Highlights

Open-Source Ground-based Sky Image Datasets for Very Short-term Solar Forecasting, Cloud Analysis and Modeling: A Comprehensive Survey

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- 72 open-source ground-based sky image datasets covering diverse climate zones are identified globally.
- A database consisting of extensive information on various aspects of the datasets is constructed.
- A multi-criteria ranking system is developed to evaluate a dataset for different applications.
- Insights and means of access are provided to the potential users of the datasets.
Open-Source Ground-based Sky Image Datasets for Very Short-term Solar Forecasting, Cloud Analysis and Modeling: A Comprehensive Survey

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\begin{abstract}
This study presents a comprehensive survey of open-source ground-based sky image datasets for very short-term solar forecasting. Related research areas which could potentially help improve solar forecasting methods, including cloud segmentation, cloud classification, and cloud motion prediction are also considered. We first identify 72 open-source sky image datasets that satisfy the needs of machine/deep learning. Then a database of information about various aspects of the datasets is constructed. To evaluate each surveyed datasets, we further develop a multi-criteria ranking system based on 8 dimensions of the datasets which could potentially have important impacts on usage of the data. Finally, we provide insights on the usage of these datasets in the open literature. We hope this paper provide an overview for researchers who are looking for datasets for training deep learning models for very short-term solar forecasting, cloud analysis, and atmospheric modeling.
\end{abstract}

\section{Introduction}
Solar energy has been recognized as one of the crucial components for transition to a next-generation sustainable energy system [1]. Though with massive potential [2], large-scale deployment of solar power, primarily photovoltaics (PVs), is hindered by the intermittency of solar energy. The variability in solar power generation is mostly associated with local weather conditions, especially cloud motion [3, 4]. For example, up to 80\% drop in power output can occur to a rooftop solar PV system in less than a minute due to a cloud passage event [5]. Under high penetration of renewable resources in future energy systems, rapid loss of megawatts or gigawatts of power from centralized PV plants can cause challenges for electricity grids. Thus, the development of accurate and reliable forecasting methods is urgently needed for handling uncertainty in solar power generation.

Depending on the time horizon it targets, solar forecasting\textsuperscript{1} can be classified into the following categories, although as yet there is no common agreement on the classification criterion [6]: (1) Very short-term forecasting, covering forecast horizon from a few seconds to 30 minutes [7], is beneficial to activities such as electricity marketing or pricing, real-time dispatch of other generators and energy storage control [8]; (2) Short-term forecasting, spanning from 30 min to 6 hours [7], is useful for renewable energy integrated power systems operation and management [6]; (3) Medium-term forecasting, covering horizons from 6 to 24 hours [7], is essential for power system electro-mechanical machinery maintenance scheduling [8]; (4) Long-term forecasting, for predicting 24 hours in advance or more [7], is suitable for long-term power generation, transmission and distribution scheduling and in power market bidding and clearing [9].

For the selection of solar forecasting methods, temporal and spatial resolution are the critical factors for consideration [3]. Ground-based sky imagers are suitable for very short-term forecasting at a single location or nearby locations, given its high temporal (from seconds to minutes) and spatial resolution (<1x kms) [10]. Satellite and numerical weather

\footnotesize{\textsuperscript{1}For simplicity, we refer to the forecast of solar irradiance and PV power output combined as solar forecasting in this study.}
prediction (NWP) both have coarse temporal (from minutes to 10x hours for satellite, from minutes up to 1000x hours for NWP) and spatial resolution (1x~100x kms) [10]. Thus, satellite fits better for short- to medium-term forecasting, while NWP is more useful for medium- to long-term forecasting. Both of those methods are more useful at larger scales. Although all of these methods may become important to the operation of power systems, in this review, we focus on ground-based sky images for very-short forecasting.

Sky-image-based solar forecasting has become more popular since 2011 [11]. Early works tend to first extract features from ground-based sky images, such as red-to-blue ratio (RBR), cloud coverage and cloud motion vectors, and then use these features for building physical deterministic models [11, 12, 13] or training machine learning models such as artificial neural networks [14, 15, 16, 17, 18]. In addition, several all-sky cameras can be used in stereo-vision mode to model the cloud cover in three dimensions to provide local irradiance maps [19, 20, 21, 22, 23]. In recent 5 years, with the development of computer vision techniques, efforts have been shifted to build end-to-end deep learning models to predict irradiance or PV power output based on a historical sky image sequence, which generally achieve state-of-the-art performance despite some limitations in their anticipation ability [24]. These deep learning models are mainly based on convolutional neural networks (CNNs), either solely using CNNs [4, 25, 26, 27, 28] or hybridizing CNNs with recurrent neural networks (RNNs), such as LSTM [24, 29, 30].

Asides from direct forecast of irradiance or PV power output, cloud analysis or modeling using ground-based sky images has also attracted wide attention as a parallel avenue of research. Clouds are one of the most important factors that affect surface irradiance and PV power generation. Research on clouds using sky images can potentially contribute to the development of more accurate and robust solar forecasting models [3]. Existing efforts include but not limited to cloud segmentation, cloud classification and cloud motion prediction.

Cloud segmentation is one of the first steps for sky/cloud image analysis [31], from which cloud pixels are identified and cloud coverage, cloud shadow projection and various cloud features can be derived for further research. Traditional methods tend to distinguish cloud and clear sky pixels by applying a threshold, either fixed or adaptive, on features extracted from the red and blue channels of sky images. This is based on the fact of different scattering behaviors of red and blue bands of the solar beam when encountering air molecules (Rayleigh scattering) and cloud particles (Mie scattering). Such features include red-blue difference [32, 33], red-blue ratio [34, 35], normalized red-blue ratio [36, 37, 38], saturation [39] and Euclidean Geometric Distance [40]. Besides manually adjusting the thresholds of these color features, learning-based methods have been used in recent years. Deep learning models, featured by CNN-based architectures such as U-Net, have seen increasing popularity [41, 42, 43, 44] and shown the highest capability according to a benchmark study by Hasenbalg et al. [45].

Identification of cloud categories is also important. Different clouds can cause different extents of attenuation of solar irradiance, e.g., low-level clouds like cumulus block sunlight more significantly than high-level clouds like cirrus [3]. Different classification criteria are observed in existing studies, which are largely based on: (1) the main cloud genera recommended by the World Meteorological Organization [46, 47, 48] (e.g., Cirrus, Cumulus, Stratus, Nimbus), (2) the visual characteristics of clouds [49, 50, 51] (e.g., patterned clouds, thick dark clouds, thin white clouds, veil clouds), or (3) the height of clouds [44] (e.g., high-level clouds, medium-level clouds, low-level clouds). Most studies are learning-based [44], and a common workflow is feature extraction followed by classification. Different classifiers are used, including machine learning models, such as k-nearest neighbors, support vector machines [32, 46, 52] and in recent years end-to-end deep learning models such as CNNs for cloud classification have emerged as a promising approach [44, 47, 52].

A better cloud motion prediction can potentially help improve the anticipation skill of the current solar forecasting models [53]. Image-based motion estimation has been studied broadly. Traditional methods based on patch matching methods, e.g., particle image velocimetry [54] and optical flow [55], to identify wind vectors and linearly extrapolating cloud motion, are usually less satisfactory as clouds are deformable and highly volatile [56, 57]. More recently, efforts have shifted to using deep learning models to predict cloud motion by generating future cloud images with end-to-end data-driven training [58, 59], which shows better performance in capturing the cloud dynamics although the generated images look blurry and generally do not consider the stochasticity of cloud motion.

Deep learning methods have recently shown promising performance in solar forecasting and related fields mentioned above. However, one of the major challenges for deep-learning-based models is the lack of high-quality data. This is especially problematic because deep learning models are often data hungry. Data collection is costly due to expensive recording devices and costs for human operators for regular maintenance, upkeep, and replacement of these devices. Making deep learning models generalize well often requires massive and diversified training data.
recent years, the increasing release of sky image datasets have provided great opportunities for researchers, while the exposure of these datasets might be limited. Although there are numerous efforts\[3, 6, 8, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74\] on reviewing different aspects of solar forecasting, including methodology, performance evaluation metrics, major challenges, technological infrastructures, etc., to our best knowledge, there are currently no reviews specifically focused on open-source sky image datasets. To fill this gap, this study presents a comprehensive survey and evaluation of open-source sky image datasets for solar forecasting, cloud analysis (i.e. cloud segmentation, classification) and modeling (i.e. cloud motion prediction). Although we were stringent in searching for such datasets, there is no guarantee that we obtained all such datasets nor that cover all aspects of the datasets correctly. We encourage the researchers to use this study as a resource for locating datasets which they can access for additional details. It should be noted that in this study, our main focus is on the datasets that are suitable for use in machine/deep learning methods for solar forecasting and related research areas, including cloud classification, cloud segmentation and cloud motion prediction using sky images, while these datasets could also be used with other traditional methods or even in completely different applications.

The rest of this paper is organized as follows: in Section 2, we describe the search processes to identify the open-source sky image datasets from different sources on the web, the information we collect from these datasets as well as the multi-criteria ranking system we developed to evaluate the datasets. Section 3 gives results, first presenting an overview of all datasets, following by a detailed description of features of the datasets, including data inclusion and specifications, spatial and temporal coverage, and a usage analysis of these datasets by the scientific community. Next, we show a comprehensive evaluation of the datasets using the multi-criteria ranking system. Finally, we summarize the findings and provides insights regarding the choices of datasets in Section 4. The detailed data specifications of each dataset and the references of studies using the datasets are provided in Appendix A and B, respectively.

2. Method

2.1. Dataset search

For datasets search, we consider literature sources including peer-reviewed journal articles, conference proceedings and pre-prints, popular open research data repositories including Mendeley Data, DRYAD and Zenodo, as well as the open-source platform GitHub. Additionally, sky image datasets from research campaigns of Atmospheric Radiation Measurement (ARM) program managed by the US Department of Energy (DOE) are included. ARM is a multi-platform scientific user facility equipped with instruments collecting ground-based measurements of atmospheric data at various locations around the world. GitHub is mainly used for code sharing and documentation and might not be often used for data storage especially when the dataset size is large, and we thus consider it more as a location for dataset tracking rather than a deposit.

Different search engines are used for the different types of sources. For literature search, Google Scholar is used as it often provides comprehensive coverage of resources in various scientific disciplines [75]. Yang et al. [65] conducted a text mining analysis on Google scholar data to establish the technological infrastructure and identify recent key innovations for solar forecasting. For research data repositories, search engines are provided on their websites. It should be noted that Mendeley Data is a comprehensive search platform, and it provides the options to include datasets from other platforms like DRYAD and Zenodo in the search results. However, the search outcome might include different versions of the same dataset, therefore, instead of using the search returned by Mendeley Data for DRYAD and Zenodo, we conduct search separately on these two platforms. For GitHub, search are conducted using Github Search. ARM Data Center 2 provides an easy access to various ground-based measurement data.

Search key words were defined and employed for searching datasets. Table 1 summarizes the search strings used in different search engines. Given the syntax and the scope of the search engines, Google Scholar, Mendeley Data and Zenodo share the same search strings, while the other three apply individual search strings. Also, instead of repeatedly defining similar words, an asterisk (*) is added to a word as a wildcard for variant versions (e.g., sky image* can retrieve sky image, sky images, sky imagery, sky imager, etc.) if it is a valid syntax in that search engine.

For search engines other than Google Scholar, we can directly obtain information about the datasets based on the aforementioned search keywords. If references or links to the relevant publications are provided, we further track them for more details about the datasets. For Google Scholar, a reading inspection is first conducted based on the initial results. In general, three types of papers are found at this stage, i.e. dataset papers, research papers and review

\[2\text{https://adc.arm.gov/discovery/#/}\]
Table 1
The initial searching strings applied in different bases

| #  | Base                          | Initial Search String                                                                 |
|----|-------------------------------|---------------------------------------------------------------------------------------|
| 1  | ARM Data Center               | "Sky imager"                                                                          |
| 2  | Github Search                 | ("Sky image*" OR "Sky patch" OR "Fish-eye camera") AND (Dataset* OR Database*)         |
| 3  | Google Scholar                | **Solar forecasting:** ("Sky image*" OR "Sky patch*" OR "Fish-eye camera") AND ("Solar forecast*" OR "Irradiance forecast*"
                           | OR "Irradiance predict*" OR "PV power forecast*" OR Nowcast* OR "PV power predict*"
                           | AND (Dataset* OR Database*))                                                    |
| 4  | Mendeley Data                 | **Cloud analysis and modeling:** ("Sky image*" OR "Sky patch*" OR "Fish-eye camera")
                           | AND ("Cloud segmentation" OR "Cloud detection" OR "Cloud classification"
                           | OR "Cloud categorization" OR "Cloud motion predict*" OR "Cloud movement predict*"
                           | OR "Cloud forecast*")                                                         |
| 5  | Zenodo                        | ("Sky image", "Sky patch")                                                         |
| 6  | DRYAD                         |                                                                                       |

After initial results are obtained, the following 4 criteria are used to exclude datasets as out of scope for our study:

1. The dataset must be open-source, i.e. everyone can download it from online data repositories, or noted in the paper that it can be requested from the authors, or it can be accessed after submitting an online form request;
2. The dataset must contain ground-based sky images of different kinds, e.g., either whole sky images or sky patches, either in the visible or infrared spectrum, either in RGB or grayscale, either normal exposure or high dynamic range (HDR). The datasets that only contain irradiance or PV power measurements are not considered in this study, although these datasets can be used for solar forecasting solely based on the time series data, e.g., the Baseline Surface Radiation Network (BSRN) [78], NREL Solar Power Data for Integration Studies (SPDIS) dataset [79], NIST Campus Photovoltaic Arrays and Weather Station Data Sets [80], National Solar Radiation Data Base [81] and SOLETE dataset [82].
3. It ought to contain “labels” that are suitable for a machine learning or deep learning setup. Such labels can be solar irradiance measurements, PV generation measurements, cloud categories, or segmentation maps (labelled manually or generated by algorithms), which can be used in a supervised learning fashion. It should be noted that it might not need to contain a label only for the case of unsupervised/self-supervised tasks, like cloud image/video prediction, i.e. predicting future sky image frames based on context frames.
4. As additional information, some datasets contain meteorological data, like temperature, wind speed, wind direction, etc., or other data types such as sky video, satellite imagery, NWP, or PV panel parameters, etc.

Table 2 shows the resulting amount of data obtained before and after applying our criteria separately. After exclusion we obtained 72 datasets, most of which mainly come from ARM and Google Scholar. It should be noted that the results returned from different search engines might have overlaps. For example, a dataset paper can be published in a journal, and meanwhile the authors could deposit the data in one of the repositories and create a GitHub page for documentation and code sharing.
Table 2
Initial search results and results after applying the screening criteria for different search engines

| #  | Search engine       | Initial search results | Results after applying screening criteria |
|----|---------------------|-------------------------|-------------------------------------------|
| 1  | ARM Data Center     | 26                      | 26                                        |
| 2  | Github Search      | 3                       | 3                                         |
| 3  | Google Scholar     | 1364                    | 50                                        |
| 4  | Mendeley Data      | 2403                    | 4                                         |
| 5  | Zenodo             | 883                     | 7                                         |
| 6  | DRYAD              | 4                       | 1                                         |

Note that the results returned from different search engines might have overlaps, i.e. search results from different search engines point to the same dataset.

2.2. Information collection

After identifying the valid datasets, we collect information about these datasets and organize them as columns in an Excel spreadsheet. An illustration of the information being collected is shown in Figure 1. In general, 7 dimensions are considered, including (1) basics of the dataset; (2) related article bibliographic information; (3) data specifications; (4) potential applications; (5) dataset accessibility; (6) dataset usage and (7) auxiliaries.

For datasets which do not provide any information on the dataset size, we estimate it based on the average file size (calculated based on a sample of days of data) and the data collection period. For datasets in which the data collection is still continuing, we present in this study the dataset size until July 1st, 2022. For potential applications of the datasets, we infer them based on the data inclusion and the data temporal resolution. Figure 2 shows how we infer the potential applications of the dataset and the inference is based on the premise that all the datasets identified contain sky images. Cloud segmentation and cloud classification can be easily inferred, as in general, if a dataset contains segmentation maps, it can be used for cloud segmentation, and similarly, if a dataset contains cloud category labels, it can be used for cloud classification. More steps are needed for checking if a dataset is suitable for solar forecasting or cloud motion prediction. Here we focus on very short-term prediction, namely, forecasting horizon less than 30 minutes. Very short-term prediction requires high temporal resolution data, so the datasets need to have temporal resolutions of at least less than 30 minutes. For dataset exposure, we consider three metrics: citations, total usage, and usage involving sky images. We track the citations of the datasets based on the citation counts of the related dataset articles returned by Google scholar, again based on the counts until July 1st, 2022. We only consider the papers written in English, so the non-English citations are not considered, and we also removed the repeated citations returned by Google Scholar as it sometimes returns different versions of the same paper that cite the datasets. Regarding the usage of the dataset, we conducted a reading inspection for each paper that cites the dataset to determine whether these papers actually use the dataset in their studies or just cite the related work. We also track the data that are used by these studies as well as the research topics or methods of these citing studies, to verify whether these studies actually use sky images and irradiance measurements to train deep learning models or only use the irradiance values for building time series models? We are mainly interested in the former type of studies in this survey.

