Journal of Environmental & Earth Sciences
https://journals.bilpubgroup.com/index.php/jees

ARTICLE

SiM: Satellite Image Mixed Pixel Deforestation Analysis in Optical Satellite for Land Use Land Cover Application

Priyanka Darbari [1*], Ankush Agarwal [1], Manoj Kumar [2]

[1] *Department of CEA, GLA University, Mathura 281406, India*

[2] *Department of CEA, GGV University, Guwahati 781021, India*

ABSTRACT

Brazil's deforestation monitoring integrates accuracy and current monitoring for land use and land cover applications. Regular monitoring of deforestation and non-deforestation requires Sentinel-2 multispectral satellite images of several bands at various frequencies, the mix of high- and low-resolution images that make object classification difficult because of the mixed pixel problem. Accuracy is impacted by the mixed pixel problem, which occurs when pixels belong to different classes and makes detection challenging. To identify mixed pixels, Band Math is used to merge numerous bands to generate a new band NDVI. Thresholding is used to analyze the edges of deforested and non-deforested areas. Segmentation is then used to analyze the pixels which helps to identify the number of mixed pixels to compute the deforested and non-deforested areas. Segmented image pixels are used to categorize the deforestation of the Brazilian Amazon Forest between 2019 and 2023. Verify how many pixels are mixed to improve accuracy and identify mixed pixel issues; compare the mixed and pure pixels of fuzzy clustering with the subtracted morphological image pixels. With the help of segmentation and clustering researchers effectively validate mixed pixels in a specific area. The proposed methodology is easy to analyze and helpful for an appropriate calculation of deforested and non-deforested areas.

Keywords: Amazon Forest; Mixed Pixel Problem; Band Math; Segmentation; Clustering

*CORRESPONDING AUTHOR:
Priyanka Darbari, Department of CEA, GLA University, Mathura 281406, India; Email: Priyanka.darbari.phd.cs20@gmail.com

ARTICLE INFO
Received: 10 November 2024 | Revised: 5 December 2024 | Accepted: 9 December 2024 | Published Online: 10 February 2025
DOI: https://doi.org/10.30564/jees.v7i2.7737

CITATION
Darbari, P., Agarwal, A., Kumar, M., 2025. SiM: Satellite Image Mixed Pixel Deforestation Analysis in Optical Satellite for Land Use Land Cover Application. Journal of Environmental & Earth Sciences. 7(2): 228–247. DOI: https://doi.org/10.30564/jees.v7i2.7737

1. Introduction

The intricate relationships that exist between humans and their environment are frequently referred to as land cover (LC) and land usage (LU)[1]. Whereas LC refers to the real physical characteristics of the Earth's landscapes, LU refers to changes in land cover brought about by human activity[2]. Researchers are quite concerned about the rapid changes in land use and land cover that have resulted from the rapid urban growth in many cities. The dramatic shifts in land use in the 21st century have exacerbated the serious problems facing the local, regional, and global environments[3].

The multi-temporal and multi-spectral data that remote sensing provides is crucial for mapping land use and cover. Examination of land cover changes and their consequences can be done thoroughly and economically by combining GIS tools with data from remote sensing[4]. With its vital information on the physical characteristics of the land that dictate its management and distribution among various users, RS is an indispensable tool in land planning and management planning[5].

Due to the significant impact on the global system, Land Use and Cover Changes (LULC) have become an international issue in many ecosystem management[6]. Deforestation, environmental harm, altered weather and water cycles, a decline in land productivity, and the devastation of ecosystems are only a few of the problems brought on by these changes[7]. Effective land resource management and sustainable urban growth depend heavily on research on changes in land use and land cover (LULC). It is necessary to perform environmental research on current and forthcoming Land Use/Land Cover (LULC) studies to address the difficulties arising from fast urban growth in cities[8].

Monitoring deforestation in the tropics via remote sensing is essential to better understand changes in ecosystem services and global land use, as well as to inform governments and civil society on the efficacy of their forest protection measures[9]. Deforestation and the growth of farming and grazing systems, mostly in tropical forests, have been strongly correlated in Brazil. Since the Brazilian Amazon is the world's largest tropical rainforest and has up until recently had the highest rates of deforestation, Brazil has been a focal point of the dynamics surrounding worldwide deforestation. Brazil has been successful in reducing illicit deforestation overall and has been at the forefront of implementing environmental policies based on monitoring efforts to prevent the practice[10, 11]. We checked the result with the Global Forest Government organization; deforestation increased rapidly from 2001 to 2022[12].

S2/MSI data is considered important for Land Use and Land Cover (LULC) and Land Use and Land Cover Change (LULCC) applications because of its interoperability, free availability, and capacity to monitor large regions. The European Space Agency (ESA) launched the Sentinel-2 (S2) satellites, S2A/MSI and S2B/MSI, in 2015 and 2017, respectively, as part of the European Union's Copernicus Earth Observation program. The Multispectral Instrument (MSI) is a piece of equipment aboard a spacecraft that covers visible to shortwave infrared (SWIR) areas. It has 13 bands and a spatial resolution of 10 to 60 meters. Data with a 290 km swath width, 16-bit radiometric resolution, and a 5-day return period are available from the S2/MSI mission[13].

The image acquisition of satellite images is based on the scattering of different objects, and every object has a different wavelength and frequency. The optical satellite uses the electromagnetic spectrum and sun rays as a source of energy to capture the images[14]. With its three Red-edge bands and two SWIR bands, the mission's spectrum characteristics make it more useful for analyzing deforestation[15]. When compared to Landsat data, these features may yield results that are more accurate since they make it possible to derive different band ratios and indices. Owing to its 16-day revisit cycle, cloud cover interference, and poorer spatial and spectral resolutions, Landsat data has limitations[16].

Researchers focus on deforestation classification using optical satellites. Optical satellites like Sentinel-2 provide hyperspectral and multispectral remote sensing datasets. Due to high spatial and spectral including temporal quality, optical satellites face a problem called mixed pixel. Now, researchers need to focus on mixed pixel deforestation classification between mixed pixel and pure pixel[17]. The below **Table 1** Literature Review to highlight research gaps provides a comprehensive overview of the current state of research on mixed pixel problems in optical satellite imagery and emphasizes areas requiring further investigation. By reducing mixed pixels, higher resolution can also aid in the reduction of thematic uncertainty[18].

Table 1. Literature review.

Ref	Methods	Performance	Limitations
[19]	Supervised classification (Neural Networks, Random Forest)	Accurate identification of mixed pixels by merging pure and mixed pixels	Unsupervised techniques struggle with pixel identification, reducing accuracy
[20]	NDVI, simulation techniques	Green-up dates improved compared to traditional NDVI threshold methods	Inconsistent results due to artifacts, observation geometry, and time composition issues
[21]	Fuzzy clustering	High accuracy and low computation time for mixed pixel classification	Deep learning could be applied to incorporate spatial and spectral components for higher accuracy
[22]	Fuzzy supervised classification	Fuzzy classification handles mixed pixels well	Does not define boundaries clearly; unsupervised clustering and discriminant analysis may improve results
[23]	Fuzzy unsupervised clustering	Membership function modifications improve fuzzy clustering results	Challenges in computing similarity between observations and partitioning for clustering
[24]	Biophysical parameter analysis	Useful for mixed pixel detection through colour composition and spectral unmixing	High-resolution data is not always available, leading to thematic uncertainty in the results
[25]	Latent Dirichlet variational autoencoder (LDVAE)	Effective for solving spectral unmixing problems	Suitable only for spectral datasets, not spatial datasets
[26]	Shannon evenness index	Effective for low-resolution datasets (e.g., Sentinel-2)	Not suitable for high-resolution datasets such as Landsat-8
[27]	Sensor-independent LAI/FAPAR/CDR	Improves spatial and temporal data accuracy for mixed pixel correction	Inconsistency in spatial-temporal images, accuracy issues remain
[28]	Efficient mixed transform for super-resolution	Enhances image quality using pixel mixer and transform network	Struggles with scale mismatch using pixel mixer block in real-world problems
[29]	Random Forest, MTMI-SMF algorithm	Low computational cost, performs well for invader classification	Invader classification is challenging due to spectral band limitations, hyperspectral images are recommended for future work
[30]	Morphological operations	Suitable for detecting mixed pixels in small-scale land-water areas	Not applicable for large-scale mixed pixel detection
[31]	Spectral mixing with morphological operations	Suitable for mixed pixel detection in land-water areas	Deep neural networks provide more accurate analysis than machine learning
[32]	Fuzzy clustering	Accurate land-water mixed pixel classification using membership functions	High model complexity

2. Research Gap and Motivation

Mixed pixel classification is a key challenge in remote sensing and earth observation, especially when dealing with high-resolution datasets. Several methods have been proposed to tackle this issue, such as supervised classification using neural networks and random forests, fuzzy clustering, and spectral unmixing techniques. However, gaps remain in terms of achieving higher accuracy, computational efficiency, and applicability across various resolutions. Supervised classification methods, such as neural networks and random forests [19], have demonstrated good performance in identifying mixed pixels by merging pure and mixed pixel data. However, these methods suffer when applied to unsupervised techniques where pixel identification becomes more complex, and errors in classification often reduce accuracy. On the other hand, fuzzy clustering methods [21, 23] show promise in handling mixed pixel classification with high accuracy and lower computation time. However, fuzzy clustering faces challenges related to determining the similarity between observations and partitioning [23]. Moreover, supervised fuzzy classification [22] struggles to clearly define boundaries, which limits its effectiveness in unsupervised settings. Morphological operations [30, 31] work well for small-scale mixed pixel detection, such as in land-water boundary regions, but do not scale well to larger or more complex datasets.

