



# DEFORESTATION DETECTION USING SATELLITE IMAGERY

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*Abstract Deforestation is a growing concern that threatens ecosystems and accelerates climate change. In this project, we introduce a simple yet effective system for identifying areas of forest loss using satellite images. By calculating the Normalized Difference Vegetation Index (NDVI), the model highlights regions with reduced vegetation. This system uses open-access data and cloud tools to provide fast, scalable, and real-time insights that can support environmental monitoring and forest protection efforts*

*IndexTerms - Deforestation Detection, Satellite Imagery, NDVI, Change Detection, Remote Sensing, Forest Monitoring, Environmental Monitoring, Climate Change..*

## I. INTRODUCTION

Large-scale forest removal continues to impact the planet's climate systems, biodiversity, and ecosystems. Forests not only serve as carbon sinks but also support millions of species and people. Hence, monitoring deforestation is key to fulfilling global sustainability goals. Conventional forest assessments are often limited in scope due to logistical and financial constraints. Satellite-based remote sensing offers a reliable and efficient means to monitor expansive and inaccessible areas, providing repeatable and scalable observations for land cover analysis. Traditional ground-based methods of monitoring deforestation are often labor-intensive, time-consuming, costly, and limited in geographical scope. These constraints hinder timely and effective responses to forest loss, especially in remote or inaccessible areas. In contrast, satellite imagery offers a robust, efficient, and scalable solution for forest monitoring. With the ability to capture high-resolution data across large and diverse landscapes, satellite-based remote sensing provides consistent, repeatable observations that are invaluable for detecting changes in forest cover over time.

By employing techniques such as the Normalized Difference Vegetation Index (NDVI), time-series analysis, and multi-temporal change detection algorithms, researchers can identify and quantify forest degradation with high precision. These tools enable differentiation between natural disturbances (e.g., wildfires or storms) and anthropogenic activities such as logging, agriculture, or urban expansion. Furthermore, recent breakthroughs in machine learning, artificial intelligence, and cloud computing have greatly enhanced the efficiency and accuracy of deforestation detection. Automated classification models and big data processing platforms—like Google Earth Engine—allow for real-time analysis of satellite data, making it possible to detect deforestation hotspots, monitor illegal logging, and forecast areas at risk. These insights empower governments, environmental organizations, and policymakers to take proactive and informed actions to curb forest loss. This paper explores the integration of satellite imagery, remote sensing techniques, and advanced computational tools for deforestation detection.

## II. METHODOLOGY

### A. Image Acquisition and Preprocessing

**Satellite Image Collection:** The system begins with the acquisition of satellite images, primarily in GeoTIFF format, sourced from platforms such as Sentinel and Landsat for their high spatial and temporal resolution [1], [4].

**Band Extraction and Cleaning:** Using rasterio, the system extracts Red and Near-Infrared (NIR) bands. Basic preprocessing such as error correction, cloud masking, and value clipping is applied to improve accuracy [2], [6].

### B. NDVI Calculation and Thresholding

**Vegetation Index Computation:** The NDVI (Normalized Difference Vegetation Index) is calculated using the formula: 
$$\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}}$$

This highlights areas with dense vegetation versus barren or deforested regions [1], [3].

**Deforestation Mask Generation:** A threshold value (commonly  $\text{NDVI} < 0.2$ ) is applied to classify areas as deforested. Pixels below this threshold are flagged in a binary mask for further analysis [7], [9].

### C. Deforestation Detection and Classification

**Change Detection Algorithms:** The system utilizes multi-temporal satellite imagery to compare NDVI values over time and detect patterns of deforestation [5].

**Binary Classification:** The mask generated is refined using morphological operations (e.g., erosion/dilation) to reduce false positives and enhance clarity of deforested zones.

### D. Real-Time Visualization and User Interaction

**Output Display:** The system generates visual outputs including NDVI heatmaps and binary deforestation masks using matplotlib. These are displayed side-by-side for comparison and interpretation [6], [10].