2.3. Dataset evaluation

Data are critical to the development of deep learning models. Not only the quantity or amount of data matter, but also the quality of the data. We develop a multi-criteria ranking system to evaluate the identified ground-based sky datasets. For a comprehensive evaluation, 8 dimensions of the datasets which could potentially have important impacts are considered. Table 3 shows the ranking system for evaluating the datasets. The ranking system provides a semi-subjective guideline, i.e. the selection of the criteria are subjective, while the results are based on objective statistical information on the datasets. For each dimension, we set the highest rank to 10, and the lowest rank to 2, with other mid-levels in between. If the information is not available for certain dimensions, they are marked as N/A.

It should be noted that the criteria are partly application dependent as each usage might favor slightly different data characteristics. Solar forecasting and cloud motion prediction are evaluated using the same criteria as both of these two tasks require the input of an image sequence with a rather high temporal resolution, while the other two tasks, e.g. cloud segmentation and cloud classification, are built upon one-on-one correlation between images and labels and do not require the input of an image sequence. To this end, we only evaluate the temporal resolution of datasets for solar forecasting and cloud motion prediction, and not for cloud segmentation and classification.
Also, the datasets used for cloud segmentation and classification generally contain very specific data types, i.e. images plus segmentation maps or images plus cloud category labels, while other data types like meteorological measurements are often missing. Therefore, the comprehensiveness criteria is not applied to datasets for cloud segmentation and classification. Since each segmentation map or cloud category label is generated by human experts, it is reasonable to assume that the data are quality checked for cloud segmentation and classification, and thus we do not apply this criteria for these two applications. The number of samples is usually reported for cloud segmentation and classification datasets, but not so frequently for solar forecasting and cloud motion prediction datasets. So we evaluate this criteria for cloud segmentation and classification, but not for solar forecasting and cloud motion prediction. One can get an estimate of the number of samples based on temporal coverage and temporal resolution of the data.
1. Comprehensiveness, essentially the broadness of data types included in the dataset. In this study, we potentially have the following data types: sky images, solar irradiance/PV power generation, segmentation map, cloud category, meteorological measurements, and other data such as sky video, satellite images, NWP and extracted features from imagery or time series data. A comprehensive dataset is expected to provide more information and suit diverse research purposes.

2. Quality control, which is important as measurements with errors (e.g., abnormal negative irradiance measurements) or irrelevant information (e.g., birds, water drop) can be detrimental to the model training.

3. Temporal coverage. A measure of the data collection period. A multi-year effort in data collection can cover the seasonal and annual variations, which are more representative of the local climate patterns.

4. Spatial coverage, i.e., collecting data from a single location or multiple locations. Different locations might have different climate conditions. Diversified samples for model training can help improve the model generalization.

5. Temporal resolution. The sample interval, how frequent the data is collected, e.g., minutely, hourly, or daily. High temporal resolution data is more suitable for the case of very-short-term solar forecasting, as low temporal resolution data might miss key ramp events, which happens within a short time frame, but cause significant changes of irradiance or PV power output.

6. Image resolution, essentially the image pixels resolution. A higher resolution sky image potentially provides more information about the sky. Although it is not necessarily better using high resolution images for model training as the computation cost increases significantly, it provides more flexibility in research. Users can customize their research by figuring out how to utilize the high resolution information without increasing computation burdens too much. For example, using a crop of the key areas of the high resolution images [83], downsampling, or fusing high resolution images with low resolution for solar forecasting model training.

7. Number of samples. We give a higher rank for more data to encourage enough samples for model training without considering other aspects such as the diversity or representativeness of data which are difficult to ascertain and somewhat context or application dependent.

8. Dataset usage, which are measured by three metrics in this study, namely, citations (C), total usage (U), and usage involving sky images (USI). Citation and total usage reflect the broad impact of a dataset, while USI measures how often a dataset is used in image-based modeling. It should be noted that all these metrics are based on the statistics returned by Google Scholar search of the dataset related publication. Although we present all three metrics, we mainly focus on the metric USI for evaluating the fitness of a certain dataset to be used in solar forecasting and cloud analysis/modeling.
Table 3
Multi-criteria ranking system for dataset evaluation.

| Common criteria for all four potential applications: SF, CS, CC and CMP | Rank |
|---------------------------------------------------------------|-----|
| **Temporal coverage**                                         |     |
| Have more than 3 years of data                                | 10  |
| Have 2 to 3 years of data                                     | 8   |
| Have 1 to 2 years of data                                     | 6   |
| Have 6 months to 1 year of data                               | 4   |
| Have less than 6 months of data                               | 2   |
| **Spatial coverage**                                          |     |
| Collect data from 5 or more different sites                   | 10  |
| Collect data from 4 different sites                           | 8   |
| Collect data from 3 different sites                           | 6   |
| Collect data from 2 different sites                           | 4   |
| Collect data from 1 site                                      | 2   |
| **Image resolution**                                          |     |
| Pixel resolution $\geq 1024 \times 1024$                     | 10  |
| $512 \times 512 \geq$ Pixel resolution $< 1024 \times 1024$   | 8   |
| $256 \times 256 \geq$ Pixel resolution $< 512 \times 512$     | 6   |
| $128 \times 128 \geq$ Pixel resolution $< 256 \times 256$     | 4   |
| Pixel resolution $< 128 \times 128$                          | 2   |
| **Dataset usage**                                             |     |
| $USI > 15$                                                    | 10  |
| $10 < USI \leq 15$                                           | 8   |
| $5 < USI \leq 10$                                            | 6   |
| $1 < USI \leq 5$                                             | 4   |
| $USI \leq 1$                                                  | 2   |
| **Unique criteria for individual applications**               |     |
| **Data comprehensiveness (SF, CMP)**                         | Rank |
| Contains sky images, labels*, meteorological measurements and other data** | 10  |
| Contains sky images, labels*, meteorological measurements or other data** | 6   |
| Contains sky images and labels*                              | 2   |
| **Data quality control (SF, CMP)**                           |     |
| Data is quality controlled                                   | 10  |
| No information released regarding the data quality            | 2   |
| **Temporal resolution (SF, CMP)**                            |     |
| Sample frequency $\leq 1$ minute                              | 10  |
| $1 <$ Sample frequency $\leq 3$ minutes                       | 8   |
| $3 <$ Sample frequency $\leq 5$ minutes                       | 6   |
| $5 <$ Sample frequency $\leq 10$ minutes                      | 4   |
| $10 <$ Sample frequency $\leq 30$ minutes                     | 2   |
| **Number of samples (CS, CC)**                               |     |
| Number of samples $> 10000$                                   | 10  |
| $5000 <$ Number of samples $\leq 10000$                       | 8   |
| $1000 <$ Number of samples $\leq 5000$                       | 6   |
| $500 <$ Number of samples $\leq 1000$                        | 4   |
| Number of samples $\leq 500$                                 | 2   |

* Labels can be either solar irradiance or PV power generation. ** Other data can be cloud fraction values derived from sky images, satellite imagery, NWP, or PV panel parameters, etc.
3. Results and discussion

3.1. Datasets overview

After the initial screening, we have identified a total of 72 open-source ground-based sky image datasets, along with various sensor measurements and data labels such as segmentation maps and cloud categories. The complete list of the datasets can be found in Table 4, with some basic information provided, including the dataset type based on its releasing party, the general data types included in the dataset, whether or not the dataset is quality controlled, the temporal resolution of image samples and the potential applications of the dataset inferred from the data inclusion and the temporal resolution of data.

Table 4
List of open-source ground-based sky image datasets

| Dataset          | Year | Type | Data inclusion                          | QC    | Image temp. res. | Potential applications |
|------------------|------|------|-----------------------------------------|-------|------------------|------------------------|
|                  |      |      |                                         |       |                  | SF | CS | CC | CMP |
| SRRL-BMS[87]     | 1981 | O    | TSI, ASI, Irrad., MM, SM-2(A)           | Yes   | 10 min*          | ● | ○ | ○ | ●   |
| SURFRAD [88]     | 2000 | O    | TSI, Irrad., MM, SM-2(A)                | Yes   | 1 hr             | ○ |    |    |     |
| SIRTA [89]       | 2005 | O    | TSI, ASI, Irrad., PVP, MM, SM-2(A)      | Yes   | 1-2 min          | ● | ○ | ○ | ●   |
| ARM-MASRAD [90]  | 2005 | O    | TSI, Irrad., MM, SM-2(A)                | Yes   | 30 sec           | ● | ○ | ○ | ●   |
| ARM-RADAGAST [91]| 2008 | O    | TSI, Irrad., MM, SM-2(A)                | Yes   | 30 sec           | ● | ○ | ○ | ●   |
| ARM-STORMVEX [92]| 2010 | O    | TSI, Irrad., MM, SM-2(A)                | Yes   | 30 sec           | ● | ○ | ○ | ●   |
| HYTA (Binary) [93]| 2011 | R    | SPI, SM-2(H)                            | N/A   | N/A              | ● |    |    |     |
| ARM-AMIE-GAN [94]| 2011 | O    | TSI, Irrad., MM, SM-2(A)                | Yes   | 30 sec           | ● | ○ | ○ | ●   |
| ARM-COPS [94]    | 2011 | O    | TSI, Irrad., MM, SM-2(A)                | Yes   | 30 sec           | ● | ○ | ○ | ●   |
| ARM-HFE [95]     | 2011 | O    | TSI, Irrad., MM, SM-2(A)                | Yes   | 30 sec           | ● | ○ | ○ | ●   |
| ARM-GVAX [96]    | 2013 | O    | TSI, Irrad., MM, SM-2(A)                | Yes   | 30 sec           | ● | ○ | ○ | ●   |
| SWIMCAT [49]     | 2015 | R    | SPI, CCL-5                              | N/A   | N/A              | ● |    |    |     |
| HYTA (Ternary) [97]| 2015 | R    | SPI, SM-3(H)                            | N/A   | N/A              | ● |    |    |     |
| ARM-CAP-MBL [98] | 2015 | O    | TSI, Irrad., MM, SM-2(A)                | Yes   | 30 sec           | ● | ○ | ○ | ●   |
| ARM-TCAP [99]    | 2015 | O    | TSI, Irrad., MM, SM-2(A)                | Yes   | 30 sec           | ● | ○ | ○ | ●   |
| TCIS [50]        | 2016 | R    | ASI, CCL-5                              | N/A   | N/A              | ● |    |    |     |
| NCU [100]        | 2017 | R    | ASI, SM-2(H)                            | N/A   | N/A              | ● |    |    |     |
| ARM-BAECC [101]  | 2016 | O    | TSI, Irrad., MM, SM-2(A)                | Yes   | 30 sec           | ● | ○ | ○ | ●   |
| ARM-ACAPEX [102] | 2016 | O    | TSI, Irrad., MM, SM-2(A)                | Yes   | 30 sec           | ● | ○ | ○ | ●   |
| ARM-MAGIC [103]  | 2016 | O    | TSI, Irrad., MM, SM-2(A)                | Yes   | 30 sec           | ● | ○ | ○ | ●   |
| ARM-GoAmazon [104]| 2016 | O    | TSI, Irrad., MM, SM-2(A)                | Yes   | 30 sec           | ● | ○ | ○ | ●   |
| ARM-NSA [105]    | 2016 | O    | TSI, Irrad., MM, SM-2(A)                | Yes   | 30 sec           | ● | ○ | ○ | ●   |
| ARM-SGP [106]    | 2016 | O    | TSI, Irrad., MM, SM-2(A)                | Yes   | 30 sec           | ● | ○ | ○ | ●   |
| ARM-TWP [107]    | 2016 | O    | TSI, Irrad., MM, SM-2(A)                | Yes   | 30 sec           | ● | ○ | ○ | ●   |
| SWIMSEG [31]     | 2017 | R    | SPI, SM-2(H)                            | N/A   | N/A              | ● |    |    |     |
| SWINSEG [108]    | 2017 | R    | SPI (Nighttime), SM-2(H)                | N/A   | N/A              | ● |    |    |     |
| SWHIMSEG [109]   | 2018 | R    | SPI (HDR), SM-2(H)                      | N/A   | N/A              | ● |    |    |     |
| Zenithal [51]    | 2018 | R    | SPI (Infrared), CCL-5                   | N/A   | N/A              | ● |    |    |     |
| CCN [47]         | 2018 | R    | SPI, CCL-11                             | N/A   | N/A              | ● |    |    |     |
| ARM-LASIC [110]  | 2018 | O    | TSI, Irrad., MM, SM-2(A)                | N/A   | 30 sec           | ● | ○ | ○ | ●   |
| NAO-CAS [111]    | 2019 | R    | ASI, SM-2(H)                            | N/A   | N/A              | ● |    |    |     |
| FGCDR [48]       | 2019 | R    | ASI, SM-8(H)                            | N/A   | N/A              | ● |    |    |     |
| LES dataset [112]| 2019 | R    | ASI, Irrad.                             | Yes   | 1 min            | ● |    |    |     |
| SWINySEG [41]    | 2019 | R    | SPI (Day+Nighttime), SM-2(H)            | N/A   | N/A              | ● |    |    |     |
| UCSD-Folsom [113]| 2019 | R    | ASI, Irrad., MM, SI, NWP, FE            | Yes   | 1 min            | ● |    |    |     |
| UoH [114]        | 2019 | R    | ASI, Irrad., MM                         | N/A   | 30 sec           | ● |    |    |     |
| P2OA-RAPACE [115]| 2019 | O    | ASI, Irrad., MM, SM-2(A)                | Yes   | 5 min            | ● | ○ | ○ | ●   |
| OHP [116]        | 2019 | O    | TSI, Irrad., MM                         | Yes   | 5 min            | ● |    |    |     |

Continued on next page
| Dataset                | Year | Type | Data inclusion       | QC  | Image temp. res. | Potential applications |
|-----------------------|------|------|----------------------|-----|-----------------|------------------------|
| OPAR [117]            | 2019 | O    | ASI, Irrad., MM      | Yes | N/A             | SF, CS, CC, CMP        |
| ARM-CACTI [118]       | 2019 | O    | TSI, Irrad., MM, SM-2(A) | N/A | 30 sec           | SF, O                  |
| ARM-HOU [119]         | 2019 | O    | TSI, Irrad., MM, SM-2(A) | N/A | 30 sec           | O, O                   |
| ARM-MARCUS [120]      | 2019 | O    | TSI, Irrad., MM, SM-2(A) | Yes | 30 sec           | O, O                   |
| El Arenosillo [121, 122] | 2020 | O    | ASI, Irrad., MM      | Yes | N/A             | SF, CS                 |
| MGCD [123]            | 2020 | R    | ASI, CCL-7           | N/A | N/A**           | SF, CS, CC, CMP        |
| GRSCD [124]           | 2020 | R    | ASI, CCL-7           | N/A | N/A**           | SF, CS                 |
| WSISEG [42]           | 2020 | R    | ASI (HDR), SM-3(H)   | Yes | N/A**           | SF, CS                 |
| WMD [125]             | 2020 | R    | ASI, SM-4(H)         | N/A | N/A**           | SF, CS, CC, CMP        |
| CO-PDD [126]          | 2020 | O    | ASI, Irrad., MM, SM-2(A) | N/A | 1-2 min         | SF, O                  |
| ARM-AWARE [127]       | 2020 | O    | TSI, Irrad., MM, SM-2(A) | No  | 30 sec           | O, O                   |
| GCD [128]             | 2021 | R    | SPI, CCL-7           | N/A | N/A**           | SF, CS                 |
| BASS [129]            | 2021 | R    | ASI (HDR), Irrad.    | N/A | 1 min           | SF, CS                 |
| NIMS-KMA [130]        | 2021 | O    | ASI (Day+Nighttime), CCL-10 | N/A | N/A**           | SF, CS                 |
| Girasol [84]          | 2021 | R    | ASI (HDR Grayscale), SPI (Infrared), Irrad., MM | Yes | 15 sec         | SF, O                  |
| SkyCam [131]          | 2021 | R    | ASI (HDR), Irrad.    | N/A | 10 sec          | SF, O                  |
| SIPM [132]            | 2021 | R    | ASI, PVP, PParam.    | N/A | 1 sec           | SF, O                  |
| SIPPIMF [133]         | 2021 | R    | ASI, PVP             | N/A | 10 sec          | SF, O                  |
| Waggle [134]          | 2021 | O    | SPI, PVP, Irrad., SM-2(A) | N/A | 15 sec           | O, O                   |
| TAN1802 Voyage [135]  | 2021 | O    | ASI (HDR), Irrad., MM, SM-2(A) | Yes | 5 min          | SF, O                  |
| ARM-SAIL/GUC [136]    | 2021 | O    | TSI, Irrad., MM, SM-2(A) | No  | 30 sec           | SF, O                  |
| SKIPP’D [137]         | 2022 | R    | ASI, ASV, PVP        | Yes | 1 min           | SF, O                  |
| TCDD [43]             | 2022 | R    | SPI, SM-2(H)         | N/A | N/A**           | SF, O                  |
| PSA Fabel [138]       | 2022 | O    | ASI, SM-3(H)         | N/A | N/A**           | SF, O                  |
| NAO-CAS XJ [139]      | 2022 | R    | ASI, CCL-4           | N/A | N/A**           | SF, O                  |
| TLCDD [140]           | 2022 | R    | SPI, SM-2(H)         | N/A | N/A**           | SF, O                  |
| ACS WSI [141]         | 2022 | R    | ASI, SM-2(H)         | N/A | N/A**           | SF, O                  |
| ARM-COMBLE [142]      | 2022 | O    | TSI, Irrad., MM, SM-2(A) | Yes | 30 sec           | SF, O                  |
| ARM-MOSAIC [143]      | 2022 | O    | TSI, Irrad., MM, SM-2(A) | Yes | 30 sec           | SF, O                  |
| ARM-ACE-ENA [144]     | 2022 | O    | TSI, Irrad., MM, SM-2(A) | Yes | 30 sec           | SF, O                  |
| Orion StarShoot [145] | N/A  | O    | ASI, Irrad., MM      | N/A | 1 min           | SF, O                  |
| LTR [146]             | N/A  | R    | ASI, Irrad., MM      | N/A | N/A             | SF, O                  |
| LOA [147]             | N/A  | O    | ASI, Irrad., MM      | N/A | N/A             | SF, O                  |
| ARM-OLI [148]         | N/A  | O    | TSI, Irrad., MM, SM-2(A) | Yes | 30 sec           | SF, O                  |

