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ARTICLE

# SIF: Satellite Image Fusion for Deforestation Analysis in the Amazon Using S-1 and S-2 Data for LULC Applications

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## ABSTRACT

Deforestation is the purpose of converting forest into land and reforestation compared to deforestation is very low. That's why closely and accurately deforestation monitoring using Sentinel-1 and Sentinel-2 satellite images for better vision is required. This paper proposes an effective image fusion technique that combines S-1/2 data to improve the deforested areas. Based on review, Optical and SAR image fusion produces high-resolution images for better deforestation monitoring. To enhance the S-1/2 images, preprocessing is needed as per requirements and then, collocation between the two different types of images to mitigate the image registration problem, and after that, apply an image fusion machine learning approach, PCA-Wavelet. As per analysis, PCA helps to maintain spatial resolution, and Wavelet helps to preserve spectral resolution, gives better-fused images compared to other techniques. As per results, 2019 S-2 preprocessed collocated image enhances 42.2508 $km^2$ deforested area, S-1 preprocessed collocated image enhances 23.7918 $km^2$ deforested area, and after fusion of the 2019 S-1/2 images, it enhances 16.5335 $km^2$ deforested area. Similarly, the 2023 S-2 preprocessed collocated image enhances 49.2216 $km^2$ deforested area, S-1 preprocessed collocated image enhances 23.8459 $km^2$ deforested area after fusion of the 2023 S-1/2 images, enhancing 35.9185 $km^2$ deforested area. These improvements show that combining data sources gives a clearer and more reliable picture of forest loss over time. The overall paper objective is to apply effective techniques for image fusion of Brazil's Amazon Forest and analyze the difference between collocated image pixels and fused image pixels for accurate analysis of deforested area.

***Keywords:*** Amazon Deforestation; Sentinel-1; Sentinel-2; Collocation Band Math; PCA-Wavelet

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# 1. Introduction

Land Use (LU) and Land Cover (LC) are fundamental components in understanding environmental change. *Land cover* refers to the physical characteristics of the Earth's surface, such as forests, water bodies, or urban structures, while *land use* describes how these surfaces are utilized by humans, such as for agriculture, infrastructure, or recreation. Monitoring changes in LU and LC is essential for managing natural resources, planning sustainable development, and addressing environmental challenges like deforestation, which is a significant challenge due to the complexity of covering vast areas with diverse land features [1–3]. Deforestation—the large-scale removal of forest covers a major global concern due to its impact on biodiversity, climate regulation, and human health. The Amazon forest has been facing this problem for many years [4,5]. Deforestation is happening in large areas because people are farming and logging in forests. Deforestation (the removal of trees) is happening more quickly than new trees are being planted, which is causing environmental and health problems [6–8]. Tracking these changes accurately and efficiently across time and space is crucial for informed policymaking and intervention. Remote sensing has become a powerful tool in this context, enabling systematic observation of land dynamics using satellite imagery. Current best practices in deforestation monitoring involve the use of high-resolution satellite imagery, integration of multi-source data, and advanced analytics to provide timely and reliable information for policymakers and conservation efforts [9,10]. This paper focuses on reviewing and evaluating different techniques used for deforestation analysis, particularly those involving remote sensing and image fusion.

However, accurately detecting deforestation continues to be a challenge, particularly in regions with frequent cloud cover or complex terrain. To address these challenges, recent studies have emphasized the value of combining different types of satellite data, such as optical and Synthetic Aperture Radar (SAR) imagery. Techniques such as those using **Sentinel-1 (SAR) and Sentinel-2 (optical)** imagery have become standard tools in global deforestation monitoring due to their free availability, high revisit frequency, and complementary sensing capabilities [11,12]. Optical satellite imagery, such as that from Sentinel-2, provides rich spectral information under clear sky conditions but is often hindered by cloud cover and limited daylight [13,14]. In contrast, Synthetic Aperture Radar (SAR) systems, such as Sentinel-1, can penetrate cloud cover and operate regardless of lighting conditions. This makes SAR particularly valuable in tropical regions where clouds are frequent. The complementary nature of these two data types has led to the adoption of data fusion techniques. By integrating information from both sources, fusion techniques can enhance land cover classification and deforestation detection beyond the capabilities of individual sensors [15–17]. Deforestation has far-reaching effects on ecosystems and climate systems; therefore, improved monitoring is essential to support sustainable land management. Monitoring and managing LULC is essential to mitigate these impacts and ensure that land use is sustainable [3,10,18]. By balancing human needs with environmental conservation, it's possible to reduce deforestation and protect ecosystems, ensuring the health of both the planet and its inhabitants. By reviewing state-of-the-art approaches and proposing an improved methodology, this work aims to support more accurate monitoring and better decision-making in environmental management.

Recent advancements in deforestation monitoring have leveraged machine learning, time-series analysis, and high-resolution remote sensing to improve accuracy and scalability. Operational systems like Global Forest Watch, the Hansen dataset, and national monitoring platforms already utilize optical and/or radar imagery to detect forest change. However, many existing methods rely on single-sensor data, which can limit their effectiveness in regions with persistent cloud cover or highly variable terrain. This study contributes to the ongoing development of deforestation monitoring practices by critically reviewing and synthesizing techniques that combine SAR and optical data. By focusing on fusion-based approaches, this paper aims to highlight how integrating multiple data sources can address current limitations, improve temporal consistency, and support more robust and responsive monitoring frameworks [19–21].

This paper aims to critically review existing deforestation monitoring techniques that utilize optical and SAR satellite data, with a particular focus on fusion-based approaches. By analyzing recent advancements and proposing a framework that integrates both data sources, this study contributes to developing more resilient, accurate, and scalable solutions for deforestation monitoring. This work is especially relevant in the current context of climate change and biodiversity loss, where timely forest change detection is critical for informed environmental management and policy decisions. Furthermore, the general aim of this investigation is to explore how the fusion of SAR and optical remote sensing data can provide a more robust and scalable solution to deforestation monitoring, particularly in regions affected by rapid land-use change. The scope of the investigation covers both methodological advancements and their practical implications in environmental monitoring. The innovative aspect of this study lies in its synthesis of recent fusion-based techniques and its emphasis on improving temporal and spatial consistency in forest change detection. This work is highly relevant in the context of intensifying interactions between human activities—such as agriculture, logging, and urban expansion—and their impact on natural resources, ecosystem integrity, and climate dynamics. By enhancing monitoring capabilities, the study contributes to more informed decision-making in land governance, conservation planning, and climate adaptation strategies. It directly addresses the urgent need for resilient monitoring systems in the face of global environmental change.

In modern remote sensing applications, particularly for deforestation monitoring, data from both optical and Synthetic Aperture Radar (SAR) satellites play crucial roles [6,21–23]. Rather than presenting a basic introduction to these technologies, this section highlights their relevance and complementary strengths in the context of this study. An optical satellite is a passive satellite that takes sunlight as a source of energy to capture images. It gives more visible images than the human eye does. Laser data offers extra information about the properties of the topography or vegetation, whereas optical satellite data provides color information that can distinguish between different vegetation kinds [7,19]. Optical satellites take imagery in the visible or near-visible portion of the electromagnetic spectrum, using the sun's radiation as it reflects from our planet and atmosphere [9,20]. Another type of remote sensing is SAR (synthetic Aperture Radar satellite), which is an active satellite that uses waves to collect active data from the sensor which produces its energy (radio wave or microwave) and records the reflected energy back after earth interaction. The help of these scattering signals with a different surface of the earth creates images that are good for observing characteristics of the surface like moisture, structure, forest biomass, etc [3,21]. SAR is good in penetrating clouds but optical is not good. SAR can capture images in bad weather but optical is not good to capture images in bad weather. SAR gives day and night view but optical gives only day view [6,16]. The combination of Optical satellite images with SAR satellite images using time series concept gives better resolution and helps us for identification and classification [17,24]. In the past few years for LULC applications, image fusion of Optical and SAR satellite image concepts has been used for accurate monitoring. Sentinel-1 and Sentinel-2 satellites, developed by the European Space Agency (ESA) under the Copernicus program, offer freely available, high-resolution, and frequently acquired datasets [10,25].

SENTINEL-1: It is a composition of two constellations of satellite Sentinel-1A (launched on 3 April 2014) and Sentinel-1B (25 April 2016) which share the same polar-orbiting. Sentinel-2B is retired, only Sentinel-1 A is working and planning to launch Sentinel-1C and Sentinel-1D. Sentinel-1A uses C-Band SAR because the spatial resolution of SAR depends on the ratio of the length of the antenna and wavelength of the sensor, that's why C-band has a 5m wavelength sensor to get 10m spatial resolution to capture images or data in day and night during all kind of weather. It can revisit in 12 days and gives 175 resolutions per cycle. This satellite is used for Marine monitoring, Land monitoring, and Emergency responses [6,11,18,26].

SENTINEL-2: It is based on a Copernicus program called Earth observation which gives high resolution up to 10m to 60m of land and coastal areas. It is also a constellation of two satellites Sentinel-2A (launch 23 June 2015) and Sentinel-2B (launch 7 March 2017) and Sentinel-2C is planning to launch [10,25]. It gives multi-spectral data with 13 bands of visible (red, green, blue), infrared (IR), and short-wave infrared (SWIR). It covers a globally large area from South to North. It can revisit every 10 days in the same orbit and one orbit was completed in 5 days, so some regions were observed twice but with different viewing angles. This satellite is used for many services and applications like agriculture monitoring, emergency response and management, water quality detection and LULC applications [12,13,27,28].

