Applied Energy 333 (2023) 120579

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Remote sensing of photovoltaic scenarios: Techniques, applications and future directions

Qi Chen [a], Xinyuan Li [a], Zhengjia Zhang [a], Chao Zhou [a], Zhiling Guo [b], Zhengguang Liu [c], Haoran Zhang [d,*]

[a] School of Geography and Information Engineering, China University of Geosciences (Wuhan), Wuhan 430074, China
[b] Center for Spatial Information Science, The University of Tokyo, Chiba 277-8568, Japan
[c] Department of Energy and Electrical Engineering, Northwest A&F University, Yangling 712100, China
[d] School of Urban Planning and Design, Peking University, Shenzhen 100871, China

HIGHLIGHTS

- This paper systematically reviews the research progress of RS technology applied to various stages of PV system development.
- We conclude that RS plays a significant role in PV potential assessment, large-scale data analysis and PV health monitoring.
- We discuss future challenges and opportunities for RS technology in PV applications for advancing the research in this area.

ARTICLE INFO

Keywords:
Solar photovoltaic
Remote sensing
Potential estimation
PV detection
PV monitoring
Sustainable development

ABSTRACT

Developing solar photovoltaic (PV) systems is an effective way to address the problems of limited fossil fuel reserves, soaring world energy demand and global climate change. The earth observation information provides a promising perspective for estimating the PV energy potential and understanding the status of the PV system development, which is critical for making scientifically sound and cost-optimal sustainable planning strategies. Remote sensing (RS), a versatile technology that captures surface information at various temporal and spatial scales, is now widely applied in different fields of the PV development. However, despite the rapid growth of related research, there is still a lack of comprehensive review on the application of RS to different stages (i.e., planning, site selection, installation, maintenance, etc.) of the PV system development. This paper systematically reviews the research progress of RS technology applied throughout various stages of the PV system development. The reviewed literatures are organized as four major parts: i) PV potential estimation, ii) PV array detection, iii) PV fault monitoring and diagnosis, and iv) other cross-cutting areas where RS can facilitate PV development. We conclude that RS technology can bridge the gap caused by the traditional methods in effective assessment of resource potential, large-scale data analysis and PV health monitoring, which can provide strong support in assisting the planning, management, and decision-making of PV systems. Finally, we discuss future challenges and opportunities for RS technology in PV applications for advancing the research in this area.

1. Introduction

1.1. Background

The development of solar photovoltaics is an important option in the transition to sustainable energy sources. Many countries are seeing significant growth in demand for solar photovoltaic (PV) energy. Remote sensing (RS) is a versatile technology that can obtain earth observation information at various temporal and spatial scales. Compared with the field investigation that requires high time consumption and labor intensity, RS can provide timely and cost-efficient observation solutions for estimating the PV energy potential and understanding the status of the PV system development.

In a typical RS application, one or multiple sensors (e.g., photography, infrared, microwave devices or a laser scanner) equipped on certain platform (e.g., satellite, aircraft, unmanned aerial vehicle (UAV)

* Corresponding author.
E-mail address: zhang_ronan@csis.u-tokyo.ac.jp (H. Zhang).

https://doi.org/10.1016/j.apenergy.2022.120579
Received 21 September 2022; Received in revised form 10 November 2022; Accepted 23 December 2022

or ground-based) capture surface images of the specified area, the advanced image processing algorithms are then applied for information extraction and knowledge inference. The diversity of the sensors and the advantages of different platforms allow RS to provide strong support throughout the entire phase of the PV system development. On the other hand, solar PV systems are evolving towards mobile and distributed models. According to different electricity demands, the PV modules are widely deployed in various scenarios such as building rooftops, cultivated land, mountainous areas, water, and road surfaces. In this context, the advantages of RS in terms of wide observation range and rapid data acquisition become more prominent.

In Fig. 1, we summarize the representative RS data acquired from typical platforms (i.e., spaceborne, airborne and ground-based), which have been applied to various PV scenarios (e.g., residential, commercial, agricultural and fishery areas). In general, the visible-light (i.e., RGB) images have been the mostly used data across the three platforms; the spectral imagery, synthetic aperture radar (SAR) imagery, aerial infrared thermography (IRT) imagery, and light detection and ranging (LiDAR) data can be obtained from different platforms to support specific applications. As an important background information, the cost of RS data is mainly influenced by the data acquisition platform, the sensor type, and the surveying area [1]. The precise price is impacted by various factors such as hardware, labor, licensing, business model and local policy, but there are still some general differences between different RS data [2]: higher spatial/spectral resolution requires higher complexity of sensors, which leads to higher cost; for large-scale applications, satellite data have significant cost advantage over other platforms; UAV captures images at relatively higher cost but can provide up-to-date data with hyperfine-resolution; LiDAR data have higher per-unit cost than the ones mentioned above, because the sensor is relatively more expensive.

As shown in Fig. 2, the RS data acquired from different platforms and sensors are handled by human interpretation, or various algorithms in types of machine vision and signal processing, thus providing spatial data products or statistical information for different applications. As a powerful toolset, RS has been applied to different stages of the PV system development such as site planning, installation, operation, and maintenance, which gives rise to several representative application scenarios: i) PV potential assessment, ii) PV facility detection, iii) PV fault monitoring and diagnosis, and iv) other cross-cutting areas where RS techniques can facilitate PV development, such as geological hazard risk estimation and techno-economic assessment for novel scenarios.

1.2. Related works

Currently, there is still a lack of comprehensive reviews focusing on the RS techniques in PV applications. Previous reviews have paid more attention to the technical issues within the solar PV system development: Livera et al. [3] have reviewed methods applied to fault detection and diagnosis in PV systems based on machine learning and statistical analysis; Gassar and Cha [4] have reviewed and discussed the studies of rooftop solar PV potential estimation; Melius et al. [5] have made a detailed summary of the methods that assess the suitability of rooftops for PV; Tina et al. [6] have summarized relevant studies on topics including PV module modeling, PV design parameter extraction, anomaly detection and energy management of PV storage systems. The contribution of RS in PV system development has not been sufficiently emphasized in these efforts.

Some other review studies have summarized the important role and significant advantages of RS technology in supporting the development of renewable energy or PV systems: Avtar et al. [7] have examined the studies revealing the application of RS in exploring the ideal locations

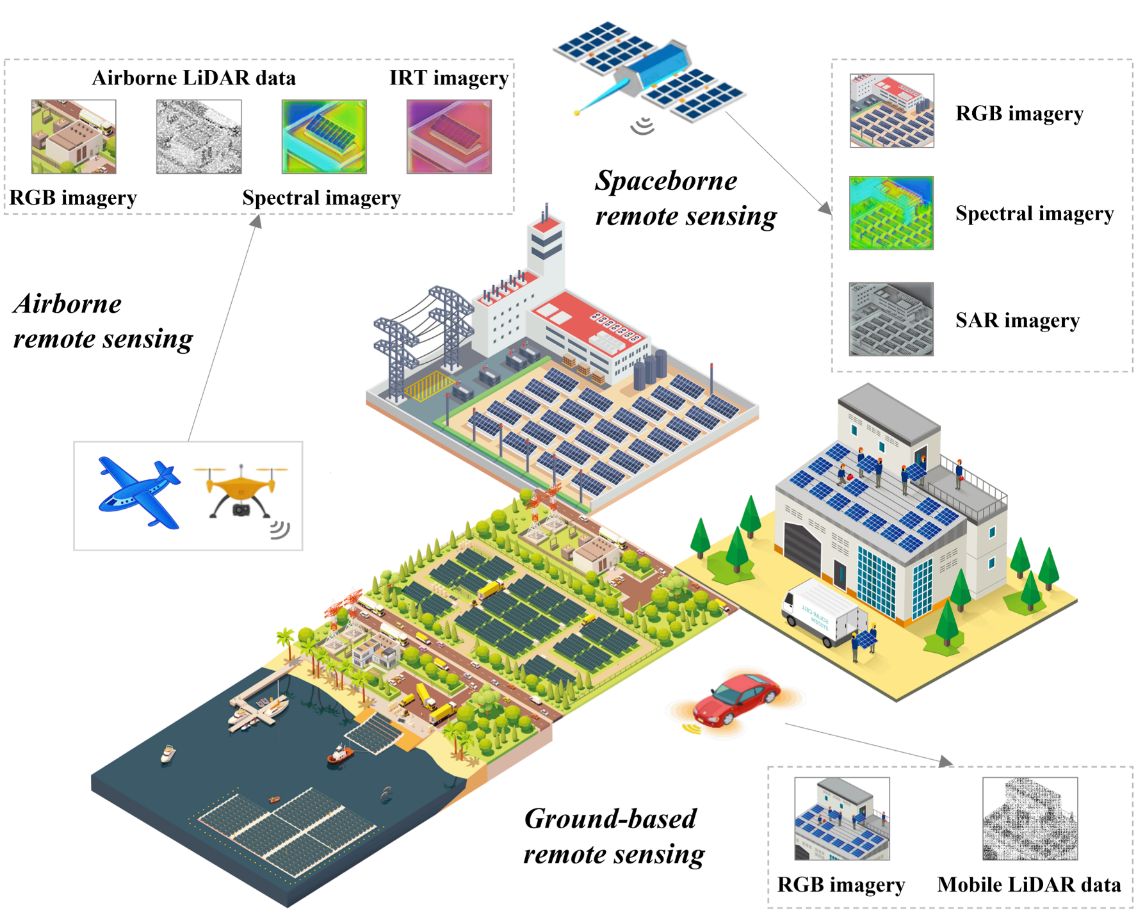

Fig. 1. The representative remote sensing (RS) data acquired from typical platforms, which have been applied to various photovoltaic (PV) scenarios.

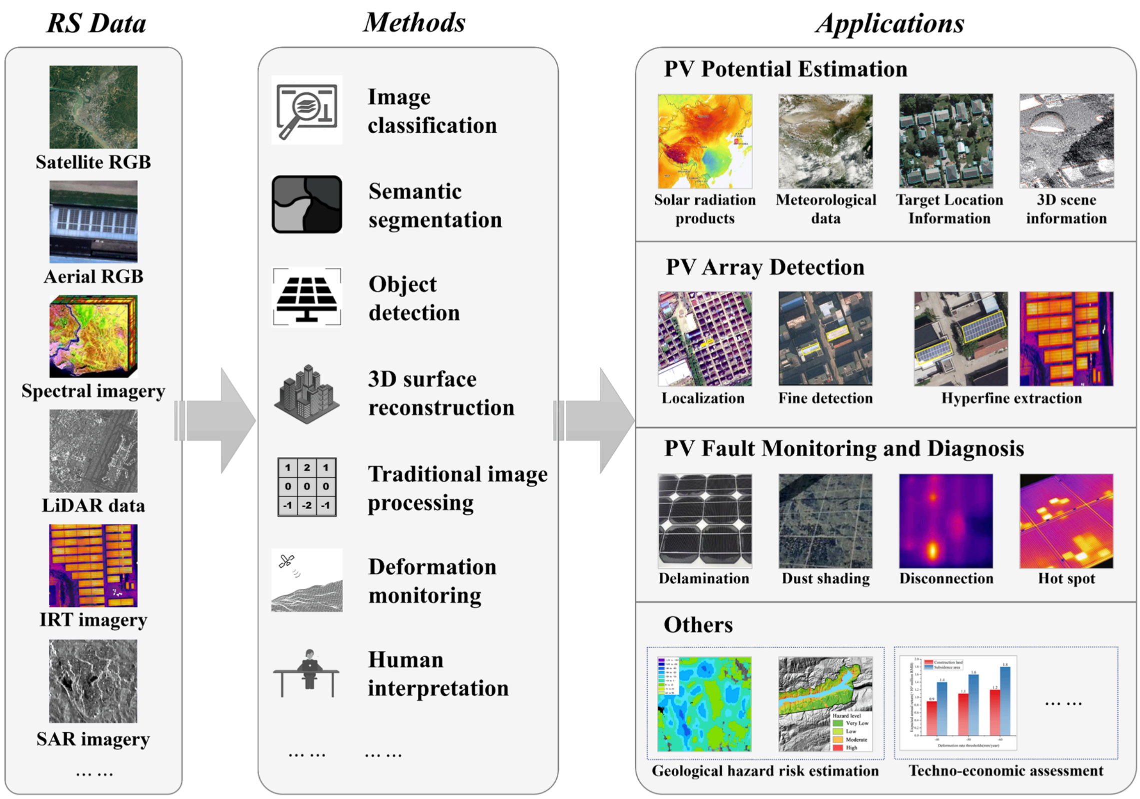

Fig. 2. The overview of the RS data and methods, which are applied to potential estimation, array detection, fault monitoring and diagnosis, and other aspects of PV system development.

for renewable energy resources; Tooke and Coops [8] have reviewed the application of RS technology to the management and planning of urban energy systems; Hoog et al. [9] have investigated the methods of using satellite and aerial images for identifying solar PV power systems; Oliveira et al. [10] have summarized the methods of performing automatic PV system inspection using IRT. However, these works have focused more on reviewing the application of RS techniques at specific stage of the PV system development; by far, the function that RS acts during the entire life cycle of the PV systems has not been comprehensively summarized and discussed.

1.3. Contributions

In this paper, we strive to systematically review the role played by RS technology in various stages of PV system development, with the aim of providing a summary of the related RS techniques, applications, and future directions. Our main contributions can be outlined as follows:

- We present an overview of the several typical RS data applied to various stages of PV system development, such as site planning, installation, and maintenance.
- By reviewing state-of-the-art research work, we summarize the development trend of RS techniques applied to PV potential estimation, PV array detection, PV fault monitoring and diagnosis, and other cross-cutting areas.
- We conclude the advantages/disadvantages of different RS techniques for major PV application scenarios and highlight the challenges and future directions.

The remainder of the paper is organized as follows. Section 2 describes objectives and methodology of the review. Sections 3, 4, and 5 discuss studies related to PV potential assessment, PV array detection, and troubleshooting of existing PV facilities, respectively. Section 6 and 7 introduce other promising applications of RS in PV development, which are geological hazard risk estimation for typical PV projects and techno-economic assessment for novel scenarios, respectively. Section 8 summarizes the conclusions, the key challenges and the future directions.

2. Objectives and methodology

The review aims at characterizing the role played by RS technology throughout the whole process of PV system development. Based on that motivation, we make a systematic survey on the state-of-the-art works and present critical analysis of this field, with the following objectives:

- To illustrate the important functions of RS technology in the development of solar resources and PV industry.
- To summarize the advantages and limitations of the state-of-the-art RS techniques and algorithms adopted in solar PV applications, thus promoting the integration and development of both fields.
- To provide informative knowledge about RS and solar PV for researchers from various disciplinary backgrounds and practitioners with different application goals.

Guided by the above objectives, as shown in Table 1, we have identified several keywords in our scope of interest and divided them into three categories: RS platforms or sensors, PV facilities or targets and application scenarios. We have retrieved a preliminary set of the published articles from Web of Science and Google Scholar by exhaustively combining the keywords from the three categories as the search criteria; then, we have screened out 281 articles from the preliminary set by checking the abstract of every paper, which are within our scope of interest and published up to Oct 2022; finally, we have carefully read every screened paper and made further summarization and discussion of the reviewed works.

