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A Comprehensive Review of Deforestation Monitoring Using Remote Sensing Imagery

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Abstract

Deforestation is a significant environmental challenge, with severe consequences like land degradation, biodiversity loss, and climate change. It is therefore important to monitor forest change to maintain ecological balance and avoid natural calamities, such as floods and landslides. Satellite remote sensing helps in observing changes in forest cover both spatially and temporally. This article offers an in-depth analysis of the primary elements in monitoring forest cover using remote sensing imagery. An extensive study on the different types of input data: optical, radar, and Light Detection and Ranging (LiDAR) imagery was conducted on bi-temporal and multi-temporal approaches with the emphasis in preprocessing techniques such as radiometric calibration and atmospheric correction to ensure data reliability. The comparison of pixel, object, and hybrid analytical approaches for capturing deforestation dynamics was done. A detailed comparison of the various algorithmic approaches from traditional statistical methods to Machine Learning (ML) and Deep Learning (DL) models is provided. This includes Random Forest (RF), Support Vector Machines (SVM), Convolution Neural Networks (CNN), U-Net, and Transformer architectures. The models were compared and evaluated based on their classification accuracy, computational efficiency, and generalization capabilities for both binary and multi-class change detection. This review will help researchers develop strategies to address deforestation and support sustainable forest management.

Keywords: Renewable Energy, Bibliometric Analysis, European Union, Balkans, VOSviewer, Economic Growth.

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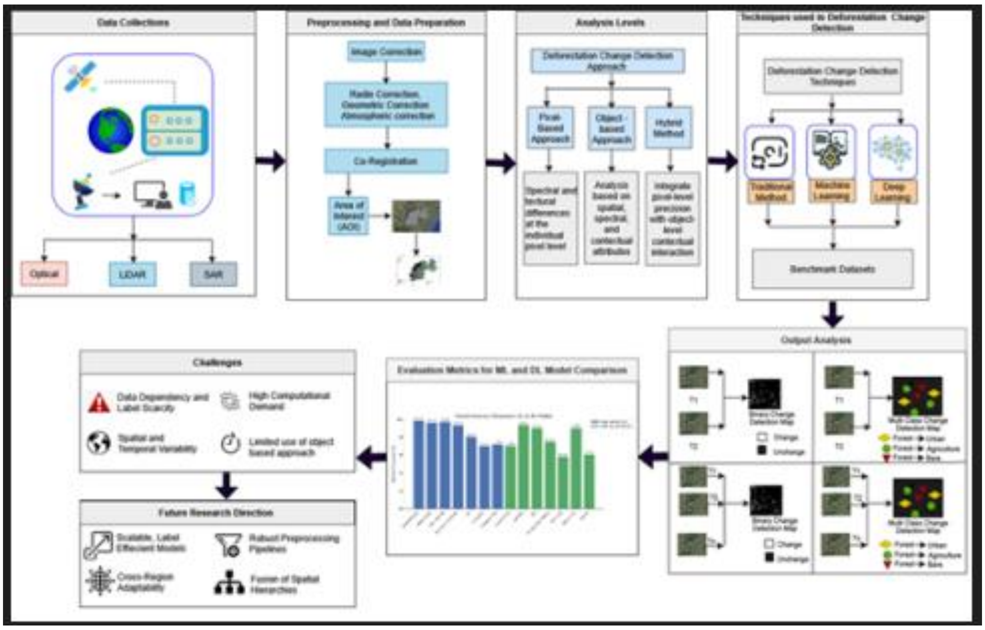
Graphical abstract



1. Introduction

Forests play a vital role in preserving ecological balance and regulating the global carbon cycle. Deforestation caused by the expansion of agriculture is now a leading environmental concern in the world (J. N. Hansen *et al.*, 2020)(M. C. Hansen *et al.*, 2013). The loss of trees accelerates global warming, reduces ecosystem resilience, and affects the entire planet (Chen *et al.*, 2022) (Desclée *et al.*, 2013). The Reducing Emissions from Deforestation and Forest Degradation (REDD+) program for preventing the cutting down of trees and the degradation of forest areas was introduced by the United Nations Framework Convention on Climate Change (UNFCCC) (Arcanjo *et al.*, 2016) with the objective of forest area monitoring. This made the governments take three major preventive measures: sustainable land use, forest management, and early detection of deforestation (J. N. Hansen *et al.*, 2020).

In recent years, remote sensing technologies have been extensively utilised for monitoring deforestation due to their ability to cover large areas, low cost, and capacity to capture temporal data. Satellites such as the Landsat series, Sentinel-2, and PlanetScope, along with sensors such as Synthetic Aperture Radar (SAR) and LiDAR, help provide the spatial and spectral data required for effective forest cover monitoring (Soto *et al.*, 2022). Spatial and multispectral data gathered from various sensors are used to detect changes in forest cover under different environmental conditions (Pulella *et al.*, 2020). However, manual image interpretation and pixel-based data analysis are very slow, difficult to handle, and error-prone when working with highly varied landscapes (Bergamasco *et al.*, 2022)(Karishma *et al.*, 2022). The application of traditional ML-based techniques for forest cover monitoring has successfully increased classification accuracy, yet they rely heavily on manual feature engineering and struggle with complex forest structures.(Nguyen Trong *et al.*, 2020)(Brovelli *et al.*, 2020). DL-based models such as CNNs, U-Net, DeepLabv3+, and transformers learn hierarchical, spatial, and temporal features automatically, thereby reducing the need for extensive preprocessing (Adarme *et al.*, 2020)(de Bem *et al.*, 2020)(Rakshit et al, 2018). Image segmentation techniques have enabled an accurate, clear determination of deforested areas by separating forest and non-forest classes (Selvaraj & Amali, 2023)(Rash *et al.*, 2023). Cloud computing platforms like Google Earth Engine (GEE) now support the processing of large amounts of data in less time (Rakshit et al, 2018)(Karmoude *et al.*, 2025)(Y. Zhang *et al.*, 2024).

Numerous studies have been conducted on monitoring deforestation, yet many of them lack a thorough comparative analysis, especially on the combination of data types, processing levels, and detection strategies (Pulella *et al.*, 2020)(Bergamasco *et al.*, 2022). Furthermore, there is a shortage of benchmark studies assessing ML and DL models in different ecosystems and over various time periods (de Bem *et al.*, 2020). These gaps highlight the need for a systematic review that examines both traditional and modern approaches, identifies challenges, and outlines future directions. This review aims to provide a systematic analysis of the various deforestation monitoring techniques.

Key Objectives:

- To examine how different satellite data sources, optical, SAR, LiDAR, and hyperspectral, contribute to bi-temporal and multi-temporal monitoring of forest cover, and highlight their relative strengths in diverse environmental settings.
- To evaluate the role of the preprocessing steps, including radiometric and atmospheric correction, co-

registration, and spectral index generation, and to assess how these procedures influence change detection outcomes.

- To compare a pixel-based, object-based, and hybrid analytical approaches for detecting forest changes in landscapes with varying spatial complexity.
- To critically assess traditional techniques, ML algorithms, and DL models with respect to accuracy, computational efficiency, robustness, and their ability to generalise across regions and time periods.
- To investigate binary versus multi-class classification outputs for forest management purposes.
- To identify persistent challenges related to data quality, temporal inconsistency, model generalisation, and evaluation practices, and to propose future research directions for developing scalable and reliable deforestation monitoring frameworks.

The rest of the paper is organized as follows: Literature collection strategy, deforestation monitoring workflow and evolution of change detection techniques is presented in the rest of section 1, followed by remote sensing data sources in section 2, preprocessing and data preparation techniques in section 3 and feature extraction and spectral indices in section 4. The complete analysis of change detection approaches with the benchmark datasets is presented in section 5, followed by performance metrics and critical analysis of the various techniques based on the output map in sections 6 and 7. Challenges, future directions and conclusion are presented in sections 8 and 9.

1.1. *Literature Search and Selection Strategy*

Databases such as Web of Science, Scopus, IEEE Xplore that are widely revered in the research community were used. Keyword searches with Boolean operators to combine terms such as "deforestation monitoring," "deep learning," "change detection," and "SAR/LiDAR" was used. The selection was done on peer-reviewed articles published between 2013 and 2026. Articles lacking standardised performance metrics or those focused solely on non-forest land cover were excluded. A total of 86 high-impact studies with primary focus on technical evolution and regional applicability. A detailed flow diagram on the process followed is presented in **Figure 1**

1.2. *Workflow for Deforestation Monitoring and Analysis*

Figure 2 illustrates the overall change detection workflow, which begins with image acquisition and preprocessing. Data collected from different sensors, such as optical, radar, and LiDAR is then pre-processed using image type adaptive preprocessing, which depends on the sensor, such as optical, SAR, LiDAR, or source-oriented preprocessing, which depends on data characteristics, like resolution and noise. The next stage in change detection is categorized into two parts, analysis level and change detection framework. Pixel-based, object-based, and hybrid are the various methods of analysis. Pixel-based change detection compares pixel values directly over time, object-based change detection works on image segmentation and hybrid change detection combines pixel and object-based approaches. Change detection frameworks consists of traditional techniques, ML, and DL. The final stage is output mapping and evaluation. The output types are categorised into binary or multi-class classification.

