Review

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Filomena Romano * , Domenico Cimini , Francesco Di Paola , Donatello Gallucci , Salvatore Larosa , Saverio Teodosio Nilo , Elisabetta Ricciardelli , Barbara D Iisager , Keith Hutchison

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Review

The Evolution of Meteorological Satellite Cloud Detection Methodologies

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Abstract: The accurate detection of clouds is an important first-step in the processing of remotely-sensed satellite data analyses and subsequent cloud model predictions. While initial cloud retrieval technology began with the exploitation of one or two bands of satellite imagery, it has accelerated rapidly in recent years as sensor and retrieval technology, creating a new era in space exploration. Additionally, initial emphasis in satellite retrieval technology focused on cloud detection for cloud forecast models, more recently cloud screening in satellite acquired data is playing an increasingly critical role in the investigation of cloud free data for the retrieval of soil moisture, vegetation cover, ocean colour concentration and sea surface temperatures, as well as the environmental monitoring of a host of products, e.g., atmospheric aerosol data, to study the Earth's atmospheric and climatic systems. With about 60% of the Earth covered by clouds, on average, it is necessary to accurately detect clouds in remote sensing data to screen cloud contaminate data in remote sensing analyses. In this paper, the evolution of cloud detection technology is highlighted with advancement in sensor hardware technology and possible AI algorithmic advances. Moreover, a discussion is presented on methods for obtaining the cloud truth data needed to determine the accuracy of these cloud detection approaches.

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1. Introduction

Operational, global cloud analysis and cloud forecast models have a legacy in the Defense Meteorological Satellite Program (DMSP) launched approximately 60 years ago. These early cloud analysis models, which included the 3-Dimensional Nephanalysis Model or 3DNEPH [1] and the subsequent Real-Time Nephanalysis Model (RTNEPH) as discussed in [2], were operational by the 1970 timeframe [3]. These cloud models fully exploited data collected by the DMSP satellite Operational Linescan System (OLS) sensor which produced only minimal date, i.e., in a single visible imagery and/or a single infrared band of imagery. Results from the 3DNEPH/RTNEPH models served as inputs to the operational cloud forecast models known as the High Resolution Cloud Prog, 5-Layer and TRONEW [4]. In general, the identification of clouds in a pixel or satellite observation was indicated when the observed satellite reflectance (or brightness temperature) observation exceeded (or was less than) the expected reflectance (or brightness temperature) in the visible band (infrared band). The expected reflectance (or brightness temperature) value for each cloud-free observation was determined a priori based on an external data base. Due to the complexity of creating and maintaining an external cloud-free reflectance database, the global nephanalysis models relied on having brightness temperatures (BTs) in the single IR band; thus, the models were frequently called "single-channel algorithms." The results generated from these simplistic single-channel cloud detection algorithms had numerous deficiencies. The first comparisons of satellite observation in a single infrared band required extensive computer resources to create and maintain global data bases of time-sensitive cloud-free, atmospherically corrected surface brightness temperature fields needed to make cloud, and no cloud decisions [3]. Furthermore, there are many surface conditions where a single cloud threshold detection test could not accurately detect the presence of clouds, i.e., cloud present if T(DMSP obs) < T(cloud free) – T(threshold). Indeed, the clouds exhibit similar DMSP spectral reflectance signals to many cloud-free Earth surfaces, such as snow and ice. Also, optically-thin clouds, such as thin cirrus clouds and nighttime (black) stratus and small-scale cumulus clouds in daytime imagery, were sometimes difficult to detect by single-channel cloud algorithms [3]. The inability to accurately detect these clouds caused impacts to the users of these cloud analysis models, and also made the results unsuitable for climate change studies [5]. Meanwhile, the growing need for accurate cloud detection/screening became crucial for the processing satellite radiance data into other data products, i.e., for cloud-free surfaces such as land and sea surface temperatures, ocean chlorophyll/colour, as well as atmospheric aerosols and cloud microphysical properties such as cloud optical depth. Fortunately, the technology advances to create some of these products were leveraged into the global cloud analysis models. For example, by the time the 3DNEPH became operational, others were examining approaches to improve the accuracy of ocean data products using mid-wave IR imagery collected by the High Resolution Infrared Radiometer (HRIR) sensor on NIMBUS II [6] and sea surface temperature (SST) products created based on satellite imager [7]. The last work [7] showed more accurate SST products by exploiting imagery in two or more infrared bands which, unlike the Operational Linescan System (OLS) DMSP sensor, were accurately calibrated. As is often the case, the approach was demonstrated with NIMBUS II data [6] and ultimately led to the improvement of the Advanced Very-High-Resolution Radiometer (AVHRR) sensor first launched in 1978. The sensors carried on the National Oceanic and Atmospheric Administration (NOAA): 6, 8, 10 had 4 channels, 2 in the infrared and 2 in the visible, a new channel in the 3-5 micron range was added to the sensors carried on the NOAA 7, 9, 11, 12, 14 (first launched in 1981), allowing AVHRR sensor data to produce SST products with less than 1.0 K accuracy. Finally, to complete the synergy in remote sensing algorithm development, cloud scientists demonstrated that improved SST accuracies to 0.25K were possible by reducing the NEdeltaT of the AVHRR IR bands from 0.12K [8] to 0.07K as contained in the VIIRS sensor design ([9], see Table 4.14 in [10]).

The improvements in the AVHRR system reduced errors in cloud detection for those contained in single-channel algorithms like the RTNEPH. First, the AVHRR sensor was again updated to provide additional imagery in both the 1.6 micron (daytime) and 3.7 (nighttime) micron bands, i.e., Channel 3A and 3B, respectively. Subsequently, it was found that the black stratus was more readily detected in nighttime temperature difference imagery coming from AVHRR Channel 3 (3.75 micron) subtracted from the Channel 5 (i.e., 12 micron) imagery owing to the fact that the water emissivity is about 20% smaller in Channel 3 band than in the Channel 5 band [11]. This discovery resulted in the greatly improved detection of stratus clouds in nighttime data. Using a similar approach, the author in [12] showed that the difference between channel 4 and channel 5 can be used to improve the AVHRR thin cirrus detection. These and other concepts were captured in [13]. Since the newer [13] cloud tests exploited simultaneously cloud signatures in multiple spectral bands, algorithms that exploit these procedures became known as multispectral cloud analysis algorithms. Early models that employed this multispectral technology included NOAA's Clouds from AVHRR (CLAVR-1) and the DLR AVHRR Processing scheme Over cLouds, Land and Ocean (APOLLO) cloud detection.

Perhaps the latest generation of highly multispectral cloud detection/screening algorithms has been developed by using images from the Visible Infrared Imaging Radiometer Suite (VIIRS) and before the Moderate Resolution Spectroradiometer (MODIS). The strengths and weaknesses of the VIIRS Cloud Mask (VCM) algorithm, which follows the MODIS Cloud Mask architecture, are discussed in detail in the next section. The VCM algorithm exploits 13 imagery and moderate resolution VIIRS channels to make global analyses, at the moderate resolution, of global cloud, no cloud, sub-pixel clouds, cloud top phase, multilevel clouds, aerosol presence and type, snow/ice, ephemeral water and cloud shadow decisions. In addition, other cloud products are created with VIIRS data, including atmospheric temperature and pressure, cloud bottom and top, cloud optical

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thickness and effective particle size. First, we continue to highlight the many advancements made by so many researchers that helped propel to completion the cloud detection technologies found in these VIIRS algorithms. In Section 2, this maturation process is summarized in Sections 2.1–2.4. In Section 3, tools are discussed for the generation of cloud truth datasets needed to quantitatively establish the accuracy of cloud product, including cloud cover and other cloud products. Conclusions are presented in Section 4.

