

An Efficient Image Processing Approach for Cloud Removal in Satellite Images

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Received: May 11, 2026 | Review began: June 09, 2026 | Review ended: August 12, 2026 | Published: September 01, 2026

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Abstract

Cloud cover can substantially restrict the information available in optical satellite images, affecting applications including agricultural monitoring, disaster assessment, and urban planning. Although deep-learning and multi-temporal techniques have improved cloud mitigation, they commonly depend on considerable computational resources, training data, or repeated observations. This study presents a classical image-processing framework for identifying cloud-covered regions and restoring the affected image areas. The proposed method uses CLAHE (Contrast Limited Adaptive Histogram Equalization)-based contrast enhancement, HSV (Hue, Saturation, Value)-based masking, connected component analysis, and a two-step inpainting algorithm. The proposed method is evaluated on the RICE dataset using mean squared error, root mean square error, peak signal-to-noise ratio, structural similarity index measure, accuracy, and area under the receiver operating characteristic curve. The resulting framework provided effective cloud detection while retaining a relatively lightweight computational requirement. Although the reconstruction quality remains lower than that of recent deep-learning approaches, the method provides an efficient baseline for resource-constrained environments where computational efficiency is prioritized.

Categories: Image Processing and Analysis, Computer Vision, Data Analysis

Keywords: cloud removal, remote sensing, image processing, clahe, inpainting

Introduction

Optical satellite imagery provides large-area and timely observations of the Earth's surface and is therefore used in applications such as meteorology, agriculture, forest monitoring, disaster assessment, and urban planning [1]. A major limitation of optical remote sensing is cloud contamination, which can conceal surface features and consequently reduce the usefulness of acquired imagery [1].

Various strategies have been investigated to mitigate cloud contamination in satellite images. Synthetic aperture radar (SAR)-optical fusion methods combine synthetic aperture radar and optical imagery to improve cloud-free reconstruction performance [2]. Multisource data-fusion techniques have also been investigated for remote-sensing applications, particularly in agricultural monitoring and classification tasks [3].

Multi-temporal approaches reconstruct cloud-affected regions by exploiting imagery of the same area acquired at different times [4]. Their effectiveness, however, depends on repeated observations of the target region, which can increase data-acquisition demands, storage requirements, and operational complexity.

How to cite this article:

Ghorpade-Aher J, Pagare R, Shenolkar M (September 01, 2026) An Efficient Image Processing Approach for Cloud Removal in Satellite Images. Cureus J Comput Sci 3 : es44389-026-00253-1. DOI <https://doi.org/10.7759/s44389-026-00253-1>

Recent review studies have highlighted the growing use of deep-learning-based cloud-removal techniques, including generative adversarial networks (GANs), convolutional neural networks (CNNs), attention mechanisms, and cloud-matting approaches [5]. Advanced architectures, such as GLTF-Net, have demonstrated strong reconstruction capability for thick cloud removal [6], while sparse Transformer-based GAN models have shown promising results for thin-cloud reconstruction [7]. Lightweight machine-learning approaches have also been explored to reduce computational complexity while maintaining acceptable performance [8].

The RICE (Remote Sensing Images for Cloud Removal) dataset has become a widely used benchmark for evaluating cloud-removal algorithms and enabling fair performance comparison across different approaches [9]. In addition, SAR-optical fusion surveys [10], spatiotemporal interactive learning frameworks [11], spatial-frequency Transformer models [12], diffusion-based cloud-removal methods [13], and multimodal sequential learning architectures [14] have further advanced the state of the art in cloud-removal research.

Despite these developments, many existing methods depend on substantial training data, computational resources, specialized hardware, or observations acquired at multiple time points. This creates a need for a lightweight single-image approach that can perform cloud removal without extensive training data, specialized hardware, or repeated satellite acquisitions. Accordingly, this study proposes a classical image-processing-based cloud-removal framework that combines contrast enhancement, HSV (Hue, Saturation, Value)-based cloud detection, connected-component refinement, and two-stage inpainting for restoring cloud-covered regions.

Need for the study

Reliable interpretation of satellite observations benefits from unobstructed surface information; however, obtaining cloud-free imagery is difficult for several reasons:

- a) Weather conditions are naturally uncontrollable and frequently introduce cloud contamination.
- b) Deep learning-based approaches generally require powerful computational resources and large quantities of annotated training data [5].
- c) Multi-temporal approaches rely on repeated satellite acquisitions, increasing operational complexity and processing requirements [4,11,14].

