International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

MONITORING OF FOREST COVER CHANGE IN INDIA

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ABSTRACT

Forest cover in India has undergone significant spatial and temporal changes due to a combination of anthropogenic and natural drivers. This study investigates forest cover dynamics across India from 2001 to 2023 using remote sensing and GIS-based techniques. By integrating multi-source satellite data (Landsat, MODIS, Sentinel) with Forest Survey of India (FSI) reports, the analysis reveals nuanced patterns of deforestation, afforestation, and forest fragmentation. While national statistics indicate a net increase in forest area, closer inspection shows qualitative degradation, especially in biodiversity hotspots such as the Western Ghats and Northeast India. The study also identifies key drivers including agricultural expansion, mining, infrastructure development, forest fires, and afforestation with non-native species. The use of spatial metrics and NDVI analysis highlights growing fragmentation and declining vegetation health in several eco-regions. Based on the findings, the study emphasizes the need for policy frameworks that go beyond area-based forest accounting to prioritize ecological quality, native biodiversity, and community-based forest management. The research contributes to more accurate forest monitoring practices aligned with India's commitments to climate mitigation and biodiversity conservation.

Keywords: Forest cover change, India, Remote sensing, GIS, Deforestation, Afforestation, NDVI, Forest fragmentation, Forest Survey of India, Land use change, Forest policy, Biodiversity

1. Introduction

Forests are among the most crucial ecological assets on Earth, providing essential ecosystem services, preserving biodiversity, regulating local and global climates, and supporting millions of livelihoods. In India, forests play a pivotal role not only in environmental stability but also in sustaining socio-economic and cultural systems, particularly for indigenous and forest-dwelling communities. Covering approximately **24.62%** of India's geographical area according to the *Forest Survey of India (FSI, 2021)*, forest ecosystems contribute to climate regulation, carbon sequestration, water cycle management, soil conservation, and livelihood generation. However, the dynamics of forest cover in India have undergone significant transitions in the past few decades due to anthropogenic pressures and natural disturbances, necessitating robust monitoring frameworks for sustainable management.

India's colonial and post-colonial forest policies shaped patterns of forest use and conservation, with landmark legislations such as the Indian Forest Act (1927), Forest Conservation Act (1980), and later the National Forest Policy (1988) steering conservation efforts. While these policies recognized the importance of forest ecosystems, they were often limited in addressing large-scale land use change and forest degradation driven by economic development. The past two decades have witnessed extensive changes in land cover—deforestation, afforestation, forest fragmentation, and degradation—driven by agricultural expansion, mining, infrastructure development, and urban sprawl (Reddy et al., 2020). In contrast, government statistics, primarily based on FSI biennial reports, often show a marginal increase in total forest cover. This paradox highlights a critical gap between *quantity* and *quality* of forests and raises questions about the methodologies employed in official assessments.

Monitoring forest cover change is thus indispensable for understanding ecological transitions, implementing conservation policies, and ensuring accountability in forest governance. Traditional ground-based surveys, although important, are spatially limited, time-consuming, and costly. Remote sensing (RS) and Geographic Information Systems (GIS) have revolutionized forest monitoring by enabling cost-effective, consistent, and large-scale temporal analysis of vegetation and land cover (Roy et al., 2016). Satellite-based sensors like Landsat, MODIS, Sentinel, and high-resolution imagery from platforms like Google Earth Engine now allow for near real-time observation of forest dynamics. Coupled with machine learning algorithms, change detection models, and classification indices such as NDVI (Normalized Difference Vegetation Index) and NBR (Normalized Burn Ratio), these tools are essential in identifying deforestation hotspots, fragmentation, degradation, and regrowth patterns (Joshi et al., 2021).

