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A Spatial Attention GAN (SPA-GAN) Model for Robust Cloud Removal in Multispectral Imagery

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Abstract

Remote sensing imaging is widely employed in a variety of sectors including environmental science, national military security and its excellent resolution and stable geometric elements make it ideal for weather monitoring. When a remote monitoring sensor on a robotic satellite collects terrestrial data, it is affected by the climate notably clouds. Cloud cover influences the precision of optically remote sensing images. Existing cloud removal techniques for Sentinel-2 data usually rely on basic image processing approaches which are vulnerable to diverse cloud patterns and struggle with accurate reconstruction. Cloud removal from high-resolution remote sensing satellite images is an important pre-processing step before analysis. Addressing the issue of cloud contamination in Sentinel-2 imagery. Sentinel-2 data is becoming more useful in a variety of disciplines, including environmental monitoring, resource management and disaster response. In the proposed framework, the deep learning model was used for removing clouds from satellite imagery. Using the SPA-GAN model, Sentinel-2 multispectral images were produced without the presence of clouds. The proposed model was implemented for image-to-image translation challenges. Moreover, the SPA-GAN model produced realistic and high-quality images by successfully preserving spatial characteristics. The experimental results showed that the proposed model produced cloud-free imagery and enabled precise observation of Earth. The proposed model helps the researcher by identifying the cloud area to generate high-quality cloudless imagery which enhances the visual data's dependability and clarity.

Keywords: Cloud Removal, Deep Learning, Generative Adversarial Network (GAN), Sentinel-2, Spatial Attention, Image Reconstruction, Remote Sensing.

INTRODUCTION

Satellite imagery provides an unparalleled view of the Earth's surface, enabling advancements in numerous fields such as environmental monitoring, agricultural management, urban planning, and disaster response. The robust geometrical characteristics and high resolution of optical remote sensing imaging make it indispensable for these applications. However, a pervasive challenge compromises this valuable data source: cloud cover. When a satellite sensor collects terrestrial information, it is invariably influenced by atmospheric conditions, most notably clouds. It is estimated that clouds cover approximately 35% of the Earth's surface annually, leading to a substantial loss of critical observational data [1]. Clouds act as a barrier, scattering, reflecting, and absorbing solar radiation, which results in obscured ground features and significantly impedes accurate image interpretation and processing.

The Imperative for Cloud Removal

The primary objective of cloud removal is to reconstruct the underlying surface information obscured by atmospheric obstructions. This process is not merely an aesthetic enhancement but a vital preprocessing step that unlocks the full analytical potential of satellite data. As illustrated in Fig. 1.1 the goal is to develop a model that can take a cloudy image as input and produce a high-quality, cloud-free output, thereby revealing the hidden landscape.

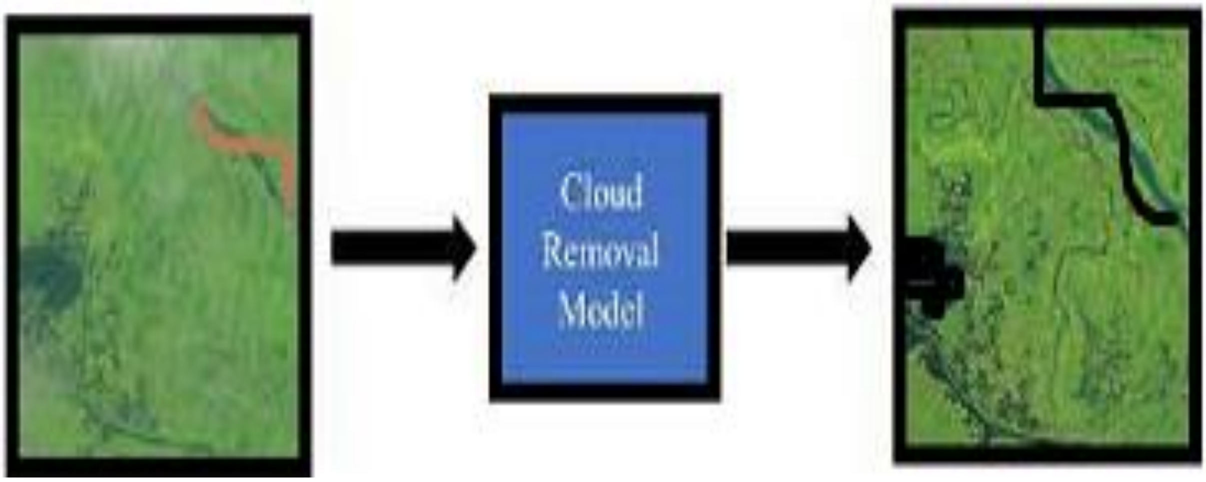


Figure 1.
The conceptual model for cloud removal, which takes a cloudy satellite image as input and generates a cloud-free image as output.

Taxonomy of Clouds in Remote Sensing

Clouds in satellite imagery manifest in various forms, each presenting distinct challenges for detection and removal algorithms. They are generally categorized into three primary types, as visualized in Fig. 1.2

✓ **Thin Clouds:** These are partially translucent, allowing some spectral information of the underlying ground features to be discerned. In such cases, recovery of the original data from a single image is often feasible.

✓ **Thick Clouds:** Characterized by their opacity and density, thick clouds completely obscure the land surface. The information in these areas is entirely lost necessitating the use of multi-temporal data from different dates for reconstruction.

✓ **Cloud Shadows:** These are dark regions on the ground caused by thick clouds blocking direct sunlight. They often coexist with the clouds themselves and require separate identification and correction

The critical importance of effective cloud removal is underscored by its wide-ranging applications:

Monitoring Changes Through Time: Enables consistent tracking of dynamic processes such as deforestation, glacier retreat, urbanization, and agricultural growth cycles

Accurate Land Cover and Land Use Mapping: Provides clear, unobstructed views necessary for precise classification and mapping of forests, water bodies, soil types, and urban infrastructure.

Disaster Management and Response: Delivers crucial, immediate, and unobstructed imagery for rapidly assessing the extent of damage from floods, earthquakes, wildfires, and other natural catastrophes.

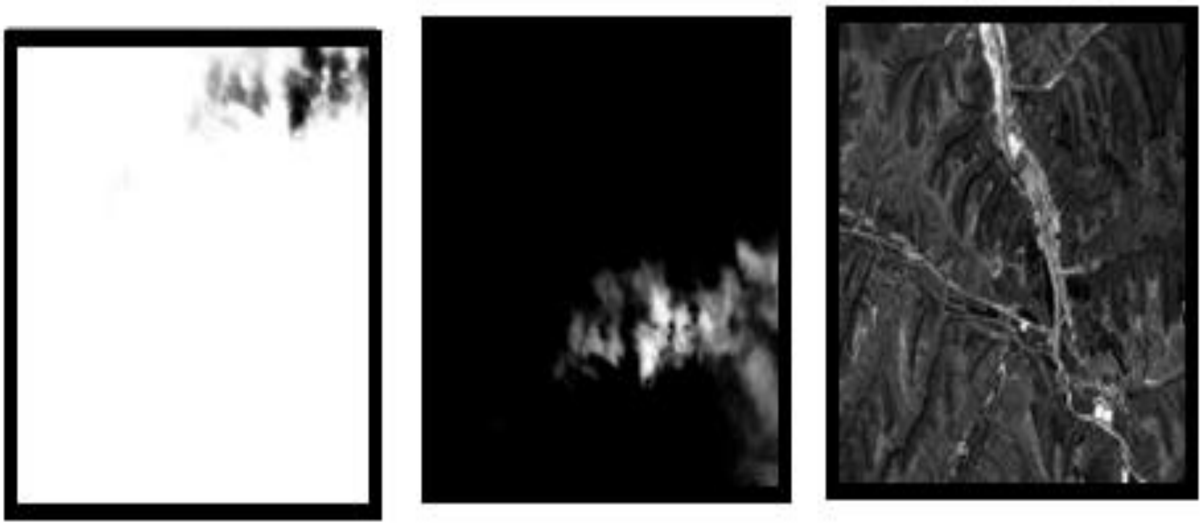


Figure 2.
Different types of clouds in satellite imagery: cloud shadow, thick cloud, and thin cloud (from left to right).