These constraints motivate a computationally efficient and dataset-independent cloud-removal method suitable for resource-constrained or near-real-time applications.

Significance of the study

Within national applications, reliable cloud-free satellite observations support crop monitoring, food-security planning, flood assessment, disaster management, forest-resource monitoring, urban development, and surveillance activities. Reliable satellite observations enable authorities to make timely decisions and improve resource management.

At the global scale, cloud-free satellite data contribute to climate studies, ecosystem observation, environmental assessment, and coordinated disaster response. Satellite-based forest monitoring has become an important tool for detecting and quantifying deforestation worldwide, thereby supporting international conservation initiatives and environmental policy implementation. Furthermore, cloud-free observations improve the accuracy of large-scale geospatial analyses and enhance the effectiveness of humanitarian and disaster-relief operations across regions [5].

Research objectives

- a) To design a computationally efficient cloud detection and removal framework using classical image-processing techniques.
- b) To generate cloud masks using HSV thresholding and refine them through connected component analysis.
- c) To apply a two-stage inpainting strategy for smooth reconstruction of cloud-covered regions.
- d) To evaluate the performance of the proposed method using standard image-quality and classification metrics.

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Materials And Methods

Literature survey

Table 1 summarizes previously reported cloud-removal approaches for satellite imagery. The comparison covers deep-learning, data-fusion, and classical image-processing techniques together with their reported advantages, limitations, and associated challenges. The challenges identified in existing studies emphasize the need for simpler and more efficient approaches.

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Ghorpade-Aher J, Pagare R, Shenolkar M (September 01, 2026) An Efficient Image Processing Approach for Cloud Removal in Satellite Images. Cureus J Comput Sci 3 : es44389-026-00253-1. DOI <https://doi.org/10.7759/s44389-026-00253-1>

No.	Paper	Year	Techniques/Algorithms	Significance (Pros/Cons)	Challenges
1	Cloud Removal in Satellite Images Using Spatiotemporal Generative Networks [1]	2020	cGAN with spatiotemporal generator (U-Net/ResNet); L1 + GAN loss	Outperforms Pix2Pix; strong PSNR/SSIM ($\approx 26.19/0.734$)	Needs paired temporal data; limited generalization
2	Efficient Cloud Removal Network Using SAR-Optical Fusion (FPNet), IEEE GRSL [2]	2024	Dual ResNet-18 encoders + feature pyramid fusion	High efficiency (96 FPS), scalable for large areas	Still modality gap between SAR and optical; heavy preprocessing
3	Cloud Removal with Multisource Data Fusion for Agriculture, IEEE WIECON-ECE [3]	2023	Nearest-neighbor fusion + Feedforward NN classifier	Improves classification vs pure MODIS	Limited to agricultural workflow; resolution mismatch
4	Removal of Clouds Using Time Compositing, ISRO Report [4]	2024	Min/Max/Hybrid compositing + NDVI slicing	Hybrid approach preserves texture; simple method	Fails in persistent cloud cover; only qualitative
5	Cloud Removal from Satellite Images Using Deep Learning (Review, Remote Sensing) [5]	2023	GANs, CNNs, Attention, Low-rank models	Provides taxonomy, baselines, metrics	No implementation; highlights complexity of real data
6	GLTF-Net (Deep Learning Network for Thick Cloud Removal) [6]	2023	CNN + Transformer hybrid; Global–Local fusion	Strong for thick cloud occlusions; high PSNR/SSIM gains	Heavy model, GPU intensive; requires temporal sequences
7	SpT-GAN: Thin Cloud Removal with Sparse Transformer [7]	2024	GAN + Sparse Transformer + Fourier blocks	Excellent for thin/veil clouds; high PSNR (36.19)	Computationally expensive; struggles on thick clouds
8	A Lightweight ML Method for Cloud Removal in Remote Sensing Images [8]	2024	Lightweight MLP with conditional constraints	Fast training; baseline comparison	Weak detail recovery; limited to simple cases