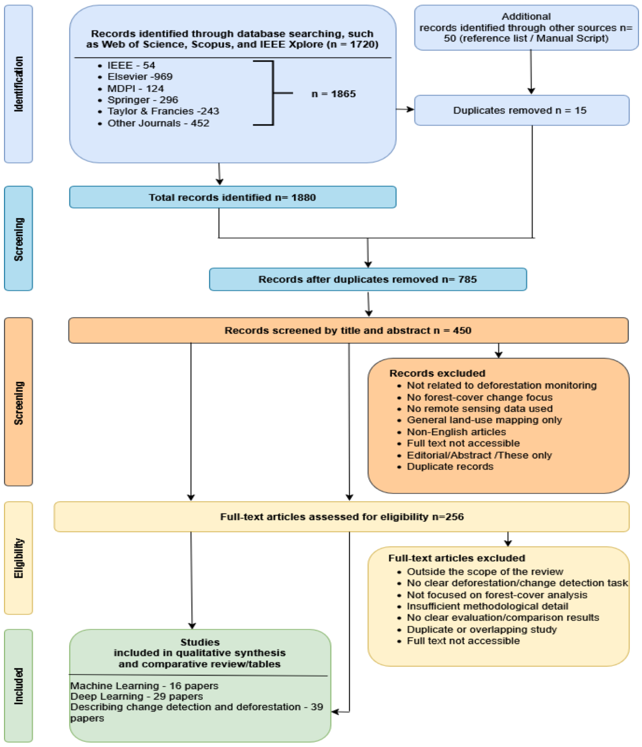


Figure 1. Flow diagram of the process used for study selection

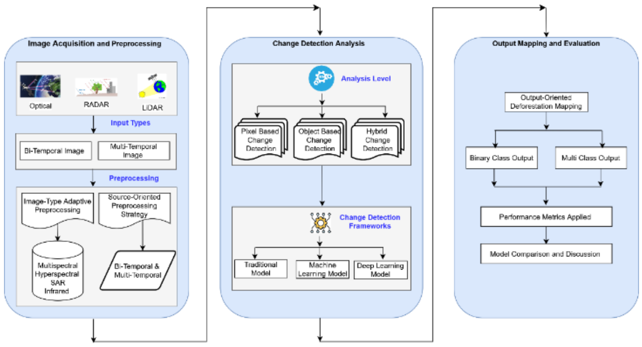


Figure 2. General framework for deforestation change detection from remote sensing data

1.3. *Evolution of Change Detection Techniques*

Change detection techniques have evolved from simple human visual analysis to the application of sophisticated ML and DL technologies. The chronological development of deforestation detection methods is shown in **Figure 3**. In the 1990s and earlier, visual methods were based on direct comparisons of satellite or aerial photographs. The decade 1990-2000 saw the emergence of pixel-based traditional techniques that made use of image differencing and Normalised Difference Vegetation Index (NDVI) differencing (Nguyen Trong *et al.*, 2020)(J. N. Hansen *et al.*, 2020), image ratioing, and post-classification comparison. In the years 2000-2010, statistical methods, namely Principal Component Analysis (PCA), Change Vector Analysis (CVA) (Laurance *et al.*, 2014) Unsupervised clustering gained popularity. The period from 2010 to 2015 was a boom for machine learning models, during which SVM, RF, and k-NN were the most widely used algorithms. The years from 2015 to 2020 saw the growth of deep learning with CNN, autoencoders, and Siamese networks.

The last couple of years have seen the development of hybrid models such as Vision Transformers (ViT), Swin Transformers, U-Net, DeepLab, ResNet, and Generative Adversarial Networks (GANs).

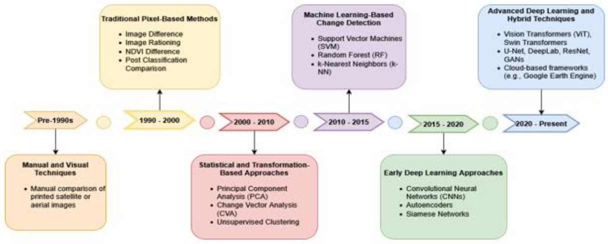


Figure 1. Evolution of deforestation change detection techniques over time

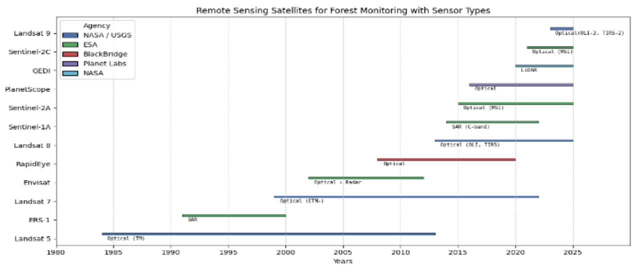


Figure 4. Timeline of Major Remote Sensing Satellite Launches for Forest Monitoring

2. Remote Sensing Data Sources for Forest Change Detection

To accurately monitor deforestation datasets for the different spatial, spectral, and temporal aspects of forest cover are needed (Brovelli *et al.*, 2020)(Pacheco-Pascagaza *et al.*, 2022).

Figure 4 presents a timeline of major satellite missions used in forest monitoring from 1980 to 2030. The chart distinguishes optical, SAR, and LiDAR sensors and highlights their operational periods and responsible agencies. These missions together form the backbone of long-term, large-scale forest observation programs and provide the valuable data needed to monitor forest cover.(Meiaraj, 2025)(Meiaraj, 2025)(Y. Zhang *et al.*, 2024).

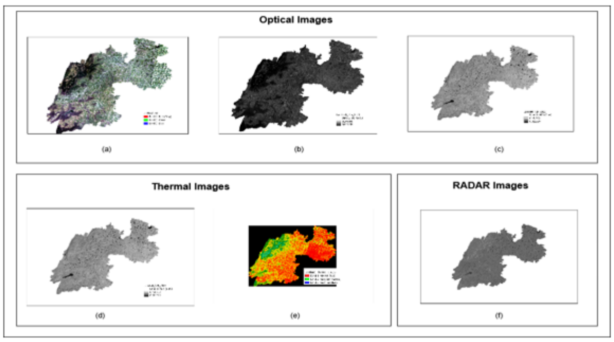


Figure 2. Comparative Satellite Imagery of Thiruvannamalai District (a) Optical RGB image (b) Panchromatic image (c) Near-Infrared (d) Thermal (Celsius) (e) Thermal (Kelvin) (f) SAR (Radar) image

2.1. *Optical Satellite Images*

Optical sensors record reflected sunlight across visible, NIR (Near Infrared), and SWIR (Short-Wave Infrared) wavelengths, used for the interpretation of vegetation vigour, soil exposure, and land cover transitions (Karmoude *et al.*, 2025). Multispectral and hyperspectral sensors provide high spectral sensitivity, making them effective for identifying forest disturbances. **Figure 5(a), (b), and (c)** illustrate optical (RGB, panchromatic, and NIR) examples from the Thiruvannamalai district in India.

2.2. *Thermal Images*

Thermal imaging is used to spot forest fires, vegetation drought, and decay, and identify temperature anomalies that are caused by the impact of cutting trees on local climate conditions (Nyamtseren *et al.*, 2025). **Figures 5(d) and 5(e)** present thermal imaging in Celsius and Kelvin, respectively.

2.3. *Radar Image*

Radar sensors, particularly SAR, emit microwave signals and receive backscattered signals from the Earth's surface, enabling consistent data acquisition regardless of time of day or weather conditions. SAR imagery covers structural forest analysis, degradation assessment, and detection of unauthorised logging activities (Neves *et al.*, 2023)(Lucas *et al.*, 2006). In **Figure 4(f)**, a SAR image shows terrain unaffected by atmospheric conditions.

2.4. *LiDAR*

LiDAR calculates distances and generates highly detailed 3D models of vegetation through a series of laser pulses. This greatly assists in obtaining canopy height, biomass, and deforestation impact estimation more accurately, particularly in areas of complex forest canopies (Boehm *et al.*, 2013)(Lucas *et al.*, 2006).

Different types of remote sensing images have distinctive characteristics that help monitor various aspects of deforestation. Optical imagery is good for showing changes in vegetation distribution and spectral characteristics, but it is affected by weather conditions. SAR guarantees reliable coverage over time and provides insights into its structure, which is crucial in tropical or monsoon climate regions. LiDAR provides an exceptional level of detail for the evaluation of forest structure and biomass, obtaining highly accurate results in the analysis of complex landscapes (Wagner *et al.*, 2023). The choice of inputs should depend on the aim of the research, geographic location, and the required precision. Often, SAR is considered the most appropriate technique for forest monitoring.

2.5. *Temporal Resolutions: Bi-Temporal vs Multi -Temporal*

Change detection can be performed using either bi-temporal or multi-temporal satellite images (**Figure 6**). Bi-temporal data involves a comparison of two images taken at different times, thus making it possible to observe if there is forest loss or not (Karmoude *et al.*, 2025)(Reading *et al.*, 2024). However, multi-temporal datasets, through the integration of a series of images taken in different periods, reveal long-term and seasonal trends (Rash *et al.*, 2023)(Richardson *et al.*, 2025).

Bi-temporal imagery clearly shows the sudden changes caused by logging or fire, whereas multi-temporal imagery records the slow loss. DL architectures, such as 3D CNNs, ConvLSTMs, and attention-based networks, utilize multi-temporal data to model complex spatiotemporal dependencies (Parente *et al.*, 2019). Thus, the combination of both architectures leads to better accuracy of deforestation monitoring in various landscapes.

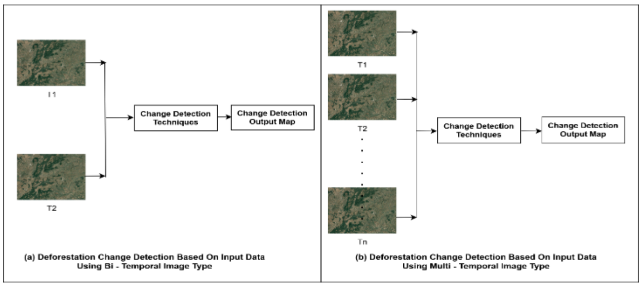


Figure 6. Deforestation change detection based on bi-temporal and multi-temporal image inputs.

3. Preprocessing and Data Preparation

Preprocessing is a method that changes the raw satellite data into uniform and ready to be analyzed datasets that can be used to monitor deforestation. A well-designed preprocessing pipeline is a key factor in greatly enhancing feature reliability and model accuracy. The steps include eliminating geometric and radiometric distortions, improving the alignment, and seasonal variations in the data.

3.1. *Image Correction*

The image correction procedure involves making the satellite images less affected by distorting factors, namely atmospheric refraction, sensor limitations, and the Earth's curvature, to the least possible extent. The accuracy of the analysis depends on this step.