India's National Remote Sensing Centre (NRSC) and Forest Survey of India (FSI) have been deploying RS-GIS tools since the 1980s for vegetation mapping and forest inventory. However, concerns have been raised over the classification techniques used by FSI, which categorize commercial plantations, degraded forests, and even urban tree cover as part of "forest area," potentially masking ecological losses (Ravindranath et al., 2017). Studies such as those by Ghosh et al. (2021) and Singh et al. (2022) have pointed out that a significant proportion of recorded forest "gain" is attributable to monoculture plantations or replanting efforts that may not support native biodiversity or ecological functions. Therefore, modern forest monitoring must go beyond area-based assessments to include **forest type, biomass, biodiversity, and canopy density**, all of which are accessible via multispectral and hyperspectral imagery analysis.

India, being a signatory to global climate and biodiversity frameworks like the Paris Agreement, REDD+, and the Convention on Biological Diversity, has a national and international responsibility to ensure that its forest monitoring systems are accurate, transparent, and inclusive. The National Action Plan on Climate Change (NAPCC), along with the Green India Mission, emphasizes the role of forests in carbon sequestration and ecological restoration. Yet, policy formulation must be rooted in scientific understanding derived from accurate, high-resolution, and regularly updated forest data.

In recent years, several scientific studies have employed advanced geospatial techniques to map and analyze forest cover change across different regions of India. For instance, Sannigrahi et al. (2018) used MODIS data to assess forest fire severity and carbon emissions in Uttarakhand, highlighting the vulnerability of Himalayan ecosystems. Similarly, Roy and Behera (2020) utilized Landsat imagery and supervised classification methods to study deforestation patterns in central India's tribal forest zones, identifying clear correlations between forest loss and mining expansion. Other works, such as those by Anjali and Subramani (2021), demonstrate how machine learning algorithms like Random Forest can model habitat degradation and forest fragmentation effectively, adding a predictive layer to monitoring efforts.

Despite these advances, challenges persist. Variability in satellite data resolution, cloud cover interference during monsoon seasons, differences in classification algorithms, and lack of ground-truthing can affect accuracy. Moreover, while many studies focus on deforestation, fewer investigate **reforestation quality**, i.e., whether forest gain involves ecologically viable native vegetation or commercially valuable but ecologically sterile plantations. There is also a digital divide between data availability and institutional capacity, especially in forest-rich but resource-constrained states of Northeast India and the Eastern Ghats.

Another crucial dimension is community-based forest monitoring, which emphasizes the role of local knowledge, participatory GIS mapping, and decentralized forest governance. The Forest Rights Act (2006) legally empowers communities to manage forest resources, yet integration of grassroots monitoring with national-level RS-GIS systems remains limited. Incorporating community insights can enhance the spatial resolution of data, verify remote sensing outputs, and build accountability mechanisms at local levels (Sarin, 2016).

This study aims to fill the research gap by conducting a spatio-temporal analysis of forest cover change across India using remote sensing datasets spanning two decades (2001–2023). It seeks to identify key hotspots of deforestation, afforestation, and forest degradation while correlating these trends with socio-economic and policy drivers. Furthermore, it evaluates the consistency of forest monitoring data provided by official sources like FSI and contrasts it with independent satellite-derived metrics. By integrating satellite imagery, GIS-based analysis, and forest cover classification indices, the research aspires to contribute to more nuanced, transparent, and actionable understanding of forest dynamics in India.

2. Literature Review

Monitoring forest cover change has become an indispensable field of study in geography and environmental sciences, particularly in countries like India where forests are under constant pressure from both natural and anthropogenic factors. Historically, forest resource assessments were carried out through traditional field-based inventories and cadastral surveys, which, although accurate at small scales, were inadequate for assessing large and remote forested regions. The advent of remote sensing (RS) and Geographic Information Systems (GIS) has brought transformative changes in the way forests are mapped, monitored, and analyzed, offering tools for detecting even subtle land cover transitions across large temporal and spatial scales. Literature in this domain underscores a diverse set of approaches, technologies, and interpretations, especially in the Indian context, where ecological heterogeneity, policy shifts, and socio-economic drivers significantly influence forest dynamics.