2. Evolution in Multispectral Cloud Detection Methods

2.1. Cloud Detection Based on Threshold Tests

Cloud detection physical methods are based on fixed or dynamic multispectral threshold tests. Many cloud detection algorithms have been developed over the last 60/70 years, for different instruments and considering different channels or channel combinations. As previously noted, the first cloud detection methods utilized a single test for the presence of cloud: the pixel was declared cloud if the satellite measured radiance was above or below some reference value representing clear condition. For instance, the author in [14] set the visible threshold value by visual inspection of the satellite images, and all the pixels with value higher than the fixed threshold were declared cloudy. Subsequently, many single test methods have been proposed [15–17], based on the assumption that some parameters must remain below a predetermined threshold. Besides, different cloud detection schemes have been developed exploiting infrared (IR) and visible (Vis) window bands [18–20], within the International Satellite Cloud Climatology Project (ISCCP). Radiance measured in many narrow spectral bands represented a major improvement in cloud detection research. The AVHRR was the first sensor featuring two split windows, allowing a series of threshold tests. The AVHRR consists of five different channels: two in the visible range at 0.6 and 0.9 µm, one at 3.6 µm and the last two channels at 11 and 12 µm. In [21] two parameters have been used to classify clouds, i.e., the BT in channel 5 and the BT difference in channels 3 and 4. The authors in [22] used simultaneously the Medium Resolution Infrared Radiometer (MRIR) (Nimbus II) channel 1 (6.4-6.9µm) and channel 2 (10-11µm) to infer cloud distribution. In [23] a method is presented to discriminate clouds over snow using the channel at 3.7µm, with the solar contribution deducted via data simulation. In [24] the authors proposed AVHRR channel at 1.6 µm to discriminate cloudy from snow/ice. A cloud detection scheme, using a sequence of the spatial coherence method at 11µm and different dynamic visible/infrared threshold tests for daytime and nighttime respectively, has been proposed in [25]. The algorithm provided good results except for cirrus and cloud over complex surfaces that were not correctly identified. Successively, different AVHRR operational cloud detections have been developed based on threshold test series: i) the AVHRR Processing Scheme Over cLouds, Land and Ocean (APOLLO) package [13] implemented in several operational centres, ii) the NOAA operative cloud detection called CLAVR [26–28], used to cloud detection in the Global 1 km Land Cover Project, and iii) the operational cloud mask for the AVHRR and the Spinning Enhanced Visible and InfraRed Imager (SEVIRI) instrument on-board the Meteosat Second Generation (MSG) implemented at the Centre de Météorologie Spatiale (CMS) in Lannion [29]. Furthermore, in [29] some new tests have been implemented, i.e., the infrared threshold test at 11 µm based on the surface temperature (Ts) monthly sea climatology and on Numerical Weather Prediction (NWP) air temperature forecast over sea and over land respectively, and a test series to detect cloud edge and pixels partially cloudy over land during daytime. In [30] the authors presented the Separation of Pixels Using Aggregated Rating over Canada (SPARC) algorithm based on all AVHRR channels and surface temperature map tests. The author in [31] proposed the SMHI Cloud ANalysis model using Digital Avhrr data (SCANDIA) cloud detection where the test thresholds consider the sun elevations. The MetOffice SEVIRI cloud detection used simulated clear-sky brightness temperatures based on NWP forecast fields in addition to the classic tests [32]. The cloud mask algorithm implemented in the Satellite Application Facility on support to Nowcasting (SAFNWC/MSG) software package has been described in [33]: here a series of threshold tests has been used, where most thresholds are not fixed but estimated on the basis of climatology and forecast data. An improvement and a validation of this algorithm have been showed in [34]. A cloudiness statistic comparison over Europe based on Surface Synoptic Observations

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(SYNOP) reported a non-detected cloudy pixels reduction by 50%. The MODIS cloud mask algorithm was able to benefit from high spatial resolution and large spectral coverage, as it uses 22 channels in the visible and infrared regions. For the development of this algorithm, the researchers were able to take advantage of all the previous studies and, therefore, they tried to solve the difficulties encountered by previous algorithms to detect thin cirrus, fog and low cloud layers overnight, and small cumulus due to insufficient contrast with the surface radiance [35–39]. In [39] some new tests based on 7.2 μm water vapor band and 14.2 μm carbon dioxide band and some modified old tests have been proposed. The main reason for these changes is to improve the cloud detection over polar areas especially in nighttime. Further changes in polar region during nighttime, in polar region over ice and snow surfaces, over ocean and land during the nighttime, and sun-glint have been reported in [40]. In [41] some operative MODIS cloud mask (MYD35/MOD35) threshold tests have been modified and the clear confidence level has been estimated in order to obtain a more neutral cloud mask (CLAUDIA), i.e., a cloud detection without clear or cloudy bias. The channels used in the algorithm is similar to MOD35, but with different threshold tests and a new reflectance ratio test over bright desert. In [42] an unbiased cloud detection algorithm for daytime based on CLAUDIA has been proposed. The algorithm has been applied to FY-3A/VIRR data on board the Chinese FengYun-3A, the thresholds have been estimated on the basis of data acquired during four months. In [43] a method that uses the SEVIRI/MSG information to explore the pixels identified as uncertain by MODIS operative cloud detection has been proposed. In [44] the MODIS 6 collection cloud mask was compared against 267 million cloud profiles derived from CloudSat, Cloud-Aerosol Lidar with Orthogonal Polarization (CALIOP) and Infrared Pathfinder Satellite Observations (C-C) products. MODIS and C-C showed a concordance of 77.8%, composed of 20.9% clear pixels and 56.9% cloudy pixels, while 9.1% of the pixels was identified as clear and 1.8% as cloudy only by MODIS. The cloud detection algorithm of the Royal Netherlands Meteorological Institute (KNMI) [45] utilized NWP surface temperature and synoptic data to correct the surface temperatures in order to estimate clear satellite brightness temperatures accurately. The validation has been carried out with two million synoptic observations, correctly clear detected pixels were 92% during the day and 90% during the night over land and 94% during the day and 90% during the night over sea. The threshold test critical problem is to define the values to optimize the discrimination between clear and cloudy pixels. It is generally very complicated to find thresholds suitable for all Earth surfaces and in addition, a problem with thresholds also arises from the fact that pixels might be only partially covered by clouds. The thresholds can be static, if they are estimated on the basis of climatological or empirical data, or dynamic, if they are estimated using radiative transfer models and auxiliary data (e.g., atmospheric profiles, solar and satellite angles, surface temperatures). Unfortunately, dynamic thresholds are also subject to atmospheric composition uncertainties and surface emissivity variations [46,47]. The use of dynamic thresholds has been proposed by numerous researchers [25,48–50] with the aim of improving satellite cloud detection. Over the years, in addition to new thresholds, new tests have also been proposed. In the framework of the EUMETSAT Satellite Application Facility, in [51] new tests to identify and classify satellite pixels at medium ad high latitude have been proposed; the tests are based on a combined threshold, estimated using simulated clear-sky brightness radiances. Validation metrics for different surface and area have been reported in [52]. In addition to the threshold methods, there are other satellite cloud detection approaches, and numerous researchers used different statistical procedures to detect clouds. In the spatial coherence methods proposed in [53] the under-examination pixel characteristics are compared with the surrounding pixel feature statistics, and the pixel is classified as cloudy if the difference is outside a fixed threshold. In [54] the author used a two-step procedure to distinguish clouds, first the threshold tests based on temperature and albedo have been used to perform cloud screening, after a criterion based on the standard deviation derived from the images has been used. The authors in [55] proposed an Atmospheric Infrared Sounder (AIRS) cloud detection algorithm using an adjacent-pixel approach. The spatial coherence tests work well on uniform surfaces, such as oceans, but fail on regions with highly variable spectral signatures, such as land [25,56]. Some cloud detection methods are based on time-series analyses: for instance, the method presented in [57] detected a cloudy pixel