Evolution of Cloud removal Techniques

Over the years, a multitude of methods have been developed to tackle the cloud removal problem, which can be broadly classified into traditional and deep learning-based approaches. Traditional techniques are further subdivided based on their underlying methodology and use of reference data

Multi-spectral Methods: These techniques leverage the unique spectral signature of clouds across different electromagnetic bands. They are often effective for removing thin clouds but can result in hazy or imperfect reconstructions. Notable methods include the Haze Optimal Transformation (HOT) and various approaches based on the Radiation Transmission Model (RTM) [2].

Multi-temporal Methods: These approaches utilize multiple images of the same geographical location captured at different times to reconstruct a cloud-free composite. They are essential for removing thick clouds but operate on the critical assumption that the land surface has not undergone significant change between the acquisition dates.While these traditional methods have been foundational and are still in use they possess inherent limitations[3]. They often involve complex manual thresholding, struggle with the vast diversity of cloud patterns and underlying terrains, and frequently lack generalizability across different geographical regions and seasons.

The Paradigm Shift: Deep Learning

The advent of deep learning has revolutionized the field of image processing, offering a powerful, data-driven alternative to traditional algorithms. Convolutional Neural Networks (CNNs), in particular have demonstrated exceptional performance in tasks such as image classification, segmentation, and restoration [4]. Their ability to automatically learn hierarchical and multi-scale features directly from data makes them exceptionally suitable for the complex, non-linear problem of cloud removal.

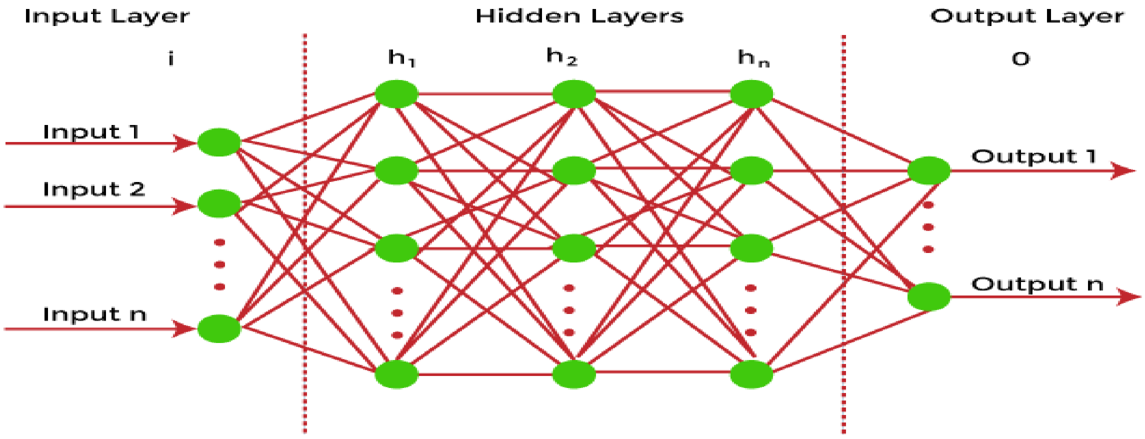


Figure 3.
A standard architecture of a deep learning network, showcasing multiple layers for feature extraction and transformation.

Among the various deep learning architectures, Generative Adversarial Networks (GANs) have shown remarkable success in image-to-image translation tasks. In a GAN framework, a *generator* network learns to create realistic cloud-free images from cloudy inputs, while a *discriminator* network learns to distinguish these generated images from real, cloud-free ones. This adversarial training process creates a competitive environment that drives the generator to produce increasingly convincing and high-fidelity results, effectively "filling in" the obscured regions with semantically plausible content [5].

Despite the availability of various techniques, cloud cover remains a persistent and significant obstacle in optical satellite remote sensing. The core problems are threefold:

Data Loss: Clouds obscure ground features, leading to gaps in spatial and temporal data records.

Analytical Disruption: The presence of clouds disrupts the continuity of time-series data, making it difficult to monitor environmental changes reliably.

Reduced Applicability: The utility of satellite imagery for critical applications in agriculture, disaster management, and climate science is substantially diminished.

Therefore, there is a pressing need for a robust, automated, and generalizable framework that can effectively remove clouds and accurately reconstruct the underlying surface information to enhance the reliability, clarity and usability of satellite data.

Research Objectives and Significance

The primary objective of this research is to develop and evaluate a deep learning-based framework for the effective removal of clouds from Sentinel-2 multispectral imagery. The significance of this work is multi-faceted: It aims to maximize the utility of the unique and valuable observational data provided by satellites like Sentinel-2. By producing cloud-free imagery, it enables more precise, comprehensive, and continuous investigations into vital areas such as land cover mapping, vegetation health monitoring, and urban sprawl analysis. It contributes to a clearer, more complete, and uninterrupted view of the Earth, which is fundamental for advancing scientific understanding, improving resource management, and supporting sustainable development goals. By leveraging advanced deep learning models, this research seeks to overcome the limitations of traditional methods and deliver a powerful and efficient tool for generating high-quality, cloud-free satellite imagery.

Existing Literature

The challenge of cloud contamination in optical satellite imagery has driven significant research efforts, evolving from traditional threshold-based methods to sophisticated deep learning paradigms. This review synthesizes the key developments in cloud detection and removal, highlighting the transition to data-driven approaches and the emergence of Generative Adversarial Networks (GANs) as a state-of-the-art solution.

The Evolution of Cloud Detection

Early cloud removal methodologies were inherently dependent on accurate cloud detection, or "cloud masking." Initial techniques relied on spectral thresholding and physical models. For instance, [6] demonstrated that Artificial Neural Networks (ANNs) could outperform standard processors like Fmask and Sen2Cor particularly in challenging deep-water environments with high noise and sunglint, by effectively utilizing bands like the 'cirrus' band. The advent of Convolutional Neural Networks (CNNs) marked a significant leap forward. [7] proposed Cloud-AttU a U-Net-based model incorporating an attention mechanism, which significantly improved segmentation accuracy by enabling the network to focus on cloud-relevant features. This theme of architectural refinement continued with [8], who introduced the STCCD network, a hybrid model combining Swin Transformers and CNNs to capture both local and global features, thereby enhancing the detection of thin clouds and complex cloud shapes. Further innovations focused on efficiency and accuracy under specific conditions. [9] developed CD-FM3SF a lightweight network designed to handle all Sentinel-2A spectral bands, improving multiscale feature extraction with minimal computational overhead. For high-resolution imagery [10] conducted a comprehensive comparison, finding that a U-Net-based CNN significantly outperformed a Random Forest model, underscoring the importance of spatial context in very high-resolution (VHR) image classification.