- **Radiometric Correction:** The correction is performed by considering both the sensor's sensitivity and atmospheric conditions to obtain the most accurate capture of the radiation that has been reflected off the Earth's surface (Neves *et al.*, 2023)(Cazzolla *et al.*, 2025).
- **Geometric Correction**: The purpose of geometric correction is to make the satellite images correspond to the actual ground coordinates by overcoming the sensor angles, Earth curvature, and terrain distortion. This leads to the correct spatial interpretation of images (Desclée *et al.*, 2013).
- **Atmospheric Correction**: This correction minimises the effects of the atmosphere, such as water vapour and aerosols, as well as scattering, to yield true surface reflectance. The corrections performed in this manner increase the accuracy of the spectral data, which is essential for both land cover mapping and longitudinal studies (Pulella *et al.*, 2020).
- **Topographic Correction**: Topographic variations in mountainous terrain create illumination imbalances that often trigger false-positive deforestation detections due to spectral distortion. Applying correction algorithms such as C-correction or Sun-Canopy-Sensor (SCS), and Minnaert correction guided by Digital Elevation Models (DEM), helps normalise reflectance across sloped surfaces. This preprocessing step improves the reliability of change detection by minimising the influence of terrain-induced shadows (Y. Li *et al.*, 2025)

3.2. *Co-registration*

Co-registration is a crucial preprocessing step because it aligns satellite images taken at different times of the same location on Earth. This makes it possible to observe the ground-truth features across all images. Geometric unification is the key to reducing positional inaccuracies, thus increasing the performance and reliability of change detection (Lucas *et al.*, 2006).

3.3. *Area of Interest (AOI)*

AOI selection restricts analysis to a specific region, improving computational efficiency and ensuring that only relevant forested areas are processed. Spatial masks derived from shapefiles of platforms such as Google Earth Engine (GEE) and Quantum Geographic Information System (QGIS) are commonly used (L. Gupta *et al.*, 2025) (Atef *et al.*, 2023). **Figure 7** illustrates AOI extraction for the Thiruvannamalai district in Tamil Nadu, India. This region is chosen for its forest cover. Thiruvannamalai district has mixed terrain, including forest, agricultural, and rocky areas. It has high spectral variability, similar signatures, such as confusion between dry forest and barren land making land use class type separation difficult.

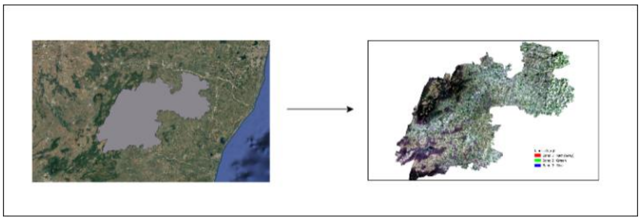


Figure 7. Extraction of Area of Interest (AOI) for Thiruvannamalai District

3.4. *Multi-Source Harmonization and Tiling*

When working with optical, radar, and thermal data, harmonization means that each data set is first resampled, co-registered, and then normalised according to the characteristics of the sensor used. Further steps, such as cloud masking, shadow removal, and radiometric calibration, will result in even more consistent datasets. The processes of AOI masking and patch tiling are done to prepare the data for ML/DL model input (Boehm *et al.*, 2013)(Lucas *et al.*, 2006).

3.5. *Preprocessing for Bi-Temporal vs Multi-temporal Inputs*

The preprocessing strategies for bi-temporal and multi-temporal inputs differ.

3.5.1. Bi-Temporal Preprocessing Workflow

Bi-temporal analysis uses images taken on different dates. Major steps are co-registration, radiometric normalisation, and cloud/shadow masking indices, like NDVI or CVA, which are then extracted to make the changes visible (Soto *et al.*, 2022)(Oca *et al.*, 2025)(Y. Zhou *et al.*, 2023).

3.5.2. Multi-temporal Preprocessing Workflow

Multi-temporal datasets on the other hand go through an extensive preprocessing pipeline that includes the steps of temporal stacking, gap-filling, and smoothing. These steps ensure that seasonal signals are preserved and thus support models designed for long-term dynamics, such as LSTM (Long Short Term Memory) or ConvLSTM networks (Ball *et al.*, 2022)(Wagner, *et al.*, 2023)(Cherif *et al.*, 2022)(Richardson *et al.*, 2025). The next step is to extract meaningful spectral and spatial features that highlight patterns of forest change.

4. Feature Extraction and Spectral Indices

After the preprocessing stage, feature extraction is the next important step in deforestation monitoring, enabling significant inferences about land cover changes and dynamic representations. Preprocessing serves to ensure data consistency, and while spatiotemporal alignment is achieved, it fails to specifically highlight the characteristics of forest change. Spectral Signatures such as NDVI, Enhanced Vegetation Index (EVI), and Normalised Burn Ratio (NBR) are very helpful for understanding features such as the amount and quality of vegetation, moisture content, and the severity of fire, all of which are important in determining the deforestation process. Feature extraction works based on spectral, spatial, and temporal characteristics, thus reducing the data dimensionality, but at the same time keeping the vital information. This process becomes the main factor that increases the input quality to the ML/DL models so they can be able to differentiate between slight vegetation changes and noise (Karmoude *et al.*, 2025).

Furthermore, spectral indices derived from satellite reflectance band combinations are crucial for improving the detection of vegetation dynamics and deforestation studies. These indices enhance the spectral contrast between forest cover and deforestation, assisting in the accurate monitoring of forest loss during bi-temporal or multi-temporal imagery (L. Gupta *et al.*, 2025)

$\mathrm{NDVI}=\dfrac{(NIR-Red)}{(NIR+Red)}$	(1)
$\mathrm{EVI}=\mathrm{G}\times\dfrac{(\mathrm{NIR}-\mathrm{Red})}{(\mathrm{NIR}+\mathrm{C}_1\times\mathrm{Red}-\mathrm{C}_2\times\mathrm{Blue}+\mathrm{L})}$	(2)
$SAVI=\dfrac{(\mathrm{NIR}-\mathrm{Red})}{(\mathrm{NIR}+\mathrm{Red}+\mathrm{L})}\times(1+\mathrm{L})$	(3)
$\mathrm{DVI}=\mathrm{NIR}-\mathrm{Red}$	(4)
$\mathrm{NDWI}=\dfrac{(\mathrm{Green}-\mathrm{NIR})}{(\mathrm{Green}+\mathrm{NIR})}$	(5)
$\mathrm{NDBI}=\dfrac{(\mathrm{SWIR}-\mathrm{NIR})}{(\mathrm{SWIR}+\mathrm{NIR})}$	(6)
$\mathrm{MSAVI}=\dfrac{2\mathrm{NIR}+1-\sqrt{(2\times\mathrm{NIR}+1)^2-8\times(\mathrm{NIR}-\mathrm{Red})}}{2}$	(7)
$\mathrm{VCI}=100\times\dfrac{(\mathrm{NDVI}-\mathrm{NDVI}_{\min})}{(\mathrm{NDVI}_{\max}-\mathrm{NDVI}_{\min})}$	(8)
$\mathrm{BAI}=1-\dfrac{1}{(0.1-\mathrm{Red})^2+(0.06-\mathrm{NIR})^2}$	(9)
$\mathrm{BSI}=\dfrac{(\mathrm{SWIR}-\mathrm{Red})-(\mathrm{NIR}+\mathrm{Blue})}{(\mathrm{SWIR}+\mathrm{Red})+(\mathrm{NIR}+\mathrm{Blue})}$	(10)
$\mathrm{NDSI}=\dfrac{(\mathrm{SWIR}-\mathrm{NIR})}{(\mathrm{SWIR}+\mathrm{NIR})}$	(11)

where Near-Infrared (*NIR*), Red , $Green$, $Blue$, and Short-Wave Infrared (*SWIR*) represent the near-infrared, red, green, blue, and shortwave infrared reflectance bands, respectively, whereas G, C_1, C_2, and L denote empirical coefficients used in the EVI formulation.

Table 1. Common Spectral Indices Used in Deforestation Change Detection.

Index	Purpose
Normalized Difference Vegetation Index (NDVI) (Nguyen Trong *et al.*, 2020)	Detects vegetation health and density, commonly used for forest loss assessment.
Enhanced Vegetation Index (EVI) (Potić *et al.*, 2023)	Reduce atmospheric and soil background noise in dense vegetation areas.
Soil Adjusted Vegetation Index (SAVI) (K. Xu *et al.*, 2021)	Compensates for soil brightness, effective in sparse vegetation zones.
Difference Vegetation Index (DVI) (J. N. Hansen *et al.*, 2020)(K. Xu *et al.*, 2021)	Quantifies vegetation density variation pre/post deforestation
Normalized Difference Water Index (NDWI) (Masolele *et al.*, 2022)(Moni *et al.*, 2025)	Identifies water presence and moisture variation in vegetation
Normalized Difference Built-up Index (NDBI) (Atef *et al.*, 2023)	Detects built-up or developed areas replacing forest cover
Modified SAVI (MSAVI) (Atef *et al.*, 2023)	Enhance vegetation detection in low-cover regions by minimizing soil influence
Vegetation Condition Index (VCI) (J. N. Hansen *et al.*, 2020)	Tracks the temporal vegetation decline for monitoring degradation
Burned Area Index (BAI) (Atef *et al.*, 2023)	Identifies fire-affected forest areas, indicating degradation
Bare Soil Index (BSI) (Masolele *et al.*, 2022)	Detects bare soil linked to deforestation or conversions
Normalized Difference Soil Index (NDSI)(Lee & Choi, 2023)	Differentiates bare soil using SWIR and NIR

As presented in **Table 1**, a range of spectral indices has been widely used in deforestation detection to evaluate vegetation health, soil exposure, water content, urban expansion, and fire damage based on satellite-derived spectral bands such as *NIR*, *Red*, and *SWIR*. These indices enhance land-cover change detection and facilitate the monitoring and quantification of forest degradation over time.

