# Cloud Detection and Removal from Optical Remote Sensing Images- An Analytical Comparison

**Anupriya Shrivastava[1], Dr. R.K. Arya[2], Dr. Asmita A. Moghe[3]**

**[1]UIT,RGPV, Bhopal, India**

**[2]Chief Scientist of MPCST, Bhopal, India.**

**[3]Department of Information Technology, UIT, RGPV, Bhopal**

**[1]er.anupriyashrivastava@gmail.com, [2]rakeshmpcst@gmail.com, [3]aamoghe@rgtu.net**

**Abstract: The presence of Clouds has always been a stumbling block of qualitative analysis of optical remote sensing (ORS) images .In order to extract relevant information and to make the estimations more precise, clouds need to be removed from the remote sensing images. This pre-processing step forms a crucial area of research in image processing. The presence of clouds of various types substantially affects the associated information despite the fact that the data being composed of high-resolution satellite imagery. Due to complexity and variety of underlying surfaces, many methods of cloud detection have difficulty in detecting cloud regions. Since the energy received by an imaging sensor can be approximated by a linear combination of the reflection from clouds and ground objects, an ORS image should be considered as an interfused image with a layer of clouds and an underneath background layer. Hence, cloud detection and then removal should be treated as a mixed image separation problem. This paper presents a comparative review of various principles and techniques which are prevalent in understanding and resolving the issues in this area of research i.e. cloud detection and removal.**

**Keywords: Remote sensing images, Cloud detection, cloud removal, convolution neural networks (CNNs), deep learning, neural network.**

## I. INTRODUCTION

The rapid progress in remote sensing technology in current times has opened up many avenues for people to better understand the environmental changes. Optical Remote Sensing, is a large family of RS imaging technologies, which has been an avid research and application area in recent times, for land monitoring, disaster management, military warfare etc. Inspite of so many applications optical RS image are marred by the fact that they are always covered by clouds and this has greatly constrained the use of optical RS for many purposes. Stubenrauch [1], has referred in his work that on an average, more than half of the Earth's surface is covered by clouds on a daily basis, which makes the research related to cloud detection is of great consequence. The cloud in an image usually presents itself in a blended form with the cloud and the ground objects underneath it. As the clouds varies in thickness, so the energy received by an imaging sensor can be approximated as a linear combination of the reflectance of clouds and ground objects, a RS image can be considered as an intermerged image with a layer of clouds and an underneath background layer Hence, the cloud detection scenario can be actually treated as a hybrid image separation.

## II. UNDERSTANDING CLOUD REMOVAL AS A MIXED IMAGE PROBLEM

Cloud detection techniques are mainly based on the physical cloud characteristics like shape, Colours, density, cloud shadow and various extracted features of Image etc. Some techniques based on optical properties, like spectral content, near and visible infrared and Thermal bands, spectral and spatial content analysis of cloud reflectance variation, brightness temperature, multi spectral and polarization characteristics etc. This article has reviewed various forms of cloud detection such as thin cloud, thick cloud, cloud or no cloud and cloud shadow.

*Cloud Detection*

This section of the article focuses on works that have been focused on the detection of cloud in RS image, many such mechanisms have been used.

Authors in [2] used concept of deep learning using multilevel image features of satellite imagery and claimed to have obtained cloud probability map, better cloud masks through various image filters. In [3] authors proposed a method where image is segmented into super pixel by using improved version of SLIC(simple linear iterative clustering) Method. Cloud detection results yield by extracting

 DOI : 10.35291/2454-9150.2022.0033 

multiscale features from each super pixels using two branches of Deep CNN.

Authors in [4] devised a classification decision tree for snow covered detection regions. The working principle is to repeat scene from vicinity and then replace each pixel with its actual surface types as a pixel, whether its land or water. In [5] a detection algorithm is built that utilized texture analysis along with neural network and applied the methodology of multi spectrum synthesis and Cloud Detection index for each pixel. Cloud detection using the Bayesian scheme [6] effectively made use of empirical lookup tables for cloudiness and radiative transfer model for cloud detection in day hours. Some in [7] Authors have used a cloud detection method using dual colour space obtained from cloud features and thereby analysing cloudy high resolution RS images. The authors further made use of extracted features by building cloud region maps based on the basis of chromatic and luminance features of clouds like hue, saturation. Another cloud detection approach is developed in [8] which has mainly two sections training and testing. Feature data like texture, colour, structure etc. and ground truth of training image is used for designing the detector. After this saliency map is obtained by the feature data of the testing image and finally cloud is detected using some cloud refinement technique.

