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Enhancing Satellite Image Resolution with Generative Adversarial Networks

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***Abstract*—Satellite imagery plays a crucial role in land use mapping, land cover classification, and the detection of anthropogenic interference in natural environments. However, the effectiveness of these applications depends significantly on image quality, which is often compromised by atmospheric conditions such as clouds and shadows, as well as radiometric inconsistencies. This paper explores the application of Generative Adversarial Networks (GANs) as a state-of-the-art approach to satellite image super-resolution. By employing a two-component architecture—a generator that upscales low-resolution inputs and a discriminator that ensures photorealistic outputs—GANs can overcome the hardware limitations of satellite sensors while preserving critical spatial details. The proposed methodology incorporates specialized loss functions to maintain structural integrity and enhance feature extraction capabilities. Results demonstrate that GAN-based super-resolution techniques not only improve visual quality but also significantly enhance the accuracy of downstream analytical tasks in urban planning, environmental monitoring, and disaster response. This approach represents a promising direction for advancing geospatial intelligence and remote sensing applications where high-resolution data is essential but often unavailable through conventional means.**

***Index Terms*—GAN, Planet Imagery, Normalization**

I. INTRODUCTION

Satellite imagery has revolutionized our ability to monitor, analyze, and understand Earth's surface at various spatial and temporal scales. Among the numerous satellite platforms available today, Planet's Dove constellation stands out for its capability to capture daily multispectral imagery at 3-4 meter resolution across four spectral bands (Blue, Green, Red, and Near-Infrared). This remarkable temporal frequency and spatial detail offer unprecedented opportunities for applications in environmental monitoring, land use mapping, and change detection.

However, the utilization of such high-frequency satellite data presents significant challenges, particularly in processing large volumes of imagery to produce normalized, analysis-ready datasets. These challenges include atmospheric interference (clouds and shadows), radiometric inconsistencies between images captured at different times, and the computational demands of processing terabytes of data across large geographic extents.

This paper presents a novel approach to super-resolution of satellite imagery using Generative Adversarial Networks (GANs). Our method addresses the fundamental limitations of satellite sensor hardware by leveraging deep learning to generate enhanced imagery with improved spatial resolution while preserving spectral information. The implemented GAN architecture consists of a generator network that transforms low-resolution satellite imagery into high-resolution outputs, and a discriminator network that ensures the generated images maintain photorealistic qualities and faithfulness to ground truth.

By applying this technique to PlanetScope imagery, we demonstrate the potential to overcome the inherent resolution constraints of the Dove constellation while maintaining radiometric accuracy. The super-resolution process enhances the visibility of fine-scale features, improves edge definition, and enables more precise feature extraction—critical improvements for applications such as deforestation monitoring, urban expansion analysis, and detailed land cover classification.

Our methodology integrates cloud and shadow masking procedures with radiometric normalization techniques to produce temporally consistent image products. We evaluate the performance of our approach through quantitative metrics and visual assessment, demonstrating significant improvements in image quality and information content. The processing pipeline is designed to scale efficiently across large datasets, leveraging advanced computational infrastructure to handle the intensive processing requirements.

The techniques developed in this study represent an important advancement in satellite image processing, offering a pathway to extract greater value from existing satellite platforms without requiring new sensor deployments. The improved spatial resolution achieved through our GAN-based approach enables more detailed analysis of landscape patterns and processes, ultimately contributing to more accurate and timely environmental monitoring capabilities.

