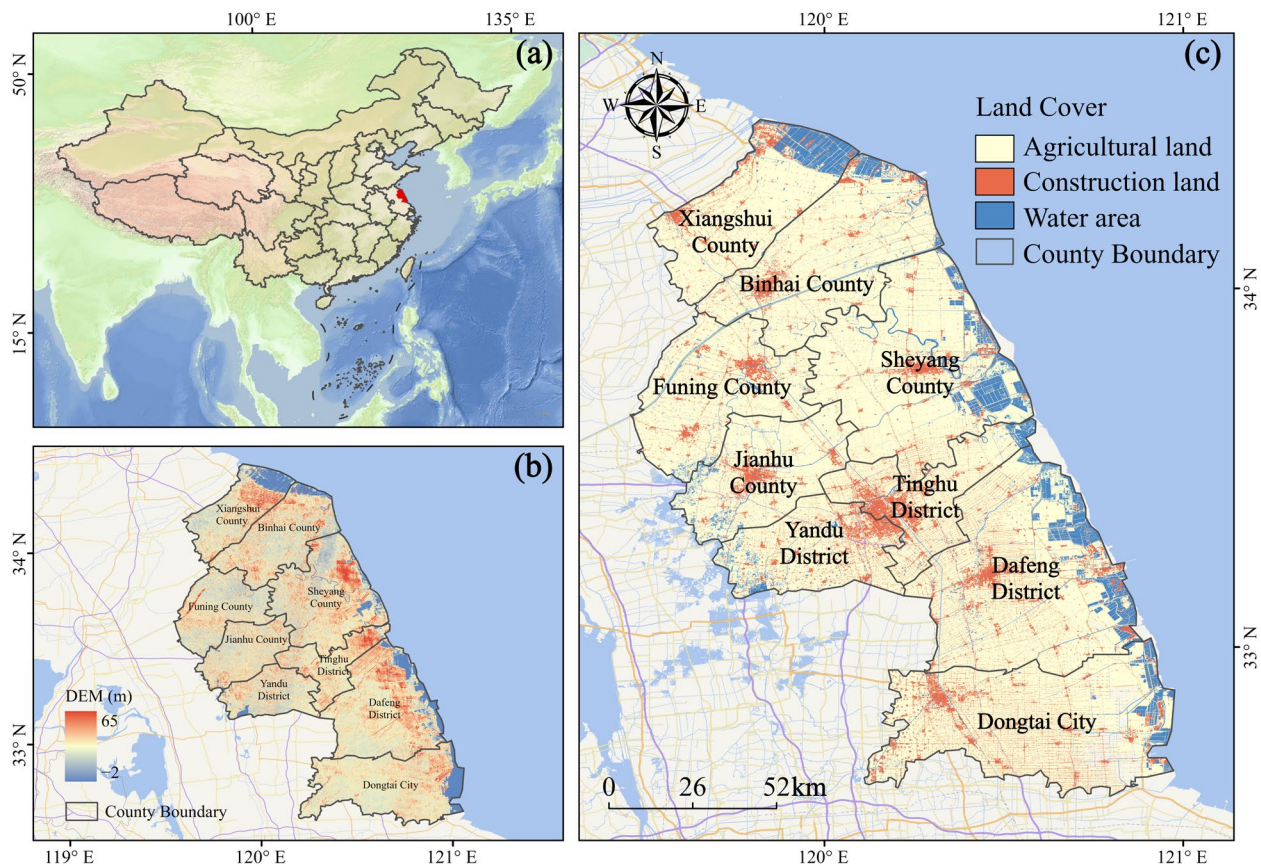


Figure 1. Maps of the study area: (a) location, (b) digital elevation model (DEM), and (c) land use.

1.2. Data

This study integrated multiple data sources, including remote sensing imagery, meteorological data, topographic data, land cover products, ecological protection zone data, and socioeconomic statistics. All datasets were preprocessed and standardized to ensure spatial consistency and analytical comparability.

1.2.1. Remote Sensing Data

Two types of remote sensing imagery were employed for PV identification. Sentinel-2A multispectral imagery provided by the European Space Agency (ESA) was accessed and processed through Google Earth Engine (GEE). Images acquired in 2023 with cloud coverage below 5% were selected, and annual cloud-free composites were generated using a median compositing approach to reduce atmospheric interference and residual cloud contamination. The dataset includes visible, red-edge, near-infrared (NIR), and shortwave infrared (SWIR) bands, with spatial resolutions ranging from 10 m to 60 m. The multispectral characteristics of Sentinel-2 imagery provide strong spectral discrimination capabilities for distinguishing PV panels from surrounding backgrounds such as water bodies and bare land. These data were primarily used to construct semantic segmentation samples for water-surface and bare-land PV installations.

In addition, very-high-resolution (VHR) optical imagery (<0.5 m resolution) from Google Maps was obtained via GEE for 2023. Although the imagery contains only RGB bands, its sub-meter spatial resolution provides detailed structural and textural information that is essential for identifying rooftop PV systems in complex urban environments. The

clear representation of rooftop geometry and panel boundaries enables more accurate discrimination between PV modules and spectrally similar urban features, such as skylights, shadows, and reflective roofing materials. Therefore, the VHR imagery was mainly used to develop rooftop PV identification samples.

1.2.2. Meteorological and Topographic Data

Meteorological and topographic datasets were used to characterize natural conditions related to PV development potential. Annual global horizontal solar radiation data (station-based, interpolated to 1 km resolution) were obtained from the China Meteorological Data Service Center. These data were used to evaluate regional solar energy availability. Topographic information was derived from the GDEM V3 30 m resolution DEM dataset, downloaded from the Geospatial Data Cloud. Based on the DEM, terrain slope and aspect were further extracted to support the assessment of topographic suitability for PV deployment.

1.2.3. Land Cover and Ecological Data

Land cover data were obtained from the ESA WorldCover product (version v200) at a spatial resolution of 10 m. Using spatial overlay analysis, PV installations in Yancheng City were classified into three categories: water-surface PV, bare-land PV, and rooftop PV. This classification framework facilitated the analysis of PV distribution characteristics across different land-use types. Ecological protection zone boundaries were derived from the World Database on Protected Areas (WDPA) through the GEE platform. These data were used to identify environmentally sensitive areas and evaluate potential conflicts between PV development and ecological conservation.

1.2.4. Socioeconomic Data

Socioeconomic data were collected to support the assessment of regional development conditions and energy demand. Key indicators, including Gross Domestic Product (GDP) and population statistics at the district and county levels, were obtained from the Yancheng Statistical Yearbook 2024 [40]. These variables were used to characterize the socioeconomic heterogeneity of the study area and to support the analysis of county-level PV development potential.

2. Methodology

2.1. General Workflow

The overall methodological framework of this study is illustrated in Figure 2. First, Sentinel-2A and Google Maps imagery were acquired and processed on the Google Earth Engine (GEE) platform to construct semantic segmentation datasets for water-surface, bare-land, and rooftop PV installations. Three deep learning models, including UNet, PSPNet, and DeepLabV3+, were trained and evaluated using Intersection over Union (IoU) and F1-score metrics. The optimal model was then applied to extract the spatial distribution of PV installations in Yancheng City and to analyze their spatial overlap with ecological protection zones. Subsequently, the Analytic Hierarchy Process (AHP) was employed to integrate factors such as slope, aspect, vegetation coverage, and land-cover type to generate a PV suitability zoning map and estimate the current development ratio. Finally, an evaluation framework incorporating resource, development, and socioeconomic indicators was established, and the entropy-weighted TOPSIS method was applied to assess and rank the PV development potential of each district and county.

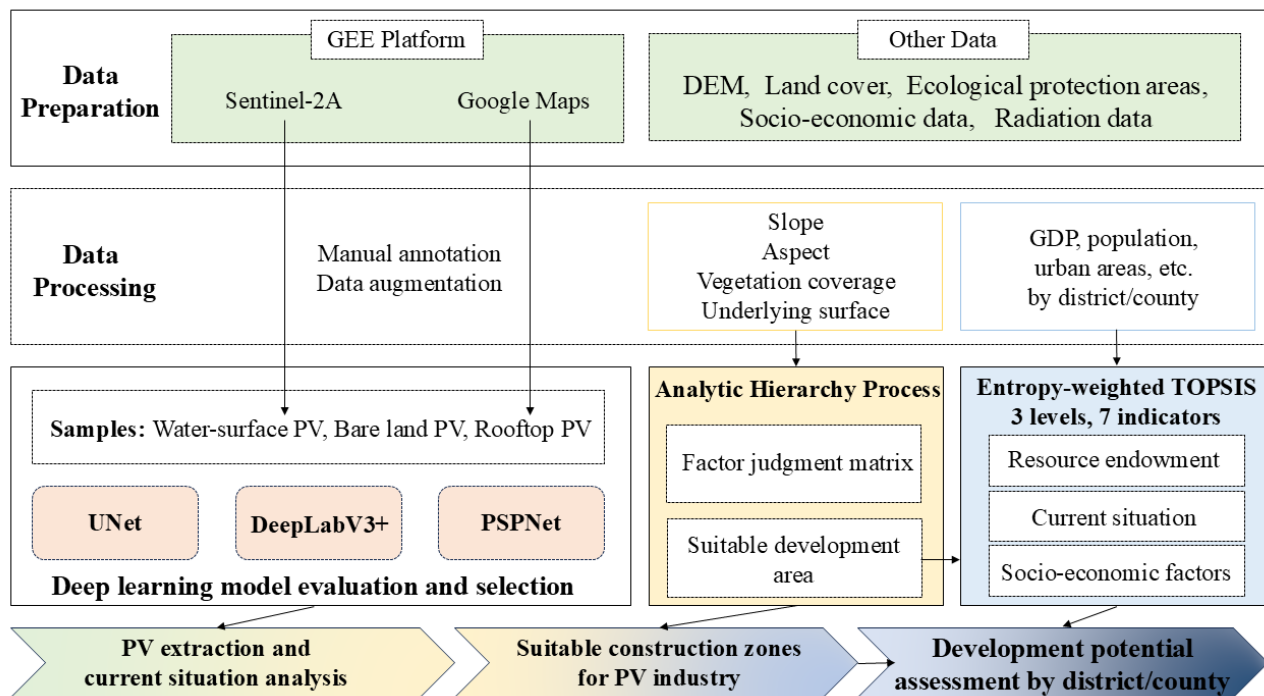


Figure 2. Overall methodological framework for PV identification and potential assessment in Yancheng City.

