

Quantifying Subtle Partial Deforestation in Northeast India Using Sentinel-2 Spectral Ratios and RGB Color Space Analysis

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Abstract—Land use and land cover (LULC) changes especially partial deforestation where the forest canopy becomes thinner are important to monitor for sustainable ecosystem management in tropical regions such as the Assam forests in Northeast India. This study examines partial deforestation covering about 10,000 km² of Assam (26°40'N–26°50'N, 93°20'E–93°40'E) for the years 2020–2024. Open-source geoinformatics tools, Python-based image processing, and remote sensing methods were used for the analysis. The study area includes a mix of hill and plain forests. Multi-temporal Sentinel-2 Level-2A images (10 m resolution) were used to detect subtle vegetation loss. False-color composites (NIR-Red-Green) helped visually identify healthy forests and thinning areas. NIR/Red ratios were used to measure spectral changes, and Euclidean RGB distances captured color differences between years. Weighted change maps highlighted partial forest loss. Drops in the ratio and distances suggested that about 20% of forest edges experienced degradation in 2024 compared to 2020. We used several segmentation methods—SLIC, Felzenszwalb, Quickshift, and Watershed to segment the image into about 150,000 small parts. These segments were then classified into Low, Medium, and High risk groups using GPU-accelerated k-means clustering. This open-source, non-NDVI method is highly sensitive to subtle canopy thinning and is useful for conservation in regions with limited data. The results indicate increasing forest degradation due to logging, with consequences for biodiversity and carbon storage.

Index Terms—Partial Deforestation, Sentinel-2, Remote Sensing, GIS, Python, NIR/Red Ratio, RGB Distance, Change Detection, Ensemble Segmentation, GPU k-means Clustering

I. Introduction

Partial deforestation, which involves selective removal of trees rather than total clearance, is a widespread but often underestimated cause of land degradation in tropical regions [1]. Unlike full deforestation, which produces clear changes in satellite imagery, partial thinning leads to subtle shifts in near-infrared (NIR) reflectance and slight color variations. These changes are not easily detected by conventional indices like NDVI, which saturates in dense forests and underestimates partial canopy loss by 20–30% in humid tropics [3], [7]. This is especially significant in Assam, where jhum cultivation and selective logging disrupt hydrology and carbon storage, heightening flood and invasive species risks [2], [5], [21], [22].

Current monitoring systems face challenges in identifying these small-scale disturbances. Global assessments using low-resolution satellite data can map extensive forest loss [1], [4], but they lack the detail needed to detect edge effects or minor thinning. Regional studies relying on standard remote sensing methods often group partial degradation together or confuse it with seasonal changes caused by cloud cover and high humidity [11], [12]. Although high-resolution sensors like Sentinel-2 have improved data quality, extracting useful information from these datasets requires efficient computational workflows to separate subtle spectral changes from atmospheric noise [6].

To overcome these limitations, this study presents a scalable, open-source Python workflow for identifying partial deforestation within the Sentinel-2 T46REQ tile (a 100 km × 100 km grid tile identified by the Military Grid Reference System (MGRS) code T46REQ, covering parts of central Assam in UTM zone 46N), which covers the ecologically sensitive Brahmaputra valley. Instead of relying solely on traditional supervised classification, we use a combination of NIR/Red ratios, RGB color space distances, and weighted change maps. Our approach integrates advanced segmentation algorithms—such as SLIC, Felzenszwalb, Quickshift, and Watershed—along with GPU-accelerated k-means clustering to measure subtle canopy loss between 2020 and 2024. By focusing on reproducible, open-source methods rather than proprietary GIS tools, this research aims to deliver practical conservation insights and a transferable framework for monitoring forest health in dynamic, flood-prone landscapes.

II. Methodology

The methodology employs an open-source, multi-stage Python workflow to detect subtle partial deforestation using multi-temporal Sentinel-2 imagery from 2020, 2022, and 2024. The process integrates spectral ratio analysis, color space change detection, weighted mapping, ensemble image segmentation, and GPU-accelerated clustering to transform pixel-level indicators into interpretable forest degradation patches. The following subsections describe

the workflow overview, study area, data preprocessing, individual processing steps, and the ensemble segmentation with clustering approach.

