Advanced Techniques for Cloud Obstruction Reconstruction in Satellite Imagery: Exploring GANs, Diffusion Models, and Alternative Approaches

Shanika Edirisinghe[a]

[a]Technological University Dublin
ORCID (Shanika Edirisinghe): https://orcid.org/0009-0007-7781-0465

1 Introduction and Motivation

Various application domains within Earth observation, including environmental monitoring, urban development, and disaster management, rely heavily on satellite imagery. However, persistent cloud cover in many regions of the Earth often obstructs time-sensitive and high-resolution analyses [11].

To address the limitations caused by cloud cover, cloud detection and removal have been studied for decades [3]. Widely used approaches include classic image processing methods such as interpolation to reconstruct missing data [9] and thresholding based on spectral reflectance to identify cloud-affected pixels [13]. Nonetheless, the traditional approaches often suffer from poor generalization across varying atmospheric and surface conditions. These methods are typically sensitive to noise, require manual tuning, and struggle with complex scenarios involving shadows, bright surfaces (like snow or concrete) limiting their scalability, adaptability, and robustness [12].

Recent developments in machine learning have led to significant improvements in addressing the challenges of cloud removal [14]. Early-stage models based on Support Vector Regression (SVR) and random forests have indicated potential in reconstructing cloud-free images by utilizing historical and multitemporal data (images of the same place taken at different times) [10]. Models such as Convolutional Neural Networks (CNNs) have significantly improved detection performance by learning from large labeled datasets and incorporating contextual information (information from nearby pixels and surrounding areas)[8]. Despite significant progress, these approaches continue to face challenges in generalizing across different satellite sensors, varying atmospheric conditions, and complex surface conditions [4]. Furthermore, reconstruction of regions covered by thick clouds remains challenging due to the significant occlusion of crucial surface features [1].

This highlights a pressing need for reliable reconstruction techniques to retrieve missing information accurately. Generative Deep learning models, such as Generative Adversarial Networks (GANs) and diffusion models, have demonstrated promising capabilities by learning complex patterns from comprehensive datasets [2, 14].

This research will build upon existing cloud detection techniques, integrating them with advanced scene reconstruction methods such as GANs, diffusion models, and other emerging approaches, to enhance the quality of reconstruction in cloud-covered regions. The fundamental research question guiding this work is: **How can deep generative models be effectively employed to reconstruct cloud-obstructed satellite scenes across varying cloud conditions and sensor types?**

2 Research Objectives

The primary objective of this research is to develop a model that combines cloud detection and advanced scene reconstruction techniques to enhance the quality of satellite imagery in cloud-obstructed regions. This framework will leverage state-of-the-art generative models, including GANs, diffusion models, and other emerging techniques. To support this goal, the research aims to:

- Evaluate and compare the reconstruction capabilities of GANs and diffusion models following accurate cloud detection.
- Investigate the potential of alternative generative techniques, such as Conditional Variational Autoencoders (CVAEs) and attention-based models, in improving both detection and reconstruction tasks.
- To establish an evaluation framework for assessing the performance of generative models in reconstructing cloud-covered scenes.

3 Proposed Methodology

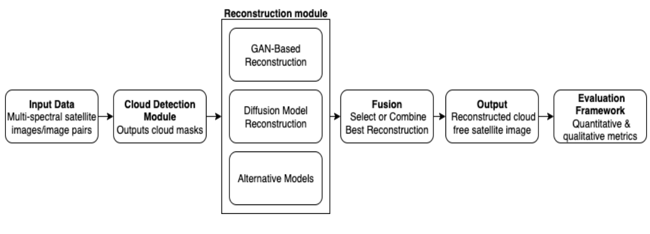

Figure 1. Flowchart for the proposed methodology.

This research follows a multi-stage methodology to address cloud-covered satellite image reconstruction as presented below. A flow chart of the proposed methodology is shown in Figure 1.