This framework improves on conventional resource-driven PV assessment in three key ways. First, traditional studies usually treat PV extraction, suitability mapping, and potential ranking as separate tasks. In contrast, our approach links them into a continuous workflow. Deep learning identifies PV locations, AHP produces suitability zones, and spatial overlay calculates development ratios. Each step feeds directly into the next. As a result, our final rankings are based on actual PV patterns observed from data, not on assumptions. Second, while conventional frameworks focus heavily on natural resources, our approach adds two missing pieces. We treat ecological protection boundaries as a firm constraint—not an afterthought—and we introduce a Development Ratio indicator to measure how much suitable land is already in use. Both factors are usually ignored in standard models. Third, most previous studies rely on either subjective weighting or objective weighting, but not both. We use them together: AHP handles suitability zoning, where expert judgment on terrain and land cover matters; entropy weighting handles the TOPSIS ranking, deriving weights objectively from the variation observed across districts.

Taken together, these changes shift the central question. Instead of asking where the best natural conditions are, we now ask the following question: Given current land use, remaining suitable land, and mandatory ecological limits, which districts offer the most realistic and balanced opportunities for near-term PV expansion?

2.2. Selection of Deep Learning Methods for PV Extraction

Deep learning-based semantic segmentation methods have been widely applied in PV extraction from remote sensing imagery because of their strong capability in feature representation and spatial delineation. Kruitwagen et al. [22] demonstrated the effectiveness of integrating heterogeneous remote sensing imagery for large-scale PV mapping, while UNet, PSPNet, and DeepLabV3+ have shown strong performance in remote sensing segmentation tasks [41–43]. Building upon these studies, this research developed a multi-source semantic segmentation framework adapted to the heterogeneous PV scenarios in Yancheng City.

Considering the distinct characteristics of different PV installation types, Sentinel-2 multispectral imagery was used for water-surface and bare-land PV extraction, whereas

sub-meter-resolution Google Maps imagery was employed for rooftop PV identification to preserve fine structural details in urban environments. To ensure labeling consistency and quality, the following guidelines were applied. PV arrays were annotated as polygons along their boundaries, without distinguishing individual panel cells within a contiguous array. Polygonal annotation was performed using Google Earth Pro and the built-in tools of GEE, with reference to high-resolution Google Maps imagery. A minimum mapping unit of 10×10 pixels was adopted to exclude isolated small objects that might introduce noise. The final dataset included 3128 bare-land PV samples, 2288 water-surface PV samples, and 5436 rooftop PV samples, which were divided into training and validation sets at a ratio of 7:3. To improve model robustness and reduce overfitting, online data augmentation strategies, including horizontal, vertical, and diagonal flipping, were applied during training.

UNet, PSPNet, and DeepLabV3+ were selected for comparative analysis because their architectural characteristics match the spatial heterogeneity of PV installations in the study area. UNet is suitable for fragmented rooftop PV extraction due to its ability to preserve fine boundary information. PSPNet performs well in identifying large and continuous PV arrays distributed across open coastal areas by integrating multi-scale contextual information. DeepLabV3+ enhances multi-scale feature extraction through atrous spatial pyramid pooling, making it effective for irregular PV structures under complex land-cover conditions. To ensure a fair comparison, all models were implemented using a unified ResNet-50 backbone.

All experiments were conducted using the PyTorch 2.0.0 framework on a Windows-based workstation equipped with an Intel Core i7-13700H CPU and an NVIDIA GeForce RTX 4060 GPU. The batch size was set to 8, and all models were trained for 100 epochs under identical parameter settings. The loss function combined Cross-Entropy Loss and Dice Loss to simultaneously optimize pixel-level classification accuracy and spatial overlap performance. Model performance was quantitatively evaluated using Accuracy, Precision, Recall, F1-score, and Intersection over Union (IoU), with metrics calculated separately for each PV category to assess segmentation effectiveness under different land-cover conditions.

2.3. AHP-Based Suitability Zoning

To evaluate the spatial suitability of PV development in Yancheng City, an Analytic Hierarchy Process (AHP)-based multi-criteria evaluation framework was established. The AHP method, originally proposed by Thomas L. Saaty [44], provides an effective approach for integrating multiple spatial factors and determining their relative importance through pairwise comparison. Owing to its ability to combine qualitative judgment with quantitative analysis, AHP has been widely applied in land suitability assessment and renewable energy planning studies.

Considering the environmental characteristics of the study area and the spatial requirements of PV deployment, four factors were selected to evaluate PV suitability: slope, aspect, vegetation coverage, and land-cover type. These variables directly influence solar radiation conditions, construction feasibility, and land-use compatibility for PV installations [27]. To ensure comparability among different indicators, all factors were standardized using a nine-point suitability scale, where 1 represents the least suitable condition, and 9 represents the most suitable condition for PV development. This scoring scheme follows the standard practice established in the AHP literature [44,45], and has been widely adopted in previous GIS-based solar site suitability studies [27,29,31,36]. The detailed classification criteria are presented in Table 1.

Table 1. Nine-point suitability classification criteria for aspect, slope, vegetation coverage, and underlying surface type.

Suitability Score	Aspect	Slope (°)	Vegetation Coverage	Underlying Surface Type
1	North	70–90	0.9–1.0	Water body
2	Northeast	60–70	0.8–0.9	
3	East	50–60	0.7–0.8	
4	Northwest	45–50	0.6–0.7	
5	West	–	0.5–0.6	Rooftop
6	–	35–45	0.4–0.5	
7	Southeast	–	0.2–0.4	
8	Southwest	29–35	0.1–0.2	Bare land
9	South	0–29	0–0.1	

A pairwise comparison matrix was established to determine the relative weights of the four evaluation factors. Comparisons were performed using Saaty’s nine-point scale, where a value of 1 denotes equal importance between two factors and a value of 9 denotes extreme importance of one factor over the other. The resulting judgment matrix and the corresponding weight coefficients are presented in Table 2. The results indicate that land-cover type has the greatest influence on PV suitability, followed by slope, aspect, and vegetation coverage. This weighting structure highlights the dominant role of land-use compatibility and terrain conditions in determining the feasibility of PV deployment.

Table 2. Pairwise comparison judgment matrix and AHP-derived weights for four PV suitability factors.

Parameter	Underlying Surface Type	Slope	Aspect	Vegetation Coverage
Underlying Surface Type	1	5	7	7
Slope	0.20	1	3	3
Aspect	0.14	0.33	1	2
Vegetation Coverage	0.14	0.33	0.50	1
Weight Coefficient	0.6431	0.1937	0.0971	0.0661

To verify the logical consistency of the pairwise comparisons, the consistency ratio (CR) was computed. The maximum eigenvalue λ_{max} of the judgment matrix was first determined, and the consistency index (CI) was calculated as:

$$CI = (\lambda_{max} - n) / (n - 1) \quad (1)$$

where $n = 4$ is the order of the matrix. The consistency ratio was then obtained by normalizing CI with the random consistency index (RI) corresponding to $n = 4$:

$$CR = CI / RI \quad (2)$$

For $n = 4$, the standard value of RI is 0.90. The calculated CR value was found to be less than 0.10, confirming that the pairwise comparison matrix exhibits acceptable consistency and that the derived weights are statistically reliable for subsequent spatial overlay analysis.

The obtained factor weights were subsequently integrated into a weighted linear combination model within a Geographic Information System (GIS) environment. Each thematic layer was multiplied by its corresponding AHP-derived weight and summed to produce a continuous suitability index raster for Yancheng City. This suitability index

was then classified into discrete categories to delineate zones of varying suitability for PV industry development.

2.4. Evaluation of PV Development Potential Using Entropy-Weighted TOPSIS

2.4.1. Establishment of the Evaluation Indicator System

The construction of a robust evaluation indicator system for PV development potential requires the integration of multiple interrelated subsystems and mutually independent indicators, thereby capturing the multifaceted nature of the evaluation object from diverse perspectives [46]. Building upon the PV suitability analysis for Yancheng City and adhering to the principles of systematicity, representativeness, scientific validity, and operational feasibility [47], a hierarchical evaluation framework comprising three tiers and seven indicators was established, as summarized in Table 3. All indicators are defined as positive indices, meaning that larger numerical values correspond to greater PV development potential.

Table 3. Photovoltaic development potential evaluation index system.

Tier 1 Indicator	Tier 2 Indicator	Indicator Description
Resource Endowment	Urban area	Approximates the available rooftop area suitable for PV installation.
	Annual horizontal solar radiation	Characterizes the abundance of solar energy resources in each district.
	Suitable development area	Total area within each district identified as suitable for PV development based on the AHP suitability zoning results.
Development Status	Development ratio	Ratio of the existing PV panel area to the total suitable development area within the delineated suitable zones.
Socio-Economic Conditions	Gross regional product (GRP)	Reflects the overall level of economic development and investment capacity of the region.
	GRP per capita	Measures the average affluence of residents and the potential capacity for distributed PV investment.
	Total population	Serves as a proxy for regional electricity demand, which scales with population size.

