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Mapping Rooftop Solar PV Potential through Multi-Source Satellite Data and Deep Learning Models

Diego Fernandez^{1*}, Pablo Moreno¹, Laura Santos²

Abstract

Rooftop solar photovoltaic (PV) systems are playing an increasingly important role in the worldwide shift toward sustainable energy. This development creates a need for precise, high-resolution geospatial assessments of rooftop PV's technical potential for policy formulation and power system planning. To tackle this issue, we introduce a comprehensive framework that integrates various satellite imagery sources with deep learning techniques to estimate rooftop PV electricity generation. The framework employs a deep learning-based inversion to estimate hourly solar radiation from geostationary satellite imagery. It uses an automated segmentation model to identify building footprints from high-resolution satellite imagery. This enables a detailed assessment of available rooftop areas and hourly simulation of power output at a 100 m spatial resolution. A case study conducted in Jiangsu Province shows that the framework works effectively over large regions and can be scaled from specific sites to broader areas across different time scales. Results indicate that the province's rooftop resources offer a potential installed capacity of 245.17 GW, which could generate 290.66 TWh of electricity annually. These findings underscore the substantial opportunity for reducing carbon emissions by expanding rooftop PV deployment.

Keywords Deep learning, Rooftop photovoltaics, Building footprints, Remote sensing, Solar energy

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Introduction

Carbon dioxide (CO₂) emissions represent the primary driver of global warming [1, 2]. The Paris Agreement, signed in December 2015, seeks to limit the rise in global average temperature to well below 2 °C above pre-industrial levels [3]. Against this backdrop, energy conservation and emissions reduction have emerged as central goals for the international community, especially for China, the world's largest emitter of CO₂ [4]. Provincial emission inventories indicate that fossil fuels, particularly coal combustion, account for roughly 80% of China's total CO₂ emissions [5]. Consequently, increasing the share of non-fossil fuels in China's energy mix is a critical step toward achieving carbon neutrality [1, 6].

Thanks to their clean and environmentally benign nature, solar photovoltaic (PV) systems offer valuable pathways for sustainable energy production [7, 8]. In the last ten years, declining costs and supportive policies have fueled rapid growth in the global solar PV sector [9]. By 2020, worldwide installed solar PV capacity had reached 707.5 GW, with China contributing 35.8% of the total [10]. Large-scale ground-mounted PV installations often encounter land-use conflicts with other human activities because they require extensive open areas [11]. This challenge is especially acute in densely populated areas, which often have high electricity demand [12, 13]. Rooftop solar PV, by comparison, avoids land-use competition and can add considerable generation capacity through numerous small-scale installations [14, 15]. It can be

installed on a wide variety of buildings, ranging from residential rooftops of several hundred square meters to expansive industrial and commercial roofs. This allows direct connection to end users, such as individual households, energy communities, cooperatives, and commercial enterprises [14, 16–18]. For these reasons, rooftop PV has received particular interest in China. For instance, the National Energy Administration initiated a pilot program in September 2021 to advance distributed rooftop PV development across counties, cities, and districts [19]. To support policymakers in developing sound strategies for resource use and to clarify the contribution of rooftop PV in displacing fossil fuels, a detailed high-resolution geospatial assessment of its technical potential is crucial.

In general, accurately evaluating rooftop PV technical potential requires local data on building footprints, incoming solar irradiance, and PV system parameters, including panel area, conversion efficiency, and overall system losses [14, 20, 21]. Current approaches for acquiring this information have notable limitations. For example, estimating solar irradiance from ground-based point measurements or simplified model simulations often lacks sufficient spatial coverage and fails to capture short-term variations driven by cloud movement [22, 23]. Regarding available rooftop space, China lacks publicly available building footprint datasets, and neither basic sampling techniques nor statistical models based on multiple variables can ensure reliable accuracy when applied across large regions [16, 24, 25]. While comprehensive building surveys are more reliable, they often rely on Light Detection and Ranging (LiDAR) data, which is difficult and costly to obtain over large areas. Moreover, processing and analyzing such data is complex and labor-intensive [21, 26]. Many existing power generation simulations only assess resource potential without modeling the actual photovoltaic conversion efficiency or system losses [27], or they are limited to assessments at a few chosen sites [28].

With this objective in mind, we aim to establish a broadly applicable framework for conducting geospatial assessments of rooftop PV technical potential. The proposed framework is intended to be economical, highly efficient, and simple to deploy across regional scales. Integrating remote sensing technologies with artificial intelligence is a powerful approach to achieving these aims. Ongoing developments in remote sensing now make it feasible to perform extensive, rapid, and three-dimensional tracking of multiple surface characteristics [29]. Modern geostationary satellites, such as Himawari-8, provide frequent imagery (e.g., at 10-minute intervals) covering wide areas, including East Asia and the Western Pacific, thereby enabling detailed observation of temporal fluctuations in surface solar radiation [30]. Satellite systems offering high spatial resolution, such as the Pléiades constellation, strike an optimal balance between detailed imaging and extensive geographic coverage. They allow multiple daily revisits to any location on the planet, with data becoming available within hours [31], which facilitates reliable identification of building footprints [27, 32]. At the same time, the growing sophistication of deep learning methods and the expanding power of cloud computing platforms enable efficient, automated parallel processing of vast datasets. Deep neural networks have found widespread application in extracting meaningful information for numerous tasks [33–35], and several studies have demonstrated their effectiveness in detecting buildings from satellite imagery [32, 36, 37]. Moreover, research indicates that leveraging freely available satellite data can significantly boost the reliability of PV output predictions [38, 39]. While individual components of rooftop PV potential evaluation have seen notable progress, a single integrated framework capable of addressing all the specified needs has yet to be realized.

To close this gap, the current research proposes an innovative framework for rooftop PV potential assessment that integrates multi-resolution remote sensing data with advanced deep learning methods. Geostationary satellite imagery, characterized by moderate spatial detail but very high temporal frequency, is processed through a deep learning inversion technique to model the space-time behavior of solar radiation, which features strong local consistency alongside fast-changing dynamics. Conversely, high-resolution satellite imagery, offering fine spatial detail but lower revisit frequency, is analyzed via an automated segmentation network to map building footprints that vary considerably across space yet remain relatively stable over time. Finally, a physics-based dynamic simulation approach is applied to determine realistic PV electricity production. The main novelty resides in harmonizing all calculations at an hourly time step and a uniform spatial resolution of 100 m. This setup substantially enhances overall efficiency by enabling distributed computation while allowing straightforward upscaling or downscaling of results to different spatial and temporal levels. Further advancements include integrating attention mechanisms and spatial pyramid pooling to improve rooftop segmentation precision, as well as a hybrid calibration method that combines satellite observations with unmanned aerial vehicle (UAV)

imagery to quantify suitable rooftop areas for PV deployment more accurately. Application of the framework in Jiangsu Province reveals that these combined innovations deliver dependable, high-resolution geospatial estimates of rooftop PV potential, serving as a robust reference for quantifying the associated carbon-emission mitigation benefits. Overall, this study introduces novel directions for combining remote sensing big data with solar energy studies and emphasizes the critical advantages of using multi-resolution remote sensing within the broader energy domain.

Materials and Methods

Study area and data

Given data accessibility and real-world application requirements, Jiangsu Province, China, was selected as the research region. Situated in the downstream areas of the Yangtze River and Huaihe River (**Figure 1**), the province boasts a robust economy and advanced adoption of PV technology. It occupies a total land area of 107,200 km² and is administratively composed of 13 prefecture-level cities along with 95 county-level units. Based on climatic conditions and degree of urbanization, the province can be approximately divided into three zones (northern, central, and southern) along the courses of the two rivers. The northern zone falls under a warm temperate climate, while the central and southern zones belong to the subtropical climate regime. Compared with the northern and central zones, the southern zone shows notably higher urbanization rates and population concentrations.