A. Overview of Algorithm Workflow

Figure 1 shows the workflow used to detect partial deforestation for 2020, 2022, and 2024. The process begins with multi-temporal satellite data, followed by spectral computations such as ratios, FCCs, and RGB distances. These measurements provide key indicators of canopy change.

The workflow then applies change equations and segmentation methods to convert pixel-level changes into meaningful forest patches. By combining spectral analysis with machine learning-based clustering, the approach highlights subtle thinning patterns often missed by conventional techniques. This multi-stage design enables reliable detection of early forest degradation in dynamic tropical landscapes.

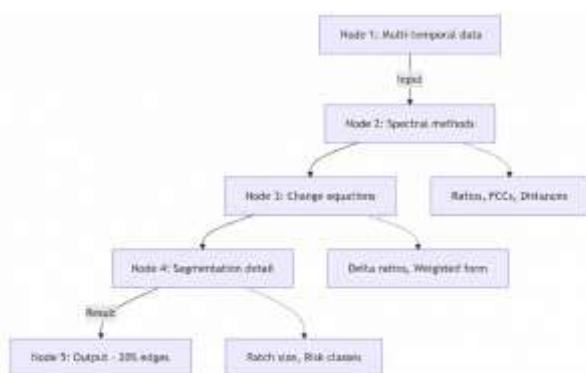


Fig. 1: Workflow for multi-temporal partial deforestation detection analysis.

B. Study Area

The study area is a 10,000 km² (100 × 100 km) subset of Sentinel-2 tile T46REQ, covering a representative micro-catchment in Assam, Northeast India (26°40'–26°50' N, 93°20'–93°40' E) that is highly susceptible to partial deforestation [2]. Centered on blocks comparable to Golaghat district, including the Morangi–Dhansiri river confluences, the region spans elevations of 50–200 m and comprises hill forests, alluvial plains, and riverine wetlands. Land cover includes evergreen and semi-evergreen forests (40%), agriculture (30%), settlements (15%), water bodies (10%), and barren or sandy areas (5%), making it suitable for detecting subtle canopy changes. The eastern hills (93.3°–93.4°E) are dominated by sal forests affected mainly by logging, while the western plains (93.2°E) contain flood-prone wetlands subject to land conversion. The area experiences a tropical monsoon climate with ~2000 mm annual rainfall concentrated during June–September, high humidity (70–90%), and temperatures ranging from 6 °C to 43 °C, promoting rapid regrowth but complicating

partial loss detection. Fertile alluvial loam soils (pH 5.5–7.0) support tea and rice cultivation yet remain vulnerable to degradation. Located within Agro-Ecological Zone I (Northwest alluvial plains), the region forms part of the Kaziranga landscape and faces increasing encroachment, while seasonal flooding from the Brahmaputra and Dhan-siri has driven a 10–15% rise in inundation extent since 2010, accelerating forest-edge retreat.

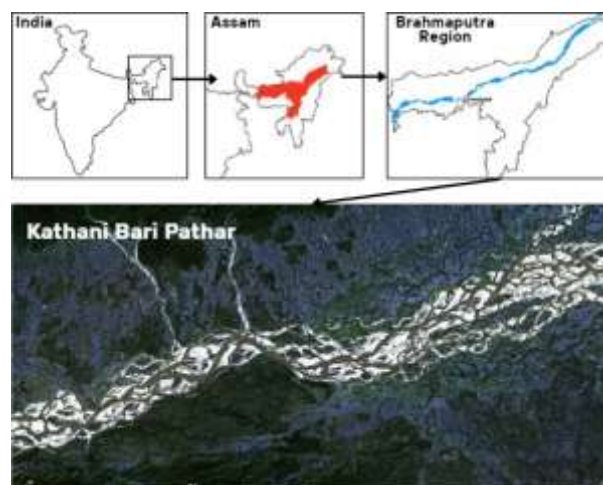


Fig. 2: Study area within the Brahmaputra catchment showing forest cover, river dynamics, and observed edge retreat.