The first tier, Resource Endowment, encompasses three indicators that characterize the natural and spatial prerequisites for PV deployment: (1) Urban area, which serves as a proxy for the available rooftop surface suitable for distributed PV installation; (2) Annual horizontal solar radiation, reflecting the abundance of solar energy resources across the region; and (3) Suitable development area, derived from the AHP-based suitability zoning results, representing the total land area within each district that is physically conducive to

PV development. The second tier, Development Status, is represented by a single indicator, the development ratio, defined as the proportion of existing PV panel area within the delineated suitable zones relative to the total suitable area. This metric quantifies the current degree of PV utilization in each district. The third tier, Socio-Economic Conditions, comprises three indicators: (1) Gross regional product (GRP), which reflects the overall economic capacity and investment potential of the region; (2) GRP per capita, an indicator of average household affluence and the potential capacity for distributed PV investment; and (3) Total population, which serves as a proxy for regional electricity demand. The adoption of the Entropy-Weighted TOPSIS model for PV potential assessment has been recognized as an effective approach in recent studies.

2.4.2. Determination of Objective Weights by the Entropy Method

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a multi-criteria decision-making method that ranks alternatives according to their proximity to an ideal solution. Its core principle lies in defining a positive ideal solution and a negative ideal solution, and then identifying the alternative that is simultaneously closest to the positive ideal and farthest from the negative ideal [48]. A central step in the TOPSIS framework is the construction of a weighted normalized decision matrix. To avoid the subjectivity inherent in expert-based weighting schemes, the entropy weight method was adopted to derive objective indicator weights. This method determines weights based on the degree of data dispersion: indicators exhibiting greater variability across evaluation units carry lower information entropy and thus receive higher weights, as they contribute more discriminatory information [32]. The computational procedure of the entropy-weighted TOPSIS model applied in this study follows the workflow established in prior work, as detailed below:

Step 1: Construction of the original decision matrix. Let there be m evaluation districts and n evaluation indicators. The original decision matrix is defined as $X = (x_{ij})_{m \times n}$, where x_{ij} represents the original value of the i -th district for the j -th indicator.

Step 2: Data normalization. To eliminate dimensional discrepancies and render indicators comparable, min-max normalization was applied. Since all indicators are positive indices, the normalized value z_{ij} was calculated as:

$$z_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (3)$$

where $\max(x_j)$ and $\min(x_j)$ denote the maximum and minimum values of the j -th indicator across all districts, respectively.

Step 3: Calculation of feature proportion. The proportion p_{ij} of the i -th district for the j -th indicator was computed as:

$$p_{ij} = \frac{z_{ij}}{\sum_{i=1}^m z_{ij}} \quad (4)$$

Step 4: Calculation of information entropy. The entropy value e_j for the j -th indicator was calculated using the following formula:

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^m p_{ij} \ln p_{ij} \quad (5)$$

A larger entropy value e_j indicates a smaller degree of data dispersion and, consequently, a lesser amount of information provided by the indicator.

Step 5: Derivation of entropy weights. The objective weight w_j for the j -th indicator was derived from the information redundancy (degree of diversification) $d_j = 1 - e_j$:

$$w_j = \frac{d_j}{\sum_{j=1}^n d_j} \quad (6)$$

Step 6: Construction of the weighted normalized decision matrix. The normalized matrix Z was multiplied by the weight vector $W = (w_1, w_2, \dots, w_n)$ to obtain the weighted normalized matrix $V = (v_{ij})_{m \times n}$, where

$$v_{ij} = w_j \cdot z_{ij} \quad (7)$$

Step 7: Determination of the ideal solutions. The positive ideal solution V^+ and negative ideal solution V^- were defined as:

$$V^+ = \{\max v_{i1}, \max v_{i2}, \dots, \max v_{in}\} = \{v_1^+, v_2^+, \dots, v_n^+\} \quad (8)$$

$$V^- = \{\min v_{i1}, \min v_{i2}, \dots, \min v_{in}\} = \{v_1^-, v_2^-, \dots, v_n^-\} \quad (9)$$

Step 8: Calculation of Euclidean distances. The Euclidean distance from each district to the positive ideal solution (D_i^+) and to the negative ideal solution (D_i^-) was computed as:

$$D_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2} \quad (10)$$

$$D_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2} \quad (11)$$

A smaller value of D_i^+ indicates closer proximity to the optimal configuration, while a larger value of denotes greater distance from the least desirable state.

Step 9: Calculation of relative closeness. The relative closeness coefficient of the i -th district to the positive ideal solution was calculated as:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (12)$$

The coefficient C_i ranges between 0 and 1. A value approaching unity signifies superior overall PV development potential, whereas a value near zero indicates lower potential. The districts were subsequently ranked in descending order C_i , thereby providing a quantitative basis for identifying priority zones for future PV expansion initiatives.

This approach was applied to evaluate the PV development potential across the nine districts and counties of Yancheng City. By deriving objective indicator weights directly from the degree of data dispersion, the method circumvents the subjectivity typical of expert-based scoring schemes. The subsequent TOPSIS ranking then translates these weighted indicators into a transparent and interpretable framework, enabling a systematic comparison of multi-faceted development potential among administrative units. The resulting closeness coefficients were used to prioritize districts for near-term PV expansion.

3. Results

3.1. Performance Comparison of Deep Learning Models on Different Underlying Surfaces

Three deep learning semantic segmentation models, namely UNet, PSPNet, and DeepLabV3+, were trained and validated using three independent datasets representing rooftop, water-surface, and bare-land PV installations. Under identical experimental settings and hyperparameter configurations, UNet consistently achieved the best performance across all PV scenarios. Its training and validation losses decreased rapidly and converged smoothly with minimal fluctuations, indicating strong training stability and generalization capability. In contrast, PSPNet exhibited noticeable instability in both validation accuracy and loss, suggesting relatively weaker adaptability under heterogeneous land-cover conditions. DeepLabV3+ achieved more stable convergence than PSPNet; however, its overall segmentation accuracy remained lower than that of UNet. The corresponding training and validation loss curves, together with the accuracy trends, are shown in Figure 3.

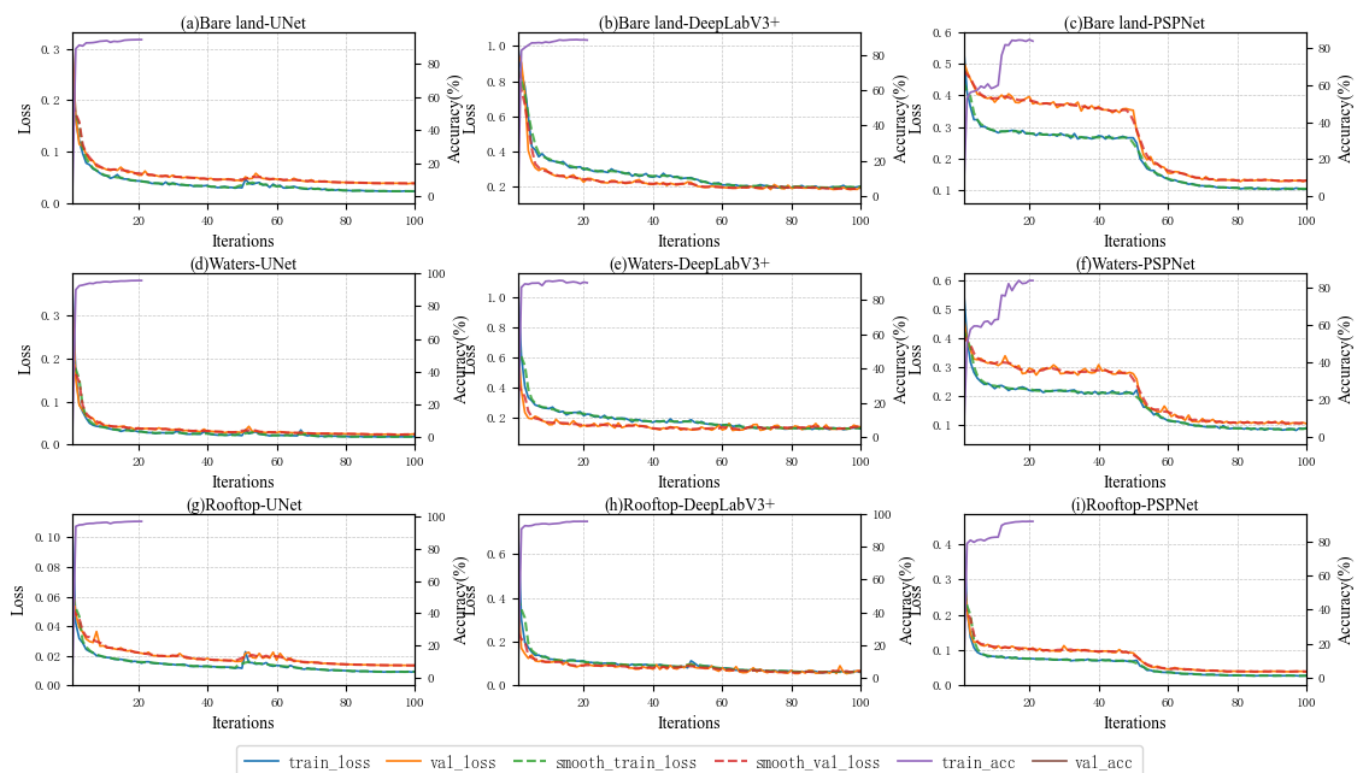


Figure 3. Training loss and accuracy curves of UNet, PSPNet, and DeepLabV3+ for bare-land, water-surface, and rooftop PV datasets.

UNet, PSPNet, and DeepLabV3+ also exhibited noticeable differences in segmentation quality under different PV scenarios. UNet generated the most coherent segmentation results, accurately preserving both the external boundaries of PV installations and fine internal structures such as access roads within PV arrays. DeepLabV3+ performed relatively well in capturing edge information; however, its sensitivity to narrow internal features remained limited. In contrast, PSPNet showed comparatively unstable predictions near image boundaries and frequently produced fragmented regions and isolated patches. Representative segmentation results, together with the corresponding remote sensing imagery and ground truth labels, are presented in Table 4.