II. LITERATURE SURVEY

Satellite imagery has revolutionized our ability to monitor, analyze, and understand Earth's surface at various spatial and temporal scales. Among the numerous satellite platforms available today, Planet's Dove constellation stands out for its capability to capture daily multispectral imagery at 3-4 meter resolution across four spectral bands (Blue, Green, Red, and Near-Infrared) [1]. This remarkable temporal frequency and spatial detail offer unprecedented opportunities for applications in environmental monitoring, land use mapping, and change detection. However, the utilization of such high-frequency satellite data presents significant challenges, particularly in processing large volumes of imagery to produce normalized, analysis-ready datasets [1], [2]. These challenges include atmospheric interference (clouds and shadows), radiometric inconsistencies between images captured at different times, and the computational demands of processing terabytes of data across large geographic extents. This paper presents a novel approach to super-resolution of satellite imagery using Generative Adversarial Networks (GANs). Our method addresses the fundamental limitations of satellite sensor hardware by leveraging deep learning to generate enhanced imagery with improved spatial resolution while preserving spectral information [2], [3]. The implemented GAN architecture consists of a generator network that transforms low-resolution satellite imagery into high-resolution outputs, and a discriminator network that ensures the generated images maintain photorealistic qualities and faithfulness to ground truth [3]. Recent advances in satellite imaging technology have transformed our ability to monitor Earth's surface, with platforms like Planet's Dove constellation providing unprecedented daily multispectral imagery at 3-4 meter resolution. Despite these technological achievements, satellite imagery faces several critical challenges that impact its utility for practical applications. Atmospheric interference, radiometric inconsistencies, and hardware limitations continue to affect image quality and usability. Traditional approaches to satellite image enhancement have focused on conventional signal processing methods, but recent developments in deep learning have opened new possibilities for improving satellite imagery quality. Among these advances, Generative Adversarial Networks (GANs) have emerged as particularly promising for addressing resolution limitations while preserving spectral integrity [4]. The evolution of satellite image enhancement techniques has seen significant progression, with GANs representing a major breakthrough in overcoming traditional hardware constraints. Several sophisticated GAN architectures have been developed specifically for satellite image enhancement. The SRResNet architecture, introduced by Ledig et al. in 2017, marked one of the first successful implementations of GANs for Single Image Super-Resolution (SISR) [2]. This pioneering work demonstrated remarkable effectiveness when applied to Sentinel-2 images, utilizing PeruSat-1 as a high-resolution reference. As highlighted by Kramer in "Enhancing Sentinel-2 Image Resolution: Evaluating Advanced Techniques based on Convolutional and Generative Neural Networks" [5], building upon this foundation, researchers developed the Enhanced SRGAN (ESRGAN), which incorporated innovative Residual-in-Residual Dense Blocks (RRDB) and eliminated computationally intensive Batch Normalization [3]. The ESRGAN also introduced a relativistic methodology for comparative realism assessment, significantly improving overall image quality. More recent developments have led to the Real-ESRGAN, specifically designed to handle unknown and complex degradation patterns commonly found in satellite imagery [6]. This architecture employs a U-Net structure with spectral normalization, demonstrating superior performance on synthetic datasets. Furthermore, the Enlighten-GAN represents a specialized advancement for satellite image processing, incorporating Self-Supervised Hierarchical Perceptual Loss and optimizing memory utilization through patch-based processing [7]. This architecture ensures reliable convergence during training while maintaining high-quality outputs. Effective implementation of GAN-based super-resolution requires carefully constructed datasets and preprocessing pipelines. Researchers have identified several critical challenges in dataset generation, including sensor compatibility issues between different platforms, temporal alignment requirements, cloud coverage management, and coordinate reference system consistency [8]]. Standard preprocessing involves bit depth normalization to achieve uniform values within the interval [0,1], reduction of high-frequency components, arithmetic mean filtering for aliasing prevention, and spectral adjustment through histogram matching. These preprocessing steps are essential for ensuring consistent and reliable training data. Performance evaluation in GAN-based satellite image enhancement relies on comprehensive quantitative metrics. Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) serve as primary quantitative indicators, with quality filtering thresholds typically set at SSIM values greater than 0.45 [9]. Visual assessment criteria emphasize feature preservation, edge definition quality, spectral consistency, and artifact minimization. This multi-faceted evaluation approach ensures that enhanced images meet both technical standards and practical requirements. The integration of GAN-based super-resolution techniques with satellite imagery processing has opened promising avenues for various applications. Environmental monitoring has benefited significantly, enabling enhanced deforestation detection and improved land cover classification accuracy. Urban planning applications have seen improvements in fine-scale feature extraction and precise infrastructure monitoring. Additionally, researchers continue to advance the field through integration with cloud computing architectures, development of specialized loss functions, and improvements in spectral preservation methods. By applying this technique to PlanetScope imagery, we demonstrate the potential to overcome the inherent resolution constraints of