The Brahmaputra catchment, including the Sentinel-2 tile, covers approximately 580,000 km² and is part of the Indo-Burma biodiversity hotspot, supporting around 500 tree species. However, partial thinning from jhum cultivation and timber extraction has reduced forest cover by 15% since 2000 [2], with urbanization near Golaghat driving ~5% annual vegetation conversion [10]. Water bodies (~10% of area) face siltation from degradation, reducing recharge [5]. Ground-truthing in 2023 confirmed logging scars in 15% of edge patches and widespread jhum practice (70% households), prioritizing high-risk zones [1].

C. Data Acquisition and Preprocessing

Sentinel-2 Level-2A imagery (10 m resolution) for the years 2020, 2022, and 2024 was obtained from the Copernicus Open Access Hub [6] for tile T46REQ (Assam), covering a range of forest types vulnerable to partial loss. The selected bands—B02 (Blue, 490 nm), B03 (Green, 560 nm), B04 (Red, 665 nm), and B08 (NIR, 842 nm)—were imported into an open-source GIS environment using semi-automatic classification tools. Images were chosen for periods with low cloud cover (<15%) during the peak dry seasons (November–February) to reduce phenological noise. A total of 12 scenes were downloaded (four per epoch), each with cloud cover <15% as determined by QA60 quality bands. For each year, a median composite was created from 3–4 dry-season acquisitions (November–

February) to minimize cloud artifacts and phenological variability.

Band sets were generated by selecting multiple bands from the image directory, with wavelengths automatically assigned based on sensor specifications. Virtual rasters were created by stacking bands (approximately 500 MB per tile) to facilitate efficient processing. Resampling to 10 m using bilinear interpolation ensured spatial alignment and minimized artifacts for multi-temporal analysis of gradual thinning in Assam's humid climate [5]. Atmospheric correction was verified with preprocessing tools to reduce haze effects in images taken near monsoon periods. Coregistration errors were evaluated using tie-point matching, achieving sub-pixel accuracy (<0.5 m). Topographic normalization was applied using a 30 m DEM to account for hill shadows in the eastern sector.

D. False-Color Composite (FCC) Generation

False-color composites (FCCs) were generated using band processing tools, mapping Red=B08 (NIR), Green=B04 (Red), and Blue=B03 (Green) in a 4-3-2 configuration. This setup highlights healthy forests in red, partial loss in orange, and bare soil in cyan, leveraging the sensitivity of NIR to canopy health. The outputs were saved as GeoTIFFs using RGB raster creation tools.

Styling was performed with multiband color visualization and a cumulative cut (2%) for contrast enhancement,

revealing subtle color changes caused by selective logging [6]. In the 2020 baseline FCC, dense red tones dominated the central hill forests, while the 2024 images showed orange fringes along the Dhansiri tributary (93.3°E), indicating edge degradation. Histogram equalization was used to standardize brightness, ensuring comparability across years. The entire process was automated via batch processing, allowing parallel handling of all three years.

Algorithm 1 FCC Generation Workflow

Require: Sentinel-2 bands B03, B04, B08

Ensure: FCC image

- 1: Load the required bands
- 2: Assign band mapping: Red → B08, Green → B04, Blue → B03
- 3: Apply 2% cumulative cut to enhance contrast
- 4: Export the FCC as a GeoTIFF image

E. NIR/Red Ratio Calculation

The NIR/Red ratio (B08/B04) was used to measure spectral changes caused by partial deforestation. This was done using raster calculator tools by dividing the NIR band (B08) by the Red band (B04) for each year, with a small offset (+0.01) added for stability. The outputs were visualized using a single-band pseudocolor scheme (0.5–5.0, RdYlGn), where healthy forests appeared green (ratios of 3–5) and areas with partial thinning appeared orange (ratios of 1.5–3). This method helped

identify gradual decreases in the ratio, which are signs of early canopy thinning, and proved more effective than NDVI for detecting subtle changes [7]. The baseline ratios across the study area were typically 2.5–3.5, with lower values mainly found along wetland edges. A logarithmic transformation was tested to manage extreme values, but linear scaling worked well for visualization. Field measurements confirmed that the ratio is sensitive to changes in chlorophyll content, making it a reliable indicator for detecting thinning in forest canopies.