Sentinel 1 and Sentinel 2 satellite images are suitable for earth observation. Sentinel 1 is good for penetrating cloud and weather dependent, which creates a problem of speckle noise which is multiplicative in nature. Similarly, Sentinel 2 gives good resolution due to the Sun as a source of energy to capture high-resolution images in the daytime which creates a problem of mixed pixels. The problem can be mitigated by using image fusion to combine both features in one image for better analysis [29–32]. These two satellite systems are particularly well-suited for image fusion applications, where their combined strengths enhance deforestation monitoring by mitigating each sensor's limitations.

This paper is organized into seven sections. The first section is the introduction that provides relevant information about the importance of LULC for deforestation monitoring including technical overview of the satellite imagery used—specifically Sentinel-1 and Sentinel-2—and their relevance to deforestation monitoring and their features. The second section is a literature review of deforestation detection techniques. The third section is based on the proposed methodology followed by materials used in this paper. The fourth section is based on methodology and divided into three sub-sections: Preprocessing, Intermediate processing and Final processing. For better visualization of the proposed model, the fifth section is based on results which are divided into three sub-sections same as methods: preprocessing results, intermediate results, and Final results. At the end of the paper, we discussed the pros and cons of the paper in the Discussion section. In the end, we concluded the paper with justification.

## 2. Related Work: Literature Review of Deforestation Detection

The objective of the paper is to provide a comprehensive review of different techniques used for deforestation detection with their motivations and their issues. For the literature survey, the reviewer reviewed quality papers with a description of the dataset and methods used. Based on **Table 1** [33–44], future discussion and conclusions are prepared. With the help of this survey, the author can analyze and identify which techniques are good for deforestation detection and understand the benefits of both Optical and SAR satellite image fusion for LULC applications.

**Research Gap and Methodology Analysis**: Based on the above literature survey, the author analyzes the research gap between multiple machine learning models and finds a suitable methodology for image fusion. The PCA-Wavelet method is chosen for its ability to effectively retain both spectral and spatial information, making it superior to other approaches in deforestation detection. Traditional machine learning methods, such as Decision Trees and Random Forest [5,8,23], have been widely used due to their interpretability and classification efficiency. However, these techniques struggle with high-dimensional, multi-temporal datasets, resulting in reduced accuracy in spectral variation analysis. Similarly, Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA) offer strong classification capabilities but face challenges related to collinearity and the need for extensive feature selection [33,35,41].

Deep learning-based approaches [4,34–36,42,44] provide high accuracy in deforestation detection by leveraging multi-temporal satellite data. However, these methods require large, labeled datasets, making them computationally expensive and susceptible to overfitting. Additionally, SAR-optical image fusion techniques using Sentinel-1 and Sentinel-2 [33,38,39] enhance structural and spectral information but often suffer from misregistration errors, leading to the loss of spectral details. PCA-Wavelet, as demonstrated in studies [45,46], overcomes these issues by preserving both spatial resolution and spectral fidelity, making it a robust choice for multi-sensor image fusion in deforestation analysis.

PCA-Wavelet offers a well-balanced approach by retaining spectral information, improving computational efficiency, and enhancing feature extraction. Unlike standalone PCA, which may compromise spectral details, PCA-Wavelet effectively balances spatial and spectral resolution. Moreover, it requires fewer computational resources than deep learning models, making it a practical choice for large-scale deforestation mapping. The wavelet transformation component enhances edge detection and classification accuracy, which is crucial for distinguishing deforested areas from surrounding vegetation.

**Table 1**. Literature Review.

| No. | Authors/Year | Study Motivation & Key Issues | Journal (Name, Not Publisher) | Dataset | Methods & Results |
|---|---|---|---|---|---|
| 1 | Mngadi et al., 2021 [33] | Uses SAR and Optical image fusion for large-scale deforestation detection; pixel-level fusion loses spectral info; feature-level fusion used instead with less accuracy. | Geocarto International | Sentinels 1 and 2 | LDA; improved discrimination but lower accuracy due to feature-level fusion. |
| 2 | Marujo et al., 2020 [34] | Semantic segmentation for multi-temporal image analysis; cloud cover poses challenges. | International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences | Landsat 8 | Deep learning with U-Net variations; good detection under clear skies. |
| 3 | Ortega Adarme et al., 2020 [35] | Deep learning vs. SVM for classification in small areas; requires large training data. | Remote Sensing | Landsat 8 | DL and SVM; DL outperformed SVM in spatial accuracy. |
| 4 | Torres et al., 2021 [36] | Detection of deforestation polygons; false degradation and image shifts cause issues. | Remote Sensing | Landsat 8, Sentinel 2 | Fully CNN; effective but challenged by false positives/negatives. |
| 5 | Fonseca et al., 2021 [37] | Pattern recognition with DL; mapping accuracy improved; slow processing due to clouds. | Pattern recognition letters | Landsat 8 and MODIS | Deep learning; accurate but computationally expensive. |
| 6 | De Luca et al., 2022 [38] | SAR and Optical data for LULC; good spatial classification, lacks detail in small features. | European Journal of Remote Sensing | Sentinels 1 and 2 | Supervised RF; strong for forest types, weak for fine features. |
| 7 | Pacheco-Pascagaza et al., 2022 [39] | NRT change detection; differentiation between forest types difficult under clouds. | Remote Sensing | Sentinel 2 | ML + PYEO Python; responsive but limited by spectral overlaps. |
| 8 | Silva et al., 2022 [40] | NRT monitoring in rainy season using SAR; overfitting in NN needs early stopping. | European Journal of Remote Sensing | Sentinel 1 | NN with MLP and MMD; good temporal response, tricky validation. |
| 9 | Saha et al., 2022 [41] | ML in Himalayan Foothill; SVM best; multicollinearity checked. | Resources, Conservation & Recycling Advances | Landsat 8 | SVM, NB, RF, etc.; high accuracy, best with SVM. |
| 10 | Matosak et al., 2022 [42] | Hybrid DL on two datasets; mislabeled samples reduce accuracy. | Remote Sensing | Landsat 8 and Sentinel 2 | LSTM + U-Net; effective, sensitive to label quality. |
| 11 | Mateen et al., 2023 [43] | Classification of fused Sentinel, Landsat, and Airbus data; RF & ANN outperform SVM. | Open Geosciences | Sentinel 2, Landsat 8, Airbus Vision 1 | RF, ANN, SVM; best results with RF and ANN, 10–3.48m resolution. |
| 12 | Kuzu et al., 2024 [44] | Self-supervised learning for forest change; contrastive learning effective but pretraining is complex. | IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing | Sentinels 1 and 2 | Self-supervised DL; promising with pixel-level contrastive learning. |

The methodology involves multiple steps to ensure accurate deforestation detection. First, satellite images from Sentinel-1, Sentinel-2, and Landsat 8 datasets are acquired. Preprocessing techniques, including cloud removal, radiometric correction, and geometric correction, are applied to refine the data. The PCA-Wavelet fusion process begins with Principal Component Analysis (PCA) for dimensionality reduction, followed by a multi-resolution wavelet transformation to preserve spatial details. The transformed components are then fused to generate high-resolution deforestation maps. Finally, classification techniques such as Random Forest and SVM are applied to classify deforested areas, with validation performed using ground-truth data and existing forest cover maps. In conclusion, PCA-Wavelet is selected due to its ability to maintain both spectral and spatial details while ensuring computational efficiency. The literature review confirms its effectiveness over other techniques in deforestation detection, making it an optimal approach for this study.

# 3. Materials and Methods

The **Materials and Methods** section is crucial in any scientific study, as it provides transparency and reproducibility. By detailing the dataset, tools, workflow, and study area, as well as the steps of preprocessing, intermediate, and final processing, other researchers can replicate the study, validate its findings, or build upon its work. Each component, from the selection of data to the application of specific tools and methods, plays a vital role in ensuring the integrity, reliability, and validity of the research outcomes. This section also serves as a roadmap, guiding readers through the systematic approach used to arrive at the study's results. In this paper, the **materials** are represented by the datasets and tools utilized throughout the research, as well as the description of the study area and the workflow followed. These resources are essential for the execution of the study and are meticulously selected to ensure that the research objectives can be effectively addressed. The datasets form the foundation of the analysis, while the tools, which include software and computational resources, facilitate data processing and analysis. The study area provides the geographical or contextual scope for the research, and the **Methods** explained in the workflow offer a systematic approach to managing the entire research process, which is divided into three sections preprocessing, intermediate processing, and final processing, ensuring that each phase is carried out effectively and efficiently. Together, these materials ensure the rigor and reproducibility of the study's findings.

## 3.1. Dataset

The dataset forms the foundation of the research. Its quality and relevance are critical for ensuring the reliability of the results. A well-curated dataset, representative of the study's objectives, is key to accurate findings. The Brazilian state of Pará has been the main cause of the decline in tree cover between 2010 and 2022. In terms of tree loss between 2001 and 2022, Novo Progresso specifically came in third place in Pará. The region saw a high volume of deforestation alerts in October 2023, mostly as a result of fires [47]. Pará is the second-largest deforestation region in the Brazilian Amazon, according to REDD+ (Reducing Emissions from Deforestation and Forest Degradation) research done over the past 15 years [44,48]. Based on these findings, the author investigated a model that was put out to solve the mixed pixel problem and categorize deforested areas using Pará data. The dataset is described by the Google Earth Pro visualizations in **Figure 1** and **Table 1**.