Type — O: datasets released by national labs or scientific organizations; R: datasets released by research groups from universities. Data inclusion — TSI: total sky image; ASI: all sky image; Irrad.: solar irradiance measurements; MM: meteorological measurements, e.g., temperature, pressure, humidity, wind speed, wind direction; SPI: sky patch image; CCL-n: n-level cloud category/cover labels; SM-n(A): n-level segmentation map generated by algorithms; SM-n(H): n-level segmentation map labeled by human; HDR: high dynamic range; SI: satellite imagery; NWP: numerical weather prediction; FE: feature extractions from irradiance and imagery data; PVP: PV power generation measurements; PParam.: PV panel parameter measurements include voltage, current and temperature; ASV: All sky video. QC — quality control. Image temp. res. — temporal resolution of image samples. Application — SF: image-based solar forecasting; CS: cloud segmentation; CC: cloud classification; CMP: cloud motion prediction; G: the dataset is suitable for a certain application; H: the dataset can theoretically be used for a certain application, but might not be preferred (e.g., segmentation maps generated by human is preferred over those generated by algorithms). * SRRL-BMS has a live-view of ASI updated minutely on its website but not archived. ** The Girasol dataset article [84] does not mention that it includes segmentation maps or cloud category labels. However, follow-up studies by the authors [85, 86] used 12 segmentation maps labeled manually and 8200 labeled images with 4 different sky conditions. Contact the authors for details. *** most of the datasets intended for use in cloud segmentation and classification generally do not provide temporal resolution as such datasets do not require image data in sequence.
The datasets are mainly released by two types of parties. The first category consists of national labs and government scientific organizations (denoted by O in the Table 4 column Type), which often have multi-site and multi-year efforts in collecting a wide range of sensor observations for the purpose of studying the Earth’s atmosphere and climate. This type of datasets generally go through stringent quality control processes. 39 out of the 72 identified datasets belong to this type, to name a few, the Solar Radiation Research Laboratory Baseline Measurement System (SRRL-BMS) [149] by the National Renewable Energy Laboratory (NREL) of the US, the National Surface Radiation (SURFRAD) Budget Network by National Oceanic and Atmospheric Administration (NOAA) [150] of US, a series of campaigns deployed by the Atmospheric Radiation Measurement (ARM) Program under the hood of Department of Energy of US (totally 26 datasets from ARM program, e.g., [93, 98, 102, 118, 127, 144]), and the Site Instrumental de Recherche par Télédétection Atmosphérique (SIRTA) [89] by Institut Pierre Simon Laplace in France. The second type of party is research groups from universities (denoted by R in the Table 4 column Type). To promote the openness and accessibility of research, researchers choose to release the datasets along with their research articles (e.g., [36, 42, 47, 48, 49, 129]) or publish specific dataset articles for their datasets (e.g., [84, 113, 131, 137]). Most datasets from this type of party are published for a specific task, e.g., solar forecasting or cloud segmentation or cloud classification, so the type of data included is generally less comprehensive compared with the type O datasets. Moreover, the data quality might vary from datasets to datasets. Some datasets note that they have a quality control process (e.g., [84, 113, 137]), while others did not released any information on that (denoted by N/A in the Table 4 column QC). It should be noted that although most of the datasets intended for cloud segmentation and classification do not mention that they have a quality control process, it is reasonable to assume that they have a quality check on the imagery data as they provide cloud segmentation maps or cloud category labels labeled by human experts and abnormal images, such as images with presence of birds, have been removed. The El Arenosillo dataset is referenced twice as it is composed of both night and day observations which were presented separately [121, 122].

To give a glimpse of data types included in each dataset, we categorize the data into the following types as shown in Table 4: (1) imagery data, i.e. ground-based sky images of various kinds, that could serve as the input of the models for solar forecasting, cloud segmentation and classification; (2) data that could potentially be used as labels for machine learning or deep learning model development, including solar irradiance (denoted by irrad.), PV power generation (PVP), segmentation map (SM) and cloud category label (CCL); auxiliary data that could potentially serve as additional input for the model, including (3) meteorological measurements (MM) such as air temperature, wind speed and direction, humidity and pressure and (4) other data, including but not limited to sky video, numerical weather prediction (NWP), and secondary data such as features extractions (FE) from sky images or time series measurements. It should be noted that besides using irrad., PVP, SM and CCL as labels, sky images itself can be used as labels, for example, for cloud motion prediction task, sky image sequence in the past can be used as context to forecast the sky image frame(s) in the future [58, 59], which works in a so-called self-supervised learning fashion. We present detailed descriptions of each data type in section 3.2.

The temporal resolution of the image samples of each dataset is also listed in the table. The detail specifications of different data types can be found in Table A.8 to A.10 in Appendix A for different applications. It should be noted that most of the datasets intended for use in cloud segmentation and cloud classification tasks generally do not provide temporal resolution information as such datasets do not require image data in sequence as solar forecasting and cloud motion prediction do. Samples are selected from a pool mostly based on their representativeness of a certain sky condition or cloud class without considering too much on their temporal dependency.

The potential applications for the datasets are inferred based on the data inclusion as well as the temporal resolution of data. The method we used for making the inference are shown in Figure 2 of Section 2.2. 47 out of 72 datasets can potentially be used for solar forecasting as well as cloud motion prediction. 51 datasets can theoretically be used for cloud segmentation, out of which 15 datasets have segmentation maps labeled by human experts, while the rest 36 datasets have algorithm-generated segmentation maps. Segmentation maps labeled by human experts are preferred over those generated by algorithms as they generally have better quality and less noise. Therefore, for analysis of cloud segmentation datasets in the following sections, we will mainly focus on the 15 datasets with human-generated segmentation maps. 13 datasets are suitable for cloud classification and all cloud category labels are generated by human experts. It should be noted that there might be overlaps between datasets for cloud segmentation and classification. Some cloud classification datasets have a pixel-level labeling of the cloud types which can also satisfy the needs of cloud segmentation. A detail analysis of the dataset applications based on the papers that use these datasets is presented in Section 3.4.
The specific ways of accessing each dataset, i.e. the links to the data repositories for downloading the data or/and
the email addresses of the corresponding authors for requesting the datasets, as well as the data policy or license
information of each dataset if available are provided in Table 5. Although most of the datasets listed here are free
and open for research use, commercial use is generally prohibited, with special notes in their data policy or enforced
licenses such as CC BY-NC 4.0 \(^3\). However, certain datasets have no restriction on commercial use with a CC0 1.0
license \(^4\), e.g., CCSN[47], Girasol [84]. We encourage the users to double check the license of the datasets or contact
the creators for more details before using these datasets in publications or for commercial purposes.

\(^3\)CC BY-NC 4.0: https://creativecommons.org/licenses/by-nc/4.0/
\(^4\)CC0 1.0: https://creativecommons.org/publicdomain/zero/1.0/
| Dataset          | Access                                      | Data policy/License information                      |
|------------------|---------------------------------------------|-----------------------------------------------------|
| SRRL-BMS [87]    | https://midcdmz.nrel.gov/apps/sitehome.pl?site=BMS | https://data.nrel.gov/submissions/7                  |
| SURFRAD [88]     | https://gml.noaa.gov/grad/surfrad/index.html | https://gml.noaa.gov/about/disclaimer.html           |
| SIRTA [89]       | https://sirta.ipsl.polytechnique.fr/index.html | Actris: https://www.actris.fr/catalogue/ (keyword: sky imager, pyranometer) |
|                  |                                             | lcare: ftp://ftp.icare.univ-lille1.fr (GROUND-BASED/SIRTA_Palaiseau) |
|                  |                                             | PV data: https://gitlab.in2p3.fr/energy4climate/public/sirta-pv1-data |
| ARM-MASRAD [90]  | https://adc.arm.gov/discovery/#/results/s::sky%20images%20MASRAD | https://www.arm.gov/guidance/datause/generalguidelines |
| ARM-RADAGAST [91]| https://adc.arm.gov/discovery/#/results/s::sky%20images%20RADAGAST |                                                      |
| ARM-STORMVEX [92]| https://adc.arm.gov/discovery/#/results/s::STORMVEX%20sky%20images |                                                      |
| HYTA (Binary) [36]| https://github.com/Soumyabrata/HYTA         | N/A                                                 |
| ARM-AMIE-GAN [93]| https://adc.arm.gov/discovery/#/results/s::sky%20image%20amie-gan | https://www.arm.gov/guidance/datause/generalguidelines |
| ARM-COPS [94]    | https://adc.arm.gov/discovery/#/results/iopShortName::amf2007cops |                                                      |
| ARM-HFE [95]     | https://adc.arm.gov/discovery/#/results/s::tsiskyimage%20HFE |                                                      |
| ARM-GVAX [96]    | https://adc.arm.gov/discovery/#/results/s::sky%20images%20gvax |                                                      |
| SWIMCAT [49]     | http://vintage.winklerbros.net/swimcat.html  | CC BY-NC 4.0 (Attribution-NonCommercial 4.0)          |
| HYTA (Ternary) [97]| https://github.com/Soumyabrata/HYTA       | N/A                                                 |
| ARM-CAP-MBL [98] | https://adc.arm.gov/discovery/#/results/s::tsiskyimage%20CAP-MBL | https://www.arm.gov/guidance/datause/generalguidelines |
| ARM-TCAP [99]    | https://adc.arm.gov/discovery/#/results/s::sky%20images%20TCAP |                                                      |
| TCIS [50]        | http://icn.bjtu.edu.cn/visint/resources/CloudImages | Email Qingyong Li (qingyongli@gmail.com), Weitao Lu (wtlu@cams.cma.gov.cn) if the link is not accessible |
| NCU [100]        | https://drive.google.com/openid=0B38yagaBviZYmRxReVBIQkVJYkk | Email Hsu-Yung Cheng (breeze.cheng@gmail.com) if the link is not accessible |
| ARM-BAECC [101]  | https://adc.arm.gov/discovery/#/results/s::BAECC%20sky%20images |                                                      |
| ARM-ACAPEX [102] | https://adc.arm.gov/discovery/#/results/s::ACAPEX%20sky%20images |                                                      |
| ARM-MAGIC [103]  | https://adc.arm.gov/discovery/#/results/s::sky%20images%20Magic |                                                      |
| ARM-GoAmazon [104]| https://adc.arm.gov/discovery/#/results/s::sky%20images%20Goamazon |                                                      |
| ARM-NSA [105]    | https://adc.arm.gov/discovery/#/results/s::sky%20images%20NSA |                                                      |
| ARM-SGP [106]    | https://adc.arm.gov/discovery/#/results/s::SGP%20sky%20images |                                                      |
| ARM-TWP [107]    | https://adc.arm.gov/discovery/#/results/s::TWP%20sky%20images |                                                      |
| SWIMSEG [31]     | http://vintage.winklerbros.net/swimseg.html |                                                      |
| SWINSEG [108]    | http://vintage.winklerbros.net/swinseg.html | CC BY-NC 4.0 (Attribution-NonCommercial 4.0)          |
| SHWIMSEG [109]   | http://vintage.winklerbros.net/shwimseg.html |                                                      |
| Zenithal [51]    | Email Qixiang Luo (qixiang_luo@aliyun.com) | N/A                                                 |