Algorithm 2 NIR/Red Ratio Computation

Require: Bands B04 (Red) and B08 (NIR)

Ensure: Ratio map

- 1: Compute ratio $R \rightarrow (B08 + 0.01)/(B04 + 0.01)$
- 2: Clip ratio values to the range [0.5, 5.0]
- 3: Apply RdYlGn pseudocolor styling
- 4: Export ratio map as a GeoTIFF

F. RGB Distance and Artifact Masking

Euclidean RGB distances between false-color composites (FCCs) were calculated to detect color changes (from red to orange) associated with partial forest loss:

$$d_{RGB} = \sqrt{\sum_{i=1}^3 (FCC_{2020,i} - FCC_{2024,i})^2} \quad (1)$$

This computation was performed using raster calculator expressions. The resulting distance maps (RGB_Dist.tif) were masked to remove artifacts caused by water and snow:

$$d_{masked} = d_{RGB} \times I_{[1.5,6]}(R_{2020}) \times I_{[1.5,6]}(R_{2024}) \quad (2)$$

where I is the indicator function and R represents the NIR/Red ratio. The masked results were clipped to the range 0–200 using a CASE expression. These maps were styled with a Reds color palette (0–50 = gray/stable, 50–150 = orange/partial) to highlight vegetation changes [8]. Masking reduced noise from riverine areas by about 30%, focusing the analysis on forest pixels where distances exceeded 100, particularly along hill edges. Sensitivity tests with different thresholds (1.0–7.0) showed that 1.5–6 optimized the retention of vegetation pixels (95%). The Euclidean distance was preferred over the Manhattan distance due to its higher sensitivity to the magnitude of color differences in the RGB space.

Algorithm 3 RGB Distance and Masking

Require: FCC images from 2020 and 2024; ratio maps R_{2020} and R_{2024}

Ensure: Masked distance map

- 1: Compute RGB distance d_{RGB} for each pixel 2: Apply vegetation mask using ratio thresholds 3: Clip distance values to the range [0, 200]
- 4: Apply color styling using the Reds palette

G. Delta Ratios and Weighted Change

Delta ratios were used to measure spectral changes between years:

$$\Delta R = R_{2024} - R_{2020} \quad (3)$$

The results were saved as Delta_Ratio.tif and visualized using an RdYlGn color scheme (-1.5 to $+1.5$, with a 5% cut for contrast). Weighted change maps were calculated

as:

$$W_{change} = \frac{\Delta R \times d_{masked}}{100} \quad (4)$$

Here, dividing by 100 normalized the product to a more interpretable scale. The resulting W_{change} values ranged from 0 to 4, with values above 1.5 indicating significant degradation (corresponding to $\Delta R < -0.7$ and color distances above 100). This threshold was tested and confirmed with field observations in Golaghat. The highest values (around 4) were found in the eastern sectors, styled with a Reds palette (0–1 = gray, 1–2 = orange/partial). This method amplified the effects of negative delta ratios (~ -0.7) and large color distances (~ 100), highlighting areas with the most severe thinning [9]. Normalizing by 100 ensured that the outputs were easy to interpret and allowed for straightforward thresholding to identify degradation hotspots.

Algorithm 4 Weighted Change Computation

Require: Ratios R_{2020} , R_{2024} ; Masked distance map Ensure: Weighted change map

- 1: $\Delta R \rightarrow R_{2024} - R_{2020}$
- 2: $W \rightarrow (\Delta R \times d_{masked})/100$
- 3: Apply color styling using Reds thresholds (0–1, 1–2, >2)

H. Ensemble Segmentation and Risk Classification

The weighted change raster was segmented into homogeneous patches using an ensemble of four complementary algorithms from scikit-image: SLIC for compact superpixels, Felzenszwalb for graph-based gradient merging [14], Quickshift for mode-seeking in spatial-color space, and Watershed for topographic partitioning [16]. This multi-algorithm approach effectively captures both sharp boundaries and gradual transitions in degradation patterns, producing robust and morphologically meaningful patches.