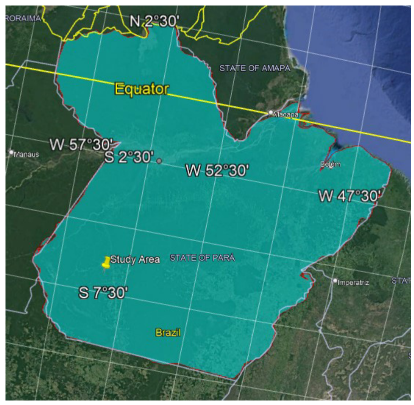



**Figure 1**. Graphical Representation of Research Area.

## 3.2. Research Area

Defining the study area is important as it contextualizes the research within a specific domain or geographical boundary. This ensures that the findings are relevant to the intended scope and audience. The dataset used in this study was sourced from both NASA and the European Space Agency's (ESA) Copernicus program. The analysis of the proposed model involved Sentinel-1 Ground Range Detected (GRD) images from 2019 and 2023, which, due to its synthetic aperture radar (SAR) capabilities, allow for accurate Earth observation regardless of weather conditions or time of day. Additionally, the Sentinel-1 system's Dual Polarization GRD mode enhances its ability to capture precise data. To complement this, Sentinel-2 Multispectral Instrument (MSI) images from the same years were employed, utilizing its 13 spectral bands that provide high-resolution daytime observations for effective environmental monitoring and analysis. Detailed information about the dataset can be found in **Table 2**.

**Table 2.** Research Area Description.

| Data Type | Year | Product Type | Acquisition Date and Time | Band | Polarization |
|---|---|---|---|---|---|
| **Sentinel-2** | 2019 | MSI | 30/08/2019 | 13 Bands (1,2,3,4,5,6,7, 8,8A,9,10,11,12) | |
| | 2023 | | 19/08/2023 | | |
| **Sentinel-1** | 2019 | IW_GRD | 21/07/2019 | | VV and VH |
| | 2023 | | 24/07/2023 | | |

## 3.3. Tools

The tools used for data analysis and processing are essential for ensuring precision, efficiency, and accuracy. These tools enable the handling of large datasets, statistical computation, and the visualization of results, making complex processes manageable and repeatable. The dataset preprocessing was carried out using the SNAP tool's latest version 9.0.8, a software developed by ESA Copernicus for Earth observation data processing. For the analysis of image fusion, the SNAP tool and Python3 Jupyter Notebook version 7.0.8 were utilized, while the classification of deforested areas and area calculations were performed using MATLAB R2023b. The Sentinel Application Platform (SNAP) is particularly suited for processing satellite images and Python3 Jupyter Notebook 7.0.8v was used for intermediate analysis, enabling more efficient and rapid fusion of SAR and optical images. MATLAB R2023b further facilitated the fast processing of large satellite image datasets during the deforestation classification and area calculation using the proposed model.

## 3.4. Methods: Proposed Workflow Model

The workflow outlines the structured approach to data handling, ensuring that each phase is conducted systematically. A clear workflow is vital for maintaining consistency and enabling researchers to trace the steps taken during the study. The main objectives of the research paper are the classification of deforestation and the analysis of the fusion of optical SAR satellite images. As seen in **Figure 2**, the suggested technique has been split into three separate phases each of which consists of three steps specifically. While optical satellite imaging provides clean, high-resolution images, the mixed pixel problem makes it more difficult to accurately identify objects within the images. A mixed pixel problem is one where a pixel has various class memberships that affect the resolution. Speckle noise is the only problem with SAR satellite imaging, yet it offers excellent-resolution photos in the daytime and nighttime regardless of the weather. Because speckle noise is multiplicative in nature, coherent imagery is similarly impacted [29]. The Image Fusion of Optical and SAR is facing a problem called Image registration. Image registration means collocation of images [30–32].

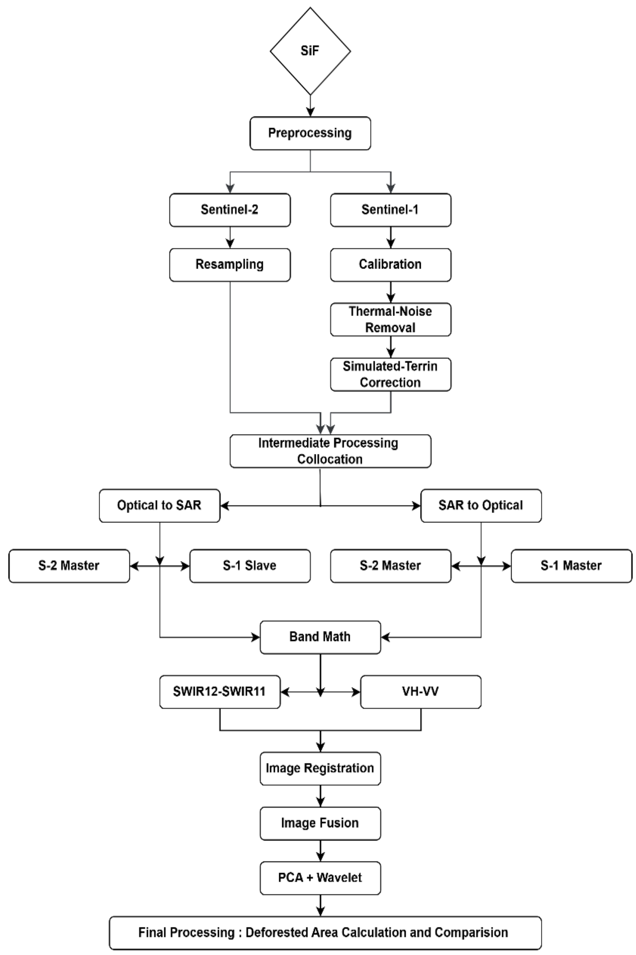



**Figure 2**. Flowchart of Proposed Methodology SIF.

This study aims to develop and evaluate an effective image fusion technique that integrates Sentinel-1 (SAR) and Sentinel-2 (optical) satellite imagery to enhance the accuracy of deforestation detection in the Amazon Forest. By leveraging machine learning–based image fusion, specifically the PCA-Wavelet approach, the study aims to improve the spatial and spectral resolution of satellite imagery, enabling more precise quantification and monitoring of deforested areas over time. This is accomplished by using the pre-processing and intermediate processing methods specified in the suggested methodology. This entails evaluating the proposed method against existing approaches to determine its accuracy and effectiveness in detecting deforested regions. The goal of this comparison is to gain a better understanding of the method's performance and to accurately quantify the extent of deforestation. By improving the precision of deforestation detection, the study aims to enhance the reliability of long-term environmental monitoring and analysis.

### 3.4.1. Preprocessing

Preprocessing is crucial for ensuring the dataset's quality and integrity. Cleaning and preparing the data helps avoid biases or inaccuracies that could otherwise skew the results, making it a vital first step in any data-driven study. The preprocessing of Sentinel 1 and Sentinel 2 is done using the SNAP tool latest version 9.0.8.

Thirteen spectral bands make up Sentinel-2 MSI; four of the bands have a spatial resolution of 10 m (Red, Green, Blue, Near-infrared), six have a resolution of 20 m (bands 5, 6, 7, 8a, 11, 12), and three have a resolution of 60 m (band 1, 9, 10). Sentinel-2 MSI's main objective is to phase two satellites 180 degrees apart in the same orbit so that they can take pictures every five days. To enable accuracy and loss validation in deep learning models, preprocessing multispectral pictures is essential. To prepare the data, this technique starts with stacking multiple bands. Only the SWIR 11 and SWIR 12 were used in the study that is cited, specifically the Short-Wave InfraRed band (B11 and B12) is used to analyze the deforestation due to less effective by smoke and cloud and provide more sensitive information of land changes. After that, resampling is carried out to modify and adapt image resolution utilizing bilinear up-sampling and mean down-sampling to adjust image resolution and alter pixel values.

Sentinel 1 is a satellite mission operated by the European Space Agency (ESA) as part of the Copernicus Program. With the ability to take pictures of the Earth's surface day or night and in any weather, it offers high-resolution Synthetic Aperture Radar (SAR) data. Applications such as mapping, environmental monitoring, and disaster management can benefit greatly from this. A C-band SAR sensor, which operates in the microwave frequency range with wavelengths of about 5.6 cm, is what Sentinel-1 employs. The satellite picks up the reflected signals from SAR systems, which shoot microwave energy pulses at the surface of the Earth. Sentinel-1 works in the microwave frequency range, with wavelengths of about 5.6 cm, thanks to the usage of a C-band SAR sensor. Microwave energy pulses are sent to the surface of the Earth by SAR devices, and the satellite records the reflected signals. Sentinel-1 functions in many modes, including Extra-Wide Swath (EW), Strip map (SM), and Interferometric Wide Swath (IW). The most popular mode for Earth observation is IW mode, which yields images with a resolution of roughly 5 meters. An IW mode image is utilized in this paper. Preprocessing of the SAR pictures is necessary before employing them for applications like change detection or surface analysis. The preprocess ensures that the data are accurate and usable for a wide variety of Earth observation applications, providing reliable and high-quality SAR images. In this paper, the authors used VH polarization band compared to VV polarization because VH polarization is highly effective for deforestation monitoring due to its ability to detect changes in forest structure, biomass, and canopy complexity, making it sensitive to both large-scale deforestation and subtle forest degradation.