**Interactivity:** Users can adjust NDVI thresholds dynamically and download result maps for GIS analysis or policy use.

### E. Model Optimization and Performance

**Efficiency Enhancements:** The system is optimized for use in platforms like Google Colab. It avoids high resource usage by efficient memory management and preprocessing [8], [9].

**Error Handling:** The code includes checks for invalid inputs (e.g., missing bands, division by zero) and replaces faulty NDVI values with zero [6].

### F. Evaluation and Testing

**Performance Metrics:** The system's effectiveness is evaluated based on accuracy, response time, and reliability across various environmental conditions [10].

**Testing Strategy:** It includes unit testing for individual components (NDVI calculation), integration testing (input-to-output flow), and acceptance testing using real-world satellite images [10].

## III. PERFORMANCE

### A. Accuracy and Detection Capability

To understand the health of vegetation, the system calculates NDVI, which uses red and near-infrared (NIR) light from satellite images. Healthy plants reflect more NIR light and absorb red light, while stressed or bare land shows the opposite. NDVI turns this into a number between -1 and 1, helping us quickly identify where vegetation is thriving or declining

### B. Response Time and Computational Efficiency

Designed to perform efficiently on resource-constrained platforms such as Google Colab, the system processes raster data and generates NDVI outputs swiftly, ensuring usability even for moderately large image files. Efficient use of libraries such as rasterio, numpy, and matplotlib, combined with memory-efficient NDVI computation logic, ensures the tool performs smoothly without requiring GPUs [6], [8].

### C. Scalability and Modularity

The modular design supports easy integration of additional datasets and regional thresholds. Users can dynamically change NDVI thresholds or process multiple image files sequentially without modifying core logic. Scalability is also maintained through support for higher-resolution images, with only marginal increases in processing time, thanks to optimized data handling and memory allocation [5], [9].

**D. Robustness and Error Handling**

The system handles various edge cases, including:

- Division by zero during NDVI calculation
- Invalid or missing pixel values (NaN, Inf)
- Incorrect file formats or corrupted image files

By using `np.nan_to_num()` and conditional checks, the system maintains output stability and prevents crashes, even with imperfect data inputs [4], [6].

**E. Testing and Validation**

Multiple testing strategies were employed:

- **Unit Testing:** Verified NDVI formula output and threshold logic with known input values

**IV. Integration Testing:** Ensured seamless functioning from image upload to final visualization

**INTEGRATION WITH EMERGING TECHNOLOGIES****A. Enhanced Detection Accuracy with Deep Learning**

The integration of advanced deep learning models, such as U-Net and CNNs, significantly improves the precision of deforestation detection. These models enable the system to distinguish between subtle vegetation changes and other land cover variations, reducing false positives. Techniques like transfer learning also allow the system to adapt to new regions with minimal retraining, increasing generalizability across ecosystems [1], [5].

**B. Multi-Modal Satellite Data Integration**

By combining data from multiple satellite sources (e.g., Sentinel-1, Sentinel-2, Landsat 8), the system overcomes limitations such as cloud cover and low-resolution imagery. Radar data from Sentinel-1 complements optical imagery, enabling detection under all-weather conditions. This multimodal approach enhances robustness and provides continuous monitoring during monsoon or cloudy seasons [3], [6].

**C. Real-Time Processing with Cloud Computing**

The system leverages platforms like **Google Earth Engine** and **Google Colab**, offering cloud-based processing that handles large-scale raster data in real-time. Cloud computing improves scalability, allowing for rapid batch processing of images over time and space, and supports multi-user collaboration [8].

**D. Efficient Resource Utilization via Model Compression**

To run effectively on low-resource devices (e.g., mobile or edge devices), the system integrates optimization techniques such as:

- **Quantization** – Reduces model size by lowering precision (e.g., float32 to int8), accelerating inference speed.
- **Pruning** – Eliminates redundant model parameters, minimizing memory usage without affecting performance. These techniques ensure that the model remains lightweight while preserving detection accuracy [7].