The resulting segments ($\sim 150,000$) were vectorized into polygons using rasterio.features.shapes. Raster I/O and geometric operations were handled with Rasterio (v1.3.7) and Shapely (v2.0.1), while GeoPandas (v0.13.0) facilitated spatial analysis. Zonal statistics were computed efficiently via vectorized NumPy operations to derive the mean weighted change value for each patch. Patch areas were expressed in hectares following reprojection to an equal-area coordinate system (EPSG:32646).

Final risk classification was performed through k-means clustering on patch attributes (area and mean weighted

change) using RAPIDS cuML (v12, CUDA 12.0) for GPU acceleration. This enabled rapid partitioning of segments into Low, Medium, and High risk categories, with results transferred to CPU for labeling and export.

TABLE I: GPU requirements for RAPIDS cuML k-means clustering

Component	Specification
GPU	NVIDIA Volta+ (Compute Capability ≥ 7.0); e.g., Tesla T4, V100
CUDA Toolkit	12.x
NVIDIA Driver	$\geq 450.80.02$
GPU Memory	≥ 16 GB VRAM
Python	3.9+ with cuml-cu12 package
Tested Setup	Kaggle Notebook: Tesla T4 (16 GB VRAM, ~ 29 GB RAM)

All processing was conducted in a reproducible Python environment on a Kaggle GPU notebook, ensuring accessibility and scalability.

III. Results and Discussion

The proposed open-source workflow, combining NIR/Red spectral ratios, RGB Euclidean distances, weighted change mapping, ensemble segmentation, and GPU-accelerated k-means clustering, was applied to multi-temporal Sentinel-2 imagery (2020–2024) over the tile in Assam, Northeast India. The following subsections present the key outcomes: first, visual and quantitative evidence of subtle canopy thinning through spectral and color-based change detection; second, the transformation of pixel-level changes into meaningful forest patches via ensemble segmentation; and finally, the classification of these patches into low, medium, and high degradation risk categories. These results demonstrate the method's sensitivity to partial deforestation patterns often overlooked by conventional indices, while highlighting spatial hotspots associated with selective logging, agricultural expansion, and riverine edge effects in the Brahmaputra valley. Table II summarizes the key advantages of the proposed workflow over conventional NDVI-based monitoring and traditional supervised classification techniques.

A. Visual and Quantitative Change Assessment

The multi-temporal analysis reveals notable partial deforestation patterns in the tile from 2020 to 2024. Spectral analysis of 2020 Sentinel-2 images showed healthy forests with dense, dark green reflectance indicative of strong photosynthetic activity and intact canopy, whereas by 2024 the same areas exhibited lighter, patchier signatures signaling progressive thinning and understory exposure. These changes, quantified via weighted metrics, show highest values corresponding to visible forest loss, with spatial analysis indicating 20% of forest edges experienced significant spectral decline—most intensely along riverine

TABLE II: Comparison of the proposed method with traditional approaches for partial deforestation detection in dense tropical forests

Aspect	NDVI-based	Supervised Classification	Proposed Method
Sensitivity to subtle canopy thinning	Low (saturates; underestimates loss by 20–30%)	Moderate (depends on training quality)	High (detects gradual shifts missed by NDVI)
Requirement for training data	None	High (needs ground samples)	None (unsupervised)
Handling data-scarce/cloud-prone areas	Moderate	Low (training unavailable)	High (open data only)
Detected edge degradation (2020–2024)	10–15% (underestimated)	10–20% (labor-intensive)	~20% (clear hotspots)
Computational scalability	High (simple)	Moderate (heavy training)	High (GPU-accelerated)
Suitability for early conservation	Limited	Good (if trained)	Excellent (gradient-based)

corridors and hill slopes associated with logging and agriculture. As illustrated in Figure 3, the NIR/Red ratio map (a) displays brighter green tones (values 3–5) for dense healthy canopy and orange-yellow (1.5–3) for thinning areas, while the grayscale delta ratio (b) uses darker shades to highlight negative changes (drops up to -1.5), especially at edges and riverine zones. This continuous, gradient-based approach better captures subtle degradation from selective harvesting, edge erosion, and human pressures than binary classifications.