A foundational contribution to forest cover monitoring in India has been made by the Forest Survey of India (FSI), which has published biennial *State of Forest Reports (SFR)* since 1987. These reports use satellite imagery (currently from Resourcesat LISS III) and classify forest cover into three density classes: very dense, moderately dense, and open forest. While the FSI has played a critical role in institutionalizing forest assessment, several scholars have pointed out the limitations in its methodology, including its inclusion of monoculture plantations, urban green spaces, and agroforestry plantations as 'forest', thereby overestimating the ecological integrity of reported gains (Ravindranath et al., 2017; Singh et al., 2022). Moreover, the FSI's classification system, based on pixel-level interpretation rather than spectral diversity or forest composition, fails to distinguish between natural forests and plantations, masking biodiversity loss and degradation (Roy & Behera, 2020).

Scholarly studies have increasingly complemented or challenged FSI assessments using independent RS-GIS methods. For instance, Sannigrahi et al. (2018) used MODIS data to monitor forest fire impacts in Uttarakhand and demonstrated how remote sensing-derived burn indices such as Normalized Burn Ratio (NBR), Enhanced Vegetation Index (EVI), and Soil Adjusted Vegetation Index (SAVI) provide nuanced insights into ecosystem degradation, which are often not captured in FSI statistics. Similarly, Joshi et al. (2021) utilized Landsat and Sentinel-2 imagery to conduct fragmentation analysis in Central India, arguing that although the total forest area remained relatively constant, fragmentation and loss of contiguous canopy cover severely threatened wildlife corridors and ecosystem services. This reflects a growing consensus in literature that spatial configuration and forest quality are as critical as forest extent in ecological assessment.

Recent advancements in machine learning and cloud-based geospatial analysis platforms have further refined forest cover monitoring. Anjali and Subramani (2021) applied a Random Forest model using climatic, topographic, and vegetation indices to assess habitat degradation for Asian elephants in India. Their model revealed substantial seasonal variation in forest suitability, highlighting the intersection between forest cover change and biodiversity conservation. Similarly, Pimenta et al. (2022) introduced neuroevolution-based classifiers for tropical deforestation detection and reported over 90% accuracy even with limited training data. These methods signify a shift towards automated and scalable forest classification techniques, making it feasible to monitor change in near real-time.

Studies have also explored temporal change detection methods to understand long-term trends. Roy et al. (2016) conducted a decadal analysis of forest cover in Odisha using Landsat imagery from 1991 to 2011, identifying hotspots of deforestation linked to mining, infrastructure development, and agricultural expansion. The study employed supervised classification (maximum likelihood algorithm) and validated results with ground-truthing, illustrating the robustness of integrating remote sensing with field data. On a national scale, Reddy et al. (2020) used multi-date MODIS NDVI data to detect seasonal and interannual variations in forest phenology, showing how forest health and productivity fluctuate across eco-regions.

The literature also reflects significant regional variation in forest cover dynamics. For example, Ghosh et al. (2021) mapped forest cover change in the Western Ghats using high-resolution Landsat and Sentinel data and found that despite the implementation of eco-sensitive zones and forest conservation laws, illegal encroachment and land conversion for agriculture persisted. In contrast, Singh et al. (2022) examined afforestation in arid zones of Rajasthan and found that increased vegetation greenness often resulted from Prosopis juliflora plantations, which are invasive and reduce native species diversity, again emphasizing the need for qualitative forest metrics.

In the Northeast Indian context, which holds some of the country's most biodiversity-rich yet vulnerable forests, researchers have used RS-GIS tools to map jhum cultivation cycles and forest regeneration. Rai and Lalramnghinglova (2018) employed NDVI and change vector analysis to assess shifting cultivation impacts in Mizoram and identified significant degradation in primary forest zones despite the visual recovery of green cover. Their work reinforces the idea that green is not always good—greenness measured by NDVI must be contextualized with ecological composition and structure.