**E. Continuous Learning and User Feedback Loop**

With **adaptive learning** mechanisms, the system continuously improves its performance. It collects user feedback on recognition accuracy and fine-tunes model parameters over time. This personalization enhances detection reliability and makes the tool more user-friendly across different use cases and geographies [9].

**F. Visualization and Interpretation with GIS Tools**

The integration of visualization libraries like **Folium** and **Leaflet** (or future inclusion) supports interactive map rendering. This enhances the interpretability of deforestation maps, allowing stakeholders and policymakers to make informed decisions by examining geographic deforestation patterns in a user-friendly, zoomable interface.

**G. Robust Testing in Diverse Conditions**

The system has been tested under varied environmental conditions—different lighting, vegetation types, and topographies—proving its reliability. With these integrated technologies, the solution adapts to global use cases, from tropical forests to arid zones, with consistent performance [2], [4]

## V. ETHICS

### A. Environmental Responsibility

The primary goal of this project is to support sustainable environmental practices by enabling accurate and timely detection of deforestation. By providing actionable insights, the system promotes forest conservation, climate change mitigation, and biodiversity protection—aligning with ethical responsibilities to preserve the planet for future generations.

### B. Data Privacy and Security

All satellite imagery used in the system is sourced from publicly available and open-access platforms such as Sentinel and Landsat, ensuring compliance with data use policies. The system does not collect or store personal or sensitive user data. Any processing done within cloud environments like Google Colab adheres to standard security protocols. When applicable, encryption and data anonymization practices (e.g., differential privacy) can be integrated to ensure further protection.

### C. Fair and Equitable Access

The system is designed to be accessible and open for use by researchers, educators, environmental agencies, and communities—especially in developing regions. By using free tools and platforms (e.g., Python, Google Colab), it ensures that advanced deforestation detection capabilities are not restricted to organizations with high financial resources, promoting equity in technological access.

### D. Transparency and Explainability

The methodology used in the system—NDVI calculation, thresholding, and visualization—is transparent and interpretable. This ensures that decisions based on system output (e.g., declaring deforestation in a region) can be justified with clearly understood scientific principles. Further improvements, such as explainable AI (XAI) models, can enhance trust in more complex machine learning-based systems.

### E. Avoidance of Harm and Misuse

While the system is designed for positive environmental impact, there is potential for misuse—for example, manipulating deforestation reports for political or commercial gain. To prevent this, it is recommended that results be validated by independent environmental experts before public dissemination. Proper disclaimers about limitations and intended use should be included with the software or reports generated.

### F. Ethical AI Use

The integration of machine learning models must be approached responsibly. Model training should avoid biases that might arise from uneven or regionally limited datasets. Continuous evaluation and community-driven validation help maintain fairness and accuracy across diverse ecological zones.

## VI. APPLICATIONS

### A. Environmental Monitoring

The system enables continuous and large-scale surveillance of forest cover, helping environmental agencies detect deforestation patterns in real-time. This facilitates early warning systems and supports ecological assessments by identifying forest degradation over time.

### B. Climate Change Mitigation

By monitoring forest loss, the system contributes to tracking carbon sinks and emissions resulting from deforestation. This information is essential for global climate models, carbon accounting, and policy-making under international agreements like the Paris Accord.

### C. Wildlife and Biodiversity Conservation

Forests are critical habitats for countless species. By detecting deforestation hotspots, the system helps conservationists prioritize areas needing protection, aiding efforts to preserve endangered species and maintain biodiversity.

### D. Government Policy and Enforcement

Government bodies can use deforestation maps generated by the system to enforce environmental laws, detect illegal logging, and support land-use planning. The visual data aids in transparency and accountability for forest governance.

