

A Result Paper on Deforestation Monitoring and Cause Detection in India Using Satellite Imagery

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Peer Review Information	Abstract
<p>Type: Article Received: 22 March 2026 Revised: 06 April 2026 Accepted: 24 May 2026 Published: 05 June 2026</p>	<p>Forests in India are disappearing rapidly. This paper presents an automated system that monitors deforestation using satellite imagery and AI. Users enter any location's coordinates. The system pulls images from Sentinel-2 via Google Earth Engine and analyzes changes over multiple years. Ten vegetation indices (NDVI, NDWI, EVI, MSAVI2, NDMI, NBR, BSI, NDBI, SAVI, GNDVI) are calculated to track plant health, soil, and water conditions. A large language model interprets the data and identifies likely causes of forest loss. A web interface built with FastAPI makes the tool accessible to non-experts. Testing on Anamalai Hills, Kerala successfully detected a severe drought event in September 2025 and tracked the forest's rapid recovery. The system shows that combining satellite data with AI enables scalable, automated forest monitoring.</p> <p>Keywords: Deforestation; Satellite Monitoring; Sentinel-2; Google Earth Engine; Normalized Difference Vegetation Index (NDVI); Artificial Intelligence; FastAPI; Forest Monitoring; Remote Sensing; Indian Forests.</p>

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Introduction

Forests are vanishing fast across India. This harms wildlife, destabilizes the climate, and disrupts water supplies. Every year, more trees fall for farms, cities, and roads. Keeping track of where and why forests disappear is a massive challenge.

Traditional methods send people into the woods for manual surveys. This takes too long, costs too much, and cannot cover large areas. Satellites now take detailed pictures of everywhere on Earth every few days. Artificial intelligence has become smart enough to analyze those pictures automatically.

This paper describes a tool we built that combines satellite data with AI. Anyone with internet access can type in coordinates and receive a clear report on forest health and what might be causing damage.

What Other Researchers Have Done

Early deforestation monitoring relied on NDVI, a simple measure of green vegetation [1]. Researchers later developed additional indices like SAVI for soil-adjusted measurements [2], EVI for dense forests [3], NDWI for water detection [4], and NDMI for plant moisture [5].

Single images only show one moment in time. Researchers began using time-series methods like BFAST to detect gradual forest decline and sudden clearing [6].

Deep learning has transformed the field. U-Net and similar architectures can classify every pixel in a satellite image [7]. Recent studies show CNNs successfully detect degraded forests using Sentinel-2 time series [8], [9].

For India specifically, multiple studies have used Google Earth Engine with NDVI and NDWI to track forest changes in the Himalayas, Dehradun, Northeast India, and Odisha [10]–[13].

Limitations Of Existing Work

Current systems have several problems. Many require manual interpretation or focus on a single index like NDVI, which misses important context. Most analyze only short time periods, failing to capture slow changes. Few tools can explain why forest loss happened. And most lack user-friendly interfaces, making them inaccessible to policymakers and local communities.

Motivation

Forests are too important to leave unprotected. India's remaining forests need constant monitoring, but old methods are slow and expensive. Free satellite data from Sentinel-2 and cloud platforms like Google Earth Engine now make large-scale analysis possible. Large language models can read numerical data and write plain-English explanations. We saw an opportunity to combine these technologies into a tool that anyone can use.

Proposed System

Problem Statement

Existing tools have three main flaws. First, they provide regional averages instead of location-specific analysis. Second, complex machine learning models are black boxes. Third, most detect change but cannot explain causes. Our system solves all three problems.

System Architecture

Our system has three layers. A web front end accepts user coordinates. A Python application built with FastAPI processes requests, pulls satellite data, calculates indices, and generates reports. A storage layer saves results.

When users submit coordinates, the system validates them and defines an area of interest. Satellite images are retrieved from Sentinel-2 via Google Earth Engine. Ten indices are calculated. Data is visualized in charts and maps. A large language model analyzes the numbers and writes a plain-English report explaining what happened and why.

Implementation Details

We implemented the system in Python. Satellite images come from Sentinel-2 accessed through Google Earth Engine's Python API. Images are filtered for cloud cover and limited to clear months.

We calculate ten indices from Sentinel-2 spectral bands: - NDVI for vegetation health - NDWI for water content - EVI for dense vegetation - MSAVI2 for soil-adjusted analysis - NDMI for moisture stress - NBR for burned areas - BSI for bare soil exposure - NDBI for urban development - SAVI for sparse vegetation - GNDVI for chlorophyll content

Index values are organized into time-series. Statistical analysis identifies anomalies and trends. Visualizations use Matplotlib. The

numerical data is fed to a large language model (cloud API or local deployment) which produces analytical reports. The web application runs on FastAPI.