Continued on next page
| Dataset         | Access                                                                 | Data policy/License information                          |
|-----------------|------------------------------------------------------------------------|----------------------------------------------------------|
| CCSN [47]       | https://doi.org/10.7910/DVN/CADDPD  
GitHub: https://github.com/upuil/CCSN-Database | CC0 1.0 Universal Public Domain Dedication                |
| ARM-LASIC [110] | https://adc.arm.gov/discovery/#/results/iopShortName:amf2016lasic      | https://www.arm.gov/guidance/datause/generalguidelines   |
| NAO-CAS [111]   | Email Chaojun Shi (474756323@qq.com), Yatong Zhou (zyt@hebut.edu.cn) | N/A                                                      |
| FGCDR [48]      | https://github.com/liangye518/FGCDR  
Email Zhiguo Cao (zgcao@hust.edu.cn) if data cannot be found | N/A                                                      |
| LES dataset [112] | http://symphony.ies.es/edu/  
Email M. Caldas (mcaldas@fisica.edu.uy) if the link is not accessible | N/A                                                      |
| SWINySEG [41]   | http://vintage.winklerbros.net/swinyseg.html  
GitHub: https://github.com/Soumyabrata/CloudSegNet | CC BY-NC 4.0 (Attribution-NonCommercial 4.0)             |
| UCSD-Folsom [113] | https://doi.org/10.5281/zenodo.2826939 | CC BY-NC 4.0 (Attribution-NonCommercial 4.0)             |
| UoH [114]       | http://observatory.herts.ac.uk/allsky/imagefind.php?c=7 | N/A                                                      |
| P2OA-RAPACE [115] | https://p2oa.aeris-data.fr/data/  
Actris: https://www.actris.fr/catalogue/ (keyword: sky imager)  
Icare: ftp://ftp.icare.univ-lille1.fr (GROUND-BASED/P2OA_Pic-du-Midi or P2OA_Lannemez) | https://www7.obs-mip.fr/wp-content-aeris/uploads/sites/71/2021/12/data_policy_P2OA.pdf |
| OHP [116]       | https://www.actris.fr/catalogue/ (keyword: sky imager)  
Icare: ftp://ftp.icare.univ-lille1.fr (GROUND-BASED/OHP_St-Michel) | https://www.actris.eu/sites/default/files/Documents/ACTRIS%2OPPPP%2Deliverables%20A%20Data%20policy.pdf |
| OPAR [117]      | https://www.actris.fr/catalogue/ (keyword: sky Imager (La Reunion station))  
Icare: ftp://ftp.icare.univ-lille1.fr (GROUND-BASED/OPAR_La-Reunion) | https://www.actris.eu/sites/default/files/Documents/ACTRIS%2OPPPP%2D2._3.ACTRIS%20Data%20policy.pdf |
| ARM-CACTI [118] | https://adc.arm.gov/discovery/#/results/iopShortName:amf2018cacti | CC-BY-NC                                                  |
| ARM-HOU [119]   | https://adc.arm.gov/discovery/#/results/s::sky%20images%2OHOU | https://www.arm.gov/guidance/datause/generalguidelines   |
| ARM-MARCUS [120] | https://adc.arm.gov/discovery/#/results/s::sky%20images%2OMARCUS | Details provided in the agreement                         |
| El Arenosillo [121, 122] | Email Carmen Córdoba-Jabonero (cordobajc@inta.es) | N/A                                                      |
| MGCD [123]      | Download the agreement: https://github.com/shuangliutjnu/Multimodal-Ground-based-Cloud-Database; Sign and return to Shuang Liu (shuangliu.tjnu@gmail.com or s.liu@tjnu.edu.cn) | Details provided in the agreement                         |
| GRSCD [124]     | Download the agreement: https://zenodo.org/record/3635497#.Y0UKR-zMKr0;  
GitHub: https://github.com/shuangliu/tjnu/  
TJNU-Ground-based-Remote-Sensing-Cloud-Database/tree/V1.0.0 | Details provided in the agreement                         |
| WSISEG [42]     | https://github.com/CV-Application/WSISEG-Database | N/A                                                      |
| Dataset | Access | Data policy/License information |
|---------|--------|---------------------------------|
| WMD [125] | https://zenodo.org/record/6203375#.YsczU-yZDrM | CC BY-NC 4.0 (Attribution-NonCommercial 4.0) |
| CO-PDD [126] | https://www.actris.fr/catalogue/ftp://ftp.icare.univ-lille1.fr (GROUND-BASED/CO-PDD_Puy-de-Dome) | https://www.actris.eu/sites/default/files/Documents/ACTRIS%20PPP/Deliverables/ACTRIS%20PPP_WP2_D2.3_ACTRIS%20Data%20policy.pdf |
| ARM-ARE [127] | https://adc.arm.gov/discovery/#/results/iopShortName::amf2015aware | https://www.arm.gov/guidance/dataset/guidelines |
| GCD [128] | Download the agreement: https://github.com/shuangliutjnu/TJNU-Ground-based-Cloud-Dataset; Sign and return to Shuang Liu (shuangliu.tjnu@gmail.com or s.liu@tjnu.edu.cn) | Details provided in the agreement |
| BASS [129] | Email Pedro C. Valdelomar (pedro.catalan@uv.es) | N/A |
| NIMS-KMA [130] | Email Bu-Yo Kim (kimbuyo@korea.kr) | N/A |
| Girasol [84] | https://doi.org/10.5061/dryad.zcrjdfn9m | CC0 1.0 Universal Public Domain Dedication |
| SkyCam [131] | Email Evangelos Ntavelis (evangelos.ntavelis@csem.ch) GitHub: https://github.com/vglsl/SkyCam | CC BY-NC-SA 4.0 (Attribution-NonCommercial-ShareAlike 4.0) |
| SIPP [132] | https://data.mendeley.com/datasets/r33r6g5y6t/1 | CC BY-NC 4.0 (Attribution-NonCommercial 4.0) |
| SIPPMIF [133] | https://data.mendeley.com/datasets/cb8t8np9z3/2 | CC BY-NC 3.0 (Attribution-NonCommercial 3.0) |
| Waggle [134] | Image: Email Seongha Park (seongha.park@anl.gov) Irradiance data: https://www.atmos.anl.gov/ANLMET/index.html PV data: https://dashboard.ioc.anl.gov/viewer.html?proj=Argonne GitHub: https://github.com/waggle-sensor/solar-irradiance-estimation | N/A |
| TAN1802 Voyage [135] | https://zenodo.org/record/4060237 | CC BY-NC 4.0 (Attribution-NonCommercial 4.0) |
| ARM-SAIL/GUC [136] | https://adc.arm.gov/discovery/#/results/s::sky%20images%20GUC | https://www.arm.gov/guidance/dataset/guidelines |
| SKIPP'D [137] | Benchmark dataset 2017-2019: https://purl.stanford.edu/dj417rh1007 Raw dataset 2017: https://purl.stanford.edu/sm043zf7254 Raw dataset 2018: https://purl.stanford.edu/fb002mq9407 Raw dataset 2019: https://purl.stanford.edu/jj716zx9049 | CC BY-NC 4.0 (Attribution-NonCommercial 4.0) |
| TCDD [43] | Download the agreement: https://github.com/shuangliutjnu/TJNU-Cloud-Detection-Dataset; Sign and return to Shuang Liu (shuangliu.tjnu@gmail.com or s.liu@tjnu.edu.cn) | Details provided in the agreement |
| PSA Fabel [138] | Email Yann Fabel (yann.fabel@dlr.de), Bijan Nouri (bijan.nouri@dlr.de) | N/A |
| NAO-CAS XJ [139] | Email Xiaotong Li (865517454@qq.com), Bo Qiu (qibi@hebut.edu.cn) | N/A |
| TLCDD [140] | Download the agreement: https://zenodo.org/record/6464743#.Y0URDOzMKrM; Sign and return to Shuang Liu (shuangliu.tjnu@gmail.com or s.liu@tjnu.edu.cn) GitHub: https://github.com/shuangliutjnu/TJNU-Large-Scale-Cloud-Detection-Database/tree/v1.0.0 | Details provided in the agreement |

Continued on next page
Table 5  
Access to and data policy/license of the open-source sky image datasets (continued)

| Dataset              | Access                                                                 | Data policy/License information                                      |
|----------------------|------------------------------------------------------------------------|----------------------------------------------------------|
| ACS WSI [141]        | Download the agreement: https://github.com/liangye518/ACS_WSI/tree/v1.0.0; Sign and return to Liang Ye (yeliang@wust.edu.cn) | Details provided in the agreement                            |
| ARM-COMBLE [142]     | https://adc.arm.gov/discovery/#/results/s::sky%20images%20comble       |                                                       |
| ARM-MOSAIC [143]     | https://adc.arm.gov/discovery/#/results/s::sky%20images%20mosaic       | https://www.arm.gov/guidance/datause/generalguidelines     |
| ARM-ACE-ENA [144]    | https://adc.arm.gov/discovery/#/results/s::sky%20images%20Eastern%20North%20Atlantic |                                                        |
| Orion StarShoot [145]| http://www.ciao.imaa.cnr.it/index.php?option=com_content&view=article&id=186&Itemid=255 | http://www.ciao.imaa.cnr.it/images/ciao/documenti/Access/ciao_data_policy.pdf |
| LTR [146]            | https://www.igf.fuw.edu.pl/en/meteo-station/lab_tr_pastura_5/            | N/A                                                      |
| LOA [147]            | https://www.actris.fr/catalogue/#aeris-metadata-platforms icare: ftp://ftp.icare.univ-lille1.fr (GROUND-BASED/LOA_Lille) | https://www.actris.eu/sites/default/files/Documents/ACTRIS%20PPP/Deliverables/ACTRIS%20PPP_WP2_D2.3_ACTRIS%20Data%20Policy.pdf |
| ARM-OLI [148]        | https://adc.arm.gov/discovery/#/results/s::sky%20images%20OLI          | https://www.arm.gov/guidance/datause/generalguidelines     |
3.2. Data types in sky image datasets

In this section, we present detailed descriptions of each data type including sky image, irradiance and PV power generation, segmentation map, cloud category label and meteorological measurements. The data specifications for each dataset, such as image pixel resolution, data temporal resolution and characteristics of segmentation maps and cloud category labels can be found in Table A.8, A.9 and A.10 in Appendix A.

**Sky image** Three general types of sky images are found in the identified datasets, namely, total sky image (TSI), all sky image (ASI) and sky patch image (SPI). Figure 3 show a few samples of sky images of different kinds from different datasets, with the general sky image type annotated above the samples and other characteristics of the images shown in the bracket, such as RGB, nighttime, infrared and high dynamic range (HDR).

![Sky image samples](image.png)

**Figure 3:** Sky image samples of different kinds (Note the images presented here do not reflect the actual resolution of the images. The actual resolution of images from different datasets can be found in Table A.8.)

Each type of sky image has its unique features. TSIs are captured by total sky imagers (e.g., Yankee Environmental Systems’s TSI-880 instrument), which use a hemispherical chrome-plated mirror to reflect the sky into a downward-pointing charge-coupled device (CCD) camera located above the mirror, and a sun tracking shadow band is equipped on the mirror to protect the CCD optical sensor from the effects of solar reflection [60]. TSIs are generally of low resolution and the presence of a black sun-blocking shadow band and a camera supporting arm prevent getting a total view of the sky dome, going against the fact that the information contained in the circumsolar area is critical to image-based solar forecasting [83]. To help alleviate this, studies use linear interpolation of surrounding pixels [151] to fill the missing part of the sky or cloud motion displacement based on two temporally near frames (e.g., 5 min difference in time stamp) to back-calculate the missing pixels in the previous frame by assuming a smooth cloud motion process [152]. Early efforts using TSIs for solar forecasting featured by works done by researchers from University of California at San Diego (UCSD), which propagate clouds using wind vectors extracted from TSIs and build physical deterministic models [11, 12, 13] or use features extracted from sky images and train machine learning models [15, 16, 17, 18]. Some recent works also use TSIs to build end-to-end deep learning models for solar forecasting [26, 28].

In comparison, ASIs tend to have much higher pixel resolution than TSI and do not have a shadow band in the images, so they can provide the whole view of the sky and are used more frequently in recent deep-learning-based short-term solar forecasting models [4, 24, 25, 27, 29, 30, 38, 153, 154]. All sky imagers are typically developed based on a camera equipped with a fish-eye lens and protected by a weatherproof enclosure [37]. Industrial sky imagers such as EKO’s SRF-02 and ASI-16 are commonly used in sky image collection, e.g., [87, 89]. Surveillance network cameras, such as Hikvision DS-2CD6365GOE-IVS and MOBOTIX Q25, are also used by researchers for solar
forecasting [23, 137]. Though much cheaper than industrial sky imagers, they work well for providing images for solar forecasting [4, 25, 38, 153, 154]. Some researchers also built their own camera system with customized setups to suit the need for cloud detection or short-term solar forecasting, such efforts including advanced all sky imagers developed by researchers from research institutions, e.g., University of Girona [34], Universidad de Granada [155], UCSD [156], PROMES-CNRS [37], and low-cost Raspberry Pi-based sky cameras by University of Texas at San Antonio [157] and University College Dublin [158].

SPIs are either taken by cameras equipped with a normal lens (in contrast to fish-eye lenses used for capturing ASI) or obtained from patches of unwarped ASIs. They only cover a portion of the sky (i.e. a limited range of zenith and azimuth angles) unlike ASIs and TSIs, which could capture the panoramic view of the sky. Additionally, SPIs do not have distorted regions, which are present in TSIs and ASIs because the lens’ field of view is wider than the size of the image sensor. Thus, the use of SPIs for solar forecasting tasks is limited, as it probably needs information from different parts of the sky for models to learn to anticipate the motion of clouds, while they are more frequently used in tasks such as cloud segmentation or classification, which do not require the model’s attention on the cloud motion.

For most studies, these three types of sky images are captured by visible light sensors, while there are studies using images taken by infrared sensors, e.g., [85, 86, 159, 160]. The advantages of using infrared sensor over visible sensor include avoiding the saturation problem of the circumsolar region as well as allowing the derivation of valuable cloud properties such as the temperature and altitude [86]. High dynamic range (HDR) is a technique used to balance the light of images by blending several images taken with different exposure time into one with high contrast. In sky imaging, it is useful in lots of scenes such as very bright direct sunlight and extreme shade of clouds. Although most sky images are captured during the day time, some are taken at night for application purposes such as weather reporting and prediction, aviation, and satellite communication [108].

**Irradiance and PV power generation** Irradiance and PV power generation are highly correlated and can both be used as target variables for solar forecasting. Generally, irradiance data is more common than PV data in terms of openness, due to privacy restriction or energy security in accessing residential or utility PV data. The same trend has been found in our identified open-source dataset, 45 datasets provide irradiance data while only 5 datasets provide PV generation data. Moreover, these PV data are from small-scale rooftop PV system or outdoor testing facility for research purposes. On the other hand, compared with irradiance forecasting, which can be adapted to different locations, PV forecasting model is hard to be adapted to other locations given the different specifications of the PV systems. Different types of solar irradiance are found in the datasets. Some commonly measured irradiance components include the global horizontal irradiance (GHI), the direct normal irradiance (DNI) and the diffuse horizontal irradiance (DHI). DNI, or beam irradiance, is the incident light directly from the Sun measured at the surface of the Earth normal to the optical path. DNI is critical for concentrated solar technologies and can be greatly affected by cloud cover and aerosol content. DHI is the irradiance received by a horizontal surface at the Earth’s surface which has been scattered or diffused by the atmosphere. GHI is the total irradiance falling on a surface horizontal to the surface of the earth, which can be calculated based on DNI and DHI using the following equation, Where $\theta_z$ is the solar zenith angle (Equation 1).

$$GHI = DNI \times \cos(\theta_z) + DHI$$

While GHI and DHI can be both measured using pyranometers placed on a horizontal plane, for measuring DHI, a black ball or disc needs to be installed together with a sun tracker to remove the direct component from the sun light. The DNI can be measured via a pyrheliometer. To maximize the PV power production, solar panels are usually tilted at an angle to maximize the irradiance reaching the panel, which is referred to as global irradiance in the plane of array $G_{POA}$, or global tilted irradiance (GTI). $G_{POA}$ or GTI is crucial for modeling the performance of PV system, and consists of three components, namely, a beam (direct) component ($G_{B,POA}$), a sky-diffuse component ($G_{D,POA}$) and a ground-reflected component ($G_{R,POA}$). $G_{POA}$ can either be measured using a pyranometer placing on the tilted panel surface or can be calculated based on transposition of GHI, DNI and DHI to the three components of $G_{POA}$ [161].

**Segmentation map** Two types of segmentation maps are identified across the datasets. The first type corresponds to segmentation maps generated by algorithms like red-blue-ratio thresholding. This type of segmentation map usually comes from datasets released by national labs or government scientific organizations, i.e. type ’O’ datasets. The second type is segmentation map manually labeled by human experts, that is generally for datasets that specifically focusing on cloud segmentation task. Besides, datasets provide different levels of segmentation for the cloud images. Algorithm generated segmentations almost only provide the binary segmentation of sky and clouds. Human labelled segmentation
contains more diversity. Although most of them provide binary segmentation maps, some datasets provide more than 2 levels of segmentation by differentiating the cloud types at pixel level, so these datasets can also be used in cloud type classification tasks. These datasets include HYTA (Ternary) [97], which provides a 3-level segmentation of sky, thin and thick clouds; FGCDR [48], which provides a 8-level segmentation of 8 different cloud categories at pixel level; WMD [125], which provides a 4-level segmentation of high-level clouds, low-level cumulus type clouds, rain clouds and clear sky and PSA Fabel [138], which provides a 3-level segmentation of low-, middle- and high-layer clouds. Figure 4 shows segmentation map samples of 2-level and 3-level labels from HYTA and WSISEG.

![Figure 4](image)

**Figure 4:** Segmentation map samples of different kinds (Note the samples presented here do not reflect the actual resolution of the images. The actual resolution of images from different datasets can be found in Table A.8.)

**Cloud category label** Another type of label data is cloud category labels, which can be further divided into image-level labels and pixel-level labels. As the name suggests, image-level labels classify images into certain cloud types, while pixel-level labels distinguish for each pixel in the image, what cloud type this pixel belongs to. The pixel-level cloud category label can also be used for the cloud segmentation tasks as mentioned before. There is no consistent agreement on the cloud type classification criteria, some are based on the main cloud genera recommended by the World Meteorological Organization (WMO) [46, 47, 48] (e.g., Cirrus, Cumulus, Stratus, Nimbus), some are based on the visual characteristics of clouds [49, 50, 51] (e.g., patterned clouds, thick dark clouds, thin white clouds, veil clouds) and some are based on the height of clouds [44] (e.g., high-level clouds, medium-level clouds, low-level clouds). Figure 5 shows samples of cloud category label data both at image-level and pixel-level.

**Meteorological measurements** Meteorological data such as temperature, wind speed and direction, pressure, humidity, etc., have varying impacts on the solar irradiance reaching the ground and the amount of power able to be generated from that irradiance. Making use of these information can potentially contribute to the development of robust solar forecasting models. However, the challenge is to make the deep learning systems pay due attention to both imagery and sensor measurement data. Imagery data is often high dimensional, i.e. an array with hundreds of thousands of entries, which might catch more attention from the deep systems than sensor measurements that might just be a vector of 10s of entries. This is actually an active field of research called data fusion, applications like self-driving [162] and robotics [163] have explored this thoroughly, while very limited studies has been found investigating this problem for sky-image-base solar forecasting. In 2019, Venugopal et al. [25] first systematically compared 28...
methods of fusion (MoF) for integrating hybrid input of sky image sequences and PV output history to forecast 15-min-ahead PV power output by using CNN as backbone. Although no other sensor data are investigated beside PV power generation, it provides a general guideline for fusing sensor data with imagery data for solar forecasting. Similarly, Ajith and Martínez-Ramón [164] developed a multi-modal fusion network based on CNN and LSTM for studying solar irradiance forecasts using IR images and past solar irradiance data with forecasting horizon ranging from 15 to 150s. More recently, Terrén-Serrano and Martinez-Ramon [165] explored fusing information from IR sky images with various sensors including pyranometer, solar tracker and weather station using a multi-task deep learning architecture based on RNNs.