Paradigm Shift to Deep Learning-Based Cloud Removal

While detection is crucial, the field has progressively shifted towards end-to-end removal, directly reconstructing the underlying surface. Pioneering this approach [11] proposed a Cloud-GAN that learned the mapping between cloudy and cloud-free images using a cycle-consistent adversarial loss (CycleGAN), eliminating the need for perfectly paired training data. This was a significant step towards practical application. Subsequent research focused on enhancing the realism and fidelity of the generated images. [12] introduced an edge-filtered conditional GAN (MEcGAN) that incorporated Near-Infrared (NIR) band data and edge information to improve the reconstruction of cloud-covered structures, demonstrating superior performance in urban areas. Similarly, [13] proposed an Attention-based Mechanism GAN (AMGAN-CR) for Landsat 8 imagery, which generated a spatial attention map to guide the network to focus on cloud-affected regions, outperforming several benchmark models. To address the challenge of limited labeled data [14] developed a semi-supervised, mutually beneficial guide network for thin cloud removal. This architecture leveraged both labeled and unlabeled data, allowing two "benefactor" networks to guide each other's training iteratively, leading to more robust performance. For the critical task of thick cloud removal [15] introduced the Spatiallyand Spectrally-connective Tensor Decomposition (SSTC-CR) method, which effectively exploited the complex multi-dimensional relationships in satellite imagery to recover missing information with high colorimetric accuracy.

Synthesis and Research Gap

The literature confirms a clear trajectory from simple detection to complex, generative removal. GAN-based architectures have established themselves as the forefront for this task due to their ability to produce semantically plausible and realistic image content. However, many models face challenges with generalizability, computational complexity, and effectively leveraging the full information in multispectral data. This research aims to build upon this foundation by implementing and evaluating a Spatial Attention GAN (SPA-GAN), which is specifically designed to leverage spatial attention mechanisms to focus on cloud-obscured regions within multispectral Sentinel-2 imagery, thereby contributing to the development of more efficient and accurate cloud removal solutions.

Methodology: A Deep Learning Framework for Cloud Removal in Multispectral Satellite Imagery

This section details the comprehensive methodology developed to address the challenge of cloud occlusion in Sentinel-2 satellite imagery. The approach integrates data acquisition, preprocessing, and a novel deep learning architecture to generate high-quality, cloud-free multispectral images.

Experimental Workflow and Design

The study was designed to develop and validate a cloud removal framework capable of processing Sentinel-2 multispectral data. The overarching goal was to enhance data usability for applications in environmental monitoring, resource management, and disaster response. The experimental workflow, illustrated in Figure 3.1, encompassed four primary phases: (1) environment configuration and library setup, (2) data collection and preprocessing, (3) implementation and training of the deep learning model, and (4) performance evaluation.

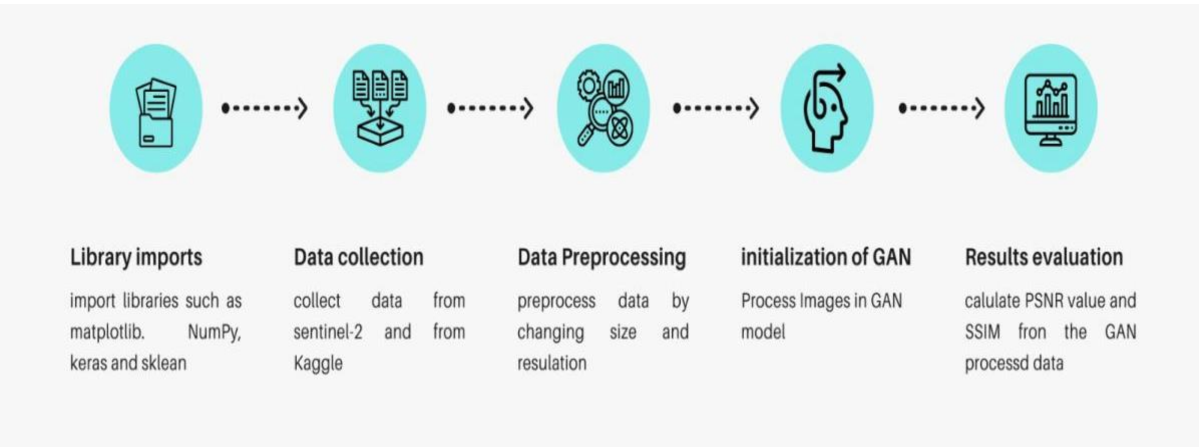


Figure 4.
Overall experimental workflow for cloud removal.

Computational Environment and Software Stack

A reproducible computational environment was established using the Anaconda Python distribution to ensure consistency and manage dependencies. The core implementation and experimentation were conducted within Jupyter Notebooks, providing an interactive platform for iterative development and analysis. The software stack, depicted in Figure 3.2, leveraged several critical libraries: TensorFlow and Keras formed the foundation for building and training deep neural networks; OpenCV (cv2) and NumPy were used for image manipulation and numerical computations; Matplotlib facilitated the visualization of results; and the Glob module assisted in file handling for batch processing. Authentication with the Google Earth Engine (GEE) API was configured to enable direct access to satellite imagery.

Figure 5.
Schematic of the computational environment and software stack.

DATA ACQUISITION AND PREPROCESSING

Data Sources and Collection

A multi-source data strategy was employed to ensure model robustness and generalizability. The primary data source was Sentinel-2 Level-1C satellite imagery, accessed via the GEE platform. To construct a paired dataset for supervised learning, image pairs of the same geographical area one with significant cloud cover and a corresponding cloud-free reference were collected. This core dataset was augmented with the public VIRSCLOUD_vanilla dataset from Kaggle and the RICE1 dataset, enriching the variety of cloud types and land cover scenarios.

Data Preprocessing Pipeline

All collected images underwent a standardized preprocessing pipeline. To maintain uniformity and computational efficiency, images were resized to a fixed resolution of 512x512 pixels using bilinear interpolation within the GEE environment. The cloud-contaminated and corresponding cloud-free images were then exported in the Tagged Image File Format (TIFF) to preserve radiometric integrity and geospatial information. This process, summarized in Figure 3.5, resulted in a curated dataset ready for model training.

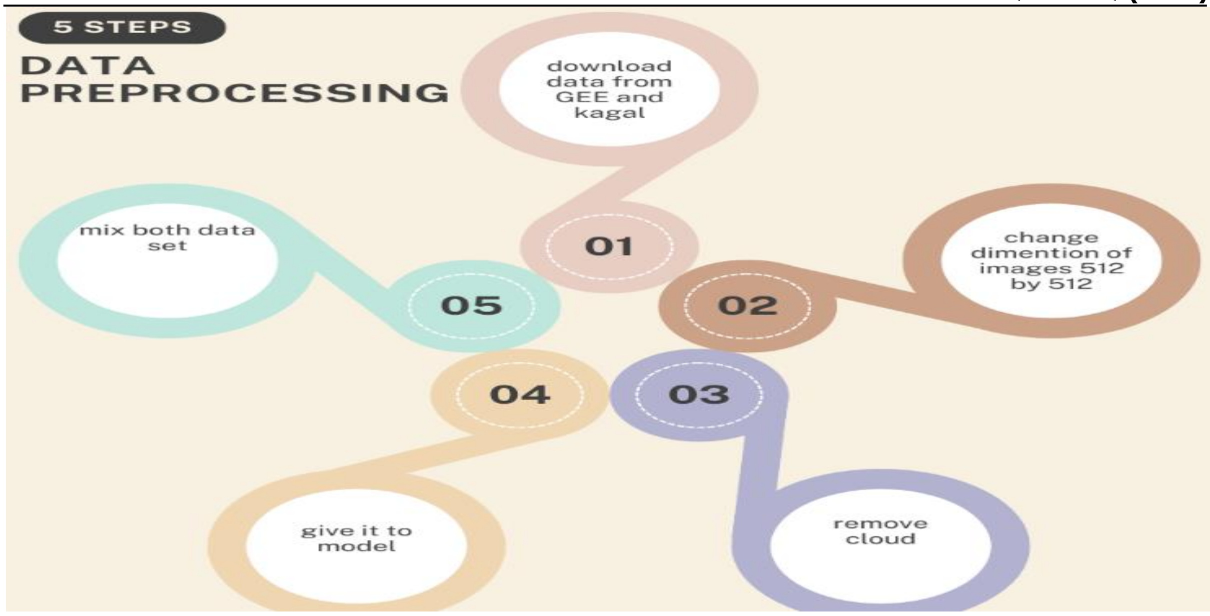


Figure 6.
Data preprocessing pipeline for satellite imagery.