Table 1
The main keywords used for retrieving published papers in our scope of interest.

Category	Keywords		
RS platforms or sensors	Remote sensing	Satellite	Aerial
	Unmanned aerial vehicle (UAV)	LiDAR | SAR	Multispectral
	Hyperspectral	Infrared imaging	Infrared thermography
PV facilities or targets	Photovoltaic (PV)	Photovoltaic system	Photovoltaic plant
	Photovoltaic power station	Photovoltaic array	Photovoltaic panel
	Solar cell	Solar array	Solar module
Application scenarios	Estimation Assessment	Segmentation	Detection
	Monitoring	Maintenance	Diagnosis
	Installation	Site selection	Risk estimation

Generally, the reviewed studies focus on diverse problems related to applications of PV or RS, from which we found that RS techniques are mostly applied to three aspects of PV deployment: potential assessment, installed PV array identification and damage detection. Specifically, the RS-based potential assessment is usually performed before PV system construction, the array identification from RS imagery can provide accurate and up-to-date installation capacity and geographic distribution of PV, while the damage detection and monitoring of PV system is of high importance in extending its service life and reducing maintenance costs. Therefore, the framework of this review is constructed mainly based on these PV application scenarios and RS techniques.

In addition, we have noticed some other studies which do not belong to the above three PV application themes but effectively use RS techniques to estimate the risk of geological hazards for PV projects on some specific land types. These works perhaps represent an important trend for future development of PV power industry; thus, we categorize them separately as the studies of geological hazard risk estimation for typical PV projects. Moreover, before making conclusion, we also summarize the studies focusing on PV systems deployed in novel scenarios where RS techniques could be useful for conducting techno-economic assessment, which demonstrate the future application potential of the RS technology.

3. PV potential estimation

The detailed and accurate estimation of solar PV potential provides important guiding information for the techno-economic assessment of planned projects and the formulation of regional energy policies. As shown in Fig. 3, by searching in Web of Science with different keyword

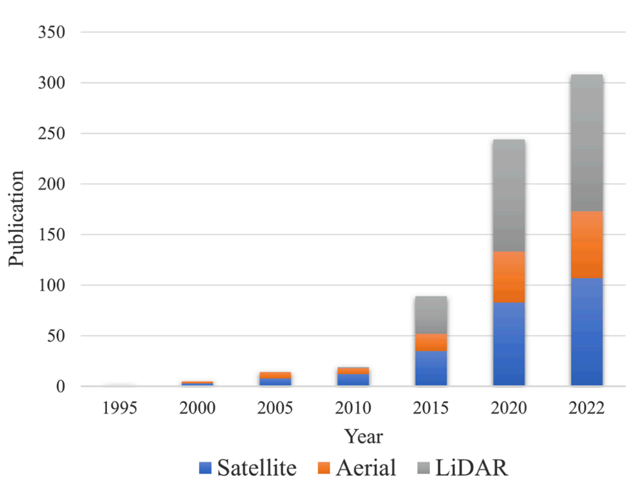

Fig. 3. The publication numbers about PV potential estimation based on different RS data since 1995.

combinations, we present the trend of publication numbers in PV potential estimation using different types of RS data. We find that the satellite imagery, aerial imagery, and LiDAR data are the three most representative RS data in this application. Specifically, the satellite data has been applied no later than 1995; the studies related with RS data have increased substantially since 2010, in which the usage of LiDAR data has the most obvious increase. The following subsections summarize the research on the PV potential estimation using the three types of data.

3.1. Satellite imagery

For a study area, the total amount of the solar energy that can be effectively received is an important indicator of the PV potential. This indicator can be assessed by satellite RS in terms of both the surface solar irradiance (SSI) as well as the area available for PV deployment. Over the past decades, many algorithms for SSI assessment from satellite observations have been developed, which can be roughly divided into two categories: i) methods based on radiative transfer model (RTM), and ii) statistical methods. The RTM-based methods [11–14] aim to quantitatively describe the physical process of solar radiation reaching the ground, considering the weakening effect of various factors such as clouds and various gas components. The statistical methods [15–18] estimate the solar radiation by determining regression coefficients between ground-based radiation and satellite measurements; the statistical correlation can be established by empirical assumption, such as Heliosat method [19], or optimally solved by machine learning techniques, such as artificial neural networks and support vector regression [20,21]. In comparison, the RTM-based methods are physically rigorous but require more measurements such as atmospheric or surface state information, while the statistical methods are essentially approximate solutions but usually practical for requiring few types of observations.

Estimating the terrestrial solar radiation based on satellite observations can be traced back as far as the 1960s, since the first meteorological satellite, TIROS-1, was successfully launched [12]. Afterwards, the emergence of the subsequent satellite missions has greatly facilitated this research area. Fig. 4 shows the launch time of several representative meteorological satellites or related projects that aim at better obtaining measurements of cloud, aerosol, atmospheric water vapor and so on, which contributes to providing RS data with high spatial, temporal, and spectral resolution and improving the accuracy of surface irradiance calculations. Furthermore, the open source of these satellite data provide a cost-effective means for generating large-scale (i.e., national or global) ground-based solar radiation products [22–26].

Apart from the solar radiance, the PV potential is also heavily influenced by the land resources available for PV deployment. The expansion of the built-up areas will result in an increasing limitation of the suitable land resources; thus, PV deployment is currently transiting to multi-purpose land use options or distributed solutions.

Buildings are considered very promising locations for urban PV installations, because building integrated PV (BIPV) systems not only require no additional space but also reduce the transport energy losses [27,28]. The planning of the BIPV projects requires detailed information about the installation area; for this purpose, the satellite RS technology can provide up-to-date image data as well as robust algorithms for data processing. Typically, Zhong et al. [29] have extracted building rooftops by applying a deep-learning-based semantic segmentation method to high-resolution satellite images, revealing that the study area (i.e., Nanjing, China) has significant potential for BIPV installation and solar power generation. Lee et al. [30] have proposed DeepRoof, a data-driven approach that uses satellite images for roof identification and leverages open-source data for extraction of roof planar segments; the results demonstrate that the proposed approach can produce accurate roof geometric features for PV installation area estimation. Other studies have attempted to extract more detailed information of rooftops to further improve the potential estimation accuracy. For example,

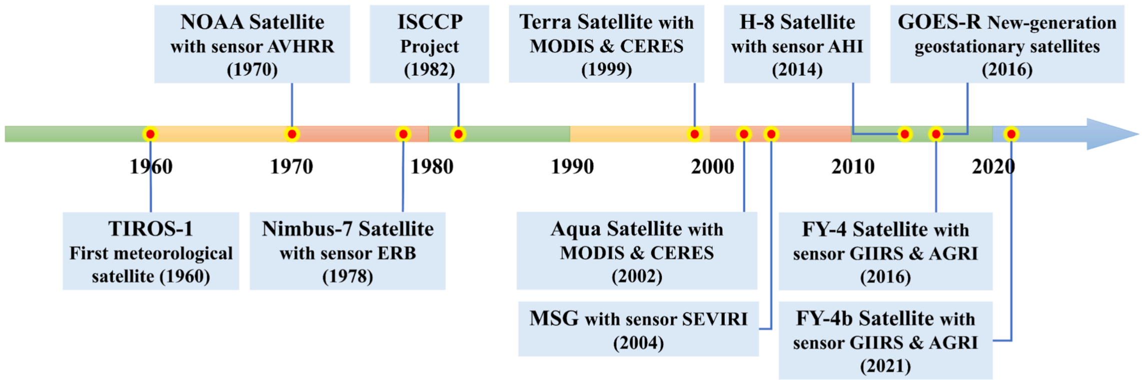

Fig. 4. The launch timeline of several representative meteorological satellites or related projects.

Mainzer et al. [31] have tried to identify the ridge lines, chimneys and windows of rooftops from orthographic satellite images for exactly calculating the partial roof areas; Sun et al. [32] have proposed a revised deep learning network for roof extraction from satellite images and classified the rural building rooftops into three categories for separately estimating the solar radiation and PV potential.

In addition, satellite RS can contribute to PV potential estimation in more scenarios by providing reliable topographic or interpretation results of earth surface. Specifically, Liu et al. [33] have adopted several RS features (i.e., elevation, slope, built-up index, etc.) obtained from satellite data for estimating road PV capacity at city-scale. Zhang et al. [34] have utilized satellite images and deep learning methods for land use classification and evaluated the PV potential on different land-use types. Ates et al. [35] have used Landsat and Sentinel satellite images for determining the shoreline of a dam and calculated the floating PV potential.

3.2. Aerial imagery

Compared with the satellite platform, Aerial RS focuses more in capturing surface information from smaller areas (e.g., a village or the central area of a city) at lower altitudes, which leads to image data with higher resolution. Aerial RS mainly consists of conventional aerial photography and UAV photography: the former is generally carried out for survey and mapping purposes and requires a manned aircraft; the latter is now more widely used due to its advantage of low cost and high flexibility.

In the field of PV potential estimation, the studies using aerial imagery have been mostly conducted for BIPV purposes; since more detailed information can be acquired in aerial imagery compared to satellite data, these studies have considered more about the slope or orientation of the rooftops as well as the impact from structures surrounding the building. Krapf et al. [36] have applied a deep learning method to aerial images for estimating the economic PV potential of each roof, in which two convolutional neural networks (CNNs) are trained to perform semantic segmentation of the rooftop and the superstructure, respectively. Mainzer et al. [37] have combined public geographic building data and aerial images to determine the roof azimuth, which helps to achieve higher accuracy of irradiance simulation and power generation than most related studies. Bergamasco et al. [38] have proposed an algorithm for extracting the available roof surface from the orthorectified aerial images of a city, which takes various factors into consideration including shadow, roof exposure and the azimuth of the installed panel.

Recognizing the shadows and superstructures on the rooftops from aerial images is essential for accurate estimation of the PV potential. However, the image features extracted by monocular-vision algorithms can provide limited information for accurate description of the identified rooftops; in contrast, the photogrammetry technique can utilize the stereo aerial images for 3D reconstruction of the study area, which better facilitates the interpretation of small structures and the shadow simulation on rooftops. An early study of solar potential estimation based on aerial photogrammetry was conducted by Wittman et al. [39], in which the rooftops in terms of position, size and azimuth have been measured using the stereo image pairs. In a more recent study, Fuentes et al. [40] have performed 3D construction based on UAV images to generate a digital surface model (DSM), which is used in the follow-up processes of shading analysis and PV panel area extraction.

The aerial images mentioned above mainly refer to images captured by visible-light sensors. Additionally, many other types of sensors can be mounted on aerial platforms to provide richer information for PV potential estimation, especially when multi-sensor integration system are applied. Specifically, Bannehr et al. [41] have employed four different RS sensors (i.e., hyperspectral, laser scanner, thermal, visible light) on an aircraft for determining comprehensive parameters of the rooftops including material characteristics, temperature distribution, slope and orientations, which facilitates accurate potential estimation for the use of PV panels. Similarly, Nadal et al. have jointly used an airborne laser scanning and a long wave infrared sensor for identifying the structures and materials of the rooftops, which can effectively support the potential estimation of constructing rooftop greenhouses [42].

3.3. LiDAR data

LiDAR, also known as laser scanning, is an active RS technique that directly captures 3D point cloud by measuring the timing and intensity of the return pulse [43]. As a sensor, the LiDAR instrument can be carried on different RS platforms, leading to various scanning types, such as airborne laser scanning (ALS), terrestrial laser scanning (TLS) and mobile laser scanning (MLS). ALS is currently the most accurate technique for DSM generation, which generally outperforms the technique of aerial photogrammetry; besides, it can also provide measurements beneath the vegetation canopy, which facilitates the generation of high-precision digital terrain model (DTM) that represents the ground surfaces. The advancement of the data processing algorithms (e.g., point cloud classification and segmentation) for LiDAR data has promoted the potential estimation of PV, especially the BIPV, to higher level in accuracy and details [44–46]. Fig. 5 shows the typical workflow of using LiDAR for PV estimation, in which the point cloud can be classified into multiple categories (e.g., vegetation, buildings and ground) for shading calculation, the structural information of buildings can be further derived for determining the available area and azimuth angles of rooftops.

There have been many studies developed for automatically estimating the solar PV potential of local buildings using LiDAR data. Voegtle et al. [44] have extracted the relevant features (i.e., size, exposition and slope) of building roof planes from ALS data for selecting the suitable areas for PV installations in urban environments. Kassner et al. [48] have also used airborne LiDAR data for the extraction of the

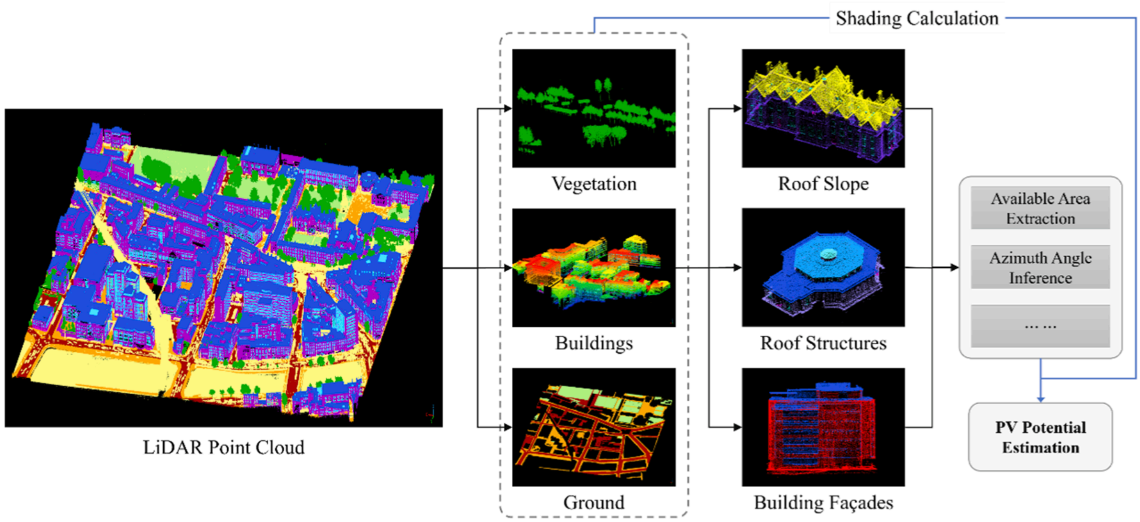

Fig. 5. The general workflow of applying LiDAR data to PV potential estimation. The annotated LiDAR point cloud of the DublinCity dataset [47] has been used for producing this figure.

roof area with high solar potential, but with a further consideration on roof shadows. Jiménez et al. [45] combined LiDAR data with aerial images for multi-type (e.g., flat, gable, saddle, etc.) roof characterization and PV potential calculation. In another typical study, Jochem et al. [49] have used MLS data to extract vertical walls for estimating the solar potential of building facades. Since LiDAR and aerial photogrammetry are both widely used for building extraction, Kaartinen et al. [50] have made an extensive comparison between the two techniques, revealing that LiDAR outperforms photogrammetry by enabling the measurement of more accurate building elevation and roof planes, as well as higher degree of automation.