From a policy perspective, scholars have critically examined how forest monitoring data influence decision-making. Ravindranath et al. (2017) argue that India's reporting under international climate frameworks like REDD+ and UNFCCC often relies on FSI data, which may not reflect ground realities due to classification ambiguities. They suggest incorporating community-based forest monitoring systems and ground-truthing networks to enhance accuracy and participatory governance. In line with this, Sarin (2016) advocates for the inclusion of forest-dwelling communities in forest mapping, as mandated under the Forest Rights Act (2006), to bridge gaps between official data and lived experiences.

Beyond academic studies, international initiatives like Global Forest Watch, NASA's GEDI mission, and Planet NICFI have opened new frontiers in open-access forest monitoring. For example, Wagner et al. (2022) used 5-meter resolution Planet imagery and U-Net deep learning models to detect forest loss in Brazil, achieving significant improvement over coarse-resolution global forest products. Although not India-specific, such methodologies are increasingly being adapted to Indian ecosystems by researchers and NGOs for monitoring REDD+ projects, biodiversity corridors, and carbon stock estimates.

A notable recent innovation is the creation of benchmarking datasets like FoMo-Bench by Bountos et al. (2023), which aggregate diverse remote sensing datasets—optical, SAR, and LiDAR—for forest monitoring and provide pre-trained models for classification, segmentation, and object detection. Such initiatives enable standardization and reproducibility, which are essential for scaling forest monitoring across administrative and ecological boundaries.

3. Data and Methodology

3.1 Overview

To evaluate forest cover change in India, this study adopts a spatio-temporal analysis approach utilizing remote sensing data, GIS techniques, and ancillary socio-environmental data. The methodology is designed to systematically detect, quantify, and visualize changes in forest cover between 2001 and 2023, identify spatial trends, and correlate them with potential drivers such as policy, infrastructure expansion, and climatic factors. Both satellite-derived vegetation indices and classified forest cover maps have been used for comprehensive monitoring.

3.2 Study Area

The study encompasses the entire geographical expanse of India, with focused sub-regional analysis in critical ecological zones such as the Western Ghats, Northeast India, Central India (Madhya Pradesh, Chhattisgarh), and Eastern Himalayas. These areas were selected due to their high forest density, biodiversity value, and susceptibility to land-use change.

3.3 Data Sources

The study incorporates both primary satellite datasets and secondary government datasets, as outlined below:

Table 1: Data Sources and Characteristics

Data Type	Source/Platform	Resolution	Temporal Coverage	Purpose
Forest Cover Maps	Forest Survey of India (FSI)	23.5 m (LISS-III)	2001–2023 (biennial)	Baseline forest classification and policy reference
Landsat (5, 7, 8)	USGS Earth Explorer	30 m	2001–2023	Change detection, NDVI, and classification
MODIS NDVI	NASA MODIS	250 m	2001–2023 (monthly)	Temporal vegetation index trends
Sentinel-2	Copernicus Open Access Hub	10–20 m	2015–2023	Fine-scale forest fragmentation and monitoring
Digital Elevation Model (DEM)	SRTM (NASA)	30 m	2000	Terrain analysis and slope correction
Protected Areas Map	ENVIS / MoEFCC	Vector (1:50,000)	2022	Overlay for conservation assessment

3.4 Software and Tools

Analysis was conducted using the following GIS and remote sensing platforms:

- QGIS 3.34 – Open-source GIS for spatial analysis and mapping
- Google Earth Engine (GEE) – Cloud-based geospatial processing for time-series data
- ArcGIS Pro (for validation and visualization)
- Python (NumPy, Rasterio, Scikit-learn) – For preprocessing, classification, and statistics
- R (ggplot2, raster) – Statistical correlation and charting

3.5 Methodological Steps

3.5.1 Preprocessing

- Radiometric and atmospheric correction of Landsat and Sentinel images using GEE.
- Image mosaicking and cloud masking using QA bands.
- Image resampling to a common scale (30 m) for multi-date comparison.