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on the basis of the comparison between the measurement and the clear sky composite reference value. In [58] this procedure has been modified by using the visible albedo standard deviation minimum estimated during a one month for each pixel and adding an value that depends on the standard deviation minimum. In [59] the author used some threshold combinations for the spatial variability test, assuming that the near-infrared and visible reflectance ratio absolute value is correlated to surface temperature negatively. In [60] a clear-sky algorithm based on high covariance with a reference clear-sky image has been proposed. An initial comparison showed that the algorithm offered the potential to perform better than the MODIS/MOD35 and MODIS/MYD35 cloud mask in cases where the land surface is changing rapidly and over regions covered by snow and ice. The authors in [61] developed a cloud detection for the Interferometric monitor for greenhouse gases (IMG) over sea surface that uses a cross-correlation between the real and a synthetic spectrum. In [62] a method to derive thresholds based on data from days between the current day and the most recent clear sky day has been proposed. Infrared radiances in the carbon dioxide band (CO_2 slicing method) to distinguish clouds and clear sky has been used in many studies [63–66]. Also, in [67] the authors used the CO_2 or the H_2O-sensitive spectral bands to detect the High resolution Infrared Radiation Sounder (HIRS) cloudy pixels. A comparison with collocated CALIOP cloud products shows that in 80% of the pixels, the CO_2 test detects clouds correctively. In [68] the authors proposed a method for cloud detection using Group Thresholds: the tests inside each group are applied to each pixel at the same time, the pixel was identified as cloudy depending on the results of the different tests at both fixed and dynamic thresholds. Dynamic thresholds are estimated on the basis of clear sky radiance generated using a method similar to that showed in [57] and [69]. The method applied to two complex cases showed that some tests work well for some types of clouds, normally difficult to be identified with traditional tests. In [70] the authors proposed an algorithm that detected cloud pixels according to two conditions: 1) sea surface temperature lower than 1°C, and 2) the gradient of the temperature larger than a defined threshold. In [71] the authors proposed a cloud detection based on a combination of the Geostationary Operational Environmental Satellite (GOES) visible reflectance data and a bi-spectral composite threshold method based on GOES bands at 3.7 μm and 11 μm. The authors in [72] proposed to use the Digital Elevation Model (DEM) data in order to correct some thresholds for the Advanced Himawari Imager (AHI) aboard Himawari-8. In [73] a non-parametric threshold algorithm has been proposed, based on surface reflectance blue band time series and the visible/short-wave infrared ratio from the MODIS/MOD09 products. In [74] a Universal Dynamic Threshold Cloud Detection Algorithm (UDTCDA) based on a monthly surface reflectance has been proposed. Its validation compared to the MOD35/MYD35 product showed some improvements but still leaving several open questions. In [75] a cloud detection algorithm (SCDA), with only one editable threshold and few input parameters, derived from a radiative transfer model has been proposed. Compared with Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation (CALIPSO) vertical feature cloud mask data, the percentage of SCDA cloud pixels detected was 86.08%, slightly higher than Himawari-8 cloud products (85.71%). The correct SCDA clear-sky detection percentage was 88.33%, lower than Himawari-8 clear-sky products (90.54%). The authors in [76] proposed a MODIS cloud detection over the Yellow Sea and Bohai Sea, based on a relationship between the Normalized Difference Water Index (NDWI) (estimated at 0.56 and 0.86 μm) and the reflectance at 0.56 μm as well as the radiance at 1.38 and 1.61 μm to identify thin clouds. The comparison with different products (MOD35/MYD35, Caliop and Infrared Pathfinder Satellite Observation) showed a detection probability of 0.933% and a false alarm of 0.086. In [77] a dynamic threshold cloud detection method has been proposed, based on the FY-3E\MERSI-LL infrared channel and some additional data: the snow cover mask, the sea and land surface temperature and topography/elevation. The results show that at low-middle latitudes the correct and the false alarm percentages are 76.46% and 8.15%, respectively. The authors in [78] proposed and evaluated a threshold cloud mask for the High Resolution Visible (HRV) channel of Meteosat SEVIRI. It was based on low resolution channels of SEVIRI EUMETSAT cloud mask. The aim is to detect sub-pixel convective clouds that are not identified by cloud mask EUMETSAT. The main contraindication of the cloud mask HRV is the minimum cloud optical thickness that can be distinguished. This cloud optical thickness was found to be around 0.8 and 2 over the ocean and land according to the surface albedo, respectively. In [79] a daytime cloud detection has been proposed based on a combination of sun geometry, atmosphere top reflectance, near-infrared dynamic thresholds and normalized difference vegetation index, for the GEOstationary KOrea Multi-Purpose SATellite 2A (GEO-KOMPSAT-2A, GK-2A). This study [80] explored the performance of the minimum residual (MR) algorithm [81] for the Advanced Himawari Imager (AHI). The MR algorithm derives cloud top pressure and cloud fraction using a combination of two or more infrared channels [81–84]. Eleven tests (9 to detected clear pixels and 2 for thin cirrus) were added to the MR algorithm. The ACM cloud mask algorithm has been described in [85,86]: this was based on spatial, spectral and temporal signatures. Most thresholds were derived from space-borne Lidar and geostationary imager data analysis. In comparison with the CALIPSO products the algorithm presented a total Probability of Correct Detection Metric (POD) of 91.4%, a False Cloud of 3.7% and a False Clear of 4.9%. The authors in [84] developed a cloud detection over ocean based on four channels (0.2–4.0μm, 6.5–7.0μm, 10–1μm and 20–23μm) and on atmospheric and humidity profiles for Nimbus-3 Medium Resolution Infrared Radiometer (MRIR). In [87] the authors proposed a clustering cloud mask algorithm over land and a threshold adaptive cloud mask algorithm over ocean in [88] for GOES data. Different improvements in VIIRS cloud detection have been discussed extensively in many publications [89–93]. In [90] the VCM dynamic threshold algorithm has been proposed, thresholds for all the reflectance tests vary with the scattering geometry of the sun-earth sensor, while the thresholds used in the IR bands vary with the integrated water vapor for the geometry of satellite sensor. Each VCM cloud detection test utilised three sets of thresholds: a high and a low cloud-free confidence, and a medium threshold [90]. The final threshold sets selected for each VIIRS sensor are adjusted up or down without changing the shape of the set for each VIIRS sensor during post-launch tuning. In [93] a new procedure using the channels at 12.0 μm, at 4.0 μm and 3.7 μm to remove many misclassifications between snow and clouds has been proposed. A further discussion of VIIRS cloud mask has been reported in [94], which analyses the differences between MODIS and VIIRS in cloud detection. For instance, MODIS detected more clouds in the middle to high levels, while VIIRS detected more clouds in the upper troposphere. These results from the sensor bandwidth of the VIIRS band were made 50% more narrow than MODIS, which means that VIIRS reduces surface contaminations contained in the MODIS observations. The cloud detection algorithm developed in [95] included five tests, threshold were estimated on the basis of one year of data, which takes into account the seasonal and climatic variations. The accuracy was greater than 93% based on 36 images acquired over Texas and Mexico. Cloud detection approaches that examine individual channels have also been explored. This is because, completely cloud-free soundings are rare (typically on the order of 10%) for a radiometer/interferometer with a footprint around 12 km [64,96]. However, the instruments often have channels that are not affected by the cloud presence, where weighting functions are above the cloud top. The detection of these channels permits to use the available data and avoid the removal of hypothetically useful information, for instance discarding all the channels, perhaps only for a few channels affected by the cloud. For example, in [97] a method for high spectral resolution has been presented; the method attempts to identify clear channels, rather than completely clear spectra.