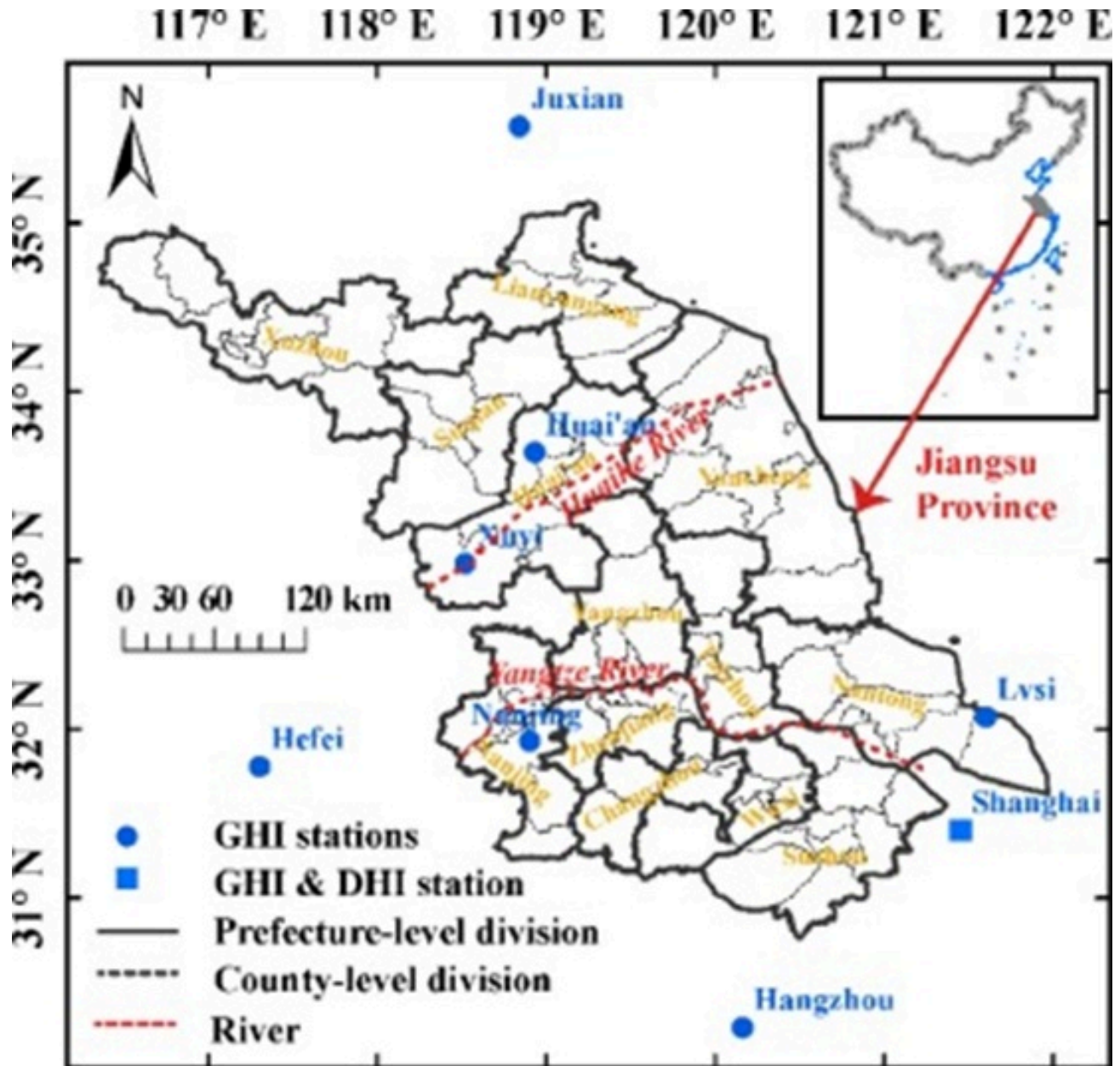


Figure 1. Location and administrative division of Jiangsu Province, China.

Multi-source remote sensing data employed for the potential assessment include visible images from the Multi-functional Transport Satellite (MTSAT-1R), imagery from the Gaofen-2 and Beijing-2 satellites, and unmanned aerial vehicle (UAV) photographs. MTSAT-1R, managed by the Japan Meteorological Agency, maintains a near-fixed position relative to Earth at 104°E above the equator and repeatedly scans the Asia-Pacific region (70 °N–20 °S, 70–160 °E) multiple times per hour. Its visible channel (0.55–0.80 μm) provides ongoing cloud monitoring at a spatial resolution of roughly 1 km, supporting the evaluation of how clouds influence surface solar radiation across space and time. Gaofen-2, belonging to China's High Resolution Earth Observation System (CHEOS), captures surface details at 0.81 m resolution in the panchromatic band and 3.24 m in the multispectral bands. Beijing-2, a three-satellite constellation dedicated to land monitoring, delivers images with a ground sampling distance (GSD) of 0.80 m in panchromatic mode and 3.2 m across the blue, green, red, and near-infrared bands. Together, Gaofen-2 and Beijing-2 provide complementary high-resolution coverage ideal for detailed building footprint mapping. UAV images are acquired through dedicated flight missions using customized equipment. The resulting georeferenced orthophotos achieve a GSD of approximately 0.1 m and a positional

accuracy of approximately 0.02 m. These UAV images enable examination of real-world PV panel arrangements, allowing determination of the proportion of rooftop area occupied by panels and collection of actual installation parameters under operational conditions.

In addition, ground-based measurements of global horizontal irradiance (GHI) from 8 stations (Figure 1) located within or near Jiangsu Province, as well as diffuse horizontal irradiance (DHI) data from the Shanghai station (Figure 1), were gathered for the year 2018. These records are utilized to validate the satellite-derived estimates of incoming solar irradiance. Furthermore, 2 m air temperature data for 2018 from the ERA5-Land project [40] were obtained to represent the surrounding environmental conditions affecting PV systems. The ERA5-Land temperature dataset offers a spatial resolution of about 9 km.

Figure 2 presents the overall framework developed for evaluating the technical potential of rooftop PV systems. Photovoltaic technology converts solar energy into electrical power using semiconductor materials. Consequently, the amount of incoming solar radiation is the dominant factor influencing PV system output. For this reason, we begin by applying a deep learning inversion model to derive hourly solar radiation values from geostationary satellite images, combined with corresponding time and geographic coordinates. Since satellite image sequences reveal the continuous movement of clouds, this approach simultaneously captures both the spatial pattern and temporal fluctuations of surface solar radiation. Such detailed information enables accurate simulation of electricity generation at high spatial and temporal resolutions. Using hourly solar radiation data, along with key solar cell specifications (such as maximum power rating, relative efficiency under standard test conditions, open-circuit voltage, and short-circuit current) and installation geometry (including panel tilt and azimuth angles), a process-based PV simulation model computes the capacity factor. This metric expresses the ratio of actual energy produced over a given period (usually one year, in kWh) to the theoretical maximum output (in kWp) under standard test conditions, defined as 1,000 W/m² at a cell temperature of 25 °C.

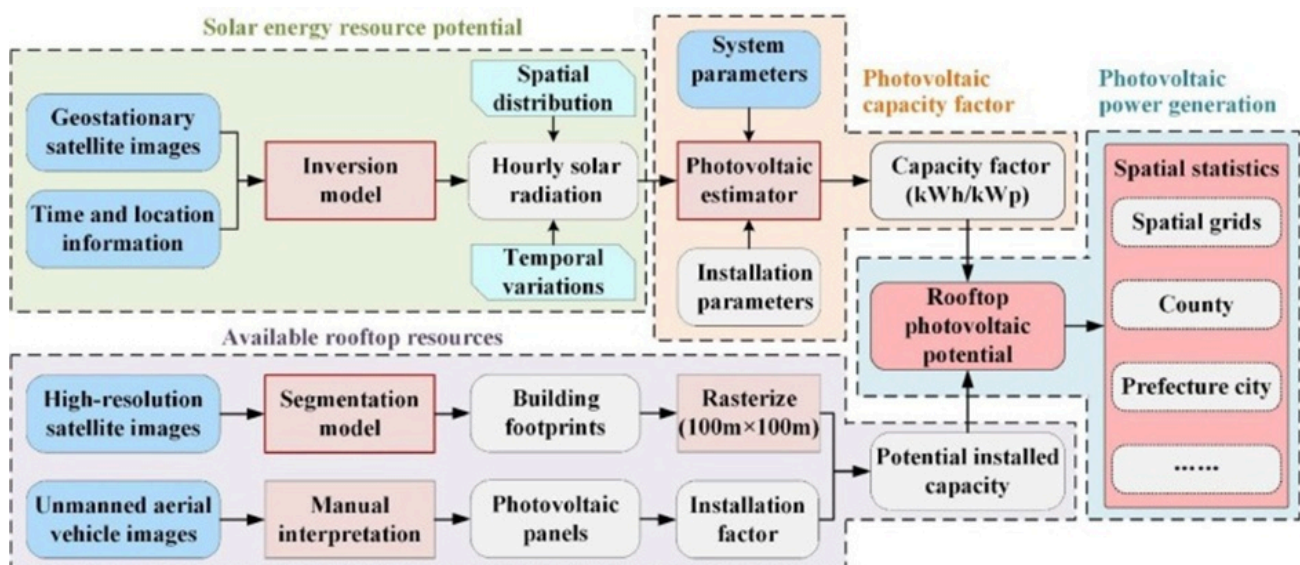


Figure 2. Overall framework for geospatial assessment of rooftop PV technical potential.

The usable area on building rooftops constrains the upper limit of installed PV capacity. In contrast, the actual energy yield per unit of capacity differs substantially across locations owing to variations in solar radiation. Therefore, both the extent and precise position of building rooftops must be determined. We employ an automatic segmentation model to extract building footprints from high-resolution satellite imagery. To support spatial computations, these footprints are rasterized into grid cells, where each cell indicates the proportional rooftop coverage. In real installations, only a portion of the available rooftop surface is used for PV panels, as extra space is needed to reduce shading between panels and to allow for system maintenance and access. In this study, the installation factor—representing the fraction of rooftop area

covered by PV panels per unit area—is derived statistically by analyzing the number and layout of individual panels visible in UAV images. By combining this installation factor with the gridded building footprint data, the potential installed capacity of rooftop PV systems can be estimated for each grid cell.

With the capacity factor and potential installed capacity already calculated, assessing the technical potential of rooftop PV is achieved directly via spatial overlay operations. Because the fundamental computations occur at the pixel level on an hourly timescale, it is straightforward to scale up the estimated power generation to broader geographic or administrative boundaries (e.g., streets, counties, or entire cities) and to different time horizons (e.g., daily, monthly, or yearly totals). In effect, the framework offers scalability from highly localized sites to extensive territories, and from hourly resolution to annual summaries. Furthermore, because the processing logic is uniform across every pixel, the system can be efficiently deployed on high-performance graphics processing unit (GPU) clusters to boost overall computational speed. In essence, the framework delivers both precise, high-resolution geospatial analysis and practical, high-efficiency applications over large areas. More information about the individual models is presented in the sections that follow.