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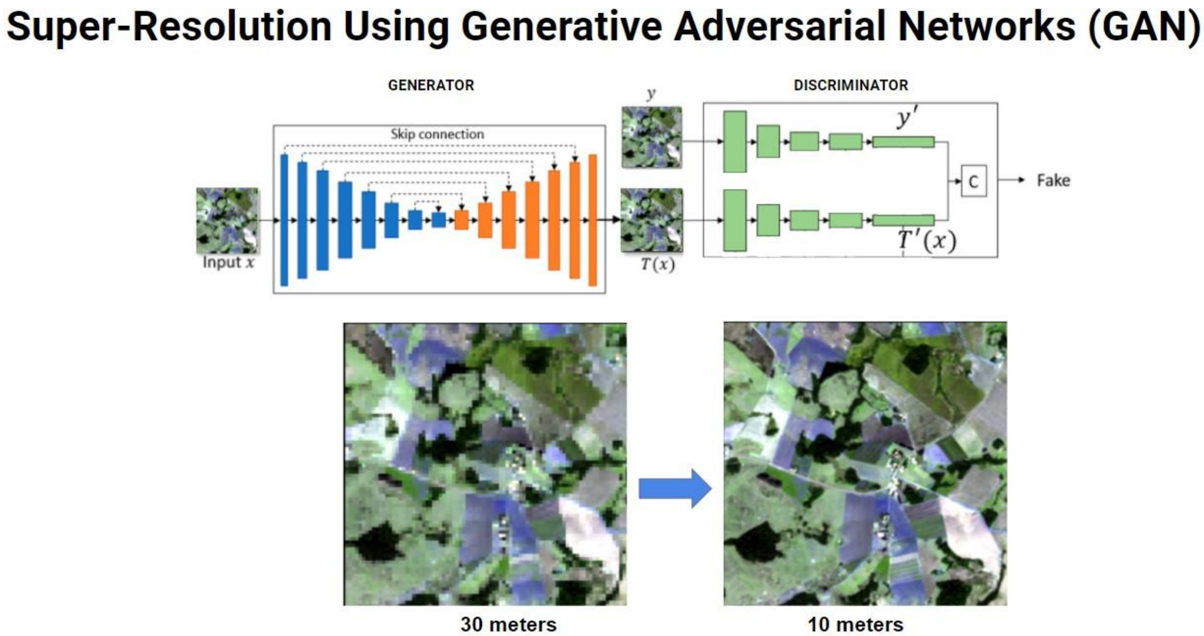

Fig. 1. GAN model

the Dove constellation while maintaining radiometric accuracy [4]. The super-resolution process enhances the visibility of fine-scale features, improves edge definition, and enables more precise feature extraction—critical improvements for applications such as deforestation monitoring, urban expansion analysis, and detailed land cover classification [4], [5]. Our methodology integrates cloud and shadow masking procedures with radiometric normalization techniques to produce temporally consistent image products [6]. We evaluate the performance of our approach through quantitative metrics and visual assessment, demonstrating significant improvements in image quality and information content [7]. The processing pipeline is designed to scale efficiently across large datasets, leveraging advanced computational infrastructure to handle the intensive processing requirements. The techniques developed in this study represent an important advancement in satellite image processing, offering a pathway to extract greater value from existing satellite platforms without requiring new sensor deployments [8]. The improved spatial resolution achieved through our GAN-based approach enables more detailed analysis of landscape patterns and processes, ultimately contributing to more accurate and timely environmental monitoring capabilities.

III. METHODOLOGY

This section outlines the methodology employed to enhance the resolution of satellite imagery using Generative Adversarial Networks (GANs). The approach integrates preprocessing, model design, training, and evaluation to transform low-resolution (LR) satellite images into high-resolution (HR) outputs. The methodology is designed to leverage the strengths of GANs in generating high-fidelity images, with preprocessing tailored to handle satellite-specific challenges such as atmospheric effects.