5. Analysis of Various Deforestation Change Detection Approaches

Figure 8 illustrates the structured classification of deforestation change detection methods divided into traditional, ML, and DL techniques. Each category is further grouped into pixel-based, object-based, and hybrid models, which show the specific algorithms used for accurate forest change analysis.

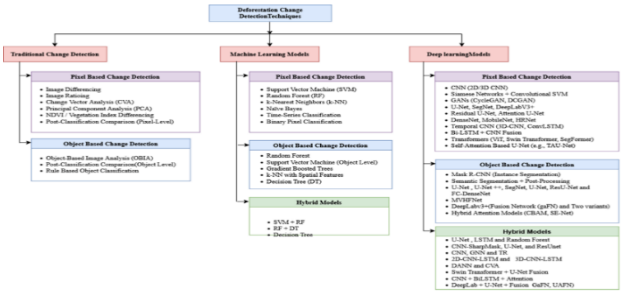


Figure 8. Classification of Deforestation Change Detection Techniques Based on Traditional, ML, and DL Approaches.

Figure 8 illustrates the structured classification of deforestation change detection methods divided into traditional techniques, ML, and DL techniques. Each category is further grouped into pixel-based, object-based, and hybrid models, which show the specific algorithms used for accurate forest change analysis. Traditional change detection methods directly compare images whereas pixel-based methods compare pixel values between images. Object-based methods work on groups of pixels instead of a single pixel. Pixel-based ML works on pixel values, object-based ML works on segmented objects, and hybrid ML combines multiple models and does so more accurately than traditional methods. DL models are advanced models that learn automatically. Pixel-based DL operates directly on images to detect patterns. Object-based DL combines deep neural networks with image segmentation to identify, delineate, and classify distinct objects within images rather than just pixels. Hybrid DL models combine multiple deep learning techniques but are highly complex.

5.1. *Pixel-Based Approaches*

Pixel-based change detection techniques monitor changes at the most basic pixel level, depending on spectral or textural properties from bi-temporal or multi-temporal satellite images. Such methods are based on the analysis of pixel-wise changes, for instance, changes in reflectance values or vegetation indices such as NDVI (Laurance *et al.*, 2014) to make the land-cover transformation visible. These techniques are very simple and less dependent on ground truth data, which gives them a major advantage in uniform forest areas. However, pixel-wise methods can be sensitive to noise, atmospheric conditions, and sensor variations; therefore, they may suffer from reduced accuracy, especially in diverse landscapes. They are computationally inefficient and do not handle the complexities of forest dynamics well. Therefore, machine learning algorithms, such as SVM, RF, and Nearest Neighbour (k-NN) (Torres *et al.*, 2021). DL frameworks have been integrated into pixel-based workflows. Models such as CNNs, U-Nets, Autoencoders, and Siamese networks assist with feature extraction and improve change detection. The main drawback is that the decisions are made for each pixel separately, which may lead to the disregard of important spatial contexts that could have increased accuracy (Wagner *et al.*, 2023)(Dong *et al.*, 2024).

5.2. *Object-Based Approaches*

Object-based change detection methods segment images into homogeneous objects based on their spatial, spectral, and contextual properties, enabling analysis at the object level rather than the individual pixel level. This approach allows for the extraction of stable and interpretable features that capture the structural patterns associated with deforestation (Laurance *et al.*, 2014) (Pulella *et al.*, 2020). Among the segmentation methods used are Simple Linear Iterative Clustering (SLIC), Simple Non-Iterative Clustering (SNIC), and Superpixels Extracted via Energy-Driven Sampling (SEED), which segment images into meaningful regions (Bergamasco *et al.*, 2022) (Desclée *et al.*, 2013). When object-based methods are combined with machine learning or deep learning algorithms, such as CNNs or decision-tree classifiers, they deliver more precise classification by incorporating spectral and geometric attributes. This is why object-based approaches are well suited for detecting subtle or fragmented changes in forested areas (X. Zhang *et al.*, 2021).

5.3. *Hybrid Approaches Combining Pixel and Object Levels*

A hybrid change detection method not only enhances accuracy but also takes advantage of the fine-grained sensitivity of pixel-based techniques and the contextual strength of object-based analysis (Selvaraj & Amali D, 2023). The integration of these methods overcomes the shortcomings of each other, such as noise in pixel detection and the ambiguity of the boundaries in object-based detection (Y. Zhang *et al.*, 2024). By integrating spectral, spatial, and temporal features, hybrid models not only improve class separability but also minimise false positives in complex forest areas. The use of SNIC-based segmentation in association with pixel-wise reflectance analysis or object classification enhanced by texture features leads to more dependable outcomes (Richardson *et al.*, 2025). In ML, hybrid techniques, such as Random Forest with rule-based spatial filtering or Support Vector Machines applied to segmented areas, have yielded better accuracy (X. Zhang *et al.*, 2021). In DL, models incorporating Convolutional Neural Networks with long short-term memory or attention modules or those that merge U-Net with object-level post-processing, successfully track both spatial structure and temporal change. These techniques are particularly effective in identifying slight, gradual deforestation trends across various landscapes (Kushwaha, 2025).

5.4. *Deforestation Change Detection Based on Traditional, ML, and DL*

5.4.1. Traditional Deforestation Change Detection Methods

As shown in **Table 2**, conventional deforestation change detection techniques utilise pixel or object-based approaches, such as NDVI, PCA, image differencing, and Object-Based Image Analysis (OBIA), to analyse temporal satellite data and identify land-cover transformations.

Table 2. Summary of Traditional Change Detection Techniques in Deforestation Monitoring.

Approach	Method	Description
Pixel-based	Image Differencing (Arcanjo *et al.*, 2016)	Identifies change by subtracting pixel values from two temporal images, highlighting areas of alteration
	Image Ratioing (Adarme *et al.*, 2020)	Divides pixel values across dates to enhance spectral variation while reducing terrain-related effects.
	PCA (Y. Zhang *et al.*, 2024)	Transforms correlated spectral bands into principal components to detect variance associated with land-cover change.
	NDVI Differencing (Masolele *et al.*, 2021)	Utilises variations in red and NIR reflectance to quantify vegetation loss between image pairs
Pixel-Based or Object-Based	Post Classification Comparison (Chen *et al.*, 2022)	Compares independently classified images to detect changes at the pixel level, useful for discrete land cover shifts
Object-Based	OBIA (Bergamasco *et al.*, 2022)	Segments imagery into homogeneous objects using spectral and spatial characteristics for refined classification
	Rule-Based Object Classification (Reading *et al.*, 2024)	Applies predefined rules on object attributes like shape and texture to assign land cover types

Traditional change detection methods, such as Image Differencing, NDVI Differencing, and PCA, work by comparing temporal image spectra and analysing pixel-wise spectral variations. In contrast, object-based approaches such as OBIA and Rule-Based Classification rely on spatial features for image segmentation. Many of these techniques struggle with classification due to spectral confusion, shadowing, and pixel mixing in mixed-forest areas. Hence, more robust ML and DL architectures are needed.

5.4.2. Machine Learning Models

ML models automatically find patterns in data, enabling efficient prediction and classification tasks. Remote sensing is used to map land cover and detect changes in deforestation through the analysis of complex, high-dimensional data, which is performed using supervised, unsupervised, or reinforcement learning strategies, and the performance is improved over time via data-driven training (Durowoju, 2025); (Selvaraj & Amali D, 2023). **Table 3** compares different ML methods for deforestation detection, including pixel-, object-, and hybrid models, along with their main findings and limitations. The models achieved very good classification results however, they had difficulties due to issues of data quality, spatial resolution, and regional variability.

Table 3. Overview of ML Models for Deforestation Change Detection: Key Findings and Limitations.

ML Models	Key Findings	Limitations
Pixel-Based Approach		
RF (Brovelli *et al.*, 2020)(Cazzolla *et al.*, 2025)(L. Gupta *et al.*, 2025)	Efficiently identified forest degradation using satellite imagery	Spatial resolution constraints in some regions.
	Delivered scalable forest loss mapping with minimal tuning.	Struggled with complex transition classes.
	Provided high accuracy for regional forest analysis using NDVI/SAVI.	Misclassified spectrally similar land types.
Maximum Likelihood (Haq *et al.*, 2021)	Highlighted human and climatic drivers of forest cover decline	Limited temporal data restricted full-scale analysis.
RF and Improved Grid Search Optimization (IGSO)(Masolele *et al.*, 2021)	Improved detection accuracy in plantation zones.	Decreased reliability in densely forested zones.
RF (Pacheco-Pascagaza *et al.*, 2022)	Enabled fast change monitoring using Sentinel 2	Geographic limitations affect generalization.
RF and Classification and Regression Tree (CART)(Karishma *et al.*, 2022)	Captured significant land cover transitions due to agriculture.	Historical data gaps limited a comprehensive assessment.
SVM (Potić *et al.*, 2023)	Increased forest classification accuracy.	Insufficient data hindered model performance.

RF, SVM, ANN, KNN, XGBoost (Rash *et al.*, 2023)	Mapped major land use changes due to urbanization	Dataset limitations affected temporal consistency.
SVM, RF, Maximum Likelihood (Atef *et al.*, 2023)	Accurately identified multiple land cover types.	Reduced accuracy in areas with high local variability.
LightGBM (Karmoude *et al.*, 2025)	Achieved fast and efficient classification using vegetation indices.	Poor performance in detecting small-scale deforestation.
SVM and RF (Meiaraj, 2025)	Offered consistent classification across periods.	Performance varies across climatic zones.
SVM (with SNIC)(Selvaraj & Amali, 2023)	Effective object-level forest classification.	Performance is reduced in mixed land types.
PVts-β, RF, NN, SVM, DT, NB (Y. Zhang *et al.*, 2024).	Integrated data sources for tropical forest detection.	The model is limited by geographic and data specificity.
Object-Based Approach		
SVM and k-NN (Selvaraj & Amali D, 2023)	Improved classification using enhanced object features.	Accuracy is impacted by input quality.
Hybrid Approach		
ML and Rule-based hybrid (Reading *et al.*, 2024)	Enabled near-real-time alerts for deforestation.	Manual verification needed; lacks full automation.
RF, SVM, DT, XGBoost, MLP, U-Net, LSTM (Richardson *et al.*, 2025)	Combined ML and DL for accurate deforestation trend mapping.	Demands extensive training and harmonized inputs.