Deep network for solar radiation estimation

Although solar radiation can be measured directly at ground stations, the total number of operational stations remains quite low (e.g., only 133 stations are active across China), and their distribution is often irregular. Because solar radiation exhibits strong spatial heterogeneity, continuous spatial datasets are far more suitable for producing trustworthy PV power generation simulations. In this study, we use a deep learning approach to derive solar radiation estimates from satellite imagery directly. The model is largely based on our earlier work [41], which introduced a deep learning method for retrieving hourly global horizontal irradiance (GHI) from geostationary satellite data. The procedure involves two primary stages: model training and subsequent estimation. In the training phase, matched pairs of satellite observations and ground-measured GHI values are fed into a convolutional neural network (CNN) architecture to learn a complex, nonlinear mapping between satellite signals and actual surface GHI. Once trained, this mapping is applied during the estimation phase to predict GHI from new satellite inputs. After extensive experimentation and iterative parameter refinement, an optimized version of the model was developed for use across China. The resulting fully trained network demonstrates strong performance and excellent spatial generalization. Convolutional neural networks prove particularly adept at capturing local spatial influences on surface radiation and at modeling intricate radiative transfer phenomena, leading to noticeably better accuracy than conventional techniques [41].

The limited availability of ground stations recording diffuse horizontal irradiance (DHI) makes it difficult to assemble a sufficiently large and representative training dataset for that variable. To address this challenge, we introduce a transfer learning strategy tailored for DHI retrieval. At its core, the CNN-based network for GHI estimation comprises two main components: a CNN that identifies cloud patterns in satellite data and a multi-layer perceptron (MLP) that maps the extracted features to the final predicted values [41]. Since the task of recognizing cloud patterns shares fundamental similarities across both GHI and DHI estimation, the CNN module parameters pretrained on GHI data can be transferred and reused. The only additional step required is to fine-tune the MLP module parameters with the modest number of available DHI samples. This strategy has been confirmed to generate realistic spatial patterns of DHI that surpass the quality of typical reanalysis products [42]. Applying the approach, we generated complete hourly GHI and DHI datasets for the year 2018. Performance in Jiangsu Province was then validated against ground measurements collected at the stations shown in **Figure 1**, using standard statistical indicators: correlation coefficient (R), root mean squared error (RMSE), and mean bias error (MBE). In general, the deep learning model delivers solid results, reaching an R value of 0.86 and RMSE of 142.10 W/m² for GHI, and an R of 0.76 and RMSE of 82.62 W/m² for DHI (**Figure 3**). On average, the satellite-derived estimates show a modest underestimation, with MBE values of 19.98 W/m² for GHI and 13.42 W/m² for DHI (**Figure 3**).

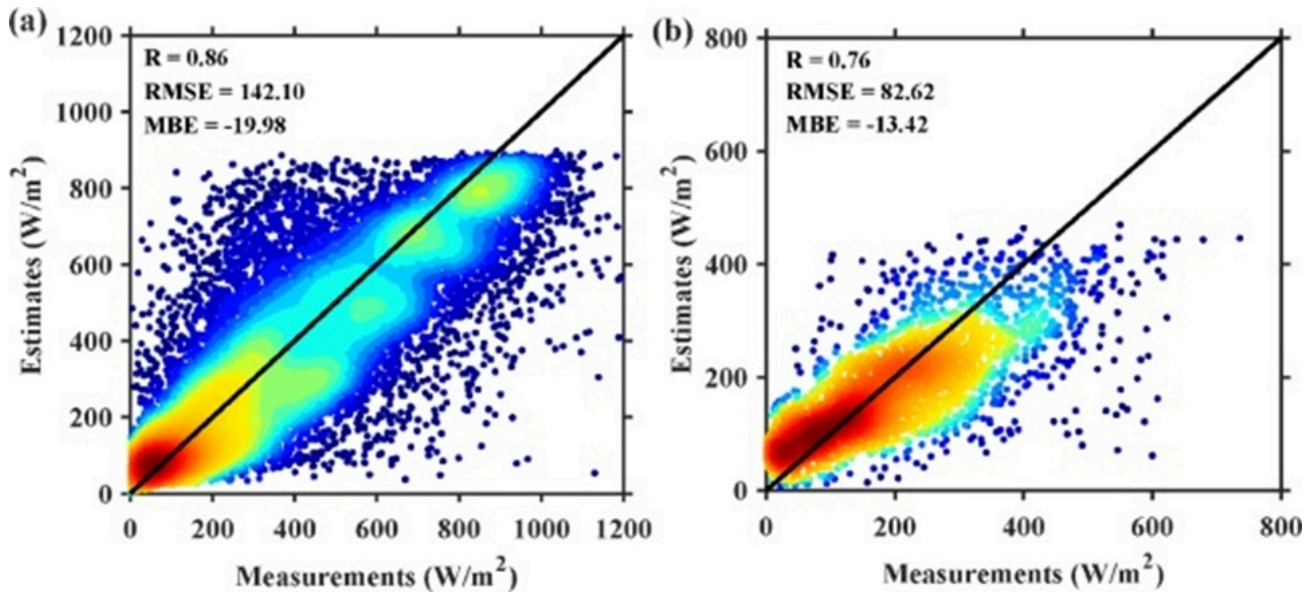


Figure 3. Validation of a deep learning-based inversion model for solar radiation estimation: (a) GHI, and (b) DHI.

Photovoltaic electricity modelling

For simulating PV electricity production, we utilize the open-source Global Solar Energy Estimator (GSEE, available at [www.github.com/renewables-ninja/gsee](https://github.com/renewables-ninja/gsee)). GSEE was developed with an emphasis on speed and simplicity of operation. These attributes are especially valuable when conducting simulations across broad regions or when near-real-time processing is needed. Additionally, GSEE has undergone extensive validation across 1,029 locations [43] and helps prevent inflated results by explicitly incorporating the photoelectric conversion efficiency and various system losses [44]. The model requires hourly GHI and DHI inputs to compute PV power output. The process begins by calculating direct normal irradiance (DNI) according to the following equation:

$$GHI = DHI + DNI \cdot \cos(\theta_z) \quad (1)$$

Where θ_z denotes the solar zenith angle, subsequently, the direct and diffuse components of irradiance on the plane of the array (POA) are determined using the following expression:

$$G = DNI_{POA} + DHI_{POA} \quad (2)$$

$$DNI_{POA} = \frac{DNI \cdot \cos(\alpha)}{\cos(90^\circ - \theta_A)} \quad (3)$$

$$DHI_{POA} = DHI \frac{1 + \cos(\alpha_t)}{2} + \alpha \cdot (DHI + DNI) \cdot \frac{1 - \cos(\alpha_t)}{2} \quad (4)$$

In which G represents the total POA irradiance, α stands for the angle of incidence on the plane, θ_A indicates the solar azimuth angle, α_t is the tilt angle of the PV panel, and α corresponds to the surface albedo (with a default value of 0.3). The incidence angle α is the angle between the incoming solar rays and the PV panel surface. It is computed according to:

$$\alpha = \cos^{-1}[\cos(z)\cos(\alpha_t) + \sin(z)\sin(\alpha_t)\cos(A - \alpha_A)] \quad (5)$$

Where α_A refers to the azimuth angle of the PV panel, expressed in degrees measured eastward from north (for example, North = 0°, East = 90°). The value of G is then further adjusted downward to account for shading, soiling, and reflection losses. A constant reduction factor of 0.98 is applied for these combined effects.

Beyond solar irradiance, the PV module temperature (T_m) also significantly influences power output. Under stable or gradually varying conditions, T_m can be approximated from the ambient air temperature (T_a) and the POA irradiance through the relation:

$$T_m = T_a + cTG \quad (6)$$

Where the coefficient cT indicates the degree to which the PV module is warmed by incoming solar radiation.

Ultimately, the electrical output of the PV system is derived from both G and T_m using the equation:

$$P_{out} = P_s \cdot \frac{G}{G_s} \cdot \eta(G', T') \quad (7)$$

Where P_s denotes the rated power output of the PV system under standard test conditions, defined as $G_s = 1,000 \text{ W/m}^2$ and $T_{ms} = 25 \text{ °C}$. The instantaneous relative efficiency (η) is expressed as:

$$\eta(G', T') = 1 + k_1 \ln G' + k_2 [\ln G']^2 + T' (k_3 + k_4 \ln G' + k_5 [\ln G']^2) + k_6 T'^2 \quad (8)$$

With the normalized variables defined as $G' \equiv G/G_s$ and $T' \equiv T_m/T_{ms}$. The coefficients k_1 through k_6 are obtained by fitting the equation to measured experimental data from one or more test locations. Empirical coefficient values for crystalline silicon (c-Si), Copper–Indium–Diselenide (CIS), and Cadmium Telluride (CdTe) module types have been recommended by Huld *et al.* [45]. In the present simulations, we focus on c-Si modules and incorporate an additional 10% loss to account for the conversion from direct current to alternating current, consistent with findings from European field studies [43]. The coefficient cT is fixed at $0.035 \text{ °C W}^{-1} \text{ m}^{-2}$ as proposed by Huld *et al.* [45], while T_a is taken from the 2 m air temperature dataset provided by ERA5-Land. Throughout the simulation, the installed capacity is set to 1 kWp. This normalization simplifies the conversion of the computed output power (P_{out}) into the corresponding capacity factor.