### 3.4.2. Intermediate Processing

Intermediate processing refines the dataset further by selecting and transforming features, which increases the efficiency and accuracy of the analysis. This step is essential for building robust models and ensuring that the results are based on relevant and well-processed data. After preprocessing, apply the collocation method. The Collocation Tool is used to merge or align multiple spatial datasets (referred to as products) so they share a common geographic reference. The data from one or more "slave" products is resampled to fit the geographic grid or raster of a "master" product; this process is called "collocating." To avoid conflicts between data with similar names from different products, users can rename the data components using this tool. A new product is generated that combines all the components of the master product with selected components of the slave products. As you can see in **Figure 2**, we collocate Sentinel 1 with Sentinel 2 and vice versa using resampling, the primary operation in collocating which involves transforming the pixel values from the slave product to match the spatial grid of the master product. For resampling Nearest Neighbor is used which provides the closest geographical point from the slave product is assigned to the master product grid. the Collocation Tool allows spatially aligning data from different sources (products), ensuring that the pixel values of slave products fit the grid of the master product.

After applying collocation, a mathematical model is used called Band Math, using existing data layers, such as bands, tie-point grids, and flags, the Band Maths Tool applies mathematical operations to create new pixel values for images. With the help of these processes, you can produce unique data from preexisting sources. The tool can help to create custom formulas to handle the data. The tool allows you to create new "derived" image data (sample values) by applying mathematical formulas to existing data. With the help of the robust Band Maths Tool, you may create new image data by modifying pre-existing data layers from geographically compatible goods using unique mathematical expressions. Complex analysis is possible because to the tool's flexibility, and you have the option of automatically displaying the resultant image or not. With the help of Band Math, more data collection and preparation can be done for deep neural networking for the final analysis of this paper.

To validate whether the collocated images of Sentinel-1 and Sentinel-2 images are registered in a specific point or not, the author applied Image registration in collocated images of both datasets using equation (3). The next step of intermediate processing is Image Fusion, the main objective of this paper. To increase quality and enhance information content for better analysis, image fusion merges images from various sensors (e.g., Sentinel-1 and Sentinel-2). Synthetic aperture radar (SAR) data is provided by Sentinel-1, a radar sensor, and multispectral optical imaging by Sentinel-2. These datasets are combined to better utilize the complimentary properties of optical and SAR data for a range of remote sensing applications, such as vegetation monitoring, land cover categorization, and urban area detection. For the image fusion of Sentinel 1 and Sentinel 2 machine learning algorithms are applied using collocated images. In this paper, the author used only Band 11 and Band 12 collocated images of sentinel 2 due to the SWIR band is crucial for deforestation monitoring due to its ability to detect moisture content, burned areas, and surface changes, making it a highly effective tool in identifying and analyzing deforested areas. Sentinel 1's VH band collocated images are sensitive to both significant and subtle forest degradation; in particular, VH polarization is a very helpful tool for tracking deforestation since it can detect changes in the biomass, canopy complexity, and structure of the forest for fusion for monitoring deforestation.

$$Fusion_{S2} = B_{12\ collocated} - B_{11\ collocated} \tag{1}$$

$$Fusion_{S1} = B_{VHcollocated} - B_{VV\ collocated} \tag{2}$$

$$Image_{Registration} = Collocated_{S1} - Collocated_{S2} \tag{3}$$

$$Fusion_{s1/s2} = PCA\ Wavelet\ Fusion\ (Fusion_{S2} - Fusion_{S1}) \tag{4}$$

Random Forest is a machine learning technique that can be used to fuse Sentinel-1 and Sentinel-2 datasets by training on labeled data to predict fused output, focusing on maximizing classification accuracy or feature extraction but requires ground truth data for better classification. PCA fuses images by transforming both datasets (Sentinel-1 and Sentinel-2) into principal components and selecting those that preserve the most significant information. The principal components are then transformed back into the spatial domain, producing a fused image that loses the spectral information. Wavelet Transform is a multiresolution analysis technique that decomposes an image into different frequency components, allowing for the fusion of spatial and spectral information at multiple scales and helps to preserve the spectral and spatial information but bit complex for fusion rule selection. Based on the above analysis, the author used a combination of PCA and Wavelet image fusion techniques to maintain both spatial and spectral information without any loss using Sentinel 2 SWIR collocated band math data and Sentinel 1 VH collocated band math data for fusion. Refer to the Image Fusion Algorithm: See **Appendix A** at the end of the paper.

### 3.4.3. Final Processing

With the help of collocated images of Sentinel 1 and Sentinel 2 including Band Math images creates the number of observations to analyze the deforestation classification using the proposed model. To calculate the deforested and non-deforested area, the author used a collocated sentinel 2 short wave infrared image of 2019 and 2023 and, similarly collocated sentinel 1 vertical horizontal polarization image of 2019 and 2023. Apply binary segmentation with global thresholding of 100 in both datasets calculate pixel areas and convert it into kilometre squares using equations 4 and 5. These segmented images are then converted into binary masks to highlight the deforested regions. The deforested area is computed by converting the number of pixels in the binary mask into square kilometers. Sentinel 2 SWIR image has 20 m resolution means 20x20 area per pixels, that's why 0.0004 is used and Sentinel 1 VH image has 10 m meter resolution means 10x10 area per pixels, that's why 0.0001 is used.

$$S_{2\ Deforestation}\ (Number\ of\ Pixels*0.0004) \tag{4}$$

$$S_{1\ Deforestation}\ (Number\ of\ Pixels*0.0001) \tag{5}$$

## 4. Results

The results analysis is divided into three sections. Pre-processed images, as listed in **Table 3**, are covered in the first section and are utilized as input for further analysis. The intermediate processing results are discussed in the second part, which uses **Table 4** as a guide to analyze collocated machine learning image fusion and apply Band Math to create new bands for data preparation for final processing based on "Equation (1)," "Equation (2)," and "Equation (3)." Referencing **Table 4**, the third section compares four distinct datasets of sentinel 1 and sentinel 2 image fusion of 2019 and 2023, similarly sentinel 2 and sentinel 1 image fusion of 2019 and 2023 for better analysis of the outcomes of the proposed model. Lastly, utilizing Equation (4) and Equation (5) and a difference analysis of the deforested area computation.

**Table 3**. Preprocessing of Sentinel 2 and Sentinel 1.

| Data Type | Pre-processing Parameters | Description | Processing Time | |
|---|---|---|---|---|
| | | | 2019 | 2023 |
| **Sentinel 2** | Resampling is a technique used in image processing to change the spatial resolution of an image by altering the number of pixels. This process adjusts the pixel values in a way that ensures the image retains as much information as possible while being resized to a higher or lower resolution. | | | |
| | **Upsampling method** | The method used for interpolation (upsampling to a finer resolution). The value must be one of {"Nearest", "Bilinear", "Bicubic"} | 19 minutes 17 seconds | 46 minutes 1 second |
| | **Downsampling method** | The method used for aggregation (downsampling to a coarser resolution). Value must be one of {"First", "Min", "Max", "Mean", "Median"} | | |
| | **Flag downsampling method** | The method used for aggregation (downsampling to a coarser resolution) of flags. Value must be one of {"First", "FlagAnd", "FlagOr", "FlagMedianAnd", "FlagMedianOr"} | | |
| | **Resample on pyramid levels** | This setting will increase performance when viewing the image, but accurate resamplings are only retrieved when zooming in on a pixel. | | |

**Table 3.** *Cont.*

| Data Type | Pre-processing Parameters | Description | Processing Time | |
|---|---|---|---|---|
| | | | 2019 | 2023 |
| **Sentinel 1** | Utilize orbit correction, which is beneficial. to give precise geometric correction by providing accurate satellite location and velocity information. The process of radiometric calibration guarantees that the SAR image's pixel values precisely depict the radar backscatter from the Earth's surface. The pixel values are standardized in this step, which is important for comparing photographs across different places and over time (temporal analysis). Elimination of Thermal Noise Eliminate any noise that was brought forth by the radar system itself (such as instrument electrical noise). The SAR data is enhanced when this noise is eliminated, ensuring that the pixel values only reflect the backscatter from the Earth's surface. Terrain Correction through Geocoding Rectify topographically induced geometric distortions in the SAR image. After undergoing terrain correction, the SAR picture with radar geometry (slant range) is converted into a map-projected image (ground range) with actual coordinates. | | | |
| | **Apply Orbit Correction** | The orbit file provides accurate satellite position and velocity information. Orbit Type: The user can select the type of orbit file for the application. | 75 seconds | 119 seconds |
| | **Calibration** | SAR calibration is to provide imagery in which the pixel values can be directly related to the radar backscatter of the scene. Source Band: All bands (real or virtual) of the source product. The user can select one or more bands for calibration Auxiliary File: The user selected the XCA file for antenna pattern correction. Some checkboxes need to be selected by the user like Scale in dB, Create gamma0 virtual band, and Create beta0 virtual band. | 25.133 minutes | 30.33 minutes |
| | **Thermal to Noise Removal** | The **Thermal Noise Removal Operator** for Sentinel-1 satellite data is a processing tool used to correct or manage the thermal noise present in synthetic aperture radar (SAR) images. This process helps improve the accuracy and quality of SAR data for better analysis and interpretation. | 35.9 minutes | 35.48 minutes |
| | **Terrain Correction** | The simulated image will have the same dimensions and resolution as the original. The **simulated SAR image** (reference) is **co-registered** with the **original SAR image** (secondary) to align each pixel in the simulated image to its corresponding position in the original image. For **terrain correction**, each DEM grid cell is mapped to a pixel in the simulated SAR image using SAR geometry to ensure accurate georeferencing and alignment of SAR data with the terrain. | 254.6833 minutes | 100.96667 minutes |