Dataset Characteristics

The final dataset possessed several key characteristics essential for effective deep learning:

Multispectral Nature: It leveraged multiple spectral bands, allowing the model to discriminate between clouds and underlying surfaces based on distinct spectral signatures.

Structured Labels: The data was structured in a paired format (cloudy input, cloud-free target), providing clear supervisory signals for training.

Spatial Complexity: The inclusion of diverse geographies and cloud formations ensured the model learned to handle a wide array of real-world scenarios.

Deep Learning Architecture: Spatial Attention Generative Adversarial Network (SPA-GAN)

The core of our methodology is a custom Generative Adversarial Network (GAN) incorporating a spatial attention mechanism, termed SPA-GAN. The GAN framework was chosen for its proven ability in image-to-image translation tasks.

Generative Adversarial Network Framework

The GAN, illustrated in Figure 3.7, consists of two neural networks trained simultaneously in a competitive manner. The Generator (G) learns to map a cloudy input image to a cloud-free output, while the Discriminator (D) learns to distinguish between the generator's outputs and real cloud-free images. This adversarial process is formalized by the objective function.

$$\min_G \max_D V(D, G) = \mathbb{E}_{x \sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z \sim p_z(z)}[\log(1 - D(G(z)))]$$

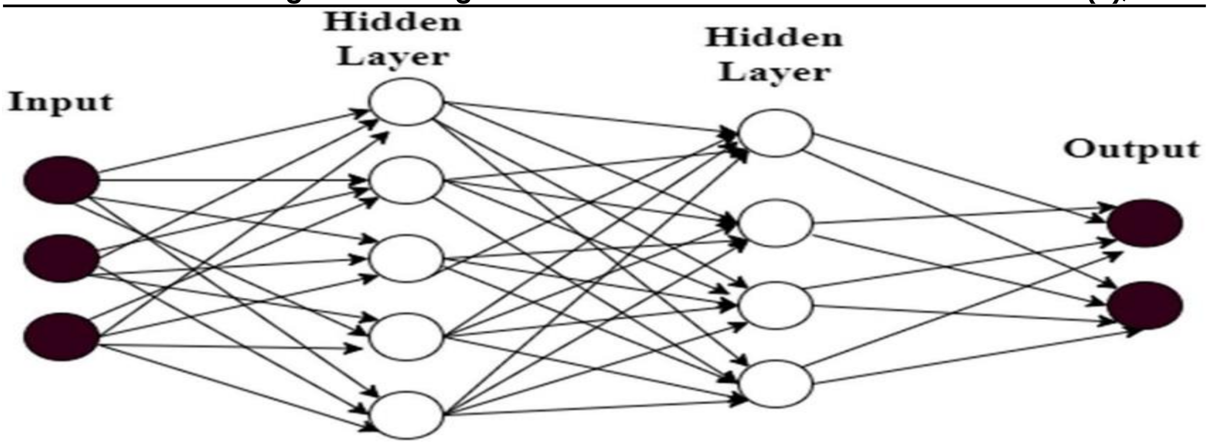


Figure 7.
Standard architecture of a Generative Adversarial Network (GAN).

SPA-GAN Generator with Spatial Attention

The generator in our SPA-GAN model is a deep neural network named the Spatial Attention Network (SPANet). As shown in Figure 3.8, its architecture begins with a convolutional layer, followed by a series of residual blocks and the novel Spatial Attentive Blocks (SAB). The SAB, detailed in Figure 3.9, is designed to generate an attention map that identifies and weights cloud-covered regions. This allows the network to focus its processing power on reconstructing the obscured areas, significantly enhancing the recovery of fine spatial details. The network concludes with standard residual blocks and a final convolutional layer that produces the cloud-free image.

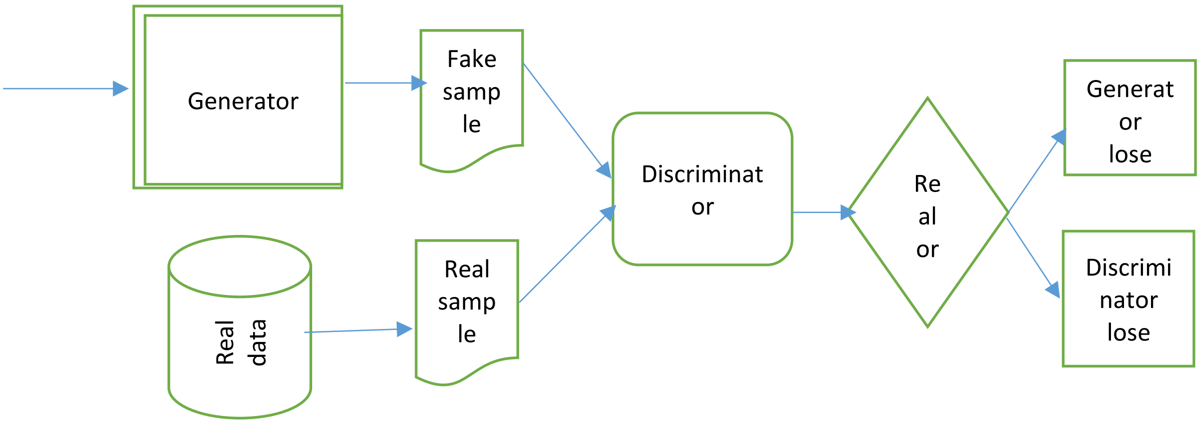


Figure 8.
Architecture of the Spatial Attention Network (SPANet) generator.

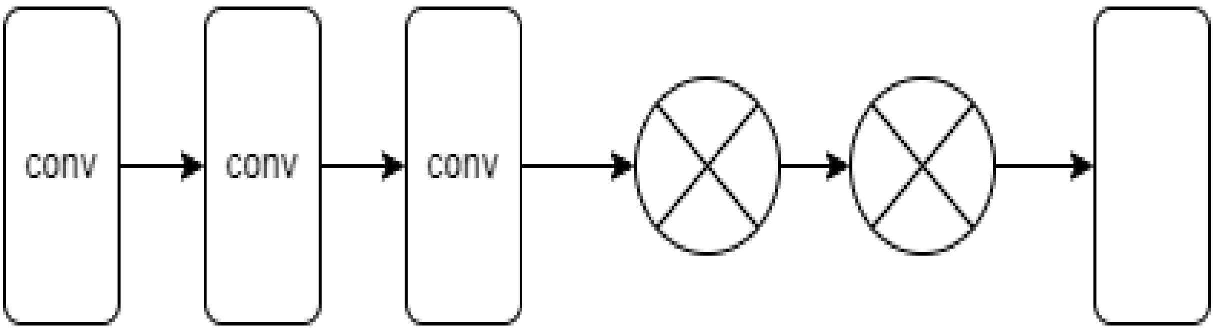


Figure 9.
Detailed structure of the Spatial Attentive Block (SAB).