Multi-scale segmentation model

Accurately outlining the boundaries of building rooftops represents a critical aspect of building footprint extraction, particularly given the wide variety in their sizes, shapes, and orientations [32, 36]. To address this challenge, we developed a multi-scale segmentation model that draws upon established techniques from natural image recognition. This approach strengthens the network's capacity for multi-scale feature extraction, geometric positioning, and detection of small objects. The overall architecture follows a classic U-shaped design (Figure 4a), originally introduced in the Tiramisu model [46] — a fully convolutional network with dense connections tailored for semantic segmentation tasks.

In this structure, the contracting path (encoder) extracts high-level semantic information, while the expanding path (decoder) restores precise spatial details. Within the encoder, we incorporate a dense deformable coordinate convolution block (DDCCB, Figure 4b) to improve feature learning and a pyramid pooling module (Figure 4c) to enable effective fusion of multi-scale information. As the network deepens, the number of convolutional layers within each DDCCB is gradually increased to capture richer feature channels. In the decoder, each upsampling stage includes a 2×2 transposed convolution to enlarge the feature map, followed by concatenation with the corresponding encoder feature map and a subsequent DDCCB to refine localization. This skip connection via concatenation is essential for compensating for the spatial information lost during downsampling.

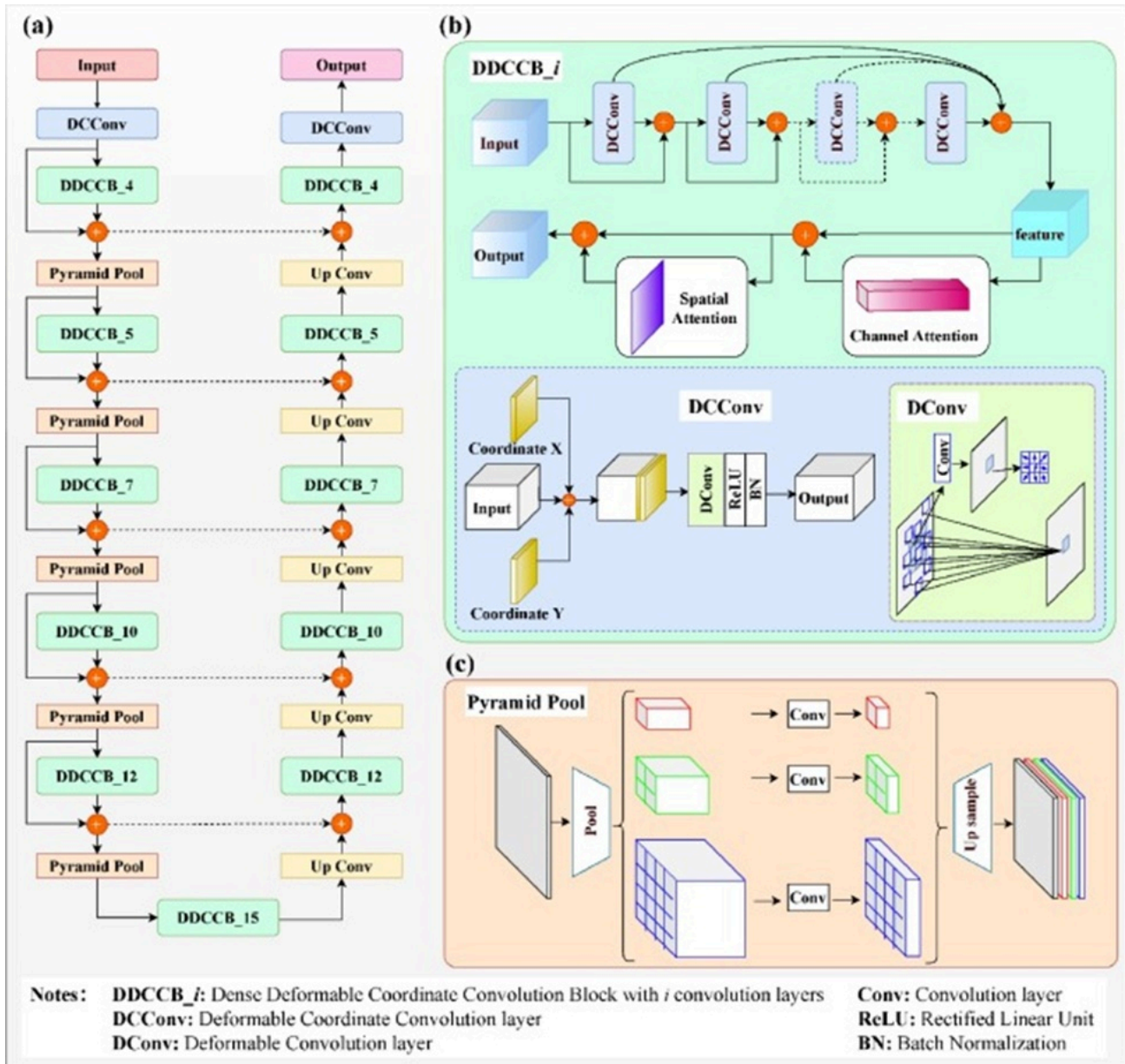


Figure 4. Multi-scale segmentation model for building footprint survey: (a) U-shaped structure of the body network, (b) internal composition of DDCCB module, and (c) multi-scale feature fusion inside pyramid pooling.

The initial section of the DDCCB consists of densely connected convolutional layers. Each layer receives feature maps from all previous layers as input, and its own output is passed forward to every following layer. This dense connectivity grants each layer direct access to both the original input signals and the gradients from the loss function, thereby providing implicit deep supervision [47]. Conventional convolution is substituted here with a deformable coordinate convolution layer (DCCConv). DCCConv uniquely integrates coordinate concatenation with deformable convolution (DConv). By appending spatial coordinate channels to the input features, the network can flexibly learn varying levels of translation invariance or dependence, effectively addressing issues arising from coordinate transformations [48].

Meanwhile, DConv enhances geometric modeling by learning additional offsets to adjust the sampling positions of the convolution kernel [49]. Following the DCCConv operation, a rectified linear unit (ReLU) activation and batch normalization (BN) are applied in the standard sequence. Thanks to DCCConv, the model gains robust capability to extract geometric characteristics of building rooftops regardless of their geographical position.

The second part of the DDCCB employs an attention mechanism [50] to boost overall representational power. It emphasizes relevant features (such as building roofs) while downplaying irrelevant background elements. Specifically, the convolved features pass sequentially through channel and spatial attention modules, which produce attention weights in both dimensions. These weights are then multiplied element-wise with the original features to achieve adaptive refinement.

The pyramid pooling module processes input features across multiple spatial scales, with receptive field sizes scaled proportionally to the input image dimensions. This design allows spatial pyramid pooling to normalize features of varying sizes into a fixed dimension without the information loss typically associated with cropping or warping [51]. Such a mechanism aligns particularly well with the multi-scale and nested nature of remote sensing imagery. For instance, understanding the full geometry of large buildings in very high resolution (VHR) images often requires analysts to repeatedly zoom in and out to integrate local details with the global context.

Model training relies on manually annotated samples derived from Gaofen-2 and Beijing-2 satellite images, with representative examples shown in Figure 5. The dataset maintains an approximately balanced distribution across urban, suburban, and rural scenes at a ratio close to 1:1:1. To improve model robustness, 30% of the original samples were randomly chosen and subjected to data augmentation techniques, including image rotation, flipping, blurring, and noise injection. In total, this process yielded 12,000 samples sized at 256×256 pixels, which were split into training (60%), validation (20%), and test (20%). It is well known that the choice of split ratios influences deep model performance, with training data generally recommended to comprise at least 60% of the dataset to support adequate learning [52]. While we acknowledge the importance of these ratios, we adopt the standard generic split without further investigation here. Given the severe class imbalance — where buildings occupy far less area than background regions — and the added difficulty of detecting smaller structures, we employ focal loss [53] as the training objective. This loss function effectively balances positive and negative samples and easy and hard examples. The expression of focal loss is:

$$FL(p_t) = -\alpha(1 - p_t)^\gamma \log(p_t), \gamma > 0 \quad (9)$$

Where p_t represents the probability assigned to the true class for a given sample, α serves as the weighting factor to balance positive and negative classes, and γ acts as the modulating factor that balances hard and easy examples. In our experiments, we configured $\alpha = 0.25$ and $\gamma = 2$. This focal loss formulation directs the training process to emphasize buildings more strongly, with special attention to smaller structures.