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9	RICE Dataset (Benchmark) [9]	2020	Public dataset	Enables fair benchmarking	Limited variety of cloud/terrain; small dataset
10	Cloud Removal with SAR-Optical Data Fusion and Graph-Based. [10]	2022	cGAN, CNNs, Hybrid, Taxonomy	Comprehensive survey of SAR fusion	Fusion complexity; modality mismatch
11	Spatiotemporal Interactive Learning for Cloud Removal [11]	2025	cGAN with spatiotemporal interaction modules	Ensures temporal consistency in declouded sequences	Requires co-registered SAR-optical; heavy computation
12	Spatial Frequency combined transformer for cloud removal of optical remote sensing images [12]	2025	Spatial-Frequency Transformer	Tackles blur/colour distortion; preserves edges	Transformer overhead; requires fine-tuning
13	DMDiff: A Dual-Branch Multimodal Conditional Guided Diffusion Model for Cloud Removal Through SAR-Optical Data Fusion [13]	2025	Diffusion model with dual branch + IAP	Promising alternative to GANs; robust	High training cost; complex architecture
14	U-SeqNet [14]	2024	U-shaped sequential deep network	Maintains sequence consistency	Limited adaptability; large dataset need

TABLE 1: Summary of Cloud Removal Approaches

cGAN, Conditional Generative Adversarial Network; CNN, Convolutional Neural Network; FPS, Frames Per Second; GAN, Generative Adversarial Network; GPU, Graphics Processing Unit; IAP, Image Adaptive Prior; MLP, Multilayer Perceptron; MODIS, Moderate Resolution Imaging Spectroradiometer; NDVI, Normalized Difference Vegetation Index; NN, Neural Network; PSNR, Peak Signal-to-Noise Ratio; RICE, Remote Sensing Images for Cloud Removal; SAR, Synthetic Aperture Radar; SSIM, Structural Similarity Index Measure

Research Gap

Recent cloud-removal studies predominantly employ learning-based architectures, including GANs, Transformer models, diffusion models, and multimodal SAR-optical fusion frameworks [1,2,6,7,10,13]. While such methods can provide high reconstruction quality, their deployment commonly involves substantial training data, computational demand, and, in many cases, graphics processing unit (GPU)-based hardware [5,6,12].

Multi-temporal methods additionally exploit information from repeated observations of the same geographic region and have shown promising reconstruction performance [4,11,14]. However, these methods depend on the availability of multiple cloud-free acquisitions, increasing data acquisition time, storage requirements, and operational complexity.

Consequently, there remains a need for a lightweight, computationally efficient, and single-image cloud-removal framework that can operate without deep learning, large training datasets, or multi-temporal observations. The present study addresses this gap by proposing a classical image-processing-based cloud-removal methodology that combines CLAHE (Contrast-Limited Adaptive Histogram Equalization)-based enhancement, HSV-based cloud detection, connected-component refinement, and two-stage inpainting for efficient cloud restoration.

Research methodology

The framework is implemented through four sequential stages: enhancement of the input image, generation of the cloud mask, refinement of the mask, and restoration of the affected regions.

Image Enhancement

Variations in illumination and atmospheric scattering can result in reduced contrast in satellite imagery. CLAHE is consequently applied to enhance local contrast while limiting excessive noise amplification. The enhancement process was performed using a clip limit of 2.0 and a tile-grid size of 8×8 . CLAHE operates on small image regions and enhances cloud visibility without affecting the overall image structure. These parameter values were selected based on commonly adopted settings in OpenCV implementations and preliminary experiments, providing improved local contrast while avoiding excessive noise amplification.

Cloud Mask Generation

The enhanced image is converted from the RGB color space to the HSV color space. In the HSV representation, cloud regions are generally associated with high brightness and comparatively low saturation. Using these characteristics, pixels meeting the fixed conditions $S < 60$ and $V > 180$ were labelled as cloud pixels. Pixels satisfying the cloud criteria are assigned to the foreground, while the remaining pixels are classified as background. The HSV thresholds were selected empirically after preliminary experiments on representative images from the RICE dataset. Multiple threshold combinations were examined during preliminary visual evaluation, and the selected thresholds provided a practical balance between cloud detection and false-positive reduction across the tested scenes. Although the thresholds were not optimized using an automated search procedure, they were kept fixed throughout all experiments to ensure consistent evaluation. Future work will investigate adaptive threshold selection methods.

Connected Component Refinement

Small isolated regions can remain in the initial mask because of bright land surfaces or image noise. Connected-component analysis is then used to identify spatially connected cloud regions. Components with areas below 50 pixels are discarded to suppress noise and reduce false cloud detections.