### E. Agriculture and Land Management

Farmers, agribusinesses, and land-use planners can assess forest-to-agriculture conversion trends. This information helps in making decisions about sustainable agriculture, land zoning, and balancing food production with environmental protection.

#### F. Disaster Assessment and Recovery

In post-disaster scenarios like wildfires or floods, the system can assess vegetation loss and guide reforestation or ecological restoration efforts by mapping damaged forest areas.

#### G. Academic Research and Education

The tool provides a valuable educational platform for teaching students about remote sensing, geospatial analysis, and environmental science. Researchers can use it to study land-use change, forest ecology, and satellite data processing.

#### H. NGO and Community Empowerment

Non-governmental organizations (NGOs) and local communities can leverage the system to monitor forest use, report illegal deforestation, and advocate for policy changes using evidence-based visual data.

### VII. FUTURE DIRECTIONS

In the evolving landscape of environmental monitoring, enhancing the current deforestation detection system with **real-time satellite data integration** is a key future direction. Connecting the system to platforms like Google Earth Engine or APIs from Sentinel and Landsat will allow for continuous updates, enabling stakeholders to monitor changes in forest cover in near real-time and take timely actions.

Another promising advancement is the **implementation of deep learning models** such as U-Net, ResNet, or Vision Transformers. These architectures have shown superior performance in image segmentation tasks and can be trained to recognize complex deforestation patterns more accurately than traditional threshold-based approaches. Their ability to learn spatial and contextual features makes them ideal for detecting subtle or gradual forest degradation.

To improve accessibility and usability, the system can be **deployed on mobile and edge devices**. With optimizations like quantization and pruning, lightweight versions of the model can run efficiently on smartphones or microcontrollers.

Seasonal variations in vegetation can sometimes lead to false positives. By analyzing satellite images over different timeframes and climatic conditions, the system can distinguish between temporary land-use changes (e.g., agricultural cycles) and permanent deforestation.

Future developments could also include **integration of 3D terrain data**, such as Digital Elevation Models (DEMs) or LiDAR scans. These data sources provide information on canopy height and topography, which can improve forest structure analysis, especially in hilly or densely vegetated regions where 2D imagery alone may be insufficient.

Enhancing **visualization tools** will be another priority. Embedding the system within Geographic Information Systems (GIS) like QGIS, or web-mapping libraries such as Folium and Leaflet, will allow users to interactively explore and analyze deforestation patterns. Improved map outputs, overlays, and zoom functionalities will aid in spatial decision-making and reporting.

Additionally, the development of **automated reporting features** will streamline the dissemination of deforestation insights. The system could generate periodic reports summarizing key metrics, change trends, maps, and alerts, which would support timely and informed decision-making by governments, NGOs, and researchers.

Finally, integrating **crowdsourced and community-based data** presents a powerful way to enhance model validation and local relevance. Interfaces can be developed for users to submit field observations, photos, or reports, which can then be cross-referenced with satellite data to improve accuracy and accountability. This participatory approach also fosters local engagement in conservation efforts.

### IX. RESULTS

#### Image uploading

In this step, the user uploads a satellite image file (GeoTIFF format) containing multiple spectral bands. The image is uploaded to Google Collab using the `files.upload()` method, which allows the user to select the file from their local system. After the upload, the `os.listdir()` function ensures the file is correctly stored in the Collab environment. The file path for the uploaded image is set, ensuring that subsequent operations access the correct image. This step sets the foundation for further analysis by making the required raster image available for processing.