Quantitative evaluation metrics, including Intersection over Union (IoU), F1-score, Accuracy, Precision, and Recall, were calculated for each model under the three land-cover conditions. Among the tested models, UNet consistently achieved the highest performance

across all evaluation metrics and PV categories, with IoU values exceeding 94% and F1-scores above 95%. DeepLabV3+ ranked second overall, whereas PSPNet produced the lowest scores in all scenarios. These results further demonstrate that UNet provides superior segmentation performance and better balances classification accuracy, precision–recall trade-offs, and spatial consistency between predicted and reference regions. Detailed quantitative results for each model are presented in Table 5.

Table 4. Qualitative segmentation results of three models on representative remote sensing images, showing original imagery, ground truth, and predictions.

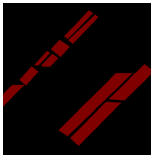
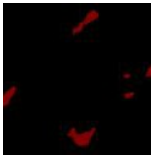
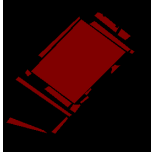
Remote Sensing Image	Ground Truth	Prediction		
		UNet	DeepLabV3+	PSPNet
				
				
				

Table 5. Quantitative evaluation metrics for different models across three land cover types.

Land Cover Type	Model	IoU (%)	F1-Score (%)	Accuracy (%)	Precision (%)	Recall (%)
Bare Land	UNet	94.79	95.43	98.30	95.61	95.26
	DeepLabV3+	88.31	92.45	95.95	92.72	92.18
	PSPNet	76.38	84.43	91.11	85.29	83.58
Water Surface	UNet	95.78	96.04	98.94	96.17	95.91
	DeepLabV3+	92.13	94.42	96.73	94.67	94.17
	PSPNet	83.46	88.38	95.46	89.29	87.48
Rooftop	UNet	97.09	96.79	99.45	96.92	96.99
	DeepLabV3+	95.47	95.76	99.09	95.98	95.54
	PSPNet	91.88	94.68	98.29	95.03	94.33

In summary, the UNet architecture with a ResNet-50 backbone demonstrated robust generalization and segmentation stability across all three underlying surface conditions evaluated in this study. Its consistently high accuracy and spatial precision make it the preferred model for semantic segmentation of PV installations in Yancheng City and, more broadly, for similar large-scale mapping applications over heterogeneous land cover types.

3.2. Spatial Distribution of Existing PV Panels in Yancheng City

Using the UNet model trained in the previous section, PV installations across Yancheng City were extracted from 2023 remote sensing imagery. The identified PV installations covered a total area of 71.11 km². Among the three PV categories, rooftop PV accounted for the largest proportion (60.35%, 42.91 km²), followed by water-surface PV (23.70%, 16.85 km²) and bare-land PV (15.95%, 11.34 km²). In addition, approximately 26.56% of the total PV area (18.89 km²) was distributed within ecological protection zones, indicating a

considerable spatial conflict between PV development and ecological conservation. Spatial distribution patterns further revealed that PV installations were mainly concentrated in Dongtai City, Dafeng District, and Tinghu District, particularly in coastal regions and areas surrounding urban centers. The detailed spatial distribution of PV installations is presented in Figure 4.

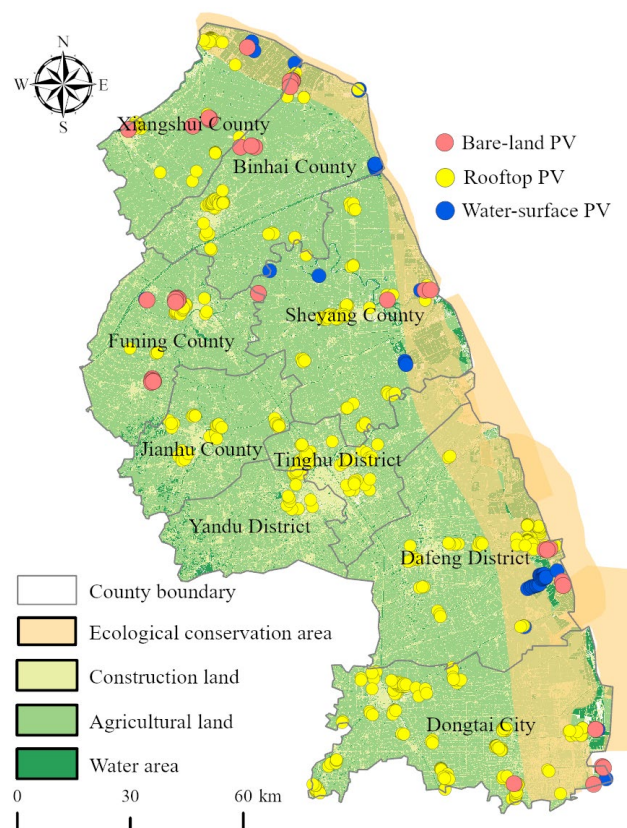


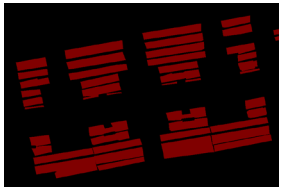
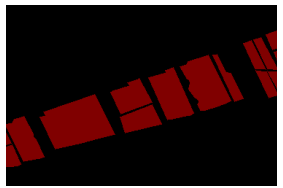
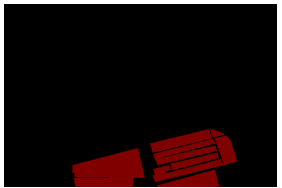
Figure 4. Spatial distribution of PV power stations in Yancheng City, 2023.

Upon close-up examination, the spatial distribution of PV installations in Yancheng exhibits a clear dichotomy. On one hand, rooftop distributed PV systems are scattered across built-up areas as small, isolated patches—limited in individual capacity and loosely arranged, often appearing as fine-grained textures in remote sensing imagery, which makes them relatively challenging to extract. On the other hand, PV facilities on water surfaces and bare land form large, contiguous arrays with orderly layouts. The latter are mostly developed under the “fishery–solar complementary” model—a composite approach that combines electricity generation on the water surface with aquaculture underneath. Spatially, extensive PV arrays interweave with surrounding paddy fields and fishponds, with neatly aligned panels standing above the water while fish and shrimp continue to thrive below, creating a distinctive “aquavoltaic” landscape along Yancheng’s coastal area. Representative examples are illustrated in Table 6.

To further investigate the specific land types involved in ecological conflicts, we conducted a detailed land-cover analysis within the ecological protection zones. Figure 5 presents the spatial distribution of PV installations overlaid with six land-cover categories—vegetation, cropland, built-up, bare land, water bodies, and herbaceous wetland—restricted to these protected areas. The results reveal that within the ecological protection zones, PV encroachment is predominantly concentrated on herbaceous wetlands, water bodies, and bare land, which together account for the majority of the conflicted area. In contrast, cropland and built-up areas show relatively limited overlap. This indicates that the primary

conflict occurs not between PV and urban or agricultural land uses, but between energy infrastructure and coastal wetland ecosystems—particularly tidal flats, salt marshes, and aquaculture ponds—within the protected areas themselves.

Table 6. Representative examples of PV extraction results of UNet for three land-cover types.

	Rooftop PV	Water-Surface PV	Bare-Land PV
Original Image			
Extraction Result			

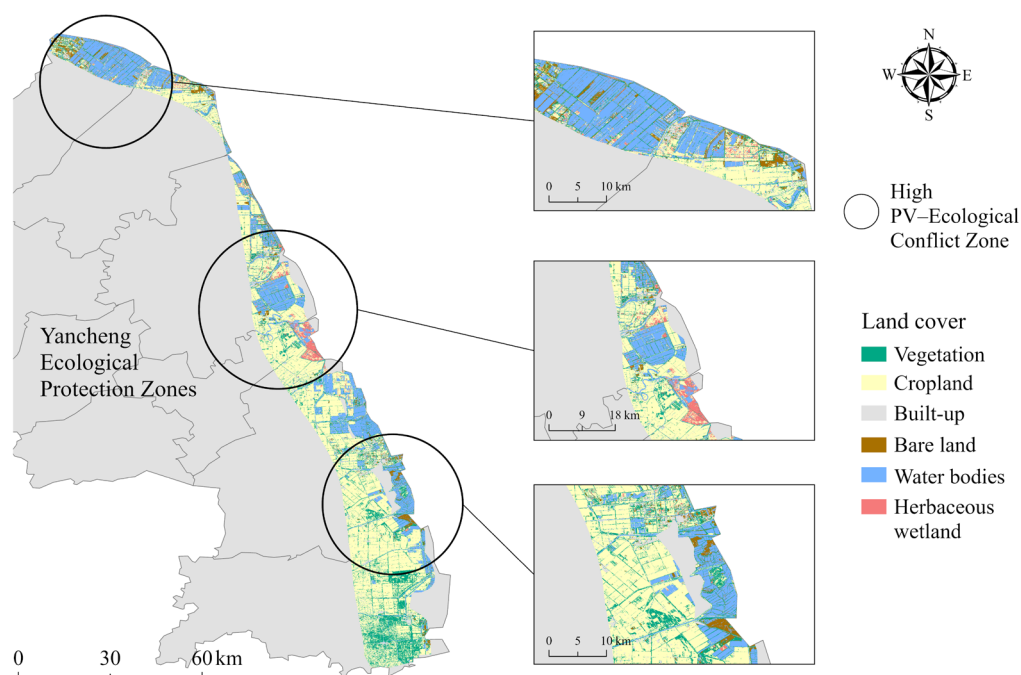


Figure 5. Land-cover composition within major PV–ecological conflict zones in Yancheng.

A district-level statistical analysis of PV area by underlying surface type revealed substantial spatial differences in both development scale and ecological conflict across Yancheng City. Dongtai City recorded the largest total PV area (23.29 km²), followed by Dafeng District (11.10 km²) and Tinghu District (10.30 km²). In terms of ecological conflict, Xiangshui County and Dafeng District exhibited the most significant overlaps between PV installations and ecological protection zones, with conflict areas of 7.94 km² and 7.31 km², respectively. These overlaps were mainly distributed within ecologically sensitive wetland and tidal flat regions. By contrast, Funing County, Jianhu County, Tinghu District, and Yandu District showed no PV development within ecological protection zones. The marked spatial disparities in PV development intensity and ecological constraints indicate that future PV planning should incorporate multiple factors, including existing development

status, suitable land availability, ecological protection requirements, and socioeconomic conditions. Detailed district-level statistics are presented in Table 7.