The accurate 3D information captured by LiDAR can provide strong support for estimating the impact of shadows from vegetation and other structures when conducting building modeling and solar potential simulation. Specifically, Jochem et al. [51] have used LiDAR point cloud for roof plane extraction and shadow effect simulation, they have also considered the cloud cover effect for roof solar potential analysis by using the meteorological data; a subsequent study has further introduced a measurement of vegetation transparency for more accurate shadow effect modeling [52]. Tooke et al. [53] have also demonstrated that representing trees as opaque objects leads to substantial underestimate of solar irradiance with the use of LiDAR data. Based on a LiDAR-derived elevation model, Levinson et al. [54] have proposed a tree growth model to more accurately measure the light loss caused by shadows for rooftop solar-energy systems. Using LiDAR data for validation, Nguyen and Pearce [55] have developed a solar irradiation model for calculating the shading losses caused by terrain topography in solar PV potential estimation.

4. PV array detection

The rapid increase of PV installations calls for accurate data collection and update of the localization and distribution about the installed capacity, because it is highly important for better planning of the energy

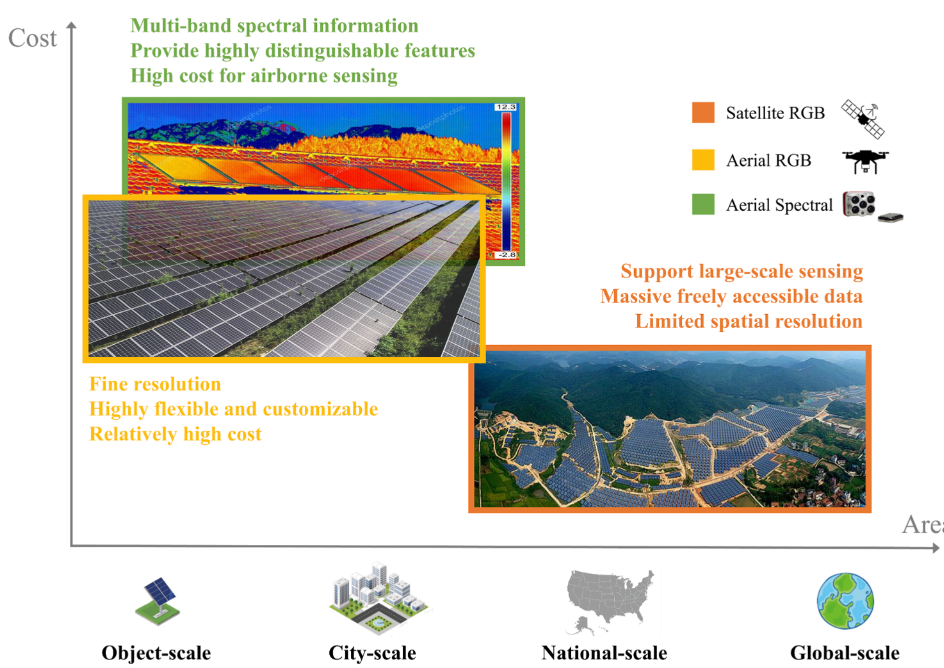

Fig. 6. The difference of three typical RS data on applicable scales and cost for PV array detection.

consumption and capacity expansion. However, obtaining the PV installation information based on field surveys and self-reports would be time-consuming, labor-intensive, and insufficiently accurate; in contrast, RS offers a time-efficient toolset for PV installation data collection at different scales, which can localize the installed capacity, especially the PV arrays, based on a series of highly automated detection algorithms. As shown in Fig. 6, several typical RS data, mainly including satellite imagery, aerial RGB images and spectral images, are considered as the most representative RS data source for PV array detection, which are suitable for application scenarios with different spatial scales, cost budgets and accuracy requirements.

4.1. Satellite imagery

As one of the most accessible RS data, satellite imagery has become one of the main sources for obtaining accurate localization information of PV along with the increase in spatial and temporal resolution of the spaceborne sensors. The early studies that have used satellite images for solar panel detection are mainly based on traditional image processing techniques. Specifically, manual designed image features such as color, edge, shape and/or texture are first described and extracted, filters, thresholding methods or machine learning classifiers are then applied to locating or segmenting the PV arrays [56–59]. However, manual-designed features could be limited in comprehensively representing the variety of imaging condition and PV material properties, which significantly hinders the generalization capability of these traditional methods.

In contrast, the recent advanced deep learning techniques, such as CNNs, which allow for adaptive representation and extraction of extremely high dimensional features, are increasingly becoming popular for PV array detection or segmentation. Several studies have successfully applied the CNNs to localization and area estimation of solar PVs from satellite imagery [60–64]. Li et al. [65] have applied the deep-learning-based segmentation methods to a comparison study, revealing that the segmentation results of PV panels from 1.2 m resolution images are nearly ineffective, acceptable accuracy can be achieved when the resolution increased to 0.3 m (i.e., 65.5 % of test images have PV segmentation IoU higher than 0.5), which is a typical resolution for many commercial optical satellites. Yu et al. [66] have made important progress by proposing DeepSolar, a deep learning framework that applied to 0.3 m satellite imagery for constructing a PV installation database, their evaluation has demonstrated that DeepSolar can achieve significantly high accuracy on PV panel segmentation and size estimation. Additionally, researchers have also attempted to extract PV installations using low-resolution (i.e., $>$ 0.3 m) satellite imagery. Golovko et al. [67] have used a CNN to achieve high segmentation accuracy (0.86 in F1-score) of PV panels on 3347 low-quality satellite images. Wang et al. [68] have used a deep siamese network to identify solar panels from low-resolution historical images by learning the correlation between the historical images and the high-resolution exemplar images.

Due to the high importance of labeled data for training a high-performance deep learning model, researchers have also contributed to construction and open sourcing of benchmark datasets in several countries and regions, mainly based on satellite images, which largely facilitates the development of related algorithms for PV array detection. Table 2 summarizes some typical image datasets indicating PV installation information, which have made the RS technology more widely applied to the analysis of PV systems.

4.2. Aerial RGB imagery

The development of distributed PV has progressively led to construction of smaller PV systems with varying sizes in different countries. Compared with satellite imagery, aerial or UAV images can capture more detailed information and are suitable for collecting localization and capacity data of small PV systems. Generally, RGB images have been the most used aerial RS data for PV array detection, the algorithms used in related studies can also be divided into traditional methods and deep-learning-based methods. The representative traditional methods include the use of support vector machine and random forest for classifying manual-designed features [72–75].

Table 2
Several benchmarking datasets of RS imagery labeled with PV installation information.

[Ref]/ Year	Data Sources	Location or Coverage	Resolution (m)	PV System & Capacity
[69]/ 2021	SPOT6/7 Sentinel-2	7.21×10^7 km^2 Global area	1.5	Non-residential PV423 (-75/ +77) GW
[57]/ 2021	Gaofen-2 Beijing-2 Aerial	107,200 km^2 in Jiangsu	0.8/0.3/0.1	PV array level 3716 samples
[70]/ 2020	Open-source imagery	UK	source-dependent	PV array level 10.66GW
[66]/ 2018	Google Static Maps	The contiguous US	0.3	PV panel level 1.4702 ± 0.0007 M samples
[71]/ 2016	United States Geological Survey	California	≤0.3	PV array level over 19,000 samples

The deep-learning-based methods usually follow the development of neural network architectures. Malof et al. [76] have explored the performance of the visual geometry group network (VGGNet) for PV panel detection. Camilo et al. [77] have applied the SegNet to solar PV panel segmentation from aerial orthophotos. González et al. [78] have used the U-Net for accurately extracting the boundaries of PV plants from UAV images, achieving 0.90 in IoU. Meanwhile, some algorithms have also been specially developed to address the unique characteristics of PV targets. Jie et al. [79] have introduced the gated fusion module into the U-Net-like architecture for better identifying small PV panels and also used a multi-task design for refining the edges of the PV segmentation results. Parhar et al. [80] have proposed HyperionSolarNet, a two-branch framework composed of an image classification model and a semantic segmentation model, presenting effective and scalable detection of solar panels by achieving 0.86 and 0.89 F1-score for classification and segmentation, respectively.

In addition to the location and size of PV panels, the 3D information, such as mounting slope and azimuth angle can facilitate more accurate estimation and pattern analysis of power generation in PV systems. Some studies have been conducted for obtaining 3D information of PV systems based on aerial images. Specifically, Edun et al. [81] have inferred the azimuth angle from the rotation of the segmented PV panel polygons by using edge detection and Hough transform. Rausch et al. [82] have combined aerial images and 3D building data to construct address-level PV registries with area, slope and orientation angle, which has been claimed as a good alternative to self-reported data. Similarly, Mayer et al. [83] have proposed the 3D-PV-Locator, a deep-learning-based integration solution of image classification, segmentation and spatial data processing, for detecting roof-mounted PV systems with 3D information (i.e., tilt and azimuth angles), which has been proven able to improve the estimation accuracy of PV panel area and capacity for residential areas.

4.3. Aerial spectral imagery

Due to the variety and the complexity of the PV materials, the imaging conditions and the installation environments, the visual characteristics of PV panels can be highly changeable and easily confused with other objects (i.e., road, rooftop, or steel structures); thus, accurate PV panel detection and segmentation from satellite imagery or aerial RGB images remains challenging. Spectral imaging is a technique that captures multi-band information across the electromagnetic spectrum, which significantly expands the spectral range of the ordinary RGB images. Typically, a hyperspectral sensor may have hundreds of narrow spectral bands, providing a detailed spectral profile for each pixel in an image, which enables the extraction of highly distinguishable features.

The solar panel materials generally present unique spectral characteristics, which leads to an overall better detection performance in spectral images. Czirjak et al. [84] have introduced the normalized solar panel index for describing the spectral features of PV solar panel reflection, verifying that PV arrays can be measured in hyperspectral images by common statistical algorithms. Karoui et al. [85] have conducted a hyperspectral-unmixing based study for PV panel detection, in which the ground measurements of the PV panel spectrum by a spectrometer has been used. However, although inspiring results have been achieved, the segmentation accuracy of the above works could be insufficient due to the neglect of the angle-induced spectral variance and the spectral diversity of materials. By taking these problems into consideration, Ji et al. [86] have conducted a physics-based approach that can significantly improve detection accuracy of PV modules in spectroscopy data, where the spectral variance caused by detection angle has been well solved with the hydrocarbon index, the material diversity has been handled by applying a carefully-constructed image spectral library.

Since considerable amount of the solar radiation received by a PV module is converted into heat, the PV panels generally would exhibit a distinct thermal signature. As a spectral sensor, infrared thermography (IRT) captures radiation at 1.4 to 15 μm wavelengths on the surface, the thermal signals represented within the captured infrared image can lead to accurate segmentation of PV modules from the background. Wang et al. [87] have applied Otsu's method to binary segmentation of infrared images for identifying the PV panel borders. Dotenco et al. [88] have proposed a statistical and data-driven approach for segmenting PV component pixels from infrared images by assuming that the PV module temperature is high and normally distributed; the approach has shown very high segmentation accuracy (0.96 in F1-score). Shen et al. [89] have combined the texture features and gradient edges for extracting PV regions from infrared images. In addition to the above methods based on low-level features, the deep learning models [90–92] have also been applied to PV segmentation from infrared images, some of which [93] has reported even higher accuracy (0.97 in F1-score).

In general, different RS techniques can provide effective support for localization and capacity estimation of PV arrays to various degrees, while the selection of specific technique is usually dependent on accuracy requirements and cost budgets. Fig. 7 shows some examples of PV array detection or segmentation from different RS images.

5. PV fault monitoring and diagnosis

The failure of PV modules can seriously affect the entire PV system. Reliable and efficient performance assessment and fault detection is of high importance for reducing safety incidents, increasing the productivity and extending the lifetime of PV systems. Compared to the traditional monitoring techniques based on electrical measuring devices, RS can provide a timely and non-contact means for damage detection and health monitoring of PV panels in complex environments or large-scale areas.

As the main component of a PV system, PV arrays are subject to damage during their production, transportation, and utilization. Numerous research efforts have discussed different failure modes of PV arrays [94–97], which can be classified as encapsulation failures, shading and soiling, cell cracking, broken interconnection and hotspot. Generally, UAV visible imaging and aerial IRT are the most widely used RS techniques for PV fault detection. Fig. 8 compares the publication percentages and sample images of the two representative techniques applied to different types of failure modes, indicating that each failure type has a unique external manifestation, which can be visually presented in different forms by both the two types of the RS images.

5.1. UAV RGB imagery

Earlier monitoring or diagnosis of PV module failures relies heavily on human visual inspection, which largely limits the detection accuracy, efficiency, and the inspector's occupational safety. The automatic detection methods from aerial RGB images have obvious advantage over the visual inspection method because they can accurately identify and locate the damage of PV systems without interrupting the PV operations. Specifically, Aghaei et al. [105] have investigated the correlation between the flight height and the detection performance of the PV module defects, suggesting that 20 m and 2 cm are ideal flight height and spatial resolution, respectively, for effectively detecting most defect types. The requirement of extremely high-resolution makes UAV the primary platform of acquiring image data for processing. Fig. 9 shows the typical fault results detected from UAV RGB imagery. In terms of the algorithms, the traditional image processing methods and the deep-learning-based methods represent a major trend of the technical development.

The traditional image processing algorithms can be effective in

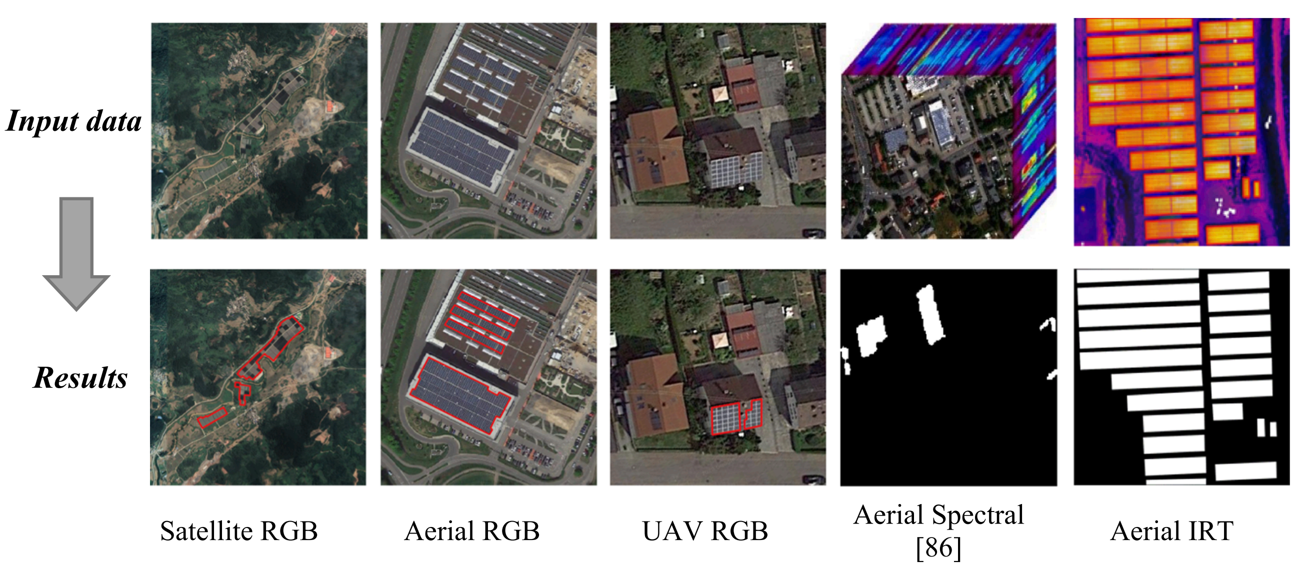

Fig. 7. The examples of PV array detection or segmentation results from different RS images.