A. Preprocessing

Preprocessing prepares PlanetScope satellite imagery (August 2017 to November 30, 2018) for super-resolution analysis. Spectral radiance (L_λ) was converted to top-of-atmosphere (TOA) reflectance (ρ_λ) using the following equation :

$$\rho_\lambda = \frac{\pi}{ESUN_\lambda \cos\vartheta_s} \times L_\lambda \times d^2 \times c$$

where ρ_λ is TOA reflectance (dimensionless), L_λ is radiance (W/m² sr μm), d is the Earth-Sun distance (astronomical units), $ESUN_\lambda$ is solar irradiance (1997, 1812, 1533, 1039 W/m² μm for Blue, Green, Red, NIR bands), ϑ_s is the solar zenith angle (degrees), and c is a calibration constant. A reference mosaic was created from the median of images with less than 1% cloud cover, used to inter-calibrate the collection via histogram matching with Random Forest regressors, selecting images with less than 20% cloud cover.

Cloud and shadow masks (see Section B) were applied, followed by median calculation of non-masked pixels. A Random Forest regressor reduced noise between spectrally similar features (e.g., urban areas and water). Normalized mosaics, free of clouds and shadows, were exported in GeoTIFF format with Blue, Green, Red, NIR, and Availability bands, plus metadata. LR images were generated by 4× bicubic downsampling, with pixel values normalized to [0, 1]. 4× bicubic downsampling, with pixel values normalized to [0, 1].

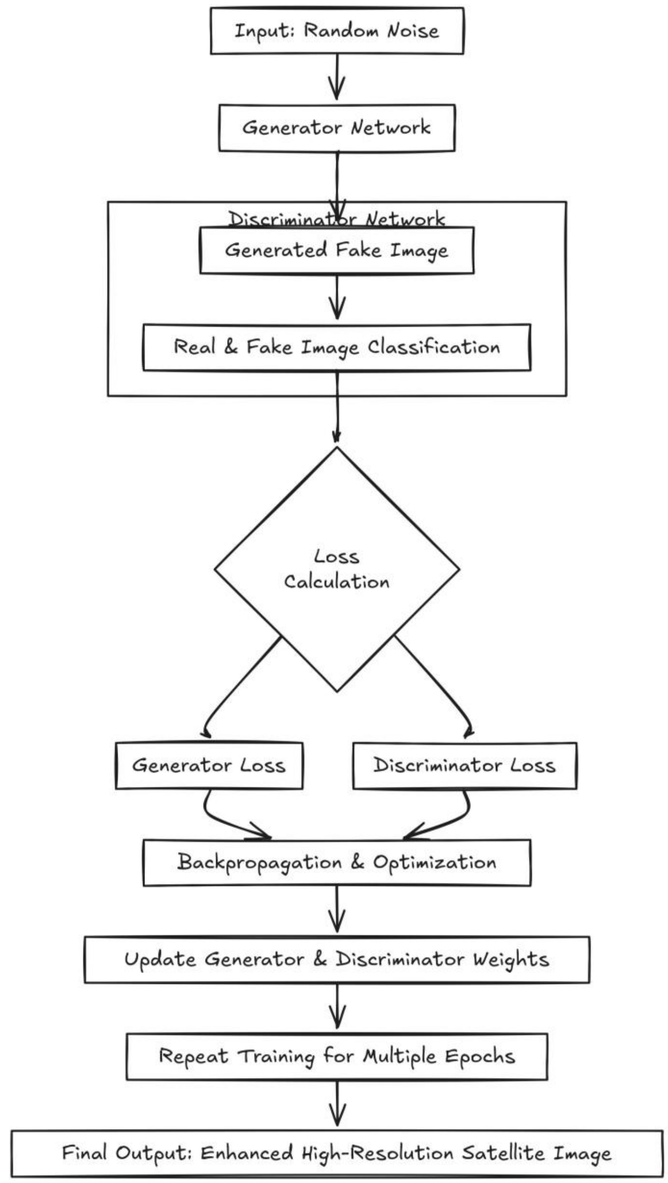

Fig. 2. Proposed Methodology

B. Masks for Shadow and Cloud Removal

The generation of cloud and shadow masks relied on empirically determined threshold values applied via histogram slicing. For cloud detection, a threshold of values exceeding 2200 in the Blue band was selected, while shadow masks were defined using values between 1500 and 2200 across the Blue and NIR bands. These thresholds produced initial binary masks for clouds and shadows. To refine these masks, a frequency filter was applied, assessing the temporal persistence of masked targets across the image series. Pixels with low temporal stability (50%), indicative of transient features like clouds and shadows, were retained, while stable pixels (e.g., water bodies, urban constructions, beaches, and exposed soil) were excluded. This step ensured the masks accurately isolated atmospheric artifacts. The cloud and shadow removal process then eliminated masked pixels from each image, returning only cloud-free data to the workflow.