3.3. Spatial and temporal coverage of datasets

The geographic locations, collection period as well as size of each dataset are shown in Table 6. If the information about the size of the dataset is not provided, we estimate it based on the data collection period and the temporal resolution of the data if available. The size of the datasets varies from 733 KB to 16 TB, depending on the number of sites and time duration for data collection, the temporal resolution of data logging as well as the type of data included. For example, SkyCam dataset logs data every 10 seconds from 3 different location for 365 days, and SKIPP’D dataset provides sky video footage. Most of the type O datasets (see Table 4) have multi-year efforts in collecting data, while for type R datasets (see Table 4), the temporal coverage of the data varied from one to another. Ideally, we would want the datasets collection spans multiple years to catch the annual variability in local weather conditions.
Table 6
Spatial and temporal coverage of the dataset.

| Dataset            | Spatial coverage (# of sites) | Locations                                        | Temporal coverage (yrs) | Collection period          | Size est. (GB) |
|--------------------|------------------------------|--------------------------------------------------|--------------------------|----------------------------|----------------|
| SRRL-BMS[87]       | 1                            | Golden, Colorado, US                             | TSI: 18.0               | 2004.07.14-present         | 4.7 (Img.)     |
|                    |                              |                                                   | ASI: 4.8                 | 2017.09.26-present         | 9.2 (Img.)     |
| SURFRAD [88]       | 7                            | Bondville, Illinois, US                          | 4.7                      | 2006.09.01-2011.05.25      | 0.4 (Tot.)     |
|                    |                              | Boulder, Colorado, US                            | 5.3                      | 2006.09.01-2011.11.30      | 0.9 (Tot.)     |
|                    |                              | Dessert Rock, Nevada, US                         | 8.4                      | 2006.09.01-2015.01.25      | 0.9 (Tot.)     |
|                    |                              | Fort Peck, Montana, US                           | 8.4                      | 2006.09.01-2015.01.25      | 1.0 (Tot.)     |
|                    |                              | Goodwin Creek, Mississippi, US                   | 4.7                      | 2006.09.01-2011.04.28      | 0.5 (Tot.)     |
|                    |                              | Sioux Falls, South Dakota, US                    | 2.7                      | 2008.10.11-2011.06.08      | 0.3 (Tot.)     |
|                    |                              | PSU, Pennsylvania, US                            | 8.4                      | 2006.09.01-2015.01.19      | 0.9 (Tot.)     |
| SIRTA [89]         | 1                            | Palaiseau, France                                | TSI: 6.7                 | 2008.10.23-2015.06.24      | N/A            |
|                    |                              |                                                   | ASI: 7.6                 | 2014.12-present            | N/A            |
| ARM-MASRAD [90]    | 1                            | Point Reyes, California, US                      | 0.6                      | 2005.02.01-2005.09.15      | 6.9 (Img.)     |
| ARM-RADAGAST [91]  | 1                            | Niamey, Niger                                    | 11.2                     | 2005.11.24-2017.01.07      | 14.5 (Img.)    |
| ARM-STORMVEX [92]  | 1                            | Steamboat Springs, Colorado, US                 | 0.6                      | 2010.09.23-2011.04.22      | 11.1 (Img.)    |
| HYTA (Binary)[36]  | 2                            | Beijing, China                                   | N/A                      | 2011.09.25-2012.02.09      | 10.1 (Img.)    |
| ARM-AMIE-GAN [93]  | 1                            | Gan Island, Maldives                             | 0.4                      | 2007.03.14-2008.01.01      | 13.2 (Img.)    |
| ARM-COPS [94]      | 1                            | Black Forest, Germany                            | 0.8                      | 2008.05.08-2008.12.28      | 7.1 (Img.)     |
| ARM-HFE [95]       | 1                            | Shouxian, Anhui, China                           | 0.6                      | 2011.07.16-2012.04.01      | 20.4 (Img.)    |
| ARM-GVAX [96]      | 1                            | Nainital, Uttarkhand, India                      | 0.7                      | 2013.01-2014.05            | 0.01 (Tot.)    |
| SWIMCAT [49]       | 1                            | Nanyang Technological University, Singapore      | 1.3                      | 2013.01-2014.05            | 0.01 (Tot.)    |
| HYTA (Ternary) [97]| 2                            | Beijing, China                                   | N/A                      | 2009.04.14-2011.01.05      | 23.6 (Img.)    |
| ARM-CAP-MBL [98]   | 1                            | Graciosa Island, Azores, Portugal                | 1.7                      | 2012.06.29-2013.07.08      | 29.9 (Img.)    |
| ARM-TCAP [99]      | 1                            | Highland Center, Massachusetts, US               | 2.0                      | 2014.01-2014.06            | N/A            |
| TCIS [50]          | 1                            | Tibet, China                                     | 2.0                      | 2014.01-2014.06            | N/A            |
| NCU [100]          | 1                            | National Central University, Taiwan              | 0.5                      | 2014.01-2014.06            | N/A            |

Continued on next page
| Dataset          | Spatial coverage (# of sites) | Locations | Temporal coverage (yrs) | Collection period | Size est. (GB) |
|------------------|-----------------------------|-----------|-------------------------|-------------------|----------------|
| ARM-BAECC [101]  | 1                           | Hyytiälä, Finland | 0.6                    | 2014.02.01-09.13  | 22.6 (Img.)    |
| ARM-ACAPEX [102] | 2                           | Honolulu, Hawaii, US San Diego, California, US | 0.1 | 2015.01.09-02.12  | 2.6 (Img.)    |
| ARM-MAGIC [103]  | 2                           | Los Angeles, California, US Honolulu, Hawaii, US | 1.0 | 2012.10.01-2013.09.26 | 19.3 (Img.) |
| ARM-GoAmazon [104] | 1                        | Manacapuru, Amazonas, Brazil | 1.9 | 2014.01.01-2015.12.01 | 54.2 (Img.) |
| ARM-NSA [105]    | 1                           | Barrow, Alaska, US | 16.3 | 2006.04.25-2022.08.20 | 350.2 (Img.) |
| ARM-SGP [106]    | 3                           | Lamont, Oklahoma, US | Site 1: 22.1 Site 2: 5.7 Site 3: 0.7 | 2000.07.02-2022.08.14 | 143.9 (Img.) |
| ARM-TWP [107]    | 3                           | Manus, Papua New Guinea Nauru Island, Nauru Darwin, Australia | 10.5 | 2003.11.30-2014.06.10 | 443.7 (Img.) |
| SWIMSEG [31]     | 1                           | Nanyang Technological University, Singapore | 1.7 | 2013.10-2015.07 | 0.2 (Tot.)  |
| SWINSEG [108]    | 1                           | Nanyang Technological University, Singapore | 1.0 | 2016.01-2016.12 | 0.003 (Tot.) |
| SHWIMSEG [109]   | 1                           | Nanyang Technological University, Singapore | N/A | 2016.01-2016.12 | 0.003 (Tot.) |
| Zenithal [51]    | 1                           | Nanjing, China | N/A | 2016.01-2016.12 | N/A |
| CCSN [47]        | N/A                          | N/A       | N/A                     | 2016.05-2017.10.31 | 36.9 (Img.)    |
| ARM-LASIC [110]  | 1                           | Ascension Island, South Atlantic Ocean | 1.5 | 2016.05-2017.10.31 | 36.9 (Img.)    |
| NAO-CAS [111]    | 1                           | China     | N/A                     | 2016.05-2017.10.31 | N/A |
| FGCDCR [48]      | 2                           | Hangzhou, China Lijiang, China | N/A | 2016.05-2017.10.31 | N/A |
| LES dataset [112]| 1                           | Salto, Uruguay | 0.1 (22 days) | 2016.05-2016.11 | N/A |
| SWINySEG [41]    | 1                           | Nanyang Technological University, Singapore | 2.7 | 2013.10-2015.07 & 2016.01-12 | 0.06 (Tot.) |
| UCSD-Folsom [113]| 1                           | Folsom, California, US | 3.0 | 2014.01-2016.12 | 49.8 (Tot.)  |
| UoH [114]        | 6                           | Bayfordbury, Hertfordshire, UK | 10.0 | 2012.07.25-present | N/A  |

Continued on next page
| Dataset         | Spatial coverage (# of sites) | Locations                                      | Temporal coverage (yrs) | Collection period                                      | Size est. (GB) |
|-----------------|-------------------------------|------------------------------------------------|-------------------------|-------------------------------------------------------|----------------|
| Hemel Hempstead, Hertfordshire, UK | 6                             | Hemel Hempstead, UK                           | 12.0                    | 2010.07-2015.04                                       | N/A            |
| Exmoor, UK      | 1.6                           | Exmoor, UK                                     | 1.6                     | 2011.10-2016.11                                      | N/A            |
| Comber, Norfolk, UK | 6.3                           | Comber, Norfolk, UK                           | 6.3                     | 2010.08-2016.11                                      | N/A            |
| Guernsey, UK    | 0.4                           | Guernsey, UK                                   | 0.4                     | 2011.08-2015.04                                      | N/A            |
| Huelva, Spain   | 1.8                           | Huelva, Spain                                  | 1.8                     | 2015.02-2017.01                                      | N/A            |
| Tianjin, China  | 1.0                           | Tianjin, China                                 | 1.0                     | 2015.01-2016.06                                      | N/A            |
| Tianjin, China  | 1.0                           | Tianjin, China                                 | 1.0                     | 2017-2018                                            | N/A            |
| Hai, Spain      | 0.2                           | Hai, Spain                                     | 0.2                     | 2015.12-2018.03                                      | N/A            |
| Tianjin, China  | 1.0                           | Tianjin, China                                 | 1.0                     | 2015.12-2017.01                                      | N/A            |
| McMurdo Station Ross Ice Shelf, Antarctica | 1.1                           | McMurdo Station Ross Ice Shelf, Antarctica    | 1.1                     | 2015.12-2017.01                                      | 28.7 (Img.)    |
| West Antarctic Ice Sheet, Antarctica | 0.1                           | West Antarctic Ice Sheet, Antarctica           | 0.1                     | 2015.12-2017.01                                      | 5.2 (Img.)     |
| El Arenosillo  | 1                             | El Arenosillo                                 | 1                       | 2020.02-2021.06                                      | N/A            |
| Huelva, Spain   | 0.4                           | Huelva, Spain                                  | 0.4                     | 2017-2018                                            | 29.3 (Tot.)    |
| Guernsey, UK    | 3.7                           | Guernsey, UK                                   | 3.7                     | 2011.08-2015.04                                      | N/A            |
| MGCD            | 1                             | Tianjin, China                                 | 1                       | 2017-2018                                            | N/A            |
| GRSCD           | 1                             | Tianjin, China                                 | 1                       | 2015.01-2016.06                                      | N/A            |
| BASS            | 1                             | Tianjin, China                                 | 1                       | 2020.02-2021.06                                      | N/A            |
| NIMS-KMA        | 1                             | Tianjin, China                                 | 1                       | 2019.01-2012                                         | N/A            |
| Griswol          | 1                             | University of New Mexico, New Mexico, US     | 1                       | 2007-2012                                            | 110.0 (Tot.)   |

Continued on next page
Table 6
Spatial and temporal coverage of the dataset (continued).

| Dataset            | Spatial coverage (# of sites) | Locations                           | Temporal coverage (yrs) | Collection period       | Size est. (GB) |
|--------------------|------------------------------|-------------------------------------|--------------------------|-------------------------|----------------|
| SkyCam [131]       | 3                            | Neuchâtel, Switzerland              | 1.0                      | 2018.01.01-12.31        | 16000 (Tot.)  |
|                    |                              | Bern, Switzerland                   | 1.0                      | 2018.01.01-12.31        |                |
|                    |                              | Alpnach, Switzerland                | 1.0                      | 2018.01.01-12.31        |                |
| SIPM [132]         | 1                            | Rio de Janeiro, Brazil              | 0.1 (26 days)            | 2019.02.25-03.23        | 0.3 (Tot.)    |
| SIPPMMIF [133]     | 2 (1.9 km dist.)             | UoW, New South Wales, Australia     | 0.0 (2 days)             | 2019.09.10-09.12        | 7.2 (Tot.)    |
| Waggle [134]       | 1                            | Lemont, Illinois, US                | 0.0 (14 days)            | 2020.06                 | N/A           |
| TAN1802 Voyage [135]| 1                          | Wellington, New Zealand and Ross Sea, Antarctica | 0.1                      | 2018.02.08-03.21        | 2.7 (Img.)    |
| ARM-SAIL/GUC [136] | 1                            | Gunnison, CO, US                    | 1.1                      | 2021.07.07-2022.08.20   | 55.0 (Img.)   |
| SKIPP’D [137]      | 1                            | Stanford University, California, US | 2.7                      | 2017.03-2019.10         | 1700 (Tot.)   |
| TCDD [43]          | 9                            | Tianjin, Anhui, Sichuan, Gansu, Shandong, Hebei, Liaoning, Jiangsu, Hainan in China | 2.0                      | 2019-2021               | N/A           |
| PSA Fabel [138]    | 1                            | Plataforma Solar de Almeria, Spain  | 1.0                      | 2017.01-2017.12         | N/A           |
| NAO-CAS XJ [139]   | 1                            | Xinjiang, China                    | 1.9                      | 2019.01-2020.11         | N/A           |
| TLCDD [140]        | 9                            | Tianjin, Anhui, Sichuan, Gansu, Shandong, Hebei, Liaoning, Jiangsu, Hainan in China | 2.0                      | 2019-2021               | N/A           |
| ACS WSI [141]      | N/A                          | China                               | 1.0                      | 2013.01-2013.12         | N/A           |
| Orion StarShoot [145]| 1                     | Tito Scalo, Italy                   | N/A                      | N/A                     | N/A           |
| LTR [146]          | 1                            | Warsaw, Poland                      | 2.0                      | 2019-2021               | N/A           |
| LOA [147]          | 1                            | Villeneuve d’Ascq, France           | 9.1                      | 2009.09.16-2018.11.05   | N/A           |
| ARM-COMBLE [142]   | 2                            | Andenes and Bear Island in Norway   | 0.3                      | 2020.01.28-06.01        | 18.0 (Img.)   |
| ARM-MOSAIC [143]   | 1                            | Central Arctic, Arctic Circle       | 0.5                      | 2020.03.23-09.20        | 16.0 (Img.)   |
| ARM-ACE-ENA [144]  | 1                            | Graciosa Island, Azores, Portugal   | 8.8                      | 2013.10.01-2022.08.01   | 153.2 (Img.)  |
| ARM-OLI [148]      | 1                            | Oliktok Point, AK, US               | 7.7                      | 2013.10.01-2021.06.15   | 107.8 (Img.)  |

Note: for size estimation column (Size est.), Img. stands for only the size of image data, and Tot. represents the total dataset size including image and all other types of data such as sensor measurements, segmentation map and cloud category label.
Figure 6 shows the geographic locations of the 72 open-source ground-based sky image datasets annotated by blue (for datasets released by national labs or scientific organizations, i.e., type O datasets) and red (for datasets released by research groups from universities, i.e., type R datasets) cross. The map is colored by Köppen–Geiger climate classes, a widely used classification system for climate. It should be noted that here we use the long-term average climate from 1901 to 2010 with the data obtained from [166]. It can be observed that the datasets’ locations cover all 7 continents on the Earth as well as a wide range of climate classes.

Deep learning model performance is heavily relied on the data used for training, not only the amount of data, but also the diversity of the samples. The success of ImageNet [167] in boosting computer vision research has provided a template for solar forecasting and related research fields. The open-source sky image datasets identified in this study can potentially be used for constructing a global dataset consisting of massive and diversified sky image samples with various weather conditions. Moreover, with such a large-scale sky image dataset, pre-training a general solar forecasting model on it and transferring the knowledge to local sites can save data and get a jump start in local model development. A recent study by Nie et al. [168] suggests that transferring learning from a large and diversified source dataset to a local target dataset can save up to 80% of the training data while achieving comparable performance for 15-min-ahead solar forecasting. A selection of the suitable datasets, processing and reconciliation are thus critical for building this large-scale dataset. Also, challenges still need to be addressed for transfer learning as the data collected from different locations are more or less heterogeneous, for example, difference in prediction variable (i.e. PV power generation versus solar irradiance), different distribution of measurements given different local weather conditions, different camera types (TSI versus ASI) and orientations, etc.