ML studies show that RF, SVM, and Maximum Likelihood classifiers have been effective in mapping deforestation using NDVI, spectral, and object-level inputs. However, these methods often cannot cope with complex forest structures and spectrally similar areas. The models are feature-based, which makes them dependent on the quality of the input data, climate variations, and timing inconsistencies. Light GBM is fast but lacks the precision of XGBoost at fine scales. The increase in data nonlinearity and the region-specific nature of forest dynamics lead ML models to perform poorly. Thus, deep learning and hybrid models that provide scalable, contextually learned, and adaptable capabilities across different landscapes for accurate deforestation monitoring are needed.

5.4.3. Deep Learning Models

Deep learning relies heavily on hierarchical neural networks and is characterised by accurate feature extraction, land cover classification, and change detection. The deep learning models applied to deforestation change detection are listed in **Table 4**, along with their major contributions to accuracy and automation. Yet, issues such as limited data, high computational costs, and regional generalization affect the performance of even complex DL models.

Table 4. Summary of Deep Learning Approaches for Deforestation Change Detection.

DL Model	Key Findings	Limitations
Pixel-Based Approach		
Early Fusion, Siamese Network, Convolution SVM (Adarme *et al.*, 2020)	Achieved improved detection accuracy with reduced noise in forest change analysis.	Requires evaluation of alternative architectures to lower false alarms.
Cycle Generative Adversarial Network (GAN)(Soto Vega *et al.*, 2021)	Enabled deforestation detection without labelled data using image translation.	Accuracy varies across tropical biome types.
Variational Autoencoder (VAE)(Zerrouki *et al.*, 2021)	Demonstrated efficient detection of land degradation patterns.	Region-specific application due to limited satellite sources.
Orthogonal Unsupervised Discriminant Projection (OUDP), Radial-Basis Function (RBF) Based Clustering.(N. Gupta *et al.*, 2021)	Unsupervised learning effectively highlighted forest changes.	Clustering output depends on sensitive parameter settings.
U-Net, ResU-Net, SegNet, FC-DenseNet, DeepLabv3+(Torres *et al.*, 2021)	CNNs accurately captured deforestation in optical imagery.	Limited data caused reduced model generalization.
CNN, GNN, Transformer (Y. Zhang *et al.*, 2024)	Attention-based methods enhanced forest change mapping	Inconsistent outcomes across varied image sources.
DeepLabv3+ semantic segmentation (de Andrade *et al.*, 2022)	Semantic segmentation improved deforestation detection in tropical forests.	Training demands high computational resources.
U-Net (Masolele *et al.*, 2022)	Accurately classified deforestation patterns using vegetation metrics.	Restricted by limited temporal and spatial coverage.
Attention U-Net (John & Zhang, 2022)	Model adapted well to image-specific deforestation detection.	Performance varied with satellite data types.

DeepLabv3+ and Deeply Supervised Image Fusion Network (Javed *et al.*, 2023)	Detected urban forest changes using fused imagery.	Temporal gaps and regional bias reduced accuracy.
RRCNN-1, RRCNN-2 and RRCNN-3(Neves *et al.*, 2023)	Applied residual and recurrent learning for SAR-based monitoring.	Constrained to limited SAR datasets.
SiamHRnet-OCR (Wang *et al.*, 2023)	Delivered high accuracy in high-resolution forest monitoring.	Dependent on satellite availability and image quality.
Unsupervised Progressive Learning Framework (UPLF).(Y. Zhou *et al.*, 2023)	Progressive learning supported unsupervised change analysis.	Performance fluctuated under image variability.
Domain Adversarial Neural Network (DANN)(Vega *et al.*, 2023)	Detected forest changes using weak supervision effectively.	Dataset imbalance affected generalization.
U-Net (Wagner *et al.*, 2023)	Demonstrated reliable forest loss detection.	Limitations in long-term monitoring due to coarse time resolution.
U-Net with EfficientNet-B3(Fodor & Conde, 2023)	Identified burned and deforested regions with high precision.	Remote area data scarcity impacted reliability.
R2U-Net, Attention U-Net, Attention R2U-Net and Nested U-Net (Lee & Choi, 2023)	Leveraged diverse inputs for comprehensive mapping.	Change detection reduced by limited revisit frequency.
DL-DEGRAD (Dalagnol, Wagner, *et al.*, 2023)	Captured tropical degradation patterns via learned features.	Failed to detect subtle changes in coarse imagery.
Self-supervised Contrastive Learning Transformer (SWCL-T)(Dong *et al.*, 2024)	Performed unsupervised change analysis robustly on SAR images.	High complexity and SAR-only support limited applicability.
Swin Transformer V2, VGG16, Mixed Feature Pyramid (MFP)(Zheng *et al.*, 2024)	Combined multiscale features for accurate binary detection.	Dual-branch model increased resource requirements.
Transformer-based model using an attention mechanism (Alshehri *et al.*, 2024)	Achieved state-of-the-art accuracy using bi-temporal imagery.	Computational cost and low interpretability are concerns.
U-Net (customized with 13 tensor inputs)(Moni *et al.*, 2025)	Enabled long-term multi-class mapping with the Landsat series.	Misclassification issues due to striping and index variations.
Hybrid Approach		
DL with Multinomial Logistic Regression + Softmax (Srivastava & Ahmed, 2024)	Mapped transitions effectively using learned pixel relationships.	Relies on prior classification; lacks end-to-end learning.
CNN Ensemble (AlexNet to Swin)(Coţolan & Moldovan, 2024)	Successfully transferred features across forest types.	Accuracy is reduced across ecosystems, and ensemble complexity is high.
Modified U-Net in Siamese structure and Feature Aggregation Module (X. Li *et al.*, 2025)	Introduced generative consistency for accurate binary detection.	Relies on controlled noise, moderately compute-intensive
Convolutional Wavelet Neural Network (CWNN), Deep Convolutional Generative Adversarial Network (DCGAN) (X. Zhang *et al.*, 2021)	Accurately detected localized forest change using wavelet-texture fusion.	Model generalizability is tested in varied environments.
DeepForest-1a/b/c, DeepForest-2a/b (Cherif *et al.*, 2022)	Provided land use classification using combined SAR and optical inputs.	Limited training data influenced regional performance.
Transformer-based Multiscale Siamese Framework (TMSF) (Tarazona *et al.*, 2021)	Achieved accurate results by fusing local-global representations.	Boundary clarity and semantic context remain limitations.
U-Net and ResNet-34(pre-trained) (Kushwaha, 2025)	Improved forest segmentation using residual learning on aerial imagery.	Limited to single-date images and mask quality.

According to DL case studies, U-Net, Res U-Net, and DeepLabv3+ have demonstrated superior performances in semantic segmentation and vegetation detection. Transformers and Siamese networks enhance spatiotemporal awareness using attention mechanisms. GANs facilitate the utilization of unlabelled data, whereas VAE, CCWNN, and contrastive learning provide robust capabilities for pattern extraction. However, several challenges remain, such as reliance on high-quality satellite imagery, computational demands of these models, and limited temporal generalization. Despite these obstacles, deep learning surpasses traditional machine learning in terms of scalability, contextual adaptability, and feature autonomy. As forest dynamics become increasingly nonlinear and data-rich, the development of advanced hybrid models that integrate multimodal inputs and cross-domain learning is crucial for accurate, generalised mapping of deforestation across diverse environments.

Deforestation change detection has evolved from spectral and index-based techniques to spatial–temporal and multimodal frameworks because early methods were often sensitive to heterogeneous landscapes, spectral confusion, and seasonal variability. As monitoring tasks became more complex, object-based, hybrid, and deep learning approaches gained importance because they could better capture contextual, multiscale, and temporal change patterns. More recently, Transformer based models have attracted attention for their ability to model long range spatial relationships, although their computational demands remain high. Despite these advances, persistent challenges include limited cross regional generalisation, domain shift across sensors and acquisition conditions, annotation scarcity, and class imbalance in deforestation datasets.

5.5. *Benchmark Datasets for Deforestation Change Detection*

To enable reproducibility and standardised evaluation, deforestation change detection based on satellite imagery has used the most widely recognised benchmark datasets. These datasets have varying spatial resolutions, temporal intervals, geographic extents, and sensor modalities, enabling rigorous cross-model assessments and increasing the reliability and generalizability of deep learning methodologies in remote sensing. The most widely used datasets for deforestation change detection are provided in **Table 5**, which includes high-resolution optical and SAR-based sources for monitoring forest loss. These datasets enable applications such as trend analysis, real-time alerts, and training deep learning models across diverse regions.

Table 5. Commonly Used Datasets for Deforestation Change Detection.

Dataset Name	Source	Description
LEVIR-CD (Zheng *et al.*, 2024),(X. Li *et al.*, 2025), (Tarazona *et al.*, 2021)	WHU, China	High-resolution RGB image pairs (1024×1024) annotated for urban change and also used in forest boundary detection.
WHU-CD (Zheng *et al.*, 2024),(X. Li *et al.*, 2025),(Tarazona *et al.*, 2021)	Wuhan University	Annotated building footprint changes, often adapted for deforestation in high-resolution imagery.
SYSU-CD (Zheng *et al.*, 2024),(X. Li *et al.*, 2025),	Sun Yat-Sen University	RGB images designed for general change detection; applied in forest cover mapping.
CDD (Tarazona *et al.*, 2021)	Cloud-CD Dataset	Bi-temporal optical imagery designed to evaluate robustness in cloud-prone scenes.
Planet Amazon NICFI (Dalagnol, Wagner, *et al.*, 2023), (Richardson *et al.*, 2025)	Planet Labs	High-resolution monthly monitoring data used for tracking tropical deforestation.
Hansen Forest (Adarme *et al.*, 2020)	Global Forest Watch	Global annual forest cover loss with pixel-level labels; used in trend forecasting.
Global Forest Change (GFC)(M. C. Hansen *et al.*, 2013)	University of Maryland,	Global maps of forest cover, gain, and annual forest loss derived from Landsat imagery.
PRODES (Wagner *et al.*, 2023)	INPE, Brazil	Annual deforestation mapping in the Legal Amazon with validated polygons.
RADD Alerts (Masolele *et al.*, 2021)	Global Forest Watch / Wageningen University	Real-time alerts for tropical forest loss based on Sentinel-1 SAR imagery.