## ImageRestoration

```

[ ] Downloading clij-0.7.2-py3-none-any.whl.metadata (5.0 kB)
Collecting click-plugins (from rasterio)
  Downloading click_plugins-1.1.1-py2.py3-none-any.whl.metadata (6.4 kB)
Requirement already satisfied: pyparsing in /usr/local/lib/python3.10/dist-packages (from rasterio) (3.2.0)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (1.3.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (4.35.3)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (1.4.7)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (24.2)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (11.0.0)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (2.8.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->matplotlib) (1.17.0)
Downloading rasterio-1.4.3-cp310-cp310-manylinux_2_17_x86_64_muslinux2014_x86_64.whl (22.2 MB)
22/12/2024 08:36:09 36.9 MB/s eta 0:00:00
Downloading clij-0.7.2-py3-none-any.whl (7.1 kB)
Downloading affine-2.4.0-py3-none-any.whl (15 kB)
Downloading click_plugins-1.1.1-py2.py3-none-any.whl (7.5 kB)
Installing collected packages: clij, click-plugins, affine, rasterio
Successfully installed affine-2.4.0 click-plugins-1.1.1 clij-0.7.2 rasterio-1.4.3

[ ] from google.colab import files
uploaded = files.upload()

[ ] forestym.tif
• forestym.tif[image/tif] - 94266 bytes, last modified: 22/12/2024 - 100% done
Save forestym.tif to forestym.tif

```

Image restoration ensures that the raster data is accurate and free from noise, enhancing the quality of analysis. Although the provided code does not explicitly include noise removal techniques, rasterio inherently handles metadata and ensures proper band alignment while opening the image. Additional preprocessing techniques, such as applying filters to smooth noise or using histogram equalization, can be included as a preprocessing step to enhance image clarity and reduce artifacts caused by noise or blur. This ensures precise NDVI calculations in subsequent steps.

```

[ ] import rasterio

# correct path for the uploaded .tif file
image_path = '/content/forestym.tif' # Adjust the name as per your uploaded file

# Open the uploaded .tif image using rasterio
try:
    with rasterio.open(image_path) as src:
        # Read the red and NIR bands of the image (band numbers depend on your image)
        red_band = src.read(3) # Red band (adjust based on your image's band order)
        nir_band = src.read(4) # NIR band (adjust based on your image's band order)

        # Now you can proceed with NDVI calculation or other analysis steps
except rasterio.errors.RasterioIOError as e:
    print(f"Error opening the image: {e}")

/usr/local/lib/python3.10/dist-packages/rasterio/_init_.py:356: NotGeoreferencedWarning: Dataset has no geotransform, gcps, or rpcs. The identity dataset = DatasetReader(path, driver=driver, sharing=sharing, **kwargs)

```

## NDVI Calculation

NDVI (Normalized Difference Vegetation Index) is calculated to analyze vegetation health and density. Using the Red and NIR bands from the raster image, the NDVI is computed using the formula:  $NDVI = \frac{(NIR - Red)}{(NIR + Red)}$