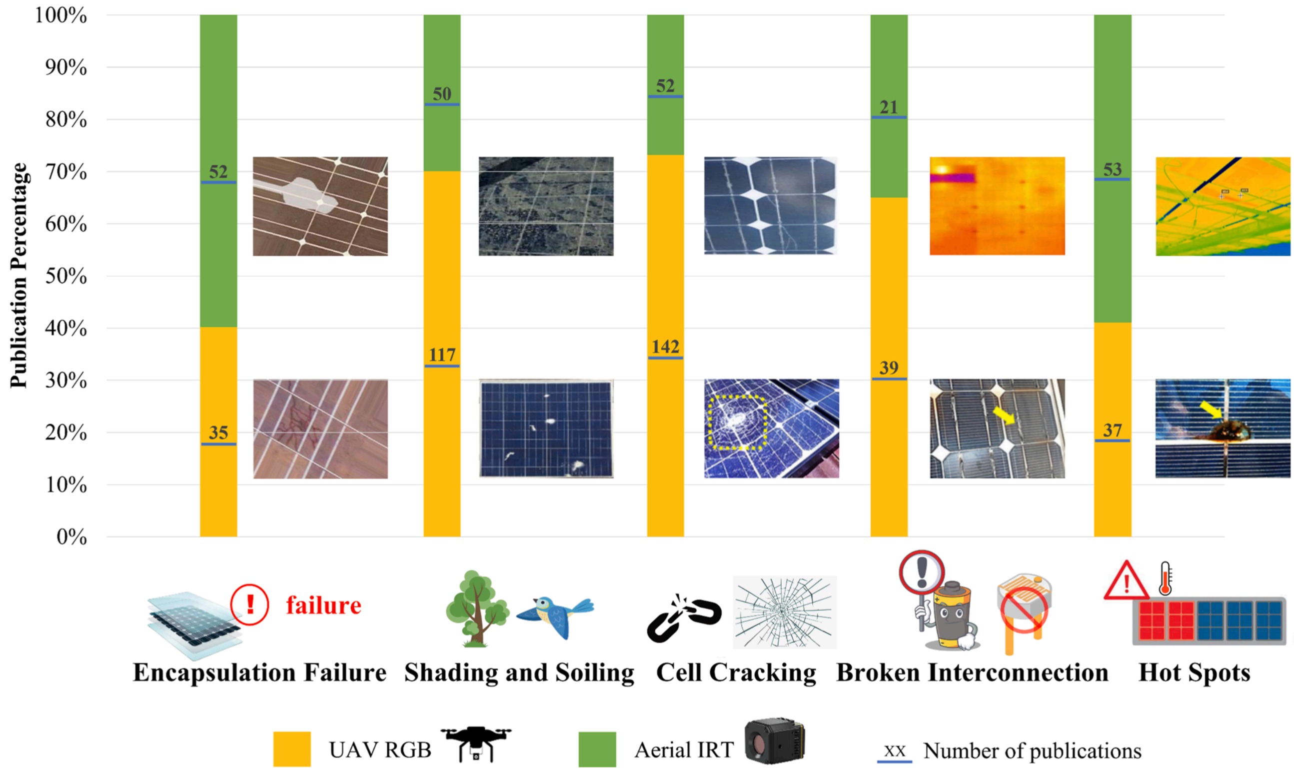

Fig. 8. The publication percentages of the two representative RS techniques (i.e., UAV RGB and aerial IRT) and the sample images (screenshots from [98–104]) for different types of PV failures.

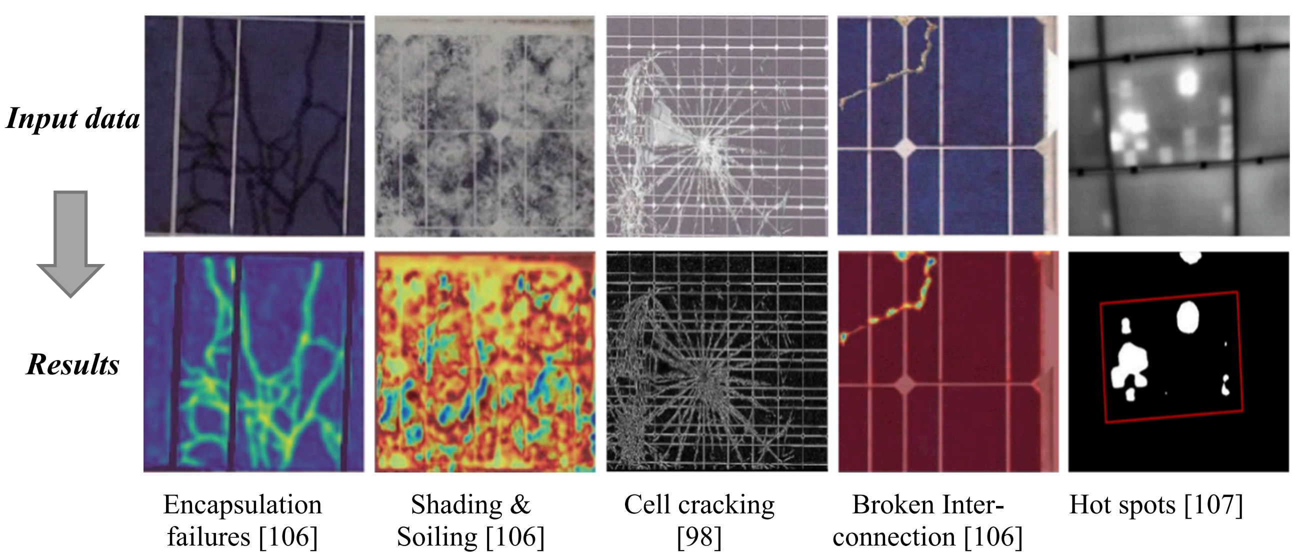

Fig. 9. The typical PV fault detection results from UAV RGB images (See above-mentioned references for further information.)

several specific tasks of PV defect detection from UAV RGB images. Li et al. [108] have used a Gaussian filter and the feature matching algorithm for detecting the snail trails and dust shading of PV modules, demonstrating that the two visible defects are be efficiently inspected and monitored. Patel et al. [109] have used the algorithms of thresholding, morphology and edge detection for detecting the damaged areas of the PV panels. Baig et al. [110] have conducted pixel-level image analysis based on mathematical morphology and edge detection algorithms for classifying healthy and unhealthy PV modules. However, the application capability of these image processing algorithms is generally limited because they are largely dependent on the manual parameter tuning and usually bonded to certain data type or imaging environments.

The deep-learning-based methods have been developed for further improving the recognition accuracy. Li et al. [106] have developed an online PV defect detection system based on a pre-trained CNN and a transfer learning design for more adaptive classification. Shihavuddin et al. [102] have constructed a image dataset of PV panel surface damages and conducted an extensive comparison study on the state-of-the-art object detection networks. Sridharan and Sugumaran [111] have augmented the dataset with limited PV samples and used a CNN model for classifying various fault types from the UAV images. Despite the advancement achieved by these studies, PV fault detection from RGB images based on deep learning is still facing challenges in detection accuracy and adaptability to different defect categories, largely because of the limited amount of labeled dataset and insufficient transferability of models.

5.2. Aerial IRT imagery

PV modules present a uniform temperature distribution during normal operation, which is an important clue for identifying the health status of PV modules. The abnormally high or low temperature spots appeared on unhealthy or damaged PV modules are usually a sign of defects and a major concern in PV operation and maintenance. IRT is an ideal technique for sensing the temperature information of PV modules. In comparison to RGB images, IRT can detect the PV damages that are invisible to the naked eye, such as internal short circuits, interconnect failures or cracked and broken cells.

Earlier IRT inspections of PV systems relied on human inspectors holding IRT cameras, which was inefficient for large-area monitoring and vulnerable to human errors. The aerial IRT, which is typically based on lightweight and inexpensive UAVs and automatic algorithms, has largely improved the inspection capability and efficiency for PV modules with different installation heights and angles.

Table 3 shows the summary of the representative studies on PV fault detection and monitoring mainly using aerial IRT data. The algorithms for detecting and identifying the PV module defects from infrared images can be mainly divided into traditional image processing methods and deep-learning-based methods. Since the damaged PV panels are usually replaced in their entirety during the daily maintenance, statistical features are designed and extracted for determining the overall state of single PV module. Meanwhile, the integration of visible-light images and infrared images has been a trend for identifying more types of PV faults.

6. Geological hazard risk estimation for typical PV projects

The rapid development of the PV industry has led to an increasing shortage of land for the construction of PV power facilities. As a result, developing PV systems on some unused land (e.g., abandoned coal mining areas or bare mountains) has been considered as a sustainable solution. However, these types of lands are often exposed to the risk of geological hazard such as subsidence and landslides. By providing a series of techniques for geological hazard risk assessment, RS has played a significant role in site selection and safety monitoring of such PV projects.

6.1. Coal mining subsidence areas

As a pillar energy industry, coal has made a significant contribution to the social economic development [129]. However, the coal mining activities would disrupt the original stress equilibrium of the overlying strata, with consequent mobile deformation such as collapse, fracture and bending, resulting in large-scale mining subsidence areas [130]. Large-scale ground deformation would pose negative impacts on the ecological environment and sustainable development of mining areas; thus, many coal mining areas have been discarded. In recent years, the coal mining subsidence areas have been gradually used for facility construction of PV systems [131,132], which is becoming popular in resource-based cities of China (Fig. 10).

Depending on the degree of ground deformation, the risk level of the settlement land can be classified as low, medium, and high subsidence. PV power plants are often built on land with evident subsidence, where it is difficult to achieve reclamation and develop other industries [133]. To ensure the security and stability of the PV power generation facilities, it is important to perform dynamic ground deformation monitoring of the exploited mining subsidence areas.

Traditional deformation monitoring methods (i.e., classical geodesy, GNSS, etc.) can provide accurate deformation measurement at point level. But these methods are difficult to achieve large-scale coverage and efficient dynamic monitoring. Differential interferometric SAR (InSAR) is an advanced RS technique of acquiring wide range of surface deformation in all weather conditions, which has been frequently applied to deformation monitoring in geological disasters and mining areas [134,135]. Besides, the technique of time-series InSAR has also been widely used in monitoring urban ground subsidence [136] and infrastructure deformation [137], which is considered capable of overcoming certain limitations of differential InSAR, such as spatial and temporal decoherence and atmospheric delays.

6.2. Mountainous areas

Some PV power plants are built in the mountainous areas for

Table 3
The representative studies on PV fault detection and monitoring mainly using aerial IRT data.

[Ref]	Sensor type	PV system	Damage localization method		Type of faults				
			Traditional image processing	deep learning	EF[a]	SS[b]	CC[c]	BI[d]	HS[e]
[112,113]	IR camera	PV components level	Anomalous temperature detection	/	●			●	●
[114]	Digital camera & IR camera	PV cell level	Discolored part identification						●
[103,115,116]	Aerial IR camera & HD photo camera	PV array level	Thermal analysis		●	●	●	●	●
[117,118]	IR camera	PV module level	Statistical analysis						●
[119]	IR camera	PV cell level	PCA, ICA, NMF algorithms	LeNet-5, VGG-16, GoogleNet		●	●	●	●
[120]	Portable thermal imager	PV array level	Canny edge detection	/					●
[121]	IR camera on moving cart	PV module level	DBSCAN clustering				●		●
[122,123]	Aerial IR camera	PV module level	Thresholding technique Laplacian and binary models						●
[124]	Digital camera & IR camera	PV module level	Thresholding technique					●	●
[125,126]	Aerial IR camera	PV array level	Laplace edge detection Hough detection	VGG-16 pre-trained model CNN-based classification model				●	●
[127]	Aerial IR camera	PV module level	/	YOLOv4					●
[128]	Dual infrared camera	PV module level		YOLOv5 & ResNet	●	●	●		●

[a] Encapsulation failures.
[b] Shading and soiling.
[c] Cell cracking.
[d] Broken interconnection.
[e] Hot spots.

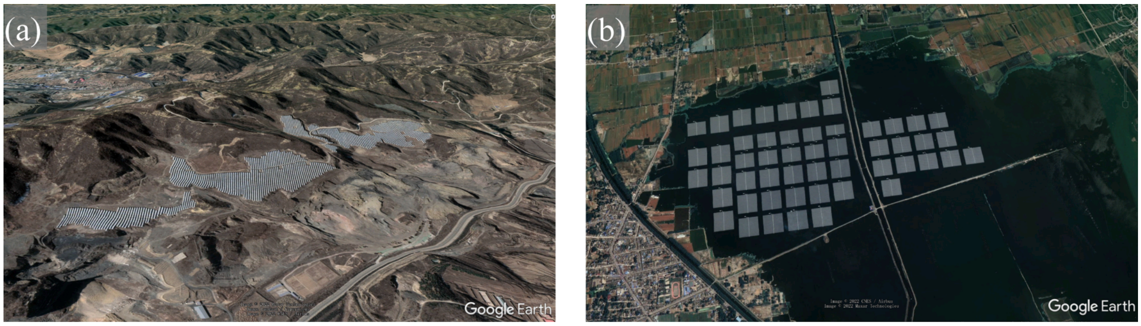

Fig. 10. PV power facilities that are constructed in typical coal mining subsidence areas of China: (a) PV panels are deployed in an area besides a closed coal mine in Yangquan; (b) PV panels are set on a coal mine subsidence lake in Huainan.

limitation of land resources. However, climatic changes and increased rainfall may lead to landslides, which poses a serious threat to the facilities. Therefore, the risk of landslides in the built area should be carefully assessed before PV project site selection to avoid additional losses caused by the hazards.

In a typical study, Kim et al. have analyzed the landslide susceptible areas to judge the reasonability of the existing government regulations for PV plant installation [138]. Generally, the distribution and situation of landslides can be constantly changing due to the impact of topography and climatic conditions (e.g., precipitation, typhoon paths), which makes it difficult to acquire data from field survey for dynamic landslide risk assessment of large-scale areas.

RS has long been an active technology for landslide risk assessment due to its capability of extracting various significant parameters, such as ground deformation velocity and slope feature [139,140]. Satellite optical and SAR imagery can effectively support detailed landslide detection, especially after events of extreme rainfall and earthquakes [141–143]. Small-scale and individual landslide risk assessment benefits a lot from UAV photogrammetry and airborne LiDAR data, which can both generate high-quality DTM for improving the interpretation of the slope structure and precise ground deformation [144,145]; moreover, LiDAR usually shows better performance in vegetated region for its vegetation penetration capability. Since ground deformation is one of the most important parameters for landslide risk assessment, the techniques of differential and multi-temporal InSAR are also frequently adopted [146,147]; thus, the infrastructure vulnerability assessment and the dynamic hazard mapping can be achieved by obtaining the ground displacement estimates with millimeter precision from large stacks of SAR images [148,149].