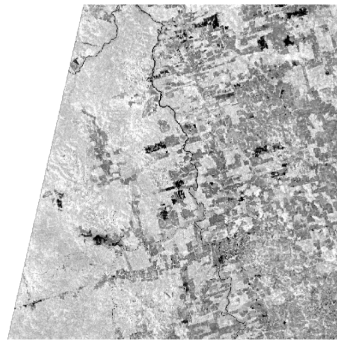
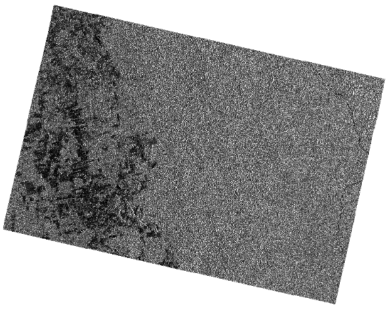
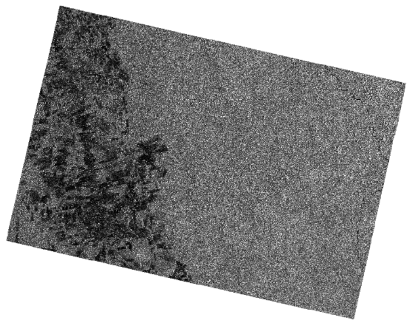
## 4.1. Preprocessing

The preprocessing stage ensured that the dataset was thoroughly cleaned, removing any inconsistencies that could compromise the analysis. This process was fundamental analysis. This process was fundamental to preparing accurate intermediate and final processing. The visualization of pre-processed steps based on **Table 3** for both datasets is shown in **Table 5**.

**Table 4**. Intermediate Preprocessing of Sentinel 2 and Sentinel 1.

| Dataset | Year | Collocation | | PCA-Wavelet Fusion | Band Math | |
|---|---|---|---|---|---|---|
| | | **Master** | **Slave** | **S2–S1 Fusion** | **Div** | **Sub** |
| **Sentinel 1** | 2019–2023 | S1 | S2 | S2 SWIR 12 fused with S1 VH | VH/VV | VH–VV |
| **Sentinel 2** | | S2 | S1 | | B12/B11 | B12–B11 |

**Table 5**. Preprocessing Results of Sentinel 2 and Sentinel 1.

| **Data Type** | **Pre-Processed Images** | | |
|---|---|---|---|
| | **Year** | **2019** | **2023** |
| **Sentinel 2** | |  |  |
| **Sentinel 1** | |  |  |

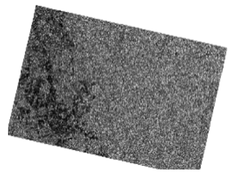
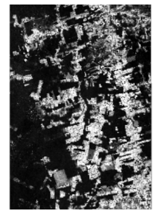
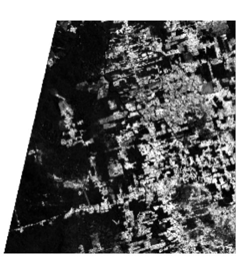
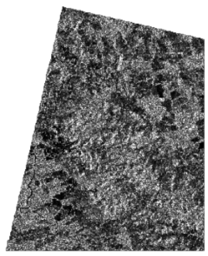
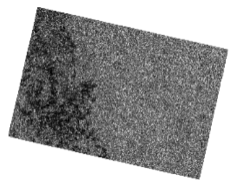
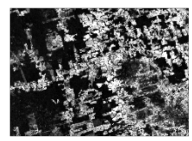
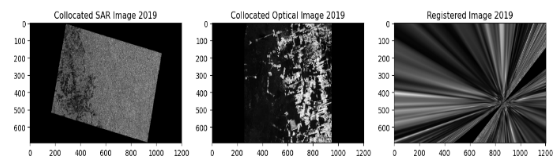
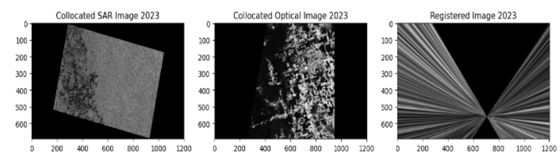
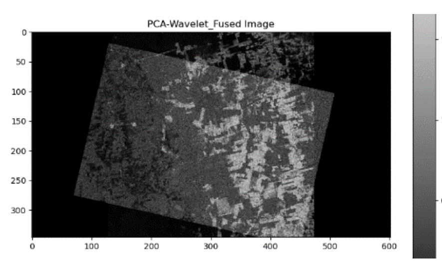
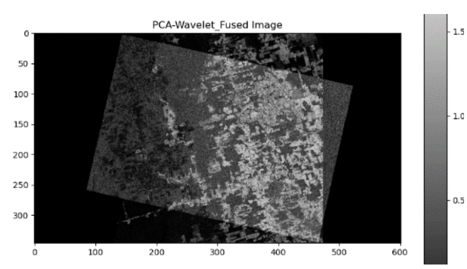
## 4.2. Intermediate Processing

Intermediate processing helped streamline the dataset, focusing on the most relevant features while ensuring proper scaling and transformation. This step proved essential in optimizing model performance and improving the overall accuracy of the analysis. With the help of intermediate processing, the author can analyze the sentinel 1 and sentinel 2 image fusion using collocation and machine learning techniques. In this paper, we used collocated sentinel 1 VH image and collocated sentinel 2 SWIR band 12 image for fusion using PCA-Wavelet machine learning. Based on **Table 4**, you can see results in **Table 6**.

For better understanding of images: Histograms are crucial in remote sensing and image fusion as they provide insights into the distribution of pixel intensity values. In this study, histograms were generated to compare collocated and fused images of 2019 and 2023 years and image types (Sentinel-1 and Sentinel-2). These histograms reflect variations in image contrast and texture: As you can see in **Figures 3–8**, Collocated images tend to have sharper peaks, indicating limited variation in pixel intensity—typical of single-band data. But Fused images, which combine spectral and spatial information from SAR and optical sources, show broader histograms. This suggests a richer distribution, contributing to improved texture representation and contrast. **Figures 3–8** visualize contrast and texture differences between collocated and fused images.

**Figure 9** illustrates pixel count differences in deforested areas across three image types (SAR collocated, optical collocated, and fused) (**Figure 9(a)** and **(b)**). Each bar is color-coded for clarity: Blue: Deforested pixels in SAR collocated images, Green: Deforested pixels in Optical collocated images and Red: Deforested pixels in Fused images. This visual representation confirms that fused images consistently detect more deforested pixels. **Figure 9** effectively supports the claim that fused imagery provides more accurate and comprehensive deforestation analysis.

**Table 6**. Intermediate Preprocessing Results of Sentinel 2 and Sentinel 1.

| | | | | |
|---|---|---|---|---|
| | | **Collocation** | | |
| **Year** | 2019 | | | |
| Data type | S2 Master | S1 Slave | S1 Master | S2 Slave |
| |  |  |  |  |
| **Year** | 2023 | | | |
| | S2 Master | S1 Slave | S1 Master | S2 Slave |
| |  |  |  |  |
| **Image Registration** | | | | |
| Year | 2019 | | 2023 | |
| Data Types | S1 Collocated VH and S2 Collocated SWIR | | | |
| |   | |   | |
| **PCA-Wavelet Image Fusion** | | | | |
| **Year** | 2019 | | 2023 | |
| Data type | S2 Collocated SWIR Band 12 | S1 Collocated VH Band | S2 Collocated SWIR Band 12 | S1 Collocated VH Band |
| |   | |   | |