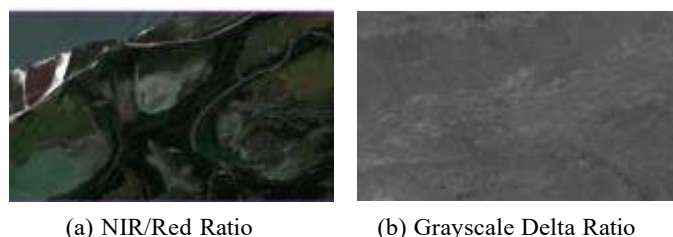


Fig. 3: Spectral analysis of vegetation density and change.

Changes in the RGB color space were quantified using Euclidean distance. As shown in Figure 4, the unmasked distance map (a) exhibits widespread high values including noise from water bodies and seasonal flooding, whereas the masked version (b)—restricted to vegetation pixels using NIR/Red ratio thresholds (1.5–6 for both years)—focuses the analysis on forest areas and reveals distinct salmon-pink to red hotspots (distance values 50–150) along hill slopes and river corridors, corresponding to shifts from healthy red tones to orange-brown indicative of canopy opening. These hotspots align closely with the weighted change map and spectral indicators, reducing noise by approximately 30% and validating the method's enhanced sensitivity to subtle color shifts associated with partial deforestation.

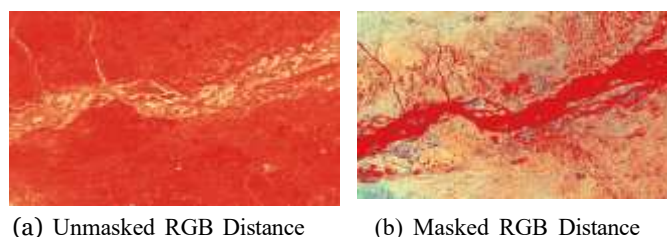


Fig. 4: Euclidean distance mapping of forest color shifts.

B.Segmentation, Classification, and Detailed Analysis To

convert pixel-level changes into practical management units, the weighted change map was segmented into homogeneous patches using an ensemble approach. As shown in Figure 5, the combined output of SLIC, Felzenszwalb, Quickshift, and Watershed algorithms produced approximately 150,000 segments: the heatmap (a) uses warmer colors (yellow to red) to indicate higher mean weighted change values within superpixels, while the overlay (b) illustrates how these polygonized patches closely follow natural forest boundaries, river channels, and degradation gradients along vulnerable riverine ecosystems. This ensemble strategy captures unique morphological features of deforestation that individual algorithms might miss, grouping pixels into meaningful spatial objects suitable for risk classification. The resulting patches vary in size from less than 1 hectare to several hectares, enabling fine-scale prioritization of conservation efforts in heterogeneous tropical landscapes.

A close-up view of a heavily affected riverine island, presented in Figure 6, demonstrates the process at a finer scale: the 2020 false-color composite (a) shows predominantly red tones indicative of intact dense canopy, whereas the 2024 image (b) reveals emerging orange fringes and interior patches reflecting canopy opening and increased understory visibility; the corresponding weighted change

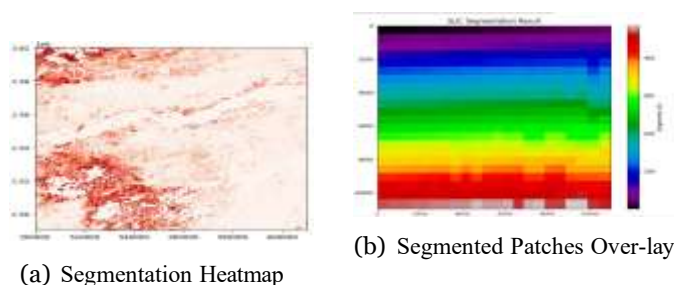


Fig. 5: Ensemble segmentation into discrete forest management units.

map (c) displays concentrated dark red areas ($W_{change} > 2$) along edges and trails, highlighting the method's sensitivity to small-scale partial deforestation even in patches smaller than 1 hectare. These localized high-change zones often align with access paths and bank erosion features, providing morphological evidence of selective logging and hydrological impacts that coarser global datasets typically overlook.