3.4. Datasets usage analysis

For analysis of the datasets usage, we first count their citations, total usage and usage involving sky images as described in section 2.3. Table 7 shows these three metrics for each one of the open-source datasets we identified. It should be noted that the counts presented here are based on statistics from Google Scholar by 2022-07-01. It’s hard to track the data sharing activities between researchers before the datasets publication, and thus we do not track the pre-publication usages of the datasets. Two exceptions are UCSD-Folsom and SKIPP’D, as they mention in their dataset papers [113, 137] about some research publications enabled by the datasets before the datasets were published.
For all 72 open-source datasets, although majority of them have citations, only 25 has been used by the scientific community and 24 has usage counts involving sky images. It can be observed that some datasets, especially those released by national labs or government scientific organizations, such as SURFRAD, SIRTA, and many datasets from ARM program like ARM-COPS, ARM-HFE, ARM-CAP-MBL and ARM-GoAmazon, tend to have high citation and total usage counts, but much less usage involving sky images. These datasets generally provide a wide spectrum of atmospheric and meteorological observations, and according to our further investigation, they are much more frequently used for climate and atmospheric modeling, e.g., surface radiation/temperature modeling, or remote sensing model validation, while limited efforts have been seen using these datasets for image-based solar forecasting or cloud modeling. The underlying reasons for that could be: (1) low temporal resolution image data that can hardly satisfy the need of short-term forecasting, for example, SURFRAD only provide imagery data in 1 hour resolution, although radiation and meteorological measurements are provided in 1~3 minutes resolution; (2) low exposure of the datasets to solar forecasting community. Some of these datasets indeed have high quality data, for example, SIRTA provide multi-year 1-min ASI as well as meteorological measurement data, but is not well-known by the solar forecasting community. Most of usage is associated with datasets released before 2020, and only 2 datasets released after 2020 have usage counts, which are Girasol and SKIPP'D. A further look shows the usage of these recent released datasets are mostly internal, i.e. the dataset is mainly used by researchers from the same research group who published the datasets. Some frequently used datasets for image-based solar forecasting (and potentially for cloud motion prediction) are SRRL-BMS (14), UCSD-Folsom (11), SKIPP’D (8), SIRTA (7), for cloud segmentation are SWIMSEG (13), HYTA (Binary) (12) and SWINSEG (6) and for cloud classification are SWIMCAT (19), CCSN (10) and TCIS (4).

Table 7
Datasets citations and usages by 2022-07-01

| Application | Dataset            | Year | Citations | Total usage | Usage involving sky images |
|-------------|--------------------|------|-----------|-------------|---------------------------|
| SF/CMP      | SRRL-BMS [87]      | 1981 | 45        | 34          | 14                        |
| SF/CMP      | SIRTA [89]         | 2005 | 235       | 201         | 7                         |
| SF/CMP      | ARM-MASRAD [90]    | 2005 | 2         | 0           | 0                         |
| SF/CMP      | ARM-RADAGAST [91]  | 2008 | 54        | 0           | 0                         |
| SF/CMP      | ARM-STORMVEX [92]  | 2010 | 2         | 1           | 1                         |
| SF/CMP      | ARM-AMIE-GAN [93]  | 2011 | 4         | 0           | 0                         |
| SF/CMP      | ARM-COPS [94]      | 2011 | 209       | 1           | 1                         |
| SF/CMP      | ARM-HFE [95]       | 2011 | 182       | 3           | 1                         |
| SF/CMP      | ARM-GVAX [96]      | 2013 | 2         | 0           | 0                         |
| SF/CMP      | ARM-CAP-MBL [98]   | 2015 | 109       | 0           | 0                         |
| SF/CMP      | ARM-TCAP [99]      | 2015 | 37        | 0           | 0                         |
| SF/CMP      | ARM-BAECC [101]    | 2016 | 64        | 1           | 1                         |
| SF/CMP      | ARM-ACAPEX [102]   | 2016 | 0         | 0           | 0                         |
| SF/CMP      | ARM-MAGIC [103]    | 2016 | 5         | 1           | 1                         |
| SF/CMP      | ARM-GoAmazon [104] | 2016 | 248       | 1           | 1                         |
| SF/CMP      | ARM-NSA [105]      | 2016 | 44        | 0           | 0                         |
| SF/CMP      | ARM-SGP [106]      | 2016 | 84        | 1           | 1                         |
| SF/CMP      | ARM-TWP [107]      | 2016 | 27        | 0           | 0                         |
| SF/CMP      | ARM-LASIC [110]    | 2018 | 1         | 0           | 0                         |
| SF/CMP      | LES dataset [112]  | 2019 | 49        | 2           | 1                         |
| SF/CMP      | UCSDF-Folsom [113] | 2019 | 49        | 18          | 11                        |
| SF/CMP      | UoH [114]          | 2019 | 4         | 0           | 0                         |
| SF/CMP      | P2OA-RAPACE [115]  | 2019 | 12        | 1           | 1                         |
| SF/CMP      | OHP [116]          | 2019 | 12        | 0           | 0                         |
| SF/CMP      | OPAR [117]         | 2019 | 12        | 0           | 0                         |
| SF/CMP      | ARM-CACTI [118]    | 2019 | 10        | 0           | 0                         |
| SF/CMP      | ARM-HOU [119]      | 2019 | 3         | 0           | 0                         |
| SF/CMP      | ARM-MARCUS [120]   | 2019 | 4         | 0           | 0                         |
| SF/CMP      | El Arenosillo [121, 122] | 2020 | 1        | 0           | 0                         |
| SF/CMP      | CO-PDD [126]       | 2020 | 11        | 0           | 0                         |
| SF/CMP      | ARM-AWARE [127]    | 2020 | 29        | 1           | 1                         |

Continued on next page
Table 7
Datasets citations and usages by 2022-07-01 (continued)

| Application | Dataset                  | Year | Citations | Total usage | Usage involving sky images |
|-------------|--------------------------|------|-----------|-------------|---------------------------|
|             | BASS [129]               | 2021 | 2         | 1           | 1                         |
|             | Girasol [84]             | 2021 | 7         | 7           | 2                         |
|             | SkyCam [131]             | 2021 | 0         | 0           | 0                         |
|             | SIPM [132]               | 2021 | 0         | 1           | 1                         |
|             | SIPPMMIF [133]           | 2021 | 2         | 1           | 1                         |
|             | Waggle [134]             | 2021 | 8         | 1           | 1                         |
|             | TAN1802 Voyage [135]     | 2021 | 3         | 0           | 0                         |
|             | ARM-SAIL/GUC [136]       | 2021 | 4         | 0           | 0                         |
|             | SKIPP'D [137]            | 2022 | 0         | 8           | 8                         |
|             | ARM-COMBLE [142]         | 2022 | 1         | 0           | 0                         |
|             | ARM-MOSAIC [143]         | 2022 | 26        | 0           | 0                         |
|             | ARM-ACE-ENA [144]        | 2022 | 10        | 0           | 0                         |
|             | Orion StarShoot [145]    | N/A  | N/A       | N/A         | N/A                       |
|             | LTR [146]                | N/A  | N/A       | N/A         | N/A                       |
|             | LOA [147]                | N/A  | N/A       | N/A         | N/A                       |
|             | ARM-OLI [148]            | N/A  | N/A       | N/A         | N/A                       |
| CS          | SURFRAD [88]             | 2000 | 429       | 286         | 3                         |
|             | HYTA (Binary) [36]       | 2011 | 182       | 12          | 12                        |
|             | HYTA (Ternary) [97]      | 2015 | 18        | 3           | 3                         |
|             | NCU [100]                | 2017 | 33        | 1           | 1                         |
|             | SWIMSEG [31]             | 2017 | 87        | 14          | 14                        |
|             | SWINSEG [108]            | 2017 | 16        | 7           | 7                         |
|             | SHWIMSEG [109]           | 2018 | 10        | 2           | 2                         |
|             | NAO-CAS [111]            | 2019 | 10        | 1           | 1                         |
|             | FGCDR [48]               | 2019 | 21        | 2           | 2                         |
|             | SWINySEG [41]            | 2019 | 26        | 5           | 5                         |
|             | WSISEG [42]              | 2020 | 20        | 1           | 1                         |
|             | WMD [125]                | 2020 | 3         | 1           | 1                         |
|             | Girasol [84]             | 2021 | 7         | 7           | 5                         |
|             | TCDD [43]                | 2021 | 5         | 1           | 1                         |
|             | PSA Fabel [138]          | 2022 | 2         | 1           | 1                         |
|             | TLCDD [140]              | 2022 | 1         | 1           | 1                         |
|             | ACS WSI [141]            | 2022 | 0         | 1           | 1                         |
| CC          | SWIMCAT [49]             | 2015 | 46        | 20          | 20                        |
|             | TCIS [50]                | 2016 | 21        | 5           | 5                         |
|             | Zenithal [51]            | 2018 | 4         | 1           | 1                         |
|             | CCSN [47]                | 2018 | 114       | 11          | 11                        |
|             | FGCDR [48]               | 2019 | 21        | 2           | 2                         |
|             | MGCD [123]               | 2020 | 8         | 4           | 4                         |
|             | GRSCD [124]              | 2020 | 12        | 1           | 1                         |
|             | WMD [125]                | 2020 | 3         | 1           | 1                         |
|             | GCD [128]                | 2021 | 3         | 1           | 1                         |
|             | NIMS-KMA [130]           | 2021 | 0         | 1           | 1                         |
|             | Girasol [84]             | 2021 | 7         | 7           | 5                         |
|             | PSA Fabel [138]          | 2022 | 2         | 1           | 1                         |
|             | NAO-CAS XJ [139]         | 2022 | 2         | 1           | 1                         |

For datasets with usage involving sky images, we further dive into the studies that use these datasets and see what research topics these studies investigate and what methods they apply. Figure 7 shows studies that use the datasets involving the usage of sky images with the detail references to these studies listed in Table B.11 in Appendix B. Figure
8 presents the research topics and applied methods of studies for each dataset that is used. It should be noted that here we ignore the datasets with only one usage count, which in most case is self-usage by the researchers who published the research articles along with their datasets. We categorize the research topics/applications into solar forecasting, cloud segmentation, cloud classification and cloud motion prediction and methods into: prediction type (deterministic and/or probabilistic) and methodology: cloud motion vectors (CMVs), which includes particle image velocimetry and optical flow; machine learning (ML) with or without feature engineering, which include artificial neural networks (ANN), support vector machine (SVM), Random forecast, nearest neighbors, k-means and XGBoost; deep learning (DL), which includes CNN, LSTM, 3D-CNN, ConvLSTM, U-Net and transformers; and ensemble modelling which combines multiple types of prediction models to achieve better performance.

As shown in Figure 8, the datasets are much less frequently used for cloud motion prediction compared with the other three research topics, solar forecasting, cloud segmentation and classification. To make it clear, the cloud motion prediction mentioned in this study is mainly for deep-learning-based motion prediction based on context sky images, and thus does not include studies using the cloud motion vector methods which linearly extrapolate cloud motion based on consecutive image frames. It’s not because the datasets cannot meet the requirement for such research, while it more points to the fact that deep-learning-based cloud motion prediction using sky images is under-studied. It can be also observed that some datasets are versatile and can be used in multiple applications (e.g., SRRL-BMS, SIRTA, etc.), while some are only used in single area (e.g., SURFRAD, HYTA (Ternary), SWINSEG, etc.). This is mostly aligned with our inference based on the data inclusion and temporal resolution of data, although some special cases are found. For example, studies used HYTA (Binary) not only for cloud segmentation [169, 170], but also solar prediction [134]. Park et al. [134] first trained and validated a deep learning model to segment sky patches using Waggle, SWINSEG and HYTA (Binary) datasets, and then the cloud cover ratio estimated by the segmentation model is then used to predict the corresponding solar irradiance level with the Waggle dataset. In terms of the prediction type, much more studies have focused on deterministic prediction (i.e., predict determined values, e.g., irradiance values, segmentation map, etc.) than probabilistic prediction (i.e., predict value distributions or probability map, e.g., irradiance prediction interval, probabilistic segmentation map, etc.), although the latter provides more valuable information for risk management for the grid. The underlying reason for this is not yet clear, while Hong and Fan [171] suggested that it might be the case that probabilistic forecasts were evaluated using the same performance metrics as the deterministic forecasts but perform worse than their deterministic counterpart. More details on the common performance metrics for deterministic and probabilistic forecasting of PV power production can be found in work by Van der Meer et al. [10]. Although we mainly focus on datasets suitable for machine-learning or deep-learning-based methods for solar forecasting and cloud modeling, due to the scope of this study, we do not provide a review of different methodology. Instead, we point the readers to the references of these studies in Table B.11 in Appendix B for more details.

3.5. Comprehensive dataset evaluation

In this study, we provide a comprehensive evaluation of each dataset based on the multi-criteria ranking system described in Section 2.3. Datasets with different applications are evaluated separately with slightly different criteria. Figure 11 shows the radar plots of each dataset for (a) solar forecasting and cloud motion prediction, (b) cloud segmentation and (c) cloud classification. It should be noted that for certain evaluation dimensions, if some datasets do not have such information, for example, dataset OPAR [117] does not release any information about the image resolution, it is marked as N/A in the center of the corresponding subfigure. Meanwhile, the names of these datasets (bold font above each radar plot) are marked with an exclamation mark (!). Readers should be cautious when looking at the dimensions of these datasets and do not confuse it with a low rank, and thus should not compare them with the same dimensions of other datasets.

For solar forecasting and cloud motion prediction, there are totally 47 datasets included in the evaluation, among which 26 are released by ARM programs. It should be noted here SURFRAD are excluded [88] from the evaluation as it provides low temporal resolution (1 hour) imagery data, which does not satisfy the requirement for very short-term solar forecasting and cloud motion prediction. For non-ARM datasets, SRRL-BMS, SIRTA, UCSD-Folsom, P2OA-RAPACE, SKIPP’D are among the top choices for ASI datasets, with relatively balanced performance for each dimension. Although most of them suffer from single-site data collection, ways to assemble these datasets can help solve this problem and help build a large-scale centralized datasets. One thing needs to be noted is that SRRL-BMS open sources multi-years of 10-min high resolution sky images from two different sky cameras. The relatively low temporal resolution of the image data can barely satisfy the need of very short-term solar forecasting due to clouds volatility.
Figure 7: Papers that use the open-source datasets involving the use of sky image data in the datasets. The datasets are clustered by their published year. Papers are represented by the last name of the first author as well as the publication years. (detailed references to the papers are presented in the Table B.11 in Appendix B)

However, SRRL-BMS provides 1-min high resolution sky images live view on their website ⁵ without archiving them. Web scrapping these 1-min sky images and corresponding irradiance and meteorological measurements could significantly improve the data quality. Girasol provide special infrared images with sun tracking so the sun is always in the center of images. ARM datasets mostly contains high temporal resolution data (30s) and all of them provide TSIs for the imagery data, some ARM datasets with good performance in most of the dimensions are ARM-SGP, ARM-TWP.

⁵https://midcdmz.nrel.gov/apps/sitehome.pl?site=SRRLASI
Figure 8: Analysis of the research topics and methods of studies that use the datasets involving the usage of sky images.

For cloud segmentation, no all-round ideal datasets are identified, and all datasets have some limitations. Also, note that a considerable amount of datasets miss the temporal coverage information. SWIMSEG and TLCDD are two good choices among all datasets while both datasets provide SPIs. HYTA dataset are widely used by the cloud segmentation
community, while it is limited in dataset size (only 32 images). Datasets provide ASIs are: NCU, NAO-CAS, FGCDR, WSISEG, WMD, PSA Fabel, ACS WSI. Although most of these datasets provide high resolution ASIs, one problem is the limited number of labeled samples, and also they generally provide data collected from a single location. Assembly of these dataset would be potentially be a good solution.

For cloud classification, SWIMCAT is so far the most used dataset, while it is limited in dataset size and image resolution. Also, SPI is provided by SWIMCAT. Some recently released datasets such as FGCDR, MGCD, GRSCD and GCD provide a large amount of samples. Among these datasets, only GCD provides SPIs. All other datasets provide high resolution ASIs. It should be noted that datasets FGCDR, PSA Fabel and WMD provide pixel-level labels for each image samples, hence can also be used for cloud segmentation, while other datasets provide image-level labels.