Two-Stage Inpainting

The refined cloud mask is first subjected to morphological dilation using a 5×5 structuring element to cover cloud boundaries completely. Subsequently, Telea inpainting is performed using an inpainting radius of 3 pixels to reconstruct cloud-covered regions by propagating information from surrounding pixels. Finally, bilateral filtering is applied with $d = 9$, $\text{sigmaColor} = 75$, and $\text{sigmaSpace} = 75$ to reduce reconstruction artifacts while preserving important image edges and textures.

The overall workflow consists of CLAHE enhancement, HSV-based cloud detection, connected-component refinement, Telea inpainting, and bilateral-filter-based post-processing for cloud-free image reconstruction.

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Evaluation metrics

Peak signal-to-noise ratio (PSNR): PSNR quantifies the reconstruction fidelity of the restored image relative to its corresponding ground-truth image. A larger PSNR value indicates lower reconstruction error and greater similarity to the reference image.

$$\text{PSNR} = 10 \log_{10} \left(\frac{\text{MAX}_I^2}{\text{MSE}} \right) \quad (1)$$

$$\text{MSE} = \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n (I(i, j) - \hat{I}(i, j))^2 \quad (2)$$

Here:

- a) $() \rightarrow$ the maximum possible pixel value (255 for 8-bit images).
- b) MSE $\rightarrow$ mean squared error between original and reconstructed images.
- c) $I(i, j) \rightarrow$ pixel value of the original (ground-truth) image.
- d) $\hat{I}(i, j) \rightarrow$ pixel value of the reconstructed image.
- e) $m, n \rightarrow$ image height and width (total pixels = $m \times n$).
- f) $I \rightarrow$ ground truth image.
- g) $\hat{I} \rightarrow$ reconstructed image.

Structural similarity index measure (SSIM): SSIM evaluates image similarity by considering luminance, contrast, and structural characteristics. The SSIM value ranges from -1 to 1 , with values approaching 1 representing stronger structural agreement.

$$\text{SSIM}(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (3)$$

where

- a) $\mu \rightarrow$ mean (average brightness).
- b) $\sigma^2 \rightarrow$ variance (contrast).
- c) $\sigma \rightarrow$ covariance (structural similarity).
- d) $C_1, C_2 \rightarrow$ small constants to stabilize the calculation.

Accuracy: Accuracy measures the proportion of correctly classified pixels (cloud vs. non-cloud).

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (4)$$

where

- a) TP = true positive.
- b) TN = true negative.
- c) FP = false positive.
- d) FN = false negative.

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ROC curve (receiver operating characteristic curve): ROC analysis assesses cloud-classification performance as the decision threshold varies by plotting:

- True positive rate (TPR) on the Y-axis.
- False positive rate (FPR) on the X-axis.

$$\text{TPR} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \quad (5)$$

$$\text{FPR} = \frac{\text{FP}}{(\text{FP} + \text{TN})} \quad (6)$$

The key metric derived from the ROC curve is area under the ROC curve (AUC).

- AUC = 1 → perfect classifier.
- AUC = 0.5 → random guessing.

A higher AUC means the model can better distinguish clouds from non-cloud regions.

Challenges

- a) Thin clouds in the satellite images that resemble terrain brightness.
- b) Preserving natural texture in the image after reconstruction.
- c) Avoiding over-smoothing in the images.

Experimental setup

All experiments were conducted using Python 3.11 with OpenCV, NumPy, Scikit-image, and Matplotlib libraries. The proposed framework was evaluated using the publicly available RICE dataset, which contains paired cloudy and cloud-free satellite images.

The evaluation included 500 image pairs, with each image processed independently and without a model-training or prior-learning stage. The processing pipeline consisted of CLAHE-based image enhancement, HSV-based cloud-mask generation, connected-component refinement, Telea inpainting, and bilateral filtering.

The CLAHE parameters were fixed with a clip limit of 2.0 and a tile-grid size of 8×8 . Cloud pixels were detected using HSV thresholds of $S < 60$ and $V > 180$. Connected components smaller than 50 pixels were removed to reduce false cloud detections. Morphological dilation was performed using a 5×5 structuring element before Telea inpainting with an inpainting radius of 3 pixels. Finally, bilateral filtering was applied using $d = 9$, $\text{sigmaColor} = 75$, and $\text{sigmaSpace} = 75$ to reduce reconstruction artifacts while preserving edge information.

Quantitative evaluation was performed using MSE, root mean square error (RMSE), PSNR, SSIM, accuracy, precision, recall, F1-score, and AUC. All metrics were calculated by comparing reconstructed images with their corresponding cloud-free reference images.