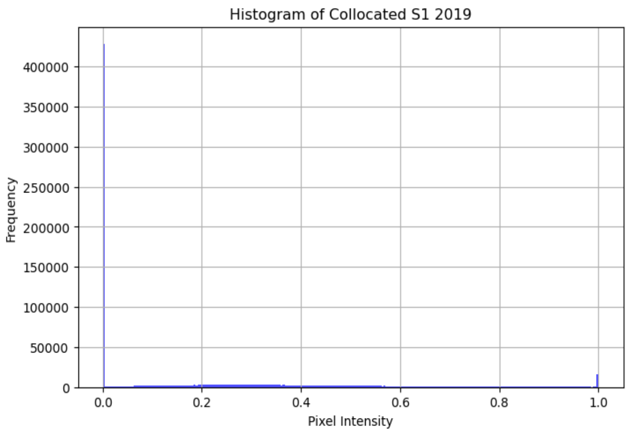



**Figure 3.** Histogram of 2019 Collocated S1.

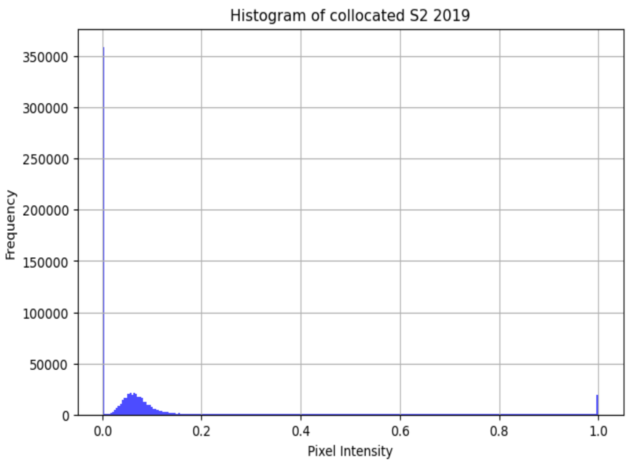



**Figure 4.** Histogram of 2019 Collocated S2.

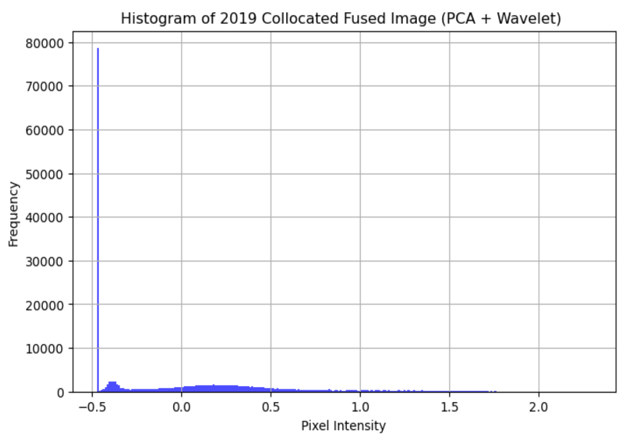



**Figure 5.** Histogram of 2019 Fused S1 and S2.

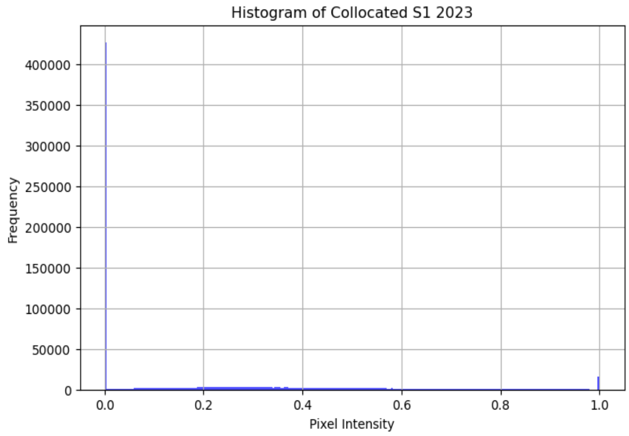



**Figure 6.** Histogram of 2023 Collocated S1.

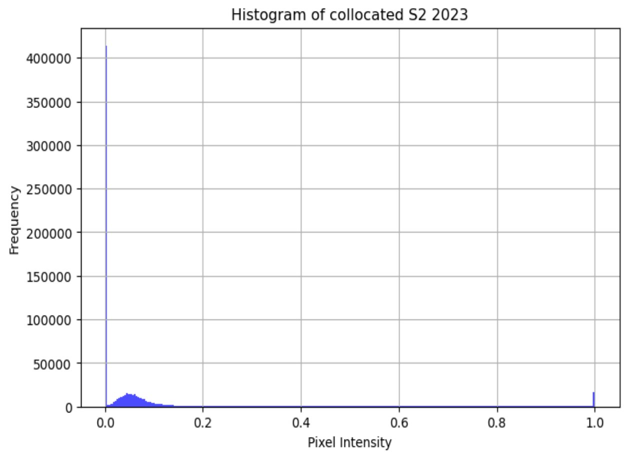



**Figure 7.** Histogram of 2023 Collocated S2.

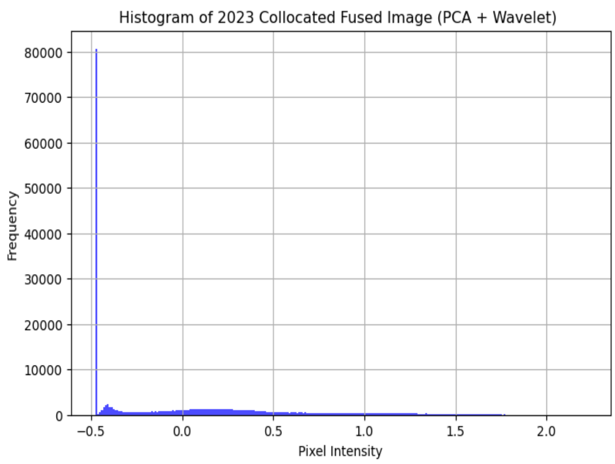
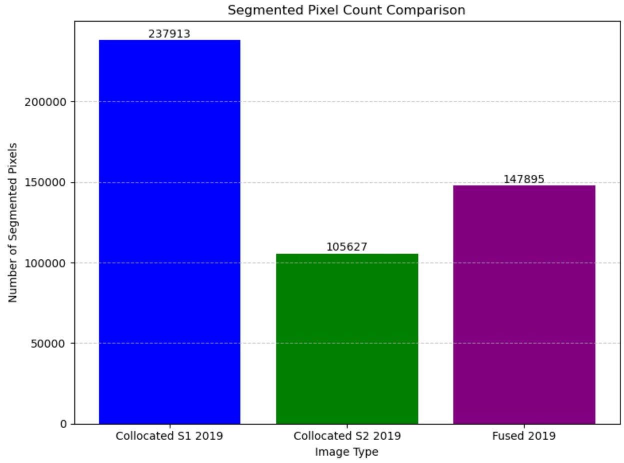
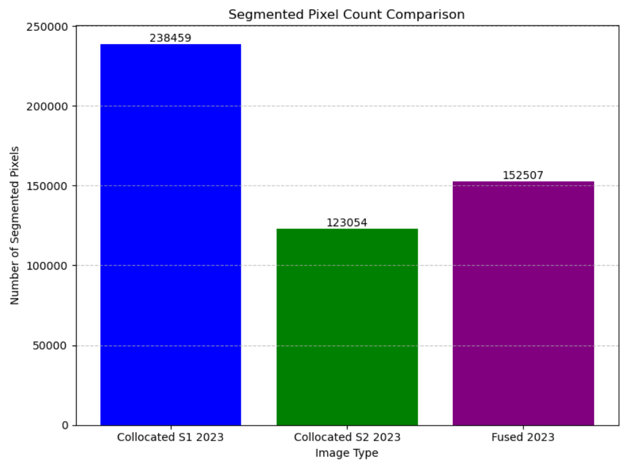



**Figure 8.** Histogram of 2023 Fused S1 and S2.




**(a)**




**(b)**

**Figure 9**. Comparison of Collocated vs Fused Image Outputs for Sentinel-1 and Sentinel-2 (2019 **(a)** & 2023 **(b)**).

## 4.3. Final Processing

The final processing yielded valuable insights, driven by the thoroughness of the previous steps. The results were validated and aligned with the study's objectives, highlighting the importance of using robust methods to achieve reliable conclusions. By detailing these steps, the **Materials and Methods** section emphasizes the significance of each stage in producing high-quality, reproducible research results. The Final objective of this paper is to analyze deforested and non-deforested classification. With the help of the proposed model, preprocessing and intermediate processing help to analyze the image and prepare the fused image dataset for deforestation and non-deforestation area calculation. For the final analysis of the proposed model, the author used collocated optical to sar and sar to optical observations, and with the help of band math image of subtraction is used for both optical to sar and sar to optical observations of the 2019 and 2023 datasets. To analyze the difference between a collocated image and a fused image, the author used a sentinel 2 collocated SWIR image fused with a sentinel-1 VH polarization collocated image and applied PCA-Wavelet image fusion in the 2019 and 2023 datasets. For a better understanding of image fusion deforestation classification analysis between deforested and non-deforested areas using graphs which are based on three types of images called fused image, collocated image, and binary segmented image using equations (4) and (5). With the help of graphs, the analysis of image fusion is much clearer see **Figure 10**. The Blue color represents the deforested area based on the collocated image of SAR, the green color represents the deforested area based on the collocated image of Optical, and the fused image deforested area is represented using red color.