The identified gaps indicate that a hybrid approach that integrates Morphological Subtraction with unsupervised clustering techniques offers the most promising methodology to overcome existing limitations: applying fuzzy clustering with subtracted morphological operations significantly enhances mixed pixel classification by leveraging the strengths of both techniques. Fuzzy clustering can deal with uncertainties and mixed pixels, while morphological operations excel at capturing spatial and spectral relationships. Such integration could address the accuracy limitations seen in current clustering techniques [21–23]. This approach could overcome the limitations of traditional methods like NDVI [20] and Shannon evenness index [26], which perform well for low-resolution datasets but struggle with higher resolutions. Combining machine learning techniques such as clustering methods could offer a balance between computational efficiency and accuracy. The best approach to improve mixed pixel detection and classification, especially for high-resolution data, is to develop a hybrid methodology that combines fuzzy clustering and NDVI morphology segmentation. This hybrid approach can tackle both spectral and spatial complexities, improve classification boundaries, and enhance performance for large-scale applications.

In summary, the identified research gaps emphasize the necessity for hybrid methodologies that synergistically combine segmentation and machine learning to analyze mixed pixel classification across various datasets and resolutions. Addressing these gaps will not only enhance the reliability of remote sensing applications but also improve the accuracy and utility of mixed pixel analysis in environmental monitoring and ecosystem management [21, 26]. In light of this literature review, the author introduces this paper by presenting an innovative approach termed SiM, which stands for Satellite Image Mixed Pixel Deforestation Analysis in Optical Satellite for LULC applications.

The primary motivation driving this research is rooted in the capabilities of optical satellites, which offer high spatial and spectral resolution—critical features for the accurate analysis and classification of Earth observation data. Additionally, optical satellites are known for their excellent temporal resolution, a characteristic that significantly aids in the validation of ground truth observations. This temporal precision not only enhances the accuracy of data interpretation but also improves the overall efficiency of monitoring environmental changes, particularly in the context of deforestation.

In this study, Sentinel-2 Multispectral Images are utilized to address the mixed pixel problem, a common issue that arises due to the very high resolution of these images. The mixed pixel problem occurs when a single pixel represents multiple classes, making object recognition and pixel classification a challenging task. To tackle this, the satellite images undergo initial preprocessing steps, including resampling for geometric correction and image registration. Following this, a process known as Band Math Merging is applied to generate new bands that facilitate detailed pixel analysis. This step is crucial in preparing a comprehensive dataset, which is then used to train a model specifically designed for analyzing deforestation and non-deforestation areas. Once the preprocessing is complete, mixed pixel detection techniques are employed to segment the images, effectively removing unwanted noise and irrelevant pixels. The paper introduces a novel methodology called SiM, designed to classify time-series satellite images with high precision. This innovative approach leverages Morphological Segmentation with Clustering to classify deforested and non-deforested regions. The results are then compared and analyzed to ensure a thorough evaluation of the methodology's effectiveness.

The paper's structure is detailed in **Figure 1** and is organized into several key sections. The first section is the introduction, which sets the stage for the study by outlining the research context and objectives. This is followed by the second section, which provides a comprehensive literature review focusing on the detection of the mixed pixel problem and the classification of deforestation. The third section delves into the materials and methods used in the study, explaining the datasets and techniques applied to identify and address the problems.

The third section is further subdivided into three critical subsections: Dataset and Tools, Methodology, and Outcomes. In the Dataset and Tools subsection, the paper provides an in-depth explanation of the datasets used, along with a detailed description of the tools selected for solving the identified problems. The Methodology subsection is also divided into three parts: preprocessing, mixed pixel identification, and deforestation analysis, each detailing the specific steps taken during the study. The Outcomes subsection mirrors the structure of the Methodology, presenting the results of the preprocessing, mixed pixel problem identification, and the deforestation and non-deforestation analysis.

This study presents a novel approach, SiM, that improves the classification of mixed pixels in high-resolution datasets by analyzing them with advanced segmentation and clustering techniques. This is the first study to apply these methods to both high- and low-resolution mixed pixel problems in deforestation monitoring.

The Discussion section offers a critical examination of the study's findings, highlighting both the advantages and limitations of the proposed approach, as well as outlining future research directions. Finally, the paper concludes with a summary of the key insights gained from the research, emphasizing the contributions and potential applications of the proposed approach in advancing the field of satellite image analysis and deforestation monitoring. The objective of this research is to develop a framework for accurately classifying mixed pixels in high-resolution deforestation data using SiM. This method aims to improve the resolution, reduce thematic uncertainty, and enhance classification accuracy compared to existing approaches.

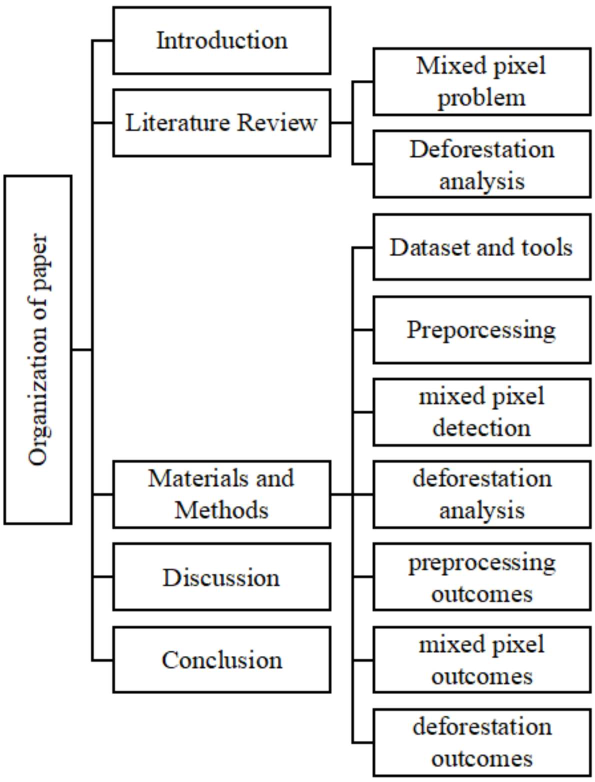


Figure 1. Structure of paper.

3. Materials and Methods

The Materials and Methods section is the cornerstone of any original research paper, as it provides the foundation upon which the entire study is built. In this paper, the materials are represented by the datasets and tools utilized throughout the research. 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 Methods portion of this section is thoughtfully divided into two main subsections: Methodology Analysis and Outcome Analysis. Each of these subsections is further subdivided into three specific categories (see **Figure 1**), to provide a detailed and structured approach to the research process.

By organizing the Materials and Methods section in this structured manner, the paper ensures that each aspect of the research is thoroughly documented and analyzed. This approach not only provides clarity to the reader but also reinforces the rigor and reliability of the study's findings.

3.1. Dataset and Tools

From 2010 to 2022, Para in Brazil has been the most responsible area for tree loss. Novo Progresso has been roughly the third most responsible region in Para for the loss of trees between 2001 and 2022. Novo Progresso received numerous alerts of deforestation in October 2023, mostly because of fire [33]. The second-largest deforestation area in the Brazilian Amazon is Para, according to an analysis conducted by REDD (Reducing Emissions of Deforestation and Forest Degradation) over the past 15 years [34, 35]. Through the study above, the author decided to examine the suggested model for identifying the mixed pixel problem and classifying deforested areas using data from the State of Para, Brazil. The Google Earth Pro visualizations of **Figure 2** and **Table 2** below show the dataset description.

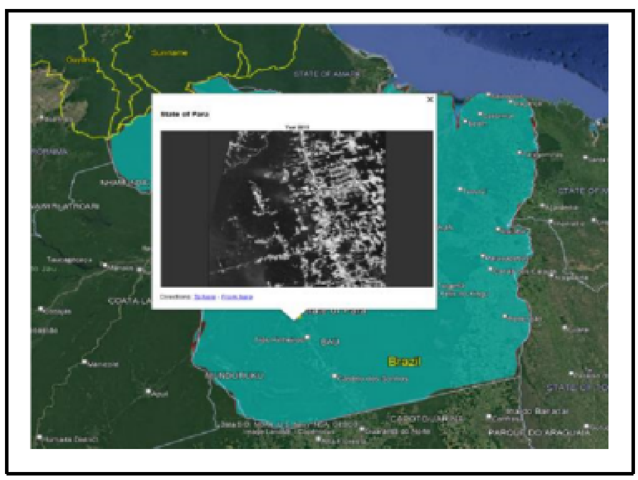


Figure 2. Geographical view of dataset.

Table 2. Dataset description.

Product	Tile ID	DOA	Type	Band
S2B MSI	T21MXN	30-08-2019	L2A	RGB, NIR
S2B MSI	T21MXN	19-08-2023	L2A	RGB, NIR

The dataset from NASA and ESA Copernicus was used in this work. The author used 2019 and 2023 Sentinel-2 MSI pictures for the examination of the suggested model. With its 15 bands, the Sentinel-2 MSI can precisely observe Earth during the day.

For the preprocessing of the dataset, SNAP tools are used. For identifying the mixed pixel problem Python3 Jupyter Notebook 7.0.8v is used and deforested area classification and area calculation are done by MATLAB R2023b. Sentinel Application Platform is a software developed by ESA Copernicus. It is a toolbox suitable for earth observation processing. The intermediate analysis tool is Python3 Jupyter Notebook 7.0.8v, which is used for better and faster analysis of pixels for identifying mixed pixels and the deforested area classification and area calculation.

3.2. Methodology Analysis

The paper is focused on addressing two primary objectives: the mixed pixel problem in optical satellite imagery and the classification of deforested areas. The proposed methodology is divided into three distinct phases, with each phase comprising three specific steps, as illustrated in **Figure 3**. Although optical satellite imagery provides high-resolution, clear images, the mixed pixel problem complicates the accurate identification of objects within the images, as depicted in **Figure 4**. The first objective of this study is to develop a comprehensive framework for detecting and resolving the mixed pixel issue in optical satellite data. This is achieved through the application of both pre-processing and intermediate processing techniques as outlined in the proposed methodology.