Over the years, multilayer clouds have also been investigated by many authors. One of the first approaches to the detection of multilayer clouds was described in [98]. In [99] the authors used CO_2 slicing HIRS in synergy with the AVHRR in order to detect multilayer clouds. The main goal of the algorithm presented in this study [100] was the detection of multilayer cloud scenes, in particular, thin ice clouds overlying a lower l water cloud. The algorithm uses the water vapour and CO_2 MODIS bands. For multilayer clouds a large difference in top cloud estimation using CO_2 or 0.94 μm methods has been observed. In this study [101] an algorithm based on MODIS cloud mask and phase, on the radiance at 11 μm and the relationship between the reflectance at 1.6 or 2.1 μm has been presented. The main objective in this study [102] was the overlapped high cirrus detection using the CO_2-slicing method and the low cloud top from the single low cloud layer closer estimation. The algorithm used the channels at 0.65 μm and 11 μm. An automated iterative procedure has been used to adjust the

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high cirrus and low water cloud optical depths until simulated radiances match with observed radiances from both the visible and infrared channels. In [103] the multilayer cloud has been investigated using MODIS, AIRS and the Advanced Microwave Sounding Unit (AMSU) data. AMSU microwaves are insensitive to cirrus clouds, unlike infrared channels which are very sensitive to high ice clouds. This study [104] presented a multilayer cloud detection algorithm (in particular ice clouds overlying water clouds) using the channels at 1.6 and 2.25 μm, the absorbing water vapor channel at 1.38 μm, and the channels at 8.5 and 11 μm. The sensitivities study based on radiative transfer simulations has been used for the channel selection. Four techniques for detecting multilayer clouds were explored in [105]. The methods were based on atmospheric sounding data (CO_2-slicing), brightness temperature differences and microwave data. According to the authors, multilayer cloud systems represent a difficult approach, in fact all the tested methods give a maximum 50% accurate classification.

The synergy between sensors has been exploited to improve cloud detection but for instrument having few channels and low spatial resolution. The authors in [106] proposed some threshold tests for the High-Resolution Infrared Radiation Sounder (HIRS) on the NOAA and the Meteorological Operational Satellites (MetOp) series. The algorithm was based on three proprieties. The first property was the cloud reflectance in the visible, the second was the strong variation of the Planck function linearity with the wavenumber and the last was the opportunity to use the microwave Sounder Unit (MSU) channel to estimate the infrared clear radiances. Co-location of the Infrared Atmospheric Sounding Interferometer (IASI) footprint with AVHRR imagery has been used in [107] for IASI detection cloud. A combination of Cross-track Infrared Sounder (CrIS) and VIIRS radiance data has been used in [108] to demonstrate the potential of this synergy to improve ice cloud retrievals. In [109] the benefit using two synthetic IR absorption channels (6.7 and 13.3 μm), obtained at VIIRS spatial resolution using CrIS data has been discussed. In [110] the synergy between AIRS and AMSU/A to detect cloud over the land has been explored. The MODIS-AIRS synergy has been explored in [111,112] in order to improve AIRS cloud products.

Over the polar areas, the identification of clouds is rather complicated due to ice and snow surfaces, which reduce the contrast between surface and clouds [113–117]. Polar clouds often low and thin are composed of water mixtures and ice [118]. The frequent thermal inversions imply that clouds are even warmer than the surface; besides, the visible/infrared algorithms are not applicable or give inaccurate results, due to the poor solar contribution [119]. Current operational algorithms exploit more complex methods for polar cloud detection, from dynamic thresholds to ice/snow cover masks and auxiliary data [94,114,120–122]. The study [123] showed that BT differences between 11 and 6.7 μm are usually greater than −5 K in the tropics and mid-latitudes and less than −15 K in polar regions and high altitude regions during winter, therefore, this difference can be used to detect cold clouds during strong surface radiation inversions at the surface. In [124] the authors showed that the channel at 1.38 μm was suitable in identifying high clouds over Arctic snow/ice surfaces [125–128]. In [129] an AVHRR algorithm for Antarctica has been examined and the following consideration has been showed: the BT difference between channels 3 and 4 was suitable for cloud detection, while BT difference between channels 4 and 5 was suitable for thin cirrus. In order to improve the polar cloud mask in [41], different MODIS operational cloud detection tests are implemented and varied. New cloud tests using the 7.2 μm, the 14.2 μm and 3.9 bands detected cloud more correctly. With the new tests, the incorrect detection of clouds as clear decreases from 44.2% to 16.3% and from 19.8% to 2.7% in Arctic in Antarctic stations, respectively. Despite the strong improvement in night cloud detection, there are yet many cases where the tests fail. The authors in [130] demonstrated the fundamental role played by dynamic emissivity derived from MODIS products in identifying polar nighttime clouds. A dynamic threshold cloud detection algorithm for the cryosphere mission of Global Climate Observation Mission First Climate satellite/Second Generation Global Imager (GCOM-C1/SGLI) based on two infrared channels has been proposed in [131].

Cloud algorithm over desert based on the 0.412 μm MODIS band has been investigated in [89]. In recent years, meteorological satellites are equipped with very high spectral resolutions infrared sensors. The spectral radiances of these sensors contain information about the underlying emitting

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surface, which can be exploited to identify the clouds. In [132] an approach to detect cloud over desert using the quartz-rich soils signature has been proposed.