Beyond their availability, these benchmarks differ in the type of evidence they provide for model design and evaluation. LEVIR-CD, WHU-CD, SYSU-CD, and CDD are primarily high-resolution remote-sensing change-detection benchmarks and are more suitable for testing fine-scale change boundaries and binary segmentation architectures than for direct ecological generalisation in deforestation studies (Cheng *et al.*, 2024) . Hansen Global Forest Change (GFC) is more appropriate for pixel-level regional or global forest-loss analysis, while PRODES is especially valuable when official annual deforestation mapping is needed for area-based assessment (Wu *et al.*, 2025)(Beyer *et al.*, 2025)(Messias *et al.*, 2024). Planet NICFI is particularly useful for monitoring small clearings because of its 5 m spatial detail and monthly tropical coverage, whereas RADD alerts are more appropriate for near-real-time monitoring in persistently cloudy humid tropics because they rely on cloud-penetrating Sentinel-1 radar (Wagner *et al.*, 2023)(Doblas *et al.*, 2022)(Welsink *et al.*, 2023). Taken together, the current benchmark landscape is still stronger for binary change detection than for standardised multiclass change mapping; this is best treated as an inference from recent benchmark reviews, which also show that transferability depends strongly on sensor type, annotation design, and geographic context (Beyer *et al.*, 2025)(Cheng *et al.*, 2024).

5.6. *Comprehensive Comparison and Applicability Analysis*

Pixel-based and traditional methods work well for spectrally clear-homogeneous data, but they underperform when there is spectral confusion. Classic classifiers such as Maximum Likelihood and CART are less commonly used than RF and LightGBM in medium-resolution applications (Karmoude *et al.*, 2025). ML models are more suitable for resource limited and large-scale operational monitoring. On the other hand, DL models perform better in heterogeneous and complex forest environments with high spatial variability. Although they require greater resources, DL models are still widely used because they offer good segmentation performance at a manageable computational cost. But transformer-based models require more memory with longer training time. They also usually require more data, especially for tasks like optical–SAR fusion and temporal modelling. The performance of advanced DL models is often limited by labelled data scarcity and cross regional generalization issues (Zheng *et al.*, 2024)(Alshehri *et al.*, 2024). Multimodal and hybrid DL frameworks improve contextual learning but increase implementation complexity. So, the choice of the algorithm should not only depend on the performance but also on the availability of the data and computing resources.

6. Deforestation Change Detection Based on Output Map

Change detection outputs in deforestation monitoring primarily fall under two categories: binary and multi-class. **Figure 10** illustrates the workflows for binary and multi-class deforestation change detection using bi-temporal and multi-temporal satellite image data. It compares direct feature-based approaches with land-cover classification methods that employ ML or DL techniques to generate change maps.

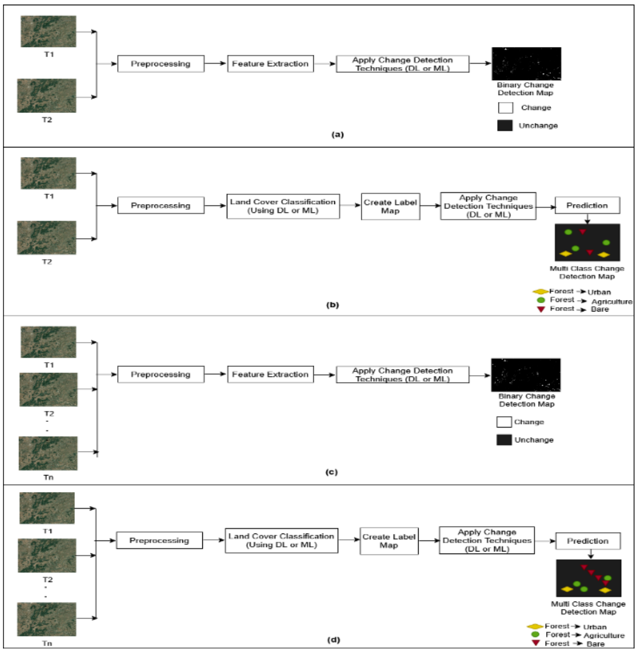


Figure 9. Workflow Architectures for Binary and Multi-class Deforestation Change Detection Using DL and ML Techniques (a) Binary Change Detection Map Using Bi-Temporal Imagery, (b) Multi-class Change Detection Map Using Bi-Temporal Imagery Binary Change Detection, (c) Binary Change Detection Map Derived from Multi-temporal Imagery, (d) Multi-class Change Detection Map Derived from Multi-temporal Imagery

Figure 9 illustrates four change detection strategies based on temporal input and output type. Comparison of bi-temporal imagery helps detect if a change has occurred or not, with multi-class change detection using bi-temporal imagery we can identify the land type and then determine if change has occurred or not. With multi-temporal imagery from different years, a model can find if any change has happened over time or can identify different land types, then determine what type of changes happened over the years.

(a) Binary Change Detection Map Using Bi-Temporal Imagery

Binary change detection using bi-temporal satellite imagery is extensively utilised in deforestation monitoring because of its efficiency in generating "change/no-change" outputs. Models such as hybrid RF-NDVI (Reading *et al.*, 2024)and LightGBM with vegetation indices (Karmoude *et al.*, 2025) offer rapid and resource-efficient mapping. Advanced approaches, such as UPLF (Y. Zhou *et al.*, 2023), Siamese CNNs (Adarme *et al.*, 2020), (X. Li *et al.*, 2025), and transformer-based models (Alshehri *et al.*, 2024), provide accurate segmentation without requiring extensive annotations. Recent innovations include SiamHRnet-OCR for high-resolution binary mapping, DeepLabv3+ for handling data imbalance (Javed *et al.*, 2023), and domain-adaptive methods using GANs (Soto-Vega *et al.*, 2021). Collectively, these methods ensure scalable and precise forest-loss detection for large-scale environmental monitoring systems.

(b) Multi-class Change Detection Map Using Bi-Temporal Imagery

The application of multi-classification to bi-temporal data has improved the analysis of deforestation, shifting from simple binary classifications to the detection of land-use changes across diverse categories. Some studies, such as those of Karishma *et al.* (Karishma *et al.*, 2022) and (Karishma *et al.*, 2022) found that scalable multi-class outputs were possible by using spectral data and NDVI-derived inputs (Cazzolla *et al.*, 2025). Although they are very complex, deep learning algorithms such as DeepLabv3+ (Javed *et al.*, 2023) and DL-DEGRAD techniques have successfully detected various types of degradation in Planet NICFI data. Moreover, the combination of Sentinel data and global bi-temporal datasets has consolidated mapping capabilities in areas with frequent cloud cover.

(c) Binary Change Detection Map Derived from Multi-temporal Imagery

Multitemporal satellite imagery is a significant advantage for binary change detection because it captures gradual deforestation patterns and minimises seasonal misclassifications. The applied combined technology of both ML and DL models, such as RF, U-Net, and LSTM on Landsat time series (Richardson *et al.*, 2025) and Random Forest in GEE using NDVI/SAVI indices (L. Gupta *et al.*, 2025) increased the temporal consistency of the studies. One of the variants of U-Net (Wagner *et al.*, 2023), (Lee & Choi, 2023), and transfer learning using CNNs (Coţolan & Moldovan, 2024) achieved high accuracy. U-Net models on the Sentinel-2 and Planet NICFI datasets (Dalagnol, Wagner, *et al.*, 2023), (Richardson *et al.*, 2025) effectively monitored deforestation in Ukraine and Brazil. Additionally, the RRCNN series (Neves *et al.*, 2023) and comparative analysis with PRODES (Wagner *et al.*, 2023) enabled consistent detection of subtle and large-scale forest changes.

(d) Multi-class Change Detection Map Derived from Multi-temporal Imagery

The use of multiclass classification with multi-temporal images has provided a robust description of land-use changes and ecological shifts, thereby facilitating more strategic forest management. Different methods, such as the supervised classification of optical data (Haq *et al.*, 2021) and ensemble ML models (Rash *et al.*, 2023), have successfully revealed the effects of human activities on the environment. The application of sequential spectral inputs is an important factor in long-term mapping (Richardson *et al.*, 2025), (Meiaraj, 2025). Among others, DL-DEGRAD (Dalagnol, Wagner, *et al.*, 2023), modified U-Net (Moni *et al.*, 2025), and DLCD (Srivastava & Ahmed, 2024) These are deep learning models that can detect a wide range of transitions. Other strong methods, such as DeepForest and CNN-based predictors that operate on multi-sensor time series, have enabled dynamic multi-class labelling. Although these models require substantial computational resources, they still play an important role in domains such as REDD+, carbon tracking, and land-use forecasting across diverse landscapes.

7. Result and Discussion

This section presents a detailed comparison of ML and DL models for detecting deforestation changes, accompanied by visual aids and performance tables. The analysis revolved around factors such as the data source, Task category, algorithmic strategies, analysis levels, and output classifications.

7.1. *Common Performance Metrics*

Evaluation metrics are essential for assessing the effectiveness of deforestation change detection models by measuring classification accuracy, error rates, and spatiotemporal reliability using indicators such as precision, recall, F1-score, overall accuracy, kappa, Intersection over Union (IoU), and user/producer accuracy. High OA might still be observed in deforestation mapping despite missing many deforested pixels because the non-deforested class usually covers most of the image. F1-score is preferable than OA as it combines both precision and recall (Z. Zhou *et al.*, 2023). IoU is also more useful because it directly measures the overlap between the predicted deforested area and the reference area. (Farhadpour *et al.*, 2024). Maxwell *et al.* showed that reporting only OA can be misleading in the presence of class imbalance, especially when the background class is dominant (Maxwell & Warner, 2026). Therefore, for rare-class problems such as deforestation detection, F1-score and IoU give a more realistic view of model reliability than OA alone.