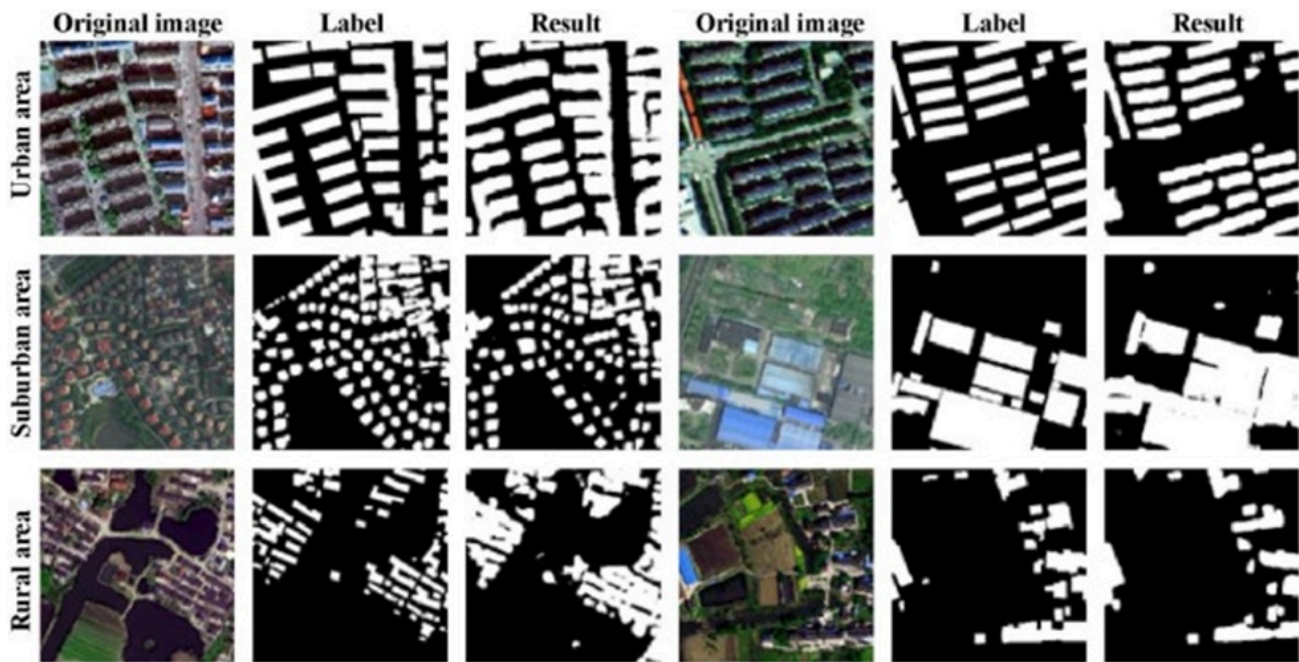


Figure 5. Examples of labeled images and segmentation results of building footprints.

The entire model was coded in Python using the PyTorch framework and trained on high-performance workstations equipped with 8 NVIDIA V100 Tensor Core GPUs. After complete training, the model delivered an average accuracy of 0.918, precision of 0.902, recall of 0.734, F1-score of 0.801, and intersection over union (IoU) of 0.778 on the independent test set. **Figure 5** displays representative cases covering urban, suburban, and rural environments. Visual inspection reveals that building boundaries are delineated more precisely when located near the center of the input patches than near the borders. This observation indicates that it is advantageous to place target buildings toward the central region of each input block. Therefore, for large-scale building footprint extraction from high-resolution satellite imagery, the source images are tiled into overlapping patches with a 256×128 or 128×256 pixel overlap between neighboring blocks. Thanks to this overlapping approach, every pixel is evaluated five times during inference, with at least one evaluation occurring when the pixel lies away from the patch edges. In this work, the final label for each pixel is determined by selecting the class with the highest predicted probability across all overlapping inferences. It is worth noting that the specific network design has a significant impact on final performance, and superior results may be achievable through alternative advanced architectural choices. Nevertheless, the current study does not delve into network optimization; rather, it concentrates on validating the practical utility of the proposed framework via a real-world case study.

Results and Discussion

Solar energy resource potential

By combining the deep learning network with hourly MTSAT-1R satellite observations, we mapped both the spatial patterns and temporal dynamics of global horizontal irradiance (GHI) and diffuse horizontal irradiance (DHI) throughout 2018 (**Figure 6**). The northern areas of Jiangsu Province possess abundant solar resources, recording an annual total close to 5200 MJ/m^2 . This places the region in the medium class within the National Energy Administration's five-tier classification system (extreme high, high, medium, low, and extreme low). Conversely, the southern regions fall into the low category, showing annual totals below 5000 MJ/m^2 . Consequently, most installed photovoltaic (PV) capacity in Jiangsu Province is concentrated in specific zones, while only a small number of utility-scale solar farms are found in the northern part [13]. A distinctive feature of Jiangsu Province is its higher DHI share than its GHI share. Apart from coastal

strips and lake surfaces, the DHI fraction remains higher than 50% over nearly the entire province (**Figure 6b**). On the temporal side, GHI attains its maximum in May, experiences a sharp drop in June, and rebounds to another peak in July (**Figure 6c**). The pronounced June decline results from the plum rain season, which generally commences in mid-June and concludes in early July. Because this rainy period predominantly influences areas south of the Huaihe River, the northern portion of Jiangsu Province suffers less disruption (red solid line in **Figure 6c**). As a result, the DHI fraction rises markedly during June owing to increased cloudiness and stronger scattering. Throughout the year, the DHI fraction consistently exceeds 50%, and a clear seasonal contrast in solar resource availability exists, with summer totals roughly twice those in winter. These patterns play a significant role in shaping PV deployment decisions, particularly the choice of optimal panel tilt angles [28, 54].

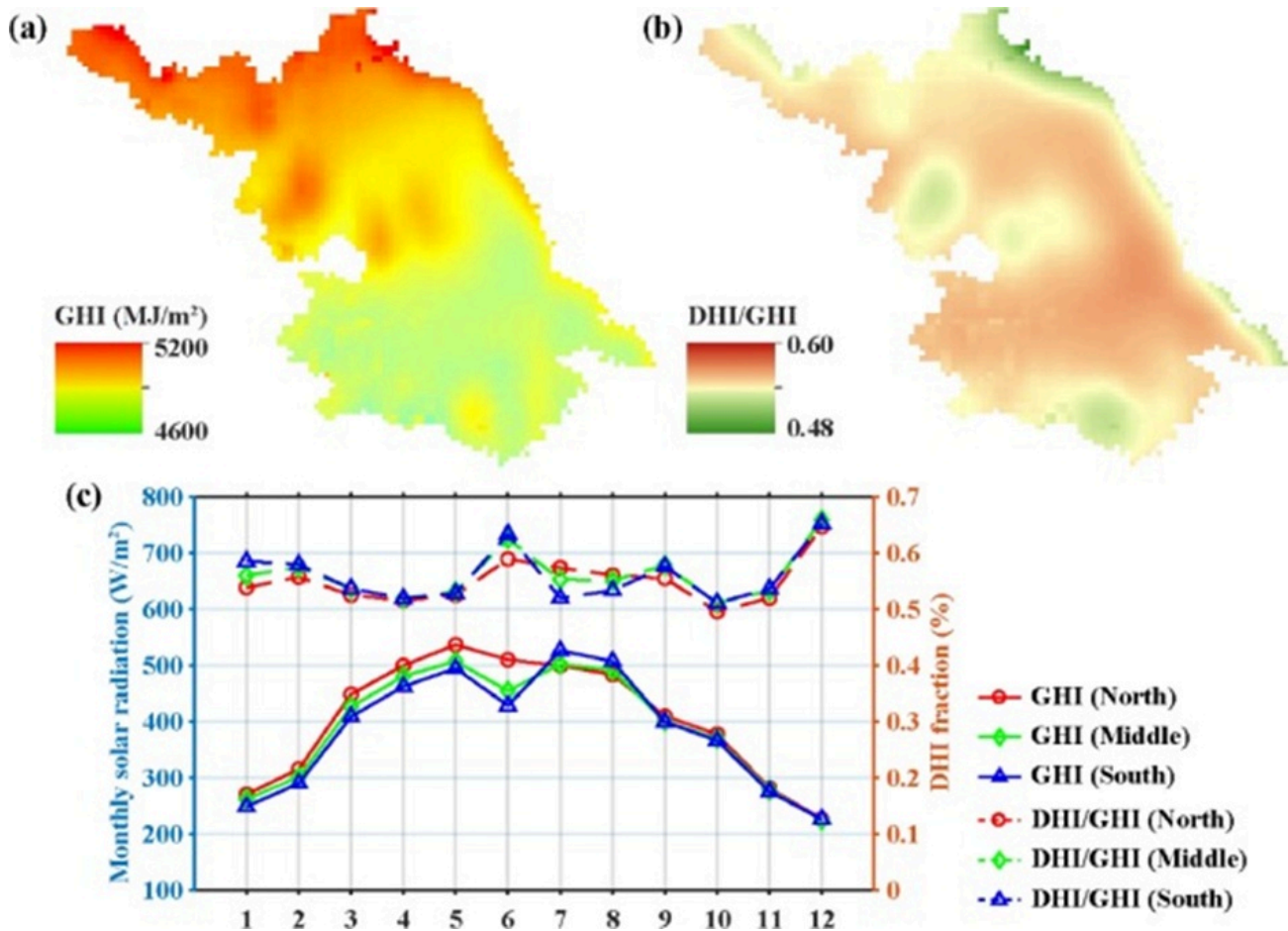


Figure 6. Solar energy resource potential of Jiangsu Province: (a–b) Spatial distribution of annual GHI (a) and DHI fraction (b) in 2018, (c) monthly variations of GHI (solid lines) and DHI fraction (dashed lines) in 2018.