The experiments were conducted on an Intel Core i5 processor with 8 GB RAM running Windows 11 and Python 3.11.

Results And Discussion

Experimental results

Performance Analysis

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Table 2 presents the evaluation metrics such as accuracy, MSE, and RMSE for each step of the cloud removal process. Figure 1 shows the performance analysis of processing steps for cloud removal.

Methods	Accuracy	MSE	RMSE
Brightness + Saturation Mask	0.935	0.065	0.255
CLAHE + HSV Mask	0.947	0.053	0.230
Component Refinement	0.958	0.042	0.205
Final Two-Stage Inpainting	0.970	0.030	0.173

TABLE 2: Performance Analysis

CLAHE, Contrast-Limited Adaptive Histogram Equalization; HSV, Hue, Saturation, Value; MSE, Mean Square Error; RMSE, Root Mean Square Error

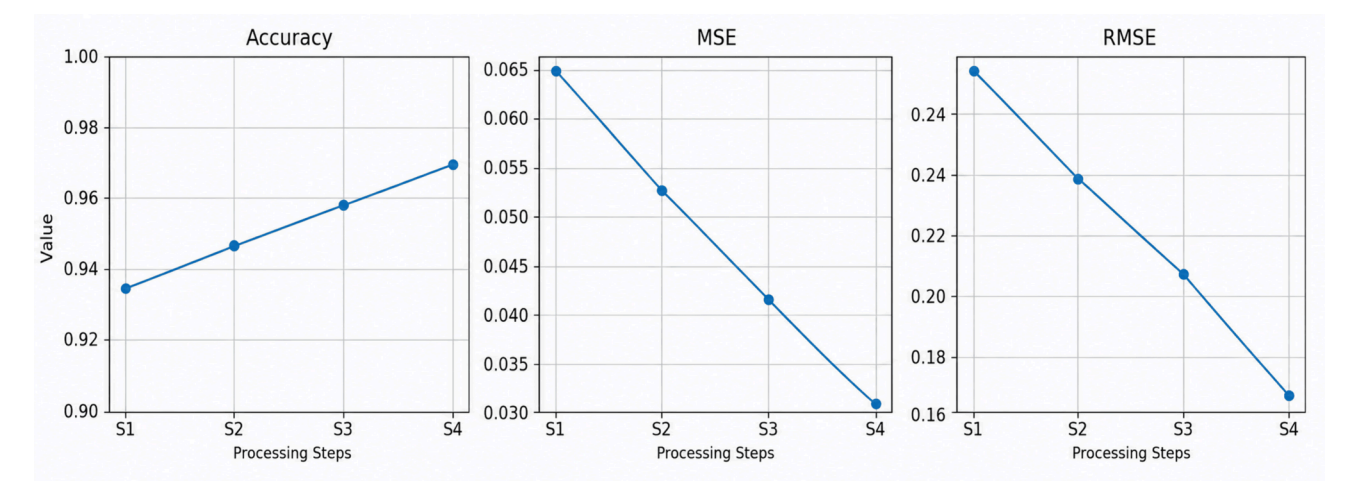


FIGURE 1: Performance Analysis of Processing Steps for Cloud Removal

CLAHE, Contrast-Limited Adaptive Histogram Equalization; HSV, Hue, Saturation, Value; MSE, Mean Square Error; RMSE, Root Mean Square Error

Accuracy increases progressively across the processing stages, resulting in progressively cleaner reconstructed outputs. The final stage produced the best result among the evaluated stages, indicating that the combined processing operations contribute to improved cloud detection and image restoration. S1: Brightness + Saturation Mask, S2: CLAHE + HSV Mask, S3: Component Refinement, S4: Final Two-Stage Inpainting

Evaluation Results

Table 3 shows the values of MSE, PSNR, SSIM, and accuracy obtained for the proposed cloud-removal framework using the RICE dataset. These metrics were computed by comparing the reconstructed images with the corresponding cloud-free reference images.

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Evaluation Metrics	Scores
MSE	401.79
PSNR	12.54
SSIM	0.7471
Accuracy	0.8124

TABLE 3: Evaluation Metrics of the Proposed Method
MSE, Mean Square Error; PSNR, Peak Signal-to-Noise Ratio; SSIM, Structural Similarity Index Measure

The accuracy values in Tables 2 and 3 correspond to different evaluation stages and should therefore not be interpreted as directly comparable. Table 2 reports pixel-level accuracy during successive mask-generation and refinement stages, whereas Table 3 represents the final reconstruction result obtained after restoration against the corresponding ground-truth images. The difference in evaluation objectives accounts for the different accuracy values.