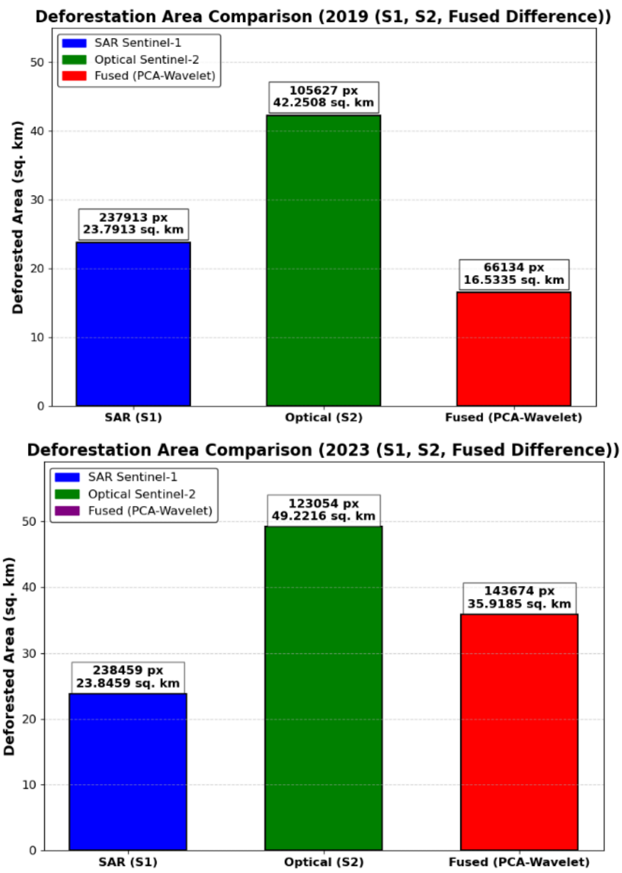


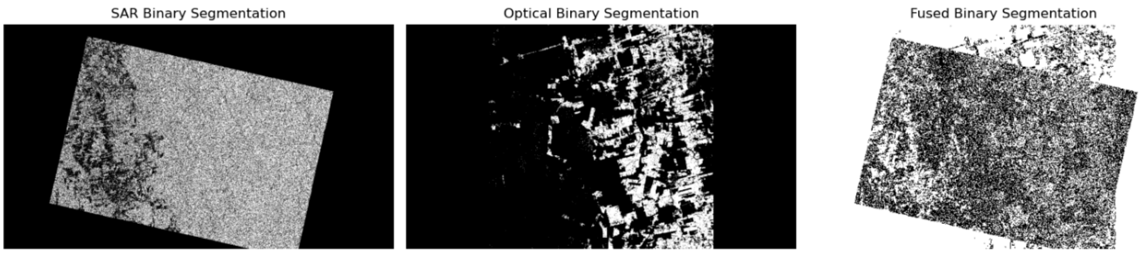

**Figure 10**. Deforested Area in Pixels and Kilometer Square in Sentinel 2 and Sentinel 1 Images of 2019 and 2023.

To analyze the above graph more appropriately and accurately, need to analyze the number of pixel areas in collocated images, fused images, and binary segmented images see **Table 7**. As you can see a difference between collocated images of deforested areas and fused images of deforested areas. With the help of image fusion of sentinel 1 and sentinel 2 gives more appropriate and accurate deforestation analysis.

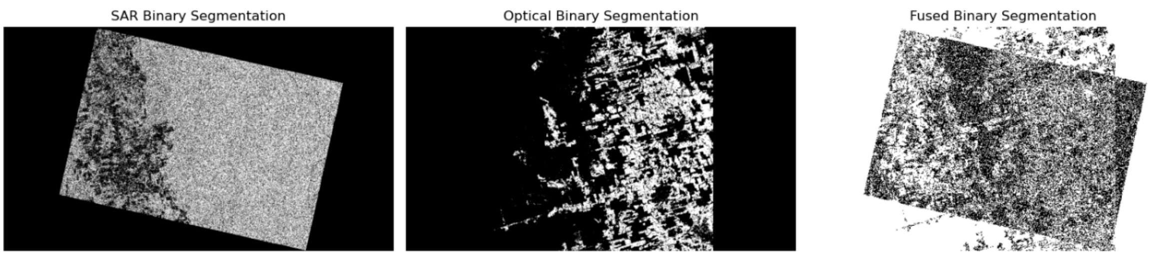
To visualize the pixels difference: Image visualizations are used to give qualitative understanding of differences between: Collocated images, Fused images, Binary segmented images (**Figure 11**). These visual comparisons reveal that fused images display better delineation of deforested regions compared to individual SAR or optical sources see below **Figure 11a,b**.

**Table 7**. Deforestation Pixels Analysis of Sentinel 2 and Sentinel 1.

| Year | Image Type | S1 | S2 | S2–S1 | S1 Area (km²) | S2 Area (km²) | S2–S1 Area (km²) |
|---|---|---|---|---|---|---|---|
| 2019 | Collocated images pixels | 237913 | 105627 | - | 23.79 | 42.25 | - |
| | Fused Images pixels | - | - | 66134 | - | - | 16.55 |
| 2023 | Collocated images pixels | 238459 | 123054 | - | 23.84 | 49.22 | - |
| | Fused Images pixels | - | - | 143674 | - | - | 35.91 |




**(a)** 2019 Image Visualization




**(b)** 2023 Image Visualization

**Figure 11**. Side-by-Side Visualization of Collocated vs Fused Images for Deforestation Classification (2019**(a)** & 2023**(b)**).

# 5. Discussion

As per the above analysis, Satellite images give four types of resolutions: Spatial, Spectral, Temporal, and Radiometric [49]. To maintain spatial and spectral information of original images, the image fusion concept is coming because SAR satellite gives more spectral information, and Optical satellite gives more spatial information. Regarding temporal resolution, both SAR and optical fusion are the best procedures because optical gives high resolution in the daytime, but SAR gives both day and nighttime. SAR is good in all weather and cloud penetration but optical is not. Considering all the pros and cons of both SAR and optical satellite image fusion gives more accurate deforestation detection based on image fusion results. By integrating both datasets through fusion techniques, this study has shown that monitoring deforestation can be more accurate and comprehensive, capturing information across different weather conditions and times of day.

The objective of this paper is how to mitigate the issue of two different sources of images using collocation and machine learning image fusion. As you can see, Sentinel 1 and Sentinel 2 are two different types of satellite images and these satellites operate differently in terms of resolution, temporal coverage, and spectral capabilities, the fusion of their images allows for more precise and reliable detection of deforestation. With the help of image registration, the author can only analyze that both datasets are registered in a specific point but how much area or tiles are registered in both datasets can be analyzed by using the collocation concept. After analyzing the collocated area of both datasets, the author applied different machine learning image fusion techniques like random forest, PCA, and Wavelet and compared which image fusion is more suitable for better visualization of deforestation and non-deforestation. Through this, we were able to significantly enhance the detection of deforested areas, increasing the accuracy of monitoring efforts.

While the PCA-Wavelet method offers many advantages, some limitations must be considered. For instance, its performance can vary with different degrees of deforestation—dense forest clearings are more easily detected than scattered or small-scale deforestation events. Furthermore, its application may yield different results depending on the geographical region due to terrain variability and the spectral characteristics of local vegetation. This suggests a need for region-specific calibration of the model for optimal results.

Image fusion with machine learning and deep learning methodology is used by many papers to give better results using hybrid combinations. Image fusion can be done in three ways: pixel level but needs an accurate registration process, which is not possible with SAR satellite images, feature level image fusion is good but does not give more accurate values compared to pixel level and the last is decision level image fusion which is based on deep learning concepts gives better results but not suitable for mislabeled data. The application of machine learning and hybrid image fusion techniques has been shown to significantly improve results. While previous studies have applied pixel-level, feature-level, and decision-level fusion techniques, each with its advantages and limitations, the proposed PCA-Wavelet method offers a more robust solution. By using a hybrid PCA-Wavelet approach, we have maintained a balanced fusion of both spatial and spectral information. PCA, a technique widely used for spatial resolution enhancement, was combined with Wavelet transformation, which effectively preserves spectral information, providing a better fusion compared to traditional methods. This fusion technique also minimizes computational requirements compared to deep learning-based approaches, making it an ideal choice for large-scale deforestation monitoring. The Wavelet transformation's ability to enhance edge detection was crucial for accurately distinguishing deforested areas from surrounding vegetation, providing more detailed and reliable deforestation maps. Using the mapping concept for different time series of SAR and optical satellite images gives more accuracy and clarity to monitor deforestation both day and night. With the help of hybrid machine learning using mapping of different time series gives more spatial and spectral information in different temporal which helps the government to monitor and generate alerts. It also helps in Land use Land cover change detection monitoring of deforestation in the future.

Many studies, who used CNN-based deep fusion for deforestation in tropical zones, who explored feature-level fusion for land-use mapping, have demonstrated the effectiveness of hybrid approaches [35,36,42]. Our results align with these findings by confirming that hybrid techniques like PCA-Wavelet provide better spatial-spectral preservation compared to single-method fusions. Moreover, limitation in detecting fragmented deforestation, our study's fusion method mitigated such gaps due to the added edge sensitivity from the Wavelet transform. Recent studies also support this direction, demonstrating that Transformer-based models fusing bitemporal Sentinel-1 and Sentinel-2 imagery can achieve high deforestation detection accuracy under challenging cloud conditions in the Amazon [5].