$P = \dfrac{TP}{TP + FP}$	(12)
$R = \dfrac{TP}{TP + FN}$	(13)
$F1 = 2 \times \dfrac{Precision.Recall}{Precision + Recall}$	(14)
$OA = \dfrac{TP + TN}{TP + TN + FP + FN}$	(15)
$K = \dfrac{P_O - P_e}{1 - P_e}$	(16)
$IoU = \dfrac{TP}{TP + FP + FN}$	(17)
$AA = \dfrac{TP + TN}{P + N} \times 100$	(18)

Precision (P), Recall (R), F1-Score (F1), Overall Accuracy (OA), User's Accuracy (UA), Producer's Accuracy (PA), Alarm Area (AA), TP-True Positive, TN-True Negative, FP-False Positive, FN-False Negative, **Table 7** enumerates the prominent evaluation metrics used to assess deforestation change detection models, namely precision, recall, F1-score, overall accuracy, IoU, kappa, and user/producer accuracy.

7.2. *Evaluation of ML-Based Models*

Table 6 presents a comparison of the performance of different ML models for deforestation change detection, indicating that these models achieve high overall accuracy and kappa, with the LightGBM- and SVM-based approaches leading. The ML models have shown excellent accuracy, especially in pixel-based implementations such as RF, SVM, and LightGBM. In particular, LightGBM (Karmoude *et al.*, 2025) achieved the highest overall accuracy (99.3%) and Kappa coefficient (0.986) using Sentinel-2 bi-temporal imagery, which was enhanced with vegetation indices. Similarly, hybrid methods that combine U-Net, RF, and LSTM (Richardson *et al.*, 2025) also yielded a 99% OA. Classic models such as Maximum Likelihood (Haq *et al.*, 2021) and optimised RF (Masolele *et al.*, 2021) were at par in terms of accuracy, scoring between 93% and 96%.

Table 6 Comparison of ML models for deforestation monitoring grouped by classification type and task category.

Category	Reference	ML Model	OA (%)	K (%)	P (%)	R (%)
Binary Classification						
Forest change/deforestation / forest-loss detection	(Brovelli et al., 2020) (Cazzolla et al., 2025) (L. Gupta et al., 2025)	RF	0.95	0.91	0.98	0.93
			80	-	-	-
			88.76	0.87	91.95	-
	(Karmoude et al., 2025)	LightGBM	84.8	0.73	0.65	-
Forest/vegetation detection and monitoring	(Potić et al., 2023)	SVM	99.01	-	-	-

Near real time deforestation alter	(Oca et al., 2025)	ML and Rule-based hybrid	91.84	-	-	-
Multiclass Classification						
Forest cover / land-cover classification and change detection	(Haq et al., 2021)	Maximum Likelihood	94.6	0.93	-	-
	(Karishma et al., 2022)	RF and Classification and Regression Tree (CART)	85	-	-	-
	(Rash et al., 2023)	XGBoost	96.67	0.96	-	-
	(Atef et al., 2023)	SVM, RF, Maximum Likelihood	95.95	0.94	-	-
	(Selvaraj & Amali, 2023)	SVM (with SNIC)	94.42	0.9207	-	-
	(Selvaraj & Amali D, 2023)	SVM and k-NN	0.92	-	-	-
	(Meiaraj, 2025)	SVM and RF	0.94	0.92	-	-
Plantation / crop-related classification	(K. Xu et al., 2021)	Improved Grid Search optimisation (IGSO)	96.08	0.94	-	-
Near-real-time vegetation / forest-loss monitoring	(Pacheco-Pascagaza et al., 2022)	RF	92.5	-	-	-
Tropical deforestation detection	(Tarazona et al., 2021)	PVts-β, RF, NN, SVM, DT, NB	95.09	93.18	-	-

Table 7. Comparison of DL models for deforestation monitoring grouped by classification type and task category.

Category	Reference	DL Model	OA(%)	F1	P (%)	R (%)	IoU (%)	K (%)
Binary Classification								
Deforestation/ Forest Change Detection	(Adarme *et al.*, 2020)	Early Fusion, Siamese Network, Convolution SVM	98.0	63.2	-	-	-	-
	(Soto Vega *et al.*, 2021)	CycleGAN	-	85.5	-	-	-	-
	(Torres *et al.*, 2021)	U-Net, ResU-Net, SegNet, FC-DenseNet, DeepLabv3+	-	78.0	-	-	-	-
	(de Andrade *et al.*, 2022)	DeepLabv3+ Semantic Segmentation	-	73.42	-	-	-	-
	(Neves *et al.*, 2023)	RRCNN-1, RRCNN-2, RRCNN-3	-	71.6	97.4	56.7	-	-
	(Wang *et al.*, 2023)	SiamHRnet-OCR	98.98	68.92	64.82	78.97	-	-
	(Vega *et al.*, 2023)	Domain Adversarial Neural Network (DANN)	-	81.6	-	-	-	-
	(Lee & Choi, 2023)	R2U-Net, Attention U-Net, Nested U-Net	-	90.0	-	-	-	-
	(Alshehri *et al.*, 2024)	Transformer (Attention-based)	93	90	84.70	84.53	-	-
Forest / Non-forest segmentation with deforestation implications	(John & Zhang, 2022)	Attention U-Net	-	97.0	-	-	-	-
	(Wagner *et al.*, 2023)	U-Net	98.11	98.0	98.0	-	-	-
	(Kushwaha, 2025)	U-Net	87.0	-	-	-	78.0	-
General change detection	(X. Zhang *et al.*, 2021)	CWNN, DCGAN	99.61	-	-	-	-	-
	(N. Gupta *et al.*, 2021)	OUDP, RBF Clustering	95.77	-	-	-	-	-
	(Y. Zhang *et al.*, 2024)	CGMMA	99.32	92.81	-	-	86.58	-
	(Y. Zhou *et al.*, 2023)	UPLF	-	95.43	94.05	96.86	-	-
	(Dong *et al.*, 2024)	Self-supervised Weighted Contrastive	98.42	-	-	-	-	93.96

		Learning with Transformer (SWCL-T)						
	(Zheng *et al.*, 2024)	Swin Transformer V2, VGG16, CBAM, SSL, and Mixed Feature Pyramid (MFP)	99.79	99.15	99.18	99.13	99.12	94.02
	(X. Li *et al.*, 2025)	U-Net in Siamese	-	92.66	93.53	91.8	86.34	-
Environmental detection other than deforestation	(Zerrouki *et al.*, 2021)	Variation Autoencoder (VAE)	98.0	98.0	-	-	-	-
	(Fodor & Conde, 2023)	U-Net	90.7	88.0	-	-	80.0	-
	(Coţolan & Moldovan, 2024)	VGG19	-	92.0	93.0	91.0	-	-
Multiclass Classification								
Land-use / Land-cover and post-deforestation mapping	(Cherif *et al.*, 2022)	DeepForest-1a/b/c, DeepForest-2a/b	77.9	92.0	-	-	-	-
	(Masolele *et al.*, 2022)	U-Net	-	79.0		-	-	-
	(Moni *et al.*, 2025)	Customized U-Net (13 Tensor Inputs)	84.0	81.0	82.0	79.0	68.0	-
Forest degradation / Semantic change mapping	(Javed *et al.*, 2023)	DeepLabv3+ and Fusion Network	-	91.5	-	-	84.4	88.7
	(Dalagnol, Wagner, *et al.*, 2023)	DL-DEGRAD	99.36	84.0	80.0	88.0	-	-
	(Srivastava & Ahmed, 2024)	DL with Multinomial Logistic Regression and softmax	91.80	-	-	-	-	-

7.3. *Evaluation of DL-Based Models*

The performance of deep learning models for detecting deforestation changes is illustrated in **Table 7**, with high accuracy and F1-scores already achieved by U-Net variants, Transformers, and GANs, indicating great potential for reliable forest monitoring. The deep learning models had the best classification power among all tasks, regardless of whether they were binary or multi-class. CNN-based architectures achieved 99.7% OA and 99.1% precision (Torres *et al.*, 2021). In contrast, transformer-based frameworks, such as SWCL-T (Dong *et al.*, 2024) and Swin Transformer V2 (Zheng *et al.*, 2024), performed very well throughout, with F1-scores of nearly 0.92. TMSF (Tarazona *et al.*, 2021), a hybrid model that fuses multi-scale and attention mechanisms, was the one that produced the most consistent outcomes (F1 > 95%, IOU > 90%).

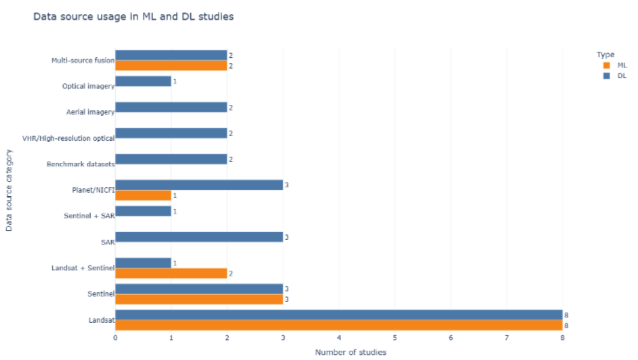


Figure 10 Distribution of data-source categories used in ML and DL studies for deforestation monitoring.