Table 7. Area of photovoltaic power stations by district in Yancheng City, 2023.

County/District	Rooftop (km ²)	Water Surface (km ²)	Bare Land (km ²)	Total (km ²)	Within Ecological Protection Zone (km ²)
Binhai County	1.23	0.72	0.23	2.18	0.30
Dafeng District	3.87	4.24	2.98	11.10	7.31
Dongtai City	14.35	4.80	4.14	23.29	0.81
Funing County	0.53	0.35	1.51	2.39	0.00
Jianhu County	2.85	0.00	0.00	2.85	0.00
Sheyang County	5.94	1.57	1.40	8.90	2.52
Tinghu District	10.30	0.00	0.00	10.30	0.00
Xiangshui County	2.30	5.17	1.08	8.55	7.94
Yandu District	1.55	0.00	0.00	1.55	0.00
Total	42.91	16.85	11.34	71.11	18.89

3.3. Suitability Zoning for PV Development

A PV suitability zoning map for Yancheng City was generated using a weighted linear combination of four factors derived from the Analytic Hierarchy Process (AHP), including aspect, slope, vegetation coverage, and land-cover type. The results indicate that suitable areas for PV development account for approximately 8.44% of the total land area. These areas are mainly characterized by south-, southeast-, or southwest-facing slopes, terrain gradients between 0° and 10°, and vegetation coverage below 0.4. In contrast, unsuitable areas are primarily associated with cropland and regions of dense vegetation, where large-scale PV construction may negatively affect existing ecological conditions. Spatially, highly suitable zones are mainly distributed in Dafeng District, Binhai County, and Dongtai City and are dominated by urban built-up land and coastal development areas. The detailed suitability classification is presented in Figure 6.

District-level analysis of PV suitability revealed substantial differences in both suitable land availability and current development intensity across Yancheng City. Dafeng District possessed the largest suitable area for PV development (705.79 km²), accounting for 20.24% of its total land area, followed by Dongtai City with 233.06 km² (6.55%) and Binhai County with 108.11 km² (5.63%). However, the development ratio, defined as the proportion of existing PV installations located within suitable zones, showed considerable spatial variation. Dongtai City recorded the highest development ratio (6.66%), indicating a relatively strong consistency between current PV deployment and land suitability conditions. Tinghu District (5.19%) and Sheyang County (4.40%) also exhibited comparatively high development levels. In contrast, Xiangshui County had the lowest development ratio (0.79%) despite possessing 83.26 km² of suitable land, suggesting substantial undeveloped potential. Although Dafeng District contains the largest suitable area, its development ratio was only 1.22%, indicating considerable room for future PV expansion. The district-level suitable area and development ratio were subsequently incorporated as key indicators in the comprehensive assessment of PV development potential. Detailed statistical results are provided in Table 8.

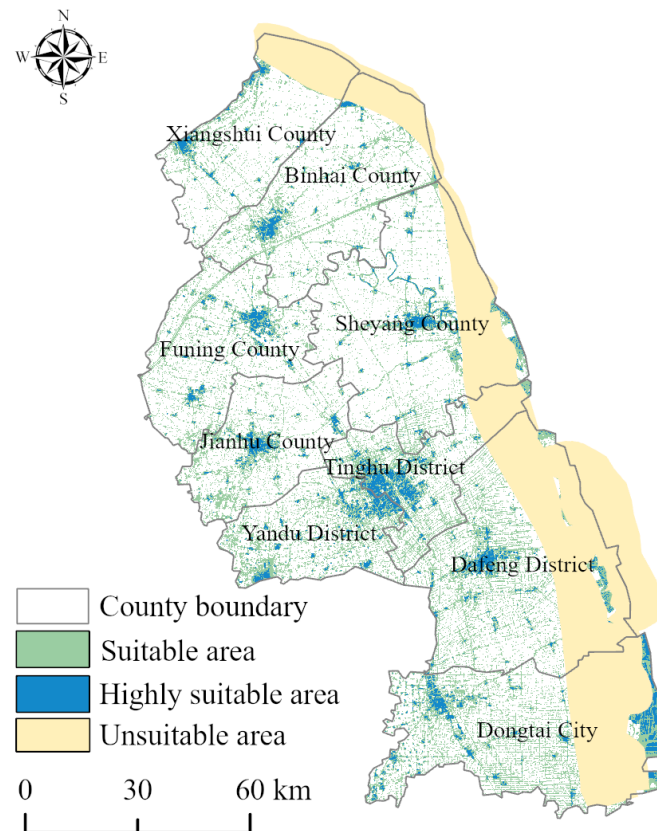


Figure 6. Suitability zoning map for PV industry development in Yancheng City.

Table 8. Suitable area for PV development and current development ratio by district in Yancheng City.

County/District	Suitable Area (km ²)	Total Area (km ²)	Suitable Area Proportion (%)	Existing PV in Suitable Area (km ²)	Development Rate (%)
Binhai County	108.11	1921	5.63	1.51	1.40
Dafeng District	705.79	3488	20.24	8.63	1.22
Dongtai City	233.06	3558	6.55	15.52	6.66
Funing County	64.50	1439	4.48	1.09	1.58
Jianhu County	43.01	1157	3.72	0.93	2.16
Sheyang County	90.48	2573	3.52	3.98	4.40
Tinghu District	59.69	790	7.55	2.94	5.19
Xiangshui County	83.26	1470	5.66	0.65	0.79
Yandu District	80.68	1016	7.94	1.04	1.29

3.4. Comprehensive Development Potential Assessment

An entropy-weighted TOPSIS model was employed to evaluate the comprehensive PV development potential of each district in Yancheng City based on the seven indicators listed in Table 3. The entropy-derived weights indicate that the Resource Endowment criterion has the largest contribution (0.6400), suggesting that differences in natural and spatial conditions are the dominant factors influencing PV development potential across districts. Within this criterion, building coverage area exhibits the highest individual weight (0.5410), highlighting rooftop availability as the most influential factor under the current PV development pattern. The Development Status criterion ranks second with a weight of 0.2775, reflecting substantial inter-district differences in the utilization of suitable land resources. In contrast, Socioeconomic Conditions (0.0522) and Electricity Demand (0.0319)

contribute relatively little to the overall assessment, indicating comparatively small regional differences in economic development and population distribution within Yancheng. In addition, annual horizontal solar radiation receives an extremely low weight (0.0002), which is consistent with the relatively homogeneous solar resource conditions and flat terrain characteristics of the study area. The detailed entropy weights for both the criterion and indicator layers are provided in Table 9.

Table 9. Entropy-based weights of evaluation criteria and indicators for PV development potential.

Criterion	Weight of Criterion	Indicator	Weight of Indicator
Resource endowment	0.6400	Building coverage area	0.5410
		Annual horizontal solar radiation	0.0002
		Suitable development area	0.0989
Development status	0.2775	Development ratio	0.2775
Economic level	0.0522	Gross regional product (GRP)	0.0234
		GRP per capita	0.0287
Electricity demand	0.0319	Total population	0.0303

As revealed by the TOPSIS comprehensive closeness coefficients and criterion-level rankings (Table 10), the PV development potential of districts and counties in Yancheng City exhibits pronounced spatial disparities. Dafeng District ranks first with a comprehensive closeness coefficient of 0.7582, primarily due to its exceptional performance in the resource endowment dimension. This district possesses 705.79 km² of suitable development area, extensive building coverage, and abundant coastal tidal-flat resources, providing favorable natural conditions for large-scale PV deployment. Dongtai City ranks second (0.3893), benefiting from the highest development status and strong economic support, with a GDP of 111.48 billion yuan and a per capita GDP of 108,800 yuan. Tinghu District ranks third (0.2201), supported by a high development status (ranked 2nd) and moderate economic conditions, making it particularly suitable for distributed rooftop PV projects. Sheyang County (0.1965) and Binhai County (0.1010) rank fourth and fifth, respectively.

Table 10. TOPSIS closeness coefficients and rankings of districts by criterion layer and comprehensive potential.

County/District	Resource Endowment		Development Status		Economic Level		Electricity Demand		Comprehensive	
	Closeness	Rank	Closeness	Rank	Closeness	Rank	Closeness	Rank	Closeness	Rank
Binhai County	0.0998	3	0.1036	6	0.1463	9	1.0000	1	0.1010	5
Dafeng District	1.0000	1	0.0733	8	0.7098	2	0.1366	7	0.7582	1
Dongtai City	0.2928	2	1.0000	1	0.8740	1	0.7498	3	0.3893	2
Funing County	0.0327	8	0.1340	5	0.3074	7	0.8048	2	0.0542	9
Jianhu County	0.0000	9	0.2333	4	0.5562	4	0.2247	5	0.0728	6
Sheyang County	0.0849	4	0.6153	3	0.3990	6	0.5337	4	0.1965	4
Tinghu District	0.0639	6	0.7498	2	0.5520	5	0.1154	8	0.2201	3
Xiangshui County	0.0657	5	0.0000	9	0.2806	8	0.0000	9	0.0621	8
Yandu District	0.0584	7	0.0852	7	0.5926	3	0.1556	7	0.0629	7

In contrast, Jianhu County (0.0728), Yandu District (0.0629), Xiangshui County (0.0621), and Funing County (0.0542) exhibit relatively low comprehensive development potential, mainly constrained by limited resource endowment and low development levels. Funing County, a traditional agricultural county, shows the lowest comprehensive closeness coefficient, suggesting that substantial policy support and infrastructure investment will be required for future PV expansion in this area. Overall, these findings provide a quantitative basis for spatially prioritizing future PV development across Yancheng City, identifying Dafeng District and Dongtai City as the most promising key areas for near-term expansion.