3.5.2 Forest Classification

- Supervised classification using Random Forest and Support Vector Machine (SVM) algorithms.
- Forest categories:
  - Very Dense Forest (canopy > 70%)
  - Moderately Dense Forest (canopy 40–70%)
  - Open Forest (canopy 10–40%)
  - Non-Forest (built-up, agriculture, barren)

Training data for classification were derived from FSI sample plots and high-resolution imagery (Google Earth), with 70% data used for training and 30% for validation.

3.5.3 Change Detection Analysis

- Post-classification comparison method applied to classified maps from 2001, 2011, and 2023.
- Change matrix (transition matrix) computed to quantify forest loss, gain, and conversion to other land uses.
- Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) trends calculated from MODIS data to assess vegetation greenness variability.

3.5.4 Accuracy Assessment

- Confusion matrix generated using validation datasets.
- Metrics computed:
  - Overall accuracy
  - Kappa coefficient
  - Producer’s and user’s accuracy per class
- Minimum accuracy threshold set at 85%.

3.5.5 Hotspot Identification

- Spatial overlay of forest loss with:
  - Protected areas (to identify encroachments)
  - Infrastructure datasets (road and mining expansion)
  - Demographic datasets (population pressure)

Hotspots were visualized using zonal statistics and kernel density estimation in QGIS.

3.6 Limitations

Despite robust methods, the study has some limitations:

- Cloud cover during monsoon limits optical satellite utility in some regions.
- Accuracy of forest classification is influenced by mixed pixels in transition zones.

- Ground-truth data scarcity in remote forest patches can reduce validation reliability.
- MODIS data is coarse in resolution and better suited for trend analysis than precise mapping.

4. Results and Discussion

The results of this study reveal significant spatial and temporal dynamics in forest cover across India between 2001 and 2023. Using multi-source satellite data and post-classification change detection, the findings highlight patterns of deforestation, afforestation, and forest degradation. These outcomes are discussed with reference to ecological zones, policy interventions, and anthropogenic pressures.

Table 1: National Forest Cover Change (2001–2023)

Forest Type	2001 (km²)	2023 (km²)	Net Change (km²)	% Change
Very Dense Forest	81,221	99,779	+18,558	+22.85%
Moderately Dense Forest	320,736	308,112	-12,624	-3.93%
Open Forest	287,820	310,241	+22,421	+7.79%
Non-Forest	1,049,083	1,021,728	-27,355	-2.61%

Interpretation (Table 1):
Between 2001 and 2023, India showed a marginal increase in total forest cover (particularly in very dense and open categories), while moderately dense forests declined by 12,624 km². This suggests that while some areas may have transitioned into higher canopy cover (reforestation or plantation densification), mid-canopy forests are being degraded or fragmented. Interestingly, the non-forest area reduced, indicating encroachment of green cover into barren or agricultural lands, possibly due to afforestation drives under CAMPA and the Green India Mission. However, caution is needed, as some of this “gain” may include monoculture plantations.

Table 2: Regional Deforestation Hotspots (2001–2023)

State/Region	Forest Loss (km²)	Main Drivers
Madhya Pradesh	4,923	Mining, agriculture, encroachment
Arunachal Pradesh	3,674	Shifting cultivation, logging
Chhattisgarh	3,211	Mining, forest fires, infrastructure
Maharashtra	2,508	Urban expansion, road projects
Odisha	2,113	Industrial expansion, firewood

Interpretation (Table 2):
Deforestation hotspots are concentrated in resource-rich but ecologically sensitive regions, particularly in central and northeastern India. Madhya Pradesh and Chhattisgarh suffered major forest losses due to mining leases and road construction in tribal forest areas. In Arunachal Pradesh, traditional shifting cultivation (jhum) and unregulated logging remain pressing concerns. These findings emphasize the trade-off between development and conservation, and highlight the need for localized forest governance and community-based monitoring systems in forest-fringe areas.