The second objective is to establish a robust framework for deforestation analysis. This involves comparing the newly proposed method with existing techniques to assess its accuracy and effectiveness in identifying deforested areas. The comparison aims to provide a clearer understanding of the methodology's performance and to precisely calculate the extent of deforestation. By enhancing the accuracy of deforestation detection, the study seeks to contribute to more reliable monitoring and analysis of environmental changes over time.

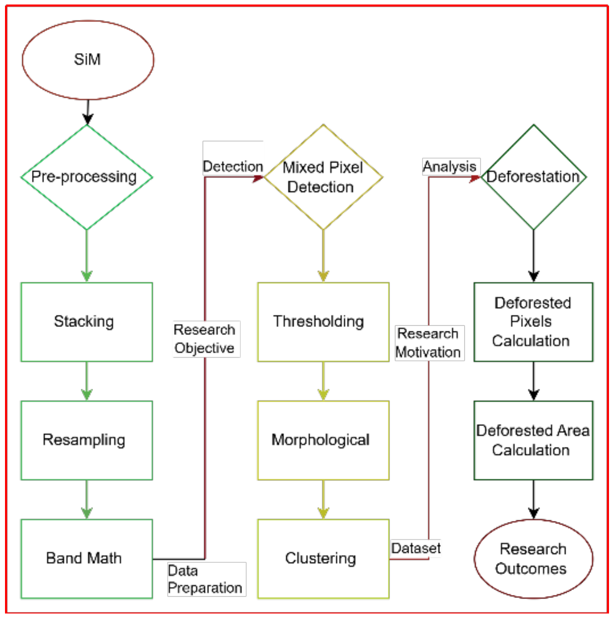


Figure 3. Workflow of proposed methodology.

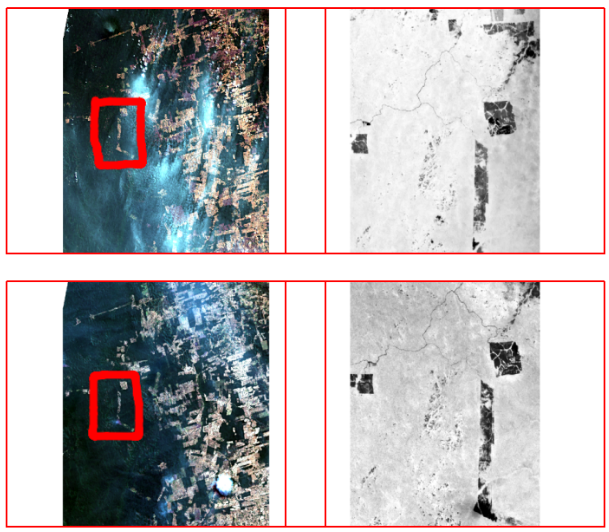


Figure 4. Study area view for mixed pixel problem.

The first objective of this paper is focused on identifying and addressing the mixed pixel problem, as illustrated in **Figure 4**. In **Figure 4**, the red box indicates the study area in the original image. Image (a) represents the original satellite image from 2019, where the white areas correspond to deforested regions, and the black areas indicate non-deforested regions. In contrast, image (b) presents the NDVI (Normalized Difference Vegetation Index) image for 2019, where the black areas are now indicative of deforestation, while the white areas represent non-deforested regions. Image (c) illustrates the original satellite image from 2023, and image (d) shows a cropped NDVI image of the specific study area of 2023, the dark regions are prominently highlighted as deforested. However, a significant challenge arises here: some of the white areas within the NDVI study area are mixed with black regions, creating a complex situation that hinders the accurate detection of deforestation.

This blending of pixels—where deforested and non-deforested regions overlap—presents a significant challenge, as it complicates the precise identification and classification of land cover. The red circles in the images provide a clear visual reference, helping to pinpoint the study areas in both the original and NDVI images. The main aim of this paper is to develop a methodology that effectively identifies and addresses the mixed pixel problem. By applying the proposed techniques, the study seeks to thoroughly investigate and resolve the issues caused by mixed pixels, ultimately leading to more accurate calculations of both deforested and non-deforested areas. This approach not only enhances the reliability of deforestation analysis but also contributes to more precise environmental monitoring and decision-making.

3.3. Preprocessing Analysis

The Sentinel-2 MSI has 13 spectral bands of 10 m resolution for four bands, 20 m resolution for six bands, and 60 m resolution for three bands of spatial domain. The main motive of S2-MSI is for two satellites to revolve in the same orbit of phase 180 degrees to capture images every 5 days. As per the proposed methodology, the initial step is preprocessing using the following procedure shown in **Figure 5**.

Figure 5. Preprocessing steps.

Preprocessing is an important task of multi-spectral images for data preparation to train the machine learning model to validate the accuracy and loss. The first step is stacking the number of bands for data preparation; in this paper, only RGB and NIR bands are used, and after that, resampling is done using bilinear upsampling and mean downsampling to alter the image resolution to change the pixel value [36]. For better visualization of pre-processed images see in **Figure 7** and **Figure 8** histogram of 2019 and 2023 S-2 MSI images.

Pseudocode of preprocessing:

- Step 1: Band Stacking
  1. Initialize Band List: Declare a list of bands: bands = [B2, B3, B4, B8]
  2. Stack Relevant Bands: Stack the bands for analysis using the declared list.
  3. Align Spatial Resolution: Align the spatial resolution of all bands for consistent processing.
- Step 2a: Resampling - Upsampling Method
  1. Identify Lower-Resolution Bands: For each band in bands.
  2. Interpolation Options: Allow selection of interpolation method: "Bilinear".
  3. Bilinear Upsampling: Uses a weighted average of the nearest four pixels

$$NewPixelValue = \left(\frac{w1P1+w2P2+w3P3+w4P4}{w1+w2+w3+w4}\right) \quad (1)$$

  Where P is the nearest pixels in the input images and w is the weights based on distance from the target pixels.
- Step 2b: Resampling - Downsampling Method
  1. Identify Higher-Resolution Bands: For each band in bands.
  2. Aggregation Options: Based on selected method: "Mean".
  3. Mean Downsampling (example):For each block of input_pixels:

$$TotalSum = \sum_{i=1}^{N} P_i \quad (2)$$

  where P represents each pixel value within the block, N is the total number of pixels in the block.

$$NewPixelValue = \frac{TotalSum}{N} \quad (3)$$

$$Output\ Image = \frac{\sum_{i=1}^{N} P_i}{N} \quad (4)$$

- Step 3: Band Math Operations

Calculate NDVI:

$$NDVI = \frac{NIR_8 - B_4}{NIR_8 + B_4} \tag{5}$$

After applying the resampling method, the band math concept is used to create new band images for data preparation. Based on the above equation, the 2019 and 2023 datasets are prepared for mixed pixel analysis. With the help of arithmetic expression, the new bands give clearer visualization of the images and help in better analysis. The band stacking and merging concept using multiple band math expressions is used to understand the combination of different bands to create a new band for analysis. The RGB band is used for better representation and analyzing vegetation and types of vegetation; the Near Infrared band helps to classify and detect vegetation [37, 38].

3.4. Mixed Pixel Analysis

For analyzing mixed pixel problems in existing data, the author used pre-processed images. As you can see in **Figure 4**, the second objective of the paper is to analyze the mixed pixel problem. To analyze the problem, we need to do four steps, as seen in **Figure 6**. As you can see the difference in **Figure 7** and **Figure 8** of the pre-processed image histogram for a better understanding of pixel analysis to proceed toward the next step for mixed pixel analysis. As we know, Sentinel 2-MSI has 13 bands, but for analyzing mixed pixels, the researcher used band 4 (red image) and band 8 (near-infrared image) for better analysis of deforested mixed pixels.

The first step is to apply edge guided OTSU thresholding. This technique is used for segmentation which helps to combine the intensity value with the information of the image edge detected. It helps to modify the image for better analysis. To create the NDVI band, Equation (7) with band 8 and band 4 is used. First, convert the NDVI image to a GRAY image and apply edge detection using the Sobel operator, and then combine the gray image with the edge-detected information. After that, apply OTSU thresholding for better segmentation, as seen in the outcome in **Figure 9**.

After applying OTSU thresholds, we can see lots of pixels are not clearly identified as deforested or non-deforested, which creates inaccuracy of analysis and generates noise as well. That's why it is necessary to apply morphological operations. First, we need to convert the NDVI image into a binary image. To handle NAN values, we need to normalize from a 0 to 1 range. Apply dilation and erosion using a disk of radius 5, as seen in **Figure 10**.

Once morphology is done, as you can see there is a clear difference between the dilation image and the erosion image. Lots of pixels are mixed and we can't analyse the appropriate number of deforested pixels for better calculations of deforestation area. The next step is to combine dilation and erosion morphological operations for a better understanding of pixels, as seen in **Figure 11**. The combined image needs more processing for better analysis by applying an overlay of dilation with the green channel and erosion with the red channel, as seen in **Figure 12**.

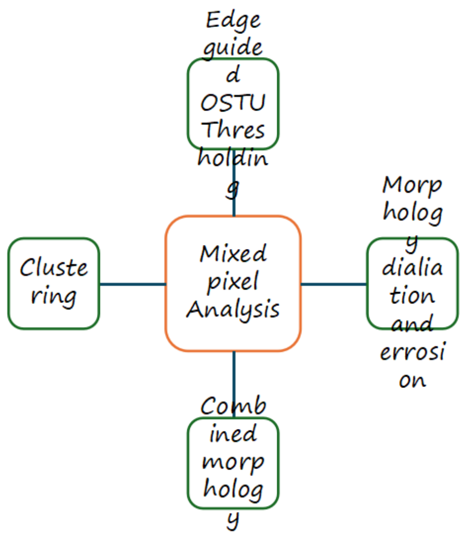


Figure 6. Mixed pixel detection steps.