7. Techno-economic assessment for novel scenarios

As a renewable energy to power a sustainable future [96], the penetration and ubiquity of solar PV will be greatly increase in the future. To reduce the land requirements of PV installation and meet regional high-power demand, many studies have attempted to explore the techno-economic potential and feasibility of integrating PV systems into unconventional scenarios. In this domain, the variety of RS data or techniques are currently getting attention and expected to play important role in improving the efficiency and accuracy of the solutions. For example, unconventional PV projects often have a complex coupling relationship between technical and economic factors; therefore, in

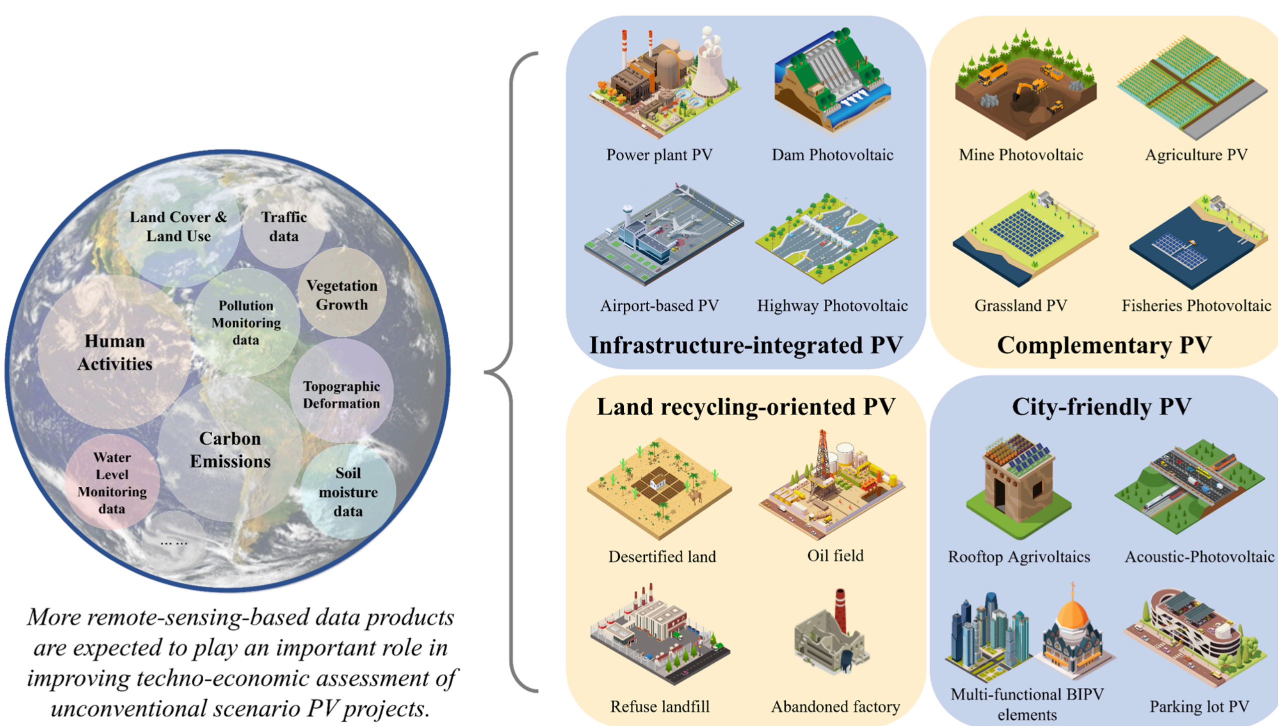

Fig. 11. The variety of the RS-based data products and several unconventional PV-integration scenarios that potentially use RS techniques for conducting techno-economic assessment.

addition to rapid acquisition of large-scale spatial information, the technical and economic assessment often requires reliable and detailed multi-modal data (i.e., environmental, ecological, user information, etc.) and low-cost planning and design. Advanced RS technologies have natural advantages in solving these problems.

In Fig. 11, beyond the above-mentioned RS applications, we highlight a few other types of RS-based data products (i.e., land cover & land use [150], human activities [151], carbon emissions [152], pollution monitoring [153], vegetation growth [154], topographic deformation [155], soil moisture [156], water-level monitoring [157] and traffic data [158]) that are potentially useful for techno-economic assessment of PV projects, which leads to a brief introduction of the research about PV integration in several other scenarios: infrastructure-integrated PV, complementary PV, land recycling-oriented PV, and city-friendly PV.

7.1. Infrastructure-integrated PV

The public infrastructures can provide large amount of open area for PV deployment. Jiang et al. [159,160] have integrated the PV system into a thermal power plant by deploying the modules on rooftops and coal storage sheds, which has facilitated flexible power generation and reduction of internal power consumption. Similarly, Qi et al. have introduced a motion-based PV system installed on a cooling tower, demonstrating that high economic benefits can be achieved [161]. Solar PV can also be integrated with other renewable energy generation systems, such as hydroelectric dams [35,162] and wind farms [163,164]. Urban transport infrastructures (high-speed railways, roads, airports, etc.) occupy large sunny public area that can be deployed with PV systems. Chen et al. [165] have estimated the PV potential along the rail lines and station rooftops of a high-speed railway, conceptually proving the profitability of the integration solution. Jiang et al. [166] have assessed the PV potential and associated economic benefits of 239 airports and concluded that terminals and car parks are optimal locations for PV installation. It has been reported that the power requirements of some airports can be fully satisfied by the PV system deployed in their open areas [167].

7.2. Complementary PV

Many PV systems can be deployed with environmental or economic complementary effects. The floating PV installed on water bodies of oceans, lakes, irrigation ponds, wastewater treatment plants, dams and canals, not only increase the power generation efficiency but also can improve the aquatic environment for fisheries [168–173]. Agrivoltaics systems utilize the land area for both PV power generation and agriculture, which can simultaneously provide electrical support and favorable environments for agricultural products [174–178]. Choi and Song [132] have also mentioned the PV system deployed in operating mines of remote areas, where the energy supply can be internally resolved by the PV power.

7.3. Land recycling-oriented PV

There are large areas of land that have been abandoned for long time due to industrial exploitation, pollution, or low habitability. As introduced in Section 6.1, the PV systems constructed on coal mining subsidence areas are a typical example of creative land recycling, which provides an option for repurposing the abandoned lands. Based on a similar concept, Salasovich and Mosey have estimated the economic and technical feasibility of implementing PV systems at a landfill site, suggesting that a key element of this solution is to find a use for the generated electricity [179]. The value of the land recycling-oriented PV systems has been promoted by government policies due to the promising economic benefits [180], probably inspiring more new integration solutions based on other abandoned lands such as industrial wasteland, oil fields or desertified land.

7.4. City-friendly PV

"Solar architecture is not about fashion, but about survival" [181]. The PV systems are appearing in a wider range of urban places, such as solar bike lanes [182], road noise barriers [183] and vehicle parking lots [184], for providing important electricity support. Considering the impact on the cityscape and environment, building city-friendly PV systems is becoming another popular research topic. Some BIPV systems use the power generation modules as architectural elements at the same time, in which the energy production unit can not only bring aesthetic comfort to the building, but also serve as insulation against heat and noises [185,186]. Since the expansion of PV facilities on the landscape may lead to unexpected phenomena and reflections, other PV-related studies have focused on the protection of architectural heritage culture [187], public perception, security, privacy, and ethical considerations [188,189].

8. Conclusion and future directions

This paper reviewed the research progress of the application of RS technology to PV system development, mainly focusing on three aspects in terms of potential assessment, facility detection, and fault monitoring and diagnosis. It can be considered that the RS techniques have addressed the shortcomings of the traditional field survey methods in efficient large-scale observation information acquisition and analysis, providing highly accurate and cost-effective data for planning, management, and decision-making of PV systems. In Table 4, as a conclusion, we try to summarize and outline the advantages and disadvantages of different RS techniques applied to the representative types of PV scenarios mentioned above.

However, despite that the RS techniques and methods strongly facilitate the PV system development, significant challenges including but not limited to the following aspects remain:

a) Microscopic-level city modeling. The accurate assessment of PV potential and capacity in complex scenes requires the detailed surface information to be observed and parametrized more accurately. Typically, for distributed PV development on rooftops, accurate installation area estimation requires precise plane parametrization (e.g., tilt angle, orientation) and exclusion of small structures (i.e., chimneys, dormers, etc.); rigorous estimation of power generation requires precise reconstruction of surrounding ground objects and their shading effect simulation. Therefore, microscopic-level 3D city modeling would be a major challenge for RS of PV systems, which poses demands on both fine-grained data acquisition and intelligent data interpretation.

b) Adaptivity to complexity of PV materials. Currently, solar PV panels are mainly made of single- or poly-crystalline silicon covered with ethylene vinyl acetate film and a protective glass cover. The mixed material composition makes them easy to be confused with many other types of structures such as roads, ponds, skylights and vegetable sheds, especially considering the changeable external environments and observation conditions. The future renewal of PV materials will also place new challenges on the previously applicable RS techniques.

c) Alleviation of high-resolution dependency. 0.3 m per pixel is currently recommended spatial resolution of images for accurate PV module segmentation, the requirement increases to 2 cm for conducting fault detection and diagnosis. However, most of the freely accessible data are relatively low-resolution satellite images, in which the solar PV panels are difficult to be identified even for professional human interpreters. Therefore, for cost reduction, it is important and challenging to broaden the applicable resolution range by developing and applying advanced algorithms.

d) Learning with limited/no labeled data. Currently, the state-of-the-art methods of PV identification and fault detection from RS imagery are mostly based on deep learning, which require massive training data relying on extensive manual annotation. However, the high-quality PV-related RS datasets are generally insufficient by far, especially for the

Table 4
The overall conclusion about advantages/disadvantages of different RS techniques for major PV application scenarios.

PV-related Scenario	RS Technique	Advantages	Disadvantages
Potential estimation	Satellite imaging	• High spatial & temporal continuity • Meteorological observation capability • Large scale applicability • Unbounded estimation area	• Dependence on observations from ground stations for SSI assessment • Limited capability of providing 3D information • Relatively low spatial/temporal resolution
	Aerial imaging	• High spatial resolution • Scalability of sensors • 3D surface reconstruction capability	• Relatively high cost • Relatively constrained geographic scope
	LiDAR	• Precise acquisition of 3D information • Component-level BIPV estimation • Reliable shadow and occlusion analysis	• Expensive cost • Limited automation degree for 3D reconstruction of roof structures
Array detection	Satellite imaging	• Large scale applicability • Abundant freely accessible datasets and labeled training samples	• Insufficient resolution for accurate detection • Relatively unstable data quality due to adverse weather and cloud cover
	Aerial RGB imaging	• Capability of detecting small PV targets • Acquisition of detailed installation parameters	• Limited application scale • Relatively time-consuming in data processing
	Aerial spectral imaging	• Stronger PV detection capability for providing richer spectral information	• Higher data volume for processing and analysis • Expensive cost for data acquisition
Fault monitoring and diagnosis	UAV RGB imaging	• Wider range in detection types of failures • Low cost for data acquisition	• Dependence on high-performance algorithms • Limited to inspection of PV panels' surface
	Aerial IRT imaging	• Special detection capability for PV damages that are invisible to the naked eye • Relatively low requirement on complexity of detection algorithms	• Limited to close range monitoring • Relatively high cost
Geological hazard risk estimation	InSAR	• Cost-effective for regional and high-accurate deformation monitoring • All weather & all day	• Limited capability for monitoring large deformation • Sparse measurement points in natural terrains
	LiDAR	• High-precision topography mapping • Vegetation penetration capability	• Expensive and inconvenience for monitoring of mountains • Limited applicability to regional scales and high-frequency monitoring

large-scale datasets of PV fault detection and diagnosis, which poses another major challenge for this field: how to conduct effective learning when having limited or no labeled data? Is it possible to transfer the knowledge learned from datasets of unrelated regions to new test areas?

The above challenges can be turned into important development opportunities and exploring directions of RS applied to PV systems, which we summarize as follows:

a) Cost-effective 3D reconstruction. Although LiDAR remains the most stable and convenient technique for urban 3D reconstruction, the advanced development of photogrammetry is facilitating more affordable 3D reconstruction with high accuracy. For large-scale PV potential estimation, the satellite stereo images with sub-meter resolution [190] can be considered as a cost-effective data source for 3D information extraction and shading calculation. On the other hand, the novel technique of UAV nap-of-the-object photogrammetry facilitates 3D reconstruction close to millimeter-level resolution [191], which strongly compares with the performance of LiDAR technique.

b) Mission-customized sensor integration. The PV-related observation missions focus on different spectral bands of radiometric information, the integration of various sensors, such as optical, laser scanning and SAR with different spatial/spectral resolutions, can facilitate processing and analysis on signals captured from more than one imaging technique. Therefore, a careful customization of integrated sensors according to specific characteristics (e.g., targets, accuracy requirement and geographic range) of the observation tasks will largely improve the application effectiveness.

c) Application of deep generative models. By far, the deep learning methods applied to PV-related scenarios are mostly discriminative models. However, the deep generative models also have wide promising applications for RS of PV systems, the technical fields where these models have made significant contribution can be paid more attention. For example, image super resolution or pansharpening methods [192,193] can be used to improve the feasibility of low-resolution RS images for PV array detection; the methods of monocular depth estimation [194] an extract 3D information from ordinary images for more accurate PV potential estimation.

d) Crowdsourcing datasets and self-supervised learning. Large-scale annotated datasets, such as ImageNet [195], have played an important role in promoting the development of deep-learning-based vision methods. For specific PV-related tasks, constructing large-scale RS datasets through online crowdsourcing could be a feasible approach for algorithmic progress in this field. On the other hand, applying advanced self-supervised learning methods, such as masked autoencoders [196], can be another important direction for reducing the dependency on massive labeled training data.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. This work has been supported by the National Natural Science Foundation of China (No. 41601506, 41801348 and 41907253) and the Key Research and Development Program of Hubei Province (No. 2021BCA219).

Data availability

No data was used for the research described in the article.

References

[1] Rogan J, Chen DM. Remote sensing technology for mapping and monitoring land-cover and land-use change. Prog Plann 2004;61:301–25. https://doi.org/10.1016/S0305-9006(03)00066-7.

[2] Lunetta RSE, Christopher D. Remote sensing change detection: environmental monitoring methods and applications. 1998.