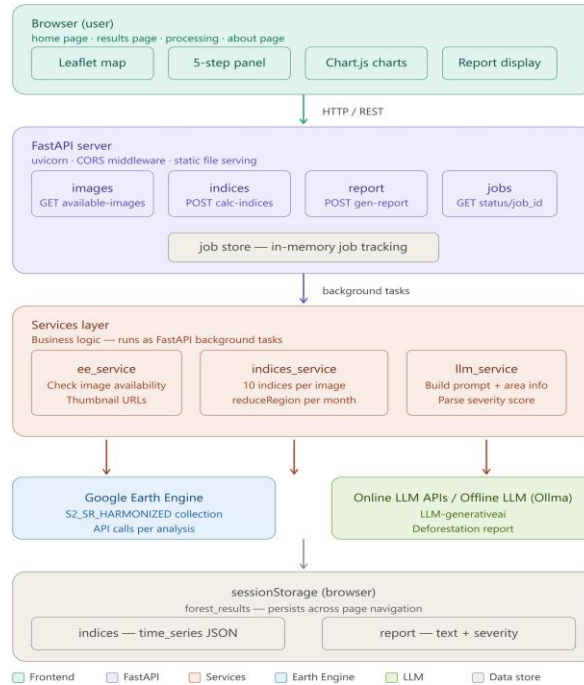


Fig. 1. System Architecture Diagram

Results And Discussion

Study Area: Anamalai Hills, Kerala

We tested the system on Anamalai Hills, Kerala (10.3123°N, 77.0924°E). The study area covered a 10 km radius (397.8 km²). Twenty-eight satellite images were processed from 2017 to 2026.

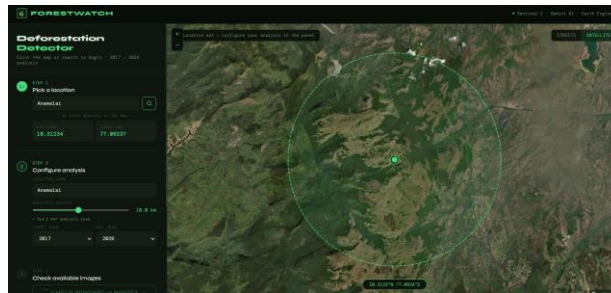


Fig. 2. System Homepage Interface

Vegetation Index Analysis

From 2017 to 2024, the forest was stable with NDVI between 0.55 and 0.75. In September 2025, all indices dropped sharply. NDVI fell to 0.436, EVI to 1.117, SAVI to 0.655, and GNDVI to 0.381. NDWI hit -0.381, indicating severe moisture deficit.

Table 1. Vegetation Indices for Anamalai Hills

Index	2019	2024	Sep 2025	Mar 2026
NDVI	0.682	0.691	0.436	0.678
EVI	1.452	1.468	1.117	1.441
SAVI	0.712	0.723	0.655	0.709
GNDVI	0.521	0.534	0.381	0.518
NDWI	0.234	0.241	-0.381	0.228

NBR	0.512	0.523	0.319	0.508
BSI	-0.142	-0.138	-0.121	-0.141
NDBI	-0.234	-0.228	-0.201	-0.231



Fig. 3. NDVI Time-Series (2017-2026)

By December 2025, all indices recovered. NDVI reached 0.68 by March 2026. This pattern suggests temporary stress rather than permanent deforestation.

Cause Attribution and Severity Assessment

The system identified drought as the likely cause. The extreme low NDWI indicated plants lost water before losing leaves. Rapid recovery ruled out permanent clearing from farming or construction. Severity score: 6/10. Confidence: medium (ground data would help confirm).

Key Findings

Anamalai Hills experienced severe temporary drought stress in September 2025 but recovered quickly. The forest is resilient but vulnerable to extreme dry periods. Recommendations include high-frequency monitoring and drought preparation strategies.

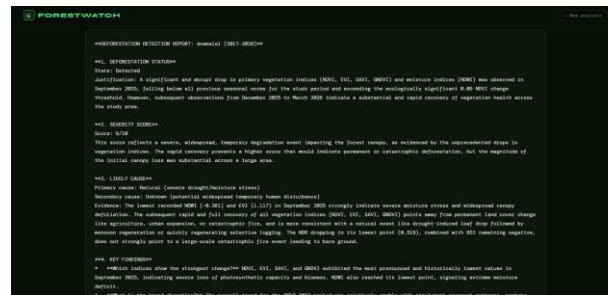


Fig. 4. Automated Deforestation Detection Report

Conclusion

We built an automated system that monitors deforestation using satellite imagery and AI. It pulls Sentinel-2 data via Google Earth Engine, calculates ten vegetation indices, and uses a large language model to write plain-English reports explaining what happened and why.

Testing on Anamalai Hills, Kerala successfully detected a severe drought event in September 2025 and tracked the forest’s recovery. The system distinguishes temporary stress from permanent deforestation.

Future improvements could include higher-resolution imagery, advanced deep learning for detailed mapping, and integration of local weather data to confirm drought events. This tool can help researchers, forest managers, and policymakers protect India’s remaining forests.

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