Visual examination of the reconstructed images further indicated substantial removal of cloud-covered areas while retaining the overall scene structure. The reconstruction was more effective for thin and moderately sized clouds than for large, dense cloud regions, where texture recovery remained challenging because of the inherent limitations of exemplar-based inpainting.

The ROC curve generated for the proposed approach is presented in Figure 2. The obtained AUC value demonstrates the effectiveness of the proposed method in distinguishing cloud pixels from non-cloud pixels.

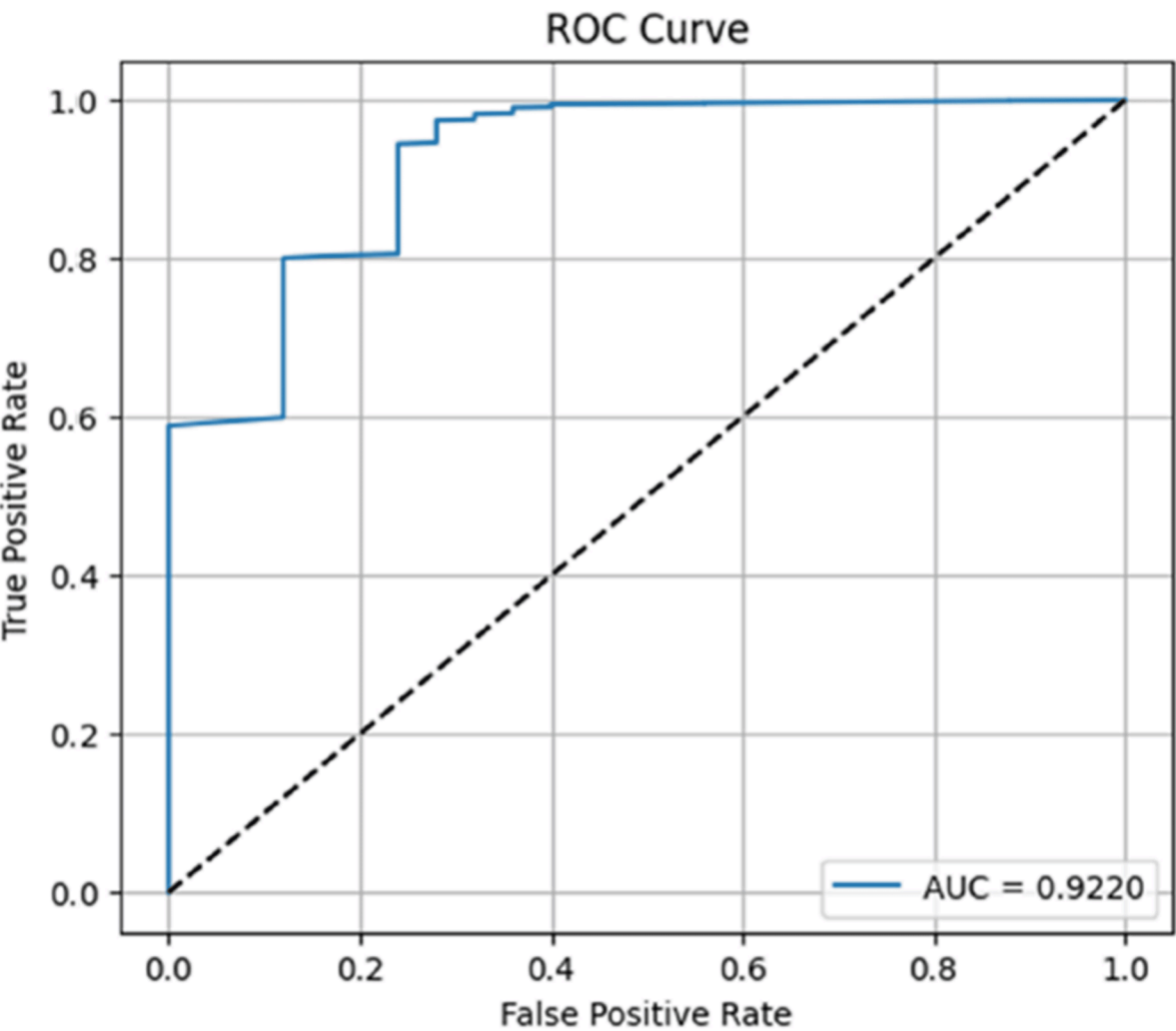


FIGURE 2: ROC curve for cloud detection performance
AUC, Area Under the ROC Curve; ROC, Receiver Operating Characteristic

The ROC analysis produced an AUC of 0.922, indicating good discrimination between cloud and non-cloud pixels. This result indicates that the framework can separate cloud-covered and non-cloud regions with a relatively low false-positive rate.