Authors of [9] proposed SVM classifier training which should using typical data set and discriminant analysis (DA) can be effectively used to find the disparity between cloudy /non cloudy sky. Authors in [10]developed another algorithm with the same objective called CSBD (Clear Sky Background Differentiation) making use of the actual image and the corresponding clear sky images. They developed a clear sky background image at different solar elevation angles and then developed the corresponding data set which has been used in the work. But the suggested CSBD algorithm has some serious limitations as it can interpret cloud pixels as clear pixels. Work in [11] involves Satellite imagery segmentation into super pixels, spectral feature extraction, texture and frequency based features. An optimal support vector machine (SVM) is then utilised as classifier for extraction of cloud mask. However, the method has been found to be computationally time using due to the algorithms being iterative and thereby hasn't been put forth much for Satellite imagery options which involves extremely high resolution and sized images.

Cloud Displacement Index (CDI) for cloud detection has been used in [12] deploying infrared bands and view angles to separate clouds from bright objects. The authors used this feature along with the Fmask algorithm developed for the Landsat satellite group.

[13] employed a method of extracting grey feature vector and frequency feature vector from RS images and then compared actual feature values and thresholds by training to estimate the cloud area.Convolution Neural Network (CNN) algorithm for detection of cloud used red, blue, green and near infrared (NIR) channels of satellite imagery [14].This algorithm attempts to learn features using spectral and spatial information of imagery.

Authors of [15] proposed a cloud detection algorithm for polarized image based on characteristics like multi spectrum and polarization. It uses dynamic thresholds obtained by statistics of various atmospheric and surface models in different time zones. [16] utilised Back Propagation Neural Network for cloud detection in Landsat8 OLI, NPP, VIIRS and Terra MODIS data. It used hyperspectral AVIRIS data with continuous spectral coverage to obtain high quality training samples.

Various colour models of multi frequency thresholds with pixel to pixel management is utilised[17] in order to identify cloud and no cloud scenario based on threshold value. However it had issues in isolating ice and cloud in the visible region due to the fact that their reflectance is same.

A Cloud-Attu model is proposed in [18] which has U-network with attention mechanism for cloud detection. Multiscale information is obtained through skip connection operation by fusing low and high level features.

Multiscale feature extraction and content aware reassembly network MCNet is proposed in[19] . MCNet uses pyramid convolution and channel attention mechanism. It results extraction of full spatial and cloud's channel information in an image. Content aware reassembly ensures that sampling on the network can recover enough in-depth semantic information and improve the model cloud detection effect. Another neural network with encoder-decoder for cloud detection named CDnetV2 is proposed in [20]. This CDnetV2uses two modules – Adaptive feature fusing model(AFFM) and High level semantic information guidance flow(HSIGF).AFFM consist of 3 submodules to fuse multilevel feature maps: channel attention fusion model (CAFM), spatial attention fusion model (SAFM) and channel attention refinement model (CARM) while HSIGF makes feature layers at decoder of CDnetV2.

In [23] authors proposed multilevel cloud detection method based on deep learning. Simple linear iterative clustering (SLIC) method is improved to segment the image into good quality super pixels. Extraction and prediction of each super pixel as thick cloud, thin cloud and non-cloud is done by using deep convolution neural network with two branches that yield the cloud detection result.

Paper [24] proposed block level label based on a weekly supervised deep learning based cloud detection (WDCD) method. Global convolution Pooling (GCP) operation is proposed in training phase to enhance the ability of the feature map while trained deep network are modified to generate the cloud activation map (CAM) through local pooling pruning(LPP) strategy in testing phase.

 DOI : 10.35291/2454-9150.2022.0033 

International Journal for Research in Engineering Application & Management (IJREAM)
ISSN : 2454-9150 Vol-07, Issue-10, JAN 2022

*Thin cloud/thick cloud*

Cloud detection of thick or thin clouds is discussed here. The works in [21] have tested multi Convolutional neural networks (MCNN) for high resolution RS images. Researchers made use of adaptive simple linear iterative clustering for the bifurcation and segmentation of the RS images. An architecture based on MCNN has been utilised to separate multiscale features from each super pixel.