[3] Livera A, Theristis M, Makrides G, Georghiou GE. Recent advances in failure diagnosis techniques based on performance data analysis for grid-connected photovoltaic systems. Renew Energy 2019;133:126–43. https://doi.org/10.1016/J.RENENE.2018.09.101.
[4] Gassar AAA, Cha SH. Review of geographic information systems-based rooftop solar photovoltaic potential estimation approaches at urban scales. Appl Energy 2021;291:116817. https://doi.org/10.1016/j.apenergy.2021.116817.
[5] Melius J, Margolis R, Ong S. Estimating rooftop suitability for PV: a review of methods, patents, and validation techniques. NREL Tech Rep 2013::35.
[6] Tina GM, Ventura C, Ferlito S, De Vito S. A state-of-art-review on machine-learning based methods for PV. Appl Sci 2021:11. https://doi.org/10.3390/app11167550.
[7] Avtar R, Sahu N, Aggarwal AK, Chakraborty S, Kharrazi A, Yunus AP, et al. Remote sensing and GIS — a review. Resouces 2019;8:23.
[8] Tooke TR, Coops NC. A review of remote sensing for urban energy system management and planning. Jt Urban Remote Sens Event 2013, JURSE 2013 2013: 167–70. doi: 10.1109/JURSE.2013.6550692.
[9] De Hoog J, Maetschke S, Ilfrich P, Kolluri RR. Using Satellite and aerial imagery for identification of solar PV: state of the art and research opportunities. In: e-Energy 2020 - Proc. 11th ACM Int. Conf. Futur. Energy Syst., Association for Computing Machinery, Inc; 2020. p. 308–13. doi: 10.1145/3396851.3397681.
[10] de Oliveira AKV, Aghaei M, Rüther R. Automatic inspection of photovoltaic power plants using aerial infrared thermography: a review. Energies 2022:15. https://doi.org/10.3390/en15062055.
[11] Pinker RT, Laszlo I. Modeling surface solar irradiance for satellite applications on a global scale. J Appl Meteorol 1992;31:194–211. https://doi.org/10.1175/1520-0450(1992)031<0194:MSSIFS>2.0.CO;2.
[12] Huang G, Li Z, Li X, Liang S, Yang K, Wang D, et al. Estimating surface solar irradiance from satellites: past, present, and future perspectives. Remote Sens Environ 2019:233. https://doi.org/10.1016/j.rse.2019.111371.
[13] Chaturvedi DK, Singh I. Solar power forecasting: a Review cognitive decision making view project solar PV power generation forecasting using neural network based approaches view project solar power forecasting: a review. Vol. 145; 2016.
[14] Antonanzas-Torres F, Urraca R, Polo J, Perpiñán-Lamigueiro O, Escobar R. Clear sky solar irradiance models: a review of seventy models. Renew Sustain Energy Rev 2019;107:374–87. https://doi.org/10.1016/J.RSER.2019.02.032.
[15] Fritz S, Rao PK, Weinstein M. Satellite measurements of reflected solar energy and the energy received at the ground. J Atmos Sci 1964;21:141–51.
[16] Hanson KJ. Studies of cloud and satellite parameterization of solar irradiance at the earth's surface. National Oceanic and Atmospheric Administration, Miami, Fla. (USA). Atlantic…; 1971.
[17] Tarpley JD. Estimating incident solar radiation at the surface from geostationary satellite data. J Appl Meteorol Climatol 1979;18:1172–81.
[18] Qin J, Tang W, Yang K, Lu N, Niu X, Liang S. An efficient physically based parameterization to derive surface solar irradiance based on satellite atmospheric products. J Geophys Res Atmos 2015;120:4975–88.
[19] Cano D, Monget JM, Albuisson M, Guillard~ H, Regas N, Wald L. A method for the determination of the global solar radiation from meteorological satellite data. Vol. 37; 1986.
[20] Akarslan E, Hocaoglu FO. A novel adaptive approach for hourly solar radiation forecasting. Renew Energy 2016;87:628–33. https://doi.org/10.1016/J.RENENE.2015.10.063.
[21] Voyant C, Notton G, Kalogirou S, Nivet ML, Paoli C, Motte F, et al. Machine learning methods for solar radiation forecasting: a review. Renew Energy 2017; 105:569–82. https://doi.org/10.1016/J.RENENE.2016.12.095.
[22] Mahtta R, Joshi PK, Jindal AK. Solar power potential mapping in India using remote sensing inputs and environmental parameters. Renew Energy 2014;71: 255–62. https://doi.org/10.1016/J.RENENE.2014.05.037.
[23] Deo RC, Şahin M, Adamowski JF, Mi J. Universally deployable extreme learning machines integrated with remotely sensed MODIS satellite predictors over Australia to forecast global solar radiation: a new approach. Renew Sustain Energy Rev 2019;104:235–61.
[24] Gherboudj I, Ghedira H. Assessment of solar energy potential over the United Arab Emirates using remote sensing and weather forecast data. Renew Sustain Energy Rev 2016;55:1210–24. https://doi.org/10.1016/j.rser.2015.03.099.
[25] Ma YT, Pinker RT, Zhang B, Zhang YC, Rossow WB. Comparison of UMD/SRB V3.1 ISCCP D1 fluxes with those of ISCCP-FD: source of differences, GEWEX Radiative Flux Assessment. New York Third Work. NASA GISS, 2007.
[26] Buffat R, Grassi S. Validation of CM SAF SARAH solar radiation datasets for Switzerland. In: 2015 3rd Int. Renew. Sustain. Energy Conf., IEEE; 2015. p. 1–6.
[27] Saretta E, Bonomo P, Frontini F. A calculation method for the BIPV potential of Swiss façades at LOD2.5 in urban areas: a case from Ticino region. Sol Energy 2020;195:150–65. https://doi.org/10.1016/j.solener.2019.11.062.
[28] Cerón I, Caamaño-Martín E, Neila FJ. 'State-of-the-art' of building integrated photovoltaic products. Renew Energy 2013;58:127–33. https://doi.org/10.1016/J.RENENE.2013.02.013.
[29] Zhong T, Zhang Z, Chen M, Zhang K, Zhou Z, Zhu R, et al. A city-scale estimation of rooftop solar photovoltaic potential based on deep learning. Appl Energy 2021: 298. https://doi.org/10.1016/j.apenergy.2021.117132.
[30] Lee S, Iyengar S, Feng M, Shenoy P, Maji S. Deeproof: a data-driven approach for solar potential estimation using rooop imagery. Proc ACM SIGKDD Int Conf Knowl Discov Data Min 2019:2105–13. https://doi.org/10.1145/3292500.3330741.
[31] Mainzer K, Schlund D, Killinger S, McKenna R, Fichtner W. Rooftop PV potential estimations: Automated orthographic satellite image recognition based on publicly available data. Proc. Eur. PV Sol. Energy Conf. Exhib. (EU PVSEC); 2016.
[32] Sun T, Shan M, Rong X, Yang X. Estimating the spatial distribution of solar photovoltaic power generation potential on different types of rural rooftops using a deep learning network applied to satellite images. Appl Energy 2022;315: 119025. https://doi.org/10.1016/J.APENERGY.2022.119025.
[33] Liu Z, Fei T. Road PV production estimation at city scale: a predictive model towards feasible assessing regional energy generation from solar roads. J Clean Prod 2021:321. https://doi.org/10.1016/j.jclepro.2021.129010.
[34] Zhang C, Li Z, Jiang H, Luo Y, Xu S. Deep learning method for evaluating photovoltaic potential of urban land-use: a case study of Wuhan, China. Appl Energy 2021:283. https://doi.org/10.1016/j.apenergy.2020.116329.
[35] Ates AM, Yilmaz OS, Gulgen F. Using remote sensing to calculate floating photovoltaic technical potential of a dam's surface. Sustain Energy Technol Assessments 2020:41. https://doi.org/10.1016/j.seta.2020.100799.
[36] Krapf S, Kemmerzell N, Uddin SKH, Vázquez MH, Netzler F, Lienkamp M. Towards scalable economic photovoltaic potential analysis using aerial images and deep learning. Energies 2021:14. https://doi.org/10.3390/en14133800.
[37] Mainzer K, Killinger S, McKenna R, Fichtner W. Assessment of rooftop photovoltaic potentials at the urban level using publicly available geodata and image recognition techniques. Sol Energy 2017;155:561–73. https://doi.org/10.1016/j.solener.2017.06.065.
[38] Bergamasco L, Asinari P. Scalable methodology for the photovoltaic solar energy potential assessment based on available roof surface area: Further improvements by ortho-image analysis and application to Turin (Italy). Sol Energy 2011;85: 2741–56. https://doi.org/10.1016/j.solener.2011.08.010.
[39] Wittmann H, Bajons P, Doneus M, Friesinger H. Identification of roof areas suited for solar energy conversion systems. Vol. 11; 1997.
[40] Fuentes JE, Moya FD, Montoya OD. Method for estimating solar energy potential based on photogrammetry from unmanned aerial vehicles. Electron 2020;9:1–21. https://doi.org/10.3390/electronics9122144.
[41] Bannehr L, Luhmann T, Piechel J, Roelfs T, Schmidt A. Eextracting roof parameters and heat bridges over the city of oldenburg from hyperspectral, thermal, and airborne laser scanning data. n.d.
[42] Nadal A, Alamús R, Pipia L, Ruiz A, Corbera J, Cuerva E, et al. Urban planning and agriculture. Methodology for assessing rooftop greenhouse potential of non-residential areas using airborne sensors. Sci Total Environ 2017;601–602: 493–507. doi: 10.1016/J.SCITOTENV.2017.03.214.
[43] Srushti Neoge. Review on LiDAR technology Srushti Neoge. Ninad Mehendale n.d.
[44] Voegtle T, Steinle E, Tóvári D. Airborne laserscanning data for determination of suitable areas for photovoltaics. n.d.
[45] Martín-Jiménez J, Del Pozo S, Sánchez-Aparicio M, Lagüela S. Multi-scale roof characterization from LiDAR data and aerial orthoimagery: automatic computation of building photovoltaic capacity. Autom Constr 2020:109. https://doi.org/10.1016/j.autcon.2019.102965.
[46] Jakubiec JA, Reinhart CF. Towards validated urban photovoltaic potential and solar radiation maps based on lidar measurements, gis data, and hourly daysim simulations. n.d.
[47] Zolanvari SM, Ruano S, Rana A, Cummins A, da Silva RE, Rahbar M, et al. DublinCity: annotated LiDAR point cloud and its applications. ArXiv Prepr ArXiv190903613 2019.
[48] Kassner R, Koppe W, Schüttenberg T, Bareth G. Analysis of the solar potential of roofs by using official lidar data. n.d.
[49] Jochem A, Höfle B, Rutzinger M. Remote sensing extraction of vertical walls from mobile laser scanning data for solar potential assessment. Remote Sens 2011;3:3. https://doi.org/10.3390/rs3040650.
[50] Kaartinen H. Benchmarking of airborne laser scanning based feature extraction methods and mobile laser scanning system performance based on high-quality test fields. Finnish Geodetic Institute; 2013.
[51] Jochem A, Höfle B, Rutzinger M, Pfeifer N. Automatic roof plane detection and analysis in airborne lidar point clouds for solar potential assessment. Sensors 2009;9:5241–62. https://doi.org/10.3390/s90705241.
[52] Jochem A, Höfle B, Hollaus M, Rutzinger M. Object detection in airborne LIDAR data for improved solar radiation modeling in urban areas. Int Arch Photogramm Remote Sens Spat Inf Sci Paris 2009;38:W8.
[53] Tooke TR, Coops NC, Christen A, Gurtuna O, Prévot A. Integrated irradiance modelling in the urban environment based on remotely sensed data. Sol Energy 2012;86:2923–34. https://doi.org/10.1016/J.SOLENER.2012.06.026.
[54] Levinson R, Akbari H, Pomerantz M, Gupta S. Solar access of residential rooftops in four California cities. Sol Energy 2009;83:2120–35. https://doi.org/10.1016/j.solener.2009.07.016.
[55] Nguyen HT, Pearce JM. Incorporating shading losses in solar photovoltaic potential assessment at the municipal scale. Sol Energy 2012;86:1245–60. https://doi.org/10.1016/j.solener.2012.01.017.
[56] Malof JM, Hou R, Collins LM, Bradbury K, Newell R. Automatic solar photovoltaic panel detection in satellite imagery. In: 2015 Int. Conf. Renew. Energy Res. Appl. IEEE; 2015. p. 1428–31.
[57] Jiang H, Yao L, Lu N, Qin J, Liu T, Liu Y, et al. Multi-resolution dataset for photovoltaic panel segmentation from satellite and aerial imagery. Earth Syst Sci Data 2021;13:5389–401. https://doi.org/10.5194/essd-13-5389-2021.
[58] Zhang X, Zeraatpisheh M, Rahman MM, Wang S, Xu M. Texture is important in improving the accuracy of mapping photovoltaic power plants: a case study of ningxia autonomous region, china. Remote Sens 2021:13. https://doi.org/10.3390/rs13193909.
[59] Xia Z, Li Y, Guo X, Chen R. High-resolution mapping of water photovoltaic development in China through satellite imagery. Int J Appl Earth Obs Geoinf 2022:107. https://doi.org/10.1016/j.jag.2022.102707.