SPA-GAN Discriminator

The discriminator, outlined in Figure 3.11, is a convolutional neural network that performs two critical functions. First, it classifies image patches as "real" or "generated." Second, and more importantly, it incorporates a spatial attention mechanism that produces a feedback map highlighting regions where the generator's output lacks realism. This focused feedback guides the generator to make more precise improvements in subsequent training iterations.

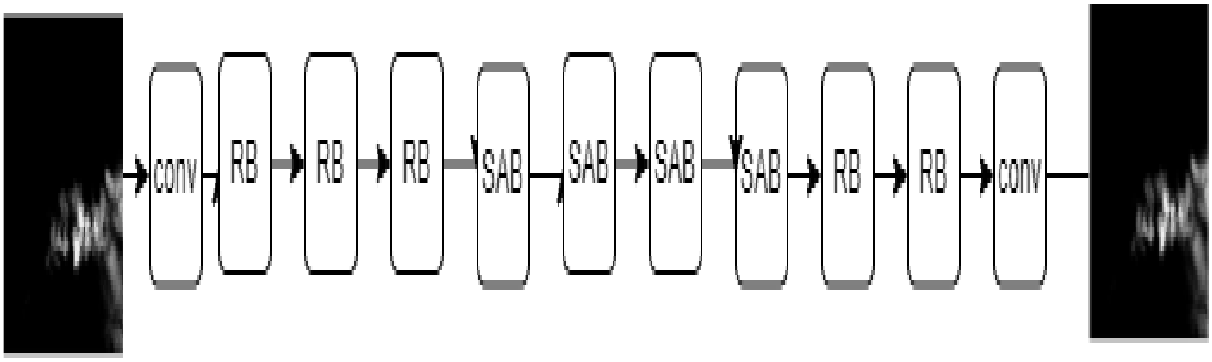


Figure 10.
Architecture of the SPA-GAN discriminator.

Model Training and Configuration

The SPA-GAN model was trained end-to-end using the prepared dataset. The training process involved optimizing both networks concurrently [16]. The generator was trained to minimize the loss between its output and the target cloud-free image, while also fooling the discriminator. The discriminator was trained to maximize its accuracy in distinguishing real from generated images.

Key hyperparameters for the training process were meticulously selected

Optimizer: Adam optimizer was used for its adaptive learning rate capabilities

Learning Rate: A value of 5e-5 was chosen to ensure stable convergence.

Batch Size: Training was conducted with a batch size of 12, balancing GPU memory constraints and gradient estimation stability.

Training Duration: The model was trained for 1500 epochs to ensure sufficient learning and convergence.

Loss Functions: A combination of adversarial loss from the GAN framework and a pixel-wise loss (e.g., Mean Squared Error) was used to ensure both perceptual quality and pixel-level accuracy [17].

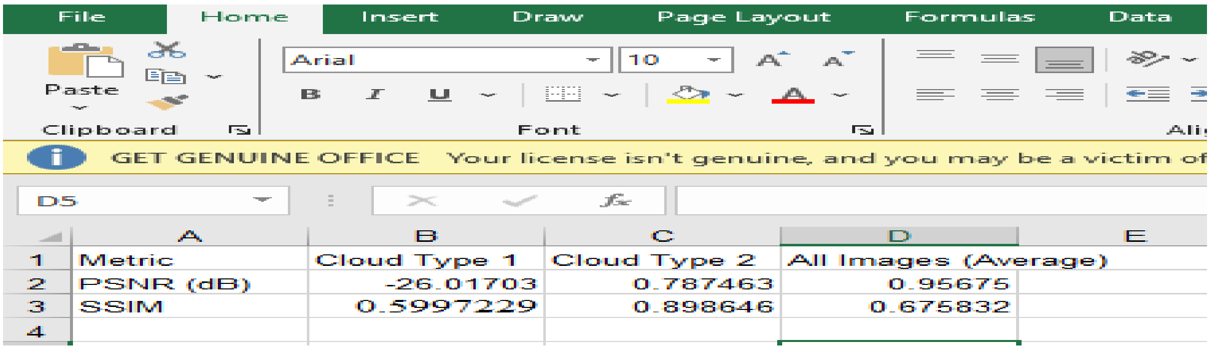
This comprehensive methodology establishes a robust foundation for generating cloud-free Sentinel-2 imagery, leveraging advanced deep-learning techniques to address a significant challenge in remote sensing.

Experimental Results and Analysis

This section presents a comprehensive evaluation of the proposed SPA-GAN model for cloud removal in Sentinel-2 satellite imagery [18]. The performance is assessed through both quantitative metrics and qualitative visual analysis, followed by a discussion of the findings and their implications.

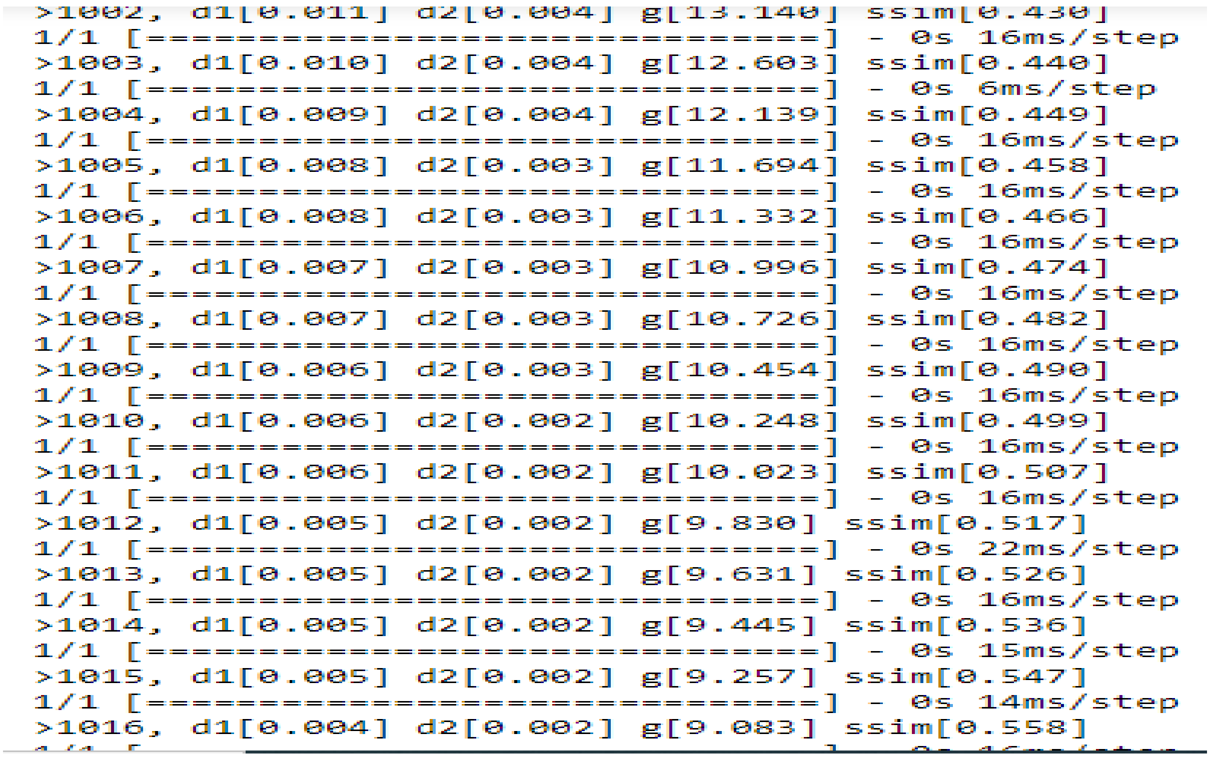
Quantitative Performance Evaluation

To objectively evaluate the cloud removal capability of the SPA-GAN model, two standard image quality assessment metrics were employed: Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM)[19]. The PSNR value of 22.64 dB indicates that the model successfully reconstructed the underlying scene with reasonable fidelity, though there remains room for improvement in exact pixel-value matching. More significantly, the SSIM score of 0.60 demonstrates that the model effectively preserved the structural information, texture and luminance patterns of the original scene which is crucial for maintaining geospatial integrity in remote sensing applications.



