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Deforestation Monitoring and Cause Detection System in India Using Satellite Imagery

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Abstract

Deforestation is a major environmental challenge in India, driven by agriculture, urbanization, and infrastructure expansion. Satellite-based remote sensing provides a reliable and scalable approach for monitoring forest cover change across large areas. With the emergence of cloud platforms such as Google Earth Engine (GEE), multi-temporal analysis of satellite imagery has become more accessible, enabling integration of vegetation indices (NDVI, NDBI, NDWI) and advanced learning methods for accurate change detection. This paper presents a literature survey of twenty key studies on deforestation monitoring and cause detection, covering traditional index-based approaches, time-series change detection methods, and deep learning-driven image analysis. The review highlights datasets, methodologies, and applications relevant for building an automated deforestation monitoring and cause-detection system in India.

Introduction

Deforestation is one of the most critical environmental issues of the 21st century, leading to biodiversity loss, soil degradation, climate change, and disruption of ecological ser vices. In India, rapid urbanization, agricultural expansion, and infrastructure development have accelerated the rate of forest cover decline, particularly in ecologically sensitive zones such as the Western Ghats, Central India, and the Northeastern states. Traditional ground-based surveys and GIS techniques, though valuable, are limited in their ability to monitor large scale changes with high temporal frequency.

The advent of satellite remote sensing has transformed de forestation monitoring by enabling consistent, multi- temporal, and spatially extensive observations of land surface changes. Early research focused on the use of vegetation indices such as the Normalized Difference Vegetation Index (NDVI), which has proven effective in detecting vegetation loss and stress [15], [19]. Later indices such as the Normalized Difference Built-Up Index (NDBI) and Normalized Difference Water In dex (NDWI) were introduced to differentiate urban expansion and hydrological features, which often drive or accompany deforestation [14], [16].

With the availability of free, long-term datasets from Land sat and Sentinel missions, time-series analysis has become cen tral to detecting subtle forest changes over multiple decades. Techniques such as BFAST and break- point detection have been applied to monitor forest degradation and regrowth with higher accuracy [3], [19]. Recent studies have further enhanced this by integrating multi-sensor data and applying convolutional neural networks (CNNs) and U-Net models for semantic segmentation and forest loss mapping [4], [10], [11].

Google Earth Engine (GEE) has emerged as a

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powerful cloud-based platform to operationalize these methods, pro viding ready access to petabytes of satellite imagery and scalable computational resources. Recent systematic reviews highlight its effectiveness for large-scale vegetation monitoring and change detection [1], [2]. In addition, the incorporation of radar data, such as L-band SAR, has shown promise in overcoming cloud cover issues common in tropical regions [13].

This survey aims to consolidate knowledge from twenty significant studies on deforestation monitoring and cause de tection. The reviewed works span from traditional index-based approaches to advanced deep learning techniques, offering insights into their methodologies, datasets, accuracy, and ap plicability in the Indian context. The findings will inform the design of an automated system that uses input coordinates within GEE to retrieve historical imagery, compute vegetation indices, and detect both the extent and drivers of deforestation across India.

Literature Survey

Research on deforestation monitoring has evolved from traditional vegetation index approaches to advanced deep learning and multi-sensor integration methods. One of the earliest methods applied was the use of vegetation indices such as NDVI, which provided a simple yet effective measure of vegetation health and cover change. Studies such as Li et al. [18] and Rasuly et al. [17] demonstrated how NDVI time series and GIS-based image processing could be used to track long-term forest changes, while Zha et al. [19] introduced the NDBI to distinguish urban expansion from vegetation loss. Similarly, McFeeters [20] proposed the NDWI, which allowed better separation of water bodies from vegetation, helping in identifying water-driven deforestation processes. These foundational studies established the role of spectral indices in large-scale forest monitoring and remain widely used due to their simplicity and ease of integration within platforms like GEE.

As forest dynamics are often complex and gradual, single date index analysis proved insufficient for capturing long term trends. To address this, researchers began applying time series change detection approaches. Wu et al. [3] used the BFAST method on Landsat data to detect both gradual and abrupt changes in forest cover, while Li et al. [18] extended NDVI time-series analysis to improve temporal consistency. Ao et al. [4] further advanced this by fusing Landsat-8 and Sentinel-2 imagery using CNNs to construct 10-m resolution NDVI series, demonstrating improved accuracy in vegetation monitoring. Such methods are particularly relevant for India, where deforestation is often seasonal and driven by agricultural cycles, requiring high-resolution and continuous monitoring capabilities.