[60] Malof JM, Li B, Huang B, Bradbury K, Stretslov A. Mapping solar array location, size, and capacity using deep learning and overhead imagery. ArXiv Prepr ArXiv190210895 2019.
[61] Hou X, Wang B, Hu W, Yin L, Wu H. SolarNet: A deep learning framework to map solar power plants in China from satellite imagery 2019.
[62] House D, Lech M, Stolar M. Using deep learning to identify potential roof spaces for solar panels. In: 2018, 12th Int Conf Signal Process Commun Syst ICSPCS 2018 - Proc 2019. doi: 10.1109/ICSPCS.2018.8631725.
[63] Liang SM, Qi FY, Ding YF, Cao R, Yang Q, Yan W. Mask R-CNN based segmentation method for satellite imagery of photovoltaics generation systems. In: Chinese Control Conf CCC 2020;2020-July:5343–8. doi: 10.23919/CCC50068.2020.9189474.
[64] Castello R, Roquette S, Esguerra M, Guerra A, Scartezzini JL. Deep learning in the built environment: automatic detection of rooftop solar panels using Convolutional Neural Networks. J. Phys. Conf. Ser. Vol. 1343. Institute of Physics Publishing; 2019. doi: 10.1088/1742-6596/1343/1/012034.
[65] Li P, Zhang H, Guo Z, Lyu S, Chen J, Li W, et al. Understanding rooftop PV panel semantic segmentation of satellite and aerial images for better using machine learning. Adv Appl Energy 2021:4. https://doi.org/10.1016/j.adapen.2021.100057.
[66] Yu J, Wang Z, Majumdar A, Rajagopal R. DeepSolar: a machine learning framework to efficiently construct a solar deployment database in the United States. Joule 2018;2:2605–17. https://doi.org/10.1016/j.joule.2018.11.021.
[67] Golovko V, Bezobrazov S, Kroshchanka A, Sachenko A, Komar M, Karachka A. Convolutional neural network based solar photovoltaic panel detection in satellite photos. Vol. 1; 2017. doi: 10.1109/IDAACS.2017.8094501.
[68] Wang Z, Wang Z, Majumdar A, Rajagopal R. Identify solar panels in low resolution satellite imagery with siamese architecture and cross-correlation. n.d.
[69] Kruitwagen L, Story KT, Friedrich J, Byers L, Skillman S, Hepburn C. A global inventory of photovoltaic solar energy generating units. Nature 2021;598:604–10. https://doi.org/10.1038/s41586-021-03957-7.
[70] Stowell D, Kelly J, Tanner D, Taylor J, Jones E, Geddes J, et al. A harmonised, high-coverage, open dataset of solar photovoltaic installations in the UK. Sci Data 2020:7. https://doi.org/10.1038/s41597-020-00739-0.
[71] Bradbury K, Saboo R, Johnson TL, Malof JM, Devarajan A, Zhang W, et al. Distributed solar photovoltaic array location and extent dataset for remote sensing object identification. Sci Data 2016;:3. https://doi.org/10.1038/sdata.2016.106.
[72] Malof JM, Collins LM, Bradbury K, Newell RG. A deep convolutional neural network and a random forest classifier for solar photovoltaic array detection in aerial imagery. In: 2016 IEEE Int. Conf. Renew. Energy Res. Appl. ICRERA 2016. Institute of Electrical and Electronics Engineers Inc.; 2016. p. 650–4. https://doi.org/10.1109/ICRERA.2016.7884415.
[73] Malof JM, Bradbury K, Collins LM, Newell RG. Automatic detection of solar photovoltaic arrays in high resolution aerial imagery 2016. doi: 10.6084/m9.figshare.3385780.v1.
[74] So B, Nezin C, Kaimal V, Keene S, Collins L, Bradbury K, et al. Estimating the electricity generation capacity of solar photovoltaic arrays using only color aerial imagery. n.d.
[75] Malof JM, Bradbury K, Collins LM, Newell RG, Serrano A, Wu H, et al. Image features for pixel-wise detection of solar photovoltaic arrays in aerial imagery using a random forest classifier. In: 2016 IEEE Int. Conf. Renew. Energy Res. Appl. ICRERA 2016. Institute of Electrical and Electronics Engineers Inc.; 2017. p. 799–803. https://doi.org/10.1109/ICRERA.2016.7884446.
[76] Malof JM, Collins LM, Bradbury K. A deep convolutional neural network, with pre-training, for solar photovoltaic array detection in aerial imagery. n.d.
[77] Camilo J, Wang R, Collins LM, Bradbury K, Malof JM. Application of a semantic segmentation convolutional neural network for accurate automatic detection and mapping of solar photovoltaic arrays in aerial imagery. ArXiv Prepr ArXiv180104018 2018.
[78] Pérez-González A, Jaramillo-Duque Á, Cano-Quintero JB. Automatic boundary extraction for photovoltaic plants using the deep learning u-net model. Appl Sci 2021:11. https://doi.org/10.3390/app11146524.
[79] Jie Y, Ji X, Yue A, Chen J, Deng Y, Chen J, et al. Combined multi-layer feature fusion and edge detection method for distributed photovoltaic power station identification. Energies 2020:13. https://doi.org/10.3390/en13246742.
[80] Parhar P, Sawasaki R, Todeschini A, Reed C, Vahabi H, Nusaputra N, et al. HyperionSolarNet: solar panel detection from aerial images 2022.
[81] Edun AS, Perry K, Harley JB, Deline C. Unsupervised azimuth estimation of solar arrays in low-resolution satellite imagery through semantic segmentation and Hough transform. Appl Energy 2021:298. https://doi.org/10.1016/j.apenergy.2021.117273.
[82] Rausch B, Mayer K, Arlt M-L, Gust G, Staudt P, Weinhardt C, et al. An enriched automated PV registry: combining image recognition and 3D building data. n.d.
[83] Mayer K, Rausch B, Arlt ML, Gust G, Wang Z, Neumann D, et al. 3D-PV-Locator: large-scale detection of rooftop-mounted photovoltaic systems in 3D. Appl Energy 2022:310. https://doi.org/10.1016/j.apenergy.2021.118469.
[84] Czirjak D. Detecting photovoltaic solar panels using hyperspectral imagery and estimating solar power production. J Appl Remote Sens 2017;11:026007. https://doi.org/10.1117/1.jrs.11.026007.
[85] Karoui MS, Benhalouche FZ, Deville Y, Djerriri K, Briottet X, Le Bris A. Detection and area estimation for photovoltaic panels in urban hyperspectral remote sensing data by an original NMF-based unmixing method. Int. Geosci. Remote Sens. Symp., Vol. 2018-July, Institute of Electrical and Electronics Engineers Inc.; 2018. p. 1640–3. doi: 10.1109/IGARSS.2018.8518204.
[86] Ji C, Bachmann M, Esch T, Feilhauer H, Heiden U, Heldens W, et al. Solar photovoltaic module detection using laboratory and airborne imaging spectroscopy data. Remote Sens Environ 2021:266. https://doi.org/10.1016/j.rse.2021.112692.
[87] Wang Q, Paynabar K, Pacella M. Online automatic anomaly detection for photovoltaic systems using thermography imaging and low rank matrix decomposition. J Qual Technol 2021. https://doi.org/10.1080/00224065.2021.1948372.
[88] Dotenco S, Dalsass M, Winkler L, Würzner T, Brabec C, Maier A, et al. Automatic detection and analysis of photovoltaic modules in aerial infrared imagery. In: 2016 IEEE Winter Conf. Appl. Comput. Vis. IEEE; 2016. p. 1–9.
[89] Shen H, Zhu L, Hong X, Chang W. ROI extraction method of infrared thermal image based on GLCM characteristic imitate gradient. Commun. Comput. Inf. Sci. Vol. 771. Springer Verlag; 2017. p. 192–205. doi: 10.1007/978-981-10-7299-4_16.
[90] Huerta Herraiz Á, Pliego Marugán A, García Márquez FP. Photovoltaic plant condition monitoring using thermal images analysis by convolutional neural network-based structure. Renew Energy 2020;153:334–48. https://doi.org/10.1016/j.renene.2020.01.148.
[91] Li B, Delpha C, Diallo D, Migan-Dubois A. Application of artificial neural networks to photovoltaic fault detection and diagnosis: a review. Renew Sustain Energy Rev 2021;138:110512. https://doi.org/10.1016/J.RSER.2020.110512.
[92] Manno D, Cipriani G, Ciulla G, Di Dio V, Guarino S, Lo BV. Deep learning strategies for automatic fault diagnosis in photovoltaic systems by thermographic images. Energy Convers Manag 2021;241:114315. https://doi.org/10.1016/J.ENCONMAN.2021.114315.
[93] Zhang H, Hong X, Zhou S, Wang Q. Infrared image segmentation for photovoltaic panels based on res-unet. In: Chinese Conf. pattern Recognit. Comput. Vis., Springer; 2019. p. 611–22.
[94] Pillai DS, Rajasekar N. A comprehensive review on protection challenges and fault diagnosis in PV systems. Renew Sustain Energy Rev 2018;91:18–40. https://doi.org/10.1016/j.rser.2018.03.082.
[95] Abdulmawjood K, Refaat SS, Morsi WG. Detection and prediction of faults in photovoltaic arrays: a review. n.d.
[96] Köntges M, Kurtz S, Packard CEC, Jahn U, Berger KA, Kato K, et al. IEA PVPS subtask 3.2: review of failures of photovoltaic modules. 2014.
[97] Triki-Lahiani A, Bennani-Ben Abdelghani A, Slama-Belkhodja I. Fault detection and monitoring systems for photovoltaic installations: a review. Renew Sustain Energy Rev 2018;82:2680–92. https://doi.org/10.1016/j.rser.2017.09.101.
[98] Li X, Li W, Yang Q, Yan W, Zomaya AY. An unmanned inspection system for multiple defects detection in photovoltaic plants. IEEE J Photovoltaics 2020;10:568–76. https://doi.org/10.1109/JPHOTOV.2019.2955183.
[99] Li X, Yang Q, Lou Z, Yan W. Deep learning based module defect analysis for large-scale photovoltaic farms. IEEE Trans Energy Convers 2019;34:520–9. https://doi.org/10.1109/TEC.2018.2873358.
[100] Moradi Sizkouhi A, Aghaei M, Esmailifar SM. A deep convolutional encoder-decoder architecture for autonomous fault detection of PV plants using multi-copters. Sol Energy 2021;223:217–28. https://doi.org/10.1016/j.solener.2021.05.029.
[101] Zyout I, Qatawneh A. Detection of PV solar panel surface defects using transfer learning of the deep convolutional neural networks; 2020.
[102] Shihavuddin ASM, Rashid MRA, Maruf MH, Hasan MA, Haq MA ul, Ashique RH, et al. Image based surface damage detection of renewable energy installations using a unified deep learning approach. Energy Reports 2021;7:4566–76. doi: 10.1016/j.egyr.2021.07.045.
[103] Vidal K, de Oliveira A, Aghaei M, Rüther R. Aerial infrared thermography for low-cost and fast fault detection in utility-scale PV power plants. Sol Energy 2020;211:712–24. https://doi.org/10.1016/j.solener.2020.09.066.
[104] Akram MW, Li G, Jin Y, Chen X, Zhu C, Ahmad A. Automatic detection of photovoltaic module defects in infrared images with isolated and develop-model transfer deep learning. Sol Energy 2020;198:175–86. https://doi.org/10.1016/j.solener.2020.01.055.
[105] Aghaei M, Dolara A, Leva S, Grimaccia F. Image resolution and defects detection in PV inspection by unmanned technologies. In: 2016 IEEE Power Energy Soc. Gen. Meet. IEEE; 2016. p. 1–5.
[106] Li X, Li W, Yang Q, Yan W, Zomaya AY. Building an online defect detection system for large-scale photovoltaic plants. In: BuildSys 2019 - Proc. 6th ACM Int. Conf. Syst. Energy-Efficient Build. Cities, Transp., Association for Computing Machinery, Inc; 2019. p. 253–62. doi: 10.1145/3360322.3360835.
[107] Aghaei M, Grimaccia F, Gonano CA, Leva S. Innovative Automated Control System for PV Fields Inspection and Remote Control. IEEE Trans Ind Electron 2015;62:7287–96. https://doi.org/10.1109/TIE.2015.2475235.
[108] Li X, Yang Q, Chen Z, Luo X, Yan W. Visible defects detection based on UAV-based inspection in large-scale photovoltaic systems. IET Renew Power Gener 2017;11:1234–44. https://doi.org/10.1049/iet-rpg.2017.0001.
[109] Patel AV, McLauchlan L, Mehrubeoglu M. Defect detection in PV arrays using image processing. In: Proc. - 2020 Int. Conf. Comput. Sci. Comput. Intell. CSCI 2020. Institute of Electrical and Electronics Engineers Inc.; 2020. p. 1653–7. https://doi.org/10.1109/CSCI51800.2020.00304.
[110] Baig HR, Murtaza AF, Salman M. Recognition of faulty modules in a photovoltaic array using image processing techniques. Ieeep New Horizons J 2018;97:22–7.
[111] Sridharan NV, Sugumaran V. Convolutional neural network based automatic detection of visible faults in a photovoltaic module. Energy Sources, Part A Recover Util Environ Eff 2021. https://doi.org/10.1080/15567036.2021.1905753.