Pseudocode of Mixed Pixel Detection:

- Step 1: Edge-Guided Otsu Thresholding on NDVI Image Extract the RGB Channels

$$I_{RGB}(x, y, c) = I(x, y, c), \quad c \in \{R, G, B\} \tag{6}$$

Convert to Grayscale—Convert to grayscale using a weighted sum of the RGB channels:

$$I_{gray}(x, y) = W_r I_{RGB}(x, y, R) + W_g I_{RGB}(x, y, G) + W_b I_{RGB}(x, y, B) \tag{7}$$

Apply Sobel Edge Detection—Compute the gradient magnitude of I_{gray} using the Sobel operator. Let S_x and S_y represent the Sobel kernels in the x and y-directions. The gradients are computed as:

$$G_x(x, y) = I_{gray}(x, y) * S_x, \quad G_y(x, y) = I_{gray}(x, y) * S_y \tag{8}$$

where * denotes convolution.

The edge intensity E(x,y) is given by:

$$E_{(x,y)} = \sqrt{G_x(x,y)^2 \pm G_y(x,y)^2} \quad (9)$$

Combine Edge Intensity with Grayscale Image

Compute the product of the grayscale image and the edge intensity:

$$C_{(x,y)} = I_{gray}(x,y).E(x,y) \quad (10)$$

Apply Otsu's Thresholding

Determine the optimal threshold T using Otsu's method, which maximizes the between-class variance $\sigma_B^2(T)$:

$$T = \underset{t}{\operatorname{argmax}} \sigma_B^2(t) \quad (11)$$

Where $\sigma_B^2(t)$ is given as:

$$\sigma_B^2(t) = \omega_1(t)\,\omega_2(t)\,(\mu_1(t) - \mu_2(t))^2 \quad (12)$$

Here, $\omega_1(t)\,\omega_2(t)$are the probabilities of the two classes separated by t, $(\mu_1(t))$ and $(\mu_2(t)$ are their respective means. Threshold the combined image

$$C_{(x,y)} : S_{(x,y)} = \begin{cases} 1, \text{ if } C(x,y) > T \\ 0, \text{ otherwise} \end{cases} \quad (13)$$

- Step 2: Morphological Operations for Mixed Pixel Detection

$S_{2019}(x,y)$: Segmented binary image for 2019, where $S_{2019}(x,y) \in \{0,1\}$.

$S_{2023}(x,y)$: Segmented binary image for 2023, where $S_{2023}(x,y) \in \{0,1\}$.

$B_{(r)}$: Structuring element (disk-shaped with radius r = 5).

Define Structuring Element: Use a disk-shaped structuring element $B_{(r)}$, where:

$$B(r) = \{(u,v)\,|u^2 + v^2 \leq r^2\} \quad (14)$$

Apply Dilation: Perform dilation on the binary image $S_{(x,y)}$ to expand the foreground region: membership value:

$$D(x,y) = \max_{(u,v)\in B(r)} S(x-u, y-v) \quad (15)$$

Apply Erosion: Perform erosion on the dilated image $D(x,y)$to remove noise and refine boundaries: membership value:

$$E(x,y) = \min_{(u,v)\in B(r)} S(x+u, y+v) \quad (16)$$

Where: u and v define the relative positions of pixels in the image S(x , y) w.r.t the origin of the structuring element.

Subtract Erosion from Dilation: Compute the difference between the dilated image and the eroded image: membership value:

$$S_{Subtract(x,y)} = D_{(x,y)} - E_{(x,y)} \quad (17)$$

Ensure Integer Precision: Convert the subtracted image to an integer format to preserve values: $S_{Subtract(x,y)\rightarrow}$ Integer

- Step 3: Fuzzy C-Means Clustering for Mixed Pixel Detection

Flatten the Images for Clustering: Convert 2D image arrays into 1D data for clustering:

$X_{subtracted} = \text{flatten}(I_{subtracted})$

$X_{dilated} = \text{flatten}(I_{dilated})$

$X_{eroded} = \text{flatten}(I_{eroded})$

Initialize Fuzzy C-Means Clustering:

Define $n_{clusters} = 2$

$U = \lceil u_{ij} \rceil$Membership matrix, where uij is the degree of membership of the jth pixel to the ith cluster.

$C = \lceil c_i \rceil$Cluster centers, where $c_i$is the center of the ith cluster.

Update Membership Matrix and Cluster Centres Iteratively: For each clustering process (subtracted, dilated, and eroded):

Update Cluster Centres: Cluster centres $c_i$are updated using: membership value:

$$c_i = \frac{\sum_{j=1}^{N} u_{ij}^m . x_j}{\sum_{j=1}^{N} u_{ij}^m} \quad (18)$$

where $x_j$is the pixel intensity, u_{ij} is the membership value, and m is the fuzzification parameter.

Update Membership Matrix: The membership values are updated as

$$u_{ij} = \frac{1}{\sum_{k=1}^{n_{cluster}} \left(\frac{\|x_i - c_i\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}} \quad (19)$$

Assign Pixels to Clusters:

Determine the cluster label for each pixel xi based on the maximum membership value:

$$\text{Cluster}_{x_i} = \underset{i}{\operatorname{argmax}} u_{ij} \quad (20)$$

Reshape the Clustered Data and Convert 1D clustered data back to 2D image form.

```
def edge_guided_otsu(image):
    rgb_image = image[:, :, :3]
    gray_image = color.rgb2gray(rgb_image)
    edges = filters.sobel(gray_image)
    combined = gray_image * edges
    threshold = filters.threshold_otsu(combined)
    segmented_image = combined >threshold
return segmented_image
    selem = disk(5)  # Structuring element
    dilated_image_2019 = morphology.dilation(segmented_image_2019, selem)
    eroded_image_2019 = morphology.erosion(dilated_image_2019, selem)
    subtracted_image_2019 = dilated_image_2019.astype(int) - eroded_image_2019.astype(int)
    dilated_image_2023 = morphology.dilation(segmented_image_2023, selem)
    eroded_image_2023 = morphology.erosion(dilated_image_2023, selem)
    subtracted_image_2023 = dilated_image_2023.astype(int) - eroded_image_2023.astype(int)
def apply_fuzzy_cmeans(image, n_clusters=3):
    image_flat = image.flatten().astype(float)
    image_normalized = (image_flat - np.min(image_flat)) / (np.max(image_flat) - np.min(image_flat))
    data = np.expand_dims(image_normalized, axis=0)
    cntr, u, _, _, _, _, _ = cmeans(data, n_clusters, 2, error=0.005, maxiter=1000
    cluster_labels = np.argmax(u, axis=0)
    clustered_image = cluster_labels.reshape(image.shape)
    return clustered_image, u
        clustered_image_2019, u_2019 = apply_fuzzy_cmeans(subtracted_image_2019, n_clusters=3)
clustered_image_2023, u_2023 = apply_fuzzy_cmeans(subtracted_image_2023, n_clusters=3)
def calculate_cluster_stats(clustered_image, pixel_resolution=1):
    unique_clusters, counts = np.unique(clustered_image, return_counts=True)
    cluster_areas = counts * pixel_resolution
```

After applying subtracted dilation-erosion image seen in Equation (2), the view of the deforested area is much clearer compared to the binary and NDVI images. There is a need to analyse the appropriate pixels to apply clustering. Clustering is a technique of unsupervised machine learning. It helps to analyse which cluster the pixel belongs to for a better understanding of the complexity of mixed pixel detection. For applying Fuzzy C-means clustering, it is necessary to convert the 2D image into a flattened dataset of rows belonging to pixels and columns belonging to bands and then apply clustering of 2 classes (pure pixels and mixed pixels). After that, it is necessary to reshape the clustered label back into image dimensions to visualize the clustered results seen in **Figure 13**.

3.5. Deforestation Analysis

To analyse the deforestation, the proposed model used morphological subtracted dilation-erosion image pixels and compares the result with Fuzzy C-means clustered image pixels seen in **Figure 12**, Satellite Image Clustering using Transpose Transformation deep neural networking. The proposed model is applied to the 2019 and 2023 datasets prepared by the Band Math new bands (NDVI) for deforestation analysis. The **Figure 3** workflow diagram helps us to understand the complete overview between pre-processing, intermediate processing (mixed pixel detection), and final processing (deforested area calculation) to analyse the output images (segmented image, dilated image, eroded image, subtracted image, clustered image). In the next section, we discuss the outputs of the pre-processed results of 2019 and 2023 datasets. After applying the mixed pixel analysis approach in pre-processed images of 2019 and 2023 for better visualization of pure pixels and mixed pixels, the number of pixels in each output image is used for area calculation. For the area calculation, the author converts the number of pixels into kilometres per square.

$$\text{Area per } km^2 = number\ of\ pixels * 0.001 \qquad (21)$$

Sentinel-2 imagery features multiple bands with varying spatial resolutions, crucial for different types of analysis. Specifically, in this paper, we use the RGB and NIR bands, and the visible and near-infrared bands—Bands 2 (Blue), 3 (Green), 4 (Red), and 8 (Near-Infrared)—each have a spatial resolution of 10 meters per pixel. This means that each pixel in these bands corresponds to a 10-meter by 10-meter area on the ground. To convert the number of pixels from these bands into an area in square kilometres, a conversion factor is used. Since each 10m x 10m pixel covers 100 square meters, which equals 0.0001 square kilometres, you multiply the number of pixels by 0.0001 to find the total area in square kilometres.

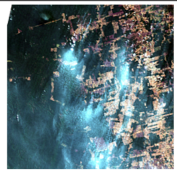
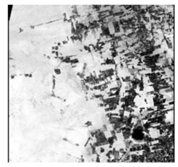
4. Outcomes Analysis

The experimental analysis is based on four sections. The first section discusses pre-processed images as input for further analysis based on **Figure 5** and Equations (1)–(5) of Band-Math for dataset preparation. The second section discusses the intermediate processing results based on **Figure 6** to analyse the mixed pixel problem using Equations (6)–(20). The third section discusses the Deforested area results based on Equation (21) and the comparison between different images and their difference analysis using graphs.