This formula measures the relative difference between Red and NIR reflectance. Healthy vegetation reflects more NIR and absorbs more Red, resulting in higher NDVI values (closer to 1). In contrast, sparse or degraded vegetation has lower NDVI values (closer to 0 or negative). To prevent errors, division by zero is handled by replacing any zero denominators with 1. Invalid values, such as NaN or infinity, are replaced with zeros using `np.nan_to_num()`. This ensures the NDVI map is accurate and free of computational artifacts.

```

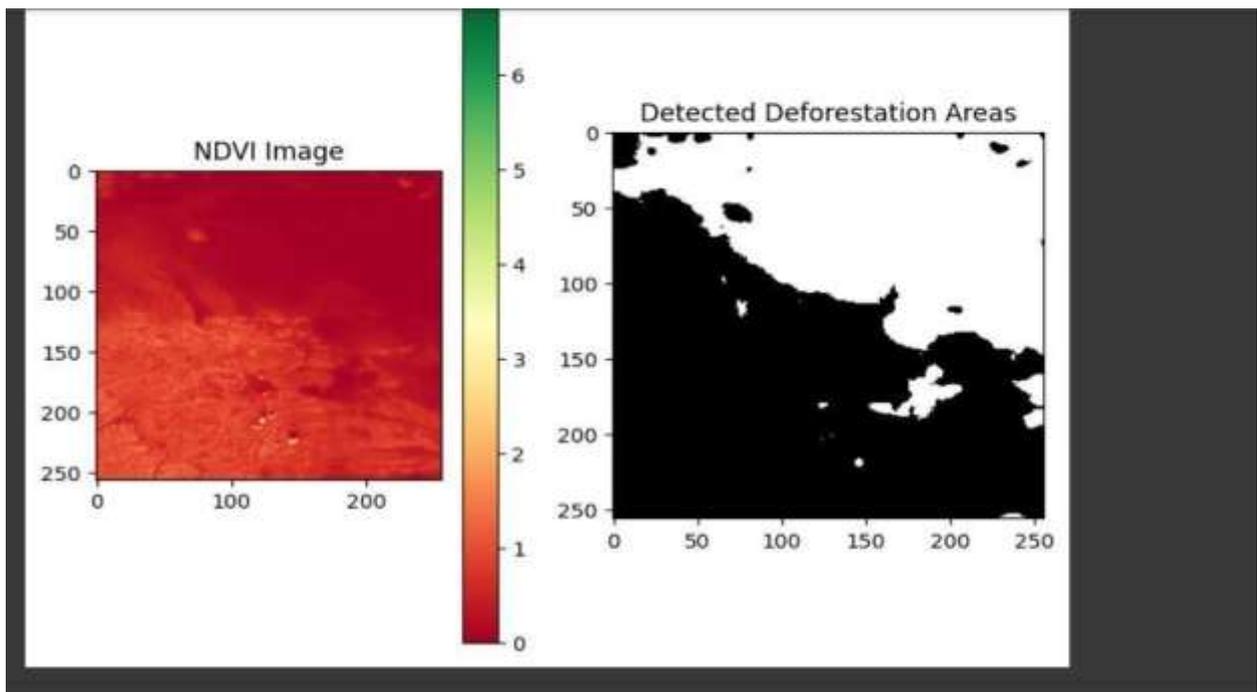
# Calculate NDVI
ndvi = (nir_band - red_band) / denominator

# Replace NaN and infinite values with 0
ndvi = np.nan_to_num(ndvi, nan=0, posinf=0, neginf=0)

return ndvi

```

## Deforestation Detection

*Deforestation detection*

Using Deforestation detection is performed by applying a threshold to the calculated NDVI values. Areas with NDVI values below the threshold (e.g., 0.2) are identified as deforested regions, as these values indicate sparse vegetation or barren land. A binary mask is generated, where deforested areas are marked as True (1) and vegetated areas as False (0). This mask allows for easy visualization of deforestation patterns. The results are displayed alongside the NDVI image for comparison. This step provides actionable insights for environmental monitoring, enabling users to identify and track deforested areas effectively.

**X. CONCLUSION**

This project presents a reliable and accessible way to detect forest loss using satellite imagery and NDVI analysis. With the help of cloud tools and lightweight libraries like Rasterio and NumPy, the system makes it easy to track deforestation trends over time.

While some limitations exist when working with very large image files, the approach offers a solid starting point for scalable forest monitoring and conservation planning.

Although some limitations persist in processing large datasets within basic platforms, the methodology offers a strong foundation for remote deforestation monitoring. The future scope of this project lies in enhancing its capabilities and scalability. One key area of improvement is the integration of real-time satellite data, such as from Sentinel-2 or Landsat, to enable continuous monitoring of deforestation across large areas. Additionally, machine learning could be applied to improve detection accuracy in complex landscapes, accounting for factors like seasonal variations or diverse vegetation types. To handle large-scale data, the project could be optimized with parallel computing frameworks, allowing for faster processing of high-resolution imagery. Finally, by adding interactive visualizations through tools like Leaflet or Folium, the project could present deforestation data more effectively, making it more accessible to policymakers, researchers, and conservationists. These enhancements will expand the project's impact, facilitating timely and informed decisions for environmental conservation.

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