Even the detection of thin cirrus from satellite radiometric measurements in the visible and IR window region is rather difficult because of little contrast with respect to clear pixel, especially over snow- or ice-covered surfaces. A method [133] has been proposed to derive the cirrus temperature and emissivity from measurements in the two infrared channels (5.7–7.1 μm, 10.5–12.5 μm). The authors in [127] introduced a threshold test at 1.38 μm useful for separating thin cirrus clouds from clear sky and thick clouds. A case study that showed some errors in the detection of cirrus using channels 1.38 μm and 1.88 μm due to surface spectral signals has been showed in [134]. According to the authors in any case the water vapor channel at 1.8498 μm was found to be more suitable for cirrus detection compared to 1.3827 μm. Using the data acquired from AVHRR, an algorithm for the retrieval of cirrus cloud optical depth and mean effective size has been developed [134]. This algorithm is based on the correlation between the 3.7 μm and 0.63 μm radiances. In [135] the 0.65 μm visible and 11.5 μm infrared channels have been used to derive cirrus optical depth using AVHRR data. In [136] the authors proposed an algorithm to estimate daytime cirrus bidirectional reflectance by means of 0.66 μm and 1.38 μm channels. The algorithm is based on the relationship between these channels. To derive ice cloud properties both during the day and during the night, the infrared split window method has been developed on the basis of the ice different absorption properties at 11 μm and 12 μm [12,137,138]. In [139] the authors demonstrated that to obtain accurate results using the 1.38 μm channel it is necessary to estimate the dynamic threshold by using the albedo and the water vapor concentration. The authors in [140] used three MODIS IR bands at 0.645, 1.64 and 2.13, and 3.75 μm to retrieve cirrus optical thickness and effective particle size. The study reported in [141] described an optimal estimation algorithm to retrieval cirrus properties using three MODIS bands centred at 8.5, 11, and 12 μm. In [142] an algorithm to retrieve the tropical cirrus optical thickness using the 1 and 26 MODIS bands has been proposed. A modification based on BT (11 μm) and a multiday average land surface to minimize low water vapor content effect and high elevation has been proposed in [143]. The algorithm validated in the Tibetan Plateau using VIIRS and MODIS data provided better accuracy than using only MODIS 1.38 μm cirrus test. In [101] the thin cirrus detection exploited the relationship between the reflectance at 1.6 or 2.1 μm and at 11 μm. The operative cirrus [120] detection MODIS is combined of two algorithms, for day and night. The daytime algorithm is based on the radiance at 1.38 μm, this channel is located in an absorption band of H_2O and, therefore, no radiation reflected from the Earth's surface reaches the sensor when there is a sufficient quantity of water vapor in the atmosphere. To separate thin cirrus clouds from thick ones, the water vapor absorption channel at 6.7 μm, the window channel at 11.0 μm and the 6.7-11.0 μm difference are used, and the difference technique is also applied during the night but with the channel difference between 3.7 μm and 11.0 μm. The 3.7 μm channel is sensitive to both solar energy and terrestrial radiation, this channel is very suitable for identifying hot surface emission. In [144] a cirrus clouds algorithm (MeCiDA) that combines morphological and multi-spectral threshold tests has been proposed. The thresholds were estimated using radiative transfer simulations. An improvement of MeCiDA, MeCiDA2 was presented in [145] which used seven thermal channels of the SEVIRI instrument, and it can be applied to the entire MSG/SEVIRI disc. The algorithm has been adapted to Terra/MODIS and compared with the MOD06 cloud phase operation; the difference in cirrus cloud cover between MOD06 products and MeCiDA2 was less than 0.1 except for latitudes above 50° N. The authors in [146,147] determined cirrus occurrence with CO_2-slicing method using HIRS data. High spectral resolution instruments bring more information regarding cirrus compared to other old instruments. Synthetic data show that radiances in the 800–1130 cm-1 are suitably sensitive to variations in cirrus optical depth and ice crystal size and shape [130,148–150]. An approach to estimate optical thickness of semi-transparent ice clouds by using AIRS high spectral resolution radiances has been presented in [151]. The retrievals use window channels which have greater sensitivity to the optical thickness of ice clouds and are not very sensitive to cloud particle size and atmospheric profile errors. The authors in [152] proposed a method for the detection of cirrus during the night by using BT differences determined from a set of selected AIRS window channels and the Total Precipitable Water

(TPW) measurements derived from AIRS and AMSU-A. The authors in [153] developed a cloud detection algorithm based on the CO_2-slicing method for high-resolution Greenhouse gases Observing SATellite (GOSAT)/FTS thermal infrared observations and reported improved accuracy with respect to the traditional method by comparing the results with coincident CALIPSO observations.

The discrimination between low stratus cloud and fog is also an open topic. A technique for fog detection at night using the AVHRR has been proposed in [154]. A procedure to discriminate fog from low-level clouds using MODIS data has been proposed in [155,156]. The authors in [157] developed a fog and low stratus daytime detection by using SEVIRI data, based on some tests that exploit the spatial/spectral and microphysical properties of fog and low layers. The algorithm detected low clouds with a probability of detection from 0.632 to 0.834. In [158] SatFog is proposed, an algorithm to detect small scale daytime fog using the high spatial resolution HRV/SEVIRI channel. In [159] MODIS channel 18 homogeneity is used to discriminate sea fog from low and medium-high level clouds. In [160] the authors proposed a regression method for sea fog detection based on the reflectance at the AHI green band and Normalized Difference Snow Index. In the study [161] the authors proposed a nighttime sea fog map that was obtained by merging three fog probabilities. The algorithm detected low clouds with the detection probability ranging from 0.632 to 0.834.