PV capacity factor

Satellite-derived GHI and DHI data and ERA5-Land temperature records serve as inputs to the GSEE model to compute the PV capacity factor. Four distinct PV configurations are evaluated: (1) horizontally fixed PVs; (2) optimally tilted PVs; (3) 1-axis east-west tracking systems; and (4) 2-axis tracking systems. For the optimally tilted configuration, the panel tilt angle is calculated according to the empirical relation developed by Jacobson and Jadhav [28]:

$$\alpha_t = 1.3793 + \phi \cdot (1.2011 + \phi \cdot (-0.014404 + \phi \cdot 0.000080509)) \quad (10)$$

In which ϕ denotes the latitude. Generally, PV panels in the Northern Hemisphere are oriented southward to receive the most direct sunlight; accordingly, the azimuth angle of each PV panel (α_A) is fixed at 180° . Simulations are carried out at hourly intervals. This approach not only enhances evaluation precision but also incorporates the time-dependent behavior of electricity generation into planning and design considerations. **Figure 7** illustrates the annual mean capacity factor throughout Jiangsu Province. Horizontally fixed PVs yield the lowest capacity factors, ranging from 0.12 to 0.14. Optimal tilt adjustment proves particularly useful in northern districts and boosts the capacity factor by approximately 0.01. Both 1-axis and 2-axis tracking systems deliver substantially higher capacity factors than the fixed and optimally tilted options, with gains ranging from 0.02 to 0.03. The four configurations exhibit a broadly consistent spatial trend — higher values in the north and lower values in the south — yet the north-south gradient appears more distinct for the tracking systems. The primary driver of this regional disparity is the greater cloud coverage prevalent in southern areas compared with the north [41]. Notably, the northeastern sector benefits from elevated GHI levels and a lower DHI fraction (**Figure 6**), resulting in the highest capacity factors.

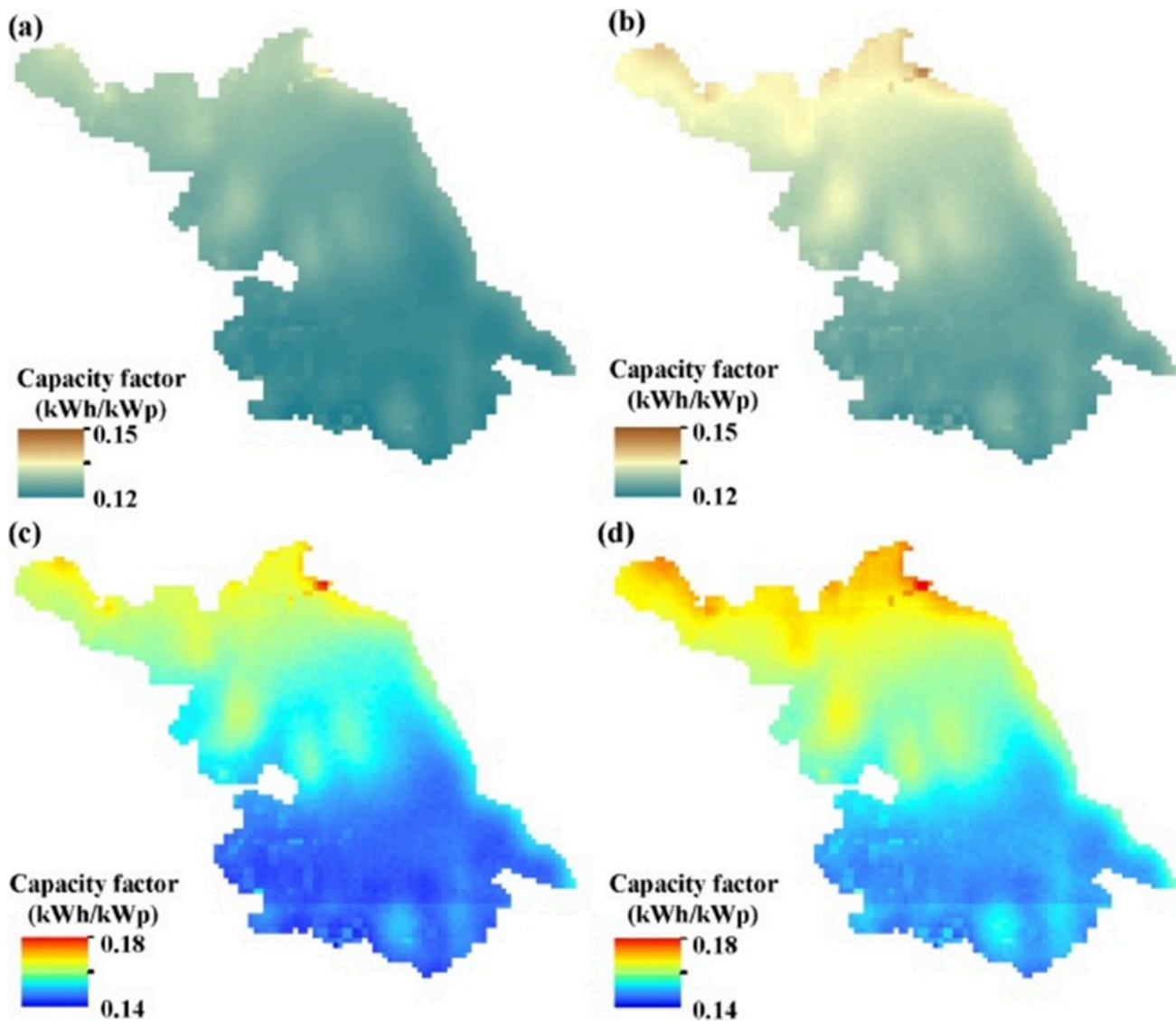


Figure 7. Capacity factor of different PV systems: (a) Horizontally fixed PVs, (b) optimally tilted PVs, (c) 1-axis tracking systems, and (d) 2-axis tracking systems.

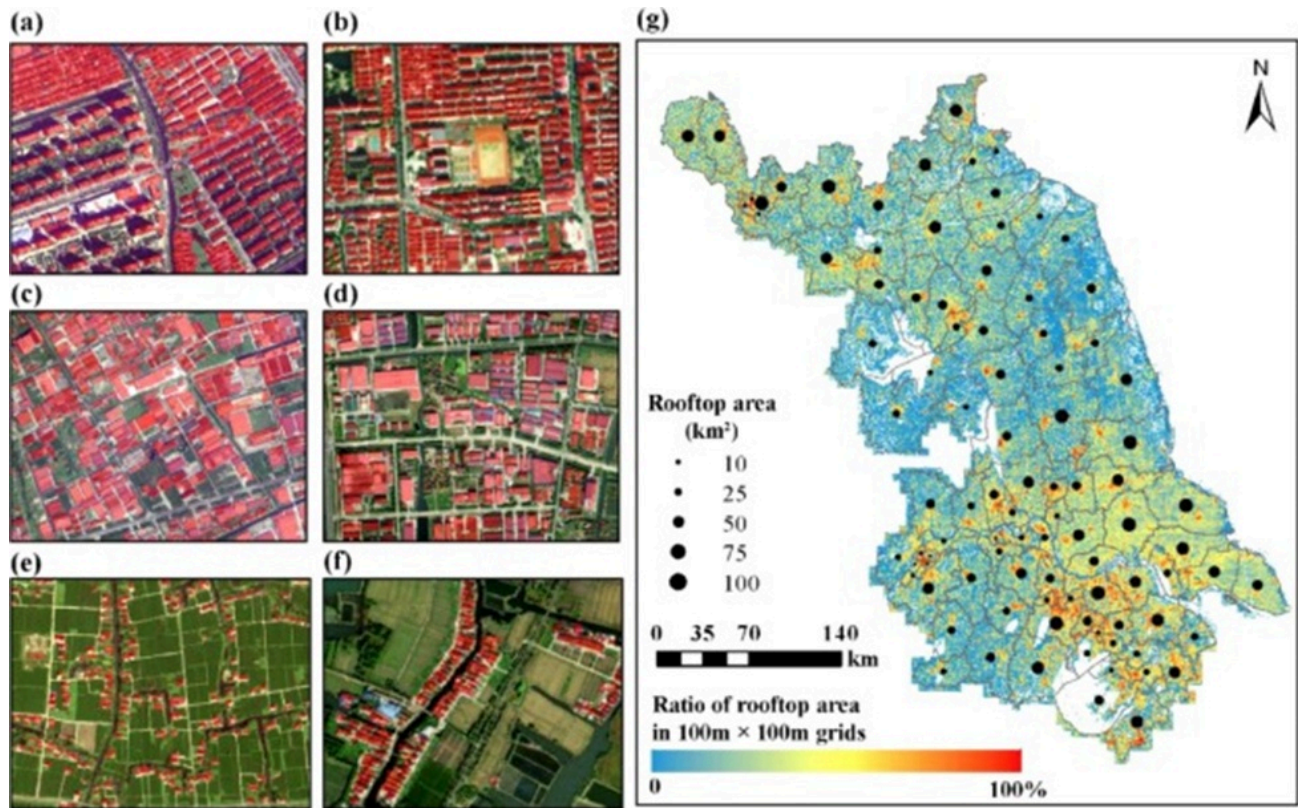


Figure 8. Building rooftop resources in Jiangsu Province: (a–f) Examples of automatically segmented building footprints in urban (a, b), suburban (c, d), and rural (e, f) areas; (g) building density of each 100m × 100m grid and rooftop area of each county-level city. Red polygons in (a–f) represent the result of automatic segmentation.

Available rooftop resources

Leveraging the multi-scale segmentation model applied to Gaofen-2 and Beijing-2 satellite imagery, building footprints — encompassing both position and outline — were mapped at 1 m resolution. **Figures 8a–8f** presents selected examples of these segmented footprints across urban, suburban, and rural landscapes, confirming the model's robust performance when dealing with buildings that vary widely in scale. The focal loss function's inherent balancing of positive versus negative samples and hard versus easy examples enables the model to maintain consistent segmentation quality across densely built and sparsely developed zones. By integrating spatial pyramid pooling and attention modules, the network successfully preserves both local details and global context, enabling reliable detection even when buildings of markedly different sizes appear together in the same image (**Figures 8c, 8d**). Building density, expressed as rooftop area per 100 m × 100 m grid and per county-level city (**Figure 8g**), was subsequently compiled (any finer unit down to 1 m × 1 m can be used if needed). These density statistics provide the essential foundation for assessing potential rooftop PV installation capacity. In the present analysis, the building footprint area is taken to be directly equivalent to the usable rooftop area. Results reveal that rooftop resources are most heavily concentrated in the southeast, with the northwest ranking second. That rooftop area across counties does not correspond to the total land area in proportion, owing to differences in urbanization intensity. **Figures 8a–8f** clearly illustrates the variation in building density among urban, suburban, and rural settings. Province-wide, the total rooftop area sums to 6,628.94 km², equivalent to 6.18% of the overall land surface.