4. Conclusion

In this study, we conducted a survey of open-source sky image datasets, which can potentially be applied in the areas of solar forecasting, cloud segmentation, cloud classification as well as cloud motion prediction. For solar forecasting and cloud motion prediction, we focus on very short-term prediction with forecasting horizon less than 30 minutes. Based on that, we have identified a total of 72 open-source datasets around the world which cover a wide range of climate conditions and include different specifications of imagery and sensor measurement data. We collect extensive information about each dataset and meanwhile provide the ways to access these datasets. According to our screening, 47 datasets are found suitable for solar forecasting and cloud motion prediction, 15 datasets can be used for cloud segmentation and 13 datasets are for cloud classification. We then propose a multi-criteria ranking system for evaluating all the datasets we identified, which covers different aspects of the datasets: comprehensiveness, quality control, temporal and spatial coverage, temporal resolution, image resolution, dataset size as well as dataset usage by the scientific community. The assessment are conducted separately for individual applications based on slightly different criteria. According to the evaluation, we provide insights and recommendations to the users on the choices of datasets for each of these application fields. Further, we highly suggest the efforts in assembling multiple suitable datasets to build a centralized large-scale dataset to overcome the limitation of individual datasets, e.g., the spatial and temporal coverage as well as the dataset size. We hope this paper can serve as a one-stop shop for researchers who are looking for datasets for training deep learning models for very short-term solar forecasting and relevant areas.
(a) Datasets for solar forecasting and cloud motion prediction
(a) Datasets for solar forecasting and cloud motion prediction (continued)
(a) Datasets for solar forecasting and cloud motion prediction (continued)
(b) Datasets for cloud segmentation
Figure 11: Comprehensive evaluation of open-source datasets for different applications. (a) datasets for solar forecasting and cloud motion prediction, (b) cloud segmentation and (c) cloud classification. Note the evaluation criteria is a bit different for each application. For certain evaluation dimensions, if datasets do not have such information, it is marked as N/A in the center of the corresponding subfigure and the names of these datasets are marked with a exclamation mark (!). Readers should be cautious when looking at the dimensions of these datasets and do not confuse it with a low rank.
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A. Data specifications of sky image datasets

The data specifications of sky image datasets intended for solar forecasting/cloud motion prediction, cloud segmentation and cloud classification are listed in Table A.8, A.9, A.10, respectively.
Table A.8
Data specifications in sky image datasets intended for using primarily in solar forecasting and cloud motion prediction

| Dataset          | Sky image                                      | Irrad./PV                          | Meteo.                                                                 | SM                                          | CCL              | Others                              |
|------------------|------------------------------------------------|------------------------------------|----------------------------------------------------------------------|---------------------------------------------|------------------|-------------------------------------|
| SRRL-BMS[87]     | 1536x1536 RGB ASI, normal and under exposure: 10-min freq.;; 288x352 RGB TSI: 10-min freq. | GHI, DNI, DHI, GTI, etc.: 1-min freq. | Sun angles, temperature, wind speed and direction, pressure, relative humidity, etc.: 1-min freq. | 2-level segmentation (cloud and sky) generated by algorithm | N/A              | Cloud fraction derived from sky image |
| SIRTA [89]       | 768x1024 RGB ASI, long (1/100 sec) and short (1/2000 sec) exposure: 1 to 2-min freq.; 480x640 RGB TSI: 1-min freq. | Downwelling GHI, DNI, DHI, infrared irradiance; Upwelling GHI, infrared irradiance: 1-min freq.; PV panel testbench | Temperature, wind speed and direction, pressure, relative humidity, precipitation rate, etc.: 1-min freq. ; Aerosol optical depth: ~15-min freq. | 2-level segmentation (cloud and sky) generated by algorithm | N/A              | Cloud fraction derived from sky image |
| ARM-MASRAD [90]  | 480x640 RGB TSI: 30-sec freq.                  | Shortwave broadband total downwelling irradiance, longwave broadband downwelling irradiance, etc: 1-min freq. | Cloud optical depth, aerosol optical depth, atmospheric temperature, cloud base and top height, radar reflectivity, atmospheric pressure, radar Doppler, etc. | 2-level segmentation (cloud and sky) generated by algorithm | N/A              | Cloud fraction derived from sky image |
| ARM-RADAGAST [91]| 480x640 RGB TSI: 30-sec freq.                  | Shortwave narrowband total downwelling irradiance, longwave broadband downwelling irradiance, etc: 1-min freq. | Cloud optical depth, aerosol optical depth, atmospheric temperature, cloud base and top height, radar reflectivity, atmospheric pressure, radar Doppler, etc. | 2-level segmentation (cloud and sky) generated by algorithm | N/A              | Cloud fraction derived from sky image |
| ARM-STORMVEX [92]| 480x640 RGB TSI: 30-sec freq.                  | Shortwave broadband total downwelling irradiance, longwave broadband downwelling irradiance, etc: 1-min freq. | Cloud optical depth, aerosol optical depth, atmospheric temperature, cloud base and top height, radar reflectivity, atmospheric pressure, radar Doppler, etc. | 2-level segmentation (cloud and sky) generated by algorithm | N/A              | Cloud fraction derived from sky image |
| ARM-AMIE-GAN [93]| 480x640 RGB TSI: 30-sec freq.                  | Shortwave broadband total downwelling irradiance, longwave broadband downwelling irradiance, etc: 1-min freq. | Cloud optical depth, aerosol optical depth, atmospheric temperature, cloud base and top height, radar reflectivity, atmospheric pressure, radar Doppler, etc. | 2-level segmentation (cloud and sky) generated by algorithm | N/A              | Cloud fraction derived from sky image |

Continued on next page
| Dataset       | Sky image | Irrad./PV                                           | Meteo.                                                                                     | SM                                                                 | CCL | Others                                    |
|---------------|-----------|----------------------------------------------------|--------------------------------------------------------------------------------------------|----------------------------------------------------------------------|-----|-------------------------------------------|
| ARM-COPS [94] | 480×640 RGB TSI: 30-sec freq. | Shortwave broadband total downwelling irradiance, longwave broadband downwelling irradiance, etc: 1-min freq. | Cloud base and top height, atmospheric pressure, moisture, temperature, aerosol optical depth, radar Doppler, precipitation, etc. | 2-level segmentation (cloud and sky) generated by algorithm           | N/A | Cloud fraction derived from sky image    |
| ARM-HFE[95]   | 480×640 RGB TSI: 30-sec freq. | Shortwave broadband total downwelling irradiance, Longwave broadband downwelling irradiance, etc: 1-min freq. | Cloud optical depth, aerosol optical depth, atmospheric temperature, cloud base and top height, radar reflectivity, atmospheric pressure, radar Doppler, etc. | 2-level segmentation (cloud and sky) generated by algorithm           | N/A | Cloud fraction derived from sky image    |
| ARM-GVAX[96]  | 480×640 RGB TSI: 30-sec freq. | Shortwave broadband total downwelling irradiance, Longwave broadband downwelling irradiance, etc: 1-min freq. | Cloud optical depth, aerosol optical depth, atmospheric temperature, cloud base and top height, radar reflectivity, atmospheric pressure, radar Doppler, etc. | 2-level segmentation (cloud and sky) generated by algorithm           | N/A | Cloud fraction derived from sky image    |
| ARM-CAP-MBL [98] | 480×640 RGB TSI: 30-sec freq. | Shortwave broadband total downwelling irradiance, Longwave broadband downwelling irradiance, etc: 1-min freq. | Cloud optical depth, aerosol optical depth, atmospheric temperature, cloud base and top height, radar reflectivity, atmospheric pressure, radar Doppler, etc. | 2-level segmentation (cloud and sky) generated by algorithm           | N/A | Cloud fraction derived from sky image    |
| ARM-TCAP [99] | 480×640 RGB TSI: 30-sec freq. | Shortwave broadband total downwelling irradiance, Longwave broadband downwelling irradiance, etc: 1-min freq. | Cloud optical depth, aerosol optical depth, atmospheric temperature, cloud base and top height, radar reflectivity, atmospheric pressure, radar Doppler, etc. | 2-level segmentation (cloud and sky) generated by algorithm           | N/A | Cloud fraction derived from sky image    |
| ARM-BAECC [101] | 480×640 RGB TSI: 30-sec freq. | GHI, DNI, DHI: 1-min freq. | Cloud optical depth, aerosol optical depth, atmospheric temperature, cloud base and top height, radar reflectivity, atmospheric pressure, radar Doppler, etc. | 2-level segmentation (cloud and sky) generated by algorithm           | N/A | Cloud fraction derived from sky image    |

Continued on next page
| Dataset          | Sky image | Irrad./PV                                      | Meteo.                                                                 | SM                                                                 | CCL   | Others                          |
|------------------|-----------|-----------------------------------------------|----------------------------------------------------------------------|----------------------------------------------------------------------|-------|---------------------------------|
| ARM-ACAPEX [102] | 480×640 RGB TSI: 30-sec freq. | Shortwave and longwave broadband irradiance, etc: 1-sec freq. | Cloud optical depth, aerosol optical depth, atmospheric temperature, cloud base and top height, radar reflectivity, atmospheric pressure, radar Doppler, etc. | 2-level segmentation (cloud and sky) generated by algorithm | N/A   | Cloud fraction derived from sky image |
| ARM-MAGIC [103]  | 480×640 RGB TSI: 30-sec freq. | Shortwave and longwave broadband downwelling irradiance, etc: 6-sec freq. | Cloud optical depth, aerosol optical depth, atmospheric temperature, cloud base and top height, radar reflectivity, atmospheric pressure, radar Doppler, etc. | 2-level segmentation (cloud and sky) generated by algorithm | N/A   | Cloud fraction derived from sky image |
| ARM-GoAmazon [104]| 480×640 RGB TSI: 30-sec freq. | Shortwave and longwave broadband downwelling irradiance, etc: 1-min freq. | Cloud optical depth, aerosol optical depth, atmospheric temperature, cloud base and top height, radar reflectivity, atmospheric pressure, radar Doppler, etc. | 2-level segmentation (cloud and sky) generated by algorithm | N/A   | Cloud fraction derived from sky image |
| ARM-NSA [105]    | 480×640 RGB TSI: 30-sec freq. | Shortwave and longwave broadband downwelling irradiance, etc: 1-min freq. | Cloud optical depth, aerosol optical depth, atmospheric temperature, cloud base and top height, radar reflectivity, atmospheric pressure, radar Doppler, etc. | 2-level segmentation (cloud and sky) generated by algorithm | N/A   | Cloud fraction derived from sky image |
| ARM-SGP [106]    | 480×640 RGB TSI: 30-sec freq. | Shortwave broadband total downwelling irradiance: 1-min freq. | Cloud optical depth, aerosol optical depth, atmospheric temperature, cloud base and top height, radar reflectivity, atmospheric pressure, radar Doppler, etc. | 2-level segmentation (cloud and sky) generated by algorithm | N/A   | Cloud fraction derived from sky image |
| ARM-TWP [107]    | 480×640 RGB TSI: 30-sec freq. | Shortwave broadband total downwelling irradiance: 1-min freq. | Cloud optical depth, aerosol optical depth, atmospheric temperature, cloud base and top height, radar reflectivity, atmospheric pressure, radar Doppler, etc. | 2-level segmentation (cloud and sky) generated by algorithm | N/A   | Cloud fraction derived from sky image |

Continued on next page
| Dataset            | Sky image | Irrad./PV                                      | Meteo.                                                                 | SM                                                                 | CCL | Others                                         |
|--------------------|-----------|-----------------------------------------------|-----------------------------------------------------------------------|---------------------------------------------------------------------|-----|------------------------------------------------|
| ARM-LASIC [110]    | 480×640 RGB TSI: 30-sec freq. | Shortwave broadband total downwelling irradiance, Longwave broadband downwelling irradiance, etc: 5-sec freq. | Cloud optical depth, aerosol optical depth, atmospheric temperature, cloud base and top height, radar reflectivity, atmospheric pressure, radar Doppler, etc. | 2-level segmentation (cloud and sky) generated by algorithm | N/A | Cloud fraction derived from sky image          |
| LES dataset [112]  | 1920×1280 RGB ASI: 1-min freq. | GHI and other radiation components: 1-min freq. | N/A                                                                 | N/A                                                                 | N/A | N/A                                            |
| UCSD-Folsom [113]  | 1536×1536 RGB ASI: 1-min freq.; Satellite imagery: GOES-15 visible and infrared band, spatial resolution 1km, temporal resolution 30 min; | GHI, DNI, DHI: 1-min freq. | Temperature, wind speed and direction, maximum wind speed, relative humidity, pressure, precipitation: 1-min freq. | N/A                                                                 | N/A | NWP; Extracted sky image and irradiance features |
| UoH [114]          | 640×480 daytime and nighttime RGB ASI: 30-sec freq. | Irradiance: 1-min freq. | Brightness temperature | N/A                                                                 | N/A | N/A                                            |
| P2OA-RAPACE [115]  | 2048×1536 RGB ASI: 5-min freq. (15-min freq. until 2017); 2272×1704 RGB ASI: 5-min freq. | Irradiance, infra-red radiation: 1-min freq. | Wind speed, wind profiles, rain, pressure, temperature, humidity: 1-min freq. | 2-level segmentation (cloud and sky) generated by algorithm [115] | N/A | Cloud fraction derived from sky image          |
| OHP [116]          | 2048×1536 RGB TSI: 5-min freq. | Irradiance: 1-min freq. | Aerosols | N/A                                                                 | N/A | N/A                                            |
| OPAR [117]         | Alcor System: RGB images: freq. N/A | Irradiance: 1-min freq. | Aerosols | N/A                                                                 | N/A | N/A                                            |
| ARM-CACTI [118]    | 480×640 RGB TSI: 30-sec freq. | Shortwave broadband total downwelling irradiance, Longwave broadband downwelling irradiance, etc: 1-min freq. | Cloud optical depth, aerosol optical depth, atmospheric temperature, cloud base and top height, radar reflectivity, atmospheric pressure, radar Doppler, etc. | 2-level segmentation (cloud and sky) generated by algorithm | N/A | Cloud fraction derived from sky image          |

Continued on next page
| Dataset          | Sky image | Irrad./PV | Meteo.                                                                 | SM | CCL | Others                                                                 |
|------------------|-----------|-----------|------------------------------------------------------------------------|----|-----|------------------------------------------------------------------------|
| ARM-HOU[119]     | 480×640 RGB TSI: 30-sec freq. | Shortwave broadband total downwelling irradiance, Longwave broadband downwelling irradiance, etc: 1-min freq. | Cloud optical depth, aerosol optical depth, atmospheric temperature, cloud base and top height, radar reflectivity, atmospheric pressure, radar Doppler, etc. | 2-level segmentation (cloud and sky) generated by algorithm | N/A | Cloud fraction derived from sky image |
| ARM-MARCUS[120]  | 480×640 RGB TSI: 30-sec freq. | Shortwave broadband total downwelling irradiance, Longwave broadband downwelling irradiance, etc: 1-min freq. | Cloud optical depth, aerosol optical depth, atmospheric temperature, cloud base and top height, radar reflectivity, atmospheric pressure, radar Doppler, etc. | 2-level segmentation (cloud and sky) generated by algorithm | N/A | Cloud fraction derived from sky image |
| El Arenosillo [121, 122]  | RGB images, Night images: freq. N/A | Irradiance: GHI, DNI: 1-min freq. | Lidar profile: 10-min freq. | N/A | N/A | N/A |
| CO-PDD [126]     | 1024×768 RGB ASI, long and short time exposures: 1 to 2-min freq.; 600×800 webcam images: 10-min freq. | Irradiance: freq. | Pressure, humidity, temperature, precipitation : 5-min freq., wind speed and wind profiles, raindrop size distribution, water profiles and columns: 15-min freq., aerosols: 1-min to 1-day freq. | 2-level segmentation (cloud and sky) generated by algorithm [115]: 10-min freq. | N/A | Cloud fraction derived from sky image |
| ARM-AWARE[127]   | 480×640 RGB TSI: 30-sec freq. | Shortwave broadband total downwelling irradiance, Longwave broadband downwelling irradiance, etc: 5-sec freq. | Cloud optical depth, aerosol optical depth, atmospheric temperature, cloud base and top height, radar reflectivity, atmospheric pressure, radar Doppler, etc. | 2-level segmentation (cloud and sky) generated by algorithm | N/A | Cloud fraction derived from sky image |
| BASS [129]       | 1600×1200 HDR RGB ASI: 1-min freq. | GHI, DHI, direct sun and sky radiance in different bands: 1-min freq. | N/A | N/A | N/A |
| Girasol [84]     | 450×450 visible HDR gray-scale ASI and 60×80 infrared SPI, with the sun centered in the frame: 15-sec freq. | GSI: 4 to 6 samples per sec. | Sun positions, temperature, dew point, atmospheric pressure, wind direction, wind velocity and relative humidity: 10-min freq. | N/A | N/A | N/A |