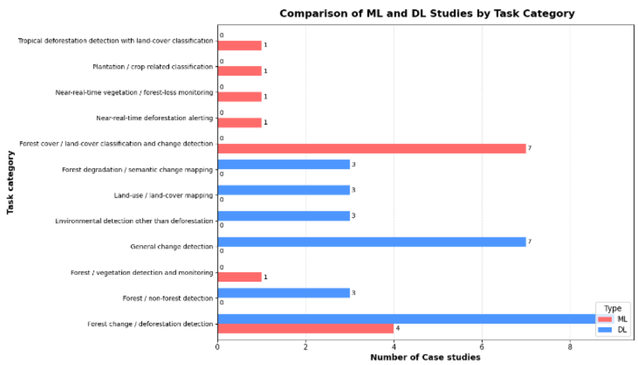


Figure 11. Comparison of ML and DL case studies across task categories for deforestation monitoring

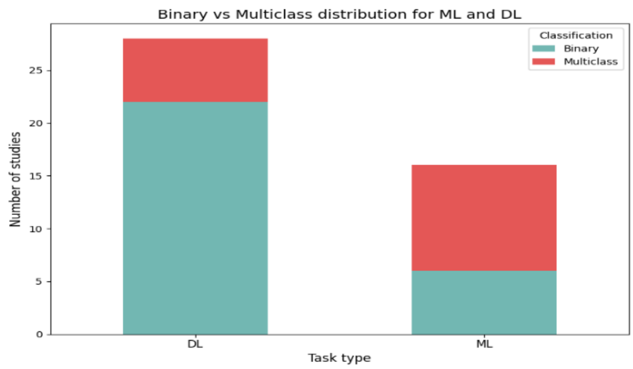


Figure 12. Binary and multiclass distribution of ML and DL studies for deforestation monitoring.

Figure 10 shows that both ML and DL studies are mainly focused on Landsat and Sentinel data, which remain the most widely used sources for deforestation-related analysis. **Figure 11** depicts the task category comparison, which suggests that DL approaches are more commonly applied to forest change detection, forest/non-forest mapping, general change detection, and semantic change analysis. **Figure 12** compares binary and multiclass study distributions for ML and DL, showing that DL is used much more often in binary classification tasks.ML studies are fewer overall and show a more balanced distribution, with multiclass studies slightly exceeding binary ones.

7.4. *Socio-Environmental Implications and Corporate Accountability*

Satellite-based monitoring developed under the REDD+ Measurement, Reporting, and Verification (MRV) system allows independent tracking of forest cover, degradation, and carbon stocks. This helps to compare the actual environmental changes with corporate sustainability claims thereby uncover greenwashing. At the same time, remote sensing data can reveal deforestation hotspots, leakage effects, and ecosystem degradation linked to commodity production, allowing the identification of climate-related physical risks across global supply chains (Brovelli *et al.*, 2020). In addition, deforestation-driven land-use changes contribute to regional air and water pollution, which can be effectively monitored by analysing satellite environmental data. Furthermore, integrating analytical methods such as PCA, Epidemic Keratoconjunctivitis (EKC), and the Tapio model helps understand linkages in pollution growth and supports green innovation and sustainable policy decisions (Ma, S. 2025) (Ma *et al.*, 2026). Environmental, Social, and Governance (ESG) is a framework used to measure a company's impact on the planet and people. High-resolution monitoring data can improve ESG rating consistency by providing a common and transparent 'truth layer' for all rating agencies. This reduces the reliance on subjective assessments and ensures consistent, real-world environmental performance (Yan *et al.*, 2025). In this study, data on 133 Chinese A-share companies from 2010 to 2022 were analysed using the Data Envelopment Analysis (DEA) model to measure green innovation performance, and a fixed-effects regression model was used to analyse the impact of ESG on innovation. ESG disclosure by companies improves green innovation and will help perform better on environmental metrics. It also makes companies transparent and trustworthy.(C. Xu *et al.*, 2025). The authors conducted the study on A-share listed companies from 2008 to 2023. They discuss how network effects or spillovers arise when companies influence each other, especially in supply chains. When it comes to climate risk external pressure and internal thinking affect companies. Due to external pressure, suppliers cannot hide information and find it hard to engage in greenwashing whereas due to internal thinking the companies avoid false environmental claims. The other important factors include power, technology and resources, which increase the supply chain pressure. These factors along with laws drive companies to improve their environmental behaviour (Zhong, Yan, *et al.*, 2026). Advanced DL models enhance transparency by analysing ESG and environmental data to identify inconsistencies in corporate sustainability claims. This empowers retail investors to detect greenwashing and take informed actions, thereby promoting greater corporate accountability and more ethical behaviour (Liu *et al.*, 2024)

8. Challenges and Future Directions

Despite significant advancements, deforestation change detection using ML and DL models faces persistent limitations. Data dependency and label scarcity remain critical, with weakly supervised models (Y. Zhou *et al.*, 2023)(Vega *et al.*, 2023) often underperforming in complex ecosystems. Temporal and spatial variabilities affect generalisation (Neves *et al.*, 2023). High-performing architectures, such as the Swin Transformer (Zheng *et al.*, 2024) and Siamese networks (X. Li *et al.*, 2025), require extensive computational resources, which limit their real-time applications. Moreover, noise and spectral confusion in optical imagery (Alshehri *et al.*, 2024)(Moni *et al.*, 2025)(L. Gupta *et al.*, 2025) degrade the classification accuracy. Multiclass classification remains challenging because of class imbalance and overlapping land cover (Srivastava & Ahmed, 2024), (Masolele *et al.*, 2022). In addition, the limited integration of object-based methods (Selvaraj & Amali, 2023) restricts their spatial interpretability. Future research must focus on scalable, label-efficient models, cross-regional adaptability robust preprocessing to counter atmospheric interference, and enhanced fusion of spatial hierarchies to support interpretable, high-resolution outputs.

Another research direction can consider the balance between fast detection and reliable forensic results. While some require quick alert systems for timely action, other tasks such as compliance reporting and environmental lawsuits require more accurate results. (Zeng *et al.*, 2025). Thus, multi-stage AI monitoring systems that combine fast screening with accurate results are valuable. Use of AI-based digital tools will improve environmental governance. With these improvements, remote sensing can not only detect forest loss but also promote transparency, accountability, and sustainable development (Ma *et al.*, 2026).

8.1. *Emerging Technologies for Next-Generation Forest Monitoring:*

New technologies will reshape forest monitoring, moving beyond cloud-centric remote sensing workflows. Low Earth Orbit (LEO) satellite constellations provide high-revisit, high-resolution observations that improve small-scale canopy disturbance detections. Recent studies using Planet NICFI and PlanetScope imagery show that fine-resolution observations improve tropical forest cover mapping during short-duration disturbance events. (Wagner *et al.*, 2023)(Pickering *et al.*, 2021) (Dalagnol, Hubert, *et al.*, 2023). In the future, AI-on-chip edge computing, where inference is performed close to the sensor and not only in the cloud, can be explored. These systems support low-latency, low-power, and communication-efficient surveillance in remote forests. (Andreadis *et al.*, 2021)(Mporas *et al.*, n.d.). This indicates that future systems will rely on integrated architectures that combine wide-area satellite surveillance with localised edge intelligence.

8.2. *Integration with Governance and Policy Frameworks:*

This study explains how the government and the courts, working together, can help companies become more responsible. It introduces a concept called Government-Court Coordination (GCC) which means governments help with policies and support, and courts handle legal processes. This leads to reduced financial pressure for companies and better human capital. This concept was implemented in China and is mainly used for bankruptcy cases. India utilises remote sensing through the Forest Survey of India (FSI) to assess forest cover and monitor degradation every two years. National Forest Policy (NFP) in 1988 aims to maintain 33% of the geographical area under forest cover. Green India Mission (GIM) aims to increase forest/tree cover by 5 million hectares (mha) and improve the quality in another 5 mha. The National Compensatory Afforestation Fund Management and Planning Authority *(NATIONAL CAMPA*) mandates the utilisation of funds for reforestation when forests are diverted for industrial use. (Zhong, Qin, *et al.*, 2026). The Indian government introduced the Forest (Conservation) Amendment Act, 2023, for better forest protection. India aims to achieve Net Zero carbon emission by 2070 through better forest protection. The government plans to increase forest and tree cover to one-third of India's land area. The Act supports forest restoration, ecological security, and sustainable development. (The Gazette of India, 2023, Section 2, Preamble)

9. Conclusion

This review article provides a systematic overview of deforestation change detection using remote sensing by evaluating key elements, including data sources, levels of analysis, algorithmic techniques, and change detection outputs. The findings indicate that combining bi-temporal and multi-temporal satellite imagery with advanced ML and DL models, such as CNNs, U-Net variants, Transformers, and hybrid frameworks, improves detection accuracy and spatiotemporal detail. Current research is still dominated by binary classification due to its simplicity and efficiency, whereas multiclass approaches, though more challenging, offer greater ecological interpretability. In addition, multi-source data fusion, pixel–object hybrid strategies, and attention-based or self-supervised methods have contributed to notable improvements in change-mapping performance across different landscape types. ML models achieve high accuracy, but performance varies across studies. DL models generally show higher and more consistent performance than ML models. Basic DL models achieve moderate accuracy from 78% to 98% in change detection tasks. Advanced DL models like transformer achieve very high performance nearly 99.79% overall accuracy and 99.15% of F1-score and better feature representation. Combining advanced DL with multi-source data clearly improves overall detection performance. However, important challenges remain, including limited model generalizability, complex preprocessing requirements, class imbalance, scalability constraints, and high computational cost. A general problem is that training the model in one region may not work well in other regions or datasets. Due to data limitations, high-performing DL models need large, labelled datasets, which are not always available. In terms of computational cost, advanced models require high memory, longer training time and powerful GPUs. Future research should therefore place greater emphasis on cross-regional generalisation and domain adaptation, so that models can be transferred more reliably across ecosystems and sensor settings. Real-time and near-real-time monitoring systems should also be designed to balance rapid alert generation with verification reliability. Standardised benchmark datasets are needed for multiclass and multimodal evaluation. Future monitoring systems will be scalable as they will combine lightweight edge-deployable models with emerging technologies such as LEO constellations. Future research will depend not only on higher accuracy but also on the development of monitoring frameworks that are robust and operationally practical.

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