4.1. Preprocessing Band Math Images

The preprocessing is based on resampling and Band-Math on the 2019 and 2023 Sentinel-2 MSI dataset (see **Table 3** below). As you can see, with the help of Band Math, merging the combination of red, green, blue, and near-infrared bands helps prepare the dataset for mixed pixel detection and deforestation analysis. For mixed pixel analysis, an NDVI image is used.

Table 3. Pre-processed Band-Math Analysis.

Year	2019	2023
Original RGB Image		
NDVI Image		

As you can see in **Table 3** above, Band Math makes the visualization of deforested and non-deforested pixels much clearer. See below for a better understanding of the difference between the 2019 and 2023 histogram analysis shown in **Figure 7** and **Figure 8**.

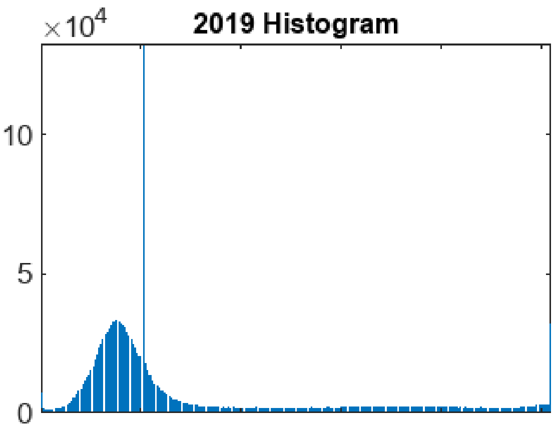


Figure 7. 2019 histogram.

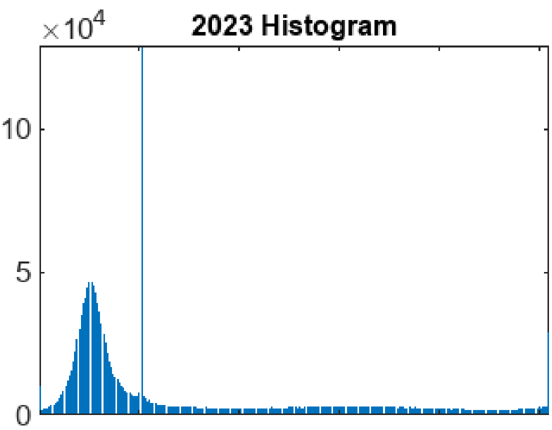


Figure 8. 2023 histogram.

4.2. Mixed Pixel Analysis

To analyze the pixels belonging to pure pixels or mixed pixels, some strategies need to be applied. For mixed pixel analysis based on **Figure 6**, four steps are needed. The first step is to apply edge segmentation using OSTU thresholding to determine the boundary edges of the 2019 and 2023 NDVI images seen in below **Figure 9**. NDVI of the 2019 and 2023 images is calculated by using Equation (1) with the help of Band 4 (Red Band) and Band 8 (Near Infra-Red). As you can see, the clear boundary of edges is gray in colour, but still lots of unwanted pixels are gray, which makes it a bit difficult to analyse the deforestation. By applying Otsu's thresholding, we effectively distinguished between vegetation and non-vegetation areas, facilitating further analysis. The thresholding process transforms the NDVI image into a binary image, where pixels above the threshold are classified as deforestation (gray) and classified as non-deforestation (black). Otsu's method is a widely used technique that automatically determines the optimal threshold value to minimize intra-class variance and maximize inter-class variance. The optimal threshold for 2019 calculated by Otsu's method is 0.08700727971631346 and the optimal threshold for 2023 calculated by Otsu's method is 0.09671167899385741. The number of pixels for 2019 is 22988 and the number of pixels for 2023 is 25479.

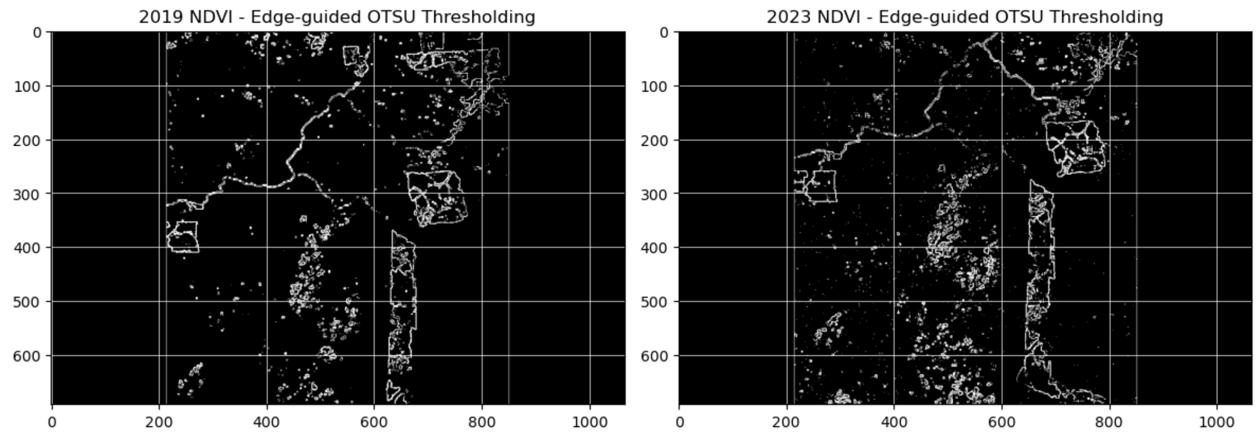


Figure 9. Study area edge detection using OTSU thresholding.

For the analysis of unwanted pixels in **Figure 9**, it is necessary to apply morphological dilation and erosion operations seen in **Figure 10**. The normalized NDVI is used for handling NaN values and then applies thresholding to create a binary image. The next image in dark green colour shows the result of dilation using a disk-like shape of structure with a radius of 5 pixels. And the dark green colour image represents the result of erosion using same disk-shaped structure with radius 5 pixels. As you can see in **Figure 10**, dilation is very clear, but erosion is still not that clear. That's why both morphological operations are subtracted using Equation (2) for better visualization in red seen in **Figure 11**. With the help of the subtracted morphological operation, we analyse mixed pixels. By applying morphological operations to refine the binary segmentation results, morphological operations, including dilation and erosion, are used to remove noise and enhance the structure of the segmented image. The dilation operation expands the boundaries of the foreground pixels (vegetation) in the binary image, filling small holes and connecting fragmented regions. Dilation enhances the representation of the vegetation areas, ensuring that smaller patches are included in the analysis. The number of pixels in the dilated image for 2019 is 137,655 and the number of pixels in the dilated image for 2023 is 182,503.

Erosion removes small-scale noise from the binary image by shrinking the boundaries of the foreground pixels. This helps to eliminate small artifacts and refine the shape of the vegetation areas. The number of pixels in Number of pixels in the eroded image for 2019 is 50,452 and the number of pixels in the eroded image for 2023 is 62,640. The subtraction of dilation followed by erosion (also known as opening) effectively cleans up the binary image, making it more representative of actual vegetation cover. It helps to analyse the mixed pixels in the 2019 subtracted image (dilated - eroded): 87,203 non-zero pixels and the 2023 subtracted image (dilated - eroded): 11,9863 non-zero pixels. With the help of the subtracted image, we analyse and compare pure pixels and mixed pixels for the accuracy of subsequent clustering techniques.

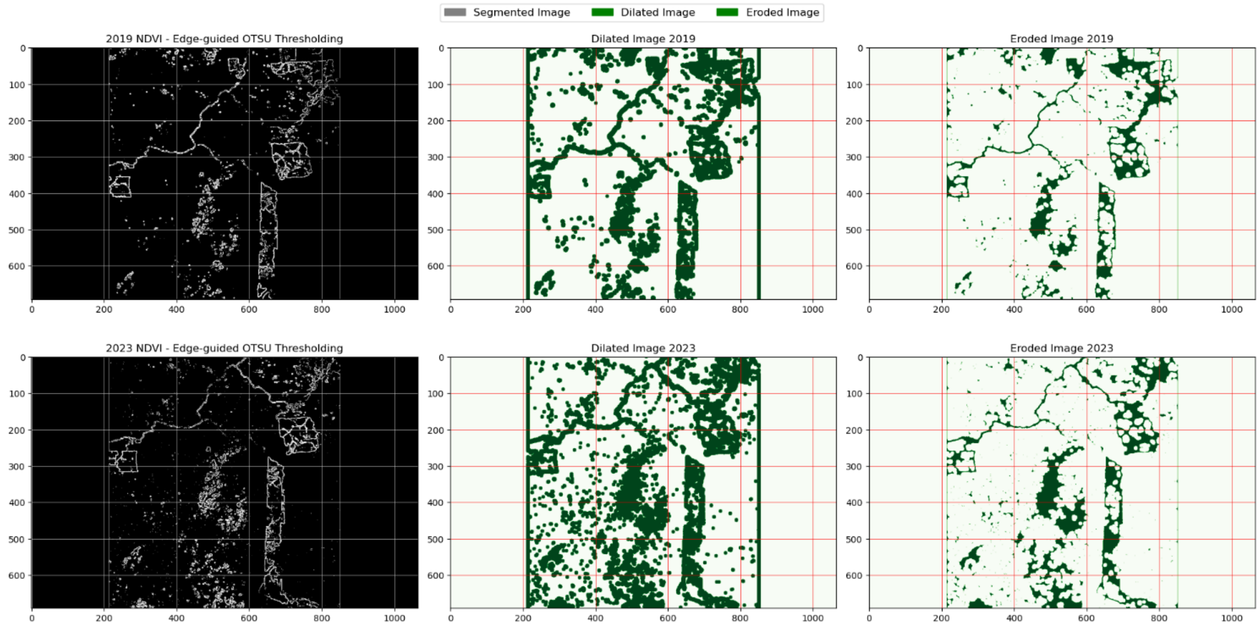


Figure 10. Study area normalized morphology operation analysis.