Authors of [22] developed a linear iterative clustering algorithm capable of isolating thin cloud, thick cloud and no cloud scenarios .They used natural scene statistics model to differentiate cloud and surface buildings . Gabor features are computed within each super pixel and Support Vector Machine (SVM) classifier distinguishes cloud from snowy regions.

Another type of mechanism called Spectral image ratio technique has been utilised by [25] for generating ratio image based on the colour transformation of the input image. Fuzzy C means clusters the ratio image and detects the clouds automatically. Ratio value of Chromatic features and Luminescence is used for cloud detection. The technique has been deployed with some success for thick clouds and thin clouds. An algorithm is proposed in [26] for thin cloud detection based on Bidirectional Reflectance Distribution Function (BRDF). It simulates minimum difference between reflectance value of atmosphere's top and bottom as baseline of clear atmosphere.

## III. CLOUD REMOVAL

Number of cloud removal algorithms has been presented over the last two decades. Given that cloud and cloud shadow removal is a process of reconstruction of missing information, cloud and cloud shadow removal approaches can be separated into four main types[27].They are: Spatial information based methods, temporal information based methods , spectral information based methods and hybrid methods. Details of these methods are as follows:

**1) Spatial information based methods:**

This is the basic method for the cloud and cloud shadow removal. This method is based on the concept that cloudy region and cloud free region have similar contextual information [28]. The spatial information based methods include interpolation-based methods, exemplar-based methods, diffusion methods and variational methods. Mostly interpolation methods can be represented as weighted averages of sampled values while diffusion methods aim to recover the missing areas in such a way as to propagate the local information from the exterior to the interior of the missing areas. The exemplar-based inpainting methods [29] are based on texture synthesis for digital images, with the aim of recovering large missing regions of texture information. Limitation of Spatial methods is that they fail to reconstruct missing information in large area.

**2) Spectral information based methods:**

In Spectral methods, incomplete spectral bands are reconstructed using one or more complete spectral bands by modelling the latent relationship between incomplete and complete band. For multispectral or hyperspectral data, the close relevance and similarity within the various spectral bands can be fully utilized [30]. For example, Closely correlated spectral bands are used for reconstruction in deadlines contaminated Aqua MODIS band 6 [31]. [32] uses Autoencoder neural network to remove clouds in multispectral images by modelling a relation between cloud free and cloud contaminated images. the two strategies developed here Perform mapping at pixel level and patch level .

**3) Temporal information based methods:** These methods are mostly used for thick cloud removal in recent years [33]. The same location revisited by satellites at different times, the obtained multi-temporal data includes complementary information used to reconstruct thick cloud covered areas [34]. The temporal based methods assume that the category and geometric position of ground objects rarely show changes over short time intervals [35].

**4) Hybrid based methods:** These methods utilize spatial, temporal, and spectral information for cloud removal. For instance, [36] proposed unified spatial–temporal–spectral framework based on a deep convolutional neural network (CNN) for reconstruction of missing information due to thick clouds, deadlines etc. Authors in [37] designed a temporal group sparse learning algorithm using multi-temporal and multi-spectral images.

In[38] Content, Texture and Spectrum generation networks based on traditional CNN are proposed. This CNN architecture can use content, texture, and spectral data as an input of the unified framework for thick clouds removal from multitemporal Ziyuan-3 Satellite Images.

The issues like thick cloud cover with large-scale areas, presence of clouds in temporal images and deficient utilization of single temporal images can be resolved through spatio-temporal patch group deep learning framework [39].The training model is optimized using the global-local loss function through cloud-covered and free regions. Along with this, progressive iteration and weighted aggregation are utilized for reconstructing the holistic results.

A thick cloud removal method temporal smoothness and sparsity-regularized tensor optimization (TSSTO)is proposed in [40]. The sparsity norm and alternation direction method of multipliers (ADMM) is used to generate the cloud, cloud shadow element and the clean element. The cloud and cloud shadow element is purified to get the cloud area while the clean area of the original cloud-

 DOI : 10.35291/2454-9150.2022.0033 

contaminated images is replaced to the corresponding area of the clean element. Finally the reference image is selected to reconstruct details of the cloud area and cloud shadow area.