Table 4 compares the strengths and limitations of deep CNNs, multi-temporal methods, and the proposed method.

Method	Strength	Weakness
Deep CNNs	High accuracy	Requires GPU + large datasets
Multi-temporal	Very precise	Needs multiple captures
Proposed Method	Lightweight, fast, hardware-friendly	Difficulty with thin clouds

TABLE 4: Comparative Analysis

CNN, Convolutional Neural Network; GPU, Graphics Processing Unit

The comparison highlights a trade-off between the computational efficiency of the proposed method and its reconstruction quality. In contrast to deep-learning approaches, the framework requires neither model training nor GPU hardware or large annotated datasets, which supports its use in computationally constrained settings. However, this computational simplicity comes at the cost of lower reconstruction quality compared with recent Transformer-, GAN-, and diffusion-based cloud-removal methods.

Designs

Architecture Diagram

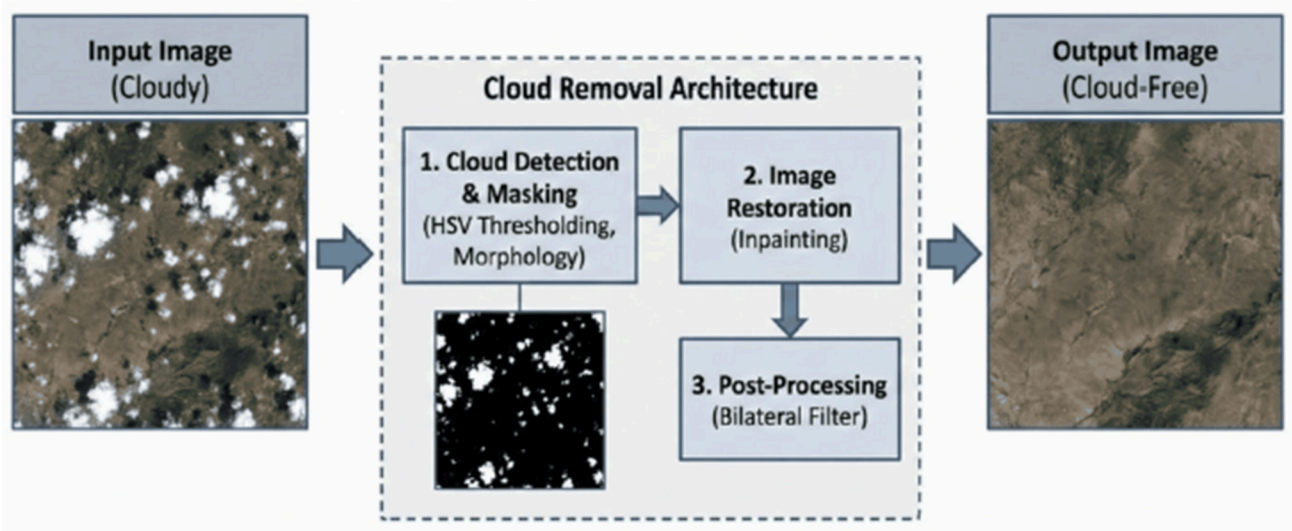


FIGURE 3: Architecture of the Proposed Cloud Removal Framework

HSV, Hue, Saturation, Value

Figure 3 illustrates the architecture of the proposed cloud removal framework, which consists of three main components.

1) Input Image (Cloudy): On the left side of the diagram, there is a cloud image which is given as input, and it is an example of a satellite image showing a landscape that is covered by numerous small, white clouds and their shadows.

2) Cloud Removal Architecture: This box contains the process broken down into three sequential steps.