Limitations arising from spatial resolution, along with effects of shadowing, observation angle, and related issues, can cause the segmented boundaries to deviate from reality or lead to misclassification of surrounding features as buildings.

While higher-resolution aerial or UAV imagery would offer greater precision, the substantial cost involved typically precludes its use for broad regional mapping. Following practices established in Europe [14], UAV imagery was collected over a designated test site (Figure 9a) to define precise building outlines. These served as reference data for calculating a correction factor to adjust the satellite-derived results. Preliminary comparison (Figures 9b–9d) indicated that automatic segmentation overestimates the rooftop area. Manually extracted building footprints from the UAV images were aggregated to 100 m × 100 m grids. The mean ratio (roughly 0.85) between UAV-based and satellite-based rooftop areas across all test grids was adopted as the correction factor. This factor was then scaled up to the provincial level, reducing the estimated total rooftop area in Jiangsu Province to 5,634.60 km².

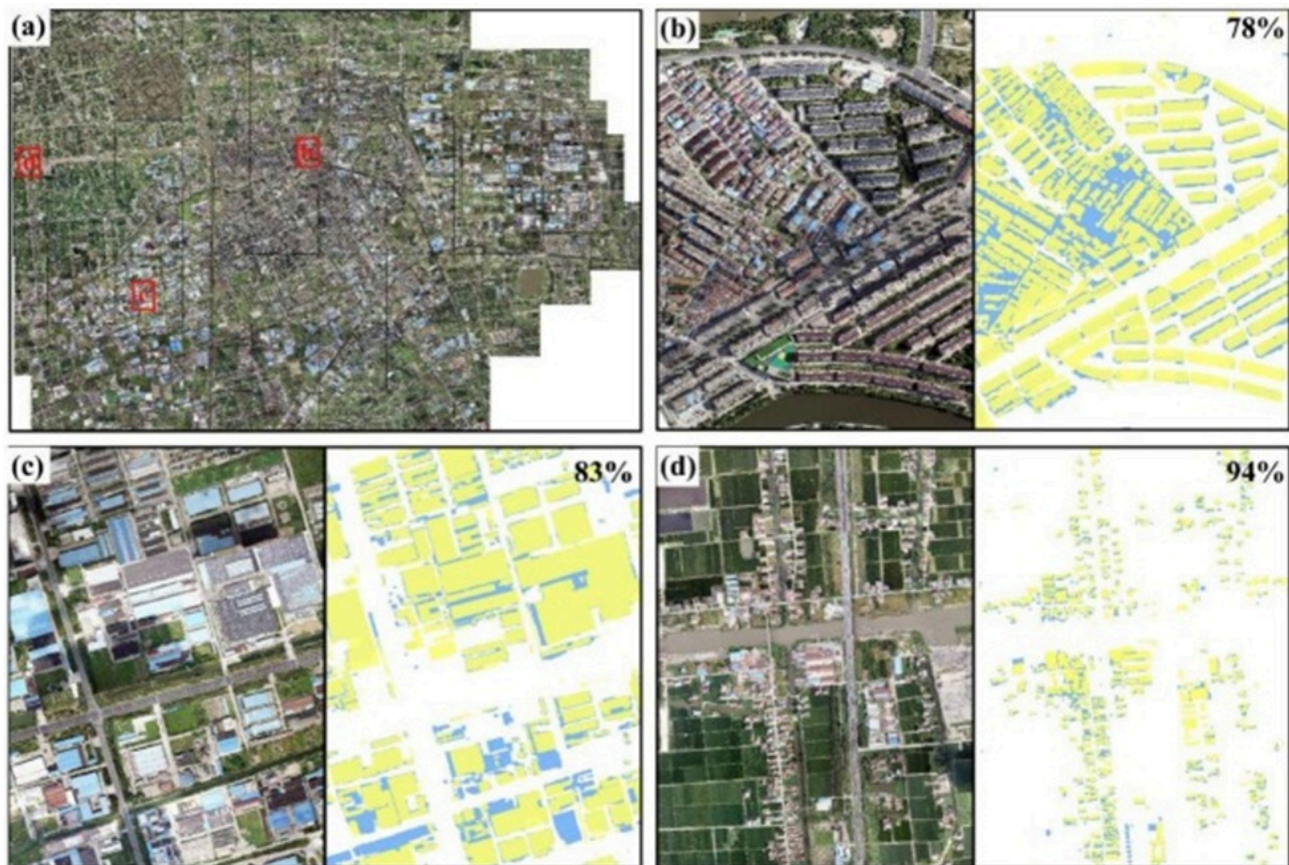


Figure 9. Correction factor for available rooftop resources: (a) Aerial images of the test area, (b–d) examples of the determined factors in urban (b), suburban (c), and rural (d) samples. Yellow polygons are the manually identified building footprints from UAV images, and blue polygons represent the result of automatic segmentation.

The usable rooftop area must be further adjusted downward to determine the portion truly appropriate for PV installation. This adjustment accounts for competing roof functions (e.g., space occupied by air conditioning equipment and chimneys), shading from surrounding objects, required gaps between PV modules, and pathways for maintenance access. The extent of this reduction is influenced by building design and the specific roof type. In line with recommendations from the National Energy Administration [19], rooftop PV deployment is encouraged across various building types, including Party and government offices, hotels, hospitals, shopping centers, factories, and rural homes. Figure 10 illustrates three representative roof categories well-suited for PV systems: steel tile roofs, flat concrete roofs, and brick roofs. Within the test area (Figure 9a), UAV imagery was used to classify suitable buildings and identify their roof types manually. Analysis of the statistics reveals that buildings deemed suitable constitute 58.8% of the total (defined as the suitability factor), and the relative shares of steel tile, flat concrete, and brick roofs are approximately 2:9:3. This proportion is assumed to apply uniformly throughout the province. Moreover, the actual net area available for mounting PV panels is derived by measuring the coverage achieved when roofs are fully exploited for solar installations (Figure

10). The resulting utilization coefficients are 0.68 for steel tile roofs, 0.57 for flat concrete roofs, and 0.52 for brick roofs. These values are calculated assuming standard c-Si PV modules, each covering an area of 1.940 m^2 ($0.992 \text{ m} \times 1.956 \text{ m}$) and delivering a peak power output of 250 W. Consequently, the average installation density across suitable buildings is roughly 74 W/m^2 . Extending this installation approach province-wide yields a total potential installed capacity of 245.17 GW.