Paper[41] proposed end to end thin cloud removal technique RSC-Net (deep residual symmetrical concatenation network).RSC-Net consist of multiple convolution layers and residual deconvolution layers. RSC-Net is trained with cloudy images as input and it produces directly cloud free images.

Based on temporal technique, along with cloud free as reference image [42] uses two auxiliary images having same wavelength and close acquisition date to reference and target images. Temporal variability of land cover is captured from two auxiliary images through a modified spatiotemporal data fusion model. Poisson equation based residual correction strategy is used to strengthen spectral coherence between recovered and remaining regions.

In [43] a new cloud removal method called Auto regression to remove clouds(ARRC)is proposed to address the issues in images like partial cloud contamination, sometimes unavability of high quality cloud free reference images. ARRC considers autocoreelation of landsat time series data and employs multilayer landsat images along with cloud contaminated images for cloud removal.

Image denoising and image inpainting combination generates a method called Cloud Aware Generative Network (CAGN) for cloud removal proposed in [44].Recurrent convolution network is used in first stage of CAGN for potential cloud region detection and an autoencoder is used in second stage for cloud removal.

## IV. CONCLUSION

As a whole, results of cloud detection and removal can be exploited in many fields such as cartography, environment evaluation, shadow detection etc. Some techniques of cloud detection and removal from satellite imagery are discussed in this paper which gives basic idea about how different types of cloud and cloud shadow can be found out and remove in remote sensing images. Basic concept and methods of cloud removal is discussed in this paper. Based on literature review it is recommended that methods for cloud detection and removal using artificial neural network, deep learning are more efficient and reduce the constraints of traditional methods.

## REFERENCES

[1] KM Cooper, SJ Goldstein, KWW Sims, MT Murrell (2003), “Uranium- series chronology of Gorda Ridge volcanism: new evidence from the 1996 eruption”, Earth Planet Science Letter, vol.206, pp 459–475.

[2] X Wu, Z Shi (2018), “Utilizing multilevel features for cloud detection on satellite imagery”, Remote Sensing,vol. 10, no.11.

[3] F Xie, M Shi, Z Shi, J Yin(2017), “Multilevel Cloud Detection in Remote Sensing Images Based on Deep Learning”, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 10, no. 8, pp 3631 – 3640.

[4] L Xu, S Fang, R Niub, J Li (2012), “Cloud detection based on decision tree over tibetan plateau with modis data”, International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences ,vol. 39-B8, pp 535-538 .

[5] X Song, Y Zhao, Z Liu (2004), “Cloud detection and analysis of MODIS image”, IEEE international geoscience and remote sensing symposium, Anchorage, pp 2764-2767.

[6] CE Bulgin, JPD Mittaz, O Embury, S Eastwood, CJ Merchant (2018), “Bayesian cloud detection for 37 years of advanced very high resolution radiometer (AVHRR) global area coverage (GAC) data”, MDPI Remote sensing, vol. 10, no. 1.

[7] W Huang ,Y Wang, X Chen (2018), “Cloud detection for high resolution remote sensing images of urban areas using colour and edge features based on dual colour models” ,International Journal on Remote Sensing, vol.39, no. 1, pp 6657–6675.

[8] K Prinsa, E Saritha(2018), “Detection and Removal of Clouds on Remote Sensing Images”,4th International Conference for Convergence in Technology,Mangalore India.

[9] H Ishida, Y Oishi, K Morita, K Moriwaki, TY Nakajima(2018), “Development of a support vector machine based cloud detection method for MODIS with the adjustability to various conditions”, Remote Sensing of Environment, vol. 205, pp 390–407.

[10] J Yang, Q Min, W Lu, Y Ma, W Yao, T Lu, J Du, G Liu (2017), “A total sky cloud detection method using real clear sky background”, Atmospheric Measurement Techniques, vol.9, no.2, pp 587–597.