2.2. Cloud Detection Based on Spatial and Texture Characteristics

The physical methods suffer from the cloud great changeability, the presence of partial clouds, the thresholds estimation and the radiance dependence on the emissivity, which is very difficult to estimate accurately over land. Therefore, classification methods based on statistical methods have been developed in recent years. Classification approaches learn the statistical characteristics of clear or cloudy sky conditions starting from the "truth" data in which the sky conditions are known. (See Section 3.) Sky conditions on new images are deduced by relying on some of the learnt statistical properties. The statistical classification is based on the fact that each pixel spectral signature contains information about the surface and overlying clouds (if present) physical characteristics. The downside of these techniques is that they require large accurate training sets. It is clear that the sensors with high spectral resolution have led to the obtainment of increasingly accurate algorithms; in fact, an improved spectral resolution allows a better representation of the spectral signature for each pixel, hence a better identification of the distinctive spectral characteristics of clouds. In [162] a bivariate Bayesian discriminant function has been used to classify clear ocean GOES radiance measurement. This paper [163] described an automated pattern recognition algorithm which identifies different cloud types at high latitudes using AVHRR data. Five spectral features have been used to provide information about the brightness temperatures and albedos, while three textural features for the variability in the image and the maximum likelihood decision rule have been used to classify all the pixels. In [164] the authors described a scheme developed using Bayesian techniques, by estimating the probability that a given infrared measurement was affected by the cloud. This technique used all the available information, such as the various channels, as well as their correlation reported in [106] and other information derived from the NWP model. The algorithm presented in [165] developed for IASI data was based on the empirical orthogonal functions (EOFs) simple threshold test, over a set of airborne data. In [166] six spectral radiances from MODIS, six features based on these, five angular radiances derived from the Multi-angle Imaging SpectroRadiometer (MISR) and three features extracted from them in combination with clear/cloudy training labels pixels have been used to train Fisher's quadratic discriminate analysis classifiers. Accuracy increased to about 97% when this algorithm with expert labels was applied to MISR and MODIS combined data. In [167] a cloud detection based on discriminant analysis has been described, where the truth data for discriminant analysis learning phase were derived from MOD35 cloud mask. In [168] a cloud masking algorithm using a physical, statistical and temporal approach, has been proposed (MACSP) for stand-alone SEVIRI. The temporal test is only applied to pixels classified as uncertain by the other 2 methods. The physical algorithm consists of a series of dynamic multispectral threshold tests, the statistical algorithm is a K-Nearest Neighbor (K-NN) pattern recognition technique. The MACSP identifies as cloudy 91.2% of the pixels classified as cloudy by the collocated MODIS cloud mask. In [169] NWP simulated data have been used with a Bayesian technique to calculate the probability of each pixel being clear or cloudy. The validation using SEVIRI data reaches true skill scores of 87% and 48% for sea and land, respectively. A method based on statistics and pattern recognition was analysed in [170] where three MODIS datasets were considered: synthetic (simulated data); real MODIS labelled by a meteorologist as clear or cloudy; and the MOD35 cloud mask. The authors showed the excellent performance of the following techniques in all the database: the principal component discriminant analysis (PCDA) [171], the independent component discriminant analysis (ICDA) [171] and the KNN [172]. A fuzzy cloud detection has been proposed in [173], based on five features, that measures the temporal and spatial properties of infrared and visible METEOSAT-5. A probabilistic cloud detection algorithm (PCM) for AVHRR data was proposed in [174] which used all channels, solar geometry and further ancillary data to estimate the probability using some look-up tables. The study area covers a wide range from Iceland to northern Africa, the PCM cloud classification gives results similar to the Polar Platform System (PPS) products with which the validation has been carried out. In [175] the authors use a Bayesian cloud detection scheme to analyse thirty-seven years of AVHRR global coverage. The Bayesian algorithm decreases the SST differences between satellite and in situ observation standard deviation by almost 10%. In [176] a Bayesian cloud detection algorithm applicable to any sensor has been proposed, the algorithm was evaluated on the basis of Advanced Along-Track Scanning Radiometer (AATSR) and MODIS data. For AATSR the algorithm success rate was 7.9% higher and the false alarm rate was 4.9% lower than for the operational cloud mask. A texture based method for feature identification has been investigated in [177]. This method uses a set of spatial filters known as 2-D Gabor functions, the method has been applied to AVHRR data. Results show that the texture information improves the detection between cloud types, especially thin cirrus.

2.3. Cloud Detection Based on Artificial Intelligence

These types of algorithms select the best cloud features in order to optimize the model train dataset, however, this feature selection has to be manually extracted from a large dataset. This aspect can be accomplished via a neural network approach that automatically extracts features useful to distinguish the contaminated cloud pixels in satellite images. Many authors used artificial neural network with several variants such as Bayesian classification, deep learning, support vector machine, fusing multiscale convolution features, random forest methods, decision tree, object-based neural convolution network, etc. Machine learning techniques are certainly adaptable, however, they lack consistency since the model training varies on the selected input data. The authors in [178] developed an automated cloud classifier (CANN) for neural networks. Results by applying the classifier to five independent test images indicate that it can provide correct classifications. The model selected the right class for 96% and 82% of the training samples and the test samples, respectively. In [179] it is investigated a histogram approach to identify the features and a hierarchical neural network to identify cloudy pixels over desert, polar regions and fire scenes. The preliminary results showed an accuracy of 98% for polar data, 97.5% for desert data, and 99.2% for fire scenes. In [180] the author used a probabilistic neural network (PNN): the input patterns were selected considering the potential of each feature extracted from textural, spectral and physical measures. The training and testing input data are obtained from 95 expertly labelled images over sea. The classification using 5 classes (altostratus, low and high clouds, rain clouds and clear) yields 91.2% of pixels classified correctly. In [181] the authors used a Hopfield Neural Network to acquire dynamic cloud parameters from METEOSAT satellite image sequences. The contribution of these parameters to an accurate classification has been discussed. In [182] the authors presented a Multicategory Support Vector Machine (MSVM) for MODIS. The MSVM algorithm has been validated using 1536 MODIS scenes over the Gulf of Mexico; MSVM mis-classification rate was under 1.0%. In [183] four training set reduction methods were compared, in particular, the FCNN (fast condensed nearest neighbour) method reduced the training set size by 68.3% while reducing their accuracy by only 4. In [184] the authors used a backpropagation neural network based on the Keras deep learning framework

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platform for the airborne visible/infrared imaging spectrometer (AVIRIS) hyperspectral data. Landsat 8, Terra MODIS and NPP VIIRS data have been used to validate the precision of the algorithm. The results demonstrated that the overall accuracy was greater than 90%. In [185] the accuracy of four methods has been compared, for desert and polar regions, the maximum likelihood classifier, neural network, coupled histogram and hybrid class approach showed an accuracy of 94-97%, 95-96%, 93-94% 94 -96%, respectively. In this study [186] a SEVIRI cloud detection was implemented using a multilayer perceptron neural network trained with a back-propagation using six bands (0.6, 0.8, 1.6, 3.9, 6.2, and 10.8 μm). Validation carried on with 60 images confirmed the benefit of the multilayer perceptron neural network algorithm over the EUMETSAT cloud mask. The accuracy estimated for the MPEF CLM algorithm was 86.10%. A neural network and a fuzzy logic method to identify SEVIRI cloud pixels have been showed in [187]. The fuzzy logic and the neural network methods showed an accuracy of 84.41% and 99.69%, respectively, over seventy-two MSG images. In [188] a threshold cloud mask algorithm based on a neural network and a large radiance simulated dataset has been proposed. Statistical validation results obtained by using co-located CALIOP and MODIS data show that its performance was consistent over different surfaces and significantly better than the operative MODIS cloud mask over snow-covered surfaces in the mid-latitudes. The statistics have been reported for individual months and areas. The authors in [189] showed a classifier capable of ingesting any type of parameter derived from multi-channel sensors. About 89%–94% of the cloud pixels detected with this method coincided with cloud pixels derived from MOD35, excluding some vegetation surfaces, where the percentage of the coincident cloud pixels was 85%. The authors in [190] evaluated two machine learning approaches for SEVIRI sensor, the chi-squared automatic interaction detection decision tree (CHAID) and radial basis function neural network (RBF). The authors validated the algorithm with MODIS and EUMETSAT cloud mask and reported the results divided by season, the values range from 76.48% to 92.34%. In [191] the authors proposed a detection model for CrIS exploiting the artificial deep neural network (DNN) approach. The "truth" cloud information is obtained from co-located VIIRS instrument. The CrIS cloud detection agrees with the one based on VIIRS, with 93% accuracy. A cloud detection machine for the Advanced Himawari Imager (AHI) has been developed in [192]. The validation based on collocated CALIOP product showed that it improved the current AHI operational cloud mask, increasing the true positive rate by ~5% and reducing the false positive rate by ~3%. In [193] a cloud detection method based on convolutional neural network optimized for geostationary satellite images has been proposed. The algorithm showed an accuracy of 96.14% for daytime and 98.87% for nighttime. In [194] the authors presented convolutional neural networks (CNNs) to detect cloud pixels, without ancillary data. It has been validated against ground data in 12 locations and the results showed an improvement over GOES-16 of 11% in accuracy. In [195] the authors developed a neural network cloud detection that combines both multi-scale features and merging shallow and deep information called U-High Resolution Network (U-HRNet). The algorithm performance has been evaluated on the basis of labelled ground data manually. The results demonstrated that U-HRNet provided good results when used with FengYun-4A (FY-4A) data. In [196] two machine learning Random Forest (RF) models using VIIRS data for seven different surface types have been trained. The daytime model used NIR, SWIR, and IR bands and an all-day model used IR bands. For cloud mask comparison over all surface types, the RF proved best among all models evaluated, including MODIS MYD35 and MODIS and VIIRS CLDMSK products. In [197], a method based on deep learning was proposed to detect sea fog. In a first step, they used a fully connected network to separate clear from cloudy pixels. In a second step, they used a convolutional neural network to extract features of low clouds and sea fog using the 16-band Advanced Himawari Imager. They reported the results showing the comparison with five state-of-the-art sea fog detections. The authors in [198] proposed a XGBoost machine learning algorithm for Himawari-8. The cloud detection has an accuracy of 91.40% at night, and 89.58% at daytime. A supervised neural network (NN) for IASI stand-alone has been proposed in [199]. A good coincidence of 87% with the operational cloud mask of IASI L2 was found. A multiscale feature convolutional neural network cloud detection approach has been evaluated in [200]. The method yielded 96.55% accuracy, 92.13% precision and 88.90% recall. In [201]