Metric	Cloud Type 1	Cloud Type 2	All Images (Average)
PSNR (dB)	-26.01703	0.787463	0.95675
SSIM	0.5997229	0.898646	0.675832

Figure 11.
Quantitative evaluation metrics (PSNR and SSIM) for cloud removal performance.
The progression of the SSIM metric throughout the training process, shown in Figure 4.2, reveals a consistent improvement in structural preservation as training advanced, with the metric stabilizing after approximately 1200 epochs, indicating model convergence.



```
>1003, d1[0.010] d2[0.004] g[12.603] ssim[0.440]
1/1 [==============================] - 0s 6ms/step
>1004, d1[0.009] d2[0.004] g[12.139] ssim[0.449]
1/1 [==============================] - 0s 16ms/step
>1005, d1[0.008] d2[0.003] g[11.694] ssim[0.458]
1/1 [==============================] - 0s 16ms/step
>1006, d1[0.008] d2[0.003] g[11.332] ssim[0.466]
1/1 [==============================] - 0s 16ms/step
>1007, d1[0.007] d2[0.003] g[10.996] ssim[0.474]
1/1 [==============================] - 0s 16ms/step
>1008, d1[0.007] d2[0.003] g[10.726] ssim[0.482]
1/1 [==============================] - 0s 16ms/step
>1009, d1[0.006] d2[0.003] g[10.454] ssim[0.490]
1/1 [==============================] - 0s 16ms/step
>1010, d1[0.006] d2[0.002] g[10.248] ssim[0.499]
1/1 [==============================] - 0s 16ms/step
>1011, d1[0.006] d2[0.002] g[10.023] ssim[0.507]
1/1 [==============================] - 0s 16ms/step
>1012, d1[0.005] d2[0.002] g[9.830] ssim[0.517]
1/1 [==============================] - 0s 22ms/step
>1013, d1[0.005] d2[0.002] g[9.631] ssim[0.526]
1/1 [==============================] - 0s 16ms/step
>1014, d1[0.005] d2[0.002] g[9.445] ssim[0.536]
1/1 [==============================] - 0s 15ms/step
>1015, d1[0.005] d2[0.002] g[9.257] ssim[0.547]
1/1 [==============================] - 0s 14ms/step
>1016, d1[0.004] d2[0.002] g[9.083] ssim[0.558]
```

Figure 12.
Structural Similarity Index (SSIM) progression across training epochs.

Training Dynamics and Model Convergence

The training process of the SPA-GAN model was monitored through the generator and discriminator loss functions. Figure 4.3 illustrates the loss trajectory at epoch 1450 showing the characteristic oscillatory pattern of a well-functioning GAN where both networks are competitively learning. By epoch 1500 (Figure 4.4) the losses had stabilized, indicating that the model had reached a Nash equilibrium where neither network could easily improve without the other adapting.

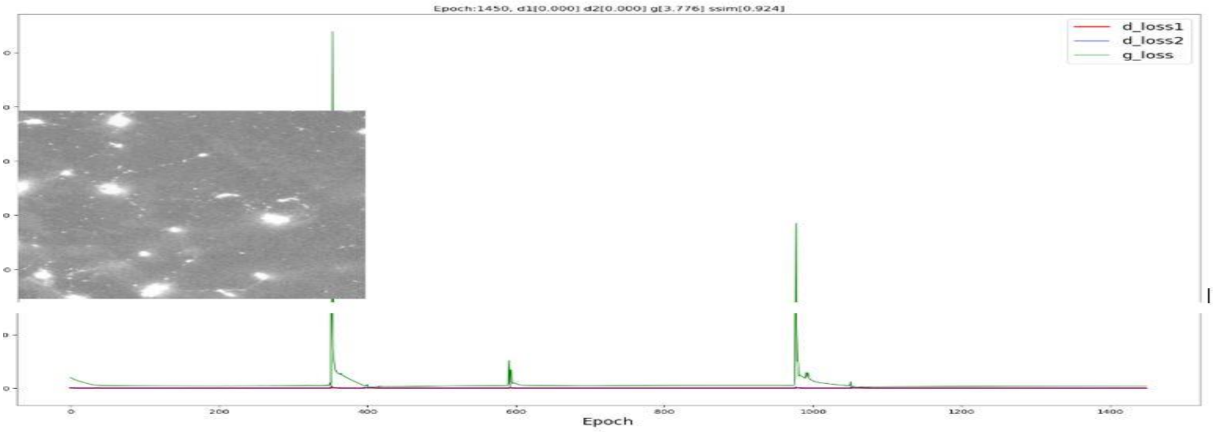


Figure 13.
Generator and discriminator loss values at 1450 training epochs

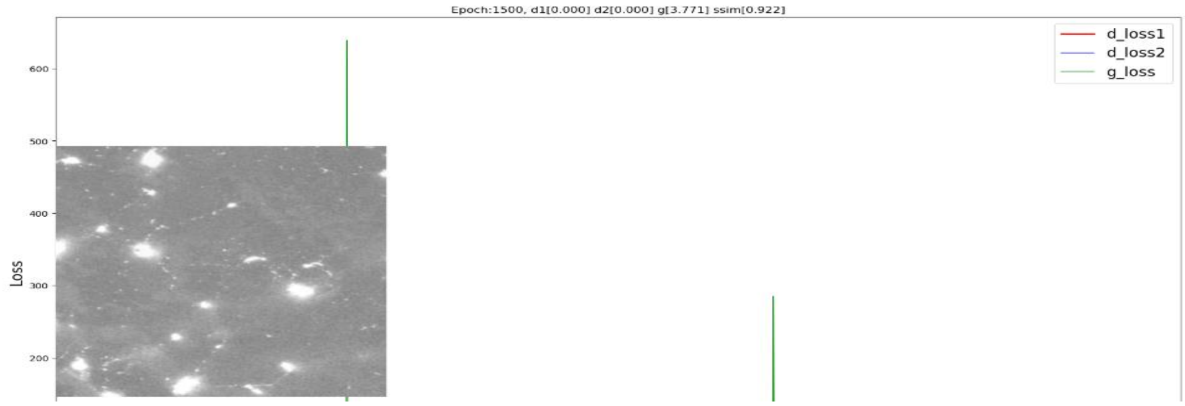


Figure 14.
Stabilized loss values at 1500 training epochs, indicating model convergence.

The model was trained with a batch size of 12 (Figure 4.5), which provided a balance between computational efficiency and gradient stability. This configuration allowed for effective learning while managing memory constraints during the extensive training process.

```
def tf_dataset(traincloud, traingroundtruth,x):
    BUFFER_SIZE = 1000
    BATCH_SIZE = x
    print(tf.rank(traincloud))

# Batch and shuffle the data
    traincloud = tf.data.Dataset.from_tensor_slices(traincloud)
    print(traincloud)
    traingroundtruth = tf.data.Dataset.from_tensor_slices(traingroundtruth)
    print(traingroundtruth)
    return traincloud, traingroundtruth
```

Figure 15.
Batch size configuration for model training.