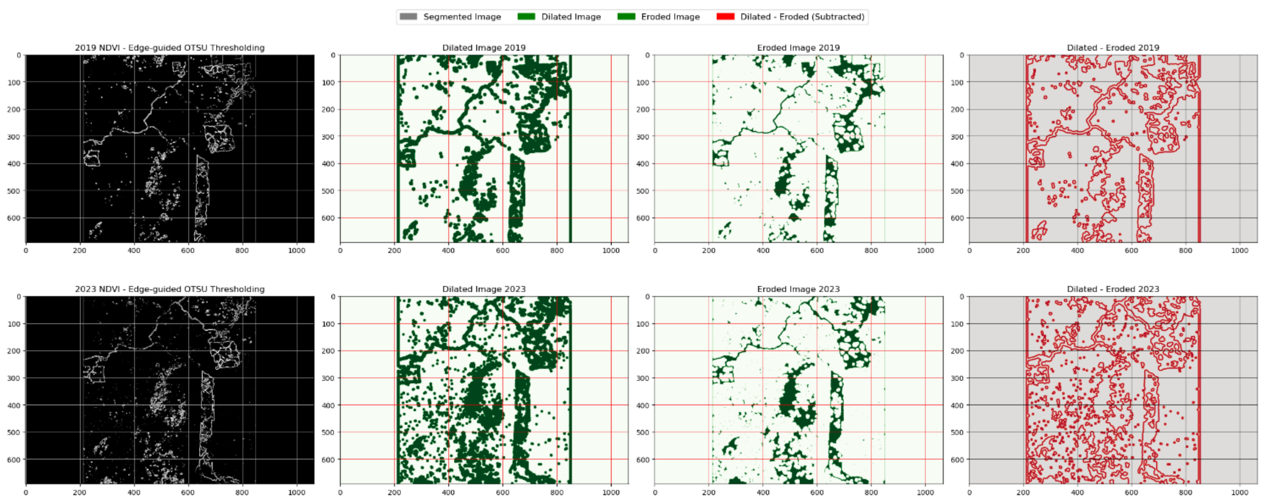


Figure 11. Study area dilation-erosion combined image analysis.

After subtracting the dilation-erosion, to compare the exact number of mixed pixels of the subtracted image and clustered image, we need to apply basic Fuzzy C-means clustering for validation. With the help of clustering, we can easily group into the classes. It helps to classify the degree of membership of each pixel's classes to analyse the pure pixels and mixed pixels for better visualization seen in **Figure 12**. The mixed pixel means a pixel belongs to multiple classes. With the help of clustering, we can easily analyse the pixel classes. Once the NDVI values were segmented and refined through morphological operations, Fuzzy C-means clustering was applied to classify the pixels into distinct clusters based on their spectral characteristics. Clustering has two types: soft (Fuzzy) and hard (K-means). As per the literature review, K-means is an unsupervised clustering algorithm that partitions data into K distinct clusters by minimizing the variance within each cluster. K-means clustering allows for a straightforward interpretation of land cover types based on spectral signatures, providing a quantitative method to classify the satellite imagery, which is not suitable for analysing mixed pixels based on spatial characteristics. The algorithm's efficiency and simplicity make it suitable for handling large datasets like satellite imagery, but the number of pixels is not correct compared to Fuzzy C-means clustering. To mitigate the K-means clustering results and account for the inherent uncertainty in pixel classification, we employed Fuzzy C-means clustering. This algorithm allows each pixel to belong to multiple clusters with varying degrees of membership, providing a more nuanced classification. For this study, we again utilized two clusters similar to K-means representing pure pixels and mixed pixels. The Fuzzy C-means approach is particularly beneficial in scenarios where land cover types exhibit spectral and spatial similarities. By allowing partial membership, we gain insight into the transitions between pure pixels and mixed pixels, leading to more robust classifications. This method helps to validate and analyse the pixels. The number of pure pixels in 2019 is 649,777 and number of pure pixels in 2023 is 617,117. The number of mixed pixels in 2019 is 87,203 and number of mixed pixels in 2023 is 119,863.

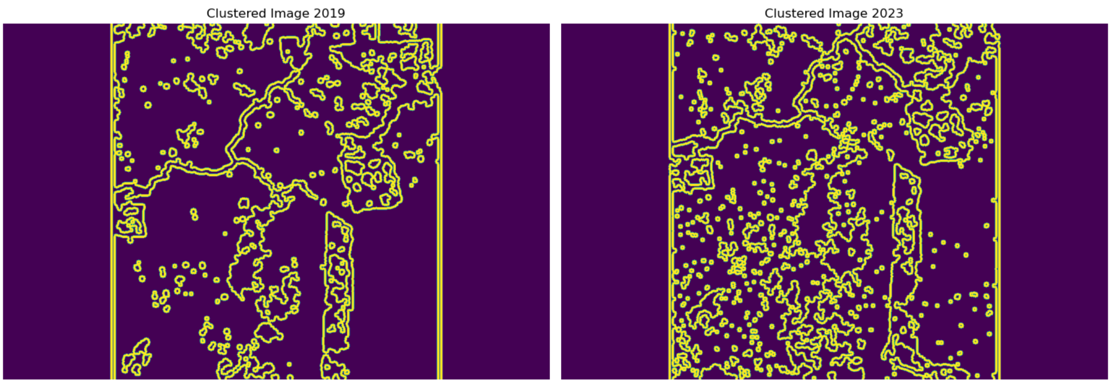


Figure 12. Study area Fuzzy C-means clustering analysis.

Fuzzy C-means (FCM) clustering is often considered superior to K-means clustering for pixel analysis in remote sensing and image processing due to several key characteristics that address the limitations of K-means, especially in scenarios involving spectral overlap, uncertainty, and complex land cover types. Here are some of the main reasons why FCM may be better suited for pixel analysis compared to K-means: In K-means clustering, each pixel is assigned to one and only one cluster, leading to hard classification. This can be problematic in cases where a pixel's spectral signature may belong to multiple land cover types (e.g., mixed pixels containing vegetation and soil). FCM allows each pixel to belong to multiple clusters with varying degrees of membership, represented by a membership value between 0 and 1. This means that a pixel can be partially classified as belonging to more than one class, capturing the inherent ambiguity present in remote sensing data. K-means struggles with spectral overlap among different land cover types, which can lead to misclassification. If two classes have similar spectral characteristics, K-means may assign pixels incorrectly to a single cluster. FCM's ability to assign membership values allows it to better accommodate pixels that fall on the boundary between two or more classes. This flexibility enhances the robustness of the classification process, especially in heterogeneous landscapes where different land cover types intermingle. There are many pros and cons in K-means compared to FCM, which offers significant advantages over K-means for pixel analysis in remote sensing applications. Its ability to handle partial membership, spectral overlap, and noise, coupled with improved classification accuracy, makes FCM a valuable tool for analysing complex land cover types and assessing vegetation health. By allowing for uncertainty and variation in land cover classifications, FCM provides a more comprehensive understanding of the landscape, making it a preferred choice in many applications involving satellite imagery and environmental monitoring.

4.3. Deforested Area Analysis

The next objective of the paper is to analyse the deforested area. As per the workflow of the paper, the third and final analysis is deforestation classification. For the analysis of deforestation, the number of pixels calculation is applied. To visualize the number of pixels in the segmented image, dilated image, eroded image, and subtracted image, are seen in **Figure 14** using a bar graph with different colour legends. To validate and compare the pixels of pure and mixed using Fuzzy C-mean showed in **Figure 15** using bar graph with different colour legend.

As you can see in **Figure 13**, the red legend explains the number of pixels in the subtracted image of dilation and erosion, and in **Figure 14**, the blue color represents 2019 mixed pixels in cluster 1, and the green color represents 2023 mixed pixels in cluster 1. The number of pixels in subtracted dilation and erosion is 87,203 in 2019 and 119,863 in 2023. Using the same image of subtracted dilated and eroded to apply Fuzzy C-means to check if mixed pxiels are the same: 87,203 in 2019 and 119,863 in 2023, which validates the exact number of pixles belonging to the study area.

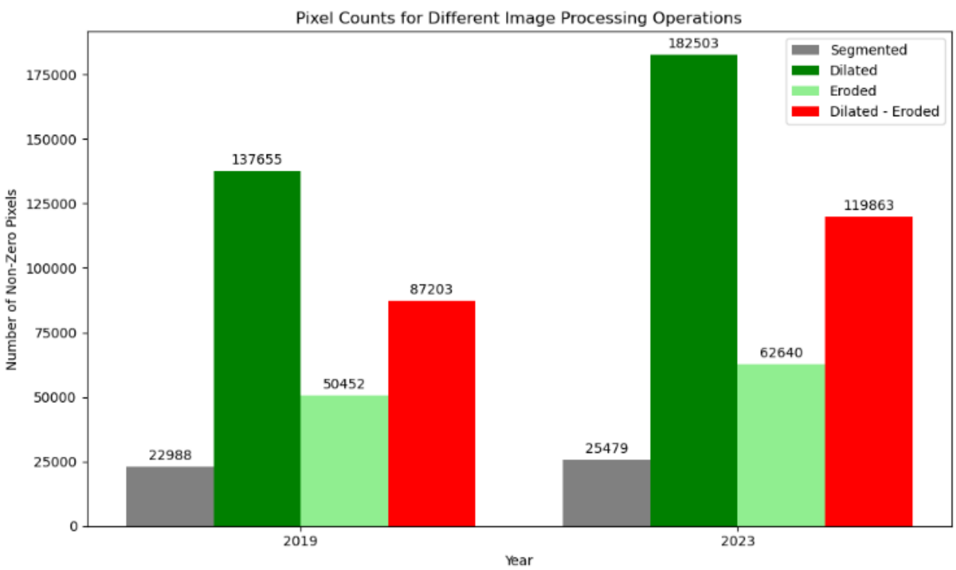


Figure 13. Study area number of pixels in OSTU thresholding and morphological operation 2019 and 2023.