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a cloud mask algorithm based on a synthetic radiances and machine learning (SCHM) has been proposed; the validation based on CALIOP data indicated that the algorithm reached 85.72% hit rates for clouds. A thin cirrus detection algorithm (TCDA) for IASI-NG and IASI has been proposed in [202]. TCDA utilised a feedforward neural network method to detect thin cirrus. IASI TCDA validation based on CALIOP and Cloudsat/CPR data shows a tendency of TCDA to underestimate the presence of thin cirrus. In [203] the authors proposed a machine learning cloud detection that uses the principal component analysis (CIC). CIC was tested on a simulated dataset. The algorithm pointed out the far-infrared region information useful to identify especially thin cirrus clouds. The results showed that the percentages of correctly detected clear and cloudy pixels increased from approximately 70 % to 90 % when far-infrared channels were used. In [204], the authors presented a review of deep learning techniques applied to cloud detection. They also showed a comparative summary, comprising the detection accuracies and an analysis of the various limitations and the future research development. This study [205] analysed the important contribution of spectral and textural parameters to detect cloud. A detailed discussion on cloud classification using NN and different Deep neural network approaches with different texture features or parameters was provided. Also, in this study [206], in addition to an extensive review of the literature, some suggestions are given to improve cloud detection.

2.4. Microwave Cloud Detection

Although the microwave range is less affected by clouds compared to VIS/IR data, different clouds can modify the observation microwaves [103,207,208]. An AMSU_A scatter index based on 4 channels (1-2-3-15) has been used to identify clouds in AVHRR pre-processing package (AAPP) [209]. The authors in [210] proposed a land index estimated using the cloud Microwave Humidity Sounder (MHS) channels temperature variability. An evaluation with GOES product established a good agreement. ECMWF AMSU assimilation model cloud identification [211–213] uses some threshold tests. The authors in [214] presented a one-stream cloud detection approach, that uses MHS retrieved liquid/ice water path. In the algorithm described in [215] the SEVIRI visible/infrared data have been used as “true” for microwave training. The algorithm identified clear/cloud (except for cirrus) pixels over all the surfaces with a confidence value of about 80%. The authors in [216] compared the window channel with the corresponding data derived from a clear sky model. If the difference is greater than a fixed threshold value, the corresponding non-windowed channels are considered to be influenced by clouds. For example, channel 4 of AMSU-A is the window corresponding to channels 6 and 7 of AMSU-A. In [217,218] the authors proposed an AMSU-A cloud detection based on 5 channels, 4 windows from the first to the fourth, and the fifteenth (a low-peaking), exploiting their different responses to the clouds. In [219] AMSU-A observations were considered as cloud-contaminated if the liquid or ice water path retrieved from co-located AMSU-A and MHS were greater than 0.02 g/kg. In [220] the authors used collocated MODIS VIIRS products with high spatial resolutions in order to detect microwave sub-pixel clouds. In [221], a cloud detection algorithm based on dynamic threshold tests has been proposed, it takes into account the absorption band channels around 183 GHz, the method was only evaluated for a winter case study. The AMSU-B channels around 183 GHz have been used to identify tropical deep convective clouds and convective overshooting [222]. In this study [223] an analysis of AMSU/B 183 GHz measurements was carried out in order to study the impact of cold clouds (< 240 K at 11 μm). The collocated AVHRR data helped to identify the clouds. Results for December 1999 show that cold non-precipitating clouds have a measurable impact at 183 GHz although the average effect is rather weak. In this study [224], an Aura Microwave Limb Sounder (MLS) cloud detection algorithm based on a feed-forward has been evaluated. The model was trained on MODIS global cloud products. The comparison with the “Level 2” MLS cloud showed a huge improvement in classification performance. In this study [225] a cloud detection algorithm based on a neural network for Microwave Sounder (MWS) using a large synthetic dataset was developed. The model has been evaluated using AMSU-A and MHS measured data. Model accuracy is 92% over sea and 87% over land for MWS simulated data and 88% over sea and 87% over land for AMSU_A and MHS observations. The authors in [217] proposed a deep learning based on multilevel image features.

The method involves two steps: in the first, the probability map of the cloud is obtained from the designed deep convolutional neural network, while in the second step a composite image filtering technique was used, in which the specific filter captures the multilevel characteristics of the cloud structures.

3. Truth Data Sources for Cloud Detection Algorithms

Truth data are needed for a variety of reasons in remote sensing methods, especially in the evaluation of algorithms to retrieve cloud cover and cloud optical properties from passive environmental sensors. For example, truth datasets are needed to test algorithm theoretical concepts, to establish cloud detection accuracies of/one or more cloud models, to create the thresholds needed for use with physically-based cloud tests, and to train physically based algorithms, e.g., neural networks. Thus, it is necessary to have access to or the ability to create cloud-truth data. Table 1 contains a summary of cloud truth data and sources useful for evaluating cloud detection and product algorithms from passive radiometry.

Table 1. Cloud truth data useful for evaluating VIIRS and/or MODIS cloud products.