[11] K Tan, Y Zhang, X Tong (2018), “Cloud extraction from Chinese high resolution satellite imagery by probabilistic latent semantic analysis and object-based machine learning”, MDPI Remote sensing, vol.8, no.11

[12] D Frantz, E Ha, A Uhl, J Stoffels , J Hill (2018), “Improvement of the Fmask algorithm for Sentinel-2 images: separating clouds from bright surfaces based on parallax effects”, Remote Sensing Environment, vol. 215, pp 471–481.

[13] Y Changhui, Y Yuanb, M Minjing, Z Menglu, (2018), “Cloud detection method based on feature extraction in remote sensing images”, International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences ,vol. 40-2/W1, pp 173-177 .

[14] M S Rozenhaimer, A Li, K Das, V Chirayath(2020), “Cloud detection algorithm for multi-modal satellite imagery using convolutional neural-networks (CNN)”, Remote Sensing of Environment, vol. 237, 111446.

[15] C Li, J Ma, P Yang, Z Li (2019), “Detection of cloud cover using dynamic thresholds and radiative transfer models from the polarization satellite image”, Journal of Quantitative Spectroscopy and Radiative Transfer, vol.222-223, pp 196-214.

[16] L Sun, X Yang, S Jia, C Jia, Q Wang, X Liu, J Wei, X Zhou (2019), “Satellite data cloud detection using deep learning supported by hyperspectral data”, International Journal of Remote Sensing, vol.41, no.4, pp 1349-1371.

[17] R Gupta, P Panchal (2015) “Advancement of cloud detection algorithm in satellite images with application to color models”,

 DOI : 10.35291/2454-9150.2022.0033 

ISSN : 2454-9150 Vol-07, Issue-10, JAN 2022

International conference on computer communication and informatics (ICCCI), Coimbatore, India, 8–10 January 2015.

[18] Y Guo , X Cao , B Liu, M Gao(2020), "Cloud Detection for Satellite Imagery Using Attention-Based U-Net Convolutional Neural Network", MDPI Symmetry, vol.12, no.6.

[19] Z Yao, J Jia, Y Qian(2021), "MCNet: Multi-Scale feature extraction and Content-Aware reassembly cloud detection model for remote sensing images", MDPI Symmetry, vol.13, no.1.

[20] H Tan, C Hou, K Li(2020) "CDnetV2: CNN-Based cloud detection for remote sensing imagery with cloud-snow coexistence" , IEEE Transactions on Geoscience and remote sensing,vol.59, no.1,pp 700 - 713

[21] Chen Y, Fan RS, Bilal M, Yang X, Wang J, Li W (2018), "Multilevel cloud detection for high resolution remote sensing imagery using multiple convolutional neural networks", International Journal of Geo-Informatics, vol.7.

[22] C Deng , Z Li , W Wang, S Wang , L Tang, C Alan (2018), "Cloud detection in satellite images based on natural scene statistics and gabor features", IEEE Geoscience and Remote Sensing Letters, vol.16, no.4,pp 608–612.

[23] F Xie, M Shi, Z Shi, J Yin, D Zhao(2017), "Multilevel cloud detection in remote sensing images based on Deep Learning" , IEEE Journal of Applied earth observations and remote sensing,vol.10,no.8,pp 3631 – 3640.

[24] Y Li, W Chen, Y Zhang, C Tao, R Xiao, Y Tan (2020), "Accurate cloud detection in high-resolution remote sensing imagery by weakly supervised deep learning", Remote Sensing of Environment , vol. 250,112045.

[25] SR Surya, P Simon (2013), " Automatic cloud detection using spectral rationing and fuzzy clustering", 2nd International Conference on Advanced Computing, Networking and Security, Mangalore, India.

[26] JM Yeom, JL Roujean, KS Han, KS Lee, HW Kim(2020), "Thin cloud detection over land using background surface reflectance based on the BRDF model applied to Geostationary Ocean Color Imager (GOCI) satellite data sets", Remote Sensing of Environment, vol.239, 111610 .

[27] H Shen, X Li, Q Cheng, C Zeng, G Yang, H Li, L Zhang(2015), "Missing information reconstruction of remote sensing data:A technical review", *IEEE Geoscience Remote Sensing Magazine*, vol.3, no. 3, pp 61–85.

[28] C. Guillemot, O. L. Meur(2014), "Image inpainting: Overview and recent advances," *IEEE Signal Processing Magazine*, vol. 31, no. 1, pp. 127–144.