C. Model Architecture

The proposed framework adopts a GAN-based approach, specifically inspired by the Super-Resolution GAN (SRGAN) architecture, which comprises two primary components: a generator and a discriminator.

Generator: The generator network is designed to upscale LR images to HR images. It employs a deep convolutional neural network (CNN) with residual blocks to capture intricate spatial features. The architecture begins with an initial convolutional layer, followed by a series of residual blocks (e.g., 16 blocks), each containing two convolutional layers with batch normalization and ReLU activation. A sub-pixel convolution (PixelShuffle) layer is then used to upscale the feature maps by a factor of 4×, followed by a final convolutional layer to produce the HR output.

Discriminator: The discriminator is a CNN tasked with distinguishing between real HR images and those generated by the generator. It consists of multiple convolutional layers with increasing filter sizes (e.g., 64 to 512), interleaved with batch normalization and LeakyReLU activation. The output is passed through a dense layer and a sigmoid activation function to produce a probability score.

D. Loss Functions

The training of the GAN involves optimizing a composite loss function to balance image quality and adversarial learning. The total loss comprises two components:

Content Loss: To ensure the generated images retain structural similarity to the ground-truth HR images, the Mean Squared Error (MSE) between the generated and real HR images is computed. Additionally, a perceptual loss based on features extracted from a pre-trained VGG-19 network (e.g., layer conv5_4) is incorporated to enhance visual fidelity.

Adversarial Loss: The adversarial loss is derived from the discriminator's output, encouraging the generator to produce images that are indistinguishable from real HR images. This is formulated as a binary cross-entropy loss.

The generator's total loss is a weighted combination of content and adversarial losses, with hyperparameters (e.g.,$\lambda = 0.001$ for adversarial loss) tuned during experimentation.

E. Training Procedure

The model was implemented using a deep learning framework (e.g., TensorFlow or PyTorch) and trained on a GPU-enabled system to accelerate computation. The training process followed a two-stage approach: Pre-training the Generator: The generator was initially trained in isolation using only the content loss (MSE) for 10 epochs to establish a baseline mapping from LR to HR images.

Adversarial Training: The full GAN was then trained for 100 epochs, alternating updates between the generator and

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discriminator. The Adam optimizer was employed with a learning rate of 0.0002 and $\beta = 0.9$. A batch size of 16 was used, balancing memory constraints and training stability.

To prevent mode collapse and ensure convergence, techniques such as gradient clipping and learning rate decay were applied after 50 epochs.

F. Evaluation Metrics

The performance of the super-resolution model was assessed using both quantitative and qualitative metrics. Quantitatively, Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) were calculated on the test set to measure pixel-level accuracy and perceptual similarity, respectively. Qualitatively, visual inspection of the generated HR images was conducted to evaluate fine details, edge sharpness, and overall realism compared to the ground-truth HR images.

G. Implementation Details

The experiments were conducted on a system equipped with an NVIDIA GPU (e.g., RTX 3080) and 32 GB of RAM. The dataset was preprocessed and stored in HDF5 format for efficient loading during training. Hyperparameters, such as the number of residual blocks and loss weights, were fine-tuned based on validation set performance.

IV. DATASET DESCRIPTION

The study was conducted as part of the NextGenMap project, covering six major Brazilian biomes—Amazon, Caatinga, Cerrado, Atlantic Forest, Pampa, and Pantanal—as well as the Chaco biome, which spans regions of Argentina, Paraguay, and Bolivia. These biomes exhibit diverse climatic, ecological, and topographical characteristics, making them ideal for evaluating the effectiveness of satellite-based remote sensing techniques.