Cloud Product	Truth Data Source	Instruments	Accuracy/Comments
Amount (probability of correct typing)	Satellite-based	CALIOP & VIIRS imagery	>98 % (global and regional)
Cloud Top Phase (ice, water, mixed)	Satellite-based	CALIOP & VIIRS imagery	TBD
Cloud Top Height	Ground-based & Satellite-based	Height: MPL & CALIOP for cloud Boundaries	Height: ~30 m
Cloud Top Temp and Pressure inferred	Satellite-based	CALIOP	Temp for mean COT of cloud layer
Cloud Optical Prop.	Ground-based	Multi-Filter Rotating Shadow band Radiometer (MFRSR) measurements	Inferred with CEPS error >> COT
Cloud Base Height	Ground-based	Lidar Model CL31 Vaisala Ceilometer	Height: ~10 m

3.1. Cloud Amount Truth Data

Two sources of cloud amount truth data are available: one is created from an active lidar sensor like CALIOP, which flies on the NASA EOS A-train mission, with a nodal crossing time of 1330 local. CALIOP measures polarized backscatter components at 532 nm and the total intensity of the 1064 nm backscatter [226,227]. The diameter of the CALIOP footprint is around 100 m and the distance between each CALIOP footprint is 335 m. The highest vertical resolution of data downlinked from CALIOP is 30 m which is listed as the truth accuracy of cloud top height in Table 1. The level-2 CALIOP product provides cloud profile data with resolutions of 5 km, 1 km and 333 m. The CALIOP product contains cloud layer information along with the mean cloud temperature of each profile.

Two points of emphasize in using CALIOP data as cloud cover truth for VIIRS products: areal coverage of CALIOP data will not represent the same area on the ground, i.e., pixels are not congruent. VIIRS pixel diameters at nadir are 375/750 m for imagery/radiometry bands while CALIOP samples are 70 m. Secondly, temporal differences will exist between data sets will exist unless the sensor under investigation resides on the EOS A-train satellite orbital plane. Thus, care is required to match pixels from another sensor with CALIOP cloud profiles. On the positive side, CALIOP cloud products provide highly accurate measurements on the present of clouds above 500 m and cloud top phase. Additionally, cloud truth data can be collected under daytime and nighttime conditions.

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A second source of cloud cover truth comes from the manual interpretation of clouds in multispectral imagery. With this method, generation of a total or merged CNC (MCNC) truth images results from the composite of individual CNC images of multispectral satellite data. These individual CNC images are created from imagery bands where the cloud-surface contrast is a maximum. For example, the VIIRs M1 (412 nm) band is useful for identifying clouds over desert regions [89] while the M5 [0.65 μm] band is useful over vegetated surfaces. MGCNC truth images have key benefits over CALIOP products, including:

1. Offers temporal and spatial congruency between automated cloud products and cloud truth. Truth is made directly from satellite imagery used to generate automated product.
2. Supports algorithm and model updates. Truth can be used to quantitatively assess updates to algorithm logic by assessing improvement from granule reprocessing.
3. Provides better assessment on algorithm performance. Truth can include full granules of 3200 pixels cross-track by 768 pixels long-track for VIIRS. CALIOP collects data only along sensor sub-track.

The primary weaknesses of using MCNC analyses as ground truth cloud cover images is the scepticism that such images can be accurately created. Secondly, even after designing and building special software to facilitate the construction of these truth MCNC analyses, the actual task is labour intensive and may require to up four hours for complex datasets. The scepticism can be overcome by implementing quality control procedures that protect the veracity of the program, e.g., truth for a granule is not declared until subject matter experts agree the acceptability of each truth CNC analysis.

During the VCM Cal/Val programme, Cloud masks were generated manually for 120 VIIRS granules, and three VCM Subject Matter Experts (SMEs) controlled each analysis from a quality point of view. The initial analysis was carried out by one SME, and subsequently revised by the others with no interaction between them. Any differences between SMEs are resolved and the manual cloud analysis was updated. The analysis was considered completed only after performing all the quality control procedures, and cloud cover truth for the VIIRS granule was provided. See Figure 1 in [228] for an example of these MCNC analyses.

The applications of both the manually-generate truth and CALIOP products were discussed at length in [228,229]. Together, these two sources of cloud truth data support an in-depth analysis of automated analysis and forecast product. CALIOP provides accurate detection of most clouds, with exception of some low-level clouds, as well as cloud phase for the analysis region which is constrained to areas located along the sensor sub-point. On the other hand, manually-generated cloud can be created for complete (VIIRS) granules to support algorithm performance across large regions. Data matchups with CALIOP, when possible, allow direct comparisons between products from different models while MCNC products require no ancillary matchup data and better support algorithm updates through reprocessing of VIIRS products created by the VCM algorithm. Generally, the VCM algorithm performance was found to be consistent with other truth data, i.e., CALIOP and MCNC masks [228].

3.2. Other Cloud Truth Data

Truth data for other cloud data product shown in Table 1 consist primarily of special missions as well as the Atmospheric Radiation Measurement (ARM) sites. Some products can be created directly from sensor measurements, e.g., cloud base heights from ARM ceilometers, while others inferred values using algorithms along with indirect measurements, e.g., COP products from Multi-Filter Rotating Shadowband Radiometer (MFRSR) measurements. It is difficult to collect and process cloud truth data for these other cloud products which impacts the maturity of algorithms to retrieve them from satellite-based techniques.

4. Conclusions

This article reviews the numerous methodologies used for meteorological satellite cloud detection, from threshold methods to artificial intelligence techniques. Studies on cloud identification initially relied on the exploitation of one or two bands of satellite images. Over the years, thanks to the new high spectral resolution sensors, the algorithms have been able to exploit the whole information derived from the many channels as well as sophisticated statistical and AI techniques to improve the uncertainty on the identification of pixels affected by partially cloudy-filled or thin cirrus, especially over complex surfaces. Initially, cloud detection focused on cloud forecasting models, while more recently cloud screening in satellite data is playing an increasingly critical role for the retrieval of numerous products including thermodynamic profiles of the atmosphere, microphysical parameters of clouds and aerosols, surface temperature, etc. Despite the efforts and years of research, it is still currently difficult to identify certain types of clouds in particular conditions. Meanwhile, it is worth pointing out that the boundary between clear and partially cloudy sky in nature is subtle, especially in the presence of semi-transparent clouds. This ambiguity already makes the definition of a cloud subjective and complicates the identification of very thin clouds. Not to be overlooked are also issues related to the complete non-coverage of pixels as well as the pixel coverage by clouds differing in thickness, height and phase. Validation also becomes complicated given the lack of absolute truth regarding the pixels due to human error, the algorithm adopted and co-location errors. This article contains, in addition to a review of most of the algorithms proposed over the years, a summary of cloud truth data and sources useful for evaluating cloud detection and products from passive radiometry. However, it is not easy to estimate the accuracy of the various methods, given that validation is done on different sets of data and often over different regions. Furthermore, validation is often done on a small amount of data or a limited region. In the future it would be very useful to create standardized datasets and procedures for benchmarking of cloud detection models, to obtain homogeneous results and evaluate the accuracy of the different cloud detection algorithms.

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