Stage 1- Literature Review and Problem Scoping: The project will conduct an extensive review of existing work on cloud detection techniques in remote sensing, reproduce state-of-the-art generative models and alternative methods to identify gaps in current approaches, and define the scope and design principles of the proposed integrated framework.

Stage 2 - Baseline Model Development and Comparison: The project will acquire multi-spectral satellite images and preprocess the datasets to align and standardize image formats and metadata. A GAN-based reconstruction model will then be developed in which the generator reconstructs cloud-obstructed regions and the discriminator ensures the realism of the reconstructed scenes, with training performed on paired cloud-free and cloud-covered samples using loss functions tailored to perceptual similarity and content consistency. In parallel, a diffusion model will be designed to iteratively refine images, with or without auxiliary information such as cloud masks, and variations in noise schedules, sampling steps, and conditioning strategies will be explored to optimize performance. Finally, the GAN and diffusion models will be compared using both qualitative visual inspection and quantitative metrics.

Stage 3 - Analysis of Model Limitations: Experiments will be conducted to assess how model performance varies across different cloud types as well as geographic and seasonal variations, and the study will identify failure modes, generalization challenges, and reconstruction artefacts.

Stage 4 - Integration of Alternative Generative Models: The project will explore the potential of CVAEs and attention-based models to accurately reconstruct cloud-covered scenes as an alternative to traditional generative approaches. If these architectures are found to be effective, they will be integrated into the framework to improve accuracy and robustness.

Stage 5 - Model Evaluation and Benchmarking Framework: Cloud masks will be applied to focus evaluation on cloud-obstructed areas and assess reconstruction quality using existing metrics. The reconstruction quality of the developed model will then be evaluated with standard metrics and its performance compared with that of baseline models. Finally, a comprehensive evaluation framework integrating both quantitative and qualitative metrics will be established.

4 Work Done So Far

The Figure 2 below illustrates the progress of the research work to date. Currently, the project is approximately halfway through stage 3, while stages 4 and 5 have not yet been initiated.

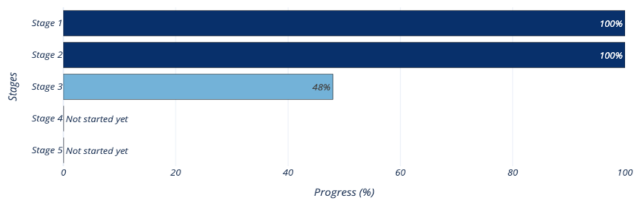

Figure 2. Progress of the Research Work.

Stage 1 - Literature Review and Problem Scoping ✓

A comprehensive review of cloud obstruction removal methods in satellite imagery, including GANs, diffusion models, and alternative approaches, was conducted; state-of-the-art generative models were reproduced, key research gaps were identified, and the design scope of a proposed integrated reconstruction framework was defined. Preliminary findings were disseminated via a research poster presented at the Faculty of Computing, Digital and Data Teaching and Research Showcase 2024, highlighting a GAN-based cloud removal experiment, and a review article titled "Generative models for cloud removal in satellite imagery" was submitted to the ISPRS Open Journal of Photogrammetry and Remote Sensing, where the manuscript is currently under peer review.

Stage 2: Baseline Model Development and Comparison ✓

GAN and diffusion-based models for cloud removal were implemented using the SEN12MS-CR dataset [5], and their performance was evaluated both qualitatively and quantitatively using standard metrics. The findings were presented at the 8th International Conference on Geoinformatics and Data Analysis (ICGDA 2025) in Nice [7], and Table 1 summarizes the evaluation results comparing both models against a state-of-the-art baseline.

Table 1. Comparison of model performances using quantitative metrics

Feature	Structural & Perceptual quality		Pixel-wise accuracy		Overall image quality & realism	
Metric	SSIM	PSNR	MAE	RMSE	FID	IS
GAN	0.893	29.34	0.027	0.032	**27.26**	2.46
Diffusion	**0.901**	**30.02**	**0.024**	**0.029**	28.63	**2.67**
UnCRtainTS [6]	0.880	28.90	0.027	–	–	–

– Indicates unreported results for the baseline model.