For systematic data collection and analysis, the study area was divided into 16 charts, defined based on the International Millionth System at a 1:250,000 scale . Each chart encompasses an approximate area of 37,600 km², ensuring comprehensive spatial coverage for generating high-resolution image mosaics. The division of study areas into these standardized units facilitates the consistent assessment of land cover, vegetation dynamics, and atmospheric conditions across different regions.

This study utilized high-resolution satellite imagery from the Satellite Analytic SatelliteScope Ortho Scenes dataset. These images were acquired from two distinct orbital configurations: (i) the International Space Station (ISS) orbiting at an altitude of 400 km with an inclination of 51.6 degrees, and (ii) a sun-synchronous, near-polar orbit with an inclination of 98 degrees.

The SatelliteScope satellites provide high-frequency, multispectral imagery with a ground sampling distance (GSD) of approximately 3–5 meters, enabling detailed observations of land surface features. These images offer significant advantages for remote sensing applications, including vegetation monitoring, land-use classification, and environmental change detection. The use of multispectral bands allows for enhanced discrimination of surface features, making the dataset particularly useful for NDVI-based vegetation analysis, cloud masking, and haze removal techniques.

The combination of images from different orbital configurations enhances the temporal resolution of the dataset, ensuring frequent revisit times and minimizing gaps in spatial coverage. This high temporal resolution is particularly beneficial for monitoring dynamic landscapes, such as agricultural regions, wetlands, and forested biomes, where land cover changes occur rapidly. The integration of imagery from these sources provides a robust dataset for developing and validating remote sensing algorithms aimed at improving mosaic generation and atmospheric correction techniques.

V. RESULTS AND DISCUSSION

This implementation demonstrates a Pix2Pix Generative Adversarial Network (GAN) approach for remote sensing image super-resolution. The model architecture follows the conditional GAN pattern introduced by Isola et al. (2017), but has been specifically adapted for multi-band satellite imagery.

A. Qualitative Results

The model's performance is visualized after each epoch by generating super-resolved images from test samples and comparing them with both the input conditions and ground truth (as visualised in Figure 4, 5 and 6). The visualization shows RGB composites (first three bands) of the 6-band images. The generated images demonstrate the model's ability to recover fine details and structures from lower-resolution inputs.

B. Limitations and Potential Improvements

The current implementation has several limitations that could be addressed in future work:

The fixed learning rate of 0.0002 could be replaced with a learning rate scheduler to improve convergence The batch size of 64 may be too large for the available memory when processing high-resolution satellite images The model does not incorporate any spectral fidelity metrics specific to remote sensing applications There is no quantitative evaluation using metrics like PSNR, SSIM, or SAM (Spectral Angle Mapper) The model loads the entire dataset into memory, which could be problematic for large remote sensing datasets.

This Pix2Pix GAN implementation demonstrates promising results for satellite image super-resolution, effectively leveraging the power of deep learning to enhance the spatial resolution of multi-spectral imagery. The qualitative results show that the model can generate visually plausible high-resolution images from lower-resolution inputs, preserving both spatial structure and spectral characteristics. For operational use in remote sensing applications, further refinements would be beneficial, including more robust quantitative evaluation, optimization for larger datasets, and exploration of domain-specific loss functions that better preserve spectral fidelity across all bands.