4. Discussion

4.1. Comparison with Previous Studies

Here, we first compare the results of this study with those from previous research. We systematically compared the performance of UNet, PSPNet, and DeepLabV3+ across three land cover types, and the results showed that UNet achieved the highest IoU and F1-score in all scenarios (Table 5). This finding aligns closely with the conclusions of Zhao et al. [41] and Li et al. [25], further confirming that the symmetric encoder–decoder structure and skip connections of UNet provide inherent advantages in preserving fine-grained spatial details such as the edges of PV panels. In contrast, PSPNet performed the worst in this study, exhibiting noticeable edge fragmentation, particularly in water and bare land scenes (Table 4), which may be attributed to excessive global context noise introduced by its pyramid pooling module when handling PV targets of vastly different scales. DeepLabV3+ performed well in extracting continuous edges but showed insensitivity to fine textures such as internal access paths within PV arrays, resulting in overall metrics consistently lower than those of UNet. This comparison offers clear guidance for model selection in PV extraction tasks across different surface types.

Regarding the spatial conflict between PV development and ecological protection, this study found that 26.56% of the PV area in Yancheng is located within ecological protection zones (Table 6), a proportion that has not been directly quantified in the existing literature. Previous studies have mostly focused on suitability assessments based on resource endowment [27,29], while overlooking the spatial overlay of existing PV distribution and ecological redlines. For example, Al Garni and Awasthi [27] applied a GIS–AHP approach to evaluate PV site suitability in Saudi Arabia, but their framework did not include an ecological conflict check for existing projects. Similarly, Sun et al. [9] considered geographical constraints when modeling PV expansion potential in China, but did not use the World Database on Protected Areas (WDPA) as a strict constraint layer. Recent studies in other coastal regions facing similar land-use constraints have also begun to address PV–ecology trade-offs. Grace et al. [49] developed a GIS–AHP framework for solar site selection in Thoothukudi, a coastal city in southern India, identifying dual-use opportunities on salt pans and flood-prone areas—an approach that resonates with Yancheng’s “fishery–solar” model. Yuan et al. [50] assessed rooftop PV potential across 349 Chinese cities, showing that eastern coastal cities will see rapid PV expansion by 2050, underscoring the need for multidimensional planning that balances carbon mitigation with land and water constraints. This study fills the gap by directly quantifying the spatial overlap between PV installations and protected areas in a coastal city context, revealing that even within resource-suitable areas, PV development can still exert pressure on ecosystems in the absence of ecological constraints—a conclusion that echoes the discussions of Wu et al. [38] and Hilker et al. [37] on the potential ecological impacts of large-scale PV deployment.

In terms of the comprehensive potential ranking at the district level, this study found that Dafeng District ranks first because of its large suitable development area (705.79 km²), yet it also exhibits the most severe ecological conflict, with 7.31 km² of existing PV located within protected zones. This seemingly contradictory result reveals an important issue: traditional resource-driven assessment frameworks may overestimate the actual developable potential of certain areas. Al-Abadi et al. [32] also reported that different weighting methods can lead to notable shifts in potential ranking when using AHP–TOPSIS and entropy-weighted TOPSIS models to assess PV site potential in Iraq, but their study did not incorporate an ecologically protected area as a constraint indicator. This study juxtaposes development status and ecological conflict.

To assess the robustness of the AHP-derived suitability rankings, we conducted a sensitivity analysis by perturbing the weights of the two dominant factors—underlying

surface type (original weight: 0.6431) and slope (original: 0.1937)—which together account for approximately 84% of the total weight. Two scenarios were tested: a 10% reduction in the surface-type weight (to 0.58) with a corresponding increase in slope weight (to 0.25), and a 20% reduction (to 0.51) with the slope increased to 0.32. The rankings of suitable areas across the nine districts remained virtually unchanged under both scenarios: the top six districts (Dafeng, Dongtai, Binhai, Sheyang, Yandu, and Xiangshui) maintained their relative order, with only minor fluctuations observed among the bottom three low-suitability districts (Tinghu, Jianhu, and Funing). These results indicate that the suitability zoning outcomes are robust to reasonable variations in AHP weight assignments, and that the derived rankings reliably reflect the inherent spatial differentiation of PV development conditions across Yancheng City.

We also checked our extraction results against official planning documents to see if the spatial patterns made sense. According to the Jiangsu Provincial Implementation Plan for Offshore PV Development (2025–2030), Yancheng is set to host 14 offshore PV projects with a total capacity of 10.46 GW, covering about 135.9 km² of sea area [51]. More recently, the city's Green Power Direct Connection Plan for coastal areas named seven key zones for development—including Dongtai Coastal Economic Zone, Dafeng Port Economic Zone, Xiangshui Industrial Zone, and Tinghu Environmental Protection Technology City—with a planned PV capacity of 39.66 GW across these regions [52]. Our extracted PV map (Figure 4) shows that the densest clusters fall right in Dongtai, Dafeng, Xiangshui, and Tinghu, which line up well with the priority areas laid out in the official plans. This spatial consistency gives us more confidence in our extraction results and shows that our findings are in step with the region's planning direction.

4.2. Limitations and Future Directions

Several limitations of this study should be addressed in future work. First, this study used only single-year imagery from 2023, which cannot capture the addition, retirement, or seasonal changes of PV panels. In particular, Kruitwagen et al. [22] demonstrated that time series remote sensing imagery can be used to build a dynamic global inventory of PV installations; future research could incorporate multitemporal Sentinel-2 or Landsat imagery to perform interannual change detection of PV in Yancheng, thereby enabling a more accurate assessment of development speed and trends.

Second, the validation of model generalization performance remains insufficient. Although UNet performed excellently across the three land cover types in Yancheng, its transferability to more heterogeneous geographical environments or imagery from different sensors has not been tested. Future studies should introduce domain adaptation or transfer learning strategies to improve model generalization across multiple regions and imaging sources [25].

Third, the completeness of the potential assessment indicator system needs to be improved. The evaluation framework constructed in this study focuses on resource endowment, development status, and socioeconomic conditions, but does not consider factors such as grid absorption capacity, land use policy restrictions, and social acceptance. In particular, the entropy weight method assigned an extremely low weight (0.0002) to annual horizontal solar radiation, a generally recognized important factor. This result is consistent with the limited spatial variability of solar radiation across Yancheng's flat terrain. However, it also reflects a limitation of the entropy weighting method itself. This method determines weights based on data variability. Thus, indicators with small spatial variation tend to receive low weights, regardless of their physical importance [53,54]. In addition, when entropy values across indicators are all close to 1, small differences in entropy can cause large differences in weights. In our case, the near-zero weight may also be influenced

by data resolution. The solar radiation data are station-based observations interpolated to a 1 km grid. Such a resolution may not capture fine-scale spatial differences, especially in a flat region where interpolation errors can smooth out local variation. Future work should use higher-resolution products, such as satellite-derived data or reanalysis datasets, and consider combining entropy weights with expert judgments.

Fourth, the precision of the suitability evaluation factors can be further improved. The DEM used in this study has a spatial resolution of 30 m; considering the sensitivity of rooftop distributed PV to local slope and aspect, higher-resolution digital surface models (DSM) could be integrated in future work for more refined analysis. Furthermore, the land cover data come from the ESA WorldCover 10 m product, and their classification accuracy in complex urban environments may cause some usable rooftops to be misclassified as non-built-up land, thus underestimating the suitable area within built-up zones.

Last but not least, beyond the CNN-based models evaluated in this study, Transformer-based architectures—including SegFormer, Mask2Former, and Swin-UNet—have recently gained traction in remote sensing segmentation by leveraging self-attention to capture long-range contextual dependencies [45,54]. In PV extraction, these models have shown promising results: Mask2Former achieves over 95% IoU in PV panel segmentation across multi-resolution imagery, outperforming conventional CNN-based models [55], and achieves a recall of 0.95 and an F1-score of 0.936 in detecting smaller and more complex PV layouts [56]; Swin-Transformer-based networks such as DSFA-SwinNet [5] and FT-UnetFormer [57] have similarly demonstrated strong performance in multi-scale PV area detection and module identification. However, these advantages come with substantial computational costs—Transformer models generally require more parameters and inference time than CNNs, and hybrid architectures often entail considerable complexity and large data requirements [45,54]. Given our objective of providing a practically transferable benchmark for PV extraction under constrained computational resources, we focused on the three most established CNN architectures. Nevertheless, we acknowledge that Transformer-based models represent a promising direction for future work, particularly for heterogeneous PV landscapes or low-contrast targets where global contextual reasoning may offer greater benefits [45].

4.3. Policy Implications for Urban Planning

The findings of this study offer important policy implications for PV spatial planning in Yancheng and similar coastal regions. First, differentiated zonal development strategies should be implemented. Dafeng District possesses the best resource endowment, but also the most severe ecological conflict; new PV projects there should strictly enforce the ecological redline spatial access. Dongtai City has the highest development ratio in the city, so its development focus should shift from incremental expansion toward quality and efficiency improvement, such as promoting building-integrated photovoltaics (BIPV) and smart operation and maintenance technologies. Tinghu District, as the main urban area, should vigorously develop distributed rooftop PV, fully leveraging its built-up area advantage. In contrast, Funing County, Jianhu County, and Xiangshui County, as traditional agricultural counties with relatively low comprehensive potential rankings, are not recommended for large-scale centralized PV deployment. Instead, they should explore micro-scale or decentralized development models that are compatible with local agricultural ecology, such as “agrivoltaics” and “fishery–solar integration” [37].

Additionally, ecological constraints should be established as a prerequisite in spatial planning. Our study found that nearly 27% of the existing PV area overlaps with ecological protection zones, indicating that ecological risk assessment was not sufficiently embedded in the spatial decision-making process during previous site approval.