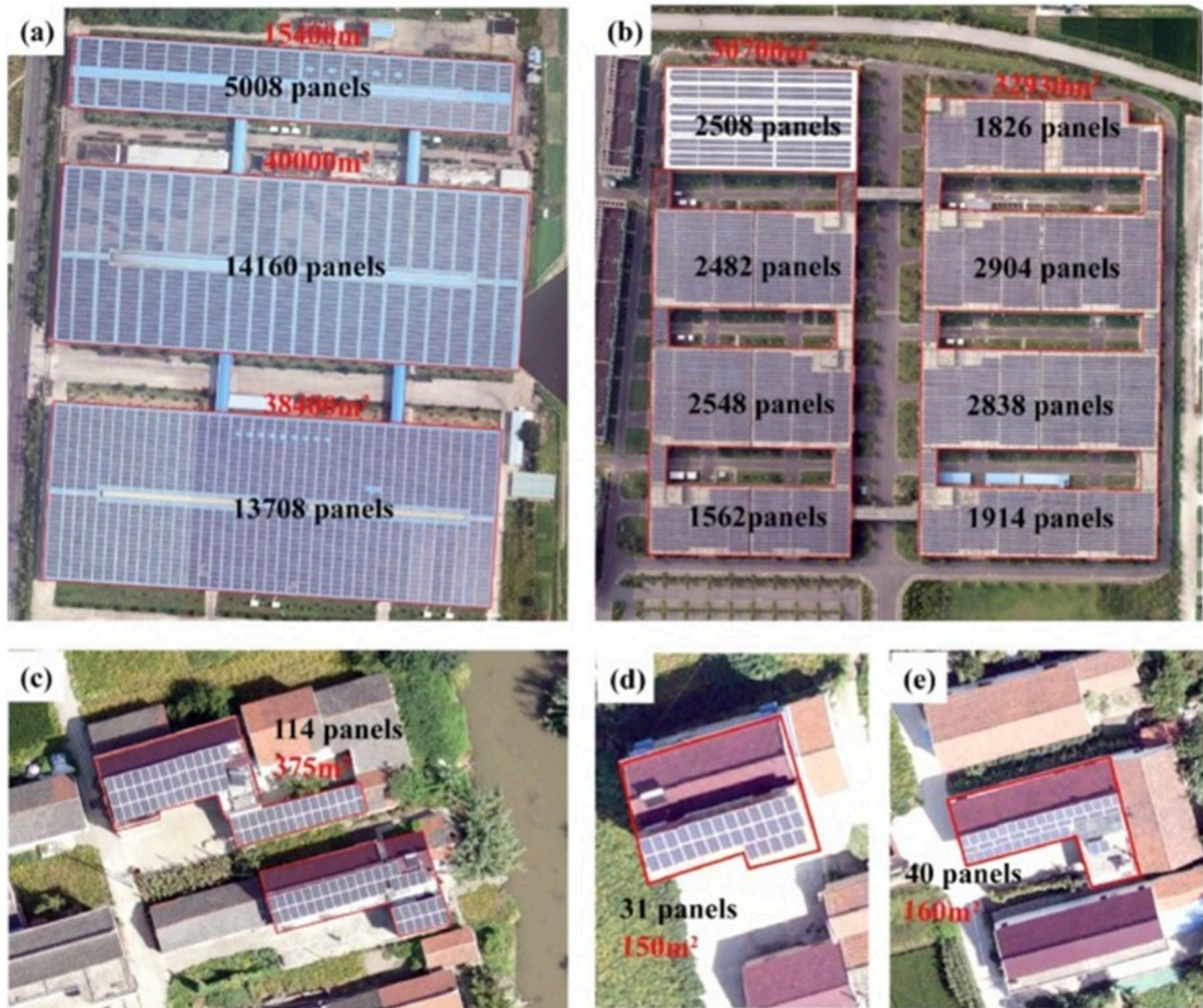


Figure 10. Proportion of suitable area for PV installation on different rooftops: (a) Steel tile roofs, (b) flat concrete roofs, and (c–e) brick roofs from UAV images. Red polygons represent the building footprints.

It is important to recognize that the assumptions adopted here may result in either inflated or understated estimates of installed capacity. For example, regions with heavier industrial activity and thus a larger fraction of steel tile roofs than in the test area would lead to underestimation. In contrast, less developed zones dominated by brick roofs would lead to overestimation. The chosen test area corresponds to a moderately developed urban setting and therefore offers a balanced midpoint. Additionally, the absence of dependable reference data prevents straightforward validation of the calculated installed capacity figures. Under extreme conditions — such as an area composed entirely of steel tile roofs or entirely of brick roofs — the potential installed capacity could shift to approximately 291.55 GW or 221.98 GW, respectively.

Rooftop PV power generation

Spatial overlay analysis, achieved by successively multiplying building density with the correction factor, suitability factor, installation factor, and capacity factor, allows quantification of the technical potential for rooftop PV systems. For a straightforward presentation, only annual figures are provided, calculated using the annual mean capacity factor. Pixel-based calculations can be summed to any spatial unit of interest, including individual counties (Figure 11a), prefecture-level cities (Figure 11b), larger regions (Figure 11c), or the full province (Figure 11d). Compared with the distribution of raw solar resource potential, the pattern of technical potential shows considerable differences. Northwestern counties stand out for their elevated technical potential, owing to the advantageous pairing of strong solar resources and ample rooftop space. Southeastern counties, despite modest resource potential, still exhibit high technical potential driven by abundant rooftop resources. Technical potential further differs depending on the PV system configuration selected. Optimally tilted systems are projected to generate 290.66 TWh annually, representing an increase of 8.50 TWh over horizontally fixed systems. 1-axis tracking systems raise annual generation to 339.90 TWh, while the incremental improvement from 2-axis tracking systems remains modest at 8.41 TWh. The methodology developed in this framework supports extending these evaluations to hourly time steps and 100 m spatial resolution when required.

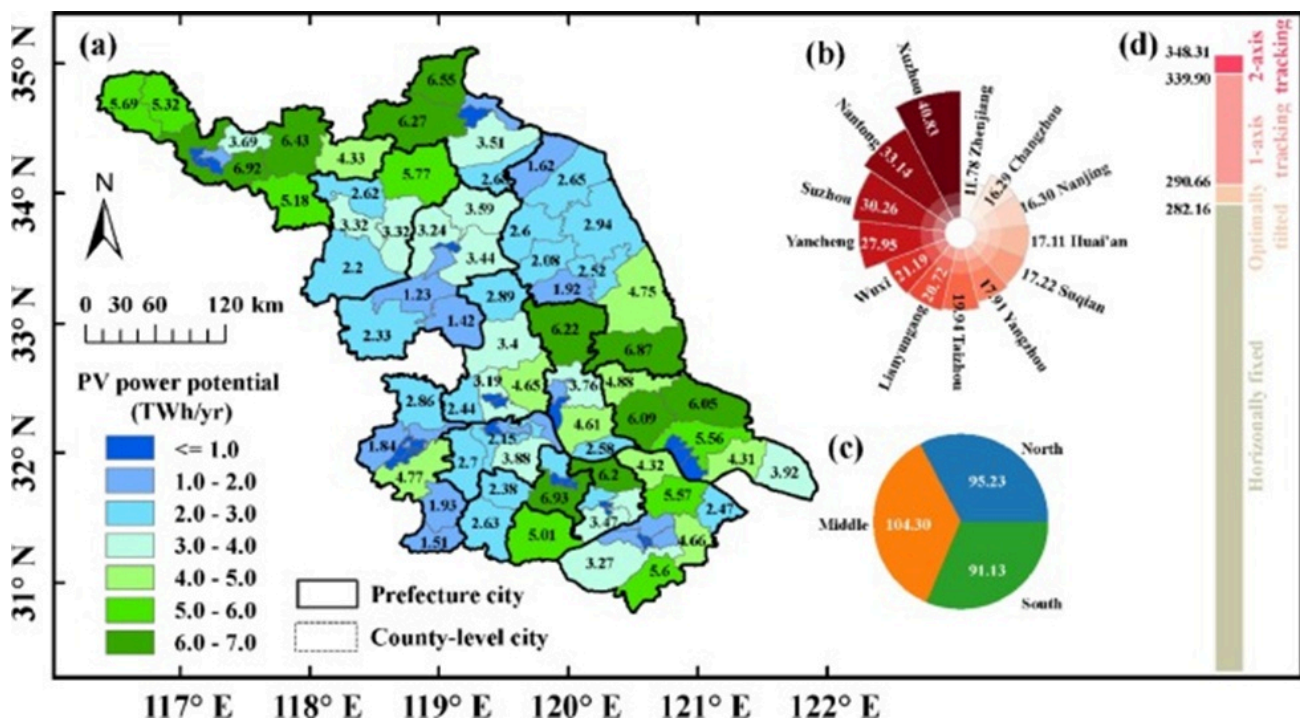


Figure 11. Potential rooftop PV power generation in Jiangsu Province. (a–c) County-level, prefecture-level, and regional statistics of the potential of optimally tilted PV systems; (d) comparison of different PV systems.

Conclusion

This study introduces a comprehensive framework for assessing the technical potential of rooftop photovoltaic systems by integrating multiple remote sensing data sources. Within this framework, geostationary satellite imagery combined with deep learning techniques is employed to evaluate solar energy resources; high-resolution satellite images paired with an automated segmentation model are used to map building footprints; UAV imagery is used to derive multiple correction factors; and a process-based PV simulation model is applied to estimate actual electricity output. The proposed framework offers a practical, economical, and straightforward approach for conducting high-resolution geospatial

evaluations of rooftop PV potential at regional scales. A key strength of the framework lies in its flexibility to operate effectively from detailed local scales to broad regional coverage, or across different time resolutions, as illustrated by the application in Jiangsu Province. Furthermore, the reliability of the assessment outcomes is supported by consistency with independent data; for instance, the derived capacity factors align closely with measurements recorded at ground stations [44], and the calculated rooftop area for Nanjing (360.54 km²) corresponds well with findings reported by Zhong et al. [27].

The framework holds strong potential for adaptation and use in other regions. When implementing it elsewhere, it is advisable to retrain or fine-tune the deep learning components with a limited set of local samples from the new area. This step is necessary because the models' generalization performance may decline if the solar radiation patterns or building characteristics in the target region differ substantially from those in the training data. The primary source of uncertainty in the current estimates stems from the assumptions used to calculate installed capacity. This uncertainty could be reduced by employing hyperspectral remote sensing to identify roof materials and LiDAR data to capture detailed rooftop geometry; however, such enhancements would significantly increase overall costs. Another constraint of the framework is the substantial demand for computational resources. Advanced hardware is essential for handling the high computational demands of deep learning models and for managing large volumes of remote sensing data.

According to the analysis, the potential installed capacity of rooftop PV systems in Jiangsu Province is 245.17 GW, roughly 14 times the current total installed capacity (16.83 TWh). This substantial difference underscores the considerable untapped development opportunities for rooftop PV in the province. Should all suitable rooftops be equipped with optimally tilted c-Si PV modules, the resulting annual electricity generation would amount to approximately 290.66 TWh. This figure represents about 45.6% of the province's total electricity consumption in 2020 (637.37 TWh). Realizing such a large-scale provincial rooftop PV initiative would lead to an estimated reduction of 200,787.9 tCO₂ emissions, based on the emission factor for China's electricity system [55] released by the Ministry of Ecology and Environment of the People's Republic of China. These outcomes demonstrate the significant economic and environmental benefits of rooftop PV development, particularly amid current climate challenges.

Nevertheless, a full evaluation of economic and market potential requires careful analysis of multiple factors, including technology costs, avoided supply expenses, competition from alternative energy sources, policy frameworks, licensing requirements, incentive programs, and social and cultural considerations. These elements fall beyond the scope of the present study. Stakeholders are therefore encouraged to thoroughly examine these additional aspects before implementing any development plans.

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Conflict of interest

None

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Ethics statement

None

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