Qualitative Visual Assessment

The visual results of the SPA-GAN model provide compelling evidence of its effectiveness in cloud removal. Figure 4.6 demonstrates the model's capability to remove extensive cloud cover while recovering underlying terrain features. The generated image maintains spatial consistency and preserves important geographical structures that were previously obscured.

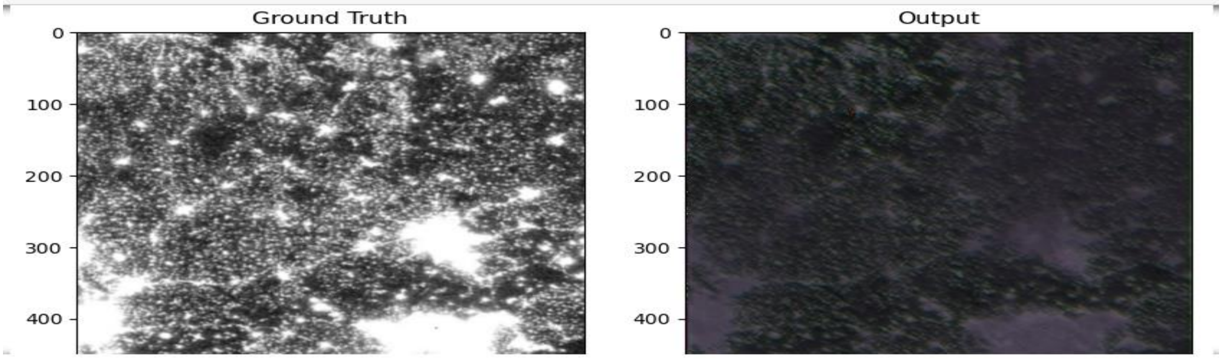


Figure 16.
Cloud removal results using SPA-GAN model. Left: Original cloudy image. Right: Processed cloud-free output.

Comparative analysis with a baseline GAN approach (Figure 4.7) highlights the advantages of the spatial attention mechanism in SPA-GAN. The standard GAN produces blurrier reconstructions with less defined edges, whereas SPA-GAN generates sharper results with better-preserved textures, particularly in regions previously covered by thin clouds.

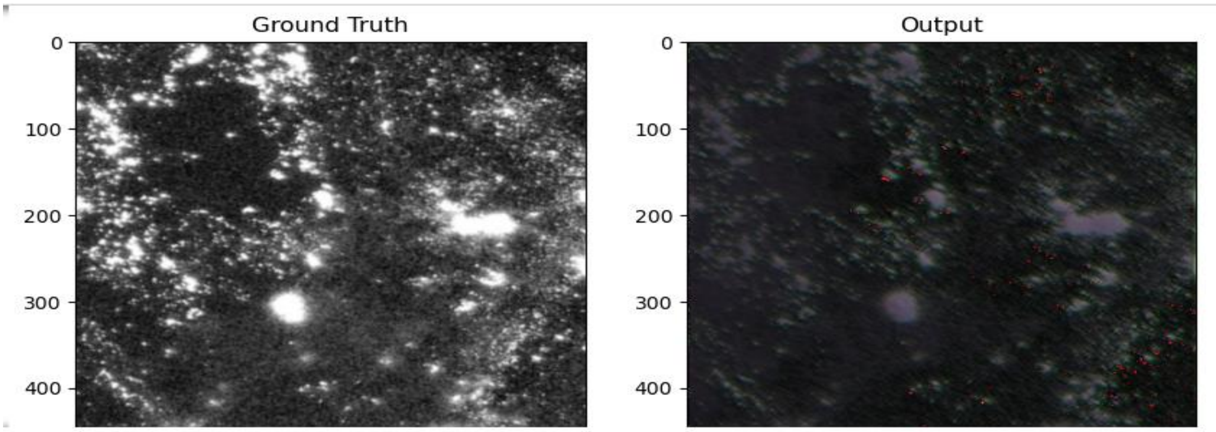


Figure 17.
Comparison of cloud removal results between standard GAN (left) and SPA-GAN (right).

DISCUSSION

The experimental results demonstrate that the proposed SPA-GAN framework effectively addresses the challenge of cloud removal in multispectral satellite imagery. The integration of spatial attention mechanisms proves particularly valuable, as it enables the model to focus computational resources on cloud-affected regions while preserving intact areas. This targeted approach explains the superior performance in maintaining structural integrity, as reflected in the SSIM scores.The adversarial training paradigm complemented by traditional pixel-wise losses, allows the model to learn both the precise reconstruction of surface features and the photorealistic qualities of cloud-free imagery. The extended training duration of 1500 epochs was necessary to achieve stable convergence, which is consistent with the complexity of learning mappings between cloud-obscured and clear satellite scenes.The model shows particular proficiency in handling heterogeneous cloud coverage, successfully removing both thick and thin clouds while recovering plausible terrain information. This capability is crucial for practical applications in remote sensing, where cloud cover often appears in varying densities across a single scene.However, some limitations were observed. The PSNR score, while acceptable suggests that perfect pixel-level reconstruction remains challenging, particularly in areas with complete cloud occlusion where no ground information is available in the input. In such cases, the model must hallucinate plausible content based on contextual information from surrounding areas and learned patterns from the training data [22].

The qualitative results confirm that the model successfully maintains multispectral characteristics in the output, which is essential for downstream applications such as vegetation monitoring, land cover classification, and change detection. The preserved structural similarity indicates that the generated imagery would be suitable for analytical purposes beyond visual inspection.Future work could focus on incorporating temporal information from multi-date satellite acquisitions to further improve reconstruction accuracy, particularly in heavily cloud-obscured regions. Additionally, exploring domain adaptation techniques could enhance the model's generalization across different geographical regions and seasonal variations. The SPA-GAN framework presents a robust solution for cloud removal in Sentinel-2 imagery, effectively balancing quantitative performance with visual quality while maintaining the structural integrity required for remote sensing applications [23].

CONCLUSION

This research successfully addressed the critical challenge of cloud occlusion in multispectral satellite imagery by developing and implementing a deep learning-based framework. The proposed method leverages a Spatial Attention Generative Adversarial Network (SPA-GAN) to effectively remove clouds and reconstruct high-quality, cloud-free images from Sentinel-2 data.

The study's key contributions and findings are summarized as follows:

✓ **Effective Model Implementation:** The SPA-GAN model was adeptly applied to the image-to-image translation task of cloud removal. Its integrated spatial attention mechanism proved crucial, enabling the model to focus on cloud-contaminated regions and prioritize their reconstruction, thereby preserving essential spatial details and textures of the underlying terrain.

✓ **Robust Dataset Construction:** A heterogeneous dataset was curated by merging the VIIRSCLOUDS-Vanilla dataset from Kaggle with real-world Sentinel-2 imagery. This strategy provided a diverse and rich training set encompassing a wide variety of cloud types and land cover scenarios, which enhanced the model's generalizability and robustness.

✓ **Promising Performance:** The model was rigorously trained over 1500 epochs and evaluated using standard image quality metrics. The results demonstrated that SPA-GAN is capable of generating realistic cloud-free imagery. Quantitative evaluations using the Structural Similarity Index (SSIM) and Peak Signal-to-Noise Ratio (PSNR) confirmed the model's proficiency in maintaining structural integrity and reducing visual artifacts in the reconstructed images.