5. Conclusions

This study selected Yancheng City as the research area. Based on Sentinel-2 and Google Maps high-resolution remote sensing imagery, we compared the accuracy of three deep learning semantic segmentation models—UNet, PSPNet, and DeepLabV3+—for identifying PV power stations under different underlying surface conditions. By integrating multi-source geospatial data, the AHP and entropy-weighted TOPSIS models were applied to evaluate the suitability of zoning and development potential of PV across districts and counties, considering both ecological constraints and current development status. The main conclusions are as follows:

- (1) UNet consistently outperformed DeepLabV3+ and PSPNet in the semantic segmentation of PV stations on rooftop, water, and bare-land surfaces. Its symmetric encoder–decoder architecture and skip connections better preserve fine spatial details such as panel edges and internal access roads.
- (2) A considerable proportion of PV panels in Yancheng are located within ecological protection zones, revealing a clear spatial conflict between PV development and ecological conservation. This conflict is most pronounced in Xiangshui County and Dafeng District.
- (3) The AHP-based suitability zoning shows that areas suitable for PV development are concentrated in Binhai County, Dafeng District, and Dongtai City. However, the actual development ratios vary substantially among administrative units, forming a clear gradient of PV exploitation stages. Dongtai has the highest development ratio, while Xiangshui has the lowest.
- (4) The entropy-weighted TOPSIS evaluation reveals that resource endowment is the dominant factor driving PV development potential. Dafeng District ranks first in comprehensive potential, followed by Dongtai City and Tinghu District. Traditional agricultural counties such as Funing, Jianhu, and Xiangshui show relatively lower comprehensive potential and are more suitable for decentralized models compatible with local agro-ecosystems, such as agrivoltaics and fishery–solar integration. The evaluation framework effectively captures the decisive role of resource endowment and the differentiated patterns of development stages and suitable directions among different counties in this region.

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References

- De Castro, C.; Mediavilla, M.; Miguel, L.J.; Frechoso, F. Global Solar Electric Potential: A Review of Their Technical and Sustainable Limits. *Renew. Sustain. Energy Rev.* **2013**, *28*, 824–835. [\[CrossRef\]](#)
- Nikolaidis, P. Solar Energy Harnessing Technologies towards De-Carbonization: A Systematic Review of Processes and Systems. *Energies* **2023**, *16*, 6153. [\[CrossRef\]](#)
- Ahmed, S.; Ali, A.; Ahmed Ansari, J.; Abdul Qadir, S.; Kumar, L. A Comprehensive Review of Solar Photovoltaic Systems: Scope, Technologies, Applications, Progress, Challenges, and Recommendations. *IEEE Access* **2025**, *13*, 69723–69750. [\[CrossRef\]](#)
- Garro-Aguilar, M.; López-González, L.M.; Picallo-Perez, A. A Systematic Review of Current Alternatives for Exploiting Solar Potential in Buildings Considering the Past, Present, and Future. *Int. J. Energy Res.* **2025**, *2025*, 4373291. [\[CrossRef\]](#)
- Zhang, H.; Zhang, X.; Yuan, J. Transition of China's Power Sector Consistent with Paris Agreement into 2050: Pathways and Challenges. *Renew. Sustain. Energy Rev.* **2020**, *132*, 110102. [\[CrossRef\]](#)
- National Energy Administration. *2024 Renewable Energy Grid Connection and Operation Status*; National Energy Administration: Beijing, China, 2025.
- Wang, F.; Liao, Z.; Hou, Y.; Cui, Z.; Wang, Y.; Gong, J.; Yu, H.; Wang, J.; Zhu, Y.; Yu, Q.; et al. SolarSegNet: A Multimodal Frequency-Aware Network for Photovoltaic Power Stations Extraction Using Sentinel-1 and Sentinel-2 Images in Coastal China. *Int. J. Appl. Earth Obs. Geoinf.* **2025**, *142*, 104693. [\[CrossRef\]](#)
- Heinrichs, H.U.; Weinand, J.M.; Kebrich, S.; Gómez Trillos, J.C.; Chen, S.; Hoffmann, M.; Tsani, T.; Chen, R.; Hu, W.; Schmidt, J.; et al. Large-Scale Resource Assessments for Solar Photovoltaics: A Review of Potential Definitions, Methodologies and Future Research Needs. *Renew. Energy* **2026**, *261*, 125080. [\[CrossRef\]](#)
- Sun, Y.; Li, Y.; Wang, R.; Ma, R. Dynamic Geospatial Modeling of Solar Energy Expansion Potential in China: Implications for National-Level Optimization of Solar Photovoltaic Plant Layouts. *Energy* **2025**, *333*, 137433. [\[CrossRef\]](#)
- Liao, Y.; Miao, S.; Fan, W.; Liu, X. A Novel Hybrid Fuzzy Comprehensive Evaluation and Machine Learning Framework for Solar PV Suitability Mapping in China. *Remote Sens.* **2025**, *17*, 2070. [\[CrossRef\]](#)
- Zandi, I.; Lotfata, A. Evaluating Solar Power Plant Sites Using Integrated GIS and MCDM Methods: A Case Study in Kermanshah Province. *Sci. Rep.* **2025**, *15*, 3288. [\[CrossRef\]](#) [\[PubMed\]](#)
- Rane, N.L.; Günen, M.A.; Mallick, S.K.; Rane, J.; Pande, C.B.; Giduturi, M.; Bhutto, J.K.; Yadav, K.K.; Tolche, A.D.; Alreshidi, M.A. GIS-Based Multi-Influencing Factor (MIF) Application for Optimal Site Selection of Solar Photovoltaic Power Plant in Nashik, India. *Environ. Sci. Eur.* **2024**, *36*, 5. [\[CrossRef\]](#)
- Li, X.-Y.; Dong, X.-Y.; Chen, S.; Ye, Y.-M. The Promising Future of Developing Large-Scale PV Solar Farms in China: A Three-Stage Framework for Site Selection. *Renew. Energy* **2024**, *220*, 119638. [\[CrossRef\]](#)
- Hosseini Dehshiri, S.S.; Firoozabadi, B. Sustainable Solar Energy in Urban Areas: A Novel Framework for Uncertainty, Reliability, and 7E Analysis. *J. Clean. Prod.* **2024**, *444*, 141136. [\[CrossRef\]](#)
- Jiang, H.; Yao, L.; Lu, N.; Qin, J.; Liu, T.; Liu, Y.; Zhou, C. Multi-Resolution Dataset for Photovoltaic Panel Segmentation from Satellite and Aerial Imagery. *Earth Syst. Sci. Data* **2021**, *13*, 5389–5401. [\[CrossRef\]](#)
- Wang, X.; Xiao, X.; Zou, Z.; Chen, B.; Ma, J.; Dong, J.; Doughty, R.B.; Zhong, Q.; Qin, Y.; Dai, S.; et al. Tracking Annual Changes of Coastal Tidal Flats in China during 1986–2016 through Analyses of Landsat Images with Google Earth Engine. *Remote Sens. Environ.* **2020**, *238*, 110987. [\[CrossRef\]](#) [\[PubMed\]](#)
- Hou, T.; Sun, W.; Chen, C.; Yang, G.; Meng, X.; Peng, J. Marine Floating Raft Aquaculture Extraction of Hyperspectral Remote Sensing Images Based Decision Tree Algorithm. *Int. J. Appl. Earth Obs. Geoinf.* **2022**, *111*, 102846. [\[CrossRef\]](#)
- Malof, J.M.; Bradbury, K.; Collins, L.M.; Newell, R.G. Automatic Detection of Solar Photovoltaic Arrays in High Resolution Aerial Imagery. *Appl. Energy* **2016**, *183*, 229–240. [\[CrossRef\]](#)
- Jie, Y.; Ji, X.; Yue, A.; Chen, J.; Deng, Y.; Chen, J.; Zhang, Y. Combined Multi-Layer Feature Fusion and Edge Detection Method for Distributed Photovoltaic Power Station Identification. *Energies* **2020**, *13*, 6742. [\[CrossRef\]](#)