Continued on next page
| Dataset          | Sky image                        | Irrad./PV | Meteo.                          | SM | CCL | Others                                      |
|------------------|----------------------------------|-----------|---------------------------------|----|-----|---------------------------------------------|
| SkyCam [131]     | 600×600 HDR RGB ASI: 10-sec freq.| Irradiance: 10-sec freq. | N/A                             | N/A | N/A | N/A                                         |
| SIPM [132]       | 640×480 RGB ASI: 1-sec freq.     | PV power output calculated based on PV voltage and current measurement: 1-sec freq. | N/A | N/A | N/A | PV voltage, current and temperature measurement: 1-sec freq. |
| SIPP-MIF [133]   | 1024×768 RGB ASI (two-camera system): 10-sec freq. | PV power output: 1-min freq. | N/A | N/A | N/A | N/A                                         |
| Waggle [134]     | 2304×1536 (raw), 300×300 (resized) RGB SPI: 15-sec freq. | Irradiance: 15-min freq.; PV power output: 5-sec freq. | N/A | 2-level segmentation (cloud and sky) generated mainly by algorithm ** | N/A | N/A                                         |
| TAN1802 Voyage [135] | 3096×2080 HDR RGB ASI: 5-min freq. | Downwelling shortwave and downwelling infrared radiation: 1-min freq. | Air temperature, dew-point temperature, pressure, wind speed, wind direction, relative humidity, sea surface temperature: 1-min freq. | 2-level segmentation (cloud and sky) generated by algorithm | N/A | N/A                                         |
| ARM-SAIL/GUC [136] | 480×640 RGB TSI: 30-sec freq. | Shortwave broadband total downwelling irradiance: 1-min freq. | Cloud optical depth, aerosol optical depth, atmospheric temperature, cloud base and top height, radar reflectivity, atmospheric pressure, radar Doppler, etc. | 2-level segmentation (cloud and sky) generated by algorithm | N/A | Cloud fraction derived from sky image |
| SKIPP’D [137]    | 2048×2048 (raw), 64×64 (resized) RGB ASI: 1-min freq. | PV power output: 1-min freq. | N/A | N/A | N/A | Sky video: 20 frames per sec.                |

Continued on next page
### Table A.8
Data specifications in sky image datasets intended for using primarily in solar forecasting and cloud motion prediction (continued)

| Dataset          | Sky image | Irrad./PV                     | Meteo.                                                                 | SM                                      | CCL | Others                                      |
|------------------|-----------|-------------------------------|-----------------------------------------------------------------------|-----------------------------------------|-----|---------------------------------------------|
| ARM-COMBLE [142]| 480×640 RGB TSI: 30-sec freq. | Net broadband total irradiance: 5-sec freq. | Cloud optical depth, aerosol optical depth, atmospheric temperature, cloud base and top height, radar reflectivity, atmospheric pressure, radar Doppler, etc. | 2-level segmentation (cloud and sky) generated by algorithm | N/A | Cloud fraction derived from sky image |
| ARM-MOSAIC [143]| 480×640 RGB TSI: 30-sec freq. | Shortwave broadband total downwelling irradiance: 1-min freq. | Cloud optical depth, aerosol optical depth, atmospheric temperature, cloud base and top height, radar reflectivity, atmospheric pressure, radar Doppler, etc. | 2-level segmentation (cloud and sky) generated by algorithm | N/A | Cloud fraction derived from sky image |
| ARM-ACE-ENA [144]| 480×640 RGB TSI: 30-sec freq. | Shortwave broadband total downwelling irradiance: 1-min freq. | Cloud optical depth, aerosol optical depth, atmospheric temperature, cloud base and top height, radar reflectivity, atmospheric pressure, radar Doppler, etc. | 2-level segmentation (cloud and sky) generated by algorithm | N/A | Cloud fraction derived from sky image |
| Orion StarShoot [145]| 768×494 RGB ASI, daytime and nighttime: 1-min freq. | GHI, DNI, Diffuse: freq. | Pressure, temperature, humidity, wind, water vapour, aerosols, cloud properties, cloud base: 15-sec to 1-min freq. | N/A | N/A | N/A |
| LTR [146]        | 3096×2080 RGB ASI (visible images), 4 cameras (1280×720): freq. N/A | Irradiance, short- and longwave radiation: freq. | Air temperature, pressure, relative humidity, vapor pressure, wind speed and direction, precipitation: 1-min freq. | N/A | N/A | N/A |
| LOA [147]        | Visible images: freq. | Infrared radiation: freq. | Weather station: aerosol, cloud profile: freq. N/A | N/A | N/A | N/A |
| ARM-OLI [148]    | 480×640 RGB TSI: 30-sec freq. | Shortwave broadband total downwelling irradiance: 1-min freq. | Cloud optical depth, aerosol optical depth, atmospheric temperature, cloud base and top height, radar reflectivity, atmospheric pressure, radar Doppler, etc. | 2-level segmentation (cloud and sky) generated by algorithm | N/A | Cloud fraction derived from sky image |

* SRRL-BMS has a live-view of ASI which updates minutely on its website, but these live-view images are not archived.
** The segmentation maps provided in Waggle dataset is generated mainly by algorithm with the pixels difficult to separate manually labeled.
| Dataset        | Sky image                       | Irrad./PV               | Meteo.                                               | SM                                                      | CCL   | Others                                      |
|---------------|--------------------------------|-------------------------|-----------------------------------------------------|----------------------------------------------------------|-------|---------------------------------------------|
| SURFRAD [88]  | 288×352 RGB TSI: 1-hour freq.  | Downwelling GHI, DNI, DHI, Upwelling GHI, etc.: 1 to 3-min freq. | Sun angles, temperature, wind speed and direction, pressure, relative humidity, etc.: 1 to 3-min freq. | 2-level segmentation (cloud and sky) generated by algorithm | N/A   | Cloud fraction derived from sky image       |
| HYTA (Binary) [36] | 32 682×512 RGB SPIs | N/A                     | N/A                                                 | 2-level segmentation (cloud and sky) labeled manually    | N/A   | N/A                                         |
| HYTA (Tenary) [97] | 32 682×512 RGB SPIs | N/A                     | N/A                                                 | 3-level segmentation (sky, thin cloud and thick cloud) labeled manually | N/A   | N/A                                         |
| NCU [100]     | 250 640×480 RGB ASIs          | N/A                     | N/A                                                 | 2-level segmentation (cloud and sky) labeled manually    | N/A   | N/A                                         |
| SWIMSEG [31]  | 1013 600×600 RGB SPIs         | N/A                     | N/A                                                 | 2-level segmentation (cloud and sky) labeled manually    | N/A   | N/A                                         |
| SWINSEG [108] | 115 500×500 nighttime SPIs    | N/A                     | N/A                                                 | 2-level segmentation (cloud and sky) labeled manually    | N/A   | N/A                                         |
| SHWIMSEG [109] | 52 500×500 HDR RGB SPIs       | N/A                     | N/A                                                 | 2-level segmentation (cloud and sky) labeled manually    | N/A   | N/A                                         |
| NAO-CAS [111] | 1124 (369 diurnal+755 nocturnal) 1408×1408 RGB ASIs | N/A                     | N/A                                                 | 2-level segmentation (cloud and sky) labeled manually    | N/A   | N/A                                         |
| FGCDR [48]    | 28638 4288×2848° ASIs         | N/A                     | N/A                                                 | 8-level segmentation (cumulus, stratocumulus, stratus, altostratus, altocumulus, cirrocumulus, cirrostratus, cirrus) labeled manually | 8 categories (pixel-level label): same as segmentation map | N/A   | N/A                                         |

Continued on next page
| Dataset                | Sky image                        | Irrad./PV | Meteo. | SM                        | CCL          | Others         |
|------------------------|----------------------------------|-----------|--------|---------------------------|--------------|----------------|
| SWINySEG [41]          | 6768 daytime (1013 original+5056 augmented) and nighttime (115 original+575 augmented) 300×300 SPIs | N/A       | N/A    | 2-level (cloud and sky) segmentation labeled manually | N/A          | N/A            |
| WSISEG [42]            | 400 2000×1944 (raw), 480×450 (resized) HDR RGB ASIs | N/A       | N/A    | 3-level segmentation (cloud, sky and undefined area) labeled manually | N/A          | N/A            |
| WMD [125]              | 2044 3264×4928 (raw), 1200×800 (resized) RGB ASIs | N/A       | N/A    | 4-level segmentation (high-level clouds, low-level cumulus type clouds, rain clouds and clear sky) labeled manually | 4 categories by cloud height (pixel-level label): same as segmentation map | N/A            |
| Girasol [84]           | 12 60×80 infrared SPIs∗∗         | N/A       | N/A    | 2-level segmentation (clouds and clear sky) labeled manually | N/A          | N/A            |
| TCDD [43]              | 2300 512×512 RGB SPIs            | N/A       | N/A    | N/A                       | 2-level segmentation (cloud and sky) manually labeled | N/A            |
| PSA Fabel [44]         | 512×512 RGB ASI: 770 labeled and 286477 unlabeled images (for un-supervised pre-training) | N/A       | N/A    | 3-level segmentation (low-, middle- and high-layer clouds) manually labeled | 3 categories (pixel-level label): same as segmentation map | N/A            |
| TLCDD [140]            | 5000 512×512 RGB SPIs            | N/A       | N/A    | 2-level segmentation (cloud and sky) labeled manually | N/A          | N/A            |
| ACS WSI [141]          | 10000 RGB ASIs (500 labeled segmentation) | N/A       | N/A    | 2-level segmentation (cloud and sky) labeled manually | N/A          | N/A            |

* No image pixel resolution information is provided by the authors of FGCDR dataset. Here, we put an estimation here based on the camera model Nikon D90, which is used for the whole sky imager.

*∗ The Girasol dataset article [84] does not mention that it includes labeled segmentation maps. However, a follow-up study by the authors [85] mentioned that it used 12 labeled segmentation maps.
Table A.10
Data specifications in sky image datasets intended for using primarily in cloud classification

| Dataset   | Sky image | Irrad./PV | Meteo. | SM      | CCL                                                                 | Others                |
|-----------|-----------|-----------|--------|---------|----------------------------------------------------------------------|-----------------------|
| SWIMCAT [49] | 784 125x125 RGB SPIs | N/A | N/A | N/A | 5 categories (image-level label) by visual characteristics: clear sky, patterned clouds, thick dark clouds, thick white clouds, and veil clouds | N/A                   |
| TCIS [50] | 5000 1392x1040 (raw), 821x821 (resized), ASIs | N/A | N/A | N/A | 5 categories by visual characteristics (image-level label): cirriform, cumuliform, stratiform, clear sky and mixed cloudiness | N/A                   |
| Zenithal [51] | 500 320x240 infrared SPIs | N/A | N/A | N/A | 5 categories by visual characteristics (image-level label): stratiform, cumuliform, waveform, and cirriform clouds and clear sky | N/A                   |
| CCSN [47] | 2543 256x256 RGB SPIs | N/A | N/A | N/A | 11 categories by WMO (image-level label): cirrus, cirrostratus, cirrocumulus, altocumulus, altostratus, cumulus, cumulonimbus, nimbostratus, stratocumulus, stratus, contrail | N/A                   |
| FGCDR [48] | 28638 4288x2848* ASIs | N/A | N/A | N/A | 8-level segmentation (cumulus, stratocumulus, stratus, altostratus, altocumulus, cirrocumulus, cirrostratus, cirrus) labeled manually | 8 categories (pixel-level label): same as segmentation map | N/A                   |
| MGCD [123] | 8000 1024x1024 RGB ASIs | N/A | N/A | N/A | 7 categories by WMO (image-level label): cumulus, altocumulus and cirrocumulus, cirrus and cirrostratus, clear sky, stratocumulus, stratus and altostratus, cumulonimbus and nimbostratus and mixed cloud | N/A                   |
| GRSCD [124] | 8000 1024x1024 RGB ASIs | N/A | N/A | N/A | 7 cloud categories by WMO (image-level label): cumulus, altocumulus and cirrocumulus, cirrus and cirrostratus, clear sky, stratocumulus and stratus and altostratus, cumulonimbus and nimbostratus, mixed cloud | N/A                   |
### Table A.10
Data specifications in sky image datasets intended for using primarily in cloud classification (continued)

| Dataset       | Sky image | Irrad./PV | Meteo. | SM | CCL | Others |
|---------------|-----------|-----------|--------|----|-----|--------|
| **WMD [125]** | 2044 3264×4928 (raw), 1200x800 (resized) RGB ASIs. | N/A | N/A | 4-level segmentation (high-level clouds, low-level cumulus type clouds, rain clouds and clear sky) labeled manually | 4 categories by cloud height (pixel-level label): same as segmentation map | N/A |
| **GCD [128]** | 19000 512×512 RGB SPIs | N/A | N/A | N/A | 7 categories by WMO (image-level label): cumulus, altocumulus and cirrocumulus, cirrus and cirrostratus, clear sky, stratocumulus, stratus and altostratus, cumulonimbus and nimbostratus, and mixed cloud | N/A |
| **NIMS-KMA [130]** | 7402 2432×2432 daytime and nighttime RGB ASIs | N/A | N/A | N/A | 10 categories based on cloud cover (image-level label) labeled manually | N/A |
| **Girasol [84]** | 8200 60×80 infra-red SPIs** | N/A | N/A | N/A | 4 categories: clear-sky, cumulus, stratus or nimbus cloud (image-level label) labeled manually | N/A |
| **PSA Fabel [44]** | 512×512 RGB ASI: 770 labeled and 286477 unlabeled images | N/A | N/A | 3-level segmentation (low-, middle- and high-layer clouds) manually labeled | 3 categories (pixel-level label): same as segmentation map | N/A |
| **NAO-CAS XJ [139]** | 5000 370×370 RGB ASIs | N/A | N/A | N/A | 4 categories based on cloud cover (image-level label): clear, outer, inner, covered | N/A |

* No image pixel resolution information is provided by the authors of FGCDR dataset. Here, we put an estimation here based on the camera model Nikon D90, which is used for the whole sky imager.

** The Girasol dataset article [84] does not mention that it includes cloud category labels. However, a follow-up study by the authors [86] mentioned that it used 8200 labeled images with 4 different sky conditions.
B. Open-source datasets usage involving sky images

The studies that use the sky image datasets involving the use of sky images are listed in Table B.11 below.

Table B.11
List of studies that use the sky image datasets involving the use of sky images

| Application | Dataset | Studies use the dataset involving using sky images |
|-------------|---------|---------------------------------------------------|
| SF/CMP      | SRRL-BMS [87] | [26, 28, 172, 173, 174, 175, 176, 177, 178, 179, 180, 181, 182, 183] |
|             | SIRTA [89] | [24, 30, 53, 83, 184, 185, 186] |
|             | ARM-STORMVEX [92] | [187] |
|             | ARM-COPS [94] | [188] |
|             | ARM-HFE [95] | [189] |
|             | ARM-BAECC [101] | [190] |
|             | ARM-MAGIC [103] | [191] |
|             | ARM-GoAmazon [104] | [192] |
|             | ARM-SGP [106] | [193] |
|             | Les dataset [112] | [112] |
|             | UCSD-Folsom [113] | [174, 194, 195, 196, 197, 198, 199, 200, 201, 202, 203] |
|             | ARM-AWARE [127] | [204] |
|             | BASS [129] | [129] |
|             | Girasol [84] | [160, 205] |
|             | SIPM [132] | [132] |
|             | SIPPMIF [133] | [133] |
|             | Waggle [134] | [134] |
|             | SKIPP'D [137] | [4, 5, 25, 38, 153, 154, 206, 207] |
| CS          | SURFRAD [88] | [208, 209, 210] |
|             | HYTA (Binary) [36] | [36, 97, 134, 169, 170, 211, 212, 213, 214, 215, 216, 217] |
|             | HYTA (Ternary) [97] | [97, 170, 214] |
|             | NCU [100] | [100] |
|             | SWIMSEG [31] | [31, 41, 134, 170, 215, 216, 218, 219, 220, 221, 222, 223, 224, 225] |
|             | SWINSEG [108] | [41, 108, 220, 222, 225, 226, 227] |
|             | SHWIMSEG [109] | [109, 228] |
|             | NAO-CAS [111] | [111] |
|             | FGCDR [48] | [48, 229] |
|             | SWINySEG [41] | [41, 220, 222, 225, 230] |
|             | WSISEG [42] | [42] |
|             | WMD [125] | [125] |
|             | Girasol [84] | [85, 86, 159, 205, 231] |
|             | TCDD [43] | [43] |
|             | TLCDD [140] | [140] |
|             | PSA Fabel [138] | [138] |
|             | ACS WSI [141] | [141] |
| CC          | SWIMCAT [49] | [49, 51, 123, 212, 213, 232, 233, 234, 235, 236, 237, 238, 239, 240, 241, 242, 243, 244, 245, 246] |
|             | TCIS [50] | [50, 242, 247, 248, 249] |
|             | Zenithal [51] | [51] |
|             | CCSN [47] | [47, 215, 223, 240, 245, 250, 251, 252, 253, 254, 255] |
|             | FGCDR [48] | [48, 229] |
|             | MGCD [123] | [123, 241, 245, 250] |
|             | GRSCD [124] | [124] |
|             | WMD [125] | [125] |
|             | GCD [128] | [128] |
|             | NIMS-KMA [130] | [130] |
|             | Girasol [84] | [85, 86, 159, 160, 205] |
|             | PSA Fabel [138] | [138] |
|             | NAO-CAS XJ [139] | [139] |
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