[112] King DL, Kratochvil JA, Quintana MA, Mcmahon TJ. Applications for infrared imaging equipment in photovoltaic cell, module, and system testing. n.d.
[113] Pilla M, Galmiche F, Maldague X. Thermographic inspection of cracked solar cells. 2002.
[114] Kaplani E. Detection of degradation effects in field-aged c-Si solar cells through IR thermography and digital image processing. Int J Photoenergy 2012 2012. https://doi.org/10.1155/2012/396792.
[115] Quater PB, Grimaccia F, Leva S, Mussetta M, Aghaei M. Light Unmanned Aerial Vehicles (UAVs) for cooperative inspection of PV plants. IEEE J Photovolt 2014;4: 1107–13. https://doi.org/10.1109/JPHOTOV.2014.2323714.
[116] Grimaccia F, Leva S, Dolara A, Aghaei M. Survey on PV modules' common faults after an O&M flight extensive campaign over different plants in Italy. IEEE J Photovolt 2017;7:810–6. https://doi.org/10.1109/JPHOTOV.2017.2674977.
[117] Jaffery ZA, Dubey AK, Irshad HA. Scheme for predictive fault diagnosis in photo-voltaic modules using thermal imaging. Infrared Phys Technol 2017;83:182–7. https://doi.org/10.1016/j.infrared.2017.04.015.
[118] Kim D, Youn J, Kim C. Automatic detection of malfunctioning photovoltaic modules using unmanned aerial vehicle thermal infrared images. J Korean Soc Surv Geod Photogramm Cartogr 2016;34:619–27. https://doi.org/10.7848/ksgpc.2016.34.6.619.
[119] Du B, He Y, He Y, Duan J, Zhang Y. Intelligent classification of silicon photovoltaic cell defects based on eddy current thermography and convolution neural network. IEEE Trans Ind Informatics 2020;16:6242–51. https://doi.org/10.1109/TII.2019.2952261.
[120] Tsanakas JA, Chrysostomou D, Botsaris PN, Gasteratos A. Fault diagnosis of photovoltaic modules through image processing and Canny edge detection on field thermographic measurements. Int J Sustain Energy 2015;34:351–72. https://doi.org/10.1080/14786451.2013.826223.
[121] Gao X, Munson E, Abousleman GP, Si J. Automatic solar panel recognition and defect detection using infrared imaging. In: Autom. Target Recognit. XXV, vol. 9476, SPIE; 2015. p. 94760O. doi: 10.1117/12.2179792.
[122] Montanez LE, Valentín-Coronado LM, Moctezuma D, Flores G. Photovoltaic module segmentation and thermal analysis tool from thermal images. In: 2020 IEEE Int. Autumn Meet. Power, Electron. Comput. Vol. 4, IEEE; 2020. p. 1–6.
[123] Aghaei M, Leva S, Grimaccia F. PV power plant inspection by image mosaicing techniques for IR real-time images. In: Conf. Rec. IEEE Photovolt. Spec. Conf. Vol. 2016- November, Institute of Electrical and Electronics Engineers Inc.; 2016. p. 3100–5. doi: 10.1109/PVSC.2016.7750236.
[124] Grimaccia F, Leva S, Niccolai A. PV plant digital mapping for modules' defects detection by unmanned aerial vehicles. IET Renew Power Gener 2017;11:1221–8. https://doi.org/10.1049/iet-rpg.2016.1041.
[125] Vidal De Oliveira AK, Aghaei M, Rüther R, Aghaei M. Automatic Fault detection of photovoltaic arrays by convolutional neural networks during aerial infrared thermography. 2019.
[126] Nie J, Luo T, Li H. Automatic hotspots detection based on UAV infrared images for large-scale PV plant. Electron Lett 2020;56:993–5. https://doi.org/10.1049/el.2020.1542.
[127] Ruan C, Tang W, Hu X, Yan W. Deep learning-based method for PV panels segmentation and defects detection with infrared images. In: Proceeding - 2021 China Autom. Congr. CAC 2021. Institute of Electrical and Electronics Engineers Inc.; 2021. p. 7166–71. https://doi.org/10.1109/CAC53003.2021.9728350.
[128] Hong F, Song J, Meng H, Rui W, Fang F, Guangming Z. A novel framework on intelligent detection for module defects of PV plant combining the visible and infrared images. Sol Energy 2022;236:406–16. https://doi.org/10.1016/j.solener.2022.03.018.
[129] Wu Y, Xiao X, Song Z. Competitiveness analysis of coal industry in China: a diamond model study. Resour Policy 2017;52:39–53. https://doi.org/10.1016/J.RESOURPOL.2017.01.015.
[130] Unlu T, Akcin H, Yilmaz O. An integrated approach for the prediction of subsidence for coal mining basins. Eng Geol 2013;166:186–203. https://doi.org/10.1016/J.ENGGEO.2013.07.014.
[131] Choi Y, Song J. Sustainable development of abandoned mine areas using renewable energy systems: a case study of the photovoltaic potential assessment at the tailings dam of abandoned Sangdong mine, Korea. Sustain 2016:8. https://doi.org/10.3390/su8121320.
[132] Choi Y, Song J. Review of photovoltaic and wind power systems utilized in the mining industry. Renew Sustain Energy Rev 2017;75:1386–91. https://doi.org/10.1016/j.rser.2016.11.127.
[133] Li W, Jia X. Ground Control Issues on Photovoltaic Power Generation Facilities Construction in Coal Sinkhole Region. In: Procedia Eng. Vol. 191, Elsevier Ltd; 2017. p. 98–103. doi: 10.1016/j.proeng.2017.05.159.
[134] Dong L, Wang C, Tang Y, Tang F, Zhang H, Wang J, et al. Time series InSAR three-dimensional displacement inversion model of coal mining areas based on symmetrical features of mining subsidence. Remote Sens 2021;13:2143.
[135] Zhang Z, Lin H, Wang M, Liu X, Chen Q, Wang C, et al. A review of satellite synthetic aperture radar interferometry applications in permafrost regions: current status, challenges, and trends. IEEE Geosci Remote Sens Mag 2022.
[136] Zhang Z, Wang C, Wang M, Wang Z, Zhang H. Surface deformation monitoring in Zhengzhou city from 2014 to 2016 using time-series insar. Remote Sens 2018;10:1731.
[137] Ma P, Li T, Fang C, Lin H. A tentative test for measuring the sub-millimeter settlement and uplift of a high-speed railway bridge using COSMO-SkyMed images. ISPRS J Photogramm Remote Sens 2019;155:1–12. https://doi.org/10.1016/J.ISPRSJPRS.2019.06.013.
[138] Kim HG, Park CY. Landslide susceptibility analysis of photovoltaic power stations in Gangwon-do, Republic of Korea. Geomatics, Nat Hazards Risk 2021;12: 2328–51. https://doi.org/10.1080/19475705.2021.1950219.
[139] Tomás R, Li Z. Earth observations for geohazards: present and future challenges. Remote Sens 2017;9:194.
[140] Zhao C, Lu Z. Remote sensing of landslides-a review. Remote Sens 2018:10. https://doi.org/10.3390/rs10020279.
[141] McKean J, Roering J. Objective landslide detection and surface morphology mapping using high-resolution airborne laser altimetry. Geomorphology 2004;57: 331–51. https://doi.org/10.1016/S0169-555X(03)00164-8.
[142] Han Z, Li Y, Du Y, Wang W, Chen G. Noncontact detection of earthquake-induced landslides by an enhanced image binarization method incorporating with Monte-Carlo simulation. Geomatics, Nat Hazards Risk 2018.
[143] Ghorbanzadeh O, Blaschke T, Gholamnia K, Meena SR, Tiede D, Aryal J. Evaluation of different machine learning methods and deep-learning convolutional neural networks for landslide detection. Remote Sens 2019;11:196.
[144] Rossi G, Tanteri L, Tofani V, Vannocci P, Moretti S, Casagli N. Multitemporal UAV surveys for landslide mapping and characterization. Landslides 2018;15:1045–52.
[145] Görüm T. Landslide recognition and mapping in a mixed forest environment from airborne LiDAR data. Eng Geol 2019;258:105155.
[146] Casagli N, Cigna F, Bianchini S, Hölbling D, Füreder P, Righini G, et al. Landslide mapping and monitoring by using radar and optical remote sensing: examples from the EC-FP7 project SAFER. Remote Sens Appl Soc Environ 2016;4:92–108.
[147] Zhou C, Cao Y, Yin K, Intrieri E, Catani F, Wu L. Characteristic comparison of seepage-driven and buoyancy-driven landslides in Three Gorges Reservoir area. China Eng Geol 2022;301:106590.
[148] Zhou C, Cao Y, Hu X, Yin K, Wang Y, Catani F. Enhanced dynamic landslide hazard mapping using MT-InSAR method in the Three Gorges Reservoir Area. Landslides 2022:1–13.
[149] Ezquerro P, Del Soldato M, Solari L, Tomás R, Raspini F, Ceccatelli M, et al. Vulnerability assessment of buildings due to land subsidence using InSAR data in the ancient historical city of Pistoia (Italy). Sensors 2020;20:2749.
[150] Liping C, Yujun S, Saeed S. Monitoring and predicting land use and land cover changes using remote sensing and GIS techniques—a case study of a hilly area, Jiangle, China. PLoS ONE 2018;13:e0200493.
[151] Levin N, Kyba CCM, Zhang Q, de Miguel AS, Román MO, Li X, et al. Remote sensing of night lights: a review and an outlook for the future. Remote Sens Environ 2020;237:111443.
[152] De Sy V, Herold M, Achard F, Avitabile V, Baccini A, Carter S, et al. Tropical deforestation drivers and associated carbon emission factors derived from remote sensing data. Environ Res Lett 2019;14:94022.
[153] Wei L, Yuan Z, Zhong Y, Yang L, Hu X, Zhang Y. An improved gradient boosting regression tree estimation model for soil heavy metal (Arsenic) pollution monitoring using hyperspectral remote sensing. Appl Sci 2019;9:1943.
[154] Xue J, Su B. Significant remote sensing vegetation indices: a review of developments and applications. J Sensors 2017; 2017.
[155] Yokoya N, Yamanoi K, He W, Baier G, Adriano B, Miura H, et al. Breaking limits of remote sensing by deep learning from simulated data for flood and debris-flow mapping. IEEE Trans Geosci Remote Sens 2020;60:1–15.
[156] Mohanty BP, Cosh MH, Lakshmi V, Montzka C. Soil moisture remote sensing: state-of-the-science. Vadose Zo J 2017;16:1–9.
[157] Crétaux J-F, Arsen A, Calmant S, Kouraev A, Vuglinski V, Bergé-Nguyen M, et al. SOLS: A lake database to monitor in the Near Real Time water level and storage variations from remote sensing data. Adv Sp Res 2011;47:1497–507.
[158] Palubinskas G, Kurz F, Reinartz P. Detection of traffic congestion in optical remote sensing imagery. In: IGARSS 2008-2008 IEEE Int. Geosci. Remote Sens. Symp. Vol. 2. IEEE; 2008. p. II–426.
[159] Jiang M, Lv Y, Wang T, Sun Z, Liu J, Yu X, et al. Performance analysis of a photovoltaics aided coal-fired power plant. Energy Procedia, Vol. 158. Elsevier Ltd; 2019. p. 1348–53. doi: 10.1016/j.egypro.2019.01.330.
[160] Jiang M, Li J, Wei W, Miao J, Zhang P, Qian H, et al. Using existing infrastructure to realize low-cost and flexible photovoltaic power generation in areas with high-power demand in China. IScience 2020;23. doi: 10.1016/j.isci.2020.101867.
[161] Qi L, Jiang M, Lv Y, Yan J. A celestial motion-based solar photovoltaics installed on a cooling tower. Energy Convers Manag 2020;216. https://doi.org/10.1016/j.enconman.2020.112957.
[162] Ravichandran N, Fayek HH, Rusu E. Emerging floating photovoltaic system—case studies high dam and Aswan reservoir in Egypt. Processes 2021;9. https://doi.org/10.3390/pr9061005.
[163] Zappa W, van den Broek M. Analysing the potential of integrating wind and solar power in Europe using spatial optimisation under various scenarios. Renew Sustain Energy Rev 2018;94:1192–216. https://doi.org/10.1016/J.RSER.2018.05.071.
[164] Mamia I, Appelbaum J. Shadow analysis of wind turbines for dual use of land for combined wind and solar photovoltaic power generation. Renew Sustain Energy Rev 2016;55:713–8. https://doi.org/10.1016/J.RSER.2015.11.009.
[165] Chen Z, Jiang M, Qi L, Wei W, Yu Z, Wei W, et al. Using existing infrastructures of high-speed railways for photovoltaic electricity generation. Resour Conserv Recycl 2022;178. doi: 10.1016/j.resconrec.2021.106091.
[166] Jiang M, Qi L, Yu Z, Wu D, Si P, Li P, et al. National level assessment of using existing airport infrastructures for photovoltaic deployment. Appl Energy 2021; 298. https://doi.org/10.1016/j.apenergy.2021.117195.
[167] Sreenath S, Sudhakar K, Yusop AF. Carbon mitigation potential of the airport-based solar PV plants in the Indian context. Int J Ambient Energy 2022;43: 1311–9. https://doi.org/10.1080/01430750.2019.1696888.

[168] Franzitta V, Curto D, Rao D. Energetic sustainability using renewable energies in the mediterranean sea. Sustain 2016;8. https://doi.org/10.3390/su8111164.
[169] Colmenar-Santos A, Buendia-Esparcia Á, de Palacio-Rodríguez C, Borge-Diez D. Water canal use for the implementation and efficiency optimization of photovoltaic facilities: Tajo-Segura transfer scenario. Sol Energy 2016;126: 168–94. https://doi.org/10.1016/j.solener.2016.01.008.
[170] Song J, Choi Y. Analysis of the potential for use of floating photovoltaic systems on mine pit lakes: case study at the Ssangyong open-pit limestone mine in Korea. Energies 2016;9:1–13. https://doi.org/10.3390/en9020102.
[171] McKuin B, Zumkehr A, Ta J, Bales R, Viers JH, Pathak T, et al. Energy and water co-benefits from covering canals with solar panels. Nat Sustain 2021;4:609–17. https://doi.org/10.1038/s41893-021-00693-8.
[172] Sairam PMN, Aravindhan A. Canal top solar panels: A unique nexus of energy, water, and land. Mater. Today Proc. Vol. 33, Elsevier Ltd; 2020. p. 705–10. doi: 10.1016/j.matpr.2020.06.017.
[173] Kumar M, Kumar A. Experimental validation of performance and degradation study of canal-top photovoltaic system. Appl Energy 2019;243:102–18. https://doi.org/10.1016/j.apenergy.2019.03.168.
[174] Wang L, Wang Y, Chen J. Assessment of the ecological niche of photovoltaic agriculture in China. Sustain 2019;11. https://doi.org/10.3390/su11082268.
[175] Xue J. Photovoltaic agriculture - new opportunity for photovoltaic applications in China. Renew Sustain Energy Rev 2017;73:1–9. https://doi.org/10.1016/j.rser.2017.01.098.
[176] Jarach M. An Overview of the Literature on Barriers to the Diffusion of Renewable Energy Sources in Agriculture. Vol. 32; 1989.
[177] Reuss M, Schuerzinger H, Schulz H. Practical applications of photovoltaics in agriculture and horticulture. In: Clean Safe Energy Forever, Elsevier; 1990. p. 277–81.
[178] Santra P, Pande P, Kumar S, Mishra D, Singh R. Agri-voltaics or solar farming: the concept of integrating solar PV based electricity generation and crop production in a single land use system. Vol. 7; 2017.
[179] Salasovich J, Mosey G. Feasibility study of economics and performance of solar photovoltaics at the refuse hideaway landfill in Middleton, Wisconsin. A study prepared in partnership with the environmental protection agency for the RE-powering America's Land initiative: siting renewable energy on potentially contaminated land and mine sites. 2011.
[180] Zhang Y, Xie P, Huang Y, Liao C, Zhao D. Evolution of solar photovoltaic policies and industry in China. IOP Conf Ser Earth Environ Sci 2021;651. doi: 10.1088/1755-1315/651/2/022050.
[181] Heinstein P, Ballif C, Perret-Aebi LE. Building integrated photovoltaics (BIPV): review, potentials, barriers and myths. Green 2013;3:125–56. https://doi.org/10.1515/green-2013-0020.
[182] Chukwu UC, Mahajan SM. V2G parking lot with PV rooftop for capacity enhancement of a distribution system. IEEE Trans Sustain Energy 2014;5:119–27. https://doi.org/10.1109/TSTE.2013.2274601.
[183] Zhong T, Zhang K, Chen M, Wang Y, Zhu R, Zhang Z, et al. Assessment of solar photovoltaic potentials on urban noise barriers using street-view imagery. Renew Energy 2021;168:181–94. https://doi.org/10.1016/j.renene.2020.12.044.
[184] Al Ali E, Ali A. Solar-powered bike lanes solar-powered bike lanes recommended citation recommended citation. n.d.
[185] Mcknight M, Tech V, Williams M. Public opinion on renewables and other energy sources. 2016.
[186] Wu AN, Biljecki F. Roofpedia: Automatic mapping of green and solar roofs for an open roofscape registry and evaluation of urban sustainability. Landsc Urban Plan 2021;214. doi: 10.1016/j.landurbplan.2021.104167.
[187] De Medici S. Italian architectural heritage and photovoltaic systems. Matching style with sustainability. Sustain 2021;13:1–23. https://doi.org/10.3390/su13042108.
[188] Ren S, Malof J, Fetter TR, Beach R, Rineer J, Bradbury K. Utilizing geospatial data for assessing energy security: Mapping small solar home systems using unmanned aerial vehicles and deep learning 2022. doi: 10.3390/ijgi11040222.
[189] Ioannidis R, Koutsoyiannis D. A review of land use, visibility and public perception of renewable energy in the context of landscape impact. Appl Energy 2020;276. https://doi.org/10.1016/j.apenergy.2020.115367.
[190] He S, Li S, Jiang S, Jiang W. HMSM-Net: Hierarchical multi-scale matching network for disparity estimation of high-resolution satellite stereo images. ISPRS J Photogramm Remote Sens 2022;188:314–30. https://doi.org/10.1016/J.ISPRSJPRS.2022.04.020.
[191] Wang W, Zhao W, Chai B, Du J, Tang L, Yi X. Discontinuity interpretation and identification of potential rockfalls for high-steep slopes based on UAV nap-of-the-object photogrammetry. Comput Geosci 2022;166:105191. https://doi.org/10.1016/J.CAGEO.2022.105191.
[192] Dadrass Javan F, Samadzadegan F, Mehravar S, Toosi A, Khatami R, Stein A. A review of image fusion techniques for pan-sharpening of high-resolution satellite imagery. ISPRS J Photogramm Remote Sens 2021;171:101–17. https://doi.org/10.1016/J.ISPRSJPRS.2020.11.001.
[193] Wang P, Bayram B, Sertel E. A comprehensive review on deep learning based remote sensing image super-resolution methods. Earth-Science Rev 2022;232: 104110. https://doi.org/10.1016/J.EARSCIREV.2022.104110.
[194] Ming Y, Meng X, Fan C, Yu H. Deep learning for monocular depth estimation: a review. Neurocomputing 2021;438:14–33. https://doi.org/10.1016/J.NEUCOM.2020.12.089.
[195] Deng J, Dong W, Socher R, Li L-J, Li K, Fei-Fei L. Imagenet: a large-scale hierarchical image database. In: 2009 IEEE Conf. Comput. Vis. pattern Recognit. IEEE; 2009. p. 248–55.
[196] He K, Chen X, Xie S, Li Y, Dollár P, Girshick R. Masked autoencoders are scalable vision learners. In: Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. 2022. p. 16000–9.