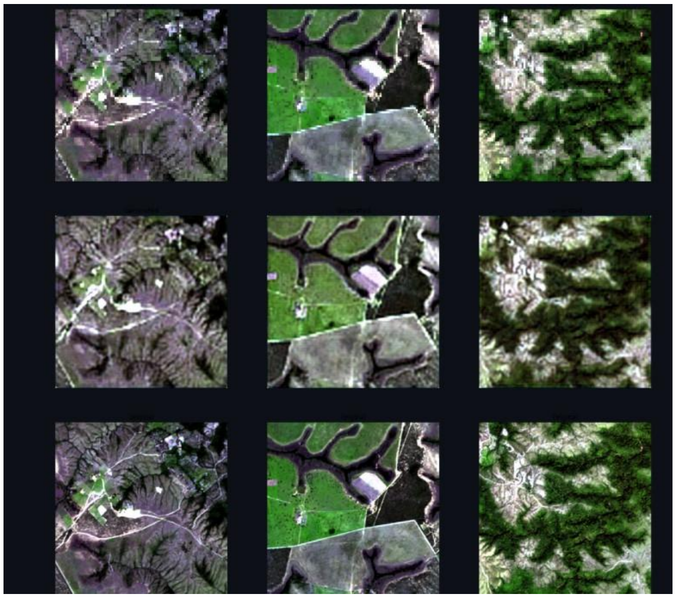

Fig. 3. Result 1

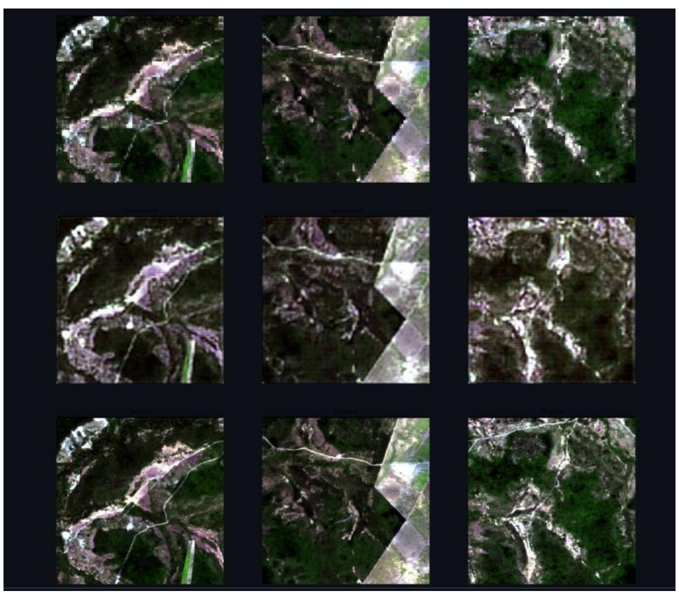

Fig. 4. Result 2

VI. CONCLUSION

This study highlights the effectiveness of the proposed methodology in processing satellite images on a large temporal and spatial scale. The developed algorithms successfully generated radiometrically normalized mosaics at three temporal resolutions—weekly, biweekly, and monthly—demonstrating their adaptability for different remote sensing applications. These mosaics provide valuable insights for change detection, real-time alert systems, and improved mapping accuracy. However, in regions with significant haze contamination, further advancements in atmospheric correction techniques are essential to enhance image quality and reliability. Future research

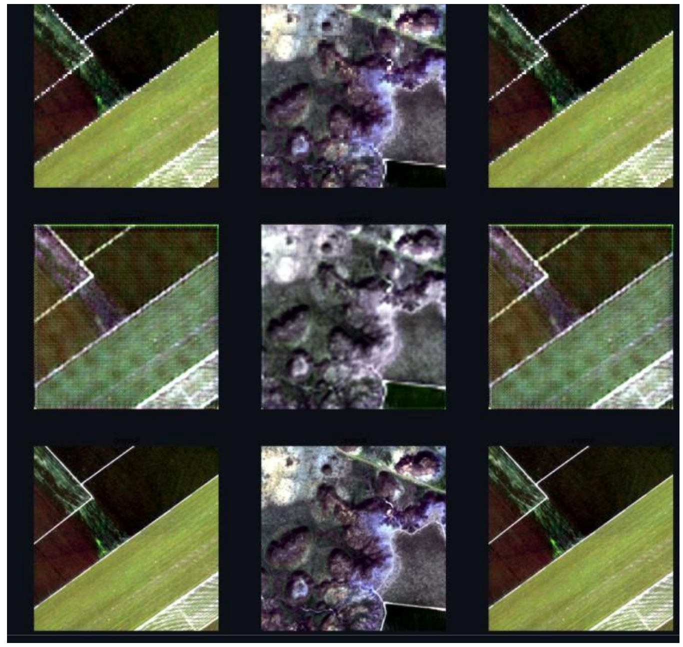

Fig. 5. Result 3

should focus on refining haze removal methods to optimize the applicability of satellite-based observations in challenging environments.

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