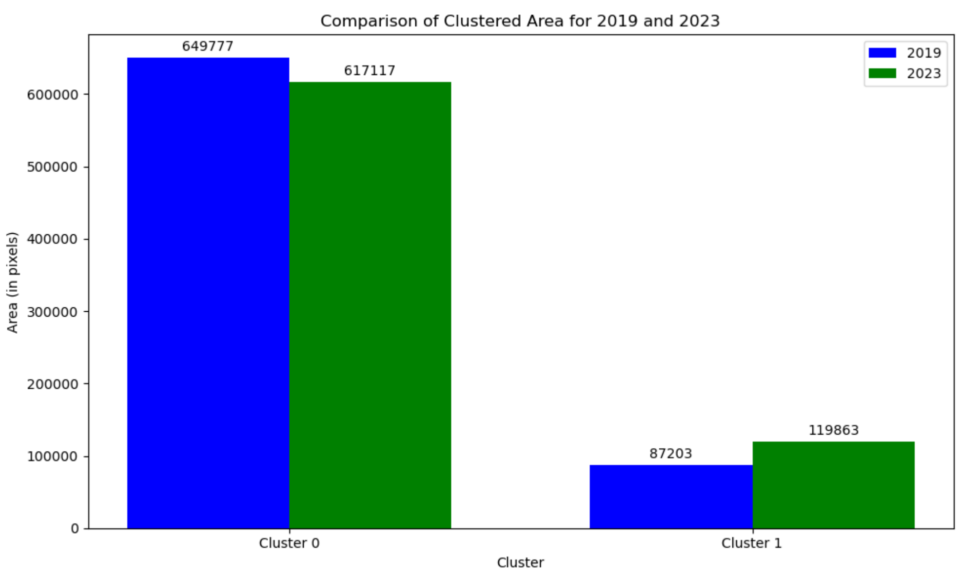


Figure 14. Study area Fuzzy C-means clustered number of pixels.

To analyse the deforested area using Equation (3) with the help of graphs for better understanding, the graphs are divided into four sections: segmented image, dilated image, eroded image, and subtracted image deforestation seen in **Figure 15** for 2019 deforestation area and 2023 deforestation area with legends.

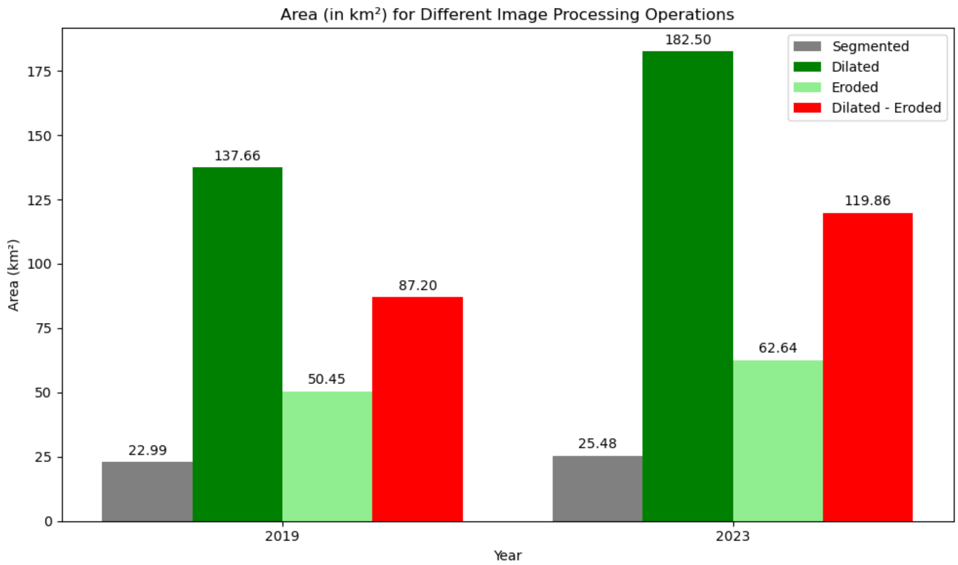


Figure 15. Deforested area 2019 and 2023.

Based on **Table 4**, from 2019 to 2023, the total pixel count in original images decreases slightly from 176,057 in 2019 to 175,868 in 2023, resulting in a small reduction in the corresponding area from 1,760.57 km² to 1,758.68 km², which indicates minimal changes in the coverage or resolution of the source data over time. The number of deforested pixels increased, which means that the proportion of deforested land has grown relative to the total area. This shift highlights a trend of increasing deforestation within a slightly smaller study area, emphasizing the need to consider both the reduction in total area and the rise in deforested pixels when assessing land cover changes.

To analyse the changes between 2019 and 2023 in the segmented image, the pixel count increases from 22,988 (22.99 km²) to 25,479 (25.48 km²), which indicates an improvement or refinement in segmentation techniques, capturing more features or objects in the image.

The dilation process results in significant growth in pixel count, rising from 137,655 (137.66 km²) in 2019 to 182,503 (182.50 km²) in 2023 which indicates an expansion in features, possibly to enhance connectivity and the eroded image shows an increase in reduced-feature pixels, growing from 50,452 (50.45 km²) to 62,640 (62.64 km²), which reflects changes in the removal of boundaries or small features. After applying the subtracted image pixel count rises significantly, from 87,203 (87.20 km²) in 2019 to 119,863 (119.86 km²) in 2023 which highlights greater differences or changes between comparative images in terms of mixed pixels.

The clustered images describe the pure pixels and mixed pixels in 2019 and 2023. The actual number of non-zero pixels decreases from 649,777 (6,497.77 km²) in 2019 to 617,177 (6,171.77 km²) in 2023 which indicates deforestation. The mixed number of pixels increases from 87,203 (87.20 km²) in 2019 to 119,863 (119.86 km²) in 2023, suggesting growing complexity in the observed data, with more areas classified as mixed pixels due to overlapping or interacting features. To validate the actual comparison of pixels in subtracted image pixels and clustered images, they are are exact the same, which means mixed pixels are present in the study area and it variates the accuracy of calculating deforestation and non-deforestation.

Table 4. Deforestation area analysis.

Image Type		Number of Pixels (2019)	Number of Pixels (2023)	Area (2019) km²	Area (2023) km²
Original image		176057	175868	1760.57	1758.68
Segmented image		22988	25479	22.99	25.48
Dilated image		137655	182503	137.66	182.50
Eroded image		50452	62640	50.45	62.64
Subtracted image		87203	119863	87.20	119.86
Clustered images	Pure pixels	649777	617177	6497.77	6171.77
	Mixed pixels	87203	119863	87.20	119.86

5. Discussion

Satellite images are widely used in applications such as land use and land cover (LULC) analysis, weather or environmental monitoring, and change detection. However, because these images are captured from long distances via sensors, they often lack clarity, which presents significant challenges during image processing. Based on a review of the literature, three key problems have been identified: Optical satellites provide clearer images compared to other types, but the presence of mixed pixels makes it difficult to accurately identify objects. A machine learning-based approach, specifically using unsupervised techniques, can be proposed to tackle the mixed pixel problem in optical satellite images. Unsupervised methods, such as fuzzy clustering, are particularly suited to address the mixed pixel issue, as these pixels often belong to multiple classes and are unlabelled. In this context, unsupervised techniques offer more effective solutions than supervised methods, which rely on predefined labels.

Optical satellites play an important role in earth observation. They provide detailed information to monitor vegetation, climate, deforestation, burned areas, water bodies, weather monitoring, etc. With the help of optical satellite, we can predict change detection for land use and land cover applications. However, optical satellites are not good enough to penetrate clouds and are not suitable for all types of weather. Due to atmospheric effects and topography effects, a problem called mixed pixel is created.

The mixed pixel problem means one pixel belongs to multiple classes, which creates a problem in identifying the object and reduces accuracy. To increase the efficiency of optical satellites, it is necessary to identify and detect the mixed pixel problem using band math and morphological segmentation. With the help of band math, researchers create NDVI images using B4 and B8 bands. For analysing mixed pixels on NDVI images, OSTU thresholding associated with morphological dilation and erosion is used for a better understanding of pure pixels and mixed pixels. Using clustering, it is easy to create clusters of different types of pixels to compare the results of subtracted morphological image pixels and clustered image pixels. Due to OSTU's optimal thresholding variation, different images reflect differences between pixels, which affect accuracy and efficiency, and in fuzzy clustering, the distribution of pixels between different clusters varies due to soft clustering, which affects pixel analysis.

As researchers mentioned, optical satellites are good for detailed monitoring of the earth but only in daytime due to active mode sensors. For nighttime monitoring, it is necessary to use SAR satellites due to passive mode and SAR is good for penetrating clouds and suitable for all kinds of weather as well. That's why researchers choose the Sentinel-2 dataset for analysing the mixed pixel problem, and researchers have already analysed the Sentinel-1 SAR satellite to resolve speckle noise [39]. In the future, researchers plan to apply image fusion of Sentinel-1 and Sentinel-2 images for better analysis in both day and nighttime [40].