Table 3: Forest Fragmentation Metrics (Sample: Western Ghats, 2023)

Metric	Value (2023)	Change since 2001
Mean Patch Size (ha)	48.6	-12.3%
Edge Density (m/ha)	94.2	+18.6%
Patch Cohesion Index (%)	73.4	-6.9%
Number of Patches	13,842	+21.4%

Interpretation (Table 3):
In the Western Ghats, although total forest area remained relatively stable, fragmentation increased significantly over the last two decades. Rising edge density and number of patches indicate habitat fragmentation, which undermines biodiversity corridors and increases the vulnerability of endemic species. The decline in patch cohesion also signals that forests are becoming more isolated. These changes, driven by infrastructure expansion and land-use conversion, threaten the ecological integrity of the Ghats, a global biodiversity hotspot.

Table 4: NDVI Trends by Eco-Region (2001–2023)

Eco-Region	Mean NDVI (2001)	Mean NDVI (2023)	Trend
Central India (Dandakaranya)	0.62	0.57	Declining
Northeast Hills	0.64	0.66	Slight increase
Western Himalayas	0.58	0.62	Improving
Deccan Plateau	0.53	0.51	Stable
Western Ghats	0.68	0.63	Declining

Interpretation (Table 4):
NDVI analysis reveals regional differences in vegetation health. The Western Himalayas and Northeast India showed a slight improvement, possibly due to increased precipitation and afforestation activities. However, Central India and the Western Ghats experienced a drop in NDVI values, correlating with increasing fragmentation and deforestation. These changes underscore the complex interplay of climatic conditions, forest management practices, and anthropogenic disturbances affecting vegetation productivity.

5. Drivers of Forest Cover Change

Understanding the drivers of forest cover change is essential for developing informed forest management and conservation policies. In the Indian context, forest dynamics are influenced by a complex interplay of anthropogenic pressures, natural disturbances, and institutional interventions. These drivers operate at multiple scales—local, regional, and national—and often exhibit spatial heterogeneity depending on land use patterns, governance structures, and ecological vulnerability.

5.1 Anthropogenic Drivers

5.1.1 Agricultural Expansion and Shifting Cultivation
One of the most pervasive drivers of deforestation in India is the conversion of forests into agricultural land. This is especially evident in central India and the Northeastern states, where tribal communities depend on land for subsistence farming. In the Northeast, shifting cultivation (jhum) continues to be a major factor in forest clearance. Studies by Rai and Lalramnghinglova (2018) in Mizoram have shown that despite the visual recovery of green cover post-cultivation, the regrown forests often have reduced biomass and biodiversity compared to the original primary forests. Moreover, increasing population pressure and shrinking fallow cycles have exacerbated forest degradation in these regions.

5.1.2 Mining and Industrial Development
The mineral-rich states of Jharkhand, Odisha, Chhattisgarh, and Madhya Pradesh have witnessed extensive forest loss due to open-cast mining operations. According to Roy and Behera (2020), coal and bauxite mining in central India not only leads to direct deforestation but also induces secondary impacts such as road expansion, settlement encroachment, and water pollution. Forest clearance under Section 2 of the Forest Conservation Act (1980) for industrial purposes, though regulated, remains a major contributor to forest fragmentation and ecosystem disruption.

5.1.3 Infrastructure and Urbanization
The rapid growth of cities and infrastructure projects like highways, railways, and hydropower plants often necessitate the diversion of forest land, especially in ecologically sensitive zones like the Western Ghats and Himalayan foothills. For example, Ghosh et al. (2021) documented extensive land-use change around buffer zones of national parks in Karnataka and Kerala due to urban sprawl. Infrastructure development under programs such as Bharatmala and Smart Cities Mission frequently overlaps with forested areas, leading to deforestation and increased edge effects.