As per the analysis of applying the hybrid methodology to maintain spatial, spectral, and temporal information, the author used PCA-Wavelet transformations image fusion techniques. Through the process of collocation, which involves aligning the pixel grids of two datasets from different satellite sources, we have improved the accuracy of the fusion process. Various resampling methods were used to adjust the alignment, ensuring that the fused image retained both spatial and spectral fidelity. The results demonstrated that using Sentinel-2 and Sentinel-1 datasets after preprocessing, followed by collocation, significantly enhanced the deforestation detection accuracy, particularly when using the PCA-Wavelet fusion technique. PCA is good for maintaining spatial information but suitable for spectral information. Wavelet is good for spectral information but not suitable for spatial information. To combine both methodologies to analyze the fusion of Sentinel 1 and Sentinel 2 collocated images for better understanding. After preprocessing both datasets, apply the collocation concept which allows spatially aligning data from different sources (products), ensuring that the pixel values of slave products fit the grid of the master product. Different resampling methods enable flexible approaches to data alignment, while the tool handles components like flags and no-data values intelligently. For detailed comparative review of fusion techniques, offering further support for the use of hybrid methods in satellite image integration for land-use monitoring [50].

In terms of real-world implications, the hybrid machine learning approach used in this study can significantly enhance deforestation monitoring efforts. Governments and organizations involved in forest conservation can use this methodology to monitor deforestation more effectively, generating timely alerts that help in the prevention of illegal logging and other environmentally harmful activities. Furthermore, the enhanced accuracy in detecting deforestation will improve land-use and land-cover change monitoring, providing better insights into how forests are being impacted over time. While the model performed well with the fusion of Sentinel-2 to Sentinel-1, future research is needed to further explore and improve the fusion of Sentinel-1 to Sentinel-2, particularly when working with different polarization bands. Additionally, integrating other datasets, such as harmonized Sentinel-2 and Landsat 8 images, could provide a more comprehensive approach to monitoring deforestation at different spatial and temporal scales. Therefore, we suggest that future studies focus on testing the PCA-Wavelet approach across multiple ecological zones, including tropical rainforests, dry forests, and mountainous terrain to evaluate its robustness. In addition, optimizing the fusion framework with adaptive algorithms or incorporating additional satellite sources such as hyperspectral or LiDAR data could further enhance accuracy and versatility. The utility of combining Random Forests and PCA-based fusion methods for improving land-use classification accuracy using SAR and optical images [51].

# 6. Conclusions

In conclusion, this study does not merely review existing fusion techniques but rather applies and evaluates a specific hybrid methodology—PCA-Wavelet—in a novel way by integrating multi-temporal and multi-source satellite imagery (Sentinel-1 and Sentinel-2) for deforestation detection. While PCA-Wavelet has been used in prior studies, its application in conjunction with a detailed collocation framework for aligning SAR and optical datasets across different years, and its performance analysis in both 2019 and 2023 datasets demonstrates a significant methodological contribution. This application is especially valuable in operational settings where computational efficiency and spatial-spectral balance are critical. As per the analysis of deforestation analysis of optical and SAR satellite image fusion for land use land cover application is concluded the proposed hybrid machine learning approach—coupling PCA-Wavelet with time-series image mapping and collocation analysis—offers improved accuracy and spatial coverage for deforestation monitoring and future alert systems. It enables better validation and verification by maintaining high spatial and spectral fidelity. It helps in validation and verification for more accurate spatial and spectral information. Specifically, the analysis revealed that the fusion of Sentinel-1 and Sentinel-2 images in 2019 enhanced a total of 16.53 square kilometers of deforested area, while the fusion of the 2023 datasets enhanced 35.92 square kilometers of deforestation. These results highlight the effectiveness of the PCA-Wavelet method in providing more accurate and detailed maps for deforestation monitoring. The fused images captured a broader range of information compared to individual Sentinel-1 and Sentinel-2 images, which demonstrated improvements of 23.79 and 42.25 square kilometers, respectively, for the 2019 dataset, and 23.84 and 49.22 square kilometers for the 2023 dataset. As a result, maintaining both spatial and spectral information proposed model is suitable for deforestation analysis. However, the study also identifies key limitations. The proposed method shows higher accuracy when fusing Sentinel-2 (optical) to Sentinel-1 (SAR) data, but the reverse—Sentinel-1 to Sentinel-2—produced reduced performance, particularly when using Sentinel-1 VH polarization and Sentinel-2 SWIR Band 12. This highlights potential bias and reduced sensitivity to certain spectral characteristics during fusion, which necessitates further refinement and testing under varied polarization and terrain conditions. With the help of band math especially subtraction of band including collocation analysis gives a better understanding of the pixel values of master and slave images which helps to understand the image fusion more accurately. As per the results, the proposed model is suitable for sentinel 2 to sentinel 1 image fusion but not suitable for sentinel 1 to sentinel 2 image fusion. The fusion of Sentinel 1 VH polarization image with Sentinel 2 Short Wave Infrared band 12 gives less accuracy using the proposed model which needs more analysis. In the future, harmonized Sentinel 2 Landsat 8 images will be used with Sentinel 1 image fusion for more understanding of different types of data fusion. Future research should also explore adaptive fusion frameworks, incorporate other satellite modalities like hyperspectral or LiDAR, and test generalizability across different ecological zones to enhance robustness. Overall, the PCA-Wavelet fusion technique—applied in this novel collocation-based framework—provides a valuable and efficient model for large-scale deforestation monitoring. By preserving both spatial and spectral information, the proposed model provides a powerful tool for accurately assessing deforestation areas, with the potential for large-scale implementation in environmental monitoring systems. This approach not only contributes to improving existing deforestation detection methods but also provides a practical solution for future applications in land-use change monitoring.

## Author Contributions

Conceptualization, P.D.; methodology, P.D.; software, P.D.; validation, P.D., A.A. and M.K.; formal analysis, P.D.; investigation, P.D.; resources, P.D.; data curation, P.D.; writing—original draft preparation, P.D.; writing—review and editing, P.D.; visualization, A.A.; supervision, P.D.; project administration, P.D.; funding acquisition, P.D. All authors have read and agreed to the published version of the manuscript.

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Not applicable.

## Data Availability Statement

The data supporting this study will be provided by the corresponding author upon reasonable request.

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## Conflicts of Interest

The authors declare no conflict of interest.

## Appendix A

```
# Image Registration after Collocation done by SNAP tools
def load_image(path):
with rasterio.open(path) as src:
image = src.read()
profile = src.profile
return image, profile
# Load Sentinel-1 (SAR) and Sentinel-2 (Optical) images
sar_image, sar_profile = load_image('collocate_VH.tif')
optical_image, optical_profile = load_image('collocate_B12.tif')
# Take the first band (for simplicity) and normalize
sar_band = sar_image[0] / np.max(sar_image[0])
optical_band = optical_image[0]   / np.max(optical_image[0])
```

```
# Convert to uint8 (necessary for feature detection)
sar_band_uint8 = (sar_band * 255).astype(np.uint8)
optical_band_uint8 = (optical_band * 255).astype(np.uint8)
# Initialize ORB detector
orb = cv2.ORB_create(nfeatures=1000)
# Detect keypoints and descriptors
keypoints_sar, descriptors_sar = orb.detectAndCompute(sar_band_uint8, None)
keypoints_optical, descriptors_optical = orb.detectAndCompute(optical_band_uint8, None)
# Match features using the BFMatcher
bf = cv2.BFMatcher(cv2.NORM_HAMMING, crossCheck=True)
matches = bf.match(descriptors_sar, descriptors_optical)
# Sort matches by distance
matches = sorted(matches, key=lambda x: x.distance)
# Extract the coordinates of the matched keypoints
src_pts = np.float32([keypoints_sar[m.queryIdx].pt for m in matches]).reshape(−1, 1, 2)
dst_pts = np.float32([keypoints_optical[m.trainIdx].pt for m in matches]).reshape(−1, 1, 2)
# Find homography matrix
homography_matrix, mask = cv2.findHomography(src_pts, dst_pts, cv2.RANSAC, 5.0)
height, width = optical_band.shape
sar_registered = cv2.warpPerspective(sar_band, homography_matrix, (width, height))
```

```
# PCA-Wavelet Image Fusion Process after collocated image registration
# Reshape the optical image for PCA (bands, pixels)
bands, width, height = optical_image.shape
optical_reshaped = optical_image.reshape(bands, width * height).T
def apply_pca(sar_image, optical_image):
    # Combine images into a 2D matrix (rows x columns x bands)
    combined_image = np.stack((sar_image, optical_image), axis=−1)
    combined_image_flat = combined_image.reshape(−1, 2)
    # Apply PCA
    pca = PCA(n_components=1)
    pca_result = pca.fit_transform(combined_image_flat)
    pca_image = pca_result.reshape(sar_image.shape)
    return pca_image
pca_image = apply_pca(sar_image, optical_image)
def wavelet_transform(image):
    coeffs = pywt.wavedec2(image, ‘haar’, level=2)
    cA2 = coeffs[0]
    cH2, cV2, cD2 = coeffs[1]
    return cA2, cH2, cV2, cD2
def inverse_wavelet_transform(cA, cH, cV, cD):
    coeffs = [cA, (cH, cV, cD)]
    return pywt.waverec2(coeffs, ‘haar’)
# Perform wavelet transform on PCA result
cA2, cH2, cV2, cD2 = wavelet_transform(pca_image)
# Combine the wavelet coefficients as needed (example combines high and low frequencies)
# You can customize this based on your fusion strategy
fused_image = inverse_wavelet_transform(cA2, cH2, cV2, cD2)
```

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