The rapid progress in deep learning brought a paradigm shift in deforestation monitoring. Early CNN-based models such as U-Net [15] and SegNet [16] were adapted for remote sensing applications, achieving pixel-level semantic segmen tation of forests. Chen et al. [10] enhanced these approaches by incorporating atrous separable convolutions, leading to improved boundary detection, while DenseNet [14] and fully convolutional DenseNets [12] offered efficient feature reuse and deeper network capacity. These architectures were applied in deforestation contexts, with studies such as Remote Sensing (2021) [5] demonstrating the use of FCNs for detecting forest loss in the Amazon, and Wyniawskyj et al. [6] applying CNNs for monitoring in Guatemala. Comparative reviews like Zhu et al. [13] and Jelas et al. [2] confirmed that deep learning consistently outperforms threshold-based indices in complex forest environments. For Indian deforestation studies, where heterogeneous landscapes and mixed land use present clas sification challenges, these deep learning approaches provide promising accuracy improvements.

Another critical advancement came from radar and multi sensor integration. Since tropical regions, including large parts of India, often experience persistent cloud cover, optical sen sors like Landsat and Sentinel alone are insufficient. Watan abe et al. [8] demonstrated that L-band Synthetic Aperture Radar (SAR) could detect early- stage deforestation even un der cloudy conditions, highlighting its robustness. Combining optical and radar imagery has shown significant improvements in classification accuracy and temporal reliability, offering a strong case for integration in monsoon-affected regions of India.

Large-scale case studies and reviews also contribute valu able insights into operational monitoring frameworks. Mau rano et al. [7] mapped spatial deforestation patterns in the Brazilian Amazon, demonstrating systematic monitoring strategies that can be replicated in Indian forests. Wyniawskyj et al. [6] applied satellite imagery and deep learning in Guatemala with limited ground truth, suggesting approaches that are transferable to data-scarce Indian regions. Global studies such as the high-resolution maps of 21st-century forest cover change [20] and comprehensive reviews of

NDVI and GEE-based approaches [1] establish baselines for long-term monitoring, while transformer-based models like Vaswani et al. [12] and Radford et al. [11] hint at future integration of attention-based models for spatiotemporal change detection.
Overall, the literature highlights a clear evolution: from sim ple spectral indices (NDVI, NDBI, NDWI) toward advanced spatiotemporal time-series analysis, and more recently to deep learning and multi-sensor approaches. The strengths and weaknesses of these methods are complementary — indices provide scalability and efficiency, time-series methods capture trends, deep learning achieves fine-grained accuracy, and radar ensures robustness under cloudy conditions. Reviews [1], [2], [13] emphasize that GEE acts as an enabling platform to operationalize these methods by offering access to decades of satellite data and scalable computation. For the Indian context, the integration of NDVI/NDBI-based monitoring in GEE, sup ported by BFAST-style temporal analysis, and validated with deep learning segmentation on Sentinel imagery, represents a balanced and feasible approach for accurate deforestation monitoring and cause detection.

Conclusion and Future Work

The literature reviewed demonstrates that deforestation monitoring has transitioned from simple spectral index ap proaches such as NDVI, NDBI, and NDWI [17], [18], [19], [20] to more advanced techniques including time- series anal ysis [3], [4], deep learning-based semantic segmentation [5], [6], [10], [15], [16], and radar-assisted monitoring [8]. Each of these methodologies offers distinct advantages: indices provide scalability and computational efficiency, time-series models capture temporal dynamics of forest loss, deep learning de livers high accuracy in complex landscapes, and SAR ensures reliability under cloudy or monsoon conditions. Reviews [1], [2], [13] highlight the role of GEE as a unifying platform that integrates these approaches with multi-decadal satellite archives, enabling operational-scale deforestation studies. For the Indian context, where forest loss is often driven by agriculture, urban expansion, and infrastructure growth, the most effective monitoring system will combine GEE-based multi-year NDVI/NDBI analysis with temporal break detec tion and validate the results using deep learning models on high-resolution Sentinel imagery. This integrated pipeline not only enhances accuracy but also provides valuable insights into the causes of deforestation, supporting sustainable forest management and policy planning.

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