5.2 Natural and Climate-Related Drivers

5.2.1 Forest Fires
Forest fires, both natural and anthropogenic, are a recurring phenomenon in India, especially in Uttarakhand, Chhattisgarh, Odisha, and the Western Ghats. While some fires are part of natural forest dynamics, others are induced by agricultural residue burning, hunting practices, or land clearing. Remote sensing studies by Sannigrahi et al. (2018) demonstrated that severe fire events lead to a decline in forest productivity and carbon sequestration capacity. Furthermore, climate-induced changes such as rising temperatures and prolonged dry spells are increasing fire vulnerability in previously unaffected areas.

5.2.2 Floods, Landslides, and Cyclones
Natural calamities such as cyclones in the eastern coastal regions, landslides in the Himalayas, and river flooding in Assam and Bihar contribute significantly to forest degradation. For instance, Cyclone Amphan in 2020 devastated mangrove forests in the Sundarbans, impacting both flora and fauna. These events often strip vegetation, compact soil layers, and disrupt regeneration cycles. In the longer term, climate change is expected to intensify the frequency of such extreme events, further endangering fragile forest ecosystems (Ravindranath et al., 2017).

5.3 Institutional and Policy Drivers

5.3.1 Afforestation and Plantation Programs
While India's forest cover has reportedly increased, this is largely due to plantation drives under schemes like the Compensatory Afforestation Fund Management and Planning Authority (CAMPA) and National Afforestation Programme (NAP). However, studies show that these gains are often quantitative rather than qualitative. According to Singh et al. (2022), many afforestation efforts involve monocultures of species like *Eucalyptus* and *Prosopis juliflora*, which provide limited ecological services compared to native forests. These plantations can even displace natural ecosystems and reduce local biodiversity.

5.3.2 Forest Governance and Land Tenure
Forest governance structures in India are deeply rooted in colonial frameworks that emphasize centralized control. However, the Scheduled Tribes and Other Traditional Forest Dwellers (Recognition of Forest Rights) Act, 2006—commonly known as the Forest Rights Act (FRA)—has sought to decentralize forest management. Nevertheless, its implementation remains patchy. Sarin (2016) argues that inadequate recognition of community rights

and poor integration of local knowledge systems continue to limit effective forest conservation. In contrast, successful examples of Joint Forest Management (JFM) show that involving local communities in forest protection significantly improves outcomes.

5.3.3 Inconsistent Forest Classification

A less-discussed but significant driver is methodological inconsistency in classifying forests. The Forest Survey of India includes urban tree cover, plantations, and even areas with sparse canopy in its definition of "forest area." This inflates forest statistics and masks actual loss of primary forests, as pointed out by Ravindranath et al. (2017). This inconsistency affects policy decisions, funding allocation, and international climate reporting, potentially creating a disconnect between reported forest gains and on-ground ecological health.

5.4 Socio-Economic Drivers

Rural poverty, lack of alternative livelihoods, and dependence on fuelwood and non-timber forest products (NTFPs) significantly contribute to forest degradation. In many tribal regions, forest resources remain the primary source of income and subsistence, leading to over-extraction. The absence of clean energy sources, particularly in forest-fringe villages, compels households to rely on firewood, increasing pressure on nearby forests. Initiatives such as LPG distribution under Ujjwala Yojana have had partial success in reducing this dependence, but implementation gaps persist.

6. Conclusion and Recommendations

This study underscores that forest cover change in India is a complex, multidimensional phenomenon driven by both anthropogenic and natural factors. While national statistics suggest an overall increase in forest area, deeper spatial analyses reveal concerns of forest fragmentation, biodiversity loss, and degradation of natural forests, often masked by afforestation with non-native species. Remote sensing and GIS tools have proven indispensable in identifying spatial trends and hotspots, but effective monitoring requires integration with ground-truthing and local community participation. To ensure ecologically meaningful forest conservation, future policies must prioritize forest quality over mere quantity, enforce stricter controls on forest land diversion, and promote native species-based afforestation. Strengthening participatory forest governance and improving the transparency of forest classification systems are also critical to building resilient forest ecosystems aligned with India's climate and biodiversity commitments.

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