Stage 3: Analysis of Model Limitations

Initiated analysis of model limitations by preprocessing the dataset and quantifying cloud density per image using cloud masks to evaluate performance under varying cloud conditions.

5 Planned Work

The planned work includes completing the analysis of model limitations across cloud densities and regions, integrating and testing alternative models (e.g., CVAEs and attention-based), developing a benchmarking framework that combines quantitative and qualitative metrics, refining and unifying the models into an integrated reconstruction framework, and progressing thesis writing alongside the ongoing research.

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References

[1] U. Anwaar, A. Naveed, and P. Ganna. Efficient diffusion models for vision: a survey. *arXiv preprint arXiv:2210.09292*, 2022.

[2] K. Bhambani and M. Takalikar. Decloud gan: An advanced generative adversarial network for removing cloud cover in optical remote sensing imagery. In *Proceedings of the 2021 4th International Conference on Computational Intelligence and Intelligent Systems*, pages 25–30, 2021.

[3] S. Das, P. Das, and B. R. Roy. Cloud detection and cloud removal of satellite image—a case study. In *Trends in Communication, Cloud, and Big Data: Proceedings of 3rd National Conference on CCB, 2018*, pages 53–63. Springer, 2020.

[4] S. Durr, Y. Mroueh, Y. Tu, and S. Wang. Effective dynamics of generative adversarial networks. *Physical Review X*, 13(4):041004, 2023.

[5] P. Ebel, A. Meraner, M. Schmitt, and X. X. Zhu. Multisensor Data Fusion for Cloud Removal in Global and All-Season Sentinel-2 Imagery. *IEEE Transactions on Geoscience and Remote Sensing*, 2020.

[6] P. Ebel, V. S. F. Garnot, M. Schmitt, J. D. Wegner, and X. X. Zhu. Uncrtaints: Uncertainty quantification for cloud removal in optical satellite time series. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 2086–2096, 2023.

[7] S. Edirisinghe, S. Hensman, and B. Schoen-Phelan. A comparative study on geospatial scene reconstruction using gans and diffusion models. Presented at the 8th International Conference on Geoinformatics and Data Analysis (ICGDA 2025), Nice, France. To appear., April 2025.

[8] A. Hasan, C. Witharana, M. R. Udawalpola, and A. K. Liljedahl. Detection of clouds in medium-resolution satellite imagery using deep convolutional neural nets. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 46:103–109, 2022.

[9] J. Holloway-Brown, K. J. Helmstedt, and K. L. Mengersen. Interpolating missing land cover data using stochastic spatial random forests for improved change detection. *Remote Sensing in Ecology and Conservation*, 7(4):649–665, 2021.

[10] G. Hu, X. Sun, D. Liang, and Y. Sun. Cloud removal of remote sensing image based on multi-output support vector regression. *Journal of Systems Engineering and Electronics*, 25(6):1082–1088, 2014.

[11] N. E. Observatory. Cloudy earth, 2015. URL https://earthobservatory.nasa.gov/images/85843/cloudy-earth. Accessed: 2024-12-28.

[12] C. Richiardi, P. Blonda, F. M. Rana, M. Santoro, C. Tarantino, S. Vicario, and M. Adamo. A revised snow cover algorithm to improve discrimination between snow and clouds: a case study in gran paradiso national park. *Remote Sensing*, 13(10):1957, 2021.

[13] H. Zhang, Q. Huang, H. Zhai, and L. Zhang. Multi-temporal cloud detection based on robust pca for optical remote sensing imagery. *Computers and Electronics in Agriculture*, 188:106342, 2021.

[14] X. Zou, K. Li, J. Xing, Y. Zhang, S. Wang, L. Jin, and P. Tao. Diffcr: A fast conditional diffusion framework for cloud removal from optical satellite images. *IEEE Transactions on Geoscience and Remote Sensing*, 62:1–14, 2024. doi: 10.1109/TGRS.2024.3365806.