6. Conclusions

Deforestation analysis is important for ecological LULC development. The optical satellite provides good visualization in daytime, but due to the mixed pixel problem, it is a bit hard to recognize the image. This paper addresses the mixed pixel issue in optical satellite images and proposes a model to analyze deforestation effectively. The methodology begins by distinguishing between mixed and pure pixels using Otsu's thresholding combined with morphological operations and clustering techniques to improve pixel classification accuracy and visualization. To detect mixed pixels, the process compares subtracted dilated and eroded image pixels with Fuzzy C-means clustering. The analysis confirms that a significant number of pixels belong to the mixed class. For precise deforestation monitoring, the study evaluates differences between segmented image areas, original image areas, and areas derived from dilated-eroded subtraction. The use of segmentation and clustering enables researchers to effectively validate mixed pixels within a specific area. This proposed methodology simplifies analysis and provides a reliable approach for accurately calculating deforested and non-deforested areas.For future research, harmonized datasets from Landsat 8 and Sentinel-2 can be employed to create larger datasets, allowing self-analysis of mixed pixels using fuzzy clustering techniques. The proposed approach efficiently and accurately identifies mixed pixels.

Author Contributions

Conceptualization, P.D., and A.A.; 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, P.D.; supervision, A.A.; project administration, P.D.; funding acquisition, no funding provided by University, APC paid by P.D.

Funding

This work received no external funding.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

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

Acknowledgement

We appreciate the help and direction provided by GLA University for their support and for giving me the chance to finish one more phase of my PhD.

Conflicts of Interest

The authors declare that they have no conflict of interest.

References

[1] Avtar, R., Tripathi, S., Aggarwal, A.K., et al., 2019. Population–urbanization–energy nexus: A review. Resources. 8(3), 136.

[2] Chamling, M., Bera, B., 2020. Spatio-temporal patterns of land use/land cover change in the Bhutan–Bengal foothill region between 1987 and 2019: Study towards geospatial applications and policy making. Earth Systems and Environment. 4(1), 117–130.

[3] Waleed, M., Sajjad, M., 2022. Leveraging cloud-based computing and spatial modeling approaches for land surface temperature disparities in response to land cover change: Evidence from Pakistan. Remote Sensing applications: Society and Environment. 25, 100665.

[4] Trujillo-Jiménez, M.A., Liberoff, A.L., Pessacg, N., et al., 2022. SatRed: New classification land use/land cover model based on multi-spectral satellite images and neural networks applied to a semiarid valley of Patagonia. Remote Sensing Applications: Society and Environment. 26, 100703.

[5] Atay Kaya, İ., Kut Görgün, E., 2020. Land use and land cover change monitoring in Bandırma (Turkey) using remote sensing and geographic information systems. Environmental Monitoring and Assessment. 192(7), 430.

[6] Roy, P.S., Ramachandran, R.M., Paul, O., et al., 2022. Anthropogenic land use and land cover changes—A review on its environmental consequences and climate change. Journal of the Indian Society of Remote Sensing. 50(8), 1615–1640.

[7] Baig, M.F., Mustafa, M.R.U., Baig, I., et al., 2022. Assessment of land use land cover changes and future predictions using CA-ANN simulation for Selangor, Malaysia. Water. 14(3), 402.

[8] Gaur, S., Singh, R., 2023. A comprehensive review on land use/land cover (LULC) change modeling for urban development: current status and future prospects. Sustainability. 15(2), 903.

[9] Griffiths, P., Jakimow, B., Hostert, P., 2018. Reconstructing long term annual deforestation dynamics in Pará and Mato Grosso using the Landsat archive. Re-

mote Sensing of Environment. 216, 497–513.
[10] Nepstad, D., Soares-Filho, B.S., Merry, F., et al., 2009. The end of deforestation in the Brazilian Amazon. Science. 326(5958), 1350–1351.
[11] Griffiths, P., Jakimow, B., Hostert, P., 2018. Reconstructing long term annual deforestation dynamics in Pará and Mato Grosso using the Landsat archive. Remote Sensing of Environment. 216, 497–513.
[12] Available from: https://www.globalforestwatch.org (cited 8 August 2024).
[13] European Space Agency, 2020. Sentinel-2: Resolution and Swath. Available from: https://sentinel.esa.int/web/sentinel/missions/sentinel-2/instrument-payload/resolution-and-swath (cited 18 August 2024).
[14] Darbari, P., Kumar, M., 2022. Satellite image enhancement techniques: A comprehensive review. Proceedings of International Conference on Communication and Artificial Intelligence: ICCAI 2021; May 10, 2022; Singapore. pp. 431–447.
[15] Roy, D.P., Li, J., Zhang, H.K., et al., 2017. Examination of Sentinel-2A multi-spectral instrument (MSI) reflectance anisotropy and the suitability of a general method to normalize MSI reflectance to nadir BRDF adjusted reflectance. Remote Sensing of Environment. 199, 25–38.
[16] Sánchez-Espinosa, A., Schröder, C., 2019. Land use and land cover mapping in wetlands one step closer to the ground: Sentinel-2 versus Landsat 8. Journal of Environmental Management. 247, 484–498.
[17] Petrou, M., 1999. Mixed pixel classification: An overview. Information Processing for Remote Sensing. 69–83.
[18] Pandey, A.C., Kumari, N., Ahmad, S., et al., 2023. Evaluating biochemical and biophysical characteristics of tropical deciduous forests of eastern India using remote sensing and in-situ parameter estimation. Remote Sensing Applications: Society and Environment. 29, 100909.
[19] Kaur, S., Bansal, R.K., 2017. Novel approach for mixed pixel extraction from remote sensing images. International Journal of Applied Engineering Research. 12, 12860–12871.
[20] Chen, X., Wang, D., Chen, J., et al., 2018. The mixed pixel effect in land surface phenology: A simulation study. Remote Sensing of Environment. 211, 338–344.
[21] Kaur, S., Bansal, R.K., Mittal, M., et al., 2019. Mixed pixel decomposition based on extended fuzzy clustering for single spectral value remote sensing images. Journal of the Indian Society of Remote Sensing. 47, 427–437. DOI: https://doi.org/10.1007/s12524-019-00946-2
[22] Sherwani, A.R., Ali, Q.M., 2022. Parametric classification using fuzzy approach for handling the problem of mixed pixels in ground truth data for a satellite image. Annals of Data Science. 10, 1459–1472. DOI: https://doi.org/10.1007/s40745-022-00383-y
[23] Sherwani, A.R., Ali, Q.M., Ali, I., 2022. A modified fuzzy clustering approach in unsupervised classification for detecting the mixed pixels of satellite images. Journal of Mathematical and Computational Science. 12, 97.
[24] Nghiyalwa, H.S., Urban, M., Baade, J., et al., 2021. Spatiotemporal mixed pixel analysis of savanna ecosystems: A review. Remote Sensing. 13(19), 3870.
[25] Mantripragada, K., Qureshi, F. Z., 2024. Hyperspectral pixel unmixing with latent dirichlet variational autoencoder. IEEE Transactions on Geoscience and Remote Sensing. 62.
[26] Kodl, G., Streeter, R., Cutler, N., et al., 2024. Arctic tundra shrubification can obscure increasing levels of soil erosion in NDVI assessments of land cover derived from satellite imagery. Remote Sensing of Environment. 301, 113935.
[27] Pu, J., Yan, K., Roy, S., et al., 2024. Sensor-independent LAI/FPAR CDR: Reconstructing a global sensor-independent climate data record of MODIS and VIIRS LAI/FPAR from 2000 to 2022. Earth System Science Data Discussions. 16(1), 15–34.
[28] Zheng, L., Zhu, J., Shi, J., et al., 2024. Efficient mixed transformer for single image superresolution. Engineering Applications of Artificial Intelligence. 133, 108035.
[29] Meerdink, S., Hiatt, D., Flory, S.L., et al., 2024. Dealing with imperfect data for invasive species detection using multispectral imagery. Ecological Informatics. 79, 102432.
[30] Jiang, L., Zhou, C., Li, X., 2023. Sub-pixel surface water mapping for heterogeneous areas from Sentinel-2 images: A case study in the Jinshui Basin, China. Water. 15(8), 1446.
[31] Nagaraj, R., Kumar, L.S., 2024. Extraction of surface water bodies using optical remote sensing images: A review. Earth Science Informatics. 17, 893–956. DOI: https://doi.org/10.1007/s12145-023-01196-0
[32] Guo, J., Du, S., 2024. Generating fuzzy membership functions for modeling wetland ecosystems from multispectral remote sensing images. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing. 17, 7640–7654.
[33] Ertel, J., Goldman, L., Spore, J., 2023. Available from: https://www.globalforestwatch.org/blog/data-and-research/tree-cover-data-comparison/ (cited 6 June 2023).
[34] Ramsay, D., 2021. Available from: https://forestsnews.cifor.org/70481/how-one-brazilian-state-is-tackling-deforestationwithin-its-borders?fnl= (cited 12 January 2021).
[35] World Rainforest Movement, 2023. REDD and the Green Economy exacerbate oppression and deforestation in Pará, Brazil. Available from: https://www.wrm.org.uy/bulletin-articles/redd-and-t

he-green-economy-exacerbateoppression-and-deforestation-in-para-brazil (cited 12 July 2024).

[36] Phiri, D., Simwanda, M., Salekin, S., et al., 2020. Sentinel-2 data for land cover/use mapping: A review. Remote Sensing. 12(14), 2291.

[37] Gurjar, S.B., Padmanabhan, N., 2005. Study of various resampling techniques for high-resolution remote sensing imagery. Journal of the Indian Society of Remote Sensing. 33, 113–120. DOI: https://doi.org/10.1007/BF02989999

[38] Home | Sentinel Hub custom scripts. Available from: https://custom-scripts.sentinel-hub.com/custom-scripts/sentinel-2/bands/ (cited 8 August 2024).

[39] Darbari, P., Kumar, M., Agarwal, A., 2024. SIT.net: SAR deforestation classification of Amazon forest for land use land cover application. Journal of Computer and Communications. 12(3), 68–83.

[40] Darbari, P., Kumar, M., Agarwal, A., 2024. Satellite image enhancement optical and SAR image fusion for LULC application: Comprehensive review for state of art. TuijinJishu/Journal of Propulsion Technology. 45(1), 1891–1906.