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- a) Cloud Detection & Masking: The image in this block is a binary mask where the area corresponding to the clouds in the input image is white, and everything else is black. It detects the clouds.
 - b) Image Restoration: In this part of the process, inpainting is conducted with the image given as input.
 - c) Post-Processing: A bilateral filter is applied to the reconstructed image to reduce artifacts while preserving edge information.
- 3) Output Image (Cloud-Free): The image on the right side of the diagram is the final image where the clouds are removed and the clear ground-earth satellite image is generated.

Discussion

The experimental findings indicate that the proposed classical image-processing framework provides a useful balance between cloud-detection capability and computational efficiency. An AUC of 0.922 was obtained, indicating effective separation of cloud and non-cloud pixels. However, the restoration results remain limited in terms of reconstruction fidelity, with a PSNR of 12.54 dB and an SSIM of 0.7471. These values indicate that although the restored images preserve a moderate level of structural information, they are not comparable to state-of-the-art deep learning approaches, which typically achieve substantially higher reconstruction quality.

The relatively low PSNR is primarily associated with the limitations of exemplar-based inpainting. When cloud-covered regions contain extensive missing areas, reconstruction relies on information from neighboring pixels, which may be insufficient for recovering complex textures and fine surface details. Accordingly, the framework is more appropriate for lightweight cloud detection and approximate restoration than for high-fidelity reconstruction.

Nevertheless, unlike deep learning methods that require GPUs, large annotated datasets, and extensive training time, the proposed method operates on a single image using only classical image-processing techniques. This makes it suitable for lightweight and resource-constrained environments where computational efficiency is a primary requirement.

Several limitations should be considered. The evaluation was conducted only on the RICE dataset, so generalization to other satellite datasets remains to be established. In addition, an ablation study was not conducted to isolate the contribution of individual processing stages. The selected parameter values were determined empirically rather than through systematic optimization. Finally, comparisons with recent deep-learning methods were based on reported literature results rather than direct experimental benchmarking.

Relative to recently reported deep-learning approaches, the proposed framework has lower computational requirements and operates without model training or GPU hardware. However, this computational advantage comes at the expense of reconstruction quality, where modern Transformer-, GAN-, and diffusion-based methods generally report considerably higher PSNR and SSIM values. The method is therefore intended primarily for lightweight applications in which computational efficiency is prioritized over reconstruction fidelity.

Conclusions

This study introduced a lightweight cloud-removal framework implemented entirely with classical image-processing operations, including CLAHE enhancement, HSV-based cloud masking, connected-component refinement, and two-stage inpainting. The framework achieved an AUC of 0.922 for cloud detection without relying on deep-learning models or multi-temporal satellite observations. However, the quantitative evaluation also demonstrates that the reconstruction quality remains limited, as reflected by the relatively low PSNR (12.54 dB) and moderate SSIM (0.7471). Accordingly, the method is best regarded as a computationally efficient baseline rather than as a substitute for contemporary deep-learning cloud-removal techniques.

Future work will focus on improving image reconstruction quality through adaptive parameter optimization, lightweight learning-based refinement, and hybrid image-processing and deep-learning approaches while preserving low computational complexity.

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Ghorpade-Aher J, Pagare R, Shenolkar M (September 01, 2026) An Efficient Image Processing Approach for Cloud Removal in Satellite Images. Cureus J Comput Sci 3 : es44389-026-00253-1. DOI <https://doi.org/10.7759/s44389-026-00253-1>

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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Drafting of the manuscript: Rasika Pagare, Madhura Shenolkar

Critical review of the manuscript for important intellectual content: Rasika Pagare, Jayshree Ghorpade-Aher, Madhura Shenolkar

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Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Data Availability Statements

The data (and/or code) supporting this study are openly available in the Kaggle repository "RICE (Remote Sensing Images for Cloud Removal)" at <https://www.kaggle.com/datasets/shubhank001/rice-remote-sensing-images-for-cloud-removal>.

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How to cite this article:

Ghorpade-Aher J, Pagare R, Shenolkar M (September 01, 2026) An Efficient Image Processing Approach for Cloud Removal in Satellite Images. Cureus J Comput Sci 3 : es44389-026-00253-1. DOI <https://doi.org/10.7759/s44389-026-00253-1>

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How to cite this article:

Ghorpade-Aher J, Pagare R, Shenolkar M (September 01, 2026) An Efficient Image Processing Approach for Cloud Removal in Satellite Images. Cureus J Comput Sci 3 : es44389-026-00253-1. DOI <https://doi.org/10.7759/s44389-026-00253-1>