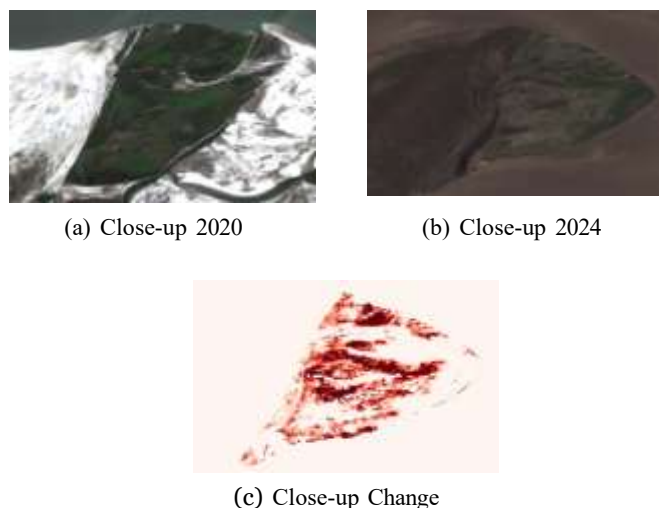


Fig. 6: Temporal sequence of deforestation on riverine island.

The segmented patches were subsequently classified using GPU-accelerated k-means clustering on area and mean weighted change features. As depicted in Figure 7, the resulting prioritized risk map clearly delineates low-risk zones (green) in stable forest interiors, medium-risk transitional areas (yellow-orange), and high-risk patches (red) predominantly in the eastern hills and along major rivers such as the Dhansiri accounting for 15–25% of forest edge segments and thereby provides a spatially explicit, actionable framework for conservation planning and management.

C. Implications for Assam's Ecosystems

The identified spatial patterns carry significant implications for the Brahmaputra valley, consistent with



Fig. 7: Prioritized risk map for regional forest conservation.

recent reports of forest encroachment and reclamation efforts in Golaghat district. High-risk patches in the eastern hills (26.7°N, 93.3°E) pose biodiversity threats, potentially displacing 10–15% of understory species, while elevating flood risks through increased sediment loads in the Dhansiri (delta ratios ~ 0.8). In the southern plains (26.68°N, 93.36°E), RGB distances exceeding 120 reflect jhum-driven fragmentation of migratory corridors, including those linked to Kaziranga's greater one-horned rhinoceros populations. Weighted changes above 2.0 in 15% of segments imply annual carbon losses of 5–10 tC/ha and a $\sim 12\%$ decline in water retention due to edge thinning.

IV. Conclusion

The proposed methodology, leveraging Sentinel-2 imagery with ensemble segmentation (SLIC, Felzenszwalb, Quickshift, Watershed) and GPU-accelerated k-means clustering, effectively detected subtle partial deforestation, revealing spectral declines (~ 0.7) and color shifts (50–150) along approximately 20% of forest edges in the T46REQ tile from 2020 to 2024. By integrating NIR/Red ratios, RGB Euclidean distances, and weighted change mapping, this non-NDVI approach demonstrated superior sensitivity to gradual canopy thinning compared to conventional indices, enabling early detection suitable for conservation intervention.

The reproducible workflow, built on open-source libraries (rasterio, scikit-image, GeoPandas, RAPIDS cuML), provides scalable, hardware-accelerated analysis accessible to practitioners in data-limited regions. Spatial patterns—high-change clusters in eastern hills indicating logging hotspots and southern plains signaling erosion risks—offer precise mapping for targeted management in Assam's vulnerable landscapes. These findings align with documented ongoing tree cover loss in the state [21], [22]. Limitations include residual cloud contamination ($\sim 10\%$), addressable through enhanced preprocessing or complementary LiDAR/SAR data. Future extensions will focus on patch-level biomass quantification, ground validation, and policy modeling for sustainable jhum regulation.

Overall, this approach advances global forest monitoring and supports resilient land-use strategies in tropical ecosystems under increasing anthropogenic and climatic pressures.