[29] A. Criminisi, P. Perez, and K. Toyama(2004), "Region filling and object removal by exemplar-based image inpainting," IEEE Transaction on Image Processing, vol. 13, no. 9, pp. 1200–1212.

[30] M Xu, X Jia, M Pickering, S Jia(2019), "Thin cloud removal from optical remote sensing images using the noise-adjusted principal components transform", ISPRS Journal of Photogrammratry and Remote Sensing, vol. 149,pp 215–225.

[31] Rakwatin, P., Takeuchi, W., Yasuoka, Y., (2009), "Restoration of Aqua MODIS band 6 using histogram matching and local least squares fitting",IEEE Transactions on Geoscience and Remote Sensing, 47 (2), pp 613–627.

[32] Salim Malek, Farid Melgani , Yakoub Bazi , Naif Alajlan (2017), "ReconstructingCloud-Contaminated Multispectral Images With Contextualized Autoencoder Neural Networks", IEEE Transactions on Geoscience and Remote Sensing.

[33] Chen, Y., He, W., Yokoya, N., Huang, T.(2019), "Blind cloud and cloud shadow removal of multitemporal images based on total variation regularized low-rank sparsity decomposition". ISPRS Journal of Photogrammetry and Remote Sensing 157, 93–107.

[34] M Xu, X Jia, M Pickering, AJ Plaza(2016), "Cloud removal based on spars representation via multitemporal dictionary learning", IEEE Transaction on Geoscience Remote Sensing vol. 54, no. 5, pp 2998–3006.

[35] G Gao, Y Gu(2017), "Multitemporal Landsat missing data recovery based on tempospectral angle model", IEEE Transanction on Geoscience Remote Sensing, vol. 55, no.7, pp 3656–3668.

[36] Q Zhang , Q Yuan , C Zeng, X Li , Y Wei(2018), "Missing Data Reconstruction in Remote Sensing Image With a Unified Spatial–Temporal–Spectral Deep Convolutional Neural Network", IEEE transactions on geoscience and remote sensing, vol. 56,Issue 8, pp 4274 – 4288.

[37] X Li, H Shen, L Zhang, H Zhang, Q Yuan, G Yang(2014), "Recovering quantitative remote sensing products contaminated by thick clouds and shadows using multitemporal dictionary learning", IEEE Transaction on Geoscience Remote Sensing, vol. 52, no.11, pp 7086–7098.

[38] Y Chen , L Tang , X Yang, R Fan, Md Bilal , Q Li (2020), "Thick Clouds Removal From Multitemporal ZY-3 Satellite Images Using Deep Learning", IEEE Journal of selected topics in Applied Earth Observations and Remote Sensing, vol. 13,pp 143-153.

[39] Q Zhang, Q Yuan, J Li, Z Li, H Shen, L Zhang(2020), "Thick cloud and cloud shadow removal in multitemporal imagery using progressively spatio-temporal patch group deep learning", ISPRS Journal of Photogrammetry and Remote Sensing , vol.162,pp 148–160.

[40] C Duan , J Pan , R Li(2020), "Thick Cloud Removal of Remote Sensing Images Using Temporal Smoothness and Sparsity-Regularized Tensor Optimization", vol.12, no.20.

[41] W Li, Y Li, Di Chen, J Chan (2019), "Thin cloud removal with residual symmetrical concatenation network", ISPRS Journal of Photogrammetry and Remote Sensing, vol. 153, pp 137-150.

[42] H Shen, J Wu, Q Cheng, M Aihemaiti, C Zhang, Z Li(2019), "A Spatiotemporal fusion based cloud removal method for remote sensing images with land cover changes", IEEE Journal of Applied Earth Observations and Remote Sensing, vol.12, no.3, pp 874-862.

[43] R Cao, Y Chen, J Chen, X Zhu, M Shen (2020),"Thick cloud removal in Landsat images based on autoregression of Landsattime-series data", Remote Sensing of Environment , vol.249.

[44] L Sun, Y Zhang, X Chang, Y Wang, J Xu (2020), "Cloud-Aware Generative Network: Removing Cloud from Optical Remote Sensing Images", IEEE Geoscience and Remote Sensing Letters, vol.4.

 DOI : 10.35291/2454-9150.2022.0033 