20. Bradbury, K.; Saboo, R.; Johnson, T.L.; Malof, J.M.; Devarajan, A.; Zhang, W.; Collins, L.M.; Newell, R.G. Distributed Solar Photovoltaic Array Location and Extent Dataset for Remote Sensing Object Identification. *Sci. Data* **2016**, *3*, 160106. [[CrossRef](#)] [[PubMed](#)]
21. Chen, Z.; Kang, Y.; Sun, Z.; Wu, F.; Zhang, Q. Extraction of Photovoltaic Plants Using Machine Learning Methods: A Case Study of the Pilot Energy City of Golmud, China. *Remote Sens.* **2022**, *14*, 2697. [[CrossRef](#)]
22. Kruitwagen, L.; Story, K.T.; Friedrich, J.; Byers, L.; Skillman, S.; Hepburn, C. A Global Inventory of Photovoltaic Solar Energy Generating Units. *Nature* **2021**, *598*, 604–610. [[CrossRef](#)] [[PubMed](#)]
23. Xie, H.; Li, P.; Shi, F.; Han, C.; Cui, X.; Zhao, Y. Spatial and Temporal Expansion of Photovoltaic Sites and Thermal Environmental Effects in Ningxia Based on Remote Sensing and Deep Learning. *Remote Sens.* **2025**, *17*, 2440. [[CrossRef](#)]
24. Buratti, Y.; Javier, G.M.N.; Abdullah-Vetter, Z.; Dwivedi, P.; Hameiri, Z. Machine Learning for Advanced Characterisation of Silicon Photovoltaics: A Comprehensive Review of Techniques and Applications. *Renew. Sustain. Energy Rev.* **2024**, *202*, 114617. [[CrossRef](#)]
25. Li, L.; Lu, N.; Jiang, H.; Qin, J. Impact of Deep Convolutional Neural Network Structure on Photovoltaic Array Extraction from High Spatial Resolution Remote Sensing Images. *Remote Sens.* **2023**, *15*, 4554. [[CrossRef](#)]
26. Qin, Y.; Wu, Y.; Li, B.; Gao, S.; Liu, M.; Zhan, Y. Semantic Segmentation of Building Roof in Dense Urban Environment with Deep Convolutional Neural Network: A Case Study Using GF2 VHR Imagery in China. *Sensors* **2019**, *19*, 1164. [[CrossRef](#)] [[PubMed](#)]
27. Al Garni, H.Z.; Awasthi, A. Solar PV Power Plant Site Selection Using a GIS-AHP Based Approach with Application in Saudi Arabia. *Appl. Energy* **2017**, *206*, 1225–1240. [[CrossRef](#)]
28. Yilmaz, İ.; Kocer, A.; Aksoy, E. Site Selection for Solar Power Plants Using GIS and Fuzzy Analytic Hierarchy Process: Case Study of the Western Mediterranean Region of Türkiye. *Renew. Energy* **2024**, *237*, 121799. [[CrossRef](#)]
29. Islam, M.R.; Aziz, M.T.; Alauddin, M.; Kader, Z.; Islam, M.R. Site Suitability Assessment for Solar Power Plants in Bangladesh: A GIS-Based Analytical Hierarchy Process (AHP) and Multi-Criteria Decision Analysis (MCDA) Approach. *Renew. Energy* **2024**, *220*, 119595. [[CrossRef](#)]
30. Galib, W.; Al-Timimi, Y.K.; Elhmaidi, D. GIS-AHP for Optimal Solar Site Selection: A Case Study of Iraq and Its Implications for Climate Change. *Int. J. Sustain. Energy Plan. Manag.* **2025**, *47*, 71–89. [[CrossRef](#)]
31. Ouerghi, S.; Al Jadaani, N.; Mohieldeen, Y. GIS-Based AHP Multi-Criteria Mapping of Potential Solar PV Power Plant Development: A Case Study in the Vicinity of Holy Sites, Saudi Arabia. *Sci. Rep.* **2026**, *16*, 17022. [[CrossRef](#)] [[PubMed](#)]
32. Al-Abadi, A.M.; Handhal, A.M.; Abdulhasan, M.A.; Ali, W.L.; Hassan, J.J.; Al Aboodi, A.H. Optimal Siting of Large Photovoltaic Solar Farms at Basrah Governorate, Southern Iraq Using Hybrid GIS- Based Entropy-TOPSIS and AHP-TOPSIS Models. *Renew. Energy* **2025**, *241*, 122308. [[CrossRef](#)]
33. Taherdoost, H.; Madanchian, M. A Comprehensive Survey and Literature Review on TOPSIS. *Int. J. Serv. Sci. Manag. Eng. Technol.* **2024**, *15*, 1–65. [[CrossRef](#)]
34. Chen Jong, F.; Mohamud Ahmed, M. Multi-Criteria Decision-Making Solutions for Optimal Solar Energy Sites Identification: A Systematic Review and Analysis. *IEEE Access* **2024**, *12*, 143458–143484. [[CrossRef](#)]
35. Muhammad, S.; Ali, T.; Khan, Y.; Abdullah, S. Optimal Photovoltaic Location Selection Systems through TOPSIS, AHP, and GIS Techniques: A Case Study in Pakistan. *Eur. Phys. J. Plus* **2024**, *139*, 1070. [[CrossRef](#)]
36. Shi, F.; Li, X.; Li, M.; Bai, B. Site Selection Strategy for Photovoltaic Power Plants Construction on Gangue Hills: An Integrated Method Based on GIS and AHP-TOPSIS. *Energy Strategy Rev.* **2025**, *59*, 101722. [[CrossRef](#)]
37. Hilker, J.M.; Busse, M.; Müller, K.; Zscheischler, J. Photovoltaics in Agricultural Landscapes: “Industrial Land Use” or a “Real Compromise” between Renewable Energy and Biodiversity? Perspectives of German Nature Conservation Associations. *Energy Sustain. Soc.* **2024**, *14*, 6. [[CrossRef](#)]
38. Wu, W.; Chen, H.; Li, C.; Lu, G.; Ye, D.; Ma, C.; Ren, L.; Li, G. Assessment of the Ecological and Environmental Effects of Large-Scale Photovoltaic Development in Desert Areas. *Sci. Rep.* **2024**, *14*, 22456. [[CrossRef](#)] [[PubMed](#)]
39. Department of Resource Conservation and Environmental Protection, National Development and Reform Commission. 2024 *National Carbon Peaking Pilot (Yancheng) Construction Experience*; Department of Resource Conservation and Environmental Protection, National Development and Reform Commission: Beijing, China, 2024.
40. Yancheng Municipal Bureau of Statistics. *Yancheng Statistical Yearbook 2024*; China Statistics Press: Beijing, China, 2024.
41. Zhao, Z.; Chen, Y.; Li, K.; Ji, W.; Sun, H. Extracting Photovoltaic Panels from Heterogeneous Remote Sensing Images with Spatial and Spectral Differences. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2024**, *17*, 5553–5564. [[CrossRef](#)]
42. Zhao, H.; Shi, J.; Qi, X.; Wang, X.; Jia, J. Pyramid Scene Parsing Network. In *Proceedings of the 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 21–26 July 2017*; IEEE: Piscataway, NJ, USA, 2017; pp. 6230–6239.
43. Chen, L.-C.; Zhu, Y.; Papandreou, G.; Schroff, F.; Adam, H. Encoder-Decoder with Atrous Separable Convolution for Semantic Image Segmentation. In *Computer Vision—ECCV 2018*; Ferrari, V., Hebert, M., Sminchisescu, C., Weiss, Y., Eds.; Springer International Publishing: Cham, Switzerland, 2018; Volume 11211, pp. 833–851.

44. Saaty, T.L. *Multicriteria Decision Making: The Analytic Hierarchy Process; Planning, Priority Setting, Resource Allocation*, 2nd ed.; with New Material Added; The Analytic Hierarchy Process Series; McGraw-Hill: New York, NY, USA, 1988.
45. Reddy, L.V.; Vurubindi, P.; Uyyala, R. A Comprehensive Review of Hybrid CNN-Transformer Architectures for Semantic Segmentation in Urban Remote Sensing Imagery. In *Proceedings of the 2026 6th International Conference on Pervasive Computing and Social Networking (ICPCSN), Salem, India, 6–8 May 2026*; IEEE: Piscataway, NJ, USA, 2026; pp. 1222–1230.
46. Yang, C. Evaluation of Wind Power and Photovoltaic Development Potential Based on Entropy Weight TOPSIS Model. *Acta Energaie Solaris Sin.* **2022**, *43*, 70–78. [[CrossRef](#)]
47. Li, F.; Gan, Y. Research on the Sustainable Development Capability of Chinese Rural E-Commerce Based on Multidimensional Perspective. *Sci. Rep.* **2025**, *15*, 11547. [[CrossRef](#)] [[PubMed](#)]
48. Hwang, C.-L.; Yoon, K. *Multiple Attribute Decision Making; Lecture Notes in Economics and Mathematical Systems*; Springer: Berlin/Heidelberg, Germany, 1981; Volume 186.
49. Grace, C.A.Z.; Soundranayagam, J.P.; Promilton, A.J.A.A.; Karupppannan, S.; Alkhurairi, W.S.; Pitchaimani, V.S.; Nahas, F.; Youssef, Y.M. Integrating Remote Sensing and Geospatial-Based Comprehensive Multi-Criteria Decision Analysis Approach for Sustainable Coastal Solar Site Selection in Southern India. *ISPRS Int. J. Geo-Inf.* **2025**, *14*, 377. [[CrossRef](#)]
50. Yuan, Q.; Meng, F.; Hu, Y.; Zhang, L.; Puppim De Oliveira, J.A.; Hao, Y.; Yang, Z. Future Rooftop Photovoltaics Will Weaken Carbon Mitigation but Offer Promising Water and Land Benefits. *Nat. Commun.* **2026**, *17*, 4417. [[CrossRef](#)] [[PubMed](#)]
51. Jiangsu Provincial Development and Reform Commission. *Implementation Plan for Offshore PV Development and Construction in Jiangsu Province (2025–2030)*; Jiangsu Provincial Development and Reform Commission: Nanjing, China, 2024.
52. General Office of Yancheng Municipal People’s Government. *Notice on Improving Green Power Direct Connection in Coastal Areas of Yancheng City*; Yancheng Municipal People’s Government: Yancheng, China, 2025.
53. Chen, L.; Wang, X.; Wang, Y.; Gao, P. Improved Entropy Weight Methods and Their Comparisons in Evaluating the High-Quality Development of Qinghai, China. *Open Geosci.* **2023**, *15*, 20220570. [[CrossRef](#)]
54. Putty, A.; Annappa, B.; Pariserum Perumal, S. Semantic Segmentation of Remotely Sensed Images for Land-Use and Land-Cover Classification: A Comprehensive Review. *IETE Tech. Rev.* **2025**, *42*, 222–237. [[CrossRef](#)]
55. García, G.; Aparcedo, A.; Nayak, G.K.; Ahmed, T.; Shah, M.; Li, M. Generalized Deep Learning Model for Photovoltaic Module Segmentation from Satellite and Aerial Imagery. *Sol. Energy* **2024**, *274*, 112539. [[CrossRef](#)]
56. Farah, S.; Nait, N.; Saadaoui, H.; Lechgar, H.; Maanan, M.; Maanan, M.; Rghioui, A.; Rhinane, H. Optimizing Photovoltaic Detection in High-Resolution Satellite Imagery Using GIS, DeepLabv3+, and Transformer-Based Models: A Case Study of the Marrakesh-Safi Region. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2026**, *XLVIII-4-W17-2025*, 431–441. [[CrossRef](#)]
57. Lukač, N.; Seme, S.; Sredenšek, K.; Štumberger, G.; Mongus, D.; Žalik, B.; Bizjak, M. Detection and Optimization of Photovoltaic Arrays’ Tilt Angles Using Remote Sensing Data. *Appl. Sci.* **2025**, *15*, 3598. [[CrossRef](#)]

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