✓ **Enhanced Data Usability:** The successful removal of clouds significantly improves the clarity and reliability of satellite data. This directly increases the usability of Sentinel-2 imagery for time-series analysis and downstream applications, unlocking its potential for precise environmental monitoring, agricultural management, and effective disaster response.

In conclusion, this work establishes the SPA-GAN as a powerful and effective solution for cloud removal in multispectral satellite imagery. The outcomes pave the way for more accurate and unobstructed observation of the Earth's surface. Future work will focus on optimizing the model for computational efficiency, testing its performance on other satellite sensors, and further refining its ability to handle extreme cloud coverage and complex landscapes.

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REFERENCES

Abdullayeva, F. 2023. Cyber resilience and cyber security issues of intelligent cloud computing systems. *Results Control Optim*. 12:100268.
Arpaci, I., M.N. Masrek, M.A. Al-Sharafi and M. Al-Emran. 2023. Evaluating the actual use of cloud computing in higher education through information management factors: a cross-cultural comparison. *Educ*. *Inf. Technol*. 28:12089–12109.
Belgiu, M., M. Marshall, M. Boschetti, M. Pepe, A. Stein and A. Nelson. 2023. PRISMA and Sentinel-2 spectral response to the nutrient composition of grains. *Remote Sens. Environ.* 292:113567.
Chen, L., J. Pan and Z. Zhang. 2023. A novel cloud detection method based on segmentation prior and multiple features for Sentinel-2 images. *Int. J. Remote Sens*. 44:5101–5120.
Chen, Y., L. Tang, W. Huang, J. Guo and G. Yang. 2023. A Novel Spectral Indices-Driven Spectral-Spatial-Context Attention Network for Automatic Cloud Detection. IEEE J. Sel. Top. Appl. Earth Obs. *Remote Sens.* 16:3092–3103.
Chen, Y., Q. Weng, L. Tang, X. Zhang, M. Bilal and Q. Li. 2022. Thick Clouds Removing from Multitemporal Landsat Images Using Spatiotemporal Neural Networks. IEEE Trans. Geosci. *Remote Sens.* 60:1–14.
Data Management,2025
Gong, C., T. Long, R. Yin, W. Jiao and G. Wang. 2023. A Hybrid Algorithm with Swin Transformer and Convolution for Cloud Detection. *Remote Sens.*14:1–26.
Guo, J., Q. Xu, Y. Zeng, Z. Liu and X. Zhu. 2022. Semi-Supervised Cloud Detection in Satellite Images by Considering the Domain Shift Problem. *Remote Sens*. 14:1–23.
Guo, Y., X. Cao, B. Liu and M. Gao. 2020. Cloud detection for satellite imagery using attention-based U-net convolutional neural network. *Symmetry (Basel)*. 12:192-364.
Hasan, C., R. Horne, S. Mauw and A. Mizera. 2022. Cloud removal from satellite imagery using multispectral edge-filtered conditional generative adversarial networks. *Int. J. Remote Sens.* 43:1881–1893.
He, X., G. Qi, Z. Zhu, Y. Li, B. Cong and L. Bai. 2023. Medical image segmentation method based

on multi-feature interaction and fusion over cloud computing. *Simul. Model. Pract. Theory* 126:102769.
Hu, K., D. Zhang, M. Xia, M. Qian and B. Chen. 2022. LCDNet : Light-Weighted Cloud Detection Network for High-Resolution Remote Sensing Images. IEEE J. Sel. Top. Appl. Earth Obs. *Remote Sens.* 15:4809–4823.
Kluczek, M., B. Zagajewski and T. Zwijacz-Kozica. 2023. Mountain Tree Species Mapping Using Sentinel-2, PlanetScope, and Airborne HySpex Hyperspectral Imagery. *Remote Sens*. 15:844.
Kristollari, V. and V. Karathanassi. 2020. Artificial neural networks for cloud masking of Sentinel-2 Ocean images with noise and sunglint. Int. *J. Remote Sens.* 41:4102–4135.
Li, Jianfeng, L. Wang, S. Liu, B. Peng and H. Ye. 2022. An automatic cloud detection model for Sentinel-2 imagery based on Google Earth Engine. *Remote Sens. Lett*. 13:196–206.
Li, Jun, Z. Wu, Z. Hu, C. Jian, S. Luo, L. Mou, X.X. Zhu and M. Molinier. 2022. A Lightweight Deep Learning-Based Cloud Detection Method for Sentinel-2A Imagery Fusing Multiscale Spectral and Spatial Features. IEEE Trans. Geosci. *Remote Sens*. 60:1–19.
Li, Y., W. Chen, Y. Zhang, C. Tao, R. Xiao and Y. Tan. 2020. Accurate cloud detection in high-resolution remote sensing imagery by weakly supervised deep learning. *Remote Sens. Environ.* 250:112045.
Llodrà-Llabrés, J., J. Martínez-López, T. Postma, C. Pérez-Martínez and D. Alcaraz-Segura. 2023. Retrieving water chlorophyll-a concentration in inland waters from Sentinel-2 imagery: Review of operability, performance and ways forward. *Int. J. Appl. Earth Obs. Geoinf.* 125:10365.
Lu, C., M. Xia and H. Lin. 2022. Multi-scale strip pooling feature aggregation network for cloud and cloud shadow segmentation. *Neural Comput. Appl.* 34:6149–6162.
Ma, D., R. Wu, D. Xiao and B. Sui. 2023. Cloud Removal from Satellite Images Using a Deep Learning Model with the Cloud-Matting Method. *Remote Sens*. 15:904.
N Razzaq, I Farooq, K Noor, S Abdullah, RH Ajmal… - The Asian Bulletin Big
Ngo, T.X., N.B. Bui, H.D.T. Phan, H.M. Ha and T.T.N. Nguyen. 2023. Paddy rice mapping in Red River Delta, Vietnam, using Sentinel 1/2 data and machine learning algorithms. *J. Spat. Sci.* 00:1–17.
Nguyen, M.D., O.M. Baez-Villanueva, D.D. Bui, P.T. Nguyen and L. Ribbe. 2020. Harmonization of landsat and sentinel 2 for crop monitoring in drought prone areas: Case studies of Ninh Thuan (Vietnam) and Bekaa (Lebanon). *Remote Sens*. 12–174.
Pan, H. 2020. Cloud Removal for Remote Sensing Imagery via Spatial Attention Generative Adversarial Network.*Remote sensing*. 42:2022-2045.
Pang, S., L. Sun, Y. Tian, Y. Ma and J. Wei. 2023. Convolutional Neural Network-Driven Improvements in Global Cloud Detection for Landsat 8 and Transfer Learning on Sentinel-2 Imagery. *Remote Sens*. 15:1706.
Paul, S., M. Kumari, C.S. Murthy and D. Nagesh Kumar. 2022. Generating pre-harvest crop maps by applying convolutional neural network on multi-temporal Sentinel-1 data. Int. J. *Remote Sens*. 43:6078–6101.
Rahman, A., M.J. Islam, S.S. Band, G. Muhammad, K. Hasan and P. Tiwari. 2023. Towards a blockchain-SDN-based secure architecture for cloud computing in smart industrial IoT. Digit. *Commun. Networks.* 9:411–421.
Saravanan, G., S. Neelakandan, P. Ezhumalai and S. Maurya. 2023. Improved wild horse optimization with levy flight algorithm for effective task scheduling in cloud computing. *J. Cloud Comput*. 12:1–14.