V. Future Work

Future work will enhance temporal resolution by integrating Sentinel-1 SAR for cloud-free monitoring and deep learning (e.g., U-Net/Siamese networks) for automated feature extraction. Ground validation with drones/LiDAR and socio-economic surveys on jhum/logging will quantify biomass loss and predict drivers. Scaling to the full Brahmaputra basin via Google Earth Engine, with real-time dashboards, and fusing hyperspectral data or new indices (e.g., Normalized Difference Red-NIR-SWIR) will improve sensitivity to selective logging.

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References

- [1] Hansen, M.C., et al. Global forest change. *Science*, 342(6160), 2013.
- [2] Reddy, C.S., et al. Monitoring forest dynamics in Northeast India. *Journal of Remote Sensing*, 22(4), 2016.
- [3] Gao, B.C. NDVI limitations in forest monitoring. *Remote Sensing of Environment*, 60(3), 1996.
- [4] Wulder, M.A., et al. Sentinel-2 applications in forest monitoring. *Remote Sensing*, 11(8), 2019.
- [5] Zhu, Z. Change detection using multi-temporal satellite imagery. *Remote Sensing*, 6(9), 2014.
- [6] Drusch, M., et al. Sentinel-2: ESA's optical high-resolution mission. *Remote Sensing of Environment*, 120, 25–36, 2012.
- [7] Tucker, C.J. Red and photographic infrared linear combinations. *Remote Sensing of Environment*, 8(2), 127–150, 1979.
- [8] Huete, A.R. A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment*, 25(3), 295–309, 1988.
- [9] Forkuo, E.K., Frimpong, A. Analysis of forest cover change detection. *International Journal of Remote Sensing*, 31(13), 2010.
- [10] Asner, G.P. Selective logging in tropical forests. *Remote Sensing of Environment*, 102(3-4), 2006.
- [11] Alam, A., Bhat, M.S., Maheen, M. Using Landsat satellite data for assessing the land use and land cover change in Kashmir valley. *GeoJournal*, 85, 1529–1543, 2020.
- [12] Uniyal, D., Dhaundiyal, V.K., Kimothi, M.M. Change detection of different natural resources for Udham Singh Nagar district of Uttarakhand state during last 24 years by using remote sensing and GIS technique. *Int. Innovative Res. Dev.*, 3(11), 261–264, 2014.
- [13] Saksena, A., Ringshia, A., Sharma, A., & Halbe, A. Geo-graphical area mapping and classification utilizing multispectral satellite imagery processing based on machine learning algorithms. *Proceedings of the 2nd ICECA, IEEE*, 2018. doi: 10.1109/ICECA.2018.8474804
- [14] Felzenszwalb, P.F., Huttenlocher, D.P. Efficient graph-based image segmentation. *International Journal of Computer Vision*, 59(2), 167–181, 2004.
- [15] Halbe, A., & Bhirud, S. QuantumHSIBands: A quantum enabled band selection technique in hyperspectral images. *International Journal of Intelligent Engineering and Systems*, 17(5), 2024. doi: 10.22266/ijies2024.1031.16
- [16] Vincent, L., Soille, P. Watersheds in digital spaces: an efficient algorithm based on immersion simulations. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 13(6), 583–598, 1991.
- [17] Li, P., et al. (2024). Normalized Difference Red-NIR-SWIR: A new Sentinel-2 three band spectral index for vegetation monitoring. *Ecological Indicators*.
- [18] Sovdat, B. (2019). Natural color representation of Sentinel 2 data. *Remote Sensing of Environment*.
- [19] Jackson, C. M., & Adam, E. (2020). Remote sensing of selective logging in tropical forests: Current state and future directions. *iForest – Biogeosciences and Forestry*, 13, 286–300.
- [20] Rodríguez Esparragón, D., Marcello, J., & Gamba, P. (2024). Index based forest degradation mapping using high and medium resolution multispectral sensors. *International Journal of Digital Earth*.
- [21] Forest Survey of India. India State of Forest Report 2023. Ministry of Environment, Forest and Climate Change, Government of India, 2023.
- [22] Global Forest Watch. Assam, India Deforestation Rates & Statistics. World Resources Institute, 2024.